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RESEARCH ARTICLE

Next Activity Prediction: An Application of Shallow Learning Techniques Against Deep Learning Over the BPI Challenge 2020

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ABSTRACT Business Process Management is a domain that is composed by different research or application areas. Process Mining is one of them and it is a data-driven approach to analyze and improve processes. In Process Mining "next activity prediction" is one of the most important task. The used data are event logs i.e., a timeseries of recorded events. The event logs are mainly processed using deep learning algorithms. In this study, it was proposed the comparison of prediction performance of shallow learning algorithms with a three block Bidirectional LSTM (Bi-LSTM) architecture in predicting the next activity. The algorithms were applied on all the events logs of the BPI Challenge 2020 dataset. Results show that shallow learning algorithms outperform the three-block architecture from a minimum of 1.5 to a maximum of 6 times. This suggest that simpler algorithms may be more effective than the three-block architecture.

INDEX TERMS Bi-LSTM, next-activity prediction, process mining, public administration, shallow learning, university processes.

I. INTRODUCTION

The area of business process management is composed by several fields of research or application. One of these fields, with a growing interest, is called "Process Mining" [1]. Specifically, thanks to the application of Data Mining and, more in general, Machine Learning techniques it is possible to gain information from processes [1]. A process is defined as a timeseries of event and such data are collected in "event logs" [2], [3], [4], [5]. Finally, the process mining is a data-driven approach that aims to gain insight from "event logs", to evaluate the quality, to discover bottleneck of processes within organization [1], [6], [7], [8], [9].

Organization involved in research and application of process mining techniques ranging from private companies [10] to public organizations that range from Universities [5], [11] to Health care organizations [12] etc. Analyzing process data and building process models, improvements of the quality of organization processes in terms of cost, time spent, and hum an resources utilized could be reached.

Considering the type event log data, process mining is related to timeseries management. In literature, a wide range of models are used to analyze data, starting from the well-known and widely used classical LSTM [13], [14] to the application of the Convolutional Neural Networks on timeseries [15], [16], [17], [18], [19]. In this way, temporal relationship of data could be highlighted and use to perform the "next activity prediction" or the "elapsed time prediction" tasks [13], [20], [21]. The first one consists of the prediction of the successive activity to perform after a sequence of activity already performed. Meanwhile, the latter consist of the prediction of the passed time between the last activity already performed and the next activity [13], [14], [16], [20], [21]. The majority of the used machine learning techniques are from the "Deep Learning" domains i.e., Convolutional Neural Networks or Long

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Short-Term Memory Neural Networks [13], [14], [16], [17], [22], [23], [24], [25].

Differently from the more recent literature, in this work it is proposed an application of "shallow learning" techniques to analyze their potentiality, on the "next activity prediction" task, compared to the use of more complex models as the Three Block Bi-LSTM [13]. In previous works, limitations have been identified as computational complexity, data requirements, and the absence of baseline performance. Hence, this work provide firstly baseline performance considering the BPI Challenge 2020, secondly this work using "shallow learning" techniques improve the state-of-art with less complex and less data hungry models.

In order to provide more robust results, experiments were performed the 6 events log that composing the BPI Challenge 2020 dataset. The term "shallow learning" identifies the area of machine learning that includes all machine learning algorithms excluding the neural networks and the deep neural networks. In literature is also possible that the "shallow learning" algorithms are also referred as "traditional/conventional machine learning" [26], [27].

The following work is organized as: Section II explain the work that inspired this work, the methods used in this work are explained in Section III, then experimental set-ups including the used dataset, results and discussion are organized in Section IV and V. Finally, in section VI conclusion are extracted.

II. RELATED WORKS

In process mining domains, "event logs" contain process-related data. Specifically, data are timeseries and each timeseries describe a sequence of performed activity for a specific case [1]. The "events logs" are analyzed in order to gain process-related insight in order to improve organization's processes. Such analysis could lead to obtain process models in order to performs performance analysis and predictions. These tasks are related to the use of machine learning models, and such tasks allow to obtain prediction for next activity or elapsed time or other indicators [1]. Particularly, the first one is called "next activity prediction", it is intended as the prediction of the next activity based on past information [1]. And the second one is called "elapsed time prediction", it is intended as the prediction of the time to spent to the next activity [1].

