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PREDICTIVE BUSINESS PROCESS MONITORING WITH CONTEXT INFORMATION FROM DOCUMENTS

Research in Progress

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Abstract

Predictive business process monitoring deals with predicting a process's future behavior or the value of process-related performance indicators based on process event data. A variety of prototypical predictive business process monitoring techniques has been proposed by researchers in order to help process participants performing business processes better. In practical settings, these techniques have a low predictive quality that is often close to random, so that predictive business process monitoring applications are rare in practice. The inclusion of process-context data has been discussed as a way to improve the predictive quality. Existing approaches have considered only structured data as context. In this paper, we argue that process-related unstructured documents are also a promising source for extracting process-context data. Accordingly, this research-in-progress paper outlines a design-science research process for creating a predictive business process monitoring technique that utilizes context data from process-related documents to predict a process instance's next activity more accurately.

Keywords: predictive business process monitoring, context information, documents.

1 How Documents can Help Making Better Process Predictions

Business process monitoring is a core task of business process management (BPM) (van der Aalst, 2012) that represents an important phase of the process cycle (Maggi et al., 2014). It is high on the strategic agendas of many large organizations such as SAP AG (Riches et al., 2018). Business process monitoring deals with the analysis of events produced during a business process's execution in order to assess the fulfillment of its compliance requirements and performance objectives (Dumas et al., 2018). Monitoring can take place offline (e.g., based on periodically produced reports) or online (e.g., via dashboards displaying the performance of currently running process instances) (Castellanos et al., 2004). Predictive business process monitoring refers to a set of online process monitoring techniques (Verenich, Dumas, La Rosa, et al., 2018) that are concerned with predicting the evolution of running process instances of a business process with quantifiable metrics (Márquez-Chamorro, Resinas, and Ruiz-Cortás, 2018) based on predictive models extracted from historical event logs (Maggi et al., 2014; Tax et al., 2017).

However, the fundamental problem of current predictive business process monitoring techniques is that their predictive quality is limited (Márquez-Chamorro, Resinas, and Ruiz-Cortás, 2018) and has even been described as being close to random (Ceci et al., 2014; Evermann, Rehse, and Fettke, 2017). van der Aalst, Schonenberg, and Song (2011) found that it could be insufficient to base predictive business process monitoring on pure process data. Additional context data that defines the context in which the process is running (da Cunha Mattos et al., 2014) can improve predictive quality as it adds valuable information to the predictive model (Márquez-Chamorro, Resinas, and Ruiz-Cortás, 2018). For example, context information can also be used to consider changes in the context (Folino, Guarascio, and Pontieri, 2012). First attempts to remedy the problem of insufficient prediction quality, suggest feeding predictive business process monitoring techniques with additional context information (intern to the process) next to process event data (Conforti et al., 2015; Di Francescomarino et al., 2015; Di Francescomarino et al., 2017; Evermann, Rehse, and Fettke, 2017; Folino, Guarascio, and Pontieri, 2012; Frey et al., 2018; Leontjeva et al., 2015; Maggi et al., 2014; Márquez-Chamorro et al., 2017; Navarin et al., 2017; Polato et al., 2014, 2018; Schönig et al., 2018; Senderovich et al., 2017; Tax et al., 2017; Teinemaa et al., 2016; Verenich, Dumas, La Rosa, et al., 2015). Given the fact that in practice electronic data exchange formats are not adopted in certain areas, e.g. for invoices in the context of the tax industry (KPMG International, 2018), leading to a media disruption, this research-in-progress project argues that process-related documents such as invoices, orders and credit notes can be promising sources for process-context information that have not yet been concerned in the predictive business process monitoring literature. Documents carry the information needed for trade to occur between companies (Sellen and Harper, 2003). Therefore, the consideration of process-attached documents has the potential to increase significantly the accuracy of process prediction. Documents saved in an unstructured data format are produced by other (external) information systems, that are not integrated via a digital interface with the current information system, where the process is running. That means information extracted from documents is not yet available in the current information system and, for example, this information can not be retrieved by executing a database query. Against this background, the exchange of data takes place via documents as a manual interface. Additionally, there are different possibilities of how documents are related to a business process. For example, a document can be attached to a specific running process activity. This document can be saved in the unstructured data format JPG and the corresponding activity includes a reference to it. However, first, the desired context information has to be extracted from the document to use it for a subsequent process prediction.

