International Workshop on
Social Space and Geographic Space

SGS’07

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Melbourne Business School, Mt Eliza, Victoria, Australia
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Preface

Social agents are embedded in both social structures and in geographical space. The combination of social and geographic space has often been neglected. With few exceptions, social network theory ignores geographic space, and artificial intelligence studies often assume local societies without sophisticated conceptualisations of social networks. Yet the multiple embeddedness of actors in both physical and social space has important implications for understanding social behaviour. In many related research areas, there is a growing recognition that associations between social structure and geographical nearness may affect social systems and social behaviours.

Research on the associations between social and geographic space occurs in disconnected scientific communities, including human geography, social network theory, and geographic agent-based simulation. The International Workshop on Social Space and Geographic Space aims to bring the social and the spatial disciplines together, to discover joint foundations in social and geographical theory, and to integrate approaches for modelling spatial context and social behaviour.

Seven papers were selected for presentation at the workshop, out of twelve papers submitted.

The chairs would like to acknowledge the support from the ARC Research Network on Spatially Enabled Social Sciences. Special thanks go to Lin-Jie Guan for typesetting these proceedings.

19 September 2007
Stephan Winter and Garry Robins
SGS’07 Chairs
Organization

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Abstract. Though often viewed as aspatial abstractions, social networks represent relationships among actors in the physical world. As such, these relationships operate under spatial and temporal constraints that have substantial implications for the structures they constitute. More profoundly, the joint consideration of space and structure gives rise to a “social geography” whose properties are not reducible to those of either element in isolation. Here, I introduce a number of basic results in the measurement and analysis of spatially embedded social networks. These include the use of spatial interaction functions to represent spatial dependence, modeling of spatially embedded networks via curved exponential families, and the extrapolative simulation of spatial macrostructure. A number of sample applications will be shown, ranging from group interactions to interorganizational collaboration networks.
Abstract. This paper examines external spatial constraints on network processes, generalising the exponential random graph class of network models. We develop a hierarchical set of nested models for social networks embedded spatially, in which the inverse square of the Euclidian distance between them is a dyadic covariate. Using a simulation approach based on the Metropolis algorithm, we explore spatial embeddings of graphs with different global features of network structure (random graphs and graphs with small-world properties). Simulation results demonstrate the way in which individuals’ geographical locations and endogenous network clustering processes combine to structure patterns in social networks.

Keywords: social networks, Euclidean distance, spatial effects, exponential random graph

1 Introduction

Social network theory often neglects the fact that social interactions occur in a particular time and place. Social network analysis mainly focuses on studying interactions at a micro-level, where behaviour, choice, information exchange and mutual influences depend on interactions with individual network partners. However, geographical space matters. Social connections are not independent of relative geographical proximity of actors, and geographical proximity plays an important role in structuring patterns of human interactions, which in turn influence people’s movements. One can not understand the emergence of organized social systems without understanding the multiple embeddings of social agents in both social and physical spaces [1].

A growing body of research indicates that physical distance is a moderator of social interactions. In 1932 Bossard’s empirical study revealed that marriages in Philadelphia tended to be among people within the same neighbourhood [3]. Further evidence for the importance of physical proximity on forming different types of relationship has come from the work of [5; 9; 16; 29]. These results all indicated that the spatial arrangement of individuals is an important factor in predicting the potential tie pool. Empirical studies have also focused on establishing a function relating social interaction to physical distance [13; 15; 26; 31]. The common finding for this body of research has been an inverse square relationship between physical distance among individuals and the probability of interaction. The Latane et al study also revealed a similar relationship between space and interactions for different human groups, regardless of their socio-economic
and cultural characteristics as well as their access to different communication technologies. In general, the consistencies in research findings over the last 50 years demonstrate that human relationships are "local" and remarkably robust to advances in technology and transportation (internet, phones, highways etc).

Despite this likely dependence between spatial locations and network ties, spatial effects are often neglected in models of interpersonal networks. As a number of commentators have observed, social network analysis often fails to incorporate spatial factors in network modelling [17; 27]. There have been relatively few attempts to understand the way in which social networks are embedded geographically, though studies by Butts [4]; Faust et al. [8]; Wong et al. [30] are notable exceptions.

The aim of this article is to understand some of the ways in which social interactions may be affected by the spatial context in which they occur. The purpose of this work is to build models that accommodate spatial context in explanations of network structure. In order to do this we develop a set of nested hierarchical models for spatially embedded network by generalizing exponential random graph models for networks [10; 19; 22; 24; 26; 28]. Section 2 of this paper presents the modelling outline. We introduce different dependence assumptions starting from the simple Bernoulli graph model and turning to more complex network models with an exogenous spatial variable. In section 3, we outline a simulation approach and discuss the main results. In the conclusion, implications of the simulation results are discussed and future developments of the modelling approach are proposed.

2 Exponential random graph models

A social network can be represented as a designated set of nodes and their pairwise interconnections. Assume $N = 1, 2, ..., n$ is a set of network nodes and an observed network is denoted by two-way binary array $x$, in which $x_{ij} = 1$ if an observed edge from node $i$ to node $j$, and $x_{ij} = 0$ otherwise). Also suppose $X$ denote a random graph or network on $N$, with which possible edge (tie) regarded as a random variable. For the purpose of this article, we regard possible ties as nondirected ($X_{ij} = X_{ji}$).

The modelling framework to be utilised here is a general class of models that has been developed for interactive network and network-based processes [e.g., see summary in 21]. In the formulation of exponential random graph models the set of nodes is regarded as fixed and the focus is on the ties as stochastic entities [21]. It is assumed that each possible tie in the network has some probability of being present or absent. This probability is dependent on different endogenous network processes as well as on exogenous factors. The ERGM approach seeks to understand the interdependencies among variables, by postulating and testing precise dependence assumptions among these variables. This approach originates in the work of Frank and Strauss [10] who showed that some fundamental theorems for interdependent observations developed in spatial statistics [2] could be applied to arbitrary dependence structures, and hence to structures with interdependent network tie variables [18]. They applied these results to a network array $X$ to obtain a general expression for $Pr(X = x)$ from a specification of which pairs of relational variables are conditionally independent, given the values of all other relational variables [10]. In general, the dependency assumptions give rise to
models expressing the importance of particular local subgraphs of the network. More technically, dependence assumptions can be represented in the form of a dependence graph $D$ [10] whose nodes are the random variables $X_{ij}$ and whose edges link pairs of conditionally dependent variables. The Hammersley-Clifford theorem [2] can then be applied to any hypothesis about the dependence assumptions for $X$ to determine the general parametric form for a probability model, $Pr(X = x)$:

$$Pr(X = x) = \frac{1}{k} \exp\left(\sum_{A} \lambda_A s_A(x)\right)$$

(1)

where:
- the summation is over all configurations $A$
- $\lambda_A$ is a parameter corresponding to the configuration $A$;
- $s_A(x) = \prod_{X_{ij} \in A} x_{ij}$ is the network statistic corresponding to the configuration $A$ (indicating whether all ties in $A$ are observed in $x$); and
- $k$ is a normalizing quantity which ensures that 1 is a proper distribution.

In such a form the model has a very large number of parameters. In order to reduce this number a homogeneity assumption is often made. In particular, it is assumed that configurations that are identical as soon as labels are removed have equal parameters. The model then expresses the probability of a network as a function of the frequency of occurrence of various configurations of type $A$ (mutual ties, $k$-stars, transitive triads and so on) and, hence, allows us to examine a variety of structural effects. In the case when a parameter is large and positive, networks with many corresponding configurations are more likely to be observed; conversely, in the case of a large negative parameter such networks are less probable [20]. Elaborations of this basic form of the model permit not only different forms of dependency assumptions but also exogenous variables (such as spatial locations, $Z$) to be incorporated.

Below we present different dependency assumptions and a set of nested hierarchical models to which they give rise.

3 Model

For the purpose of this paper, we represent a social network by a non-directed graph, defined by two sets $(V, E)$, where $V = v_1, v_2, ..., v_n$ represents the set of nodes and $E = e_1, e_2, ..., e_m$ is a set of edges. Each edge $e_k$ corresponds to a pair $(u, v)$ of actors. In addition, every node is assigned a coordinate $(x_i, y_i)$ in the Euclidean space $R^2$ according to some spatial distribution.

The starting point of the modelling approach is the idea that network ties of one pair of nodes is both potentially dependent on and, in turn, influential of, the network ties of others [10]. These mutual dependencies take place in the context of individuals’ residential locations. To understand the consequences of these dependencies, we develop an empirically grounded social network model.

As mentioned earlier, a crucial step in formulating a model is to specify the dependence assumptions between variables appropriately, since the dependencies determine
the form of the network configurations parameterised in the model. Different types of dependencies, which may influence network topologies, can be identified in the literature on modelling networks. For the purpose of our modelling, we focus only on Bernoulli dependence [7] and Markov dependencies [10]. Sometimes exogenous factors may limit the extent to which potential dependencies can be realized. For example, possible ties \( X_{ij} \) and \( X_{kl} \) might be considered as conditionally dependent on each other only if the individuals share a common social setting. Social settings have been used to represent external social constraints on network processes [18]. These various dependence assumptions give rise to a hierarchy of increasingly complex models that allow us to explore hypotheses about spatially embedded network structures. It is worth noting that so far the impact of spatial information on network model specifications is unknown.

3.1 Bernoulli model

The simplest dependence assumption is that possible tie variables are independent. This assumption gives rise to the Bernoulli random graph model which assumes that the probability of a tie to be present is the same across entire network. It suggests that the only possible configuration in the model is a single tie. We can write the probability equation from the general model:

\[
Pr(X = x) = \left(\frac{1}{k}\right) exp\left(\sum_{i,j} \lambda_{ij}x_{ij}\right)
\] (2)

In this model, every set \( A \) comprising a single edge \( x_{ij} \) is a configuration in the model, \( \lambda_{ij} \) is a parameter for each of these configurations, and network statistics\(^1\) \( s_A(x) \) is \( x_{ij} \), which tells us whether that configuration is observed. Applying a homogeneity assumption we equate the effect for each tie as well as parameters \( (\lambda_{ij} = \theta) \), and the form of the model can be rewritten:

\[
Pr(X = x) = \left(\frac{1}{k}\right) exp\left(\sum_{i,j} \theta L(x)\right)
\] (3)

where \( L(x) \) relates to the number of ties in the network, and the parameter \( \theta \) is a function of the network density, the probability of an edge occurring between any two nodes\(^2\). Model (3) is known to be inadequate for representing social networks, but is useful as a baseline probability model to compare against more complex models.

3.2 Markov random graph model

The next type of dependence assumption is a Markov assumption in which all potential ties sharing a node are regarded as potentially conditionally dependent on one other [10]. This assumption gives rise to Markov random graph models with the following possible network configurations depicted in Figure 1.

---

\(^1\) Network statistics are counts for a particular configuration across the graph.

\(^2\) the density of the graph can be calculated as a proportion of the number of observed edges to the total possible number of edges, namely, \( 2L/n(n-1) \).
A general form of Markov models is:

$$P_r(X = x) = \left(\frac{1}{k}\right) \exp\left(\sum_{i,j} \lambda_{ij} x_{ij} + \sum_i \sum_l \sigma_{il} x_{il} + \sum_{i,j,k} \tau_{ijk} x_{ij} x_{jk} x_{ik}\right)$$ (4)

These configurations are of particular interest in the modelling of social networks. For a Markov dependency assumption, 2-stars, 3-stars, and triangles have been used a number of times [21]. The 2-star parameter relates to the propensity for 2-stars to be present in the network, and hence to the tendency for individuals to have connection with multiple network partners. However, to interact with others, individuals must spend their time and energy. Hence, to some extent in forming relationships with others, individuals reach a critical point when the cost of additional partners outweighs their benefit. In order to control for this non linear dependence of the probability of observing a tie on the number of existing partners, a 3-star parameter is included. The idea of clustering, which is represented by triangle parameter, is of particular interest in network theory. It is related to the idea of structural balance [6; 12], whereby individuals are assumed to be consistent in their relationships with others, for instance, friends are more likely to be friends of their friends. Hence, for the purpose of this paper, the four configurations just described are of interest. Imposing isomorphic homogeneity constraints a probability model for non-directed networks is then:

$$P_r(X = x) = \left(\frac{1}{k}\right) \exp\left(\Theta L(x) + \sigma_2 S_2(x) + \sigma_3 S_3(x) + \tau T(x)\right)$$ (5)

where $L(x)$ corresponds to the number of ties, $S_2(x)$ and $S_3(x)$ are counts of 2-stars and 3-stars, respectively, and $T(x)$ relates to the number of triangles across entire network$^3$, and $\lambda$, $\sigma_2$, $\sigma_3$, and $\tau$ are the corresponding parameters.

This model allows to understand the impact of local self-organising network processes on global network structure.

### 3.3 Bernoulli model with spatial covariate

As mentioned earlier, geographical space is a very strong constraint on the potential tie pool [29]. Most modelling approaches have shown that there is an inverse relationship between tie formation and distance between nodes [4; 14; 15; 25; 30; 31]. Hence, given that all other things are equal, the probability of a tie between two nodes is expected to decrease as a function of the distance between the nodes.

$^3$ It is apparent that a triangle and 3-stars comprise three 2-stars.
To reproduce this relationship, we first develop a network-based model where ties are independent Bernoulli random variables, and the probability of observing a tie is dependent only on the distance between nodes. We propose that nodes are embedded in a Euclidean space $\mathbb{R}^2$ and we let $d_{ij}$ denote the Euclidean distance between nodes $v_i$ and $v_j$. For the purpose of the simulations presented below, we assume that spatial locations are either laid out according to a rectangular finite grid, or that the spatial location of the nodes are randomly scattered in the Euclidean space according to a homogeneous Poisson process. The main property of a homogeneous Poisson process is that the nodes are independently and identically distributed. In the case of the rectangular grid, it is assumed that ties are more likely to be observed between neighbours (Figure 2a); in the Poisson process case, ties are assumed to be more likely among the nearest nodes (Figure 2b).

Fig. 2. Spatial location of nodes generated by regular finite grid(2a) and Poisson processes(2b).

As a result, the general form of the model for both cases is:

$$Pr(X = x) = \frac{1}{k} \exp\left(\sum_{i,j} \lambda_{ij} x_{ij} + \sum_{i,j} \delta_{ij} \varphi(d_{ij})\right)$$

As the distance between nodes ($d_{ij}$) is a continuous measure our model includes a function of the $d_{ij}$. Based on the previous empirical studies, which strongly suggest that the likelihood of observing a tie between two nodes not only drops off with physical distance, but is an inverse square function of distance [13; 15; 25; 31], we assume the same functional relationship between tie formation and distance. Hence, applying an isomorphic homogeneity assumption the model is:

$$Pr(X = x) = \frac{1}{k} \exp(\lambda L(x) + \sum_{i,j} \delta(1/d_{ij}^2))$$

where $L(X)$ corresponds to the number of ties, $d_{ij}$ to the Euclidian distance between nodes, and $\lambda$ and $\delta$ are the corresponding parameters.

This model allows us to understand some of the ways in which social interactions may be affected by the spatial context in which they occur.

4 In spatial modelling other function are also used, for instance, a step function [30] or a negative exponential [14]
3.4 Hybrid model

Above we simplified the potential complexity of social interaction by examining features in isolation. In order to understand the impact of spatial constraints and endogenous social processes we need to develop a more complex model which takes simultaneous account of the multiple embeddedness of individuals in both physical and social spaces.

This approach leads to a more complex model which allows us to determine how much in the social networks is spatially induced, and what is the impact of endogenous network processes on the structure of networks. Hence, the overall model is:

\[
Pr(X = x) = \frac{1}{k} \exp(\Theta L(x) + \sigma_2 S_2(x) + \sigma_3 S_3(x) + \tau T(x) + \sum_{i,j} \delta(\frac{1}{d_{ij}}))
\]  

(8)

In principle, this model allows us to assess the functional form of the spatial dependence of network variables while also recognising the likely presence of endogenous network processes. In addition, it can be generalized to include some very plausible interactions between spatial proximity and endogenous network processes.

By developing a hierarchical set of nested models, we are also able to compare simpler with more complex models, assess the contribution provided by a more complex dependency structure and so gain an understanding of social behaviour when a more complex dependency assumption improves explanatory power. One of the specific advantages of using a hierarchical set of nested models is that it allows us to compare the forms of clustering in networks that arise through spatial and network processes. Thus, while several models predict clustering, we are not sure how to detect the differences that might arise through spatially-induced or endogenously generated clustering patterns. The simulation experiments described below are intended to show how the hybrid model class can assist us to understand the consequences of these different processes.

4 Simulation approach

4.1 Simulation description

The Metropolis algorithm [e.g., see 23] is used for all simulations. The algorithm starts with a randomly chosen graph \( w \). At each iteration a new graph \( w^* \) is proposed as a candidate for the next step in a Markov chain. The candidate graph is determined from the current graph \( w \) by choosing at random an edge and changing the value of the edge from 1 to 0 or from 0 to 1. We accept the change whenever the new value has an increased probability of being observed according to the model equation. When the probability is not increased we accept the change with the probability \( r \), where \( r \) is the conditional odds ratio

\[
r = \frac{Pr(w^*|rest)}{Pr(w|rest)}
\]  

(9)

If the proposed graph is accepted, \( w \) is replaced by \( w^* \). The algorithm defines a Markov chain [e.g., see 11]. It is worth noting that the simulation does not converge to a particular graph. What is produced is a distribution of graphs. Graphs in this distribution
will be more probable and so more likely to appear in our sample if they express the properties implied by the model with given parameter values. In the simulations presented here, we use 1,000,000 iterations and sample every 1000th graph to ensure that graphs are not highly correlated. The sampling rate does not depend on graph size as graphs are all the same size across the distribution. This appears to give ample burn-in for the Metropolis algorithm [11]. The estimates of the network statistics for each draw are calculated as the simple averages from the post-burn-in period. For the simulations below, we use a variant of the above procedure that guarantees that all graphs have the same density. In this variant, the candidate \( w^* \) is determined from the current graph \( w \) by randomly switching an edge in \( w \) with a non-edge.

Each individual data point below is a random draw from the distribution of graphs with 144 nodes. For each sampled graph we calculate the statistics associated with model parameters, namely, 2-stars, 3-stars, triangles, and average inverse squared distance, as well as the following additional measures: a count of different types of 4-node subgraphs, and the clustering coefficient. There are a number of possible approaches that could be made in order to understand global structure through comparing a graph of interest to a range of different graph distributions of increasing complexity [18]. Here we use the Bernoulli model (Bernoulli graph distribution) as a baseline. We simulate the comparative Bernoulli graph distribution by fixing the density at a low value. We calculate the mean number of 2- and 3-stars from the sample. We then simulate graph distributions based on equations 5, 7, and 8 with similar expected number of 2- and 3-stars, setting graph density to the same value. This enables us to assess whether the clustering patterns differ for different models, by examining the estimates of the statistics for the clustering coefficient, and 4-node subgraphs of different types.

In our simulations we have chosen various parameter values based on exploration of the parameter space and some commonly observed empirical patterns, simply to illustrate various points. We fixed the network density to 0.02 across all simulations. The vectors of parameter values for each model are presented in Table 1.

Table 1. Parameter values for all models (NB: the same parameter values are used for Poisson case and regular finite grid case)

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>2-stars</td>
<td>0</td>
<td>0.1</td>
<td>0</td>
<td>0.1</td>
</tr>
<tr>
<td>3-stars</td>
<td>0</td>
<td>-0.06</td>
<td>0</td>
<td>-0.06</td>
</tr>
<tr>
<td>Triangles</td>
<td>0</td>
<td>1.42</td>
<td>0</td>
<td>1.42</td>
</tr>
<tr>
<td>Distance</td>
<td>0</td>
<td>0</td>
<td>0.0068</td>
<td>0.0068</td>
</tr>
</tbody>
</table>

So, the positive 2-stars and negative 3-stars parameter pattern suggests that people tend to have connections with others however experience cost in having too many. The positive triangle parameter suggests that two friends are likely to have other friends in common, and the substantive interpretation of positive distance parameter is that people are less likely to be linked to people who are far away.
The number of edges for all graphs was set at 205. Table 2 presents the basic graph statistics for all four models. It can be seen that the mean for the basic edge and star statistics are similar, but that the statistics for triangles, distance, and clustering coefficient differ.

**Table 2.** Mean statistics with standard deviation in brackets

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>Edges</td>
<td>205</td>
<td>205</td>
<td>205</td>
<td>205</td>
<td>205</td>
<td>205</td>
</tr>
<tr>
<td>2-stars</td>
<td>577.1 (23.269)</td>
<td>577.25 (22.67)</td>
<td>578.75 (23.428)</td>
<td>578.08 (22.469)</td>
<td>599.04 (23.8)</td>
<td>577.54 (22.73)</td>
</tr>
<tr>
<td>3-stars</td>
<td>536.27 (69.219)</td>
<td>514.04 (58.208)</td>
<td>537.87 (68.893)</td>
<td>538.11 (66.925)</td>
<td>571.95 (64.6)</td>
<td>514.13 (57.99)</td>
</tr>
<tr>
<td>Triangles</td>
<td>3.827 (1.973)</td>
<td>13.97 (3.93)</td>
<td>9.6760 (2.394)</td>
<td>3.849 (1.9)</td>
<td>33.13 (6.8)</td>
<td>13.68 (3.68)</td>
</tr>
<tr>
<td>Distance</td>
<td></td>
<td></td>
<td>129465.6 (2534.24)</td>
<td>4583.78 (567.916)</td>
<td>134063.1 (1917.61)</td>
<td>3680.76 (136.377)</td>
</tr>
<tr>
<td>Cluster coefficient</td>
<td>0.02 (0.01)</td>
<td>0.07 (0.02)</td>
<td>0.05 (0.01)</td>
<td>0.02 (0.009)</td>
<td>0.2 (0.03)</td>
<td>0.071 (0.018)</td>
</tr>
</tbody>
</table>

In Table 2 the maximum difference among the four means does not exceed 1 standard deviation for the 2-stars and 3-stars statistics, but for the triangles, distance, and clustering coefficient the largest difference is more than 2 standard deviations. These results suggest that there is a substantial clustering effect driven by both local network structure and exogenous spatial processes.

