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Research on the Hierarchical Model of Marketing Value in the Automotive Industry Based on Dynamic Programming

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Abstract

The automotive industry is undergoing a profound transformation from "product-centered" to "user-centered", and traditional extensive customer stratification methods based on demographics and recent purchase intentions have become difficult to meet the demands of lean marketing. This paper aims to construct a marketing value stratification model based on dynamic programming theory applicable to the automotive industry. The model views the customer journey as a multi-stage sequential decision-making process, forming a Markov decision-making process framework by defining customer states, marketing actions, state transition probabilities, and immediate benefits. The core is to use the reverse induction of dynamic programming to find the optimal marketing intervention strategy that maximizes the lifetime value of each customer in every state. Value stratification is no longer just a static description of a customer's historical value, but an optimal dynamic classification based on their potential future value. Compared with traditional methods, this model can significantly improve the efficiency of marketing resource allocation, maximize the total value of customer lifetime, and provide an innovative theoretical framework and practical guide for automotive enterprises to achieve refined and intelligent user operation in the era of stock competition.

Keywords

Dynamic Programming; Marketing value stratification; Customer lifetime value; Precision marketing.

1. Introduction

In the context of the current deep application of big data and artificial intelligence in marketing, the volume of user data is surging, and demands are increasingly personalized and dynamic. Traditional value stratification methods based on static data are difficult to adapt to the dynamic evolution of user value over time - high-value users may be downgraded, and low-value users also have growth potential, resulting in misallocation of enterprise resources, rising customer acquisition costs and low retention rates. The data shows that China has more than 1 billion Internet users. The average customer acquisition cost for enterprises has increased by 60 percent compared to five years ago, but the user retention rate is generally below 30 percent. Therefore, building a hierarchical system that can dynamically respond to changes in user value has become the key to improving marketing efficiency. Dynamic programming provides a new solution for building such dynamic hierarchical models because of its advantages in multi-stage decision-making and uncertainty problems.

Existing research on marketing value stratification has mostly focused on the construction of static metric systems and the optimization of clustering algorithms, lacking a systematic analysis of the dynamic evolution mechanism of user value. This paper deeply integrates dynamic programming theory with marketing value stratification, clarifies the transfer

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patterns of user value at different life cycle stages, builds a multi-stage dynamic optimization model, and enriches the methodological system of marketing stratification theory; At the same time, it breaks through the limitation of traditional CLV models that only focus on transaction value, incorporates behavioral value and potential value dimensions, improves the theoretical framework of user value evaluation, and provides new theoretical support for dynamic marketing decision-making research.

The application of dynamic programming in marketing mainly focuses on multi-stage decision optimization. For example, in order to solve the problem that distributed energy scheduling is affected by many uncertain factors, a stochastic dual dynamic programming method integrating n-order autoregressive models is proposed in the literature[1]. This method extends the traditional SDDP framework and can effectively capture the time dependence of wind power output. This approach strikes a better balance between computational efficiency and time cost compared to traditional stochastic programming methods. The literature[2] proposes an average field multi-intelligent vehicle dynamic path planning method based on graph attention mechanism for urban road network congestion. The method builds a vehicle influence relationship graph, aggregates the observed states of neighboring vehicles using the attention mechanism, and introduces the mean field theory to update the Q-value function to select the optimal path. Experiments in scenarios such as the Hangzhou riverside road network have shown that this method can effectively reduce the average travel time of vehicles in different road conditions. But existing research has not applied dynamic programming systems to the entire process of marketing value stratification, lacking a complete framework from metric construction, stratified modeling to strategy optimization.

Based on these factors, this paper proposes a model of "Research on the Automotive Industry Marketing Value Stratification Model Based on Dynamic Programming", which can capture the changing trends of user value in real time, provide enterprises with dynamic and differentiated marketing solutions, implement retention strategies for high-value stable users and cultivation strategies for high-potential growth users, Activation strategy for low-value dormant users. This model can effectively enhance the efficiency of marketing resource allocation, reduce the cost of ineffective marketing, extend the user life cycle, increase the long-term value of users, and provide practical guidance for enterprises to build core competitiveness in the fierce market competition.

2. Research Route

The research roadmap of this paper is structured in four layers: the core theory of value stratification, the core theory of dynamic programming, the method of determining index weights, and the method of dynamic model programming and solution, as shown in Figure 1 below.

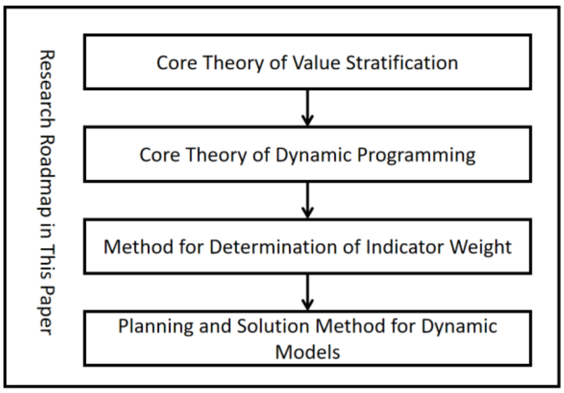

Figure 1 Research Roadmap of this paper

2.1. Core Theory of Value Stratification

(1) User lifetime value theory

The User Lifetime Value Theory (CLV) refers to the present value of the net cash flows that a user creates for the enterprise throughout the entire life cycle from acquisition to loss. The CLV theory emphasizes the long-term and dynamic nature of user value and provides a core evaluation basis for marketing stratification. The calculation formula of CLV is shown in Formula (1).

