Text-Aware Predictive Monitoring of Business Processes with LSTM Neural Networks

Master's Thesis

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Abstract

The real-time prediction of business processes using event data of historical executions is a critical capability of business process monitoring systems. Existing process prediction methods are limited in terms of the type of data they are able to utilize and the prediction tasks they can perform. In particular, almost no technique is able to utilize text documents of natural language, which can hold process-critical information. This work describes the design, implementation and evaluation of a novel text-aware process prediction model based on long short-term memory (LSTM) neural networks and natural language models. The proposed model is able to take categorical, numerical and textual attributes in event data into account to predict the activity and timestamp of the next event, the outcome and the cycle time of a running process instance. Experiments show that the text-aware model is able to outperform state-of-the-art process prediction methods on simulated and real-world event logs containing textual data.

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Chapter 1

Introduction

1.1 Motivation

The rapid growth of data generated and collected in large-scale information systems leads to new opportunities for society and businesses. By the end of 2020, the total amount of generated data is estimated to be 44 trillion gigabytes of which 90% has been created in the last two years [1]. In order to benefit from the massive amount of data, efficient solutions are required, that are able to extract potential value in form of insights or predictions.

A remarkable subset of this data is described as *event data*, which are generated by *process-aware information systems* during the execution of processes [2]. Process-aware information systems are used to define, manage and execute business processes of many organizations. With the non stopping rise of digitization of business processes, increasingly more event data becomes utilizable, thus the potential value of this data is rising sharply.

The scientific engagement aiming to discover, analyze and improve real processes based on event data led to *process mining*. Process mining bridges the gab between the data-driven characteristic of data science and the process-centric view of process science [3]. The ongoing success of progress mining in research has been transferred to businesses, that successfully offer or utilize this technology. Celonis, which is often considered as one of the biggest commercial providers of process mining, has been valued 2.5 billion dollar only 9 years after the company was founded [4].

Modern process mining software tends to focus on continuous monitoring of business processes, in contrast to traditional offline and project-based approaches, that are not integrated within the remaining IT infrastructure of a company. The integrated and continuous application of process mining mostly realized by *business process monitoring systems* is a key success factor for many organizations. These systems allow to understand and supervise all processes of a company in real-time during the execution of the processes. The core idea of this approach is to automate process mining and keep a persistent data connection between the information system and the monitoring system, that provides the analytical capabilities. Figure 1.1 visualizes such an infrastructure and the interaction between the systems and internal and external process stakeholders. The operational

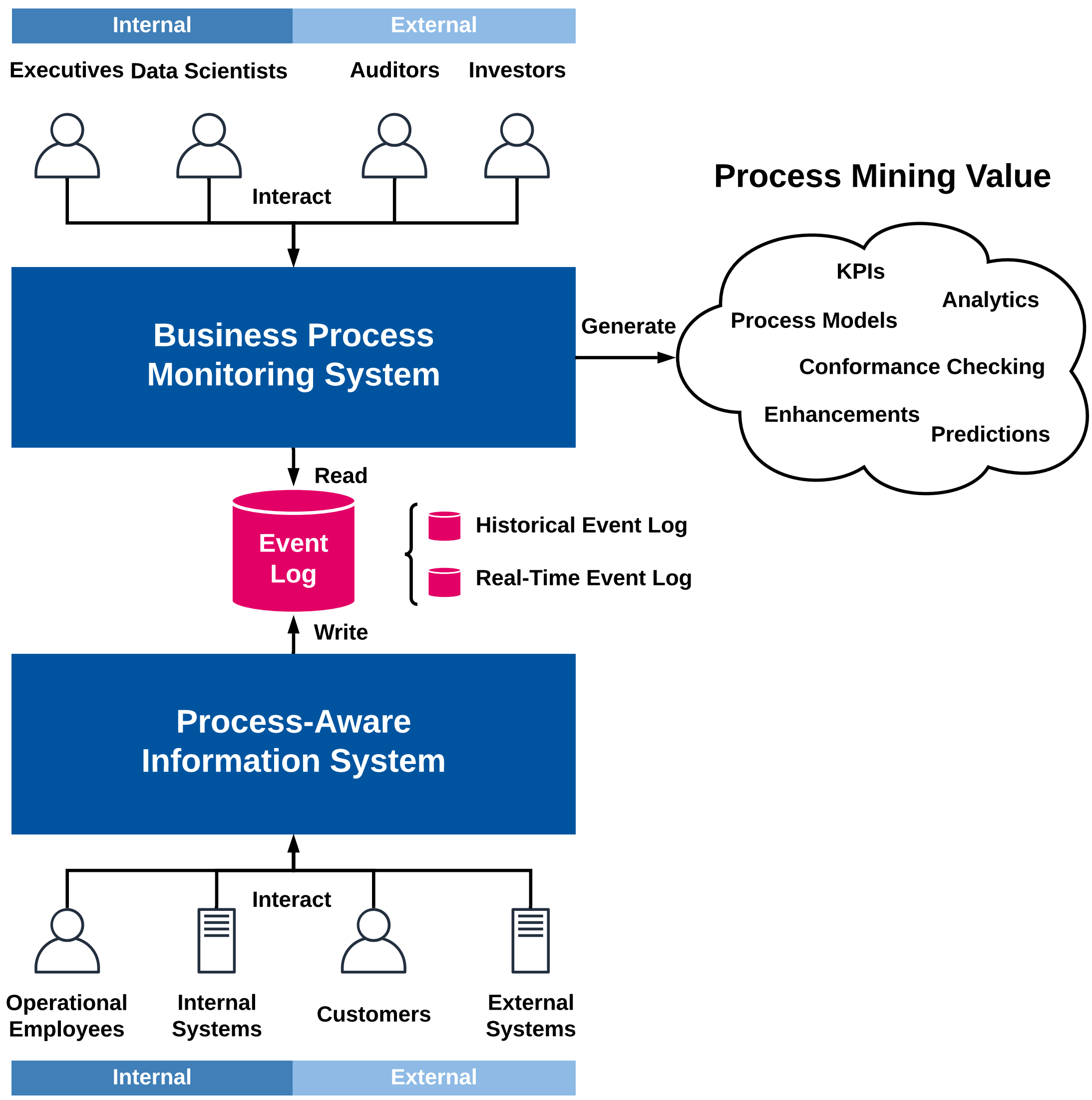


Figure 1.1: Business process monitoring allows to continuously apply process mining in an automated fashion in order to generate value for internal and external process stakeholders. The required event data is generated by a process-aware information system during the execution of the processes.

employees, customers and connected software systems interact with the process-aware information system and are part of the processes themselves. In contrast, executives, data scientist, auditors and investors are supervising the processes using the business process monitoring system.

Traditional process mining tends to be backward-looking [5], i.e. the main focus relies on analyzing past executions of a process rather than providing insights for running process instances in form of predictions or recommendations. Businesses can develop a competitive advantage, if their process mining solution also offers predictive capabilities to anticipate the future of a running process instance. For example, if it can be expected, that a running process instance will likely exceed its deadline, measures can be initiated before damage occurs. Therefore, including the forward perspective is crucial for any competitive process mining software, especially in the context of business process monitoring.

1.2 Problem Statement

Although, many approaches for process prediction have been suggested in the literature (see Chapter 3), current solutions are limited regarding the data they are able to consider and the prediction task they can perform. Many approaches derive their prediction purely from the control flow of a process instance ignoring additional data attributes in the event log. Most notably, almost no approach is able to consider textual data for process prediction. However, textual data is highly available in many systems and might hold important information, that can be used to improve the prediction performance. For example, millions of emails are sent everyday and their content influences processes inside of organizations.

In addition, process-critical information like a diagnose in a hospital often comes in textual form and therefore has to be considered for prediction. Most of the existing prediction methods focus on a single prediction task only, for example they just predict the remaining time or cycle time of a process instance. Depending on the context, information about the next event or the future path of process instance can be of interest. In some scenarios, processes instances have an outcome like success/failure or accepted/rejected that can be predicted.

In data science, predictions are usually derived using *predictive inference* [6], i.e. correlations in past observations are used to estimate target variables for new observations. In the context of process mining, past observations come in the form of historical event log data, that has been logged during the execution of a process and describes completed process instances.

In order to overcome the limitations of existing methods, an advanced prediction model is required. Given an event log with past executions of a process holding numerical, categorical and textual data and a running (i.e. not completed) process instance, the process prediction model should be able to perform the following prediction tasks:

- Next activity prediction: What will happen next in the running process instance?
- Next event time prediction: When will the next event happen?
- Case outcome prediction: What is the outcome of the process instance?
- Case cycle time prediction: What is the total duration of the process instance?

A general description of such a process prediction model is illustrated in Figure 1.2. Existing models follow the same framework, but they are less flexible in terms of input data types and prediction targets. Including textual data for process prediction brings up new research questions, which are concretized in the next section.

1.3 Research Questions and Methodology

This thesis aims to improve current state-of-art approaches for process prediction in order to extend the capabilities of process monitoring software. The main research goal is to

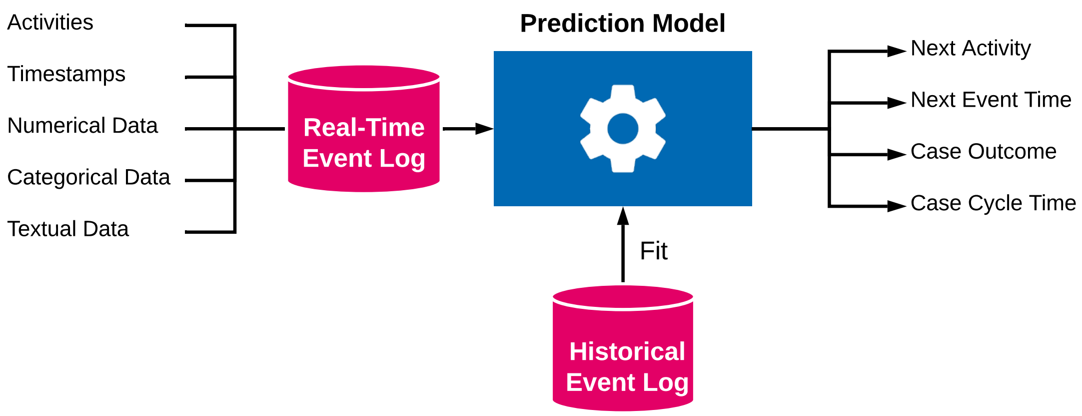


Figure 1.2: A general process prediction framework. Predictive business process monitoring includes a prediction model, that is able to predict the future of running cases using historical event data. Current approaches differ in terms of the considered input data, the underlying prediction method and the prediction targets.

design, implement and evaluate a predictive model for event data that is able to take advantage of additional textual data associated with events in the process. Since most current approach are not able to handle textual data, the goal is to investigate if and to what extend textual data can improve the quality of process prediction. Furthermore, the impact of different design choices and text models for text-aware process prediction are of interest and potential trade-offs need to be discussed. Finally, the text-aware process prediction model has to be compared to current state-of-the-art process prediction methods.

These goals lead to the formulation of the following three research questions:

1. To what extend can the utilization of textual data improve the performance of process prediction?
2. How does the choice of the text model and other parameters influence the prediction results?
3. What are the advantages and disadvantages of the approach compared to existing methods?

Based on these research questions, a text-aware process prediction model is conceptualized, implemented and evaluated.

1.4 Contribution

In this thesis two main contributions are made. First, a text-aware process prediction model is designed and implemented, which additionally counts in textual data associated with events. The approach is realized by combining LSTM neural networks and text models in order to capitalize on correlations between the process flow and the (textual) data. It prioritizes high prediction performance and flexibility, i.e. it is applicable to a wide range of processes in terms of variability, underlying data types and process complexity.

The implementation of the proposed prediction model is purely based on Python and additional open-source packages.

The second contribution is a comprehensive evaluation and analysis of the approach based on simulated and real-world event data. This includes performance measurements of differently parameterized models and a comparison with existing methods. In addition, advantages and limitations of the approach are discussed.

1.5 Thesis Structure

This thesis is structured in seven chapters. In Chapter 2 the basic notations, definitions and concepts used in this work are introduced. This includes an brief introduction to process mining, text mining, supervised learning and LSTM neural networks. Chapter 3 summarizes relevant scientific contributions that focus on process prediction in process mining and gives an overview of already available methods and their capabilities. In Chapter 4 a novel text-aware process prediction model as the main conceptional contribution is presented. Moreover, Chapter 5 covers the implementation details of the model on a technical level. In Chapter 6 the performance of the new approach is evaluated and compared to current state-of-the-art prediction methods. Finally, the conclusion is given in Chapter 7 by wrapping up the key achievements and discussing the limitations of the approach. Furthermore, an outlook towards future potential research questions on process prediction in the context of business process monitoring is given.

Chapter 2

Preliminaries

In this chapter the basic concepts of process mining, text mining, supervised learning and long short-term memory networks are presented. Furthermore, necessary formal definitions and notations are introduced.

2.1 Processes and Process Mining

Definition 2.1 (Business Process)**.** A *business process* is a collection of activities that are performed in a specific order to achieve a goal. A single execution of a process is a *case* or *process instance*, which is identified by a case ID.

Each performed activity belongs to specific case and is completed at a certain time [7]. For example, a case can be a patient treated in a hospital, a customer journey or an online order. The time on which an activity for a certain case is performed is specified by a timestamp. The associated case ID, the performed activity and the timestamp form together an *event*. An event can have any number of additional attributes, e.g. an attribute describing the resource that carries out the activity.

If the execution of a business process is logged by an information system, the resulting event data is called *event log*. Depending on the format of the event log, it can also contain additional data on case level. Typical formats for event logs, are comma-separated values (CSV) and eXtensible Event Stream (XES) [8], which can be extracted from databases of process-aware information systems. A table-based representation of an artificial event log describing patient treatments in a hospital can be seen in Table 2.1. Besides the case ID, activity and timestamp, the event log also contains information about the identity executing the activity, the costs of the activity and a text comment as an example for a categorical, numerical and textual attribute.

Definition 2.2 (Process Mining)**.** *Process mining* is the discipline that covers all approaches aiming to generate value out of event data. As an umbrella term, process mining includes or utilizes concepts of business process management, data mining, business process intelligence, big data, workflow management, business process monitoring [3] as well as machine learning [9].

