Improving Agent-Based Models of Diffusion

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Purpose. To review the validation of assumptions made in agent-based modeling of diffusion and the completeness of the mechanisms assumed to operate.

Design. One well-cited paper is re-examined.

Findings. Evidence is presented that casts doubt on the assumptions and mechanisms used. A range of mechanisms is suggested that should be evaluated for inclusion in modeling.

Originality. The need for validation of assumptions has been stressed elsewhere but there has been a lack of examples. This paper provides examples. The emphasis on the completeness of the mechanisms used has not been highlighted elsewhere.

Keywords: Agent-based modeling, ABM, word of mouth, WOM, diffusion, social networks, modeling assumptions

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1. Agent-Based Modeling

Agent-based modeling (ABM) sets out to show how patterns of behavior emerge from the individual-level actions and interactions of agents. In this paper, an agent is considered to be a consumer, but the approach can cover other entities that act on each other in a system. Assumptions are made about the choices facing agents and the way they make decisions, which are expressed as decision rules. Because these choices occur in a network, one agent's choice affects the behavior of other agents and, when the whole system is computed and run, the interaction plays out and collective effects emerge. Therefore, there is a direct link between initial assumptions and outcomes. The ABM may be seen as an inference engine that leads to conclusions by logic and mathematical procedures. However, in order to derive true conclusions from this inference engine, the assumptions that are made should be both *validated* and *sufficient*. By validated, we mean that the assumptions have empirical support and, by sufficient, we mean that these assumptions cover all substantial processes and limitations relevant to the inferences made with the model. ABM has been applied to a variety of problems; here, we are only concerned with its application to the diffusion of innovation where the complexity of the exercise makes validation and sufficiency more problematic and we focus on one paper by Goldenberg, Libai, Moldovan, and Muller (2007), which we abbreviate to GLMM.

Rand and Rust (2011) review good practice in ABM. These authors argue against the use of untested assumptions but give few examples; we build on their work to show how the assumptions used in one very well known ABM paper are not supported by subsequently gathered evidence. This gives substance to the problem of using untested or poorly-tested assumptions. Rand and Rust also include a test of model output in their specification of validation and state that this is the key test of a model's validity. This type of validation tests predictive validity and is relevant if the purpose of the model is to predict outcomes as, for example, is the case for aggregate-level Bass (1969) modeling. But the truth of outcomes does not imply the truth of assumptions, only that these assumptions have not yet been falsified by a finding contrary to evidence [1]. By contrast, true assumptions in a valid

[1] Here, implication rests on deductive validity as it is understood in logic as a property of a well-formed argument. For example: *The King of France is blue-eyed, I am the King of France, therefore I am blue-eyed* is a

argument lead inexorably to true conclusions. Thus, if agent-based modelers want to go beyond simply predicting diffusion outcomes and to explain the processes governing social network change, they need to validate their assumptions.

The validation exercise does not cover the sufficiency of these assumptions. By sufficiency we mean that all relevant processes and conditions are conceptualized and represented in the model. For this to be covered in the validation exercise, modelers would need to go through all the limiting conditions and possible mechanisms that might be involved, investigate them and include those that have significant effect. If this is not done, the model may be insufficient and fail to represent the processes in the actual social network. Instead, it will represent processes in a hypothetical social network that does not exist.

Agent-based modelers talk of experimenting with the model: they may try various values for the assumptions and observe the outcomes produced. Another procedure is to eliminate an element of the model to see how this changes the network outcome. This was done, for example, by Watts and Dodds (2007) when they tried removing opinion leaders from the modeling. Similarly, GLMM compare outcomes with and without NWOM being produced. This is a form of experimentation *within the model* but the model itself is not an experiment. If the assumptions of the model are false, or insufficient, multiple runs that vary the input data will not solve the problem.

