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A Location–Time-Aware Factorization Machine Based on Fuzzy Set Theory for Game Perception

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Abstract: Game user perception is of great significance for game developers and network operators for improving service quality and operational efficiency. At present, the most common approach is to use the linear model that considers only the impact of network factors evaluation on user perception. The interpretation process is complex and useful, but invisible feature interaction data are not taken into account. As a result, user perception evaluation can only be interpreted by experienced experts, which is both time-consuming and laborious. In this paper, aiming at the shortcomings of existing algorithms, a location–time-aware factorization machine model (LTFM) is proposed by exploiting the location projection and time projection of users and services and fuzzy set theory. Our proposed LTFM can be decomposed into two parts: first, an original game quality of experience (QoE) dataset is extended. LTFM uses location and time information to map to latent vectors, which increases the number of records in each game data, involving no additional information. Then, LTFM utilizes fuzzy set theory to strengthen the positive feature interactions and reduce the negative feature interactions. The factorization machine is used to mine a number of potential features in the user's invoking service behavior. The multiplayer online battle arena (MOBA) game perception dataset is obtained with reference to the ITU-T standard to verify the advanced nature of the proposed model. Experimental results show that LTFM outperforms existing algorithms in terms of prediction accuracy and model interpretability. Not only can accurate user experience quality categories be produced, but also the impact of individual characteristics and their feature interactions can be explained, which helps operators to make better optimization decisions.

Keywords: machine learning; game perception; QoE; factorization machine

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1. Introduction

Game user perception is a hot topic in user perception [1,2], which aims to predict the difference in user perception evaluation under different game services and user characteristics. In order to provide better game services to players, game developers and network engineers strive to improve the quality of game software and network infrastructure, respectively. Among the many tasks where perceptual data may be applied, it is particularly important to capture hidden connections between game user perception evaluation data from similar combinations of service and user characteristics. Therefore, we need to obtain a model that can systematically, efficiently, and reliably measure game quality in a given environment.

Game user perception assessment is essentially a classification problem. With the help of an in-perception assessment model, user perception can be classified into different perception levels. Operators can make different optimization decisions for different levels based on the perception scoring results. The corresponding maintenance of network equipment or broadband upgrade, etc., improves the user experience.

Realistic data characteristics are mostly sparse, and the performance fluctuations of the model have to be taken into account. A new location–time-aware factorization machine model (LTFM) model based on fuzzy set theory is proposed to overcome the problems of existing algorithms. First, LTFM uses location projections and time projections to increase the number of records for services in each game without introducing additional information, thus alleviating sparse data. Then, LTFM uses fuzzy set theory to reinforce the positive feature interactions and reduce the negative feature interactions to overcome the challenge of performance fluctuations. The main contributions of this paper are summarized as threefold:

1. We use location projection and time projection to extend a QoE dataset, which can mitigate sparse data. The method increases the number of records of services by projecting to the location vector and time vector directions of users and services. There is no additional information introduced into the method while extending the game QoE dataset.
2. We construct a similarity calculation based on fuzzy set theory to ensure the robustness of LTFM. A membership module is introduced to enhance the positive feature interactions and reduce the negative feature interactions, ensuring robustness.
3. We conduct several experiments on a real QoE dataset derived from experiments set up according to the ITU-T standard to evaluate the performance of the LTFM. The experimental results show that our proposed LTFM exhibits good performance, which performs better than existing methods in the accuracy and robustness of game QoE prediction.

The structure of this study is as follows: Section 2 summarizes the literature relevant to this study. Section 3 proposes the framework of LTFM in detail. Section 4 reports the method performance and makes our discussion. Section 5 concludes this study.

2. Related Work

In the field of user experience, most of the related work on game user perception focuses on the impact of traditional service quality parameters on subjective user-perceived quality [3–5]. Traditional data-driven models use linear models to generate user game perception scores such as logistic regression and linear regression models [6]. In recent years, most user perception prediction models have been predicted using machine learning techniques. For example, research uses nonlinear support vector machines for QoE modeling, which uses random forests to build prediction models [7], etc. These methods offer important advantages for effective user perception prediction. However, latent variable models [8] have shown that these machine learning models have not learned the potential but useful feature interactions well in the game QoE task dataset. Factorization machines (FM) [9] provide a predictor which can model and take feature interactions into account efficiently in linear time complexity.

