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Translucify: Enhancing Event Logs with Enabled Activities Beyond the Control-Flow Perspective

Bachelor's Thesis

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Chapter 1

Introduction

Process Mining is a field of computer science aiming to reconstruct the latent process model from a manifest event data. Together with the surge of data availability, process mining has become a hot topic in the fields of data science and business intelligence.

The foundation of all process mining discovery algorithms is the so-called *event logs*: A chronologically ordered list of every event recorded in a business system. Event logs have three mandatory feature columns. *Case ID* represents which case the event belongs to. *Activitiy* portrays what kind of event happened. *Timestamp* logs the time of occurrence of that specific event.

(Insert an example event log here)

The tree major phases of process mining are *Process Discovery*, *Conformance Checking*, and *Process Enhancement*. Process Discovery is where a process model is extracted from a submitted event log. In Conformance Checking, the quality of the discovered process model is evaluated in terms of various criteria, e.g. fitness, precision, generalization, and simplicity. Finally, in the *enhancement* phase, the idea is to extend or improve the existing process model using the data present in the event log.

1.1 Motivation

Business processes are seldom linear. Instead, they are usually a messy, chaotic, intertangled mash of activities where its golden path is meticulously hidden. On top of that, event logs have no guarantee of completeness. The quality of the process model produced by process-discovery techniques is therefore entirely dependent on the quality of its event log.

In an ideal world where perfect process discovery is conceivable, an event log would be *transparent*, containing metadata of structural properties of the corresponding process model, e.g., state information in a Petri net setting. Event logs, however, are usually *opaque* - one cannot identify the underlying process model straight away by solely looking at the log. One must instead utilize process-discovery algorithms to generate corresponding models. By its nature, process event logs primarily focus on what *happened*. However, they often do not take into consideration what *could have happened* instead. An event log is *translucent* if the log contains the information which potential, alternative realities of the past could have occurred instead of the activity occurred in the real world. Logs of this nature are called *translucent event logs* and are extremely beneficial to enhance the quality of existing process-discovery algorithms.

Let us consider a small example as motivation. Suppose the underlying model of our business process is represented as the petri net below.

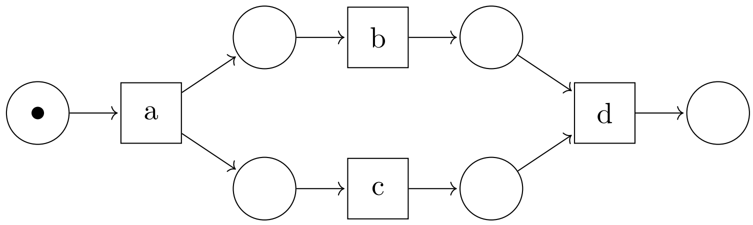

Figure 1.1: Example business model represented as a petri net.

We play-out the model fifty times and retrieve the event log $\mathcal{L}_1 = [\langle a, b, c, d\rangle^{48}, \langle a, c, b, d\rangle^{2}]$ in the process. We can then leverage widely used process-discovery algorithms to rediscover the process model described in Figure 1.1.

This works under the assumption of log completeness, but what would happen if the trace $\langle a, c, b, d\rangle$ occurs so rarely that we weren't able to capture the behavior? Given the incomplete log $\mathcal{L}_1 = [\langle a, b, c, d\rangle^{50}]$, every process-discovery algorithm will return a linear process model. The translucent variant would look like $\mathcal{L}_2 = [\langle \underline{a}, \underline{b}c, \underline{c}, \underline{d}\rangle^{50}]$, where all enabled activities are listed and the executed activity is underscored. Here, the choice situation between activities b and c is clearly visible, thus preventing the linear modelling of our process.

Despite its benefits, lucent models and translucent event logs are relatively new concepts and are therefore scarcely researched. As a result, translucent event logs are hardly available in real-life process logs. This motivates us to devise novel methods to generate translucent event logs from a non-translucent event log.

1.2 Problem Statement

1.2.1 Limitations of Previous Methods

Insufficient Previous Methods

The problem of embedding translucent information in the event log is relatively new and few methods have been proposed so far. This prompts us to explore new methods to annotate event logs with enabled activities.

