Online Predicting Conformance of Business Process with Recurrent Neural Networks

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Abstract: Conformance Checking is a problem to detect and describe the differences between a given process model representing the expected behaviour of a business process and an event log recording its actual execution by the Process-aware Information System (PAIS). However, such existing conformance checking techniques are offline and mainly applied for the completely executed process instances, which cannot provide the real-time conformance-oriented process monitoring for an on-going process instance. Therefore, in this paper, we propose three approaches for online conformance prediction by constructing a classification model automatically based on the historical event log and the existing reference process model. By utilizing Recurrent Neural Networks, these approaches can capture the features that have a decisive effect on the conformance for an executed case to build a prediction model and then use this model to predict the conformance of a running case. The experimental results on two real datasets show that our approaches outperform the state-of-the-art ones in terms of prediction accuracy and time performance.

1 INTRODUCTION

The executed process in reality often deviates from the original process model that is used to set the expected behaviour and configure the Process-aware Information System (PAIS) (Aalst, 2009) due to the variant and dynamic environment. These PAISs record detailed business process execution trails and these records can be extracted into an *event log* consisting of sequences of events that occurred in an execution of a process (called *process instance*, case, or *trace*). *Conformance checking* is such a technique to detect whether all executions of a process recorded in event log is consistent with the desired behaviour of a reference process model and utilizes a metric to measure the extent of consistency. This means that the compliance of an execution of process can only be determined when it is already completed. In other words, this technique is offline and delayed to determine whether an execution of a process is in line with its process model. However, the originators of process tend to know if the process deviates when it is running instead of a few days later or even longer (Burattin and Carmona, 2017). The reason is that such analysis after the execution of process, in some contexts, is too late. For example, in terms of a *patient-treatment process*, the conformance detection is too late to make sense with considering the case where an execution of the process is the treatment of a patient during her/his life and the model is the given clinical guidelines to follow for a disease (Burattin et al., 2018; Zelst et al., 2019). Therefore, it is necessary to detect the deviation of a running process instance (i.e. an on-going process instance or an on-going case) without delay so as to take actions in advance. In this paper, for the purpose of process improvement, we focus on the problem of online predicting conformance of a running process instance in real-time.

Up to now, only a few approaches for online conformance checking have been proposed. Almost all of them focus on the completed event stream occurred in on-line stage as well as the reference process model and then study their relation from some perspectives such as the behavioural patterns, prefix alignment and so on (Burattin et al., 2018; Zelst et al., 2019). However, whether or not an on-going process instance is in line with the desired

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behavioural of a reference process model should be determined not only by the event stream, but also by a set of attributes involved in these occurred events. Similarly, the *predictive (business) process monitoring* (PPM) techniques that aim at making predictions about the future state of an on-going process instance has been paid much more attention in recent years such as the prediction of remaining execution time (Tax et al., 2017), the next activity to be executed (Mehdiyev et al., 2017), and the final outcome (Maggi et al., 2014; Teinemaa et al., 2019).

Inspired by PPM techniques, in this paper, we propose an approach to predict the conformance of an on-going case based on deep learning. This approach involves two stages, one is *offline stage* where we research on the relation between the historical completed process instances (cases) in event log and their conformance computed by applying an alignment-based method and then construct a classification model, and the other is *online stage* where we make prediction for a running case by using this model. In this case, we explore some corresponding variants of Recurrent Neural Networks (RNN) for constructing an effective and efficient classification model. The reason is that each case (trace) in event log is a sequence of events with ordered and these RNN variants are proved to have a distinct advantage in sequential data prediction tasks such as semantic relation classification (Tang et al., 2015; Zhang et al., 2018), text classification (Liu et al., 2016) and so on. In summary, the major contributions of this paper are as follows.

- We introduce the calculation of trace fitness for measuring the conformance and take into consideration the relationship between the historical completed process instances with recorded various attributes and their conformances.
- We propose RNN-based approaches called Base-RNN, LSTM RNN and GRU RNN for constructing a classification based on the event log and the reference process model.
- We conduct a series of experiments and compare with other approaches to verify the effectiveness and efficiency of our approaches.

The rest of paper is structured as follows. After discussing the related work in Section 2, Section 3 introduces some basic definitions and describes the problem we try to resolve. Then Section 4 presents the solutions in detail. Afterwards, Section 5 demonstrates the effectiveness and efficiency of our approach based on the experiments. Finally, Section 6 concludes the paper and discusses the future work.

2 RELATED WORK

In terms of a business process, once given a reference process model and the corresponding executed event log, researchers addressing *conformance checking* need to adopt or design an algorithm to compare them. Based on the proposal from (Aalst et al., 2012), the related researches are mainly focused on two general approaches that are *log replay* algorithms and *trace alignment* algorithms. *Log replay* is to replay every trace, event by event, against the reference process model and then use distinct computing techniques to determine a conformance metric, such as the *token-based* log replay proposed in (Rozinat and Aalst, 2008). As for *trace alignment*, both the input event log and the process model are transformed into event structures firstly and then they are aligned as far as possible by moving elements in them such as A* algorithm (Adriansyah et al., 2011), cost function algorithm (Leoni, M. and Marrella, A., 2017), heuristic algorithm (Song et al., 2017).

Besides, no matter which approach is used for conformance checking, the metric of conformance should be determined first. There are four quality metrics can be used such as *fitness*, *simplicity*, *precision*, and *generalization* (Aalst et al., 2012). Among them, the most similar to the conformance is *fitness* metric, which represents the ratio of traces in an event log that can be replayed successfully against the reference process model. Hence, it is often used such as the *token-based fitness* (Rozinat and Aalst, 2008) and *the cost-based fitness* (Adriansyah et al., 2011; Aalst et al., 2012).

The most related to our work are some proposals about online conformance checking. For example, Burattin implemented an algorithm that can dynamically quantify the deviation behavior (Burattin, 2017) and then proposed a framework for online conformance checking by converting a Petri net into a transition system in (Burattin and Carmona, 2017). Then they presented another generic framework to determine the corresponding conformance by representing the underlying process as behavioural patterns and checking whether the expected behavioural patterns are either observed or violated (Burattin et al., 2018). Besides, Zelst et al. proposed an online, event stream-based conformance checking technique based on the use of prefix-alignments (Zelst et al., 2019). Different from them, the proposed framework in this paper aims at predicting the conformance online based on the historical event log and a reference model in terms of an underlying process.