At present, although FM has not been applied in the field of game perception, it has carried out a lot of research in the quality of services (QoS) prediction of network services. QoS prediction for network services only focuses on the impact of network parameters on QoS. Different from the service quality prediction of network services, game user perception not only pays attention to network parameters but also pays attention to the user's personal characteristics and the influence of service characteristics in the game on the end user's evaluation of experience quality. Their ultimate purpose is the same: to enhance the quality of service to improve user perception.

Wu et al. [10] first introduced a factorization machine into the quality-of-service prediction and proposed an EFMPred model by combining embedding techniques. Yang et al. [11] proposed an LBFM model by converting location information to neighborhood information in the factorization machine. Then Chen et al. [12] proposed the LANFM model, which added the location information to the factorization machine by one-hot encoding. Wang et al. [13] proposed an LDFM model which uses location projections to extend the record of database and information entropy to enhance valid features. In the case of low data volume as well as few features, these algorithms expand the dataset, adding features by combining features and performing well in the case of sparse data. However, the weights for different cross-features are the same, which will introduce noise and make the model choose a suboptimal solution. He et al. [14,15] proposed the AFM model, which used a neural network modification of FM and added an attention mechanism to assign different weights to the second-order combinations of different features. Subsequently, Hong et al. [16] proposed an IFM model by introducing an interaction-aware mechanism consisting of feature aspects and field aspects. While these algorithms improve the performance of the model by introducing an attention mechanism to obtain the weights of feature interactions, the training time increases significantly and consumes more computational cost.

In conclusion, game user perception based on machine learning is becoming an increasing research hotspot. Some research exists on linear user perception evaluation based on network parameters. However, there are some research gaps in the field of game user perception models that consider the nonlinear effects of multiple factors. On the one hand, linear models are restrictive. The factors in real life are not simply linear, and the data are mostly sparsely distributed, which requires further research on machine learning algorithms. On the other hand, existing research has only built models based on network parameters. The effects of other factors and interactions between features on perception are not considered. In summary, we refer to FM in the study. The existing FM has the same weight for different feature interactions, and the performance is improved after adding the attention mechanism, but it also consumes more resources. Thus, further research on combining feature data with building game user perception models needs to be conducted.

3. Problem Formulation and Algorithm

In this section, we present a data-driven game user perception evaluation problem. For this problem, a fuzzy set theory-based prediction is proposed to compute the similarity between feature interactions and final evaluation results. We then design an LTFM as the primary predictive model for game user perception valuation, where the fuzzy set theory-based similarity calculation is used as a weighting module.

3.1. Problem Description

In this work, the game user perception evaluation problem is described as a supervised machine learning model which aims to predict users' future game perception ratings using a diverse of real-valued features extracted from game-related dimensions. In our dataset, each game record uses an identifier number to distinguish it uniquely. The identifier is used to specify all relevant features in the data preprocessing step for each game and extract the features contained therein, as shown in Table 2 of Section 4.1.

The feature representation of the game played $i \in \{1, 2, \ldots, N\}$ is denoted as the real-valued feature vector $\mathbf{x}_i = \left\{x_1, x_2, \ldots, x_J\right\} \in \mathbb{R}^J$, where the total number of unique features is J. Each feature $\mathbf{x}_j = \left(x_{1j}, \ldots, x_{Nj}\right)^T$ belongs to only one of two categories: service or user features. Each game i has a label $y_i \in \mathbb{R}$ that represents its future user perception evaluation score. Let $\mathcal{H} = \{h : \mathbf{X} \to \mathbf{y}\}$ denote a hypothesis class, and $\mathcal{L} = (\cdot, \cdot)$ denote a loss function. The goal of the user game perception evaluation prediction problem is to find the best hypothesis $h_{best} \in \mathcal{H}$ with a given training dataset $\{\mathbf{x}_i, y_i\}_{i=1}^N$, which minimizes the expected empirical risk $\Pr(h) = \mathbb{E}[\mathcal{L}(h(\mathbf{X}, \mathbf{y}))]$. The following empirical risk minimization is a state-of-the-art approach, as shown in Equation (1).

$$h_{best} = \underset{h \in \mathcal{H}}{\text{argmin}} \Pr(h) = \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}(h(\mathbf{x}_i), y_i) \quad (1)$$

3.2. Location Information and Time Information

A research article [17] showed that if two users located in the same region have similar network conditions, then the experience which calls the same service in the same region is also similar. Other research [11,18] found that it is common for individual users and independent services to be located in two or more overlapping areas. Thus, user and service information are projected into the potential space [19] in the direction of its location vectors to generate new data. Figure 1 shows that User1, User2, and User3 are located in the same user region with similar location information, and the QoS values they invoke are also similar. Both S3 and S4 are located in service region two with a similar quality of service values. In practical scenarios, the environment and quality of the network are usually similar in terms of neighboring geographic locations, which plays an important role in the prediction of experience quality for different users. After the location projection, the number of records of users calling services and the number of users and services increase without introducing additional information. Thus, it is useful to take location information from users and services into account for game user perception evaluation prediction.