Although all three extensions of the Bernoulli model clearly demonstrate the presence of clustering effects, it is important to assess the ways in which geographical locations and endogenous network clustering processes combine to structure patterns in social networks. This assessment can be based, in part, on the number of different types of 4-node subgraphs depicted in Figure 3.

**Fig. 3.** Configurations for 4-node subgraphs.

It is clear from Table 2 and Figure 4 that, in comparison to the spatial model, the Markov model gives rise to more 3- and 4-cycles (i.e. triangles and D41) and also more configurations of the form of D42. Conversely, spatial clustering (Poisson case) gives rise to relatively more 3-path structures. When these two effects are combined in the
hybrid model, a substantial increase in many statistics is observed, most notably in the higher order clique structure, $D_6$.

![Fig. 4. 4-node subgraphs distribution for: (1) Bernoulli model, (2) Markov model, (3) Bernoulli model with spatial covariate (Poisson case), (4) Bernoulli model with spatial covariate (regular finite grid), (5) Markov model with spatial covariate (Poisson case), (6) Markov model with spatial covariate (regular finite grid). Boxplots indicate the range of 4 node subgraphs across the samples.](image)

It is worth noting that there is a substantial difference in spatial clustering between Poisson case and the regular finite grid. It is clear from Table 2 and Figure 4 that when spatial locations are generated using a regular grid there is no substantial increase in number of 3- and 4-cycles between Markov and spatial models. This can be explained because in the regular grid case each node has only four close neighbours, all at the same distance (Fig 2a). In contrast, the spatial array for the Poisson process produces nodes located in clumps (Fig 2b). In other words, although the nodes cover the same space, there is greater variation in the average distance to close neighbours in the Poisson arrangement. This means that a substantial proportion of nodes have more than four close neighbours, and the distance between pairs of such neighbours may be shorter than for the regular grid. This increases the probability of edges among such subsets of nodes, a process that is then reinforced by positive star and triangle effects to create denser subgraphs with high clustering.

Although this pattern of results pertains to a single set of four models, it is plausible that these characteristics would be observed more broadly. This simulation experiment suggests that it will be possible to detect possible differences in the basis of clustering
by careful attention to the fit not just of triangles but of higher order clustering structures such as stars, paths, cycles, and cliques.

5 Conclusion

In this paper we have developed a nested family of exponential random graph models for social networks embedded spatially [10; 19; 22; 26]. We have demonstrated the clustering properties of networks that may arise from endogenous Markov network processes, from dependence on an underlying homogeneous Poisson process generating node locations, and from a combination of the two. Most importantly, we have demonstrated that the forms of clustering exhibited by these processes may be subtly different and that, in order to diagnose the potential forms of clustering in empirical settings, it is necessary to incorporate both effects in the model. The question of the way in which spatial context, individuals’ residential locations and their neighbourhood, shapes network structure is essentially an empirical one and therefore in need of further elaboration. For the current model it would be necessary to fit empirical data on observed locations and estimate corresponding parameters, which to some extent will allow us to ascertain the form of spatial embedding of an observed network. More generally, it would be desirable to develop more complex models incorporating potential interactions between spatial factors and network processes that can be used to evaluate empirical evidence for spatial and network clustering.

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Bibliography


Labour Market Disadvantage in Metropolitan Regions

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Abstract. There has been growing awareness that in order to understand issues of social disadvantage it is necessary to undertake an appraisal that includes reference to the impact of individuals and the local contexts they operate in. By focusing on the interactions between local labour market regions and individual characteristics this paper presents an analysis of unemployment risk that moves beyond studies that simply focus on the individual aspects of unemployment or the broad patterns that exist across spatial aggregations. The paper finds that significant weight should be given to explanations of unemployment that move beyond a simple focus on individual employability by considering the impacts of broader contextual factors that may operate net of individual factors.

Keywords: unemployment, local labour markets, area effects, employability, social space, geographic space

1 Introduction

An on-going focus within urban sociology and other spatially oriented social sciences is that space and place matter. The classic research by scholars from the Chicago School into the human ecology of cities was based on a firm belief that space was important it acted as a ‘great sifting and sorting mechanism, which ... infallibly selects out of the population as a whole the individuals best suited to life in a particular region and a particular milieu’ (Park 1952, 79). Similar themes have continued to pervade the research output of urban sociologists to varying degrees since this time. While the human ecology arguments may now have less currency, contemporary researchers have begun to consider a broader research project that focuses on the interplay between individuals and their local context. Here the work of American sociologist Wilson [58]...
drew attention to the interactions between poverty concentration and social isolation in inner city neighbourhoods and over the past decade there has been an increasing interest in understanding neighbourhoods or local areas may be thought of as traps, stepping stones or springboards impacting on individual and household prosperity and well-being [8; 9; 21; 23].

The context for this paper can be placed as part of larger international social science endeavour that seeks ‘to link a myriad of changes from the global to the local, or the very macro to the very micro, and understand the effects of those changes on human life’ [9]. These endeavours, which are often discussed under the umbrella of neighbourhood, area or contextual effects hypothesise that the hierarchical nature of social phenomena means that individual-level opportunity and vulnerability is reflected in the uneven spatial impacts on labour markets, housing markets and other broad contextual issues, together with the impact of individual level characteristics arguing that the broad impacts are linked because of where particular people live and their roles in society and the economy. In short patterns of socio-economic opportunity and vulnerability are the outcome of people based and place based influences. The growing international literature focusing on these issues has established a conceptual and empirical background for considering a people and space/place approach to understanding socio-economic opportunity and vulnerability [55]. Moreover, the broad social changes and public debates that have characterised life in contemporary industrial society have meant that the types of issues considered under the people and space/place framework have remained in the policy agenda. Understanding the effects of people and space/place is crucial as individuals, households and local communities face continued economic restructuring and large-scale social and demographic change and as policy makers and researchers try to understand the impacts and outcomes of these changes. The recently published collection of research undertaken in Europe and the USA [23] clearly illustrates these concerns, as have the vast amount of research work reported in international journals such as Urban Studies, Housing Studies and Economic Geography3. Within Australia, despite the excellent work by researchers including Borland [6], Hunter [36], Cardak and McDonald [13], Andrews et al. [1], and Shields and Wooden [56] an understanding of the impact of space and place on individual outcomes remains largely undeveloped. This paper responds to this by making a further contribution to this growing area of research interest.

The particular focus of this paper is in understanding the role that local labour markets (place) play in influencing labour market outcomes net of individual characteristics (people). Within Australia while policy makers are quick to point out that strong growth has had an important and timely impact on reducing unemployment numbers, there has been a significant level of research that has pointed to the spatial concentration of unemployment in some communities or localities despite the widely heralded positive economic performance [4; 50]. A significant question therefore arises relating to what might be the possible drivers of these outcomes. Although policy doctrine focuses on addressing individual flaws that act to increase the risk of labour market disadvantage

3 Sampson et al. (2002, 444) report ‘after spurts in the 1960s and 1970s followed by a decline, the mid 1990s to the year 2000 saw more than a doubling of neighbourhood studies to the level of about 100 papers [published] per year’.
and on reaching full employability of the individual rather than full employment [49], these supply-side approaches only address part of the issue. Within local labour markets, the ability to access available jobs become an important part of the labour market disadvantage equation, and is often overlooked. These types of arguments are at the heart of research that has considered the spatial mismatch hypothesis whereby already disadvantaged workers face further disadvantage through the mismatch that exists between place of residence and the location of suitable employment [2; 31; 35; 38; 42; 52]. In particular concentrations of disadvantage within particular localities are seen as a reflection of a lack of jobs in an acceptable commuting area rather than the impact solely of characteristics of the individual. The flavour of these types of arguments is contained in the work by Gordon and Turok [28] and others who point out that a focus on increasing labour market flexibility (individual employability) has very little relevance in addressing concentrations of joblessness, rather it is a focus on local job creation that is more salient. Moreover, they argue that the ‘persistence of unemployment is fundamentally a consequence of a weak pressure of demand for labour in particular city-regional labour markets and should be largely reversible through sustained employment growth’ [28]. They counter current policy foci by suggesting that

It is not our view that marginalisation makes many people permanently unemployable, but that rather it substantially reduces the competitive prospects of those effected, while at the same time congesting the lower rungs of the labour market where they would otherwise have realistic chances of gaining employment [28].

The dilemma posed by these differing views provides the very specific background to this paper. The paper reports on analysis of individual unemployment risk set within a broad employability framework. The analysis uses data from wave 1 of the Household, Income and Labour Dynamics in Australia (HILDA) survey together with aggregate census level data to model unemployment risk, treating the risk of unemployment as a function of individual factors, the impact of family background, the impact of other contextual effects such as social networks or social capital and the impacts of local labour market conditions. In what follows we first place the research within the broader context for understanding employment outcomes before presenting a discussion of our methods and the data used. Following this we present the findings of our analysis prior to presenting a discussion and a consideration of the broader implications.

2 A context for understanding unemployment risk

As a genre of broader labour market research, the study of unemployment can be understood from a range of conceptual approaches developed across a number of social science disciplines. Often these approaches are piecemeal, focusing on narrowly defined drivers and processes. However, there has been an increasing movement towards utilising a broader framework focusing on aspects of employability. While various definitions have been applied, including those narrowly focused on simple supply side characteristics only, a more holistic definition of employability would include
the capability to move into and within labour markets and to realise potential through sustainable and accessible employment. For the individual, employability depends on: the knowledge and skills they possess, and their attitudes; the way personal attributes are presented in the labour market; the environmental and social context within which work is sought; and the economic context within which work is sought [18, p. 7].

A broad employability context therefore includes both supply side characteristics and demand side characteristics of the labour market.

Heuristically, the broad employability framework resembles the model shown in figure 1 with individual labour market outcomes seen as a function of three interrelated factors including individual and personal circumstances and external or contextual factors [46], [see also 25]. The first two relate to individual and personal circumstances and are thought of as labour supply factors. The third set of factors are considered largely external to the individual and can be seen as representing a broad range of contextual factors including those characteristic of labour market demand [46].

**Fig. 1.** Heuristic model of individual unemployment risk.

Individual characteristics, both malleable and indelible, that includes skills and attributes such as basic education, transferable skills, demographic characteristics, health and well-being, job seeking skills and an individual’s level of adaptability and mobility. Ascribed and achieved personal characteristics, such as education formal and learned job skills, social status, age etc are often included in models attempting to understand labour market outcomes. In particular, the ‘operations of the opportunity structure objectively vary greatly across individuals, depending on their personal characteristics and how these characteristics are evaluated by the markets and institutions operative in the
individual’s place of residence’ [25]. Other factors such as an individual’s health and wellbeing, together with an individual’s job seeking behaviour and knowledge which may act to funnel information about known jobs (possibly in connection with an individual’s social networks) are also important. Lastly, adaptability and mobility refers to the extent to which an individual is willing to change/adapt to meet changing labour market conditions or in some cases be geographically mobile [46].

Personal circumstances include many socio-economic contextual factors which generally relate to an individual’s social, family and household circumstances. Family background can impact on an individual’s opportunity structure via the influence of personal characteristics of the individual, but also through the impact of social networks and social capital of parents and other intergenerational effects which impact on social capital more generally [14]. Importantly, the impact that social networks might have on an individual’s employment outcomes is widely discussed in the research literature and includes the impact on perceived and real opportunity structures and individual aspirations and preferences [12; 20; 33]. Following a ‘network model’ Buck [12] suggests that an individual’s links into social and interpersonal networks provide critical information and support that are important to understanding eventual employment and other social outcomes. In situations where social networks are not widely developed, and this is often compounded by residential concentrations in disadvantaged neighbourhoods or localities, job search including information regrading employment opportunities are thought to be less effective and hence are associated with negative individual employment outcomes.

The impact of local or regional resources or local context effects is most often related to the quality, quantity and diversity of institutions at a neighbourhood or local level. It refers to ‘the array of markets and institutions that provide the potential means of social mobility within which an individual may interact, such as labour, housing and financial markets, schools and the social welfare and criminal justice systems’ [24]. McQuaid [46] refer to these context effects as a range of external factors that include local labour market demand and enabling support factors such as local jobs policies. In understanding labour underutilisation the spatial organisation of metropolitan labour market opportunities is important. Although researchers such as Buck [12] question whether local labour demand can be considered as a source of local or regional contextual effect, others including Green [31], Noble and Smith [52], Gould and Fieldhouse [29], Jargowsky [38], Flynn [22] and Sunley et al. [57] all point to its necessary inclusion in an analysis of individual labour market outcomes. Significantly ‘there is no such thing as a national labour market, but rather a complex geographical mosaic of overlapping local and sub-national labour markets’ [57] which will have differential effects on individual’s opportunity structures and hence on employment outcomes.

3 Data and methodology

The investigation of the impacts and associations individual behaviour and outcomes has, as pointed out by [24] assumed several methodological guises with the focus often being on the best way to account for data is hierarchical or composed of indicators taken at different levels of measurement. In the case of the current research we are faced
with data measured at the individual level together with data measured at the labour market region level. In order to consider the issues raised in this paper we run a series of multivariate logit models which take into account the clustering of observations at the level of the local labour market region. This provides us with a modelling technique that produces robust outcomes in the face of the two level structure of our data. Prior to fitting the final set of models several alternative approaches were considered including the fitting of multilevel models that specifically take into account the hierarchical nature of the data [26]. While this type of approach has become increasingly popular, it was not used in the final analysis as initial modelling suggested that with reference to the data set and sample we use no additional benefit is gained by fitting a multilevel model versus a standard logit model accounting for clustering.

The use of multivariate logit models in this case is warranted as we have a dichotomous dependent variable (unemployment/employment) and a range of predictor variables that are dichotomous, categorical or continuous. In a standard logit model we assume that labour market outcomes for individual \(i\) is denoted \(Y_i\), with a conditional expectation \(P_i\). In this case the logit of \(P_i\) can be expressed as a function of the individual explanatory variables so that:

\[
\text{Logit}(P_i) = \beta_0 + \beta_1 X_i + \beta_2 C_i + \mu_i, i = 1, \ldots, n; j = 1, \ldots, m
\]  

(1)

Where the risk of unemployment is a function of a constant (\(\beta_0\)) plus a range of individual level characteristics \((X_i)\), contextual characteristics for individual \(i\) \((C_i)\) and a residual. In modelling unemployment risk we proceed by first fitting a reduced model with only individual level predictors and then move to fitting subsequent models that include predictors of contextual characteristics.

The main data used in this paper has come from the Household, Income and Labour Dynamics in Australia (HILDA) survey together with aggregate census data. The HILDA survey is a broad social and economic survey conducted annually which contains information on employment, individual socio-economic characteristics and household/family characteristics. It also contains identifiers to allow broad spatial characteristics (such as labour market or local area available from census data and labour force surveys) to be considered. This current paper considers the first wave of the HILDA survey (2001) with subsequent papers considering longitudinal outcomes. The wave one survey file contains a total of around 19,000 respondents. A reduced data set is used in this paper which includes individuals currently in the labour force (employed or unemployed) living in the metropolitan capital cities. This reduced data set includes 5044 individuals.

The dependent variable used in this paper is whether the respondent is unemployed or employed and is coded 0 and 1. The individual level predictor variables are those often associated with the risk of unemployment and are similar to those used elsewhere in micro-level studies of employment status [5; 10; 15; 17; 19; 44]. We have included the following independent variables: Age (1 if less than 25 (reference category), 2 if aged 25 to 44 years, 3 if aged 45 to 64 years), Gender (1 if female, 0 if male), Education (1 if educated up to year 12 (reference category), 2 if educated beyond year 12, but not university (secondary plus), 3 if university bachelor degree or higher (degree plus)), marital status (1 if married, 0 otherwise), ATSI background (1 if ATSI, 0 otherwise), disability (1 if have disability, 0 otherwise), self reported English proficiency (1 if poor
very/ poor English, 0 otherwise), single parent (1 if single parent, 0 otherwise) and residential mobility (1 if respondent had moved in the past 12 months, 0 otherwise).

Two predictor variables were included to account for the impact of family background. One measured the impact of parental employment (employed role model/parent in childhood- 1 if no employed adult role model/parent, 0 otherwise), while the other accounted for the ethnic background of parents (parent country of birth- 1 if one or both parents born in NESB country, 0 otherwise).

The HILDA data set allows us to include proxies for the impact of social networks on unemployment risk. Two measures are included; one is an index accounting for an individual’s social networks and one is an interaction between an index of neighbour contacts and the collection district unemployment rate. The former is included to account for the potential impact that social networks may play in unemployment risk, while the later is included to account for the impact of local socialisation and unemployment. Given that these two mechanisms may impact on potential employment either through information regarding job opportunities or through the provision of positive or negative role models, their inclusion is thought to be important.

The final variable included accounts for the impact of local labour market demand (local labour market strength) on employment outcomes. Several possible indicators have been use in past research and have largely focused on understanding how the availability of jobs is reflected in broad levels of employment or alternatively unemployment [3; 22; 45]. In this paper we use the employment rate of Labour Force Survey Regions. Labour Force Survey Regions are aggregated Statistical Local Areas and represent broad labour commuting regions or travel-to-work-areas. The employment rate therefore provides a proxy measure for the extent to which an individual is able to find employment within a suitable commuting zone.

4 Unemployment risk: individual and context effects

Unemployment risk and individual level characteristics

In order to investigate unemployment risk we fit a series of logit models beginning with a reduced model containing only the individual level predictors. The results are presented in Table 1 with the exponential of the \(\beta\) interpreted as the odds of being unemployed relative to the reference category. From the previous discussion certain individual level predictors are thought to be more likely to be associated with increased unemployment risk than others.

4 The social network index was constructed by considering the main components from a PCA of questions coded on a five point likart scale. The questions included in the index are: People don’t come to visit me as often as I would like; I often need help from other people but can’t get it; I don’t have anyone I can confide in; I have no one to lean on in times of trouble; I often feel very lonely. The neighbour contacts index was constructed by considering the main components from a PCA of questions coded on a five point likart scale. The questions included in the index are: Neighbours helping each other out; Neighbours doing things together. Both indices were constructed using PCA in SPSS. Tests for the robustness produced alpha above 0.7 in both cases.
Table 1. Regression results: individual level predictors and unemployment risk

<table>
<thead>
<tr>
<th>Predictor</th>
<th>( \beta )</th>
<th>Standard error</th>
<th>( P &gt; z )</th>
<th>( e^\beta )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-1.81</td>
<td>0.179</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(age less than 25 reference)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25 to 44</td>
<td>-0.74</td>
<td>0.14</td>
<td>0.000</td>
<td>2.09</td>
</tr>
<tr>
<td>45 to 64</td>
<td>-0.62</td>
<td>0.15</td>
<td>0.000</td>
<td>1.85</td>
</tr>
<tr>
<td>Gender (1=female)</td>
<td>-0.36</td>
<td>0.97</td>
<td>0.000</td>
<td>1.4</td>
</tr>
<tr>
<td>ATSI background (1= ATSI background)</td>
<td>1.27</td>
<td>0.34</td>
<td>0.000</td>
<td>3.6</td>
</tr>
<tr>
<td>Poor English (1= poor English)</td>
<td>1.69</td>
<td>0.27</td>
<td>0.000</td>
<td>5.4</td>
</tr>
<tr>
<td>Single parent (1=single parent)</td>
<td>0.28</td>
<td>0.97</td>
<td>0.003</td>
<td>1.3</td>
</tr>
<tr>
<td>Moved in the past 12 months (1=moved in past 12 months)</td>
<td>0.47</td>
<td>0.10</td>
<td>0.000</td>
<td>1.6</td>
</tr>
<tr>
<td>Disabled (1=disabled)</td>
<td>0.45</td>
<td>0.14</td>
<td>0.002</td>
<td>1.6</td>
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<tr>
<td>Currently married (1=currently married)</td>
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<td>0.17</td>
<td>0.018</td>
<td>1.5</td>
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<tr>
<td>Education</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>(year 12 or less reference)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Secondary plus</td>
<td>-0.47</td>
<td>0.16</td>
<td>0.003</td>
<td>1.6</td>
</tr>
<tr>
<td>Degree plus</td>
<td>-1.02</td>
<td>0.27</td>
<td>0.000</td>
<td>2.8</td>
</tr>
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</table>

Log Pseudo likelihood -1047.22

It is likely that the risk of unemployment will be influenced considerably by the level of educational attainment, with some arguing that it is arguably the most important indicator of labour market outcomes [10; 37; 44]. The data in table 1 indicate that there is a significant association between educational attainment and unemployment risk with those with lower education levels being at higher risk. Considering the regression coefficients more specifically we evaluate unemployment risk relative to those with education of year 12 or less. Individuals with some post secondary education but no university education are over one-and-a-half times \( (e^{0.478} = 1.6) \) less likely than the reference category to be unemployed, while those individuals with a university education are almost three times less likely \( (e^{1.02} = 2.77) \) than the reference category to be unemployed.

Within research and policy there is significant concern regarding the associations between age and unemployment risk [11; 39; 43; 54]. Many empirical models illustrate a potential u-shaped relationship between age and unemployment with higher unemployment rates being found at both younger age groups and older age groups [11; 39; 54]. While we do not find strong evidence of a u-shaped relationship those aged between 25 and 44 did have the lowest unemployment risk. In our model we compare those respondents aged between 25 and 44 and 45 an 64 with those aged less than 25. In both cases being in the younger age group is associated with increased risk of unemployment, although the risk for the older age group is also higher than for the middle age group. In particular, those respondents aged between 25 and 44 were more...
than twice less likely to be unemployed \((e^{0.74} = 2.09)\), while those aged 45 to 64 years were twice less likely to be unemployed \((e^{0.62} = 1.85)\).

The inclusion of gender in an unemployment model often results in varying outcomes depending on the level of analysis considered and the sample used [7; 44]. In our model the variable for gender suggests that the risk of unemployment is higher for males than for females, with females being 1.4 times less likely \((e^{0.364} = 1.4)\) to be unemployed than males.