3 PRELIMINARIES AND PROBLEM STATEMENT

3.1 Definitions

In terms of a business process, the conformance of an on-going case can be predicted based on an event log and a reference process model. The event log records a set of executed process instances (cases), and each case consists of some event records where each one of them has some attributes. These attributes can be divided into *event attributes* and *case attributes* based on the attribute value is owned by an event or shared by a case. In addition, a reference process model can be represented as a Petri net regardless of the modelling language (i.e., Petri nets, UML, BPMN, EPCs, etc.). In this paper, we use basic *transition system* to represent a reference process model with ignoring the difference of modelling languages.

Definition 3.1 (Process Model). A *process model* represented as $M = (S, S_{start}, S_{end}, A_M, T)$ is a transition system over a set of activities A_M with states S, start state $S_{start} \subseteq S$, end state $S_{end} \subseteq S$, and transitions $T \subseteq S \times A_M \times S$.

According to the transition rules in T, the transition system can start from a start state in S_{start} and moves from one state to another. For instance, $(S_1, a, S_2) \in T$ indicates that the transition system can move from state S_1 to state S_2 while producing an event labelled a. Keep repeating this operation until an end state in S_{end} can be reached.

Definition 3.2 (Executable Behaviour). All executable traces (i.e. executable behaviour) described in process model M can be represented as $\mathcal{T}(M) \subseteq A_M^*$, in which all possible traces start with a state in S_{start} and end with a state in S_{end}.

For example, given a process model $M = (\{s_1, s_2, s_3, s_4\}, \{s_1\}, \{s_4\}, \{a_1, a_2, a_3, a_4, a_5\}, \{(s_1, a_1, s_2), (s_2, a_2, s_3), (s_2, a_3, s_3), (s_3, a_4, s_2), (s_3, a_5, s_4)\})$, we get corresponding executable behaviour (traces) $\mathcal{T}(M) = \{a_1a_3a_5, a_1a_2a_5, a_1a_3a_4a_5, a_1a_2a_4a_5, \dots\}$.

Definition 3.3 (Event, Event log). An *event*, defined as a tuple $e = (a, c, t_{start}, t_{end}, d_1, \dots, d_m)$, is related to an activity a in A_L (all activities occurred in event log), in which c is the case id which the event occurred in, t_{start} is the start timestamp, t_{end} is the end timestamp, and $d_1, \dots, d_m$ ($\forall i \epsilon [1, m], d_i \epsilon \mathcal{D}_i$) indicates a set of additional attributes. All executed events are recorded as *event log* L.

Definition 3.4 (Trace, Prefix Trace). A *trace*, denoted as $\sigma =< e_1, e_2, \dots, e_{|\sigma|} >$, is a sequence of events that occurred in a process instance (case) orderly where $\forall i, j \epsilon [1, |\sigma|], e_i.a \epsilon A_L, e_j.a \epsilon A_L, e_i.c = e_j.c$. Given a trace σ, a *prefix trace* is a first part of σ with specific length $l (l \leq |\sigma|)$, which can be described as $\sigma^l =< e_1, e_2, \dots, e_l >$ representing the first l executed events in this process instance.

Definition 3.5 (Alignment). An alignment between *process model* and *trace* is defined as a pair $(x, y) \in A_L^- \times A_M^-$ where $A_L^- = A_L \cup \{-\}$ indicates a set of possible activities in event log as well as the placeholder "$-$" and $A_M^- = A_M \cup \{-\}$ indicates a set of possible activities in process model as well as the placeholder "$-$", such that:

- (x, y) is a *move* in trace if $x \in A_L$ and $y = -$,
- (x, y) is a *move* in model if $x = -$ and $y \in A_M$,
- (x, y) is a *move* in both if $x \in A_L$ and $y \in A_M$,
- (x, y) is all *illegal move* if $x = -$ and $y = -$.

Let $\sigma_L \in L$ be a trace of an event log and let $\sigma_M \in \mathcal{T}(M)$ be a completed execution trace of model, we can get an alignment of them that is a sequence $\kappa \in \{(x, y)^* | x \in A_L^-, y \in A_M^-\}$ where each element is a legal *move* mentioned above. For example, there are two examples of alignment.

$$\kappa_1 = \begin{matrix} a_1 & a_2 & a_3 & a_4 & a_5 & a_4 \\ a_1 & a_2 & a_3 & a_4 & a_5 & a_4 \end{matrix}$$

$$\kappa_2 = \begin{matrix} a_1 & a_2 & a_3 & a_4 & a_5 & - \\ a_1 & - & a_3 & a_4 & a_5 & a_6 \end{matrix}$$

Here, we define a cost function on legal *moves* to measure the alignment: $\delta(\kappa) = \sum_{(x,y)\in\kappa} \delta(x, y)$, where

$$\delta(x, y) = \begin{cases} 0, & if\ x = y \\ 1, & if\ x = -\ \ or\ y = - \\ \infty, & if\ x \neq y. \end{cases} \quad (1)$$

Moreover, we define an *optimal alignment* κ for a trace in event log and a reference process model: $\forall \kappa' \in \mathcal{K}_{\sigma_L, \mathcal{T}(M)}, \delta(\kappa') \geq \delta(\kappa)$ where $\mathcal{K}_{\sigma_L, \mathcal{T}(M)} = \{\kappa | \exists \sigma_M \in \mathcal{T}(M), \kappa\ is\ an\ alignment\ of\ \sigma_L\ and\ \sigma_M\}$. To relate executable traces in the reference model for matching full execution sequence, we define a mapping of a trace $\sigma_L \in L$ and the best matching executable trace in the model as $\pi_M(\sigma_L) = \{\kappa \in \mathcal{K}_{\sigma_L, \mathcal{T}(M)} | \forall \kappa' \in \mathcal{K}_{\sigma_L, \mathcal{T}(M)}, \delta(\kappa') \geq \delta(\kappa)\}$ and its cost as $cost(\sigma_L, M) = \delta(\pi_M(\sigma_L))$.

Definition 3.6 (Fitness). A trace in event log with good *fitness* means that it has a best matching full executable trace in the model. To normalize the fitness as a number between 0 (very poor fitness) and 1 (prefect fitness), we define as:

$$fitness(\sigma_L, M) = 1 - \frac{cost(\sigma_L, M)}{|\sigma_L| + min_{\sigma_M \in \mathcal{T}(M)} \sum_{y \in \sigma_M} \delta(-, y)} \quad (2)$$

where $cost(\sigma_L, M)$ divided by the maximum possible cost, $|\sigma_L|$ is the length of trace σ_L, and $min_{\sigma_M \in \mathcal{T}(M)} \sum_{y \in \sigma_M} \delta(-, y)$ is the total cost of making moves on model only.

