Chapter 3

Brand Switching of Rural and Urban Consumers using Markov Models

3.1 Introduction

In marketing research, it is necessary to study the frequently purchased, low priced products or one of frequent switching among different brands in the same product class. This phenomenon is known as brand switching or multi brand buying. Different consumers choose the different brands of a product class at different times which is explained by changing tastes. The frequency with which consumer change their purchasing decisions calls for a more economical theory explaining patterns of choice with relatively few parameters.

However, the consumer choices are past history dependent. McAlister and Pessemier (1982) identify such patterns brand loyalty and variety seeking behavior. These phenomena were first introduced into stochastic models by Jeuland (1979) (brand loyalty) and by McAlister (1982) and Trivedi, Bass and Rao (1994) (Variety Seeking behavior). Guadagni and Little (1983) propose a model of choice probabilities depend on the whole history of consumer choices. Chintagunta, The greater variety of brands is forcing consumers to make more choices between brands (Ambler 1997), exacerbating the need for greater brand choice research.
In marketing research it is necessary to study the brand switching behavior of consumer. Lipstein (1959) tried to apply a first order Markov model of brand choice of consumer. Kuehn (1962) also used a linear learning model for the study of brand choice behavior. The work of Kuehn on linear learning models leads Frank (1962) to the development of an alternative learning model. His approach postulated a Bernoulli model for each household but assumed that the brand choice probabilities for different households were likely to differ from one to another. Morisson (1965) suggest a compound Bernoulli model which is same as proposed by Frank. The advantage of Bernoulli model proposed by Morrison model is that it lends itself for a much better statistical analysis. In this model, short histories of each of consumers would be used. He used the term compound denotes the fact that explicit provision for a distribution of relevant parameter values included in the model. Morrison (1965,b) also developed the compound Markov model which differs from the compound Bernoulli model only in terms of the order of the individuals purchasing process? In the compound Markov model only the last purchase influences the current purchase behavior. The compound Markov model allows for the first order behavior and compound Bernoulli models allows for zero order behavior. Massy (1966), applied the approach followed by Frank to the Markov model in order to test for population heterogeneity effects.

Howard (1963), postulated a Markov model where transition probabilities are related to the time the last purchased occurred. Telster (1963) developed a Markov model in which the parameters are functions of marketing variables.
Lipstein (1965) developed Markov model in which the matrices are estimated from data covering two different time periods.

Duhamel (1966) estimate the taking Telsert’s variable Markov model using individual household data. Kuehn and Rohloff (1967) developed a learning model considering the learning operators are functions of the time since the last purchase. Jones (1969) extended Montgomery’s probability diffusion model, so as to include the learning characteristics.

Jones (1969) took the major step forward by allowing individuals to differ in the order of the stochastic process using the process parameters. The model individuals are allocated to Bernoulli, Markov and linear segments.

Grover and Dillon (1985) developed a probabilistic model which can be used to test alternate market structures. Grover and Srinivasan (1987) presented a new approach to market segmentation. They developed a latent class based approach to analyze market structure by using brand switching data. Colombo and Morrison (1989) proposed a two class Hard Core Loyal and Potential Switcher Latent model for the analysis of brand switching data. They showed how this simple model can be easily estimated using a standard log linear approach. Zahorik (1994) tried to generalize models based on latent class analysis by accounting for heterogeneity among consumers and by allowing for brand switching across clusters, in order to depict variety seeking. Lattin and McAlister (1985) developed a model of consumer variety seeking behavior. This model incorporates brand switching between complementary products to fulfill consumers’ desires for variety. The model serves as the basis for developing a
technique that allows determination of which products covered by brand switching data may be considered to be substitutable and which should be considered complementary.

Many marketing researchers have proposed stochastic models for analyzing the multiband purchasing behavior of households for frequently purchased products. Kahn et al (1986) formulated a first order Markovian model for consumer purchasing behavior and inter purchase times are independently and identically distributed (i.i.d) exponential random variables. Jain and Niu (1994) considering the model proposed by Kahn et al (1986) that the results holds for any arbitrary interpurchase time distribution that has density over some interval.

Ehrenberg (1965) proposed a Markov brand switching model of first order. Whitaker (1978) developed a technique for extracting a measure of brand loyalty of a product in a competitive market from aggregate data. The approach is to fit a Markov brand switching model to data upon brand shares and a measure of purchasing pressure by the method of least squares. Givon (1984) developed a stochastic model of variety seeking behavior of brand choice. The model yields a measure of variety seeking for each individual consumer. Laughland and Nair (1974) study the dynamic nature of brand switching. They have used Markov chain theory extensively. They developed a stochastic game model for determining the optimal promotional strategies of the companies and the unique minimax value of the game in terms of market share. The structure of the model developed is that of a two person zero-sum, two-state stochastic game. Allenby and Rossi (1991) developed a model which leads asymmetric responses to price
promotions where switching up to high quality brands are more likely than
switching down. Novak and Stangor (1987) provide a general frame work for the
analysis of brand switching data using weighted least squares analysis of
categorical data. Urban, Johnson and Hauser (1984) present a straightforward
technique for analyzing aggregate forced brand switching data base on $Z$-
statistics. Iacobucci et al (1996) developed a model data that represent consumer
brand switching in the French and British automobile marketplaces. They
describe the network methods that include the modeling of multiple networks
simultaneously to study such phenomena as dynamic markets and cross-cultural
competitive market structure.