In our work, we try to overcome insufficient prediction quality that arises if only process event data is used with our *research goal*: providing a concept for a document-aware predictive business process monitoring technique. A design-oriented research methodology has been carried out to reach the goal and, in addition, to answer the *research question*, can context information (extracted) from documents improve the prediction quality of predictive business process monitoring. For answering this research question, we focus on the prediction task of predicting a process instance's next activity.

The paper is structured as follows: Section 2 presents related work on context-aware predictive business process monitoring and reveals the research gap of document-related context for predictive business process monitoring. In section 3, the applied research methodology is described. Section 4 covers the design and development of the document-aware business process prediction technique. Further, section 4 outlines implications and further research need. The paper concludes with a summary in section 5.

2 Related Work of Context-Aware Predictive Business Process Monitoring

In this work, we are proposing a predictive business process monitoring technique extracting context from documents internal to the process. Some works in the context of predictive business process monitoring have already considered context information internal or external to process as input data next to event process data (Márquez-Chamorro, Resinas, and Ruiz-Cortás, 2018). At this point, we want to delineate work that considers context information external to the process, e.g., the work from Yeshchenko et al. (2018). Further, existing work can be distinguished according to *source of context* and *structure of context*. On the one hand, there are different sources of process context information (e.g., emails or system-related performance metrics). On the other hand, process context information can be accessible in a structured format (e.g., resource), in an unstructured format (e.g., textual messages) or in a semi-structured format (e.g., seasonal changes for the number of applications). Table 1 provides a summary of research classified according to the source of context and the structure of context. Note, according to the four different perspectives described by de Leoni, van der Aalst, and Dees (2016) - control-flow perspective, data-flow perspective time perspective and resource/organization perspective - works are specially listed using data-flow-related context information. Based on this, we can observe that the majority of the works on context-aware predictive business process monitoring relies on structured context data created by the information system itself like process performance metrics.

Approach	Source of context	Structure of context
Schönig et al. (2018); Senderovich et al. (2017); Conforti et al. (2015); Leontjeva et al. (2015); Frey et al. (2018); Verenich, Dumas, La Rosa, et al. (2015); Di Francescomarino et al. (2015); Navarin et al. (2017); Márquez-Chamorro et al. (2017); Polato et al. (2014); Maggi et al. (2014); Polato et al. (2018)	Information system	Structured
Folino, Guarascio, and Pontieri (2012); Di Francescomarino et al. (2017)	Information system	Structured and semi-structured
Teinemaa et al. (2016)	Emails and comments	Structured and unstructured

Table 1. Related context-aware predictive business process monitoring papers considering data attributes.

Teinemaa et al. (2016) use unstructured context information from emails and comments. However, no work considers context information from process-attached documents. Therefore, in this paper, we address the gap of document-related context for predictive business process monitoring.

3 Applied Methodology

For the development of the proposed context-aware predictive business process monitoring technique, this paper adopts the design-science research methodology (DSRM) introduced in Peffers et al. (2007). The applied methodology represents a structured approach for constructing IT artifacts tailored towards solving a given problem statement. Exemplary IT artifacts can range from prototypes and instantiations to models and methods (Hevner et al., 2004). This paper proposes a technique for predictive business process monitoring using context information as the central IT artifact. The design of the artifact follows the six steps of the DSRM, which consists of problem identification and motivation, objectives of a solution, design and development, demonstration and evaluation. It should be noted that the research presented in the following focuses primarily on the phases problem identification, objectives and design resp. development. Since the contribution is part of a larger scale project and an in-depth demonstration and evaluation will be part of future work. Regarding the first two steps of the DSRM procedure, both the introductory section and the related works section reveal the necessity for a document-aware predictive business process monitoring technique. Additionally, the introductory section defines the essential objectives of the solution. Section 4 covers the design and development step.