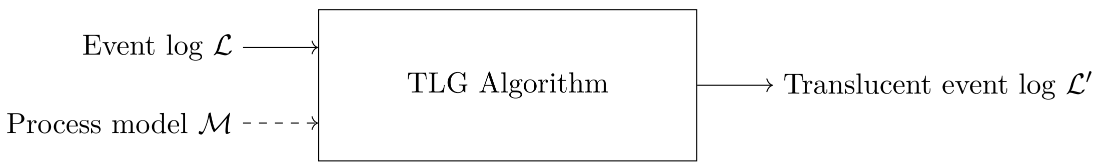

Figure 1.2: Workflow of Translucify. The algorithm takes an event log $\mathcal{L}$ and and optional process model $\mathcal{M}$, then returns an annotated translucent event log $\mathcal{L}'$.

Limitations of Previous Methods

Among the previously suggesting methods, one of them involves annotating the event log with activities which are in turn pattern-matched by labeling the user's system interface. This requires manual labour of labeling individual patterns and are rather unrealistic for real-life systems with a sizable variety of system interfaces. Another method suggests replaying the event log on the provided process model and annotating the enabled activities in the log. This method is more feasible, but the quality of the annotation, i.e., the accuracy of the enabled activities, is heavily dependent on the quality of the process model. As process models returned by process-discovery algorithms such as the Inductive Miner tend to be underfitting, the method above will likely take a superset of enabled activities for each event, thereby reducing its accuracy.

Neglecting the Data-Centered Aspect

Current methods of translucent log annotation are solely focused on the control-flow aspect, even though the data attributes of event logs also contain valuable information and have an impact on activity enablement.

1.2.2 Problem Declaration

Taking these aforementioned aspects into account, our problem statement can be formulated as the followng.

> ***Translucent Log Extension:*** *Given an event log and an auxillary process model, annotate the event log with translucent information while incorporating the data attributes into the computation.*

1.3 Research Questions

In the scope of the thesis, we define the five research questions below:

RQ1. Which techniques can detect enabled activities considering solely the log?

RQ2. Which techniques can detect enabled activities considering the log-model pair?

RQ3. How do these methods compare to each other in terms of accuracy and runtime?

RQ4. How can we design and implement an intuitive, user-friendly tool to demonstrate our results?

1.4 Research Goals

The principal resarch goal of this thesis paper is to explore different methods to annotate event logs with translucent information. Furthermore, by building a meaningful, easily operable end-user framework dedicated to translucent log annotation, the **Translucify** framework should be able to evaluate these methods systematically with respect to its accuracy and runtime.

We hereby explicitly state that while the generated translucent log could be applied for further use, especially for process discovery to enhance previously discovered models, the exact application of generated translucent event logs is not the scope of this thesis. Instead, our sole focus lies on the log enhancement phase.

1.5 Contributions

Chapter 2

Preliminaries

Definition 2.1 (Multisets and sequences)**.** The set of all multisets of a set A is denoted with $\mathbb{B}(A)$. $\sigma = \langle a_1, a_2, \ldots, a_n \rangle \in A^*$ denotes a sequence over A of length $|\sigma| = n$.

2.1 Process Mining

2.1.1 Petri Nets

Definition 2.2 (Petri net)**.** Let P, T be finite, disjoint sets, where T is a set of *places* and T set of *transitions*. A *Petri net* is a triple $N = (P, T, F)$, where $F \subseteq (P \times T) \cup (T \times P)$ is a set of directed arcs between places and transitions.

Petri nets are the standard process model used in process mining, whose biggest advantage is the ability to model concurrent systems. Places of a Petri net correspond to states of a process, whereas transition of a Petri net correspond to event activities. In order to portray this behavior, we label transitions with activity names.

Definition 2.3 (Marked Labeled Petri net)**.** Let $N = (P, T, F)$ be a Petri net. A *labeled Petri net* is an extended tuple $N = (P, T, F, \mathcal{A}, l)$, where $\mathcal{A}$ is a set of activity labels and $l : T \to \mathcal{A}$ is a labeling function. A *marked Petri net* is an ordered pair (N, M) where $M \in \mathbb{B}(P)$ is a multiset over P.

There are cases where a transition does not correspond to any of the activity names in the event log, as some are only used to model the control flow of a Petri net. These transitions are called *silent transitions* (also τ-transitions) and are denoted with the activity name τ.

Definition 2.4 (Firing rule)**.** Let (N, M) be a marked Petri net. A transition $t \in T$ is *enabled* in M if and only if ${}^\bullet t \leq M$. We also characterize this property using the notation $(N, M)[t\rangle$. The set of enabled transitions in a marked Petri net (N, M) is denoted as $en(N, M) = \{t \in T \mid {}^\bullet t \leq M\}$.