3.2 Why Switching?

When the customer is dissatisfied with the current brand then he/she
switches the other brand. Kasper (1988) summarized three actions when
customers feel dissatisfied. According to Kasper, customers may complain about
the products or services, or may express a negative attitude to their friends and
family about the brand they are unsatisfied with, or they may even switch to other
brands. In addition, Kasper (1988) argued about the study conducted by
Andreasen (1977), which applied the level of repeat purchase and brand-
switching as the measurements of final satisfaction and dissatisfaction. The later
research on brand-switching and customer satisfaction, such as the research
conducted by Lin, Wang and Hsieh (2003), seems more reasonable and valid, and
different types of brand switching have been considered, including both satisfied
switching and dissatisfied switching.
Lin, Wang and Hsieh (2003) conducted a research on brand-switching behavior across three different customer groups. Customers were classified into “satisfied and dissatisfied switchers, and stayers”, and the differences between these three groups have been analyzed in terms of “customer satisfaction, customer involvement, and customer loyalty”. The result shows that there is a very little difference between advertising responsiveness across three groups of customers.

It is true that dissatisfaction can cause brand-switching, and customers may express their dissatisfaction through switching to other brands. However, dissatisfaction is not the only reason causing brand-switching, even satisfied customers may not stay on the same brand (Kasper, 1988). Customers’ brand choice decision does not seem simple, and other influential factors need to be studied. Kasper (1988), suggested that the influences of “product and store characteristics, marketing mix variables, and antecedents of behavior like involvement, attitudes, and cognitions on brand-switching and loyalty for durables, nondurables, and services” all need to be examined at the same time.

### 3.3 Conceptual Framework

The main attempt of this chapter is to compare the brand switching behavior of rural and urban consumer considering the staple goods. In case of staple goods the brand switching behavior is one of the important aspects of study. Staple goods are those goods which are frequently purchased by the consumer. So, there is a more chance to competition among the brands than the
brands of other goods. Accordingly, there is more chance that a consumer switches from one brand to another brand.

Again it is seen that rural and urban consumers are heterogeneous in nature. The buying behavior of rural consumer are different than the urban consumer because it is observed from the Chapter 2, that the inclusion of a brand in rural consumer consideration set is different from the urban consumer for the staple goods rice, salt and edible oil. However, in case of tea there is one brand (Tata) which is just opposite. Another reason for studying the brand switching behavior of rural and urban consumers is to understand how their standards of living, taste, availability of the store, awareness of brand differ. So, it is necessary to evaluate, whether the brand switching behavior of rural and urban consumers differs or not.

This brand switching behavior is studied using Markov model. The basic concept of Markov model is illustrate below

3.3.1 Basic definitions and Mathematical properties of first order Markov Chain

A process is called first order Markov when it has a finite number of states and every individual state depends only on its previous states. Markov chains are characterized by many properties but in the case of buying behavior the basic concepts are

(i) The states of Markov Chain,
(ii) The transition matrix,

(iii) The steady state probabilities and

(iv) Stationarity

(i) The State of Markov Chain, X(t)

The state of a stochastic process at time \( t \) is the value of the process at time \( t \). Hence, if we have a sequence of purchases in time \( t \), the state of an individual at time \( t \) is the brand that he/she bought at time \( t \).

(ii) The Markov Transition Matrix

The transition matrix of a Markov Chain with \( n \) states has the following form:

\[
\begin{bmatrix}
1 & \cdots & j & \cdots & n \\
1 & \vdots & \vdots & \ddots & \vdots \\
1 & \vdots & P_{i1} & \cdots & P_{in} \\
1 & \vdots & \vdots & \ddots & \vdots \\
1 & \vdots & \vdots & \vdots & P_{n1} \\
1 & \vdots & \vdots & \vdots & P_{nj} \\
1 & \vdots & \vdots & \vdots & P_{nm}
\end{bmatrix}
\]

where the transition probability matrix \( p_{ij} \) is the conditional probability that the consumer will be in state \( j \) at time \( t+1 \), given that he/she was in state \( i \) at time \( t \).
(iii) Steady State probabilities

Let \( \pi = (\pi_1, \pi_2, \ldots, \pi_n) \) be the n component row vector that is found by solving the system equations

\[
\pi = \pi P
\]  

\( \ldots \) (3.1)

These \( \pi_i \) are called Steady-state probabilities, and can be interpreted as the proportion of time that the Markov chain is in state \( i \) when the chain is observed over a long period of time.

(iv) Stationary

Additionally, it is assume that the Markov chain is stationary. This means that the transition matrix \( P(t) \) is independent of \( t \) i.e. the value of \( p_{ij} \)'s do not change with time (probabilities do not change).

3.3.2 Zero Order Models

Zero-order models assume that a consumer, regardless of what he/she is exposed to, has a constant purchase probability of buying a brand. In other words, in zero-order models the purchase probability of the brand on the \( (n+k)^{th} \) occasion, \( p_{n+k} \), is equal to the purchase probability of the brand on the \( n^{th} \) occasion \( p_n \). The zero order models that are presented in this chapter, differ in the assumptions made about consumer preferences and choice and in the number of brands they consider. The most important models used in order to describe consumer behavior are presented in the following.
3.3.3 Bernoulli Model

The simplest stochastic model for describing consumer behavior is the Bernoulli Process.

