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 can 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.

Keywords: Predictive Process Monitoring, Process Mining, Text Mining, LSTM Neural Networks

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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. These have to be able to extract potential value in the form of insights or predictions.

A remarkable subset of this data is described as *event data*, which are recorded 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 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 gap between the data-driven characteristic of data science and the process-centric view of process science [3]. The ongoing success of process mining in research has been transferred to businesses, which successfully offer or utilize this technology. Celonis, which is often considered as one of the biggest commercial providers of process mining, has been valued at 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, which are not integrated within a company's remaining IT infrastructure. The integrated and continuous application of process mining realized by *business process monitoring systems* is a key success factor for many organizations. These systems allow users to understand and supervise all processes of a company in real-time during their execution. 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, which 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 employees, customers and connected software systems interact with the process-aware information system and are

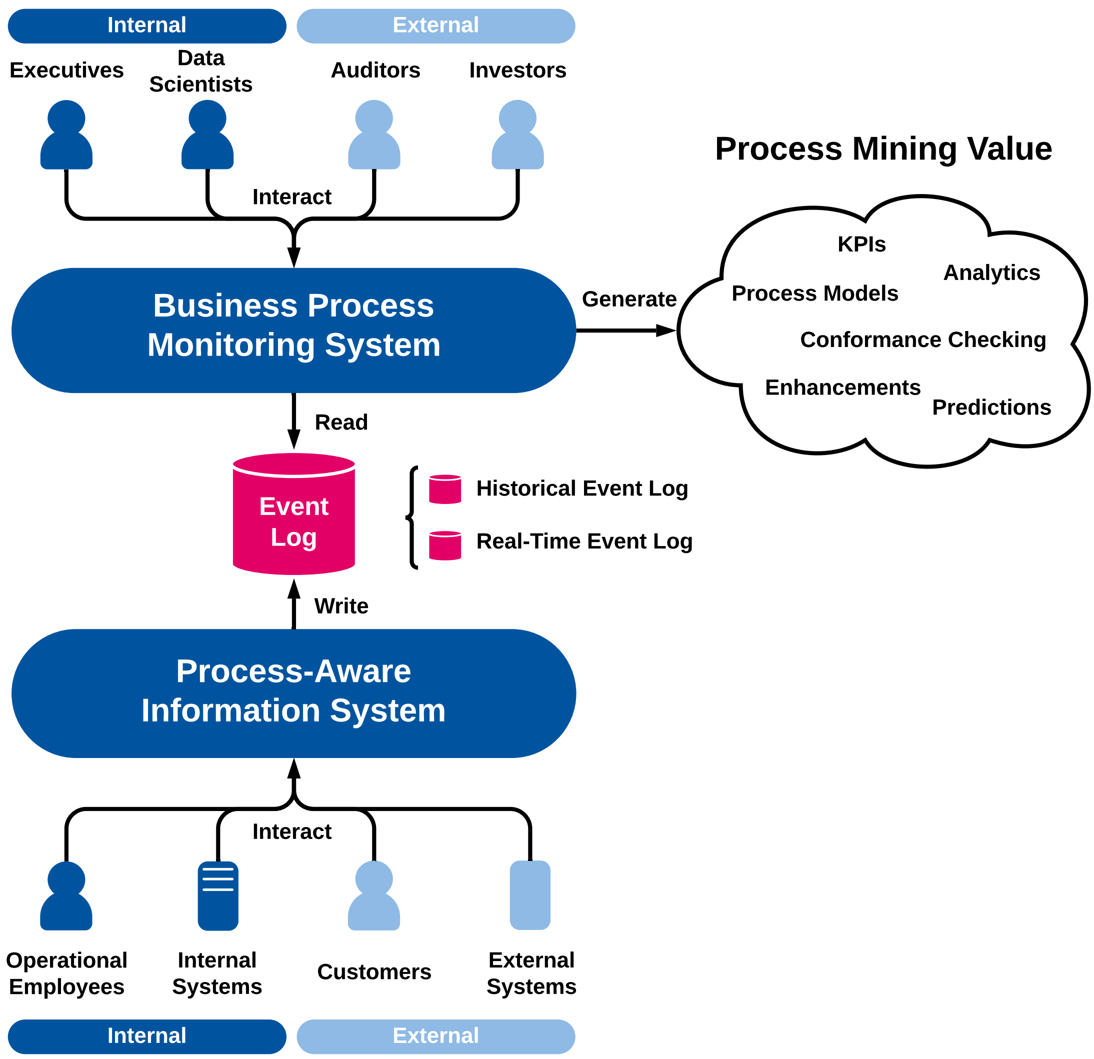


Figure 1.1: Business process monitoring allows to continuously apply process mining in an automated fashion in order to generate value for internal and external process stakeholders. The required event data is generated by a process-aware information system during the execution of the processes.

part of the processes themselves. In contrast, executives, data scientists, auditors, and investors supervise 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 proposed 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*, i.e., the sequence of performed activities, of a process instance ignoring additional data attributes in the event log. Notably, most approaches do not 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 every day, and their content influences processes inside of organizations.

In addition, process-critical information, like a diagnosis 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 exclusively predict the remaining time or cycle time (time between start and end) 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, process 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 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?
- Outcome prediction: What is the outcome of the process instance?
- 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, 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 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 approaches cannot handle textual data, the goal is to investigate if and to what extent textual data can improve the quality of process prediction. Furthermore, the impact

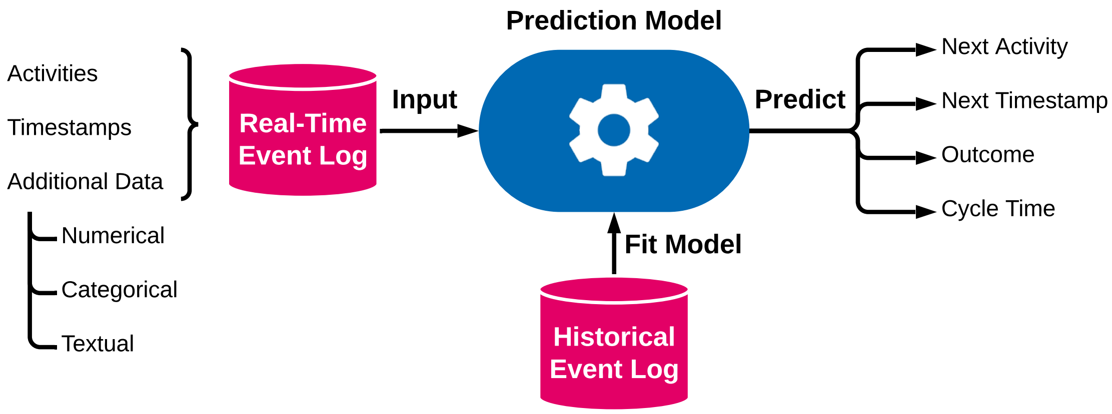


Figure 1.2: A general process prediction framework. Predictive business process monitoring includes a prediction model that is able to predict the future of running process instance using historical event data. Current approaches differ in terms of the considered input data, the underlying prediction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

of different design choices and text models for text-aware process prediction is 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 extent can the utilization of textual data improve the performance of process prediction?
2. How do 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 on simulated and real-word event data.

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. For this, individual properties of the tested data sets are taken into account. In addition, the advantages and limitations of the approach are discussed.

1.5 Thesis Structure

This thesis is divided into seven chapters. In Chapter 2, the basic notations, definitions, and concepts used in this work are introduced. This includes a 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 available methods and their capabilities. Additionally, related contributions to text mining, natural language processing, and supervised learning are discussed. In Chapter 4, a novel text-aware process prediction model as the main conceptional contribution is presented. Moreover, Chapter 5 covers the technology and architecture of the model on a more technical level. In Chapter 6, the performance of the novel 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 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 (Process)**.** A *process* is a collection of activities 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 a 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. A timestamp specifies the time on which an activity for a certain case is performed. The associated case ID, the performed activity, and the timestamp together form an *event*. An event can have any number of additional attributes, for example, 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 of the person executing the activity, the costs of the activity, and a text comment as an example for a categorical, numerical, and textual attribute.

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 discovery aims to generate process models out of event data in order to understand the

Case	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	Test: 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	S. 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.

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, 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

To formalize the concepts described before, a few notations are introduced in the following. 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 2.2 (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^* describes the set of all sequences over A. 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 $1 \le i \le n$. 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 for $0 \le k \le n$.

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, i.e., $a \in \sigma = \langle a_1, a_2, \dots a_n \rangle \iff \exists_{1 \le i \le n}\colon a = a_i$.

2.3 Events, Traces, Event Logs

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

Definition 2.3 (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. The set of possible timestamps $\mathcal{T}$ is required to be totally ordered by some relation $\le$. 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 $1 \le i \le m$ and some fixed language-dependent alphabet Σ.

Definition 2.4 (Trace)**.** A *trace* is a finite sequence of events $\sigma = \langle e_1, e_2, \dots \rangle \in \mathcal{E}^*$ with non-decreasing timestamps, in which all events of the trace share the same case ID, i.e., $\pi_{\mathcal{T}}(e_i) \le \pi_{\mathcal{T}}(e_j)$ for $1 \le i < j \le |\sigma|$ and $\forall e_i, e_j \in \sigma\colon \pi_{\mathcal{C}}(e_i) = \pi_{\mathcal{C}}(e_j)$.

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.* A trace contains all the data that is logged during the execution of single process instance.

Definition 2.5 (Event Log)**.** An *event log* $\mathbb{L} = \{\sigma_1, \sigma_2, \dots, \sigma_l\}$ is a set of traces, where each case ID is unique per trace, precisely $\forall e_i \in \sigma_r \, \forall e_j \in \sigma_s \, \forall \sigma_r, \sigma_s \in \mathbb{L}\colon \pi_{\mathcal{C}}(e_i) = \pi_{\mathcal{C}}(e_j) \iff \sigma_r = \sigma_s$.

2.4 Text Mining and Natural Language Processing

With the consideration of textual data in event logs, the concepts of *text mining* become 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 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.

Besides text mining, *natural language processing* (NLP) is another important research field dealing with textual data. While the concepts of text mining and natural language processing have a lot of overlap, both subfields differ in term of the goals they aim to achieve. The focus of text mining mainly relies in analyzing statistical patterns and extracting new information from textual data. In contrast, natural language processing aims to make computers understand the semantic meaning of natural languages to realize certain applications, like speech recognition or machine translation.

Both subfields share the concept of feature learning aiming to derive mathematical representations of textual data that can be interpreted by learning algorithms. To derive such mathematical representations of textual data, a text model has to be applied using the documents of the whole text corpus. Popular text models for documents are *Bag of Words* [12], *Bag of N-Gram* [13], *Paragraph Vector* (a.k.a. Doc2Vec) [14], and *Latent Dirichlet Allocation* [15], which are discussed in more detail in the Sections 4.4.2 through 4.4.5. Most models do not work with the raw textual data but require a text normalization step, where the text is cleaned from linguistic variation as well as meaningless words and symbols [16].

2.5 Supervised Learning

In *supervised learning*, an unknown function is learned (i.e., approximated) from a set of example input-output pairs [17]. In contrast, in *unsupervised learning*, no target outputs are available, and the goal is to identify pattern in the data [18].

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 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 the training set, the hypothesis is *underfitting*.

In many real-world applications, the true function $f(X)$ is stochastic, i.e., a conditional probability function $P(Y|X)$ (classification problem) or a conditional expectation $E(Y|X)$ (regression problem) needs to be estimated for the prediction. Therefore, the prediction quality is always limited by the randomness of the true distribution. Typical supervised learning methods are linear regression [19], decision trees [20], support vector machines [21], or neural networks, including long short-term memory networks [22].

