Incremental Predictive Process Monitoring: How to Deal with the Variability of Real Environments

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Abstract. A characteristic of existing predictive process monitoring techniques is to first construct a predictive model based on past process executions, and then use it to predict the future of new ongoing cases, without the possibility of updating it with new cases when they complete their execution. This can make predictive process monitoring too rigid to deal with the variability of processes working in real environments that continuously evolve and/or exhibit new variant behaviors over time. As a solution to this problem, we propose the use of algorithms that allow the incremental construction of the predictive model. These incremental learning algorithms update the model whenever new cases become available so that the predictive model evolves over time to fit the current circumstances. The algorithms have been implemented using different case encoding strategies and evaluated on a number of real and synthetic datasets. The results provide a first evidence of the potential of incremental learning strategies for predicting process monitoring in real environments, and of the impact of different case encoding strategies in this setting.

Keywords: predictive process monitoring, incremental learning, concept drift

1 Introduction

Predictive process monitoring [21] is a research topic aiming at developing techniques that use the abundant availability of event logs extracted from information systems in order to predict how ongoing (uncompleted) process executions (a.k.a. cases) will unfold up to their completion. In turn, these techniques can be embedded within information systems to enhance their ability to manage business processes. For example, an information system can exploit a predictive monitoring technique to predict the remaining execution time of each ongoing case of a process [30], the next activity that will be executed in each case [13], or the final outcome of a case, wrt. a set of possible outcomes [24,26,27].
Existing predictive process monitoring techniques first construct a predictive model based on data coming from past process executions. Then, they use this model to predict the future of an ongoing case (e.g., outcome, remaining time, or next activity). However, when the predictive model has been constructed, it cannot be updated with new cases when they complete their execution. This is a limitation in the usage of predictive techniques in the area of business process monitoring: well-known characteristics of real processes are, in fact, their complexity, variability, and lack of steady-state. Due to changing circumstances, processes evolve, increase their variability, and systems need to adapt continuously. A coexisting problem concerns the abundance of data from which to learn models and the impact on memory resources. While one may argue that building models for highly variable scenarios can be tackled by exploiting large and complex historical logs, not always their size is consistent with the system memory limits and a dilemma may arise on where to actually cut the boundaries of a good training set.

Incremental learning algorithms have been proposed in the literature as a way to incrementally construct predictive models by updating them whenever new cases become available [10]. In this paper, we start from that to propose a set of techniques for learning the predictive models incrementally from streaming event data. In particular, we update the predictive model using new cases as soon as they complete by storing information only about the most relevant ones in a limited budget of memory. The proposed techniques have been developed considering that: (i) the complete dataset cannot be stored but only part of it is used to build the predictive model; (ii) in the case of concept drifts, i.e., when the process is explicitly changing while being analyzed, the trained model should be quickly adapted to cope with the changes; (iii) the training of the predictive model is robust to noise, i.e., slight variations in the data do not affect the predictions. The focus of the developed techniques is on outcome predictions, such as predictions on whether an ongoing case will end by following the happy path or not, or on whether an ongoing case will terminate quickly or slowly. The techniques have been implemented using different case encoding strategies and classification algorithms, as well as evaluated on different real datasets.

The evaluation aims at investigating three main aspects: (i) whether the incremental approaches allow for improving the prediction accuracy with respect to traditional offline approaches; (ii) whether the incremental approaches allow for improving the time performance when compared to the periodic rediscovery of the predictive model with non-incremental approaches; (iii) how the incremental approaches behave when dealing with concept drifts. The results demonstrate that, on real datasets, the incremental update of the predictive model improves, in most of the cases, the accuracy of the predictions with respect to the training of the predictive model once and for all (even without explicit concept drifts). In addition, we show that the rediscovery of the predictive model from scratch when a certain amount of new cases becomes available provides an accuracy that is comparable to the one obtained with the incremental learning of the model. However, as expected, the periodic rediscovery of the models is more inefficient.
Finally, we investigate which predictive techniques are especially suited for predictive monitoring with concept drift. We believe that these results provide a first insight on the potential of incremental learning strategies for predicting process monitoring with real log data.

