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Predicting Customer Purchase Monetary with Advertising

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ABSTRACT

This paper constructs a stochastic model to describe customer's online shopping spending and e-commerce effects. This paper focuses on the reflection of advertising effect which can directly predict customer spending. It assumes that customer purchase monetary can be composed by adverting volumes and its lagged effect which is the duration that customer is still interested to this product after exposing the advertising. Based on these two variables, it can be calculated the probability distribution and the expected value of purchase monetary. The empirical data which is from an online shopping site of women clothes, bags and shoes is demonstrated to estimate the parameters of the proposed model. When the customers browse the web page, and the popup ad of relative product will show up. The unit of observation time is a month (30 days). It can obtain the data of advertising effect from the volumes of popup ad when this customer starts to browse the site and the data of spending amount. It shows the proposed model has good fitness with empirical data. This result can be applied to company profit management through measuring the ad effects to predict customer monetary spending

1. Introduction

The topic of advertising effects (Ad effects) has been discussed in marketing area many years ago. Advertising can influence customers' preference for a product and be effective in presenting information to or persuading, buyers. It can also affect customers' purchase behaviour (Srinivasan et al., 2010). Ad effects can interact with other elements in the marketing mix in creating sales. Because small changes in people's preference for a product can have lasting impact resulting in increased sales over time. After all, advertising is supposed to do is to increasing company's sales and profits (Gary and Rangaswamy, 2004). Many studies discuss how advertising affects how consumers "think" and "feel," which in turns affects what they buy (Bruce et al., 2012). For example, Bruce, Peters, and Naik (2012) explore the dynamic relation between upper purchase funnel activities and sales. Thus**,** advertising is viewed as one of the most important and promotional tolls of modern marketing management (Gary and Rangaswamy, 2004).

Every advertisement includes some element of information (Puto and Wells, 1984). This information can be a trigger which push customer to make purchase decision especially in the internet context. In the electronic business, sales can be converted from consumer's interest in seeking information about the focal product prior to making a purchase decision (Hu et al., 2014). An advertisement can be designed with the intention of providing information. It is called informational advertisement which provides consumers with factual, relevant brand data in a clear and logical manner such that they have greater confidence in their ability to assess the merits of buying the brand after having seen the advertisement (Puto and Wells, 1984). Thus, it can refer that the volume of informational advertisement can help to predict current consumer demand in a diverse set of industries (Hyunyoung and Varian, 2012). This demand can transform into product sales (Srinivasan et al., 2010).

This paper stands on this point of view to include advertising volumes as a factor to compose the proposed ad effect model. Another important factor to impact the product sales is the advertising lagged effect which is also called carry-over effect (Berkowitz et al., 2001; Kim and Joo, 2013). The advertising lagged effect is defined as the effect of given advertising exposing is distributed over time. Many empirical advertising studies (Clarke, 1976; Berkowitz et al., 2001; Kim and Joo, 2013; Kim et al., 2015; Tull, 1965; Bass and Clarke, 1972; Givon and Horsky, 1990) find that the customer's reaction to the advertising is delayed and spread over a period of time. These previous researches test the lag relationships between sales and advertising and the result show that advertising in one period can continue to influence sales performance in subsequent periods (Berkowitz et a, 2001). Thus, we consider lagged effect into our model to predict product sales. To sum up, the advertising effect model is composed by advertising volumes and its lagged effect.

In the next section, firstly, we will introduce the literature review of advertising effect and its modelling. Based on this previous research (Kim and Joo, 2013; Kim et al., 2015; Berkowitz et al., 2001) we will develop our model. We use customers' monetary spending to represent the concept of sales (the ad effect). And advertising volume and its lagged effects are proposed to predict customers' monetary spending. Secondly, the probability density function(pdf) and cumulative distribution function (cdf) of advertising volume and its lagged effects are calculated. Then, the full model of customers' monetary spending is demonstrated by composing advertising volume and its lagged effects. Thirdly, an empirical data is collected to estimate the parameters and validate the proposed model. Finally, the conclusion is made.

