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PRICING SCHEME FOR TARIFF PACKAGES FOR MOBILE OPERATORS IN COMPETITIVE CONDITIONS

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Introduction

Nowadays, user behavior itself is a complex system in the digital age. In order to develop commercial and marketing activities, Internet service providers must understand consumer preferences and interests [1-4]. In economics there is also the problem of finding a solution to this problem. Marketing of telecommunication services has been studied in various studies that belong to the economic literature on the telecommunication sector [5-6]. In fact, free streaming packages are largely negotiated between ISPs and mobile operators without taking into account the actual needs of users. According to research, there are similarities between people's online behavior. Models of online user behavior are used to design traffic packet patterns based on their general properties [7, 8]. World experience has shown that it is advisable to use artificial intelligence technologies when solving even economic problems. Therefore, in this article, when developing a pricing scheme, we propose the use of a machine learning algorithm to obtain more accurate quantitative economic calculations. The main task in this case is to determine the types of traffic plans that have a positive impact on the profits of telecom operators and social welfare. The optimal solution is obtained by the inverse solution method, and different traffic plans are evaluated from a pricing perspective. To develop a free streaming package, this study uses this commonality as a model of online user behavior. The Softmax algorithm is used to calculate the price, which helps compensate for the shortcomings of the economic model.

Previous works.

Currently, there are many developments to fundamentally measure generalists and specialists on online platforms to optimize investments so that social relations can encode community relations very well [9]. Using media platforms such as Twitter, signs of suicide were measured and posts containing suicidal intent towards one person were identified [10]. As social networks become more popular, ethical and privacy concerns arise regarding how they manage user data and how they train algorithms to organize the content they display. Based on the user profile, a technology for recommending equipment accounting in electrical power systems has been proposed [11].

A method based on Markov chains was developed in [12] using individual sequences of web page access information. To solve this problem, researchers used user information and product information to propose a method for predicting review ratings based on user context and product context [13]. Additionally, it has been proposed to add user sentiments (acoustic, conversational, and textual) to end-to-end learning environments to improve user adaptability [14]. A recommendation algorithm using matrix factorization technology combines user information and project information [15]. Different behaviors can be used to differentiate and represent different tasks. The models noted above gave good results. The traditional method of forecasting consumption for the next period involves using a time series model based on UDR data, which takes a long time to calculate and store.

To develop different plans for different users, users should be divided into different groups. K-means and other clustering algorithms are commonly used to segment groups of users. Using pricing schemes, [16] presented a new conceptual approach to improve the performance of public bicycle sharing systems.

System Model

This section proposes the joint use of machine learning technologies and economic methods for the development of tariff plans. Key challenges include online user behavior characterization and pattern extraction; selecting package contents; design of utility functions of the user, Internet provider and mobile operator; and a model under various target conditions for optimizing the solution method. The design pattern is divided into two groups: package content and package cost. The contents of the package include extracting behavior properties and extracting behavior patterns. At the same time, the cost of the package includes the design of utility functions, a two-sided market model .

To develop a traffic plan, a factor model analyzes the user's Internet characteristics. This model is usually expressed as follows [22] :

$$\Re \cong PQ^T \qquad (1)$$

Where$P \in \mathbb{R}^{M\times K}$ And$Q \in \mathbb{R}^{N\times K}$ are a matrix of factors for the user and the content being accessed, consisting of a vector of factors for the user or the content being accessed.M represents the number of users.N represents the amount of content available.K - the number of factors, which is usually much less than N And M. Matrix$\Re$ is a matrix of ratings for different users for different content, which can also consist of a vector of ratings for all content accessed by different users, as shown in formula (2).

$$\Re = \begin{pmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{pmatrix} = \begin{pmatrix} R_1 \\ \vdots \\ R_m \end{pmatrix} \qquad (2)$$

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The original factor model does not take into account changes in user interests and loses some information in the data. People's behavior on the Internet has similarities. This ensures that the user U It has$k$ distinct and independent characteristics of Internet synchronization, written as $Pattern_k$. Each template has a different weight $w(Pattern)$, which affects user behavior. A higher weight indicates a stronger influence. The user transfer matrix consists of $Pattern_k$and $w(Pattern)$. Timing and current content $A_t$work together to determine upcoming content access A_{t+1}. Meaning$Pattern_k$ this is supposed to be $f(Pattern_k, A_t, A_{t+1})$. A higher value indicates that the access preferenceA_{t+1} under the previous condition is stronger [22].

$$P(u, A_t, A_{t+1}) = \sum_k w(Pattern_k) \times f(Pattern_k, A_t, A_{t+1}) \qquad (3)$$

Formula (3) is converted to volume as shown in Formula (4) , and the user profile problem is converted to a tensor decomposition problem.

$$P(U, A_t, A_{t+1}) = F(Pattern, A_t, A_{t+1}) \times W(Pattern, U) \qquad (4)$$

Where$P\ (U, A_t, A_{t+1})$ a tensor consisting of the user's probability$U$ accessA_t currently and access A_{t+1} in the next moment.$W(Pattern, U)$ the weight of another portrait$K$ for the user u.$F(Pattern, A_t, A_{t+1})$ — access intensity tensor, consisting of an access intensity matrix for different portraits.

To perform tensor decomposition, the data is processed using non-negative tensor factorization and high order singular value decomposition (HOSVD). Basic formula of HOSVD [22]:

$$\mathbb{R} = \mathcal{X} \times_1 A \times_2 B \times_3 C \qquad (5)$$

This article uses the formulas:

$$W\ (Pattern, U) = A \qquad (6)$$

$$F(Pattern, A_t, A_{t+1}) = \mathcal{X} \times_2 B \times_3 C \qquad (7)$$

$W\ (Pattern, U)$ is the user's weight matrix, and$F(Pattern, A_t, A_{t+1})$ – access intensity tensor, composed of access intensity matrices from different profiles.