The rest of the paper is structured as follows. Section 2 provides the necessary background on predictive process monitoring and incremental learning; Section 3 presents two exemplifying scenarios of process variability in real environments; Sections 4 and 5 illustrate the proposed techniques, their implementation, and their evaluation on four datasets of different nature. We finally provide some related work (Section 6) and concluding remarks (Section 7).

2 Background

2.1 Predictive Process Monitoring

The basic Predictive Process Monitoring Framework, presented in [9,14], collects a set of machine learning techniques that can be instantiated and used for continuously providing predictions to the user. In detail, the framework takes as input a set of past executions and tries to predict how current ongoing executions will develop in the future. For this purpose, before the process execution, a pre-processing phase is carried out. In this phase, state-of-the-art approaches for clustering and classification are applied to the historical data in order to: (i) identify and group historical case prefixes with a similar control flow, i.e., to delimit the search space on the basis of the control flow (control flow-based clustering); (ii) get a precise classification based on data of cases with similar control flow (a data-based classifier is built for each cluster).

Clusters and classifiers computed as outlined above are stored and used at runtime to classify new cases during their execution. In particular, a given case prefix is matched to a cluster, and the corresponding classifier is used to estimate the (class) probability for the case to achieve a certain outcome and the corresponding (class) support (that also gives a measure of the reliability of the classification algorithm outcomes). The overall picture of the framework is illustrated in Fig. 1. Within such a framework, we can identify four main modules: two for the encoding (of the control flow and data), one for the clustering and one for the supervised classification learning. Each of them can be instantiated with different techniques.

Examples of case encodings are frequency-based (a.k.a. term-frequency [9,20]) and sequence-based [9,16]. These encodings can then be passed to a clustering technique such as dbscan clustering [12], k-means clustering [23] and agglomerative clustering [32]. The supervised learning module can instead include learning techniques like decision tree and random forest. The framework has been implemented as an Operational Support (OS) provider of the OS Service 2.0 of the ProM toolset [14]. In particular, the OS service is able to interact with external workflow engines by receiving at runtime streams of events and processing them through the providers. The same framework has also been implemented in the Nirdizati web application [21].
An alternative to the approach contained in the Predictive Process Monitoring Framework, hereafter called clustering-based approach, is the usage of index-based encodings presented in [22]. In the index-based encoding, the data associated with events in a case is divided into static and dynamic information. Static information is the same for all the events in the case (e.g., the information contained in case attributes), while dynamic information changes for different events (e.g., the information contained in event attributes). The resulting feature vector \( g_i \), for a case \( \sigma_i \), is:

\[
g_i = (s_{i1}, s_{i2}, \ldots, s_{iu}, event_{i1}, event_{i2}, \ldots, event_{im}, h_{i1}^{1}, h_{i2}^{1}, \ldots, h_{im}^{1}, \ldots, h_{i1}^{r}, h_{i2}^{r}, \ldots, h_{im}^{r}),
\]

where each \( s_i \) is a static feature, each \( event_{ij} \) is the event label at position \( j \) and each \( h_{ij} \) is a dynamic feature associated to an event. In this approach, the case prefixes are grouped per prefix length and a classifier is trained from each group of prefixes. At runtime, predictions on a prefix of an ongoing case of a given length are made by using the classifier trained with prefixes of the same length.

### 2.2 Incremental Learning and Concept Drift Detection

When dealing with machine learning algorithms, we can categorize them in offline and online algorithms [17]. In offline learning, the training data is available all together and is used to build the predictive model once and for all. In online learning, a model is produced with a reduced training set and continuously updated as data arrives. Incremental learning refers to online learning approaches characterized by the incremental update of the learned models in a way that they maintain an accuracy comparable to the one obtained by training the models from scratch with all the data available [19].