2.6 Long Short-Term Memory Networks

Long short-term memory (LSTM) is an advanced recurrent neural network architecture for sequential data originally presented by Hochreiter and Schmidhuber in 1997 [22]. This approach addresses the well-known vanishing or exploding gradient problem [23] of traditional recurrent neural networks by introducing more complex LSTM cells as hidden units. The proposed architecture has been improved several times [24] [25] 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 networks combined with large data sets and GPU hardware have been reported for sequence to sequence tasks like text translation [26].

Gated recurrent units (GRU) [27] are the competing gating mechanism by Cho et al. with fewer parameters and performing similar to LSTM networks. However, more recent studies show that LSTM networks outperforms GRU consistently in neural machine translation tasks [28].

A simple feedforward neural network 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 a non-linear activation function [29]. 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 to minimize the loss function [30].

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 LSTM 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 $\boldsymbol{h}_{t-1}$

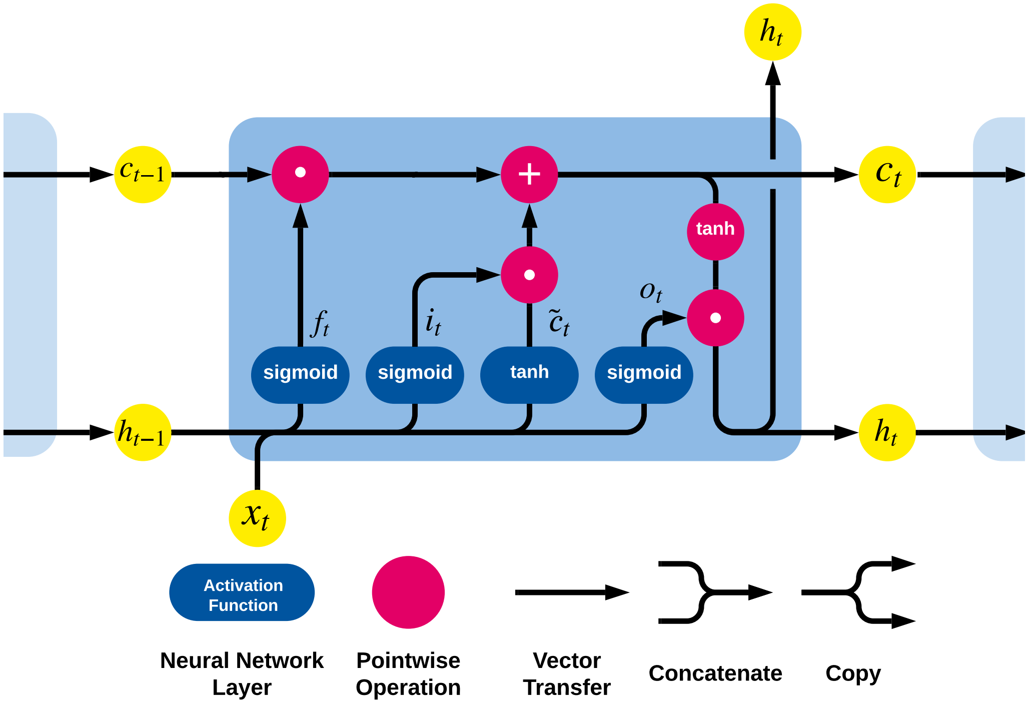


Figure 2.1: LSTM module with four sublayers that manipulate the cell state and compute the module's output. The graphic is adapted from [31].

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 $\mathrm{sigmoid}(x) = \frac{1}{1+\exp(-x)}$ or $\tanh(x) = \frac{\exp(x)-\exp(-x)}{\exp(x)+\exp(-x)}$ activation functions elementwise to vectors, leading to the following equations:

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

$\boldsymbol{W}_f$, $\boldsymbol{W}_i$, $\boldsymbol{W}_c$ 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.

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

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.

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

In the training phase, the networks weights are adjusted to minimize the loss for the input-output pairs provided by the training set. The total number of passes through the training set is called *epochs*. The update rules describing the weight adjustments are defined by the *optimizer* that is used for training. The weights are usually updated in the descent direction of the gradient of the selected loss function.

An important hyperparameter of the optimizer algorithm is the learning rate that controls the step size of the weight updates. Modern optimizer adapt the learning rate during training to speed up convergence and avoid overshooting of minima. To avoid overfitting, a set of regularization techniques have been developed. For example, *dropout* randomly removes a fraction of weight connections during training, which can reduce overfitting [32]. Other techniques, like *early stopping*, implement rules to stop training, if the error on unseen data does not decrease anymore [33].

LSTM networks can backpropagate a more stable error using their 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 very suitable prediction model for processes.

Chapter 3

Related Work

Text-aware process prediction requires to combine methods from several scientific fields. Therefore, in this chapter, scientific contributions to process prediction, text mining, natural language processing, and supervised learning that are related to this thesis are discussed.

3.1 Contributions to Process Prediction

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 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, which generalizes from a historical event log.

Five different non-parametric regression predictors for forecasting the cycle time of an unfinished case have been presented by van Dongen et al. [34]. The estimates are based on activity occurrences, activity duration, and other attributes.

Furthermore, van der Aalst et al. proposed building a transition system using a set, bag, or sequence abstraction, which is annotated with time-related data to predict the cycle time of case [35]. 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 [36].

Rogge-Solti and Weske showed how a stochastic Petri net could be used to predict the cycle time of a process instance [37]. 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 to relate running traces to similar historical traces [38]. A decision tree is then used to predict the next activity and the cycle time of a case.

Contribution	**Year**	**Model(s)**	**Data-Aware**	**Text-Aware**	**Predictions**
Van Dongen et al. [34]	2008	Regression	✓	✗	Cycle time
Van der Aalst et al. [35]	2011	Transition system	✗	✗	Cycle time
Pandey et al. [36]	2011	Hidden Markov	✗	✗	Cycle time
Rogge-Solti and Weske [37]	2013	Stochastic Petri net	✗	✗	Cycle time
Ceci et al. [38]	2014	Sequence tree Decision tree	✓	✗	Next activity Cycle time
Teinemaa et al. [39]	2016	Random forest Logistic regression	✓	✓	Outcome
Evermann et al. [40]	2016	LSTM	✗	✗	Next activity
Tax et al. [41]	2017	LSTM	✗	✗	Next activity Next event time Cycle time Future path
Navarin et al. [42]	2017	LSTM	✓	✗	Cycle time
Polato et al. [43]	2018	Transition system SVR Naive Bayes	✓	✗	Next activity Cycle time Future path
Park and Song [44]	2019	LSTM	✓	✗	Next activity Next event time
This contribution	2020	LSTM	✓	✓	Next activity Next event time Cycle time Outcome

Table 3.1: Comparison of process prediction methods.

Teinemaa et al. applied text vectorization techniques like Bag of N-Gram, Latent Dirichlet Allocation and Paragraph Vectors to textual data of processes in order to predict a binary label describing the process outcome [39]. In this approach, event traces are encoded as vectors. Then, random forest and logistic regression classifiers are trained for each prefix of a trace.

Most recently, several authors have applied recurrent neural networks in the 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 [40].

Tax et al. use a one-hot encoding of the activity and the timestamp of an event to predict the activity and timestamp of the next event [41]. 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 [41] and extends the encoding by also utilizing additional data attributes associated with each event [42] 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 [43]. The authors implement different encodings for events in this contribution including a simple one-hot encoding and a more advanced state-based encoding using transition systems. Furthermore, they enhance the approach in [35] 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 [45].

Park and Song showed how LSTM-based predictions could be used to solve a resource allocation problem, leading to direct recommendations for process improvement [44].

The most extensive benchmark of sequential prediction models has been realized by Tax et al. [46]. The authors show that black-box process prediction methods from the machine learning field outperform process model-oriented techniques on next-element prediction tasks. However, the latter are more efficient and offer higher interpretability at the cost of prediction quality.

A comparison of the process prediction methods is presented in Table 3.1. The table shows the underlying model that is used to generalize from historical event data for each approach. In addition, it states whether the methods use additional textual or non-textual data, and which prediction targets are supported.

3.2 Contributions to Text Mining and Natural Language Processing

The statistical analysis of texts is one of the earliest applications of text mining and dates back to the pre-computer era. In 1887, Mendenhall analyzed the distribution of word lengths to determine the authorship of literary works [47]. Through the comparison of the authors' writing characteristics, controversial authorship can be validated or falsified to a certain extent.

In the 1960s, text mining became relevant alongside with *information retrieval* (IR), a research field that deals with concepts of searchable data bases [48]. The SMART system [49] by Salton and Lesk was an milestone in IR, which introduced an information retrieval system using a vector space model. The vector space model is a widely adopted model that represents text documents and search queries as vectors based on term and document frequencies [50].

With the rise of machine learning methods, word and document embeddings became an important subfield in text mining and natural language processing. Statistical topic models, like Latent Dirichlet Allocation (LDA) [15], have been utilized to represent documents as a mixture over latent topics. The topics are distributions overs words, which can be derived using statistical inference together with the document mixtures.

Furthermore, neural networks have been applied to compute word [51] and document embeddings [14] using supervised learning. A wide range of network architectures have been proposed that learn distributed vector representations by predicting words using their contexts or vice versa. These methods map words or documents to a lower dimensional but continuous vector space. Then, these vectors can be utilized for other machine learning problems.

Most recently, pre-trained *transformer* models, like BERT [52] by Devlin et al., achieve state-of-the-art performance on many natural language processing tasks. These highly parallelizable deep learning models are pre-trained on large text corpora (unsupervised) and then fine-tuned to solve text-related supervised learning problems, like next-sentence prediction or reading comprehension. The underlying concepts of the model that lead to the high performance are not yet completely understood [53].

3.3 Contributions to Supervised Learning

The foundations of supervised learning were laid with *Bayes' theorem* published in 1763 [54]. This theorem was the basis for a wide range of statistical Bayesian methods, like the naive Bayesian classifiers, which can be used to address supervised learning problems. The naive Bayesian methods assume independence of the feature variables to efficiently classify instances based on conditional probabilities [55].

Another early application of supervised learning is the *least square regression* method. It can be used to fit the parameters of a function to a data set of points by minimizing the sum of squared residuals. The method was originally published by Legendre in 1805 [56]. However, there are several indications that Gauß used least square regression ten years before Legendre [57].

In 1957, the *perceptron* algorithm was invented by Rosenblatt [58]. The perceptron is binary classifier that can learn linearly separable patterns. As a single-layer feedforward neural network, the perceptron is not able to learn functions that are not linearly separable, like the XOR function [59]. However, with the introduction of multi-layer neural networks, this limitation could be overcome. Using the backprogatation algorithm, multi-layer neural networks can approximate any continuous functions within a compact set [60].

Alongside neural networks, decision trees [20] and support vector machines [21] became popular. Decision trees are used to classify instances in the leafs of a tree data structure in dependence of their feature variables. The tree can be computed, inter alia, by iteratively splitting tree nodes based on the feature variables of their instances, so that the information gain is maximized. Support vector machines are classifiers that separate instances by a hyperplane, so that the margin between the hyperplane and the instances is maximized.

With recurrent neural networks (RNNs), a new class of neural networks was introduced, which is able to process sequences of input data [30]. By that, these networks can learn dynamic behavior. Unlike feedforward neural networks, reccurrent neural networks keep a state across inputs. The LSTM neural network is one of the most popular RNN architectures available, which addresses the vanishing gradient problem of many-layered and recurrent neural networks [22].