Definition 3.7 (Conformance Labelling). A single conformance class label $Y(\sigma_L)$ with domain of $\{0,1\}$ is assigned to trace σ_L in event log for binary classification based on the predefined threshold of fitness ξ such that:

$$Y(\sigma_L) = \begin{cases} 0 & if\ fitness(\sigma_L, M) < \xi \\ 1 & otherwise \end{cases} \quad (3)$$

where 1 denotes that the conformance of this case is consistent with the reference model and 0 is the opposite.

Definition 3.8 (Event Encoding). An *event encoding* is defined as a function $f: e \to \mathbb{R}^p$ that encodes each event e as a vector with specific dimensions p based on the all the attributes of this event.

Definition 3.9 (Classification Model). A *classification model*, i.e., a prediction model, defined as $Y: \sigma_L \to \{0,1\} (\sigma_L \epsilon L, \forall e \epsilon \sigma_L, e \to \mathbb{R}^p)$ which indicates the conformance prediction (class label) of a (prefix) trace based on the encoded vectors of events.

3.2 Problem Definition

In this paper, the problem to be solved is to predict the conformance (class label) of an on-going case. The main solution aims at training a classification model (i.e., classifier or prediction model) from a historical event log. In this log, the conformance (class label) of each completed case can be determined firstly. On the basis of this classification model, we then predict the conformance class label of a running case. This problem can be formally described as follows.

Input: an event log $L = \{\sigma_1, \sigma_2, \ldots, \sigma_s\}$ of m completed process instances, a reference process model M, and a running case to be predicted $\sigma' = < e_1, e_2, \ldots, e_{|\sigma'|} >$;

Middle Operation: calculating the fitness of each trace in L, conformance labelling based on the threshold of fitness ξ, training a classification model C;

Output: the conformance (class label) prediction of σ'.

As shown in Figure 1, some historical executed cases $\sigma_1, \sigma_2, \ldots, \sigma_s$ in event log can be labelled conformance class (*regular* vs. *deviant*) based on the computed fitness and the predefined threshold firstly. Then a classification model can be trained from these labelled cases by using neural networks. Finally, taking a running case σ' as input of this classifier, the conformance (class) prediction of σ' can be determined based on the executed events occurring in σ'.

4 RNN-BASED ONLINE CONFORMANCE PREDICTION

To address the conformance prediction problem of a running case, we focus on constructing a classification

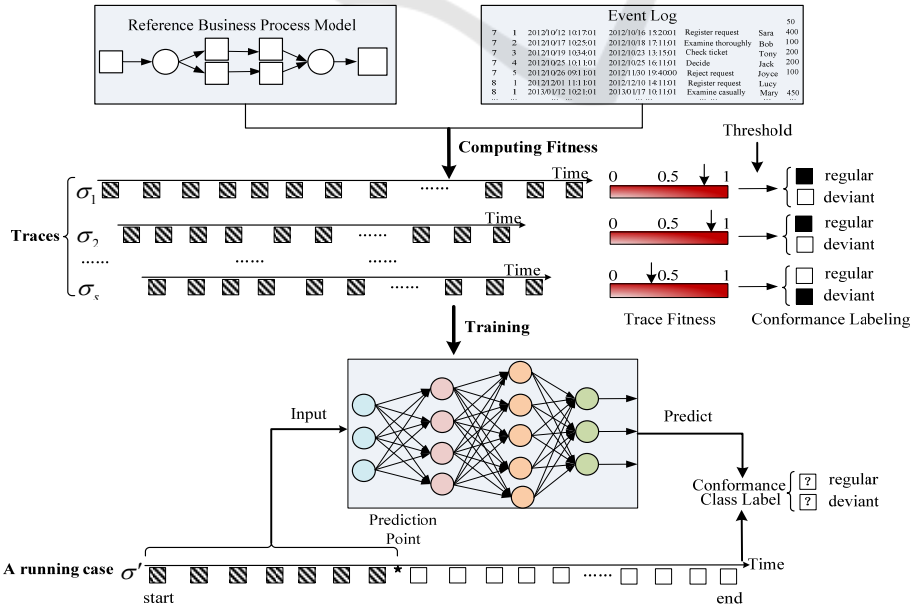


Figure 1: The overall framework of online conformance prediction.

model to reflect the relation between the executed cases in event log and its conformance based on deep learning techniques. As mentioned above, each completed case (trace) in event log is a sequence of events orderly and RNN is proven to be effective in the prediction task of sequential data. Compared with the general neural networks, RNN has different states at different time t (i.e., the t-th input event of a trace) and the output of hidden layer at time $t-1$ (i.e., the $(t-1)$-th input event of a trace) can have an effect on the hidden layer at time t. However, RNN cannot apply the information far away from the current moment t to the hidden layer at this moment because it lacks memory units. Some variants of RNN, such as Long Short-Term Memory (LSTM) RNN and Gates Recurrent Unit (GRU) RNN, can improve the shortcomings of base-RNN based on the additional gate units in their neural cells. By training, these gate units can choose not only the useful information to memorize but also the useless information to forget automatically.

Therefore, we present RNN-based approaches, called Base-RNN, LSTM RNN, and GRU RNN, to construct a prediction model for conformance prediction online by capturing the features that have a decisive effect on the conformance for a case. Similarly, we also present the multi-layer RNN-based approaches to construct a classification model for capturing more decisive features from a case. In this section, we will describe how to construct a prediction model based on the above approaches. At first, a vectorization representation of each event in a case is obtained by encoding its attributes in different ways according to the types of attribute values. Then, these RNN-based approaches are used to extract key features from events according to the fact that the conformance of a case is determined by the occurred events as well as their attributes. Finally, in terms of an on-going case, the probability of conformance class label is calculated based on the extracted feature vectors. As shown in Figure 2, the architectures of single RNN-based approaches (i.e., Base-RNN, LSTM RNN, and GRU RNN) and multi-layer RNN-based approaches consist of 4 layers such as Input Layer, Encoding Layer, RNN/LSTM/GRU Layer, and Output Layer.

Input Layer. Given an event log $L = \{\sigma_1, \sigma_2, \dots, \sigma_s\}$ with s cases (traces), the i-th trace is represented as $\sigma_t =< e_{t1}, e_{t2}, \dots, e_{tn} > (n = |\sigma_t|)$, in which $e_{ti}(1 \le i \le n)$ is the i-th event in trace σ_t. Taking this trace as input of RNN can be viewed as training the classification model once.

Encoding Layer. In order to obtain the input vector, all attributes of each event in trace σ_t can be encoded based on the type of attribute value. If the value type is categorical, the attribute value can be encoded with one-hot method. If the type is numerical, we can normalize the attribute value according to the range of all possible values for this attribute in event log. In this way, we can get the vector of each event for all traces with p-dimension length, expressed as $\vec{x}_{ti} = [x_{ti,1}, x_{ti,2}, \dots, x_{ti,p}](1 \le i \le n)$.

