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Extracting deep information from limited observations on an evolved social network ☆

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Abstract

We provide empirical evidence that in a social network which evolves over time, it is possible to extract deep information about the system from limited observations. In this paper, we consider a simple piece of readily available evidence on access to financial services by individuals in the UK. Detailed statistical analysis has shown that the decisions of agents on whether or not to have a basic financial account such as a bank account is heavily influenced by other individuals on their social network. We consider a small amount of straightforward and readily accessible information. We deduce from this, using an agent-based model, the type of social network across which information and influence on behaviour flows between agents in this context. Specifically, we show that information appears to flow across a small world network.

Keywords: Empirical social network; Agent-based model; Small world

1. Introduction

There is a growing literature on the empirical evidence on the topologies of how agents in social and economic systems are connected in different circumstances. The world wide web has been studied intensively (for example [1]). Other examples include the sexual contacts of individuals [2], connections between movie actors [3], the dissemination of heresy in medieval Europe [4], the interlocking structure of membership of corporate boards [5], and collaborations between scientists (for example [6]).

An important property of networks which evolves over time is that they permit the extraction of deep information about the system from limited observations [7,8]. In this paper, we consider a simple piece of readily available evidence on access to financial services by individuals in the UK. The decisions of agents on whether or not to have a basic financial account such as a bank account is heavily influenced by other individuals on their social network [9]. We deduce from this basic evidence the type of social network across which information flows and agents influence each other's behaviour in this context.

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Section 2 sets out the background, and Section 3 describes how we extract information on the topology of the relevant social network across which information spreads in the context of deciding whether or not to have a bank (or other basic financial service) account.

2. The background

Almost one in 10 adults in Britain do not use mainstream financial services. Most of them are not in paid employment. However, most people without paid work have accounts. Two hypotheses have been put forward to account for the behaviour of the minority without accounts: (i) reluctance by financial institutions to serve low-income customers; and (ii) information failure on the part of non-consumers. Using logistic regression analysis of two different data sources, Meadows et al. [9] show that non-consumers of financial services are distinguishable from consumers only by belonging to social networks where financial services usage is relatively low. As social networks play a key role in transmitting information, this supports the information failure hypothesis.

Information on whether or not individuals in the UK have access to financial services is available in two official survey databases. The first is the Family Resources Survey. This is an annual survey undertaken on behalf of the Department of Social Security whose primary purpose is to inform government policy on benefits and pensions. The sample size is large (41,800 adults living in 23,500 households) and nationally representative in order to provide detailed information about the assets and incomes from different sources of recipients of state benefits. It also contains information about usage of financial services and extensive information about household circumstances. The data contain information on the use of financial services by other members of the household of individuals in this data set.

The second database enabled us to extend the concept of the social network beyond that of members of the immediate household to encompass both friends and relatives more generally. This was derived from the monthly Omnibus Survey carried out by the Office of National Statistics (ONS). Each month the survey interviews a nationally representative sample of around 1600 adults. In addition to standard questions, which are used for classificatory purposes, special questions are inserted mainly on behalf of government departments or research organisations. For the purposes of this research, we included four questions in the Survey in March and April 2000. The first asked all of the 3450 adults interviewed whether they had a bank, building society or Post Office account, and which sort of account they had. The other three asked the 1627 who were not in paid work:

- "How many of the other people in your household do you think have bank, building society, post office, or similar accounts?"
- "How many members of your family do you think have bank, building society, post office, or similar accounts?"
- "How many of your friends do you think have bank, building society, post office, or similar accounts?"

The statistical analysis in Ref. [9] examines both databases in detail, but here we use two simple pieces of information from the smaller, less detailed Omnibus Survey to reveal the topology of the social network across which information spreads in this context.

3. Approximating the topology of the social network

In this section, we deduce an approximation to the type of social network which is relevant in this context. There is no direct evidence on this, for we simply have the information for each agent without an account on whether 'all or many', 'some' or 'few or none' of the agents on his/her social network have accounts. This is why we need to deduce indirectly the type of network which this is likely to be.

We set up a simple agent-based model, in which the decision of an agent to take up an account is determined probabilistically by the proportion of agents on his/her network who already have an account.

We have two empirical findings against which we can calibrate a theoretical model. The first is taken from the ONS Omnibus Survey and is set out in Table 1.

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Table 1
Use of financial services by family and friends (Source: ONS Omnibus Survey March/April 2000)

Use of accounts by friends and family	Proportion of people who do have accounts (%)	Proportion of people who do not have accounts (%)
All or most have accounts	87	38
Some have accounts	6	26
Few or none have accounts	2	14
Don't know	6	21
Total	100	100

Once we have eliminated the 'Don't knows', the percentage of friends and family with accounts is as follows, for people who themselves do not have an account: all or most of friends and family have an account 49%; some 33%; few or none 18%. Any theoretical model must be able to approximate this distribution. The distribution is completely different from those with accounts. The second finding is that in terms of the population as a whole, around 90% have accounts.

