A PRELIMINARY FORECASTING WITH DIFFUSION MODELS: TWITTER ADOPTION AND HASHTAGS DIFFUSION

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ABSTRACT

Twitter, a global social media, enriches the user's experience of real-time information communication. Considering Twitter and its hashtag function as innovations, this study applies diffusion of innovation theory to gain understanding of Twitter adoption and hashtag diffusion. This study utilizes both automatic data collection from the Twitter API platform and secondary data collection to aggregate trend and adoption data. Two diffusion models, the Bass and logistic models, are chosen to perform forecasting growth patterns of Twitter adoption and hashtag diffusion. The preliminary forecasting results are productive though the models can be refined by taking into account more explanatory variables.

Keywords: Diffusion of innovations, Bass model, forecasting, microblogging, Twitter.

INTRODUCTION

Studying diffusion theory in the context of innovation is important because an innovation affects the life of individuals, communities, organizations, and countries, regardless of the form of innovation. Since the diffusion theory of innovation has been applied to various disciplines, including economics, marketing, sociology, and technology management, the notion of innovations can refer to new products, ideas, services, methods, or inventions. Innovation research requires typologies accounting for market and technology dimensions, which provide a structure to define innovation constructs and the applied domains [7]. These typologies imply that innovations are fundamentally different in various combinations of markets and technologies. Microblogging, a new type of information communication technology, allows users to publish and share short messages through multiple access points, such as mobile phones, Web, or instant messaging services. Therefore, diffusion theory appears to be germane for explaining the spread of new microblogging applications in the Web 2.0 environment.

Twitter, a popular global social media platform supporting by its microblogging service, enriches the user's experience of real-time information communication without being tied to a single device. Twitter hashtags, a novel tagging convention by prefixing keywords with the symbol (#) and proposed and adopted by active users in 2007, serve as retrieval cues associating daily events with information resources. To get certain topics or hashtags show trends, users have to mobilize in a critical mass to include specific words or hashtags while diffusing the tweets. Like texture cues, the surfaced trending topics and hashtags reflect human interactions with the disseminated tweets. To make successful message diffusion possible, Dodd [4] suggested three chief factors: interactions among people (e.g., actors and reactors), acts (e.g., telling and hearing), and time. This study draws on the diffusion of innovation theories to explore the initial use of the Twitter service as an innovation adoption and user decision to continuously adopt Twitter. In addition, understanding the interaction between early adopters and follow-up adopters to diffuse trending topics provides a good case for analyzing continued use-behavior. As such, the first part of the exploration focuses on estimating the growth of Twitter adopters over five years; the second part emphasizes Twitter adopters' continued use by investigating Twitter trend diffusion patterns.

THEORETICAL FRAMEWORK

Diffusion of Innovation Theory: Two Research Streams

Rogers, who developed the first model of diffusion, defined diffusion of innovation as: "the process by which an innovation is communicated through certain channels over time among the members of a social system." [11]. For its adopter, an innovation could be any: "idea, practice, or object that is perceived as new by an individual or other unit of adoption." [12]. The diffusion process consists of four key elements: innovation, the social system which the innovation affects, the communication channels of that social system, and time. [12]. One of the most influential theories of communication in marketing, diffusion theory focuses on the means by which information about an innovation is disseminated. Although Rogers' model is classic and widely established, it has several limitations regarding its predictive power related to the dissemination of an innovation [1]. Therefore, Bass proposed his eponymous model to explain his discovery of how the number of adopters during a time period is almost identical to the number of sales throughout most of the diffusion process. This suggests that the number of adoptions in a time period serves as a good proxy for sales. Thus, the Bass model has been revised and implemented in forecasting innovation diffusion in multiple fields. [9]. While the Bass model has potential to predict the distribution of the adoption curve, Rogers' model serves as a comprehensive framework for understanding the diffusion process of an innovation and its underlying factors driving the diffusion.

