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Research on New Media User Profile Construction and Precision Marketing Strategy Based on Deep Learning

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SUMMARY: *In response to the problems of rough user segmentation, inaccurate churn prediction, low recommendation efficiency, and low conversion rate in traditional new media marketing, this paper proposes a new media user profile construction and precision marketing strategy based on the C-ATT-LSTM model. Firstly, construct a complete new media user profile from three dimensions: basic attributes, behavioral attributes, and statistical attributes; Secondly, design a C-ATT-LSTM network that integrates convolution, attention mechanism, and LSTM to achieve high-dimensional feature extraction and temporal dependency capture; Thirdly, SOM clustering is used to stratify users and independently model and identify high churn users for each group; Finally, by combining collaborative filtering and content recommendation, personalized coupons can be accurately pushed. The experiment was validated using real data from an online daily necessities store from July 2024 to July 2025.7, and the results showed that the proposed method significantly outperformed baseline algorithms such as LR-RF, ANN, and Adaboost in accuracy and F1 score; The ablation experiment showed that the complete solution achieved a user conversion rate of 13.69%, a conversion rate growth rate of 387.66%, an estimated sales increase of 5.68% compared to the benchmark, and the optimal input-output ratio. Research has shown that the proposed model can accurately characterize user characteristics, efficiently identify churn risks, and provide feasible technical solutions for precision marketing of new media platforms.*

KEYWORDS: *deep learning; New media; User profile; LSTM; Precision marketing; personalized recommendation*

1 Introduction

With the continuous emergence of new data carriers such as social media information, user click streams, and search logs, the scale of analyzable data sources in the field of marketing has shown explosive growth, providing basic support for the landing and application of artificial intelligence (AI) technology and tools in business and marketing scenarios [1]. The research scope of marketing based on artificial intelligence covers multiple core scenarios, including modeling of new media user behavior, analysis of user price sensitivity and purchasing decision mechanisms, construction of personalized recommendation systems, risk management of new media user churn, and new user expansion.

Traditional research often considers all new media users as a homogeneous whole when constructing artificial intelligence prediction models. However, different new media user groups have differentiated transaction patterns and behavioral characteristics, and the modeling

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assumption of treating all new media users as a single homogeneous group lacks rationality [2]. Based on the behavioral tendency profile of new media users, group segmentation and implementation of group modeling can achieve precise customization of marketing strategies. The online shopping environment can collect and store real-time user behavior characteristic data, and rely on historical behavior data of new media users to mine user behavior patterns and preference characteristics, which can significantly improve the conversion efficiency of online new media users. The classic RFM new media user segmentation model is based on three core indicators: recent consumption time (Recency), consumption frequency (Frequency), and consumption amount (Monetary), ignoring the multiple potential factors that affect the value of new media users [3]. It does not include multidimensional user behavior data and individual characteristic information, making it difficult to achieve a comprehensive characterization of the behavioral tendencies of new media users. The segmentation of new media users based on their behavioral tendencies can effectively identify potential churn groups, construct customized churn prediction models, and integrate new media user attribute characteristics, historical behavior records, and multi-dimensional correlation data to predict the trend of new media user churn and output risk warning signals. In recent years, ensemble learning and deep learning frameworks have gradually been applied to research on predicting user churn in new media [4]. Existing literature has constructed an ensemble framework for churn prediction that integrates Genetic Programming (GP) and AdaBoost algorithms, and introduced Particle Swarm Optimization (PSO) algorithm to solve the problem of imbalanced sample datasets; There are also studies that use a two-layer artificial neural network (ANN) to extract high-dimensional features, and then use Naive Bayes (NB) algorithm to classify the churn status of new media users.

Personalized recommendation system is an important research direction in the field of artificial intelligence marketing. Targeted promotion of personalized coupons is a simple and efficient marketing intervention method. By screening real-time high-risk users and matching them with customized discount coupons, it can effectively improve the level of user purchase conversion. Traditional personalized recommendations often use association rule analysis or single item purchase probability estimation methods. Currently, collaborative filtering and content-based recommendation algorithms have been widely applied on mainstream e-commerce platforms such as Taobao and JD.com. To further improve the conversion rate of new media users in online shopping scenarios, this paper constructs a new media user profile construction and precision marketing promotion system based on the C-ATT-LSTM model. The core innovations are as follows: (1) for online shopping scenarios, deep learning technology is introduced into real-time click stream data analysis, and new media user profiles are used to complete new media user segmentation; (2) Introduce C-ATT-LSTM models for different groups of new media users to accurately identify high probability churn users. (3) By integrating collaborative filtering and content-based recommendation algorithms, customized coupons for different categories are targeted and pushed to layered new media users, effectively improving their actual conversion efficiency.