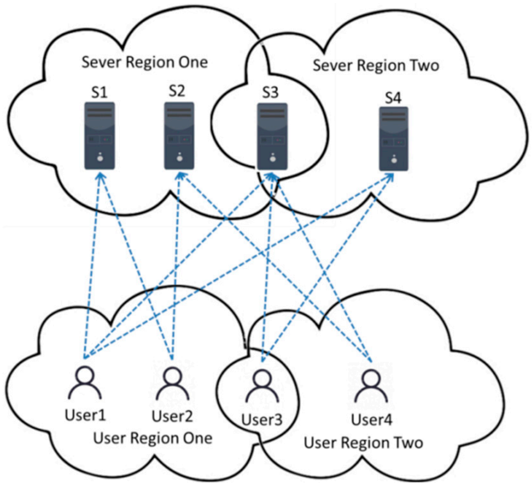


Figure 1. A real game service invocation scenario.

In real scenarios, the network is divided into idle time and busy time. These two concepts are relative. For example, busy time means that the network will be slower during the daytime when there are more people using or grabbing the network. The network speed will be faster during idle time. Different regions have different network usage habits, and the resulting idle time and busy time are also different. What we need to consider is that the basic network parameters (for players to enter the game during busy hours) are worse than those when they are idle, which will cause game users to perceive poorly. We need to understand the changes in user perception in different time periods, predict the user perception evaluation in different situations, and point out the direction for operators to choose optimization decisions to improve user perception. Our experiments are based on the Xinjiang University campus network. The time periods for teachers and students to access the Internet can be divided into four time periods, as shown in Table 1.

Table 1. Internet time allocation for teachers and students.

Time Period	Time Name
2:00–10:00	Idle time
10:00–14:00	Morning
14:00–20:00	Noon
20:00–2:00	Night

We chose to test in the latter three time periods, to be more instructive, and divided into three time periods in chronological order: morning, midday, and evening. However, the busy hours in these three time periods are 13:00–15:00, 19:00–21:00, and 24:00–2:00, respectively. These three busy hours are the time periods when teachers and students take their meals and breaks. They are two overlapping areas in the three time periods, so using the idea of location projections, each busy time is divided into two, and two new time periods are obtained for each. Combining user and time information to obtain new features, we find two new pieces of game data after time projections. Our experiments are tested based on the Xinjiang University campus network, and the default user location information is similar, so we integrate the projections of both the location information and time information of the service into the new service matrix. The above two ideas expand our dataset without introducing additional information. However, this aggravates the challenge posed by data sparsity.

3.3. Similarity Calculation

Game user perception is a multidimensional nonlinear problem. In actual experiments, we found that under similar network conditions, different players or other conditions may lead to different final user perceptions. The features of each instance and its corresponding label are represented as an association, which is considered a correlation [20,21], similarity, or likelihood distribution [22]. The relationship between each sample and its corresponding label can also be represented by the correlation. To address this issue, we introduce the fuzzy set theory, which uses a membership function to determine the similarity between data points and the centroid vector of each label.

In our work, the membership function is based on the similarity point of view, by the distance to the perfect sample-based similarity point of view [23]. We adopt a multidimensional Gaussian function as the membership function [24], which is widely used in many applications because of its simple form [25]. The multidimensional membership function in our proposed method is defined as:

$$u_{ij} = \exp\left(-\frac{\|x_{ij} - c_{ij}\|^2}{2\sigma^2}\right), i \in \{1, 2, \ldots, N\}, j \in \{1, 2, \ldots, L\} \quad (2)$$

where u_{ij} is the membership value and $0 \leq u_{ij} \leq 1$. Here σ is the dispersion of the radius, x_{ij} is the inner product value of the feature interaction and c_{ij} is the center vector of the corresponding label. The centroid vector c_{ij} is calculated as follows:

$$c_{ij} = \frac{1}{|q_j|} \sum_{q_j} x_i \quad (3)$$

where $q_j = \{x_i | x_i \in l_j\}$, l_j is the j-th label corresponding to the instance x_i, and $|q_j|$ is denoted as the element number of the set q_j. The membership function in Equation (2) is used to measure the similarity between the feature interaction and the centroid vector. If the sample value is close to the centroid vector, then its membership is higher. Conversely, its membership is lower the farther it is from the centroid vector.