DIFFUSION THEORY AND TWITTER ADOPTION

Despite the fact that Twitter has become a prevailing microblogging service as a global social media platform, there is currently a lack of diffusion research on microblogging or Twitter applications. From a technology acceptance viewpoint, one study used the Unified Theory of Acceptance and Use of Technology (UTAUT) to model microblogging adoption within the enterprise [6]. Another recent and relevant study examined the impact of word-of-mouth on Twitter retweeting behavior employing content and social network analysis [14].

Twitter Adopters

When it comes to adopters of an innovation, Rogers assumes that the relationship between the number of adopters and time of adoption appears as a normal distribution. Rogers' adopter category indicates that the innovators (top 2.5% of total adopters) and early adopters (top 16% of total adopters) play important roles in influencing potential customers in deciding to adopt the innovation. Without their influence, the diffusion process will not be able to continue. Moreover, the fast growing number of cumulative Twitter adopters confirms that users' decisions to adopt Twitter rely on internal influences, i.e., interpersonal word-of-mouth or informal advertising, within the social structure instead of external influences (formal advertising or mass media). On the other hand, the Bass model emphasizes the two major categories of adopters, innovators and imitators, whose adoption are decisions driven by innovators' influences.

Information Interaction in Twitter Hashtags Diffusion

All the Twitter adopters are potential Twitter hashtag users. The list of Twitter daily top 30 trends demonstrates the competition between trends with hashtags and without hashtags, i.e., regular keywords. To get certain topics or hashtags to trend, Twitter adopters have to make efforts to mobilize a critical mass of adopters to include specific words or hashtags while diffusing the tweets. Like texture cues, the surfaced trending topics and hashtags reflect human interactions with the disseminated tweets. However, the conditions necessary for hashtag and non-hashtag diffusion to increase their use rates differ. While keywords diffuse as the (re)tweets contain the combinations of keywords, hashtag diffusion requires the inclusion of the hashtag symbol (#) in the (re)tweets. This study primary focuses on hashtag diffusion as hashtags serve as retrieval cues assisting in navigation and refindability.

Diffusion of innovation theory has established a solid theoretical foundation to study an innovation across disciplines; therefore, researchers can learn and benefit from what has been discovered in other disciplines. Through the lens of Diffusion of innovation theory and information interaction theory, it assists in evaluating hashtag life cycles and thus offering information required for decision-making, in regard to hashtag management [3].

FORECASTING TWITTER DIFFUSION PATTERNS: THE BASS MODEL

In order to study the phenomena of Twitter adoption and Twitter hashtag diffusion, different diffusion models can be used to analyze and predict diffusion patterns.

The Bass Model

Inspired by Rogers, Bass provided a mathematical theory for explaining the diffusion of an innovation. The Bass model assumes that adoptions or sales of an innovation are influenced by satisfied customers at a particular time. Early adopters who like the innovation spread the word and encourage potential customers to adopt it. Notably, the Bass Model has been examined in many industries and with many new technological innovations and services. There are two methods used to estimate the parameters of the Bass model from historical data: either finding analogous product estimates or using nonlinear regression. [13]. One study [8] in particular organized a list of the innovation *(p)* and imitation *(q)* parameters of the Bass model across more than 30 product/technology categories. Not only do microblogging services have yet to be tested using the Bass model but there seem to be no analogous products available. Hence, this study uses nonlinear regression to estimate the Bass model to forecast Twitter adoption. The variables for parameter estimation or for forecasting in the Bass models are composed of: the potential market *(M)*, the coefficient of innovation *(p)*, and coefficient of imitation *(q)*. The Bass model has several forms of equation; here is the diffusion equation for estimating the Bass model using nonlinear regression:

$$S(t) = a + bN_{t-1} + cN_{t-1}^2$$

where

S(t): the number of adopters or sales in period *t*
N(t): the cumulative number of adopters up to time *t*

The values of *a*, *b*, *c* may be determined from ordinary least-squares regression. The formula of calculating *p* and *q* based on the values of *a*, *b*, *c* can then be obtained as follows:

$$\overline{N} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

p: coefficient of innovation (coefficient of external influence)

$$= \frac{a}{N}$$

q: coefficient of imitation (coefficient of internal influence)

$= p + b$

$N > 0$, $b \geq 0$, and $c < 0$.