Today, a rapidly expanding set of supervised learning methods is available to solve complex tasks in computer vision, natural language processing, and many other fields.

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, much textual information in the context of processes is available, such as 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 [61]. A first approach has been presented by Teinemaa et al., which encodes traces with textual data as single vectors. Then, a random forest classifier is learned for each prefix length [39].

This chapter presents a novel approach for text-aware process prediction 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 capture 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 functions $f_{\mathrm{a}}, f_{\mathrm{t}}, f_{\mathrm{o}}$, and f_{c} that predict the next activity, next timestamp, outcome and cycle time respectively, 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 $f_{\mathrm{a}} \colon \mathcal{E}^+ \to \mathcal{A} \cup \{\blacksquare\}$ returns the activity of the next event or an artificial activity $\blacksquare$ if the given trace is already completed, formally:

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

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

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

The outcome of a case 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 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:

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

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 so that the prediction error is minimized for new, unseen, and incomplete traces. Due to probabilistic behavior of real-world processes, the prediction accuracy is limited by the randomness of the process behavior.

An overview of the framework is shown in Figure 4.1. The proposed framework consists of preprocessing, encoding and prediction model components, 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 components. Given a historical event log $\mathbb{L} = \{\sigma_1, \dots, \sigma_l\}$ 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 distinguishes between categorical and numerical data that can be encoded directly and textual data prepossessed and encoded based on a separate text model. The text model is an exchangeable component and is fitted 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 $f_\mathrm{a}, f_\mathrm{t}$, and f_o corresponds to one training example for an LSTM network that finally realizes the predictions. The cycle time f_c is not predicted directly. Instead, the remaining time is predicted and added to the already elapsed time. The total number of training examples generated from 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, 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

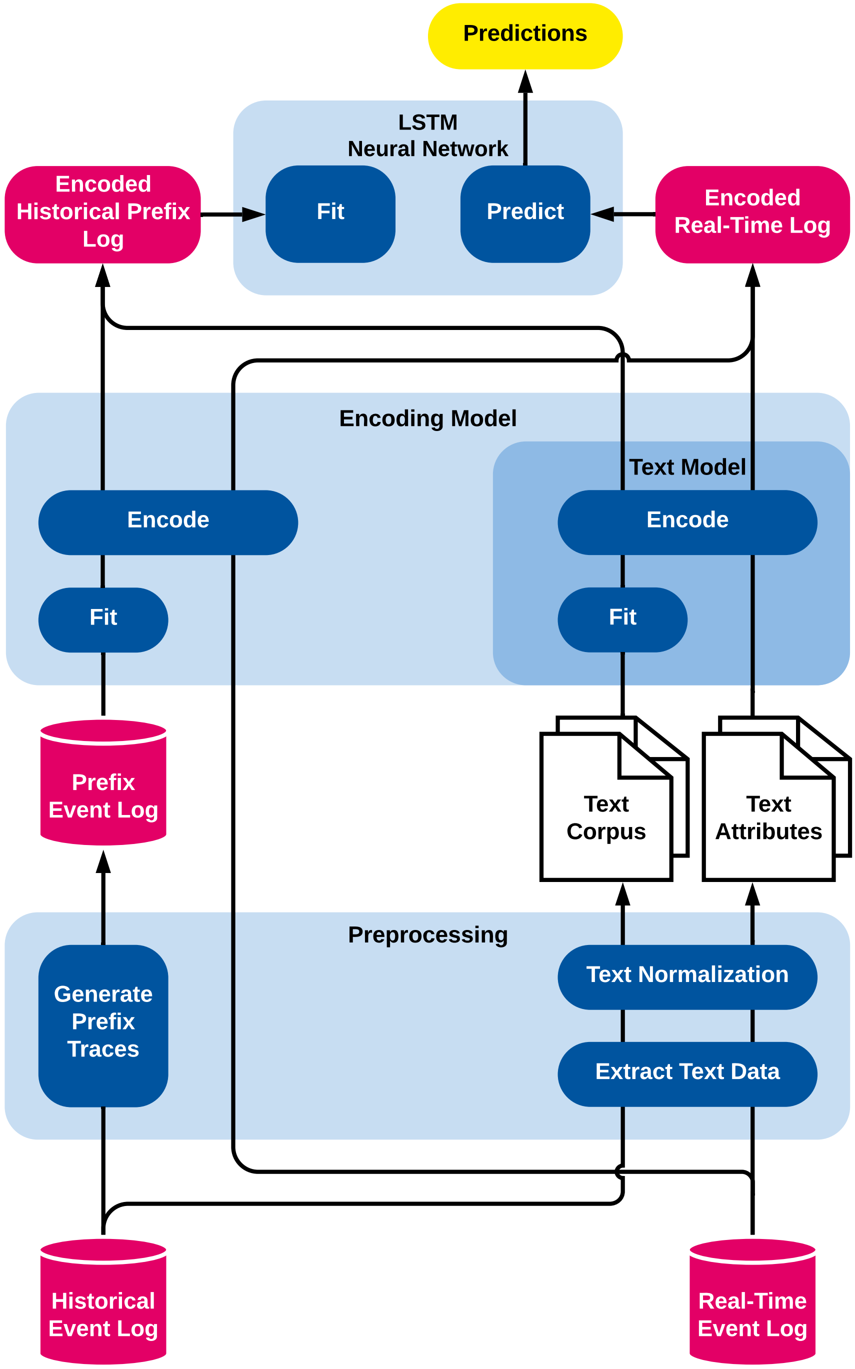


Figure 4.1: Overview of the text-aware process prediction model. Predictions for real-time processes are realized by an LSTM model that is fitted using an encoded representation of all prefixes of the historical event log. The encoding of textual attributes is realized by a text preprocessing pipeline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

Feature Vector	Construction	Dimension	Description
$\boldsymbol{a_i}$	$\mathbb{1}_{\mathcal{A}}(\pi_{\mathcal{A}}(e_i))$	$\lvert\mathcal{A}\rvert$	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
$\boldsymbol{d}_{ij}^{\text{cat}}$	$\mathbb{1}_{\mathcal{D}_j^{\text{cat}}}(\pi_{\mathcal{D}_j^{\text{cat}}}(e_i))$	$\lvert\mathcal{D}_j^{\text{cat}}\rvert$	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.

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. It is assumed that each event has $r \in \mathbb{N}_0$ 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, constructed from the attributes in the event data.

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

An overview of each feature vector that is part of the event encoding is provided in Table 4.1. The activity of the event is represented by a vector $\boldsymbol{a_i}$ using *one-hot encoding* [62]. 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 a one-hot encoding transformation for the set of all activities $\mathcal{A}$. The timestamps of the events are used to compute a six-dimensional vector $\boldsymbol{t_i}$ of time-related features, 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, which 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).

4.3 Capturing Temporal Dependencies

A set of time-based features is computed from the timestamp data in the event log to profit from the time-related pattern in the process. As part of the complete encoding $\boldsymbol{x}_i$ for an event e_i in a prefix trace $\sigma = \langle e_1, \ldots, e_k \rangle$, 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 [63] 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 event's absolute time 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 event's time 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 many more customers in summer, affecting the process execution in many ways. Each feature $t_i^1, \dots, t_i^6$ is min-max normalized so 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 challenge in text mining and natural language processing [64]. 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 attributes is collected in the 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* [16]. 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 in the corpus after preprocessing. It is indexed by a bijective index function $index_V \colon V \to \{1, 2, \dots, |V|\}$. 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 Sections 4.4.2 through 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., split) 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 tokenization 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.

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- and

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.

context-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, representing 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 [50]. 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. 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 the opposite. Second, the vector representations are sparse and of high dimensionality, since they depend on the size of the vocabulary. However, the dimension can be reduced by limiting the vocabulary’s size. For example, words that rarely appear in the corpus can be excluded. 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 latter's missing word order awareness [13]. 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 larger 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 [14]. The idea is inspired by the word embedding model presented by Bengio et al. [65], which can learn distributed fixed-length vector representations for words. In this model, words are mapped to vectors, trained to predict words from their context, i.e., words that appear before or after the target word in the training documents. Several variants of this approach exist, 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*) [51].

The core idea of the Paragraph Vector model is to extend the model introduced in [65] in such a way that an additional document (i.e., paragraph) vector is trained together with the word vectors. The document vector is unique for each document. Fig. 4.2 shows the architecture of the distributed memory variant of the Paragraph Vector model (PV-DM). It is realized by a neural network, which takes one-hot encoded words and a 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 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, so 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.

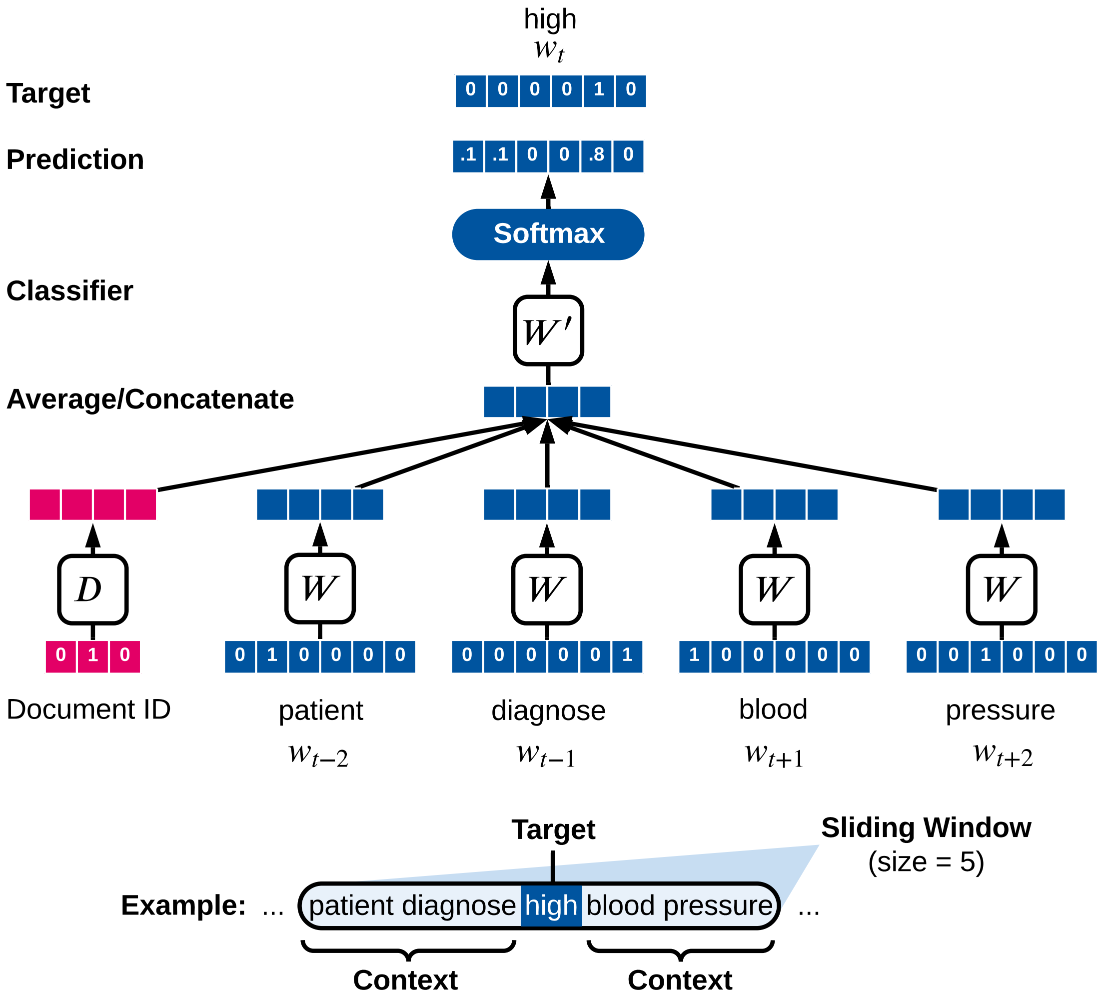


Figure 4.2: The Paragraph Vector model in the distributed memory variant (PV-DM) is a neural network that is designed to predict a word w_t from its context $(w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2})$ and derives fixed-length representations of documents and words via the learned matrices $\boldsymbol{D}$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

4.4.5 Latent Dirichlet Allocation

The *Latent Dirichlet Allocation* (LDA) presented by Blei et al. in 2003 [15] is a generative statistical text model, representing documents as a mixture of a small and fixed number of topics. Topics are defined by a multinomial (i.e, categorical) probability distribution over all words in the vocabulary and are learned by the model in an unsupervised manner. The number of topics is specified a priori.

