Neural Hierarchical Factorization Machines for User’s Event Sequence Analysis

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Abstract
Many prediction tasks of real-world applications need to model multi-order feature interactions in user’s event sequence for better detection performance. However, existing popular solutions usually suffer two key issues: 1) only focusing on feature interactions and failing to capture the sequence influence; 2) only focusing on sequence information, but ignoring internal feature relations of each event, thus failing to extract a better event representation. In this paper, we consider a two-level structure for capturing the hierarchical information over user’s event sequence: 1) learning effective feature interactions based event representation; 2) modeling the sequence representation of user’s historical events. Experimental results on both industrial and public datasets clearly demonstrate that our model achieves significantly better performance compared with state-of-the-art baselines.

CCS Concepts
• Security and privacy → Economics of security and privacy;
• Computing methodologies → Supervised learning by classification.

Key Words
Neural Hierarchical Factorization Machines; Event Sequence Analysis; Event Representation; Sequence Representation

1 Introduction
The success of many prediction tasks (e.g., CTR prediction [2, 4–6, 13], fraud detection [14], etc) in real-world applications to a large extent depend on mining effective features via analyzing user’s rich historical event sequence information.

In this section, we present the related work in two-fold: feature interactions and user’s event sequence analysis.

Factorization Machine (FM) [9] is a widely used method to model second-order feature interactions automatically. Recently, some studies have also combined the advantages of the FM on modeling
second-order and the neural network on modeling higher-order feature interactions [4, 5]. However, these above efforts addressed the input as a single sparse vector and failed to capture user’s event sequence information.

For most prediction tasks, it is necessary to capture user’s event sequence information. A method called Multi-temporal-range Mixture Model (M3) [10] has been proposed to apply MLP to concatenate feature embedding vectors for extracting the event representation, and then employ a mixture of models to deal with both short-term and long-term dependencies. Some other studies have also attempted to take user’s historical event sequence into consideration [1, 10, 13]. Nevertheless, these studies paid more attention to the event sequence information but ignored the internal feature relations of each event (e.g., they usually only utilize simple concatenation or MLP for the internal features of each event), which failed to obtain an effective event representation.

3 METHODOLOGY

In this section, we first formulate the problem, then present the details of the proposed NHFM as shown in Figure 2.

3.1 Problem Statement

Given a user’s event sequence \( E = [e_1, e_2, ..., e_T] \), where \( T \) is the event sequence length. \( e_t = [x_{t1}, x_{t2}, ..., x_{tn}] \) is the \( t \)-th event of the user, where \( n \) is the size of feature dictionary. For categorical fields, \( x_{ti} \) (1 \( \leq i \leq n \)) is 1 if \( e_t \) has the value in the current categorical field, otherwise is 0. For numerical fields, \( x^2_{ti} \) is the normalized real value. A simple example of event sequence \( E \) is shown in Figure 1. The task is to make a prediction for the current event \( e_T \) according to the user’s historical event sequence \( [e_1, e_2, ..., e_{T-1}] \) and available information of the current event \( e_T \).

3.2 Event Extractor

As shown in Figure 1, most of the features are one-hot encoding categorical features, the dimension is usually high and the vectors are sparse. FM is an effective method to address such high-dimensional and sparse problems.

Firstly, we project each non-zero feature \( x_i \) to a low dimension dense vector \( v_i \). The embedding layer learns one embedding vector \( v_i \in \mathbb{R}^k \) (1 \( \leq i \leq n \)) for each feature \( x_i \), where \( n \) is the size of feature dictionary and \( k \) is the dimension of embedding vectors. For both categorical and numerical features, we rescale the embedding via \( x_i v_i \). Therefore, we only need to include the non-zero features, i.e., \( x_i \neq 0 \).

Next, in order to extract internal feature interactions of each event for the event representation, we apply the FM for \( t \)-th event \( e_t \) as follow:

\[
e_t = FM(x^t) = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} x^t_i v_i \odot x^t_j v_j. \tag{1}
\]

Figure 1: A simple example of event sequence \( E \).

Different from traditional FM, which uses inner product to get a scalar, we apply Hadamard product \( \odot \) to get the vector representation of each event. Hadamard product denotes the element-wise product of two vectors \((u_i \odot v_i)_{jk} = u_{jk} v_{jk}\).