Incremental learning algorithms are built to find a good trade-off in the so-called stability-plasticity dilemma, i.e., in allowing a system to remain stable and robust to noise in the data, while being plastic, i.e., able to adapt to new data when it evolves over time [19]. These changes in the data over the time are known as concept drifts.
**Incremental Learning Algorithms** Incremental learning approaches have been developed for different tasks both supervised and unsupervised. In the following, we describe three incremental learning approaches that will be used in the evaluation: (i) an incremental clustering algorithm (Canopy); (ii) an incremental classification algorithm that does not explicitly deal with the problem of concept drift (Hoeffding tree); (iii) an incremental approach that explicitly tackles the concept drift problem (Adaptive Hoeffding Tree).

Canopy [32] is an incremental unsupervised learning approach for clustering used when the clustering task is challenging either in terms of dataset size, or in terms of number of features, or in terms of number of clusters. The idea is building clusters in two phases. In the first phase, subsets of the dataset items - called canopies - with a distance lower than a given predefined threshold $T_1$ from a central point are computed by leveraging a distance metrics that is fast to compute although not very precise. The result is that an item can belong to more than one canopy and should belong at least to one canopy. The intuition is that dataset items that do not share any canopy do not belong to the same cluster. In the second phase, the actual clusters are computed by using a more precise and costly metrics and a second threshold $T_2$, which allows for the precise identification of the clusters.

Hoeffding tree [10] is an incremental decision tree learning algorithm that is capable of learning from massive data streams, assuming that the distribution generating the examples does not change over time. Hoeffding trees exploit the fact that a small sample can often be enough to choose an optimal splitting attribute. This idea is supported mathematically by the Hoeffding bound, which quantifies the number of observations (the examples) needed to estimate some statistics within a prescribed precision (the goodness of an attribute). A theoretically appealing feature of Hoeffding trees not shared by other incremental decision tree learners is that it has sound guarantees of performance. Using the Hoeffding bound one can show that its output is asymptotically nearly identical to that of a non-incremental learner using infinitely many examples.

Adaptive Hoeffding tree tackles the problem of concept drift. Differently from the Hoeffding tree algorithm, it keeps statistics about data and use them to provide a better estimation of the splitting attributes. In detail, in order to deal with concept drifts, it uses the ADWIN (ADaptive WINdow) approach [8] (i.e., a sliding window of variable size) to monitor the performance of branches on the tree and to replace them with new branches when their accuracy decreases if the new branches are more accurate.

**3 Two Motivating Examples**

We aim at assessing the benefits of incremental learning techniques in scenarios characterized by high process variability and/or concept drift phenomena. In this section, we introduce two motivating scenarios, which refer to some of the datasets used in the evaluation described in Section 5.
Scenario 1. Dealing with Process Variability. Information systems are widely used in healthcare and several scenarios of predictive analytics can be provided in this domain. Indeed, the exploitation of predictive techniques in healthcare is described as one of the promising big data trends in this domain [6].

Despite some successful evaluation of predictive process monitoring techniques using healthcare data [8,24], predictive monitoring needs to consider a well known feature of healthcare processes, i.e., their variability [31]. Whether they refer to non-elective care (e.g., medical emergencies) or elective care (e.g., scheduled standard, routine and non-routine procedures), healthcare processes often exhibit characteristics of high variability and instability. In fact, these processes often result in spaghetti-like models where it is difficult to distill a stable process. Moreover, small changes in the organizational structure (e.g., new personnel in charge of a task, unforeseen seasonal variations due to holidays or diseases) may originate subtle variability not detectable in terms of stable concept drifts, but nonetheless relevant in terms of predictive data analytics.

In such a complex environment, deciding a priori which portion of information system data to use for training a predictive algorithm is challenging. The first challenge is related to the amount of data to consider. Even in the big data era, cleaning, integrating, and processing relevant amounts of data is a challenge that not all the organizations are equipped to deal with. Thus, resorting on considering years of data so to consider enough variations is often impracticable.

The second challenge concerns the emergence of new behaviors: regardless of how much data we consider, an environment highly dependent on the human factor is likely to exhibit new variants that may not be captured when stopping the training at a specific time. Similarly, some variants may become obsolete, thus making the forgetting of data equally important.