Gunnarsson et al. [13] proposed a Bi-Directional Long Short-Term Memory (BiLSTM) based Neural Network architecture in order to perform "next activity prediction" and "elapsed time prediction". Specifically, the work [13] proposed an architecture with three main blocks: the first one analyze data and extract features, the others two blocks analyze features and predict one the "next activity" the second the "elapsed time", intended the time passed to obtain the next activity. Furthermore, the three blocks are equal, and this means that three Bi-LSTM were used.

Ni et al. presented a Hierarchical Transformer in order to perform "next activity prediction" and "remaining time prediction" [28]. The latter differs from "elapsed time prediction" by the time predicted: "elapsed time prediction" is related to the time to next activity meanwhile "remaining time prediction" is related to the time remained to the end of activity trace [1]. Considering the Hierarchical Transformer its architecture was based on the use of a three-layer transformer that manage information at three distinct levels: event-level, subsequence-level, and instance-level.

Klein et al. in [11] presented an analysis of process dataset. It needs to be highlighted the use of Decision Tree in order to reveille the latent structures in the event logs. In particular, the "activity" label was use as target class to be predicted. In this way, relationship among attributes and events were highlightable.

Agostinelli et al. presents a work in which the analysis of event logs allows to obtain deterministic finite state automata [2]. In particular, the purpose was to evaluate the performance of machine learning algorithms to be used for the development of Business Process Mining tools.

Hence, in this work is proposed the use of several machine learning algorithms, specifically shallow learning algorithms (e.g., Decision Tree), in order to perform the next activity prediction against the three block Bi-LSTM proposed in [13]. In this way, it is possible to obtain baseline performance using "shallow learning" techniques. Furthermore, the proposed models provide less complex and less data hungry solutions.

III. METHODS

This section is related to the used methods to perform "next activity prediction". In particular the used machine learning algorithms are of two macro-categories: shallow learning and deep learning. Surface learning and deep learning refer to two areas of machine learning. The first includes all machine learning algorithms, excluding neural networks. The second, on the other hand, refers to neural networks with different architectures and different depths (number of layers) [27].

In order to select the surface learning algorithms to be used, the rationale was to choose those widely used in the literature. In addition, the choice of algorithms was also influenced by [11]. Hence, Decision Tree, Random Forest, AdaBoost, Gradient Boost, K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) were the selected as shallow learning techniques.

Meanwhile, in order to select a deep learning algorithms, it was selected the three blocks Bi-LSTM as the same architecture presented in [13]. Specifically, the architecture consists of three blocks. Each block is a Bi-LSTM. Hence, the architecture is: the first block analyze the data and it propagate the output, a sequence of hidden states, to the other two separated Bi-LSTM. The two separated Bi-LSTM learn from the output of the first Bi-LSTM and predicts two different information: next activity and elapsed time to the next events. The described architecture is showed in Figure 1.

Hence, the purpose of the "next activity prediction" was reached using several machine learning algorithms. Finally, all the used algorithms were indicated in Table 1.

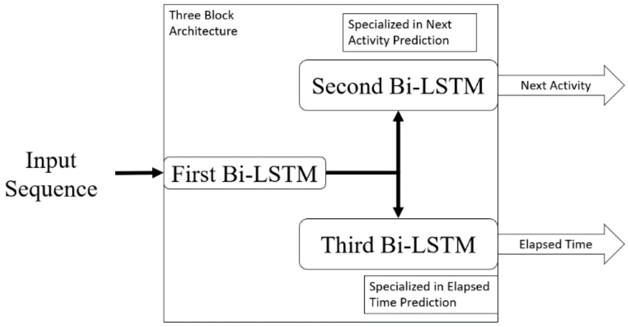

FIGURE 1. Three block Bi-LSTM.

TABLE 1. Machine learning algorithms used to perform experiments.

Machine Learning Algorithm used
Decision Tree
Random Forest
AdaBoost
Gradient Boost
K-Nearest Neighbor
Support Vector Machine
Three Block - BiLSTM

IV. DATASET

In this work, the used dataset is the BPI Challenge 2020 (BPIC20) [29]. It was built recording activity performed by University of Technology of Eindhoven (TU/e) and it was presented for the Business Process Intelligence Challenge 2020. The recorded activities were collected from the 2017 to 2018.

The BPIC20 dataset is organized as a collection of five "event logs". Specifically, the "event logs" are called: Domestic Declarations [30], Request for Payment [31], International Declarations [32], Travel Permit Data [33] and Prepaid Travel Costs [34]. Each one of the event logs is publicly available.

