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Technology diffusion: Shift happens — The case of iOS and Android handsets

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ABSTRACT

The diffusion of technology artifacts is often marked by abrupt events and incremental evolutionary moves, resulting in shifts in diffusion parameters as well as the underlying mechanics. In this paper, we model the diffusion of Android and iOS based handsets, where new models and operating system versions are released periodically. We relax a common assumption in IT diffusion studies, of holding diffusion parameters constant, and find that there are clear breaks in their values at specific points in time. Using the system dynamics methodology, we then develop and calibrate a causal model of the underlying mechanics. Significant events during evolution of the two platforms are matched temporally with the observed breaks, and the changing mechanics of diffusion across the breakpoints are identified using this causal structure. We find that iOS and Android handset diffusion patterns, although superficially similar, were driven by different mechanics. Our study contributes to the IT diffusion literature by (i) establishing the need to test for, and model, shifts in diffusion parameters over the horizon of interest (ii) offering a method to identify changes in diffusion mechanisms accompanying these shifts and (iii) demonstrating that similar temporal diffusion patterns need not imply similar underlying mechanics.
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1. Introduction

The diffusion of technology artifacts has been studied in the literature for a long time and from a variety of perspectives. One major perspective models the temporal pattern of diffusion, with the aim of explaining the observed shape and/or forecasting how the pattern will evolve in the future. The Bass diffusion model (Bass, 1969) is perhaps the best known early work of this genre. Such models typically have one or more parameters which are calibrated using temporal data about the diffusion pattern. A common practice during calibration has been to assume that the model parameters remain unchanged over the time horizon of analysis (Gujarati, 2004). However, for IT artifacts specifically, diffusion is marked by incremental as well as significant abrupt events.

For instance, wireless routers have experienced incremental improvements in transmitted power and antenna design, as well as abrupt events such as introduction of the 802.11n standard. Flat panel displays have incrementally increased in size and have also experienced abrupt changes such as the introduction of liquid crystal technology over plasma. Similar mixes of incremental and abrupt changes have been witnessed in hard disk (magnetic to solid state) and optical drives (recording formats). We also see that, while these events frequently affect diffusion in a positive manner, it is not always the case. For example, shortly after Apple introduced iPhone 6 with iOS 8, it introduced an update in the form of iOS 8.0.1. Many users complained about loss of network connectivity and malfunctioning of the Touch ID fingerprint sensor. This event did not help iOS 8 diffusion.

The specific IT diffusion context in our study is the diffusion of Android and iOS based mobile handsets. We briefly review relevant characteristics of their diffusion patterns which, together with the general observations above, motive our research question that is presented immediately following this discussion. Mobile operating systems (mOS) offer a platform on which handsets can provide rich functionality to end users, beyond telephony, through a variety of applications (Apps). Worldwide, the installed base of smartphone handsets grew from 237 million in 2008 to 2562 million in 2016 (Statista, 2016). Table 1 shows the share of mOS as a percentage of handheld units shipped[1]. Android and iOS account for a lion's share of this market. Clearly, the growth of these two platforms represents a major IT diffusion phenomenon.

Figs. 1 and 2 show annual sales and change in sales of Android and iOS smartphones from inception until 2014 (Gartner, 2017). Note that the sales curves for both platforms exhibit changing patterns like decline, stagnation and growth. Moreover, during the timespan covered by Figs. 1 and 2, both platforms experienced incremental and abrupt events. Examples of the former include improvements in battery life and ergonomics. The latter include new handset model and mOS version introduction and developer policy changes instituted by Apple.

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[1] Data available from International Data Corporation at http://www.idc.com/prodserv/smartphone-os-market-share.jsp, accessed 18th January, 2016.

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Table 1
Market share of mOS worldwide.

Period	Android	iOS	Windows Phone	BlackBerry	Others
Q1 2016	84.1%	14.8%	0.7%	0.2%	0.2%
Q1 2015	78.0%	17.5%	2.5%	0.4%	0.5%
Q1 2014	81.2%	15.2%	2.5%	0.5%	0.7%
Q1 2013	75.5%	16.9%	3.2%	2.9%	1.5%
Q1 2012	59.2%	22.9%	2.0%	6.3%	9.5%

The presence of multiple archetypes – decline, stagnation, growth – in the diffusion pattern of IT artifacts as seen above, and the accompanying incremental and abrupt events, lead us to surmise that the underlying mechanisms and parameters driving the diffusion change over time. This leads to the following research question: how can we model IT diffusion patterns in a way that reveals changes in underlying causal mechanisms and which accommodates changes in model parameters over time caused by incremental and abrupt events that frequently accompany these phenomena. As we will find in the literature review, the common practice in modeling technology diffusion is to assume that the driving mechanics and process parameters remain constant. This ignores the reality that IT artifacts undergo both gradual and abrupt changes during their diffusion. Hence our research question frames the IT diffusion phenomenon in a more realistic manner and our findings should therefore be of theoretical interest. Moreover, our interest in revealing the changing mechanisms driving the phenomenon is of practical interest in managing the diffusion process because we get a better understanding of the relationships between specific temporal events and their effects on the diffusion patterns, and helps produce actionable information for handset manufacturers and mOS firms.

