Social Anti-Percolation, Resistance and Negative Word-of-Mouth

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Abstract

We model dynamics of positive and negative word-of-mouth spread in a social network. The classic percolation model is modified by introducing local negative effects due to non-adoption. The resistant agents inform their neighbors, and as a result the neighborhood becomes less susceptible to the spreading product. We introduce two parameters, quantifying the effect on the direct neighbors (a) and on the neighbors of second degree (b). The increase in the percolation threshold is measured by simulating a product spread on regular square lattices. The local influence of non-adopting agents is the cause for the effectiveness of the negative word-of-mouth - since the product spreads by means of a front propagating through the lattice, the resistance always affects the most "relevant" part of the network. A dramatic result is measured above certain levels of b, where a complete blocking of any product is achieved while affecting only 0% of the network.

Introduction

Many new products fail to meet their expected market share; While preliminary market surveys may report a large percentage of potential buyers, the actual sales might reach only a negligible fraction of the market (Bobrow & Shafer, 1987; McMath & Forbes,

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1998). Massive scientific research, as well as large financial, human, media and technological resources, have been invested to improve market sampling. However, there seems to be a "glass ceiling" to the success rate of sales prediction. In the present paper we explain this phenomenon in terms of a "market percolation phase transition". We show that the eventual market share of a product depends crucially on the nature of interactions between potential buyers, more so than simply on their number (Bass, 1969) or even their network of connections (Solomon, Weisbuch, Arcangelis, Jan, & Stauffer, 2000; Solomon & Weisbuch, 1999; Weisbuch & Solomon, 2002).

In general, Percolation theory describes the emergence of connected clusters. Historically, the first challenge that was met by this theory was in chemistry, when Flory and Stockmayer studied Gelation as a percolation process on a Bethe lattice (Stockmayer, 1943). Since then, percolation theory was studied extensively by both mathematicians and physicists, and was applied to a variety of other subjects, from epidemiology to oil fields (Bunde & Havlin, 1999).

Mort (1991) suggested the application of percolation theory to marketing: a new product percolates among adopters in the market and might be blocked by resisters or gatekeepers. Solomon and Weisbuch (1999) also proposed to look at the market as a network through which the product tried to percolate. In the right conditions a large adoption cluster will appear, and the product will gain its respective market share; however, if a product is below the "percolation threshold", its spread would be essentially restricted, and it would fail to meet its potential, due to the inherent resistance of the social network that constructs the potential market.

Although insightful, this casting of percolation theory to marketing was in a sense trivial - the proclaimed infinite sensitivity to the product's quality is just the basic observation of percolation theory about the emergence of critical phenomena. In this chapter we extend this model by introducing effects of negative word of mouth (NWOM), creating a novel model that was never studied before by percolation methods.

Negative Word-of-mouth in marketing

From marketing research we learn that NWOM has a profound effect on adoption patterns. For example, Leonard-Barton (1985) found that an innovation reached only 70% of its market potential due to resisting consumers. In addition, Herr et al. (1991) found that NWOM may decrease product evaluations. Two main characteristics of NWOM have been stated in marketing literature: It is more informative than positive word of mouth, and thus may have a stronger effect (Hauser, Urban, & Weinberg, 1993; Herr et al., 1991), and it may be contagious and spread independently of exposure to the product (Marquis & Filiatrault, 2002). Both these attributes are addressed by our model.

Some models incorporating NWOM were suggested in marketing theory (e.g. (Kalish & Lilien, 1986; Mahajan, Muller, & Kerin, 1984; Midgley, 1976; Moldovan & Goldenberg, 2004)), but none of these models address the context of the underlying social network. The standard way to describe market share progression in marketing theory, is by using differential equations (ODE), and most models used today are extensions of the classical Bass model (Bass, 1969). Predictions on adoption dynamics are made by fitting the parameters of these differential equations according to empirical sales data. The main criticism on the ODE approach is that it is inefficient at the early stages of product spread, as it is too sensitive to early fluctuations in the adoption process (Malcolm Wright & Lewis, 1997). This renders the forecast method less efficient, because by the time enough data points were collected, most of the "damage" (e.g. over- or under-production) is already done. We believe that this failure is inherently linked to the fact that the ODE framework pre-assumes "mean-field" conditions (i.e. all agents may interact with all others, without respect to social networks), and ignores the underlying social network.

