Simulating Digital Businesses Using an Agent Based Modeling Approach

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Abstract: This paper proposes a complex systems approach to understand the growth and decline of Digital Businesses. Digital Businesses are characterised by unique factors such as a highly networked online customer base, where word of mouth spreads very fast, and minimal cost of incremental users due to economies of scale. Thus online businesses peak and plummet rapidly making it difficult to fathom their success. Through an Agent Based Modeling approach we propose that online businesses can be represented as simulation models which can enable forecasting, what-if analysis and optimization of business parameters.

1 INTRODUCTION

Digital businesses encompass the entire gamut of ventures, from online sale of products and services to social collaboration platforms, and have become a vital engine for the new economy. Understanding this new economy has been a challenge for companies that were tuned to the traditional ways of doing business and were armed with traditional product development and marketing philosophies. Most companies that rushed into the dot-com bubble in the early part of the last decade perished (Goodnight & Green 2010). However, we also saw the emergence of new business giants such as Google and Amazon, who did the right things at the right time to emerge as winners.

Today Digital Business managers often rely on experience and intuition to set up business models and pricing strategies. Though marketing surveys, have been traditionally used in gauging consumer willingness to pay, a big challenge is to predict business growth, customer adoption and customer response to specific business and pricing models. Online Businesses are complex interacting systems where online users interact and share opinions and experiences at a rate far greater than traditional brick and mortar businesses. These user opinions are shared through offline and online word of mouth (WOM) channels, in addition to various marketing channels. Customer Satisfaction is a key to spread of positive or negative WOM, which influences new customer adoption rate. System Dynamics have often been used to model consumer adoption (Stermann 2000). However System Dynamics require the rules of the behavior to be written at a higher level, such as how the whole population of consumers will respond to a marketing activity rather than how a particular individual will respond (Rand & Rust 2011).

Online businesses are examples of a complex system, where the behavior of individual users can be used to model the growth or decline of a business proposition (Zutshi et al. 2014a). This could provide an analytical approach to develop models that can be used by businesses as a decision support system. Such models can perform a range of objectives, such as making business forecasts, calculating the implications of a change in product pricing, optimization of different price plans, and simulating the impact of a change in the Business Model.

Agent Based Modeling is the most appropriate tool to implement this complex systems approach. Agent Based Modeling is a new computational method through which macro-level consequences are explained through simplified representation of micro level interactions between agents that represent real life entities (Zutshi et al. 2013). These autonomous agents represent online users with

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individual characteristics as well as independent internal decision making capabilities.

In this paper, we propose a Dynamic Agent Based Modeling Framework (DYNAMOD), that incorporates Agent Based Modeling (ABM) techniques to develop and test digital business models that can be potentially applied to a variety of online market scenarios. We also make a discussion on how to manage probabilities from the simulation results using probability management techniques.

New tools and techniques are necessary to help model the complex nature of online products and services (Zutshi et al. 2012; Grilo et al. 2012). Hence we need to develop a customizable simulation environment that can capture the dynamics of an online market, and provide Business Managers with tools to simulate and forecast, thus aiding to perfect their Business Model. Online markets can be represented as a network of interconnected online users which share positive and negative feedbacks and respond to different online products and services. If the behavior of individual agents can be sufficiently well modeled, then a large range of application possibilities open up such as forecasting, what-if analysis and business model simulation.

2 ABM IN BUSINESS

ABM is build on proven, very successful techniques such as discrete event simulation and object oriented programming (North & Macal 2007). Discrete-event simulation provides a mechanism for coordinating the interactions of individual components or "agents" within a simulation. Object-oriented programming provides well-tested frameworks for organizing agents based on their behaviours. Simulation enables converting detailed process experience into knowledge about complete systems. ABM enables agents who represent actors, or objects, or processes in a system to behave based on the rules of interaction with the modelled system as defined based on detailed process experience. Advances in computer technology and modelling techniques make simulation of millions of such agents possible, which can be analysed to make analytical conclusions.

The literature review reveals that applications of ABM have been made to model specific areas of Business (Zutshi et al. 2014b). These include prediction of financial distress (Cao & Chen 2012), product adoption [(S. Kim et al. 2011), (Diao et al. 2011)], consumer behaviour [(Vanhaverbeke & Macharis 2011)], market share (Kuhn et al. 2010), Urban Management (Gao et al. 2012) and demand forecasting (Ikeda et al. 2004). (Kuhn et al. 2010) demonstrated the possibilities of predicting market share based on certain BM attributes of Frontier Airlines. (Bellman et al. 2013) addresses the issue of capturing Internet behaviour to deliver relevant advertisements. ABM approaches can also be used for modeling user response to different sources of advertising. It can also be used to model response to identify the most critical target groups, complementing traditional approaches for the same.