3.4. LTFM Based on Fuzzy Set Theory

In this section, an LTFM model under the FM framework is proposed as a solution to the user game perception evaluation problem, as it has the advantage of capturing nonlinear feature interactions efficiently for sparse data. Unlike the standard FM model, LTFM takes the projection of location and time information into account. We construct an LTFM model that can effectively capture the projection information of location and time information as additional information without introducing additional information, and the similarity between feature interactions and labels obtained based on fuzzy set theory to improve the predictive strength of the model for user game perception valuation.

The structure of FM is shown in Equation (3). Inspired by this, our data will be encoded as $\mathbf{x} = [\mathbf{x}_{users}, \mathbf{x}_{services}]$. Each element of $\mathbf{x}_{users}$ represents a user, and each element of $\mathbf{x}_{new\ services}$ is a game service after time and location projections. The projection information of location and time information is integrated into the new service matrix, and the new data is represented as $\mathbf{x} = [\mathbf{x}_{users}, \mathbf{x}_{new\ services}]$, which is presented into the FM model's pairwise feature interaction module, as shown below.

$$y_{FM}(\mathbf{x},\Theta) = w_0 + \sum_{i=1}^{N} \mathbf{w}_i\mathbf{x}_i + \sum_{i=1}^{N}\sum_{j=1}^{N}\langle \mathbf{v}_i,\mathbf{v}_j\rangle \cdot \mathbf{x}_i\mathbf{x}_j \tag{4}$$

$$y_{new}(x) = \sum_{i=1}^{N}\sum_{j=1}^{N}\langle \mathbf{v}_i,\mathbf{v}_j\rangle \cdot \mathbf{x}_{users}\mathbf{x}_{new\ services} \tag{5}$$

At this point, the LTFM can be expressed as

$$\begin{aligned} y_{LTFM}(\mathbf{x};\Theta) &= \phi_{LTFM}(y|\mathbf{x},\Theta) \\ &= y_{FM}(\mathbf{x};\Theta) + y_{new}(\mathbf{x};\Theta) \\ &= w_0 + \mathbf{w}_{users}\cdot\mathbf{x}_{users} + \mathbf{w}_{services}\cdot\mathbf{x}_{services} \\ &+ \sum_{i=1}^{N}\sum_{j=1}^{N}\langle \mathbf{v}_i,\mathbf{v}_j\rangle \cdot \mathbf{x}_{users}\mathbf{x}_{services} + \sum_{i=1}^{N}\sum_{j=1}^{N}\langle \mathbf{v}_i,\mathbf{v}_j\rangle \cdot \mathbf{x}_{users}\mathbf{x}_{new\ services} \end{aligned} \tag{6}$$

where w_0 is the weight of the global bias, and $\mathbf{v}_i$ is the hidden vector of the i-th variable in $\mathbf{x}_{user}$. $\mathbf{v}_j$ is the hidden vector of the j-th variable in $\mathbf{x}_{services}$. $\langle \mathbf{v}_i,\mathbf{v}_j\rangle$ is the inner product of the hidden vectors of the user matrix and the service matrix. The inner product value can represent the pairwise interactions between the users and the services.

As introduced in the discussion in Section 3.3, feature interactions that are less predictable are given lower weights since they contribute less to the game perception evaluation. The lack of ability to distinguish the predicted strength of pairwise feature interactions may lead to additional computational resources and suboptimal predictions. It means that embeddings of less important feature interactions are ignored. Thus, the similarity between pairwise interaction features and labels is captured in the output weights to reformat the pairwise part of FM as follows.

$$\sum_{i=1}^{N}\sum_{j=1}^{N} u_{ij}\langle \mathbf{v}_i,\mathbf{v}_j\rangle \cdot \mathbf{x}_{users}\mathbf{x}_{services} \tag{7}$$

The calculation of u_{ij} is given in Equation (2), which considers the influence of the correlation between pairwise interaction features and labels on the predicted strength of the user's game perception evaluation. The same can be applied to new feature interactions.

Combined with the above description, the final network architecture of our LTFM algorithm is shown in Figure 2, which consists of three layers: the input layer, the middle layer, and the output layer.