The underlying assumption of the LDA model is that the text documents were created by a statistical process that sampled the words of the documents from sampled topics. The process can be described in three steps:

1. For each document, a multinomial topic distribution is drawn from a Dirichlet distribution parameterized by a vector $\boldsymbol{\alpha}$.

2. For each topic, a multinomial word distribution is drawn from a Dirichlet distribution parameterized by a vector $\boldsymbol{\beta}$.
3. For each document, the document's words are sampled by iteratively drawing a topic from the document's topic distribution (1) and then drawing a word from the chosen topic (2).

Using the LDA model, a document is encoded as a vector by its topic distribution. Its dimension is equal to the number of topics and each component indicates the probability that the corresponding topic was chosen to sample a word in the document. The distributions and, therefore, document encodings, 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

With the encoding strategy described before, any trace can be transformed to an encoded sequence of event vectors. Using the historical event log with completed traces, an encoded historical prefix event log can be computed. Finally, this encoded 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, outcome, and cycle time) together in order to benefit from their correlations. In the basic variant, the network consists of an input layer, a shared LSTM layer, a specialized LSTM layer for each prediction target, and a fully connected output layer for each target. Furthermore, layer normalization [66] can be applied after each LSTM layer, which standardizes the hidden output 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 outcome prediction to estimate the probability for each target value. The softmax function normalizes a vector of real numbers into another vector of the same dimension, so that all components are in the interval [0,1], and the sum of all components is equal to 1. Hence, the transformed vector can be interpreted as a probability distribution while keeping the vector's original proportions. The softmax function is described with

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

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 lengths, shorter traces are pre-padded [67] with zero vectors. Hence, a prefix trace of encoded events $\boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x_k}$ is represented in the training set by a 2-dimensional matrix $(\mathbf{0}, \ldots, \mathbf{0}, \boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x_k})$, so 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.

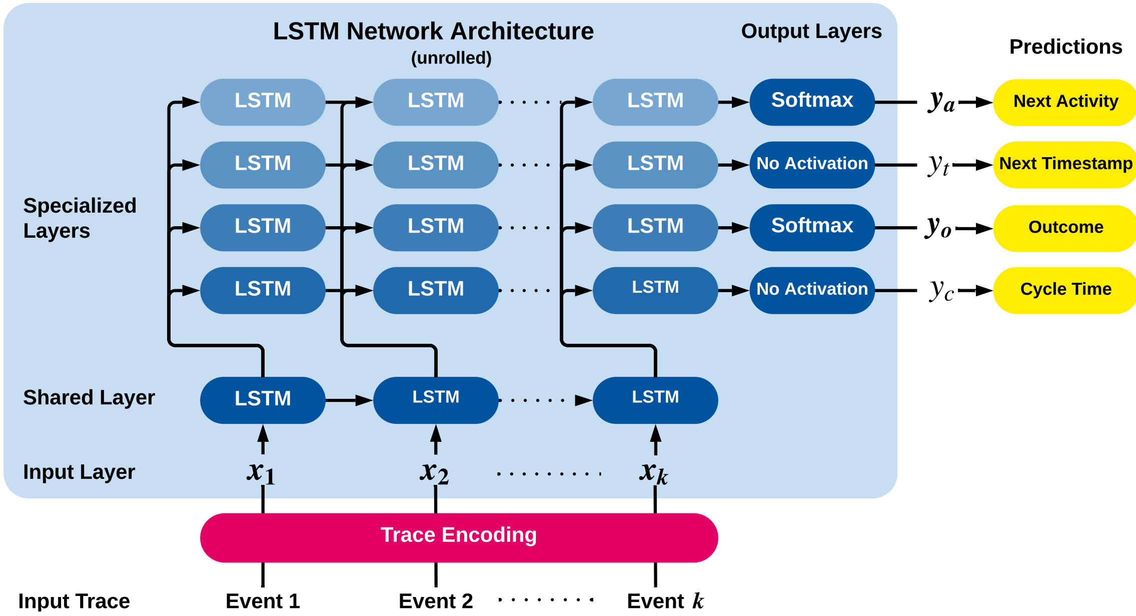


Figure 4.3: LSTM model architecture to simultaneously predict the next activity ($\boldsymbol{y_a}$), next event time (y_t), outcome ($\boldsymbol{y_o}$) and cycle time (y_c) for an encoded prefix trace $\boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x_k}$.

The training is realized using a learning algorithm based on gradient descent and back-propagation through time (BPTT) [68] updating the weights of the network using the update rules of the Adam optimizer with Nesterov momentum [69]. 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 $\mathrm{CE}(\hat{\boldsymbol{y}}, \boldsymbol{y}) = -\sum_{i=1}^{k} y_i \cdot \log \hat{y}_i$.

4.6 Predictive Business Processing Monitoring

During online business process monitoring, predictions are realized by a forward-pass of the encoded, incompleted traces through the LSTM model. The component with the highest value of the softmax outputs for the next activity ($\boldsymbol{y_a}$) and the 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 to compute the final prediction value. Since the network is trained to predict the remaining time of a process instance, the already elapsed time during the process is added to y_c.

With every new event 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 which is updated whenever new information in the 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 the running process instance can be predicted. The trace of a process instance is assumed to be completed when the model predicts the artificial ■ activity. With this technique, the model can indirectly 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 described.

5.1 Technology

The implementation of the text-aware process prediction model is purely based on Python 3.8 [70]. 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 [71]	Fraunhofer Institute for Applied Information Technology	Event log parsing and handling
TensorFlow [72]	Google Brain Team et al.	Construction and training of LSTM model
NTLK [73]	Bird et al.	Text preprocessing
Scikit-learn [74]	Cournapeau et al.	Bag of Words and Bag of N-Gram tf-idf encoding
Gensim [75]	Řehůřek et al.	Latent Dirichlet Allocation and Paragraph Vector encoding

Table 5.1: Python packages used for implementation.

PM4Py [71] 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 [72] is a dataflow-oriented framework originally developed by Google, including a diverse set of neural network models and serves with its LSTM implementation using the Keras API [76].

Furthermore, the packages NTLK [73], Scikit-learn [74], and Gensim [75] are applied for the preprocessing and encoding of textual data. NTLK is used to realize the tokenization, word lemmatization and stop word removal. For the lemmatization of English texts, the WordNet lemmatizer based on the WordNet database [77] is utilized to normalize each word. In case of other languages, the more simplistic Snowball stemming algorithm [78] is chosen instead. The stop words are provided directly by the NLTK package[1]. 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()`, which 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 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 extracted text corpus and compute the text encodings.

During the fitting phase of the `LogEncoder`, all possible values for the categorical attributes are indexed, and the parameters for the normalization of numerical attributes are computed. Regarding the text encoding model, the indexed vocabulary of all words (after preprocessing) in the historical event log is constructed during fitting. In the 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.

[1] Stop words: https://github.com/nltk/nltk_data/blob/gh-pages/packages/corpora/stopwords.zip

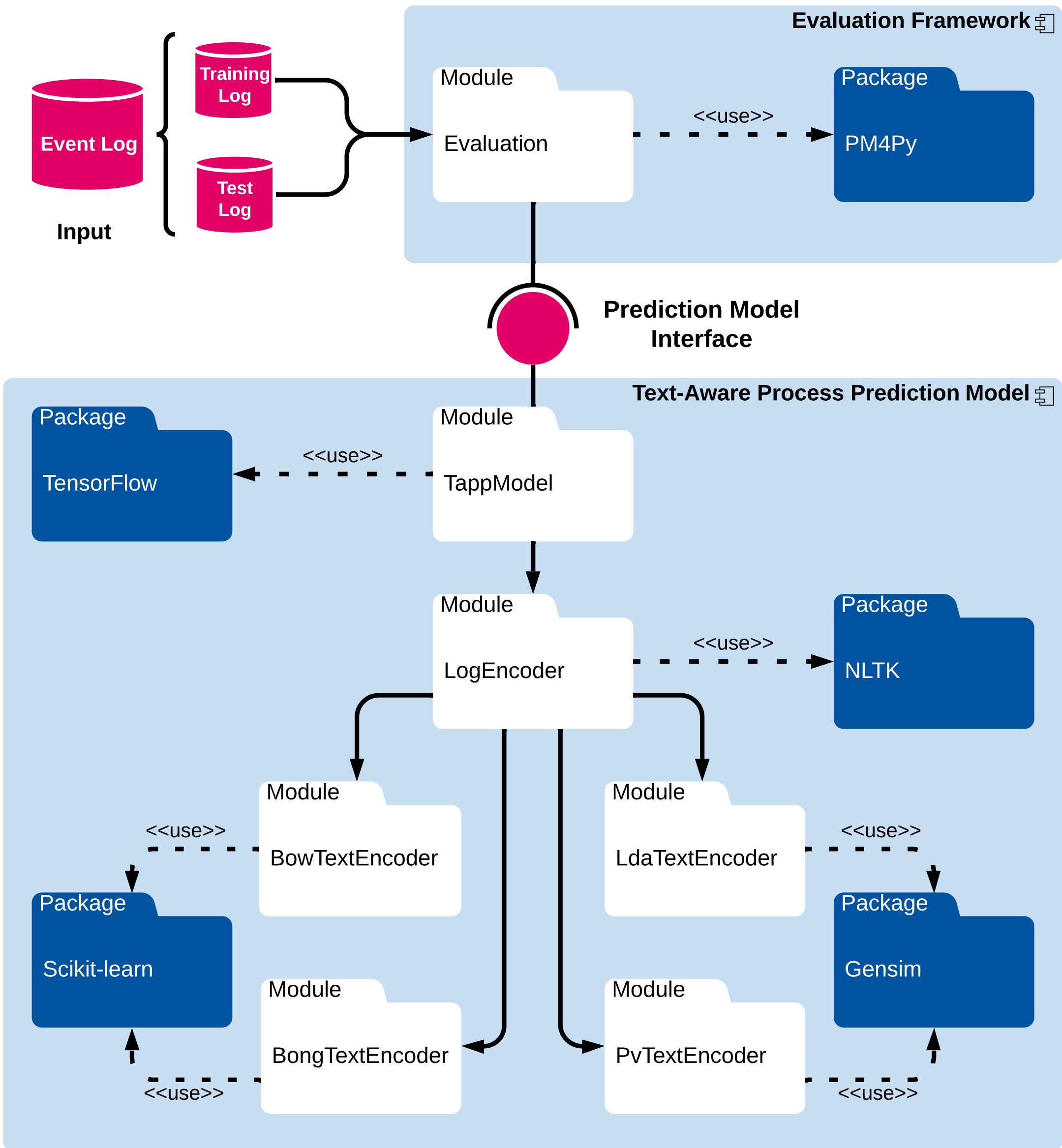


Figure 5.1: Component diagram of the implementation. The text-ware process prediction component provides an interface to fit the model and realize predictions. The evaluation component uses this interface to evaluate the prediction performance. The diagram shows the internal Python modules and external Python packages that are part of the implementation.