The stochastic process \( \{X_t, t \in T\}, X_t \in \mathbb{R} \) where \( \mathbb{R} = (0, 1) \) and \( T = 0, 1, 2, \ldots \) is a Bernoulli Process if and only if

\[
P \left( X_t = 1 \mid X_{t-1}, X_{t-2}, \ldots, X_{t-n} \right) = p
\]

for all \( (X_{t-1}, X_{t-2}, \ldots, X_{t-n}) \in \mathbb{R}^n, n=1,2,3,\ldots \).

In the case of buying behavior, the above implies that the probability \( p \) is constant over time and independent of the consumer's actual purchase decisions in the past. Thus, at any purchase decision (in a particular product category) the consumer has the same probability \( p \) of purchasing brand \( i \).

It is important to remember that households usually differ in many ways, and some of these may affect use opportunities or brand preferences for particular products. Similar to other models, the Bernoulli model of buying behavior attempts to identify, explain or take account of population heterogeneity.

The heterogeneous Bernoulli model assumes that in a population of customers, each one has a constant probability \( p \) of buying one of the two brands in the market. Additionally, we don’t assume that each consumer has the same \( p \). In the case that we have a heterogeneous population, we assume that \( p \) follows a Beta distribution over the individual in the population. So, we have that
It is obvious that the Beta distribution is an objective measure of heterogeneity in the consumer population. The variance of the beta distribution will give us a quantification of the heterogeneity in the population.

### 3.3.4 Beta Distribution

The beta distribution is a family of continuous probability distribution defined on the interval (0,1) with two positive shape parameters $\alpha$, $\beta$. The probability density function of Beta distribution is given below

$$f(p) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} p^{\alpha-1} (1 - p)^{\beta - 1}, \text{ for } \alpha > 0, \beta > 0 \text{ and } 0 < p < 1$$

$$= 0 \text{, Otherwise}$$

The Beta distribution is a flexible distribution as different values of the parameters $\alpha$ and $\beta$ the density function can produce almost all different types of curve like U shaped, Bell-shaped, J shaped, L shaped, even a spike at any point and several other shapes. Some forms of the density function for different values of the parameters $\alpha$ and $\beta$ are shown in the following figure 3.1.
Figure 3.1 Beta Density Curves for Different Combination of the Values of the Parameters

3.3.5 Bootstrap

Bootstrap method is an emerging powerful tool for constructing inferential procedures in modern statistical data analysis. It is an alternative to the traditional statistical technique of assuming a particular probability distribution.
The usual assumption to make about data that are being bootstrapped is that the observations are independent and identically distributed. It is a method for estimating the distribution of an estimator or test statistics by resampling the data. The data are generated by sampling the estimation data randomly with replacement. For example from a sample, suppose we have got one statistic (assume mean) but we do not know the confidence interval of the mean or distribution of the mean. In such cases, bootstrap technique gives more detail on the distribution or confidence interval of this mean. However, if the data are not the population, the bootstrap provides only an approximation to the coverage probability of a confidence interval (Horowitz, 1998). But if the data are the population, the coverage probability of a confidence interval could be computed with arbitrary accuracy by Monte Carlo simulation (Horowitz, 1998). As a result, the bootstrap approximation is often more accurate than the approximation obtained from asymptotic distribution theory.

3.4 Objective of this Chapter

The main objective of this chapter is to explore the brand switching behavior of rural and urban consumers. Since rural and urban consumers differ in their purchasing capacity, culture and the markets differ in the availability of products. So, their brand switching behavior is supposed to differ due to the dynamic change of market place. To understand the brand switching behavior of rural and urban consumers, some convenience goods with special reference to the staple goods viz. rice, salt, edible oil and tea is considered for the study. The
objective of this paper is to compare the brand switching behavior of rural and urban consumers using Markov model.

### 3.5 Hypotheses of this Chapter

In the study, we are comparing the customer of rural and urban area of south Assam. To attain the objectives the major hypotheses are as follows:

\( H_0: \) There is no significant difference between the ‘Brand Switching behavior’ of the rural and urban consumers.

Markov Model is used to compare the brand switching behavior of rural and urban consumer.

### 3.6 Methodology

The methodology which is adopted for the study is as follows:

Suppose there are \( n \) brand of a product in market which is reduced to a two brand market. Considering “Brand 1” and “Brand 0” where “Brand 1” represents a particular brand of that product category that particular family’s favorite brand while “Brand 0” indicates all other brands in that category. So, a family’s purchase history can be described by a sequence of 0’s and 1’s. It is clearer if a 1 is used to indicate the purchase of a family’s favorite brand 0 is used for other brand for a product category.

Let \( \{ X_t, t \in T \} \) be a random process which determines if a given customer purchases a brand of a product category at time \( t \). Thus, for a consumer, \( X_t = 1 \), if
the consumer purchases his/her favorite brand at time \( t \). For \( X_t = 0 \), otherwise. Thus, state space of the stochastic process is binary i.e. \{0, 1\}. The transition probability matrix is given below

\[
\begin{bmatrix}
1 & 0 \\
0 & P_{10} & P_{12}
\end{bmatrix}
\]

where,

\( p_{ij} \) = the conditional probability of purchasing Brand \( j \) at time \( t \), given that Brand \( i \) was purchased at time \( t-1 \).