An enabled transition can be fired, which removes a token from each of its input places and adds a token to each of its output places.

Definition 2.5 (Firing rule)**.** Let (N, M) be a marked Petri net. The firing of a transition $t \in T$ is denoted as $(N, M)[t\rangle(N, M')$, where $M' = (M / {}^\bullet t) \cup t^\bullet$.

Let $\sigma = \langle t_1, t_2, \dots, t_n \rangle \in T^*$ be a sequence of transitions. $(N, M)[\sigma\rangle(N, M')$ denotes that there exists a sequence of markings $\langle M_1 = M, M_2, \dots, M_{n+1} = M' \rangle$ so that $(N, M_i)[t_i\rangle(N, M_{i+1})$ for all $1 \leq i \leq n$. The set of all reachable markings from M is denoted as $[N, M\rangle = \{M' \mid (N, M)[\sigma\rangle(N, M')\}$ for some $\sigma \in T^*$.

(Show example of a marked Petri net and the firing sequence)

Definition 2.6 (Lucency)**.** Let (N, M) be a marked Petri net. (N, M) is *lucent* if and only if:

$$\forall M_1, M_2 \in [N, M\rangle : en(N, M_1) = en(N, M_2) \Rightarrow M_1 = M_2.$$

Definition 2.7 (Stoachastic Data Petri net)**.** Let $N = (P, T, F, \mathcal{A}, l)$ be a labeled Petri net. A tuple $(P, T, F, \mathcal{A}, l, \omega)$ is *stochastic* if and only if $\omega : T \times \Delta \to \mathbb{R}^+$ is a weight function.

Given a state $p \in P$ and a data state $\delta \in \Delta$, the probability that the Petri net N fires a transition $t \in p^\bullet$ is given as the following equation:

$$p(t \mid p, \delta) = \frac{\omega(t, \delta)}{\sum_{t' \in p^\bullet} \omega(t', \delta)}.$$

2.1.2 Event Logs

Definition 2.8 (Event)**.** Let $\mathcal{E}$ be the event universe. An *event* $e \in \mathcal{E}$ is a logical abstraction of a real-life process event. An event possesses multiple named attributes. We define the universe of all attribute names as $\mathcal{AN}$ and the universe of all attribute values as $\mathcal{AV}$.

Based on this, we define the attribute projection function $\pi : \mathcal{E} \times \mathcal{AN} \to \mathcal{AV} \cup \{\bot\}$, where π is a partial function mapping the attribute name of every event to an attribute value (otherwise a none value $\bot$). Following the convention in [1], we denote the signature $\pi(e, n)$ as $\pi_n(e)$ for all $e \in \mathcal{E}, n \in \mathcal{AN}$.

Subsequently, a collection of events form an event log of a system process.

Definition 2.9 (Event Log)**.** Let $\mathcal{C}, \mathcal{A}, \mathcal{T} \subseteq \mathcal{AV}$, where $\mathcal{C}$ is the universe of case identifiers, $\mathcal{A}$ the universe of activity names, and $\mathcal{T}$ the universe of timestamps. An event log $\mathcal{L} \subseteq \mathcal{E}$ is a subset of the event universe such that for all events $e \in \mathcal{L}$:

- $\pi_{case}(e) \in \mathcal{C}$ is the case identifier,
- $\pi_{act}(e) \in \mathcal{A}$ is the activity name,
- $\pi_{time}(e) \in \mathcal{T}$ is the timestamp.

We further assume that in a conventional event log, there exists a total order $<_{time}$ on $\mathcal{L}$ such that for all $e, e' \in \mathcal{L} : e <_{time} e' \Leftrightarrow \pi_{time}(e) < \pi_{time}(e')$, i.e. the events are sorted by their timestamps in chronological order.

We can further group events by their case identifiers. A sequence of events with the same case identifier ordered by $<_{time}$ is called a *trace*. Note that the set of all traces of an event log is pairwise disjoint, i.e., there is no event $e \in \mathcal{E}$ which is an element of two different traces. Hence, an event log can also be represented as a set of traces.

Definition 2.10 (Trace)**.** Let $\mathcal{E}$ be the event universe. A *trace* is a sequence of events $\sigma = \langle e_1, e_2, \ldots, e_n \rangle \in \mathcal{E}^*$ such that for all $i \in \{1, \ldots, n-1\} : \pi_{case}(e_i) = \pi_{case}(e_{i+1})$.