Applying the Bass Model to Twitter Diffusion

Data Source

Twitter adoption data were collected from the company data website, Infochimp.org. This dataset counts the number of users who created accounts and sorts them by year, month, and day between March 2006 and March 2010. Because the monthly dataset has no missing data, this study uses it as the chief data source for estimating the Bass model for Twitter adoption. In total, the number of past periods (between March 2006 and February 2010) for fitting the Bass model estimation is 47 months after removing the outlier (March 2010).

The Bass model assumes that *M* is constant; however, it often changes in practice. Two approaches to estimating potential market [2]: either a fixed constant or a function that changes over time with the decision variables. This study assumes a constant due to the short term time series data (47 months). Combining the data from Infochimp.org (March 2006~ February 2010) and the Twitter announced statistics in March 2011, we plotted the cumulative number of Twitter adoptions (Figure 1) by year since Twitter's introduction in March 2006.

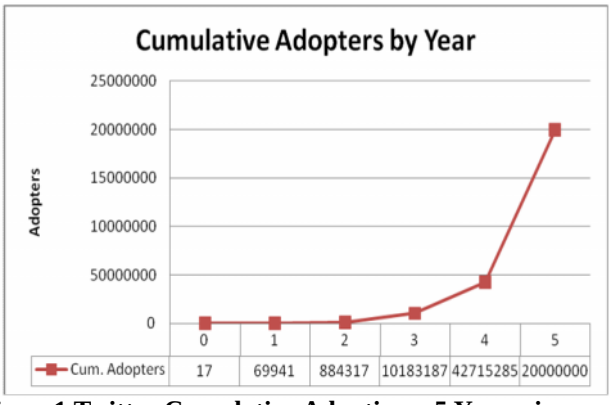

Figure1 Twitter Cumulative Adoptions: 5 Years since Introduction
Source: This study.

Generally, this study found that the number of adopters over five years has grown significantly. However, as shown in Table 1, the growth rate has become more stable within these two years.

Table1 Twitter Adoption Growth Rate

Year	Cum. Adopters	Growth Rate
1	69941	
2	884317	1164%
3	10183187	1052%
4	42715285	319%
5	200000000	368%

Source: This study.

Therefore, in order to determine the maximum market potential *(M)*, this study projects the potential Twitter adopters to be 700 million for the following year based on the assumed growth rate of approximately 350%.

Estimating parameters of the Bass Model

The Bass model is characterized by describing the interaction between innovators and imitators. It is also called a *model of social contagion* where *p* (the innovator coefficient) denotes the probability of initial adoption independent of others' decisions to adopt the new product or service; *q* (the imitator coefficient) measures the social contagion effect (like word-of-mouth) on adoption. The results of the estimated nonlinear regression using Stata 11 are displayed in Figure 2. The coefficients (*b* and *c*) on both cumulative adopters lagged one month (laadopters) and the square of cumulative adopters lagged one month (sqlaadopters) are statistically significant at 5% in terms of predicting the cumulative adopters in period *t*.

```
      Source |       SS       df       MS              Number of obs =      47
-------------+------------------------------           F(  2,    44) -11811.29
       Model |  8.9224e+15     2  4.4612e+15           Prob > F      =  0.0000
    Residual |  1.6619e+13    44  3.7771e+11           R-squared     =  0.9981
-------------+------------------------------           Adj R-squared =  0.9981
       Total |  8.9390e+15    46  1.9433e+14           Root MSE      =  6.1e+05

------------------------------------------------------------------------------
cum.adopters |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  laadopters |   1.407299   .0322452    43.64   0.000     1.342818    1.472285
sqlaadopters |  -9.69e-09   8.88e-10   -10.90   0.000    -1.15e-08   -7.90e-09
       _cons |   72290.04   113448.3     0.64   0.527     -300930.9    156349.2
------------------------------------------------------------------------------
```

Figure 2 Output of the Estimated Nonlinear Regression
Source: This study.