Feature Extraction Layer (RNN/LSTM/GRU Layer) is also called hidden layer. In terms of trace σ_t, the input of this layer is a sequence of encoded event vectors $\vec{x}_{t1}, \vec{x}_{t2}, \dots, \vec{x}_{tn}$. As for each cell in this layer, we can obtain two outputs of $h_{ti}(1 \le i \le n)$ and $o_{ti}(1 \le i \le n)$ as well as some trainable parameters by these equations as follows.

$$h_{ti}, o_{ti} = RNN(h_{t,i-1}, \vec{x}_{ti}), i \in [1, n] \quad (4a)$$

$$h_{ti}, o_{ti} = LSTM(h_{t,i-1}, \vec{x}_{ti}), i \in [1, n] \quad (4b)$$

$$h_{ti}, o_{ti} = GRU(h_{t,i-1}, \vec{x}_{ti}), i \in [1, n] \quad (4c)$$

Please note that how to get these outputs has significant difference in different neural networks that we proposed. And the detailed difference will be given below.

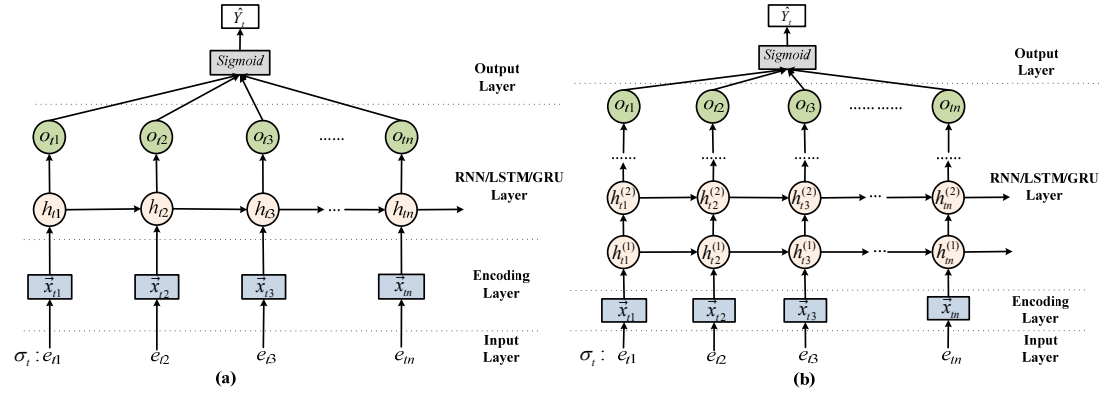


Figure 2: The architecture of our approaches: (a) Single-layer Base-RNN/LSTM RNN/GRU RNN (b) Multi-layer Base-RNN/LSTM RNN/GRU RNN.

Output Layer. The input of this layer is the obtained $o_t = [o_{t1}, o_{t2}, \dots, o_{tn}]$ from the last layer. It can be used to estimate the conformance class (label) of trace σ_t by using $Sigmoid$ activation function. The final estimated probability $\hat{Y}_t$ of the conformance class (label) with 1 for trace σ_t can be calculated as follows:

$$\hat{Y}_t = Sigmoid(W_c o_t + b_c) \quad (5)$$

where W_c and b_c are the trainable parameters of weight matrix and bias in this layer.

After that, we use a binary cross-entropy loss function to measure the loss between the actual conformance class Y_t and the estimated probability $\hat{Y}_t$ from neural networks for trace σ_t as follows.

$$loss(Y_t, \hat{Y}_t) = -(Y_t log\hat{Y}_t + (1 - Y_t)\log(1 - \hat{Y}_t)) \quad (6)$$

Similarly, we obtain the sum of loss for each trace in event log $L = \{\sigma_1, \sigma_2, \dots, \sigma_s\}$ by the below equation.

$$Loss(L) = \sum_{\sigma_i \in L} loss(Y_i, \hat{Y}_i) \quad (7)$$

Here, in order to train the classification model by neural networks, some optimized gradient descent algorithms such as RMSProp (Root Mean Square Prop) and Adam (Adaptive Moment Estimation) can be applied to train the above parameters and constantly adjust their values until a distinct set of parameters are determined with the minimum $Loss(L)$. Finally, we can obtain a classification model of conformance prediction that is a neural network with determined a set of parameters.

The detailed differences of Feature Extraction Layer in our proposed approaches are described as follows.

Base-RNN Approach. We propose an approach called Base-RNN to construct a classification model by using the original RNN network. As shown in Figure 2, the architecture of (Single-layer/Multi-layer) Base-RNN approach has 4 layers and the Feature Extraction Layer is determined as RNN Layer. The cell unit in this layer is shown in Figure 3.

Single-layer Base-RNN is the simplest case of Base-RNN approach with the only one hidden layer in RNN Layer. As for Equation (4a), the final both outputs of RNN Layer are calculated in detail by:

$$h_{ti} = tanh(W_h[h_{t,i-1}, \vec{x}_{ti}] + b_h) \quad (8a)$$

$$o_{ti} = softmax(W_o h_{ti} + b_o) \quad (8b)$$

where $h_{t,i-1}$ is the output of RNN Layer of the last event $e_{t,i-1}$, $\vec{x}_{ti}$ is the encoded vector of the current event e_{ti}, and W_h, b_h are the trainable parameters of weight matrix and bias. As shown in Equation (8a), the extracted hidden vector $h_{t,i-1}$ from the last event $e_{t,i-1}$ can have an effect on the current event. Meanwhile, based on the current inputted event, the new hidden vector h_{ti} can be calculated by using $tanh$ activation function and applied to the feature vector extraction of the next event. Equation (8b) shows another output o_{ti} of this cell by $softmax$ activation function, in which W_o and b_o are another set of weight matrix and bias.

