Research on manufacturing service recommendation method based on Product-based Neural Network

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Abstract. Addressing the issue of overwhelming information on cloud-based manufacturing service platforms due to an excessive volume of service-related data, a manufacturing service recommendation method based on Product-based Neural Network (PNN) is proposed, which successfully solved the shortcomings of traditional recommendation technology in utilizing manufacturing service characteristics. By predicting the manufacturing service rating, the manufacturing service recommendation to the user is completed. Findings indicate that the PNN-driven rating forecast model markedly augments the accuracy of the recommendation system.

Keywords: Product-based Neural Networks (PNN), Manufacturing Service Recommendation

1 INTRODUCTION

The rise of service-based manufacturing has prompted companies to leverage industrial cloud platforms to promote and deliver services. In a complex industrial environment, the recommendation system integrates service resources and accurately pushes required services.

Traditional recommendation methods such as Collaborative Filtering(CF) [8] are difficult to extract features in practice [1][4][7][9]. Compared with the traditional recommendation algorithm[2][3][10], the recommendation algorithm based on deep learning can save time, effectively mine potential features, and alleviate data sparsity. Liu et al. built Deep Neural Networks (DNN) to analyze candidate services and provide personalized recommendations [5]. Lin et al. optimized the traditional CF method through the deep learning framework, making the recommendation system more accurate and efficient in recognition. [6]. However, these methods are often based only on user or service similarity, ignoring service attributes. PNN combines product features and service quality to make comprehensive and accurate recommendations.

This paper proposes PNN manufacturing service recommendation method, which combines Quality-of-Service (QoS) attributes and user service data to capture service

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relationship, realizes personalized recommendation and improves recommendation performance.

2 METHODOLOGY

2.1 Problem Formulation

Set $U=(u_1,u_2,\ldots,u_n)$ and $S=(s_1,s_2,\ldots,s_m)$ represents the set of users and manufacturing services provided on the industrial cloud platform. Assuming that user u_i interacts with T manufacturing services, which are denoted by $[s_{i1},s_{i2},\ldots,s_{iT}]$. The observed ratings that given to these items by user u_i are denoted by $[y_{i1},y_{i2},\ldots,y_{iT}]$. Using the classic QoS perception in the manufacturing field: time q^{time}, cost $q^{\cos t}$, credibility $q^{\text{credibility}}$ and reliability $q^{\text{reliability}}$ as the input characteristics of PNN. Finally, manufacturing service recommendation is carried out by predicting the user's rating $\hat{y}_{ij}$ of manufacturing service from the service set.

2.2 Framework

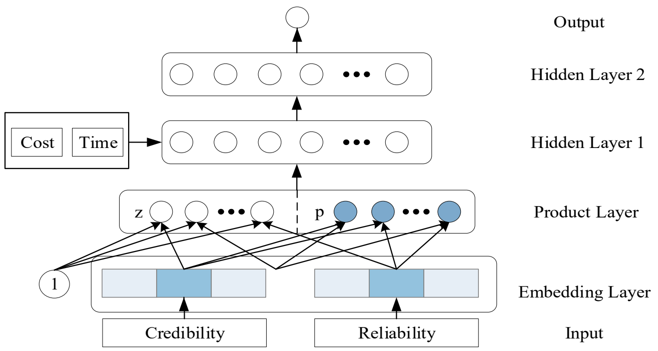

Fig. 1. The framework of PNN.

As show in figure 1. The model takes the user ID of manufacturing services u_i, the ID of manufacturing services interacting with users s_j, $q_{ij}^{\cos t}$ and q_{ij}^{time} as continuous features l_{ti}, and takes $q_{ij}^{\text{credibility}}$ and $q_{ij}^{\text{reliability}}$ as discrete features. Firstly, the discrete features $q_i^{\text{credibility}}$ and $q_i^{\text{reliability}}$ of the user u_i are encoded by one-hot and then embedded into the embedding layer to form the discrete feature embedding vectors f_1^i and f_2^i. Product layer implements the linear part z and the nonlinear combination part p, and obtains the product layer outputs l_{zi} and l_{pi}. For the linear part l_{zi}:

$$
\begin{aligned}
& z=\left(z_1^i, z_2^i\right) \triangleq \left(f_1^i, f_2^i\right) \\
& l_{zi}=\left(l_{zi}^1, l_{zi}^2, \ldots, l_{zi}^n, \ldots, l_{zi}^{D_1}\right), \quad l_z^n=W_{zi}^n \odot z=\sum_{s=1}^{2} \sum_{t=1}^{M}\left(W_{zi}^n\right)_{s,t} z_{s,t}^i
\end{aligned} \tag{1}
$$

W_{zi}^n is the weight of the product layer, the shape is determined by z, D_i represents the size of the hidden layer, M is the dimension of the Embedding layer.