2. Advertising effect and its modelling

The hierarchy-of-effects models is the well-known concept to evaluate advertising effect. Because advertisement exposure moves customer forward through a hierarchical sequence of events, including cognition, affect, attitude and behaviour. Moreover, this hierarchical sequence has also been used in the evaluation of brand performance from a customers' perspective. Numerous researches of hierarchy-of-effects models have been developed as a practical framework for integrating the distinct impacts of advertising on the different mental and behavioural stages that consumers go through prior to making a purchase decision (Hu et al., 2014). But the ad effects typically play out over time may be nonlinear and can interact with other elements in the marketing mix in creating sales (Srinivasan et al., 2010). Also, hierarchy-of-effects model does not provide a numerical concept to predict sales directly by its hierarchical sequence. Thus, other researchers develop mathematical model to make ad effect more quantitative and can directly forecast the product sales.

The classical advertising response model was proposed by Vidale and Wolfe (1975). This model demonstrates the rate of change of sales when advertising had both immediate and lagged effects:

$$Q_t = \frac{rX\left(V-Q\right)}{V} - \alpha Q$$

In which Q_t is the change in the rate of sales at time t, Q is the sale volume, X is advertising spending rate, V is market volume, r is sales response constant which can be demonstrated as sales generated per dollar of advertising, X when sales, Q=0 and αis sale decay constant which is the proportion of sales lost per unit of time when advertising, X=0.

Hu et al. (2014) decompose the overall impact of advertising on sales (Y_{jt}) into its impact on generating information-seeking consumers (Q_{jt}) and its impact on converting information seekers into purchasers (R_{jt}). Q_{jt} follows log normal distribution and we denote R_{jt} is the interest duration that customer toward the brand. R_{jt} follows geometric exponential distribution.

$$Y_{jt} = Q_{jt} \cdot R_{jt}$$

Using the combination of Vidale and Wolfe (1975) and Hu et al. (2014) to propose the ad effect model to predict customer's spending monetary (represents the sales concept) by advertising volumes and its lagged effects. Defining that M_i is i^{th} as purchase monetary amount of the customer which are the overall impact of advertising on sales. M_i is decomposed by Adverting volumes, AD_i and advertising lagged effect, *lagged E*. The advertising lagged effect can be explained as the duration that customer is still interested to this product after exposing the advertising. It is also converting the advertising effect into customer purchase behaviour. The model is as following,

$$M_i = AD_i \cdot lagE \quad \textbf{(1)}$$

This model is based on Huang (2014) but some modifications were added to better match the predictor variables of this study.

2.1. Adverting volumes

The Adverting volume is denoted as x which is a random variable and follows log normal density as

$$\begin{aligned} AD_i &= f(x|\mu,\sigma^2) \\ &= \frac{1}{x\sqrt{2\pi\sigma^2}} exp\left[-\frac{(log\,x-\mu)^2}{2\sigma^2}\right] \end{aligned} \quad \textbf{(2)}$$

2.2 The advertising lagged effect

According to the literature review, the interpurchase time of a customer is dynamic. When the customer is attractive by other competitive brands, his interpurchase interval toward this brand will become larger. Therefore, we the advertising lagged effect $lagged\,E$ is follows exponential density which is denoted as

$$\begin{aligned} lagged\ E &= g(y|\lambda) \\ &= \lambda e^{-\lambda y} \end{aligned} \tag{3}$$

2.3 The full model

The c.d.f of M_i is given by *H(m)*

$$\begin{aligned} {}_iH(m) &= P(M_i < m) \\ &= P(AD_i \cdot lagE < m | AD_i = X, laggedE = Y) \\ &= P(X \cdot Y < m) \\ &= \int_0^\infty P(y < \frac{m}{x} | X = x) f(x)\ dx \\ &= \int_0^\infty \left(1 - e^{-\frac{\lambda m}{x}}\right) \frac{1}{x\sqrt{2\pi\sigma^2}} exp\left[-\frac{(log\ x - \mu)^2}{2\sigma^2} \right] dx \\ &= \frac{1}{\sqrt{2\pi\sigma^2}} \int_0^\infty \frac{1}{x} \left(1 - e^{-\frac{\lambda m}{x}}\right) exp\left[-\frac{(log\ x - \mu)^2}{2\sigma^2} \right] dx \end{aligned} \tag{5}$$