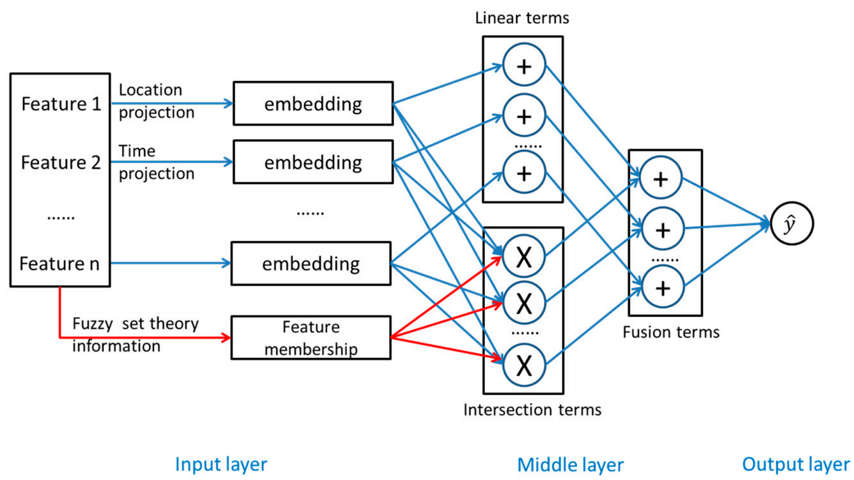


Figure 2. The network architecture of the proposed location-time-aware factorization machine (LTFM) based on fuzzy set theory.

The input layer: LTFM performs feature embedding based on the embedding matrix. Every feature is represented by dense vectors. It also can be seen as a fully connected layer, which implements array lookup. In the input layer, the key point is able to multiply the matrix fully. The inputs multiply with the weight matrix, which also takes the bias vector into consideration so that the spatial dimensionality and the projection of sparse to dense representations can be handled efficiently.

The middle layer: The model is inspired by the FM model. LTFM also needs to find how to represent the latent relationship in pairwise features which can be solved by the inner product. The set of pairwise feature interactions is represented as $\mathcal{P} = \left\{ \left(v_j, v_{j'} \right) x_j x_{j'} \middle| j, j' = 1, 2, \ldots J; j \neq j' \right\}$ depending only on the embedding matrix. The middle layer has listed the potential vectors in interactions. The input layer has given feature embedding vectors. Each latent vector is the product of previous embedding vectors. Therefore, we use the idea of using neural networks to design and build into this layer to roughly express the FM model.

The output layer: We compress all feature interactions based on distinguishing their importance in the embedding space. Then, we project them onto the final perceptual prediction scores. The predicted similarity of a paired feature interaction is calculated based on Equation (2). In conclusion, the LTFM proposed in this paper can be expressed as follows.

$$\begin{aligned} y_{LTFM}(\mathbf{x};\Theta) &= \phi_{LTFM}(y|\mathbf{x},\Theta) \\ &= w_0 + \mathbf{w}_{users} \cdot \mathbf{x}_{users} + \mathbf{w}_{services} \cdot \mathbf{x}_{services} \\ &+ \sum_{i=1}^{N}\sum_{j=1}^{N} u_{ij}\langle \mathbf{v}_i, \mathbf{v}_j \rangle \cdot \mathbf{x}_{users}\mathbf{x}_{services} + \sum_{i=1}^{N}\sum_{j=1}^{N} u_{ij}\langle \mathbf{v}_i, \mathbf{v}_j \rangle \cdot \mathbf{x}_{users}\mathbf{x}_{new\ services} \end{aligned} \tag{8}$$

In order to evaluate the parameters in Equation (8), the main method is to minimize the sum of losses on the observed dataset.

$$\min R_{LTFM}(\Theta) = \sum_{i=1}^{N} \mathcal{L}(\phi_{LTFM}(y_i|x_i,\Theta), y_i) + R(\Theta) \tag{9}$$

where $\mathcal{L}$ denotes the loss function and R denotes the regularization term on Θ, which is usually used to avoid overfitting. The overfitting problem cannot be ignored when optimizing machine learning models and FM models [26]. In this study, our regularization term is $R(\Theta) = \frac{1}{2}\|\theta\|^2$.

Neurons in paired interaction layers can easily cooperate with each other to adapt, which leads to overfitting. In this study, the LTFM model captures interactions that are predictive and useful. We control the regularization strength by the L2 regularization method and further prevent overfitting of the LTFM model by the dropout method on paired interaction layers [27]. The dropout method prevents the complex cooperative adaptation of neurons to the training data. The main idea is to randomly drop out some neurons along the connections during the training process. The dropout module is applied for model training when the entire network architecture is used for prediction and is disabled for testing. Dropout has the additional side effect of using smaller neural networks for averaging, which may improve performance. Therefore, the dropout method is used in the middle-paired interaction layer of the LTFM model to deal with the overfitting problem.

