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GCN-ONLSTM: Process Next Event Prediction Method based on Spatio-Temporal Feature Fusion

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Abstract: The task of predicting the next event of a process is the focus of research in the field of predictive process monitoring. Most of the existing methods to achieve this task only process the event log trace as a one-dimensional sequence or regular two-dimensional image data, without considering the simultaneous internal synchronization of the event log. It contains temporal and spatial feature information. In addition, existing studiesignore that trace data is a non-Euclidean structure with topological relationships. In order to solve the above problems and further improve the accuracy of model prediction, this paper constructs a GCN-ONLSTM network that fuses temporal and spatial dimension features, constructs the spatial relationship between events through a two-layer graph convolution network, and improves the feature expression ability of data. And combined with ONLSTM (Ordered Neurons LSTM) network to process the hierarchical structure of trace sequence, to further solve the long-term dependency problem. The ablation experiments and comparison experiments are carried out through 6 BPI public event log data. The results show that the proposed method has significantly improved prediction accuracy in each event log compared with other existing deep learning methods, and the highest is higher than the traditional LSTM (Long Short-term Memory) increased by 8.63%, it can be considered that this method has better performance for the next event prediction task of the process.

Keywords: Prediction of the next event; Graph convolution neural network; ONLSTM; Predictive monitoring; Deep learning

1. INTRODUCTION

Process Mining (PM)[1] is the systematic use of event data to analyse and improve business operational processes, using this technique to identify bottlenecks and deviations in production processes, diagnose compliance issues, reduce failure rates and avoid repetitive tasks [2][3].

As a branch of the process mining field, Predictive Process Monitoring (PPM) [4] aims to predict the future of ongoing process execution, often using historical complete executions to predict open (incomplete) case scenarios. This includes predicting the outcome of process execution in advance [5], the next event in the business process [6][7], and the time remaining in the business process [8], and has demonstrated its value in a number of domains and scenarios such as finance, healthcare, and education, for example, helping organisations to reduce non-essential maintenance costs, provide decision making for process executors, and prevent non-compliant tasks from occurring [9][10].

Most of the existing deep learning-based methods only focus on the temporal correlation of events in event logs and ignore the spatial correlation, and a few scholars consider the spatial connection between events but do not explore the topological relationship between the spaces where the events are located in depth. The above problems lead to deep learning models that can only extract the temporal features contained in the event logs during training, failing to make full use of the rich spatial feature information for learning, resulting in low accuracy and poor interpretability of the models.

To address the above limitations, this paper proposes a spatio-temporal feature fusion model for process next event prediction, which uses Graph Convolution Network (GCN) [11] to extract and compress the spatial feature information of event logs, and further solves the long-term dependency problem of sequence data by Ordered Neurons LSTM (ONLSTM)[12], and captures the temporal features of the data, by making full use of the spatial features and temporal features in the event logs by the above method The spatial features and temporal features in the event logs are fully utilized by the above method, and the next event prediction task for the process is achieved based on the trained feature information. Experimental results in six real event logs show that this spatio-temporal feature fusion model significantly improves the prediction accuracy compared with existing deep learning models.

2. RELATED WORK

In recent years, with the vigorous development of deep learning and predictive process monitoring, more and more researchers combine the two and begin to use deep learning technology to solve the problem of predicting the next event. For example, Theis[13] et al. proposed a DREAM-NAPr method, which regarded time characteristic information as element variable. In this paper, the next event task of the process was divided into two categories according to the nature of feature information extracted by the deep learning model.

Next event prediction methods based on temporal feature information: Everman[14] et al. used a combination of two LSTMs for next event prediction using trajectory prefixes. tax [15]et al. were inspired by the above methods and made the prediction model perform better by multi-task learning. nguyen[16] et al. proposed a time-aware T- LSTM method, while introducing a cost-sensitive learning approach to address the uneven distribution of event log activities, with a significant improvement in prediction accuracy over other methods.Lin[17] et al. proposed an encoder-decoder framework, MM-Pred, by separately encoding attributes such as event name, timestamp, and event status as inputs to the model, which recoded the event internal dependencies to establish a connection and use LSTM networks to complete the prediction. jalayer[18] et al. built on the above by introducing a hierarchical attention mechanism to assign different weights to each attribute and combined with BiLSTM networks to further improve the prediction accuracy of the model.

Next event prediction methods based on spatial feature information: unlike the first type of methods, other researchers have argued that the spatial feature information in logs can be well extracted by CNNs. For example, Al-Jebrni[19] et al. used a five-layer one-dimensional convolutional neural network to process sentences, combined with a convolutional neural network to learn the spatial local information in them for subsequent prediction Pasquadibisceglie[20] et al.converts each track prefix in the historical event log into a two-dimensional image data structure. However, limited by the CNN structure, it is difficult to solve the problem of long-term data dependence.In the authors' subsequent study [21], the next event prediction task was still converted to an image classification task by recoding the event data as RGB images and introducing the Inception structure to improve the network structure.

