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Retraction

Retracted: Game User Preference Data Analysis and Market Guidance Based on Dynamic Attention GRU

Discrete Dynamics in Nature and Society

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] X. Yang, J. Bai, and X. Wang, "Game User Preference Data Analysis and Market Guidance Based on Dynamic Attention GRU," *Discrete Dynamics in Nature and Society*, vol. 2021, Article ID 5666405, 10 pages, 2021.

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Research Article

Game User Preference Data Analysis and Market Guidance Based on Dynamic Attention GRU

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With the development of Internet technology and social model, game products have become an important product of people's life for entertainment and recreation, and the precise marketing of game products has become a winning means for enterprises to improve competitiveness and reduce labor cost consumption, and major game companies are also paying more and more attention to the data-based marketing model. How to dig out the effective information from the existing market behavior data is a powerful means to implement precise marketing. Achieving precise positioning and marketing of gaming market is the guarantee of innovative development of game companies. For the research on the above problem, based on the SEMAS process of data mining, this paper proposes a mining model based on recurrent neural network, which is named as Dynamic Attention GRU (DAGRU) with multiple dynamic attention mechanisms, and evaluates it on two self-built data sets of user behavior samples. The results demonstrate that the mining method can effectively analyze and predict the player behavior goals. The game marketing system based on data mining can indeed provide more accurate and automated marketing services, which greatly reduces the cost investment under the traditional marketing model and achieves accurate targeting marketing services and has certain application value.

1. Introduction

With the development of the ever-changing network culture, the Internet infrastructure equipment is becoming more and more perfect, so it also brings the rapid growth of the Internet user scale. Benefiting from the development and perfection of the Internet infrastructure industry, Internet users have shown explosive growth, and the industrial industry of online games in China has been developed rapidly. At present, the scale of online game users shows a large-scale growth trend [1], and the online game players in China reached 0.67 billion in 2008, and by 2017, the scale of game player users in China had reached 538 million, of which the growth amount reached 27.17%.

China's online game became popular in the 1990s [2], and at the early stage of network development, its network users were small, so there were not many players. But with the popularity of Internet technology and the development of China's online game camping mechanism, the player users of China's online game have entered a high growth stage since 2003 [3]. Because online games have the characteristics of low investment and high return and other capital flow, the game market space is large, which attracts a lot of capital to enter, and at the same time, the marketing of online games has become an emerging industry to get the attention of many enterprises.

Taking Tencent Game Company and Netease Company as the research objects, it is not difficult to find that, in the game industry, Tencent Company and Netease Company have been in the leading development stage in the game market positioning, but with the development of China's game industry, the industry competition has become more and more intense, and the continuous emergence of high-quality games has made the game market complex and diverse. Therefore, with the different needs of players for games, the development of the game market has entered a slow period, so that the existing games of the game business can no longer effectively meet the needs of customers, and

the rapid emergence of new games will be the marketing atmosphere of the game market becoming tense; therefore, how to carry out accurate marketing of new games and classic games [4] is the key for game development companies to compete in the market.

In recent years, Internet-mediated marketing methods have emerged [5], and the traditional mode of TV advertising can no longer adapt to the rapid development of the game industry and the speed of game product change. Internet-mediated marketing methods mainly enter people's eyes with web ads, video ads, message pop-ups (QQ), etc., which can quickly attract users' attention. This has a more detailed targeting and success rate than the traditional advertising mode which is directed to all TV users. However, there are still some disadvantages of this marketing model, such as high cost and low return rate for users in terms of corporate profits, and unfavorable effects in terms of user perceptions with pop-up advertising. In order to implement more accurate advertising and marketing strategies, various representative game operating companies have started to seek more accurate marketing models.

Game companies analyze the customer behaviors of existing marketing successes [6], so as to discover the patterns and then develop more optimal marketing strategies to meet different user needs. However, with the massive increase of online users and behavioral data, the traditional statistical methods for player behavior information mining are no longer sufficient to meet the needs of the game industry operation model. Therefore, it gradually evolved to adopt data mining algorithms to explore users' consumption behaviors. This model was initially adopted and developed in the telecom industry. Data mining-based customer churn prediction accurately predicts if and when potential customers will churn. With this knowledge [7], marketers can gain significant benefits and implement actions to prevent churn, such as personalized promotions or excellent service updates.