Traditionally, process mining is divided into a set of subdisciplines mainly process discovery, conformance checking, process enhancement and process analytics [10]. Process

ID	Activity	Timestamp	Resource	Costs	Comment
0	Register patient	2020-02-01 14:12	SYSTEM	0	-
	Consultation	2020-02-01 14:34	J. Brown, MD	24.32	The patient reports persistent nausea.
	Blood test	2020-02-01 15:12	K. Smith	14:23	Tests: Complete blood count
	Evaluate test	2020-02-01 16:35	J. Brown, MD	38.67	No abnormalities in the complete blood count.
	Release patient	2020-02-01 17:24	SYSTEM	0	-
1	Register patient	2020-02-02 08:20	SYSTEM	0	-
	Consultation	2020-02-02 14:12	J. Simpson, MD	24.32	Noticeable tachycardia. No chronic pre-existing conditions are known.
	MRI	2020-02-02 16:10	Sara Taylor, MD	352.87	-
	Release patient	2020-02-02 18:33	SYSTEM	0	-
2	Register patient	2020-02-02 09:08	SYSTEM	0	-
	Consultation	2020-02-02 09:14	J. Simpson, MD	24.32	The patient has severe leg injuries due to a motorcycle accident.
	Hospitalization	2020-02-02 09:20	M. Johnson	130.37	-
...	...	...	...	...	...

Table 2.1: An artificial event log of patient treatments in a hospital. Each row corresponds to one event. The events are grouped by their case IDs, each representing a single patient.

discovery aims to generate process models out of event data in order to understand the control flow of a process and enable further analysis. Conformance checking is about comparing the intended and observed behavior of a process and identifying deviations. On top of these diagnostic approaches, process enhancement deals with the improvement of processes regarding compliance, performance and complexity.

Finally, process analytics focuses on the metric and performance evaluation of processes. Similar to conformance checking, this term is closely related to business process monitoring, a rising subfield enabling the analysis of running business processes in real-time. Driven by the fast and ongoing development of quantitative prediction methods in data science and machine learning, also prediction-based methods have been applied to event data. These methods add the forward perspective to business process monitoring and deal with forecasting the future of a running process instance, which is also the main focus of this work.

2.2 Basic Notations and Sequences

The set $\mathbb{N}$ denotes the set of all natural numbers $\{1, 2, 3, \dots\}$ and $\mathbb{N}_0 = \mathbb{N} \cup \{0\}$ denotes the set of natural numbers including 0. The subset of natural numbers up to number n is noted as $[n] = \{1, 2, \dots, n\} \subset \mathbb{N}$ with $[0] = \emptyset$.

Definition 2.3 (Sequence)**.** A *sequence* of length $n \in \mathbb{N}_0$ over a set A is an ordered collection of elements defined by a function $\sigma\colon [n] \to A$, which assigns each index an element of A. A sequence of length n is represented explicitly as $\sigma = \langle a_1, a_2, \dots, a_n \rangle$ with $a_i \in A$ for $1 \leq i \leq n$. In addition, $\langle\rangle$ is the empty sequence of length 0.

Given a set A, A^n describes the set of all sequences $\langle a_1, a_2, \dots, a_n \rangle$ over A of length n. The set A^0 is defined as $\{\langle\rangle\}$, the set that only contains the empty sequence. $A^* = \bigcup_{i \in \mathbb{N}_0} A^i$ is the set of all sequences over A and $A^+ = \bigcup_{i \in \mathbb{N}} A^i = A^* \setminus \{\langle\rangle\}$ is the set of all sequences over A with a length of at least 1.

Given sequences σ_1 and σ_2, the concatenation of both sequences is denoted by $\sigma_1 \cdot \sigma_2$. Moreover, the i-th element of a sequence $\sigma = \langle a_1, a_2, \dots, a_n \rangle$ is accessed using $\sigma(i) = a_i$ for $1 \leq i \leq n$. The length of a sequence is denoted by $|\sigma|$. For a sequence $\sigma = \langle a_1, a_2, \dots, a_n \rangle$, the function $hd^k(\sigma) = \langle a_1, a_2, \dots, a_k \rangle$ gives the head or prefix of length k of σ and $tl^k(\sigma) = \langle a_{k+1}, a_{k+2}, \dots, a_n \rangle$ the tail or suffix of length $n-k$ for $0 \leq k \leq n$. Note that $\sigma = hd^k(\sigma) \cdot tl^k(\sigma)$ for $0 \leq k \leq n$ and any sequence σ.

A function $f \colon A \to B$ can be lifted element-wise to sequences over A, precisely:

$$f(\sigma) = \begin{cases} \langle\rangle & \text{if } \sigma = \langle\rangle \\ \langle f(a_1), f(a_2), \dots, f(a_n) \rangle & \text{else} \end{cases}$$

If an element $a \in A$ appears in a sequence $\sigma \in A^*$, the set membership notation $a \in \sigma$ is used for simplification.

2.3 Events, Traces, Event Logs

Based on the definition of sequences, the concepts of events, traces and event logs can be formalized.

Definition 2.4 (Event)**.** An *event* is a tuple $e = (c, a, t, d_1, \dots, d_m) \in \mathcal{C} \times \mathcal{A} \times \mathcal{T} \times \mathcal{D}_1 \times \dots \times \mathcal{D}_m = \mathcal{E}$ where $c \in \mathcal{C}$ is the case ID, $a \in \mathcal{A}$ is the executed activity and $t \in \mathcal{T}$ is the timestamp of the event. Furthermore, each event contains a fixed number $m \in \mathbb{N}_0$ of additional attributes $d_1, \dots, d_m$ in their corresponding domains $\mathcal{D}_1, \dots, \mathcal{D}_m$. In case that no additional attribute data is available ($m = 0$) the event space $\mathcal{E}$ (set of all possible events) is reduced to its minimal form $\mathcal{C} \times \mathcal{A} \times \mathcal{T}$.

Each attribute $d \in \mathcal{D}$ of an event (including activity, timestamp and case ID) can be accessed by a corresponding projection function $\pi_D \colon \mathcal{E} \to \mathcal{D}$. For example, the activity a of an event e is retrieved by $\pi_{\mathcal{A}}(e) = a$.

Throughout this thesis, $\mathcal{C} = \mathbb{N}_0$, $|\mathcal{A}| < \infty$ and $\mathcal{T} = \mathbb{R}$ is assumed, where $t \in \mathcal{T}$ is given in Unix time, precisely the number of seconds since 00:00:00 UTC on 1 January 1970 minus the applied leap seconds. Each additional attribute is assumed to be numerical, categorical or textual, i.e. $\mathcal{D}_i = \mathbb{R}$, $|\mathcal{D}_i| < \infty$ or $\mathcal{D}_i = \Sigma^*$ for $1 \leq i \leq m$ and some fixed language-dependent alphabet Σ.

Definition 2.5 (Trace)**.** A *trace* is a finite sequence of events $\sigma = \langle e_1, e_2, \dots \rangle \in \mathcal{E}^*$ with increasing timestamps, i.e. $\pi_{\mathcal{T}}(e_i) < \pi_{\mathcal{T}}(e_j)$ for $1 \leq i < j \leq |\sigma|$.

A trace can be transformed into a sequence of attributes by applying a projection function to the trace. For example, $\pi_{\mathcal{A}}(\sigma)$ gives the sequence of the activities of the events in σ. The sequence of activities is also called *path* or *trace variant*.

Definition 2.6 (Event Log)**.** An *event log* $\mathbb{L} = \{\sigma_1, \sigma_2, \ldots, \sigma_k\}$ is a set of traces, where each event of a trace is unique in the log and all events of a trace share a case IDs, which is unique per trace.

2.4 Text Mining

With the consideration of textual data in event logs, the concept of *text mining* becomes relevant. Text mining describes all techniques that aim to generate value out of unstructured or semi-structured textual data. It combines concepts of natural language processing, machine learning and data mining [11].

The base object in text mining is a *document* containing textual data. The textual data can be completely unstructured, i.e. it does not conform to a pre-defined data model, or semi-structured, like in an email, where text information is assigned to sender, subject, message etc. In this setting, a document $d \in \Sigma^*$ (i.e. textual data) is always a sequence of symbols from a fixed alphabet Σ. A collection of documents is called *text corpus*, which forms the basis for many text mining techniques.

In order to derive a mathematical representation of textual data that can be interpreted by learning algorithms, a text model has to be applied using the whole text corpus. Popular text models for documents are *Bag of Words* [12], *Bag of N-Gram*, *Paragraph Vector* (a.k.a. Doc2Vec) [13] and *Latent Dirichlet Allocation* [14]. Most models do not work with the raw text data, but require a text normalization step, where the text is cleaned from linguistic variation as well as meaningless words and symbols [15].

2.5 Supervised Learning

In *supervised learning* an unknown function is learned (i.e. approximated) from a set of example input-output pairs [16]. In contrast, in *unsupervised learning* no target outputs are available and the goal is to identify pattern in the data [17].

An input instance in the supervised scenario is usually described by a tuple of *feature variables* X and the output is defined by a *target variable* y. The target variable y is either continuous (regression problem) or discrete (classification problem). Given a *training set* of input-output pairs $\{(X_1, y_1), (X_2, y_2), \ldots, (X_m, y_m)\}$, that were generated from an unknown function $y = f(X)$, the goal is to compute a hypothesis function $h(X)$, which is as close as possible to the true function f(X), i.e. $h(X) \approx f(X)$.

The challenge in supervised learning is to generalize from the training set of input-output pairs in such a way, that the learned hypothesis function $h(x)$ can also successfully predict the target variable for unseen problem instances. In order to evaluate a hypothesis, the function is tested on a separate *test set* of input-output pairs, which has not been used for the construction of $h(X)$.

A hypothesis is assumed to generalize well, if its prediction performance is high on the training set and on the test set. However, if the prediction performance is high on the training set, but the hypothesis performs poorly on unseen data, the hypothesis is *overfitting* with respect to the training data. In this case, the model fails to generalize. In contrast, if the model is too simple to fit any data from training set, the hypothesis is *underfitting*.

In many real-world applications, the true function $f(X)$ is stochastic, i.e. we need to estimate a conditional probability function $P(Y|X)$ (classification problem) or a conditional expectation $E(Y|X)$ (regression problem) for the prediction. Therefore, the prediction quality is always limited by the randomness of the true distribution. Typical supervised learning methods are linear regression, support vector machines [18], decision trees [19] or neural networks including long short-term memory networks [20].

2.6 Long Short-Term Memory Networks

Long short-term memory (LSMT) is an advanced recurrent neural network architecture for sequential data originally presented by Hochreiter and Schmidhuber in 1997 [20]. This approach addresses the well-known vanishing or exploding gradient problem [21] of traditional recurrent neural networks by introducing more complex LSTM cells as hidden units. The proposed architecture has been improved several times [22] [23] and is currently considered as one of the most successful recurrent neural network models. Although, LSTM networks have been available for a long time, the breakthrough of this technology is dated around 2016 after many success stories of LSTM in combination with large data sets and GPU hardware have been reported for sequence to sequence tasks like text translation [24].

Gated recurrent units (GRU) [25] are the competing gating mechanism by Cho et al. that have fewer parameters and perform similar to LSTM. However, more recent studies show, that LSTM outperforms GRU consistently in neural machine translation tasks [26].

A simple feedforward neural networks consists of an input layer, arbitrarily many hidden layers and an output layer, where each layer consists of neurons that compute and output the weighted sum of the cells of the previous layer that has been passed to an non-linear activation function [27]. These networks can learn and compute complex functions in supervised learning settings, where input and output pattern in form of vectors are provided. The network computes a loss function for each training pattern and adjusts its weights with gradient descents using a back-propagation algorithm in order to minimize the loss function [28].

Recurrent neural networks extend traditional feedforward networks with backfeeding connections between hidden layers. This enables the network to keep a state across inputs and allows the neural network to process arbitrarily long sequences of input data while learning temporal dependencies.

In LTSM networks the layers are replaced by more complex LSTM modules, where each module contains four different sublayers. The architecture of a single LSTM module is shown in Figure 2.1. The module uses as input the state $\boldsymbol{c}_{t-1}$ and the hidden output $\boldsymbol{h}_{t-1}$ of the module in the previous time step as well as the output of the previous layer $\boldsymbol{x}_t$ to compute a new cell state $\boldsymbol{c}_t$ and a hidden output $\boldsymbol{h}_t$.