Thus, a way for adapting the predictions to these changes, and an investigation of which incremental learning strategies are particularly suited to highly variable and realistic process executions would be of great impact.

Scenario 2. Dealing with Concept Drift. The second scenario focuses on a situation where a clear concept drift happens, due to some well understood restructuring of an organizational procedure. We consider here two examples of concept drift in the insurance claim handling process already introduced in [25].

The initial process model is depicted in Figure 2 using the BPMN language. The process considers two different checks of claims, a basic one and a complex one, depending on the value of the claim and, after the decision is taken, the claimant is notified using different communication means depending on some specific conditions. In parallel, a questionnaire is sent to the claimant which can be received back before a certain deadline.

The two concept drifts we illustrate here (a slight simplification of the ones introduced in [25]) concern data used on the guards and the control flow, respectively. The first drift assumes that the distinction between the basic check and the complex check is now done based on the age of the claimant (instead of the value of the claim): if the claimant is 50 yrs old or more, the check will be a complex one. Otherwise it will be a basic one. Also, the policy for accept-
Fig. 2. A BPMN model for insurance claim handling

...ing claims changes from favoring claimants with no previous cases - as before the drift - to favoring claimants with high status among VIP, Gold, Silver, and Regular. The second drift assumes that for cost reduction purposes, hospitals are no longer contacted as part of the complex claim checking. This activity is therefore removed from the process (model). Moreover, the scenario assumes a change of distribution in the claimants and claims characteristics resulting in a higher percentage of older patients and complex claim checks.

As we can easily see, ignoring these drifts could lead to a loss in terms of prediction accuracy and a further investigation that advances the work of [25] in understanding which predictive techniques are especially suited for predictive monitoring with concept drift would be very relevant.

4 Incremental Predictive Process Monitoring

4.1 Architecture

In order to overcome the typical problems of online learning, we equipped state-of-the-art predictive process monitoring approaches with incremental learning techniques. In detail, we focused on two different predictive process monitoring approaches, which have shown competitive results in terms of quality of predictions: the clustering-based approach [9] and the index-based approach [22], both introduced in Section 2. We describe in the following the Incremental Clustering-based approach and the Incremental Index-based approach built starting from the clustering-based and the index-based approach, respectively.

As described in Section 2, the case prediction in the Predictive Process Monitoring Framework is based on two steps. First, the approach leverages the control flow information in order to cluster together cases with a similar control flow. Then, data information is exploited in order to classify an ongoing case and predict its outcome. Whenever a new (complete) case becomes available, one or more clusters could need to be updated first and then the corresponding classifiers. Indeed, the additional information available (all the case prefixes of the current case) could cause the creation of new clusters, a change in the existing
structure and/or an update of the existing clusters. Figure 3 shows how Incremental Clustering-based works: whenever a new complete case is available, first, one or more clusters are updated with the new set of case prefixes; then the classifiers corresponding to each cluster are also updated with the new data.

In the Incremental Index-based approach, no unsupervised step is applied and both the control flow and the data flow information is taken into account in the supervised step. In this case, whenever a new case is completed and available for updating the classifiers, each of its prefixes is used for updating the corresponding classifier. Figure 4 shows the logical architecture of the update mechanism: each prefix of the new complete case is used for updating the classifier trained with prefixes of the same length.