Chapter 6

Evaluation

In this chapter, the text-aware process prediction model's performance 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 logs based on four prediction tasks: next activity, next timestamp, outcome, and cycle time 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. [41] and Navarin et al. [42] is considered, which only uses the activity, timestamp, and additional non-textual attributes of each event. This approach can be considered the state-of-the-art in process prediction if prediction performance is the only criteria.

The second baseline is the process model-based prediction method originally presented by van der Aalst et al. [35]. 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. During the prediction phase, running traces are mapped to the corresponding state of the transition system, and the measurements of the state are used to compute a prediction.

While the original work by van der Aalst et al. focuses on regression tasks, Tax et al. [46] describe how an annotated transition system can also be used for classification tasks, like the next activity prediction. For classification tasks, the measurements of each state are used to compute a probability distribution over the prediction target. During prediction, the most likely class is predicted, given the probability distribution of the corresponding state. For regression tasks, the mean of the measurements of each state is computed. The eight most recent events of a trace are considered for the construction of the state space. Experiments with different horizon lengths (1, 2, 4, 16) mostly led to worse result, so that these are not reported.

Each prediction model is evaluated with 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. Because of the temporal dimension in event data and the potential existence of concept drifts, no cross-validation is applied. For each trace σ in the training and test log, all prefixes $hd^k(\sigma)$ of length $1 \leq k \leq |\sigma|$ are considered instances.

For classification (i.e., categorical prediction) task, like next event and outcome prediction, the weighted-average F_1 score is utilized as metric. The F_1 score is a metric to measure the quality of predictors on binary classification tasks developed by van Rijsbergen [79].

In a binary classification setting, instances from a data set have either a positive or negative label that needs to be predicted. A predictor classifies each instance and separates them in four different groups: correctly classified positive instances (true positives), incorrectly classified positive instances (false positives), correctly classified negative instances (true negatives), and incorrectly classified negative instances (false negatives). Figure 6.1 visualizes these four basic measures of binary classification.

Given these measures, the precision and recall of a binary classifier can be computed [80]. The precision of a binary classifier is the number of true positives divided by the total number of positive classified instances, i.e.,

$$\text{precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}} \in [0, 1].$$

The recall is defined as the number of true positives divided by the total number of actually positive instances, i.e.,

$$\text{recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}} \in [0, 1].$$

The F_1 score combines both metrics. It is defined as the harmonic mean of precision and recall [80]:

$$\mathrm{F}_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} = \frac{\text{true positives}}{\text{true positives} + \frac{1}{2}(\text{false positives} + \text{false negatives})} \in [0, 1].$$

The precision, recall and F_1 score of a binary classifier can have values between 0 and 1, where 1 is the best possible value. The F_1 score can be extended for multi-class classification by averaging over the one-vs.-rest F_1 scores per class. The weighted-average F_1 score weights each class-dependent F_1 score with its support, i.e., the number of true instances per class.

Let $C > 2$ be the number of classes, and let n be the total number of instances. Furthermore, let F_1^i be the one-vs.-rest F_1 score of class $i \in [C]$, and let n_i be the number of instances with class i. Then, the weighted-average F_1 score is defined as

$$\mathrm{F}_1^{\text{weighted}} = \frac{1}{n} \sum_{i=1}^{C} \mathrm{F}_1^i \cdot n_i \in [0, 1].$$

This evaluation metric is preferred over accuracy to address imbalanced distributions of target variables. Since only multi-class prediction tasks are considered in this evaluation, F_1 is written to describe $\mathrm{F}_1^{\text{weighted}}$ in the following.

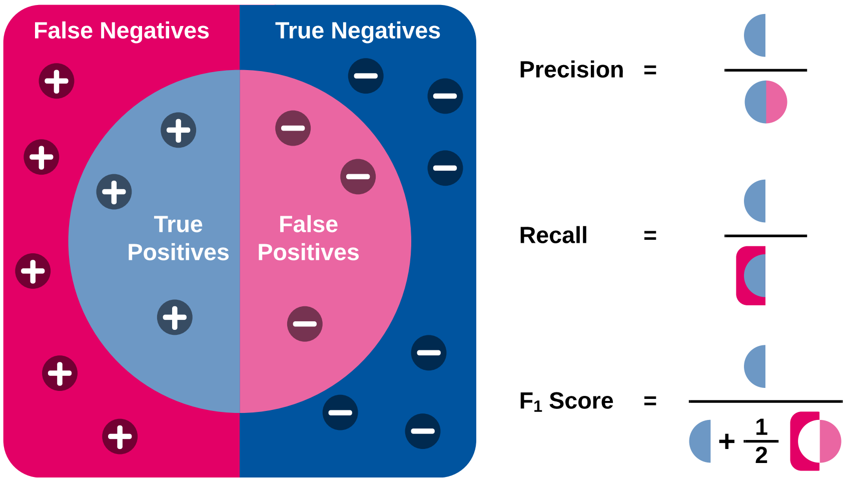


Figure 6.1: Visualization of binary classification and its performance measures. Instances are either positively or negatively labeled.

For regression tasks, like the next event time and the 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, i.e.,

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

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). A MAE of 0 is the most desirable result.

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 ($n = 2$). The Paragraph Vector model is trained for 15 epochs using a sliding window of size 8 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. If the error does not decrease 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.

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.

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	1001	2784
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	1203	4973
Vocabulary after preprocessing	185	817	4633
Text attribute	Email	Customer question	Diagnosis
Additional non-textual attributes	-	Gender Age	Admission type Insurance

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

Job Application (simulated log) This event log describes a simple job application process. First, the applicant starts an application in the company's system. The candidate then uploads a curriculum vitae (CV) and optionally a cover letter in random order. 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 whether 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 the applicant is rejected, the email is generated with sentences from typical rejection emails instead. 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. A model of the simulated process is shown in Figure 6.2 using BPMN [81] notation.

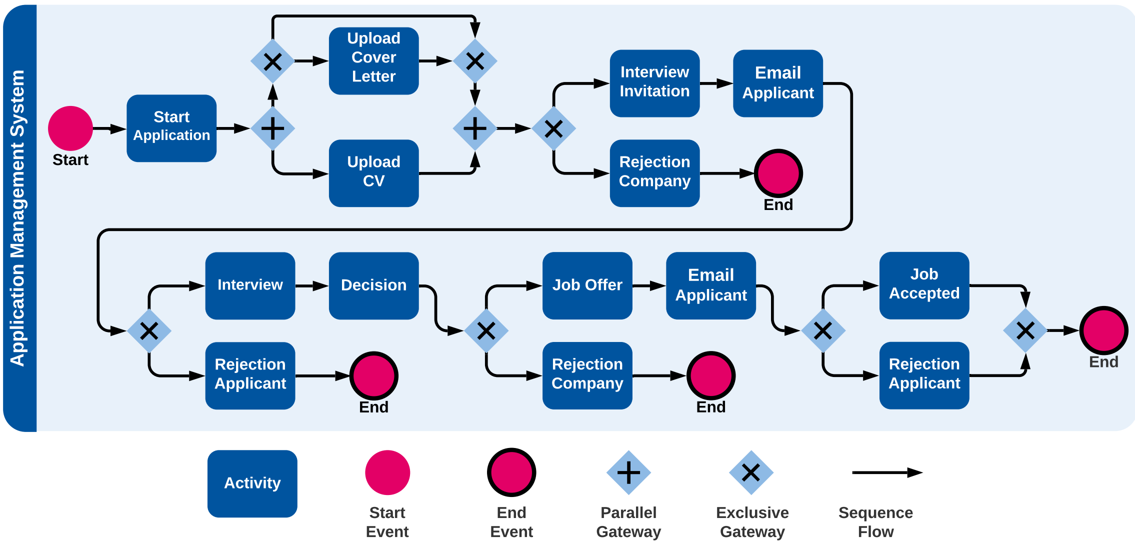


Figure 6.2: BPMN model of the job application process. For simplicity, only the performed activities and the control flow are modeled. An enlarged version of this figure is provided in Appendix A.

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 provided in the BPI Challenge 2016 [82], 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 derive a detailed view of customer contacts on the web and the phone. For each phone call, the customer'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 (grouped) 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 fewer 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 [83] 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, so 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, 1001 trace variants, and 817 unique words. The hospital admission log is the most complex with 26 activities, 2784 trace variants, and 4633 unique words. Short snippets of all three event logs with the considered data attributes are provided in Appendix B.

6.3 Next Activity and Timestamp Prediction

First, the prediction performance regarding the next event's activity and timestamp 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 F_1 score 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.

		Job Application		**Customer Journey**		**Hospital Admission**	
Text Model	Text Vector Size	Activity F_1 Score	Time MAE (days)	Activity F_1 Score	Time MAE (days)	Activity F_1 Score	Time MAE (days)
Text-Aware Process Prediction (LSTM + Text Model)							
BoW	50	0.8549	0.1037	0.4251	0.1764	0.5389	29.0819
BoW	100	0.8806	0.1053	0.4304	**0.1763**	0.5487	31.4378
BoW	500	0.8550	0.1037	**0.4312**	0.1798	**0.5596**	27.5495
BoNG	50	0.8386	0.1335	0.4270	0.1767	0.5309	27.5397
BoNG	100	0.8803	0.1088	0.4237	0.1770	0.5450	28.3293
BoNG	500	0.8629	0.1053	0.4272	0.1773	0.5503	27.9720
PV	10	0.7988	0.1814	0.4112	0.1812	0.5265	29.4610
PV	20	0.8451	0.1175	0.4134	0.1785	0.5239	**27.2902**
PV	100	0.8619	0.1162	0.4162	0.1789	0.5292	28.2369
LDA	10	0.8547	0.1033	0.4239	0.1786	0.5252	28.8553
LDA	20	0.8583	0.1039	0.4168	0.1767	0.5348	27.8830
LDA	100	**0.8830**	**0.1032**	0.4264	0.1777	0.5418	27.5084
LSTM Model Prediction Baseline							
LSTM [41]+[42]		0.6987	0.2499	0.4029	0.1781	0.5187	27.7571
Process Model Prediction Baseline (Annotated Transition System)							
Sequence [35]+[46]		0.7239	0.2553	0.4005	0.2387	0.4657	64.0161
Bag [35]+[46]		0.7159	0.2553	0.3634	0.2389	0.4681	64.6567
Set [35]+[46]		0.7065	0.2553	0.3565	0.2389	0.4397	63.2042

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

Compared to the baseline approaches, the text-aware model can improve the next activity and timestamp prediction on all data sets with at least one parameterization. Markedly, the impact of the consideration of textual data varies a lot between the data sets and the prediction tasks. A reason for that might be 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 F_1 score of the next activity prediction goes up to 0.8830 using the LDA text model. This is an improvement of 0.1843 compared to the LSTM baseline. The next timestamp prediction is improved by up to 0.1467 days (around 3.5 hours). The other encoding models perform similarly with the exception of the PV model in combination with a small 10 dimensional text encoding. Since this log contains rather long text documents, the small encoding size is not able to represent the textual data sufficiently. The process model baselines using the annotated transition system perform similarly to the LSTM baseline approach but significantly worse than the text-aware approaches. The transition system created using a sequence abstraction performs slightly better than the other baselines. Nevertheless, the trace abstraction method has a rather small impact on the prediction quality.