(Roozmand et al. 2011) propose an Agent Based Model to simulate consumer decision making based on culture, personality and human needs and relates them to car purchase decisions. Tesfatsion introduced Agent-Based Computational Economics (ACE) as the computational study of dynamic economic systems modeled as virtual worlds of interacting agents. (Somani & Tesfatsion 2008) have applied ACE to retail and wholesale energy tradings in the Power Markets. In this paper we extend the concept of Agent-Based Computational Economics, to develop DYNAMOD- An Agent Based Modeling Framework for online Digital Business Models.

3 OTHER RELEVANT AREAS OF RESEARCH

3.1 Diffusion of Innovations

Diffusion of Innovations has been an active research area and reflects adoption decisions made by individual consumers. These decisions are made in a complex, adaptive system and result from the interactions among an individual's personal characteristics, perceived characteristics of the innovation, and social influence (Schramm et al. 2010). There are two major approaches to modeling diffusion: econometric and explanatory. The concept of Econometric Modeling was first introduced by (Bass 1969). Econometric approaches forecast market uptake by modeling the timing of first-purchases of the innovation by consumers and are more applicable when market growth rate and market size are of primary interest. Explanatory approaches, as first proposed by (Gatignon 1985) establish that the diffusion of a product in a defined market is equivalent to the aggregation of individual consumer adoption decisions. The adoption decisions are dependent on: Personal characteristics, perceived product characteristics, and social influence.

In earlier works, diffusion of innovation has been approached with mathematical modeling (Goldenberg 2001; Goldenberg et al. 2010; Goldenberg et al. 2007). However as computational powers increased, relatively recent attempts have been made to complement these classic approaches with Agent Based Modeling tools. (Delre et al. 2007; Stonedahl et al. 2008; Diao et al. 2011). We have used these works as the basis for developing the DYNAMOD model with the application of specific characteristics that relate to online businesses.

3.2 Word of Mouth

Literature has assumed word of mouth (WOM) to be the influence of neighbors over an individual (Feng & Papatla 2011). This is a relevant assumption for offline word of mouth since such communication is mostly limited by geographical location. (Keller 2006) estimates that 90% of WOM conversations for traditional goods and services takes place offline.

Word of mouth communication is more effective when the transmitter and recipient of information share a relationship based on homophily (tendency to associate with similar persons), trust and credibility.

(Feng & Papatla 2011) state that the incentive to spread word of mouth reduces if a product gets well known. They go further to deduce that elevated awareness is created by a high advertising budget, reduces the word of mouth propagation. They also deduce that highly satisfied or highly dissatisfied customers are likely to engage in more word of mouth than other customers. The DYNAMOD model incorporates this by ensuring that agents with a high or low satisfaction score have a greater influence on their neighbours.

(Goldenberg et al. 2007) state that for a traditional product, negative word of mouth spreads up to 2 levels of agent chains but a positive word of mouth can go on spreading much further. They also predict that the net effect of advertising at early stages when the product is still not stable could enable a larger creation of negative influence, which could possibly reduce the subsequent market uptake of a product. Thus at an early stage digital products can be negatively impacted by a high degree of advertisement and subsequent adoption, especially when the product is still at a rudimentary state.

While the extent may vary, there is general agreement in the literature that a dissatisfied customer influences others more than a satisfied one (Herr & Kardes 1991). This consensus is built both on evidence that dissatisfied customers communicate with others more than satisfied ones and that recipients of this communication place more weight on negative information.

Thus the DYNAMOD model incorporates these findings by incorporating them into the way Word of Mouth propagates amongst the user Agents.

3.3 Network Structure

Cellular Automata, is a form of lattice network and has been used by numerous authors to mathematically model word of mouth. They represent users as cells in a cellular grid like network, with each a cell getting influenced by static neighbouring cells surrounding them. (Goldenberg 2001) used cellular automata and introduce the concept of strong ties and weak ties while discussing word of mouth. However the static nature of the network makes it unsuitable to represent the dynamic nature of online user networks. Another form of a network is a random network where the cell distance is randomly distributed. Another common network methodology is the small-world network which starts with a random network randomly rewiring some of the edges (Stonedahl & Rand 2010).

