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Analysis of Application of Markov Chain in Consumer Behavior Prediction

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Abstract:

The present paper focuses on the application of Markov Chain, a memoryless stochastic model, in predicting consumer behavior and thus optimizing marketing strategies for firms. The ability to model transitions between states based on conditional probabilities makes the Markov Chain a useful tool in foresight concerning the actions of consumers regarding purchasing, loyalty, and brand switching. The paper starts with the introduction of Markov Chains as an important means of predicting future states given the present state and presents a simplified consumer behavior model having states for browsing, purchasing, and leaving. The paper analyzes how businesses can use Markov Chains to realize consumer behavior in trends and preferences in the context of market analysis, consumer loyalty, and determination of the best marketing strategies. The paper, within the section on consumer loyalty, explains how Markov Chains can be applied in modeling brand loyalty and predicting the probabilities of switching over to other brands, having been using a case study on sports shoe brands to show the long-term trend in brand loyalty. Then, it goes on with the application of the Markov Decision Process in determining optimal strategies for Customer Lifetime Value maximization, including rewards and a discount factor that will determine the value of some approach. The paper ends by comparing the Markov Chain with other predictive models, such as the Neural Networks, outlining the fact that Markov Chains are simpler and suitable for situations with scarce data availability.

Keywords: Markov Chain; Consumer Behavior; Market Analysis; Consumer Loyalty; Customer Lifetime Value.

1. Introduction

As a certain random process, the Markov Chain is characterized by lacking memory of previous states, indicating that only the present state affects the next orientation [1]. Illustrated through mathematical concepts, Markov Chain denotes the fact that within a discrete-time process $\{X_0, X_1, X_2, X_3, \ldots, X_n\}$, the probability of the process being in a certain state at time n, given all previous states, depends only on the

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state of X_{n-1}. Therefore, it can be expressed as conditional probability: $P(X_n \mid X_0, X_1, X_2 \dots X_{n-1}) = P(X_n \mid X_{n-1})$.

Forecasting the future trajectory of a process serves as a powerful and effective strategy for improvement in the marketing and promotion of services [2]. Markov Chain yields significant insights into prediction and forecasting efforts with various and broad aspects, including but not limited to health conditions, weather forecasts, and consumer behavior.

Prediction with Markov Chain necessitates the possession of the initial state and state transition matrix. Take a simple consumer behavior prediction in a local store as an example. This simplified scenario limits the states to browsing (B), purchasing (P), and leaving (L) with probabilities for transitioning between states as the following Fig. 1. Further transferring the diagram into Table 1, which can therefore be represented as the transition matrix P.

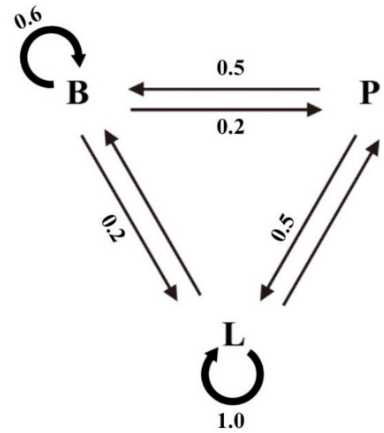

Fig. 1 Transition diagram of browsing, purchasing and leaving (Photo credit: original)

Table. 1 Transition table

	Browsing	Purchasing	Leaving
Browsing	0.6	0.2	0.2
Purchasing	0.5	0	0.5
Leaving	0	0	1

$$P = \begin{bmatrix} 0.6 & 0.2 & 0.2 \\ 0.5 & 0 & 0.5 \\ 0 & 0 & 1 \end{bmatrix} \quad (1)$$

Assuming the consumer starts by browsing, the initial state vector is expressed as $v_0 = [1 \quad 0 \quad 0]$. The prediction of the consumer's distribution of states after one transition is calculated by multiplying the initial state vector and transition matrix:

$$v_1 = v_0 \bullet P = [1 \quad 0 \quad 0] \bullet \begin{bmatrix} 0.6 & 0.2 & 0.2 \\ 0.5 & 0 & 0.5 \\ 0 & 0 & 1 \end{bmatrix} = [0.6 \quad 0.2 \quad 0.2] \quad (2)$$

Similarly,

$$v_2 = v_1 \bullet P = [0.6 \quad 0.2 \quad 0.2] \bullet \begin{bmatrix} 0.6 & 0.2 & 0.2 \\ 0.5 & 0 & 0.5 \\ 0 & 0 & 1 \end{bmatrix} = [0.46 \quad 0.12 \quad 0.42] \quad (3)$$

Continually consumer's behavior can be predicted through the process, formally illustrated as $Prediction = InitialStateVector \times TransitionMatrix$.