4 Towards a Document-Aware Predictive Business Process Monitoring Technique

We propose a technique for a document-aware predictive business process monitoring. The technique extracts structured context from documents to enrich the event log, therefore, should enhancing the predictive monitoring results. The overall procedure of the technique is depicted in Figure 1 and consists of four steps. First, an initial vector-oriented data set is created based on the event log. In the second step, a vector-oriented data set with extracted information in the form of a defined set of data attributes from process-attached documents is created. Third, the initial data set and the data set, including extracted data attributes from documents, are merged. The technique finishes with a prediction model that is learned based on the data set from step three.

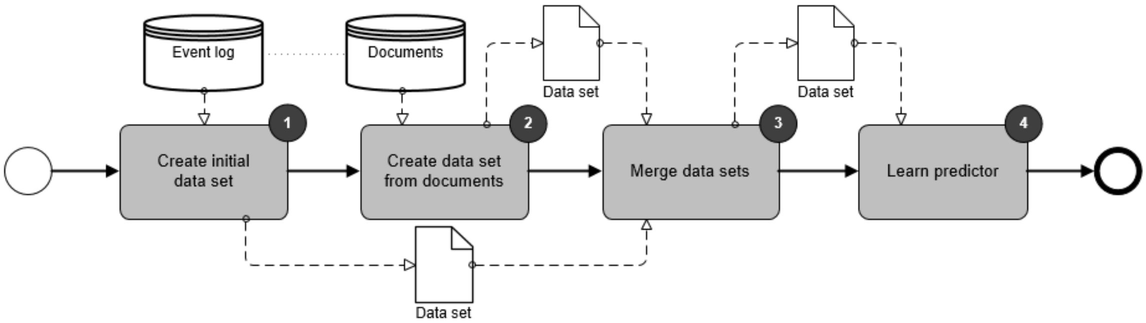

Figure 1. Our proposed technique for a document-aware predictive business process monitoring.

In the following section, each step of the proposed technique will be detailed.

4.1 Four Steps of the Technique

Create initial data set. Our predictive business process monitoring technique takes as input an event log. An event log is a set of recorded processes instances, and each process instance corresponds to an individual process execution. Each process instance consists of a multi-set of time-ordered activities (events). We assume that events have an explicit reference to a process instance and this condition is commonly respected in real-world event logs (van der Aalst, 2016). For instance, an excerpt of a process event log encoded in the XES logging format (Verbeek et al., 2010) on the left side of Figure 2 shows the recorded information of the start event of the activity *Apply for credit* performed by resource *MAT*. In addition, a credit application is attached to this event. Note, it is assumed that this activity is started in the 234th process execution. Based on the given event log the representation is changed from a log-oriented to a vector-oriented to apply a machine learning algorithm for process prediction on it. Next to the excerpt, Figure 2 depicts on the right side the structure of the resulting vector-oriented data set.

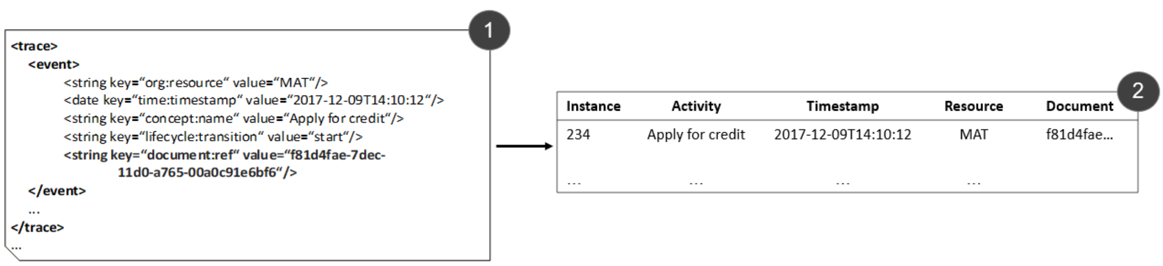

Figure 2. From log-oriented to vector-oriented data set.

