Authors: D’Alessandra, S., Winzar, H.

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From i-phone 3G to i-phone 4G: A two-stage complex systems model of the two stage diffusion process

Steven D’Alessandro  
School of Management and Marketing  
Charles Sturt University  
Panorama Avenue, Bathurst, NSW, Australia  
Telephone +612 63384286  
Email sdalessandro@csu.edu.au

Hume Winzar  
Department of Marketing and Management  
Macquarie University  
Macquarie, Sydney, NSW, Australia  
Telephone +612 9850 6468  
Email: hume.winzar@mq.edu.au
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Abstract

We present a conceptual model where agents are prompted to adopt a new technology through a two-step process: information from neighbours prompts an upgrade, and the option purchased may be influenced by the one demonstrated by the neighbour. In a network world with two options available we systematically manipulate (1) the initial number of neighbours with White compared to Black, (2) rate of naturally-occurring upgrade, (3) chance of upgrade prompted by a neighbour using White relative to Black, and (4) the relative chance of choosing White instead of Black having decided to upgrade. Not surprisingly, adoption speed is influenced by starting users, natural upgrade, and relative upgrade chance. Market share, on the other hand, is influenced only by the relative chance of choosing White over Black, with no influence at all from the other predictors. We find that this result applies regardless of the type or complexity of network.

Keywords: Complexity Theory, Agent-based modelling, Diffusion

Introduction

Steenkamp, Hofstede and Wedel (1999) estimated that two thirds of new products fail, at an average cost of around $US 15 million for each such product. However, they also noted that many major companies, such as Gillette and Hewlett-Packard, rely on new products for profits and growth. Thus, consumer’s acceptance of new products is vital, which means a greater understanding of the consumer diffusion process is crucially important to many organizations.

Typically, the innovation process has been studied as process of interpersonal influence, where opinion leaders help spread the acceptance of an innovation (Rodgers 1995). Opinion leaders spread an innovation more effectively than the mass media by visible demonstration or by word-of-mouth communication. They are crucial change-agents who champion innovation and are well positioned to become aware of and adopt innovations (Chau and Hui 1998). It is possible though, that acceptance of an innovation may be considered as a two-stage process, where there is both the social pressures to “upgrade” technology, and then the type of model or design of the new product that is selected (Lam et al., 2012; Woisetschläger et al., 2011). One may argue that it is the acceptance of a particular brand of product, rather than new technology, per-say, is the real focus of diffusion-of-innovation studies in marketing. Scholars have argued that the social process of the acceptance or rejection of a two-stage process of innovation (new product and product variant) is best studied by analysing social networks (Goldenberg et al., 2002; Bohlmann et al., 2010). These social networks are best studied as dynamic and complex structures by the use of Agent-Based Modelling (ABM). Rand and Rust (2011), list application areas suitable for ABM as; diffusion of information and innovations, retail location decisions, inter-firm relationships, strategy and competition, marketing mix models and retail and servicescape design. In relation to this study, (Goldenberg, Mazursky, & Solomon, 1999) note that many new innovations and product choices in markets can be modelled accurately with as few as six parameters.
Cellular Automata – Agent-Based Modelling

In the present context, we use ABM to study a two-stage adoption effect: for example, deciding to buy a tablet computer and then choosing between an Apple iPad and a Samsung Galaxy. For simplicity’s sake we consider upgrading from a 3G to a 4G iPhone and the choice of either a white or black colour handset. We were particularly interested in how signalling (of say, a white phone compared to a black phone) triggers the decision to adopt and what model was then selected. This is analogous to a brand choice following on from a decision to upgrade to the latest technology. It has also been suggested that the degree of consumer confusion over the myriad of marketing offers leads them to rely on very simple strategies such as seeking word-of-mouth information or advice (Turnbull, 2000), which means social network effects are likely to be important in explaining two-stage diffusion-of-innovation behaviour. The key research objectives of the study were therefore:

1. Model the effect of brand choices (white or black) in social networks as to how it influences the rate of acceptance of new technology (4G versus 3G).
2. Model how the brand choices of agents (white or black) affect the brand choices of other agents’ new technological upgrades.
3. Examine how 1. and 2., are affected by different types of social networks (which model the effect of different personal influence structures).