The complexity analysis of our proposed LTFM model has the following two points. First, the parameters of the feature embedding matrix $\mathbf{v} \in \mathbb{R}^{K \times J}$ are $K \times J$. Thus, the entire spatial complexity of the LTFM model is $\mathcal{O}(KJ)$, which means it is comparable to the standard FM model in terms of spatial complexity. The computational cost is $\mathcal{O}(C_J^2 K)$. For model prediction, since the membership score is computed by fuzzy set theory techniques, the computational effort of the middle layer is reflected by the complexity $\mathcal{O}(C_J^2 K)$ of the inner product of the two vectors. The overall time complexity of the LTFM model is

$\mathcal{O}(C_J^2 K)$. In conclusion, our proposed LTFM algorithm can be trained in linear time. This complexity analysis shows that the LTFM model is very efficient.

4. Experiments and Results in Discussion

4.1. Research Data

We selected the most popular Chinese domestic mobile game, "Glory of Kings," as the game entity, which is based mainly on the UDP protocol for interaction in the game and has extremely high requirements for real-time and user immersion. Since there is no existing dataset on user perception of this MOBA game, we have determined the test process in a controlled laboratory environment after consulting the relevant IUT-T literature [28,29] and finally obtained 789 pieces of game data. Each piece of data represents the data of both users and services in each game. Each data set has 21 dimensions, including 3 dimensions of user data, 17 dimensions of service data, and the last dimension of data is the user's perception. The details of these data are shown in Table 2.

Table 2. Characteristic description.

Feature	Data Type	Description	Factor Matrix
Player Id	Categorical	Participant number	Users
Sex	Binary	Participant sex	Users
Skill	Categorical	Skill level of participants	Users
Time	Numeric	End time of each game	Services
Game IP	Numeric	The IP address of the game server	Services
IP Home	Categorical	Home of game server	Services
Service Operator	Categorical	The operator of the game server	Services
Game Result	Binary	The final result of the game	Services
Game Mode	Categorical	Test the different game modes selected	Services
Game Team	Categorical	Team of participants entering the game	Services
Extra Delay	Numeric	Additional accumulated delay	Services
Extra Jitter	Numeric	Additional accumulated jitter	Services
Extra Packet Loss	Numeric	Additional accumulated packet loss	Services
Delay	Numeric	Total delay per game	Services
Jitter	Numeric	Total jitter per game	Services
Packet Loss	Numeric	Total packet loss per game	Services
Max-Min	Numeric	The difference between the best value of the total delay per game	Services
Kill	Numeric	Kill record in the game	Services
Death	Numeric	Death record in the game	Services
Assistant	Numeric	Assistant record in the game	Services
Score	Categorical	Game perception evaluation score	Label

4.2. Evaluation Metrics

For the game user perception problem, we choose the area of area under curve (AUC curve), precision, recall, F-measure, and training time for evaluation. The metrics are listed in Table 3. First, we should know that true positives (TP) is the number of users who are predicted to be positive classes. False negative (FN) is the number of users who predict the positive class as the negative class. True negative (TN) is the number of users whose negative class is predicted as a negative class. False positive (FP) is the number of users who predict negative classes as positive classes.

Table 3. Performance metrics to compare prediction models.

Evaluation Metric	Formula
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F-measure	$\frac{2\times precision\times recall}{precision+recall}$