Create data set from documents. We consider process attached-documents as images that are stored as unstructured images. In general, there are four possibilities of how an individual document can be attached to a process instance. First, an individual document can be attached to a single activity of a process instance. Second, an individual document can be attached to more than an activity of the same process instance. Third, an individual document can be attached to more than one activity of different process instances. Fourth, more than one document is attached to an individual activity. In all cases, a text-based approach for automated information extraction (Schuster, Hanke, et al., 2013) is used to extract information from documents. Such an approach focus on the document's text and use its structure and occurrence to identify relevant terms of a document. Figure 3 depicts the general procedure of a text-based information extraction approach (Schuster, Muthmann, et al., 2013).

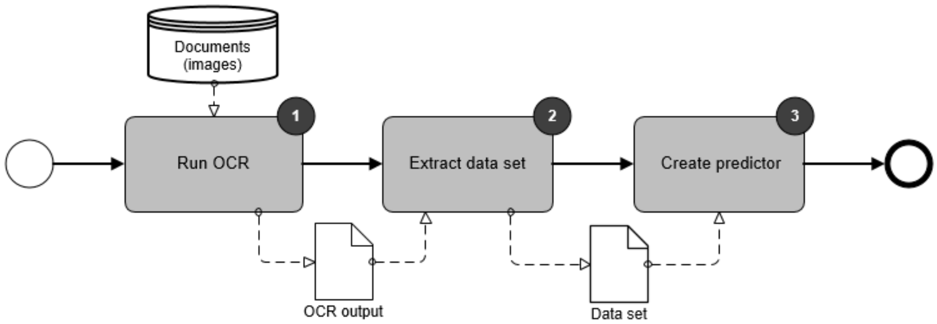

Figure 3. Procedure of a text-based information extraction approach (based on Schuster, Muthmann, et al. (2013)).

The procedure begins with an optical character recognition (OCR) for each document represented as an unstructured image. The OCR translates the unstructured document to a semi-structured data format like XML. For example, such an XML-file includes for each recognized term (consisting of characters) its value as well as its structural information such as the vertical position and the horizontal position on the document. For instance, the content of a document can comprise *The ABC Corp. located in Nuremberg received an Invoice on day 12 of this month* and the first term of this document is *The* and the last one is *month*. Further steps of the technique will be explained on the basis of this example. Note, for the recognition of terms machine learning algorithms are used. However, according to our purpose, we consider the OCR step as a black box. Further, a data set is extracted based on the OCR output. That means the output of the OCR has to be transformed into a vector-oriented representation according to the current learning task - the recognition of a defined set of data attributes. First, we assume that attributes to be extracted should not be too specific since the goal is to extract as equal as possible information from different types of documents. If a document does not contain a defined attribute, a standard value will be used instead. For example, Table 2 depicts an excerpt of possible attributes based on the example document explained above.

Name of Attribute	Abbreviation	Type of Attribute	Possible Value
Name of receiving company	Attribute_1	Discrete	ABC Corp.
Day of receiving	Attribute_2	Continuous	12
Location of receiving company	Attribute_3	Discrete	Nuremberg
Type of document	Attribute_4	Continuous	Invoice

Table 2. Possible attributes of an exemplary document.

Further, each object description $\vec{x}$ of a feature vector $\langle \vec{x}, y \rangle$ can represent a (textual) term of a document. Each $\vec{x}$ consist of one feature for the (textual) term (cf. Feature_1 in Table 3) itself and manually created features like the number of characters of a (textual) term (cf. Feature_2 in Table 3). In order to apply a supervised learning algorithm like a neural network, where weights are calculated through a variant of gradient descent, values for textual features must be mapped to integers (starting at 0 and increased by 1). Finally, values for each feature are min-max normalized, where min is 0 and max is 1, to grant equality among the features and therefore, not to implicitly give one feature more relevance than another. Label y can describe different data attributes for predicting. Finally, the data set for learning can represent $D = \{\langle \vec{x}_1, y_1 \rangle, \cdots, \langle \vec{x}_n, y_n \rangle), n \in \mathbb{N}\}$. The label value *Not relevant* is included to filter out unimportant (textual) terms. Exemplary, Table 3 depicts the data set for extracting data attributes based on the OCR output.

