
Text-Aware Predictive Business Process Monitoring with LSTM Networks

Master's Thesis

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Abstract

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Chapter 1

Introduction

1.1 Motivation

The rapid growth of data generated by large-scale information systems leads to new opportunities for society and businesses. In order to turn the massive amount of data into value, efficient techniques are needed, that are able to extract useful information. The generated value comes in different forms, for example visualizations, models, aggregated data or predictions can be of interest.

A remarkable subset of this data is described as *event data*, which is generated by *process-aware information systems* in order to manage, execute and monitor business processes [1]. With the non stopping rise of digitization of business processes more and more event data becomes utilizable, thus the potential value of this data is exploding.

The scientific engagement aiming to discover, analyze and improve real processes using 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 [2]. The ongoing success of process mining in research has been transferred to businesses, that successfully offer or utilize this technology. Celonis, which is often considered as one of the biggest commercial providers of process mining, has been valued 2.5 billion dollar only 9 years after the company was founded [3].

Modern process mining software tends to focus on continuous analysis rather than the traditional offline and project-based approaches. These business process monitoring systems are a key success factor for many organizations, since they allow to understand and supervise all connected processes of a company in real-time as the data is flowing. The core idea of this approach is to automate process mining and keep a persistent connecting between the business process data and the analytical capabilities.

However, traditional process mining tends to be backward-looking [4], i.e. it rather focuses on answering the question "What did happen?", rather than "What will happen?" or even "What should be done?". Therefore, new techniques are required to add the forward-perspective to process mining software.

1.2 Problem Statement

Businesses can develop a competitive advantage, if their process mining software has predictive capabilities, that allow to predict the future of a running process instance. For example, if it is known beforehand that a running process instance will probably exceed its deadline, measures can be initiated before damage occurs. Furthermore, information about the next event or the future path of process instance can be of interest. In some scenarios, processes instances have an outcome like success/failure or accepted/declined that can be predicted.

Precisely, given an event log with past executions of a process and a running (i.e. not completed) process instance, we would like to answer the following questions:

- What will happen next?
- When will it happen?
- What is the most likely future path of the instance?
- When will the instance finish?
- What is the outcome of the instance?

1.3 Research Goals

This thesis aims to improve current state-of-art approaches for process prediction to improve 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 attribute and textual data associated with each event. Since most current approach are not able to handle textual data, we would like to know to which extend textual data can improve the quality of process prediction. Furthermore, we want to evaluate different design choices for a text-aware process prediction model and point out potential trade-offs.

1.4 Contribution

1.5 Thesis Structure

This thesis is structured in seven chapters. In Chapter 2 the notations, definitions and concepts used in this contribution are introduced. Chapter 3 summarizes relevant scientific contributions which focus on the problem of prediction in process mining to give an overview of already available methods and their capabilities. A novel text-aware process prediction model is presented in Chapter 4. Moreover, the details regarding the implementation of the model are given in Chapter 5. In Chapter 6 the performance of the model is evaluated and compared to current state-of-the-art prediction methods. Finally, in Chapter 7 a conclusion about all findings and an outlook towards future potential research on process prediction is given.

Chapter 2

Preliminaries

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

2.1 Processes and Process Mining

A *business process* is a collection of activities that are performed in a specific order to archive a goal [5]. A single execution of a process is a *case* or *process instance*, which is identified by a case ID. Each performed activity belongs to specific case and is completed at a certain time. For example, a case can be a patient in a hospital, a customer journey or an online order. The time on which an activity for a certain case is performed is specified by a timestamp. The trinity of case, activity and timestamp is called *event*. An event can have more attributes, for example resource, costs or transactional information.

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) [6], which can be extracted from databases. A table-based representation of an artificial event log about patient treatment in a hospital can be seen in Table 2.1.

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 [2] as well as machine learning [7].

Traditionally, process mining is divided into a set of subdisciplines mainly process discovery, conformance checking, process enhancement and process analytics [8]. Process discovery aims to generate process models out of event data in order to understand a process and enable further analysis. Conformance checking is about comparing the intended and observed behavior of a process. On top of these diagnostic approaches, process enhancement deals with the improvement of processes regarding compliance, performance or complexity.