Now, we apply the event extractor (i.e., Equation (1)) to each event in the user’s event sequence, and we get the event representations \( E = [e_1, e_2, ..., e_T] \) thereafter for the sequence extractor.

3.3 Sequence Extractor

The sequence extractor, which contains a parameter-free module and a module with parameters, can capture event interactions and event self-importance sequence information, respectively.

3.3.1 Event Interactions Module. In user behavior sequence analysis, user’s final behavior is strongly correlated with the user’s past several behaviors. For example, in card-stolen fraud detection scenario, the fraudster’s behaviors are associated with his/her abnormally frequent payment attempts and the changing of payment environment. Therefore, in this level, we adopt the FM to capture event interactions, combining with the feature interactions in the first level forming a hierarchical structure:

\[
s_{\alpha} = FM(E_{his}) = \sum_{i=1}^{T-2} \sum_{j=i+1}^{T-1} q_i e_i \odot q_j e_j, \tag{2}
\]

where \( E_{his} = [e_1, ..., e_{T-1}] \) is the historical events, \( q_i \in \{0, 1\} \) indicates whether the \( i \)-th event \( e_i \) exists. The learned sequence representation \( s_{\alpha} \) is concatenated with the current prediction event \( e_T \) and then fed to an MLP to form our basic NHFM-\( \alpha \) model.

It is worth pointing out that the NHFM-\( \alpha \) does not introduce extra parameters\(^1\) compared with the NFM [5], and more importantly, it not only inherits the advantages of NFM on modeling second-order and higher-order feature interactions, but also could model the hierarchical structure information, which significantly improves its prediction performance comparing with the NFM.

3.3.2 Event Self-importance-aware Sequence Module. Even though the NHFM-\( \alpha \) considers event interactions, it does not consider the event sequence information. To address this problem, we design an event self-importance-aware sequence module instead of the FM in the second level of the NHFM-\( \alpha \) to form the NHFM-\( \beta \). The module takes the relative importance and order information of

\(^1\)The total parameters of the model are in the embedding layer and MLP.
Table 1: Summary statistics for the datasets.

| Dataset       | #pos | #neg | #fields | #events |
|---------------|------|------|---------|---------|
| C1            | 15K  | 1.37M| 56      | 4.28M   |
| C2            | 10K  | 1.93M| 56      | 3.57M   |
| C3            | 5.7K | 174K | 56      | 35K     |

different events into consideration. Different historical events of users have different importance. Therefore, we design an event self-importance-aware attention to learn the importance of different events. The self-importance weight is defined as scaled dot-product:

\[
\hat{a}_t = \frac{< F_1(\mathbf{e}_t), F_2(\mathbf{e}_t) >}{\sqrt{k}}, \quad a_t = \frac{\exp(\hat{a}_t)}{\sum_{i=1}^{T-1} \exp(\hat{a}_i)}, \quad (3)
\]

and the importance weighted event sequence is represented as:

\[
s_{self} = \sum_{t=1}^{T-1} a_tF_1(\mathbf{e}_t), \quad F_1, F_2, F_3 \text{ represent the feed-forward networks to project the input event vector to one new vector representation.}
\]

Besides, for learning short and long-term dependencies, we adopt the bidirectional LSTM (Bi-LSTM) [3] whose basic idea is to present each sequence forward and backward to the recurrent net, both of which are summed to get the sequence representation: \(s_{RN} = Bi - LSTM(E_{bi})\), where \(s_{RN} \in \mathbb{R}^{h}\) and \(h\) is the dimension of the LSTM output. For every event in the event sequence, the network has complete sequential information before and after it, so the network can capture long range event dependent information. The output of the event self-importance-aware sequence module is the concatenation of \(s_{self}\) and \(s_{RN}\):

\[
s \beta = [s_{self};s_{RN}]. \quad (4)
\]