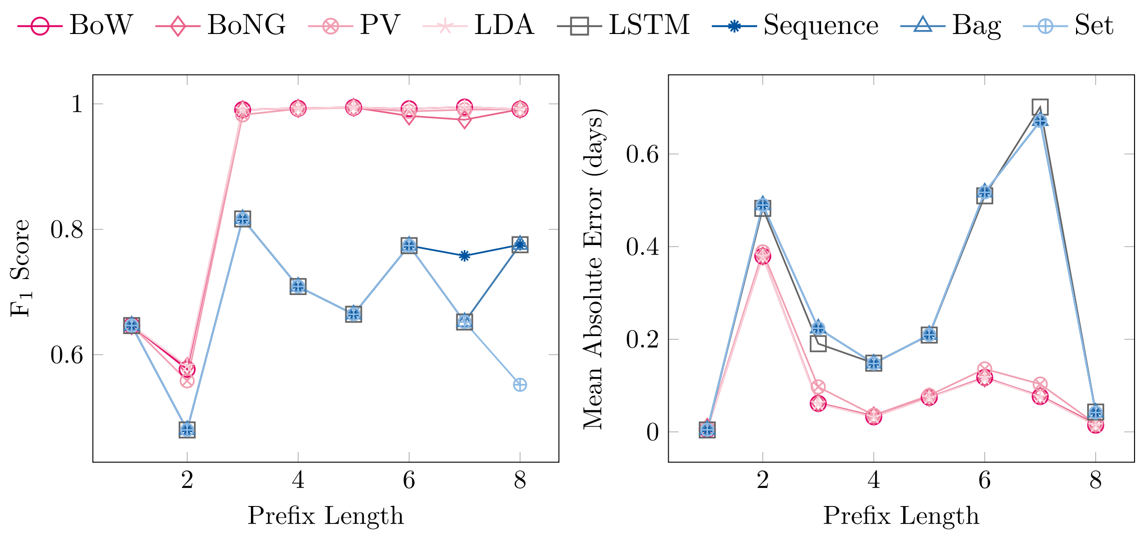
In contrast, on the customer journey log, the next activity F_1 score is improved by at most 0.0283 using the BoW model compared to the LSTM baseline. The impact of the text-awareness on next timestamp prediction is negligible on this log. Seven out of the twelve text-aware models improve the next timestamp prediction, while five are slightly worse. The annotated transition system generates slightly worse next activity and timestamps predictions. Again, the sequence abstraction outperforms the other trace abstractions.

The F_1 score is improved on the hospital admission log by up to 0.0409 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 with 4 633 unique words has the largest vocabulary by far, and therefore larger text encodings are required. Regarding the next timestamp prediction, the PV model with 20 dimensional text vectors performs the best. However, the positive impact of the textual data is questionable since some text models also perform worse, like the BoW model with 100 dimensional text encoding. The process model baselines fall back clearly on both prediction tasks on the hospital admission log. It is assumed that the huge amount of trace variants on this log is disadvantageous for prediction models with a discrete set of states. In contrast, the LSTM models can profit from their noise resistance.

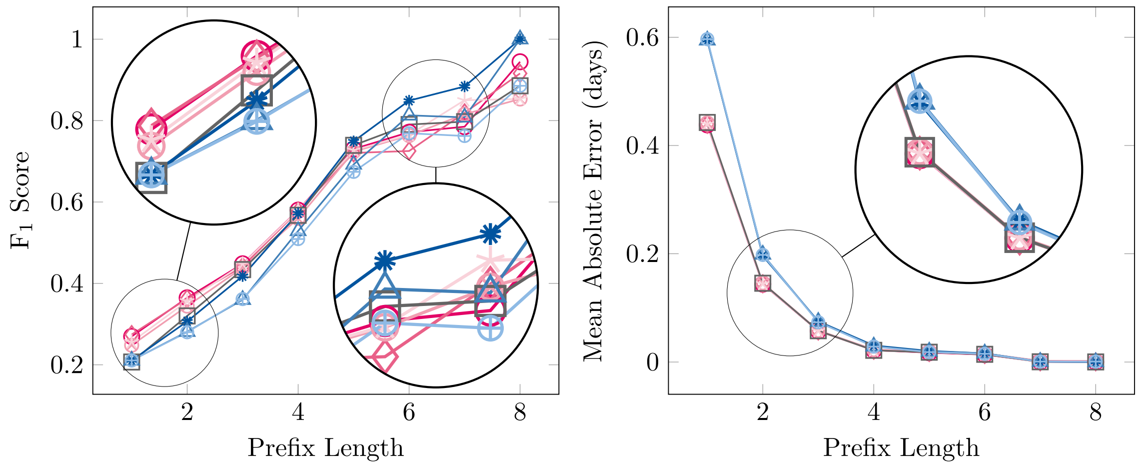
The choice of text model has a rather small impact on the results on all event logs. Notably, the BoW and LDA model perform most consistently on all data sets and all text encoding lengths. The PV model reaches slightly worse results, especially when a small text embedding size is used. The BoNG model 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. Figure 6.3 shows the F_1 score and next timestamp MAE for every prefix trace of length $1 \leq k \leq 8$. Please note that the results on shorter traces are supported by a much larger set of traces due to prefix generation during the construction of the training and test data sets. For the text-aware models, only the best text encoding length is shown in the diagram.

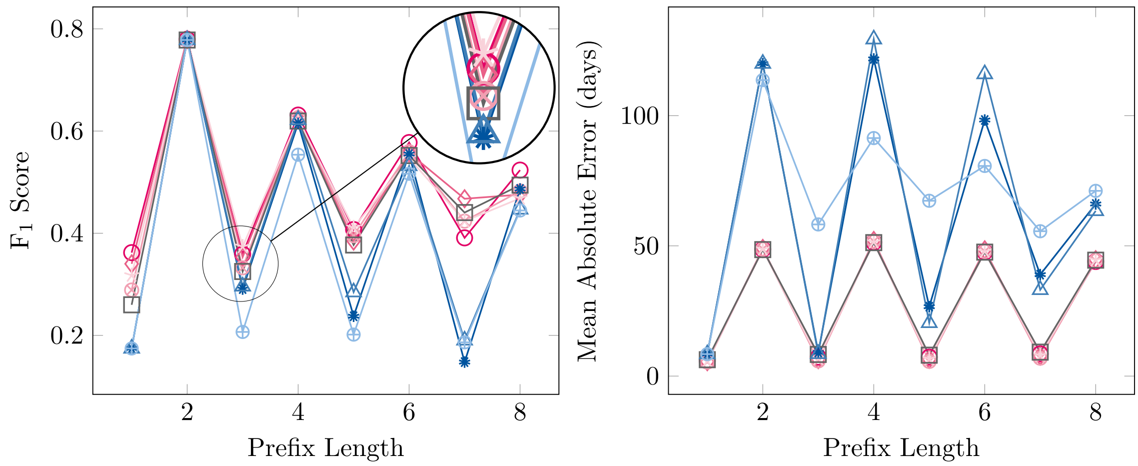
On the job application event log, all text-aware process models almost perfectly predict the next activity after three events (i.e., after the application documents are available). The baseline approaches cannot take advantage of the emails and reaches an F_1 score of around 0.75 after the first three events. This shows that all text-aware approaches can



(a) Job application event log.



(b) Customer journey event log.



(c) Hospital admission event log.

Figure 6.3: Next activity (left) and timestamp (right) prediction performance depending on the prefix length for each evaluated event log.

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 in the activity prediction lead consequently to significantly better timestamp predictions on this log.

On the customer journey log, the prediction performance of all models correlates positively with the available prefix length of the trace. The next activity F_1 score is improved from under 0.3, when only the first event is available, to over 0.8 after eight events for all models. All text-aware prediction models surpass the baseline approaches on very short prefix traces of length 3 or shorter. There are two possible explanations for this. First, the events holding textual data seem to appear mostly at the beginning of the traces in this log. Furthermore, in order to generalize from the textual data, usually, more training data is necessary. Since there are always more short prefixes available in the training set, the text-aware models benefit disproportionately on shorter traces. The transition system created using a sequence abstraction underperforms on shorter prefixes but outperforms all LSTM approaches on longer prefixes. The MAE on the next timestamp prediction rapidly drops when more events are available independent of the prediction model. The LSTM-based models have a slight advantage over the process model baseline on short 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. Therefore, the prediction accuracy varies between odd and even prefix lengths. The text-aware prediction models generate slightly better predictions on admission events since only these contain the diagnosis as text attribute, which can be utilized by the text-aware models. The prediction performance of the LSTM models 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.

6.4 Outcome and Cycle Time Prediction

The outcome and cycle time prediction are 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 an outcome, the final activity of the trace is predicted as described in Section 4.1. The MAE of the 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 an F_1 score of up to 0.6535 using the BoW text model compared to 0.5296 using the LSTM baseline approach. Therefore, the prediction can be improved by up to 0.1239. Other text models perform similar to the BoW model except for the PV model with 10 dimensional text vectors with an F_1 score of only 0.5935. The MAE on the cycle time prediction can be reduced to 1.3615 days with the BoW model compared to 1.6765 days on the LSTM baseline approach. The annotated transition system achieves an F_1 score of up 0.5551 and a cycle time MAE of 1.8066 days.

Text Model	Text Vector Size	**Job Application** Outcome F_1 Score	Cycle MAE (days)	**Customer Journey** Outcome F_1 Score	Cycle MAE (days)	**Hospital Admission** Outcome F_1 Score	Cycle MAE (days)
Text-Aware Process Prediction (LSTM + Text Model)							
BoW	50	0.6516	**1.3615**	0.4732	0.2357	0.6120	69.2953
BoW	100	0.6523	1.3642	0.4690	**0.2337**	**0.6187**	70.9488
BoW	500	**0.6535**	1.3678	0.4690	0.2354	0.6050	70.1084
BoNG	50	0.6449	1.4003	0.4789	0.2365	0.6099	69.4456
BoNG	100	0.6509	1.3700	0.4819	0.2373	0.6094	69.3619
BoNG	500	0.6492	1.3670	0.4692	0.2358	0.6052	70.6906
PV	10	0.5935	1.5122	0.4670	0.2424	0.6007	73.5219
PV	20	0.6401	1.3917	0.4732	0.2417	0.5962	69.6191
PV	100	0.6464	1.3855	0.4707	0.2416	0.6058	69.4793
LDA	10	0.6421	1.3622	0.4755	0.2394	0.6017	**69.1465**
LDA	20	0.6530	1.3620	0.4747	0.2375	0.6071	69.6269
LDA	100	0.6504	1.3662	**0.4825**	0.2374	0.6106	69.3189
LSTM Model Prediction Baseline							
LSTM [41]+[42]		0.5296	1.6765	0.4673	0.2455	0.5976	70.2978
Process Model Prediction Baseline (Annotated Transition System)							
Sequence [35]+[46]		0.5551	1.8067	0.4669	0.2799	0.5479	171.5684
Bag [35]+[46]		0.5544	1.8066	0.4394	0.2797	0.5451	173.7963
Set [35]+[46]		0.5544	1.8069	0.4381	0.2796	0.5588	171.4487

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

On the customer journey log, the text-awareness leads to much smaller improvements as observed for the next event prediction. The best outcome prediction is realized with the LDA text model resulting in an F_1 score of 0.4825. The cycle time MAE using the BoW model is 0.2337 days, which improves the LSTM baseline prediction by 0.0118 days (= 16.99 minutes). All text-aware models outperform the LSTM baseline by a small amount on the cycle time prediction. The sequence-abstracted transition system predicts the outcome with an F_1 score of 0.4669 and hence stays in line with the LSTM-based models. The bag- and set-abstracted models fall back slightly. The cycle time MAE of the annotated transition systems is at least 0.0341 days (= 49 minutes) worse compared to the LSTM-based approaches.