The input vector $\boldsymbol{x}_t$ is concatenated with the previous hidden output $\boldsymbol{h}_{t-1}$ and transferred to four neural network layers, which are designed to decide what part of the cell state will remain (forget gate $\boldsymbol{f}_t$), how it is updated (update gate $\boldsymbol{i}_t$ and $\tilde{\boldsymbol{c}}_t$) and what the output of the layer will be (output gate $\boldsymbol{o}_t$ leading to $\boldsymbol{h}_t$ considering the updated cell state $\boldsymbol{c}_t$). The sublayer apply $\text{sigmoid}(x) = \frac{1}{1+\exp(-x)}$ or $\tanh(x) = \frac{\exp(x)-\exp(-x)}{\exp(x)+\exp(-x)}$ activation functions

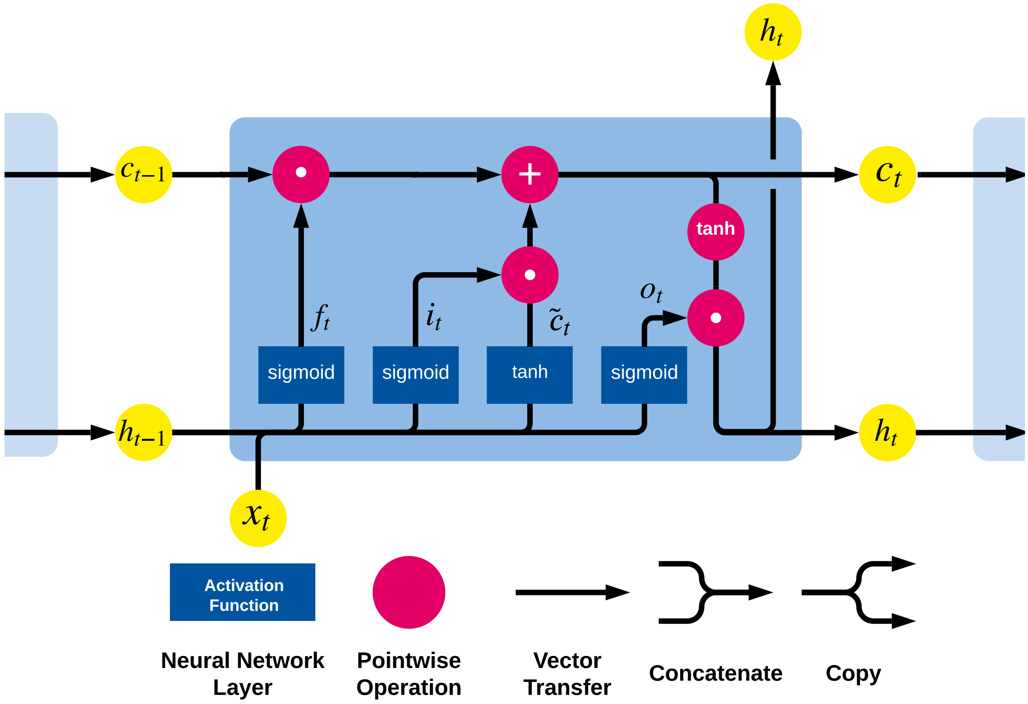


Figure 2.1: LSTM module with four sublayers that manipulate the cell state and compute the module's output. The graphic is adapted from [29].

elementwise to vectors, leading to the following equations:

$$\begin{aligned}
\boldsymbol{f}_t &= \text{sigmoid}(\boldsymbol{W}_f \cdot (\boldsymbol{h}_{t-1}, \boldsymbol{x}_t) + \boldsymbol{b}_f) \\
\boldsymbol{i}_t &= \text{sigmoid}(\boldsymbol{W}_i \cdot (\boldsymbol{h}_{t-1}, \boldsymbol{x}_t) + \boldsymbol{b}_i) \\
\tilde{\boldsymbol{c}}_t &= \tanh(\boldsymbol{W}_c \cdot (\boldsymbol{h}_{t-1}, \boldsymbol{x}_t) + \boldsymbol{b}_c) \\
\boldsymbol{o}_t &= \text{sigmoid}(\boldsymbol{W}_o \cdot (\boldsymbol{h}_{t-1}, \boldsymbol{x}_t) + \boldsymbol{b}_o)
\end{aligned}$$

$\boldsymbol{W}_f$, $\boldsymbol{W}_i$, $\boldsymbol{W}_c$ and $\boldsymbol{W}_o$ are the sublayer's learned weights and $\boldsymbol{b}_f$, $\boldsymbol{b}_i$, $\boldsymbol{b}_c$ and $\boldsymbol{b}_o$ are the corresponding biases. The new cell state $\boldsymbol{c}_t$ is then a combination of the old cell state $\boldsymbol{c}_{t-1}$ and the result of the update gate $\tilde{\boldsymbol{c}}_t$, where the layer computations $\boldsymbol{f}_t$ and $\boldsymbol{i}_t$ determine the proportions by a pointwise multiplication ($\odot$) with the cell states.

$$\boldsymbol{c}_t = f_t \odot \boldsymbol{c}_{t-1} + \boldsymbol{i}_t \odot \tilde{\boldsymbol{c}}_t$$

The result of the output gate $\boldsymbol{o}_t$ is pointwise multiplied with the tanh-activated new cell state to calculate the hidden output $\boldsymbol{h}_t$ of the module.

$$\boldsymbol{h}_t = \boldsymbol{o}_t \odot \tanh(\boldsymbol{c}_t)$$

LSTM networks are able to backpropagate a more stable error with this gating mechanism, such that these networks are much more capable of learning complex functions for sequences compared to standard recurrent neural networks. As a machine learning model that naturally supports sequential data, LSTM networks are a suitable prediction model for processes.

Chapter 3

Related Work

The prediction of the future course of a process instance has been an important subfield in process mining research, aiming to enhance process monitoring capabilities. Depending on the use case, for example predicting time-related attributes, the next activity or the the outcome of a case can be of interest. Most approaches presented in the literature either use process models or machine learning methods to construct a predictor, that generalizes from a historical event log.

Five different non-parametric regression predictors for forecasting the total cycle time of an unfinished case have been presented by van Dongen et al. [30]. The estimates are based on activity occurrences, activity duration and other attributes.

Furthermore, van der Aalst et al. proposed to build a transition system using a set, bag or sequence abstraction, which is annotated with time-related data in order to predict the cycle time of case [31]. The core idea of this approach is to replay unfinished cases on the learned transition system and compute the prediction using the historical measurements in the annotations.

Pandey et al. use a hidden markov model to predict the cycle time of a case using the activity and timestamp data of an event log [32].

Rogge-Solti and Weske showed how a stochastic Petri net can be used to predict the cycle time of a process instance. The model naturally supports parallelism in business processes and considers future events, which are expected to occur.

Ceci et al. presented an approach, where a sequence tree is learned in order relate running traces to similar historical traces [34]. A decision tree is then used to predict the next activity and the cycle time of a case.

Teinemaa et al. applied text vectorization techniques like Bag of N-Gram (BoNG), Latent Dirichlet Allocation (LDA) and Paragraph Vectors (PV) to textual data of processes in order to predict a binary label describing the process outcome [35]. In this approach random forest and logistic regression classifiers for each prefix length of a trace are trained.

Most recently, several authors have applied recurrent neural networks in form of LSTM networks for process prediction. Evermann et al. encode events using an embedding matrix as it is known for word embeddings. The embedded events are then used as input for an

LSTM network that predicts the next activity [36].

Tax et al. use an one-hot encoding of the activity and the timestamp of an event to predict the activity and timestamp of the next event [37]. This is done by using a two-layered LSTM network architecture.

The work by Navarin et al. adopted the idea of using an LSTM network [37] and extends the encoding by also utilizing additional data attributes associated with each event [38] to predict the cycle time of a case.

Polato et al. presented a set of approaches that use support vector regression for cycle time prediction [39]. In this contribution the authors implement different encodings for events including a simple one-hot encoding and a more advanced state-based encoding using transition systems. Furthermore, they enhance the approach in [31] by taking additional data attributes into account.

Teinemaa et al. reported an in-depth review and benchmark of outcome-oriented predictive process monitoring approaches. The study showed that aggregated encodings like counting frequencies of activities are the most reliable encoding for predicting the outcome of a case [40].

Park and Song showed how LSTM-based predictions can be used to solve a resource allocation problem, leading to direct recommendations for process improvement [41].

The most extensive benchmarking of sequential prediction models has been realized by Tax et al. [42]. The authors show that black-box process prediction methods from the machine learning field outperform process model-oriented techniques. However, the latter are more efficient and offer a higher interpretability at the cost of prediction quality.

A comparison of the process prediction methods is presented in Table 3.1.

Contribution	Year	Model(s)	Data-Aware	Text-Aware	Predictions
Van Dongen et al. [30]	2008	Regression	✓	✗	Cycle time
Van der Aalst et al. [31]	2011	Transition system	✗	✗	Cycle time
Pandey et al. [32]	2011	Hidden Markov	✗	✗	Cycle time
Rogge-Solti and Weske [33]	2013	Stochastic Petri net	✗	✗	Cycle time
Ceci et al. [34]	2014	Sequence tree Decision tree	✓	✗	Next activity Cycle time
Teinemaa et al. [35]	2016	Random forest Logistic regression	✓	✓	Case outcome
Evermann et al. [36]	2016	LSTM	✗	✗	Next activity
Tax et al. [37]	2017	LSTM	✗	✗	Next activity Next event time Cycle time Future path
Navarin et al. [38]	2017	LSTM	✓	✗	Cycle time
Polato et al. [39]	2018	Transition system SVR Naive Bayes	✓	✗	Next activity Cycle time Future path
Park and Song [41]	2019	LSTM	✓	✗	Next activity Next event time
This contribution	2020	LSTM	✓	✓	Next activity Next event time Cycle time Case outcome

Table 3.1: Comparison of process prediction methods.

Chapter 4

Text-Aware Process Prediction

Text-aware process prediction aims to utilize unstructured text information in historical event data to improve predictions for unfinished cases. While many prediction methods have been applied to event data, almost none of them is able to handle textual data. Nevertheless, a lot of textual information in the context of processes is available, for example in form of business emails, documents or notes by employees or customers. These texts in natural language might hold process-critical information and should consequently be considered for process prediction. However, taking advantage of textual data remains a major challenge, since natural language is predominantly context-sensitive and ambiguous [43]. A first approach has been presented by Teinemaa et al., which encodes traces with textual data as vectors and a random forest classifier is learned for each prefix length [35].

In this chapter a novel approach for text-aware process prediction is presented that considers the control flow and additional numerical, categorical and textual data of the process. An exchangeable text model is used to vectorize textual data and take advantage of potential text-related correlations. The model aims to captures temporal dependencies between events, seasonal variability and concept drifts using an event-wise encoding and a sequential LSTM prediction model. The main application scenario for the model is inside of real-time business process monitoring software, where prediction capabilities for running processes can provide a competitive advantage.

4.1 Overview

The framework is designed to approximate prediction functions $f_{\mathrm{a}}, f_{\mathrm{t}}, f_{\mathrm{o}}$ and f_{c}, that predict the next **a**ctivity, next **t**imestamp, case **o**utcome and case **c**ycle time given any prefix $hd^k(\sigma)$ of length $1 \leq k \leq |\sigma| = n$ of the complete, but unknown trace $\sigma = \langle e_1, \dots, e_n \rangle \in \mathcal{E}^+$. The next activity prediction function $f_{\mathrm{a}} \colon \mathcal{E}^+ \to \mathcal{A} \cup \{\text{END OF PROCESS}\}$ returns the activity of the next event or an artificial END OF PROCESS activity, if the given trace is already completed, precisely:

$$f_{\mathrm{a}}(hd^k(\sigma)) = \begin{cases} \text{END OF PROCESS} & \text{if } k = |\sigma| \\ \pi_{\mathcal{A}}(\sigma(k+1)) & \text{else} \end{cases}$$

Furthermore, $f_{\mathrm{t}} \colon \mathcal{E}^{+} \to \mathbb{R}$ returns the timestamp of the next event in relation to the last event in the prefix:

$$f_{\mathrm{t}}(hd^{k}(\sigma)) = \begin{cases} 0 & \text{if } k = |\sigma| \\ \pi_{\mathcal{T}}(\sigma(k+1)) - \pi_{\mathcal{T}}(\sigma(k)) & \text{else} \end{cases}$$

The case outcome of traces depends on the context of the process. For example, it can be a binary label describing if the case has been successful or has failed. In some applications the case outcome is defined by the activity of the final event of a case. In that scenario, the outcome function $f_{\mathrm{o}} \colon \mathcal{E}^{+} \to \mathcal{A}$ returns the last activity of the trace:

$$f_{\mathrm{o}}(hd^{k}(\sigma)) = \pi_{\mathcal{A}}(tl^{1}(\sigma(|\sigma|)))$$

Finally, $f_{\mathrm{c}} \colon \mathcal{E}^{+} \to \mathbb{R}$ returns the total duration of the process, i.e. the time difference between the first and the last event of the trace:

$$f_{\mathrm{c}}(hd^{k}(\sigma)) = \pi_{\mathcal{T}}(\sigma(|\sigma|)) - \pi_{\mathcal{T}}(\sigma(1)).$$

All functions are approximated via an LSTM model using historical event log data, i.e. a set of completed traces with full information about the course of the process instances. The goal is to generalize from the completed traces in such a way, that the prediction error is minimized for new, unseen and uncompleted traces. Due to the probabilistic behavior of real-world processes, the prediction accuracy is always limited by the randomness of the process behavior.

An overview of the framework is shown in Figure 4.1. The proposed framework consists of a preprocessing, encoding and prediction model component, which operate in an offline and online phase. In the offline phase, a historical event log with completed traces of a process is used to fit the encoding and prediction component. Given a historical event log $\mathbb{L} = \{\sigma_1, \ldots, \sigma_l\}$ with completed traces, the set of all prefix traces $\mathbb{L}_{\text{prefix}} = \{hd^{k}(\sigma) \mid \sigma \in \mathbb{L}, 1 \leq k \leq |\sigma|\}$ is computed and each trace is encoded as a sequence of event vectors.

The encoding component distinguish between categorical and numerical data that can be encoded directly and textual data that is prepossessed and encoded based on a separate text model. The text model is an exchangeable component and is fit to the text corpus, which is extracted from the textual data in the event log $\mathbb{L}$. Before the textual data of the event log is utilized by the text model, the data is normalized using a text preprocessing pipeline.

Each encoded prefix sequence with its desired prediction target values according to $f_{\mathrm{a}}, f_{\mathrm{t}}, f_{\mathrm{o}}$ and f_{c} corresponds to one training example for an LSTM network, that finally realizes the predictions. The total number of training examples that can be generated out of the log is $\sum_{\sigma \in \mathbb{L}} |\sigma|$, which is exactly the number of events in the log.

In the online phase, the model applies the learned prediction function to predict the activity and time of the next event as well as the outcome and cycle time of new, unseen and unfinished traces in the real-time event log, that is monitored by the business process monitoring system.