$$CLV = \sum_{t=1}^{n} \frac{P_t - C_t}{(1+r)^t} \tag{1}$$

Here, is the contribution profit for the TTH user, is the marketing cost for the TTH period, r is the discount rate, and n is the length of the user lifecycle. P_t C_t

User lifecycle stage theory

The user life cycle encompasses four stages: acquisition, growth, maturity, and decline, with distinct user value and behavioral characteristics at each stage: Starting from the low frequency and behavioral uncertainty in the initial stage, to increasing frequency and value in the growth stage, to stable loyalty in the maturity stage, and finally facing the risk of churn. The theory provides a key temporal dimension basis for dynamic stratification.

Differentiation Marketing Theory

Differentiated marketing refers to enterprises that develop targeted product, price, channel and promotion strategies based on user stratification results to achieve "precise matching and resource optimization." The theory requires that stratified models not only divide user tiers but also provide actionable marketing strategies for different tiers, providing theoretical support for the design of decision variables in dynamic programming models.

2.2. Core Theory of Dynamic Programming

(1) Core elements of dynamic programming

Dynamic programming is a mathematical approach to solving multi-stage decision optimization problems. The core idea is to break down complex problems into interrelated subproblems, using the properties of "optimal substructure" and "overlapping subproblems", by filling in tables to record and reuse the optimal solutions of the subproblems, avoiding duplicate calculations, and ultimately efficiently constructing the global optimal solution[3-4].

The basic elements of dynamic programming include: state definitions, state transition equations, initial conditions, and boundary conditions.

State definition: Precisely define the solution to a subproblem. d_{p_i}

State transition equation: The core formula that defines the recursive relationship between states, namely formula (2) (2) $d_{p_i} = f(d_{p_{i+1}}, d_{p_{i-1}}, \cdots)$

(3) Initial condition: the solution of the smallest sub-problem is the starting point of the state transition.

(4) Boundary conditions: Constraints and termination points of state transitions.

(2) Multi-stage decision optimization logic

Dynamic programming optimizes multi-stage decision problems through both reverse and sequential solution paths. Among them, the reverse solution starts from the final stage and gradually deduces the optimal sub-strategies of each stage forward and backward, embodying the forward-looking planning idea of "beginning with the end in mind"; The sequential solution method starts from the initial stage and builds the sequence of optimal strategies backward one by one, reflecting the cumulative effect of progressive decision-making. Although the two methods are opposite in computational direction, they are essentially the construction of the global optimal solution by decomposing complex problems and establishing state transition relationships.

This multi-stage optimization mechanism is highly compatible with the phased evolution characteristics of the user lifecycle. In the four typical stages of the user life cycle - acquisition, growth, maturity, and decline - each stage has both independent behavioral characteristics and value manifestations and is interrelated through state transitions. By establishing a phased decision-making model based on dynamic programming, the optimal resource input strategy can be designed for different life cycle stages: either the nurturing plan for the growth stage can be reverse-derived from the mature stage goals, or the growth path can be positively predicted based on the characteristics of the acquisition stage. This dynamic recursive optimization approach can align short-term single-stage strategies with long-term global goals, and through the precise allocation of marketing resources at each stage, ultimately achieve the continuous maximization of user lifetime value (CLV), providing a scientific decision-making methodology for enterprises to enhance user asset return rate in the era of stock competition.

2.3. Method for determining the weights of indicators

(1) Determination of evaluation indicators

In this paper, based on the characteristics of the user lifecycle stage and the value dimension, the evaluation indicators adopt a “3+8” model, namely 3 first-level indicators and 8 second-level indicators. The evaluation indicators of this paper are shown in Table 1 below.

Table 1 Evaluation Indicators of This Paper

Primary indicators	Secondary indicators	Notes
Interactive behavior	App/ mini-program activity	Login frequency, feature usage duration, content browsing depth
	Official community engagement	Posts and interactions in brand communities and social media groups
	Marketing campaign response rate	Open, click, and conversion rates for historically pushed ads and promotions
Service and vehicle condition behavior	In-store service frequency and mileage	Reflecting vehicle usage intensity and maintenance habits
	Complaints and Satisfaction	Number of historical complaints, resolution efficiency, and the latest satisfaction score
Customer attributes	Demographic characteristics	Age, income, region, etc
	Vehicle Attributes	Model, price range, configuration level, purchase channel
	Life cycle stages	First purchase, additional purchase, trade-in

(2) Determination of indicator weights

Entropy weighting is an objective weighting method that determines weights based on the degree of dispersion of the data itself, effectively overcoming the problem of arbitrariness in subjective weighting, and the results are more scientific and reliable. The core process consists of four steps[5]: data normalization, index weighting calculation, information entropy calculation, and weight calculation. The calculation process of the entropy method is shown in Figure 2.