4.2 The Incremental Predictive Process Monitoring Framework

Both the approaches have been implemented in the Incremental Predictive Process Monitoring Framework. The Incremental Predictive Process Monitoring Framework comes with two components: a server part, which has been implemented as a ProM plug-in and a client part, which has been realized as a standalone application. Both the components have been equipped with the incremental approaches described in the previous section. In detail, the Weka framework has been used for the implementation of the incremental unsupervised algorithm Canopy, while the incremental supervised approaches leveraged the MOA (Massive Online Data Analytics) framework, an open source framework for data manipulation. In order to allow the communication with the two Java frameworks, a new module in charge of transforming MOA instances into Weka instances - the MOAConverter - has been implemented.
| Dataset     | Outcome Formula                                                                 |
|-------------|-------------------------------------------------------------------------------|
| BPIC2011    | $\phi_{11} = F(\text{tumor marker CA} - 10 - 9) \lor F(\text{ca} - 125 \text{ using meia})$ |
| BPIC2011    | $\phi_{12} = G(\text{CEA} - \text{tumor marker using meia} \rightarrow F(\text{squamous cell carcinoma using meia}))$ |
| BPIC2011    | $\phi_{13} = \neg (\text{histological examination} - \text{biopsies no}) \lor (\text{squamous cell carcinoma using meia})$ |
| BPIC2015    | $\phi_{21} = F(\text{start WABO procedure}) \land F(\text{extend procedure term})$ |
| BPIC2015    | $\phi_{22} = F(\text{receive additional information}) \lor F(\text{enrich decision})$ |
| BPIC2015    | $\phi_{23} = G(\text{send confirmation receipt} \rightarrow F(\text{retrieve missing data}))$ |
| Drift1      | $\phi_{41} = F(\text{Accept Claim})$ |
| Drift2      | $\phi_{51} = F(\text{Send Notification by Phone}) \land F(\text{Send Notification by Post})$ |

Table 1. The outcome formulas

The tool allows users to specify the type of encoding(s) (e.g., index-based) and the incremental algorithm(s) (e.g., Adaptive Hoeffding tree) to be used, as well as to customize the corresponding hyperparameters. The application also allows users to test more than one configuration and compare the results, in a fashion similar to the one described in [8].

5 Evaluation

The evaluation reported in this paper aims at understanding the potential of incremental learning in predictive process monitoring in a broad sense. In particular, we want to examine the impact of incremental learning techniques on real event logs wrt. traditional offline learning (i.e., without updating the models when new cases become available) in terms of prediction accuracy. In addition, we want to compare the performance of the incremental learning wrt. the periodic rediscovery of the predictive models. In particular, we want to estimate whether the gain in terms of efficiency of the incremental learning wrt. the rediscovery is not reflected into a loss in terms of accuracy. Finally, we want to investigate how the proposed techniques for incremental predictive process monitoring (Incremental Clustering-based and Incremental Index-based) perform when applied to logs containing concept drifts (using the synthetic logs provided in [25]).

5.1 Datasets

For the evaluation of the proposed approaches, we used four datasets. Two of them are real event logs provided for the BPI Challenges 2011 [1] and 2015 [11]. These datasets were chosen because of the presence of data attributes. They do not contain explicit concept drifts. The third and the fourth dataset, instead, are taken from [25] and explicitly contain concept drifts. They refer to the second example illustrated in Section 3.

Due to lack of space, we only report here, in a compact manner, the main characteristics of each dataset, while the outcomes to be predicted for each dataset are contained in Table 1. Following an existing practice in predictive process monitoring [8,24], we formulated the outcomes to be predicted in terms of satisfaction of Linear Temporal Logic (LTL) formulas [29].

The first dataset consists of an event log pertaining to the treatment of patients diagnosed with cancer in a Dutch academic hospital. The log contains
1,140 cases and 149,730 events referring to 623 different activities. The second dataset was provided for the BPI Challenge 2015 by a Dutch Municipality. It is composed of 1,199 cases and 52,217 events referring to 398 activities. The log contains all building permit applications received over a period of four years.

In [25], the authors provide 3 different datasets for their evaluation. A baseline dataset (B), one for a first concept drift (CD1) and one for a second concept drift (CD2). All these datasets are split into 15 sub-logs, say $B_1, \ldots, B_{15}; CD_{11}, \ldots, CD_{115}; CD_{21}, \ldots, CD_{215}$, and recombined in different manners. The third and fourth datasets used in our experiments, hereafter simply called Drift1 and Drift2, are obtained by concatenating $B_1$ with $CD_1$, and $B_1$ with $CD_2$, thus generating two event logs, each with a different concept drift. They are both composed of 8,000 cases referring to 17 activities. Drift1 contains 88,334 events, while Drift2 contains 87,978 events.