2 Related work

2.1 Research on Precision Marketing

The concept of precision marketing was first proposed by Philip Kotler, defining it as a low-cost, high-yield marketing paradigm that relies on refined control of marketing behavior and implementation effects to develop comprehensive implementation plans [5]. The core logic lies in deep mining and analysis of new media user needs, achieving efficient matching of user needs. Kotler further pointed out that precision marketing designs and implements marketing communication strategies with a results-oriented approach as the core, while advocating for face-to-face communication with offline sales personnel to carry out marketing investment. During his visit to China in 2006, he clearly stated that the traditional mass marketing model has gradually come to an end, and precision marketing will become the mainstream development trend of marketing in the future [6].

Karanisa et al. [7] measured demand elasticity by fitting demand curves, quantitatively evaluated consumer surplus scale, and provided data basis for market-oriented pricing strategies. Empirical research shows that the application of big data technology can create up to $2.9 billion in consumer surplus value for enterprises. Okeleke et al. [8] pointed out that precision marketing can identify target consumer preference characteristics through massive multi-source data mining, achieving efficient advertising resource placement and marketing effectiveness improvement. Toscano et al. [9] systematically reviews the current application status of big data analysis in cross-border precision marketing on online platforms, analyzes the current implementation bottlenecks, and provides targeted optimization solutions. Al Khaldy et al. [10] proposed that in the context of rapid iteration of information technology and big data, enterprises should deeply explore the value of big data technology to provide scientific support for marketing layout and strategic decision-making. Abate et al. [11] believes that the essence of precision marketing is to rely on appropriate communication channels and push matching information to the target customer group at the appropriate time, thereby effectively intervening in consumer purchasing decisions, and proposing the classic 4R principles of precision marketing. Aliahmadi et al. [12] conducted research on the application of precision marketing in the segmentation and market positioning of new media user resources, emphasizing the optimization of marketing effectiveness through refined segmentation of new media users and precise market positioning, especially in the application value of intelligent communication service systems. This can significantly reduce the implementation cost of large-scale precision marketing and further optimize marketing output benefits. Philip Kotler proposed that modern business has entered the era of Marketing 4.0 supported by big data, social networks, value concepts, and data mining technology, completing the paradigm shift from traditional marketing to digital intelligent marketing. Kurdi et al. [13] explores the training path that adapts to the marketing talent needs of small and medium-sized enterprises. Although the research does not directly focus on precision marketing, it provides theoretical support for clarifying the marketing ecosystem background of small and medium-sized enterprises. Naz & Kashif [14] conducted empirical analysis on the curation format of beauty products and confirmed that the stability of big data sharing plays a key role in maintaining trust among new media users. Wendy K. Benoni explores the implementation path of integrating marketing resources, accurately reaching brand target customer groups, and formulating growth paths through social media platforms. She proposes that empowering precise marketing with new media tools can effectively improve the overall marketing and operational efficiency of the fashion industry. Akbari et al. [15] conducted innovative research on click through rate (CTR) prediction models for precision marketing scenarios, constructing a multi-channel MCGM CTR prediction model to provide a new technical solution for estimating traffic conversion in precision marketing.

2.2 Marketing Model

At the beginning of the 21st century, the concept of algorithm modeling gradually emerged and received widespread attention and in-depth research from various disciplines, becoming an important support for promoting the development and progress of modern society. Chai et al. [16] defines big data as a vast, rapidly growing, and diverse information asset, and points out that specialized processing and deep mining of big data can effectively enhance organizational decision-making, cognitive insights, and execution efficiency. Vargo et al. [17] believes that big data is a large-scale and structurally diverse collection of data, which has also promoted the popularization and application of the concept of big data in various industries. Srivastava & Bag [18] proposed that big data belongs to datasets that traditional data processing software cannot efficiently carry and parse, and urgently needs to rely on emerging technology architectures to complete data collection, cleaning, processing, and intelligent analysis. From a business application perspective, Ali et al. [19] believes that algorithm modeling provides a new path for innovative intelligent management models in enterprises, and relying on data analysis capabilities can help market entities build differentiated competitive advantages. Noranee & bin Othman [20] added two dimensions, Value and Veracity, on the basis of traditional 3V features, and constructed a 5V feature system, further improving the definition of the connotation of big data. Sharabati et al. [21] pointed out that the rapid development of the e-commerce industry is one of the important driving forces for the rapid rise of algorithm technology and big data applications. E-commerce platforms have accumulated massive amounts of user behavior and transaction data, which have important application value in various industries, especially in commercial marketing scenarios. E-commerce enterprises can build precise marketing systems at low cost through deep data mining, thereby improving user consumption conversion levels and enterprise operating profits.