4.2 Event Encoding

In the offline training phase as well as during online prediction, traces are encoded as sequences of event vectors. The prefix log $\mathbb{L}_{\text{prefix}}$ is encoded as a training set in the offline

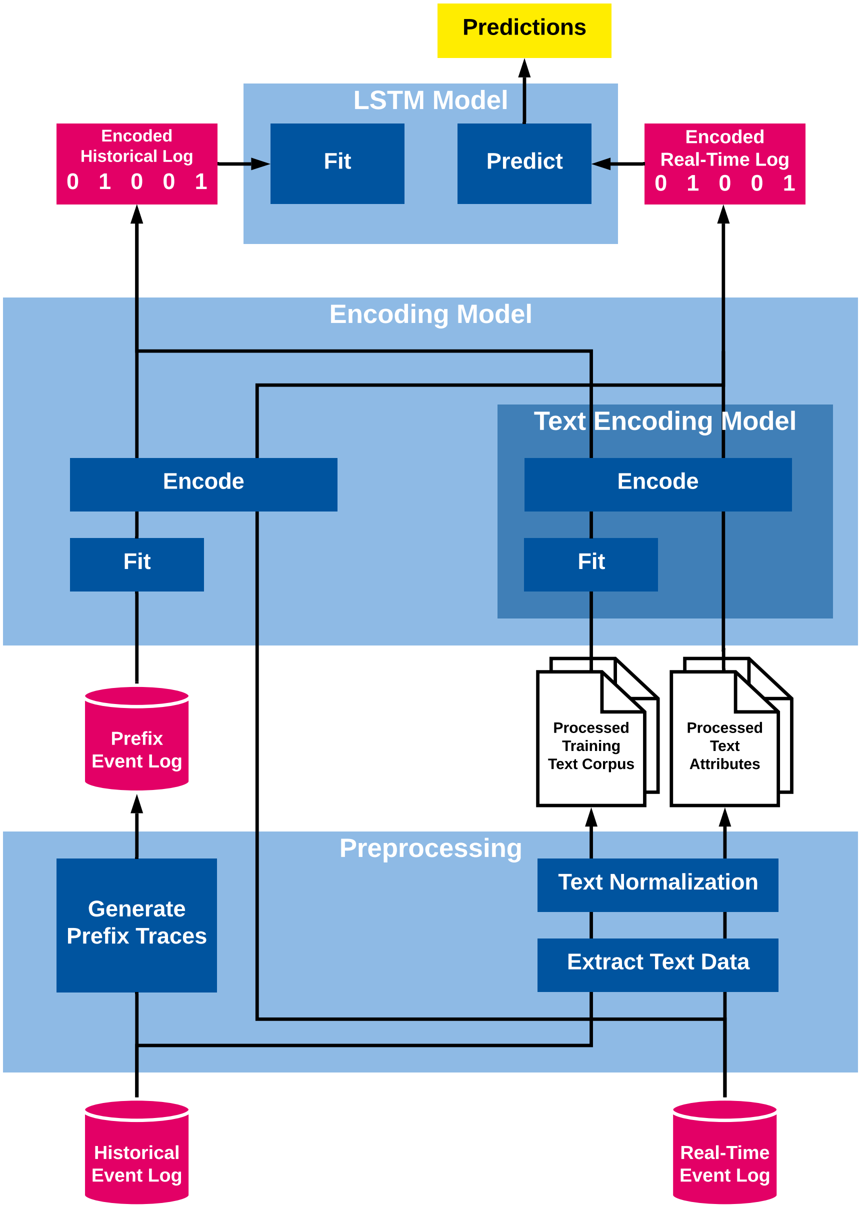


Figure 4.1: Overview of the text-aware process prediction model. Predictions for real-time processes are realized by an LSTM model that is fitted using an encoded representation of all prefixes of the historical event log. The encoding of textual attributes is realized by a text preprocessing pipeline and an exchangeable text encoding model.

phase, while in the online phase running cases are encoded for prediction. Strictly speaking, an encoding function is realized by the encoding component, that transforms prefix traces of length k to vector sequences of the same size, i.e. $encode(\sigma) = \langle \boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x_k} \rangle$ with $\sigma = \langle e_1, e_2, \ldots, e_k \rangle$ for $k \in \mathbb{N}$. Each event e_i is encoded as a fixed-length vector using the activity, timestamp and additional categorical, numerical and textual data that is associated with each event. We assume to have $r \in \mathbb{N}_0$ numerical, $s \in \mathbb{N}_0$ categorical and $u \in \mathbb{N}_0$ textual attributes, i.e. $e_i \in \mathcal{C} \times \mathcal{A} \times \mathcal{T} \times \mathcal{D}_1^{\text{num}} \times \cdots \times \mathcal{D}_r^{\text{num}} \times \mathcal{D}_1^{\text{cat}} \times \cdots \times \mathcal{D}_s^{\text{cat}} \times \mathcal{D}_1^{\text{text}} \times \cdots \times \mathcal{D}_u^{\text{text}}$. Each encoded event vector $\boldsymbol{x_i}$ is the concatenation of a set of feature vectors, which are constructed from the attributes in the event data.

$$\boldsymbol{x_i} = (\boldsymbol{a_i}, \boldsymbol{t_i}, d_{i1}^{\text{num}}, \ldots, d_{ir}^{\text{num}}, \boldsymbol{d}_{i1}^{\text{cat}}, \ldots, \boldsymbol{d}_{is}^{\text{cat}}, \boldsymbol{d}_{i1}^{\text{text}}, \ldots, \boldsymbol{d}_{iu}^{\text{text}})$$

The activity of the event is represented by a vector $\boldsymbol{a_i}$ using *one-hot encoding*. More precisely, given the set of possible activities $\mathcal{A}$, an arbitrary but fixed ordering over $\mathcal{A}$ is introduced with a bijective index function $index_{\mathcal{A}} \colon \mathcal{A} \to \{1, \ldots, |\mathcal{A}|\}$. Using this function, the activity is encoded as a vector of size $|\mathcal{A}|$, where the component $index_{\mathcal{A}}(\pi_{\mathcal{A}}(e))$ has value 1 and all the other components have value 0. The function $\mathbb{1}_{\mathcal{A}} \colon \mathcal{A} \to \{0,1\}^{\mathcal{A}}$ is used to describe the realization of such an one-hot encoding transformation for the set of all activities $\mathcal{A}$. The timestamp of the events are used to compute a six-dimensional vector $\boldsymbol{t_i}$ of time-related features, which is explained in detail in Section 4.3.

Additional attributes of the events are encoded based on their type, i.e. if they are numerical, categorical or textual. Categorical attributes are encoded using one-hot encoding in the same way as the activity, i.e. $\boldsymbol{d}_{ij}^{\text{cat}} = \mathbb{1}_{\mathcal{D}_j^{\text{cat}}}(\pi_{\mathcal{D}_j^{\text{cat}}}(e_i))$ is the vector describing the j-th categorical attribute of the i-th event.

All additional numerical attributes $\pi_{\mathcal{D}_i^{\text{num}}}(e_i)$ are scaled to the interval $[0, 1]$ to improve learning efficiency using min-max normalizing. The scaling for a numerical attribute x is realized with the transformation

$$\hat{x} = \frac{x - \min(x)}{\max(x) - \min(x)},$$

where $\min(x)$ is the lowest and $\max(x)$ is the highest value x can take. If the limits are not bounded conceptually, the lowest or highest value of x in the historical event log is used for scaling.

Textual attributes are vectorized via a dedicated text model, that is explained in Section 4.4. The dimensions of the text vectorizations can be tuned individually per attribute using the parameter z_j, which is the encoding dimension of the j-th textual attribute.

All in all, the encoding of an event e_i results in a vector of size

$$|\boldsymbol{x_i}| = |\mathcal{A}| + r + \sum_{i=1}^{s} |\mathcal{D}_i| + \sum_{j=1}^{u} z_j + 6$$

having r numerical, s categorical and u textual additional attributes (besides activity and timestamp). An overview of each feature vector that is part of the event encoding is provided in Table 4.1.

Feature Vector	**Construction**	**Dimension**	**Description**
$\boldsymbol{a_i}$	$\mathbb{1}_{\mathcal{A}}(\pi_{\mathcal{A}}(e_i))$	$\|\mathcal{A}\|$	One-hot encoding of the activity.
$\boldsymbol{t_i}$	See Section 4.3	6	Time-based feature vector.
d_{ij}^{num}	$\widehat{\pi_{\mathcal{D}_j^{\text{num}}}(e_i)}$	1	Normalized value of the j-th numerical attribute
$\boldsymbol{d}_{ij}^{\text{cat}}$	$\mathbb{1}_{\mathcal{D}_j^{\text{cat}}}(\pi_{\mathcal{D}_j^{\text{cat}}}(e_i))$	$\|\mathcal{D}_j^{\text{cat}}\|$	One-hot encoding of the j-th categorical attribute.
$\boldsymbol{d}_{ij}^{\text{text}}$	See Section 4.4	z_j (parameter)	Fixed-length vectorization of the j-th text attribute.

Table 4.1: Feature vectors as part of the event encoding $\boldsymbol{x_i}$ for an event e_i.

4.3 Capturing Temporal Dependencies

A set of time-based features is computed from the timestamp data in the event log in order to profit from time-related pattern in the process. As part of the complete encoding $\boldsymbol{x}_i$ for an event e_i in a prefix trace $\sigma = \langle e_1, \dots, e_k \rangle$, a time vector $\boldsymbol{t_i} = (t_i^1, t_i^2, t_i^3, t_i^4, t_i^5, t_i^6)$ of dimension 6 is computed. A summary of all time-related features can be seen in Table 4.2.

Feature	**Description**
t_i^1	Normalized time since previous event
t_i^2	Normalized time since case start
t_i^3	Normalized time since first recorded event in the log
t_i^4	Normalized time since midnight (beginning of the day)
t_i^5	Normalized time since last Monday (beginning of the week)
t_i^6	Normalized time since last January 1 00:00 (beginning of the year)

Table 4.2: Time-based features as part of event encoding $\boldsymbol{x_i}$.

Using these features time-related correlations can be captured and utilized for prediction. The feature t_i^1 describes the time difference between the current event e_i and previous event e_{i-1}, while t_i^2 gives the time difference between the current event and the first event of the case e_1, i.e. the time since the start of the case. Furthermore, t_i^3 is the time difference between the current event and the first event that is recorded in the log. This feature indicates the absolute time position of an event in the recorded data. This information is important to detect concept drifts [44] in the process. Most real-world processes are not static, i.e. the behavior of the process changes over time. For example, in earlier process executions customers might have been informed by a letter, whereas in more recent cases customers are messaged using email or app notifications. Therefore, the knowledge about the absolute time of the events can be used to relate cases in similar periods of time.

The features t_i^4, t_i^5 and t_i^6 describe the time of the event in relation to the beginning of the day, week and year. They are used to capture daily, weekly and seasonal trends. For example, some activities might only be executed during office hours or before the weekend. Also, many businesses expect seasonally fluctuating demand, for example a booking platform for vacation usually has much more customers in summer, which can affect the process execution in many ways. Each feature $t_i^1, \dots, t_i^6$ is min-max normalized such that $t_i^j \in [0, 1]$ for $j \in [6]$.

4.4 Text Vectorization

In order to prepare the textual data of the event log for a prediction model, the texts have to be encoded in a compact, finite and useful numerical vector representation using a text model. Useful in that context means, that texts with similar semantic meanings should also have similar representations. The vector representation of textual data is an important task in *Natural Language Processing* (NLP) [45]. Extracting the meaning of textual information remains a challenge even for humans, because textual data is unstructured, language dependent and domain specific. Many words are ambiguous, for example the word “apple” might denote a fruit or a global technology company. In addition, grammatical variations and the importance of context in language makes extracting the semantic meaning even more difficult for computers.

In this setting, the text vectorization for textual attributes is realized in a two step procedure. First, all textual data associated with the events in the corresponding textual attribute is collected in a so called *text corpus*. Each document in the text corpus is then preprocessed in order to filter out linguistic noise or useless information. This step is called *text normalization* [15]. Finally, the normalized text corpus is used to build up a *vocabulary* and a text vectorization technique is applied to encode the text of the attribute into a fixed-length vector. The vocabulary of a text corpus is a set V of all relevant words that appear after preprocessing in the corpus, which is indexed by a bijective index function $index_V : V \to \{1, 2, \dots, |V|\}$. As text vectorization techniques the *Bag of Words*, *Bag of N-Grams*, *Paragraph Vector* and *Latent Dirichlet Allocation* text models are considered, which are discussed in more detail in the Sections 4.4.2 to 4.4.5.

4.4.1 Text Normalization

In the text normalization step each document of the text corpus is transformed by a preprocessing pipeline, which performs the following four steps:

1. Letters are converted to lowercase
2. The document is tokenized (i.e. splitted) by word
3. Each word is lemmatized
4. Stop words are filtered out

The first step eliminates all capital letters in the text. In the tokenenization step a document is split up into a sequence of words. Each word is then lemmatized, i.e. it is converted to its canonical form. The idea is to unify words that have a very similar meaning and filter out grammatical variations. For example, the words “go”, “going”, “goes”, “gone” and “went” are all transformed to the basic form “go”. Lemmatization significantly reduces the complexity of textual data while accepting a hopefully small loss of information.

Step	Transformation	Example Document
0	Original	"The patient has been diagnosed with high blood pressure."
1	Lowercase	"the patient has been diagnosed with high blood pressure."
2	Tokenization	⟨"the", "patient", "has", "been", "diagnosed", "with", "high", "blood", "pressure", "."⟩
3	Lemmatization	⟨"the", "patient", "have", "be", "diagnose", "with", "high", "blood", "pressure", "."⟩
4	Stop word filtering	⟨"patient", "diagnose", "high", "blood", "pressure"⟩

Table 4.3: Text preprocessing transformation of an example document containing a single sentence.

Ultimately, all stop words are filtered out of each document. Stop words are words with low information value like "the", "a", "of" or "here". Stop word lists are language dependent and can be more or less aggressive at filtering. Usually they contains articles, auxiliary verbs, prepositions and generic verbs like "be" and "have". In addition, punctuation marks and numerical symbols are excluded. An example application of the text normalization pipeline is shown in Table 4.3. Using the corpus of normalized documents (i.e. texts), a text model is fitted in the offline phase to construct the vocabulary and realize the encoding of the textual attributes. In the following, four different text models are presented that are suitable to construct vector representations of documents.

4.4.2 Bag of Words

The *Bag of Words* (BoW) model is a simple text model, which represents documents based on the *term frequencies* of its words, while ignoring their order [12]. Given the learned vocabulary V, a document is represented by a vector of size $|V|$, where the i-th component gives the number of occurrences in the document of the word indexed with i in the vocabulary.

Since this approach does not reflect the prior distributions of words in the corpus, i.e. how likely certain words appear in a document in general, the term frequencies are usually normalized by the so-called *inverse document frequency* (idf) of a word. The inverse document frequency indicates the specificity of a word in the corpus and is computed by dividing the total number of documents by the number of documents that contain the specific word and scaling that value logarithmically. The resulting value is the tf-idf score of a word in a document.

The Bag of Words model is easy to build and effective for certain applications, but limited in several ways. First, the model completely ignores the order of words, which is often crucial for understanding the semantic meaning of a sentence. For example, the sentences "The patient's health state went from stable to critical." and "The patient's health state went from critical to stable." would result in the same vector representation, while the meaning is clearly inverted. Second, the vector representations are sparse and of high dimensionality since they depend of the size of the vocabulary. However, the dimension can be reduced by limiting the size of the vocabulary. For example, words that rarely appear in the corpus can be excluded from the vocabulary. Unseen words, that appear during online prediction and are not part of the learned vocabulary are not considered.