Finally, we combine the NHFM-\(\alpha\) and NHFM-\(\beta\) in the second level to capture event interactions and self-importance sequence information simultaneously, then they are concatenated with current prediction event \(e_T\) and fed to an MLP. The output of the MLP is combined with a linear “wide” part, and then fed to the activation function to form the final NHFM model:

\[
s = [s_\alpha; s_\beta; e_T], \quad \hat{y} = sigmoid(MLP(s + f(x))), \quad (5)
\]

where \([s_\alpha; s_\beta]\) models user’s history behaviors (e.g., in fraud detection, it can be regarded as the risk of user’s historical behaviors, and in recommender systems, it can be regarded as user’s historical preference), and \(e_T\) is user’s current risk or preference representation. Besides, \(f(x)\) is the “wide” part just like the part in Wide&Deep [2]:

\[
f(x) = \sum_{i=1}^{T} \sum_{j=1}^{n} w_i x_i^j + w_0, \quad \text{where } w_i \text{ indicates the importance of the feature } x_i. \quad \text{For binary classification tasks, we need to minimize the negative log-likelihood.}
\]

4 EXPERIMENTS

In this section, we perform experiments to evaluate the NHFM against state-of-the-art methods on both industrial and public datasets.

4.1 Experimental Setup

Datasets. The industrial datasets contain the card transaction samples from one international e-commerce platform. We utilize three countries (C1, C2, C3) data. The task is to detect whether the current payment event is a card-stolen case. The public dataset is the MovieLens-1M dataset. We binarize the ratings following the common process [8]. We regard each user’s rating for each movie as an event. The statistics of all datasets are shown in Table 1.

Baselines. We compare the proposed method with feature interactions based models (W&D [2], DeepFM [4], NFM [5], AFM [12], xDeepFM [6]) and event sequence based models (LSTM4FD [11], LCRNN [1], M3 [10]).

Evaluation Metrics. We use the standard metric: AUC (Area Under ROC). Besides, in our real card-stolen fraud detection scenario, we should increase the recall rate of the fraudulent transactions, in the same time, disturbing as few normal users as possible. In other words, we need to improve the True Positive Rate (TPR) on the basis of low False Positive Rate (FPR). Therefore, we also adopt the standardized partial AUC (AUCCPR\(\leq\)1%) [7] (The standardized area of the head of ROC curve when the FPR \(\leq\) 1%). For all experiments, we report the above metrics with 95% confidence intervals on five random runs. * indicates that the improvement is statistically significant compared with the best baselines at p-value < 0.05 over independent samples t-tests.

4.2 Performance Comparison

The experimental results are presented in Table 2. From these results, we have the following insightful observations:

- For the feature interactions based models, the performance of W&D is inferior compared with other baselines, perhaps because it can not automatically learn feature interactions. Considering all datasets, the performance of other feature interactions based models is similar. They all attempt to capture high-order feature interactions via combining the FM and neural network but ignore the event sequence information.

- For the event sequence based models, the overall performance of M3 and LCRNN is slightly better than LSTM4FD due to theirs more complex improved models based on the LSTM.

- For C3 dataset, it has fewer positive, negative samples and available events than C1 and C2 as shown in Table 1, so the feature interactions can not play his role well. The confidence intervals on C3 dataset is obviously larger than the C1 and C2 datasets. For the public MovieLens dataset, the overall AUC performance of different baselines varies very little. It makes sense that the public dataset have fewer fields in each event as shown in Table 1, so the feature interactions can not play his role well. Therefore, the feature interactions based and event sequence based baseline models achieve almost similar performance.

Table 2: AUCCPR\(\leq\)1% and AUC performance (mean±95% confidence intervals) on datasets of C1, C2, C3 and MovieLens.