Marketing theory distinguishes between two types of forces affecting the consumer - the "internal" (local) force, a name for all the influences cast on individual consumers by peer consumers (e.g. word of mouth), and the "external" (global) force, the kind of influences that are cast upon all consumers equally (e.g. marketing efforts). It is accepted in marketing that on the long run, internal forces are of greater significance for the adoption pattern of a product (although the external force is important for product awareness, or for "activation" of the internal force). An estimation of the effect of the two forces, internal and external, shows that after takeoff, the word of mouth effect is 10 times larger than marketing efforts (Goldenberg, Libai, & Muller, 2001) and may be responsible for as much as 80% of the sales (Mahajan, Muller, & Srivastava, 1990).

Despite the fact that the internal force is more powerful that the external force, the standard effector employed for marketing is advertising, often by addressing an entire market. This introduces a bias into marketing research as well, which tends to focus on the external forces. The Social Percolation (SP) framework suggests modeling internal forces as local interaction between agents on a social network, and observing the properties of the resulting adoption patterns. Investigating the effects of internal forces in this manner can provide useful insights to market behavior, even if we ignore overall effects of external forces (The framework of social percolation can easily be extended to incorporate external forces as well(Proykova & Staufer, 2002)). In this chapter we divide the internal force into positive and negative effects, and explore the effect of negative word of mouth in the SP framework. This will provide a focus on the internal force in a structured context.

The Model

Classical Social Percolation

We start by repeating the basic ideas of SP (Solomon et al., 2000; Solomon & Weisbuch, 1999; Weisbuch & Solomon, 2002). The basic element of the model is an agent, representing a consumer. Each agent i is characterized by a "preference" value, p_i. The agents are located in a social network with a fixed structure. In the current chapter, like in the original SP paper, we mainly focus our attention to regular lattices with non-periodic boundary conditions; they are considered a "zero-order" approximation for social networks, and a large body of classical comparable work can be found for such topology. However this is straightforwardly generalized: the only crucial point necessary for the arguments is the generic existence of a percolation phase transition in the network. The model is made complete by introducing a product, represented by a global "product quality" value, denoted Q. The product spreads in the network according to the Leath algorithm: one random agent is "exposed" to Q. Then, the product spreads on the lattice according to the following adoption rule:

ADOPTION - Agent i will adopt the product if a neighboring agent adopted the product AND the product's quality is higher than the agent's preference: $Q > p_i$.

Thus, the potential market for a product consists of all the agents whose p is smaller than Q. Although this parametrization of the model suggests a false interpretation that a unique well-defined value of quality may be assigned to a product, we do not claim that this is the case. Even as different consumers may have different perceptions of a product's quality, we choose to incorporate all such inter-personal diversity in the variability of the random values p_i. Since adoption is determined only by comparing the "global" Q to the "private" p_i, introducing variance to Q is equivalent to introducing global variance to p_i.

Incorporating Resistance Into Social Percolation

Now we introduce our variant of the model, including NWOM. In what we described so far, the case $Q < p$ had no consequences: failing to meet a consumer's standards only meant that the product was ignored and the information about the product was not passed on to the consumer's neighbors. In the present model, we see this case as the equivalent of "disappointment", one of the roots of NWOM.

In order to introduce NWOM to the model, we propose to look at another property of the product, uncorrelated with its "Value" (that is represented by Q). We wish to refer to the product's "susceptibility to NWOM", and parameterize it as a number between 0 and 1, following the (trivial) assumption that certain products are more sensitive to dynamics of NWOM than others. The value chosen may be connected to the marketing strategy, the degree of novelty, and to many other aspects of the product domain. This parameter pertains to the response created in a potential customer after an encounter with the product that results in non-adoption: If agent i was exposed to the product, but has not adopted it ($Q < p_i$), we may say that the agent"resisted" the product. In that case, the agent may spread resistance to the product with her neighbors, spreading NWOM. The effect of such negative spread is that the affected neighbors become less receptive towards the product, i.e. their chances of adopting it decrease. We model this effect in the following way: in the case of $Q < p_i$, we denote $p_i - Q$ as D_i (note that $D_i > 0$ always). We introduce a parameter a, denoting the extent one agent's resistance influence its neighbors. The spread of resistance (i.e. NWOM) is modeled by increasing p_j by aD_i for all agents j that are neighbors of I.