As prediction contributes greatly towards producers, helping firms to make choices, decisions and changes, this paper delves into the application of the Markov Chain on consumer behavior prediction and its usage for firms to decide future marketing strategies, raising firms' understanding towards the market and optimizing strategy determination for profit maximization.

2. Application Analysis of Markov Chain

Markov Chain serves as a pivotal tool for businesses to uncover the complicated layers of consumer behavior, revealing trends and preferences of purchasing actions. The adoption of Markov Chain guides companies through the perspectives of consumer consumption habits, pushing them to reach the goal of profit maximization. The application includes but is not limited to predicting consumer preferences, forecasting consumer loyalty, and calculating the value of consumers to promote policies and methods for budget distribution.

2.1 Market Analysis

Market Analysis can reveal consumers' requirements and preferences for products, tracking changes and traits in consumers' habits of purchasing and browsing, providing insights into specific target markets of firms and the consuming behavior of customers. The application of the Markov Chain allows for the prediction of the probability of consumers transitioning between states of preference. Through examining characters of transition probabilities, firms can anticipate shifts in consumer behavior and adjust strategies accordingly. In the study by Yao Tao in 2015, the preferences of car consumers are analyzed through the adoption of the Markov Probability Transition Matrix, used for predicting the trend of preference of consumers toward car products [3]. Yao Tao employed a sample survey to achieve the initial data, applying the irritation method to improve the accuracy of numerical value within the matrix, ultimately solving the consumer preference state transition matrix. The paper draws into conclusion that for the next four years, 2015~2018, the percentage of preference of economic aspects for vehicles will increase, indicating consumers' gradual increasing focus on the economy of cars, which aligns perfectly with the annual trend report of Roland Berger in 2015 that describes the increased percentage on purchasing economical cars, proving the accuracy of Markov Process prediction [4].

Furthermore, in the realm of e-commerce, Markov Chain has been utilized to predict consumer behavior and preference. Berlin and Heidelberg discuss the e-consumer purchasing trend by introducing Markov-based-concept Customer Behavior Model Graphs (CBMG) [5]. CBMG captures users' navigation patterns on websites through a state-transition diagram. State illustrates different webpages or transaction states users might be in, while transitions present the movement between webpages. The transition probability matrix denotes the likelihood of transferring from one state to another. CBMG can derive extensive and key information, such as the user's average session length and throughput, providing businesses with consumer preference analysis, further presenting the broad application of Markov Chain.

2.2 Consumer Loyalty

Increasing numbers of firms have realized the significance of consumer loyalty in selling products, and the rise in consumer loyalty might be featured as one of the most important predictors of companies' profitability [6]. Harary and Lipstein have delved into the Markovian modeling of brand loyalty, predicting the probability of consumers' brand-switching approaches [7]. They split the process into several periods with certain amounts of brands that serve as different states, through analyzing the number of consumers in each brand for different periods, the probability of brand switching can be obtained, which stands for the transition matrix. As same as the traditional approach, through irritated multiplying the initial state and transition matrix, a stabilized probability matrix is formed.

The approach is further visualized and exhibited in the study by Uslu and Cam, where they applied the Markov Chain to brand loyalty in the area of sports shoes [8]. A questionnaire of 531 undergraduate students of Istanbul in Turkey was conducted, ultimately forming a Markov Matrix representing the transitioning nature between 11 leading brand sport shoes. The Chapman-Kolmogorov Equation is further applied to calculate the presence of a balanced and stable vector that reflects long-term brand loyalty. Chapman-Kolmogorov Equation denotes how to calculate multi-step transition probability through one-step transition probability. Express in the formula:

$$P_{ij}^{(m+n)} = \sum_k P_{ik}^{(m)} P_{kj}^{(n)} \tag{4}$$

Where k indicates a possible intermediate state. As the process continues, the Markov Chain tends to reach a stable state, where long-term behavior becomes independent of the initial state.

Uslu and Cam's study reveals that brand-switching behavior is least frequent in consumers of Nike and Adidas, indicating the highest consumer loyalty.

2.3 Determine Optimal Strategy with Markov Decision Process

To maximize profit, Markov's consumer behavior model can be employed in strategy choosing for companies. The policy or strategy π determines which action to choose under each state, further determining the future state and reward. Researchers have classified customers into 4 states based on consumption amount and frequency; through analyzing the past data of consumers, the author estimates probabilities of transitioning between different states and constructs the transition matrix in the Markov Chain, leading to the single stationary distribution, which stands for predicted probabilities of consumer behavior in transitioning between states of consuming [9].