Considering this, Morrison (1966) developed two models viz. brand-loyal and last purchase loyal models. The discussion of these models is given below:

### 3.6.1 Brand Loyal Model

The Brand loyal population of consumers is defined as follows:

Each individual family follows a first order 0-1 process with transition probability matrix,
Where, \( p \) be the conditional probability that a customer is prime at time \( t+1 \), given that he was a prime customer at time \( t \), i.e.

\[
p = P[X_{t+1} = 1 \mid X_t = 1]
\]

Some ‘recency’ effect to be required. That is, a given customer may be more likely to be choose brand “1” in time \( t + 1 \) if he/she were a choose brand “1” in time \( t \) (Morrison et al, 1982). Thus,

\[
P[X_{t+1} = 1 \mid X_t = 0] = kp
\]

Recency effect means consumer who have recently bought a brand of a product which are more likely to buy again the same brand of that product. The ‘recency’ effect is captured by the parameter \( k, 0 < k < 1 \). The smaller the value of \( k \) the more influence the current state has on the future state of the customer (Morrison et al, 1982). A direct measure of ‘recency’ is given by

\[
R = 1 - k.
\]

More the value of \( R \), more is the influence that the current state has on the future state of the customer.
Since $p$ is distributed according to a probability density among individuals in the population, some individuals will have high values of $p$ and other individuals will have low values. The brand loyal model states that an individual with a high probability of remaining with Brand 1 (a high $p_{11} = p$) will also have a higher probability of leaving brand 0 to buy brand 1 (higher $p_{01} = kp$) than an consumer with low probability of remaining with brand 1 (a person with a low value of $p$). Consumer with high values of $p$’s are more suitable to stick with brand 1 and are also more suitable to switch to brand 1 than people with lower $p$’s. High loyalty of consumers is directly toward a particular brand of a product category. Therefore, this model is classified as the brand-loyal model.

### 3.6.2 Last Purchase Loyal Model

The last purchase loyal population of consumers is defined as follows:

Each individual family follows a first order 0-1 process with transition probability matrix,

$$
\begin{pmatrix}
    p & 1 - p \\
    1 - kp & kp
\end{pmatrix}
\quad \ldots \quad (3.3)
$$

Where, $p$ and $k$ is same defined in the section Brand Loyal model.
The last purchase loyal population proceeds in a way of opposite from the brand loyal population of consumers. In the transition probability matrix it is seen that \( P_{00} \) is not \( 1 - kp \) but \( kp \). In that case, a consumer with high values of \( p \) is more loyal to the brand he/she last purchased than a consumer with lower \( p \). Here, if high loyalty exists, then a consumer demonstrates loyalty towards the brand of product class that a consumer happened to have last purchased. This model is called the last purchase loyal model.

Medhi (1994) has shown that in case of a two state Markov chain with the following one step transition probability matrix,

\[
P = \begin{pmatrix} 1 - a & a \\ b & 1 - b \end{pmatrix}, \quad 0 < a, b < 1 \quad \ldots (3.4)
\]

The corresponding transition probability matrix at the \( n^{th} \) step where \( n \to \infty \) is given by,

\[
\lim_{n \to \infty} P^n = \begin{pmatrix} b/(a + b) & a/(a + b) \\ b/(a + b) & a/(a + b) \end{pmatrix} \quad \ldots (3.5)
\]

Under certain assumption related to the Eigen values of the matrix \( P \).

Comparing (3.3) and (3.4) we have, \( a = 1 - p \) and \( b = kp \). Replacing these in (3.5) we have,
Thus, in the long run a customer will be in State 1 (Choosing the Brand 1) and State 0 (Choosing the Brand 0) the following proportions of time:

\[
\pi_1 = \frac{kp}{1 - p + kp} \quad \text{... (3.6)}
\]

\[
\pi_0 = \frac{1 - p}{1 - p + kp} \quad \text{... (3.7)}
\]

The customers may be heterogeneous and their behaviors would not remain the same. Thus, the value of \( p, \) vary from consumer to consumer. So, \( p \) should not be considered as a constant but as a random variable and can be explained by the probability density function, \( f(p). \) As, \( 0 \leq p \leq 1, \) and is continuous in nature, so one probable distribution is the Beta Type-I. The distribution is given by the density function,

\[
f(p) = \frac{1}{\beta(\alpha, \beta)} p^{\alpha-1} (1 - p)^{\beta-1}, \quad 0 < p < 1 \text{ and } \alpha, \beta > 0
\]

\[
= 0, \quad \text{otherwise}
\]

Here,

\[
\beta(\alpha, \beta) = \int_0^1 p^{\alpha-1} (1 - p)^{\beta-1} dp
\]
The mean of the distribution is given by,

\[ E(p) = \frac{\alpha}{\alpha + \beta} \]

On obtaining several estimates of \( p \) from the bootstrap samples the distributional pattern of \( p \) is tested using the Kolomogorov-Smirnov (K-S) statistic. For performing the K-S statistic the theoretical distribution needs to be completely specified i.e. the values of the parameters need to be known.

The heterogeneity amongst the customers can be measured by the heterogeneity index the details of which can be found in Sabavala and Morrison (1977). The index is given by,

\[ H = \frac{1}{\alpha + \beta + 1} \]

… (3.8)

The index \( H \) lies between 0 and 1. \( H = 1 \) implies maximum heterogeneity amongst the customers while \( H = 0 \) implies the customers are most homogeneous.

Thus, the model is dependent on three parameters viz. \( \alpha, \beta \) and \( k \).