The general information about the five event logs is reported in Table 2. In details, a "case" identifies a sequence of events (each one with an activity label) related to costs reimbursements of travels intra- or inter- national. An "activity" is a single action take following the path of the reimbursements e.g., from submission to payment. An "events" is the recorded "activity". For each event are available several information stored in the attributes. Such information could be case-related or activity-related. Furthermore, each event has its own timestamp, indicating when the event was recorded.

After the analysis reported in [11], relationship among "event logs" were highlighted. The "event logs" contains information categorizable in three subprocess: "permit subprocess", "request for payment process" and "declaration process". Indeed, Domestic declaration include only activity related to declaration process. Similarly, International declaration include declaration process's activities as well as permit subprocess activities. Meanwhile, Request For Payment contains only activities related to request for payment process and Prepaid Travel Cost contains similar activity as Request For Payments but it includes also permit process's activities. Finally, Total Permit Data contains information of all the three subprocess.

This characteristic is due to the processes recorded. Indeed, in Total Permit Data is possible to highlight link with the case of International Declaration and Prepaid Travel Cost. This behavior is not replicated among other "event logs".

The attributes for each "event log" are reported from Table 3 to Table 7. Furthermore, in each table is reported the number of unique "activity label" for each "event log".

Since the focus of this work is on the next activity prediction, the crucial information is "activity label". This information is contained in the "concept:name" attribute.

TABLE 2. Meta-data about the five event logs of BPIC 20. Each row describe a different event log.

Event Log Name	N° cases	N° activities	N° events	N° attributes
Prepaid Travel Cost	2,099	29	18,246	17
International Declarations	6,449	34	72,151	18
Request For Payment	6,886	19	36,796	9
Total Permit Data	7,065	51	86,581	168
Domestic Declarations	10,500	17	56,437	5

TABLE 3. Attributes names and types of the event log "Domestic declaration". The attribute that contains the "activity label" is "concept:name" and the number of values is 17.

Attribute Name	Attribute Type
case:Amount	float
case:BudgetNumber	string
case:concept:name	string
case:DeclarationNumber	string
case:id	string
concept:name	string (number of values 17)
id	string
org:resource	string
org:role	string
time:timestamp	TIMESTAMP

V. EXPERIMENTS

In this section the data-preprocessing techniques and the experimental set-ups are explained in order to make clear how experiments were performed.

A. DATA PREPROCESSING

In each event logs are possible to detect several "case". A case is described as a sequence of events. In literature, the case is also called "trace". Assuming T as trace, its representation is $T = < e_1, e_2, e_3, e_4, e_5 >$ where each e_i identify a recorded event. Each event e_i contains several attributes.

TABLE 4. Attributes names and types of the event log "International declaration". The attribute that contains the "activity label" is "concept:name" and the number of values is 34.

Attribute Name	Attribute Type
case:AdjustedAmount	float
case:Amount	float
case:BudgetNumber	string
case:concept:name	string
case:DeclarationNumber	string
case:id	string
case:OriginalAmount	float
case:Permit ActivityNumber	string
case:Permit BudgetNumber	string
case:Permit ID	string
case:Permit id	string
case:Permit OrganizationalEntity	string
case:Permit ProjectNumber	string
case:Permit RequestedBudget	float
case:Permit TaskNumber	string
case:Permit travel permit number	string
case:RequestedAmount	float
case:travel permit number	string
concept:name	string (number of values 34)
id	string
org:resource	string
org:role	string
time:timestamp	TIMESTAMP

TABLE 5. Attributes names and types of the event log "Prepaid Travel Cost". The attribute that contains the "activity label" is "concept:name" and the number of values is 29.

Attribute Name	Attribute Type
case:Activity	string
case:concept:name	string
case:Cost Type	int
case:OrganizationalEntity	string
case:Permit ActivityNumber	string
case:Permit BudgetNumber	string
case:Permit id	string
case:Permit OrganizationalEntity	string
case:Permit ProjectNumber	string
case:Permit RequestedBudget	float
case:Permit TaskNumber	string
case:Permit travel permit number	string
case:Project	string
case:RequestedAmount	float
case:Rfp_id	string
case:RfpNumber	string
case:Task	string
concept:name	string (number of values 29)
id	string
org:resource	string
org:role	string
time:timestamp	TIMESTAMP

The number of attributes varies depending on which "event logs" is analyzed. Indeed, as reported in Table 2, the number of attributes vary. But attributes could be categorized in two main groups: case-related and activity-related. The first group

TABLE 6. Attributes names and types of the event log "Request For Payment". The attribute that contains the "activity label" is "concept:name" and the number of values is 19.