Churn prediction models are combined with churn prevention activities to significantly increase sales, business benefits, and growth. In the field of game, with the increasing number of game types and users, to recommend a new game to its potential customers is a guarantee that the new game of the same company will be promoted and developed [8]. Similarly, when recommending a game that a user does not like to that user, it will bring great damage to the user's experience. At present, in the booming game market, the traditional game marketing methods have encountered a bottleneck, and how to quickly and precisely locate the user population to reduce the effect of high cost and low return brought by traditional marketing is an important research direction to realize game precision marketing based on data mining methods at present [9].

The purpose of precision marketing in game market is to continuously optimize the resource allocation, improve the cost return of advertising investment, continuously improve the accuracy of discovering new users and recommending new games, and improve the reliability of data mining applied to game market for precision marketing. Based on this, the main focus of this paper is to improve the accuracy rate of game marketing and automate the marketing data mining by marketers. The main purpose is to enhance the market competitiveness of enterprises.

2. Related Work

Internet technology was developed in foreign countries. Therefore, the research field of data mining-based marketing model has been well developed in foreign countries.

The famous 4P marketing theory was proposed around the 1960s [10]. In 1990, the American scholar Robert Lauterborn proposed the 4C theory. 4C theory also focuses on the consumer as the core of the precision targeting marketing model. Later, as the amount of data studied by marketing theory gradually increased, a marketing system with data mining as the core model began to take shape. An article on precision marketing published by [11] points out that data relevance has an impact on precision marketing. This author explains how to go about finding and discovering correlations between two different things and then outlines its application in the precision marketing process. For the first time in his own academic research, Alexandru [12] places his marketing research on businesses in the context of the mobile Internet, and by automating the processing and analysis of user data, he proposes a corporate marketing concept of precision marketing with the help of Internet devices.

In his theory, he proposed the precise targeting of audience groups and the dissemination of precise marketing messages, so as to achieve the dissemination of corporate culture and branding. In [13], while studying the problem of precision marketing, the authors proposed and constructed a decision framework for precision marketing in which each operator can input the potential characteristics of different categories of customers in order to provide precise marketing services to the corresponding companies. Pedram et al. [14] conducted an overview of the tobacco industry, while reviewing the tobacco industry's adoption of new technological tools such as data mining, data warehousing, and other key data mining techniques such as clustering and correlation to improve the sales performance of tobacco, and this mining method greatly improves the level of precision marketing and the competitiveness of enterprises. Coffman et al. [15] proposed a method to construct several very simple traditional algorithmic models using very limited user information and then fuse the prediction results of each model to output, with the goal of quickly screening a portion of potential users with high activity for precise marketing of game products within the range of ten million users, so as to improve the download rate and usage of game products. Barbar et al. [16] studied the dilemma and countermeasures of enterprise precision marketing. The study summarized and analyzed the current situation of precision marketing of exhibition enterprises based on data mining and formed certain ideas and new models by drawing on the experience of some developed exhibition enterprises, which can bring important support to carve user portraits and provide precision marketing strategies for enterprises by using data seizure, management, and analysis to summarize the laws.

In [17] data mining technology was also used to realize the mining and analysis of marketing system and electricity consumption analysis and collection system. The authors conducted relevant experiments based on the data of electric power companies and the experimental results can be obtained where the data mining method for abnormal data detection has a higher accuracy rate, which is much higher than the manual implementation. Staton et al. [18] applied big data technology to e-commerce enterprise marketing and conducted a systematic analysis of relevant marketing methods and patterns, and the conclusions drawn from the paper show that the feasibility of applying big data technology is combined with data mining methods in enterprise marketing.

Complementary tools and comprehensive analysis services are specifically for game data mining or user behavior analysis [19, 20]. However, game-specific data marketing mining tools are still in their infancy.