Based on the values of \( \hat{p} \) obtained from the different bootstrap samples, the estimated values of \( \alpha \) and \( \beta \) are obtained using the method of maximum likelihood (Johnson and Kotz, 1970). The estimated values are given by,

\[ \hat{\alpha} = m_1 \left[ \frac{m_1(1-m_1)}{m_2} - 1 \right] \]

… (3.9)
and \[ \phi = (1 - m_1) \left( \frac{m_1 (1 - m_1)}{m_2} - 1 \right) \] ...(3.10)

Here,

\( m_1 = \text{mean of the values of } \hat{p} \)

\( m_2 = \text{variance of the } \hat{p} \text{ values} \)

The value of \( k \) can be estimated as a ratio of two conditional probabilities, \( i.e. \)

\[ \hat{k} = \frac{P(X_{t+1} = 1 | X_t = 0 \cap X_{t-1} = 1)}{P(X_{t+1} = 1 | X_t = 1 \cap X_{t-1} = 0)} \]

### 3.7 Findings and Analysis

Based on the methodology the computation is done. On obtaining several estimates of \( p \) from the bootstrap samples the distributional pattern of \( p \) for different product under study is tested using the Kolomogorov-Smirnov (K-S) statistic. For performing the K-S statistic the theoretical distribution needs to be completely specified \( i.e. \) the values of the parameters need to be known. In this chapter the parameters are estimated form data. The following table gives the parameter of the distribution of \( p \) for the product rice, salt, edible oil and tea.
Table 3.1 Parameter Estimation Table

<table>
<thead>
<tr>
<th>Products</th>
<th>Rural Parameters</th>
<th>Urban Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \alpha )</td>
<td>( \beta )</td>
</tr>
<tr>
<td>Rice</td>
<td>12.55192</td>
<td>20.07637</td>
</tr>
<tr>
<td>Salt</td>
<td>3.4698</td>
<td>9.643303</td>
</tr>
<tr>
<td>Edible Oil</td>
<td>4.04967</td>
<td>27.25602</td>
</tr>
<tr>
<td>Tea</td>
<td>8.729001</td>
<td>25.26396</td>
</tr>
</tbody>
</table>

Table 3.1 highlighted the parameters estimated using equation (3.9) and (3.10) for rural and urban consumer for the product rice, salt, edible oil and tea.

Table 3.2 Kolmogorov Smirnov One Sample Test

<table>
<thead>
<tr>
<th>Products</th>
<th>Value of the Kolmogorov-Smirnov One Sample Test</th>
<th>Comment on the hypothesis that “p” follows Beta Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rural</td>
<td>Urban</td>
</tr>
<tr>
<td>Rice</td>
<td>0.03845</td>
<td>0.03593</td>
</tr>
<tr>
<td>Salt</td>
<td>0.03751</td>
<td>0.03373</td>
</tr>
<tr>
<td>Edible Oil</td>
<td>0.04200</td>
<td>0.04021</td>
</tr>
<tr>
<td>Tea</td>
<td>0.03638</td>
<td>0.04289</td>
</tr>
</tbody>
</table>
The critical value of the Kolmogorov-Smirnov One Sample test at 5% level of significance is 0.043.

From the table 3.2 it is observed that the calculated value of the Kolmogorov-Smirnov one sample test for all the products are less than the tabulated value at 5% level of significance. So, the null hypothesis is accepted as evident from the $p$ values for different products under study follow the Beta distribution of first kind.

The transition probability matrix of Brand Loyal model for the products rice, salt, edible oil and tea of rural and urban consumer is given in table 3.3, table 3.4, table 3.5 and table 3.6 as follows
### Table 3.3 Transition Probability Matrix of Brand Loyal Model for Product Rice

<table>
<thead>
<tr>
<th>Purchase Occasion 1 and Purchase Occasion 2</th>
<th>Purchase Occasion 2 and Purchase Occasion 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Rural</strong></td>
<td></td>
</tr>
<tr>
<td>0.739575 0.260425</td>
<td>0.434922 0.565078</td>
</tr>
<tr>
<td>O.86832 0.13168</td>
<td>O.320598 0.679402</td>
</tr>
<tr>
<td>0 1</td>
<td>0 1</td>
</tr>
<tr>
<td><strong>Urban</strong></td>
<td></td>
</tr>
<tr>
<td>0.783871 0.216129</td>
<td>0.342222 0.657778</td>
</tr>
<tr>
<td>0.8996 0.104</td>
<td>0.474242 0.525758</td>
</tr>
<tr>
<td>0 1</td>
<td>0 1</td>
</tr>
</tbody>
</table>

**Product: Rice**

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### Table 3.4 Transition Probability Matrix of Brand Loyal Model for Product Salt

<table>
<thead>
<tr>
<th>Purchase Occasion 1 and Purchase Occasion 2</th>
<th>Purchase Occasion 2 and Purchase Occasion 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>Rural</td>
</tr>
<tr>
<td>( \begin{pmatrix} 0.8718 &amp; 0.1282 \ 0.2637 &amp; 0.7363 \end{pmatrix} )</td>
<td>( \begin{pmatrix} 0.9073 &amp; 0.0927 \ 0.1594 &amp; 0.8406 \end{pmatrix} )</td>
</tr>
<tr>
<td>Purchase Occasion 1 and Purchase Occasion 2</td>
<td>Purchase Occasion 2 and Purchase Occasion 3</td>
</tr>
<tr>
<td>-------------------------------------------</td>
<td>-------------------------------------------</td>
</tr>
<tr>
<td>Rural</td>
<td>Rural</td>
</tr>
<tr>
<td><strong>Product: Edible Oil</strong></td>
<td><strong>Product: Edible Oil</strong></td>
</tr>
</tbody>
</table>

Table 3.5 Transition Probability Matrix of Brand Loyal Model for Product Edible Oil