Then, it can be derived that the p.d.f of M_i

$$\begin{aligned} h(m) &= \frac{d}{dm} \left\{ \int_0^\infty \left(1 - e^{-\frac{\lambda m}{x}}\right) \frac{1}{x\sqrt{2\pi\sigma^2}} exp\left[-\frac{(log\ x - \mu)^2}{2\sigma^2} \right] dx \right\} \\ &= \int_0^\infty \frac{d}{dm} \left(1 - e^{-\frac{\lambda m}{x}}\right) \frac{1}{x\sqrt{2\pi\sigma^2}} exp\left[-\frac{(log\ x - \mu)^2}{2\sigma^2} \right] dx \\ &= \frac{1}{\sqrt{2\pi\sigma^2}} \int_0^\infty \frac{1}{x^2} exp\left[-\frac{(log\ x - \mu)^2}{2\sigma^2} - \frac{\lambda m}{x} \right] dx \end{aligned}$$

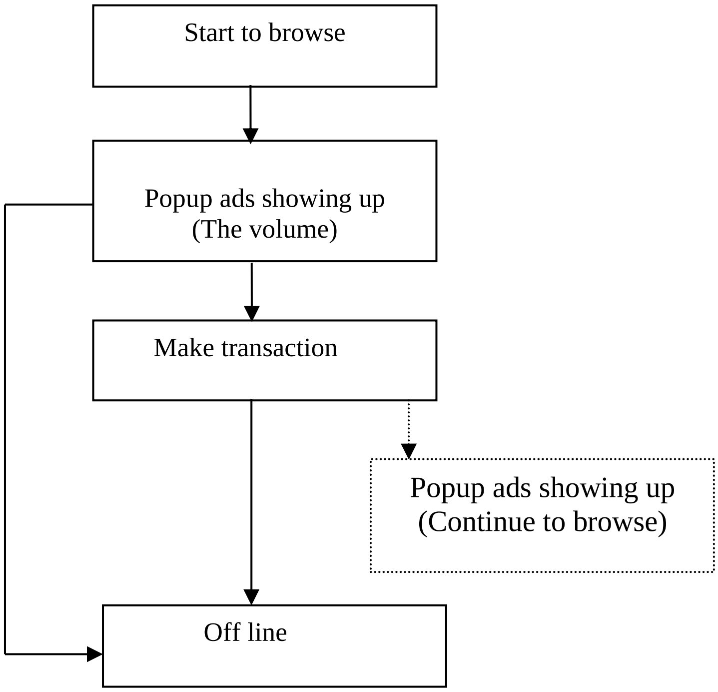
The expectation value of *m* is

$$E(m) = \int_0^\infty m \cdot h(m)\, dm$$
$$= \int_0^\infty m \cdot \left\{ \frac{1}{\sqrt{2\pi\sigma^2}} \int_0^\infty \frac{1}{x^2} exp\left[-\frac{(log\, x - \mu)^2}{2\sigma^2} - \frac{\lambda m}{x} \right] dx \right\} \quad dm$$
$$= \frac{1}{\sqrt{2\pi\sigma^2}} \int_0^\infty \int_0^\infty \frac{m}{x^2} exp\left[-\frac{(log\, x - \mu)^2}{2\sigma^2} - \frac{\lambda m}{x} \right] dx\, dm$$

3. Empirical data analysis

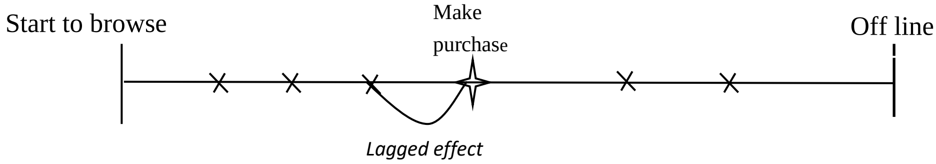
The empirical data is from an online shopping site of women clothes, bags and shoes. The observation process is at figure 1.

Figure 1: Observation process



When the customers browse the web page, and the popup ad of relative product will show up. The unit of observation time is a month (30 days). We can obtain the data of *AD* from the volumes of popup ad when this customer stars to browse this site and the data of *M* from the total monetary he makes purchase. The term” time lagged effect" refers to the delay between the time of an intervention or exposure onset (Gail, 2005). Thus, in our study, the lagged effect (*lagged E*) is calculated by the time length between last time the customer saw the popup ad and the point of time he conducts the transaction (see scenario 1).