3. Overview of Game Marketing Theory

3.1. Game Marketing Scenario Analysis. At present, there are various kinds of online games, and their profit models are just two kinds: one is the paid game; the profit model of this game is mainly the player through the purchase of game rights to make profits. The other is the free game with virtual product fee; with this type of game any player can get the right to experience the game, but the game manufacturers sell the virtual products in the game to obtain profits [21, 22].

At present, the market is dominated by free-to-play games, and their profit model is abstracted as CSP model, which is also the main product feature studied in this paper. The marketing of this type of game currently contains the following marketing modes: positioning marketing, advertising marketing, cultural marketing, and event marketing, which are shown in Figure 1. The latter three marketing modes are summarized as the comprehensive marketing mode with large investment. This comprehensive marketing model is mainly based on advertising marketing, which mainly means that when users browse the relevant content online, the advertising window of the relevant game pops up to attract users' attention. This kind of forced advertising and marketing mode will often make users rebellious. It will bring a negative impact on the image of the game product.

The advertising and marketing model in the picture is the mainstream game marketing scenario at present, the first step of which is to invest a lot in advertising for the game business, and the audience is wider at this time. Players who feel interested can click the relevant link to enter the game for registration and login. So far, this is the come to stage of CSP mode. However, marketing in this way often requires large capital investment, and the forced advertising plants often bring negative effects to the promotion of the product. Therefore, this stage is replaced by data mining methods. Finally, the players who stay in the game will choose whether to spend according to their own situation. This is the ultimate goal of game marketing, which is to stimulate game players to spend [23].

However, with the development of computer technology [24], the targeting marketing mode based on data statistics has become the mainstream marketing mode. That is, instead of investing a lot of money in advertising, this marketing model will predict what game the user may want to play in the future according to the user's habits and then carry out precise game promotion.

3.2. The Use of Data Mining Methods in Precision Marketing. According to CSP game model [25], a precise game marketing model is one that can predict in the first step. The main reasons for data mining application owners to use data mining are as follows: too much data and not enough information needed to extract useful information from the data and interpret that data.

4. Construction and Implementation of Mining Models

Combined with the characteristics of the data to be mined in this experiment, an algorithmic model with a composite structure is used to accomplish the target label classification task. The input of this experiment is time series data features, so the correlation between some data features is difficult to be distinguished by single-layer GRU network only. Traditional data mining methods usually use feature filtering according to preprocessing methods. For example, correlation analysis is performed on whether a player is about to achieve virtual spending behavior with the frequency of playing games and the amount of money played by that player, and then that familiar feature data that best reflects the player's behavior is selected [26]. Therefore, the traditional method has the need of compromising information integrity in correlation calculation and feature processing, and although the data feature attribute analysis can select the most effective feature dimension to predict the player's behavioral goals to a certain extent, the attribute analysis of goals often ignores the correlation between individual information features. Based on this, a simpler and more reliable mining model structure is proposed, which is a neural network mining model based on dynamic attention mechanism. The model structure of the model is shown in Figure 2, and the construction process of the mining model in this paper is outlined in layers next.

Input layer: This layer is the input interface for the model. In order to run the DAGRU mining model robustly and effectively, the input data of the experiment are processed in advance with features, i.e., high-dimensional data that can reflect the characteristics of the data after normalization. Assuming that the input dimension of the data is n, the input data of the sample at a certain time period can be expressed as x_i.

GRU feature extraction layer: The input to this layer is the input data of the input layer; assuming that the input sequence data is $X = [x_0, x_1, x_2, \ldots, x_n]$, then the data feature extraction process of GRU can be expressed as follows:

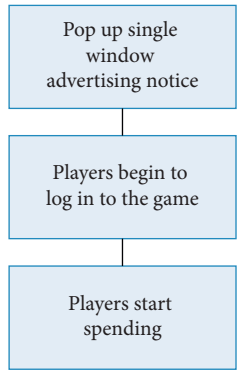

Figure 1: Free game marketing model process.

