Deep Learning for Predictive Process Behavior

Thuzar Hnin, Khine Khine Oo
University of Computer Studies,Yangon,Myanmar
thuzarhninn@ucsy.edu.mm,khinekhineoo@uscy.edu.mm

Abstract

Today's many modern organizations, to get competitive advantages, have been already implemented business process management (BPM). However, as part of a larger business process management initiative, especially predictive business process monitoring and continuous optimization of business process are still challenging for companies. Predictive business process monitoring is concerned with the analysis of events produced during the execution of a business process in order to predict as early as possible the final outcome of an ongoing case. In existing work, there are a lot of proposed methods to predict process behaviors. Still, deep learning (DL), a very hot research area, has been blooming for applying in predictive process behavior. Predictive business process monitoring methods exploit logs of completed cases of a process in order to make predictions about running cases thereof. This paper investigates Long Short-Term Memory (LSTM) neural networks as an approach to build consistently accurate models for a wide range of predictive process monitoring tasks. Therefore, this paper aims to propose new deep learning using LSTM Neural Network for predictive business process behaviors by taking into account process metrics.

Keywords: *Deep Learning, Predictive Process Monitoring*

1. Introduction

Deep Learning is a type of Neural Network Algorithm that takes metadata as an input and process the data through a number of layers of the non-linear transformation of the input data to compute the output. It has unique feature, which mean features can be automatically extracted by using DL. It can be applied to solve higher complex problems such as biological analogs, image classification, natural language processing (NLP), automatic text generation, drug discovery.

In recent years, as far as we know [2], DL has only successfully started to apply in predicting process behaviour problem and yet it has historically succeed in other areas. Therefore, we conduct a very short review for only using DL to predict business process behavior.

Generally, in the digital age, process-aware information systems(PAIS) , such as Enterprise Resource Planning (ERP) systems, Customer Relationship Management (CRM) systems, and Business Process Management Systems (BPMS) have been usually using in modern organizations. These systems record a range of events that occur during the execution of the processes. These event records produced by PAIS can be extracted and used to predict the future behaviour of a business process to assess the fulfillment of its compliance requirements and performance objectives.

The remainder of this paper is structured as follows: predictive process monitoring problem is discussed in Section 2. Section 3 is arranged with our contribution to briefly describe the survey of selected studies. In the section 4, we summarizes our studies and conclusion is made in the final section.

2. Predictive Process Monitoring

Predictive business process monitoring is the action of making predictions about the future state of ongoing cases of a business process (i.e. behaviour), based on their incomplete execution traces and logs of historical (completed) traces. If process owner (business manager), can predict the trend of running process instances in advance, they can create more value for the customer and for the business by preventing delays or undesirable situations. As the results of these benefits, it has received significant attention in the previous years due to the increasingly persistent availability of fine-grained event data while its executions. In addition, to be clearer, predictive process performance can be seen as an extension of the traditional business activity monitoring that taps also into historical data to allow process participants to steer the execution of the process by taking preemptive actions to achieve the desired process objectives [4] as shown in the

following figure. And a general predictive process monitoring framework architecture is also proposed in the paper [4].

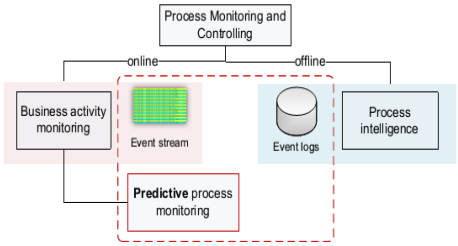

Figure 1. Process monitoring and controlling methods

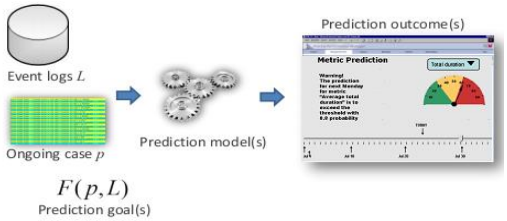

Figure 2. Predictive process monitoring framework architecture

Certainly, predicting business process covers an array of different techniques, objectives, and data sources. In fact, the predict process target (business process behaviour) can be monitored and predicted from the three main perspectives such as time, risk and failure. Thus, various existing techniques such as Naive–Bayes (NB) and (support vector regression) SVR approach, decision trees and clustering methods had been occurred for those perspectives. According to the paper [6], moreover, various methods for predictive business process monitoring can be divided according to the prediction target into the following categories:

- Remaining time prediction (regression tasks),
- Next activity prediction (multi-class classification), and
- Outcome-oriented prediction (binary classification).