Attribute Name	Attribute Type
case:Activity	string
case:concept:name	string
case:Cost Type	int
case:OrganizationalEntity	string
case:Project	string
case:RequestedAmount	float
case:Rfp_id	string
case:RfpNumber	string
case:Task	string
concept:name	string (number of values 19)
id	string
org:resource	string
org:role	string
time:timestamp	TIMESTAMP

TABLE 7. Attributes names and types of the event log "Permit Log". The attribute that contains the "activity label" is "concept:name" and the number of values is 51.

Attribute Name	Attribute Type
case:Activity_#	string
case:ActivityNumber	string
case:BudgetNumber	string
case:concept:name	string
case:Cost Type_#	float
case:dec_id_#	string
case:DeclarationNumber_#	string
case:id	string
case:OrganizationalEntity	string
case:OrganizationalEntity_#	string
case:Overspent	bool
case:OverspentAmount	float
case:Project_#	string
case:ProjectNumber	string
case:RequestedAmount_#	float
case:RequestedBudget	float
case:Rfp_id_#	string
case:RfpNumber_#	string
case:Task_#	string
case:TaskNumber	string
case:TotalDeclared	float
case:travel permit number	string
concept:name	string (number of values 51)
id	string
org:resource	string
org:role	string
time:timestamp	TIMESTAMP

of attributes contains information about the case (e.g., the amount of the reimbursement), meanwhile the second group contains information about recorded activity (e.g., activity label or the timestamp). In this work, the timestamp is used to sort the events and the activity labels are used as data features.

The traces are initially sorted by the timestamps of each event, to ensure that the first event (e_1) of the trace is the

TABLE 8. Example of preprocessing of a trace $T =< e_1, e_2, e_3, e_4, e_5 >$. Label is the next activity to predict.

t	w	Prefix(T,k,w)	Label
1	3	$0, 0, e_1$	e_2
2	3	$0, e_1, e_2$	e_3
3	3	e_1, e_2, e_3	e_4
4	3	e_2, e_3, e_4	e_5

earliest in chronological order. In addition, a second sorting is performed on the list of traces, using the initial timestamp of each trace (i.e., the timestamp of the first event, e_1). The result is a sorted list of traces in which both traces and events within each trace are sorted according to their timestamps.

B. EXPERIMENTAL SET-UPS

In order to perform a fairly comparison, the experimental set-up was implemented following [13]. Firstly, the list of traces was initially split in 75/25 in order to obtain train and test dataset. Then the train dataset was further filtered. In particular, the traces in the train dataset that ends after the start of the first trace in the test dataset were deleted. Moreover, to obtain comparable results and following the pipeline in [13], the remaining train dataset was again split in 75/25. In this way, the 75 is the effective train dataset and the 25 is deleted.

In this work, the purpose is the "next activity prediction". Hence, to this purpose, each trace was processed using a so called "Prefix" function. Prefix is defined as a function applied on a trace T that return a sub-trace starting from the position k and with size w, $Prefix\,(T, k, w) \;=< e_{\{k-w\}}, \ldots, e_{\{k\}} >$. Furthermore, if $k < w$, a zero padding was applied. The associated label with a prefix consists in e_{k+1}.

In this work, the used windows size $w = 3$ and the prefixes are extracted as reported in Table 8.

Once prefixes and labels were extracted, from each event the used attribute was the activity label. In particular, the activity labels were coded performing the following steps:

1. The activities labels were One-Hot Encoded
2. On each one one-hot encoding was applied an argmax function in order to obtain the position of the 1 in the one-hot encoding.

In this way, a codification of activities labels was obtained. A representation of such codification is reported in Figure 2.

Finally, the shallow learning models listed in Table 1 were trained on the train set and tested on the test set.

VI. RESULTS AND DISCUSSION

A. RESULTS

Once the experiments were performed, predictions were evaluated accordingly to the following metrics:

Categorical Accuracy: The proportion of the correctly predicted "next activity label" on the total number of predicted "next activity label". The obtained results are reported in Table 9 and represented in Figure 3.