5.2 Research Questions

In our evaluation, we investigate the following three research questions:

- **RQ1.** Do the incremental approaches allow for improving the prediction accuracy wrt. traditional offline learning (i.e., without updating the models when new cases become available)?
- **RQ2.** Do the incremental approaches allow for improving time performance while getting predictions as accurate as the ones obtained with the periodic rediscovery of the predictive models?
- **RQ3.** How do the proposed techniques for incremental predictive process monitoring (Incremental Clustering-based and Incremental Index-based) perform when applied to logs containing concept drifts?

**RQ1** focuses on the evaluation of the quality of the predictions returned by the incremental algorithms wrt. traditional offline learning. **RQ2** investigates, instead, the gain in terms of execution time of the incremental algorithms wrt. the periodic rediscovery. Finally, **RQ3** deals with the evaluation of the performance of Incremental Clustering-based and Incremental Index-based in the presence of concept drifts.

5.3 Metrics

In order to answer the research questions, we use the following metrics:

- **Accuracy and avg F-measure.** These metrics are defined wrt. a gold standard that indicates the correct labeling of each case. In our experiments, we extracted the gold standard by evaluating the outcome of each completed case in the testing set. Given the gold standard, we classify the predictions made at runtime into four categories: (i) true-positive ($T_P$: positive outcomes correctly predicted); (ii) false-positive ($F_P$: negative outcomes predicted as positive); (iii) true-negative ($T_N$: negative outcomes correctly predicted); (iv)
false-negative ($F_N$: positive outcomes predicted as negative). The accuracy indicates how many times a prediction was correct. The F-measure, which intuitively represents the proportion of correctly classified positive results wrt. all the possible cases, is defined as: $F\text{-}measure = \frac{2TP}{2TP + FP + FN}$. The avg F-measure is computed as the average of the F-measure obtained by considering the satisfaction of the LTL formula as a positive outcome and the F-measure obtained by considering the satisfaction of the formula as a negative outcome.

- **Execution time.** The execution time indicates the time required to create and update (in the case of incremental algorithms) the predictive models.

In the tables showing the results of our evaluation, we only report the percentage increase/decrease of accuracy, F-measure and execution time.

### 5.4 Procedure

In our evaluation, we used the following procedure: (1) dataset preparation; (2) classifier training; (3) testing; (4) metrics collection. In order to answer the three research questions, we simulated three different scenarios.

In the first scenario, we are interested in comparing the behavior of incremental and non-incremental algorithms by assuming that, while for non-incremental approaches, the predicted model is built once and for all, for the incremental ones, the model can be updated at runtime (e.g., as soon as cases complete, their label is known and they are available to be used for training purposes). To this aim, we used 80% of the real datasets for training both the non-incremental and the incremental models, and the remaining 20% for testing purposes. For the incremental techniques the remaining 20% is also used for incrementally training the predictive model.

In the second scenario, we compare the behavior of incremental and non-incremental algorithms in condition of periodical retraining (e.g., assuming that, after the initial training of the model, new data is periodically available for retraining the model from scratch or updating it). To simulate this scenario, we divided the real datasets into 40% − 20% − 20% − 20% and assumed that the first 40% is used for the initial training of the predictive models and that the other sets become available later. However, while in case of non-incremental approaches the model needs to be retrained in order to take into account also the new data, this is not the case for the incremental approaches that can directly update the model. We hence compared the accuracy of the results obtained using 60% and 80% of data for training and the remaining 20% for testing and we computed the time required for the initial training and the retraining(s) in the case of non-incremental approaches and the time required for the initial training and the updates in the case of incremental approaches.

Finally, in the last scenario, we want to understand the impact of incremental techniques that do not explicitly deal with concept drifts and those that, instead, are robust to concept drifts, when used in the context of clustering-based and index-based approaches. To this aim we leverage synthetic logs with a concept
drift occurring at 50% of the log. We used 40% of the log (i.e., before the concept drift occurrence) for the training and we tested the generated models on the remaining 60%.

