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An integrated two-stage diffusion of innovation model with market segmented learning

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ABSTRACT

With the aid of the Internet, both firms and customers have access to vast amounts of data. The aim of the proposed model is to provide a method that utilizes data to understand and predict how potential customers will value innovations, and communicate thoughts in a non-fully connected market. Innovation diffusion models have been studied extensively, and are often formulated using either macro-level approaches that aggregate much of the market behavior, or using micro-level approaches that employ microeconomic information pertaining to the potential market and the innovation. We propose a two-stage integrated model that benefits from both the macro- and micro-level approaches, and we add emphasis to modeling when, what, and how customers communicate and process information. The proposed model incorporates heterogeneous potential customers and adopters, segmented Bayesian learning, and the adopter's satisfaction levels to describe biasing and word-of-mouth behavior in a non-fully connected market.

1. Introduction

The marketplace today is filled with a variety of products and services, each of which are competing for the customer's attention. Although there are examples of breakthrough successes, the marketplace is littered with products and services that never gained momentum. For instance, before the successes of the iPad and iPhone, Apple released the Newton MessagePad in 1993, which is believed to have been far ahead of its time as noted by Schau and Muniz (2006). However, McCracken (2012) explains that the public sentiment towards the Newton quickly turned negative when people realized that the handwriting recognition did not work. Furthermore, McCracken (2012) notes that even though the Newton was the most advanced personal digital assistant at that time, most peoples' perception was that it was not good enough to be useful. The first generation of the Newton did not meet user's expectations, and the spread of negative word of mouth hurt the Newton brand. As a result, Apple was far from reaching its goal of selling one million Newtons in the first year.

The problem in the example above is that Apple considered the innovativeness of the first generation of the Newton to be the dominant factor that would dictate its fate. However, the market's expectations, the inability of the Newton to meet those expectations, management behavior, and pressure from competition led Apple to abandon the project. Now consider the current state of the marketplace; with the aid of the Internet, potential adopters have access to many sources of information such as social networks, blogs and discussion forums that will allow these individuals to form dynamic expectations and opinions on products, policies, and services before actually adopting them. Thus, gaining an understanding of how, what, and when potential adopters process information is incredibly important in the innovation diffusion process.

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It is also realistic to assume that before any individual adopts an innovation, she needs to become aware that the innovation exists. To address this issue, many researchers have developed multi-stage diffusion processes such as Sharif and Ramanathan (1982), Jones and Ritz (1991), Hauser and Wisniewski (1982), Shih and Venkatesh (2004), and Landsman and Givon (2010) to name a few. However, a majority of the multi-stage diffusion processes employ a macro-level approach to model how individuals flow from one market segment to another, or in the case of Landsman and Givon (2010) the potential customers are not segmented according to when they became aware. As a result, an understanding of when, and what information individuals are accessing and how they are processing it is not possible. In addition, Peres et al. (2010) explain that the Bass model and most of its extensions assume that the social system describing the market potential is homogeneous and fully connected.

To understand the limitations of these assumptions, consider an individual that became aware of a particular innovation today. This individual will likely have a completely different valuation of the innovation when compared to another individual that became aware one year ago, and has researched details and reports that pertain to the innovation. Thus, to assume that today both individuals have the same likelihood of adoption is very unrealistic. Furthermore, if we assume that the market is fully connected, it means that any information pertaining to the technology is accessible and received by all potential customers. This is also unrealistic, because not all individuals have access to the same channels of information, and some may not be savvy or interested enough to access them.

In this paper we propose an integrated two-stage innovation diffusion model that utilizes the benefits of both the macro- and micro-level approaches. Orbach and Fruchter (2011) highlight that many studies apply retrospective analysis by utilizing detailed sales data, however our approach aims at predicting the evolving nature of a networked marketplace, and utilizes adoption, word-of-mouth, and sentiment data that are available in problems within the context of 'big data'. McAfee and Brynjolfsson (2012) explain that there are three main characteristics of 'big data' that differentiates it from traditional data sets: (1) Volume; (2) Velocity; and (3) Variety. Furthermore, McAfee and Brynjolfsson (2012) emphasize the value of utilizing 'big data' intelligently to improve business performance.

The contributions of this work are a novel formulation that takes into account segment specific word-of-mouth behavior that allows for biases depending on the level of satisfaction experienced, a heterogeneous aware market that is segmented according to the time in which individuals become aware, and potential customers that are non-fully connected. The significance of these contributions are that the proposed model relaxes many of the unrealistic assumptions that exist in previous literature, which in turn improves the ability to realistically forecast market behavior and provide valuable managerial insights.

The remainder of this paper is organized as follows: In Section 2 we provide a review of the relevant literature; the proposed model is presented in Section 3; a numerical example and results are presented in Section 4; and the paper is concluded by conclusions and future studies in Section 5.

2. Literature review

Innovation diffusion models have been studied extensively to forecast and explain the adoption process. Mahajan et al. (2000) explain that empirical research shows that the growth of many natural processes can be described by an "S-curve". Mahajan and Peterson (1985) further note that although the diffusion process of most innovations can be modeled as an S-curve, the exact shape of the curve may change depending on the formulation.

The first to utilize an S-curve to describe the adoption process of an innovation was Griliches (1957), and this work hypothesized that the rate of diffusion of an innovation can be explained in terms of its supply and demand in varying markets. Similarly, Mansfield (1961), David (1969), Davies (1979), and Stoneman (2002) address the economic factors that may affect the diffusion of innovations. In addition to the economic factors, researchers have examined other factors that affect the diffusion process such as the attributes that define the innovation, and word-of-mouth activities. We divide the work on these into three domains: (1) macro-level diffusion models; (2) micro-level models; and (3) customer satisfaction and word-of-mouth modeling.

2.1. Macro-level diffusion models

A general mixed-influence macro-level model is proposed by Bass (1969) that takes into account both the external and internal factors involved with the innovation diffusion process. The advantage of the Bass (1969) model is that forecasts and other analyses may be performed with the requirement of estimating few parameters. As a result, the use of the macro-level model has been extensive and many model extensions have implemented the macro-level approach.

For example, a number of works have included decision variables to the macro-level formulation in order to aid decision makers. Pricing decisions are explored by Robinson and Lakhani (1975), Bass (1980), Kalish (1985), Kamakura and Balasubramanian (1988), Jain and Rao (1990), and Horsky (1990). Other researchers have aimed at providing advertising insight such as Horsky and Simon (1983), and Simon and Sebastian (1987). While others have extended the Bass (1969) model to include both price and advertising variables such as Bass et al. (1994), another example of a macro-level extension includes multi-stage diffusion processes such as Sharif and Ramanathan (1982), Hauser and Wisniewski (1982), Kalish (1985), Jones and Ritz (1991), Shih and Venkatesh (2004), and De Marez and Verleye (2004).

In this paper, we also extend the macro-level model proposed by Bass (1969) to include pricing, and a two-stage diffusion process. In the first stage potential adopters become aware of the innovation. In the second stage aware individuals process information pertaining to the innovation that is available to them, and decide whether to adopt the innovation or not. Since the first stage of becoming aware involves no decision making or information processing by the potential adopter, we employ a macro-level diffusion process to model the first stage. Thus, we take advantage of the aggregation that exists in macro-models, and the ease of