This increase of p_j will have no effect if j has already adopted the product. Yet, if $p_j < Q$ and $p_j + aD_i > Q$, then this agent is said to have been blocked by NWOM. The increase of p_j is additive - if several agents "project" resistance on one agent, all their individual NWOM effects add together on top of the original p_j. So, if $p_j + aD_i < Q$, this change has no immediate effect (as j may still adopt if one of her neighbors will expose her to the product), but this agent is now more prone to blocking by subsequent NWOM, and the NWOM he is prone to spread will be bigger.

Since Q is limited to the range [0,1], an agent i with $p_i > 1$ will reject all products, the same as if p_i were 1. On the other hand, if p_i is allowed to grow freely beyond one, the resistance that this agent may cast on its surrounding is essentially unbound. This allows the spread of NWOM to "block" completely the affected agents.

Although it may be argued that this property is dynamic, and bears inter-personal variance, we simplify matters by accepting it as a static scalar parameter of the product.

In our model, NWOM spread occurs on a faster time scale than exposure to the product. This means that in case of resistance spread, the increase of all p_j happens instantly, before any further exposures of new agents to the product are considered. The rationale is simple: the typical time scale for casting NWOM is one conversation with one friend; Exposure to the product, on the other hand, is a slower process - the potential customer has to act (e.g. visit the point-of-sale) in order to potentially acquire the product (in a sense, one can say that "bad news travel faster").

In accordance with Marquis & Filiatrault (2002), we characterize another parameter, b, that pertains to the product's susceptibility to "bad rumors", NWOM that is not based on actual exposure to the product. So, the effect of resistance may travel to second-neighbors as well, and their p is increased by bD_i. At first glance, this modelling scheme seems primitive - why not parameterize the effect to the n-th neighbor? Yet we wanted to avoid "giving wings" to such rumors - if NWOM is allowed to propagate freely on the social network, an unrealistic dynamics occur in the model, as the NWOM behaves like another product. Therefore we restrict our attention to spread of NWOM to second-order neighbors.

In summary, we introduce the following rule of interaction to the SP framework, in addition to ADOPTION:

RESISTANCE - If i was exposed to the product and $p_i > Q$, then
for every agent j neighboring i p_j changes to $p_j + aD_i$
AND
for every agent k that is a second neighbor of i, $p_k = p_k + bD_i$

Thus, every case of adoption generates potential for further adoption, and every case of disappointment casts a "cloud" of NWOM around it. Figure 1 summarizes all rules of interaction.

Simulations

Method

The indexed set $\{p_i\}_{i=1}^{N}$ that specifies the "personal" values of p for every agent was randomly generated at the beginning of every simulation, with every such p_i chosen uniformly from the range [0,1]. At every iteration, values are fixed for Q, a and b, and the simulated dynamics start from a "seed" of one adopting agent selected at random, who spreads the product to her neighbors. These agents are added to the "adoption front", a list of agents who are waiting for evaluation of the product. At every time step, an agent i from the adoption front is randomly selected, and his current value of p_i (possible increased by previous spreads of resistance) is compared to Q. If $Q > p_i$, the agent is marked as 'adopter', and all her neighbors are put on the adoption front. If $Q < p_i$, D_i is spread to i's first and second neighbors according to the values of a and b. Thus, the front expands away from the starting point (seed) in a random fashion, and the iteration ends when the front exhausts itself. This happens either when it traverses the entire lattice and reaches the boundaries, or when all the agents on the front reject the product (so their neighbors are not added to the front). The first case corresponds to the product meeting its market potential and passing the percolation threshold, and the second corresponds to the product being blocked by the population of agents.

The product's "strength" may be measured in two ways: a percolation measure - whether the product percolated successfully through the lattice 'from side to side'; and market penetration - what is the size of the adoption cluster. Notice that these two measurements may not coincide, as a product may percolate and still achieve a small adoption rate. In regular lattices of three dimensions and up this happens near the percolation threshold, where the percolating cluster has a fractal structure and a minimal density.