The under-representation of individuals from a non-English speaking background or those with an indigenous background in employment is an important social and economic issue and has been commented on elsewhere [37; 40; 47; 48]. The predictor accounting for indigenous background (ATSI) was highly significant with individuals from an Aboriginal and Torres Strait Islander background facing increased unemployment risk \((e^{1.27} = 3.6)\). Ethnic background is accounted for here by self reported English proficiency and was associated with increased unemployment risk. Respondents reporting that they have poor/very poor English skills were more than five times more likely to be unemployed than those with good/very good English skills \((e^{1.69} = 5.42)\).

Having a disability is also likely to be associated with increased risk of unemployment [32; 41]. The predictor accounting for disability was highly significant and suggested that those with a disability were over one-and-a-half times as likely to be unemployed than those without a disability \((e^{0.449} = 1.6)\).

Household and family characteristics have been shown to have an influence on labour market outcomes with high unemployment being associated with individuals who are single, divorced or separated [16; 44]. In our model the predictor for single parents was significant, with single parents being almost one-and-a-half times \((e^{0.285} = 1.30)\) more likely to be unemployed than others. Several hypotheses are provided regarding the association between marital status and unemployment risk [44]. Here the variable marital status measures if the individual is currently married and is significant suggesting that the risk of unemployment is 1.5 times less \((e^{0.408} = 1.50)\) for those currently married than others.

It has been argued that there may be a relationship between period of residence and unemployment risk with individuals those moving recently being less attractive to employers looking for a sign of stability in their work force [11; 34; 54]. In our model those individuals who had moved in the past 12 months were more than one-and-a-half times more likely to be unemployed \((e^{0.474} = 1.60)\).

4.1 Unemployment risk: individual characteristics and social capital/social network effects

To extend the model of individual predictors we fit a logit regression including the predictors associated with social capital and social networks (Table 2). The individual level predictor variables are similar to those in the previous model, although they have changed slightly in the size of the impact within the model. The risk of unemployment still remains higher for individuals from a ATSI or NESB background, those in a single parent family, those who moved in the past twelve months and those who have a disability, while being female, being aged older than 25 or having education above basic secondary school reduces the unemployment risk at the individual level.
Table 2. Regression results; individual level predictors, social networks/social capital predictors and unemployment risk

<table>
<thead>
<tr>
<th></th>
<th>$\beta$</th>
<th>Standard error</th>
<th>$P &gt; z$</th>
<th>$e^{\beta}$</th>
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<td>(age less than 25 reference)</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25 to 44</td>
<td>-0.65</td>
<td>0.15</td>
<td>0.000</td>
<td>1.9</td>
</tr>
<tr>
<td>45 to 64</td>
<td>-0.39</td>
<td>0.18</td>
<td>0.028</td>
<td>1.5</td>
</tr>
<tr>
<td>Gender (1=female)</td>
<td>-0.36</td>
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<td>0.000</td>
<td>1.4</td>
</tr>
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<td>1.41</td>
<td>0.33</td>
<td>0.000</td>
<td>4.09</td>
</tr>
<tr>
<td>Poor English (1= poor English)</td>
<td>1.12</td>
<td>0.28</td>
<td>0.000</td>
<td>3.09</td>
</tr>
<tr>
<td>Single parent (1=single parent)</td>
<td>0.28</td>
<td>0.10</td>
<td>0.005</td>
<td>1.32</td>
</tr>
<tr>
<td>Moved in the past 12 months (1=moved in past 12 months)</td>
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<td>0.11</td>
<td>0.000</td>
<td>1.8</td>
</tr>
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<td>Disabled (1=disabled)</td>
<td>0.47</td>
<td>0.15</td>
<td>0.001</td>
<td>1.59</td>
</tr>
<tr>
<td>Currently married (1=currently married)</td>
<td>-0.34</td>
<td>0.17</td>
<td>0.044</td>
<td>1.4</td>
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<tr>
<td>Education</td>
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<tr>
<td>(year 12 or less reference)</td>
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<td>0.001</td>
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<tr>
<td>Parental non-employment (1=parental non employment)</td>
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<td>0.26</td>
<td>0.038</td>
<td>1.71</td>
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<td>Parental Ethnic background (1=parent(s) born in NES country)</td>
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<td>0.000</td>
<td>2.36</td>
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<td>Social network index</td>
<td>0.34</td>
<td>0.06</td>
<td>0.000</td>
<td>1.39</td>
</tr>
<tr>
<td>Neighbour influence interaction</td>
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<td>0.007</td>
<td>0.790</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Log Pseudo likelihood -1006.81
An interesting finding from our analysis has to do with the potential of intergenerational transfers of disadvantage [15; 53]. The measure of parents unemployment relates to any periods of non-employment (either unemployment or being outside the labour market) during the respondents childhood (age 14) and suggests that those individuals who had both parents not working or one parent in a single parent family were over one-and-a-half times as likely \((e^{0.543} = 1.71)\) to be unemployed as individuals who had positive parental employment role models as children. Moreover it is hypothesised that parental ethnic background may also be influential. In our model the predictor accounting for parental ethnic background considers those individuals who have one or both parents born in non-English speaking countries. The significant regression coefficient suggests that individuals in this group are over twice as likely to be unemployed \((e^{0.337} = 1.39)\).

Of the two predictor variables included to account for social networks only the social network index is significant. The index is constructed such that higher scores indicate weaker social networks generally. The significant coefficient indicates that those respondents with higher scores on this index (assumed to indicate weaker social networks) have a higher unemployment risk \((e^{0.337} = 1.39)\).

4.2 Unemployment risk: individual characteristics, social capital/social network effects and local labour market effects

The final model considered here includes all the individual, family and social capital/network variables plus the predictor accounting for labour market strength (Table 3). The predictors associated with individual/family level characteristics and the social capital/social network characteristics are similar to the previous model, changing only in terms of magnitude.

Existing aggregate level analysis is suggestive of the association that exists between unemployment risk at the individual level and the strength of the local labour market [i.e., see 4; 27; 50; 51; 57]. In weak labour markets, those lacking job opportunities, it is expected that the risk of unemployment will be higher. In our model labour market strength is accounted for by the proportion of persons in the labour market region who are employed. The risk of unemployment for individuals was 1.08 times \((e^{0.08} = 1.08)\) lower with each 1 percent increase in the percent employed within a given labour market region.

5 Discussion

The analysis presented in this paper sets out to model various predictors of individual unemployment risk using a combination of data from the Household, Income and Labour Dynamics in Australia (HILDA) survey and aggregate employment data from the census. Recognising that there exists a range of existing explanations of unemployment we cast the research in terms of a model that considers unemployment risk to be a function of a range of individual and family level impacts together with a range of contextual effects that include the role of social networks and social capital and labour
Table 3. Regression results; individual level predictors, social networks/social capital predictors, labour market predictor and unemployment risk

<table>
<thead>
<tr>
<th>Predictors</th>
<th>β</th>
<th>Standard Error</th>
<th>P &gt; z</th>
<th>e^β</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>5.43</td>
<td>2.76</td>
<td>0.05</td>
<td>1.46</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(age less than 25 reference)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25 to 44</td>
<td>-0.66</td>
<td>0.15</td>
<td>0.000</td>
<td>1.93</td>
</tr>
<tr>
<td>45 to 64</td>
<td>-0.38</td>
<td>0.18</td>
<td>0.033</td>
<td>1.46</td>
</tr>
<tr>
<td>Gender (1=female)</td>
<td>-0.34</td>
<td>0.10</td>
<td>0.001</td>
<td>1.4</td>
</tr>
<tr>
<td>ATSI background (1=ATSI background)</td>
<td>1.33</td>
<td>0.33</td>
<td>0.000</td>
<td>3.78</td>
</tr>
<tr>
<td>Poor English (1=poor English)</td>
<td>1.15</td>
<td>0.28</td>
<td>0.000</td>
<td>3.16</td>
</tr>
<tr>
<td>Single parent (1=single parent)</td>
<td>0.28</td>
<td>0.10</td>
<td>0.005</td>
<td>1.32</td>
</tr>
<tr>
<td>Moved in the past 12 months (1=moved in past 12 months)</td>
<td>0.58</td>
<td>0.12</td>
<td>0.000</td>
<td>1.78</td>
</tr>
<tr>
<td>Disabled (1=disabled)</td>
<td>0.47</td>
<td>0.15</td>
<td>0.001</td>
<td>1.58</td>
</tr>
<tr>
<td>Currently married (1=currently married)</td>
<td>-0.34</td>
<td>0.17</td>
<td>0.045</td>
<td>1.4</td>
</tr>
<tr>
<td>Education (year 12 or less reference)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Secondary plus</td>
<td>-0.43</td>
<td>0.17</td>
<td>0.015</td>
<td>1.54</td>
</tr>
<tr>
<td>Degree plus</td>
<td>-0.88</td>
<td>0.29</td>
<td>0.003</td>
<td>2.41</td>
</tr>
<tr>
<td>Parental non-employment (1=parental non employment)</td>
<td>0.56</td>
<td>0.26</td>
<td>0.031</td>
<td>1.75</td>
</tr>
<tr>
<td>Parental Ethnic background (1=parent(s) born in NES country)</td>
<td>0.88</td>
<td>0.14</td>
<td>0.000</td>
<td>2.41</td>
</tr>
<tr>
<td>Social network index</td>
<td>0.34</td>
<td>0.06</td>
<td>0.000</td>
<td>1.4</td>
</tr>
<tr>
<td>Neighbour influence interaction</td>
<td>-0.003</td>
<td>0.007</td>
<td>0.094</td>
<td>1.0</td>
</tr>
<tr>
<td>Local Labour market employment</td>
<td>-0.08</td>
<td>0.03</td>
<td>0.006</td>
<td>1.08</td>
</tr>
<tr>
<td>Log Pseudo likelihood -1003.20</td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>
market demand. Such a model has been widely discussed in various formats and is generally taken to present a useful representation and framework with which to begin an empirical investigation of unemployment risk.

The results of our empirical investigation need to be tempered by the fact that the types of context effects we have attempted to measure here are extremely difficult to model in a way that produces a clear cut understanding of causal direction and rather what we have found is associations between a number of variables and the individual risk of unemployment. Keeping this caveat in mind, the modelling undertaken in this paper has shown that there is an association between individual characteristics including age, human capital, ethnic background/race, gender, disability and marital status. Ascribed characteristics such as ethnicity and race had significantly large impacts on unemployment risk, as did malleable factors such as achieved human capital. These findings are not surprising and reflect the results of a range of existing empirical studies. However, over and above these individual factors, which are often the focus of those arguing to increase the flexibility and employability of unemployed workers are a range of contextual factors which in our model include the potential role of social capital, social networks and local labour market strength. Importantly we have found that individuals with strong social networks, as measured here, have reduced risk of unemployment. This suggests as has been discussed elsewhere that ‘social isolation impedes individual success in the labour market because it denies residents informal job contacts that are critical not only for finding jobs but good jobs that promote prolonged labor force attachment’ [20]. Additionally the role that family background may have through parental employment patterns and/or ethnic background has been highlighted. In particular, individuals who have had parental role models who have been outside paid employment for some period during the individual’s childhood have an increased risk of being unemployed. Similarly, those whose parent(s) where born in a Non-English speaking country also were associated with an increased risk of unemployment. Finally, we have also shown that the strength of the local labour market has a significant impact on unemployment risk suggesting that labour markets that are insufficiently dynamic and strong impact negatively on individual outcomes net of other factors.

The modelling presented here provides guidance for further research. To date we have not accounted for the impacts of dynamic labour market processes nor have we considered the dynamic nature of housing market impacts. These issues will be the subject of further modelling using later waves of the HILDA survey, combined with other aggregate level longitudinal variables. Moreover, the heuristic model presented earlier pointed to a range of factors that have not been included in the modelling presented here. For instance, we were not able to develop a predictor which accounted for differences in the types of social networks that might impact on job finding and hence differentiate between Granovetter [30] strong and weak ties, nor could we include a direct measure that accounted for the impact of preferences or aspirations on unemployment risk. These kinds of data issues can only be dealt with by using a purpose designed social survey, rather than a generic survey such as HILDA.

These issues aside and given the policy and research divide noted in the introduction research such as that presented in this paper is important as it helps to highlight important policy questions and issues. Considering different policy responses, unemployment
can be tackled through micro level responses or through macro level responses. If, as seems to be the view of many current policy makers, unemployment is primarily seen to be an outcomes of the characteristics of individuals then policies and programs aimed at intervening to address individual deficiencies may be more appropriate. Alternatively, if unemployment is primary considered to an outcome of more contextual effects including the impact of labour market demand, then a different policy approached needs to be followed. Given the analysis presented in this paper, we would argue that in the first instance it is policies which focus on the later which are more appropriate. In chorus with researchers such as Gordon and Turok [28] we hold that the problem of concentrated unemployment and disadvantage has less to do with employability and labour flexibility and the more appropriate focus should be on the impacts of a range of contextual factors and most importantly the impact of weak local labour markets. While current polices such as the Federal government’s welfare to work programs focus keenly on moving to full employability, focusing on these individual characteristics of workers only acts to shuffle the queue in a rationed job market [49].

Bibliography


What Do We Have to Add to a Social Network to Get a Society?

Answer: Something like What We Have to Add to a Spatial Network to Get a City

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Abstract. Recent years have seen great advances in social network analysis. Yet, with a few exceptions, the field of network analysis remains remote from social theory. As a result, much social network research, while technically accomplished and theoretically suggestive, is essentially descriptive. How then can social networks be linked to social theory? Here we pose the question in its simplest form: what must we add to a social network to get a society? We begin by showing that one reason for the disconnection between network theory and society theory is that because it exists in space-time, the concept of social network raises the issue of space in a way that is problematical for social theory. Here we turn the problem on its head and make the problem of space in social network theory explicit by proposing a surprising analogy with the question: what do you have to add to an urban space network to get a city. We show first that by treating a city as a naïve spatial network in the first instance and allowing it to acquire two formal properties we call reflexivity and nonlocality, both mediated through a mechanism we call description retrieval, we can build a picture of the dynamics processes by which collections of the buildings become living cities. We then show that by describing societies initially as social networks in space-time and adding similar properties, we can construct a plausible ontology of a simple human society.

1 The problem: societies as space-time networks

For much of the twentieth century, the concept of network was among the most fertile sources of empirical insights into the working of societies (for overviews see Albrecht et al. [1], Pool and Kochen [14]; also Fischer et al. [3], Granovetter [5]). The concept had the dual advantage of being both readily quantifiable and permitting the direct investigation of the society as it appears in space-time. More than any other, the concept of network offered to put sociology on the kind of foundation we associate with orthodox science by linking mathematical expression to empirical testing. At the start of the twenty first century it is the concept of social network, and its comparability of networks occurring in the natural world, that has brought sociology into the common realm of scientific discourse [for example 2, 16].
But so far the notion of network has made little impact on social theory. For example, both Giddens’ *The Constitution of Society* [4] and Luhmann’s *Social Systems* [13], arguably the two most influential social theory texts of the late twentieth century, make liberal use of the concept of ‘system’ to express the interconnectedness of things, but do not admit the concept of network as a significant element of theory. No less strikingly, Alan Wilson in his remarkable synthesis of a century and a half of mathematical geography, *Complex Spatial Systems* [17], makes virtually no use of the formal concept of network, even in the section of the book which looks forward to future developments.

Why should this be? Why should social theory be so reluctant to embrace at a theoretical level a concept which has proved so potent methodologically? Why should the gap seem, if anything, to be widening as network theory advances? The suspicion must be that paradigm issues are involved. Here it is suggested that they are, and that they are related to the problem of space. Networks are space-time entities. It is this that makes them so promising methodologically. As space-time entities, it is natural to follow the usual practice of seeing them, as other space-time phenomena, as the space-time outputs of whatever underlying processes are creating and sustaining the society. The implication is that the social network is a dependent variable of the ‘real’ social processes, just as in spatial studies the space-time pattern is usually seen as the spatial output of economic processes.

The trouble is, the more it is possible to assign quantifiable structure to a network, the less likely it seems that it is simply a dependent variable and the more likely it is that the network is in some sense implicated in system dynamics through their structural properties. But to admit this in the case of social networks would mean to admit a structured space-time entity into social dynamics, and so potentially into social causation. This is where the paradigm problem may lie: in the linking of network agency to space-time agency. Admitting the concept of network in this sense would undermine any paradigm which, implicitly or explicitly, required the exclusion of space-time entities from social agency, and this means most twentieth century paradigms within which social theories have been set. In the nineteenth century, of course, writers like Herbert Spencer tries to realize the concept of society as an organism [15], and so as a space-time entity, but it was perhaps the naïve physicalism of this attempt that was one factor in giving subsequent authors confidence that any kind of space-time description as a plausible foundation for social theory was to be rejected.

There is in this then a solid reason for social scientists to prefer the notion of ‘system’ to express the interconnectedness of things. A ‘system’ is a set of elements and relations, and so agency can rest at the level of elements rather than relations. The ‘system’ concept is thoroughly compatible with a ‘dependent variable only’ view of interconnectedness. ‘Network’ is an altogether more abstracted notion, and describes pure relations while backgrounding the properties of elements. The notion of network in this sense implies structural agency. This is difficult enough for social theory within present paradigms. To link it to the issue of spatial agency is enough to lead to its ‘structural exclusion from thought’.
2 Comparing social and spatial networks

It is here that we can propose a useful parallelism between social and spatial studies, between, that is, the paradigm issues raised by Giddens and Luhmann formulations and those raised by Wilson’s. Both cities (and the wider regional systems of which they are part) and societies manifest themselves to us as a primitive space-time networks, primitive in the sense that they offer unmediated and direct experience in manifestly network form. In cities, it is the network of streets and spaces formed by buildings that link the city into a single system. In societies it is the network of interactions that link individuals into a community or society. But, as with social networks, the primitive spatial network has usually been rendered invisible in geographical theories of space. As with the social theorists, Wilson prefers the concept of system, and agency in his system lies in the impact of economic forces on the ‘discrete zone’ elements that he divides the city into, and the dynamics interactions between them, and little follows from the structural properties of the network that connects them other than through some notion of distance. As with social theories, the space-time system that we are primitively aware of as the city, is assumed to be the space-time output of the ‘real’ economic processes, spatialised by distance costs, that drive the city.

This paradigm of the city has however been challenged in recent years by the space syntax approach, which begins by modeling the naïve network of space and discovering in its structures an alternative key to the dynamics of the space time city we experience. The paradigmatic novelty of this approach is that it brings to the fore and seems to find a resolution to the paradoxical problem that we identified as lying at the heart of social theory. It shows that the space time network which dominates our direct experience of the city is, not only a dependent variable of social and economic processes, but also an independent variable in the processes by which collections of building evolve into living cities. At the same time it internalizes space into the definition of what a city is. It does so through a precise set of concepts which seem on the face it to offer promise for translation into the study of social networks.

These are the theme of this paper. We first outline the network based processes through which space syntax sees the city as evolving, and show they depend on both spatial laws and human agency working together to create emergent patterns. We then show that to evolve a city from a spatial network, two concepts must be added which we term reflexivity and nonlocality, both mediated through a universal process mediating the relation between mind and world which we call description retrieval. We then apply these concepts to space-time social networks, and suggest how from this a plausible ontology for a simple society can be constructed, one which reflects pervasive properties of all human societies and at the same time internalizes space into the definition of what a society is. We begin by looking at the ‘city as space-time object’, that is, as the patterns of buildings, spaces and land uses that we would expect to find represented on a map.

3 Urban processes: network emergence and network agency

There are two processes which form the space-time city. We can call them network emergence and network agency. Both happen through the mediation of spatial laws.
The first process is the aggregation of buildings to form emergent patterns of space. This is constrained by simple mathematical laws which relate the placing and shaping of objects in space to the emergence of configurational properties in the ambient space. For example, an object placed in the centre of a bounded space will, ceteris paribus, increase mean trip length and decrease intervisibility from all points to all others in the ambient space, and so will an elongated object compared to a square object of equal area. As objects become dense in space, as in cities, the only way to avoid a high trip length labyrinth is to extend at least some spaces linearly, if necessary at the cost of making others shorter. What we find is that all cities, however grid like their structure, grow in such a way as to construct a network made up at every scale of a small number of longer lines, often connected by ‘nearly straight’ angles, against a background of a much larger number of shorter lines, for the most part connected at near right angles. The former roughly corresponding to the network of major public spaces where public and economic activity takes place, and the second to the background of predominantly residential space. This is the process of network emergence [7].

The second process takes place against this background and is set in motion by the impact of the emergent network of space on movement within the network. It is this that shapes the emergent patterns of and uses and densities which give the space-time city its functional character. The process is as follows. As in any non-uniform network, spatial elements—in this case street segments between junctions—will vary on standard graph measures of closeness and betweenness. These correspond to the two components of human movement: the selection of destinations, and the selection of the series of spaces to pass through to get there. Human trips are on average distributed so that there are more short trips than long, so the closeness of a node to all others within a defined radius indicates its potential as a destination from all other nodes up to that radius. Betweenness then measures the propensity for each node to lie on shortest or simplest (depending how you measure distance) routes between each pair of nodes in the system. So each measure reflects one component of human movement. This means that we should mathematically expect the structure of the network to have independent effects on the pattern of real movement flows, and research since 1987 has amply shown that this is the case, most strongly so by recent research which shows that people calculate distance using a geometrical and topological model of the street network rather than direct computations of metric distance [11].

Once we understand the effect of the emergent street network on movement, then the logic of land use patterns becomes clear. Movement seeking land uses such as retail migrate to locations which the network has made movement rich, while others such as residence often prefer movement poor locations. Attractor land uses in movement rich locations than attract more movement, and this attract other, and more diverse land uses, so setting up multiplier effect by which mixed use patches emerges in the network roughly in proportions to their positioning in the grid. In this way, cities acquire their more or less universal form of a network of linked centres and sub-centres at all scales set into a background of residential space. In effect, the space of cities is generated by a dual process: a public space process which is driven largely by micro-economic factors which are invariant and tend to give cities a similar global structure; and a background
residential space process, driven by cultural factors and thus tend to make cities locally different [6; 8].