5.5 Results

Table 2 reports the results obtained by applying Incremental Clustering-based and Incremental Index-based to the two real event logs provided for the BPI Challenges 2011 and 2015 (first scenario described in the previous section). In particular, the table shows the difference in percentage of average F-measure and accuracy of the two techniques implemented using Hoeffding tree (HT) and Adaptive Hoeffding tree (AT), with respect to standard classification algorithms (random forest). The table suggests that, when applied to real event logs possibly characterized by high variability, the incremental approaches improve the results in most of the cases, except for few ones in which only a small decrease of accuracy and F-measure is registered. This is especially true for the Incremental Clustering-based approach, which allows us to reach an increase in terms of F-measure up to 74.1%. This discussion positively answers research question RQ1, i.e., incremental techniques perform better than standard ones when applied to real event logs.

Table 3 shows the results related to the second scenario described in the previous section obtained by applying Incremental Clustering-based and Incremental Index-based to the log provided for the BPI Challenge 2011. In particular, the table shows the difference in percentage of average F-measure, accuracy and execution time of the approaches implemented using Hoeffding tree (HT) and Adaptive Hoeffding tree (AT) with respect to the periodic rediscovery using random forest. The results show that the accuracy metrics obtained using Incremental Clustering-based are always very close to the ones obtained with random forest. The difference is higher when using Incremental Index-based with a general increase of the accuracy (up to 27.4%) and a decrease of the F-measure (up to 38.9%). As expected, the time performance always improves with a reduction of the execution times up to −68.1%. Therefore, we can conclude that when using real event logs possibly characterized by high variability, the incremental techniques allow for getting predictions as accurate as the ones obtained with the periodic rediscovery of the predictive models but in a shorter time (RQ2).

Table 4 shows the results obtained by applying Incremental Clustering-based and Incremental Index-based to the synthetic logs Drift1 and Drift2. In particular, the table shows the difference in percentage of average F-measure and accuracy of the approaches implemented using Adaptive Hoeffding tree (AT) with respect to Hoeffding tree (HT). The results show that the improvement in the prediction accuracy when using explicit concept drift handling is higher for Incremental Clustering-based with an increase of the F-measure up to 114.8%. These results confirm that, although no significant differences exist between Adaptive Hoeffding tree and Hoeffding tree when dealing with the variability characterizing real event logs, in the presence of concept drifts, incremental techniques with
### Table 2. Increase and decrease of avg. F-measure ($Fm$) and accuracy ($acc$) of incremental techniques wrt. non-incremental techniques.

| Log  | $\phi$ | Clustering-based | Index-based | Clustering-based | Index-based |
|------|--------|------------------|-------------|------------------|-------------|
|      |        | $Fm$ | $acc$ | $Fm$ | $acc$ | $Fm$ | $acc$ | $Fm$ | $acc$ |
| BPIC2011 | $\phi_{11}$ | -0.056 | +0.062 | -0.192 | -0.001 | -0.212 | +0.171 |
|        | 0 | 0 | 0 | 0 | -0.422 | -0.022 | 0 | 0 | -0.347 | -0.075 | -0.28 | +0.005 |
| BPIC2015 | $\phi_{12}$ | -0.192 | -0.217 | 0.74 | +0.083 | -0.005 | +0.144 | -0.009 | +0.019 |
|        | $\phi_{13}$ | +0.389 | 0.013 | -0.031 | -0.011 | -0.001 | +0.212 | +0.171 |

### Table 3. Increase and decrease of avg. F-measure ($Fm$), accuracy ($acc$) and execution time ($time$) of incremental techniques wrt. non-incremental techniques.

![Table 3](image)

Overall, we observe that the approach used (Incremental Clustering-based versus Incremental Index-based) has an impact on the results. The incremental techniques seem to work better with the clustering-based approach. This can be possibly due to the fact that the incremental techniques work better with classifiers trained using a lower number of features.