Percolation threshold measurement

In the present work we focused on measuring the percolation threshold. in order to determine whether a product 'percolated', we checked how far it spread across the network, in terms of the distance from the initial seed. We looked at the "shell" structure of the network around the initial node, marking all the nodes found at distance d from the initial seed as belonging to shell d. Then we identified the biggest shell and percolation was marked successful if at least one agent from the biggest shell adopted the product. This definition is equivalent with classical measures of percolation on regular lattices, and it generalizes it to cases of irregular networks as well.

We employed a binary search method of dichotomy for the estimation of the percolation threshold. For every instance of random values $\{p_i\}$, the threshold Q_c is a number such that for $Q > Q_c$ the product percolates, and for $Q < Q_c$ the product does not percolate. We estimated it by repeatedly exposing the lattice to different Q's, and changing Q in an adaptive way, according to the success or failure of the last iteration. If at iteration i the product of quality Q_i percolated, in the next iteration Q will be increased: $Q_{i+1} = Q_i + \frac{1}{2^{i+1}}$; accordingly, if at iteration i the product was blocked, Q_{i+1} will be decreased by the same amount.

Due to resistance spread, the values of $\{p_i\}$ change in the course of an iteration, and so we reset them to their original values between iterations. For every instance of random values $\{p_i\}$ and fixed a and b, we did 10 iterations of adaptive Q, and so effectively estimated the threshold within an uncertainty margin of size $\frac{1}{2^{10}}$.

Results

In the present work we measured how negative word-of-mouth affects the percolation threshold. This was simulated by applying different values to a and b, and measuring the percolation threshold under these conditions. Fig. 2 shows the threshold's dependence on a and b for lattices of various dimensions.

At the corner of $a = b = 0$, the measured threshold corresponds to the classical threshold. As a and b increase, the threshold increases, until it saturates near 1 for high enough values. The increase of both a and b causes an increase of the threshold; however, it is clear to see that the dominant effect is that of b, with an effective threshold of > 0.9 for b as low as 0.55 in the 4D case (Fig. 2).

Of course, the number of second neighbors increases with lattice dimension (8 in 2D, 18 in 3D, and 32 in 4D), but on a careful observation, a stronger , autocatalytic effect can be noticed, which is a result of the synergy between the neighbors. Since the front spreads from one point out, two nearby agents have big probability to be on the front at the same time. Since resistance spreads from agents who are on the front, their neighbors, hit by the local effect of NWOM, are probably on the front as well. These are exactly the agents that will be evaluated next, and therefore an increase to their p is the most significant (see Fig. 1c-d). In a sense, the NWOM hits the product where its the most sensitive - if the resistance would be spread to far-away agents, the front might only get there in a long time, or never get to that part of the network, which will render the blocking impact of the resistance less effective. Without any long-range effects, the local spread of resistance ensures maximum negative impact to the NWOM, while affecting only a finite number of agents (and so their proportion approaches 0% in the limit of large networks).

In the standard percolation model, the threshold decreases as the dimensionality of the lattice increases. This is due to the increase in the average number of neighbors, which brings about an abundance of paths between every two nodes. This number increases with the dimension, and therefore the product is less likely to be blocked, because there is greater probability of finding at least one path through which the product can percolate. At the extreme case of a highly connected irregular network, for example with a power-law distribution of the degrees, the percolation threshold was shown to be exactly 0 (Albert, Jeong, & Barabasi, 2000). However, when NWOM is introduced, the increased connectivity of the network has the opposite effect - since resistance can spread to more neighbors, it is prone to have a greater impact on the front, and hence on the progress of the product. Since resistance is spread only from agents who are evaluated, i.e. on the front, the impact of NWOM on the front is greater when more agents on the front are close to each other. This number increases with the dimension - in 2D, every one of the 8 second neighbors has 4 of the other as her own second neighbor; in 4D, each one of the 32 second neighbors has 12 of the others as second neighbors.

It is worth noting that all the above regular lattices are without triangles. Since only first neighbors are added to the front in case of adoption, every group of agents being added to the front have no links between its members. A more interconnected front is more susceptible to effects of a, because every event of resistance would spread NWOM to more agents on the front. In a network with a greater clustering coefficient, a is prone to have a bigger effect. To demonstrate this, we compare between a regular 2D lattice with a 4-neighbor topology (von-Neumann) and 8-neighbor topology (Moore). The results are presented in figure 3, where it can be seen that the increase of the percolation threshold due to the increase of a in the 8-neighbor lattice is greater.