The values of the Bass model parameters are then calculated using Stata 11 as follows (Figure 3):

```
------------------------------------------------------------
cum.adopters |      Coef.   Std. Err.      t    P>|t|
-------------+----------------------------------------------
           p |   .0000195   .0000329     0.59   0.557

           q |   1.407318   .0322304    43.66   0.000
------------------------------------------------------------
```

Figure 3 Output of the Estimated Parameters for The Bass Model
Source: This study.

The estimated parameters reveal that the innovation effect (*p*), .00002, is not statistically significant (p value = .557 > .05) in predicting cumulative Twitter adoption while the imitation effect (*q*), 1.4073, is statistically significant (p value = .000 < .05) in predicting cumulative Twitter adoption. The small innovation effect indicates that the intrinsic tendency for a user to adopt Twitter is insignificant, whereas the high imitation effect shows that significant social contagion effect drives an acceleration of Twitter adoption. It is worth noting that when the *q* value is equal to 1, it means that non-adopters will adopt Twitter for certain once they hear about it from a previous adopter [8].

Forecasting analysis using the Bass model

The historical time series data (from March 2006 to February 2010) was used to generate the model. Although the recent one year adoption data is not available, the most recent adoption data Twitter announced is used to compare the inflection point. As a result, the estimated Bass forecasting model is consistent with the recent Twitter adoption data (approximate 200 million adopters as of March 21, 2011). However, when maximum market potential (*m*) is assumed to reach 700 million adopters, the forecasting inflection point was reached (in the end of 2009) about one year earlier than the actual data. As the market potential changes, the inflection point approaching the saturation level also changes. Even so, the model with M = 700 million fits better than those with lower or higher M values. Since this preliminary study estimated the basic Bass model, there is still room for improvement. The forecasts for different scenarios or extending the basic Bass model by including significant decision variables might help reduce the bias and further improve the forecasting accuracy.

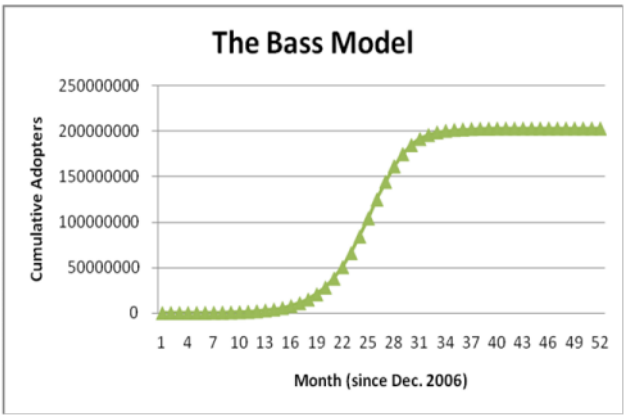

Figure4 Twitter Diffusion Pattern Estimated by the Bass Model
Source: This study.

The observed diffusion pattern from the Figure 4 presents the S curve indicating the imitation effect dominating the innovation effect. In pursuit of model optimization, some extensions of the standard Bass model have been proposed to account for repeat purchases (uses) of a product (an innovation), allowing varying market potential (M), examining the effects of incorporating marketing variables over time, and so forth.

PREDICTING TWITTER HASHTAG DIFFUSION PATTERNS: LOGISTIC GROWTH MODEL

As the historical data for hahstag initial use is unavailable, the logistics curve is considered a more appropriate model.

Simple Logistic Growth Model

The logistic growth equation is one of the most widely applied models for technology forecasting. This model features its symmetric inflection point, the time at which the number of adopters stops accelerating upward and starts reaching the saturation level. This model helps investigate the pattern of a technology's life cycle from slow growth, rapid growth, and decreasing growth to decline.

The logistic equation is express as

$$Y_t = \frac{L}{1 + ae^{-bt}}$$

where
Yt is the market share (or adoption rate)
L refers to the saturation level, and *a* and *b* describe the curve

Applying Simple Logistic Growth Model to Twitter Hashtag Diffusion

Data Source

Many leading Web 2.0 companies release application programming interfaces (APIs) to encourage the use of their data and services in the development of new applications. As such, utilizing APIs has become a method for collecting Web system actual use data. Twitter makes public its API enabling developers or researchers in order to encourage the use of programming languages to enhance existing functions or communicate with the Web servers in order to fetch data. Thus, this study uses Twitter API to assist in Twitter trend data acquisition.

