A Deep Learning Model for Mining Behavioral Preference of Home Care Demanders to Suppliers

Hongying Fei and Mingzhu Xu

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Hongying Fei[1], Mingzhu Xu*[1]

[1]School of management
Shanghai University
Shanghai, 200444, China
Feihy@shu.edu.cn, Xumingzhu97@shu.edu.cn

Abstract.

This study aims at developing a deep learning prediction model for the preference of home care service demanders to suppliers available in a health care management platform. Firstly, a Node2vec-based algorithm enhanced by minimizing patients' preference difference, is developed for capturing behavioural pattern of demanders; then an advanced deep learning GRU model, combing attention mechanism for service categories, is constructed to predict the visiting preference to various service suppliers by taking into account not only the constraints of technical requirement but also personal behavioural preference. Experimental results show that the proposed deep learning model, compared to the traditional deep learning GRU model, can significantly improve the quality of behavioural preference prediction, which can help improve the recommendation success rate of service suppliers to demanders.

Keywords: home care service; deep learning; attention mechanism; preference prediction

1. INTRODUCTION

With an aging population, increasing prevalence of chronic diseases and patients' desire for home care, the demand for home care services is increasing rapidly[1]. Home care services can not only help reduce the pressure of medical resources and improve the utilization rate of medical services, but also provide patients with affordable, cost-effective[2], more convenient and professional medical care services, and significantly reduce the readmission rate and risk of death[3, 4]. As indicated in Healthy China strategy, home care service (HCS) is becoming an important part of national health system in China. Since the patients who need to reserve home care services prefer high-level hospitals or public home care sectors rather than private institute even when the latter can offer high quality service as well, it can be observed that high level public healthcare sectors are always overcrowded while the health care service resources of community hospitals or private institutions are under-utilized. Therefore, it is necessary to take efficient measures to help balance the utilization of home care service resources from various sectors to improve overall service efficiency in field of home care service.

In recent years, with the development of *Internet +* technologies, especially the advancement of *Smart City* projects, various health care management platforms have been constructed. Considering that historical data relevant with home care services can be extracted from the database of health care management platform, machine learning technologies can help improve the understanding of platform users' behavioral patterns, making it possible to balance resource utilization by impacting the selection of home care patients with dedicated recommendation system.

This study focuses on mining behavioral patterns of users registered on a home care management platform. The purpose is to develop an efficient recommending model for home care services, wth an objective to not only improve the response to home care service demanders but also balance the utilization of various home care resources.

* Mingzhu Xu: E-mail: Xumingzhu97@shu.edu.cn

2. LITERATURE REVIEW

Health Care Industry (HCI) has become one of the largest economic sectors in the world[5]. As an important part of HCI in many countries, Home Health Care (HHC), providing service to patients at their home, attracts more and more attention from researchers[7]. In China, numerous HHC service platforms were constructed in recent years though the majority of such platforms are used as bulletins rather than coordinators[7].

Traditional methodologies for learning behavioral preference of users on e-commerce platforms are mainly based on analyzing the characteristics of users or objects/projects, and the purpose of the recommendation system based on such behavioral learing technoques is mainly to maximize the profit. However, the recommendation system dedicated to home care services should consider ethical issues rather than commercial purpose, and the continuity of services should also be considered when recommending home care service suppliers to demanders [6].

According to the literature, machine learning techniques have been widely applied in predicting user behavioral preference. As an important part of machine learning , Deep Learning (DL) ,such as Deep Neural Network (DNN), can be applied to mine high-order interactive features, and the Recurrent Neural Network (RNN) , like Gated Recurrent Unit (GRU), has been successfully applied to mining user behavioral features based on time series data[8]. Furthermore, some researchers combined RNN with attention mechanism model to reduce feature sparsity and improve solution quality.

In this study, a deep learning GRU model, combined with attention mechanism, is developed to extract the behavioural preference of home care demanders to service suppliers, based on historical data collected from an HHC platform.