Another result is the emergence of local resistance leaders. In the classic percolation model, cluster size increases monotonically with Q. This is not the case when NWOM is incorporated into the model: for a given randomization, the cluster size may decrease with increasing Q (Fig. 4). This surprising result of the NWOM dynamics is due to particular micro-level setting: if in a particular section of the network the first agents exposed to the product are of high p, they are bound to spread significant resistance, and perhaps block the entire section. We call such agents "Resistance Leaders", as it is certain that they would be resistant to most products.

The blocking effect of such resistance leaders depends very much on the particular circumstances of the product spread - the question whether a resistance leader, or rather her neighbor, would be exposed first to the product might have a crucial effect on the progress of the product's spread in that section, and this depends totally on the micro-conditions there. If most of the agents in her neighborhood already adopted the product, the NWOM spread by an resistance leader may have little effect. This novel feature of the model happens both above and below the percolation threshold.

discussion

The model we presented here is introducing two new parameters to the percolation model - the negative impact of non-adoption on the first neighbors (a) and on the second neighbors (b). These parameters are not a vague idealization - their real-world counterparts are easy to define.

a has to do with the nature of the disappointment caused by an event of non-adoption. Consumers can be disappointed and reject an innovation from several reasons such as a publicity campaign that creates high expectations that are not confirmed (Bearden & Oliver, 1984); fear of the new and unfamiliar, or resistance to change (Ashesh & Hoyer, 2001; Jager, 2001), low expectations from a new technology, no benefits or high pricing (Abrahamson, 1991; Bearden & Oliver, 1984). The problem is that disappointed consumers tend to spread more NWOM and have higher effect on other consumers (Herr et al., 1991; Richins, 1983).

Moreover, consumers may spread NWOM to their friends just on the basis of their exposure to negative information, and without any trial or contact with the product. The parameter b represents the extent to which consumers tend to tell each other stories about products they never tried. The above reasons to rejecting the innovation can serve as reasons to spread NWOM further on, a phenomena that was found in previous studies (Marquis & Filiatrault, 2002). Leonard-Barton (1985) found that 20% of dentists were familiar with, yet rejected, a $successful$ dental innovation, many of them were not willing to try it, as a result of NWOM. Consistent with the theme of "bad news travel faster", consider the following anecdotal report of a major taxi company in New Zealand which lost almost 60% of its business as a result of an angry customer spreading her story to thousands of women throughout New Zealand (Cecil, 2001).

These cases can be documented, but can hardly be understood or predicted. Standard techniques of estimation of the potential market give little or no attention to the emergent effects of consumer interaction. Focus groups and random sampling may give an accurate estimate of the potential in a naive market, but as soon as the product is actually introduced, the naive market changes shape by effects of word of mouth whose source are the early adopters. A product may seem to be good enough at the preliminary probing of the market, and yet fail due to the effect of NWOM.

Therefore, it would be very helpful if marketing research could estimate the parameters of the endogenous social interaction of the market. A more complexity-aware probing of the market should also estimate the "interaction value" of a disappointed customer, paying attention to the probability of people discussing the product without ever being exposed to it. Our model shows that these aspects of the product and the market context have great impact on the eventual success or failure of the product.