Finally, process analytics focuses on metric and performance evaluation of processes. The

ID	Activity	Timestamp	Resource	Cost	Comment
0	Register patient	01.02.2020:14.12	SYSTEM	0	-
	Consultation	01.02.2020:14.34	John Brown, MD	24.32	The patient reports persistent nausea.
	Blood test	01.02.2020:15.12	Kim Smith	14.23	Tests: Complete blood count
	Evaluate test result	01.02.2020:16.35	John Brown, MD	38.67	No abnormalities in the complete blood count.
	Release patient	01.02.2020:17.24	SYSTEM	0	-
1	Register patient	02.02.2020:08.20	SYSTEM	0	-
	Consultation	02.02.2020:14.12	Jana Simpson, MD	24.32	Noticeable tachycardia. No chronic diseases are known.
	MRI	02.02.2020:14.12	Sara Taylor, MD	352.87	-
	Release patient	02.02.2020:14.12	SYSTEM	0	-
2	Register patient	02.02.2020:09.08	SYSTEM	0	-
	Consultation	02.02.2020:09.14	Jana Simpson, MD	24.32	The patient has severe leg injuries due to a motorcycle accident.
	Patient hospitalized	02.02.2020:09.20	Mike Johnson	130.37	-
...

Table 2.1: Artificial event log of patient treatment in a hospital

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

2.2 Basic Notations and Sequences

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

Definition 2.1 (Sequence). A *sequence* of length $n \in \mathbb{N}_0$ over a set A is an ordered collection of elements defined by function $\sigma: [n] \rightarrow A$, which assigns each index an element of A . A sequence of length n is represented explicitly as $\sigma = \langle a_1, a_2, \dots, a_n \rangle$ with $a_i \in A$ for $1 \leq i \leq n$. In addition, $\langle \rangle$ is the empty sequence of length 0.

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

Given sequences σ_1 and σ_2 , the concatenation of both sequences is denoted $\sigma_1 \cdot \sigma_2$. Moreover, the i -th element of a sequence $\sigma = \langle a_1, a_2, \dots, a_n \rangle$ is accessed by $\sigma(i) = a_i$ for

$1 \leq i \leq n$. The length of a sequence is denoted by $|\sigma|$. For a sequence $\sigma = \langle a_1, a_2, \dots, a_n \rangle$, the function $hd^k(\sigma) = \langle a_1, a_2, \dots, a_k \rangle$ gives the prefix of length k of σ and $tl^k(\sigma) = \langle a_{k+1}, a_{k+2}, \dots, a_n \rangle$ the suffix of length $n - k$, for $0 \leq k \leq n$. Note that $\sigma = hd^k(\sigma) \cdot tl^k(\sigma)$ for corresponding k .

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

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

2.3 Events, Traces, Event Logs

Definition 2.2 (Event). An *event* is defined by tuple $e = (a, c, t, d_1, \dots, d_m) \in \mathcal{C} \times \mathcal{A} \times \mathcal{T} \times \mathcal{D}_1 \times \dots \times \mathcal{D}_m = \mathcal{E}$ where $c \in \mathcal{C}$ is the case ID, $a \in \mathcal{A}$ is the executed activity and $t \in \mathcal{T}$ is the timestamp of the event. Furthermore, each event contains a fixed number $m \in \mathbb{N}_0$ of additional attributes $d_1 \dots d_m$ in their corresponding domains $\mathcal{D}_1, \dots, \mathcal{D}_m$. In case that no additional attribute data is given ($m = 0$) the event space \mathcal{E} (set of all possible events) is reduced to $\mathcal{C} \times \mathcal{A} \times \mathcal{T}$.

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

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

Definition 2.3 (Trace). A *trace* is a finite and non-empty sequence of events $\sigma = \langle e_1, e_2, \dots \rangle \in \mathcal{E}^*$ with increasing timestamps, i.e. $\pi_{\mathcal{T}}(e_i) < \pi_{\mathcal{T}}(e_j)$ for $1 \leq i < j \leq |\sigma|$.

By lifting the projection functions to sequences a trace can be transformed into a sequence of attributes by applying the projection function to the trace. For example, $\pi_{\mathcal{A}}(\sigma)$ gives the sequence of the activities of the events in σ .

Definition 2.4 (Event log). An *event log* $\mathbb{L} = \{\sigma_1, \sigma_2, \dots, \sigma_k\}$ is a set of traces, where each event of a trace is unique in the log and all events of a trace share a case IDs, which is unique per trace.