In the case of DYNAMOD, we shall be using a dynamic random network where user agents start being randomly distributed over a flat world, and get influenced by agents in a fixed radius. However the agents themselves slowly make random walks, and thus the agents within their sphere of influence keep changing. This represents an online world where users constantly meet the opinion of new users through online posts and forums.

4 THE DYNAMOD FRAMEWORK

4.1 DYNAMOD Components

The DYNAMOD Framework has been developed based on the academic literature collected regarding the unique aspects of an online business. Its purpose is to provide researchers and companies engaged in online businesses with a tool for quickly developing Computational Modeling Systems that can represent their Business Models and their Business Environment, in order to perform advanced simulations for predicting business growth dynamics. DYNAMOD is based on Agent Based Modeling, which enables dynamic representation of the online marketplace. Every online user that could be a potential customer for a product or service is represented as an Agent in DYNAMOD (See Figure 1). These agents interact with each other and share information about new products and services. At the same time, they are influenced by Advertising and Social sites. The model captures these influences, and simulates their impacts in order to predict future scenarios.

The model is customizable and extendible to implement a diverse set of Business Model components, and to make a variety of simulations. Figure 2 shows a conceptual relationship of the various components the DYNAMOD Framework. The model core consists of many interacting agents that represent a market. The model includes standard variables and logics for implementing influence and satisfaction scores for each agent. This core component handles the simulation and interaction, and defines what constants are needed to initialize the key features of the model.

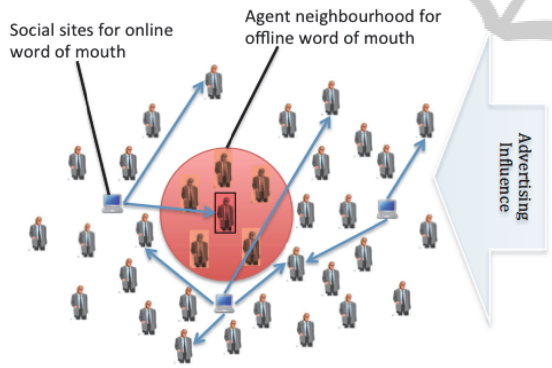

Figure 1: Conceptual Representation of The DYNAMOD Framework.

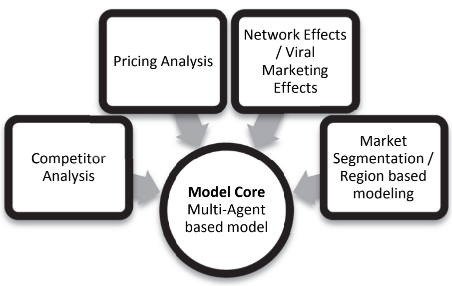

Figure 2: DYNAMOD Framework Component Architecture.

Other features are added to the model in the form of modules, as and when necessary, for different case scenarios. In the current scope of the model, four additional modules have been envisaged, namely Competitor Analysis, Effects, and Market Based Modeling.

Competitor Analysis involves introduction of competitors who can have competing influences on consumers, and then monitoring the switching behavior of consumers. **Pricing Analysis** involves introduction of various charging units, and their impacts on consumer adoption. It also involves the introduction of Freemium Business Models into the model, and simulates the adoption of Free and Paid components of the Businesses. This module is not needed in case of Free Business Models. Businesses that have an inherent **Network Effect** or are based on **Viral Marketing** need to add additional logics that change the rate of product adoption. The **Market Based Segmentation** or **Region Based Modeling** changes the dispersion of agents in the model space, to represent different clusters of agents. This can represent different classes of customers with varying purchasing powers, or can represent customers on different continents.

Diffusion of Innovation literature has used two major forms of adoption functions (Stonedahl & Rand 2010). In the Bass like model, adoption occurs through individual innovation or through peer imitation(Bass 1969). In the threshold model, each user adopts only when a certain threshold of its neighbors have adopted(Gatignon 1985).

4.2 The Adoption Function

The adoption function is a critical component of the DYNAMOD Framework, since it determines when an Agent will become a client and when it ceases to be a client. We shall use a hybrid adoption function that shall account for all the various sources of influences as detailed below:
The Influence score of i^{th} Agent A_i shall be on a scale of 0 to 1. For an agent to adopt a particular product,

$A_i^{Influence} \geq 0.25$ (Adoption Threshold).

This adoption threshold has been specifically defined for the DYNAMOD model, and while asking users for satisfaction/influence scores in the sample survey, this value has been kept in mind while developing the scoring scale.

Also, if the online service is not free then for adoption, the price offered must be lower than his willingness to pay.

