Switching from Static to Dynamic Modeling to Forecast Market Share

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Abstract:

In a poly-business environment, a business organization is always keen to enhance its customer base by minimizing the switching over of loyalty of its existing customers to other firms and offering incentives to attract the new ones. To understand this phenomenon, the market researchers usually formulate this switching phenomenon using static models, which in general, fail to capture the upheavals of the dynamics of the business environment. A linear dynamic system model is proposed to cope with the static model problem. The proposed model in this paper, apart from providing insight into the existing business environment be expected to assist the decision-makers in foreseeing the short, medium, and long-term future of their business.

Keywords: Customers loyalty, Market share, Static Models, Linear Dynamic Market Share Model

1. Introduction

The importance of forecasting to managerial decision making cannot be overlooked. It is through forecasting that management steps into the future with confidence. Nearly every decision depends on some forecasting for its resolution. For example, in the light of forecasts, the administration of a business organization can decide whether to introduce a new product or stick to the old one and improve its market strategy to enhance its profit.

Since the introduction of Markov Chains and in general, the Markov Processes by Andrey Markov (1906), a Russian Mathematician, his work is widely used in studying the evolution and transition of many systems over multiple and repeated trails in successive periods. His concept also leads the statisticians to develop a dynamic system and state-space models, such as that of Harrison-Akram (Harrison P.J-Akram M, 1983) and Akram (Akram M, 1988).

In marketing, Markov chains are frequently used to describe consumers' behavior about their loyalty towards a brand which in turn is used to determine the market share of a business organization for the planning of business strategies.

In the past, some work has been done by some researchers in the dynamic forecasting, such as Terui N., 1997. Most Market share analysis mainly based on regression models, where market shares are explained by marketing mix variables and some environmental variables (causal data). The predictions by these models are conducted by assuming the future values of these explanatory variables. The specification of future values for marketing variables of competing brands (or companies) can lead to distinctive prediction errors.
The dynamical mechanism of the model does not automatically generate the predicted share by these models, and in this sense, these regression-based models are the static models.
), Kumara (Kumara V., 2002), Quagrainie K. Kwamena, 2004) and Dura (Dura C., 2006).

Most of their work is related to the study-state probabilities, which is static in nature (sweeny, Anderson). Their work is useful for systems whereby interest is to look into the far-flung future by making use of transition probabilities, where the likelihood of being in a particular state at any one period depends only on the state in the immediately preceding period, without updating.

Today, we are living in an era of an ever-changing dynamic world where microprocessors have become part and parcel of our lives. The products based on microprocessors, such as digital cameras, mobiles, and computers, are being updated so fast that we cannot wait for a long time to enjoy the fruit of new technologies. We wish to acquire them at the earliest possible.

From a business point of view, mainly to estimate and forecast market share of these products; therefore, we need to involve dynamic system models since static models cannot capture ups and downs of market share, as these models are not short-sighted.

To cope with this problem, the LDMS model is introduced. This model, dynamic in nature, is entirely capable of forecasting short to long term market share of a product in an optimum manner.

2. LDMS Model

For observations y_1 and y_2, at time t, on loyalty to the businesses B_1 and B_2 respectively, the LDMS (Linear Dynamic Market share model) is defined as follows.

$$y_t = F\theta_t + V_t$$

$$\theta_t = G\theta_{t-1} + W_t$$

Where:

$$y_t = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}_t \quad \text{a Vector of Observations}$$

$$F = \begin{bmatrix} f_1 & f_2 & 0 & 0 \\ 0 & 0 & f_3 & f_4 \end{bmatrix} \quad a\ Matrix\ of\ Known\ Functions$$

$$\theta_t = \begin{pmatrix} \theta_{10} \\ \theta_{11} \\ \theta_{20} \\ \theta_{21} \end{pmatrix} \quad (State\ Vector\ of\ Parameters)$$

$$G = \begin{bmatrix} G_{11} & 0 \\ 0 & G_{22} \end{bmatrix} \text{ (Transition Matrix)}$$

$$G_{11} = \begin{bmatrix} 1 & 0 \\ 0 & \lambda_1 \end{bmatrix}$$

$$G_{22} = \begin{bmatrix} 1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

$$0 = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$\lambda_1\ and\ \lambda_2\ are\ eigen\ values\ of\ the\ Loyalty\ Matrix$

$$L = \begin{bmatrix} L_{11} & L_{12} \\ L_{21} & L_{22} \end{bmatrix}$$

$$V = \begin{pmatrix} V_1 \\ V_2 \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix} , \begin{pmatrix} V_1 & 0 \\ 0 & V_2 \end{pmatrix}\right]$$

$$w = \begin{pmatrix} w_{10} \\ w_{11} \\ w_{20} \\ w_{21} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} , \begin{pmatrix} w_{10} & 0 & 0 & 0 \\ 0 & w_{11} & 0 & 0 \\ 0 & 0 & w_{20} & 0 \\ 0 & 0 & 0 & w_{21} \end{pmatrix}\right]$$