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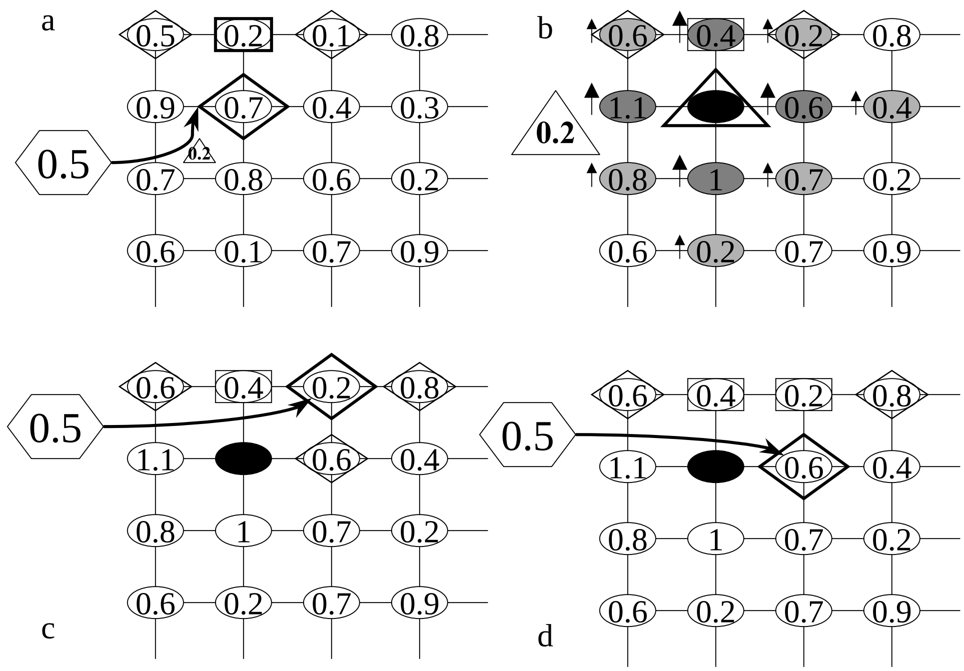

Figure 1. (a) Q, marked as a hexagon, is 0.5. The agent marked in square is the seed, with $p = 0.2$, and so it adopts the product and all its neighbors are added to the front (marked in diamonds). Next, the agent marked in a bold diamond is evaluated. Since its $p = 0.7$ is bigger than Q, this agent dos not adopt, but rather spreads resistance ($D = 0.2$), marked in a triangle. (b) The agent is now marked in black, indicating that it will not adopt anymore. The resistance is immediately spread from the agent in a triangle to all its neighbors: for $a = 1$ and $b = 0.5$, the first neighbors' p increases by 0.2 (marked in dark grey), and the second neighbors' p increases by 0.1. Red arrows to the left of the agents mark the increase of p. Note how the agent to its left, whose p was 0.4, now has $p = 0.6$. This agent is no longer a potential buyer, but a potential spread of resistance; it was blocked by the NWOM. (c) Next, another agent is selected from the front. This agent is now marked in a bold diamond, and since its $p < Q$, it adopts the product and all its neighbors are added to the front. (d) Another agent is selected from the front. This time its $p > Q$, and this will cause spread of resistance. This agent was originally part of the potential market, but was blocked by NWOM, and now will generate more NWOM. This illustrates the auto-catalytic nature of NWOM.