However, when discussing about traces, we oftentimes refer to them as a sequence of activities. This is firstly for the sake of simplicity, but also due to the fact that the control flow is considered to be the most crucial aspect in process mining, in particular when constructing process models. Event logs where each trace is solely represented as a sequence of activities is called a *simple event log.*

Definition 2.11 (Simple Event Log)**.** Let $\mathcal{L}$ be an event log and $\sigma \in \mathcal{L}$ a trace. We expand the attribute projection function analogously for traces as the following: $\pi_n(\sigma) = \pi_n(\langle e_1, e_2, \ldots, e_n \rangle) = \langle \pi_n(e_1), \pi_n(e_2), \ldots, \pi_n(e_n) \rangle$. $\mathcal{L}'$ is a simple event log of $\mathcal{L}$, if:

$$L' = \bigcup_{\sigma \in \mathcal{L}} \pi_{act}(\sigma).$$

Since we are projecting only the activity names of each event, we lose the uniqueness of each event, resulting in losing the uniqueness of each trace as well. In the simple event log setting, we therefore need to represent the event log as a multiset of traces.

The objective of our thesis is to transform conventional event logs into translucent event logs by annotating each event $e \in \mathcal{E}$ with an additional attribute *en*. *en* specifies all activities which could have happened the moment $\pi_{act}(e)$ occurred. We formally define the notion of translucent event logs below.

Definition 2.12 (Translucent Event Log)**.** Let $\mathcal{L}$ be an event log. $\mathcal{L}$ is *translucent* if and only if for all $e \in \mathcal{L} : \pi_{en}(e) \subseteq \mathcal{A} \wedge \pi_{act}(e) \in \pi_{en}(e)$.

(Example of a translucent event log)

2.1.3 Transition Systems

Definition 2.13 (Transition System)**.** Let S be the set of states, A the set of activities, and $T \subseteq S \times A \times S$ the set of transitions. A *transition system* is a triple $TS = (S, A, T)$. We denote the set of initial states as S^{start} and the set of final states as S^{end}, where $S^{start}, S^{end} \subseteq S$.

Transition systems are an alternative method next to Petri nets to represent processes of a system. Due to its structural property, silent transitions are absent in transition systems. This relieves us from the need to compute alignments when replaying the event log on the model.

Definition 2.14 (Prefix Automaton)**.** Let $\mathcal{L}$ be an event log and $l^{state} : \mathcal{L} \times \mathbf{N} \to S$ a state representation function. $TS_{L,l^{state}} = (S, A, T)$ is a transition system based on $\mathcal{L}$ and l^{state} with the following properties:

- $S = \{l^{state}(\sigma, k) \mid \sigma \in \mathcal{L} \wedge 0 \leq k \leq |\sigma|\}$ the state space,
- $A = \{\sigma(k) \mid \sigma \in \mathcal{L} \wedge 1 \leq k \leq |\sigma|\}$ the set of activities of the event log,
- $T = \{(l^{state}(\sigma, k), \sigma(k+1), l^{state}(\sigma, k+1)) \mid \sigma \in \mathcal{L} \wedge 0 \leq k < |\sigma|\}$ the set of transitions,
- $S^{start} = \{l^{state}(\sigma, 0) \mid \sigma \in \mathcal{L}\}$ the set of initial states, and
- $S^{end} = \{l^{state}(\sigma, |\sigma|) \mid \sigma \in \mathcal{L}\}$ the set of final states.

(Show example of a prefix automaton)

Frequently used examples of a state representation function take the prefix function hd^k as its baseline mechanism. Among diverse methods of process representation using transition systems, we focus on the list, set, and multiset representations.

(Show example of the set and multiset variant of previous example)

All these three variants have their own advantages and disadvantages. The list representation is the most precise, as it preserves the activity order of each trace. However, analyzing parallel situations is difficult due to the very same characteristics of order preservation. Moreover, the representation fails at recognizing loops in the inherent process model and is therefore susceptible to overfitting.

The set representation, on the other hand, is more general and does not suffer from order preservation issues as the list representation does. Although the property of order negligance is practical for local loops and parallel situations, it is critical for larger loops. Consider e.g. nested loops or a loop situation where all activities have been already visited in the first iteration. This would lead to drastic state simplification and the resulting information loss. here, it is crucial to select an optimal prefix length k.

The multiset representation is a compromise between the list and set representations. However, it is still not able to correctly capture the loop behavior, as each iteration would create a new set of states.