| Model          | C1 AUCCPR\(\leq\)1% | C2 AUCCPR\(\leq\)1% | C3 AUCCPR\(\leq\)1% | MovieLens AUC |
|----------------|---------------------|---------------------|---------------------|---------------|
| W&D            | 0.6997±0.0014       | 0.7776±0.0023       | 0.8202±0.0092       | 0.7553±0.0006 |
| DeepFM         | 0.7076±0.0060       | 0.7722±0.0035       | 0.8476±0.0070       | 0.7651±0.0023 |
| NFM            | 0.7467±0.0032       | 0.7931±0.0074       | 0.8310±0.0221       | 0.7583±0.0007 |
| AFM            | 0.7086±0.0047       | 0.8061±0.0065       | 0.8499±0.0073       | 0.7586±0.0028 |
| xDeepFM        | 0.7391±0.0044       | 0.7883±0.0084       | 0.8557±0.0147       | 0.7643±0.0021 |
| LSTM4FD        | 0.7118±0.0087       | 0.7356±0.0084       | 0.7762±0.0066       | 0.7959±0.0001 |
| LCRNN          | 0.7099±0.0068       | 0.7847±0.0109       | 0.8162±0.019        | 0.7613±0.0009 |
| M3             | 0.7294±0.0060       | 0.7897±0.0053       | 0.7618±0.0268       | 0.7688±0.0003 |
| NHFM-\(\alpha\) | 0.7643±0.0054       | 0.8268±0.0071       | 0.8524±0.0096       | 0.7678±0.0005 |
| NHFM-\(\beta\) | 0.7697±0.0048       | 0.8399±0.0064       | 0.8628±0.0100       | 0.7696±0.0005 |
| NHFM           | 0.7753±0.0037       | 0.8551±0.0055       | 0.8742±0.0089*      | 0.7798±0.0006* |

W&W http://www.grouplens.org/datasets/movielens/
Table 3: The extracted high risk and low risk features, the "Amount" is of payment, the "Expiration" is of bank cards (Year), the "Time" is the time when the event occurs (Hour: Minute) and the "Category" is of goods.

| Amount ($) | Expiration | Time | Category |
|-----------|------------|------|----------|
| High      | 1500-2000  | 2035 | 03:00    |
| Risk      | 1000-1500  | 2037 | 01:00    |
|           | 800-1000   | 2036 | 05:00    |
| Low       | 0-20       | 2022 | 17:00    |
| Risk      | 20-40      | 2021 | 12:00    |
|           | 40-60      | 2025 | 14:00    |

Figure 3: The extracted high-risk event sub-sequences from positive samples, the bold events have higher weights.

- We also construct ablation experiments over NHFM-\(\alpha\), NHFM-\(\beta\) and NHFM. NHFM-\(\alpha\) and NHFM-\(\beta\) utilize Event Interactions Module and Event Self-importance-aware Sequence Module in their sequence extractor, respectively. The proposed NHFM combines the NHFM-\(\alpha\) and NHFM-\(\beta\) in the sequence extractor and obtains the significantly best performance, which indicates both two modules matter for the performance.

These improvements also indicate that the proposed NHFM can better handle the task via capturing the hierarchical structure.

4.3 Case Study
In this subsection, we make some analysis on the interpretability of the proposed NHFM model.

Firstly, in the feature level, we extract some high-risk and low-risk features according to the learned weights in the "wide" part. We present the features in Table 3. From these results, we have the following findings. 1) The larger the amount range, the higher the risk. 2) The expiration of bank cards is usually less than 10 years, so the cards whose expiration is more than 10 years are abnormal and high-risk. 3) Fraudulent transactions usually take place in the middle of the night, so the risk is higher at 00:00 - 06:00. 4) In e-commerce platform, digital goods belong to high-risk category, so the fraud risk is higher than that of common goods. Then, in the event level, we extract some high-risk event sub-sequences from positive samples (the fraud label is 1) according to the learned event self-importance weights in Equation (3). These event sub-sequences can be regarded as the modeling of users’ behavior patterns. We present the behavior patterns in Figure 3. First, for sub-sequence (1), after the first payment fails, the user modified the IP several times in a minute, which led to multiple payment failures and had a high risk. Therefore, the last three payment events obtain higher weights. Then, for sub-sequence (2), after the failure of the first large payment, the user tried two small payments and succeeded with another card. Then he tried to make a large payment with the card he used for the first time, but failed. Therefore, the two large payments obtain higher weights. In sub-sequence (3), the account was initially used by a normal user and purchased common goods. Then, the account was stolen by the user with different device in another country to buy high-risk digital goods, so the last payment event has a higher weight.

These results show that our NHFM can effectively find the important features and events for mining high-risk behavior patterns.

5 CONCLUSION
In this paper, we designed a NHFM for event sequence analysis. Specialy, we applied event and sequence extractors as a hierarchical structure to learn event and sequence representations. The experimental results on industrial and public datasets show significant improvement compared with various state-of-the-art baselines.

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