Document	Term	Feature_1	Feature_2	Label	Prediction
f81d4fae...	The	0.00	0.14	Not relevant	?
f81d4fae...	ABC	0.06	0.14	Name of receiving company	?

Table 3. Data set for extracting data attributes based on OCR output.

In the last step, a predictor is created. Based on the data set D the task is to learn a classification function $f(x, \theta) = y$ with a supervised learning algorithm θ that for each (textual) term based on the object description $\vec{x}_i$ finds the best representation for a data attribute y_i. After performing the prediction, the attribute values must be determined from Table 3 for each document. We plan to use a state-of-the-art supervised machine learning algorithm as a classifier since our focus is not on the automated information extraction. However, in the first step, the contents from documents are manually extracted. Later, we plan to apply a text-based approach for automated information extraction as demonstrated in Figure 3. Given this approach, we will learn the predictor for information extraction based on a deep (feed-forward) neural network, because deep learning enables to detect complicated interactions from features (Liang et al., 2017). Note, we will also feed manually constructed features into the deep neural network since the pre-processed text for each (textual) term seems insufficient to learn automatically an effective feature representation (Palm, Winther, and Laws, 2017). Finally, Table 4 shows the created data set from documents.

Document	Attribute_1	Attribute_2	Attribute_3	Attribute_4
f81d4fae-7dec-11d0-a765-00a0c91e6bf6	ABC Corp.	12	Nuremberg	Invoice

Table 4. Created data set from documents.

Merge data sets. In this step, the two already created data sets are merged into a final data set for the subsequent learning of the predictor. We use as the key for mapping the document id to merge the data sets because the document id is included in both data sets. The resulting data set is depicted in Table 5.

Instance	Activity	Timestamp	Resource	Attribute_1	...	Attribute_4
234	Apply for credit	2017-12-09T14:10:12	MAT	ABC Corp.	...	Invoice

Table 5. Final data set.

Learn predictor. The predictor is learned based on the data set from step three. However, as already mentioned, pre-processing is necessary because depending on the used learning algorithm. We plan to use a recurrent neural network, esp. long-short term memory neural network (LSTM), for next activity prediction, because these networks are designed to handle temporal dependencies in sequences (LeCun, Bengio, and Hinton, 2015). As with the information extraction, first textual features have to be mapped to numerical ones followed by a min-max normalization for all features. In addition, a LSTM requires

3D-structured input data. The three dimensions are sequence (process instance), time step (activity) and feature (describing the activity). Finally, we plan to follow the proposed pre-processing procedure from Tax et al. (2017). Regarding the prediction of a process instance's next activity, the underlying data set is represented as $D = \{\langle\vec{x}_1, y_1\rangle, \cdots, \langle\vec{x}_n, y_n\rangle), n \in \mathbb{N}\}$. The task is to learn a classification function $f(x,\theta) = y$ with a supervised learning algorithm θ that for each activity based on the object description $\vec{x}_i$ of a feature vector $\langle\vec{x}_i, y_i\rangle)$ finds the best representation for a process instance's next activity y_i considering the data set.