2.2 Machine Learning Algorithms

2.2.1 Conventional Machine Learning Algorithms

Random Forest

Logistic Regression

2.2.2 Deep Learning Algorithms

Transformer Architecture

Chapter 3

Related Work

3.1 Data-Aware Process Mining

Conventional process discovery algorithms only consider the control-flow aspect of the process, i.e., the activity attribute of the event log, thereby ignoring the data attributes the event log provides. Data-aware process mining, on the other hand, attempts to incorporate both the control-flow and data attributes of the event log. The prevalent repretoire is to discover decision points in the model and to annotate them with guard functions, which in turn are discovered with decision trees. This method of process enhancement is called *decision mining* [2–4], and is a well-estalished field of research within process mining. [4] proposes a Petri net with data *(DPN-net)* setting to expand the notation of Petri nets. While previous papers worked with the assumption of deterministic, mutual exclusive transition behavior in decision points, they do not take into account how certain decisions cannot be modeled dichotomously. Often, one needs a softer classification assumption, stating that data attributes affect the decision probabilistically. [5] further extends the concept of data-annotated Petri nets by integrating stochastic information into the model. In the paper, the authors introduce the concept of stochastic labeled data Petri nets *SLDPNs* and propose a method to generate an SLDPN from a Petri net and an event log. Each transition will be mapped with its own weight function learned with the activiation instances of individual transitions using logistic regression.

3.2 Translucent Event Logs

Little research has been performed on the topic of translucent event logs. Being a relatively young concept in the field of process mining, they were first hinted in 2018 by [6], where a possible event log revealing the set of enabled activities is mentioned. [7] formally introduces and defines translucent event logs and relates concepts of lucency and translucency by showing that a lucent process model can be rediscovered by using a translucent event log retrieved from the model. Methods of creating translucent event logs are first discussed in [8]. Here, a system's screenshot is matched with the labelled activity pattern and annotated with the corresponding activities. Furthermore, a model-based approach is introduced by replaying the event log on the model and annotating enabled activities. [9] formally introduces a precision measure between a Petri net and a translucent event log by comparing log-enabled activities and model-enabled activities.

3.3 Predictive Process Monitoring

- Explain the term and list previous differnet approaches
- Lin et al. [10]: Next event and next data attribute prediction using RNNs
- Gunnarsson et al. [11]: Remaining trace and runtime prediction using LSTMs
- Bukhsh et al. [12]: Next activity, next event time, and remaining time prediction using transformer architecture
- General overview of the field is given in [13].

Chapter 4

Translucifying the Event Log

4.1 Framework Overview

In order to look deeper into the main problem of this thesis, we first formally define our problem as described below.

Definition 4.1 (Translucent Log Extension Problem)**.** Given an event log $\mathcal{L}$ as input, produce a translucent event log $\mathcal{L}'$ where the set of enabled activities are added as attributes.

There is a variant of the *Translucent Log Extension Problem*, where a process model is provided along with the event log.

Definition 4.2 (Translucent Log Extension Problem - Process Model Variant)**.** Given an event log $\mathcal{L}$ and a process model $\mathcal{M}$ as inputs, produce a translucent event log $\mathcal{L}'$ where the set of enabled activities are added as attributes.

The second variant differs from the first, as the model is meant to act as a reference model; the set of enabled activities is intended to be constrained by the process model. Note that the function of $\mathcal{M}$ is to provide an upper bound on the set of enabled activities, and the log is there to provide further constraints to enrich the model. Of particular interest are parallel and choice situations, since we are able to deduce supplementary patterns not demonstrated in the process model using log data. We name the first variant defined in Definition 4.1 as *Bottom-up Translucent Log Extension Problem*, whereas the second variant in Definition 4.2 is named as *Top-down Translucent Log Extension Problem.*

4.2 Top-down Approaches

4.2.1 Petri Net-based Approaches

The basic notion of Petri nets was introduced in the previous chapter. . . .

Given a Petri net and an event log, the program utiltizes the alignment-based appraoch presented in [8] as its baseline algorithm. After computing the alignment for each trace, the program replays the alignment on the reachabiliy graph trace by trace in order to circumvent the silent transitions. For each activity, the algorithm then augments the event log with the corresponding transitions situated in outgoing arcs of the current state. After creating a basic translucent event log, the log can be refined by further algorithms.

...

When annotating the event log with enabled activities, it might make sense to assume that not all activities enabled in the model are enabled in reality. The model might be too permissive to guarantee its fitness to the event log, and the set of enabled activities depicted in the model should therefore be considered as an upper bound of the actual set. Here, instead of applying a hard-line policy by adding guards to the transitions as done in the field of decision mining, we can utilize a probabilistic approach to filter out the activities. An important question would be how we should compute the transition probability of the model. This is where the PLDPN model comes into play.