On the hospital admission log, the text-aware approach delivers an F_1 score of 0.6187 on the outcome prediction task using the BoW model. This improves the LSTM baseline's F_1 score by 0.0211. However, the cycle time prediction error is around 70 days for all LSTM-based approaches. Nine text-aware models perform better than the LSTM baseline, the other three perform slightly worse. As observed during the next timestamp prediction, the text-aware models have difficulties to clearly improve the performance on time-related regression tasks on this particular log. The transition systems predict the outcome with an F_1 score of up to 0.5588 and have a much larger error on the cycle time prediction of at least 171.4487 days using the set abstraction. The other abstraction methods perform noticeably worse. Since the log contains many trace variants, the stronger set abstraction has an advantage. Nevertheless, the extreme variability in the log creates difficulties for the process model-based approaches. Furthermore, the unevenly distributed cycle times of the processes might be disadvantageous for the transition systems.

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. Strikingly, the best predictions have always been generated by a text-aware model using either the BoW or the LDA text model. 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 6.4 depicts the outcome F_1 scores and cycle time MAE per prefix on every event log and approach. On the job application log, the F_1 score is improved with longer prefixes from under 0.3 after the first event to over 0.8 after eight events using any text-aware prediction model. The F_1 score of the baseline approaches peaks after five events but always stays below 0.7. 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 to 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 an F_1 score of under 0.4 independent of the prediction model, but the prediction is improved noticeably with every additional event. The sequence-abstracted annotated transition system outperforms all LSTM approaches after six events. The other two abstractions perform slightly worse on all prefix lengths. The text-aware models and the LSTM baseline perform slightly better on short prefixes of length one or two. The cycle time prediction is improved in particular within the first three events for all models. The text-aware approaches slightly outperform the baseline approaches on very short prefixes. However, the cycle time prediction performance is very similar for all models after three events on this log.

The outcome prediction 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 odd prefix lengths since these traces end on admission events that contain the diagnosis as textual data. Differently compared to the other logs, the cycle time prediction gets worse for longer prefixes regardless of the model used. Since the hospital log contains shorter traces in a significantly higher amount, the prediction performance on longer traces is more imprecise. All transition systems perform significantly worse due to the huge amount of trace variants and outlier traces.

6.5 Key Findings and Discussion

The text-aware process prediction model outperforms the baseline approaches on all evaluated event logs and prediction tasks. However, the influence of textual data on the prediction performance varies greatly per event log. It can be observed that the impact

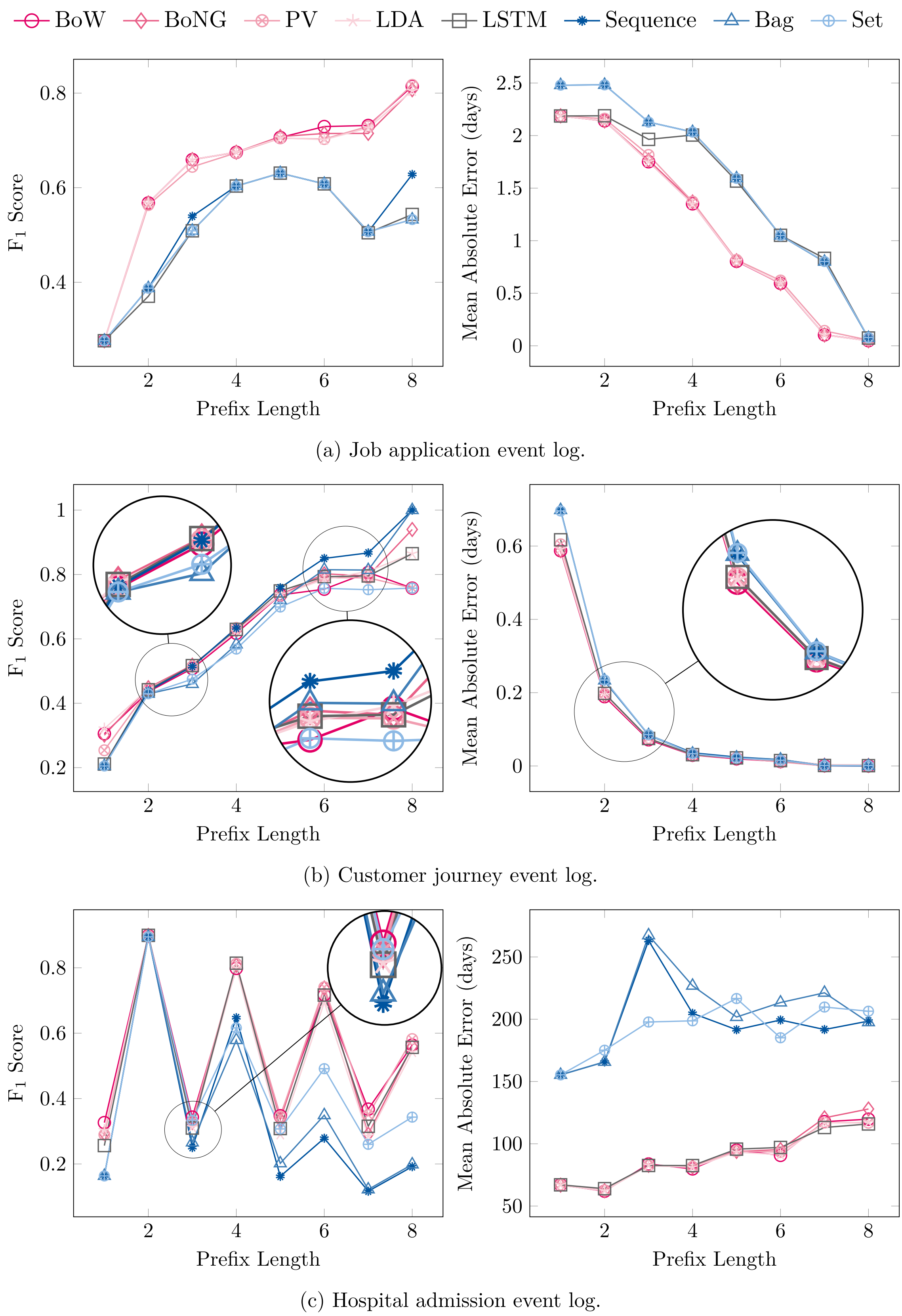


Figure 6.4: Case outcome (left) and cycle time (right) prediction performance depending on the prefix length for each evaluated event log.

of the text consideration on the classification tasks is significantly higher compared to the regression tasks. Regarding the choice of text model, all evaluated text models are suitable to capture textual data and deliver similar results on most prediction tasks. Nevertheless, the text-aware process prediction model with BoW and LDA text models performs slightly better than with 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 larger vocabulary of words usually requires longer text encodings.

A few parameterizations of the text-aware prediction models perform worse than the LSTM baseline on some prediction tasks on the hospital log. 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 for 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 mostly improve a lot. However, for longer traces, the prediction performance can also decrease since there is less knowledge (i.e., training data) about longer traces available.

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 terms 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 cannot be utilized in this case, and the prediction performance is noticeably worse on unstructured processes. The limitations of process model-based approaches follows from the discrete set of process states from which the predictions are derived. When additional structured and unstructured data is considered, distributed vector representations for process states, like the hidden vectors in LSTM neural networks, are required to encounter the high dimensionality of the event data. However, this requires compromises in terms of interpretability.

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 a natural language like emails or documents hold process-critical information, purely control flow-oriented approaches are limited in delivering well-founded predictions. In order to overcome these limitations, a text-aware process prediction model is proposed in this thesis. The model encodes process traces of historical process executions to sequences of meaningful event vectors using the control flow, timestamp, textual, and non-textual data attributes of the events. An interchangeable text model is utilized to realize the vectorization of textual data. Given an encoded prefix log of historical process executions, an LSTM neural network model is trained which predicts the activity and timestamp of the next event, the outcome, and the cycle time of a running process instance.

The proposed concept of a text-aware process prediction model has been implemented in Python 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 outperform state-of-the-art process prediction methods 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. For classification tasks, more significant improvements could be achieved than for regression tasks. The model benefits particularly on short traces since more training data for short sequences is available through the generation of prefixes during training. Furthermore, the prediction model is robust to outlier traces in the event log and can generalize from structured and chaotic processes. It is one of the most flexible in terms of the input data that can be used for prediction and the types of prediction targets.

Four different text models (Bag of Words, Bag of N-Gram, Paragraph Vector, and Latent Dirichlet Allocation) have been considered to compute vector representations of textual data. Each text model has been proven to be viable, whereby the BoW and LDA models have performed most consistently even with low-dimensional text vector embeddings. The optimal encoding dimension of textual data depends on, inter alia, the size of the vocabulary, i.e., the number of distinct words in the event logs.

7.1 Limitations and Outlook

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

In certain contexts, high and reliable prediction performance is not sufficient as the interpretability of the 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 [46]. While the prediction performance has been prioritized in this contribution, 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 cannot be naturally extended for this purpose.

Another 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. However, 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 [84]. The ascertainment of causality is a significantly 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 might be of interest to evaluate text-aware process prediction in contexts where the linguistic style is less technical but rather subtle and personal. In this case, the textual data would be 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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Appendix A

Job Application Process Model

Figure A.1 shows the BPMN model of the job application process described in Section 6.2.