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Table 3.6 Transition Probability Matrix of Brand Loyal Model for Product Tea

<table>
<thead>
<tr>
<th>Purchase Occasion 1 and Purchase Occasion 2</th>
<th>Purchase Occasion 2 and Purchase Occasion 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Rural</strong></td>
<td><strong>Urban</strong></td>
</tr>
</tbody>
</table>
| \[
\begin{pmatrix}
0.83872 & 0.23297 \\
0.16128 & 0.76703
\end{pmatrix}
\] | \[
\begin{pmatrix}
0.83956 & 0.23297 \\
0.16144 & 0.76703
\end{pmatrix}
\] |

Chapter 3 Brand Switching of Rural and Urban Consumers using Markov Models

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From the table 3.3, it is observed that for the product rice corresponding value of $p (=p_{11})$ for the purchase occasion 1 and purchase occasion 2 of rural consumer have a low probability with his favorite brand and also have low probability of leaving brand 0 to buy brand 1 i.e. the most popular brand while in case of urban consumer has high probability of remaining with the favorite brand and also have a higher probability of leaving brand 0 to buy brand 1. But in case of the purchase occasion 2 and purchase occasion 3, rural consumer has low probability with his favorite brand than urban consumer since corresponding value $p$ of the rural consumer is less than the urban consumer. In both the occasion it is observed that urban consumer have high probability to stick with the favorite brand and also high probability to switch to the most popular brand than the rural consumer.

From the table 3.4, for the product salt it is observed that the corresponding value of $p (=p_{11})$ of urban consumer is greater than the rural consumer for the purchase occasion 1 and purchase occasion 2. This means that urban consumer have high probability to remain with his favorite brand and also have high probability of leaving brand 0 to buy brand 1 than the rural consumer. Again for the purchase occasion 2 and purchase occasion 3, it observed that rural consumer have the high probability to stay with his favorite brand than the urban consumer. Since corresponding $p$ value of the rural consumer is greater than the urban consumer.

It is observed from the table 3.5, that for the product edible oil, urban consumers have higher $p$ than the rural consumers for the purchase occasion 1 and purchase occasion 2. It indicates that urban consumer has higher probability to remaining with his favorite brand than the rural consumer. It also highlighted that urban consumer has high probability of leaving brand 0 to buy brand 1. Again for the purchase occasion 2 and purchase occasion 3, it is observed that urban consumer has the high $p$ than the rural consumer. It follows that urban
consumers have higher probability to stay with the favorite brand than the rural consumers and have more chance of leaving the brand 0 to buy brand 1.

For the product tea, from the table 3.6, it is highlighted that the corresponding $p$ value of the urban consumer is more than the rural consumer. This indicates that urban consumer has more chance to stay with the favorite brand and high probability of leaving the brand 0 to buy the brand 1 while rural consumer has less chance to stay with the favorite brand and less chance to leave the brand 0 for the purchase occasion 1 and purchase occasion 2. It is also observed that for the purchase occasion 2 and purchase occasion 3, urban consumers have the more chance to remaining with his favorite brand than the rural consumer. This indicates that the urban consumer has the more chance to leave the brand 0 to buy the brand 1. It is more depicted from the following table.
Table 3.7 Rural and Urban Consumers Comparison for the Brand Loyal Model

<table>
<thead>
<tr>
<th>Products</th>
<th>Purchase Occasion I and II</th>
<th>Purchase Occasion II and III</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rice</td>
<td>Rural customers have the low probability to stay with his/her favorable brand while urban consumer have the high probability to stay with his favorable brand.</td>
<td>Similar comment as the purchase occasion I and purchase occasion II</td>
</tr>
<tr>
<td>Salt</td>
<td>Urban consumers have the high probability to stay with his favorite brand than the rural consumer.</td>
<td>Rural consumers have the high probability to stay with his favorite brand then the urban consumer.</td>
</tr>
<tr>
<td>Edible Oil</td>
<td>Urban consumers have the high probability to stay with his/her favorite brand then the rural consumer.</td>
<td>Similar comment as the purchase occasion I and purchase occasion II</td>
</tr>
<tr>
<td>Tea</td>
<td>Rural consumers have less chance to stay with his/her favorite brand while urban consumer is just opposite.</td>
<td>Similar comment as the purchase occasion I and purchase occasion II</td>
</tr>
</tbody>
</table>

Again, the transition probability matrix of Last purchase loyal model for the products rice, salt, edible oil and tea of rural and urban consumer is given in table 3.8, table 3.9, table 3.10 and table 3.11 as follows:
Table 3.8 Transition Probability Matrix of Last Purchase Loyalty Model for Product Rice

<table>
<thead>
<tr>
<th>Purchase Occasion 1 and Purchase Occasion 2</th>
<th>Purchase Occasion 2 and Purchase Occasion 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Purchase Occasion 2</td>
<td>Purchase Occasion 3</td>
</tr>
<tr>
<td>Rural</td>
<td>Rural</td>
</tr>
<tr>
<td>0.68571 0.31429</td>
<td>0.8571 0.1428</td>
</tr>
<tr>
<td>0.2907 0.7093</td>
<td>0.0250 0.9750</td>
</tr>
<tr>
<td>0.0250 0.9750</td>
<td>0.0075 0.9925</td>
</tr>
</tbody>
</table>

Urban

Table 3.8: Transition Probability Matrix of Last Purchase Loyalty Model for Product Rice