3. PROBLEM FORMULATION

Assumptions are as follows:

(1) Necessary information of available home care service resources is recorded in the targeted HHC platform, and this platform is accessible to all residents in the corresponding area.

(2) Historical information of services offered by suppliers to demanders are recorded in the HHC platform and can be used for assessing the performance of users when necessary.

(3) Each user, service supplier or demander, has a unique account in the HHC platform.

(4) There is no significant difference between the suppliers that can offer the same type of home care services, in other words, service quality of available suppliers is equivalent.

(5) Home care service suppliers can just provide the types of services pre-registered on the HHC platform, i.e., the types of services required by home care demanders must be considered.

Table 1. Parameter setting of patient access behavior preference prediction model based on attention mechanism

Notation	Description
$T \in [t_{min}, t_{max}]$	the time range of data used on the HHC platform
$U = \{u_1, u_2, u_3, \ldots, u_n\}$	n users on the HHC platform, i.e., n home health care demanders
$V = \{v_1, v_2, v_3, \ldots, v_m\}$	m home health care service organizations on the HHC platform
$S = \{s_1, s_2, s_3, \ldots, s_i\}$	i home health care service categories on the HHC platform
$L = \{(u_1, v_1, t_{min}, s_1), \ldots, (u_n, v_m, t_{max}, s_i)\}$	Visiting and service information recorded in this time range on the HHC platform

3.1. GENERAL FRAMEWORK OF THE USER BEHAVIORAL PREFERENCE MINING

As shown in Fig. 1, the User Behavioral Preference Mining (UBPM) model dedicated to HHC platform mainly consists of four layers:

(1) Input layer: behavior-related data and service-related data are put into the UBPM model.

(2) Embedding layer: one-hot and node2vec considering minimizing patients' preference difference are

respectively used to different data from input layer.

(3) Preferred feature mining layer: short-Term visiting preference mining (STVPM) considering service category attention mechanism and long-term visiting preference mining (LTVPM) based on feature intersection are introduced in this layer.

(4) Prediction layer: the preference of home care demanders to organizations are predicted.