Multi-layer Base-RNN is another complex case of our proposed Base-RNN approach, which has multiple hidden layers in RNN Layer (as shown in Figure 2(b)). Considering an RNN Layer with k hidden layers in Figure 4, the new extracted feature vectors $h_{ti}^{(1)}, h_{ti}^{(2)}, \dots, h_{ti}^{(k)}$ for each hidden layer and the final output o_{ti} can be calculated by:

$$h_{ti}^{(1)} = tanh(W_h^{(1)}[h_{t,i-1}^{(1)}, \vec{x}_{ti}] + b_h^{(1)}) \quad (9a)$$

$$o_{ti}^{(1)} = softmax(W_o^{(1)} h_{ti}^{(1)} + b_o^{(1)}) \quad (9b)$$

$$h_{ti}^{(2)} = tanh(W_h^{(2)}[h_{t,i-1}^{(1)}, o_{ti}^{(1)}] + b_h^{(2)}) \quad (9c)$$

$$o_{ti}^{(2)} = softmax(W_o^{(2)} h_{ti}^{(2)} + b_o^{(2)}) \quad (9d)$$

....

$$h_{ti}^{(k)} = tanh(W_h^{(k)}[h_{t,i-1}^{(k-1)}, o_{ti}^{(k-1)}] + b_h^{(k)}) \quad (9e)$$

$$o_{ti}(o_{ti}^{(k)}) = softmax(W_o^{(k)} h_{ti}^{(k)} + b_o^{(k)}) \quad (9f)$$

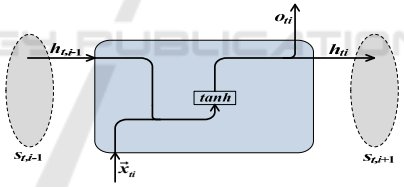


Figure 3: The structure of general RNN cell.

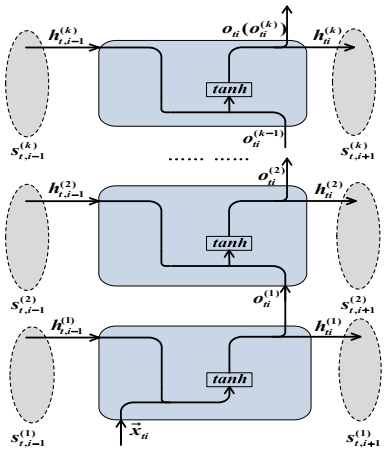


Figure 4: The structure of RNN cell in Multi-layer Base-RNN.

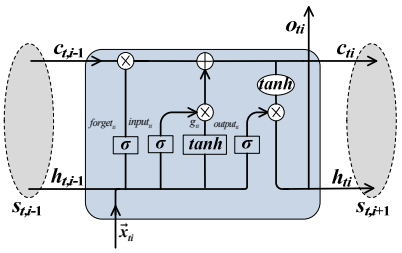


Figure 5: The structure of LSTM cell.

Long Short-Term Memory (LSTM) RNN approach. We propose an approach called LSTM RNN to construct a classification model by using LSTM network. Compared with Base-RNN approach, the difference is that LSTM RNN approach utilizes LSTM Layer in Feature Extraction Layer. The cell unit in this layer is shown in Figure 5.

Single-layer LSTM RNN is the simplest case of LSTM RNN approach with the only one hidden layer in LSTM Layer (as shown in Figure 2(a)). Compared with the cell in RNN Layer, the difference is that the LSTM cell has three gates to control the context information, one is the *input gate* $input_{ti}$ determining how much information can flow into this cell, the second is the *forget gate* $forget_{ti}$ determining how much information is forgotten, and the last is the *output gate* $output_{ti}$ determining how much information can be outputted from this cell. As for Equation (4b), the final both outputs of LSTM Layer are calculated in detail by:

$$forget_{ti} = F_1(W_f \cdot [h_{t,i-1}, \vec{x}_{ti}] + b_f) \quad (10a)$$

$$input_{ti} = F_1(W_i \cdot [h_{t,i-1}, \vec{x}_{ti}] + W_i) \quad (10b)$$

$$g_{ti} = F_2(W_g \cdot [h_{t,i-1}, \vec{x}_{ti}] + b_g) \quad (10c)$$

$$c_{ti} = forget_{ti} * c_{t,i-1} + input_{ti} * g_{ti} \quad (10d)$$

$$output_{ti} = F_1(W_o \cdot [h_{t,i-1}, \vec{x}_{ti}] + b_o) \quad (10e)$$

$$o_{ti}, h_{ti} = output_{ti} * F_2(c_{ti}) \quad (10f)$$

where F_1 denotes $Sigmoid$ activation function, F_2 denotes $tanh$ activation function, and all of W as well as b are the trainable parameters. At first, Equation (10a) determines the information to forget from the inputs of $h_{t,i-1}$ and $\vec{x}_{ti}$ by the forget gate $forget_{ti}$. Then, Equations (10a), (10b) and (10c) determine the information to be memorized, in which c_{ti} denotes the new updated state, $forget_{ti} * c_{t,i-1}$ denotes the information to forget from the last cell, and $input_{ti} * g_{ti}$ denotes the information to put in this cell. Finally, we obtain the output to the next layer o_{ti} and the output to the next cell h_{ti} by the output gate $output_{ti}$ as shown in Equation (10f).

Multi-layer LSTM RNN is another complex case of LSTM RNN approach, which has multiple hidden layers in LSTM Layer (as shown in Figure 2(b)). Considering a LSTM Layer with k hidden layers in Figure 6, the new extracted feature vectors $h_{ti}^{(1)}, h_{ti}^{(2)}, \dots, h_{ti}^{(k)}$ for each hidden layer and the final output o_{ti} can be calculated by:

$$o_{ti}^{(1)}, h_{ti}^{(1)} = LSTM(h_{t,i-1}^{(1)}, \vec{x}_{ti}) \quad (11a)$$

$$o_{ti}^{(2)}, h_{ti}^{(2)} = LSTM(h_{t,i-1}^{(2)}, o_{ti}^{(1)}) \quad (11b)$$

$$\dots\dots\ \dots\dots$$

$$o_{ti}(o_{ti}^{(k)}), h_{ti}^{(k)} = LSTM(h_{t,i-1}^{(k)}, o_{ti}^{(k-1)}) \quad (11c)$$

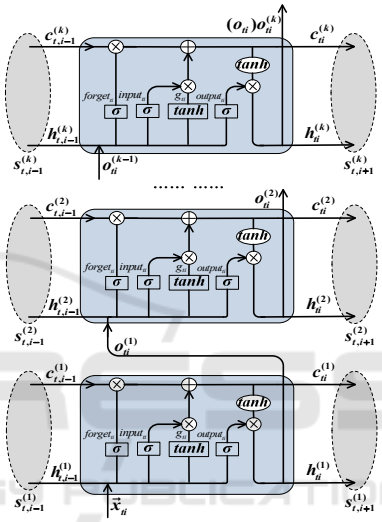


Figure 6: The structure of LSTM cell in Multi-layer LSTM RNN.

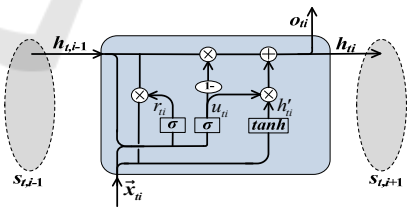


Figure 7: The structure of GRU cell.