The paper is organized as follows. In the next section we survey relevant literature on IT diffusion models focusing on modeling techniques and assumptions. A summary of the evolution of iOS and Android follows, highlighting several abrupt events which illustrate the contextual characteristics that motivated this modelling effort. Then, using time series data, we check for the presence of 'breaks' in the diffusion pattern. The existence of breaks suggests changes in the underlying diffusion mechanism. In the subsequent section, a causal model of iOS and Android growth is developed using the system dynamics methodology, and then calibrated to accommodate the pattern shifts identified earlier. This model is then analysed to *identify the dominant mechanisms* that drive the diffusion patterns and *how they change over time as the patterns shift*. We conclude with a discussion of the contributions of this

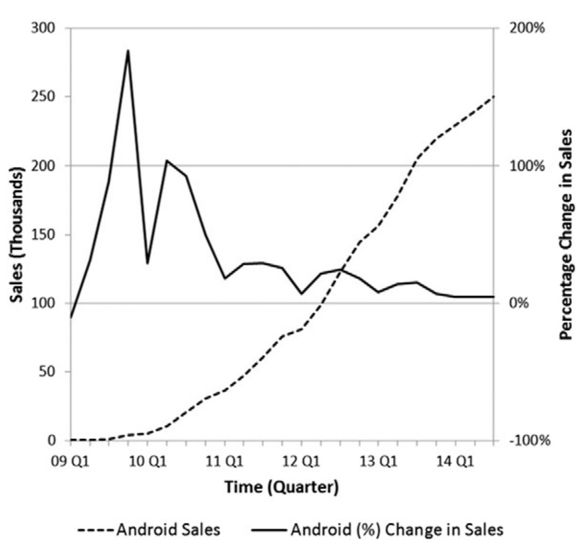

Fig. 1. Sales of Android handsets.

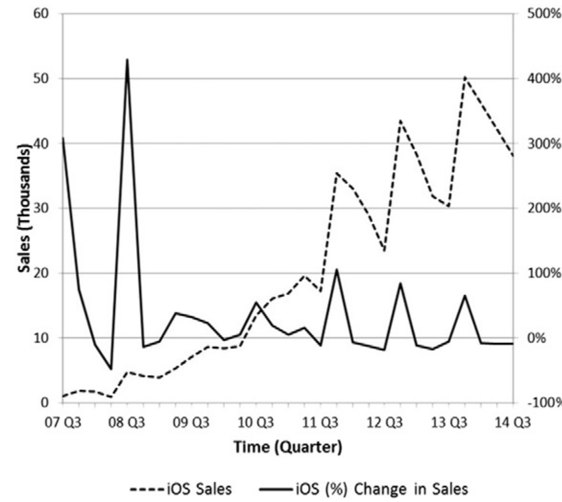

Fig. 2. Sales of iOS handsets.

study to the IT diffusion literature, applications to other technology diffusion settings, and limitations.

2. Literature review

Given the broad literature surrounding technology diffusion, it is necessary to focus on the segment that is directly relevant to our investigation. As noted earlier, our specific interest is in modelling shifts in the temporal pattern of diffusion and uncovering the *changing* mechanisms that result in the observed pattern shifts. Thus we will review the diffusion literature through this filter and exclude other established themes, such as organizational and individual enablers of and barriers to diffusion (Gupta and Jain, 2014) and impact of public policy and regulation (Cho and Choi, 2015).

One pervasive presence in diffusion modeling has been the Rogers diffusion of innovations model (Rogers, 1962) whose underlying mechanism is that of *contagion*, where actual adopters influence potential adopters. Different parameters, such as propensity to innovate or imitate, modulate the diffusion. Numerous studies have used this classical model to understand large scale technology diffusion (Baskerville and Pries-Heje, 1998; Fichman, 1992, 2004), although a weakness in capturing shifts in diffusion patterns has also been noted (Kauffman and Techatassanasoontorn, 2009). Information technologies which have been examined using this model include multimedia message service (Hsu et al., 2007); mobile phone adoption (Kauffman and Techatassanasoontorn, 2012; Watanabe et al., 2009); BITNET adoption in academe (Levin et al., 2012); open source software such as Apache web servers (Lakka and Michalakelis, 2012); and mobile social networking (Scaglione et al., 2015). Variants of the contagion mechanism have also appeared, such as punctuated equilibrium (Loch and Huberman, 1999), social networks (Susarla et al., 2012) and proportional hazards (Greenan, 2015).

Bitnet growth was modeled in Gurbaxani (1990) using the Logistic and Gompertz functions, both of which are consistent with a contagion mechanism. The Gompertz model was found to be a good fit for diffusion of mobile telephony in a developing country context (Gupta and Jain, 2014). Internet growth was earlier modeled in Rai et al. (1998) using the same two functions and the exponential function. Interestingly, although the exponential function is not based on a contagion mechanism, it produced the best fit among the three models. One reason offered by the authors for the poorer fit of the Logistic and Gompertz models was the assumption that contagion parameters remain unchanged over the period of analysis. Some recent studies have examined this scenario of changing diffusion parameters. Meade and Islam (2006) review diffusion studies which attempt to capture the time varying

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