One implication of this is that space can be, and is, used in two modes. By creating different movement potentials, and so different densities of movement, space can, on the one hand, be used to reflect and embody a cultural pattern, as in the residential areas (and even more strikingly in domestic interiors), where space as laid out to give reality to a culturally given pattern of activity, and so reinforce and reproduce it. We can call this the conservative use of space, since space is being used to reflect and so reproduce a given social pattern by controlling and structuring co-presence. On the other, space can be used to create potential social patterns by morphogenesis, as in the public space process, since by shaping movement, space also creates a denser pattern of natural co-presence in space. We can call this the generative use of space, since we are using space to create the potentials for new co-presence and potentially for social relations. This distinction will be important below when we talk about social networks [6; 8].

4 The human subject and the city

From the point of view of the problems we described earlier of linking the concept of social network to theory, this account of the emergence of the space-time city is of some interest. First, it shows that the spatial network is both a dependent variable of the first, space-creating process, and an independent variable in the second ‘city-creating’ process. Second, it shows that both processes happen within the constructive constraints imposed by spatial laws. Third, it incorporates both spatial agency and network agency in a way which does not seem to raise the ghost of spatial determinism. This has been possible because the spatial network has been put at the heart of the system, and its description as a separate entity, independent of factors with which it interacts, was the first step in research. Without this prior description, it would not have been possible to bring to light either the process of network emergence or that of network agency. In fact, of course, in practices the two processes run concurrently, and at every stage both processes are going on and being modified. But at every stage both processes centre around what we might call the embedded spatial network.

So how can a process which involves both space and laws not be accused of spatial determinism? Two key factors have not so far been brought to the fore. First, all the spatio-temporal events we have described in the two phases of the process are actions taken by—at least partly knowledgeable—human individuals or human agencies. Since these events are the means by which the spatial laws are expressed in space, it follows that the human actions that create the city have in some sense reflected these laws. Human action, it seems, must be the medium through which spatial laws shape the emergent city. This is a less surprising idea than it might appear at first sight. When someone throws a ball of paper so that its parabola leads it to land in a waste paper basket, that person has intuited—perhaps even felt—the laws of mathematical physics without of course doing the calculations. Cognitive science would describe such familiar phenomena as ‘intuitive physics’. Similar evidence can be accrued that people intuit the spatial laws we have described in a similar way, so that spatial behaviour embodies and reflects these laws in the same way as it must embody and reflect physical laws [9].
Second, the embedded spatial network has a peculiar property: although the form of the system has evolved through the first process is bottom-up, its functioning through the second process is top-down, in the sense that the movement flows which drive the evolution of the system reflect the position of each space in the large scale configuration, not the local properties of the space. In this sense, the properties of spaces which are critical to its functioning are non-local and reflect remote, as well as local, connections. This poses a challenging, and highly interesting, question. In order to produce the patterns of flows we find, people must be using some kind of non-local internal representation of the space network with both geometrical and topological properties [11]. In fact, both the network emergence process and the network agency process depend on a human ability to cognize the system in order to act on it. In taking decisions about new street alignments to ensure well formed growth, or working out how to go from a to b in such a way that the functional dynamics of the city are maintained, both require some kind of non-local picture of the spatial configuration as it exists at that point. Since cities, like any complex space, are such that they can only be experienced a bit at a time, we can see that this will depends on a prior ability to turn discrete experiences of the bits of the city into a overall picture of some kind — to turn knowledge of routes for example, into a knowledge of maps, or survey knowledge as cognitive science puts it. This is essentially a process of synchronisation. The experience of the bits is dispersed in time as well as space, and by building routes into maps, or parts into wholes, we are converting experiences dispersed in time into synchronous pictures with some kind of ‘all at once’ geometric order.

5 Description retrieval

It is worth looking at this process of synchronisation more closely since the next stage of our argument in a sense depends on it. It is part of a process we call description retrieval, by which human beings retrieve abstract information from concrete events [10]. Suppose one person builds a house and another person builds a house next to it, we can see that this is the case in a concrete sense, but we can also see that one house is in a next to relation to the other (Fig. 1). This relation is symmetrical, in that if a is b’s neighbour then b is a’s neighbour, unlike, for example, above or below, or behind and in front which are asymmetrical. By retrieving the abstraction next to from the event

![Fig. 1. The generation of simple forms from simple rules](image-url)
we could then treat it as a *rule* and follow it, or not as the case may be. So rules do
not have to reside in heads, but can be derived from spatio-temporal events. But that is
not all that happens. If the process continues, a new form emerges (Fig. 1). If we do not
retrieve a rule and follow it, a random pattern emerges of which we cannot retrieve a
description, but if we do, a linear form emerges. If we vary the rule, other forms emerge
(Fig. 2). We are then able to retrieve a description of these by *synchronising* the discrete
events into an overall shape.

Is this overall synchronisation distinct from the repetition of the local rule? We can
demonstrate that it is. In Fig. 3, the left figure is no less recursive than the right figure
but we only retrieve it as a repeated local pattern, not as a whole. The one to the right
we are more or less able to synchronise as a whole because lines have appeared as a
whole, the one on the right clearly so. This process of *synchronisation* is the upper level
of the *description retrieval* process, and refers to emergent products of local activity.
We retrieve a *template* rather than simply a rule. There are good grounds for thinking
that *templates* are distorted by cognitive input—we make space more orderly than it is—and this becomes more so as the realities it deals with become more complex. We
simplify in order to understand.

Now these *two levels of description retrieval* (the retrieval of abstract information
from concrete events), the level of the *rule* and the level of the emergent *template*, are
I believe fundamental to all the complex system that human beings make and inhabit:
not only cities, but cultures, economic systems and even whole societies. It is exactly analogous to Levi-Strauss’s machines for the suppression of time (to use Leach’s felicitous translation). Kinship in human societies, for example, arises from events similarly dispersed in time and space. But a kinship system, or a set of kinship rules, synchronises these dispersed events into a logical template. This mechanism for turning time into the non-time of logical order was the heart of the Levi-Straussian project. It can operate either by knowing rules, in which case the emergent pattern is poorly understood, but present, or by knowing the logical system, in which we can use it locally as a problem solving device.

The presence of the description retrieval cycle in a process such as settlement growth imparts to it two critical properties we can call reflexivity and nonlocality. Reflexivity means the ubiquitous intervention of human minds first between the forces that bring the city into existence and the form it takes, and as we have seen reflexivity reflects spatial laws which are known intuitively to people. Reflexivity between mind and created world, is then not simply a mechanism, but a pervasive explanation of form. Nonlocality means effects emerge spatial or functional patterns in systems which depend on remote rather than proximate elements. The simple fact that human movement depends on nonlocal factors is the clearest and simplest instance of this, but once the concept is admitted it can be seen to be quite pervasive both in the network emergence and network agency phases of the process.

So we arrive at a model of the city in which socio-economic processes, human cognition and spatial laws all played an interconnected role, one which, I suggest, requires us to see the city as a semi-autonomous system — that is a system which is in part determined by external forces, and in part through into own internal laws, through which these extraneous forces are turned into something new and distinctively urban. We showed this by internalising space into the model of the city, and showing that space was the source of its essential forms and dynamics. We also showed that what we might call the DNA of the city is in its physical and spatial patterns, and we interact with it through the two level description retrieval and embodiment mechanism. The patterns of the city embody social information—using the term in its broadest sense—and this is what we aim to retrieve through syntactic analysis. As was suggested in [10], a city is like a machine whose programme is in its output. This is why we must see our urban surroundings as both a spatio-temporal and informational or conceptual reality.

6 Cities and societies

Now this is something like what Giddens said about society in 1984 (the same year as The Social Logic of Space was published). Societies, he said, were virtual structures realised and reproduced through situated practices acted out in space-time. The informational content of society exists in and in reproduced through spatio temporal activity. His model was language, mine biology (though turned on its head, in that the DNA is exosomatic), but the conceptual model was similar. But Giddens said little after this. Having shown in principle that space and time can be internalised into social theory, he does not then try to show how and why it happens. In fact, at the end of the 1984 book he turns away from space in the real sense of what we find in buildings and cities and
replaces it with the—to my mind—much weaker concept of the *spatiality* of social and economic processes, just as the old urban modellers did.

But the need to internalise space into social theory is an urgent issue, to my mind the outstanding problem of social theory because without it we cannot say what kind of a thing a society is [6]. The twentieth century accumulated an array of potent findings pointing to a powerful and systematic relationship between society and space, but these have never been formalised into a theoretical model. For example, Durkheim’s assignation of the sources of the shift from mechanical to organic solidarity to what he called ‘moral density’, Service’s conclusion that in Australia greater dispersal was associated with more sodality like behaviour and vice versa, Turner’s cultural comparison of the Talense and the Ndembu and their different settlement forms, to name only a few. In the late twentieth century a substantial array of work linking real spatial and social processes from authors like Bintliff’s work on settlement scales and social morphology, Kristiansen and Rowlands on settlement and social structures, Perring (and others in the remarkable Rich and Hadrill-Wilson reader), Maisels and others. While most disciplines have talked endlessly about space but baulked at the real space of buildings and cities, archaeology has done it in spades — but never really called it space. If ever there was a body of work looking for a spatial theory this is surely it.

My aim here is to suggest that an ontology by which space can be internalized into society, and the space-time network made central, by making what might seem at first a preposterous comparison between *society* and the *city*. It is less preposterous perhaps if we call it a comparison between spatial and social space-time networks. They do after all have a lot in common prima facie: both can be represented as graphs and shown to share surprising large scale mathematical regularities, for example in that each has the property of being both sparse—nearly all elements are not connected to each other—and shallow—graph distances between elements are surprisingly small considering the number of elements. Both kinds of system are *dual* in the sense that they combine the spatio-temporal and the informational, so you never get one without the other; both have the DNA ‘out there’; and both seem to relate to human cognition through some kind of description retrieval process. What I will propose adds nothing to knowledge. It merely suggests an ontological framework for a society as a spatio-temporal and conceptual system, through which the twentieth century findings and theories and space and society can make sense together.

7 First steps towards an ontology: the issue of evolution

The most basic question for an ontology of society is: why do human beings form societies in the first place? The answer must involve evolution, since if societies were did not offer evolutionary advantage, then it is unlikely they would exist. This poses an apparent problem, because the common view of evolution is that it is driven by competitive struggle of all against all. This seems to many to pose a problem for understanding societies because although societies may involve competition, in some more than others, societies are essentially *co-operative* phenomena, and this is certainly true of the simplest societies of which we have a record. Language provides interesting clues. ‘Social’ behaviour means cooperative behaviour towards fellow members, and although most
people would accept that there are social benefits in economic competition, we would not normally describe competitive behaviour as ‘social’ behaviour—even though in a broader sense it clearly is.

But, on closer examination, the evolution problem for society turns out to be illusory. It dissolves when we focus on the actual mechanism of evolution rather than its metaphorical embedding. The mechanism of evolution is focused on only one thing: success in producing offspring. The more certain groups rather than others have more offspring, they more their genetic characteristics will dominate the future gene pool, and so be more like them than others. As soon as this is clarified, the supposed contradiction between evolution and society disappears. Societies will be favoured by evolution if they increase the capability of social members to have offspring, and of course this is exactly what societies do. This is what societies are and what they are for. Societies favour the production of surviving children, because whatever else they are, they are set of interdependencies amongst individuals which spread risk amongst those individuals, so that if something goes wrong with one person’s circumstances, then others can help, and vice versa. So other things being equal social members are statistically more likely to have the dependable and secure circumstances in which they can produce more progeny than those who are not social members. At root, we might say, societies are insurance policies: they take risk from the level of the individual to that of the society, so over evolutionary time, human beings who are members of societies are more likely to influence the gene pool than those who are not.

So in evolutionary terms, a society is at least some network of relations which is projected through time to makes the interdependencies possible. This suggests that the fact of relatedness may be more critical than the form of relatedness. Any system of relatedness which allows risk to be spread would work to give the evolutionary advantage that must be the reason for society’s existence. The fact of being some system of relations is then the foundational notion for society, before we consider either the specific form those relations take or the causes which brought them into existence. The function of a society, we might say, is to exist, and through its existence to provide the security through interdependence that on the evolutionary time space leads to decisive advantage. We might even take this one stage further and suggest that the larger the society, and the more individuals involved in the system of relations, then the more successful the society ought to be in evolutionary terms. So other things being equal, evolution is likely to select for those forms of society which grow large at the expense of those that remain small. If this is so, we do not need to account for social growth, since evolution would already select in favour of societies which are able to grow.

But scale is also evolutionary issue in a more basic sense. If the existence of a ‘society’ means, as seems likely, that members inter-marry with each other more than with non-members, then the society must be large enough to provide an adequate genetic diversity. Mathematical models suggest that this cannot fall below about 500 members. This has a critical implication for an ontology. Since in the simplest situations most environmental circumstances requires people to live in cohabiting groups of a size well below the intermarrying threshold, it follows that for a reproducible society to be created, it must succeed in creating durable relations across spatial groups, and so non-local relations. So society, if it is to exist, must respond to two kinds of pressure.
to create a non-local grouping which is much very much larger than the co-residence group. This is of course what societies are in the first instance: they are arrangement of exchange and interdependence between co-habiting groups. This is the first step in our ontology. ‘Society’ must be sought initially in the non-local relations among dispersed co-habiting groups, not within the local cohabiting group—though we would expect signs of the non-local society also to appear there.

8 Societies as space-time networks

Within this framework, a society is first and foremost a network existing in a spatial region within which there are a number of local cohabiting groups. This network will be sustained by social practices, but it these social practices are the means by which the network is realized and reproduced, not the society itself. It is not the social practices that gives evolutionary advantage, but the network they create and sustain. So if anything it is the network which comes closer to being at the heart of what a society is. In what follows, we will see social practices as means of creating, controlling and mutating theses networks and their structures, especially under conditions of growth.

As with the city, then, we can and should put the graph of the social network at the heart of our model, and propose that for an evolutionary advantageous society to exist in the form of a network of local and non-local groupings there must be two things:

- mechanisms for overcoming space to create the non-local grouping—we could call them mechanisms for overcoming dispersal, or even for overcoming space
- mechanisms for controlling local space, that is securing the local grouping against dispersal, for example by having ways to settle disputes short of fission

The two interact in that fission of the local group can be a means to create the non-local grouping, and the non-local grouping will often means a means to create and re-create the local group. But in general we can say that to come into existence, society has to solve two spatial problems: roughly those posed by dispersal and those posed by proximity.

9 Spatial and conceptual groupings

How the are non-local relations created? In some simple societies this is a matter of exchanging people with high frequency, so that the very fluidity of the spatial group is a means by which a larger scale social network is continuously recreated [12]. Moving to another group is also a standard way of solving disputes within the local group. Almost universally, however, we find that societies define, over and above local, or spatial, groups, groups which are defined non-spatially in that membership is defined by a label, and so can be thought of as conceptual groupings. Households, village and universities are spatial groupings. Families, clans and academic disciplines are conceptual groupings, and so independent of space. Conceptual groupings have distinct forms and patterns of social behaviour associated with them, as do spatial groupings. For example, ceremonial and ritual activity is often through the conceptual grouping.
Where then do social labels come from? In general we can say: by description retrieval from the spatio-temporal graph, and so by reflexivity. At the simplest level social labels like sister or father are the roots of j-graphs (or graphs justified from each node considered as root) of sets of relations, and each node in the graph acquires a label which implies all the others. Social behaviours appropriate to the label then inherit the formal properties of their position in the graph, so in metaphorical extensions ‘sisterly’ behaviour reflects the symmetry of the sister relation, and so equality, while fatherly behaviour reflects the asymmetry of the parental relation, and so inequality. A clan system, in constrast, is a template retrieved from the space time graph by synchronising events dispersed in space and time—birth, reproduction and death—into a time-free logical picture. Clans can also inherit the formal properties of their space time origins. In this sense, the way in which we simplify and so bring order into complex social networks seems to resemble the way we do it to cognise spatial networks: we turn relations into abstractions and order them into formal geometrical and logical schemes.

System of labels in general, are then reflexive constructions from the space-time graph, with abstract properties as well as space-time realisations. As soon as they exist, they create potential for some socio-spatial dynamics. Consider two cases in which we have two spatial, or cohabiting, groups and two conceptual labels, say the pink and the blue. In one the membership of the spatial group and the conceptual groups correspond, in another they do not. So if, in the ‘correspondence’ case, being a member of the blue or pink clan corresponds to spatial group membership, so that all members of the group are the same colour, then everyday activities and ceremonial activities associated with the conceptual group reinforce the same group of people. Local identities will become stronger, and non-local weaker. The spatial group will tend to need boundary control, and stronger internal rules, to preserve its single colour. In practice, we tend to find groups of this kind are territorial and internally hierarchical. In the non-correspondence case, being in blue or pink does not correspond to spatial group membership, so everyday activity merges blues and pinks, while ceremonial activities reinforce non-local blue or pink connections, and so increases the density of the non-local network at the expense of the local. Local boundaries are weaker as there is no need to control for colour. In this model the non-local network is stronger, and local identities weaker. But freeing the local group from ceremonial identity allows local political interaction to become stronger. In practice, we tend to find such societies less hierarchical, less territorial and more political.

10 Graph generating and graph-directed behaviour: short and long models

The distinction between spatial and conceptual groupings also relates to another invariant across societies. All societies deploy resources and activity at two levels: the level of everyday production of the material conditions of life, and so the biological survival of individuals; and at a level devoted to seemingly biologically unnecessary activities which serve to reproduce social relations. One expression of this is the difference between everyday events, with their short term recursion periods, and special, more ceremonial events, like births, marriages, deaths, seasonal festivities and so on, which have
longer term recursion periods. We can call the upper level the reflexive level, since the object of its behaviours is to reproduce existing patterns in the space-time graph. Its behaviours can be seen as graph-directed, while behaviours at the lower level generate graph relations as a by-product. Where we find templates operating at this upper level we call them institutions or institutional structures.

We find different kinds of behaviour associated with the two levels. All human encounters are made up of two elements; the space time elements of co-presence and interaction; and the abstract elements such as labels, classification and rules which shape the form the interaction takes. The spatio-temporal aspects are the hardware of social transactions, the labels and rules the software. The software however has some very interesting dynamic properties of its own. In all societies human encounters vary on the dimension formal-informal. For example, where encounters are asymmetric we find more formal content — use of titles and forms of address, more formal language, special behaviours, and so on. We can conceptualise this as the ratio of rules to events: the higher the ratio the more formal, the less the more informal, and index it as the length of the string of symbols we must write to describe the rules that control events. The longer the sequence of symbols required—the longer the model—the more the spatio-temporal event is formal, and the shorter the required string, that is the shorter the model the more that is allowed to vary randomly and the less formal it is, while retaining some degree of conceptual intervention.

The limiting case of a long model event is the ritual: everything must happen in a certain sequence, be carried out be certain people, follow an exact format, and so on, so that it would take many symbols to write the formula down. But everyday life also varies across cultures and with phases of culture in the length of model. So while all human encounter is rule governed in some sense, the degree to which it is rule-governed is a variable, and this variable can be in principle quantified (though in reality only with great difficulty). The length of the model indexes the degree of conceptual intervention in a space time event. Now the longer the model is the more the events are reproductive of patterns that already exist, because more of what happens is governed by the rule; while the shorter the model, the more the events lead to morphogenesis in the system of relations, because less of what goes on in the space-time encounter field is rule governed and more is randomised. A ritual is a reinforced description of relations that already exist in society and this is why it has a long model. This mirrors the distinction between the conservative and generative mode of creating space, in a more precise form. There are more rules in conservative space.

Long and short models have their own socio-spatial and temporal dynamics. In everyday life, activity patterns will tend to have a shorter recursion period, involve a great deal of everyday activity, and bring together a local group and use a short model, that is a low ratio of rules to events; while ceremonial activities will tend to have a longer recursion period, take the form of special events rather than everyday activity, and involve a wider group of people and use a longer model, that is a higher ratio of rules to events. So time is involved as well as space, time being a kind of distance. We can generally say that the shortness of the model is inverse to spatial and social distance. This is why it is in the nature of things that the ceremonial fund is essentially the non-local fund, and why we tend to find the ‘social’ more in the relations between spatial groups.
than within them. It is the primary means by which society creates a non-local network and it is the primary means by which space and time are internalised into society.

11 An ontological model for society as a space-time network

We can now outline an ontological model for society based on these ideas (Fig. 4).

<table>
<thead>
<tr>
<th>Spatial</th>
<th>Transpatial</th>
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<tbody>
<tr>
<td>Space-time events - low conceptual intervention</td>
<td>Special events - higher conceptual intervention</td>
</tr>
<tr>
<td>The production and reproduction of descriptions at the generative level of the microsociety i.e. everyday life and interaction</td>
<td>The production and reproduction of descriptions at the emergent level of complex descriptions or institutional structure</td>
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</table>

**Fig. 4.** An ontological model for a society as a space-time network. Note that the word ‘transpatial’ is used to express the independence of conceptual descriptions from space, so they work naturally across space.

The foundation is the space-time graph and the model is about what we have to add to it to arrive at a society. The horizontal axis distinguishes the spatial from the conceptual, and the vertical the nonreflexive from the reflexive. Bottom left we have everyday life in which elementary ‘description’ in the graph are generated by co-presence. Bottom right is the conceptual content of these co-presences. Top right we have the realm of ceremony and ritual through which template level conceptual content are realised in space-time through enactment. Top left we have the negotiation and control of template level descriptions, or the realm of politics.