2.1. Untested assumptions

For this aspect of the paper, we focus on the GLMM study. We do not claim that our specific criticisms of this paper can be extended to all ABM applications to diffusion but the problems that we highlight may be found in other papers such as Watts and Dodds (2007) and Goldenberg, Libai, and Muller (2010). GLMM use ABM to explore how negative word of mouth (NWOM) may undermine the take-up of a new product. They suggest that a higher proportion of customers recruited by advertising will become dissatisfied with the product compared with those recruited by positive word of mouth (PWOM) and that these dissatisfied customers will then give more NWOM, which they define as an outcome of dissatisfaction. Their analysis suggests that the proportion of dissatisfied customers is particularly harmful because of the impact of NWOM.

GLMM's work has important and controversial managerial implications since, to minimize the effect of NWOM, they argue that promoters of a product should limit

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valid argument irrespective of the truth of the assumptions and, if I am not blue-eyed, one or both of the premises is false.

advertising when the product is launched. Crucial to GLMM's argument is whether ad-recruited customers are substantially more dissatisfied. Uncles, East, and Lomax (2013) found that ad-recruited customers were more dissatisfied but the difference between them and referral-recruited customers was fairly small. In a projection of their findings, Uncles et al. showed that it took several years for the advantage of referral customers to emerge strongly.

Another part of GLMM's argument is that NWOM is more potent than PWOM; they conceptualize two groups: rejecters who, without buying the product, may dissuade others and disappointed adopters, who have bought the product and are dissatisfied. NWOM from these groups may turn adopters against the product and may block off whole clusters of potential customers. Thus GLMM follow an assumption made by Midgely (1976) that NWOM has two effects: it dissuades non-users from adopting and also turns positive adopters into disappointed adopters, who then give NWOM. GLMM represent this process and give NWOM twice the impact of PWOM. As support for the greater weight of NWOM, they point out that research in the negativity bias field shows that negative information has a greater impact than positive information (e.g. Mizerski 1982). They also asked MBA students about the judged effect of positive and negative information on behavior. This evidence falls short of validation.

First, PWOM may have parallel effects by creating adoption and also changing the dispositions of negative adopters so that they give PWOM; this needs to be checked because it would match the influence of PWOM and NWOM.

Second, the negativity bias research shows effects on attitude and cognition rather than on behavior such as adoption. Intention to purchase is normally seen as closer to behavior than attitude and work conducted after GLMM's study has shown that PWOM has more impact on purchase intention than NWOM (East, Hammond, and Lomax 2008, Sweeney, Soutar, and Mazzarol 2014). This weakens GLMM's claim that NWOM is more powerful than PWOM.

Third, asking MBA students about the hypothetical impact of PWOM and NWOM seems wide open to bias from lay theory (Craik and Lockhart 1972). Our experience has been that business people expect NWOM to have more impact but when we investigated this in a sample of the general population, PWOM and NWOM had much the same support.

We turn now to the relationship between dissatisfaction and NWOM. GLMM saw NWOM as the product of dissatisfaction but the relationship is not one to one. People may give negative advice about products that they like because they believe that these products are unsuited to the needs of the receiver of advice. If a substantial proportion of NWOM is *not* based on satisfaction, GLMM's assumption that NWOM is always (or even mostly) based on dissatisfaction will lead to error. GLMM cite evidence from Anderson (1998), showing that there is more WOM produced by dissatisfied than satisfied customers but the difference that Anderson found was quite small.

Additional evidence is needed to clarify this matter. First, what is the proportion of NWOM produced primarily as a consequence of dissatisfaction? For services, this averaged 37% while 40% of the PWOM came from satisfied customers in a study by East et al. (2015). Second what is the ratio of satisfied to dissatisfied customers? This depends on the product field but a figure of about 10:1 can be derived from Peterson and Wilson (1992) who studied a range of products. These data indicate that the volume of NWOM produced by dissatisfied customers is quite small compared to the PWOM produced by satisfied customers. These incidence differences need to be represented in ABM models. The volume of NWOM derived from dissatisfaction may be still lower for tangible products. These are thought to produce less dissatisfaction because the purchaser can judge the product more easily and the seller can control quality more effectively. GLMM find a very strong effect on adoption from increases in the proportion of dissatisfied customers so, if they overestimate the amount of NWOM produced by dissatisfied customers, the effect will be much reduced.

