

Chapter LIII

Social Anti-Percolation and Negative Word of Mouth

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ABSTRACT

Many new products fail, despite preliminary market surveys having determined considerable potential market share. This effect is too systematic to be attributed to bad luck. We suggest an explanation by presenting a new percolation theory model for product propagation, where agents interact over a social network. In our model, agents who do not adopt the product spread negative word of mouth to their neighbors, and so their neighborhood becomes less susceptible to the product. The result is a dramatic increase in the percolation threshold. When the effect of negative word of mouth is strong enough, it is shown to block any product from spreading to a significant fraction of the network. So, rather than being rejected by a large fraction of the agents, the product gets blocked by the rejection of a negligible fraction of the potential market. The rest of the potential buyers do not adopt the product because they are never exposed to it: the negative word of mouth spread by initial rejectors suffocates the diffusion by negatively affecting the immediate neighborhood of the propagation front.

INTRODUCTION

Many new products fail to meet their expected market share. While preliminary market surveys may report a large portion of potential

buyers, the actual sales might reach only a negligible fraction of the market (Bobrow & Shafer, 1987; McMath & Forbes, 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 this chapter, 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, & Stauûer, 2000; Solomon & Weisbuch, 1999; Weisbuch & Solomon, 2002).

Percolation Theory

In general, percolation theory describes the emergence of connected clusters. Historically, percolation problems were first studied in chemistry, when Flory and Stockmayer studied Gelation as a percolation process on a Bethe lattice (Stockmayer, 1943). Since then, percolation theory has been developed extensively by both mathematicians and physicists (Stauûer, 1985), and was applied to a variety of other subjects, from epidemiology to oil fields and forest fires (Bunde & Havlin, 1999).

The main phenomenon studied in percolation models is the emergence of a phase transition: a dramatic change in the qualitative behavior of the system, triggered by an infinitesimal change in the parameters. For example, a small difference in virulence can make the difference between a seasonal flu and a global epidemic. Percolation theory offers a broad body of knowledge for the study of such phenomena, and by casting a problem in percolation terms one can gain access to a wide set of intuitions and rigorous results.

In short, percolation models involve agents that interact across a network. The interaction consists usually of influencing the state of a neighbor agent (i.e., a “sick” agent can poten-

tially change the state of its “healthy” neighbors by infecting them). Obviously, the affected neighbor can now further affect one of its neighbors, and so allow the effect to diffuse across the network. Percolation theory studies the conditions in which the set of affected agents reaches a macroscopic size (a non-vanishing fraction of the entire set of susceptible agents). Interestingly enough, percolation theory predicts that often such a “global” diffusion will not take place, as the propagation may die out before any significant fraction of the system is reached by the diffusion dynamics. The transition to the percolating regime, where almost all susceptible agents are infected, is usually very sharp. The values of the parameters at which this happens are called “critical values.” As one varies the parameters through their critical values, the system abruptly passes from the “seasonal flu” phase to the “epidemic” one. This is the famous percolation phase transition.

Mort (1991) suggested the application of percolation theory to marketing: a product spreads among adopters and can be said to percolate (or not) through the social network. Solomon and Weisbuch (1999) proposed looking at “Social Percolation”; they regard society as a network through which a social phenomenon (information/belief/product/behavior) may or may not percolate. In the right conditions a macroscopic cluster of adopters emerges, and most of the susceptible people will eventually be influenced. However, if the adoption rate (“social virulence”) or the typical number of neighbors per agent are below their critical values (“percolation threshold”), the spread would stop before any significant fraction of the susceptible adopters is reached. As seen in Figure 1, if the proportion of susceptible agents is below the percolation threshold, they form disjoint little islands (Figure 1(a)). In this case a propagation that starts on one of the islands can

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