Simplifying, we can see that the left side unreflexive level of activity can be seen as **graph generative** activity in that it continually poses new co-presences as candidates for description retrieval as enduring relations in the graph, while the right side can be thought of as the conditions of reproduction for those relations. The upper reflexive level can be conceptualised as **graph-directed** activity, aimed at the structure of the network itself, either by reinforcing its patterns by embodying them in enriched description realisations we call rituals, or by seeking to solve problems that arise as society grows and changes, the realm of politics and law.
12 Society is how we overcome space

Society is then an evolutionary advantageous form that is achieved by overcoming space by using reflexive mechanisms to create non-local relations. Ecological factors like environment, technology and density, and so the conditions for the production of biological survival, set the problem which is solved by how space is overcome. So in conditions in which people can only survive sparsely, society will have to overcome dispersion, while under conditions of density the problems will one of proximity. Exactly what mechanisms evolve in a particular society could involve chance, in that any set of social practices which realised advantageous non-local groupings in a stable way could and perhaps would become normative in that society simply because they created the conditions of evolutionary advantage. This 'normative hypothesis' would even make sense of random variation in social forms, as well as permitting dramatic change to take place.

But under conditions of growth, different mechanisms would be activated. If there are a number of spatial groups in a landscape and population increases, then either the number or the size of groups must increase, or both. If the number increases, the problem remains that of dispersion and, since under dispersed conditions non-local integration tends to happen through the conceptual groupings and associated ritual, rather than politics, this should leads to ritual intensification as the mean of holding the society together. If the size of groups increases then the problem shifts from overcoming dispersion to overcoming the problems of proximity. The left side reflexive level of the model—politics, dispute settlement and so on—is prioritised over the right, ceremonial side. This is why with urbanisation a large proportion of the complexity of ‘tribal’ societies eventually disappears, including elaborate kinship systems and associated forms of ritual.

Our model then suggests that one of the great discontinuities in human social history from tribal to urban reflexive structures actually arises from what societies are and how they can be created under different spatial conditions. So by seeing societies by analogy with space as spatio-temporal graphs with reflexivity and non-locality, we can internalise space into our model of society and capture some significant interactions between the social and spatial dimensions.

One final observation: Our analysis of cities suggested that we needed to see the spatial network as a semi-autonomous system meaning that although clearly shaped and driven by exogenous economic and social forces, we do not understand exactly how this is so unless we also understand that it also evolves under the scope of internal spatial laws. In fact it is through the intermediary of these laws that economic and social processes are able to express themselves in space. The same is surely true of societies. What we name as 'society' seems to be a semi-autonomous system in something like the same sense.

Bibliography


The Production of Space in Social Simulation Models

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Abstract. In this paper I will present work which, over a number of years, has sought to include richly structured representations of spatial relations in dynamic simulation models. A simple agent-based model of segregation will be described that progressively includes the capacity for its spatial structure to change in a variety of ways in response to the spatial distribution of the agent population. In this model, the actions of agents collectively produce reconfigurations of the space, which in turn act back on the behaviour of agents. Prospects for the explicit incorporation of social networks in this kind of model will be considered. Implications of this model for analytical approaches will also be examined.
Simulating Place Selection in Urban Public Parks*

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Abstract. How do people choose their place when walking into an urban public park? This question is important in the context of socially sustainable recreational spaces and thus interesting to park managers and designers. Our aim is to systematically investigate park management and design options using analyses and simulations of the behavior of park visitors. The first step towards this goal is to model place selection in public parks. How can we model this highly individualized and dynamic process? One theory asserts that park users perceive affordances of the park furniture and choose a place according to their needs. Needs are largely influenced by the intended activities but also by expected social interactions. In our multi-agent simulation we model the notion of affordances of park furniture with respect to (a small number of) goal activities. Early simulation results indicate that affordances and activities alone are not sufficient to explain place selection. Currently we are implementing the notions of personal and social space as well as affordances of park users, thus introducing a social dimension into the model. Once our model has been verified and validated, it can be used to evaluate alternatives in park design and management.

1 Motivation

Urban public parks offer a great potential to raise the quality of life for urban citizens, while at the same time their creation and maintenance requires substantial amounts of money. Surveys have shown that citizens consider parks to be an important element for their well-being, even if they use parks only occasionally. We assume that the specific behavior settings of a park (in the sense of Schoggen [15] and Barker 1968) and management strategies [8] strongly affect visitors behavior by affording certain activities while discouraging others. Thus, both the design and the management can contribute to minimize usage conflicts and ensure social sustainability. Consequently, the design and management of public parks and recreation areas have attracted a substantial amount of interest. Academic research ranges from technical aspects of counting visitors, the usage of parks, gender issues [13] to more conceptual and theoretical publications on the social construction of public space and its appropriation [9].

On the application side, “until now, there has been no tool for recreation managers and researchers to systematically investigate different recreation management options. Much of the research is based on interviews or surveys, but this information fails to

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inform the manager how different management options might affect the overall experience of the park user. More importantly when you have different, conflicting recreation uses, how do different management options increase or decrease the potential conflicts? None of these questions can be answered using conventional tools” [5].

We propose to use multi-agent simulation as a method to investigate park usage and as a basis for research on the influence of park management options. Simulation is used in many contexts, including the modeling of natural or human systems in order to gain insight into their functioning. Simulation can be used to show the eventual real effects of alternative conditions and courses of action.

The aim of our research is to model the human-environment interaction, the social interaction and the resulting space usage in urban public parks at the micro level of individuals. We would like to show that it is possible to approximate the complex interpersonal processes of space use and appropriation in a park using a relatively simple model. This model implements concepts from anthropology and environmental psychology.

In our project we have observed and mapped the behavior of park visitors (Fig 1) in several parks in Zurich (Switzerland). In addition to the spatial and temporal information we also recorded gender, age group, primary and secondary activity, as well as group affiliation. We will use data from one park to verify our model and validate the model predicting visitor behavior in another park, comparing prediction and recorded behavior.

Fig. 1. Snapshot of the behavior of park visitors in Wahlenpark, Zurich, Switzerland

Visitors in a public park are a naturally occurring multi-agent system [17] that we endeavor to simulate using a multi-agent simulation tool. The simulation of human behavior is an extremely powerful and interesting research method to advance our understanding of the interaction between human beings and their environment [3]. Multi-agent systems offer the possibility to simulate space appropriation with different sam-
amples of park users and to try out the effects of various elements of park design on visitor behavior and location choice.

The goal of this paper is to describe a model and a multi-agent implementation of place selection in urban public parks. How do people choose their goal location when entering an urban public park? Which places attract or repel the park visitor and which factors contribute to this judgment? The ecological theory [4] asserts that park users perceive affordances of the park furniture and choose a place according to their needs. Needs are largely influenced by the intended activities but also by expected social interactions. In our first model, we use affordances of park furniture and activity types to model place selection. In order to facilitate the modeling process, the "environment", i.e. the simulation world, must be enriched with information lending itself for the information gathering and processing of the agents. This corresponds to the idea of contextual categorization [2; 16]—i.e., the activity determines the context and thus the world is categorized according to the current activity. In a second model (work in progress) we add personal and social spaces to the agents’ sensory and cognitive abilities. We believe that a combination of affordances (of park furniture and of people), activities, and personal/social space will yield results highly similar to our observed behavior.

The paper is structured as follows: the second section introduces the conceptual model in more detail, the third section describes the implementation of the model in an multi-agent system called SeSAm, and the fifth section presents conclusions from the modeling and some future work.

2 A Model of Place Selection in Public Parks

How do people choose their goal location when walking into an urban public park? Our model posits that a visitor enters a park, surveys the (visible) park objects that suits her goal activity, chooses one goal object and walks towards the object. This choice process can be enriched with many different criteria, e.g., current occupancy, the distance to the nearest neighbor, the activities of neighbors, current distance to the object, weather it has special properties such as lighted, shaded, secluded, open etc. While walking towards the object, any of these properties might change. If this happens, the choice process starts again.

As noted above, the selected location must satisfy certain needs of the park visitor. Needs are largely influenced by the intended activities but also by expected social interactions. In our model the driving need of the visitor is represented by his/her goal activity, the personal space requirements resulting from the activity, as well as the desired social contact due to the intended activity or to group membership.

During our extended observations in public parks of Zurich [14] (see also Osterman and Timpf [12], Osterman and Timpf [11]), the following groups of activities have been observed:

- non-interactive activities (sleeping, reading, and working),
- interactive activities (chatting, observing, overseeing children),
- eating (picnicking and BBQ),
- formal ball games (soccer, badminton),
– activities relying on infrastructure (such as playgrounds, water basins),
– activities on the spot, and
– activities involving localized movement.

Some activities require a specific location or a specific infrastructure. If these requirements are not fulfilled, i.e., the park visitor cannot carry out the activity, then she leaves the park.

2.1 Matching spatial affordances

Requirements for activities are modeled using the concept of perceived affordances. Affordances of objects tell us how those objects could be used [4]. E.g., a chair affords sitting, a flat surface affords walking or skidding, and a swing affords sitting and swinging. In our study human users of parks perceive objects or object groupings that allow them, i.e. afford, to carry out an activity. There has been some debate in the literature about how to determine affordances, since a chair also affords standing on it or even writing on it. We model “typical” affordances as attributes of objects in the park. The potential set of affordances is determined by the possible activities of the park visitor. This approach conforms to the concept of contextual categorization [16]. It lowers the potentially infinite number of affordances of an object by constraining them to those affordances usable for a certain activity the park visitor might wish to pursue.

Our model currently matches the affordances of an activity (see Table 1) and the affordances of visible park furniture. For example, a park visitor wishes to read, which requires the affordances for sitting or laying. As a result, the visible park furniture that carries these affordances will be selected.

Table 1. Affordances of recreational activities

<table>
<thead>
<tr>
<th>Activity</th>
<th>for_sitting</th>
<th>for_laying</th>
<th>for_writing</th>
<th>for_eating</th>
<th>for_walking</th>
<th>for_climbing</th>
<th>for_group-Play</th>
<th>for_water-Play</th>
<th>free-space</th>
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<tbody>
<tr>
<td>Reading</td>
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</table>

After this first selection, the selection process differs for single park visitors and for groups of park visitors. For a single park visitor with an activity for a single person,
currently occupied park furniture is culled from the selection. For a group of park visitors, park furniture needs to be found that provides enough seating or places for the number of people in the group. This amounts to culling park furniture with less space from the selection. If the resulting set is empty, then the park furniture with the least number of occupants is selected. Finally the location is chosen using a combination of random selection and nearest furniture selection.

2.2 Social affordances and group behavior

The concept of affordances of objects can be extended to define social affordances, i.e., affordances of persons or groups of persons. Such social affordances might be belonging (being part of a group), talking (or other interaction at one place), playing (or other interaction with local movement), and more. In our model these affordances are also tightly linked to the intended activity, but activity does not account for all potential social interaction. Therefore, we also introduced the social affordances for talking and cooperating for park visitors, as well as for belonging for groups of park visitors.

The affordance for belonging requires modeling the behavior of groups of park visitors, i.e., persons who come to the park at the same time and share their intended activity. A prominent (small) group in our observations, i.e., about 30% of the park visitors, are groups of parents with children. This type of group is highly interactive and cooperative - they tend to congregate. This is in contrast to the groups of people that tend to separate themselves from others (single or groups of park users) to pursue their own activities, be they interacting or playing (formal) games.

Group membership has a profound influence on location selection. The group tries to find a resource where all required affordances can be found. The decision making process is not very transparent. In our model we defined a leader of the group (randomly) who will make the decision and will be followed by all other group members. These group members will not choose their own location. Instead, the group, i.e., the group leader chooses the location using the procedure presented in the previous sub-section with the additional constraint of group size.

2.3 Keeping personal and social distance

The previous sub-sections dealt with the conscious choice of a location in the park. While consciously choosing a location the visitor moves into the park and most probably keeps on walking. Incidental evidence from our observations shows that about 95% of the park visitors just keep on walking while apparently scanning the park. Only about 5% stop walking, scan the park and resume walking in a chosen direction. While walking in the park they keep their distance from stationary obstacles and evade other agents to avoid collisions. This behavior is on-going while they are moving about. It conforms to the notion of personal (and social) distance proposed by the anthropologist Hall [6] (see also Altman [1]) and modeled in the form of a dissatisfaction-minimizer developed by Beltran et al. [2]. In our simulation we use a modified social force model [7] to achieve this kind of behavior.

The model also extends to location choice: distances between the potential location and nearby agents/activities are estimated and incorporated into the choice process.
After the set of park furniture with enough seating or with the least occupants has been determined, the potential locations are tested for conformance to similar activity, similar group, or similar age. The chosen location is then selected from the resulting set using a combination of nearest location and random choice.

3 Simulating place selection

SeSAm – (Shell for Simulated Agent Systems [10]) provides a generic environment for modeling and experimenting with agent-based simulation. It is specially focused on providing a visual tool for the easy construction of complex models, which include dynamic interdependencies or emergent behavior (www.simsesam.de). The underlying programming language is Java. SeSAm provides a basis for spatially explicit autonomous agents in continuous space.

An autonomous agent is a computer simulation, which is based on concepts from Artificial Life research. Agent simulations are built using object oriented programming technology. The agents are autonomous because once they are programmed they can move about the world like software robots. The agents can gather data from their environment, make decisions from this information and change their behavior according to
the situation they find themselves in. Each individual agent has its own physical mobility capabilities, sensory capabilities, and cognitive capabilities. This results in behavior that echoes the behavior of real animals (in our case humans) in the environment.

The process of building an agent is iterative and combines knowledge derived from empirical data with the intuition of the programmer. By continuing to program knowledge and rules into the agent, watching the behavior resulting from these rules and comparing it to what is known about actual behavior, a rich and complex set of behaviors emerge.

Models in SeSAm require three parts: the world, a number of resources, and a number of agents. The world in our case represents the park, park furniture are resources, and agents represent park visitors (see Fig. 2 on the left).

The world requires a situation (see the map in Fig. 2), has a temporal component and knows the number of agents currently living in the world. Each resource class represents a furniture type. Currently 14 resource classes are modeled: bench, fountain, red beech, play gear, light, water basin, table and benches, shade tree, blue band, paved paths, lawn, exit and patch. Each class has a number of attributes needed as information input for the reasoning process of the agents.

![Fig. 3. Activity Graph of the reasoning “Visiting Park” of the ParkVisitor agent](image)

The main agent class is the class ParkVisitor. In addition to attributes, ParkVisitor includes three reasoning mechanisms: visiting park, moving, and perceiving. The whole simulation is controlled using these mechanisms. The most important of these reasoning mechanisms is “visiting park” (see Fig. 3).

As described in Section 2 above, the agent first surveys the visible resources (SurveyResources in Fig. 3), then selects the place containing the resource. If no resource can be found, she leaves the park.
Once a resource is selected, the reasoning “moving” takes control (Fig. 4). Each reasoning mechanism runs concurrently to the others. This means that the moving about takes place while the agent surveys her resources.

If a resource has been selected, the agent moves towards the place, i.e., the location of the selected resource (see “MoveToPlace” in Fig. 4). Once the agent is near the place, a specific location (e.g., on the bench) needs to be selected according to the criteria discussed in the previous section. Finally, the agent carries out her goal activity, which might be more complex than shown here.

4 Results, conclusions and future work

The first testing of methods and the results show that our goal of modeling spatial interaction at the micro level is already possible with the use of only the most relevant input information, namely environment, type of activity and group behavior. The preliminary results of the simulation are encouraging. They show a valid movement behavior of the agents (for some movies of the simulation see www6.informatik.uni-wuerzburg.de/~timpf/parksim/). However, the model was developed with a specific park in mind and with the data we observed there. We will need to validate our model using a different park setting. Fortunately, we have observed several parks in Zurich and will use a second park for validation of the model.

Our model, if it has been validated, can be used to determine appropriate management measures in existing parks and to evaluate the design of new parks. Park managers can influence the setting of the park. This means that they can introduce or leave out
additional furniture, change its location, or provide restricted access to it. The resulting new situation and its place selection process can be simulated beforehand using our model. It might be necessary to adapt the model and its input parameters, i.e., a map with objects on it and a table showing the affordances of the objects and corresponding observed or wanted activities.

The model envisioned in the application scenario above requires extensions of the model. Currently park furniture affords an activity equally well. However, there might be differences in the perception of these affordances, such that e.g., the affordance for reading of a bench is perceived to be a better fit than the same affordance of the lawn. This would require a rating or bidding mechanism to be included in the reasoning of the agent.

Currently, we cannot model trajectory perception, i.e., when humans walk towards an object, and see another person walking towards the same object, then one of them will decide relatively early to choose another object or to keep on walking. In order to include this reasoning step, the spatial primitives in SeSAm need to be extended.

Our agents at the moment come into the park without any pre-conceptions. It would be interesting to implement a pre-selection of the chosen location (which would be analogous to the agent having a coarse mental map of the park) or a ranking of locations according to stored behavior patterns of the agent. However, this extension of the model requires a set of spatial reasoning primitives and structures that do not (yet) exist in SeSAm. We are working with the developer’s group of SeSAm to incorporate more spatial primitives and structures into the multi-agent system.

On the theoretical side, we aim at deriving from these case studies the smallest set of spatial functions/primitives that needs to be included in a simulation environment. We have identified that topological concepts need to be included or modeled explicitly, i.e., the nearness relation, spatial overlap and include relations. A systematic investigation will be conducted in the near future.

Bibliography

Simulating Visitor Behaviour: Algorithms for a Recreational Agent Model

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Abstract. Autonomous agent models are becoming increasingly common in studies of visitor behaviour in recreational landscapes. One such system is currently being developed at the University of Melbourne, Australia, and aims to replicate visitor movement patterns in the Royal Botanic Gardens (RBG) Melbourne. The Intelligent Recreational Agent Simulator (iRAS) uses autonomous, reactive and proactive agents to produce a range of behaviours observed within the real environment. When hundreds of these individuals are generated using input data obtained from field-based surveys and behavioural experiments, the resulting collective movement patterns are highly correlated with observations. This paper will introduce the approaches used to create, parameterise, calibrate, and validate the iRAS agent system, but will focus on the principles and algorithms used to model the required agent behaviours.

Keywords: Autonomous agents, recreational behaviour, Royal Botanic Gardens Melbourne, multi-agent systems, iRAS.

1 Introduction

Since the early 1990’s individual and multi-agent-based models have been developed as a popular approach to modelling spatially explicit ecological phenomena. Much of this initial development involved the simulation of creatures with simpler behavioural rules than human tourists. However, autonomous agent models have since evolved to a point where the actions of many complex individuals can be computed [1] with several contexts being explored including human behaviour [6; 11].

A few researchers have sought to combine spatially explicit agent modelling with Geographic Information Systems (GIS) in order to model behavioural outcomes in realistic environments [e.g., 9; 11]. REPASt [for example, 4], provides innovative and effective ways to both spatially analyse and display the complex outcomes of agent simulations. More recently, spatial agent-based modelling techniques have been used in studies of pedestrian movement in urban environments and shopping centres [5; 17], simulations of evacuations at large events or after major disasters [13; 14], and in the generation of probable routes for tourists in recreational areas [3; 8; 10].

Various methodologies and approaches can be taken from previous studies such as these, however, as Bishop and Gimblett [2] concede, building an agent model is an iterative process which requires knowledge derived from both empirical data and
experience with the landscape, along with intuition on the part of the programmer. This means that, while it may be useful to apply some aspects of prior research into a model, agent behaviours should ultimately reflect those observed in the study environment, and so this is where the majority of research should be focussed. “By continuing to program knowledge and rules into the agent, watching the behaviour resulting from these rules, and comparing it with what is known about actual behaviour, we can observe a rich and complex set of behaviours” [2].

Indeed, after careful parameterisation and calibration using data collected via a range of methods (discussed briefly below), the iRAS system was able to generate quite realistic results. While the validity of this output is constrained to a finite set of experimental conditions, agents nonetheless behave in an intelligent manner and the resulting collective movement correlates exceptionally well with observed movement at a number of real intersections in the Royal Botanic Garden (RBG), Melbourne.

Fig. 1. The path usage of simulated agents compared with that of observed visitors at four intersections within the Royal Botanic Gardens between 2pm and 4pm on a sunny weekday afternoon. The correlation coefficient between the two data sets was calculated to be 0.85 for directional (in & out) usage and 0.92 when total path usage was compared. These figures are very similar to the correlations between actual movements on two different observation days (of similar conditions), calculated as 0.86 and 0.89 respectively. This suggests that a higher correlation would be neither realistic nor meaningful. The results obtained are therefore as good as is possible for this subset of intersections and certainly suggests that the simulation as it stands is quite valid under the conditions applied.

2 Understanding the Visitor and the Landscape

Due to the complex nature of typical human-landscape interactions and the depth of understanding required to simulate realistic behaviour, the collection, compilation and analysis of large quantities of high-quality data is essential. Gathering such data is not
a simple process and in turn requires a relatively complex, multi-faceted approach, employing a variety of contrasting procedures.

Technologies available to the modern researcher range from computer-based tools such as virtual environments and geographic information systems, to field-based equipment such as pedestrian counters, and global positioning system (GPS) receivers. However, as Gimblett [7] argues, to obtain comprehensive information on human behaviour (both spatial and non-spatial), technology-driven experiments can be combined with traditional social survey techniques. For the Royal Botanic Gardens simulation, data collection methods ranged from simple visitor and staff interviews to large-scale, high-tech experiments. These are briefly described below.

**Initial visitor questionnaire (IVQ).** People were approached within the gardens and asked a set of pre-defined questions relating to their current or usual movements, as well as preferences for visual features, plant collections, and path attributes.

**Location-based questionnaires (LBQ).** Hand-held, GPS-enabled applications were developed using Personal Digital Assistants (PDAs) in order to gather context-sensitive visitor responses regarding personal and environmental influences on path choices.

**Virtual environment questionnaire (VEQ).** A number of three-dimensional computer-generated landscape simulations were modelled and used to collect virtual path-choice responses along with indications of the relative importance of numerous visual influences.

**Intersection observation surveys (IOS).** Actual path-usage data was gathered at a number of RBG intersections; recording entrance path, chosen path and various demographics for every visitor or group passing through each intersection during the experiment timeframe.

**Visitor speed survey (VSS).** Visitor movements were timed over pre-measured path sections in order to ascertain the distribution of average visitor speeds.

**Staff opinion surveys.** Opinions were collected from RBG experts relating to the relative popularity of various attractions within the gardens.

**RBG people-counters.** Sensor devices, placed at every gardens entrance as well as at strategic internal locations, continuously collected data for analysis per gate, per hour, day, week, month, and year.