In models of social networks, the network connections must be specified. Actual networks will show clusters and voids when interaction is mapped, representing the greater association between some people and the relative isolation of others. This pattern needs to be represented if the computer model is to be realistic. GLMM assume a structure of connected clusters. That is, there is a relatively large interaction within the cluster, mainly between strong ties, and a lesser interaction between clusters where the ties tend to be weak. Mukherjee (2014) shows that variation in the network alters outcomes, which makes the assumptions that are made about network structure important. Nitsan and Libai (2011) have researched telephone interaction in a network of a million subscribers; this gives evidence of actual connections. The use of such evidence should improve network representation but there remains a problem that interaction patterns may vary with the category and product type being studied. On such product differences, GLMM are generally silent. We do not have evidence to add on network structure but uncertainty about the appropriate network structure adds to doubts about the output from ABMs.

This review suggests that: ad-recruited customers are not much more dissatisfied than referral customers, the amount of dissatisfaction is low, a substantial proportion of the NWOM expressed has little relationship to dissatisfaction, the evidence on the supposedly greater impact of NWOM is questionable, and that different assumptions about network structure might produce different results.

2.2. Insufficiency of the model

We now turn to the sufficiency of assumptions – that nothing important has been left out. Assumptions should cover all mechanisms and constraints that are relevant to outcomes. Here we give one example of a mechanism and one example of a constraint that seem to be missing from the GLMM research. Further consideration of mechanisms that may be needed in diffusion models is left to the Discussion.

Central to GLMM's suggestion about the effect of initial advertising is the proposition that NWOM would flow from the higher proportion of disappointed purchasers produced by advertising. Data relevant to this were gathered by East et al. (2015). They used an established typology of triggers of WOM response and found that four percent of NWOM was elicited primarily by advertising for the service. They also found that three percent of NWOM was elicited by advertising for another service, indicating that a brand's advertising could stimulate negative comment on other brands, which could be to the advantage of the focal brand. This mechanism of responding negatively to Brand A because of advertising on Brand B does not seem to be represented in the model used by GLMM. It offsets any generation of NWOM on a focal brand as a result of its advertising.

One constraint on the modeling is the overall proportion of NWOM compared to PWOM. GLMM's claims about the detrimental effects of NWOM would lose importance if the ratio of PWOM to NWOM volume were high because, then, NWOM would be crowded out by PWOM. The proportions of PWOM and NWOM are measured by the Keller Fay Group; USA data supplied to us for 2009 shows that that 65% of brand-related conversations are mostly positive, 8% are mostly negative, 15% are mixed and 12% are neutral. Even if mixed conversations are treated as both positive and negative, this evidence shows that NWOM is a relatively small proportion of total WOM. GLMM do not address the ratio of PWOM to NWOM in their review of evidence.

2.3. Comparison with car crash modeling

These criticisms of the modeling of diffusion effects may be compared with a field where the modeling is unquestionably successful. In car crash modeling, the car body is specified and, unlike network structure, does not need to be discovered; the mechanisms involved such as energy transfer, heating and bending are well understood and can be sufficient; the input data can be precisely specified; and predictions can be tested by direct physical observation, which will reveal insufficiencies in the modeling.

3. Discussion

In this paper, we build on the critique of ABM practice by Rand and Rust (2011) by providing more specific evidence on the assumptions used in one study that applies ABM to diffusion processes. We show that important assumptions made by GLMM are not supported by evidence gathered after their study was completed. However, our wider concern is that recommendations based on ABMs of diffusion may be erroneous because of untested assumptions and that GLMM's recommendation of restraint in launch advertising may lead practitioners astray. Such restraint is contrary to normal practice at launch where heavy advertising is justified by the work of Lodish et al. (1995) showing much higher ad elasticities at this time than at product maturity. Relevant here is evidence by East et al. (2011) showing the user status (current, previous, never) of those giving NWOM. On average, across 15 studies, only 22% of current users give NWOM whereas 55% of previous users do so (and 22% of never-users). At the launch of a new product, there are no previous users, which reduces NWOM and gives a honeymoon period for new products.