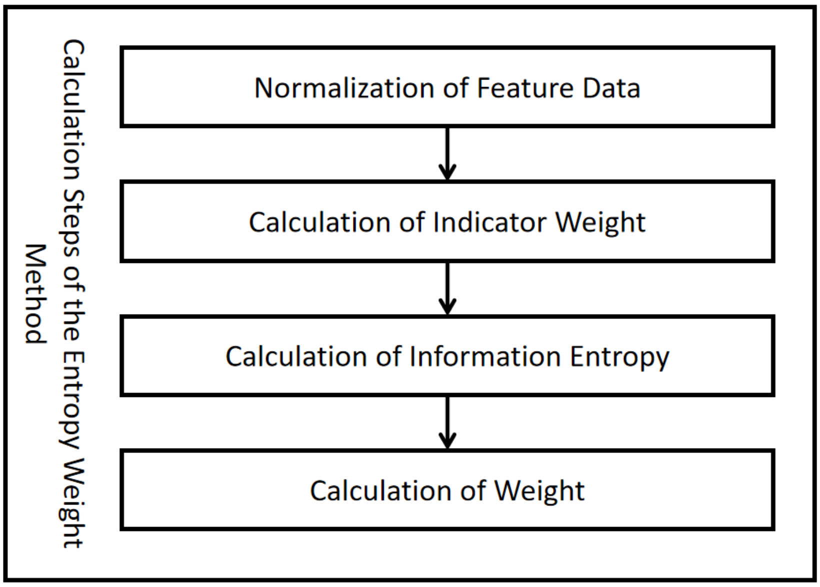

Figure 2 Calculation process of entropy method

① Feature data normalization

Data normalization is one of the key steps in data preprocessing, which aims to convert feature data of different ranges and dimensions into numerical values at a uniform scale, eliminate dimensional differences and magnitudes between variables, and make it easier for the model to learn the patterns[6-7] in the data.

The principle of data normalization: Scale the data to a specified interval to eliminate the influence of dimensions. It can be used for datasets with a uniform numerical distribution and no obvious outliers. The maximum and minimum normalization formula is as shown in Formula (3).

$$d' = \frac{d - \min(d)}{\max(d) - \min(d)} \tag{3}$$

Here, is the normalized data, is the maximum value of a column of feature data, is the minimum value of a column of feature data. d' $\max(d)$ $\min(d)$

② Calculate the metric weights $p_{i,j}$ as shown in Formula (4) below:

$$p_{i,j} = \frac{d'}{\sum_{i=1}^{m} d'} \tag{4}$$

③ Calculate the information entropy

The entropy of the feature is calculated as shown in Formula (5) :

$$e_j = -\frac{1}{\ln(m)} \cdot \sum_{i=1}^{m} p_{i,j} \cdot \ln p_{i,j} \tag{5}$$

④ Calculate the weight of each column indicator as shown in Formula (6) :

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n} (1 - e_j)} \tag{6}$$

2.4. Dynamic Model Programming and Solution Methods

The methods for solving dynamic programming can be selected based on the nature of the problem and the state space, mainly including classical recursive solution, value iteration/policy iteration, approximate dynamic programming, reinforcement learning, etc. This paper selects the most fundamental and intuitive classical recursive solution approach, which is applicable to problems where both stages and states are discrete and definite. The core idea of the classical recursive solution approach is to calculate the optimal value for each state step by step forward (backward) starting from the final stage. The calculation process of the classical recursive solution is as follows.

Initialize the boundary conditions of each state in the final stage n. $f_n(s_n)$

For k=n-1,n-2,,,,,,1, use the state transition equation

$f_k(s_k) = opt\{V(s_k, a_k) + f_{k+1}(s_{k+1})\}$ Forward recursion.

Starting from the first stage f_1(s_1), trace the optimal decision path forward.

3. Discussion and Outlook

This study provides a scientific decision-making framework for enterprises to achieve precise allocation of marketing resources and value maximization throughout the user lifecycle by constructing a hierarchical model of marketing value in the automotive industry based on dynamic programming. However, when the user state space is overly segmented or there are too many combinations of marketing actions, it can trigger a "curse of dimensionality", leading to a surge in computational effort for solving the model. This is a considerable engineering challenge for large user groups that require near real-time decision-making, and again, the model's accuracy is highly dependent on high-quality, full-chain data. The integration and cleaning of vehicle-to-vehicle data, transaction data, and interaction data is also a huge challenge.

Therefore, this paper will introduce an online learning mechanism in reinforcement learning in the future, enabling the model to dynamically adjust its strategies based on users' real-time feedback on marketing strategies (such as clicks, conversions), forming an automatic optimization closed loop of "planning - execution - feedback - update" to solve the adaptability problem of the model to environmental changes and make it a living, evolving decision-making system. At the same time, expand the model from a single "OEMs - users" relationship to the entire automotive ecosystem including dealers, financial services, insurance, charging networks, used cars, etc. State definitions and return functions need to take into account the benefits and cost-sharing of ecosystem partners.

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