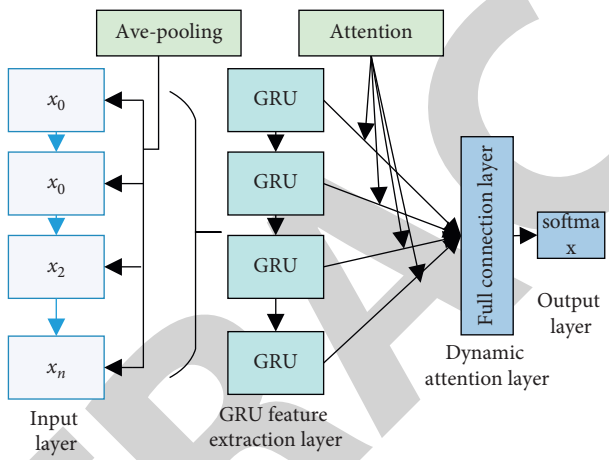

Figure 2: Structure of DAGRU model.

$$h_i = \mathrm{GRU}(X_i), \tag{1}$$

h_i is the result of the input data X after the GRU neural network layer feature processing. The output data after this layer is more reflective of the obvious relationship between data features and labels, and the output of this layer is used as the input of the next layer of the network model in order to be able to find out the implicit relationship between the target attribute features.

Dynamic attention layer: Attention mechanism is introduced in this layer in order to be able to identify the characteristic data that effectively respond to the behavioral target. The traditional attention mechanism is a model that simulates the human brain's ability to maintain attention to a specific thing in a specific context, which essentially reflects the rational allocation of human brain resources. The attention mechanism was first applied to tasks related to computer vision and has proven its effectiveness and achieved significant results. In layman's terms, the attention mechanism serves to deepen attention to what is important. However, in this paper, the experimental data are to respond to the correlation between data features to predict the player's behavioral goals. Therefore, the attention mechanism with dynamic planning characteristics is proposed to pay attention to the attribute features.

First, by averaging the feature pooling process for each column of feature data of the input data, the purpose of the average pooling process is to first determine the correlation between two attributes. These fully connected pooled data features are then used as input to the attention mechanism to derive the attention matrix. Suppose the input data $X = [x_0, x_1, x_2, \ldots, x_n]$, whose equation response is as follows:

$$\begin{aligned} g_m &= \mathrm{fatten}\left(\mathrm{ave}\left(x_i, x_j\right)\right), \\ \alpha_i &= \frac{\exp\left(\mathrm{score}\left(\overline{g}, g_i\right)\right)}{\sum \exp\left(\mathrm{score}\left(\overline{g}, g_j\right)\right)}, \end{aligned} \tag{2}$$

where g_i is the result of averaging pools performed for each column of feature attributes, which, after full concatenation, constitute the input to the attention mechanism, g is a vector of input data feature representations one level higher than the word and is initialized randomly at the beginning, and $\mathrm{score}(\overline{h}, h_i)$ is calculated using the following:

$$\mathrm{score}\left(\overline{h}, h_i\right) = w^T * \tanh\left(W\overline{h} + Uh_i + b\right), \tag{3}$$

where W, U are the weight matrices, initialized within the neural network and trained with the appropriate weight

values, and b is the bias. After the attention layer, the input classifiers are low-dimensional feature matrices, which are represented as follows:

$$V = \sum_{i=0}^{t} \alpha_i * \mathbf{g}_i. \tag{4}$$

Output layer: The input of this layer is the matrix of feature matrices after the attention mechanism, which is v, and softmax function is the function used to handle the multiclassification task. Among them, the softmax function is formulated as follows:

$$a_j^L = \frac{e^{z(L/k)}}{\sum_k e^{z(L/k)}}, \tag{5}$$

where z_j^l denotes the input of the jth neuron of the last layer, a_j^l denotes the output of the jth neuron of the LSTM neural network layer, and e denotes the natural constant. $\sum_k e^{z(L/k)}$ represents the sum of the inputs of all neurons in the last layer. Therefore, the output of this layer is

$$y = \text{soft max}\left(w_v.v + b_v\right), \tag{6}$$

where softmax is the normalized exponential function mostly used in multiclassification problems, V is the feature vector of the input classifier, and y is the final output category label.

5. Experimental Data Set

5.1. Experimental Data Set Acquisition. In order to be able to obtain the experimental simulation data set [27], this paper uses python to write a web crawler or a data set interface for the game League of Legends which is a network with the following interface: http://api.xxe.io/?resource=event&fusc=match&event_id=1.