In summary, most of the existing studies only deal with event log data from a single perspective, but the data can be regarded as a kind of graph structure with both spatio-temporal characteristics, while temporal attributes such as timestamps play a key role in the prediction effect of the model, so it is necessary to use both temporal feature information and spatial feature information of the data together to complete the next event prediction task. In this paper, we propose a spatio-temporal feature fusion network combining GCN and ONLSTM, extracting spatial feature information in event days by GCN, and ONLSTM network by introducing a hierarchical structure to fully extract temporal feature information and further solve the problem of long- and short-term dependency of event log data.

3. A PROCESS NEXT EVENT PREDICTION MODEL WITH SPATIO-TEMPORAL FEATURE FUSION

3.1 Model Overview

In order to improve the accuracy of business process next event prediction and make full use of the temporal and spatial information of the event sequence, a process next event prediction model with fusion of temporal and spatial features is proposed, and its model structure is shown in Figure 1.

The proposed spatio-temporal feature fusion process next event prediction model is constructed by GCN and ONLSTM, which can build hierarchical relationships between events and further improve the next event prediction accuracy by considering the event time series and using the spatial structure between events, mainly including the following steps:

(1) Constructing the graph structure of the event log and extracting spatial features: the events in the trajectory are constructed as nodes in the graph structure, and the temporal order occurrence relationship of the events is constructed as the structural features between the nodes, from which the adjacency matrix of the graph structure of the event log can be constructed. The constructed adjacency matrix is used as the input to the graph convolutional neural network to extract the spatial features of the event log.

(2) Extracting the temporal relationships and hierarchical structure between events: The output of the graph convolutional neural network is used as the input to the ONLSTM, which determines the preservation and deletion relationships between historical and input information through two update mechanisms.

(3) Iterative training: The method proposed in this paper carries out iterative training on top of the next event prediction, changing the input trace prefix after each training, so as to achieve the prediction of subsequent events, which can be followed up in real time in real business processes.

4. RELATED EXPERIMENTS AND ANALYSIS

This chapter verifies the feasibility of the GCN-ONLSTM model in the process next event prediction task by designing relevant ablation experiments and comparison experiments, aiming to analyse whether the model can make full use of the inter-event correlation in this task and the impact of using only temporal feature information and fusing temporal feature information on the prediction accuracy.

4.1 Experiment-related Environment

All experiments in this paper were done on Windows 10, using a GeForce RTX 2070 SUPER 8GB graphics card, programming language Python 3.7, and code built with the deep learning algorithm library Pytorch 1.1.0.

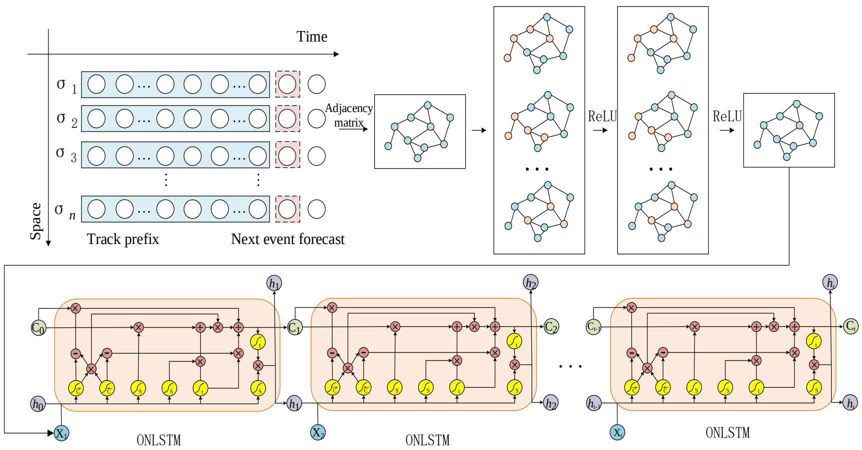

Figure. 1 Process next event prediction method based on spatio-temporal feature fusion

4.2 Introduction to the Event Log

To exemplify the effect of each comparative experimental model on the prediction effect of the next event task in a real scenario, six 4TU Center for Research open source real event logs were selected for this paper, namely:

(1) Helpdesk event log: data related to a company's ticket management.

(2) BPIC_2012_A event log: data related to a financial institution's loan application and follow-up process.

(3) BPIC_2012_O Event Log: A financial institution's data related to loan application matters and subsequent processes.

(4) Prepaid_Travel_Costs Event Log: Data related to the travel reimbursement of employees in a department for domestic or international travel.

(5) Road Traffic Fine Management Process (RTFM) Event Log: Data relating to penalties for road traffic violations by a traffic management department.

(6) Hospital Billing Event Log: Data related to a hospital's medical service process.