There is a third, more general observation relating to the nature of social networks. The clustering coefficient is typically greater than zero.[1] In other words, agents connected to another agent are more likely to be connected to each other than are agents who do not share a connected agent in common. Empirical estimates of the size of the clustering coefficient vary substantially. For example, defining Hollywood movie actors as being connected if they have appeared in the same film, a clustering coefficient of 0.78 is found. Perhaps the most relevant in this context is a study of friends, relatives, and neighbours in the UK [10], which estimated a clustering coefficient of 0.34, and cited several other similar kinds of study in which coefficient of between 0.16 and 0.44 were reported. This therefore seems a reasonable range for the clustering coefficient of the network in this particular context.

In the model described here, the only factor which determines whether an individual will decide to set up an account is a recommendation from another agent whose opinion he or she respects on this matter. In other words, we abstract from differences between agents' social and economic characteristics. Given that almost everyone without an account is on some form of state benefit, this is not unreasonable. Further, we abstract from the supply side of financial services, and assume that an agent who applies for an account is automatically given one. This is not completely accurate, but again is a reasonable approximation to reality.

The agents in the model are connected to each other by a network, and differ only in terms of the composition of the network. An agent is connected only to those agents whose opinion is taken into account in deciding whether to have a financial account.

In terms of the formal model, an agent can be in one of two states of the world. He or she can either not have an account (state 0), or have an account (state 1). We start the model with N agents, each of whom initially is in state 0, apart from 1 randomly drawn agent who begins in state 1. The model then evolves in a series of discrete steps. In each step, an agent is drawn at random to consider whether or not to change his or her state of the world. If the agent is in state 1, he or she remains in state 1, and the model moves onto the next step. An implication of this is that agents never move from state 1 back to state 0. Whilst this is not a completely accurate description of reality, it is nevertheless a very good approximation to it. Once someone has an account, it is rare to move back to not having one.

If the agent is in state 0, the agent examines the state of the k individuals whose opinions he or she respects in this matter. At any particular step of the solution, m of these will be in state 1, where $0 \leqslant m \leqslant k$. The agent decides to move immediately to state 1 with probability m/k. The model then proceeds to the next step, where another agent is drawn at random to decide. The draw is done with replacement.

[1]The clustering coefficient of an agent in a network is defined as the number of connections between that agent's neighbours on the network, divided by the total possible number of connections between that agent's neighbours on the network. The clustering coefficient for a network is defined as the mean of the clustering coefficients of all the agents on the network.

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The model evolves step by step until 90% of all N agents in the model are in state 1. This is to match the statistic that around 90% of all individuals out of work in the UK have financial accounts (are in state 1 of the world).

We compare the results for a variety of networks, and the model is solved 500 times for each of them. The number of agents which is likely to influence the decision of any given agent to take up an account is small, and in the results discussed here we choose networks in which on average each agent is influenced by 4 other agents (to the nearest whole number).

We examine the results for each solution of the model once 90% of all agents are in state 1. Considering an agent still in state 0. If 3, 4, or more of the agents on his/her network are in state 1, we say that 'all or most' have an account. If 2 are in state 1, we say 'some' and if 0 or 1 we say 'few or none'.

We considered a range of network types: random, k-nearest neighbour, Barabasi's power law, and small world.

The random network is generated by starting with N nodes then for each ordered pair (i,j), having node i influence node j with probability 0.008. Thus with 500 nodes, each node influences, on average, 4 other nodes. The k-nearest neighbour network is generated by randomly placing N nodes in two-dimensional euclidean space. Each node is then influenced by the 4 nodes to which it is nearest. In the Barabasi power law network, we start with 4 nodes and proceed by adding nodes in turn, each of which are influenced by 4 nodes already in the network. New nodes are more likely to be influenced by nodes which already influence a large number of other nodes. In the small world network, the agents are placed on a ring, and each agent is influenced by its 2 immediate neighbours on either side. In the results reported here, with a probability of 0.2, each connection is then randomly rewired.

The actual empirical distribution of agents on the network of those without accounts is that in 49% of cases, 'all or most' have accounts, in 33%, 'some', and in 18%, 'few or none'. In Table 2, these desired outcomes for the model, along with the clustering coefficient, are compared to the averages across 500 solutions of the model for each of the network types.

On balance, the small world network gives the best approximation to the type of network on which agents influence each other in the decision as to whether or not to obtain a bank account. Intuitively, a small world representation of the network across which influence flows seems reasonable in this context. We can think of it as implying that people are mainly influenced by those closest to them, such as family members, but with a number of more long range connections, as it were, across their network of friends.

4. Conclusion

We provide empirical evidence that in a social network which evolves over time, it is possible to extract deep information about the system from limited observations. We consider a simple piece of readily available evidence on access to financial services by individuals in the UK. Detailed statistical analysis has shown that the decisions of agents on whether or not to have a basic financial account such as a bank account is heavily influenced by other individuals on their social network.

Table 2
Empirically observed and model properties, averaged across 500 solutions, agents without accounts

	Average percentage of agents with accounts connected to agents without accounts			
	All or many	Some	Few or many	Clustering coefficient (average)
Empirically observed theoretical network	49	33	18	0.16–0.44
Random	49	20	31	0.01
K nearest neighbours	3	4	93	0.54
Barabasi	13	26	62	0.56
Small world	48	27	25	0.26

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