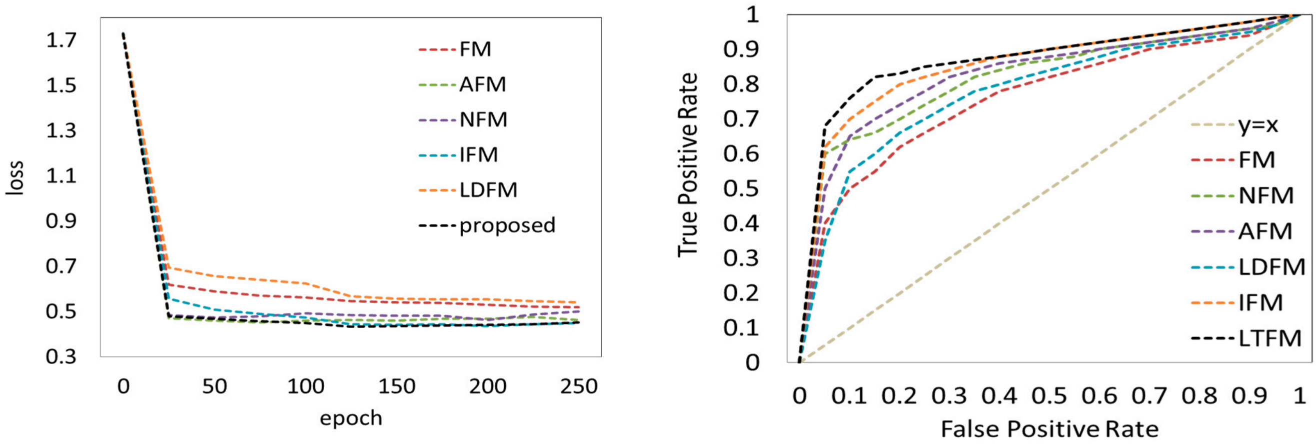
The AUC curve represents the area under the receiver operating characteristic curve (ROC curve). The larger the AUC, the better the model performance. Precision is used to calculate the proportion of correct predictions among all samples with a positive prediction class. The recall is the proportion of positive class samples correctly determined by the classifier to the total number of positive class samples. In general, the higher the accuracy rate, the lower the recall rate. In order to balance the effects of precision and recall and to evaluate a classifier more comprehensively, a comprehensive metric, the F-measure, was introduced. The value of the F-measure will be high when both accuracy and recall are high. The training time is used to compare the running speed of each algorithm. The shorter the time, the faster the algorithm runs.

4.3. Comparison Algorithm

In our experiments, we consider the diversity of influencing factors and want the model to find out the rules from the data as much as possible, so we randomly divide the dataset into 80% as the training set and 20% as the test set. We demonstrate the predictive performance of LTFM and baseline models for game user perception prediction. In view of the fact that there are few types of research on game perception (most of them are to explore network factors and finally obtain relevant formulas) when choosing the baseline model, we chose the algorithm that is homogeneous with FM and the comparison of popular classification algorithms on our dataset, including random forest (RF), decision tree (DTree), multilayer perceptron (MLP), light gradient-boosting machine (Lightgbm), Extreme Gradient Boosting (Xgboost), Catboost, FM [9], NFM [14], AFM [15], IFM [16], and LDFM [13]. In our experiments, we design three kinds of LTFM, import the projections of location and time information, and add the membership calculation to finally obtain the best performance of LTFM.

4.4. Experimental Analysis

We consider training time and convergence speed to choose the batch size. A larger batch size will speed up training per epoch time, but convergence is relatively slow. To cope with this problem, L2 regularization, discarding, and early stopping are introduced. The early stopping strategy for training is executed when the F1 score increases for five consecutive epochs on the test set. The convergence speed of the model is examined through experiments, as shown in Figure 3a. We summarize the loss convergence of each model under the same epoch, and we find that the convergence speed of the proposed LTFM is the fastest and most stable among FM and its variants. We can also see LTFM has been higher than others in ROC curves, which means LTFM is more stable.



(**a**) (**b**)

Figure 3. The performance for comparison FMs (**a**) comparison of model convergence (**b**) ROC curves of different comparison algorithms.

In addition, we verify the effect of learning rate on the prediction performance of perceptual evaluation of LTFM games through extensive experiments in this paper, and the results are shown in Table 4. For trade-off considerations, we chose $lr = 10^{-2}$ in LTFM. The experimental results of the model performance comparison are shown in Table 5.

Table 4. Learning rate effect.

Lr	AUC	Precision	Recall	F-Measure	Time (s)
0.1	0.7572	0.7901	0.7975	0.776	16.225
0.3	0.7862	0.7842	0.7595	0.7867	14.15
0.5	0.7493	0.7903	0.7835	0.7848	14.4
0.01	0.8093	0.8328	0.8228	0.8178	16.4
0.03	0.7796	0.8235	0.7848	0.7867	15.025
0.05	0.7862	0.8089	0.7848	0.7837	15.025
0.001	0.7843	0.8256	0.7342	0.753	15.4
0.003	0.7777	0.8213	0.7468	0.7595	14.825
0.005	0.7701	0.827	0.7848	0.7735	15.25

Table 5. Model performance comparison.