$W_{10} = (1-\beta)\ (1 + \lambda_1)\ (\lambda_1 - \beta)V_t /(\lambda_1\beta)$

$W_{11} = (1-\beta)\ (\lambda_1 - \beta)\ (1-\lambda_1\beta)\ (\lambda_1^2 - \beta)\quad V_t/ \lambda_1\ \beta^2$

$W_{20} = (1-\beta)\ (1+ \lambda_2)\ (\lambda_2 - \beta)\ Vt / (\lambda_2\beta)$

$W_{21} = (1-\beta)\ (\lambda_2 - \beta)\ (1-\lambda_2\beta)\ (\lambda_2^2 - \beta)\quad V_t/ \lambda_2\ \beta^2$

β is a smoothing coefficient, such that $0 < \beta < \min(\lambda_1^2, \lambda_2^2)$

3. Estimation of the parameters of the model

At time t-1, For known data $D_{t-1} = \{ y_1,\ldots, y_{t-1}\}$ the prior $(\theta_{t-1} | D_{t-1}) \sim N[m_{t-1} ; C_{t-1}]$ the posterior $(\theta_t | D_t) \sim N[m_t ; C_t]$ is obtained through the following recurrence equations:

$$R_t = G\, C_{t-1}\, G' + W_t$$
$$A_t = R_t\, F[I + F\, R_t\, F']^{-1}$$
$$C_t = [I - A_t\, F]\, R_t$$
$$m_t = G\, m_{t-1} + A_t\, [y_t - F\, G\, m_{t-1}]$$
$$e_t = y_t - F\, G\, m_t$$

To which time t:

R is a system matrix

C is a Covariance matrix

A is an updating or gain vector

I is an identity matrix.

F and **G** are as defined earlier.

All matrices and vectors are assumed to be compatible in dimensions with their associated vectors and matrices of the system. Analogous to linear control theory, these stochastic difference equations cluster themselves into an ensemble of a closed loop of the linear system(Akram M.Chaudhry and Irfan Ahmed 2007).

$V_1$and V_2, the observation variances of market share, are found from the past observed data and used for computation of $w_{10}, w_{11}, w_{20}, w_{21}$ the components of the W matrix.

For more discussion, see Akram, 1990 & 1994).

4. Forecasting the Market Share

By the updated estimate of m_t of the parameterθ, the K=1, 2…, steps ahead forecasts $\mathfrak{I}_{t+k}$ of market share are generated through the forecast function:

$\mathfrak{I}_t(k) = \mathfrak{I}_{t+k} = FG^k\, m_t$

5. Special Cases

(i) Generally, for non-seasonal and non-cyclical data, the components of the F- vector: $f_1 = f_2 = f_3 = f_4 = 1$ are considered.

(ii) The model is written in a diagonal form. However, If required, It may be transformed into a canonical form using the transformation procedure of Akram (Akram M,1988).

6. Model Practical Implications

To apply the model and estimate its parameters through the above recurrence equations, prior information is provided as follows.

$$m_0 = \begin{pmatrix} m_{10} \\ m_{11} \\ m_{20} \\ m_{21} \end{pmatrix}$$

Where:

m_{10} *and* m_{11} are prior information of n the parameters θ_{10} *and* θ_{11}, the level and growth state vector parameters of the model.

m_{20} *and* m_{21} are prior information on the parameters θ_{20} *and* θ_{21} the level and the growth state vector parameters and the growth state vector parameters of the model.

$$C_0 = \begin{pmatrix} C_{10} & 0 & 0 & 0 \\ 0 & C_{11} & 0 & 0 \\ 0 & 0 & C_{20} & 0 \\ 0 & 0 & 0 & C_{21} \end{pmatrix}$$

Where:

C_{10} and C_{11} are the prior information on the variances of the state vector parameters "θ_{10} *and* θ_{11}" of the model.

C_{20} and C_{21} are the prior information on the variances of the state vector parameters θ_{20} *and* θ_{21} of the model.

Here, it is assumed that the priors are known. If the priors are unknown, then flat priors may be considered. In this case, the effect of the priors eliminated after about 30 iterations of the parameter updating mechanism. For more discussion, see Akram (Akram M, 1994).

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