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Heterogeneity in diffusion of innovations modelling: A few fundamental types

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ABSTRACT

Heterogeneity of agents in aggregate systems is an important issue in the study of innovation diffusion. In this paper, we propose a modelling approach to latent heterogeneity, based on a few fundamental types, which avoids cumbersome integrations with not easy to motivate a priori distributions. This approach gives rise to a discrete non-parametric Bayesian mixture model with a possibly multimodal distributional behaviour. The result is inspired by two alternative theories: the first is based on the Rosenblueth two-point distributions (TPD), and the second is related to Cellular Automata models. From a statistical point of view, the proposed reduction allows for the recognition of discrete heterogeneous sub-populations by assessing their significance within a realistic diffusion process. An illustrative application is discussed with reference to Compact Cassettes for pre-recorded music in Italy.

1. Introduction

Consumer response to innovation is a general issue in marketing research characterized by three main aspects: customer innovativeness, growth modelling of new products, and network externalities, as highlighted, for instance, in Hauser et al. [17], Meade and Islam [22], and Peres et al. [23]. Customer innovativeness is an individual property that expresses a willingness to adopt innovations and is usually considered a function of cultural, behavioural, demographic, and economic characteristics. As such, it has a natural variability among agents and over time. Due to costs and reliability problems related to collecting personal information, new product growth modelling, substantially beginning with Bass [2], is focused on an aggregate level. The cumulative adoption process is dynamically governed by two latent and separate forces: an external influence, associated to innovators, and an internal one, associated to imitators. The Bass model opened a new way in the characterization of new product life-cycle, despite some limitations due to an assumed homogeneity of agents and a uniform accessibility to innovations. Stability of its parameters over the cycle, over different countries, and over product categories brought into question some of its typical assumptions jointly with the need to introduce interaction or control variables in it. Bass et al. [3] is an outstanding answer for describing the effect of external time dependent control effects on diffusion. Moreover, the presence of phases in the life-cycle, such as take-off, slowdown and saddle, also required convenient modifications of basic model assumptions and related equations. For instance, the take-off of many products may be prevented by network externality effects. Network externality modelling (direct and indirect) is a relevant area of research, which may link individual and aggregate levels in innovation diffusion. Cellular Automata modelling, and related mean-field approximation, define a fruitful bridge between Complex Systems representations, usually based on simulative tools, and System Analysis based on aggregate descriptions through differential equations. See,

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for instance, Guseo and Guidolin [12,13], where S-shaped growth curves (or their modified versions) emerge from social contagion or through the increasing affordability of heterogeneous consumers with a different willingness-to-pay. In [13], latent heterogeneity is micro-modelled through a threshold, which generates a dynamic market potential with a precise take-off effect when a sufficient critical mass is reached.

A micro-modelling of latent heterogeneity of agents was also proposed in Chatterjee and Eliashberg [6] through a mixing distribution in the definition of the adoption process. However, the direct application of the model was partially limited by its complex nature.

A comparison between Agent-Based models (AB) and differential equation models (DE) is examined in Rahmandad and Sterman [24] relaxing the homogeneity of agents and perfect mixing in network hypotheses. They examine a classical SEIR model (Susceptible, Exposed, Infective, Removed) by considering an AB representation as a 'real-world' reference and a DE as an inferential counterpart. Results of their simulations highlight strong effects when different network topologies are considered. Heterogeneity of agents appears less sensitive to variations. We may notice that all simulations are performed under a unimodality hypothesis, thus excluding possible alternative multimodal patterns.

Most studies on heterogeneity in innovation diffusion have generally focused on latent structures. A different contribution, among others, dealing with observed heterogeneity, based on duration models, is due to Sinha and Chandrashekaran [28].

In this paper, we focus our interest on the latent case: in particular, we suggest that the lack of homogeneity may be related to the different relationships among agents that generate stationary or dynamic networks in a complex system. In the Bass models, interactions among agents are assumed to be homogeneous over space and time. The corresponding word-of-mouth effect, WOM, is described through a share q of all possible interactions, i.e., $qF(t)\,(1-F(t))$, where $F(t)$ defines the relative cumulative number of adoptions (or adopters) at time t.