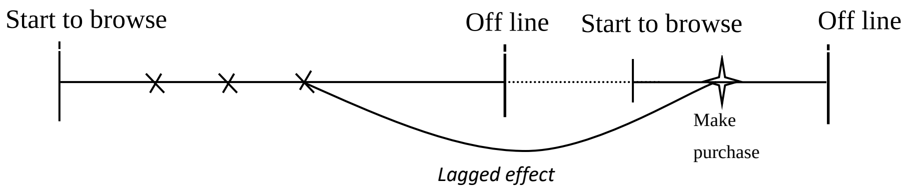
Scenario 1



x demonstrates the pop ad shows up
☆ demonstrates the customer makes purchase

If the customer doesn't make purchase at this time of browsing then the volumes of popup ad are cumulated from the customer first browsing to his first purchase (see scenario 2).

Scenario 2



The researcher screens the customers who only browse the web and do not make any transactions during the observation time. There are 2587 customers in the database and each customer has the tri-data of *AD*, *M* and *lagged E* at least once. The data of *AD* and *lagged E* are conduct to estimate the parameters of the full model. Then we use results of parameter estimation to poll the simulation data. Finally, the root-mean-square deviation (RMSD) is calculated by comparing *M* both in empirical data and simulation data.

3.1 Parameter estimation and model validation

Using MLE (maximum likelihood estimate) to estimate the parameters. Let m_j denote the monetary spending by customer *j*. And let *L* denote the likelihood of the monetary spending of total customers:

$$L(\lambda,\mu,\sigma^2)=\prod_{j=1}^{n} h_m(m_j)$$
$$=\frac{1}{(2\pi\sigma^2)^{n-1}}\int_0^{\infty}\frac{1}{x^{2n}}exp\left[-\frac{n(log\,x-\mu)^2}{2\sigma^2}-\frac{\lambda n m}{x}\right]\,dx$$

(2.12)

The differentiation $L(\lambda,\mu,\sigma^2)$ respectively regarding λ, μ, σ^2 and set them equal to zero. That is,

$$\frac{\partial}{\partial \lambda} L\left(\lambda,\mu,\sigma^2\right)=\frac{mn}{-x\left(2\pi\sigma^2\right)^{n-1}}\int_0^\infty \frac{1}{x^{2n}} exp\left[-\frac{n(log\, x-\mu)^2}{2\sigma^2}-\frac{\lambda\, nm}{x}\right] dx=0$$

$$\frac{\partial}{\partial \mu} L\left(\lambda,\mu,\sigma^2\right)=\frac{n}{\sigma^{2n}\left(2\pi\right)^{n-1}}\int_0^\infty \frac{(log\, x-\mu)}{x^{2n}} exp\left[-\frac{n(log\, x-\mu)^2}{2\sigma^2}-\frac{\lambda\, nm}{x}\right] dx=0$$

$$\frac{\partial}{\partial \sigma^2} L\left(\lambda,\mu,\sigma^2\right)$$
$$=\frac{1}{\sigma^{2n+1}\left(2\pi\right)^{n-1}}\int_0^\infty \left(x\right)^{-2n}\left[2\sigma^3(1-n)+n(log\, x-\mu)^2\right] exp\left[-\frac{n(log\, x-\mu)^2}{2\sigma^2}-\frac{\lambda n m}{x}\right] dx$$
$$=0$$

(2.13)

We take the solutions of (2.13) as MLE for λ , μ , σ^2. The results of parameters estimation are shown in table 1

Table 1: The results of parameters estimation

λ	μ	σ^2
0.2	17	1.32

The researcher uses the results of parameter estimation to poll the simulation data. In order to comparing difference (or closed) between simulation data and empirical data, 2587 simulation data are poll. Root-mean-square deviation (RMSD) is 0.8857 which is smaller than 1. It shows the proposed model has good fitness with empirical data.

4. Discussion

This paper proposed a probability model to predict customer monetary spending by ad volume and its lagged effect. The contribution of this study is to provide a mathematic view of point to explore the relations between ad effect and customer behaviour (customer monetary spending). And this model shows good fitness with empirical situation in which the on-line information ad and its lagged effect can trigger customer purchase after the cumulative pop ad showing up.

This research considers the ad volume and lagged effect follow respectively as log normal and exponential distribution. In the future, other distribution can be tried to construct the model and test the different model validation.

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Conflict of interest statement

The author state that there are no conflicts of interest to declare. There is no financial or commercial conflicts of interest or self-benefits when the study was conducted.

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