Therefore, from the emergence of a rich field of proposed methods for each category, this study focuses on collecting of only DL approaches.

3. Deep Learning for Predictive Process Monitoring

The author, [2] has discovered and firstly highlighted the potential for applications of deep learning in business process management at runtime and to describe an initial application by getting motivation of the popular application of deep learning to natural language process (NLP). The author has implemented deep learning, especially recurrent neural networks with LSTMcells using TensorFlow framework on BPI Challenge 2012 and 2013 datasets, to the problem of predicting the next event in a running process.

In 2017, the authors [3] have extended their early work by adding more advanced neural network cells, separation of training and validation samples for cross-validation to prevent overfitting, empirical assessment of the effect of different neural network parameters and by making prediction not only of next events but of case remainders, interpretation and visualization of neural network states, encoding of timing information. In addition, they have also made an extended discussion of the similarities and differences between natural language processing and process event prediction.

After that, the author, [10] puts forward LSTM architectures for predicting: (i) the next activity in a running case and its timestamp; (ii) the continuation of a case up to completion; and (iii) the remaining cycle time. The outlined LSTM architectures are empirically compared against tailor-made approaches with respect to their accuracy at different prediction points, using four real-life event logs. The author has used LSTMs as a baseline to tackle a similar problem: predicting the next activity and its timestamp and shown how LSTMs can improve over it while providing higher generalizability. The author has found that predicting the next activity and its timestamp via a single model (multi-task learning) yields a higher accuracy than predicting those using separate models. They also can provide higher generalizability by addressing two other predictive process monitoring problems: predicting the entire continuation of a running case and predicting the remaining cycle time.

The paper [6] has conducted a systematic review by (i) performing a systematic literature review of outcome-oriented predictive process monitoring methods; (ii) providing a taxonomy of

existing methods; and (iii) performing a comparative experimental evaluation of eleven representative methods, using a benchmark of twelve predictive monitoring tasks based on four real-life event logs. From this, we note that there is still less research effort of deep learning approaches for predictive business process monitor than in other area. And we believe that there may be research potential of using deep learning approach for above problem.

More recently, the author [9] has proposed LSTM Networks for Data-Aware, (DA-LSTM) Remaining Time Prediction of Business Process Instances by improving the idea of paper [8] and demonstrated the quality of their proposal with experiments on several real-world datasets.

Moreover, the author from [6] has defined a notion of temporal stability and proposed methods based on XGBoost and LSTM neural networks exhibit the highest temporal stability. In paper [5], the author showed that temporal stability can be enhanced by hyperparameter-optimizing random forests and XGBoost classifiers with respect to inter-run stability. The author evaluated the temporal stability of five existing predictive monitoring methods, including single and multiclassifiers using random forest, XGBoost, and LSTM. The experiments were done on twelve prediction tasks formulated on six real-life publicly available datasets. Then the author found that the highest temporal stability is achieved by a single classifier approach with XGBoost, followed by LSTM.

Finally, the author [1] has discussed that a predictive event-driven process analytics method by integrating aspects from business activity monitoring and process intelligence. In addition, the author also has pointed out the evaluation criteria for a predictive method. Among them, the soundness of predictions, predictive process controlling uses measurements on events or abstract process states formed by events to predict metrics on instance level only. Measurements over several running process are not yet implemented. In contrast, business process intelligence (BPI) provides instance and process level predictions. Thus, the capability to predict categorical and numerical process metrics on different levels is also a requirement for predictive methods. From the paper [1], we have relieved that process metrics are also important in predictive process monitoring. However, according to the literature review, there are no existing deep learning approaches, which are not in view of process metrics for predictive process monitoring domain.