The adoption influence is updated on each iteration by averaging it with a new computed value of the $A_i^{Influence}$

$$A_i^{Influence} = \frac{Old\ A_i^{Influence} + A_i^{Influence-Coefficient} \times New\ A_i^{Influence}}{1 + A_i^{Influence-Coefficient}}$$

(Eq.1)

The $^{New}A_i^{Influence}$ is computed through a combination of the following components: Offline word of mouth, Brand influence and Ad Influence, Network Effect and Viral Marketing:

$$\begin{aligned} {}^{New}A_i^{Influence} &= \\ &A_i^{OfflineWOM\text{-}Friends\text{-}Influence} . Avg\left(\textstyle\sum_R A_j^{Influence}\right) \\ &+ A_i^{Brand\text{-}Influence} . Avg\left(\textstyle\sum A_j^{Influence}\right) \\ &+ A_i^{Ad\text{-}Influence} . Cost^{Ad} \\ &+ N\text{-}CONST . A_i^{Network\text{-}Effect} \\ &+ C_{Viral\ Marketing} \end{aligned} \qquad \text{(Eq.2)}$$

The degree of Influence from Neighbours, Global or Advertisements is determined by the 3 coefficients $A_i^{OfflineWOM\text{-}Friends\text{-}Influence}$, $A_i^{Brand\text{-}Influence}$, and $A_i^{Ad\text{-}Influence}$. Each Agent responds differently to these different sources of influence. Through a sample survey we gather the value of these 3 coefficients for every respondent and then compute the mean and standard deviation values. These values are then used to assign these coefficients to these agents.

Network Effect Coefficient: In order to model the network effects, we have introduced a network effect coefficient (N-COF) in our model (See Figure 3). When the percentage of users who are clients within the neighbourhood of an agent is below the critical membership lower limit, the value of the network coefficient is -0.5. This causes a slowdown in the adoption requirement, owing to a chilling effect of network externalities (Goldenberg et al. 2010). Within the critical membership range, the coefficient moves from -0.5 to +0.5, and we begin to see a higher growth rate. Network effects tend to cause a hockey stick growth pattern to be more skewed. In the case of double sided network effect.

$C_{Viral\ Marketing}$ is added to increase the influence rate for such products that have a high viral marketing. The Viral Marketing coefficient is triggered if a large percentage of respondents state to having become clients based on automated mails from acquaintances.

Once an Agent becomes a Client, then onwards, the key parameter will be the Satisfaction and not Influence. The satisfaction level will not be influenced by neighbours or advertisements but rather be a function of the product's utility. In this model we have used the satisfaction scores that have been collected from sample surveys. Hence:

If A_i = Client, $A_i^{Influence} = A_i^{Satisfaction}$ (1.)

And A_i continues to remain a client unless $A_i^{Satisfaction} < 0.25$. In this current model, once the user stops being a client, he doesn't become a client a second time. However this is specific to the context of the business being modeled.

5 STEPS FOR DEVELOPMENT OF AN ABM MODEL

The following steps outline a generic approach to developing an Agent Based Model for an online business.

1. *Identification of the Scope and Objectives of the Model* like forecasting future market penetration, forecasting revenue based on changes in pricing, optimization of pricing bundles, predicting customer adoption based on optimizing marketing mix, etc.
2. *Identification of Business Model Components & associated variables that define the business case.*
   eg. Pricing, Product offering, Product characteristics - like Network Effects, Viral Marketing.
3. *Identification of Agents and Agent Parameters.*
   eg. Buyers, Sellers, Facilitators
4. *Model initialization through data obtained sample surveys.*
   eg. Market size, Average willingness to pay, product satisfaction, WOM influence.
5. *Develop the model and validate it using the DYNAMOD Framework.*
6. *Obtain historical records of the growth data.* Divide the data into initialization and validation phase.
7. *Initialise the model coefficients.* Run the simulation model to ensure the simulation output is as close to the validation phase historical data as possible by adjusting the model coefficients.
8. *Compare the simulated data with the Validation data.* Compare the accuracy of this forecast with other methods like ARIMA. If the forecast is acceptable them the model is set to be complete and ready for use.

9. *Use the Model* as required, by changed the relevant business model parameters and measuring the impact.

6 CONCLUSION

This paper discusses a novel approach of studying a digital business as a complex system, and using an Agent Based Modeling approach to develop specific purpose simulators that can be used for a wide variety of what-if scenarios and as a tool for optimization of Business Parameters. This approach has already been implemented by our research group for some online case studies such including facebook.com, custojusto.pt and vortal.biz.

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