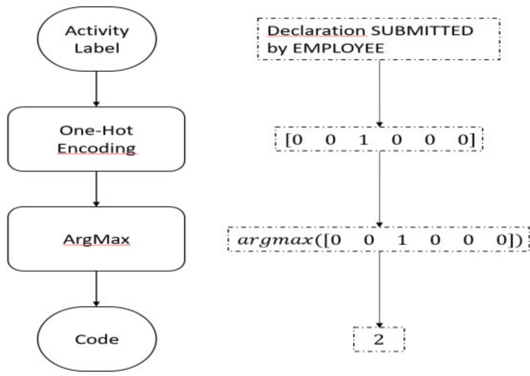

FIGURE 2. Representation of activity label codification. The first graph (on the left) reports the conceptual description of the codification steps. The second graph(on the right) report an example input and an expected outputs.

TABLE 9. Experimental results performed with both models on the BPIC-2020.

Machine Learning Algorithms	Domestic Declar.	International Declar.	Total Permit Data	Prepaid Travel Cost	Request For Payment
Three blocks Bi-LSTM [13]	0.42	0.25	0.19	0.12	0.61
Decision Tree	**0.89**	**0.84**	**0.80**	**0.81**	**0.88**
Random Forest	**0.89**	**0.84**	0.79	**0.80**	**0.88**
AdaBoost	0.77	0.26	0.23	0.52	0.66
Gradient Boost	**0.89**	**0.84**	**0.80**	**0.81**	**0.88**
K-NN	**0.89**	0.82	0.79	0.8	**0.68**
SVM	**0.89**	0.79	0.75	0.76	**0.88**

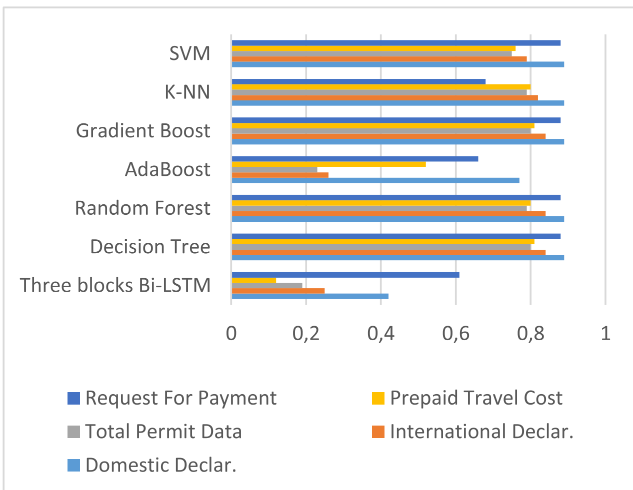

FIGURE 3. Representation of the experimental results reported in Table 9.

B. DISCUSSION

In Table 9 (and in Figure 3) are reported all the results obtained from the application of the experiments. Specifically, it is noticeable that the application of Decision Tree and Gradient Boost outperforms the application of than the three blocks architecture based on the Bi-LSTM on all the event logs. Indeed, the accuracy performance improvements of shallow learning algorithms over deep learning algorithms range from a minimum of 1.5 to a maximum of 6 times.

Furthermore, the accuracy performance on the Domestic Declaration is higher than on the others event logs. This results could be related to the nature of the event logs, i.e., the domestic declaration is simpler than the Total Permit Data and the other event logs.

Moreover, the results suggest also that simpler algorithms, than the three blocks architecture, are more capable to detect patterns in event logs. Hence, from results less complex and less data hungry models are more accurate than a more complex and more data hungry model and these could be considered as baseline results for further works.

VII. CONCLUSION

In this work, the use of several machine learning techniques is compared on a dataset related to processes. Specifically, the comparison aims to detect the system with a higher capability to predict the ''next activity'' and to establish whether less complex and less data hungry models have higher performance than complex model.

The results show that shallow learning techniques outperform than the three blocks architecture based on Bi-LSTM. Furthermore, Decision Tree and Gradient Boosting reached the top performance in all the event logs. These results suggest that the shallow learning algorithms are more effective in detect patterns in event logs than the three blocks architecture.

Future works could improve the performance of the used machine learning techniques by including more event information than the only use of the event's activity label. Furthermore, the number of machine learning techniques could be increased. In this way, it might be possible to highlight which techniques, with their properties, are most likely to perform better. Future work could confirm these results using more datasets.

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