The phantomjs headless browser is used to simulate the crawler's continuous work in the browser. The python function to call the phantomjs headless browser uses webdriver, and the code to implement it is shown below:

```
fro m selenium import webdriver
driverwebdriver.PhantomJS
(executable_path = r"phantomjs -2.1.1-windows\bin
\phantomjs.exe")
```

Using this data we can only get some anonymous game data of the players, such as the win rate and number of games played, etc. In order to get more behavioral data, part of the open source data set was obtained by contacting the game formula. Then we do some preprocessing of the data set, such as removing null values, removing useless data, and finally integrating all the obtained data that is turned into the data set that can be used in this experiment.

5.2. Description of the Experimental Data Set. Taking "League of Legends," a free online game promoted by Tencent, as the research object, we first use the player behavior features with time series as the data set for the training of the mining model when conducting whether players will play the game. The player's feature data and the label data of the mining model mainly come from two different adjacent time domains, so that the data set can be constructed to abstract the marketing problem into a prediction problem that can be solved by the algorithmic model [28, 29].

In mining whether a web player is a potential player of the League of Legends, whether is used as a label for the player behavior data. But on the final output, the output predicts the probability of that dichotomous label as the probability of that player's next time period and time series data set construction as shown in Figure 3. Among them, the player's web behavior log contains information about the basic characteristics of the player, such as Internet user ID, age, gender, etc. This basic information can reflect whether the player is a basic population playing online games; if the age is between 18 and 35 years, then this feature can be obviously expressed as the web user may be a potential population of League of Legends game; if the age of the web user is 70 years, obviously the web user is not necessary for the promotion of this game. In addition to the above basic characteristics, the web user's recent web browsing and time spent online are also collected in the web behavior log. All these basic features can reflect the characteristics of potential game players. The types of games played by some players in the recent period and the time spent playing and spending are collected.

In the prediction of whether the game player will spend, the data set is built based on the player who has played the game, the main characteristics of the collected player data such as level: the game level indicates the player's love of the game; the higher level indicates that the player has played the game for more time and with experience; average score: the player's score in each game indirectly indicates the player's proficiency in the game; the more skilled the player is at the game, the more likely the player is to spend money; the number of games per day: since League of Legends is a match game, the number of times the player plays each day can also indicate the player's love for the game, which can also best tell whether the player has the desire to spend money on the game; money, player gender, age, free virtual prop shopping data, the number of friends in the station [30], the total number of logins, and a series of game behavior characteristics. The form of data characteristics is shown in Figure 4.

In the next data description, the data set that predicts whether a player plays the game next is referred to as the data set, and the data set that predicts whether a player makes a game purchase is referred to as the data set.

6. Experimental Data Set Construction

Data set of a negative sample construction: In order to be able to effectively train the model, a negative sample will be constructed for the data set after the collection of a valid data set. The construction process is as follows: the data set is mainly used to predict whether the network players will play the League of Legends game; i.e., the initial construction of the data set is to collect their