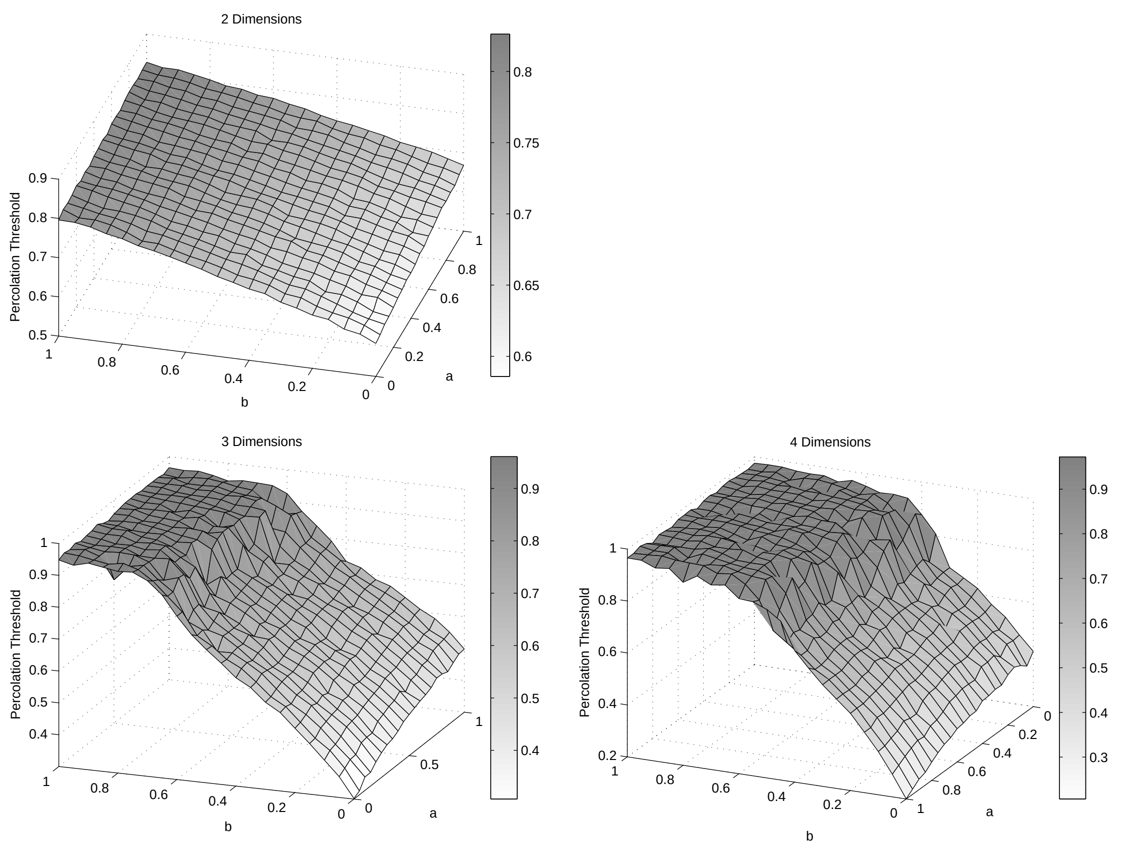

Figure 2. These plots show the the percolation threshold (Z axis) as dependent on the parameters a and b (the X-Y plane). In the corner of $a = b = 0$ the percolation threshold corresponds to the standard results, and it increases with both a and b. However, it is evident that b has a greater influence, and above a certain level, the network becomes totally impenetrable to the product. Figure 2a is for 2 dimensions:$1000^2 = 1,000,000$ agents; Figure 2b is for 3 dimensions: 80^3=512,000 agents; Figure 2c is for 4 dimensions:40^4=2,560,000 agents.

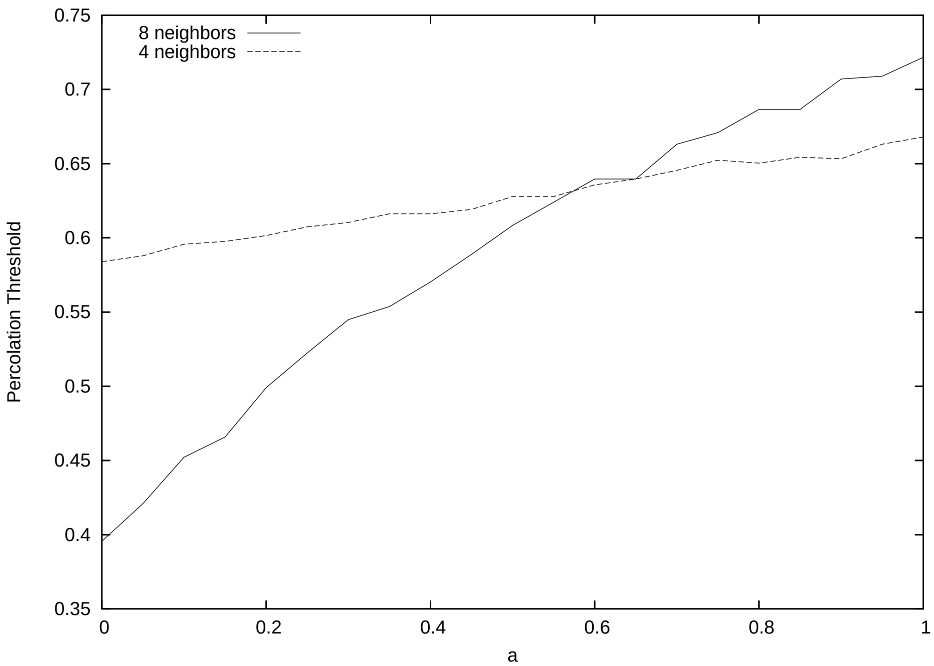

Figure 3. Here the importance of the clustering coefficient is demonstrated by comparing the effect of a on two different two-dimensional topologies: 4 neighbors (dashed line) and 8 neighbors (full line). In the 4 neighbor topology the front is not a disconnected set, since newly added agents would have links with other agents on the front already; but the front is more interconnected in networks of greater clustering coefficient. Thus, the network is more susceptible to effects of a, because more agents on the front would be affected by every event of resistance.