In recent years, the cross-fusion research of machine learning algorithms and marketing management has become a hot topic in both academia and industry. This is because marketing scenarios have complex characteristics such as non-linear consumer behavior and dynamic changes in market environment, which can force traditional statistical modeling methods to gradually evolve towards intelligent algorithm paradigms such as deep learning and reinforcement learning. Kedi et al. [22] constructed a machine learning model based on LSTM and applied it to marketing business scenarios, verifying the practical value of the model in medium and long-term trend prediction based on years of marketing time-series data. Senapaty et al. [23] proposed that the combination architecture of LSTM and CNN, which integrates text, image, and transaction behavior data, has become a mainstream research trend in the field of marketing data analysis. Sharma et al. [24] study confirmed that LSTM, with its gating mechanism, can effectively solve the problem of long-term dependence on time-series data, and its comprehensive performance in e-commerce sales forecasting tasks is significantly better than traditional statistical models. Kedi et al. [25] combines Long Short Term Memory (LSTM) networks with Graph Neural Networks (GNN) to synchronously mine spatial and temporal correlation features of data by introducing skip connection structures, effectively improving the prediction accuracy of epidemic transmission prediction models. De Mauro et al. [26] found that traditional economic models such as Logit regression are difficult to adapt to high-dimensional feature scenarios, while ensemble learning algorithms such as random forests and gradient boosting trees can achieve optimal selection and optimization of pricing variables through feature importance ranking. Soundappan [27] pointed out that LSTM has been widely used in consumer purchase intention prediction and personalized recommendation tasks based on temporal data and user historical behavior characteristics. It can synchronously capture spatiotemporal features and is suitable for research scenarios such as video advertising effectiveness evaluation and online user behavior analysis.

3 Construction of new media user profiles

For personalized content recommendation on the platform, if accurate push of interest based content can be achieved for individual users of new media, it can significantly improve user stickiness, platform activity, and user dependence. After users obtain content resources that match their preferences, their satisfaction with platform usage will increase, making it easier for them to engage in spontaneous sharing and word-of-mouth behavior. From this, it can be seen that building accurate user profiles for new media is a prerequisite and key for platforms to achieve efficient personalized recommendations.

3.1 Basic attributes of new media users

The basic attributes of new media users are partly derived from the information actively filled in during the user registration process, while the other part is composed of basic user data collected by the data platform through compliance channels. The specific content of the basic attribute portrait of new media users is detailed in Table 1.

Table 1: Basic Attribute Profile of New Media Users

No.	attribute	feature	meaning	source
1	foundation	gender	Female/Male/Unknown total 2.67 million+coverage rate 0.22 Female 165000+Male 437000+Other unknown	background data
2	foundation	age	Coverage rate 0.28 Non air 750000+ Under the age of 8-60, 680000 yuan+ The coverage rate is 0.25, which is generally close to a normal distribution. Among them, 21 years old (53000), 51 years old (26000), and 52 years old (91000) can be retained near the peak. After removing abnormal data from 51 years old and 52 years old, the available data coverage rate is about 0.21	Data platform collection
3	foundation	level	Level interval [0150], where high and low levels represent activity level	background data
4	foundation	country	For example, Middle Eastern users should prioritize recommending Middle Eastern anchors	background data
5	foundation	login platform	Web/IO S/Android	background data
6	foundation	Do you have a profile picture	User Quality	background data
7	foundation	Drainage platform	Which platform did the user import from	The data platform collects backend data
9	foundation	Registration date	The level of new and old media users	background data
7	foundation	Do you want to register on Facebook, Google, Instagram, or other platforms	Can determine which social platforms users mainly use in their daily lives	The data platform collects backend data

3.2 New Media User Behavior Attributes

The behavioral attributes of new media users are mostly generated throughout the entire process of using platform products, and then collected and summarized by the data platform through compliant methods. The specific content of the behavior attribute portrait of new media users is detailed in Table 2.

Table 2: New Media User Behavior Attribute Profile Table

No.	attribute	feature	meaning	source
1	behavior	List of broadcasters followed by new media users	Record positive behaviors of new media users	background data
2	behavior	List of broadcasters who give gifts to new media users	Record positive behaviors of new media users	Data platform collection
3	behavior	List of anchors commented by new media users	Record positive behaviors of new media users	Data platform collection
4	behavior	Channel viewing behavior list	Statistics on the viewing duration, frequency, and interval of game channels watched by new media users (mid-term 7 days, long-term 30 days)	Data platform collection
5	behavior	List of broadcasters watched by users	Statistics on the duration and frequency of anchor viewing by new media users, with a statistical interval of 7 days in the mid-term and 30 days in the long-term	Data platform collection
6	behavior	List of broadcasters watched during daily time periods	The length of time that new media users watch during the morning, afternoon, and evening periods of a day, and the statistical interval (7 days in the middle and 30 days in the long term)	background data
7	behavior	List of broadcasters watched during weekly time periods	The duration of viewing by new media users on Saturdays, Sundays, and workdays, and the statistical interval (long-term 30 days)	Data platform collection
8	behavior	Distribution of active time periods for users	Time periods: 00-06, 06-12, 12-18, 18-00	Data platform collection
9	behavior	Total/Chat frequency in the past 3/7/30 days	Representing the activity level of new media users	Data platform collection
10	behavior	Total/number of gift giving times by new media users in the past 3/7/30 days	The willingness of new media users to pay	Data platform collection
11	behavior	Total value of gifts given by new media users in the past 3/7/30 days	Some new media users may give gifts less frequently, but the value of gift giving is high. Some new media users may give gifts frequently, but their value may not be high.	Data platform collection

3.3 New Media User Statistics Attributes

The statistical attributes of new media users are also collected and obtained in a compliant manner through data platforms. The specific content of the attribute portrait of new media user statistics is detailed in Table 3.