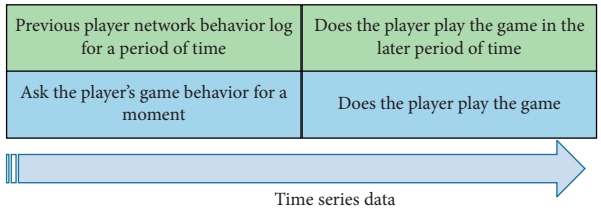

Figure 3: Time series data set construction.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	渠道名称	是否付费	性别	年龄	登录天数	登录次数	经验值	身上货币量	比赛最高输	比赛输出	登录总次数	站内好友数	经验值	游戏次数	赢局数	输局数
2	渠道B	否	男	39	5天以上	61-100次	2.1E+09	403237	151268700	11264000	4	1	4023	1792	270	1522
3	渠道E	否	男	50	5天以上	51至60次	8000	20000	2774724	939132	4	0	1010	289	79	210
4	渠道G	否	男	38	6天以上	31至40次	303023394	532722	131950000	10280000	5	3	2898	2334	379	1955
5	渠道G	否	男	53	3天	31至40次	50606	10605	7211504	2040000	5	1	2374	926	135	791
6	渠道K	否	女	28	3天	31至40次	4000	54000	1.529E+09	248700000	5	1	4097	4710	1558	3151
7	渠道E	否	女	37	5天以上	31至40次	8043211	236456	392813	160528	5	1	1467	651	113	538
8	渠道I	否	女	49	3天	31至40次	3174485	16948	16390	5621	5	0	1115	169	21	122
9	渠道E	是	男	52	5天以上	51至60次	17581452	24864	32296	16722	4	1	1641	363	103	260
10	渠道K	是	女	31	5天以上	31至40次	4350	42350	8982778	2691000	5	0	1791	678	149	529
11	渠道E	是	男	42	5天以上	31至40次	34022340	47577	572931	189594	4	1	2590	1396	312	1084
12	渠道E	是	男	37	3天	31至40次	2.78E+09	5749607	1.36E+09	219700000	4	1	1931	659	192	467
13	渠道K	是	男	30	2天	61-100次	312717876	98138	106138	28020	5	5	1685	367	118	249
14	渠道B	否	女	23	5天以上	31至40次	1000	50	107434	40100	4	1	915	123	36	87
15	渠道M	否	男	32	3天	31至40次	1.582E+09	160	21929664	5244000	5	5	2032	679	106	563
16	渠道D	是	男	40	2天	31至40次	1.493E+09	1407490	4319570	998500	6	8	3030	1063	240	797
17	渠道P	否	男	34	1天	31至40次	2643473	9600	10651600	2303000	4	3	1440	494	119	375
18	渠道F	否	男	25	5天以上	51至60次	4480	3620	45708	18950	5	3	1465	267	67	200
19	渠道H	否	男	32	5天以上	31至40次	92473540	160184	167984	46450	5	0	1794	365	82	283
20	渠道M	否	男	38	5天以上	31至40次	8000	3050	26330157	7266001	6	11	2318	1034	116	916
21	渠道E	是	女	43	5天以上	51至60次	1284733	539100	2018915	557000	6	5	2505	669	249	418
22	渠道K	是	男	40	5天以上	31至40次	1800	1800	137799	32000	4	3	1774	620	107	513
23	渠道I	否	女	54	3天	31至40次	515161	1465	470067	289500	6	1	1084	239	93	141
24	渠道F	否	男	35	3天	2至10次	2046775	33722	25921	1470	5	3	2742	364	78	217
25	渠道P	否	男	43	5天以上	31至40次	2.595E+09	2065412	161220641	20160000	5	0	3697	3636	396	3240

Figure 4: Player behavior consumption data set display.

network logs through the existing user player IDs, who have all started to experience the game at some time. Therefore, players who downloaded the game client but did not actually play the game through a certain advertising input of League of Legends were used as one of the negative samples, and in order to reflect the expensiveness of the data, this experiment additionally found other random web users as the negative sample data of this data set.

Data set partitioning: With experimental data set construction process as shown in Figure 5, after the complete data construction, a total of 45600 samples were obtained, among which 23400 samples indicated whether the players consumed the game or not, and the rest were all data samples of whether the players played the game or not. In order to reasonably train the model and evaluate the training effect of the proposed model, the random segmentation function of python is used to divide the training and testing samples. The random split function is train_test_split; it randomizes the data into training set and test set. A 35% data set is set as the test data set. The core code is shown below:

Train_data, test_data,label_train_data, label_test_data = train_test_split (nor_data,la.

bel,test_size = 0.35)

Results of the final dataset assignment for training and testing

7. Experimental Structure and Analysis

7.1. Achievement of Evaluation Indicators. In this experiment, a unified evaluation criterion is used for the evaluation index of the prediction results, which are accurate, F value, and the recall rate; the specific formula is expressed as follows:

$$\begin{aligned} \text{precision} &= \frac{\text{TP}}{\text{TP} + \text{FP}}, \\ \text{recall} &= \frac{\text{TP}}{\text{TP} + \text{FN}}, \\ F - \text{score} &= \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}, \end{aligned} \tag{7}$$

where TP denotes the number of correctly detected positive relational instances, FP denotes the number of negative relational instances predicted to be positive by the model, and FN denotes the number of positive instances not detected by the model. Precision represents the number of positive samples actually classified into positive instances in the classification task, recall represents the number of correctly determined positive instances among the total positive instances, and F is the summed average of recall and precision that reflects the performance of the classification model in general.