2.4 Text Mining

Text mining describes all techniques to generate value out of unstructured or semi-structured textual data. It combines concepts of natural language processing, machine learning and data mining [9]. The base object in text mining is a *document* containing textual data. The text can be completely unstructured, i.e. it does not conform to a pre-defined data model, or semi-structured, like in an e-mail, where text information is assigned to sender, subject, message etc. A collection of documents is called *text corpus*, which forms the basis for many text mining techniques.

In order to derive a mathematical representation of the text data that can be interpreted by a computer, a text model has to be build using the text corpus. Popular text models are Bag-of-words, Bag-of-n-gram, Paragraph vector (a.k.a. Doc2Vec) [10] and Latent Dirichlet Allocation [11]. Most models require a text normalization step, where the text is cleaned from linguistic variation as well as meaningless words and symbols [12].

2.5 Supervised Learning

2.6 Long Short-Term Memory Networks

Long short-term memory (LSMT) is an advanced recurrent neural network architecture for sequential data originally presented by Hochreiter and Schmidhuber in 1997 [13]. This approach addresses the well-known vanishing and exploding gradient problem [14] of traditional recurrent neural networks by introducing more complex LSTM cells as hidden units. The proposed architecture has been improved several times [15] [16] and considered as one of the most successful recurrent neural network models. Although LSTM networks have been available for a long time, the breakthrough of this technology is dated around 2016 after many success stories of LSTM in combination with large data sets and GPU hardware have been reported for sequence to sequence tasks like text translation [17].

Gated recurrent units (GRU) [18] are the competing gating mechanism by Cho et al. that have fewer parameters and perform similar to LSTM. However, more recent studies show, that LSTM outperforms GRU consistently in neural machine translation tasks [19].

A simple feedforward neural networks consists of an input layer, arbitrarily many hidden layers and an output layer, where each layer consists of neurons that compute and output the weighted sum of the cells of the previous layer that has been passed to a non-linear activation function [20]. These networks can learn and compute complex functions in supervised learning settings, where input and output pattern are provided. The network computes a loss function for each training pattern and adjusts its weights with gradient descents using a back-propagation algorithm in order to minimize the loss function [21].

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

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

The input vector \mathbf{x}_t is concatenated with the previous hidden output \mathbf{h}_{t-1} and fed to four neural network layers, which are designed to decide what part of the cell state will remain (forget gate \mathbf{f}_t), how it is updated (update gate \mathbf{i}_t and $\bar{\mathbf{c}}_t$) and what the output of the layer will be (output gate \mathbf{o}_t leading to \mathbf{h}_t). The sublayer have pointwise $\text{sigmoid}(x) = \frac{1}{1+e^{-x}}$

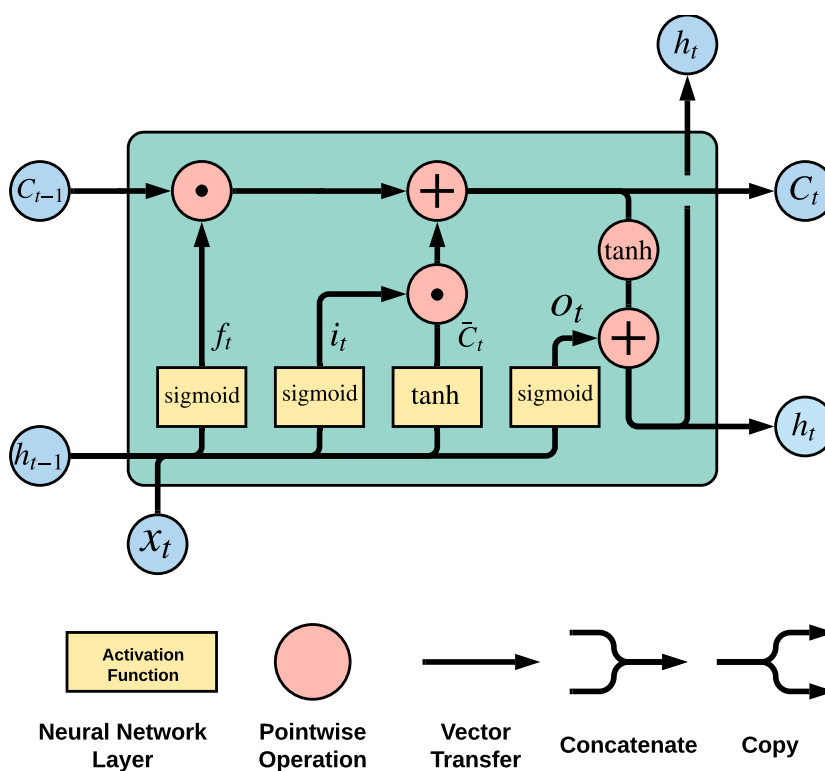


Figure 2.1: An LSTM module with four sublayers that manipulate the cell state and compute the module's output. Graphic adapted from [22].