Table 3: Profile of New Media User Statistics Attributes

No.	attribute	feature	meaning	source
1	statistics	Number of days for new media users to log in	Analyzing the stickiness of new media users within a statistical interval (mid-term 7 days, long-term 30 days)	Data platform collection
2	statistics	The number of times new media users watch videos	Analyzing the activity level of new media users within a statistical interval (7 days in the mid-term and 30 days in the long-term)	Data platform collection
3	statistics	The number of valid views of new media users exceeding 5 minutes	Analyzing the activity level of new media users within a statistical interval (7 days in the mid-term and 30 days in the long-term)	Data platform collection
4	statistics	List of broadcasters corresponding to the number of valid views generated by new media users exceeding 5 minutes	Analyze the content that users are interested in within the statistical interval (mid-term 7 days, long-term 30 days)	Data platform collection
5	statistics	List of top 10 hosts with the highest number of chats in the past 7/30 days	Analyze the content that users are interested in within the statistical interval (mid-term 7 days, long-term 30 days)	Data platform collection
6	statistics	Top 10 broadcasters with the most gift giving frequency in the past 7/30 days	Analyze the content that users are interested in within the statistical interval (mid-term 7 days, long-term 30 days)	Data platform collection
7	statistics	List of top 10 broadcasters with the highest total gift value in the past 7/30 days	Analyze the content that users are interested in within the statistical interval (mid-term 7 days, long-term 30 days)	Data platform collection

4 Precision marketing promotion system based on CNN-LSTM model

4.1 Framework of Precision Marketing Promotion System

The framework proposed in this study adopts the C-ATT-LSTM model deep learning architecture and recommendation system method to achieve precise delivery of digital coupons. The process is shown in Figure 1. According to the framework of the precision marketing promotion system shown in Figure 1: (1) Based on the two-dimensional new media user stickiness index, hierarchical clustering of new media user groups is completed through new media user portraits, and new media users are divided into different feature types; (2) Deploy the C-ATT-LSTM model separately for each new media user group to achieve accurate identification and screening of high-risk churn users; (3) Introduce recommendation algorithms to push customized digital coupons to target new media users, and quantitatively evaluate the user conversion efficiency of precision marketing promotion strategies.