4.2 Discussion and Further Research Need

The predictive business process monitoring techniques proposed in extant research have a low predictive quality so that applications are rare in practice and the inclusion of process-context data has been discussed as a way to improve the predictive quality. The technique as the main IT artifact of this research in progress is designed to address this challenge by providing a concept of a document-aware predictive business process monitoring technique to predict a process instance's next activity. A crucial prerequisite for concrete support for participants performing a business process in practice is the integration of a document-aware predictive business process monitoring technique in common information systems, in which the participants may be guided activity-by-activity through a business process. For each next activity prediction (by high-level predictor), information from possible attached documents are previously extracted (by low-level predictor). Since the predictor for information extraction is trained before process predictions begin and subsequently integrated into next activity prediction, quality of the provision is not burdened in time and cost for producing data for the purpose of the next activity prediction. In the context of enterprises, the technique opens up new possibilities as well: Being integrated into business processes including important decisions, the developed technique may reduce the rate of wrong decisions and the costs that arise thereby. For example, the supplier of a specific product has been changed due to a not acceptable delivery time extracted from a process-attached offer. Moreover, the proposed technique is significant for issues of system heterogeneity. For example, it improves data integration between companies with non-integrated information systems (maybe legacy systems) that support core B2B processes (like order-to-cash) and where data exchange takes place on the basis of process-attached documents. Note, the technique is also suitable for B2C processes, where private customers create documents with the help of programs like Microsoft Word. Additionally, the proposed technique can be customized to specifically adjust to the organization's needs. Exemplary, an organization can propose own, organization-specific attributes which are to be extracted from documents. Regarding research, the technique serves as a basis for further work in terms of context-aware predictive business process monitoring. By applying and subsequently refining the prediction technique, detailed insight with respect to the interaction between context information extracted from documents and the used machine learning algorithms can be gained, which facilitates the selection of context-benefiting machine learning algorithms. Additional research potential can also be seen in the enrichment of the extracted information from documents in the context of linked data. For example, based on an extracted description for a specific product from a process-attached offer, further details for this product can be determined by API's of leading online shopping companies to increase additionally the prediction quality. For the design of the technique, some assumptions had to be made limiting its applicability: First, the technique is tailored towards a rather "good quality" of documents. Regarding the information extraction from process-attached documents in the form of images, we assume that these documents are available in a reasonable quality in terms of content, structure and external appearance. If necessary, first, documents with a poor quality must be filtered out. Finally, we plan to implement a deep (feed-forward) neural network for information extraction to address the problem of the necessity of "good quality" of documents to a certain degree. Deep learning could be more robust to that problem since it combines lower level features to form more abstract, a higher level representing features, whereby distributed feature representations of data can be discovered (Wang, Raj, and Xing, 2017). Second, an eye has to be kept on the complexity. The technique assumes event logs with events

including an optional reference to one or more documents saved as images. However, in practice, this may not be the case, at least in one global event log that can be directly used for the proposed technique. Additionally, if necessary, the reference between the event log and documents must first be created.
Further research on this topic will have to put special emphasis on an in-depth evaluation and demonstration in order to conclude a first iteration of the DSRM. In particular, we will determine one or more appropriate data sets with a possible reference to documents. As already mentioned, we will use a deep (feed-forward) neural network to extract context information from documents and a LSTM to predict a process instance's next activity taking into account context information from documents. Subsequently, implementation will follow in Python based on Tensorflow and results will be presented and evaluated. Ultimately, the evaluation may shed light on a context-aware technique for predictive business process monitoring that is able to improve the predictive quality.

5 Conclusion

Given the fact that the predictive quality of existing predictive business process monitoring techniques is limited we have discussed in our introduction and based on the identified research gap through our literature review on context-aware predictive business process monitoring, we argue that there is a crucial need for a document-aware business process prediction technique in research and practice. With the four steps of our developed artifact in Section 4, we realized our *research goal*: a concept for a document-aware business process prediction technique. In sense of the predictive business process monitoring community, our technique supports the need and understanding of context information for predictive business process monitoring. By considering current context-aware business process prediction techniques (cf. chapter 2 for an overview) and by integrating consolidated work related to automated information extraction, especially the theorizing of different approaches for information extraction from documents provided by Schuster, Hanke, et al. (2013), the technique is anchored in literature and builds upon the existing knowledge base. In-depth demonstration and evaluation will follow in future work.

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