Gates Recurrent Unit (GRU) RNN Approach. We propose an approach called GRU RNN to construct a classification model by using GRU network. Compared with RNN LSTM approach, the difference is that GRU RNN approach utilizes GRU Layer in Feature Extraction Layer and reduces the gating signals to two gates. The cell unit in this layer is shown in Figure 7.

Single-layer GRU RNN is the simplest case of GRU RNN approach with the only one hidden layer in

GRU Layer (as shown in Figure 2(a)). Compared with RNN cell, GRU can make each recurrent cell to adaptively capture dependencies of different event lengths. Similar to the LSTM cell, GRU cell has two gates to control the context information, one is the *reset gate* r_{ti} that determines how much information from the previous cell can be viewed as a part of candidate h'_{ti}, and the other is the *update gate* u_{ti} controlling the degree to which information from the previous cell flows into the current cell. The higher the value of u_{ti} is, the more the previous cell information is brought in. As for Equation (4c), the final both outputs of GRU Layer are calculated in detail by:

$$r_{ti} = F_1(W_r \cdot [h_{t,i-1}, \vec{x}_{ti}] + b_r) \quad (12a)$$

$$h'_{ti} = F_2(W_h \cdot [r_{ti} * h_{t,i-1}, \vec{x}_{ti}] + b_h) \quad (12b)$$

$$u_{ti} = F_1(W_u \cdot [h_{t,i-1}, \vec{x}_{ti}] + b_u) \quad (12c)$$

$$o_{ti}, h_{ti} = (1 - u_{ti}) * h'_{ti} + u_{ti} * h_{t,i-1} \quad (12d)$$

where F_1 denotes $Sigmoid$ activation function, F_2 denotes $tanh$ activation function, and all of W as well as b are the trainable parameters. At first, Equation (12a) determines the newly generated information from the inputs of $h_{t,i-1}$ and $\vec{x}_{ti}$ by the reset gate. On the basis of this, the candidate of the current event, i.e. the new memories generated by the current event, can be determined by $tanh$ activation function as shown in Equation (12b). After that, Equation (12c) determines the importance of the hidden state $h_{t,i-1}$ of the previous event $e_{t,i-1}$ by $Sigmoid$ activation function. Finally, based on them, we obtain the output to the next layer o_{ti} and the output to the next cell h_{ti} as shown in Equation (12d).

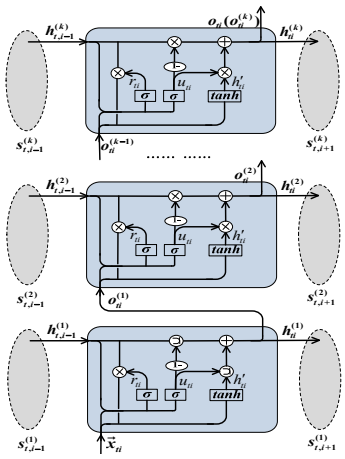


Figure 8: The structure of GRU cell in Multi-layer GRU RNN.

Multi-layer GRU RNN is another complex case of GRU RNN approach, which has multiple hidden layers in GRU Layer (as shown in Figure 2(b)). Considering a GRU Layer with k hidden layers in Figure 8, the new extracted feature vectors $h_{ti}^{(1)}, h_{ti}^{(2)}, \dots, h_{ti}^{(k)}$ for each hidden layer and the final output o_{ti} can be calculated by:

$$o_{ti}^{(1)}, h_{ti}^{(1)} = GRU(h_{t,i-1}^{(1)}, \vec{x}_{ti}) \quad (13a)$$

$$o_{ti}^{(2)}, h_{ti}^{(2)} = GRU(h_{t,i-1}^{(2)}, o_{ti}^{(1)}) \quad (13b)$$

$$\dots\dots \quad \dots\dots$$

$$o_{ti}(o_{ti}^{(k)}), h_{ti}^{(k)} = GRU(h_{t,i-1}^{(k)}, o_{ti}^{(k-1)}) \quad (13c)$$

5 EXPERIMENTS AND RESULTS

5.1 Experimental Settings

In this section, we evaluate the effectiveness and efficiency of our proposed RNN-based approaches (i.e., Base-RNN, LSTM RNN and GRU RNN) by comparing with the following approaches because that a recent empirical research on 165 datasets has shown that RF (Random Forest) and gradient boosted trees (XGBoost) often have a good performance than other classification algorithms (Olson et al., 2018).

RF-based Approaches. Inspired by (De Leoni et al., 2016), we select the method of single bucket to make trace bucketing for building a classifier. In other words, all prefix traces are involved in the same bucket and only a single classifier is trained on the whole prefix log. Afterwards, we utilize two different methods to encoding the events of prefix traces in the bucket for training a classifier. One is the *last state* method where only the last state (i.e. the last event of the prefix trace) information is considered, the other is the *aggregation* method where all events are considered from the beginning of the case while neglecting the order of these events. Here, we compare two methods of *RF_single_laststate* and *RF_single_agg* with our proposed RNN-based approaches.

XGBoost-based Approaches. Similarly, inspired by (Senderovich et al., 2017), we compare two methods of *XGBoost_single_laststate* and *XGBoost_single_agg* with our proposed RNN-based approaches.

We apply the above seven approaches to two real datasets and then use prediction accuracy and time performance for comparison. These approaches are implemented in Python and all experiments run using the scikit-learn library on the server with 2 x 12 Inter(R) Xeon(R) Gold 5118 CPU @2.30GHz 256GB memory and three NVIDIA Tesla V100 GPUs.

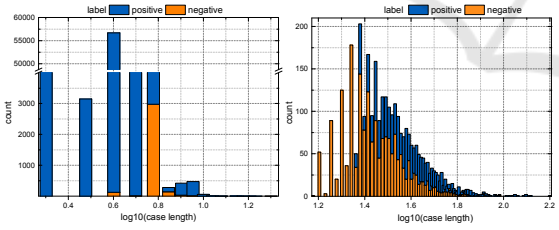
5.1.1 Datasets

Our experimental datasets are from two event logs of *Traffic Fines and BPIC2012* in terms of two different processes, which are all from the public 4TU Centre for Research Data (https://researchdata.4tu.nl/home/). The detailed information are as follows.

Traffic Fines. The log comes from a police station in Italy, which mainly contains the sending of tickets and payment activities, as well as some information related to individual cases. This log contains 150,370 traces, 11 distinct event classes, and a total of 561,470 events.

BPIC2012. This log was originated from the Business Process Intelligence Challenge in 2012, which records the execution history of a loan application process in a Dutch financial institution. It contains 13,087 traces, 36 distinct event classes, and a total of 262,201 events.