4.4.3 Bag of N-Grams

The *Bag of N-Grams* (BoNG) model is a generalization of the Bag of Words model, which addresses the missing word order awareness of the latter. Instead of single words, the vocabulary consists of n-tuples of words, that appear consecutive in the documents. The unigram model ($n = 1$) is equivalent to the BoW model. For the bigram model ($n = 2$), the vocabulary consists of pairs of words that appear next to each other in the documents. For example, for the preprocessed document ⟨ "patient", "diagnose", "high", "blood", "pressure"⟩, the pairs ("patient", "diagnose"), ("diagnose", "high"), ("high", "blood") and ("blood", "pressure") are added the vocabulary. For $n > 2$ n-tuples are generated accordingly. The feature vector is constructed by computing the tf-idf score for each vocabulary entry like in the BoW model.

Compared to the BoW model, n-grams also take the order of words into account, which is beneficial in many scenarios. However, the vocabulary size is usually even higher than in the BoW model. In order to generate more compact vectors, distributed text representations are needed for larger text corpora and vocabularies.

4.4.4 Paragraph Vector

The *Paragraph Vector* model (also known as *Doc2Vec*), originally presented by Le and Mikolov in 2014, is an unsupervised algorithm that learns distributed fixed length vector representations for documents of variable length using a simple feedforward neural network [13]. The idea is inspired by the word embedding model presented by Bengio et al. [46], which can learn distributed fixed-length vector representations for words. In this model words are mapped to vectors, that are trained to predict words from its context, i.e. words that appear before or after the target word in the training documents. Several variants of this approach exits, notably the *Continuous Bag of Words* model, which ignores the order of the words in the context and the *Continuous Skip-gram* model, which predicts the skip-gram context for a word vector (also known as *Word2Vec*) [47].

The core idea of the Paragraph Vector model is to extend the model introduced in [46] in a way, that an additional document (i.e. paragraph) vector is trained together with the word vectors, that is unique per document. Fig. 4.2 show the architecture of the distributed memory variant of the Paragraph Vector model (PV-DM). Its is realized by a neural network, that takes one-hot encoded words and an one-hot encoded document ID as input. These are mapped to vector representation via weight matrices $\boldsymbol{D}$ and $\boldsymbol{W}$, which are learned during training with gradient descent. The distributed representations are then averaged or concatenated to a vector in order to predict the one-hot encoded target word using another mapping $\boldsymbol{W'}$ and a softmax activation function. The training set is constructed using a sliding window over every document, such that the input is the context of the target word and the document ID. After training, each column in $\boldsymbol{D}$ represents the distributed encoding of the corresponding document.

The network is also able to learn a representation for unseen documents through an inference step. In this phase, the word matrix $\boldsymbol{W}$ and the prediction matrix $\boldsymbol{W'}$ are fixed and only the document vector is trained. The paragraph vector model tends to perform better than non-distributed models, however since new documents are vectorized via inference, a bigger training corpus of documents is usually required.

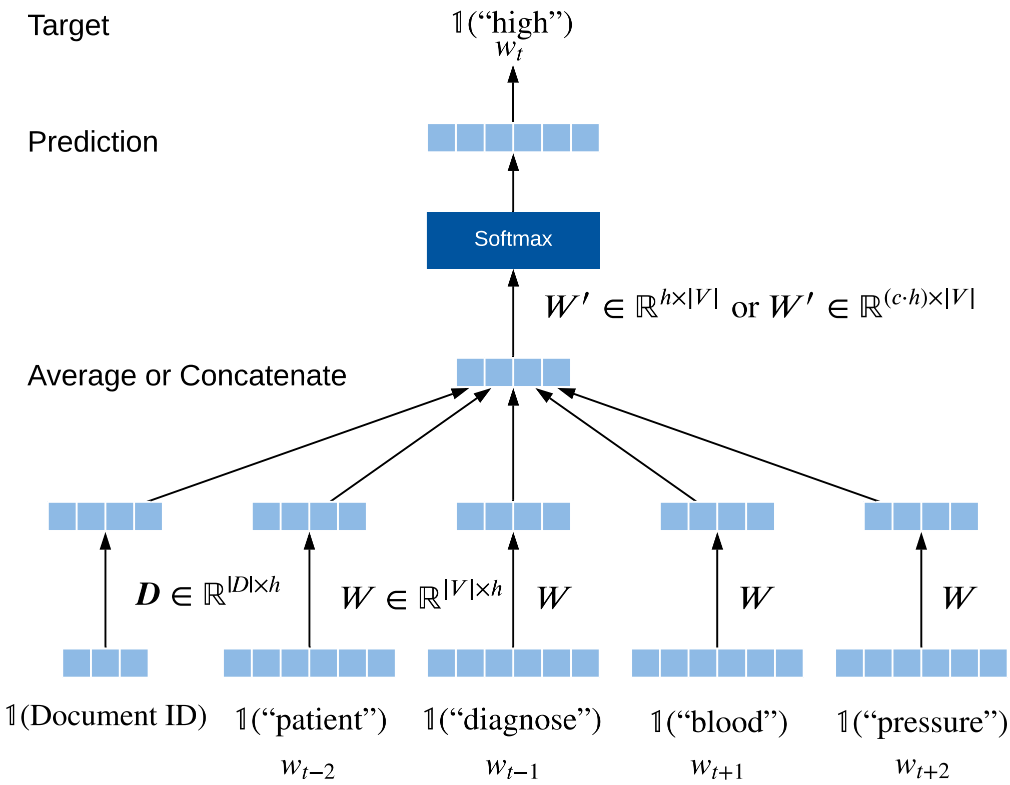


Figure 4.2: The Paragraph Vector model in the distributed memory variant (PV-DM) is a neural network that is designed to predict a word w_t from its context $(w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2})$ and derives fixed-length representation of documents and words via the learned matrices $\boldsymbol{D}$ and $\boldsymbol{W}$. The dimension of the representations are defined before by a parameter h.

4.4.5 Latent Dirichlet Allocation

The *Latent Dirichlet Allocation* (LDA) presented by Blei et al. in 2003 [14] is generative statistical text model, which represents documents as a mixture of a small and fixed number of topics. Topics are defined by a probability distribution over all words in the vocabulary and are also learned by the model in an unsupervised manner. The underlying assumption of the LDA model is that the documents were created by a statistical process, that sampled the words of the document from sampled topics. A document is encoded as a vector, whose dimension is equal to the number of topics and each component indicates the probability that the corresponding topic distribution was chosen to sample a word in the document. The distributions and therefore document encoding can be learned with statistical inference algorithms like Monte Carlo Simulation, Variational Bayes or maximum likelihood estimation using the words of each document. Compared to the other text models, LDA can generate very compact document encodings, since the documents are only described by their degree of affiliation to each topic. Similar to the BoW model, LDA does not consider the order of words in the document, which can be disadvantageous for some text corpora.

4.5 Network Architecture and Training

The encoded historical prefix event log is used to fit an LSTM model. The LSTM network is designed to be trained with all prediction targets (next activity, next event time, case outcome and case cycle time) at once, in order to benefit from correlations between these. In the basic variant, the network consists of an input layer, an shared LSTM layer, an specialized LSTM layer for each prediction target and an fully connected output layer for each target. Furthermore, layer normalization [48] can be applied after each LSTM layer, which standardizes the hidden output in order to speed up the training convergence. The network architecture is shown in Figure 4.3. Note that the LSTM layers in the figure are unrolled in time, i.e. the same layer is displayed once for every time step.

The fully connected output layer uses a softmax activation function for the next activity and case outcome prediction to estimate the probability for each target value. The softmax function normalizes a vector of real numbers into another vector of same dimension, such that all component are in the interval [0,1] and the sum of all component is equal to 1. Hence, the transformed vector can be interpreted as a probability distribution, while keeping the proportions of the original vector. The softmax function is described with

$$\mathrm{Softmax}(\boldsymbol{x})_i = \frac{\exp(x_i)}{\sum_{j=1}^{n} \exp(x_j)} \text{ for } i = 1, \ldots, n \text{ and } \boldsymbol{x} = (x_1, \ldots, x_n) \in \mathbb{R}^n.$$

The whole training set of encoded prefix traces is represented for efficiency by a 3-dimensional matrix of real values, where the three dimensions specify the prefix traces, the events per prefix trace and the features per event. Since the prefix traces have different length, shorter traces are pre-padded [49] with zero vectors. Hence, a prefix trace of encoded events $\boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x_n}$ is represented in the training set by a 2-dimensional matrix $(\mathbf{0}, \ldots, \mathbf{0}, \boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x_n})$, such that the zero vectors fill up shorter traces to the length of the longest trace in the training set. All prefix traces together form a 3-dimensional training matrix.

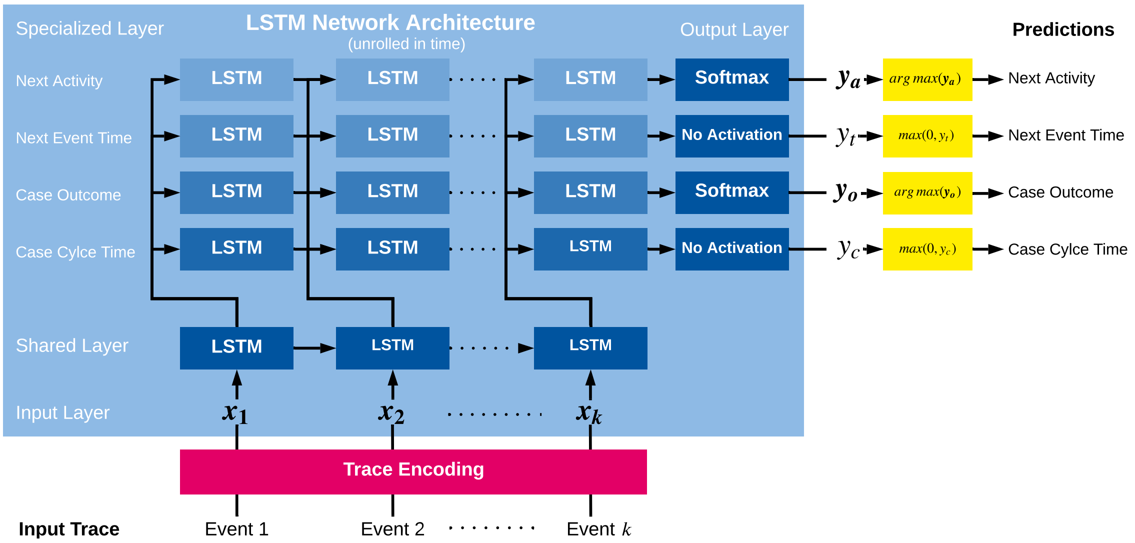


Figure 4.3: LSTM model architecture to simultaneously predict the next activity ($\boldsymbol{y_a}$), next event time(y_t), case outcome ($\boldsymbol{y_o}$) and case cylce time (y_c) for an encoded prefix trace $\boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x_k}$.

The training is realized using a learning algorithm based on stochastic gradient descent and backpropagation through time (BPTT), which update the weights of the network using the update rules of the Adam optimizer with Nesterov momentum [50]. The loss for numerical prediction values $\hat{y}$ and the true value y is the absolute error $\mathrm{AE}(\hat{y}, y) = |\hat{y} - y|$, while the loss for categorical prediction values is computed using the categorical cross entropy error $\mathrm{CE}(\boldsymbol{\hat{y}}, \boldsymbol{y}) = -\sum_{i=1}^{k} y_i \cdot \log \hat{y}_i$.

4.6 Predictive Business Processing Monitoring

During online business process monitoring, predictions are realized by a forward-pass of the encoded, uncompleted traces through the LSTM model. The component with the highest value of the softmax outputs for the next activity ($\boldsymbol{y_a}$) and the case outcome ($\boldsymbol{y_o}$) indicates the categorical prediction. The output values for the next event time (y_t) and case duration (y_c) are clipped to 0 for negative outputs and the normalization is reverted in order to compute the final prediction value.

With every new event, that is registered by the business process monitoring system, the prediction can be updated with another forward-pass through the model. This guarantees a continuous forward-projection on running process instances, that is updated whenever new information in form of new events becomes available. By predicting the timestamp and activity of the next event in an iterative way, the complete future path of running process instance can be predicted. The trace of a process instance is assumed to be completed, when the model predicts the artificial END OF PROCESS activity. With this technique the model indirectly can predict the completeness of a case.

Chapter 5

Implementation

This chapter covers the implementation of the text-aware process prediction model presented in the previous chapter. In Section 5.1 the underlying technology is depicted, whereas in Section 5.2 the architecture of the implementation is defined.

5.1 Technology

The implementation of the text-aware process prediction model is purely based on Python 3.8 [51]. The set of Python packages that are utilized for the implementation are summarized in Table 5.1. All packages follow the open-source development model and are mostly community-driven.

Package	**Developer(s)**	**Purpose**
PM4Py [52]	Fraunhofer Institute for Applied Information Technology	Event log parsing and handling
TensorFlow [53]	Google Brain Team et al.	Construction and training of LSTM model
NTLK [54]	Bird et al.	Text preprocessing
Scikit-learn [55]	Cournapeau et al.	Bag of Words and Bag of N-Gram tf-idf encoding
Gensim [56]	Řehůřek et al.	Latent Dirichlet Allocation and Paragraph Vector encoding

Table 5.1: Python packages used for implementation.

PM4Py [52] is a Python package developed by the Fraunhofer Institute for Applied Information Technology, which offers a wide range of process mining algorithms and event log operations for the Python environment. It is used for event log parsing and its internal event log representation.

TensorFlow [53] is a dataflow-oriented framework originally developed by Google, which includes a diverse set of neural network models and serves with its LSTM implementation using the Keras API [57].

Furthermore, the packages NTLK [54], Scikit-learn [55] and Gensim [56] are applied for the preprocessing and encoding of textual data. NTLK is used to realize the tokenization, word lemmatization and stop word removal, whereas the implementation of the text models is supported by the Scikit-learn (Bag of Words, Bag of N-Gram) and Gensim (LDA, Paragraph Vector) packages.

5.2 Model Architecture

The interface of the text-aware process prediction model (tapp) is realized through a class `TappModel`, which implements the functions `fit()`, `predict()` and `evaluate()`, that can be used to fit the model to an event log with historical data, compute prediction for an event log with uncompleted traces and evaluate the performance of the prediction model. The `TappModel` manages the underlying LSTM model and can be configured with the number of shared and specialized layers as well as the dimension of the hidden neurons per LSTM layer.