or $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ activation functions, leading to the following equations:

$$\mathbf{f}_t = \text{sigmoid}(\mathbf{W}_f \cdot (\mathbf{h}_{t-1}, \mathbf{x}_t) + \mathbf{b}_f) \quad (2.1)$$

$$\mathbf{i}_t = \text{sigmoid}(\mathbf{W}_i \cdot (\mathbf{h}_{t-1}, \mathbf{x}_t) + \mathbf{b}_i) \quad (2.2)$$

$$\bar{\mathbf{c}}_t = \tanh(\mathbf{W}_c \cdot (\mathbf{h}_{t-1}, \mathbf{x}_t) + \mathbf{b}_c) \quad (2.3)$$

$$\mathbf{o}_t = \text{sigmoid}(\mathbf{W}_o \cdot (\mathbf{h}_{t-1}, \mathbf{x}_t) + \mathbf{b}_o) \quad (2.4)$$

\mathbf{W}_f , \mathbf{W}_i , \mathbf{W}_c and \mathbf{W}_o are the sublayer's learned weights and \mathbf{b}_f , \mathbf{b}_i , \mathbf{b}_c and \mathbf{b}_o are the corresponding biases.

The new cell state \mathbf{c}_t is then a combination of the old cell state \mathbf{c}_{t-1} and the result of the update gate $\bar{\mathbf{c}}_t$, where the layer computations \mathbf{f}_t and \mathbf{i}_t determine the proportions by a pointwise multiplication (\odot) with the cell states.

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \bar{\mathbf{c}}_t \quad (2.5)$$

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

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t) \quad (2.6)$$

LSTM networks are able to backpropagate a more stable error with this gating mechanism, such that these networks are much more capable of learning complex functions for sequences compared to standard recurrent neural networks.

Chapter 3

Related Work

The prediction of the future behavior of an process instance has been an important sub-field in the process mining research, that aims to enhance process monitoring capabilities. Depending on the use case e.g. predicting time-related attributes, the future path or the the outcome of a case can be of interest. Most approaches presented in the literature either use machine learning based or process models based methods.

van Dongen et al. presented five different non-parametric regression predictors for forecasting the total cycle time of an unfinished case[23]. The estimates are based on activity occurrences, activity duration and attributes.

van der Aalst et al. proposed to build a transition system using a set, bag or sequence abstraction, which is annotated with time-related data in order to predict the remaining time of case [24]. The core idea of this approach is to replay unfinished cases on the learned transition system and compute the prediction using the annotated data.

Pandey et al. use a hidden markov model to predict the remaining time of a case using the activity and timestamp data of an event log [25].

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

Ceci et al. presented an approach, where a sequence tree is learned in order relate a running traces to similar historical traces [27]. A decision tree is then used to predict the next activity and the remaining time of a case.

Teinemaa et al. applied text vectorization techniques like bag-of-n-grams (BoNG), Latent Dirichlet Allocation (LDA) and Paragraph Vectors (PV) to textual data of processes in order to predict a binary label describing the process outcome[28]. In this approach random forest and logistic regression classifiers for each prefix length of a trace are trained.

Most recently, several authors have applied recurrent neural networks in form of LSTM networks for process prediction. Evermann et al. encode events using an embedding matrix as it is known for word embeddings. The embedded events are then used as input for an LSTM network that predicts the next activity[29].

Tax et al. use an one-hot-encoding of the activity and the timestamp of an event to predict

the activity and timestamp of the next event. This is done by using a two-layered LSTM network[30].

The work by Navarin et al. adopts the idea of using an LSTM network [30] and extends the encoding to additional data attributes associated with each event[31] to predict the remaining time of an case.

Polato et al. presented a set of approaches that use support vector regression for remaining time prediction[32]. In this work the authors implement different encoding for events including simple one-hot-encoding and a more advanced state based encoding using transition systems. Furthermore, they enhance the approach in [24] 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 encoding like counting frequencies of activities as most reliable encoding for outcome-prediction [33].