3.1. Transmission of WOM by adopters who hear PWOM on the brand

WOM has two direct effects on the acceptance of new products. One is to affect adoption and the second is to influence the further transmission of WOM. It seems likely that PWOM will produce a greater effect because it is more common. In particular, adopters who receive PWOM on their brand may give extra PWOM, some of which may result in adoption. Relevant to this, East, Romaniuk, and Lomax (2011) find that 93% of PWOM comes from existing or prior owners. Work in progress shows that those who have heard their current brand recommended give twice as many recommendations as those who have not heard such recommendation. A significant effect persists when the influence of major covariates is controlled. Thus, we think that there is a strong case for incorporating PWOM transmission effects into models of diffusion.

3.2. Saturation effects

A PWOM transmission effect would have most impact when the brand is large and has many owners who originate, receive, and transmit WOM. Thus, a runaway feedback effect would occur in large brands unless a saturation mechanism operates to dampen WOM. The motivation to transmit WOM is likely to recede as a product becomes widely known. Some evidence for this comes from Dost, Sievert, and Oetting (2010). They found that people did not pass on WOM because they lost interest in it or because they perceived that the receiver had little interest in the matter.

3.3. Decay of effect after product experience

Some products/services are used intermittently or once only. When this applies, we may expect a fall in WOM about the product after product experience. This decay is very rapid in some fields such as retail fashion and movie attendance so that much of the WOM that occurs happens in the week after product use (East et al. 2014). In other fields such as cell phones, the WOM is spread over a much longer period. GLMM do allow for decay, unlike the aggregate Bass (1967) model. Such decay effects need to be incorporated into any modeling of diffusion.

3.3. Customer retention

Uncles et al. (2013) found that, on average, referred customers were slightly better retained than customers acquired through advertising. They found that this retention was the major factor increasing the value of referral customers, rather than their greater use of WOM. There were indications that, in some categories, retention might be large and, if this were confirmed, differential retention would need to be included in diffusion models.

3.5. Reflexive effects

When people give WOM, there may be self-induced learning effects, which increase the likelihood of giving WOM on a subsequent occasion. We have no direct evidence on this but a finding of Chandon, Morwitz, and Reinartz (2005) suggests that reflexive effects may occur. They found that those who reported their intentions in a survey were more likely to engage in the intended behavior than those who had not been asked for their intentions.

3.6. Better models of diffusion

The defects of mature methods such as surveying are well known and commonly expressed. ABM is relatively new; it has stirred interest and seems to yield insights that are exciting. For example, the widely cited paper by Watts and Dodds (2007) has raised discussion on the moribund two-step flow account of diffusion (Lazarsfeld, Berelson, and

Gaudet 1944, Katz and Lazarsfeld 1955). However, the potential for omitting important processes from ABM models seems large. To develop work in this field, we need to include currently available evidence and to conduct research on the additional mechanisms that could affect diffusion.

Modelers in this field may justify simpler models by reference to Axelrod's (1997) KISS maxim (*Keep It Simple, Stupid*). Theories and methods that are simple may be more easily comprehended and explained to others and are attractive for this reason. However, when a problem is complex, such as the spread of an innovation in a social network, the KISS maxim may lead researchers astray. It appears to be a modern-day expression of Occam's razor but William of Occam was against *unnecessary* complexity rather than complexity per se. We argue that the range of mechanisms and circumstances that can operate in diffusion makes the field very complex to model and that this complexity cannot be avoided. More complex modeling is a daunting prospect, but one which we hope that agent-based modelers will undertake.

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