Agent-based models are generally computer-based simulations of complex systems. Typically independent "agents" operate concurrently and interact with each other in space and time. This makes it possible to explore the connection between the micro-level behaviour of individuals and the macro-level patterns that emerge from the interaction of many individuals (Wilensky, 1999). Where economists and financial analysts in the past have regarded a marketplace as a single object to be analysed with a mathematical equation, Complexity Theory recognises that a marketplace is simply the aggregation of individual behaviours. Cellular automata are the tool for which we can model or simulate behaviour at the level of the individual and observe their aggregation.

The models

The authors chose to use NetLogo (Wilensky, 1999) for this study. NetLogo is a programmable modelling environment for simulating natural and social phenomena. NetLogo is freely available. Two Netlogo models use in this study consisted of the following parameters:

Each agent, or “turtle”, owns a 3G phone. Each has an independent chance of upgrading to a 4G phone, say when a contract expires (stage one of the acceptance process). Having decided to upgrade, there is an independent chance of choosing white or black. Connected neighbours can affect the chance of upgrading. A neighbour who owns the new phone is likely to influence an agent. The model owned may differentially affect upgrade likelihood. For example, an owner modelling a White phone may prompt upgrade more than the owner of a Black phone. There is also a possibility of imitation from a neighbour owning a white or black iPhone. These values can be adjusted so that the effect of individual versus interpersonal influence can be modelled.
Two different social networks are modelled. Figure 1 illustrates a random network, with variation in the average node degree (average number of connections for each agent). In such a network, frequently used for virus dispersion models, some nodes may be isolated in distinct islands not-connected with other nodes. The second social network in Figure 2 is a scale-free network created using preferential-attachment connections where all nodes are connected, and some nodes are hubs connecting large numbers of other nodes.

The two network structures are very different. A Random network does not guarantee that there is a link between any one agent and all other agents. In such a model, then we should expect to see slower diffusion as a result of modelling and imitation. The Scale-Free network, on the other hand, has all nodes connected to all other nodes.
We expect that all conditions will affect speed of diffusion and choice of brand. What is more important is the relative influence of each condition, so we manipulated the chances of upgrading to White relative to the chances of upgrading to Black. That is, we held Black parameters constant, and manipulated the White parameters around those Black values. Using the Behaviour Space function on Netlogo the following conditions were tested: All models had 500 agents. The chance of upgrading as a result of seeing a neighbour with a Black upgrade was fixed at 1%, and the chance of choosing a White phone, after upgrading due to a Black prompt, was fixed at 50%. The chance of upgrading as a result of seeing a neighbour with a White upgrade was set at three levels: 0.5%, 1%, and 2%. The chance of choosing a White phone, after upgrading due to a White prompt, was set at three levels, 25%, 50%, and 75%. The chance of upgrading without any modelling from neighbours was set at two levels, 0.01% and 0.02%. As a starting point, one agent was randomly selected as a Black upgrade, and other agents were randomly selected as White upgrades. The number of White upgrades was: 0, 1, 2, or 4. Experimental manipulations are summarised in Table 1. In the Random network model, the Average Node Degree was manipulated at three levels: 2, 4, or 8. We found that Node Degree had no significant effect on our results so, for comparison purposes, the effects of Node Degree were partialled out of the results.
Table 1: Parameters Manipulations

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Number of Black</td>
<td>1</td>
</tr>
<tr>
<td>Initial Number of White</td>
<td>0, 1, 2, 4</td>
</tr>
<tr>
<td>Upgrade-Chance</td>
<td>0.005%, 0.01%, 0.02%</td>
</tr>
<tr>
<td>Black-upgrade-chance</td>
<td>1%</td>
</tr>
<tr>
<td>White-upgrade-chance</td>
<td>0.5%, 1%, 2%</td>
</tr>
<tr>
<td>Black-Imitation-chance</td>
<td>50%</td>
</tr>
<tr>
<td>White-Imitation-chance</td>
<td>25%, 50%, 75%</td>
</tr>
</tbody>
</table>

A full-factorial experimental design then is $4 \times 3 \times 3 \times 3 = 324$ runs. These were repeated five times to give a total of 1620 runs for each of the two network models.