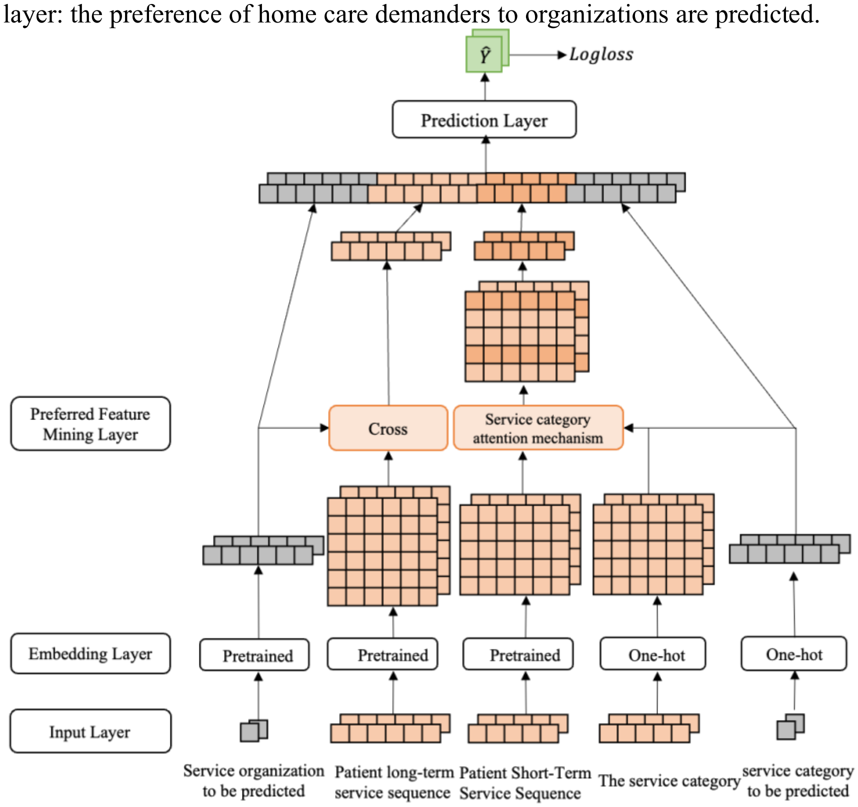

Fig. 1. General Framework of UBPM model

3.2. Input Layer

At the input layer, the UBPM model receives both historical data and online data extracted from HHC platform. The historical data consists of the information of home care service organizations and possible service records. The online data are relevant with the patient's requirement, such as the patient's ID, type of the desired service etc. Accordingly, the data can be classified into two parts: behavior-related data and service-related data.

(1) Behavior-related data

The behavioral data considered in this study are: 1) Type of service offered by home care organizations to patients; 2) Date when the home care service took place, which can be used to identify the service sequence offered by HHC organizations to patients.

Considering that the recent behavior may have greater impact on the decision, the UBPM model is enhanced by combining shot-term and long-term records from the targeted HHC platform in this study. Here below are the definition of these two categories of data: Short-Term Service Sequence (STSS), and Long-Term Service Sequence (LTSS).

Definition 1: **Short-Term Service Sequence**

For any patient $u \in U$, all the service records extracted from the HHC platform are sorted in descending order of timestamps. Set t as the cut-off time threshold, all the records observed within the period $(t - t_{short}, t]$ is classified to short-term service sequence, noted as $L_{short} = \{(u, v_1, t - t_{short} + 1, s_1), \ldots, (u, v_m, t, s_i)\}$.

Definition 2: **Long-Term Servicing Sequence**

For any patient $u \in U$, all the records observed within the period $\left(t - t_{short} - t_{long}, t - t_{short}\right]$ are classified as long-term records, and the corresponding long-term service sequence is noted as $L_{long} = \{(u, v_1, t - t_{short} - t_{long} +$

$1, s_1), \ldots, (u, v_m, t - t_{short}, s_i)\}$.

(2) Service-related data

The service-related data, so called "prediction target" in the input layer, consists of two kinds of data:

1) "service category to be predicted": refers to the type of service required by patients.

2) list of HHC service organizations with available resources to provide the service desired by the patient.

3.3. EMBEDDING LAYER

Receiving data from the input layer, two embedding functions are processed at the embedding layer, service category embedding and service organization embedding. Service categories are embedded using one-hot. For example, E_s^o is the embedding vector of service category s using one-hot. And service organizations are embedded as follows.

Step 1. **Construct patient behavioral preference matrix**

In this study, the patient behavioral preference matrix is constructed based on Term Frequency-Inverse Document Frequency (TF-IDF). Considering that the patient's behavioral preference may change over time, a hyperbolic function is applied here to fit Ebbinghaus's nonlinear forgetting curve [9], formulated as (1)-(4).

$$P_{u,v} = TF_{u,v} \times IDF(v) \times h(u) \tag{1}$$

$$TF_{u,v} = \frac{\sum_{l'=1}^{l} I_{u,v,l'}}{\sum_{v'=1}^{m} \sum_{l'=1}^{l} I_{u,v',l'}} \tag{2}$$

$$IDF(v) = \log\left(\frac{\sum_{u'=1}^{n} \sum_{v'=1}^{m} \sum_{l'=1}^{l} I_{u',v',l'}}{\sum_{u'=1}^{n} \sum_{l'=1}^{l} I_{u',v,l'}}\right) \tag{3}$$

$$h(u) = (1-\theta) + \theta\left(\frac{t_{vmax} - t_{min} + 1}{t_{max} - t_{min} + 1}\right)^2 \tag{4}$$

where $P_{u,v}$ represents the preference of patient u to HHC service organization v; $TF_{u,v}$ represents the proportion of the services provided by the organization v for patient u; $IDF(v)$ represents the proportion of institution v in all service records L; $I_{u,v,l}$ indicates the proportion of occurrences in L. $I_{u,v,l}$ is equal to 1 if the organization v served patient u in record l, and 0 otherwise; t_{vmax} represents the time corresponding to the latest service provided by HHC service institution v to the patient u (time unit: one day); t_{min} and t_{max} represent the earliest and latest times that the patient u received home care service from the organizations registered in the HHC platform respectively; θ represents the forgetting coefficient.