Model	AUC	Precision	Recall	F-Measure	Time (s)
RF	0.7302	0.7385	0.7595	0.7444	—
DTree	0.722	0.7087	0.7215	0.7133	—
MLP	0.7422	0.7526	0.7608	0.7538	—
Lightgbm	0.7164	0.7197	0.7595	0.7283	—
Xgboost	0.7258	0.7324	0.7646	0.7428	—
Catboost	0.7319	0.7259	0.7722	0.7174	—
Standard FM	0.7549	0.7189	0.7215	0.7008	16.91
NFM	0.7721	0.7789	0.7595	0.7778	14.6
AFM	0.7862	0.8052	0.7848	0.7972	184.82
IFM	0.7908	0.8158	0.7975	0.801	56.31
LDFM	0.7288	0.796	0.7975	0.7802	18.24
LTFM (time)	0.8014	0.8207	0.7975	0.8010	—
LTFM (time + location)	0.8017	0.8259	0.8101	0.8069	—
Proposed	0.8093	0.8328	0.8228	0.8178	16.4

The proposed LTFM model performs better than all baseline models in the experimental results, which indicates the projection (considering both the location information and time information) is very beneficial for the overall performance improvement. We experimentally confirm that LTFM, considering projection information, obtains better performance than the baseline and improves performance than models that do not consider feature interactions (RF, MLP, etc.). These results demonstrate the importance of modeling feature interactions for perception prediction. Compared with AFM, IFM, etc., which consider the importance of feature interactions, LTFM shows better performance improvement and trains faster. LTFM effectively considers the similarity information between feature interactions and labels through fuzzy set theory, which enhances the ability of LTFM to capture positive feature interaction information. We can observe that the projection of location and time information and the use of similarity information bring about a 5% and 11% performance improvement with respect to FM.

4.5. Discussion

The proposed user game perception valuation method combines relevant features of multiple information domains as much as possible. It has advantages over existing models based on network factors only. The ability of the model to interpret the obtained evaluation results with high precision at the level of label and feature interaction is another advantage of our approach.

There are two main reasons why the LTFM model shows better performance than the standard FM model. First, FM optimizes the learning objective using stochastic gradient descent and uses a fixed learning rate for all parameters. In comparison, we use the Adam optimization factor module in the LTFM model to adjust the learning rate according to the frequency of each parameter. Smaller updates are used for the frequent parameters, and larger updates are used for the infrequent parameters. Then, while L2 regularization is used to prevent FM from overfitting, the LTFM model uses the dropout method, which can be more effective due to the average effect of the model. Finally, the additional improved contribution of membership to the LTFM model for user game perception evaluation is considered.

5. Conclusions

The LTFM model has the key advantage that FM models efficiently capture nonlinear feature interactions between single features in sparse datasets. It utilizes the idea of projection of location and time information to enhance the predictive performance of standard FM models while using fuzzy set theory to consider enhancing the correlation between feature interaction and labels. The membership module can directly compute correlations between categorical features and continuous features (or feature sets) and be used to weigh and purify interactions between individual features from different data domains. Then, we apply the proposed LTFM to the user game perception prediction problem with a dataset that records the user and service factors and the final user perception ratings for each game. Experiments show that the proposed LTFM outperforms the benchmark model in prediction results, proving the effectiveness of the algorithm. Our proposed LTFM model can be used for decision analysis on how operators can optimize user perception as an integral part of a decision support system, which can help to better describe, predict, and provide effective guidelines for the prevention of poor user perception. The implementation of predictive user game perception analysis can provide operators and game developers with an easy-to-use evaluation management tool, thus reducing operational costs and improving efficiency.

There are still some limitations of our study and potential research worth exploring further. First, external macro conditions and contextual features of playing games (e.g., at home, subway, etc.) may have important effects on user game QoE evaluation. Considering these features, which are not well structured in the game database, in subsequent studies will further improve the plausibility of the overall prediction model performance. Second, different cognitive criteria among different users may result in sample statistical bias to accumulate rich valuation prediction features. One way to overcome this feature deficit problem is to include domain knowledge from experts of these companies as additional predictive features in future work.

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Abbreviations

The following abbreviations are used in this manuscript:

LTFM	Location-Time-Aware Factorization Machine
QoE	Quality of Experience
MOBA	Multiplayer Online Battle Arena
IUT-T	ITU-T for ITU Telecommunication Standardization Sector
QoS	Quality of Services
FM	Factorization Machine
NFM	Neural Factorization Machine
AFM	Attention Factorization Machine
EFMPred	embedding based factorization machine
LBFM	Location-based Factorization Machine
LANFM	leveraging location information Factorization Machine
IFM	Interaction Factorization Machine
LDFM	Location-based Deep Factorization Machine
$\mathbf{x}_{users}$	User matrix
$\mathbf{x}_{services}$	Service matrix
$\mathbf{x}_{new\ services}$	New service matrix after time and location projections

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