The encoding of traces as described in Section 4.2, 4.3 and 4.4 is computed in the `LogEncoder` module, which is controlled by the `TappModel`. The `LogEncoder` is also fitted to the historical log and can transform traces to the encoded matrix format via functions `fit()` and `transform()`. It is configured with one out of the four text encoding models described in the Sections 4.4.2 to 4.4.5 (`BoWTextEncoder`, `BoNGTextEncoder`, `LDATextEncoder` and `PVTextEncoder`), that realize the vectorization of textual data. Similar to the `LogEncoder`, the text encoding models offers the functions `fit()` and `transform()` to adapt to the historical data and compute the text encodings.

During the fitting phase of the `LogEncoder`, all possible values for categorical attribute are indexed and the parameters for the normalization of numerical attributes are computed. With regard to the text encoding model, the indexed vocabulary of all words (after preprocessing) in the historical event log is constructed during fitting. In case of the Paragraph Vector model, the encoding network is trained with the training corpus.

The text-aware process prediction model can be used in any business process monitoring software to provide prediction capabilities using the methods of the `TappModel`. In order to evaluate the performance of the model, an experiment using the `Evaluation` module is performed, which is described in-depth in Chapter 6. The module reads an event log using PM4Py, divides it into a training and test log and measures the prediction performance of differently configured instances of the text-aware process prediction model. An overview of the different components of the implementation is shown in Figure 5.1.

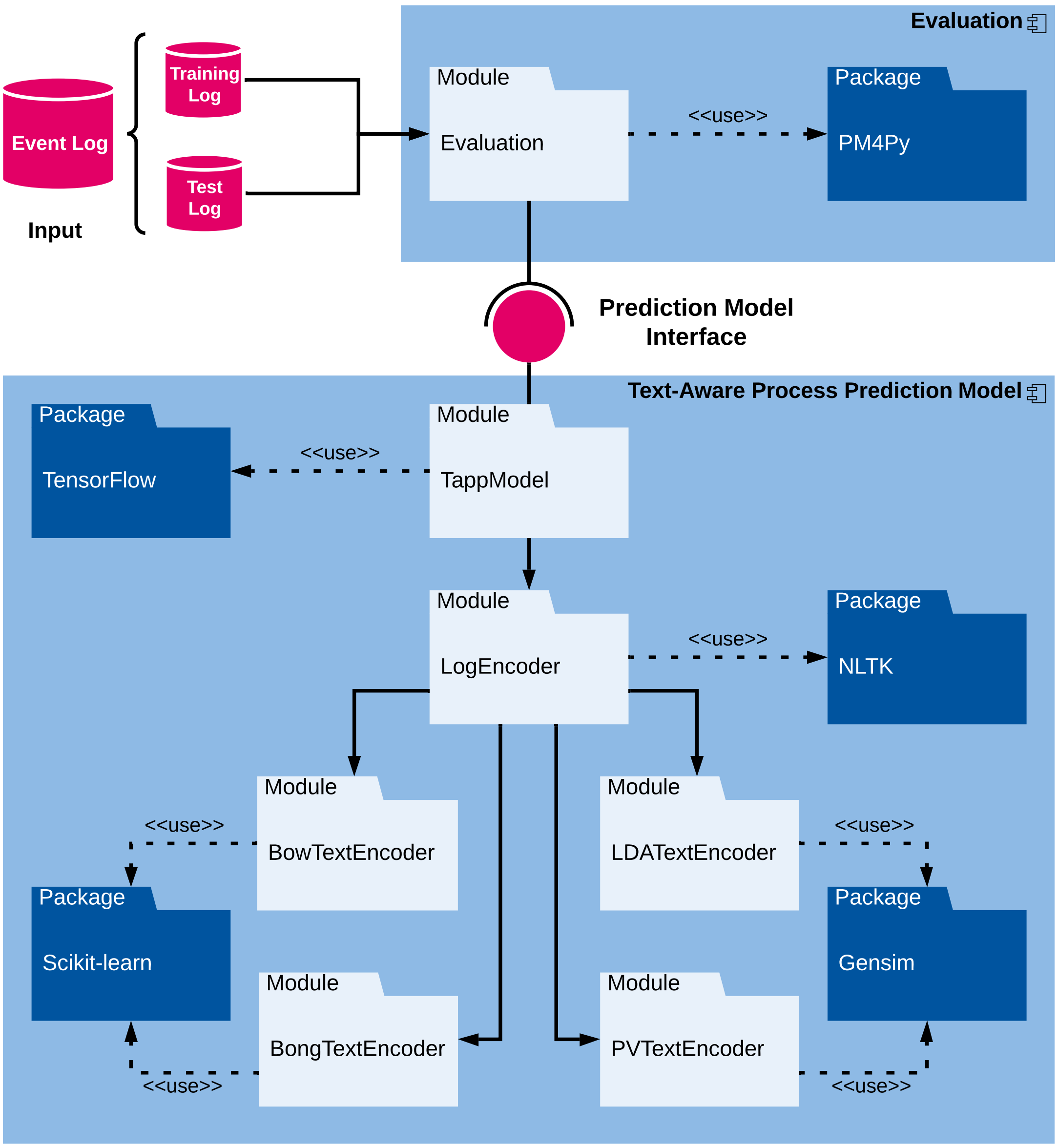


Figure 5.1: Component diagram of the implementation.

Chapter 6

Evaluation

In this chapter, the performance of the text-aware process prediction model is evaluated based on simulated and real-world event data. First, the evaluation method and the data sets are described. Then, the performance of differently parameterized text-aware prediction models on the data sets is analyzed in-depth and compared to two current state-of-the-art process prediction methods.

6.1 Evaluation Method

The text-aware process prediction model is evaluated on three event event logs based on four prediction tasks, namely next activity, next timestamp, case cycle time and outcome prediction. The text-aware model is compared to two other process prediction methods. First, the pure LSTM approach based on the ideas of Tax et al. [37] and Navarin et al. [38] is considered, that only uses the activity, timestamp and additional non-textual attributes of each event. This approach can be considered as the current state-of-the-art in process prediction, if the prediction performance is the only criteria. The second baseline is the process model-based prediction method originally presented by van der Aalst et al. [31]. This approach constructs an annotated transition system for a log using a sequence, bag or set abstraction. Each state of the transition system is annotated with measurements of historical traces, that can be used to predict target values for unseen traces. While the original work focuses regression tasks, Tax et al. [42] describe how an annotated transition system can also be used for classification tasks like the next activity prediction. For the construction of the state space the eight most recent events of a trace are considered. Experiments with different horizon lengths mostly led to worse result, so that these are not reported.

Each prediction model is evaluated in the same consistent procedure. In the first step, the event log is separated into a training and test log. The training log consists of the first 2/3 chronologically ordered traces and is used to fit the prediction model to the historical event data. The remaining 1/3 of traces are used to measure the prediction performance. For each trace σ in the training and test log all prefixes $hd^k(\sigma)$ of length $1 \leq k \leq |\sigma|$ are considered as instances.

For classification (i.e. categorical prediction) task, like next event and outcome prediction, the accuracy is utilized as metric. The accuracy is computed as the number of correct predictions t divided by the total number of predictions n, i.e.

$$\text{accuracy} = \frac{t}{n} = \frac{\#\text{ correct predictions}}{\#\text{ total predictions}} \in [0,1].$$

For regression tasks, like the next event time and the case cycle time prediction, the mean absolute error (MAE) is computed to measure the prediction performance. The mean absolute error indicates the average absolute difference between the predicted value $\hat{y}$ and the true value y, precisely

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \in [0,\infty).$$

This error metric is favored, since it gives a more intuitive interpretation and is less sensitive to outliers compared to similar metrics like the mean squared error (MSE). An accuracy of 1 and a MAE of 0 is the most desirable.

The text-aware process prediction model is evaluated with all presented text models namely the Bag of Words, Bag of N-Gram, Paragraph Vector and Latent Dirichlet Allocation. Each model is tested with three different encoding lengths for textual data. The BoW and BoNG models are evaluated with 50, 100 and 500 dimensional text vectors. The PV and LDA models are tested with smaller text encodings of size 10, 20 and 100, since they generate distributed representations. For the BoW and BoNG model the encoding length is adjusted by only considering the most frequent terms in the vocabulary after preprocessing. The encoding dimension of the non-textual data depends on the considered attributes and their number of the distinct values in the event logs. The Bag of N-Gram model is used with bigrams ($N = 2$) and the Paragraph Vector model is trained for 15 epochs to learn the text representations.

The LSTM network uses 100 hidden neurons per layer. Experiments with less (75) and more (125) neurons led to slightly worse results, so that these are not reported. The network is trained with at most 25 epochs and the learning rate is initialized with 0.001. During the training of the LSTM model, 20% of the training log is used for validation. If the error on the validation log is not decreasing for two epochs in a row, the training rate is reduced by a factor of 10. In addition, if the error is not decreasing for three epochs in a row, the training is stopped in order to avoid overfitting. Furthermore, the LSTM layers use dropout of 20% during training as an additional measure against overfitting. Dropout is a regularization technique by which a random subset of nodes is ignored at every training iteration in order to perform model averaging [58].

6.2 Data Sets

The process prediction models are evaluated on one simulated and two real-world event logs. The three event logs describe a job application, customer journey and hospital admission process. Each event log contains events with textual data and is described in the following. An overview of the key properties of the logs is summarized in Table 6.1.

Job Application (simulated log) This event log describes a simple job application process. First, the applicant starts an application in the company's system. Then, the candidate uploads a curriculum vitae (CV) and optionally a cover letter in a random order.

Event Log	Job Application	Customer Journey	Hospital Admission
Log type	Simulated	Real-world	Real-word
Cases	20 000	15 001	46 520
Trace variants	41	1 001	2 784
Events	118 811	55 220	117 952
Events per case (mean)	5.941	3.681	2.536
Median case duration (days)	1.9876	0.224	7.579
Mean case duration (days)	3.1524	0.713	121.154
Activities	11	18	26
Words before preprocessing	3 050 594	247 010	171 938
Words after preprocessing	1 519 199	98 915	165 285
Vocabulary before preprocessing	237	1 203	4 973
Vocabulary after preprocessing	185	817	4 633
Text attribute	Email	Customer question	Diagnosis
Additional non-textual attributes	-	Gender	Admission type
		Age	Insurance

Table 6.1: Overview of evaluated event logs with their key properties.

When the documents have been received, the applicant is either directly rejected by the company or invited to an interview. In case of an invitation the applicant responds with an acceptance or rejection email. After the interview a decision is made and sent to the applicant that states, if the applicant gets a job offer or is rejected. In case of a job offer, the applicant answers again with an acceptance or rejection email. In total the process contains up to 5 text documents (CV, cover letter, accept/reject interview email by the candidate, job offer/reject email by the company and accept/reject job offer email by the candidate).

The timestamp of each event is determined by sampling from a normal distribution, which mean and variance is unique per activity. The CV, cover letter and all emails are available as a text attribute in the event log. The text information is generated by sampling 10 times from sets of full and partial sentences depending on the control flow of the process instance. For example, if an applicant gets a job offer, the generated email contains text fragments from typical job offer emails. If on the other hand the applicant is rejected, the email is generated with sentences from typical rejection emails. With this text generation mechanism, all texts in the event log are unique, but the words and sentences in the texts correlate with the path of the corresponding case. Furthermore, noise is added by introducing a 1% probability after each event that the process stops immediately and is not finished properly.

Customer Journey (real-world log) This event log describes customer's journeys of the Employee Insurance Agency commissioned by the Dutch Ministry of Social Affairs and Employment. The log is aggregated from two anonymized data sets, that were provided in the BPI Challenge 2016 [59], containing click data of customers logged in the official website werk.nl and phone call data from their call center. Both data sets are joined based on the customer ID to derived a detailed view on customer contacts in the web and on the phone. For each phone call the costumer's question is available as a text attribute in English. Click events on the website do not contain any textual data. In addition, the customer's age group and gender are considered as additional attributes. The event log is filtered to remove outlier activities (threshold <0.5%) and infrequent trace variants (2 or less traces with the same variant).

Hospital Admission (real-world log) This log is generated from the MIMIC-III (Medical Information Mart for Intensive Care) database [60] and contains hospital admission and discharge events of patients in the Beth Israel Deaconess Medical Center between 2001 and 2012. Next to the admission and discharge locations that define the activity, the admission type (e.g. emergency) and insurance (e.g. private) of the patient are considered as additional attributes. Furthermore, each admission event contains a short diagnosis as a text attribute. A case contains all the admission and discharge events of a single patient. Admission and discharge events occur alternating such that every admission event is followed by a discharge event.

All three logs represent different levels of process complexity and variability. The job application log is the most structured log containing 11 different activities, 41 trace variants and a vocabulary of 185 unique words after preprocessing. Therefore, this log can be considered as quite simple and is subsequently easier to predict. In contrast, the customer journey log has 18 different activities, 1 001 trace variants and 817 unique words. The hospital admission log is the most complex with 26 activities, 2 784 trace variants and 4 633 unique words.

6.3 Next Activity and Timestamp Prediction

First, the prediction performance regarding the activity and timestamp of the next event is evaluated for all prefix traces in the test log. The results are summarized in Table 6.2. Each line in the table states the prediction accuracy for the next activity and the mean absolute error in days for the next timestamp prediction of a single model on each evaluated event log.

Compared to the baseline approaches, the text-aware model is able to improve the prediction performance for the next activity and timestamp on all data sets with at least one parameterization, except for the next timestamp prediction on the hospital admission log. Markedly, the impact of the consideration of textual data varies a lot between the data sets and the prediction tasks. A reason for that is, that the textual data in the simulated log clearly correlates with the control flow by design, where in the real-world event logs the correlation is only assumed and probably significantly lower.

On the job application log the accuracy of the next activity prediction is increased by up to 12.47 percentage points using the BoW model compared to the LSTM baseline. The next timestamp prediction is improved by up to 0.1462 days (around 3.5 hours) with the BoNG encoding. The other encoding models perform similarly with the exception of the PV and LDA model in combination with short 10 dimensional text encodings. Since this log contains rather longer text documents, the short encodings seem to be not able to represent the textual data sufficiently. The process model baseline approaches using the annotated transition system performs very similar to the LSTM baseline approach. The trace abstraction method has a rather small impact on the prediction quality.