4.3 Experimental Results and Analysis

In order to ensure the uniformity of variables in the comparison experiments, the experiments in this paper were trained to full convergence for each model, the optimiser was set to Adam, the initial learning rate was 1×10^{-4}, and the regular term coefficient was 5×10^{-4}. Accuracy was selected as the evaluation index to assess the prediction effectiveness of the model, and in order to avoid the random situation of the deep learning model in the next event prediction task of the process, the comparison Experiments were all conducted using a 5-fold cross-validation approach.

In order to explore the effect of mining sufficient information of temporal features on the prediction effect of the model, a set of pairwise experiments were designed in this paper, in which LSTM and its related variants, GRU and its related variants were selected as the prediction models, and the experimental results are shown in Table 2.

Table 2. Experimental results comparing the predictions of LSTM and GRU and their variants

Predictive models	Data sets					
	Helpdesk	BPIC_2012_A	BPIC_2012_O	Prepaid_Travel_Costs	RTFM	Hospital Billing
LSTM	0.7593	0.7347	0.7698	0.8528	0.7685	0.8626
ATT-LSTM	0.7781	0.7378	0.7866	0.8501	0.7658	0.8672
BiLSTM	0.7675	0.7353	0.7805	0.8570	0.7665	0.8637
ATT-BiLSTM	0.7914	0.7623	0.8173	0.8769	0.7836	0.8818
GRU	0.7659	0.7232	0.7952	0.8684	0.7517	0.8645
ATT-GRU	0.7592	0.7303	0.8084	0.8701	0.7536	0.8694
BiGRU	0.7615	0.7311	0.8103	0.8779	0.7498	0.8602
ATT-BiGRU	0.7829	0.7485	0.8291	0.8826	0.7683	0.8793

Table 3. Experimental results of ATT-BiLSTM, ATT-BiGRU, ONLSTM and GCN-ONLSTM network prediction comparison

Predictive models	Data sets					
	Helpdesk	BPIC_2012_A	BPIC_2012_O	Prepaid_Travel_Costs	RTFM	Hospital Billing
ATT-BiLSTM	0.7914	0.7623	0.8173	0.8769	0.7836	0.8818
ATT-BiGRU	0.7829	0.7585	0.8291	0.8826	0.7683	0.8793
ONLSTM	0.8132	0.7802	0.8318	0.8809	0.7913	0.8804
GCN-ONLSTM	0.8287	0.8018	0.8561	0.9174	0.8059	0.8962

Among the variant structures of the various types of deep learning models in the comparison experiments, BiLSTM and BiGRU both refer to the bi-directional structure of the original model and aim to jointly compute the model output by introducing a reverse sequence in combination with the original input sequence for extracting richer contextual feature information; ATT-LSTM, ATT -BiLSTM and ATT-GRU, ATT-GRU the attention mechanisms introduced in the model are all self-attentive structures, aiming to make the model take more account of the interrelationships that exist between events when calculating in this way.

In this paper, we consider that any complete trace in an event log can be mapped to a hierarchical structure that can be abstracted as information about the temporal features contained in the data, and if the model can be made to better understand the hierarchical structure, then the model can be considered to adequately extract the temporal information contained in the data. To test this idea, a set of comparative experiments was designed in this paper, and the model predictions in each event log are shown in Table 3.

The above results demonstrate that ONLSTM performs better in most event logs in a business process context, i.e. it proves that by using the sequential information of neurons and thus learning the hierarchical structure of the event logs, the temporal feature information in the data can be better extracted.To further validate the importance of fusing spatio-temporal feature information for the prediction task, this paper compares the performance of GCN-ONLSTM and other models in each real-event task, and the results are shown in Table 3.

The experimental results show that the GCN-ONLSTM model has better prediction robustness and significantly better prediction results than the ONLSTM model, i.e. the model incorporates spatio-temporal feature information that is more useful for the prediction task, and also shows that the GCN is able to incorporate the sequential nature of the business process task, and for non-Euclidean data such as event logs, the GCN improves the data by modelling the spatiality of the trace data For non-Euclidean data such as event logs, GCN improves data representation by modelling the spatiality of the trace data, while using a two-layer GCN is able to learn more relevant positional relationships between events by increasing the perceptual field of the convolutional kernel, which in turn leads to better prediction results.

5. CONCLUSION

In order to simultaneously utilise the spatio-temporal feature information in the event day, this paper designs a GCN-ONLSTM spatio-temporal feature fusion network as a way to build a model for the process next event prediction task, which fully extracts spatial feature information by introducing a two-layer graph convolutional network structure to correlate up the spatial relationship between events, while using the ONLSTM structure to learn the hierarchical structure contained in the trace The long-term dependency of the data is further addressed.

Although the method proposed in this paper is able to make full use of the information on temporal and spatial features contained in the event log, there are still other problems. This study models the spatial and temporal correlation of events from their timestamp attributes, and does not analyse the impact of other attributes of events on the prediction effectiveness of the model.

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