### 3 Defining the Agent and the Virtual Environment

There is ongoing debate and some controversy about what an agent actually is, since the various attributes associated with agent modelling depend greatly on the application. While there is a general consensus that autonomy is central to an agent system, no universally accepted definition currently exists. Two useful explanations relevant to this project are nonetheless presented below.

"An agent is a computer system that is situated in some environment and that is capable of autonomous action in this environment in order to meet its design objectives” [16]
"The concept of autonomous agent modelling is that each agent... has their own set of rules which describe their behavioural (and potentially emotional) response to particular sets of circumstances. After placing a number of agents in a site... a simulation is run with each agent acting autonomously. After a period of model operation a picture emerges of collective behaviour" [2].

There are also a number of key elements, acknowledged as being commonplace in the field, even if they are not necessarily of paramount importance in every context. Some of these aspects, often referred to when attempting to explain usual agent capabilities, are described in further detail below, including their relevance (or lack thereof) to visitor simulation within the Melbourne Royal Botanic Gardens.

3.1 Agent Capabilities

**Autonomy.** As mentioned previously, autonomy is perhaps the key agent concept. An agent must be able to complete its objectives using predefined tasks without requiring any form of user interaction. This is indeed a key component of iRAS. Visitor agents enter the virtual gardens at a given time and location with predefined properties and capabilities, however, after the simulation has begun, the behaviours produced are based completely on each agent’s own choices. The user does not interact or influence these choices in anyway; they are computed entirely using the agent’s current perception of its environment, its desires, its feelings, and its goals as parameters.

**Reactivity.** In general, a reactive agent receives sensory input from its environment, makes some decision by comparing this input with its own personal attributes, and then performs some action which in turn affects its environment. This interaction then repeats itself and continues until the system is terminated. Reactivity to the virtual RBG environment is naturally one of foundations of the system design and while a visitor’s reactions will not physically alter the landscape, their perception of the environment certainly does change with their own actions, and with the actions of other agents.

The most common visitor action is simply to move to a new location, in which case the agent’s sensory input is altered based on the properties of this new section of the environment. Agents already within close proximity to this location also receive altered sensory inputs as the area becomes more crowded with the new agent’s presence. Other actions may include pausing to rest, eat, or admire the scenery, all of which have an impact on the agent’s perspective, and thus the environment is sensed differently. For example, a steep path may appear quite unattractive to an exhausted agent, however, after a short action of rest, the same path may be perceived differently.

Environmental stimulus is not the only influence an agent reacts to however, nor is the environment the only thing effected by an agent’s actions. The state of the agent itself—its internal properties—can and do change with action, and these parameters in turn have an impact on behaviour. In this model an agent is influenced by a number of properties, preferences and feelings which may or may not vary with time, distance, or experience. When an agent decides which action to take next, all of these properties are examined along with any environmental sensory inputs.

**Proactivity.** Intelligent agents are generally able to exhibit proactive, goal-based behaviour. This essentially involves taking the initiative in order to satisfy some design
objective, as opposed to simply reacting to sensory inputs. In reality a recreational visitor will certainly display this kind of behaviour; not only making decisions based on current conditions and stimuli, but also by deciding on a plan of action in order to satisfy some need or desire. In the Botanic Gardens such goals can include resting, eating, using the toilet, or simply visiting a certain location, as well as entering and exiting the park itself.

**Mobility.** Mobility is not a necessary capability for all agent models, especially those which are more abstract, such as distributed systems or economic models. For agents designed to replicate actual people however, mobility is usually a basic requirement. Recreator simulation is no exception, as the movement of visitors is often actually the focus of the investigation anyway. In order to achieve spatial mobility, the agent environment must be created to allow agents to move in two or three dimensions as well as to sense various attributes at different locations.

**Social Activity.** For the majority of multi-agent systems, social activity is one of the fundamental traits, with agents being able to communicate, negotiate and cooperate with one another in order to achieve their individual design objectives. When simulating a recreational agent, which can be a single visitor or a decision-making party of any size, these abilities are generally not required however. For the most part, the experience of a park such as the RBG is a private affair, with little if any social interaction between agents. This being said, one might ask what the point of creating a multi-agent system is—surely each agent could be run separately, without the need for simultaneous generation? However, just because the agents do not interact with each other, does not mean that they do not affect each other. Agents are still able to perceive the presence of other agents, which does indeed influence their decisions, particularly where large numbers of agents are congregated. In one sense, the tendency to avoid or pursue crowded areas could be seen as social ability, however no actual communication is required if crowding is simply assumed to be a dynamic attribute of the environment. Indeed, this is the approach taken to synthesize such interaction in this simulation.

**Learning Ability.** Finally, agents in many applications require the ability to learn new actions or methods as they progress in their virtual "life". Learning capacity can indeed be an important agent capability; however it is not central to agency—especially where the simulated time period is particularly short (as is the case for a single visit to the Botanic Gardens). It is assumed therefore that RBG agents already know how to perform any actions required of them throughout the day’s visit, and so these actions can be defined prior to their entrance and remain unaltered for the duration of the simulation.

### 3.2 The Agent Environment

Environmental properties have a great impact on the complexity of the agent design process as well as the complexity of possible agent behaviour. As such it is important to understand how certain aspects of the environment effect system design. Russell and Norvig [15] classify four main properties of an agent environment.

**Accessible Versus Inaccessible.** An environment is accessible if the agent is able to obtain complete, accurate, and up-to-date information about the environment’s state. In general, the more accessible the environment, the simpler it is to design agents to
populate it since the quality of an agent’s decisions is obviously dependent on the quality of the information it receives. In reality the level of accessibility is much higher than it is possible to simulate, and so it is important to design an agent environment which consists of features that are most important to the behaviours being replicated.

**Deterministic Versus Non-deterministic.** A deterministic environment is one where the result of any given action is always guaranteed. Clearly this is simpler and preferable from a design perspective, however as a simulation becomes sufficiently complex (as those attempting to replicate some form of reality tend to do) even an environment that actually is deterministic will begin to behave as though non-deterministic. In practice, any realistic environment should be regarded as non-deterministic for all intents and purposes. That is, agents should always be designed to determine for themselves whether a given action will actually produce the desired result under current circumstances, and further check that this outcome was in fact achieved.

**Static Versus Dynamic.** A static environment is one whose properties can be assumed to remain unchanged throughout the duration of a simulation, with the exception of changes induced by agent actions. A dynamic environment can therefore be described as one that has non-agent processes operating on it; factors which are subsequently beyond the agents’ control. In all physical environments, conditions are certainly dynamic, with a multitude of uncontrollable events and properties experienced in every day life. The Botanic Gardens environment is no exception. Possibly the first dynamic property immediately recognisable, especially in a city like Melbourne, is the weather, which can change rapidly, causing visitor behaviour to change with it. This factor in itself could be considered reason enough to develop a dynamic RBG agent environment, and perhaps in the future, such modifications will be made. For now however, the environment is designed to remain static for the duration of the simulation, allowing results to be compared with real data obtained during similarly constant conditions. A warm, sunny, summer day was chosen as the basis for all simulations, observations, and comparisons thereby eliminating the effects of dynamic environmental influences for the sake of uncomplicated experimental design.

**Discrete versus continuous.** An environment is considered discrete if there are a fixed, finite number of actions and perceptions which can take place within it. In the case of a spatial environment, we could further define a discrete environment as one in which the agent’s movement is constrained to a set of finite locations, while in a continuous environment the agent can move freely in any direction to any possible position. While in reality, visitors to the Botanic gardens can theoretically walk anywhere within the park, the majority of movement is constrained to the path network. Any movement away from this network is generally across grassed areas in order to sit down, visit points of interest located within the grassed area, or cross the lawns in order to reach another path more quickly. This being the case, it seems natural that the agent environment should simply be a constrained discrete network, taking into account certain grassed routes.

Some discussion took place regarding this point, and as to whether the environment should in fact be continuous. However it was argued that a constrained network such as this is certainly able to replicate the most common movement patterns observed in the Botanic Gardens (that is, movement along the many paths), and that the end result of a given simulation is generally focussed on the compilation and comparison of *path
usage, so that exact positioning on or off the path network becomes somewhat superfluous. Also, while a network consisting of interconnecting paths and nodes implies that agent movement is direct between intersections, certain functions can still be introduced to compensate for the small pauses often made along a particularly interesting path (i.e. to take a photograph, read an information sign, or admire a view).

4 Algorithms for Human-Landscape Interaction

4.1 Agent properties

Along with a number of general attributes (both static and dynamic) such as start time, entrance, current position, speed, bearing, etc, an iRAS agent is defined by three behavioural controllers: Preferences, Feelings, and Goals. These properties, combined with perceived environmental attributes, control the agent’s movement and choice of activities over simulated space and time.

Using this range of behavioural influences, iRAS agents can display a wide variety of commonly observed behaviours depending on the unique values assigned to them. Agents can choose to move directly towards specific locations (via a calculated route) in order to fulfil certain goals; they can wander the path network with no apparent purpose, other than to choose the most appealing paths they come across; and they can pause at specific locations to admire the scenery, rest, eat, or use the toilet.

Each type of influence is used to generate specific behaviours that have been observed through experiments in the real and virtual world [see 12, for further information].

Preferences simulate individuality in terms of the stimuli that a visitor generally finds appealing or unappealing (either consciously or subconsciously). These preferences could be for wide, open views or for close proximity to water, or they could be against crowded areas or noise from external road traffic. Each agent preference relates to a specific attribute that can be sensed within the environment, and is assumed to be static throughout the duration of their visit. A preference value (denoted $\rho_x$, where $x$ is the related attribute) ranges between $-1$ and $+1$, where a positive value indicates an attraction to a certain feature and negative indicates repulsion.

Feelings relate to the dynamic needs or desires common to all RBG visitors. The rate-of-change of these feelings will vary from person to person, but the resulting behaviours remain constant. For example, a critical feeling of hunger will always cause an agent seek food, a feeling of exhaustion will always require rest, and toilet need will always prompt the agent to find a toilet. The feeling of boredom is also used in iRAS to simulate the desire (or time-related need) to exit the gardens. Feelings will usually be dependent on distance or time as well as some duration factor, which affects the feeling’s progress. For example, equation 1 illustrates how the feeling of hunger ($f_H$) increases over time ($t$) with respect to the agent’s individual hunger duration factor ($\tau_H$).

$$\Delta f_H = \Delta t / \tau_H$$

(1)

Feelings can also be dependent on further variables. For example, Equation 2 shows the feeling of exhaustion ($f_E$) increasing over distance ($d$) with respect to agent fitness...
Fitness is the individual exhaustion duration factor, and is defined as ‘distance to exhaustion over flat terrain’. This rate therefore increases with (uphill) slope ($\beta$), where $\beta$ is a fraction of 90°.

$$\Delta f_E = (1 + \beta) \cdot \Delta d/ft$$

(2)

All feelings range from 0 to 1. When a value of 1 is reached, the feeling cannot increase further but usually the agent will generate a relevant goal in an attempt to decrease the feeling.

Goals represent conscious decisions to move directly to some position with a specific purpose in mind. In the Botanic Gardens, these goals can simply be to visit and admire a particular attraction, or they can be the direct result of the feelings mentioned above. For example, when exhaustion reaches 1, the agent will generate a goal to rest at the nearest possible rest point (a bench or a grassed area, for example). Of course, the agent need not wait until its feeling of exhaustion reaches this critical point; if its exhaustion levels are high, it can spontaneously choose to rest anytime that it passes a valid rest point (i.e., without forming a goal to rest). In this way, a distinction is made between actions that are incidental to the visitor’s chosen walk and actions that require a conscious deviation.

Goals can range in importance, having a value between 0 and 1, and are ranked by the agent depending on both importance and proximity (with nearer and more important goals having higher priority). The highest priority goal at any given time will influence the appeal of paths leading towards that goal’s destination. However, if the goal’s importance equals 1, then the agent will choose to achieve it immediately by taking the quickest route. Once an agent reaches its goal, it will generally undertake some action associated with the goal purpose (e.g., rest, eat, use the toilet, admire the scenery, etc).

In equations, goal importance is denoted $g_n$, where $n$ is the goal’s priority (eg. 1st priority = 1, etc).

4.2 Path Choice Decisions

When an agent is wandering the path network arbitrarily (ie. without any critical feelings or goals to cause direct route calculation), each new intersection encounter means a new path choice calculation. The appeal ($\alpha$) of any given path is based on the agent’s current position, preferences, goals and feelings at the time. When an agent is deciding on a preferred path, the path with the highest appeal value will be chosen. The appeal of any given path is the sum of the appeal values for all path features, each of which is calculated using a specific algorithm. These algorithms always involve at least one path-dependent variable and at least one agent-dependent variable.

Most path attribute values range between 0 and 1, but are often transformed within the algorithm so that the possible range is essentially between $-1$ and 1. Usually, the agent’s feelings and goal importance values are similarly modified within the formula, while preferences naturally range between $-1$ and 1. The agent variable (preference, feeling, goal importance, or a combination of these) is then multiplied with the appropriate path attribute so that the resulting appeal value is also (usually) between $-1$ and 1. In this way, the majority of path features either add to or detract from the overall
appeal of a path by a fraction of one. Path feature weights \( \omega \) are then used to uniformly increase or decrease the effect of any given path attribute in order to increase or decrease its relative importance. The resulting equation for final path appeal is hence:

\[
\alpha_{Total} = (\alpha_1 \cdot \omega_1) + (\alpha_2 \cdot \omega_2) + \ldots + (\alpha_n \cdot \omega_n)
\]  

Equation 4 demonstrates how agent preferences can relate to their corresponding environmental attribute in a very simple manner. The path’s rescaled water visibility factor \( wt \) is simply multiplied with the agent’s water visibility preference \( \rho_{wt} \) to give the appeal value \( \alpha_{wt} \).

\[
\alpha_{wt} = (2 \cdot wt - 1) \cdot \rho_{wt}, \text{ such that } \alpha| - 1 \leq \alpha \leq 1
\]  

Equation 5 combines path (upward) slope factor \( \beta \) with the agent’s preference \( \rho_{\beta} \), as well as its feeling of exhaustion \( f_E \). In much the same way as the rate of exhaustion is dependent on the slope of the terrain (as mentioned above), so is the appeal of a sloping path dependent on the agent’s exhaustion level at the time of evaluation.

\[
\alpha_{\beta} = \beta \cdot (\rho_{\beta} - f_E), \text{ such that } \alpha| - 1 \leq \alpha \leq 1
\]  

Feelings can also cause certain paths to become more appealing because they lead to specific types of points. In Equation 6, \( lR \) is a boolean value indicating whether the path in question connects to a rest node. This value (being 1 or 0) is multiplied with the agent’s scaled feeling of exhaustion, so that once exhaustion exceeds approximately 0.66, rest points become increasingly more attractive as exhaustion approaches 1. (Note that the output range is clipped to ignore negative values in this case since the existence of a rest point does not make a path less appealing when the agent is not tired.)

\[
\alpha_{lR} = lR \cdot (3 \cdot f_E - 2), \text{ such that } \alpha|0 \leq \alpha \leq 1
\]  

The appeal of path direction is split into three components \( \alpha_{\theta1}, \alpha_{\theta2}, \alpha_{\theta3} \), as illustrated in equations 7–9 respectively. A path becomes more appealing when its direction \( \theta_p \) is comparable with the agent’s current direction \( \theta_q \)—this algorithm replicates the tendency for visitors to follow a generally straight path, avoiding erratic changes in direction. Similarly, if a path heads in roughly the same direction as the agent’s priority goal \( \theta_{g1} \), then this path becomes proportionally more appealing with goal importance \( g1 \). Finally, the appeal of a path’s direction is also influenced by the agent’s desire to leave the gardens (its feeling of boredom—\( f_B \)). When an agent begins its journey, it will tend to move against the direction of its desired exit gate \( \theta_x \). Once its feeling of boredom has increased past 0.5, exit direction becomes gradually more appealing. In this way, if the agent is entering and exiting the gardens at the same gate, it will tend to move in a natural circular route, much as visitors tend to do in the real RBG environment.

\[
\alpha_{\theta1} = 1 - \frac{2\phi}{\pi}, \text{ where } \phi = |\Delta \theta_{p-a}| \text{ and } \alpha| - 1 \leq \alpha \leq 1
\]  

\[
\alpha_{\theta2} = g_1 \cdot (1 - \frac{2\phi}{\pi}), \text{ where } \phi = |\Delta \theta_{p-g_1}| \text{ and } \alpha| - 1 \leq \alpha \leq 1
\]
\[ \alpha_{\text{B3}} = (2f_B - 1) \cdot (1 - \frac{2\phi}{\pi}) \], where \( \phi = |\Delta \theta_{p-x}| \) and \( -1 \leq \alpha \leq 1 \) \hspace{1cm} (9)

These algorithms highlight just a few of the many agent-environment interactions that are simulated in iRAS. While there are a great number of other factors, which influence agent path-choice decisions, they are generally handled in a similar fashion to the examples given above (ie. \( \alpha_n \) = path property \( n \times \) related agent properties, such that \( \alpha_n \) adds or subtracts from total path appeal \( \alpha_{\text{total}} \)).

5 Conclusion

While the iRAS system has only been tested for validity under a limited set of experimental conditions in a single study environment, many of its approaches and algorithms are applicable to further recreational agent-based studies. The iRAS model approach acknowledges that an agent system must be customized to the landscape and population being simulated, and therefore assigns the majority of system variability into agent and environmental input values. The algorithms themselves use these variables in an attempt to approximate human decision making processes in a streamlined manner, without resorting to abstract or unintelligible shortcuts. This causes agent behaviour to be understandable and realistic on an individual scale, as well as resulting in accurate collective movement patterns.

Bibliography


Abstract. Using geographic and social network data collected in the field, this study explores the statistical characteristics of three distance measures (Euclidean, Actual, and Least-Cost) relative to their use in the social setting of dyadic ties in a network of secondary school headteachers \((n = 69)\) in Mukono Uganda. While the mathematical distinction between these three measures is self-evident, their potential for differential use in statistical analysis is the focus of this study. Thus, the study explores four questions regarding the three distance measures: (1) are they statistically related (using Pearson correlation and Cronbach’s Alpha), (2) are they statistically non-equivalent (using ANOVA and Student-Newman-Keuls), (3) for each distance measure, are the mean distances between network ties and non-ties statistically different (using t-tests), and (4) are they different in predicting ‘frequent interaction’ network ties (using Logistic regression)?

Keywords: Geographic Science; GIS; Social Network Analysis; Education; Uganda.

1 Introduction

The fields of geographic science \([11; 13; 17]\) and social network analysis \([3; 14; 18]\) each have a long and rich history. The intersection of these fields presents intriguing new opportunities to address more complex research problems than either field alone. From geographic science, this research paper addresses the problem of comparing geographic distance measures. From social network analysis, this research seeks predictors of social relationships. At the intersection of these two research questions lies the potential to explore the relationship between geographic and social space in the identification of geographic predictors of network ties.
In that light, this paper examines the intersection of the relationship between geographic and social space by addressing four research questions: (1) are the three geographic distance measures explored in this study statistically related, (2) are they statistically non-equivalent, (3) for each distance measure, are the mean distances between network ties and non-ties statistically different, and (4) are they different in predicting ‘frequent interaction’ network ties?

2 Background and Hypotheses

Discussions of proximity and distance in the literature of both geographic science and social network analysis have been common for decades [1; 5; 9; 11; 19]. The discourse in geographic science is broad, focusing on questions ranging from the mechanisms employed to make distance measurements more cost-effective and/or mechanically efficient to what geo-social implications (sometimes even at the ontological and epistemological levels) are implicated in geographic reasoning. While distance is often mentioned in social network research as an interesting and important factor, it is nonetheless typical that ‘distance has not been an explicit variable’ [21] and that ‘few studies have exact spatial locations for both ego and alters’ [15].

2.1 GIS Distance Measures

In geographic science, spatial analysis focuses on the question of ‘how physical and human activities vary across space – in other words, how these activities change with distances from reference locations or objects of interest’ [16]. In geographic science literature, the two most frequently mentioned types of distance measurement are Euclidean (straight-line, air, or ‘as-the-bird-flies’ distance) and network distance (least-cost, or shortest-path distance). A third way of measuring distance is what we will call in this study ‘actual’ distance. Actual distance is computed by taking the unimpeded, unweighted network distance between two locations.

With three possible ways of measuring distance, the obvious questions arise as to how these measures differ. When we discuss ‘difference’ in this study, we are referring to the statistical, not mathematical distinctions between the three measures. Obviously the mathematical differences—the unavoidable real differences between, say, Euclidean and network distance—are self-evident. But not all mathematical differences necessarily lead to meaningful distinctions in a statistical framework, and being statistically distinct can lead to important decisions and activities in planning and implementing research at the geo-social intersection. For example, if two mathematically distinct variables are statistically equivalent, then either one could theoretically, and for most typical implementations, serve as a valid proxy for the other in a statistical analysis. Consequently, both measures would not technically be necessary in a given study, and either one of the two could be chosen for use based on criteria other than the distinct or unique interpretive or predictive contribution to the statistical model. For example, if both options are statistically equivalent (could serve as a proxy for the other) and one of the potential measures is significantly less expensive (financially and/or technically),
then it could be used as a low cost alternative to the other with little or no loss of inferential and/or explanatory ability in a statistical sense. On the other hand, if various distance measures are not statistically equivalent, and therefore bring different statistical value to the study, then both options or the more expensive options may need to be pursued.

2.2 Emerging Overlaps between Geographic and Social Space

Network theorists are beginning to more regularly incorporate considerations of geographic space in their research questions and analyses [2; 7; 8; 15]. This inclusion is based on assumptions that there is a theoretically and practically significant intersection between geographic and social space. The geographic/social space intersection is also found in geographic science literature where discussions about the social embeddedness of geographic analysis within social space are seen with increasing regularity [6; 12; 20]. This intersection is also found in social network research in the concepts of political and cultural embeddedness [22] and, more recently, in Barney’s suggestion for a more nuanced approach to new analytic possibilities in ‘a geographically embedded view of relations’ [2].