Consumers using Markov models

Chapter 3: Brand Switching of Rural and Urban
<table>
<thead>
<tr>
<th>Purchase Occasion 1 and</th>
<th>Purchase Occasion 2 and</th>
<th>Purchase Occasion 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Purchase Occasion 1</td>
<td>Purchase Occasion 2</td>
<td>Purchase Occasion 3</td>
</tr>
<tr>
<td>Product: Salt</td>
<td>Product: Salt</td>
<td></td>
</tr>
<tr>
<td>0.989352 0.009112</td>
<td>0.989352 0.009112</td>
<td></td>
</tr>
<tr>
<td>0.010648 0.990888</td>
<td>0.010648 0.990888</td>
<td></td>
</tr>
<tr>
<td>0.000000 0.000000</td>
<td>0.000000 0.000000</td>
<td></td>
</tr>
<tr>
<td>Rural</td>
<td>Rural</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.9 Transition Probability Matrix of Last Purchase Loyal Model for Product Salt

Chapter 3: Brand Switching of Rural and Urban Consumers using Markov Models
<table>
<thead>
<tr>
<th>Purchase Occasion 1 and Purchase Occasion 2</th>
<th>Purchase Occasion 2 and Purchase Occasion 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Rural</strong></td>
<td><strong>Rural</strong></td>
</tr>
<tr>
<td>0.077816 0.022184 0</td>
<td>0.047732 0.022184 0</td>
</tr>
<tr>
<td>0.271839 0.128161 0</td>
<td>0.247732 0.128161 0</td>
</tr>
<tr>
<td>0.022184 0.077816 0</td>
<td>0.022184 0.077816 0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Urban</strong></th>
<th><strong>Urban</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>0.084387 0.015613 0</td>
<td>0.052174 0.015613 0</td>
</tr>
<tr>
<td>0.104833 0.095167 0</td>
<td>0.104833 0.095167 0</td>
</tr>
<tr>
<td>0.015613 0.084387 0</td>
<td>0.015613 0.084387 0</td>
</tr>
</tbody>
</table>

Table 3.10: Transition Probability Matrix of Last Purchase Loyal Model for Product Edible Oil

Consumers using Markov Models

Chapter 3 Brand Switching of Rural and Urban
### Table 3.11: Transition Probability Matrix of Last Purchase Loyal Model for Product Tea

<table>
<thead>
<tr>
<th>Purchase Occasion 1 and Purchase Occasion 2</th>
<th>Purchase Occasion 2 and Purchase Occasion 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Rural</strong></td>
<td></td>
</tr>
<tr>
<td>Purchase Occasion 1</td>
<td>Purchase Occasion 2</td>
</tr>
<tr>
<td><img src="matrix_rural" alt="Transition Matrix" /></td>
<td><img src="matrix_rural" alt="Transition Matrix" /></td>
</tr>
<tr>
<td><strong>Urban</strong></td>
<td></td>
</tr>
<tr>
<td>Purchase Occasion 1</td>
<td>Purchase Occasion 2</td>
</tr>
<tr>
<td><img src="matrix_urban" alt="Transition Matrix" /></td>
<td><img src="matrix_urban" alt="Transition Matrix" /></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Product:</strong> Tea</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Table 3.11:</strong> Transition Probability Matrix of Last Purchase Loyal Model for Product Tea</td>
</tr>
</tbody>
</table>

Consumers using Markov Models

Chapter 3: Brand Switching of Rural and Urban
From the table 3.8, it is observed that for the product rice the corresponding $p$ value of the rural consumer is less than the urban consumer for the purchase occasion 1 and purchase occasion 2. This indicates that urban consumer is more loyal to the brand he/she last purchased (be it Brand 0 or Brand 1) than the rural consumer. However, it is also observed that for the purchase occasion 2 and purchase occasion 3 the corresponding $p$ value of rural consumer is greater than the urban consumer. This gives that rural consumer is more loyal to the brand he/she purchased last than the urban consumer.

For the product salt, it is observed from the table 3.9, that corresponding $p$ value of rural consumer is greater than the urban consumer. This signifies that rural consumer is more loyal to the brand he/she purchased last while the urban consumer is less loyal to the brand he/she purchased last for the purchased occasion 1 and purchased occasion 2. For the purchase occasion 2 and purchase occasion 3 it observes that the rural consumer is more loyal to the brand he/she purchased last than urban consumer. Since, corresponding $p$ value of rural consumer is greater than the urban consumer.

Table 3.10, highlighted that for the product edible oil, the corresponding value of $p$ of rural consumer is less than the urban consumer. This signifies that the urban consumer is more loyal to the brand he/she purchased last than the consumer of rural for the purchase occasion 1 and purchase occasion 2. For the purchase occasion 2 and purchase occasion 3, it is observed that urban consumer is more loyal to the brand he/she purchased last than the rural consumer.
For the product tea, it is observed from the table 3.11, that the corresponding $p$ value of urban consumer is greater than the rural consumer. This means that urban consumer is more loyal to the brand he/she purchased last than the rural consumer for the purchase occasion 1 and purchase occasion 2. However, for the purchase occasion 2 and purchase occasion 3, it is observed that the corresponding $p$ value of rural consumer is greater than the urban consumer. This indicates that rural consumer is more loyal to the brand he/she purchased last than the urban consumer either for the brand 1 or brand 0. The above discussion is more depicted from the following table:
### Table 3.12 Rural and Urban Consumers Comparison for the Last Purchase Loyal Model