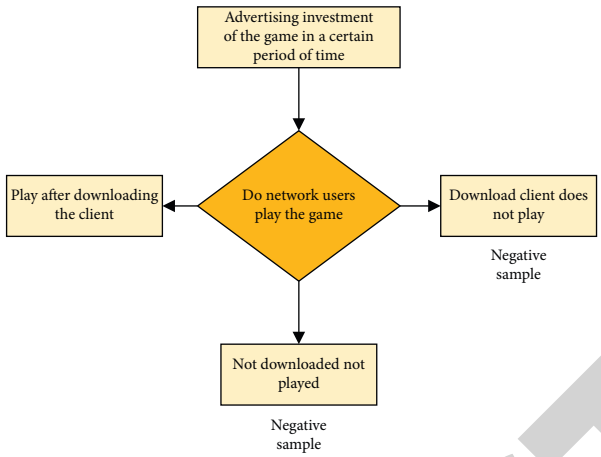

Figure 5: Experimental data set construction process.

7.2. Analysis of the Results of Experiments on Whether or Not Players Conduct Game Experience. The constructed model is used in the task of predicting whether the player will play the game or not, and the results are evaluated by building the skeleton library to automatically produce the evaluation functions of P, R, F. The functions are shown below:

P = thresholds, R = precision_recall_curve (y_testset, svmNN.predict (x_testset));

The results of P, R, F can be obtained as shown in Table 1.

The accuracy of the DAGRU model on the training set is 0.7939, while the accuracy of the test set is 0.7989, indicating that the SVM model does not overfit the text data. To further evaluate the performance of this mining model, the ROC curve of this DAGRU on the test set is drawn. The ROC curve is an evaluation criterion adapted to the dichotomous classification task, with the sensitivity metric as the vertical coordinate data value. Its false positive indicator is plotted as the horizontal coordinate or a combination of both. This ROC curve is highly sensitive to dichotomous classification problems. It tends to be that the curve has a bow shape, and the fuller its bow curve is, the better the classification of this model method is. The area enclosed by its bow is called AUC, which is a numerical representation used as a comprehensive measure for this dichotomous classification task. Figure 6 demonstrates the ROC curve of DAGRU on the test set: From the figure, it can be seen that DAGRU is able to have a good classification ability on the data.

In order to further measure the ability of the proposed mining model to effectively predict player behavior, the feasibility of the metrics is analyzed by further developing a P-R plot. A good result for both of them indicates that the model is well suited for the classification task of this data set. The P-R diagram is shown in Figure 7.

Therefore, the analysis of the results shows that the proposed method does have some reliability in mining the question of whether players perform the experience of this game or not. In order to compare the superiority of the method, this data set was used to predict the classification results using the decision tree method, and the comparison of the results is shown in Table 2.

From the results in the table, it can be seen that the F value of player behavior mining using the deep learning approach has a significant improvement of about 4% over the decision tree approach. Therefore, it can be concluded that this implementation of customer behavior goal prediction using the proposed deep learning based method has some realistic value.

8. Analysis of the Results of the Experiment on Whether Players Conduct Virtual Consumption

The algorithmic model is tested by the first problem, and the approach constructed in this paper is applied to the paper's final goal of the research: whether the game player will make virtual consumption in the process of free game experience when an event comes; the constructed training data set of whether the player makes virtual consumption is iterated on the DAGRU network model, and the model is initially judged whether the model is outfitted by observing the value of the loss function, and it is found that, after 10 iterations, the loss function decreases slowly, and the number of times the model is trained is determined. The loss function is binary_crossentropy; the optimization function is ameba function, where the model training adopts adaptive learning rate, and the input batch is 200; finally, the accuracy of the training set is 0.903, and the accuracy of the test set is 0.926. The "yes" means that the player will make virtual consumption after a period of time, while the "no" means that the player will not make consumption after a period of time, and the P, R, F of the test set are as shown in Table 3.