A first way to relax this assumption may be found in Easingwood et al. [7], where a simple modulation of interactions is proposed to act on the basic factor responsible of WOM, $F(t)$. Its exponential form induces an acceleration or delay of adoptions which is not uniform over time. The selected interaction component is $qF^{\delta}(t)\,(1-F(t))$. For $\delta<1$, we have a rapid concentration of sales for increasing time t, and vice versa, a delay for $\delta>1$. This non-uniform influence gives rise to an asymmetric behaviour as compared with the Bass model, though preserving a unimodal distribution of adoptions over time. In the past, analogous transformations of the basic interaction effects $F(t)\,(1-F(t))$ were introduced: see, for instance, Gompertz [11], Floyd [9], Sharif and Kabir [27], and Jeuland [18]. Previous expressions of heterogeneity are described through differential equations whose solutions are not always explicit.

Based on a mixture of special densities, a different approach in heterogeneity modelling is considered by Bemmaor [4] and Bemmaor and Lee [5]. The basic hypothesis expresses heterogeneity of agents by assuming that some parameters characterizing local Bass-like dynamics are stochastic over the current population. Starting, in particular, with a shifted-Gompertz distribution,

$$F(t|\eta,p+q)=\left(1-e^{-(p+q)t}\right)exp\left\{-\eta e^{-(p+q)t}\right\}, \tag{1}$$

where $(p+q)$ is considered fixed, the parameter η that defines agents' propensity to buy, is assumed gamma distributed, $\eta\sim G(\lambda=1/\beta,A)$.

Based on the moment generating function, the marginal mixture is an immediate result:

$$\begin{aligned}F(t)&=\int_0^\infty F(t|\eta;p+q)\frac{1}{\Gamma(A)}\left(\frac{1}{\beta}\right)^A\eta^{A-1}e^{-\frac{\eta}{\beta}}d\eta\\&=\left(1-e^{-(p+q)t}\right)/\left(1+\beta e^{-(p+q)t}\right)^A.\end{aligned} \tag{2}$$

For $A=1$ and $\beta=q/p$, the standard Bass model results as a special barycentric case. Parameter $A>0$ characterizes different asymmetries, even though $F(t)$ in Eq. (2) is always unimodal. Low levels of parameter A, $A<1$, define homogeneous agents with a common propensity to buy and a corresponding acceleration of the adoption process. Vice versa, high levels of A, $A>1$, denote heterogeneous agents with different propensities that determine a distributed delay of the adoptions.

Notice that previously introduced models, and in particular, Bass [2], Bemmaor and Lee [5], Easingwood et al. [7], among others, and further covariate dependent models, such as Bass et al. [3], consider the market potential as fixed, $m(t)=m$, over the whole life-cycle. A different possibility may be the definition of a more flexible market potential $m(t)$. In Guseo and Guidolin [12], for instance, a generic market potential $m(t)$ is introduced through Cellular Automata representations, and in particular, its dynamic is obtained by exploiting a latent evolving network of relationships that mimics the heterogeneity of agents over space and time. The proposed cumulative model is $m(t)\left(1-e^{-(p+q)\int_0^t x(\tau)d\tau}\right)/\left(1+\beta e^{-(p+q)\int_0^t x(\tau)d\tau}\right)$, and it may represent, for $x(t)=1$, at most bimodal situations of the corresponding rate process not yielded through a classical mixture. Interpretations of both components are effective in applied contexts. See, in particular, Guseo and Guidolin [13,14].

An alternative perspective considers heterogeneity as characterized by a discrete number of different types or segments. In this sense, the hazard of the category process, $h(t)=f(t)/(1-F(t))$, is composed through different local hazards, $h_i(t)=f_i/(1-F_i(t))$, $i=1,2,\cdots,k$, where k is the number of separate sub-populations. The non-homogeneity of composed hazards recognizes a kind of clustering effect in the development of diffusion with different local dynamics. An example among others, based on a discrete mixture of Gompertz distributions, may be found in Robertson et al. [25] where information on separate segments is known through separate time series. A more interesting and common context would be the analysis of composed dynamics under an aggregate time series that does not distinguish the separate origins of adoption data.

The purpose of this paper is to deal with latent heterogeneity in innovation diffusion, but unlike previously cited papers, we focus our attention on modelling processes that do not have a unimodal behaviour, but rather a multimodal one. Such multimodality results from the co-existence of different sub-populations of adopters in the diffusion process. In doing so, we propose a reduced approach based on a few latent types avoiding difficult integrations through not

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