With these few issues in mind, the following hypotheses represent the conditions tested in this brief study:

**HYPOTHESIS #1**: The Euclidean, Actual, and Least-Cost measures of distance between headteachers in Mukono Uganda are statistically related (correlated).

**HYPOTHESIS #2**: The means of the Euclidean, Actual, and Least-Cost measures of distance between headteachers in Mukono Uganda are statistically non-equivalent.

**HYPOTHESIS #3**: The Euclidean, Actual, and Least-Cost measures of distance between headteachers in Mukono Uganda demonstrate statistically different mean distances between network ties and non-ties.

**HYPOTHESIS #4**: The Euclidean, Actual, and Least-Cost measures of distance between headteachers in Mukono Uganda will differentially predict the existence of ‘Frequent Interaction’ network ties.

3 Methods

3.1 Data Collection

Data on network ties was drawn from the population of secondary schools in Mukono District, Uganda using a snowball sample, a common procedure for network research [10]. The initial sample included all 10 secondary schools within 5 kilometers of Mukono Town (the largest population center within Mukono District). At each of these 10 schools, the headteacher completed a network survey in an interview setting with field researchers and identified other headteachers with whom they frequently interacted by name, school and town. These 10 headteachers identified another 35 schools. In the second round, headteachers of these 35 schools were completed the network survey indicating headteachers with whom they interacted frequently, adding another 24 schools. Thus, after three rounds of snowball sampling, 69 headteachers had been included in the network sample, completed the network survey, and identified a total of
175 dyadic ties (average of 2.53 ties per school). The network data were imported into UCINet software [4] for analysis of network centrality. The graphical map of social space was calculated and drawn using NetDraw software [3].

The non-tie data was generated from these same 69 schools. Using a random number generator, a sample of non-ties \( (n = 175) \) was drawn for further analysis. Thus, the analyses of tie existence used the same sample of schools with equally-weighted, same-sized samples of ties and non-ties.

Shown in Figure 1, the geographic location of the 69 schools in Mukono District was obtained by university undergraduate field researchers who visited each school to obtain the necessary data using handheld GPS units. The transportation data (including the road system) was obtained from the Ugandan Government GIS unit in Entebbe. All geo-spatial data and analysis was facilitated in ESRI’s ArcGIS program.

![Fig. 1. All 69 network schools and roads in Mukono District, Uganda.](image_url)

Euclidean distance was calculated by using the ArcGIS measure tool between each of the two schools with network ties. Actual distance was calculated by measuring the distance along each of the roads (regardless of surface type) between the two schools that totaled the lowest actual distance of all options. Finally, Least-Cost distance was
Fig. 2. Least-Cost and Euclidean distance measures for six dyads.
calculated by assigning each of the five types of roads an impedance factor. These factors were calculated by taking the average sustainable travel speeds on each type of road and computing a relative speed factor using tarmac road speed as the index value (see Table 1). Distances on each of the five types of roads were factored by these impedance factors. The travel route that totaled the lowest impeded distance was used as the Least-Cost distance. Perhaps due to the relatively simple nature of the road network (there are relatively few options for travel between schools), the Actual and Least-Cost routes were the same, with the only difference being the use of impedance factors on the Least-Cost distance. Examples of six schools and their associated Euclidean and Least-Cost distance are represented in Figure 2.

<table>
<thead>
<tr>
<th>Road Type</th>
<th>Average Sustainable Speed</th>
<th>Impedance Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tarmac</td>
<td>56kph</td>
<td>1.00</td>
</tr>
<tr>
<td>Marrum</td>
<td>26kph</td>
<td>2.15</td>
</tr>
<tr>
<td>Dry Weather</td>
<td>21kph</td>
<td>2.67</td>
</tr>
<tr>
<td>Small Town*</td>
<td>11kph</td>
<td>5.09</td>
</tr>
<tr>
<td>Self-Maintained</td>
<td>10kph</td>
<td>5.60</td>
</tr>
</tbody>
</table>

* Small Town roads were included in the Least-Cost and Actual distances, but do not appear on the maps in Figures 1, 2 & 4 because they are not visible at those scales.

Using NetDraw [3], the graphical network map of the headteacher network, as shown in Figure 3, illustrates the position of each school and their ‘frequent interaction’ relations in social space. Figure 4 illustrates these same schools and dyadic relations in geographic space. Figures 3 and 4 illustrate a specific emphasis on the six schools that are most ‘central’ in social space using undirected degree centrality.

3.2 Data Analysis

In the analyses, the existence of a tie \( (0 = \text{non-tie}; 1 = \text{tie}) \) served as the dependent variable, and the three interval distance measures served as independent variables. Using SPSS 14, correlational (Pearson’s R) and reliability analysis (Cronbach’s Alpha) were used to examine the statistical relationship between the three distance measures (Hypothesis \( \sharp1 \)). ANOVA and Student-Newman-Keuls post-hoc tests were used to explore the statistical equivalence of the three measures (Hypothesis \( \sharp2 \)). T-tests were employed to investigate the potential differences between the means of the distances between ties and non-ties (Hypothesis \( \sharp3 \)). And finally, binary logit regression was used to explore the predictive ability of each measure relative to the existence of ‘frequent interaction’ network ties (Hypothesis \( \sharp4 \)).
Fig. 3. Social space: the Netdraw graphical mapping of all dyadic relationships. The six most central schools are shown as large square icons. The same six schools are shown as large square icons in the map in Fig. 4 for a visual comparison of the difference between ‘location’ in geographic versus social space.

Fig. 4. Geographic location of all dyads in the social network.
4 Findings

4.1 Hypothesis ♯1: Statistical Relationship

In testing Hypothesis ♯1, the Pearson correlational analysis of the three distance measures indicated that all three measures were highly correlated ($p < .01$; see Table 2). The Cronbach’s Alpha reliability analysis, which calculates the ‘average correlation’ of the three distance measures and expresses the extent of the internal consistency, agrees with the Pearson analysis that these three distance measures are highly similar in a statistical context ($\alpha = .909$). While plots of the relationships between each pairing of three measures showed a somewhat heteroskedastic relationship, the consequent potential threat to underestimation of variances does not appear to be sufficient to cast doubt upon subsequent analyses due to the size of the t-test scores reported below. Based on the results of these two tests, Hypothesis ♯1 is retained.

Table 2. Correlation and Cronbach’s Alpha of Distance Measures

<table>
<thead>
<tr>
<th>Distance in Kilometers</th>
<th>Correlation Coefficients</th>
<th>Cronbach's Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euclidean</td>
<td>13.52</td>
<td>10.31</td>
</tr>
<tr>
<td>Actual</td>
<td>18.43</td>
<td>14.43</td>
</tr>
<tr>
<td>Least-Cost</td>
<td>30.66</td>
<td>22.72</td>
</tr>
</tbody>
</table>

*p ≤ .01

Consequently, while each distance measure is in fact mathematically different, these initial statistical analyses indicate that they are closely related (i.e., they are highly correlated, or statistically associated). This finding indicates that the obvious mathematical differences between the three measures are muted in a statistical environment. If the analysis were to end here, it could defensibly be asserted that any of the three measures could be used as a proxy measure for the others. This would have significant implications in terms of what geo-spatial data would need to be collected, and at what financial and technical cost. However, we believe that further analysis is needed before this type of assertion should be made.

4.2 Hypothesis ♯2: Statistical Non-Equivalence

To explore Hypothesis ♯2, we used a one-way ANOVA, which takes into account variability within each of the three distance measures, to determine whether the means of each distance measure were statistically equivalent to each other. We applied blocking on the ties in the ANOVA, which is similar to pairing in t-tests. We then factored by type of distance measure and used distance as the outcome (dependent) variable. The results of the ANOVA indicate that the means of the three distance measures are statistically non-equivalent ($F = 98.477; p \leq .0001$).

The ANOVA, however, indicates only that there is a statistical difference between the means when all three are included together. To explore whether each measure was
statistically different from each of the other two measures we employed the Student-
Newman-Keuls post-hoc test. The results of the post-hoc test indicated that each of the
three distance measure means was different from the others at the \( p \leq 0.05 \) level.

As a result of these two statistical tests, Hypothesis \( \sharp 2 \) is retained. Bringing forward
the analysis from Hypothesis \( \sharp 1 \), we find that although the three measures are statisti-
cally correlated, they should be considered as statistically distinct measures of distance.
Thus, while the analysis for Hypothesis \( \sharp 1 \) might have indicated that any of the three
could be used as a proxy for the others, this second analysis casts doubt on the statistical
defensibility of that assertion.

4.3 Hypothesis \( \sharp 3 \): Distances Between Ties and Non-Ties

For Hypothesis \( \sharp 3 \), t-tests indicated a statistically significant difference (\( p < 0.01 \); see
Table 3) in means for each of the three distance measures between the tie and non-
tie samples, with school dyads in the non-tie sample having statistically greater mean
distances on all three measures. This finding indicates all three measures performed
equally well in validating that distances between school dyads in the sample with ties
were statistically different from distances in the random sample of those without ties.
Thus, based on t-tests, Hypothesis \( \sharp 3 \) is retained.

<table>
<thead>
<tr>
<th>Tie?</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>T</th>
<th>df</th>
<th>Sig.(2-tailed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euclidean</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>175</td>
<td>10757.54</td>
<td>9280.80</td>
<td>5.197</td>
<td>348</td>
<td>( p \leq 0.01 )</td>
</tr>
<tr>
<td>No</td>
<td>175</td>
<td>16283.58</td>
<td>10568.47</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>175</td>
<td>14406.30</td>
<td>12671.77</td>
<td>5.461</td>
<td>348</td>
<td>( p \leq 0.01 )</td>
</tr>
<tr>
<td>No</td>
<td>175</td>
<td>22500.05</td>
<td>14962.49</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Least-Cost</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>175</td>
<td>25457.35</td>
<td>20841.79</td>
<td>4.399</td>
<td>348</td>
<td>( p \leq 0.01 )</td>
</tr>
<tr>
<td>No</td>
<td>175</td>
<td>35869</td>
<td>23369.85</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: The mean and standard deviation (SD) distances are given in kilometers.

4.4 Hypothesis \( \sharp 4 \): Predicting Network Ties

Logit regression was used to examine the relationship between distance measures and
their prediction of ‘frequent interaction’ network relations. The ‘enter’ method was used
in all of the models. As seen in Table 4, each of the three measures predicts the existence
of ‘frequent interaction’ network ties at an equally high level of statistical significance.

While there is a difference between the total percent of correct prediction between
the three measures, the range of 2.6% between the highest (Actual distance at 62.3%) and
lowest (Least-Cost at 59.7%) correct prediction does not appear to be sufficient
to warrant a claim of an important difference between the measures. Consequently,
even though the analysis provides sufficient grounds to retain Hypothesis \( \sharp 4 \), the fact
that each measure predicts ‘frequent interaction’ ties at a statistically significant level,
Table 4. Logistic Regression of Distance Measures on Network Ties

<table>
<thead>
<tr>
<th>Model</th>
<th>Constant</th>
<th>Euclidean</th>
<th>Actual</th>
<th>Least-Cost</th>
<th>Chi-square</th>
<th>Total % Correct Prediction</th>
<th>Nagelkerke R-squared</th>
<th>Cox &amp; Snell R-Squared</th>
<th>−2 Log Likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>.746*</td>
<td>.000*</td>
<td>.000*</td>
<td>.000*</td>
<td>26.109*</td>
<td>61.1</td>
<td>.096</td>
<td>.072</td>
<td>459.094</td>
</tr>
<tr>
<td>Model 2</td>
<td>.776*</td>
<td>.000*</td>
<td>.000*</td>
<td>.000*</td>
<td>28.967*</td>
<td>62.3</td>
<td>.106</td>
<td>.079</td>
<td>456.236</td>
</tr>
<tr>
<td>Model 3</td>
<td>.653*</td>
<td>.000*</td>
<td>.000*</td>
<td>.000*</td>
<td>19.028*</td>
<td>59.7</td>
<td>.071</td>
<td>.053</td>
<td>466.175</td>
</tr>
</tbody>
</table>

* = p < .01

combined with a small range from highest to lowest amount of correct prediction, the strength of the predictive differences would be considered marginal.

5 Discussion

5.1 Retention of All Four Hypotheses

All four of the hypotheses were retained on the basis of the analyses. What does it mean, then, that: (1) all three measures are highly correlated (i.e., could be used as proxies for each other), (2) each of the three measures are statistically unique (i.e., are not statistically equivalent), (3) each of the three measures identifies a difference between the mean distances of the ties and non-ties, and (4) while each of the three measures predicts the existence of ‘frequent interaction’ ties, the differences in correct prediction are relatively small?

It would seem reasonable to conclude that while each measure is indeed statistically (as well as mathematically) unique, the fact simply remains that in a statistical environment none proves inherently superior to any other option. Certainly there seems to be little statistical evidence that the clearly higher level of cost (of all kinds) necessary to produce the more complex distance measures (Actual and Least-Cost) can be justified. That is, if a researcher is interested in collecting the more complex and costly data required for distance measures such as Least-Cost, then justification must be sought in an arena other than a statistical one. This is particularly true if one considers that the predictive ability of the clearly most expensive distance measure (Least-Cost) is the lowest—the greatest expense in generating distance data can’t even be supported by a small advantage in predictive power. Consequently, a researcher would seem to be defensively justified in choosing the least expensive method for collecting and computing distance and using it as a proxy for the more costly alternatives.

While it was anticipated that more complex and costly distance measures would provide defensibly higher predictive power and distinctive statistical qualities worth note, it simply did not result from this analysis. Perhaps more extensive analyses, such as computing more complex predictive models would yield greater variation between
the three measures. Either more sensitive analytical frameworks will need to be used, or the expectation that ‘more is better’ will need to be tempered by findings such as these.

5.2 Implications for Geographic and Social Space Research

We should be careful not to lose in the analysis and findings the simple, and highly important fact, that the principal implication of this study for geographic and social space research is that measures of distance and proximity can and do predict the existence of ‘frequent interaction’ network ties—that is, participation in a social network. This initial inquiry also provides early evidence that more ‘costly’ measures of distance may not be necessary in achieving sufficient predictive (and/or interpretive) power. If these findings hold true in future work, more easily (less costly) obtained map data might preclude the necessity of more costly in-field data collection—which certainly functions to inhibit exploratory geographic work—and allow for the more cost-efficient use of increasingly available map resources on the internet.

However, we maintain that the more costly fieldwork provides richer information than simply distance and map data, and provides a much deeper qualitative and quantitative basis for research on the more nuanced and ‘geographically embedded view of relations’ promoted by Barney [2] and others. We certainly find ourselves positively disposed to this viewpoint, even though we readily concede this research indicates the sufficiency of non-field map data for function of statistical prediction of ties. Further research of the intersection of geographic and social space should be designed considering the net benefits of cost, interpretive and predictive value of distance data beyond its direct statistical value.

We are careful to point out that different contexts (urban vs. rural, developed vs. developing country, etc.) and social space dependent variables may produce different results. These findings are limited to a rural context in a developing country with a simple road system (not as complex as would be found in other major urban centers) and to a single network relation in social space. Other contexts and network relations may demonstrate different sensitivities to distance measures.

Bibliography


Social network analysis has traditionally ignored the role of place and geographic space in forming social bonds and networks. Here we introduce a richer model by introducing the notion of co-placement as a factor for social bonds. A hierarchical categorization of co-placement and the inferred strength of relations at different scales and granularity are discussed. This research shows that the geography of places is instrumental in determining the strength of social bonds, which is studied using the case of academic collaborations in form of published papers between researchers in the GIScience and COSIT conference communities.

1 Introduction

Places are said to originate and contain activities in space and also determine behaviour in the real world. Places are also said to be the containers in which communications and connections in real world take place, connecting similar characteristics, behaviours and activities. This research proposes that places also underlie social networks and are indicative of connections and communications across a social network- one that does not exist in the real geographic space. As opposed to hyperspace, we are interested in investigating the effect of real places and co-placement in space and in time as a measure for social cohesions and networks. Social network analysis has previously indicated that social friendships are independent of real world geographies. In this case, we demonstrate that the real world geographies, not as real world spatial proximity, but as a place-based geography is instrumental in formation of social networks and of determining and maintaining the strength of connections in these networks.

A social network has geography-real or virtual. Urry [13] has pointed out how important physical co-presence is to keep social connections alive. But social network analysis has traditionally ignored the role of geographic proximity or spatial operators in determining the cohesion or strengths of links in social networks. Especially in this global, digital and world wide web age where spatial proximity is often not necessary to develop social links and proximities and communications can happen in digital environments, this research is an attempt to identify the role of geographic place-based proximities in development of social networks and connections.

The general view is that in this age, context of work and collaboration is changing from a stable, physically located model to one where collaborations happen between people who never meet in traditional work environments. But, is this really true? Is
place becoming obsolete in forming social connections? In this paper, researcher biographies are studied. Biographies describe place-based trajectories, which enables to talk about co-placement in space and time. It is demonstrated that place has played an important role in determining connections and links within a research community. So, is research collaboration determined by co-placement? And are there barriers of geographic separation that determine the nature of collaboration?

With these research questions we aim beyond current research. Social network research started with links between people and topological concepts of distance in the social network. We postulate that a strong constituent for social links is co-placement, and distance has to be based on this bi-modal network of people and places. Hence, this research is also instrumental in development of scale-based notions of ‘placeness’ and of co-placement in space and in time. Here the term co-placement is proposed as an extension to co-location to consider the overlapping of trajectories at some point in time and to allow for a range of granularities and spatial scale. The hypothesis is that the higher the degree of co-placement, the stronger the links in terms of social connections and collaboration. The emergence of global social networks, and the growing interaction with global information networks impacts the sense of place of users and on processes of place production. Halbwachs [7, p. 134] proposed the terms ‘implacement’ and ‘displacement’ for social reactions to urban changes. By the same token, the simultaneous sensing of places may be termed ‘co-placement’. The major aspect in this regard is the growing tension between the distant and the local, the absent and the present, or between disembedded space and place, expressed in distanciation and time-space compression [see 6].

The research presented in this paper explores and analyses the influence of geographic space and the places that we inhabit and share in shaping the social connections and links that we form. In this paper, we demonstrate that geographic space-not as geometry of spatial proximity, but as geography of places is instrumental in formation of social networks and of determining and maintaining the strength of connections in these networks. Our case study considers a social network that is typically perceived as highly independent from geography and strongly relying on electronic communication-networks between university researchers. Our objective is to understand the role of space and time in forming landscapes of collaboration between university researchers and to express and understand the relationships between sharing and experiencing space and forming social bonds. Thereby, the networks considered here are between individuals rather than at the organizational, societal or community level. Although the study makes the knowledge flows in the community visible through mapping the collaboration landscape, prolific and active organizations and individuals, it is more explicitly targeted at understanding whether the places that these individuals share and experience have an impact on their choice of who these researchers share their information and knowledge with.

The domain of study that exemplifies our approach is the semantic network formed by the scientific community intimately related to Geographical Information Science. Social network analysis is being used to understand patterns of collaborations in this field, and to what degree locations of researchers at different points of time and the way that their trajectories intersect impact the formation of a network of communities.
To illustrate the approach we consider two major international conferences of the field: the Conference on Spatial Information Theory (COSIT) and the GIScience Conference from 2001-2006. The components that constitute the elements of the network are researchers having full papers published at these conferences as joint collaborative work, and connections given by the strength of these collaborations, i.e., the number of papers, etc. The objective of the study is not to study individuals and their networks, but rather to analyse the composite network of collaborations and the respective affiliations of these researchers. We also consider the attendance at these conferences as a measure of sharing a specific event in a specific space and time, and thereby as a measure of co-placement at a specific spatio-temporal granularity.

The paper starts with a review of the relevant background literature in Section 2. In Section 3, the different co-placement relations and categories (and hierarchies) proposed in this research are outlined. The nature of social bonds resulting from co-placement and the role of space and time in determination of the strength of these social connections is discussed in Section 4. The experimental design, analysis and results are presented in Section 5, and Section 6 presents the conclusions and future work.

2 Background

A social network is commonly defined as a set of people who share a common interest and have connections of some kind [14], and in doing so, provide useful insights into ways that the social communities are formed and interact. Social networks have been widely studied over the past years, particularly from the applied mathematical and statistical research [10; 12], and have been applied to many application domains such as epidemiology [9], environment [5] and scientific citation [11].

The spatial dependence of social links is a quite recent area of interest in social network analysis. Butts [3], for example, studied the relationship between distance and the probability of (the emergence of) a social tie. His argument is related to the one in the present paper, although there are significant differences: (i) the measure of distance in this paper is place- or granularity-based, and hence discrete and logarithmic, and (ii) in this paper there is a claim that people far from each other do not form ties, but there is no claim that people close to each other will form links. [2] reverse this perspective by investigating the relationship of existing social ties and the willingness of people to travel over distances to the end of the ties. Again, the present paper uses the same argument: that people interested in forming a social tie are bared by distance.

Related to this paper is also the work studying the social networks of scientists. Prominent in this regard is for example the Erdős Number Project\(^3\), introducing a social distance between scientists by co-author relationships. The present paper argues in the same way: social ties in the case study-researchers of a research community-will be observed by their joint publications. Less strict ties are formed by influence connections\(^4\), or simply by citations\(^5\). Also in this category is previous work [1] studying social ties in the research community that this present paper will focus on as well. However,

\(^3\)http://www.oakland.edu/enp/
\(^4\)http://mike-love.net/
\(^5\)http://scholar.google.com/
these previous studies have neglected the spatial aspect of co-placement, or any spatial condition for the ties in the social network. Since the hypothesis claims exactly such a relationship between collaboration and co-placement (as one example of the relation between social links and geographic nearness), the next step will be to identify and categorize the relationships considered, and then to formalize them for a formal social network analysis.

3 Complementary Structures of Social and Geographic Space

Since the hypothesis claims a relationship between social networks (of collaboration) and geographic space (or co-placement), the first step of investigation is to identify and categorize the relationships considered in this paper.