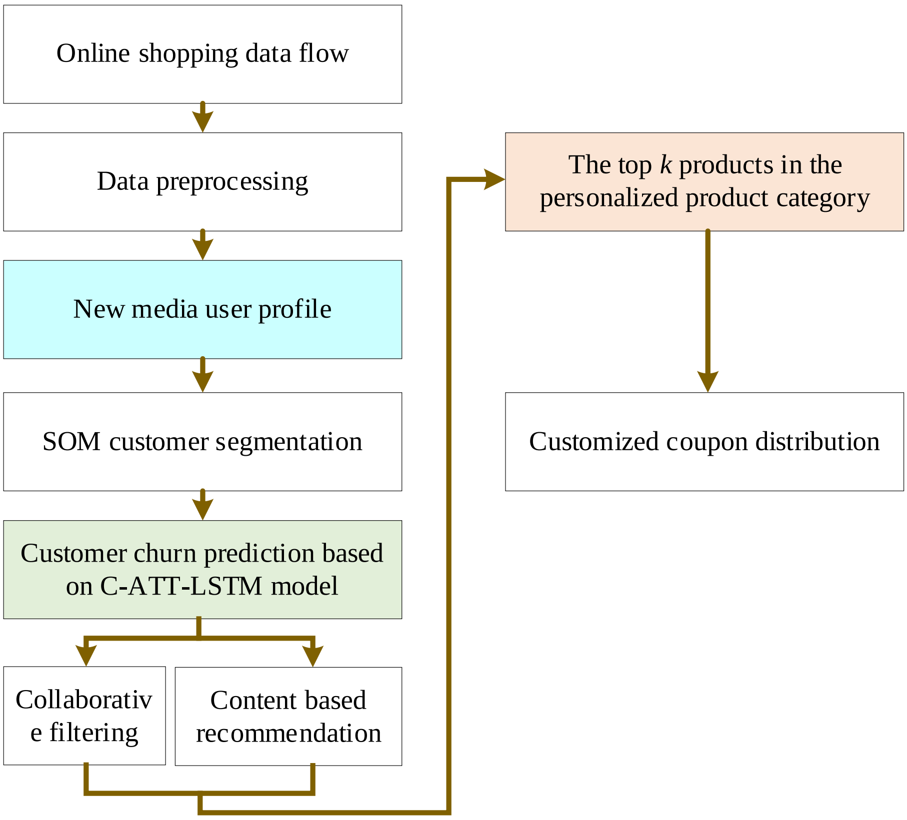

Figure 1: Flow Chart of Precision Marketing Promotion System

4.2 C-ATT-LSTM Model

This article proposes a neural network structure based on Convolutional Attention Long Short Term Memory Network (C-ATT-LSTM, convolution attention long short term model), as shown in Figure 2, for estimating the construction of precision marketing promotion systems. In this network architecture, Convolutional Neural Networks (CNNs) are used as local feature extractors, while Convolutional Attention Modules are introduced to enhance the feature extraction performance of CNNs. Long Short Term Memory Networks (LSTMs) are responsible for capturing the dynamic features of temporal data, with a focus on mining the temporal dependencies between the current joint state and the previous state. The collaborative integration of CNN and LSTM can achieve accurate evaluation of marketing and promotion for new media users.

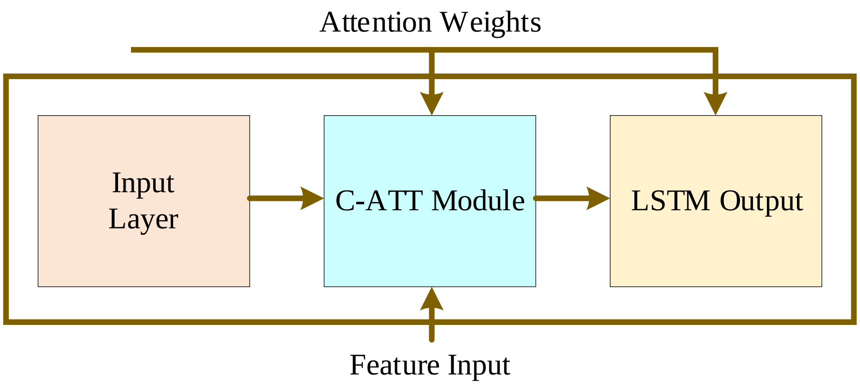

Figure 2: C-ATT-LSTM Network Structure

By using two-layer one-dimensional convolution operation, short-term feature patterns of data are extracted within each time window, and ReLU activation function is used to introduce nonlinear characteristics, which are then integrated into the attention module to enhance the weight allocation of key features. Define the input tensor as $X \in R^{F \times T}$, where T is the time window size and F is the feature number.

In the C-ATT-LSTM network structure, the operation of the two-layer convolutional layer is as follows:

$$Q_1 = ReLU\left(W_1 * X\right) \tag{1}$$

$$Q_2 = ReLU\left(W_2 * X_1''\right) \tag{2}$$

where, W_1 and W_2 are convolution kernels, * is the convolution operation, and X_1'' is the refined output after the first convolution attention module.

As shown in Figure 2, the convolutional attention module is introduced after the convolutional layer, and the output of each convolutional layer enters it to generate the channel attention tensor M_c and spatial attention tensor M_s in sequence. The entire process can be summarized as follows:

$$X' = M_c\left(Q_l\right) \otimes Q_l \tag{3}$$

$$X'' = M_s\left(X'\right) \otimes X' \tag{4}$$

where, Q_l is the output of the convolutional layer in the l-th layer of the C-ATT-LSTM network, $\otimes$ represents element multiplication, and X'' is the final refined output.

As shown in Figure 2, the channel attention module aggregates the information of the feature tensor through average pooling and maximum pooling operations, generating two different context descriptors: (1) average pooling feature X_{avg}^{c}; (2) Maximum pooling feature $X_{\max}^{c}$. Then, the two descriptors are forwarded to a multi-layer perceptron shared network (MLP) consisting of a hidden layer and two convolutional layers to complete feature concatenation and generate the channel attention tensor M_c. At the same time, in order to reduce the computational complexity of the hidden layer parameters, the output channel of the convolutional layer before the hidden layer is set to C/ratio (C is the number of input channels, and ratio is the channel reduction rate), and then the output of the hidden layer is transferred to another convolutional layer with input channels of C/ratio and output channels of C for weighted fusion with the original input channels. The shared network MLP uses the element summation method to merge the output feature vectors:

$$\begin{aligned} M_c(X) &= \sigma(\mathrm{MLP}(\mathrm{AvgPool}(X)) + \mathrm{MLP}(\mathrm{MaxPool}(X))) \\ &= \sigma\left(W_{cl} * \mathrm{ReLU}\left(W_{c0} * \left(X^c_{\mathrm{avg}}\right)\right) + W_{cl} * \mathrm{ReLU}\left(W_{c0} * \left(X^c_{\max}\right)\right)\right) \end{aligned} \tag{5}$$

where, $\mathrm{MaxPool}$ is the max pooling operation, $\mathrm{AvgPool}$ is the average pooling operation, * is the convolution operation, and W_{c0} and W_{cl} are shared on both inputs. σ is the Sigmoid function, and W_{c0} and W_{cl} are the convolution kernels.