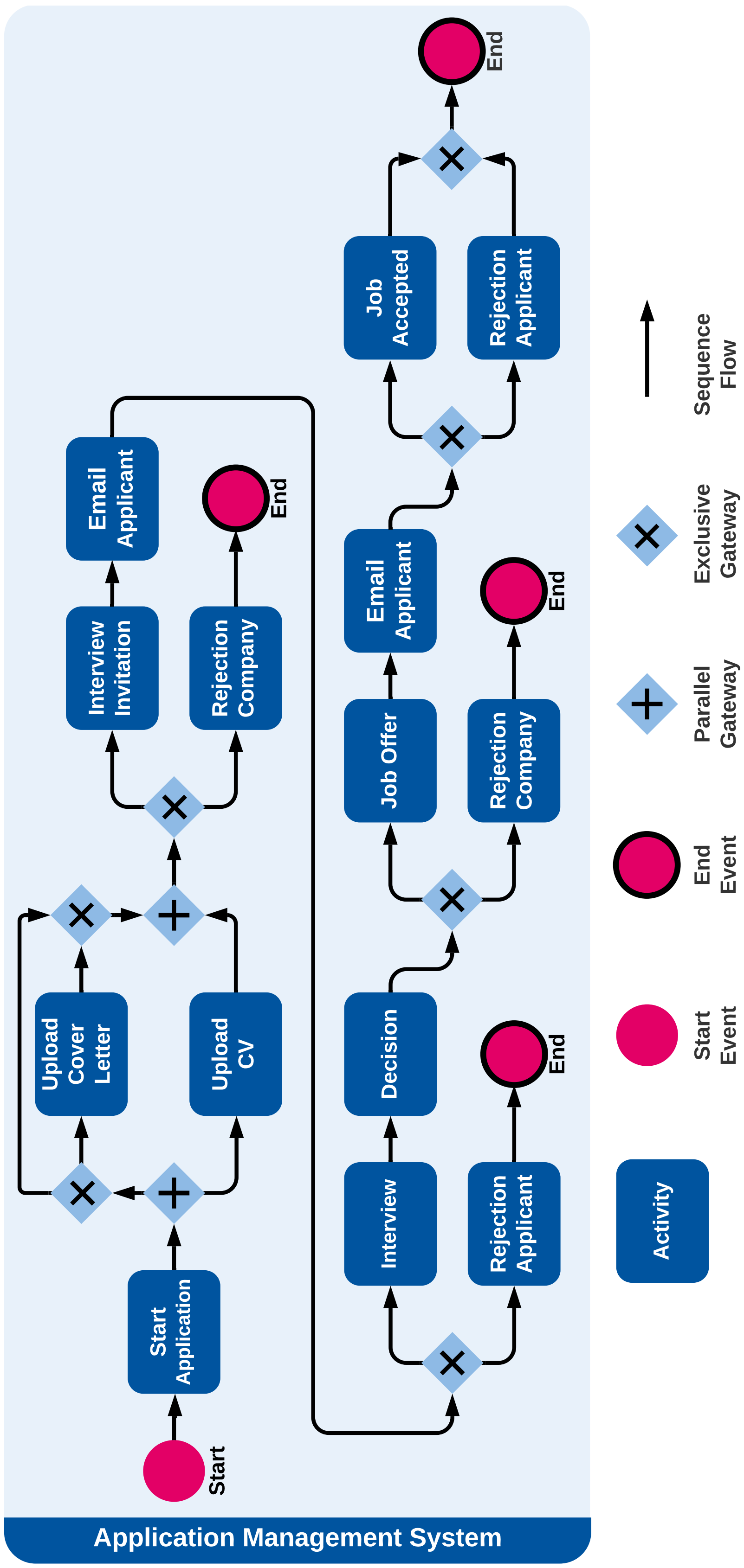

Figure A.1: Enlarged BPMN model of the job application process.

Appendix B

Event Log Snippets

The following tables show snippets of the three event logs described in Section 6.2.

Case	Activity	Timestamp	Email
14587	start application	2025-06-28 04:03:44.597790	
14587	upload cv	2025-06-28 04:39:32.836847	i studied data mining i have a degree in data bases i studied data [...]
14587	interview invitation	2025-06-29 15:04:04.041641	
14587	email by applicant	2025-06-29 22:34:55.861625	i am looking forward to let us make an appointment outstanding [...]
14587	interview	2025-06-30 22:53:10.875933	
14587	decision	2025-07-03 12:40:05.252017	you will be asked to sign a contract would like to formally offer you [...]
14587	job offer	2025-07-06 00:55:55.570263	
14587	email by applicant	2025-07-06 06:52:56.156498	thank you please send me let us make an appointment please [...]
14587	job accepted	2025-07-06 09:42:27.776267	
14588	start application	2025-07-29 18:11:59.618476	
14588	upload cv	2025-07-29 18:42:50.763586	i can do negotiation for many years i do presentation i can do [...]
14588	upload cover letter	2025-07-29 19:01:11.889307	i am confident that i would be a valuable asset to the team [...]
14588	interview invitation	2025-07-31 01:36:46.319451	
14588	email by applicant	2025-07-31 10:55:21.452244	you can reach out to me please tell me the date when i am [...]
14588	interview	2025-08-01 07:56:00.594860	
14588	decision	2025-08-03 16:54:16.736287	we received a large number of job applications after carefully [...]
14588	rejection by company	2025-08-03 22:42:14.838405	
14589	start application	2025-07-04 17:01:42.829690	
14589	upload cv	2025-07-04 17:31:12.394144	i studied micro services i have developed skills data models i have [...]
14589	upload cover letter	2025-07-04 17:48:34.418263	i am available to talk at your convenience i am available to talk [...]
14589	interview invitation	2025-07-06 04:09:59.775358	
14589	email by applicant	2025-07-06 12:57:27.321095	you can reach out to me if you need additional information please [...]
14589	interview	2025-07-07 09:24:42.576997	
14589	decision	2025-07-09 13:00:11.681470	we will not be able to hire you thank you for your application for the [...]
14589	rejection by company	2025-07-09 18:01:29.714866	
14590	start application	2025-05-16 07:38:17.143582	
14590	upload cv	2025-05-16 08:09:12.449789	i studied process mining i have a degree in web services my key skill [...]
14590	interview invitation	2025-05-17 14:33:47.787646	
14590	email by applicant	2025-05-17 23:39:30.979391	it is not possible for me i can not i already found a job i am not [...]
14590	rejection by applicant	2025-05-18 03:28:38.824214	

Table B.1: Snippet of the job application log.

Case	Activity	Timestamp	Age	Gender	Message
40154127	question	2015/12/15 12:24:42.000	50-65	M	Can you send me a copy of the decision?
40154127	taken	2015/12/30 15:39:36.000	50-65	M	
40154127	mijn_sollicitaties	2015/12/30 15:39:42.000	50-65	M	
40154127	taken	2015/12/30 15:39:46.000	50-65	M	
40154127	home	2015/12/30 15:39:51.000	50-65	M	
23245109	question	2015/07/21 09:49:32.000	50-65	M	Law: How is the GAA (Average Number of Labor)?
23245109	question	2015/07/21 09:54:28.000	50-65	M	Dismissal Procedure: Stops my contract automatically after two years of illness?
23245109	question	2015/07/21 10:05:43.000	50-65	M	Dismissal: Am I entitled to a transitional allowance?
23245109	question	2015/07/21 10:05:56.000	50-65	M	Chain Determination: How often may be extended a fixed-term contract?
23245109	mijn_werkmap	2015/07/27 09:54:03.000	50-65	M	
23245109	mijn_berichten	2015/07/27 09:54:13.000	50-65	M	
23245109	mijn_cv	2015/07/27 10:04:20.000	50-65	M	
21537056	taken	2015/10/30 13:16:48.000	50-65	M	
21537056	question	2015/10/30 13:22:00.000	50-65	M	How can I add a document/share with my consultant work through the workbook?
21537056	taken	2015/10/30 13:23:24.000	50-65	M	
21537056	mijn_werkmap	2015/10/30 13:24:39.000	50-65	M	
19290768	question	2015/09/21 12:41:21.000	30-39	V	Filling: What should I do if I made a mistake when filling out the Income Problem?
19290768	home	2015/09/22 10:09:53.000	30-39	V	
19290768	taken	2015/09/22 10:10:14.000	30-39	V	
19290768	home	2015/09/22 10:11:12.000	30-39	V	
41636987	question	2015/12/23 11:17:08.000	30-39	V	When is/are transferred my unemployment benefits?
41636987	home	2015/12/23 11:52:50.000	30-39	V	
41636987	taken	2015/12/23 11:52:53.000	30-39	V	
41636987	mijn_berichten	2015/12/23 11:53:17.000	30-39	V	
41636987	taken	2015/12/23 11:57:55.000	30-39	V	
53244594	mijn_berichten	2016/02/25 09:10:40.000	40-49	M	
53244594	question	2016/02/25 13:27:38.000	40-49	M	When is/are transferred my unemployment benefits?
53244594	question	2016/02/29 10:04:23.000	40-49	M	Problem: I have to pay sv € 0 and further fill only the amount of holiday pay. What should I do if I get an error?
53244594	question	2016/02/29 10:10:52.000	40-49	M	Why did you change the amount of my payment?

Table B.2: Snippet of the customer journey log.

Case	Activity	Timestamp	Admission Type	Insurance	Diagnosis
3	EMERGENCY ROOM ADMIT	2101-10-20 19:08:00	EMERGENCY	Medicare	HYPOTENSION
3	SNF	2101-10-31 13:58:00	EMERGENCY	Medicare	
4	EMERGENCY ROOM ADMIT	2191-03-16 00:28:00	EMERGENCY	Private	FEVER DEHYDRATION FAILURE TO THRIVE
4	HOME WITH HOME IV PROVIDR	2191-03-23 18:41:00	EMERGENCY	Private	
5	PHYS REFERRAL/NORMAL DELI	2103-02-02 04:31:00	NEWBORN	Private	NEWBORN
5	HOME	2103-02-04 12:15:00	NEWBORN	Private	
6	PHYS REFERRAL/NORMAL DELI	2175-05-30 07:15:00	ELECTIVE	Medicare	CHRONIC RENAL FAILURE SDA
6	HOME HEALTH CARE	2175-06-15 16:00:00	ELECTIVE	Medicare	
7	PHYS REFERRAL/NORMAL DELI	2121-05-23 15:05:00	NEWBORN	Private	NEWBORN
7	HOME	2121-05-27 11:57:00	NEWBORN	Private	
8	PHYS REFERRAL/NORMAL DELI	2117-11-20 10:22:00	NEWBORN	Private	NEWBORN
8	HOME	2117-11-24 14:20:00	NEWBORN	Private	
9	EMERGENCY ROOM ADMIT	2149-11-09 13:06:00	EMERGENCY	Medicaid	HEMORRHAGIC CVA
9	DEAD/EXPIRED	2149-11-14 10:15:00	EMERGENCY	Medicaid	
10	PHYS REFERRAL/NORMAL DELI	2103-06-28 11:36:00	NEWBORN	Medicaid	NEWBORN
10	SHORT TERM HOSPITAL	2103-07-06 12:10:00	NEWBORN	Medicaid	
11	EMERGENCY ROOM ADMIT	2178-04-16 06:18:00	EMERGENCY	Private	BRAIN MASS
11	HOME HEALTH CARE	2178-05-11 19:00:00	EMERGENCY	Private	
12	PHYS REFERRAL/NORMAL DELI	2104-08-07 10:15:00	ELECTIVE	Medicare	PANCREATIC CANCER SDA
12	DEAD/EXPIRED	2104-08-20 02:57:00	ELECTIVE	Medicare	
13	TRANSFER FROM HOSP/EXTRAM	2167-01-08 18:43:00	EMERGENCY	Medicaid	CORONARY ARTERY DISEASE
13	HOME HEALTH CARE	2167-01-15 15:15:00	EMERGENCY	Medicaid	
16	PHYS REFERRAL/NORMAL DELI	2178-02-03 06:35:00	NEWBORN	Private	NEWBORN
16	HOME	2178-02-05 10:51:00	NEWBORN	Private	
17	PHYS REFERRAL/NORMAL DELI	2134-12-27 07:15:00	ELECTIVE	Private	PATIENT FORAMEN OVALE PATENT FORAMEN OVALE MINIMALLY INVASIVE SDA
17	HOME HEALTH CARE	2134-12-31 16:05:00	ELECTIVE	Private	
17	EMERGENCY ROOM ADMIT	2135-05-09 14:11:00	EMERGENCY	Private	PERICARDIAL EFFUSION
17	HOME HEALTH CARE	2135-05-13 14:40:00	EMERGENCY	Private	
18	PHYS REFERRAL/NORMAL DELI	2167-10-02 11:18:00	EMERGENCY	Private	HYPOGLYCEMIA SEIZURES
18	HOME	2167-10-04 16:15:00	EMERGENCY	Private	
19	EMERGENCY ROOM ADMIT	2108-08-05 16:25:00	EMERGENCY	Medicare	C 2 FRACTURE
19	REHAB/DISTINCT PART HOSP	2108-08-11 11:29:00	EMERGENCY	Medicare	
20	PHYS REFERRAL/NORMAL DELI	2183-04-28 09:45:00	ELECTIVE	Medicare	CORONARY ARTERY DISEASE CORONARY ARTERY BYPASS GRAFT SDA
20	HOME	183-05-03 14:45:00	ELECTIVE	Medicare	

Table B.3: Snippet of the hospital admission log.