Step 2. **Evaluate behavioral preference of HHC demander to supplier**

A network graph can be obtained based on patient behavioral preference matrix from step 1, which has patients and institutions nodes and service records' edges. Node2vec is a graph embedding method that considers both deep sample and breadth sample. In this paper, the goal of minimizing user preference differences is integrated into Node2vec to improve the effectiveness of feature embedding.

First, every node will be the starting point of ρ paths, whose length is q. If the starting point is t , the sampling probability $a_{t,x}$ of the neighbor node x of node t is the preference constructed from step 1, formulated as (5).

$$a_{t,x} = P_{t,x} \tag{5}$$

Second, the sample probability $\alpha_{t,x}$ of the rest nodes in the paths is considering minimizing user preference differences, formulated as (6). In particular, the network node in this paper is different from the general Node2vec, there is no patient- patient or institution- institution edge, so there is no $d_{tx} = 1$ case.

$$\alpha_{t,x} = \begin{cases} \frac{1}{\lambda} & if\ d_{t,x} = 0 \\ \frac{max\ (p_{t,v}, p_{v,x})}{|p_{t,v} - p_{v,x}|} & if\ d_{t,x} = 2 \end{cases} \tag{6}$$

where t is the last node in the sampled path; v is the penultimate node in the sampled path. x is one of the neighbor nodes of t. $p_{t,v}$ is the patient behavioral preference between node t and v; $p_{v,x}$ is similar. λ controls the probability of sampling duplicate node v.

Finally, to get embedding vectors of demanders and suppliers, we use Skip-gram to maximum likelihood optimization, formulated as (7).

$$max_f \sum_{t \in U,V} logPr(N_w(t)|E_t^n) \tag{7}$$

where t is node in the network graph; $N_w(t)$ are neighbor nodes of t in the window w;E_t^n is the embedding vector of node t using node2vec.

Now we can embed all the service sequences by embedding the organizations and service categories. The short-term service sequence $L_{short} = \{(u, v_1, t - t_{short} + 1, s_1), \ldots, (u, v_m, t, s_i)\}$ can be embedded as $E_{L_{short}} =$

$\{(u, E^n_{v_{t-t_{short}+1}}, t - t_{short} + 1, E^o_{s_{t-t_{short}+1}}), \ldots, (u, E^n_{v_t}, t, E^o_{s_t})\}$. And the long-term service sequence $L_{long} = \left\{\left(u, v_{t-t_{short}-t_{long}+1}, t - t_{short} - t_{long} + 1, s_{t-t_{short}-t_{long}+1}\right), \ldots, \left(u, v_{t-t_{short}}, t - t_{short}, s_{t-t_{short}}\right)\right\}$ can be embedded as $E_{L_{long}} = \left\{\left(u, E^n_{v_{t-t_{short}-t_{long}+1}}, t - t_{short} - t_{long} + 1, E^o_{s_{t-t_{short}-t_{long}+1}}\right), \ldots, \left(u, E^n_{v_{t-t_{short}}}, t - t_{short}, E^o_{s_{t-t_{short}}}\right)\right\}$.

3.4. PREFERRED FEATURE MINING LAYER

Receiving short-term and long-term embedded sequences data from the embedding layer, the preference feature mining layer considers different feature mining functions: Short-Term Visiting Preference Mining (STVPM) considering the target service category and Long-Term Visiting Preference Mining (LTVPM) considering the target organization.