Park and Song showed how LSTM-based predictions can be used to solve a resource allocation problem, leading to direct recommendation for process improvement [34].

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

Contribution	Year	Model(s)	Data-Aware	Text-Aware	Predictions
van Dongen et al. [23]	2008	Regression	✓	✗	Remaining time
van der Aalst et al. [24]	2011	Transition system	✗	✗	Remaining time
Pandey et al. [25]	2011	Hidden Markov	✗	✗	Remaining time
Rogge-Solti and Weske [26]	2013	Stochastic Petri Net	✗	✗	Remaining time
Ceci et al. [27]	2014	Sequence Tree Decision Tree	✓	✗	Next activity Remaining time
Teinemaa et al. [28]	2016	Random Forest Logistic regression	✓	✓	Case outcome
Evermann et al. [29]	2016	LSTM	✗	✗	Next activity
Tax et al. [30]	2017	LSTM	✗	✗	Next activity Future path Next event time Remaining time
Navarin et al. [31]	2017	LSTM	✓	✗	Remaining time
Polato et al. [32]	2018	Transition system SVR Naive Bayes	✓	✗	Next activity Future path Remaining time
Park and Song [34]	2019	LSTM	✓	✗	Next activity Next event time
This contribution	2020	LSTM	✓	✓	Next activity Future path Next event time Remaining time Case outcome

Table 3.1: Comparison of process prediction methods.

Chapter 4

Text-Aware Process Prediction

Text-aware process prediction aims to utilize unstructured text information in event data to improve predictions for unfinished cases. While many prediction methods have been applied to event data, almost none of them are able to handle textual data. An exception is the approach presented in [28], where traces with text data are encoded as fixed vectors and a classifier is learned for each prefix length.

In this chapter a novel approach for process prediction is presented that considers control flow, additional numerical, categorical and textual data, captures temporal dependencies, seasonal variability and concept drifts using an event-wise encoding and a sequential prediction model (LSTM).

4.1 Overview

The proposed framework consists of a preprocessing, encoding and prediction model component, which operate in an offline and online phase. The encoding component distinguishes between categorical or numerical data that can be encoded directly and textual data, which requires a textual model.

In the offline phase a historical event log with completed traces of a business process is used to train the prediction model. Given an event log $\mathbb{L} = \{\sigma_1, \dots, \sigma_l\}$ with historical event data, the set of all prefix traces $\mathbb{L}_{\text{prefix}} = \{\sigma(1, k) \mid \forall \sigma \in \mathbb{L}, 1 \leq k \leq |\sigma|\}$ is computed. Each prefix with the desired target value corresponds to one training example for the prediction model. The total number of training examples that can be generated out of the log is $\sum_{\sigma \in \mathbb{L}} |\sigma|$, which is exactly the number of events in the log.

As target the activity and timestamp (relative to case start) of the next event as well as the outcome and cycle time (time between first and last event) of the case is chosen. For completed cases the next event's activity is an artificial "<Process End>" with the same timestamp as the final event.

The text data of the historical log is extracted to build a text corpus and construct a text model.

The prefix traces are encoded to sequences of fixed-length event vectors using the text model.