Based on these two datasets, we obtain the corresponding reference model expressed as Petri net by ProM (http://www.promtools.org) inspired by (García-Bañuelos, 2017). Then we calculate the fitness of each case based on Equation (2) and determine the conformance class label of them by the given threshold of fitness. Here, we set the fitness threshold as 0.8. Afterwards, in terms of these labelled event logs, the histograms for positive and negative classes are shown in Figure 9. We can find that the samples in these logs are imbalanced, especially *Traffic Fines* log.



(a) (b)

Figure 9: Case length histograms for positive and negative classes in event logs: (a) *Traffic Fines* and (b) *BPIC2012*.

5.1.2 Evaluation Metrics

A good online prediction for an on-going case should be *accurate* in *early stage* because such prediction makes sense only in real time. In this paper, we choose accuracy and execution time to evaluate our proposed approaches.

Accuracy. We choose AUC (the area under the ROC curve) to measure the accuracy of prediction in this paper because other indicators need a predefined threshold of probability for (*positive* vs. *negative*) classes and the value of threshold greatly affects the calculation of accuracy. Moreover, in terms of AUC, the ROC curve is able to remain constant even when the sample distribution is not uniform.

Execution Time. To evaluate the efficiency of online conformance prediction, we select two time metrics, one is *offline time* that related to the total time required to train a classification model, and the other is *online time* that related to the average time required to predict the conformance class (label) of an on-going case.

5.1.3 Parameter Settings

In terms of the above labelled event logs, they are divided into 80% training set (cases) and 20% test set (cases) based on the temporal order respectively so as to simulate the real scenario of conformance prediction. Meanwhile, to better compare these approaches, we optimize each one by further dividing the training set into 80% training data and 20% validation data randomly. That is, the cases in training set are divided into two parts, the classification model is trained with training data, and the performance is evaluated with the remaining validation data so as to find a set of optimized hyper-parameters. Here, these parameters are optimized by using random search method and their distributions as well as value ranges in different approaches are shown in Table 1 inspired by (Teinemaa et al., 2019). Moreover, the number of epochs for our proposed RNN-based approaches is fixed to 50. Based on Table 1, we choose 16 combinations of parameters for each approach and then choose one with the highest AUC in validation data. At last, we compare the AUC and execution time for these determined classification models with a set of hyper-parameters.

5.2 Experimental Results

In order to evaluate the effectiveness and efficiency of the above approaches, we apply them to the training set of each event log. In online conformance prediction, to simulate the on-going cases, we first extract all prefix traces with different length from each completed trace in test set of each event log. And then we calculate the AUC of each length of prefix traces separately as well as the overall AUC for each dataset under different approaches. Similarly, we calculate the offline training time and online predicting time for each dataset under different approaches. Table 2 shows the optimized hyper-parameters for each dataset under different approaches.

Table 1: The hyper-parameters and distributions used in optimization via random search method.

Approach	Parameters	Distribution	Value
RF-based	the number of estimators (*n_estimators*)	Random-integer	$x \in [150,1000]$
	the number of max features (*max_features*)	Log-uniform	$x \in [0.01,0.9]$
XGBoost-based	the number of estimators (*n_estimators*)	Random-integer	$x \in [150,1000]$
	the initial learning rate (*lr*)	Uniform	$x \in [0.01,0.07]$
	the ratio of subsampling (*subsample*)	Uniform	$x \in [0.5,1]$
	the number of max depth (*max_depth*)	Random-integer	$x \in [3,9]$
	the ratio of sampled columns (*colsample*)	Uniform	$x \in [0.5,1]$
	the minimum sum of weight in a child (*min_child*)	Random-integer	$x \in [1,3]$
RNN-based	the number of hidden layers (n_layer)	Categorical	$x \in \{1,2,3\}$
	the number of units in hidden layer (n_hidden)	Log-uniform	$x \in [10,150]$
	the initial learning rate (*lr*)	Log-uniform	$x \in [0.000001,0.0001]$
	batch size (*batch*)	Categorical	$x \in \{8,16,32,64\}$
	dropout	Uniform	$x \in [0,0.3]$
	optimizer	Categorical	$x \in \{rmsprop, adam\}$

Table 2: The optimized hyper-parameters for different approaches.

Dataset	Approach	Parameter					
Traffic Fines		***n_estimators***				***max_features***	
	RF_single_agg	975				0.256	
	RF_single_laststate	984				0.369	
		n_estimators	***lr***	***subsample***	***max_depth***	***colsample***	***min_child***
	XGBoost_single_agg	306	0.0258	0.957	8	0.531	1
	XGBoost_single_laststate	404	0.0436	0.503	8	0.737	1
		n_layer	***lr***	***n_hidden***	***batch***	***dropout***	***optimizer***
	Base-RNN	2	8.27e-05	88	16	0.0655	adam
	LSTM RNN	3	7.30e-05	128	32	0.1432	adam
	GRU RNN	3	5.65e-05	142	32	0.0777	adam
BPIC2012		***n_estimators***				***max_features***	
	RF_single_agg	994				0.185	
	RF_single_laststate	912				0.072	
		n_estimators	***lr***	***subsample***	***max_depth***	***colsample***	***min_child***
	XGBoost_single_agg	258	0.0628	0.807	3	0.5975	2
	XGBoost_single_laststate	642	0.0297	0.711	4	0.7317	1
		n_layer	***lr***	***n_hidden***	***batch***	***dropout***	***optimizer***
	Base-RNN	3	4.26e-05	130	8	0.2497	rmsprop
	LSTM RNN	1	4.46e-05	139	32	0.2162	adam
	GRU RNN	2	9.20e-05	85	64	0.1573	rmsprop

Table 3: The comparison of overall AUC of different approaches.

Approach	Dataset		*Mean*
	Traffic Fines	BPIC2012	
RF_single_agg	0.849	0.768	0.809
RF_single_agg_1	0.842	0.767	0.805
XGBoost_single_agg	0.842	0.784	0.813
XGBoost_single_agg_1	0.850	0.785	0.818
RF_single_laststate	0.848	0.697	0.773
RF_single_laststate_1	0.846	0.698	0.772
XGBoost_single_laststate	0.836	0.713	0.775
XGBoost_single_laststate_1	0.843	0.707	0.775
Base_RNN	0.854	0.786	0.820
Base_RNN_1	**0.856**	0.789	0.823
LSTM RNN	0.853	0.793	0.823
LSTM RNN_1	**0.856**	0.793	0.825
GRU RNN	0.854	**0.803**	0.829
GRN RNN_1	**0.856**	**0.803**	**0.830**

Accuracy Comparison. To compare the accuracy, Table 3 shows the overall AUC, i.e., the AUC for all prefix traces (to be predicted) in each dataset, and the mean overall AUC for different approaches. Here, we add the additional 7 approaches suffixed with "_1", by adding class weight for sample imbalanced. At first, in this table, we can find that GRU RNN can achieve the best performance with the highest overall AUC on these two event logs whether or not it adds the weighted class. In terms of the average overall AUC on two event logs, the best one is also GRU RNN, followed by LSTM RNN, and then Base-RNN. And we also find that all the approaches of RF-based and XGBoost-based are also worse than the RNN-based approaches. Moreover, the overall AUC of the RNN-based approaches added class weight (i.e., suffixed with "_1") has improved especially in *Traffic Fines* log while this dataset is very unbalanced. This finding indicates that the added class weight in RNN-based approaches can make sense for class imbalanced evet log.