Markov Decision Process, known as MDP, indicates a stochastic sequential decision process, that serves as an extension of the traditional Markov Chain, it takes consideration into rewards and discount factors, enabling it to calculate the value of certain approaches [10]. MDP involves the Bellman equation, the basic state value func-

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tion $V^{\pi}(s)$:

$$V^{\pi}(s) = E_{\pi}[R_s + \gamma V^{\pi}(S_{t+1}) \mid S_t = s] \tag{5}$$

where E_{π} stands for expected value under policy π, R_s As the immediate reward obtained under state s. γ acts as the discount factor, which determines the present value of future rewards, and its value is between 0 and 1. $V^{\pi}(S_{t+1})$ is the expected return when starting from the next state S_{t+1} under policy.

With the holding of the model of consumer behavior prediction, MDP can be adopted to calculate the level of consumer profitability to a firm, which generally can be referred to as Customer Lifetime Value (CLV) [11]. Kotler and Armstrong define a profitable customer as "a person, household, or company whose revenues over time exceeds, by an acceptable amount, the company costs of attracting, selling, and servicing that customer" [12]. The excess is called CLV, it has gained significant success in marketing issues, such as pricing decisions [13].

In Markov Decision Process, Ching and others deal with the distribution of promotion budgets for firms to maximize CLV. Their model is presented as follows [9].

$$v_i(t) = max\left\{c_i^{(k)} - d_k + \gamma \sum_{j=0}^{N-1} p_{ji}^{(k)} v_j(t-1)\right\} \tag{6}$$

Where N indicates the total state number, k stands for the action taking place, d_k represents the resources required to carry out action k, while $c_i^{(k)}$ illustrates the revenue gained from a customer under state i with action k, $p_{ji}^{(k)}$ shows the transitional probability for the customer transferring from state j to i with action k.

CLV under different situations of actions can therefore be calculated through MDP, determining the expectation value obtained from the whole process period of a customer. The approach enables companies to confirm the optimal strategy for marketing, hence helping to increase profit, further illustrating the advantage of process and prediction associated with Markov Chain.

3. Comparison of Markov Chain and Other Approaches

3.1 Neural Networks

Neural Network is categorized as an innovative model inspired by human brain structure, mimicking the way signals are transmitted between brain neurons to solve problems and make decisions. Neural Networks are utilized to predict consumer behavior through the constructions such as deep neural network (DNN) in a study done by Zhang, Wang and Hu [14]. Neural networks consist of multiple layers of neurons, including the input layer, hidden layers, and output layer. The input layer receives raw data, the hidden layers process data and obtain features, and the output layer produces the final results--the prediction. Through the training process of calculation of the difference between predicted data and actual data, errors obtained are sent and the model is adjusted using an algorithm.

The team improves the traditional DNN to the Recurrent Deep Neural Network model, serving as an advancement. The new model introduces a random sampling technique to address the class imbalance prevalence of existing consumer data sets, ensuring the model is not biased towards frequent classes, and improving the accuracy of consumer prediction.

Compared to the Neural Network, the Markov Chain reveals characteristics of simplicity and transparency, providing a clear understanding of probabilities of shifting between states, effectively modeling the future states of consumers without being influenced by multiple external factors. It is specifically beneficial in scenarios of limited data availability, providing useful prediction without the need for tremendous information that the DNN model typically requires, also offering efficiency and fast speed; while Neural Network takes an advantage in predicting non-linear relationships, modifying complex and intricate data sets to reach the results and predictions.

3.2 Decision Trees

Decision trees are a simple but powerful machine learning algorithm that predicts the target variable by learning decision rules between data features. This model recursively divides the dataset into smaller subsets, with each division based on a test of feature values, forming a tree-like structure.

Comparing approaches of Markov Chain and Decision Trees, decision trees can easily manipulate a variety of types of data with easily constructed models, but they do not experience a benefit at capturing temporal features, illustrating the suitability of constructing models that need to be straightforward and clear. On the other hand, the Markov Chain successfully provides accurate predictions on consumers with obvious serial dependencies, reducing the complexity through the trait of memorylessness, drawing long-term conclusions, and stable results.

4. Conclusion

In conclusion, the adoption of Markov Chain models in business analytics serves as a powerful tool, benefiting firms from various aspects with its potential to improve marketing strategies and enhance profitability through accurate consumer behavior prediction, helping firms to target the right consumers with the right messages at right time, effectively improving and enhancing useful efforts with efficient usage of market resources. The simplicity and effectiveness of Markov Chains make them a compelling choice for businesses looking to leverage data-driven insights in their strategic planning, especially attractive to firms that may not have extensive data sets, driving them closer to goals of profit maximization and brand loyalty of consumers.

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