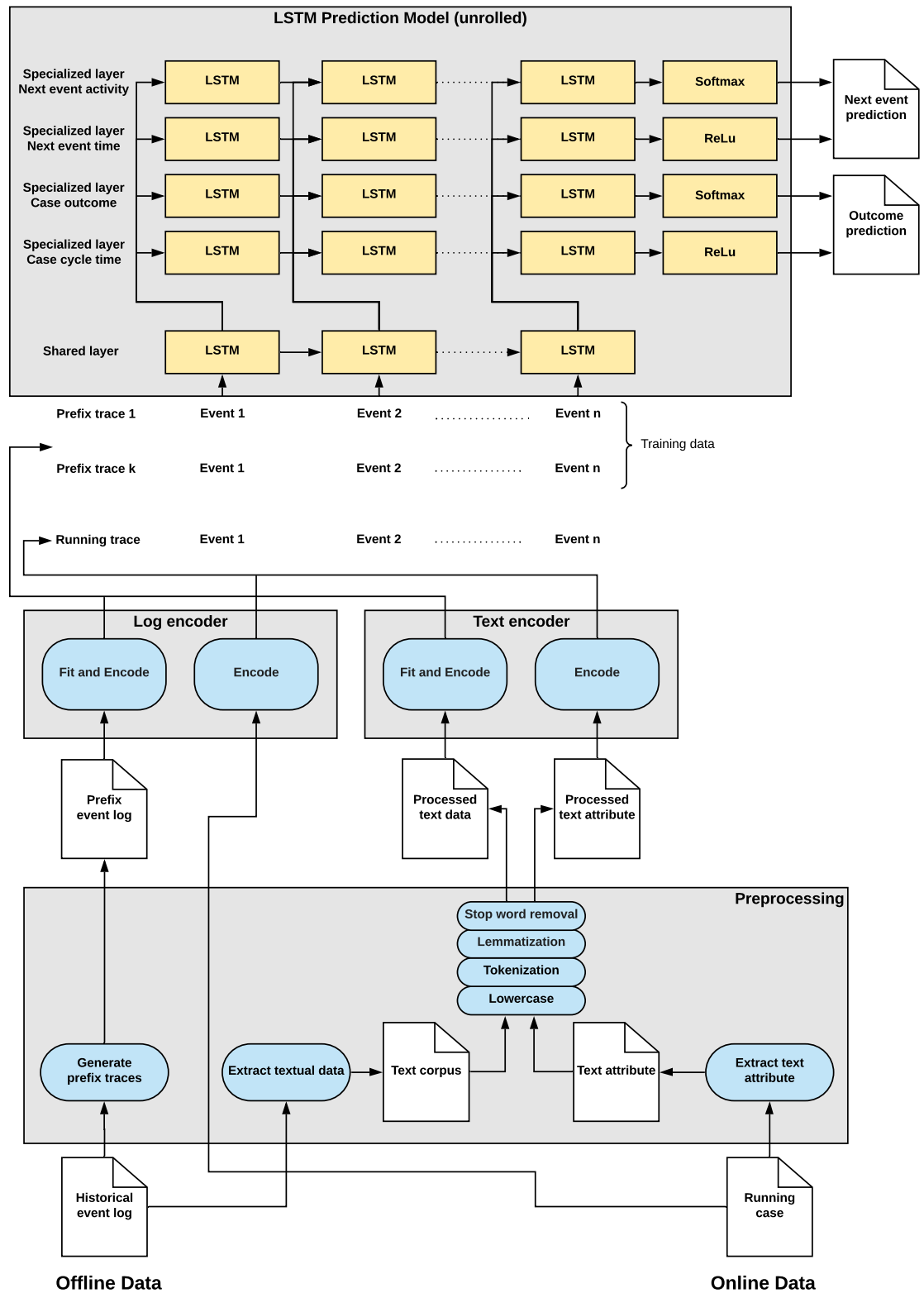


Figure 4.1: Framework

4.2 Event Encoding

In the offline training phase as well as during online prediction, traces are encoded as sequences of event vectors. Each event is encoded as a fixed-length vector using the event’s activity, timestamp and additional categorical, numerical and textual attributes. The encoded event vector is the concatenation of feature vectors, which are constructed from the event data.

The activity of an event is represented using *one-hot encoding*. Given the set of possible activities \mathcal{A} , an arbitrary but fixed ordering over is introduced with a bijective index function $index_{\mathcal{A}} \in \mathcal{A} \rightarrow \{1, \dots, |\mathcal{A}|\}$. 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. We write $\mathbb{1}$

The timestamp of an event is used to compute a set of time-related features, which is

$$\mathbf{x}_e = (\mathbf{a}_e, \mathbf{t}_e, \mathbf{d}_1^{\text{num}}, \dots, \mathbf{d}_r^{\text{num}}, \mathbf{d}_1^{\text{cat}}, \dots, \mathbf{d}_s^{\text{cat}}, \mathbf{d}_1^{\text{text}}, \dots, \mathbf{d}_u^{\text{text}}) \quad (4.1)$$

Feature Vector	Construction	Dimension	Description
\mathbf{a}	$\mathbb{1}(\pi_{\mathcal{A}}(e))$	$ \mathcal{A} $	One-hot encoding of the activity.
\mathbf{t}	See Section 4.3	6	Time-based feature vector.
$\mathbf{d}_i^{\text{num}}$		1	Normalized value of the i -th numerical attribute
$\mathbf{d}_i^{\text{cat}}$	$\mathbb{1}(\pi_{\mathcal{D}_i^{\text{cat}}}(e))$	$ \mathcal{D}_i $	One-hot encoding of the i -th categorical attribute.
$\mathbf{d}_i^{\text{text}}$	See Section 4.4	z_i	Fixed-length vectorization of the i -th text attribute.