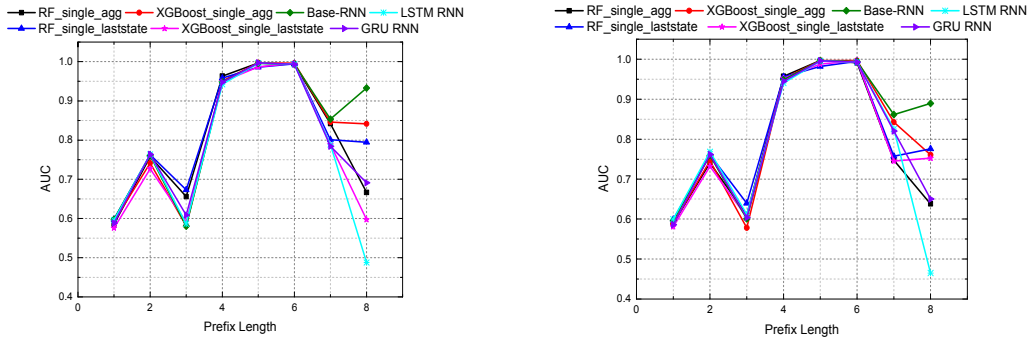


Figure 10: The comparison of AUC of conformance prediction for different lengths of prefix traces in Traffic Fines: (a) different approaches and (b) different approaches with added class weight.

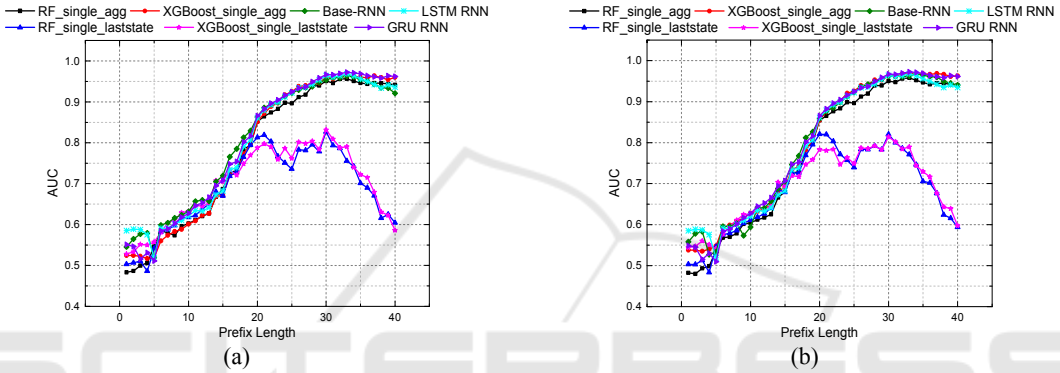


Figure 11: The comparison of AUC of conformance prediction for different lengths of prefix traces in BPIC2012: (a) different approaches and (b) different approaches with added class weight.

Besides, for further comparison, Figures 10 and 11 present the AUC of test samples (i.e., prefix traces, on-going cases) with different length for two datasets. In these subfigures, each point represents all the prefix traces with a specific length and the AUC of these prediction for them. For instance, a prefix length of 5 indicates all the running cases with length of 5 indicates all the running cases with only 5 events executed. As Figures 10 and 11 shown, the variation trend of AUC with the increased prefix length is similar in subfigures (a) and (b). However, the trends of AUC under different approaches in Figure 10 change dramatically with the prefix length increases.

This phenomenon may be due to the occurrence of the coming events that interferes the conformance of an on-going case. Moreover, in Figure 11, we can find that the AUCs of most approaches keep increasing normally as the prefix length increases, but *RF_single_laststate* and *XGBoost_single_laststate* approaches start to decrease and fluctuate when the prefix length reaches a specific value about 20. Hence, we can infer that these two approaches are sensitive to the occurrence of a key activity in business process that has a decisive effect on the conformance.

Table 4: The comparison of time performance of different approaches.

Approach	Traffic Fines		BPIC2012	
	off- (s)	*on-* (ms)	*off-* (s)	*on-* (ms)
RF_single_agg	117	21	27	9
RF_single_agg_1	115	47	34	11
XGBoost	116	16	60	5
XGBoost_single_agg_1	115	13	27	5
RF_single_laststate	115	18	27	3
RF_single_laststate_1	116	14	47	3
XGBoost_single_laststate	114	20	27	4
XGBoost_single_laststate_1	115	19	27	4
Base-RNN	1,687	5	1,126	2
Base-RNN_1	1,621	4	1,116	2
LSTM RNN	4,914	2	352	2
LSTM RNN_1	5,293	2	340	2
GRU RNN	1,608	2	790	2
GRN RNN_1	1,806	2	816	2

Time Performance Comparison. Table 4 shows *offline* time (*off-*) in seconds for training a classification model under different approaches and *online* time (*on-*) in milliseconds for predicting the conformance of all prefix traces in test set in each dataset. In this table, we can find that the offline total time of RF-based and XGBoost-based approaches is

much less than that of RNN-based approaches while the online average time of RF-based and XGBoost-based approaches is more than 20 times as much as that of RNN-based approaches. As we known, in practical applications, the online prediction time is much more important than the offline model construction time. In particular, the online average time of RNN-based approaches is about 2ms, which is negligible. Moreover, in terms of these RNN-based approaches, GRU RNN has the best performance, followed by Based-RNN and then LSTM RNN.

6 CONCLUSIONS AND FUTURE WORK

We proposed three RNN-based approaches called Base-RNN, LSTM RNN and GRU RNN, for online conformance prediction in this paper. These approaches can automatically capture more contextual features even far from the prediction point by using RNN, LSTM and GRU networks. As evaluated on two real datasets from different business processes, our proposed RNN-based approaches have the better performance in both effectiveness and efficiency than existing traditional machine learning methods in real-time prediction applications. In the future, we plan to continue the work presented on this paper by considering more contextual information to construct a conformance prediction model and by conducting experiments on more real-life datasets.

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