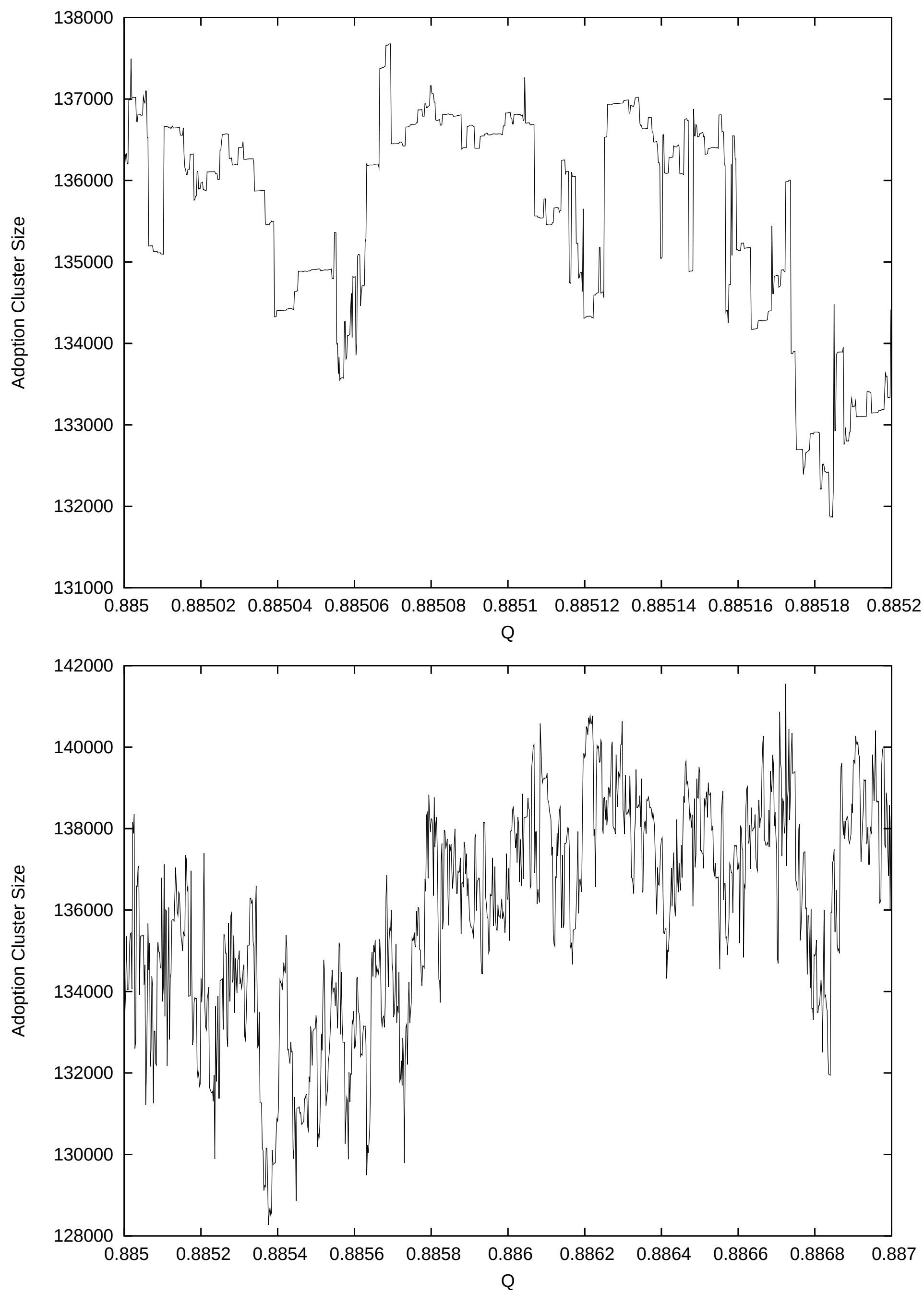

Figure 4. The dependence of the percolation on Q is non-monotonic, and a better product may have smaller sales; this is due to the effect of local resistance leaders, agents with high p that block their entire neighborhood if the product reaches them first.