Table 4.1: Feature vectors for event encoding.

$$|\mathbf{x}_e| = |\mathcal{A}| + r + \sum_{i=1}^s |\mathcal{D}_i| + \sum_{j=1}^u z_j + 6 \quad (4.2)$$

4.3 Capturing Temporal Dependencies

For timestamp prediction of the next and final event of running process instance a set of time-based features is computed from the timestamp data in the event log. Given an event log \mathbb{L} an event e_i from a trace $\sigma = \langle e_1, \dots, e_n \rangle$ the following time features are computed for the encoding of e_i :

Feature	Description
$t_1 = \pi_{\mathcal{T}}(e_i) - \pi_{\mathcal{T}}(e_{i-1})$	Seconds since previous event
$t_2 = \pi_{\mathcal{T}}(e_i) - \pi_{\mathcal{T}}(e_1)$	Seconds since case start
$t_3 = \pi_{\mathcal{T}}(e_i) - \min\{\pi_{\mathcal{T}}(e_j), \forall e_j \in \sigma_k, \forall \sigma_k \in \mathbb{L}\}$	Seconds since first recorded event
t_4	Seconds since midnight
t_5	Seconds since last Monday
t_6	Seconds since last January 1 00:00

Using the time features a set of time-dependent trends can be captured and utilized for prediction. The features t_1 and t_2 give information about the time between events and

the time of the event in the case. Using t_3 the absolute time position of an event in the data can be determined. This is important to detect concept drift in the process. The features t_4, t_5 and t_6 are used to capture daily, weekly or seasonal trends. For example, some activities might only be executed during office hours, before the weekend, during summer.

Each feature t_1, \dots, t_6 as well as all additional numerical attributes d_i are scaled to the interval $[0, 1]$ to improve learning efficiency using min-max normalizing. The scaling for a numerical feature 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 event log is used for scaling.

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 text data is an important aspect in *Natural Language Processing* (NLP). 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 our setting, the text vectorization is realized in a 2-step procedure. First, all text data associated with the events in the corresponding textual attribute is collected in a so called *text corpus*. Each document in the text corpus is then preprocessed in order to filter out linguistic noise or useless information. Finally, the text corpus is used to build up a vocabulary and a text vectorization technique is applied to encode the text attribute to a fixed of vector.

4.4.1 Text Normalization

In the preprocessing step each document is transformed by a processing pipeline which consists of the following four steps:

1. Letters are converted to lowercase
2. Document is tokenized by word
3. Each word is lemmatized
4. Stop words are filtered out

Step	Transformation	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 4.2: Preprocessing transformation of an example document.

In the tokenization step a document is split up in a list 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". Ultimately, all stop words are filtered out of each document. Stop words are words with low information value like "the", "a", "of" or "here".

Stop word lists are language dependent and can be more or less aggressive at filtering. Usually they contain articles, auxiliary verbs, prepositions and generic verbs like "be" and "have". In addition, punctuation marks or numerical information are excluded.

4.4.2 Bag-of-Words

The *bag-of-words* (BoW) Model is a simple text model, which represents documents based on the *term frequencies* of its words [35]. 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 of the word indexed with i in the document.

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

The 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 inverted. 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 size of the vocabulary. For example, this can be realized for example by omitting certain words.

4.4.3 Bag-of-N-Grams

The *bag-of- n -grams* model is a generalization of the Bag-of-Words model, which addresses the missing word order awareness of the latter. Instead of single words, the vocabulary consists of n -tuples of words, that appear consecutive in the corpus. The unigram model ($n = 1$) is equivalent to the BoW model.

4.4.4 Paragraph Vector

The *Paragraph Vector* also known as *Doc2Vec*, originally presented by Le and Mikolov, is an unsupervised algorithm that learns distributed fixed length vector representations for documents [10].

4.4.5 Latent Dirichlet Allocation

4.5 Network Architecture and Training

4.6 Online Prediction

Chapter 5

Implementation

Chapter 6

Evaluation

Chapter 7

Conclusion

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