(1) **STVPM Module**

First, the short-term embedded sequence $E_{L_{short}} = \{(u, E^n_{v_{t-t_{short}+1}}, t - t_{short} + 1, E^o_{s_{t-t_{short}+1}}), \ldots, (u, E^n_{v_t}, t, E^o_{s_t})\}$ is put into GRU module to learn time series feature $E^{GRU}_{L_{short}} = \{(u, E^{GRU}_{v_{t-t_{short}+1}}, t - t_{short} + 1, E^o_{s_{t-t_{short}+1}}), \ldots, (u, E^{GRU}_{v_t}, t, E^o_{s_t})\}$. Second, considering the similarity between the service category at each time step and the target service category, the attention mechanism is used. This paper adopts the inner product method to measure the attention similarity, formulated as (8) and (9).

$$short_u = \sum_{T=t-t_{short}+1}^{t} \alpha\left(E^o_S \odot E^o_{s_T}\right) E^{GRU}_{v_T} \tag{8}$$

$$\alpha_T = \frac{e^{E^n_{v_T}}}{\sum_{i=0}^{t} E^n_{v_i}} \tag{9}$$

where $E^{GRU}_{v_T}$ is the deep feature get from GRU model; E^o_S is the one-hot embedding of the target service category; $E^o_{s_T}$ is the one-hot embedding of user's service category at time T; $\odot$ is the dot product operation, which is used to calculate the similarity between the target service category and the sequence behavior service category; α_T is the attention weight obtained by normalizing the similarity; $short_u$ is the user's short-term visiting preference.

(2) **LTVPM module**

First, considering the target organization, the long-term embedded sequence $E_{L_{long}} = \left\{\left(u, E^n_{v_{t-t_{short}-t_{long}+1}}, t - t_{short} - t_{long} + 1,\ E^o_{s_{t-t_{short}-t_{long}+1}}\right), \ldots, \left(u, E^n_{v_{t-t_{short}}}, t - t_{short},\ E^o_{s_{t-t_{short}}}\right)\right\}$ is put into long cross module to learn interactive feature $E^{cross}_{L_{long}} = \left\{\left(u, E^{cross}_{v_{t-t_{short}-t_{long}+1}}, t - t_{short} - t_{long} + 1, E^o_{s_{t-t_{short}-t_{long}+1}}\right), \ldots, \left(u, E^{cross}_{v_{t-t_{short}}}, t - t_{short}, E^o_{s_{t-t_{short}}}\right)\right\}$, and then we concatenate all interactive features, formulated as (10). Second, we can get deep long-term visiting preference $long_u$ by put $long^{cross}_u$ into DNN.

$$long^{cross}_u = \sigma\left(E^n_{v_{t-t_{short}-t_{long}+1}} \odot E^n_v\right) \oplus \ldots \oplus \sigma\left(E^n_{v_{t-t_{short}}} \odot E^n_v\right) = E^{cross}_{v_{t-t_{short}-t_{long}+1}} \oplus \ldots \oplus E^{cross}_{v_{t-t_{short}}} \tag{10}$$

where E^n_v is the embedding vector using node2vec of target organization; $E^n_{v_{t-t_{short}}}$ is the embedding vector of the service organization in user's long-term sequence at time $t - t_{short}$; $E^{cross}_{v_{t-t_{short}}}$ is the cross feature of the service organization in user's long-term sequence at time $t - t_{short}$.

3.5. PREDICTION LAYER

In the Prediction layer, we consider the all behavior-related feature and service-related data, so called "prediction target". We concatenate target service category embedding vector using one-hot, target organization embedding vector using node2vec from embedding layer, the short-term visiting preference $short_u$ and long-term visiting preference $long_u$ from preferred feature mining layer. And we put them into DNN module to predict the probability y_{uvs} of visiting organization v when a user u with service sequence L under the demand of service category s.