The spatial attention module focuses on the features of "key positions" in the input information, which can effectively compensate for the limitations of the channel attention module and form a complementary effect. For the sample data of precision marketing evaluation for new media users, differentiated weights are assigned to each time step within the corresponding time window of the input data, in order to highlight the importance of different time step characteristics for precision marketing evaluation of new media users. Collect channel information from feature maps through average pooling and max pooling operations, generate two tensors X^s_{avg} and $X^s_{\max}$, and then concatenate and convolve these features through standard convolutional layers:

$$M_s(X) = \sigma\left(W_{s0} * ([\mathrm{AvgPool}(X); \mathrm{MaxPool}(X)])\right) = \sigma\left(W_{s0} * \left(\left[X^s_{\mathrm{avg}}; X^s_{\max}\right]\right)\right) \tag{6}$$

where, MaxPool is the max pooling operation, AvgPool is the average pooling operation, σ is the Sigmoid function, W_{s0} is the convolution kernel, and * is the convolution operation.

The output data of the C-attention layer is input to a Long Short Term Memory (LSTM) network, which achieves effective learning of short-term dependencies across time steps by setting a multi-layer network structure and a reasonable number of hidden units. LSTM, through its built-in memory unit and forget gate mechanism, can accurately model the individual behavior dependency relationship of new media users between the current time step and multiple previous time steps.

Calculation of input gate, forget gate, and output gate:

$$\begin{cases} i_t = \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right) \\ f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \\ o_t = \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right) \end{cases} \tag{7}$$

Update of Memory Unit Status:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh\left(W_e x_t + U_c h_{t-1} + b_e\right) \tag{8}$$

Calculation of hidden states for each time step:

$$h_t = o_t \odot \tanh\left(c_t\right) \tag{9}$$

where, σ is the Sigmoid activation function, and $\odot$ is element wise multiplication.

Through LSTM time series modeling, the network is able to recognize dynamic patterns between multiple time steps. Its output takes the hidden state h_T of the last time step in the time window as the final feature, which is mapped to the output space through a fully connected layer. The operation is as follows:

$$\hat{\tau}_{ext} = W_{fc} h_T + b_{fc} \tag{10}$$

where, Output $\hat{\tau}_{ext} \in R^{7\times 1}$ as the estimated torque values for 7 joints, W_{fc} and b_{fc} as the weights and biases of the fully connected layer.

4.3 Recommended Coupon Distribution

The proposed framework aims to distribute digital coupons in real-time to new media users with high churn risk, and predicts the product categories that new media users like by combining collaborative filtering and content-based recommendation algorithms. Among them, collaborative filtering algorithms recommend products that match customers' interests by analyzing their historical behavior data; The content-based filtering algorithm recommends similar products or services to customers based on their past purchasing behavior and preferences. Then, combining the ratings of the two algorithms to complete personalized product recommendation, the personalized recommendation model is as follows:

$$r'_{ui} = \alpha \cdot r'^{CF}_{ui} + (1-\alpha) \cdot r'^{CB}_{ui} \tag{11}$$

where, α is the parameter for adjusting the scoring weights of the two algorithms, r'^{CF}_{ui} is the prediction score based on collaborative filtering algorithm, r'_{ui} is the comprehensive prediction score of user u for item i, and r'^{CB}_{ui} is the prediction score based on content recommendation.

5 Experimental analysis

5.1 Dataset

Collect user session data from a daily necessities store on an online shopping platform, covering the period from July 2024 to July 2025. To ensure data privacy and security, store subject information and all personal information of new media users are anonymized. This daily necessities store has a total of 743 products listed, covering 18 product categories, with an average daily sales of about 5735 yuan, an average daily visit of about 13438 people, and an average daily page view of about 19865 pages. The detailed operational statistics of this store are shown in Table 4.

Table 4: Statistics of Online Stores

Name	Value
Daily average number of conversations	11145
Daily average webpage views	9438
Daily average visitors	13438
Daily average new visitors	5790
Average session duration	1 minute, 28 seconds

The system stores log data for each webpage of the store, which includes multi-dimensional user behavior information such as page click records, purchase behavior history, shopping cart operation records, order fulfillment history, and search behavior history. The study uses a new media user profiling model to stratify and segment user groups, and based on this, applies a real-time new media user churn rate prediction model based on the C-ATT-LSTM model to dynamically predict and accurately identify the risk of new media user churn. For identified high churn risk new media users, the system will issue targeted coupons with a discount of 15%, which will be pushed to the target new media users in the form of pop ups, with an effective duration of 2.5 hours to ensure the timeliness and pertinence of marketing interventions.