		Job Application		**Customer Journey**		**Hospital Admission**	
Text Model	Text Dimension	Activity Accuracy	Time MAE	Activity Accuracy	Time MAE	Activity Accuracy	Time MAE
Text-Aware Process Prediction (LSTM + Text Model)							
BoW	50	0.8892	0.1043	0.4896	0.1787	0.5982	27.9673
BoW	100	**0.8894**	0.1046	**0.4906**	**0.1767**	0.6045	27.8268
BoW	500	0.8890	0.1067	0.4842	0.1796	**0.6134**	30.7915
BoNG	50	0.8734	0.1315	0.4889	**0.1767**	0.5916	27.6287
BoNG	100	0.8870	0.1087	0.4875	0.1783	0.6010	27.9706
BoNG	500	0.8888	**0.1040**	0.4867	0.1829	0.6020	28.3840
PV	10	0.8316	0.1749	0.4802	0.1789	0.5877	28.9150
PV	20	0.8760	0.1180	0.4825	0.1781	0.5889	27.6080
PV	100	0.8869	0.1194	0.4825	0.1777	0.5896	27.4488
LDA	10	0.8754	0.1370	0.4833	0.1783	0.5859	27.7591
LDA	20	0.8892	0.1045	0.4886	0.1780	0.5920	27.9961
LDA	100	0.8892	0.1045	0.4878	0.1772	0.6027	28.0485
LSTM Model Prediction Baseline							
LSTM [37]+[38]		0.7647	0.2502	0.4740	0.1779	0.5870	**27.3528**
Process Model Prediction Baseline (Annotated Transition System)							
Sequence [31]+[42]		0.7644	0.2553	0.4733	0.2387	0.5480	64.0161
Bag [31]+[42]		0.7630	0.2553	0.4617	0.2389	0.5477	64.6567
Set [31]+[42]		0.7556	0.2553	0.4596	0.2389	0.5254	63.2042

Table 6.2: Experimental results for the next activity and timestamp prediction.

In contrast, on the customer journey log the next activity prediction is improved by at most 1.66 percentage points using the BoW model. The impact of the text-awareness on next timestamp prediction is negligible on this log. The prediction is improved by 0.0012 days (1.73 minutes) using the BoW model, but is also worse for some text models and text encoding sizes. Again, the BoW model with 100 dimensional text vectors performs the best compared to the other text models and the baselines. The transition system generates slightly worse next activity predictions, but has a significant higher error on the next timestamp prediction. The transition system created using a sequence abstraction has a small advantage compared to the bag and set abstracted transition system.

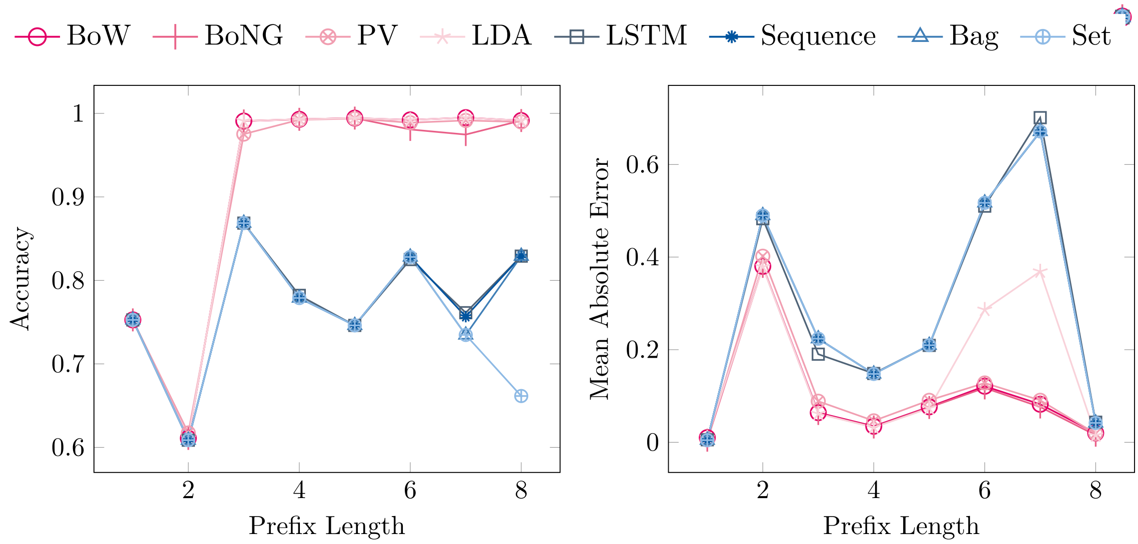
On the hospital admission log the prediction accuracy is improved by up to 2.64 percentage points using the BoW model and a 500 dimensional text encoding compared to the LSTM baseline. It can be observed that on this log the high dimensional encodings tend to perform better. This probably comes down to the fact that the hospital log has the biggest vocabulary by far with 4 633 unique words and therefore larger text encodings are required for the BoW and BoNG model. Regarding the next timestamp prediction, no text-aware approach is able to surpass the LSTM baseline approach on this log. This is surprising, since the improvements on the next activity prediction can not be translated to improvements on the timestamp prediction.

The choice of text model has a rather small impact on the results on all event logs. Notably, the BoW and LDA model perform most consistently on all data sets and all text encoding lengths. The PV model reaches similar results using a hundred dimensional text vector, but performs worse when a small text embedding size of 10 or 20 is used. The BoNG model has a similar performance compared to the BoW model. Surprisingly, the word order awareness of the BoNG model does not lead to better prediction results in general.

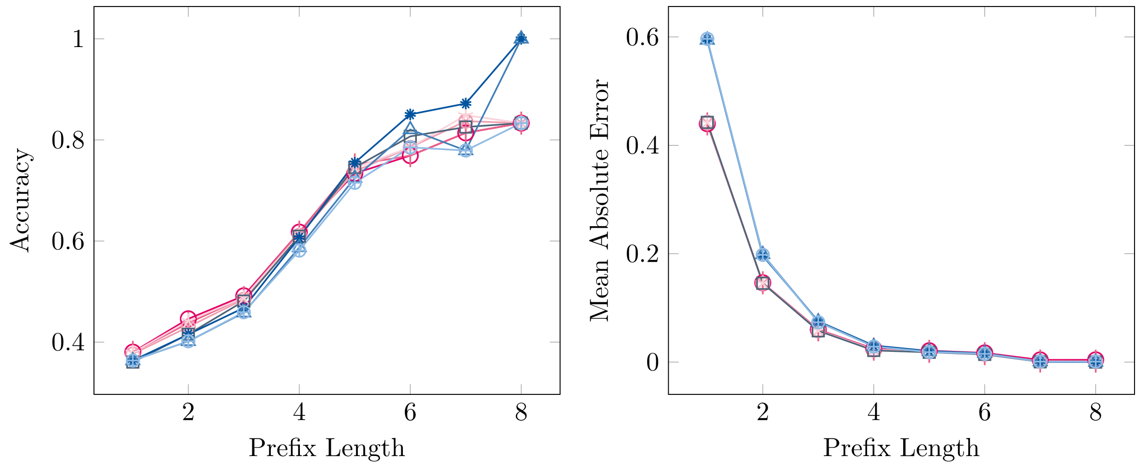
In addition, the prediction performance is reported per prefix length for each event log. Please note that the results on shorter traces is supported by a much larger set of traces due to prefix generation during the construction of the training data. Figure 6.1 shows the next activity prediction accuracy and next timestamp MAE for every prefix trace of length $1 \leq k \leq 8$. For the text-aware models only the best text encoding length is shown in the diagram.

On the job application event log all text-aware process models almost perfectly predict the next activity after three events (i.e. after the application documents are available). The baseline approaches can not take advantage of the emails and reaches a prediction accuracy of around 80% after the first three events. This shows that all text-aware approaches can unequivocally take advantage of the textual data at every decision point in the process, despite the fact that all documents in the log are unique. The improvements on the activity prediction lead consequently to significantly better timestamp predictions on this log.

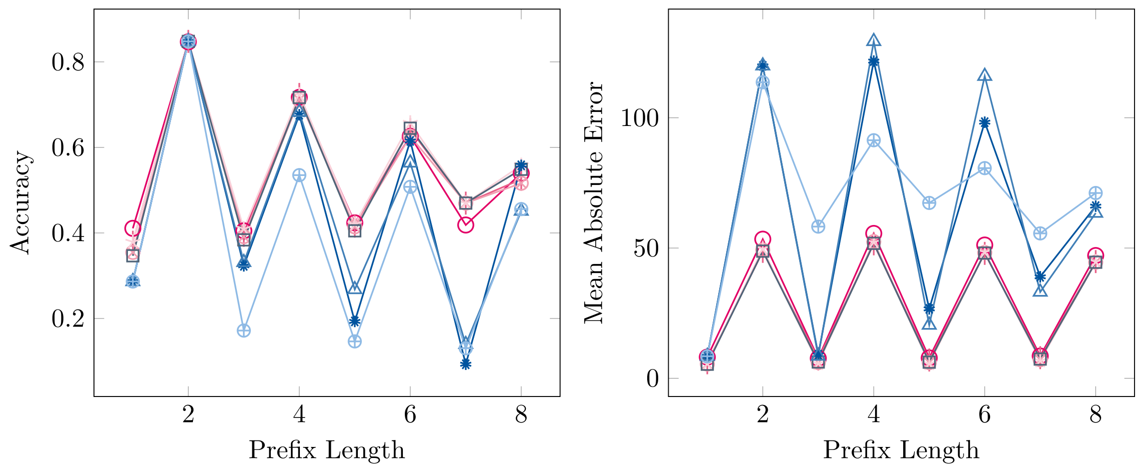
On the customer journey log the prediction performance of all models correlate positively with the available prefix length of the trace. The next activity prediction is improved from under 40%, when only the first event is available, to over 80% after eight events. All text-aware prediction models surpass the baseline approaches on very short prefix traces of length 3 or shorter. In order to generalize from the textual data usually more training data is necessary. Since there is always more short prefixes available in the



(a) Next activity accuracy and timestamp MAE on the job application event log.



(b) Next activity accuracy and timestamp MAE on the customer journey event log.



(c) Next activity accuracy and timestamp MAE on the hospital admission event log.

Figure 6.1: Next activity and timestamp prediction performance depending on the prefix length.

training set, the text-aware models benefit disproportionately on shorter traces. The transition system created using a set abstraction outperforms the LSTM approaches on longer prefixes. The MAE on the next timestamp prediction rapidly drops when more events are available. The LSTM approaches have a slight advantage again on shorter prefixes. However, no difference between text-aware models and the LSTM baseline is recognizable on this prediction task.

The hospital admission log is characterized by the alternation of admission and discharge events. The text-aware prediction models generate slightly better predictions on admission events, since only these contain the diagnosis, which can be utilized by the text-aware models. The prediction performance on admission events is slightly increased with longer prefixes, while the accuracy on discharge events decreases. Regarding the next timestamp prediction, higher errors after discharge events and very low errors after admission events are observed. This can be explained by the rather short hospital stays compared to longer time periods between two hospitalizations. The annotated transition system clearly falls behind on both prediction task on this log. A possible reason for this is, that the huge amount of trace variants on this log is disadvantageous for prediction models with a discrete set of states.

6.4 Outcome and Case Cycle Time Prediction

The case outcome and cycle time prediction is evaluated analogously to the next activity and timestamp prediction. In contrast to the next event prediction, the target values are case properties, i.e. they are the same for every prefix trace of a case. As outcome the final activity of the trace is predicted as described in Section 4.1. The MAE of the case cycle time prediction is measured in days. The results of all evaluated prediction models are summarized in Table 6.3.

On the job application log the text-aware prediction model can predict the outcome of the case with up to 67.62% accuracy using the BoW text model compared to 58.36% accuracy on the LSTM baseline approach. Other text models perform similar to the BoW model except the PV model with 10 dimensional text vectors with only 62.53% accuracy. The MAE on the case cycle time prediction can be reduced to 1.4132 with the LDA model compared to 1.7144 on the LSTM baseline approach. The annotated transition system can predict the outcome with up to 58.43% accuracy and the cycle time with 1.8066 using the bag abstraction.

On the customer journey log the text-awareness leads to much smaller improvements as it has been observed for the next event prediction. The best outcome prediction is realized with the LDA text model (51.65% accuracy), which improves the LSTM baseline prediction by 0.83 percentage points. The case cycle time MAE using the BoNG model is 0.2995 days, which improves the LSTM baseline prediction by 0.0163 days (= 23.47 minutes). Strikingly, some text-aware models have slightly worse predictions like the BoW and BoNG models with 500 dimensional text encodings on the outcome prediction tasks. A possible reasons for that is that with a vocabulary size of 817 after preprocessing also infrequent words are encoded, which provide a rather low prediction value. The best cycle time prediction on this log is realized by the annotated transition system using a set abstraction with MAE of 0.2796.

		Job Application		Customer Journey		Hospital Admission	
Text Model	Text Dimension	Outcome Accuracy	Cycle MAE	Outcome Accuracy	Cycle MAE	Outcome Accuracy	Cycle MAE
Text-Aware Process Prediction (LSTM + Text Model)							
BoW	50	**0.6762**	1.4150	0.5095	0.3144	0.6136	94.8308
BoW	100	0.6687	1.4203	0.5011	0.3136	0.6190	97.2484
BoW	500	0.6757	1.4146	0.4984	0.3090	**0.6198**	100.8792
BoNG	50	0.6632	1.4495	0.5115	0.2995	0.6149	95.8228
BoNG	100	0.6746	1.4237	0.5040	0.3105	0.6151	91.5891
BoNG	500	0.6694	1.4235	0.4968	0.3068	0.6081	96.1264
PV	10	0.6253	1.5803	0.5123	0.3173	0.6050	92.6440
PV	20	0.6644	1.4951	0.5106	0.3141	0.6057	92.7924
PV	100	0.6678	1.4577	0.5083	0.3167	0.6103	93.0984
LDA	10	0.6684	1.4541	0.5099	0.3225	0.6065	92.6729
LDA	20	0.6750	**1.4132**	**0.5165**	0.3129	0.6057	101.0274
LDA	100	0.6744	1.4183	0.5114	0.3091	0.6125	**91.1070**
LSTM Model Prediction Baseline							
LSTM [37]+[38]		0.5836	1.7144	0.5083	0.3158	0.6043	91.6329
Process Model Prediction Baseline (Annotated Transition System)							
Sequence [31]+[42]		0.5838	1.8067	0.5119	0.2799	0.5533	171.5684
Bag [31]+[42]		0.5843	1.8066	0.4943	0.2797	0.5509	173.7963
Set [31]+[42]		0.5843	1.8069	0.4921	**0.2796**	0.5641	171.4487

Table 6.3: Experimental results for the outcome and cycle time prediction.