Results

Regression analysis was used to examine each of the research objectives. Negative betas indicated that an increase in the level of a predictor causes a decrease in the dependent variable. For example, increasing the upgrade chance reduces the speed of acceptance of an innovation. Results are summarised in Table 2 and Table 3.

Adoption Speed

We defined Adoption Speed as the number of time clicks taken for all members in the social network to upgrade. Significant factors were the upgrade chance ($\beta = -.22, p < .01$, across both types of networks) and relative upgrade chance to white, ($\beta = -.29, p < .01$ for viral networks, and $\beta = -.75$ for preferential networks). As we expected, the model works best for scale-free (preferential) networks ($R^2 = .62$), than for random (viral) networks ($R^2 = .13$). That is, for networks with a high clustering coefficient, and low average node-to-node distance.

Table 2: Regression Results: Standardised Betas

<table>
<thead>
<tr>
<th>Adoption Speed</th>
<th>Viral Network</th>
<th>Preferential Attachment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial White Size</td>
<td>-.05</td>
<td>-.05</td>
</tr>
<tr>
<td>Upgrade Chance</td>
<td>-.22</td>
<td>-.22</td>
</tr>
<tr>
<td>Relative White upgrade change</td>
<td>-.29</td>
<td>-.75</td>
</tr>
<tr>
<td>Relative White Imitation</td>
<td>.01</td>
<td>.02</td>
</tr>
<tr>
<td>Adj R-sq</td>
<td>.13</td>
<td>.62</td>
</tr>
</tbody>
</table>

Market Share

Market Share is simply the proportion of White when all members of the social network have upgraded. We were surprised to see that the only significant factor was the level of Relative White Imitation ($\beta = .95, p < .01$, across both types of networks). The other three factors had no effect at all on the proportion of White chosen. Interestingly, the parameter estimates are almost identical in both network types. We also checked for interaction effects, particularly between Relative White Upgrade chance and Relative White Imitation, and found no change in outcome.
Table 3: Market Share: Standardised Betas

<table>
<thead>
<tr>
<th>Proportion White</th>
<th>Viral Network</th>
<th>Preferential Attachment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial White Size</td>
<td>.02</td>
<td>.01</td>
</tr>
<tr>
<td>Upgrade Chance</td>
<td>-.01</td>
<td>-.01</td>
</tr>
<tr>
<td>Relative White upgrade chance</td>
<td>.01</td>
<td>.02</td>
</tr>
<tr>
<td>Relative White Imitation</td>
<td>.95</td>
<td>.95</td>
</tr>
<tr>
<td>Adj R-sq</td>
<td>.91</td>
<td>.91</td>
</tr>
</tbody>
</table>

The results for speed of adoption are consistent with research by Hirschman (1980) who argued that consumer novelty seeking and creativity are important antecedents to acceptance of an innovation. This is shown by the effect of relative white upgrade chance triggering the acceptance of 4G handset.

In terms of the proportion of agents deciding on a white iPhone, the results from both types of network structures show this to be dependent purely on relative white imitation. That is, the degree of susceptibility to interpersonal influence. This reflects a two-stage adoption model, the decision to upgrade being based on personal factors such as innovativeness and novelty seeking, the second based on interpersonal influence and being accepted as part of a reference group.

Future Research

This is an early model in a larger research stream. We have not explored other known issues in the network interpersonal influence area. For example, in this model the strength of influence of each role-model agent was the same for all agents. Classic network theory suggests that agent strength or persuasiveness is a function of the number of connections to and from that agent (Borgatti & Halgin, 2011). We posit that while option choice is likely to be still a function of the attractiveness or novelty of the option itself, the role-modelling influence of actors with varying levels of connection will cause greater variance with repeated modelling.

References