3.6. TRAINING LAYER

The learning layer in this paper uses Logloss as the loss function, formulated as (11).

$$Logloss = -\frac{1}{|Y|} \sum_{y_{uvs} \in Y} [y_{uvs} log \widehat{y_{uvs}} + (1 - y_{uvs}) log\, (1 - \widehat{y_{uvs}})] \tag{11}$$

where $y_{uvs} \in \{0,1\}$ is the real label value of whether user u with service sequence L visits organization v under the demand of service category s; Y is the set of real labels, $\widehat{y_{uvs}}$ is the predicted probability of visiting organization v when a user u with service sequence L under the demand of service category s.

4. EXPERIMENTS AND RESULTS

4.1. DATA PREPARATION

The data used in the experiment in this paper is a simulation data set generated based on the home service data table of fengxian District Civil Affairs Comprehensive service for the elderly obtained from Shanghai Public Data Open Platform[10] and combined with the characteristics of home care service demand referring to the definition of service categories in "Shanghai Regulations on Nursing Services of Long-term Care Insurance Community Home and Elderly Care Institutions (Trial)" [142] of Shanghai municipality. Without loss generality, the number of service categories considered in this study is set as 20. And the patient data was anonymized.

As shown in Table 2, when generating experimental data, we divided patients into six grades[11]. Considering the long-term sustainability of home care services and the periodicity of user needs, the corresponding frequency of visits should be set for each service category according to the evaluation and grading standards of user care needs in "Shanghai Long-term Care Insurance Policy 108 questions"[11]. At present, users with assessment grade 1 do not meet the user requirements of Shanghai long-term care insurance, and the service frequency is defined as one visit per week in this paper. The proportion of Patients of each grade and the corresponding proportion of demand service categories are in columns 4 and 5. The service records of the experimental data set covered a time span of six months and about 26 weeks and contained 274,300 service records from 1000 users to 100 home care providers.

Table 2. Proportion of patients with different levels of care in the experimental dataset

Patient Grade	Nb. Visits Per Week	Proportion of Patients	Demand Category Proportion
CL 1	1	35%	5%
CL 2	3	20%	10%
CL 3	3	20%	10%
CL 4	5	10%	15%
CL 5	7	10%	30%
CL 6	7	5%	30%

4.2. PARAMETER SETTING AND OPERATING ENVIRONMENT

All the algorithms are coded with Python on the Jupyterlab platform with an Apple laptop (M1 Pro CPU, 16GB memory). As proposed by [20], 80% of the samples are used for training and the rest is reserved for validation. The details of parameter setting are shown in Table 3.

Table 3. Parameter setting of patient access behavior preference prediction model based on attention mechanism

Patient Grade	Value
Number of Sampling Paths per Node ρ	80
Path length q	10
the probability of sampling repeated nodes λ	0.25
Time window in path w	5
Feature vector embedding dimension	128
Number of Iterations	3000
The number of GRU network layers	3
Learning rate	0.001

4.3 EXPERIMENTAL RESULTS

According to the experimental results, it is observed that the AUCs for the training set, verification set, and test set are 0.881, 0.865 and 0.858 respectively, which are all greater than 0.85. As shown in Fig. 2, when the number of iterations increases, the logloss decreases gradually to 0.3, and the accuracy rate of the top 10 most favorable suppliers is near to 0.8. Furthermore, it is observed that when learning rate is 0.001, the model preform the best. In consequence, it is reasonable to verify that the proposed DL model can effectively extract the preferences of home care demanders to service suppliers. The results of our study can help improve the quality of recommending service suppliers to home care demanders since it is reasonable that the higher the accuracy of the model in predicting the patient's behavior preference, the greater the probability of prediction accuracy will be.