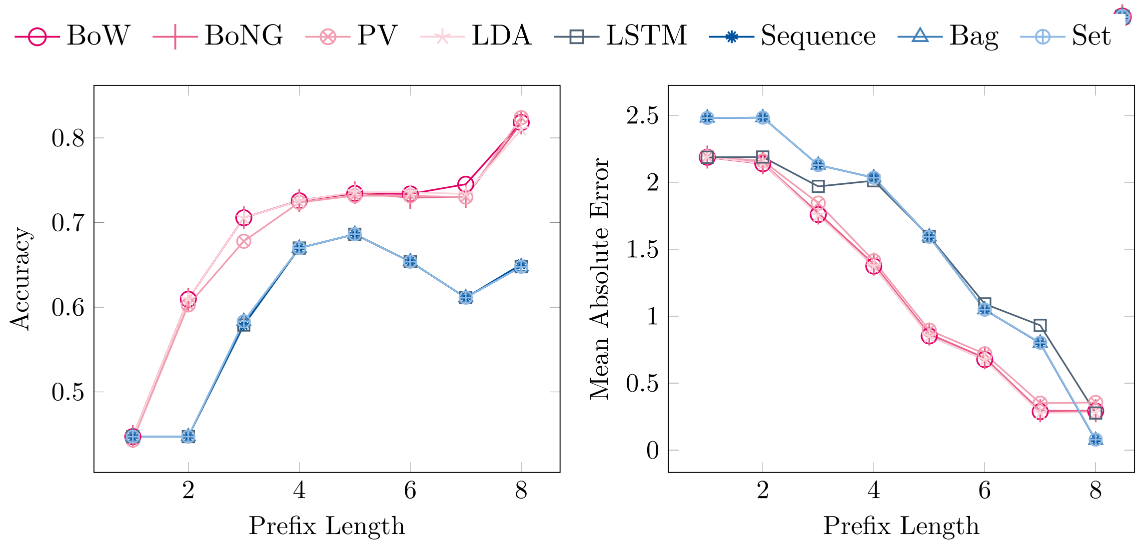
On the hospital admission log the text-aware approach delivers improvements on the outcome prediction task by up to 1.55 percentage points using the BoW model. However, the cycle time prediction is worse for almost all text-aware models except the LDA and BoNG model with 100 dimensional text encodings. As observed during the next timestamp prediction, the text-aware models have difficulties to improve on time-related regression task on this particular log. The transition system predicts the outcome with only 56.41% accuracy and has a huge error on the cycle time prediction of 171.4487 days using the set abstraction.

Again, the choice of text model has a rather small impact. The BoW and LDA models perform slightly better than the BoNG and PV model. Notably, the PV model can not achieve the best performance on any log and prediction task. Compared to the next activity and timestamp prediction, the improvement through the text-awareness is smaller on the case-based prediction tasks.

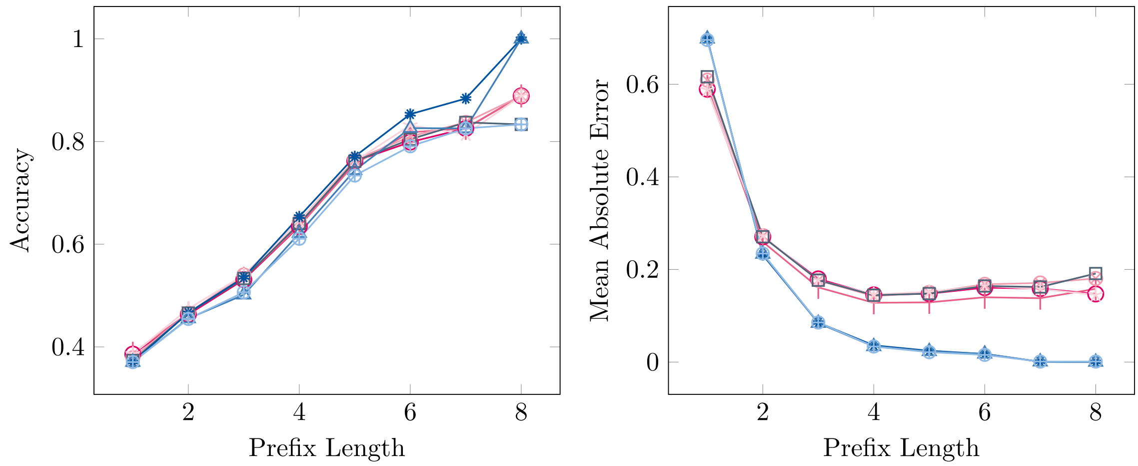
In addition, the prediction results are computed depending on the prefix length of the traces. Figure 6.2 depicts the outcome accuracy and cycle time MAE per prefix on every event log and approach. On the job application log the accuracy is improved with longer prefixes from under 50% after the first event to over 80% after eight events using any text-aware prediction model. The accuracy of the baseline approaches peaks after five events, but always stays below 70%. The biggest quality improvements of the outcome prediction can be realized within the first three events. The MAE on the cycle time prediction is reduced with every event on all models consistently by around 0.4 days per event. Nevertheless, the text-aware models are able make similar good predictions two events before the baseline models. This shows that the text-aware approach can improve the earliness of the prediction.

Also on the customer journey log an explicit positive correlation between the prefix length and the prediction performance is observed. After the first event the outcome is predicted with under 40% accuracy, but the prediction is improved noticeably with every additional event. After eight events the accuracy of the text-aware models is around 90%, while the LSTM baseline approach predicts the outcome with 82% accuracy. The sequence-abstracted annotated transition system outperforms the LSTM approaches after six events. The other two abstractions perform slightly worse on all prefix lengths. The cycle time prediction is improved in particular within the first three events for all models. The text-aware approach using a BoW or BoNG model slightly outperforms the LSTM baseline for all prefixes. After four events the prediction gets slightly worse on all LSTM approaches. The transition systems can improve the prediction with every new event. They outperform all LSTM approaches except for prefixes of a single event.

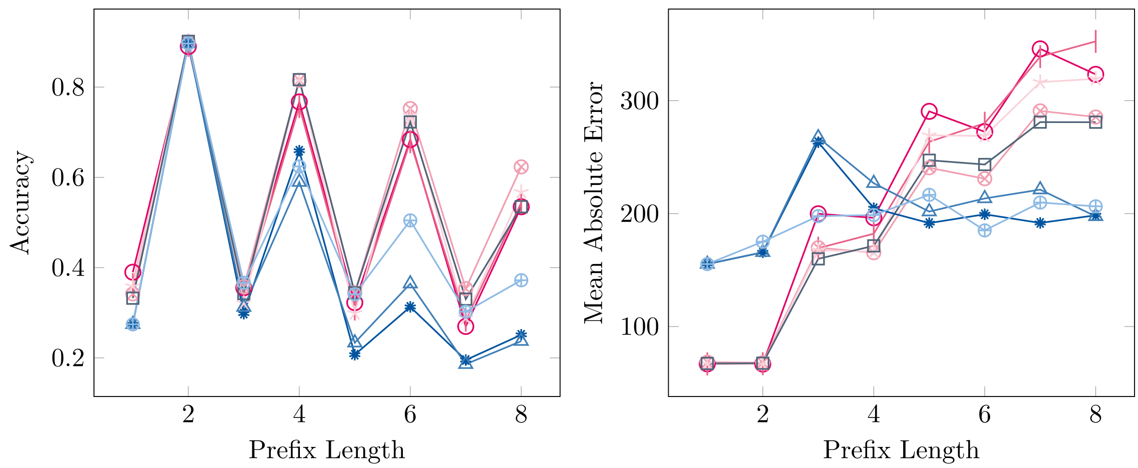
The outcome accuracy on the hospital log varies a lot between the admission and discharge events. The LSTM approaches outperform the transition system especially on longer prefixes. The text-aware models capitalize again on shorter traces and perform similar to the LSTM baseline on longer ones. Differently compared to the other logs, the cycle time prediction is getting worse for longer prefixes and the baseline approach predicts better then most text-aware models. Since the hospital log contains significantly more shorter traces, the prediction performance on longer traces is more imprecise. The transition systems generate stable errors on all prefixes, i.e. they underperform on short traces and outperform on longer ones.



(a) Case outcome accuracy and case cycle time MAE on the job application event log.



(b) Case outcome accuracy and case cycle time MAE on the customer journey event log.



(c) Case outcome accuracy and case cycle time MAE on the hospital admission event log.

Figure 6.2: Case outcome and cycle time prediction performance depending on the prefix length.

6.5 Key Findings and Discussion

The text-aware process prediction model outperforms the baseline approaches on most evaluated event logs and prediction tasks. The influence of textual data on the prediction performance varies greatly per event log. It is observed that the impact of the text consideration on the classification tasks is significantly higher compared to the time regression tasks. All evaluated text models are suitable to capture textual data and deliver similar results on most prediction tasks. Nevertheless, the BoW and LDA text models perform slightly better then the BoNG and PV models on most parameterizations and event logs. The optimal encoding dimension of textual data varies depending on the data set. A bigger vocabulary of words usually requires longer text encodings.

On the hospital admission event log it can be observed, that the cycle time prediction is noticeably worse, if textual data is considered. This shows that text-aware process prediction does not necessarily guarantee predication improvements. On the real-world event logs the text-aware models could capitalize mostly on short trace prefixes. Since more training data with short prefix traces is available, it is easier for the text-aware model to generalize shorter prefixes. Considering the number of events that are available for a prediction, two effects can be observed. First, the prediction performance is usually improved when more events of the case are available. In particular, after the first few events the predictions are mostly improved a lot. However, for longer traces the prediction performance decreases slightly, since there is less knowledge (i.e. training data) for longer traces available. It can be observed that the annotated transition system can deal better with the missing training data for longer traces at the costs of worse predictions on shorter traces.

The realization of a text-aware process prediction approach using LSTM and text models has advantages and disadvantages. The prediction model belongs to the most flexible process prediction methods in term of input data that can be utilized for the prediction. This is a major advantage for processes, where the control flow is driven by additional textual and non-textual data and not only the control-flow. Furthermore, the consideration of textual data improves the prediction compared to the current state-of-the-art approach, if the textual data sufficiently correlates with the prediction targets. Therefore, using this model can lead to a prediction quality on event logs with textual data that could not be realized before.

Nonetheless, the text-aware process prediction model is a black-box model, which does not give insights about how the input data relates to the final prediction. In addition, the hyper parameter space is large, since the LSTM *and* the text model have to be configured, and the training of the LSTM network is resource-heavy. Using an annotated transition system can be favorable, when less training data is available, computing resources are very limited or a black-box model is inadequate. However, textual data can not be utilized in this case and the prediction performance is noticeably worse on unstructured processes.

Chapter 7

Conclusion

The prediction of the future course of business processes is a major challenge in business process mining and process monitoring. When textual artifacts of natural language like emails or documents hold process-critical information, purely control flow-oriented approaches are unable to deliver well-founded predictions. In order to overcome these limitations, in this thesis a text-aware process prediction model is proposed. The model encodes process traces to sequences of meaningful event vectors using the control-flow, timestamp, textual and non-textural data attributes of the events. The encoding of textual data is realized by an interchangeable text model. Given an encoded prefix log of historical process executions, an LSTM neural network model is trained, that predicts the activity and timestamp of the next event, the case outcome and case cycle time of a running process instance.

The concept of a text-aware process prediction model has been implemented with current open source technology and evaluated on simulated and real-world event data. It is shown that the utilization of textual data can improve the prediction performance and the model is able to outperforms state-of-the-art process prediction approaches on many prediction tasks using textual data. The impact of text-awareness varies noticeably across the evaluated data sets and mainly depends on the degree of correlation between the textual data and the process course. The model benefits particularly with short sequences, since more training data is available for short sequences through the generation of prefixes. Each considered text model (Bag of Words, Bag of N-Gram, Paragraph Vector and Latent Dirichlet Allocation) has been proven to be viable, whereby the BoW and LDA models have performed most consistently even with low-dimensional text vector embeddings. The proposed technique is robust to outlier traces in the event log and can generalize from structured and chaotic processes.

7.1 Limitations and Outlook

The text-aware process prediction model is able to take advantage of textual data in predictive business process monitoring and can improve the prediction quality by exploiting correlations in the (textual) data. The generalizability of the evaluation in Chapter 6 is limited due the small amount of evaluated data sets. To further validate the approach, more event logs with textual data need to evaluated. However, the data in common use cases like help desk or hospital processes is maintained under high privacy regulations. Since textual data can not easily be anonymized for evaluation and is highly sensitive, the data acquisition remains challenging.

In certain contexts, a high and reliable prediction performance is not sufficient as the interpretability of prediction model is necessary. LSTM-based methods are usually unable to deliver insights about the construction of the prediction and the influence of individual feature variables. The frequently observed trade-off between prediction performance and interpretability in machine learning, is also recognizable in process prediction [42]. While in this contribution the prediction performance has been prioritized, interpretable text-aware prediction models could be viable. Nevertheless, the utilization of textual data is an additional barrier and current interpretable methods based on process models can not be naturally extended for this purpose.

Another for the most part unsolved problem is to identify causality in processes with respect to prediction. In order to derive predictions for processes, correlations in the event data are sufficient. But when predictive methods are applied to support decision making, it is important to identify the main forces that really *influence* the future of the process. The ascertainment of causality is a significant harder problem, since it requires a much deeper understanding of the individual process. Therefore, tailor made methods might be necessary that are specific to the field of use. Gained insights could then be utilized to improve process prediction by not only considering event data, but also additional background knowledge about the process.

Finally, the extension with textual data transfers typical challenges of text mining to process prediction. Textual data is heterogeneous and has to be interpreted with the corresponding cultural background in mind. However, it is hard for computers to read between the lines. It could be of interest, how text-ware process prediction would perform in contexts, where the linguistic style is less technical, but rather subtle and personal. In this case, the textual data is influenced by the cultural background and character traits of the persons involved in the process. This raises questions regarding privacy and discrimination, if the data is utilized to predict processes and actions are implemented based on the prediction results. Therefore, it is assumed that additional concepts are required to ensure non-discriminatory and responsible text-aware process prediction.

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