3.1 Person-Person Relationships

Although people form social bonds for many reasons and in various contexts, the links considered in this paper are formed between researchers by collaboration. In the current climate of pressure to publish (‘publish or perish’), collaboration can be observed by joint publications.

Collaboration is a purely social bond, and not bound to physical encounter, geographic nearness or co-placement. Two (or more) researchers can find each other by references from other members of their community, or by encountering previous publications of the partner researcher. These encounters are nowadays supported by means of electronic communication and search in electronic databases, which is possible with access to the Web from anywhere anytime. Cairncross [4] coined the term death of distance when characterizing this ubiquity of access and contact.

Two (or more) researchers can also find each other by occasional encounters at academic meetings. More generally, physical encounter—an explicitly spatial event—of researchers can lead to collaboration, too. Other examples of spatially formed interpersonal relationships are sharing an office, being neighbors at work or at home, or participating (physically) at the same event.

It is clear from the discussion above that spatially formed relationships are not a pre-condition for collaboration, and social networks formed by collaboration between researchers can be studied by classic social network theory alone [1]. However, our hypothesis suggests a dependency of collaboration and spatially formed relationship (co-placement). The rationale behind the hypothesis is that interpersonal relationships, although they can be established by virtual encounter, are stronger if they are supported by face-to-face encounters or bodily experience. While people do form links in electronic spaces such as chat rooms, virtual worlds, or per email, they typically do want to meet physically if they want to intensify their relationship. The hypothesis states that it needs in fact these stronger ties formed by face-to-face encounters for researchers to collaborate.
3.2 Person-Place Relationships

Data about physical encounters between researchers is not available to us (and for many other types of social network analysis). What is available for researchers and for many other types of social network analysis, are biographies. Researcher biographies show their employment history, and their list of accepted conference papers. Research homepages as well as conference websites also provide data on conference participation. Being at the same place at the same time creates the opportunity for physical encounters. Limiting to researchers working in the same domain (otherwise they would not collaborate), means they have an interest to meet, and will take the opportunity at least if they intend to collaborate. A spatially formed relationship between two researchers is then constructed by being at the same time at the same place, or co-placement: the more specific this place is, the more likely is that the two collaborating researchers have met physically.

Time geography introduces space-time paths to describe the movements of individuals in space over time [8]. Such paths can be represented with various spatial and temporal granularities. Biographies do provide space-time stations—phases of space-time paths characterized by the absence of movement, because the place provides resources for stationary activities—in different, but generally small scale spatial (departments, universities, cities, countries) and temporal granularity (years, months, down to days of conference visits).

Formally, a relationship between a person and a place is established between a start time and an end time (Figure 1). Note that overlapping or nested time intervals are allowed in biographies, caused by circumstances such as shared appointments, or visits during an ongoing employment (time intervals of Place 2 and Place 3, Figure 1). Some biographies also contain gaps.

**Fig. 1.** Space-time stations in the biography of person X.

Within this paper, place and co-placement shall refer exclusively to geographic places. Hereby, places in semantic space—i.e., in any domain that can be spatialized, or has a concept of distance—are deliberately excluded. In the landscape of conferences, for example, COSIT (as a conference series) is a place. COSIT is close to the GIScience Conference, if one considers the overlap of the participants. In semantic spaces, co-placement exists as well. For example, two researchers are co-placed in the landscape of conferences when both of them went to a COSIT, maybe in different years. Going to the same conference means that these researchers must share some interests. Now,
instead of including semantic co-placement in the current investigation, an alternative perspective will be studied: the perspective of a semantic relation between geographic places (Section 3.3).

### 3.3 Place-Place Relationships

Co-placement can be established by being at the same geographic place at the same time. However, other relationships between the places of person $A$ and person $B$ exist that still support some affordance to meet physically. These relationships are here identified and characterized by strength of co-placement.

In particular, these relationships will be investigated:

- co-placement from equal place references,
- co-placement from neighborhood or nearness, relations between place references,
- co-placement from partonomic relations between place references, and
- co-placement from semantic relations between place references.

The most primitive relationship between places is equality\(^6\). Yet the nature of the places, i.e., their spatial granularity, influences the strength of co-placement. Two equal place references can be at levels such as office numbers or countries. With a hierarchical organization of space, strength of co-placement can be linked to the level of granularity.

Two researchers working at the same university department are more likely to meet than two researchers in the same city.

A second type of relationships between places is given by neighborhood or nearness. The distinction is made for extended and bounded conceptualizations of places—which may have a neighborhood relation—and point-like conceptualization of places, which may be near to each other. References to neighboring or near places form co-placement, but weaker than by equal places. While two people working in institutions near to each other may still realize their desire to meet and collaborate, the physical and mental barrier to do so is higher than in the case of being colleagues at the same institution.

A third type of place relationship is partonomy, as reflected in hierarchical cognitive conceptualizations of space, or map series of different level of granularity. Partonomy also provides a weaker form of co-placement. Two persons may refer in their biographies to places of employment at different levels of granularity. If these two places hold a partonomy relation, the two persons still have the opportunity to meet and collaborate, although their nearness is only specified to the level of the super-ordinate place. The larger the area of the super-ordinate place the higher is the likelihood of a physical or mental barrier for a meeting and collaboration. – This type of co-placement holds for example when one researcher reports an employment at University College London and another researcher reports employment in London.

A fourth sense of co-placement can be derived from geographic places that have a semantic relationship. For example, the places of Ittingen, Switzerland, and Ellicottville,  

\(^6\) Note that in this paper a place is merely a reference to a place, i.e., a symbol. Equality between places means equality of symbols, not equality of the conceptualizations of the places by different people.
NY, have a semantic relationship: they both hosted COSIT once (in 2003 and 2005, respectively). In the given context, semantic relations can form a weak co-placement: two people participating in one type of event, but in different geographic places, share some experience, and hence, may share some interests, and may have a desire to meet and collaborate. A person participating in COSIT’03 and a person participating in COSIT’05 most likely share some interests, but their physical chance to meet is not specified by these references to different events.

While equality, neighborhood and nearness, and semantic relationships are all symmetric (but see Worboys [15] for a more detailed study of nearness), partonomic relationships are directed (1 : n) relationships: a person or an event in Ittingen is at the same time in Switzerland, but a person or event in Switzerland is not necessarily in Ittingen. Figure 2 characterizes the latter three types of co-placement by different symbolizations.

![Fig. 2. Semantic, neighborhood/nearness and partonomic place relationships, with different line symbols.](image)

Fig. 2.

4 Social Bonds from Co-Placement

Co-placement was introduced in Section 2.1 to develop a conceptual model of links establishing a social network. The reasoning was that co-placement gives a motivation, and in case of strong co-placement also the chance to meet physically. For researchers working in the same domain, for example, this could be the motivation to seek collaboration. With the identified types of place relationships, some notion of strength of co-placement came up. This strength will now be formalized. For the purpose of this paper, given only textual resources (biographies), an ordinal measure of strength will be favored over any continuous (ratio) measure of place similarity.

Let us assume that the context of each social network analysis defines a range of relevant spatial and temporal levels of granularity. Then the strictest, and hence, strongest case of co-placement is equality of places at the in this context highest level of granularity (Figure 3, left). Strength decreases in order of the level of actual granularity.

The temporal aspect of co-placement can also be used for modeling strength: the longer the period of co-placement, one could argue, the stronger the co-placement. This aspect is neglected here. Another temporal relation is depicted in Figure 3, right: two biographies referring to the same place may refer to different time periods. Although this may form a (weak) social bond (“You just moved to Vienna? I was living there a
Fig. 3. Two persons X and Y are at the same time at the same place (left), or visit the same place at different times (right).

few years ago."), it does not allow for a physical meeting and hence, is excluded in this paper.

Partonomy relations (Figure 4) can be ranked only by the granularity level of the super-ordinate place. With this ranking rule, a partonomy relation becomes as strong in co-placement as an equality relation of the super-ordinate place. The two researchers, one at the University College London, the other one in London, are co-placed in London.

Nearness or neighborhood shall be considered only for places at the same level of granularity. Then a simple condition for nearness or neighborhood is their containment in the upper level of granularity. For example, University College London and Kings’ College London are both in London, and hence, are counted as being near or neighbors according to this condition. With this definition, it becomes clear that the strength of co-placement for near or neighboring places (Figure 5) should be the same as for equality at the next lower level of granularity. In the given example, two researchers, one of them working at the University College London and the other one at Kings’ College, have a co-placement at the level of London.

Finally, semantic relations (Figure 6) form clearly the weakest form of co-placement, since they do not relate directly to a chance of a physical encounter. Both persons have to make an effort to meet, and this effort is not correlated with their semantic co-placement. Hence, if this type of relationship should be considered at all, then it should be ranked last in the order of co-placement relationships.
The discussion from the previous sections can be summed up through this following example. Researcher $A$ and $B$ were both in London at same time, although at different universities. This affords them a lesser chance of a true physical encounter (and hence a meeting instrumental in initiating a discussion and collaboration) than working at the same university. But the notion of co-placement allows to consider the notion of London as a place at some level of granularity. This means that these two researchers have a higher sense of co-placement (and possibly a greater potential for social connectivity) than $A$ has with another researcher $C$ who was in UK at the same time but in Nottingham. However, $A$ has a higher chance of collaboration with $C$ than with researcher $D$, who was at $A$’s university but at a different time than $A$. $A$ and $D$ therefore will have a weaker co-placement than $A$ and $C$. If it is seen that $A$ and $B$ have co-authored more papers together than $A$ and $C$ or $A$ and $D$, then the hypothesis is validated that scale-based place geographies play a significant role in social networks, especially in case of research collaborations.

5 Geographic Space as a Constituent for Social Networks

To validate our hypothesis regarding co-placement and collaboration patterns between researchers, as indicative of social bonds and networks in the GIScience community, a study is carried out, results of which are presented here. The collaboration networks between academic researchers is extensive and for the purposes of our study, we focused on the Geographic Information Science community and their collaborations as represented by two major biennial conferences in this domain, i.e., the International Conference of Geographic Information Science (GIScience) and the Conference on Spatial Information Theory (COSIT). The collaborations were considered to be the full papers published at these conferences from 2001-2006. The data for authors and their
affiliations at the time of publication was collected from the conference websites and proceedings, authors’ own web pages (where available) and from the DBLP publication server. Data was also collected and validated by personal email communication, where necessary. As the focus was the map the collaboration patterns, each author was assigned equal importance irrespective of the order of authorship.

The primary parameters considered for the purposes of the study were:

– What is the strength of co-authorship, i.e., how many papers have they co-authored together?
– Where were the authors located at different stages of their career?
– Where were the authors located at the time of collaboration (university, city, country, etc., where available)?
– Who were the authors co-placed with? Where and when, for how long?

Amongst the patterns and trends to explore, the ones we consider are the key conferences in the research area of interest, the collaborations at these conferences, and degrees of compactness versus spread of the collaboration network to identify the clusters, isolates and peripheral players. The primary purpose of this experimental work was to address the question: can we deduce a direct co-relation between social cohesion and proximity/links and geographic proximity or strength of co-placement? It is expected that the analysis of the graph and geographically-based emerging properties of this semantic network should help in making apparent and for qualifying the degree of integration of the research community.

Figure 7 is a snapshot of the nature of the collaborations between the researchers active in contributing to these two conferences between the six year period from 2001 – 2006. Network analysis shows strong composite nature of the collaboration network,
with a few tight-knit clusters lying as isolates to the larger more central community. The nodes are the researchers collaborating and the ties demonstrate the collaborations/papers co-authored at COSIT and GIScience conference published as full papers in the Springer series from 2001 – 2006. In this figure, the ties are the papers published together by these authors, and in this particular illustration, the relative strength of these connections (in terms of number of papers co-authored) is not considered significant, instead focusing on the nature of clustering and a relatively closely knit community that these collaborations indicate. Figure 8 illustrates the relative strengths of links between the different actors in the network, with most links having a weight of 1 (1 paper co-authored) ranging to a maximum of 4.

Key player metrics and centrality analysis on the collaboration network in Figure 9 shows the nature of the collaboration bonds and the roles that the individual researchers play in maintaining the composite nature of this collaboration network and in maintaining a sense of the community. The key player metrics and the centrality measure when mapped to the nodes are indicative of the researchers that afford the maximum connectivity in the network and enable maximum connectivity between the different individual clusters in the network.

![Fig. 8. Strength of ties illustrates the value of collaborative bonds (number of papers co-authored) Here the values of ties range from 1-4.](image)

Following the exploration of the nature of the collaboration network in general which shows the composite nature of the collaboration landscape in this particular research community, the analysis and mapping of between groups and within groups in Figure 10 shows the existence of a large central social group composed of researchers connected to each other through collaboration. This analysis shows that the social proximities between the different authors in the network are relatively high, and collaboration ties are well-distributed between the researchers. The lack of well-defined clusters and isolates is also evident from this analysis with the clusters of individuals that are collaborating only within their particular group (blue ties) shown to be relatively few.
Fig. 9. Centrality network and key connections are shown as being instrumental in forming a dense collaboration network for the 6 conferences- also showing key player metrics.

Fig. 10. Composition of collaboration network shown here with between groups and within groups collaboration ties shown in red and blue respectively.
Figure 11 shows the 2-mode network of collaboration showing person-person and person-place relationships. The circular nodes represent the individual researchers and the academic institutions are represented by the square-shaped nodes. The ties (red) represent the academic affiliations extracted from authors’ biographies; these include the academic affiliation at the time of collaboration as well as current academic affiliation. In a large number of cases, these have not changed. The other ties (in blue) show the collaboration links as in previous figures, joining the researchers that have collaborated and published a full paper together at these conference series proceedings.

In Figure 12, the proximities are mapped between researchers illustrated by the relative thicknesses of the ties that represent the number of collaborations resulting in full papers. Here it can be seen that the researchers that show a higher level of collaboration have all been affiliated to the same academic institution (as a measure of co-placement).

The centrality measures are analysed and mapped in Figure 13 and shows the key players (indicated by the larger node sizes as relative to their measure of centrality in the network) in the network that are forming the most links with other researchers and/or affording the connectivity in the network to maintain a sense of integrity in the collaboration network. This figure also shows the relative proportion of researchers that have collaborated with other researchers outside their own groups as compared to the ones that have only collaborated with researchers within their group. The square nodes represent the academic institutions as in previous figures and the centrality measure mapped to these nodes (also shown by relative sizes of the nodes) indicate the Universities that have played the major role in supporting the most collaborations with other clusters in the network. The centrality measures give us an indication of the key actors, researchers and academic institutions that shape the composite nature of the network, maintaining the density of the network, affording maximum links between groups, and thereby being instrumental in preventing isolates and several disjointed clusters.
Fig. 12. Strength of collaboration ties shown between researchers indicating the number of collaborations (ranging from 1 to 4)

Fig. 13. Showing the key players in the collaboration network that have collaborated with researchers outside their immediate affiliated academic institution, and key universities that have supported these between-group collaborations.
Thereafter, the heterogeneity indices for the network are mapped out and the researchers and academic institutions with higher heterogeneity index are shown as square nodes in Figure 14. Here, these nodes indicate the key actors that have afforded the between group links- person-person relationships with other individuals outside their own academic institutions, and place-place relationships between universities that have hosted such partnerships enabling links between researchers that have not been affiliated to the same academic institutions. The red and blue ties indicate the between groups and within groups collaborations respectively, and the thickness of links show the number of collaborations. Figure 15 show only these ‘cut-points’ from this analysis, showing the low number of researchers and academic institutions that do not satisfy the hypothesis that ‘collaborations have been enabled by co-placement’ by providing links to other academic institutions and/or other researchers.

This kind of analysis provides us an indication of the relative incidence of within-group and between-group collaborations showing that the majority of collaborations have occurred between researchers that have been co-placed at some point of time.

Fig. 14. The network showing relative incidences of between group and within group links as well as the cutpoints and the actors that validate the hypothesis.

Figure 16 shows just only the network of researchers as nodes with the collaborations as ties. In this case, however, the centrality measures are combined with the affiliation measures over all the nodes between collaboration and academic association (both at time of publication as well as current association). Here, it is clearly visible that the number of researchers who have formed significant academic collaborations with other ‘similar’ researchers (those that have been associated with the same academic institutions in the past and/or currently) far outnumber those (blue nodes)) that have formed significant academic links with researchers that are not co-placed with
Fig. 15. The network showing the links between researchers that have collaborated with not co-placed individuals and/or have moved away from the academic institution that their collaboration occurred them. Again, these results emphasize upon the role that place and co-placement has played in forming collaborations and academic networks in the GIScience community.

These figures and analysis have shown that there is a higher likelihood of co-placement leading to collaborative links, as indicated by past research from 2001 – 2006 for the GIScience community. The collaboration network for this community is integrated and dense, and there are fewer researchers that have collaborated with individuals that they have not been co-located with in the course of their academic trajectories, as compared to the ones that have collaborated mostly with other researchers that they have been co-located with at the time of the collaboration. To further validate our hypothesis leading from this person-person and person-place relationships, we performed significance tests to test the significance of links between co-placement and collaboration.

Table 1 and 2 show the results of these significance tests, showing a high significance of correlation between collaboration and co-affiliation.

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SSQ</th>
<th>F-Statistic</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment</td>
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<td>0.00</td>
<td>0.0349</td>
<td>0.9998</td>
</tr>
<tr>
<td>Error</td>
<td>86</td>
<td>0.99</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>87</td>
<td>0.99</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Further to testing out hypothesis with person-place relationships as represented by academic associations, we also considered conference attendance as representative of an event co-placement. Academic collaborations, as considered in our analysis for the purposes of this paper, did not take into consideration whether co-placement was in
exact moment of time, instead focusing on co-placement at a higher level of temporal granularity. Although it did consider location of researchers at the time of collaboration, it was very difficult to zoom into details of whether the academic trajectories of these researchers did indeed coincide and did they actually physically meet while being associated with the same academic institution at the same time. For the purposes of considering this temporal granularity and the possibility of actual physical co-placement as a factor in collaboration, event attendance provided the necessary constraints. Conferences such as COSIT and GIScience provide focussed forums with many social opportunities for interactions and two people attending the same conference have a much higher likelihood of meeting face to face and sharing ideas and opinions. Numbers are not huge and moreover these are at a specific spatial scale (such as a particular hotel in Maryland or a retreat in Ittingen) with the conference lasting between specific dates. So, it was considered that the attendance at these conferences provided a good indication of co-placement within a specific temporal and spatial scale. Considering conference attendance, therefore, helps in putting constraints on the time frame and the granularity of spatial location.

Data for this analysis was collected from conference websites, mailing lists, and individual researchers’ own webpages. Conference attendance for COSIT 2001, 2003, 2005 and GIScience 2002, 2004 and 2006 was only collected for the sample researchers included in our previous analysis for academic association. The conferences (places) are shown as square nodes and the researchers as circle in Figure 17. Ties between person-

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**Fig. 16.** Blue nodes representing researchers that have significant collaborative links with researchers not co-placed out-numbered by those in red that represent the ones that have collaborated primarily with researchers that have been co-placed with them.

**Table 2.** T-test showing significance between the collaboration and affiliation networks.

<table>
<thead>
<tr>
<th>Difference in Means</th>
<th>One tailed tests</th>
<th>Two-tailed test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Group 1 &gt; 2</td>
<td>Group 2 &gt; 1</td>
</tr>
<tr>
<td>0.034</td>
<td>0.965</td>
<td>1.000</td>
</tr>
</tbody>
</table>
person represent collaboration and between person-place represent attendance at that particular conference. The graph in Figure 17 shows the relation between collaboration and co-placement in time, showing the layout with lengths of ties indicating the attractiveness of the nodes assuming equal weightage to all ties. Presence of a core central tight-knit group demonstrates the affiliation between collaboration and numbers of conferences attended, with the innermost layer of researchers being most affiliated and the outer layer of relatively few researchers are those that have collaborations but not co-placement at these conferences. Figure 18 shows the 3 ‘cut points’ that show the nodes that connect outside actors (those who were not present at any of these events) to the collaboration network. The relative proportion of the cutpoints to the other nodes in the network is indicative of the fact that the co-location at these events has helped in maintaining and establishing the connectivity and density of the collaboration network in this research community.

Fig. 17. Graph showing repulsion and attractivity measure for the different nodes as related to collaboration and co-placement at specific scale and time.

6 Conclusions and Future Work

In the current digitally connected age, the degrees of separation are becoming lower every day. The proliferation of email and other networking media such as blogs, chat rooms, video messaging, etc. have enabled us to form links and collaborations across the world without meeting face-to-face. The notions of familiarity related to social groups have transformed from physical proximities to digital proximity and connectivity. This research tests the hypothesis that despite the loss of physical connectivity in forming social networks, space and more significantly ‘place’ enables the strengthening of links in a network. The research introduces a richer model for social network that links space,
Fig. 18. Graph showing that there are only three ‘cut-points’ in this network that represent the actors that have collaborated with other actors that have not been co-placed with the rest of the network at the conferences.

and more specifically place as a vessel for forming the social bonds. A new notion of co-placement is introduced in this paper, and the hypothesis tested using the case of researchers forming academic collaborations in form of full papers in Springer series for the GIScience and COSIT community from 2001 – 2006. The analysis has shown evidence of co-placement as being a significant factor in forming academic collaborations. Spatial and temporal scales were tested with the consideration of academic associations and conference attendance respectively. Significant correlations and affiliations were shown from a range of graph-based and statistical analysis between the strength of collaboration and co-placement at specific spatial scale, i.e., academic association, and specific temporal scale, i.e., attendance at same conferences lasting for a specific period of time at a specific spatial location.

This model provides further proof of the way places structures our behaviour, activities and the way that we share information and knowledge. It also shows that geography plays an important role in forming social networks and bonds.

Further analysis will include time-specific snapshots to consider specific time granularity as well as taking the particular spatial granularities into account to see the affect of scale based co-placement. Also, the length of co-placement has not been taken into account in this paper and future work will look at the correlation between length of co-placement and strength of network ties. The analysis will also be extended to take into account a wider network of collaborations in the community to validate the results from this analysis as well as to test out hypothesis further.
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