<table>
<thead>
<tr>
<th>Products</th>
<th>Purchase Occasion I and II</th>
<th>Purchase Occasion II and III</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rice</td>
<td>Urban customers have the high probability to stay with his/her brand which they purchased last than the rural consumer.</td>
<td>Rural consumer has the high probability to stay with the brand he/she purchased last while urban consumer is just vice versa.</td>
</tr>
<tr>
<td>Salt</td>
<td>Rural consumers have the high probability to stay with the brand he/she purchased last than the urban consumer.</td>
<td>Similar comment as the purchase occasion I and purchase occasion II.</td>
</tr>
<tr>
<td>Edible Oil</td>
<td>Urban consumers have the high probability to stay with the brand he/she purchased last then the rural consumer.</td>
<td>Similar comment as the purchase occasion I and purchase occasion II.</td>
</tr>
<tr>
<td>Tea</td>
<td>Rural consumers have less chance to stay with the brand which he/she purchased last while urban consumer is just opposite.</td>
<td>Rural consumer is more loyal to the brand he/she purchased last than the urban consumer.</td>
</tr>
</tbody>
</table>
Heterogeneity index gives the heterogeneity among the customer. So, it is necessary to study the heterogeneity of consumer of rural and urban. Heterogeneity index is given in the table 3.13 as follows:

**Table 3.13 Product wise Heterogeneity Index**

<table>
<thead>
<tr>
<th>Product</th>
<th>Rural</th>
<th>Urban</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rice</td>
<td>0.2974</td>
<td>0.043140</td>
</tr>
<tr>
<td>Salt</td>
<td>0.070856</td>
<td>0.078389</td>
</tr>
<tr>
<td>Edible Oil</td>
<td>0.030954</td>
<td>0.029952</td>
</tr>
<tr>
<td>Tea</td>
<td>0.028577</td>
<td>0.031499</td>
</tr>
</tbody>
</table>

Table 3.13 highlighted that heterogeneity of consumer of rural and urban in buying the brand of a product category. In case of rice, the urban customers are more homogeneous to buying a brand/variety than the rural consumer. Since corresponding value of heterogeneity index of rural consumer is greater than the urban consumer. But in case of salt the rural consumer and urban consumer are homogeneous in nature since the heterogeneity index of rural consumer and consumer are approximately same and very close to zero. In case of edible oil and tea, the heterogeneity index values are approximately same and very close to
zero. This indicates those both rural and urban consumers are homogeneous in nature to buying a brand.

Table 3.14 Product Wise Recency Effect

<table>
<thead>
<tr>
<th>Product</th>
<th>Rural</th>
<th>Urban</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rice</td>
<td>0.193333</td>
<td>0.178571</td>
</tr>
<tr>
<td>Salt</td>
<td>0.1</td>
<td>0.152941</td>
</tr>
<tr>
<td>Edible Oil</td>
<td>0.428571</td>
<td>0.046667</td>
</tr>
<tr>
<td>Tea</td>
<td>0.342308</td>
<td>0.162222</td>
</tr>
</tbody>
</table>

From the table 3.14, it observed that for the product rice and salt the recency effect of rural and urban consumer are approximately same and close to zero. This indicates that the current state of both rural and urban consumer cannot influence the future state much. However, for the edible oil, the recency effect on rural consumer is greater than the urban consumer. This indicates that the influence of the current state on the future state of rural consumer is much than the urban consumer. In case of the product tea, the recency effect of rural consumer is greater than the urban consumer. It means that the influence of current state on future state of rural consumer is greater than the urban consumer.
3.8 Conclusion

This study enable us to understand the brand switching behavior of rural and urban consumer considering the staple goods viz. rice, salt, edible oil and tea. For the product Rice it has been seen that in case of the urban population there is a tendency for purchasers to opt for the most popular brand. The consumers of the most popular brand generally sticks to it and the consumers of other brands generally switches over to the most popular brand. But in the rural population no such prediction can be made as there is a high chance of switching from the most popular brand to the other brands of rice as observed in the different purchase occasions.

Amongst the different products considered brand switching for salt seems to be the lowest. This is true for both rural and urban customers.

For edible oil there is a huge tendency of brand switching in the consecutive purchase occasions. Brand switching is more in case of rural area compared to urban area.

Understanding the brand switching in case of tea is confusing as at different purchase occasions different scenario is available. In case of first two consecutive purchase occasions there is a tendency is both rural and urban customers to move towards the most popular brand. But in the next two consecutive purchase occasions no such tendency is noticed for both the rural and urban customers. Basically there are several brands of tea competing that are
having high probability of being preferred by the customers resulting to such a confused state related to brand switching.

Two more things are executed from the study are the heterogeneity index and the recency effect. The heterogeneity index executed the heterogeneity among the consumer of rural and urban consumer to buying a brand from a product category under study. For product the rice, urban consumers are more homogeneous in buying same brand than the rural consumers. However, for the product salt, edible oil and tea, both the rural and urban consumers are homogeneous in their nature of brand switching.

Also from the recency index gives, for the product rice and salt, the recent status of both the rural and urban consumer cannot influence the future state much. This means improve of recent marketing strategy of the brand whose customers are stolen by another brand shall definitely help to get back the customers in future. In case of edible oil and tea, the marketing strategy and policy of the brand at the recent state will not depend on future state i.e. the brand whose customer is stolen by the other brand need to improve the marketing strategy in rural area. The availability of data at three discrete time points only, guided the researcher to use the bootstrapping technique for understanding the distributional pattern of $p$. Other efficient techniques of data analysis could have been used in case of availability of data for several other time points.