5.2 Model Configuration

Preprocess the shopping data collected from new media users: (1) To strictly protect user privacy and data anonymity, completely delete all information containing personal identification and privacy related information; (2) Perform abnormal filtering on log data, delete log records with web page views exceeding 100 times in a single session, to eliminate interference from machine programs such as web crawlers on model training. (3) Divide it into training set, validation set, and testing set in a ratio of 6:2:2, respectively, for model training, parameter tuning, and performance validation.

The new media user churn prediction method proposed in this article adopts a new media user profile construction and precision marketing strategy model based on the C-ATT-LSTM model. During the model training process, an ADAM optimizer is selected for parameter optimization, and a binary cross entropy function is used as the loss function. The learning rate is set to 0.001, the training epochs are 30, and the batch size is 32 to ensure the stability and convergence of the model training.

5.3 Experimental Results

To evaluate the practicality and effectiveness of the precision marketing promotion system proposed in this article in real shopping scenarios, four different comparative schemes were designed and analyzed through ablation experiments. The core components included in each scheme are detailed in Table 5. Among them, Scheme 1 serves as the benchmark control group, without using any optimization algorithm, and randomly distributes coupons to users; Option 2 does not perform segmentation of new media users and directly applies the C-ATT-LSTM model to predict new media user churn. Subsequently, the hybrid recommendation algorithm proposed in this article is used to push personalized coupons to target users; Option 3 first subdivides user groups through new media user profiles, and then applies the C-ATT-LSTM model to predict churn risk for each new media user clustering group. Only random product coupons are distributed to identified high-risk churn users; Option 4 is the complete solution proposed in this article, which is based on the segmentation of new media user profiles and identification of high churn risks, and targeted distribution of personalized coupons to target users.

Table 5: Different Experimental Scenarios

	Segmentation of New Media User Profile	C-ATT-LSTM model	Hybrid recommendation algorithm
Option 1	No	No	No
Option 2	No	Yes	Yes
Option 3	Yes	Yes	No
Option 4	Yes	Yes	Yes

Three algorithms, LR-RF, ANN, and Adaboost, were selected as baseline comparison algorithms. Figure 3 shows the performance comparison results of different new media user churn prediction methods on the validation dataset. Among them, the method proposed in this article adopts the experimental setup of scheme 4, which divides the new media user group through new media user portraits, and deploys C-ATT-LSTM models for churn prediction for each new media user cluster group separately.

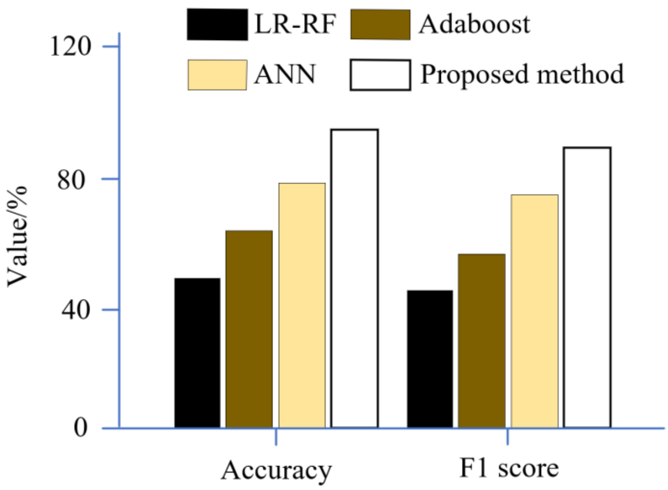

Figure 3: Prediction performance of new media user churn using different methods

According to the results in Figure 3, the ANN method has the ability to learn complex nonlinear relationships, but it is prone to overfitting in small sample data scenarios. The GP Adaboost method has better predictive performance than a single classifier, but it is more sensitive to outliers in the data and easily affected by interference, which can affect the prediction accuracy. The poor predictive performance of LR-RF method is mainly due to its insufficient fitting ability to nonlinear data and the tendency to overfit. The method proposed in this article combines the advantages of the new media user portrait segmentation model and the C-ATT-LSTM model, fully utilizing the unsupervised learning characteristics of the new media user portrait segmentation model to mine the inherent distribution features of the data. At the same time, the C-ATT-LSTM model mechanism captures and assigns weights to key features, effectively improving the predictive performance and generalization ability of the model while retaining the original structural information of the data. All performance indicators are superior to other comparative methods.

Conversion rate is a core evaluation indicator in the field of online marketing and promotion, with an average conversion rate of about 2% to 3% for online stores. Table 6 shows the conversion rates of new media users corresponding to different experimental schemes.