From Table 3 and Figure 7 of experimental results, it can be concluded that the neural network model based on dynamic attention mechanism has better implementation results in mining the problem of player's consumption behavior. It has high accuracy compared to the problem prediction of whether a player performs a game experience using this model. It may also be that the base model constructed with a strong data set of behavioral features of customer data is more capable of accurately mining the behavioral goals of users.

Table 1: Results of whether or not the player conducts the game experience.

	Precision (P)	Recall (R)	f_score (F)
No	0.8356	0.9303	0.8804
Yes	0.9236	0.8514	0.8696
Average results	0.880	0.8759	0.875

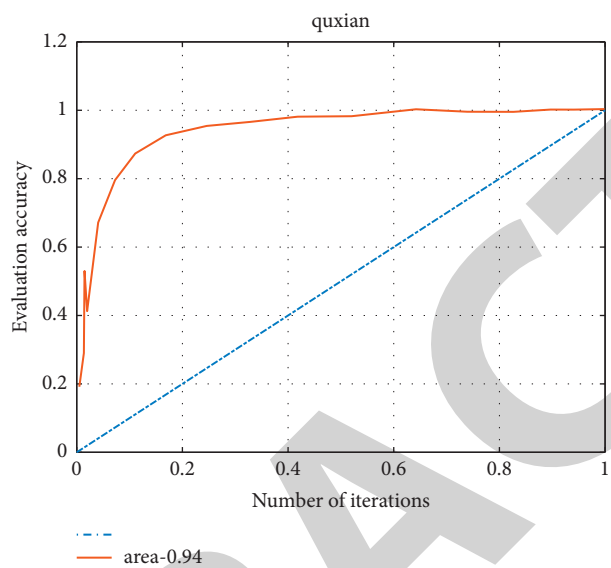

Figure 6: ROC graph.

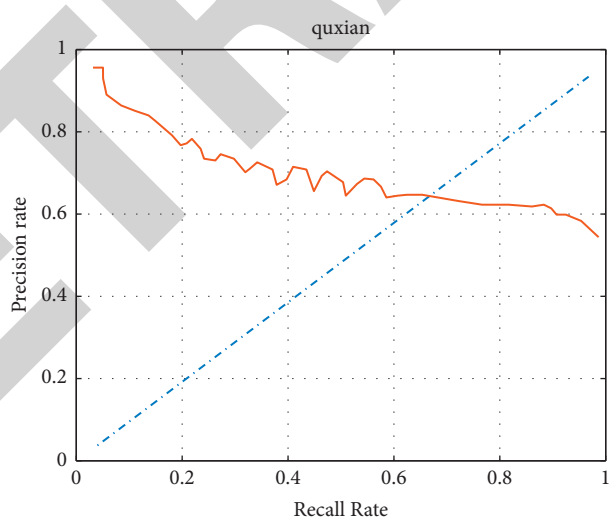

Figure 7: R-P curve.

Table 2: Results of whether or not players perform game mining.

Model	P	R	F
DAGRU	0.8801	0.8752	0.8709
Decision tree	0.8202	0.8673	0.8468

Table 3: DAGRU model player consumption forecast results table.

	Precision (P)	Recall (R)	f_score (F)
No	0.8087	0.9579	0.8770
Yes	0.9499	0.7790	0.8560

9. Conclusions

With the development of Internet technology and social model, game products are becoming an important product of people's life for entertainment and recreation day by day. The precise marketing of game products has become a winning means for enterprises to improve competitiveness and reduce labor cost consumption, and major game companies are increasingly focusing on data-based marketing model. In this paper, a mining model based on a recurrent neural network is proposed and evaluated on two self-built data sets of user behavior samples. The results show that the mining method proposed in this paper can effectively analyze and predict the player behavior goals. The implemented system is tested and the system meets the system requirements in the field of software engineering with certain security and applicability. The game marketing system based on data mining can indeed provide more accurate and automated marketing services, greatly reduce the cost investment under the traditional marketing model, achieve accurate targeting marketing services, and has certain application value.

Data Availability

The data set used in this paper is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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