Therefore, this paper considers to propose a new deep learning approach based on LSTM neural networks by taking into account of process metrics to support business process intelligence in future.

4. Summary

We, here, summarize our above short review by showing tabular form in the table 1. In the table 1, According to the literature, each of proposed DL methods are implemented on the real world dataset as shown in the table. All of authors did their experiments and used mean absolute error (MAE) and prediction accuracy to evaluate performance measure. As far as we know, most of authors in table 1 emphasizes on time related prediction target for the application domain.

Table 1. Summarize

Primary Study	DL Method	Prediction Target	Datasets
Evermann et. al	RNN with LSTM cells	• Remaining Time	• BPI Challenge 2012 and 2013 datasets
Evermann et. al	RNN with LSTM cells by adding more advanced neural network cells	• Next Event • Remaining Time	• BPI Challenge 2012 and 2013 datasets
N. Tax et al.	LSTM neural networks	• Next Activity • Its timestamp	• Helpdesk dataset • BPI'12 subprocess W dataset
Navarin et. al	DA-LSTM	• Remaining Time	• Helpdesk2017 • BPI12 • BPI12 oneEndAct
Teinemaa et. al	• XGBoost • LSTM neural networks	• Outcome-oriented prediction	• BPIC 2011. • BPIC 2015 • BPIC 2017 • Insurance

5. Conclusion

In conclusion, this study can be clearly realized that future research effort in predictive process monitoring problem can put by using deep learning. The foremost contribution of this paper is a technique to predict the next activity of a running

case and its timestamp using LSTM neural networks. We showed that this technique outperforms existing baselines on real-life data sets. Additionally, we found that to other prediction tasks, such as prediction of aggregate performance indicators and case outcomes. The latter task can be approached as a classification problem, where in each neuron of the output layer predicts the probability of the corresponding outcome. Long-short term memory (LSTM) networks have recently gained attention in predicting remaining time and next activity of a running case of a business process . Accordingly, to predict of business behaviour from not only time perspective but also outcome perspective, we suppose that we can propose a new deep learning approach, as a next step of our research work.

References

[1] B. Schwegmann, M. Matzner, and C.Janiesch, “A Method and Tool for Predictive Event-Driven Process Analytics”, Wirtschaftsinformatik Proceedings 2013, Association for Information Systems.

[2] J. Evermann, J.-R. Rehse, and P. Fettke.: “A deep learning approach for predicting process behaviour at runtime”. In: Proceedings of the 1st International Workshop on Runtime Analysis of Process-Aware Information Systems. Springer (2016)

[3] J. Evermann, J.-R. Rehse, and P. Fettke. “A Deep Learning Approach for Predicting Process Behaviour at Runtime”, pages 327–338. Springer International Publishing, Cham, 2017

[4] I Verenich, M Dumas, M La Rosa, FM Maggi, C Di Francescomarino ," A general framework for predictive business process monitoring", International Conference on Advanced Information Systems Engineering, 186-202, 2016. 5, 2016.

[5] I. Teinemaa, M. Dumas, A. Leontjeva , F. M.Maggi , “Temporal Stability in Predictive Process Monitoring”

[6] I. Teinemaa, M. Dumas, M. L. Rosa, and F. M.Maggi, “Outcome-Oriented Predictive Process Monitoring: Review and Benchmark”

[7] M.-Chamorro AE, Resinas M, Ruiz-Cortes A (2017) Predictive monitoring of business processes: a survey. IEEE Transactions on Services Computing

[8]M. Polato, A. Sperduti, A. Burattin, and M. de Leoni. “Data-aware remaining time prediction of business process instances.” In 2014International Joint Conference on Neural Networks (IJCNN), pages 816–823. IEEE, jul 2014

[9] N. Navarin, B, Vincenzi, M. Polato and A. Sperduti, “LSTM Networks for Data-Aware Remaining Time Prediction of Business Process Instances “.

[10] N. Tax, I. Verenich, M. L. Rosa, and M. Dumas, “Predictive business process monitoring with LSTM neural networks,” in International Conference on Advanced Information Systems Engineering (CAiSE). Springer, 2017, pp. 477–492.