Table 6: Conversion Rate Results

	C-1	C-1-N	C-2	C-2-N
Option 1	3.76%	1031	2.86%	99643
Option 2	7.25%	1943	2.07%	76430
Option 3	5.68%	864	3.03%	58081
Option 4	13.69%	978	2.41%	76328

According to the data in Table 6, the C-1 conversion rates of Scheme 1 to Scheme 3 are 3.76%, 7.25%, and 5.68%, respectively, all of which are higher than the industry benchmark range; The corresponding C-2 conversion rates are 2.86%, 2.07%, and 3.03%, which are basically in line with the industry's conventional level, indicating that conventional marketing can only maintain basic conversions, and coupon placement can effectively drive conversion improvement. The C-1 conversion rate of Scheme 4 reached 13.69%, far exceeding the other three schemes. From the perspective of the rationality of the distribution of conversation sample size, both C-1 and C-2 have sufficient sample support to ensure the reliability of the results, and the conversion rate of 2.41% in the control group of Scheme 4 is still within the normal range of the industry. In summary, the conversion rate of the C-1 group who received coupons from various schemes was significantly higher than that of the C-2 group who did not receive coupons. The precision marketing promotion system proposed in this article had the best effect, effectively verifying the effectiveness and practicality of the strategy in new media marketing scenarios.

Assuming that the benchmark sales revenue without coupon distribution is 100, the sales revenue after coupon distribution is quantitatively estimated based on the proportion of new media users who receive coupons and the discount rate. The estimated changes in sales revenue for each scheme are detailed in Table 7.

Table 7: Estimated Sales Growth Results

	Coupon distribution rate	Growth rate of conversion rate	estimated sales
Option 1	1.07%	25.53%	100.05
Option 2	2.17%	185.64%	105.65
Option 3	0.68%	60.73%	100.61
Option 4	1.20%	387.57%	105.57

According to the data in Table 7, Scheme 1 has a distribution rate of 1.07%, a conversion rate growth rate of 25.53%, and an estimated sales revenue of only 100.05, indicating weak growth; The distribution rate of Plan 3 is only 0.68%, the conversion rate growth rate is 60.73%, and the sales revenue has increased to 100.61, with limited overall driving force. Option 2, with a high distribution rate of 2.17%, achieved a conversion rate growth of 185.64% and an estimated sales revenue of 105.65, the highest among all groups. The distribution rate of Scheme 4 in this article is moderate at 1.20%, with a conversion rate growth rate of up to 387.57% and an estimated sales revenue of 105.57%, which is close to Scheme 2. Comparison shows that all four schemes achieve positive returns, but there are significant differences in growth effects. Simply increasing the distribution rate is not the optimal path. The precision marketing strategy proposed in this article achieves significant revenue gains with lower advertising costs, verifying its superior input-output ratio and commercial application value.

6 Conclusion

This article focuses on the practical problems of incomplete construction of user profiles, insufficient accuracy in churn prediction, extensive coupon delivery, and low marketing conversion rates in the context of new media. A new media user profile construction and precision marketing strategy based on the C-ATT-LSTM model is proposed: (1) From the three dimensions of basic attributes, behavioral attributes, and statistical attributes, a new media user profile system covering multi-dimensional features such as user registration information, viewing behavior, interaction frequency, consumption preferences, and active time periods is constructed to compensate for the shortcomings of traditional RFM models, which have a single dimension and are difficult to depict users' true preferences, providing data support for user stratification and accurate identification. (2) Propose a C-ATT-LSTM model that integrates convolution, attention mechanisms, and long short-term memory networks. Utilize CNN to extract high-dimensional local features, strengthen key feature weights through channel attention and spatial attention, and capture temporal dependencies of user behavior using LSTM to achieve accurate prediction of high-risk churn users; Combining SOM clustering to achieve user group segmentation, independently modeling different groups, effectively improving prediction stability and generalization ability. (3) Design a personalized recommendation mechanism that integrates collaborative filtering and content recommendation, targeting high churn risk users to push category matching coupons, forming a complete closed loop of "user profile churn prediction precise push".

This article provides a feasible technical solution for precision marketing on new media platforms. Subsequent research directions include: (1) introducing unstructured data such as live interaction, short video retention, social sharing, and cross platform behavior to enhance the integrity and dynamic updating ability of user profiles; (2) Optimize model lightweighting and real-time inference performance, reduce computational overhead, and improve the real-time performance and response speed of coupon push; (3) Taking into account indicators such as conversion rate, user retention, average order value, and marketing costs, construct a dynamic coupon strategy that balances efficiency and fairness; (4) Move the proposed framework to new media formats such as cross-border e-commerce, short video e-commerce, and private domain operations to form a more universal intelligent marketing solution.

About the Author

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