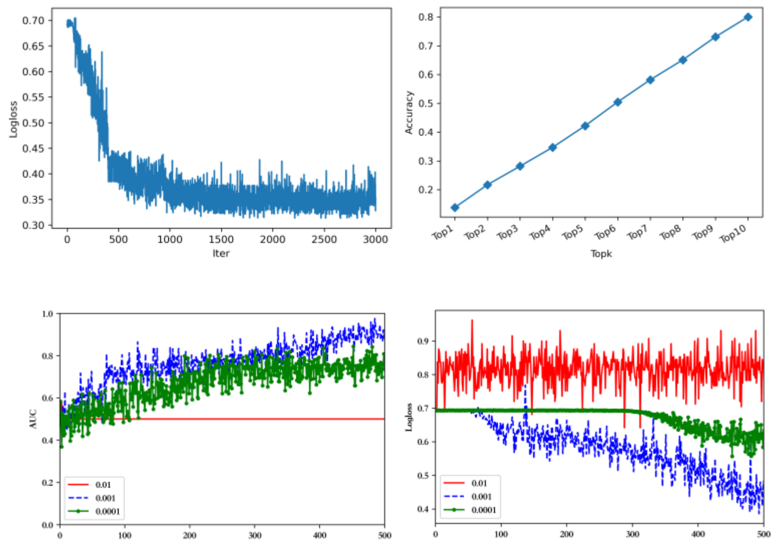

Fig. 2. Experimental results

To analyze the impact of short-term historial results on the prediction results, the attention mechanism is applied to improve the learning model in this study. In addition, both long-term and short-term historical data that may reveal different behavior features are combined as well to enhance the quality of prediction results. In order to verify the performance of the advanced model, the model not only using attention mechanisom to mine short-term behavior characeristics but also implementing cross embedding of long-term behavior characteristics (Model DL-SA-L-C), three benchmarks are constructed as follows:

Model DL-NS-L-NC: do not use short-term behavior data; use long-term sequence data but do not mine long-term behavior features, i.e. use directly the traditional depth neural network to predict the behavioral preference of home care demanders.

Model DL-SM-L-NC: mine short-term behavior features with deep cyclic neural network without attention mechanism; use deep neural network to learn long-term behavior features, but do not crossover long-term behavior features with short-term features.

Model DL-NS-L-C: do not mine short-term behavior feature; Implement cross embedding of long-term behavior characteristics.

And we compare our model with Wide&Deep, DeepFM, DCN. As shown in Table 3, it can be observed that (1) the AUC of model DL-SM-L-NC is better than that of model DL-NS-L-NC, indicating that patients' preferences are affected by short-term behavior, and the short-term behavior mining model based on deep GRU is effective in predicting patients' preferred behavior; (2) the AUC of model DL-NS-L-C is better than that of the model DL-SM-L-NC, indicating that the model using feature crossover can help improve the prediction of long-term behavior features; (3) the model DL-SA-L-C always outperforms the model DL-NS-L-C, indicating that both the attention mecanishm and the crossover of short-term and long-term behavioral preference can help improve the accuracy of prediction accuracy. At this problem, our model is best among the compared models.

Table 3. AUC of different models

Model	AUC in Test Dataset	AUC in Train Dataset	AUC in Valid Dataset
DL-NS-L-NC	0.697	0.699	0.701
DL-SM-L-NC	0.825	0.781	0.817
DL-NS-L-C	0.812	0.790	0.829
DL-SA-L-C	0.881	0.865	0.858
Wide&Deep	0.502	0.503	0.500
DeepFM	0.586	0.616	0.608
DCN	0.586	0.631	0.622

Furthermore, it is observed that about 50% of the demanders' actual selection can be observed within list of HHC suppliers ranked as the top 5 most preferred service suppliers, and the rate increases to 80% when the list of suppliers extended to the top 10, indicating that the proposed prediction model can be applied to provide good quality solution for predicting the preference of HHC demanders to various suppliers available in HHC platform, which can be applied further in the recommendation system to balance the utilization of valuable HHC service resources and patients' satisfaction.

5. Summary

In this study, an advanced deep learning model, combined with attention mechanism for mining the short-term preference demanders to service suppliers and crossover of short-term features with long-term features relevant with specified service type, is constructed for predicting the visting preference of a user to home care service suppliers on an HHC platform. Experimental results show that the proposed model can effectively mine HHC demanders' behavioral preference and give valuable recommendation information to home care demanders.

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