### 5.6 Threats to Validity

One of the main threats to the external validity of the evaluation is the application of the incremental techniques to a limited number of event logs. The use of more logs would clearly allow for more general results. However, this threat is mitigated by the fact that two of the datasets used in our evaluation are real event logs with a number of traces and events that usually characterize these scenarios. A second threat is the choice of the outcome formulas used in the evaluation. Also in this case, we limited ourselves to four formulas. However, we believe that they represent realistic rules for the considered scenarios.

One of the main threats to the construction validity is related to the lack of an exhaustive experimentation with several different hyperparameter values. We tried to limit this threat by using standard techniques for hyperparameter optimization.

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$^1$ Note that in the clustering-based approach the information related to events and their payloads is separately leveraged for training clusters and classifiers, while in the index-based approach the information related to both control flow and data flow is encoded in the feature vectors.
| Log  | Clustering-based | Index-based |
|------|------------------|-------------|
| AT   | Fm   | acc | AT   | Fm   | acc |
| Drift1 | +1.148 | +0.407 | +0.048 | +0.047 |
| Drift2 | +1.321 | +0.338 | -0.005 | -0.005 |

Table 4. Increase and decrease of average F-measure (Fm) and accuracy (acc) of concept drift aware techniques wrt. concept drift unaware techniques.

6 Related Work

The body of previous work related to this paper is the one concerning predictive process monitoring. A first group of approaches deals with time predictions. In [2], the authors present a family of approaches in which annotated transition systems, containing time information extracted from event logs, are used to: (i) check time conformance; (ii) predict the remaining processing time; (iii) recommend appropriate activities to end users. In [15], an ad-hoc clustering approach for predicting process performance measures is presented, in which context-related execution scenarios are discovered and modeled through state-aware performance predictors. In [30], stochastic Petri nets are used to predict the remaining execution time of a process.

Other works focus on approaches that generate predictions and recommendations to reduce risks. For example, in [7], the authors present a technique to support process participants in making risk-informed decisions with the aim of reducing process failures. In [28], the authors make predictions about time-related process risks by identifying and exploiting statistical indicators that highlight the possibility of transgressing deadlines. In [33], an approach for Root Cause Analysis through classification algorithms is presented.

A third group of approaches in the process monitoring field predicts the outcome (e.g., the satisfaction of a business objective) of a process [34]. In [24] an approach is introduced, which is able to predict the fulfillment (or the violation) of a boolean predicate in a running case, by looking at: (i) the sequence of activities already performed in the case; (ii) the data payload of the last activity of the running case. The approach, which provides accurate results at the expense of a high runtime overhead, has been enhanced in [9] by introducing a clustering preprocessing step that reduces the prediction time. In [22], the authors compare different feature encoding approaches where cases are treated as complex symbolic sequences, i.e., sequences of activities each carrying a data payload consisting of attribute-value pairs.

While a first batch of experiments showing the benefits of incremental techniques has been performed in [25] explicitly focusing on synthetic logs with concept drift, in this paper we aim at taking three steps further: first, we aim at examining the impact of incremental learning techniques on real event logs where high variability may be present without an explicit concept drift. For this we exploit real event logs provided for the BPI Challenges. Second, we aim at comparatively investigating the exploitation of incremental learning techniques in the presence of concept drift and in the presence of high variability. Do these characteristics matter? And to what extent? Third, we aim at investigating the
impact of specific predictive process monitoring approaches (clustering-based and index-based) on the incremental learning techniques.

7 Conclusions

In this paper, we have provided an investigation of the application of incremental learning techniques to the field of business process monitoring. In particular, we have implemented incremental learning algorithms for outcome predictions using different case encoding strategies and evaluated them on a number of real and synthetic datasets. The results provide a first evidence of the potential of incremental learning strategies for predicting process monitoring in real environments and of the impact of different case encoding strategies on their application. An avenue for future work is the extension of the Incremental Predictive Process Monitoring Framework with other incremental classifier learners, e.g., naive Bayes [5], as well as with incremental algorithms for predicting continuous values, such as the remaining time or the cost of a given case (using incremental regressor learners). Also, the drift detection mechanism (DDM) could be added to the framework by combining it with any incremental learner in order to get a Single Classifier Drift [18].

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