Unlike traditional manufacturing enterprises, platform enterprises are not directly involved in the production of goods, but create a “platform ecosystem.” The system connects consumers of goods with producers of goods and receives the corresponding benefits from the trading process of the two groups. In a two-sided market model, the consumer and platform form one side, and the producer and platform form the other. Researchers refer to the market architecture of platform enterprises as two-sided markets. The mobile operator, as a platform enterprise, connects to hundreds of millions of users and provides information and communication services; on the other hand, it connects to a number of service providers who offer certain additional services to users through the platform.

In the package pricing problem, the platform is mobile operators, and the two-sided market consists of Internet providers and user groups. Utility is defined as

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the benefit received by participants in a two-sided market model, which is usually expressed using a utility function [20-22].

User utility function

$$u_1 = a_1 n_2 - P_1 \quad (8)$$

ISP utility function:

$$u_2 = a_2 n_2 - P_2 \quad (9)$$

MNO utility function :

$$\pi = P_1 n_1 + P_2 n_2 - f \quad (10)$$

Where u_1 And u_2 represent the utility of the user and the ISP, respectively. a_1 And a_2 represent user requirements and ISP network externality parameters, respectively.n_1 And n_2 represent the number of participants on the demand side and on the producer side under normalized conditions, respectively. P_1 And P_2 represent the cost of the two parties submitting a request to the platform, and$f$ this is the cost of the platform.

Pricing scheme in competitive conditions. In a competitive environment, mobile operators offer a variety of packages from which users can choose, and users can choose the most effective package based on their needs. Mobile operators continue to charge users and internet service providers for using the platforms.

In this scenario, the telecom operator develops$m$ different packages. Users and online sellers are treated as a small group$M$ users, and each package corresponds to a group of users and a group of Internet providers. For a certain group of users, the utility function looks like this [22]:

$$u_{1m} = \alpha_1 \times \ln(1 + F_m \times n_{2m}) - P_{s1m} \quad (11)$$

Whereu_{1m} represents the user group utility corresponding to the package m,F_m represents the traffic covered by the packet m,n_{2m} represents the number of Internet providers matching the package m, and P_{s1m} represents the subscription fee charged for the package m.

A user's utility is equal to the sum of the utilities of all user groups.

$$u_1 = \sum_{m=1}^{M} u_{1m} \quad (12)$$

ISP utility corresponding to the package$m$ is

$$u_{2m} = \alpha_2 \times \ln(1 + F_m \times n_{1m}) - P_{s2m} \quad (13)$$

Utility of Content Demand

$$u_2 = \sum_{m=1}^{M} u_{2m} \quad (14)$$

The platform's utility function represents the sum of fees paid by different groups:

$$\pi = \sum_m (P_{s1m} - C \times F_m - f) \times n_{1m} + \sum_m P_{s2m} \times n_{2m} \quad (15)$$

The number of users (n_{1m}) is related to the user's utility u_{1m}:

$$n_{2m} = \phi_{2m}(u_{2m}) \quad (16)$$

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In practice, even if Internet producers do not participate in the above package, there is a certain utility u_j:

$$u_j = \alpha_2 \times \ln\left(1 + F_j\right) \qquad (17)$$

Various works provide evidence that the traffic used by users to access the Internet is associated with the price per unit of traffic [17-19]:

$$F_j = g_k \times e^{-(1+P)} \qquad (18)$$

Let us assume that at a price per unit of trafficP_{t1} access traffic of Internet vendors is equal to F, and at a price per unit of traffic the traffic P_{t2}used by Internet vendors F'_j, according to Formula (19), we obtain formula (32):

$$F'_j = \exp(P_{t1} - P_{t2}) \times F_j \qquad (19)$$

We have assumed that the mobile plan is unlimited data, the price per unit of data is 0 as follows:

$$F'_j = \exp(P_{t1}) \times F_j \qquad (20)$$

WhereF_j using users in a traditional way,P_{t1} is the price per unit of data in traditional packages.

Selection of unknown functions in a competitive environment is the main issue of this section. It is recommended to use the SoftMax model to meet the above functions.

$$n_{1m} = \phi_1(u_{1m}) = \frac{e^{W_{1m} \times u_{1m}}}{\sum e^{W_1 \times U_1}} \qquad (21)$$

W_1 is$M \times M$ Softmax parameter matrix. ISPs may be involved in setting up multiple packages at the same time, and this article uses a logistics model suitable for the number of ISPs [20-22]:

$$n_{2m} = \phi_{2m}(u_{2m}) = \frac{1}{1+e^{W_{2m} \times U_{2m}}} \qquad (22)$$

Where W_{2m} — the parameter value obtained during the training process of the package m.

Conclusion

The considered approach for pricing tariff plans based on the behavior of the Internet user taking into account content is labor-intensive, but more accurate tools for telecom operators. Video content consumes the majority of traffic, suggesting that it is possible to create a free traffic package that satisfies basic user needs.

Future research should cover more application scenarios to improve comprehensive analysis of user behavior and facilitate the development of appropriate services. In addition, improvements in data processing techniques are needed to enable analysis of larger data. In addition, accurate determination of external network parameters is critical to clarify the results. The study focused on the static partitioning of a two-sided market using operations research procedures.

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Future work will integrate game theory to enable dynamic partitioning of the model.

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