To better quantify Twitter hashtag usage, this research will deploy an automated data collection method through the writing of a self-designed program with Java and MySQL database to directly retrieve data via the Twitter API. For example, weekly trends return the top 30 trending topics for each day in a given week. In the database, the three primary tables containing trends, country, and city, were created to gather data.

Like keywords, the hashtags that are being most widely used will be displayed as the top ten trending topics. Ideally, instead of keywords, hashtags should be promoted as cues or indices to efficiently organize and share Twitter messages. Based on a recent three-month observation of Twitter, 2~3 out of the daily top 10 worldwide trending topics contain hashtags. However, the distributions may be uneven across different countries. Accordingly, the diffusion theory of innovation can help examine whether hashtag use activity varies as it is disseminated during different time periods and across cities or countries. This preliminary study starts with the logistic diffusion model focusing on the hashtag growth rate during certain time periods. The comparative analysis of hashtag growth rates across cities and countries will be conducted in the next research stage.

Estimating Logistic Growth Model

As summarized in Table 2, this study retrieved 5522 trends from April 2010 to December 2010 as the sample for examining hashtag diffusion.

Table2 Summary of Sampled Trending Topics

	Hashtag	Total
Distinct Trends	1117 (26.64%)	4193 (60%)
Repeated Trends	381 (28.67%)	1329 (40%)
		5522 (100%)

Source: This study.

While 40% of trends have occurred more than once, 60% of trends are distinct trends appearing one time. It implies that Twitter adopters have routinely reused or recycled hashtags in order to exchange tweets. In both distinct and repeated trend categories, hashtag rates are 26.64% and 28.67%, respectively. The hashtags rate is a little higher in the repeated trends than the distinct one.

Estimating logistic growth with an unknown saturation level is very difficult. To resolve this issue, we utilize the Twitter API to retrieve the daily top 30 trend (with or without hashtags) data to examine hashtag growth patterns. Therefore, in the case of Twitter top hashtag use, the saturation level is known. Since the data collected for estimating the logistic model consists of the daily Twitter top 30 trends, we can easily obtain the market share of hashtags (meaning the percentage of hashtags takes over the top 30 trends) and assume that the saturation point is 1. We aggregated the daily hashtag rate data (between 2010/4/11 and 2010/12/31, total sample size is 231 cases) to monthly hashtag rate data by calculating the average hashtag rate for each given month.

Forecasting Analysis Using the Logistic Model

The logistic curve can also be used to estimate the growth rate for the following terms. As displayed in Table 3, the monthly hashtag rate (market share) and the least-squares fit to the logistic function are used to predict the values of projected hashtag rates. The forecast provided by the logistic equation shows hashtag rate ranging from .25 to .39, with an average around .0308. To ensure the accuracy of the forecast, we have observed and recorded the hashtag rate in daily top 10 trends since Jan. 1st, 2011. The pattern is consistent with the hashtag rate, in the range .20 to .30, with an average equal to .25.

Table 3 Forecasting Analysis of Hashtag Rates

Year/Month	Hashtag Rate	Regression fit of exponential growth
2010-Apr.	0.09	0.0838
2010-May.	0.25	0.0969
2010-Jun.	0.20	0.1120
2010-Jul.	0.17	0.1294
2010-Aug.	0.21	0.1496
2010-Sep.	0.25	0.1729
2010-Oct.	0.34	0.1998
2010-Nov.	0.29	0.2309
2010-Dec.	0.30	0.2669
	Forecast	**Extrapolation**
2011-Jan,	0.24	0.3084
2011-Feb.	0.26	0.3564
2011-Mar.	0.29	0.4119
2011-Apr.	0.32	0.4761
2011-May	0.35	0.5502
2011-Jun.	0.39	0.6359

Source: This study.

By fitting a logistic curve to the 9-month hashtag use data (from April 2010 to December 2010), we are presented with the stable growth of hashtag use because the rapid growth of Twitter adoption occurred during the time periods. As more adopters use hashtags, they influence other adopters to adopt and diffuse the hashtags. It indicates that there might be a network effect assisting the hashtag diffusion.