For the nonlinear combination part p, considering the different interactions between the two features, two kinds of nonlinear composite parts based on inner product and outer product are proposed.

$$
\begin{aligned}
& p_{s,t}=q\left(f_1^i, f_2^i\right) \\
& l_{pi}=\left(l_{pi}^1, l_{pi}^2, \ldots, l_{pi}^n, \ldots, l_{pi}^{D_1}\right), \quad l_{pi}^n=W_{pi}^n \ \mathrm{e} \ p=\sum_{s=1}^{N} \sum_{t=1}^{N}\left(W_{pi}^n\right)_{s,t} p_{s,t}
\end{aligned} \tag{2}
$$

$p_{s,t}=q\left(f_1^i, f_2^i\right)$ is the interaction between f_1^i and f_2^i, W_{pi}^n is the weight of the product layer, and the shape is determined by p.

In the inner product model, pairwise feature embedding vectors are used for inner product operations.

In the outer product model, pairwise feature embedding vectors are used for outer product operations. The final product layer outputs D_1 scalar values.

$$
p=\sum_{s=1}^{N} \sum_{t=1}^{N} f_s^i f_t^{iT}=f_{\Sigma}\left(f_{\Sigma}\right)^T, \quad f_{\Sigma}=\sum_{s=1}^{N} f_s \tag{3}
$$

The inner product and outer product of the product layer are either combined with the linear part for output. After passing through the product layer, D_1 scalar values will enter the first hidden layer:

$$
l_{1i}=relu\left(l_{zi}+l_{pi}+l_{ti}+b_{1i}\right) \tag{4}
$$

l_{1i} then enters the second hidden layer. The final output layer finally gets the total rating $\hat{y}_{ij} \in (1 \sim 5)$ of user u_i on manufacturing service s_j, and the activation function adopts $relu$.

$$
\hat{y}_{ij}=\sigma\left(W_{G_1}^i l_{2i}+b_{3i}\right) \tag{5}
$$

The loss function $\mathcal{L}(y, \hat{y})$ is calculated as follows.

$$
\mathcal{L}(y, \hat{y})=\frac{1}{N} \sum_i \mathcal{L}_i=-\frac{1}{N} \sum_i \sum_{c=1}^{5} y_{ij} \log\left(\hat{y}_{ij}\right) \tag{6}
$$

3 EXPERIMENTS

3.1 Dataset and Experimental Settings

The experiment selects the multi-attribute evaluation data of 101 kinds of services from 88 users on the mixed gas manufacturing service collaborative platform. The dataset was divided into 5 subsets, namely C1, C2, C3, C4 and C5. The learning rate is 0.001.

3.2 Model performance

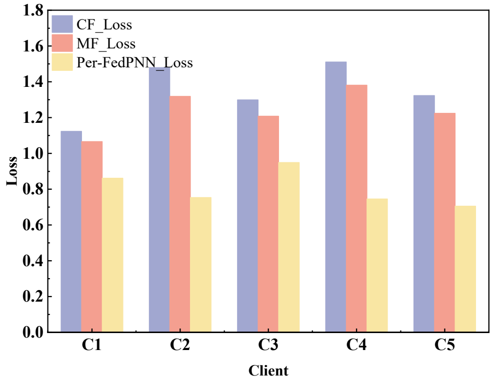

Fig. 2. Loss comparison with recommendation algorithms.

The experiment compared PNN with classical recommendation algorithms, including CF and Matrix Factorization (MF). The comparison of loss values based on experimental data sets is shown in **Fig. 2.** Loss comparison with recommendation algorithms. Compared with the classical algorithms CF and MF, the Loss of PNN is reduced by 19.20% to 42.82% and 23.32% to 50.62%, respectively. The experimental results show that PNN can obtain better recommendation performance than the previous method.

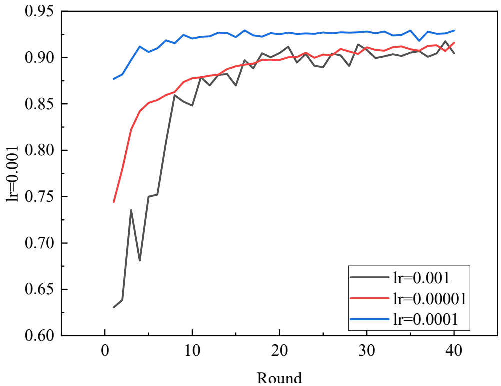

Fig. 3. Accuracy under different learning rates.

In the experiment shown in **Fig. 3.** Accuracy under different learning rates. the learning rate lr of PNN was set to 0.001, 0.0001 and 0.00001 for hyperparameter analysis. The findings from the experiment indicate that the PNN model achieves peak performance with a learning rate of 0.001, so the learning rate lr of PNN in this paper is 0.001.

4 CONCLUSION

PNN accurately captures user requirements through QoS attributes to enhance personalized recommendations and satisfaction. The model learns service key attributes, analyzes attribute interactions, reveals the impact of service characteristics, and provides customized recommendations Utilizing PNN for recommending manufacturing services enhances the precision of the recommendations, accommodates the intricate nature of industrial settings, and advances the investigation of artificial intelligence applications within the manufacturing sector.

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