Implications

Viewing Twitter as an innovation, we applied the basic Bass model to understand the interactions between innovators and imitators and the impacts on their decisions to adopt the innovation. Surprisingly, our findings show that Twitter early adopters, i.e., innovators, were not significantly affected by external communication effects attributed to advertising campaigns. However, the imitation effect coming from interpersonal word-of-mouth communication has a significant impact on Twitter adoption. The faster growth rate of adoption might associate with the characteristics of Twitter, such as perceived relative advantage of adoption, compatibility with existing user experience, observed benefits, and so forth. Additionally, based on the logistic growth model, Twitter hashtags diffusion would be likely to progress in the same manner as Twitter adoption. The more people that are talking about a hashtag, the more people in the social system will adopt its use.

CONCLUSIONS

The Bass model helped postulate that the Twitter adoption and diffusion rely on word-of-mouth communication process between innovators (i.e. early adopters) and imitators. The Twitter adoption and diffusion process was modeled and represented as an S-shaped trend curve illustrating the life cycle of Twitter growth. With historical observations, the Twitter diffusion modeling also assisted in predicting time period to reach maturity.

The prelude of diffusion modeling characterized the process of Twitter adoption and diffusion: in terms of consumer

adoption decisions, Twitter early adopters, namely innovators, were not significantly affected by external communication effects attributed to company advertising or marketing strategies. However, the innovators generated significant imitation effects through interpersonal word-of-mouth communication to motivate the adoptive behavior of potential customers. In addition, the rapid growth rate of Twitter adoption and diffusion patterns might associate with the Twitter characteristics, such as perceived relative advantage of easy adoption, compatibility with existing user experience, observed benefits of real-time information sources, etc.

Moreover, similar to the original Bass model, there are other diffusion models facilitating explanations of various diffusion paths according to different assumptions, data requirements, or refinements of the Bass model. Meade & Islam [10] succinctly summarized the widely accepted diffusion models applicable to forecasting the diffusion of innovations and suggested several principles pertinent to model selections, prediction intervals, and uncertainties.

Likewise, based on the logistic growth model, Twitter hashtag diffusion would be likely to progress in the same manner as Twitter adoption. The imitation effect from word-of-mouth communication on the hashtag diffusion was significant. Hashtag diffusion acted both directly on hashtag adoption and indirectly as interactive communication occurred to promote hashtag awareness. In other words, the more Twitter adopters that are talking about a hashtag, the more adopters in the social system will consider its use. The power of social contagion explains the rapid increase in Twitter adoption over five years and allows Twitter hashtag diffusion to quickly define trends.

FUTURE RESEARCH DIRECTION

IS/IT adoption and diffusion research in the Web2.0 context is still in the infancy stage and warrants further investigation. Further research is necessary to explore applicable theories, predictors, linkages between variables, and new methods to share the accomplishments and bridge the gaps across domains. Much more needs to be known about the way people locate, exchange, and preserve real-time web content they find useful and relevant in the Web 2.0 environment.

The diffusion models (i.e. the basic Bass model and the simple logistic curve model) in the first empirical data analysis provide an exciting first step to determine the contagious interaction between innovators and imitators to diffuse the trends. However, future research is obviously required to further investigate the social interaction of "telling-and-hearing a message" [4] over time across locations. To make tweet diffusion predictable, an important area for future research will be in the refinement of approaches to the analysis of various diffusion models, in particular measuring the correlation of innovator (i.e. actor of a hashtag) and imitator (i.e. reactor of a hashtag) effort to communicate.

Diffusion modeling [5] studies are concerned with observed patterns in which innovations appear at growing speed and diffusing in scope as they spread across potential adopters over time. The observed differences between low innovation and high imitation effects on Twitter adoption and hashtag diffusion led us to the question of the significant impacts of social interaction or mobilization. Several experimental studies controlling for trend category or temporal intervals could be undertaken to determine different use case scenarios of social interactions. The potential of the meaningful use of such social interaction during the time-based events clearly needs further exploration by diffusion modeling.

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