A method to incorporate the data attributes is to implement multivariate regression. Similar to the setting in [5], we construct a training data set for each transition of a Petri net consisting of data attributes and a boolean label indicating whether the transition was executed given the data attributes as input. We then perform a regression analysis on the training data set for each transition. The resulting dictionary of transitions and regression functions can be employed to filter out transitions lying below a certain probability threshold p in each decision point during replay.

The method how to construct an SLDPN is already introduced in Christopher's paper. Should I repeat them here, or should I just refer to the paper? I think it would be better for the reader to repeat them here, but does it count as plagiarism?

4.2.2 Transition System-based Approaches

... One of the advantages of utilizing transition systems over Petri nets is the lack of silent transitions. When trying to replay a trace on a Petri net in the presence of silent transition, the algorithm must decide which path of the firing sequence it should take by computing alignments with a certain cost function, then taking the path with the minimal cost. This can be computationally expensive and time-consuming, especially for larger models where the number of silent transitions is high. Transition systems can benefit us in this regard.

Definition 4.3 (Frequency-Annotated Prefix Automaton)**.** Let $\mathcal{L}$ be a simple event log. A *Frequency-Annotated Prefix Automaton (FAPA)* is a tuple $PA_{freq} = (S, A, T, f)$, where (S, A, T) is a prefix automaton $TS_{L,hd}$ following the definition 2.14 and $f : S \to \mathbb{N}, \sigma_{pref} \mapsto |\{\sigma \in \mathcal{L} \mid \sigma_{pref} \sqsubseteq \sigma\}|$ is a frequency labeling function.

Let us look at a small example. Consider the simple event log $\mathcal{L} = [\langle a, b, c\rangle^{30}, \langle a, b, d\rangle^{10}]$. In order to generate an FAPA from $\mathcal{L}$, we can use the following algorithm:

The resulting FAPA is depicted in 4.1. The frequency labeling function f is represented as in the usual superscript notation used in trace multiset of simple event logs.

Given a certain threshold, a simple algorithm would be to iterate over each trace in the event log and annotating the enabled activities with transitions lying above the threshold. For a threshold value of e.g. $t = 0.5$, the resulting simple translucent event log would be: $[\langle \underline{a}, \underline{b}, \underline{c}\rangle^{30}, \langle \underline{a}, \underline{b}, c\underline{d}\rangle^{10}]$. Note that annotating enabled activites using conventional prefix automata can be considered as a special case of this problem with threshold $t = 0$.

Algorithm 1: FAPA Generation

for $\sigma \in \mathcal{L}$ **do**
    for $i \in |\sigma|$ **do**
        $\sigma_{pref} \leftarrow hd_i(\sigma)$;
        $f(\sigma) \leftarrow f(\sigma) + 1$;
    end
end

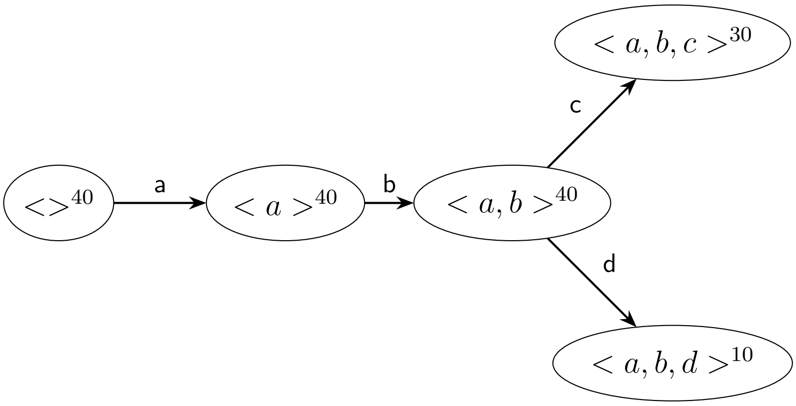

Figure 4.1: Resulting FAPA from $\mathcal{L}$.

4.3 Bottom-up Approaches

- Given an event log, we compute the set of unique activities and generate a next-activity matrix $\mathcal{A}$, where the entry $\mathcal{A}_{ij}$ represents the number of times activity j follows activity i. We can then easily transform $\mathcal{A}$ into a probability matrix $\mathcal{A}'$ by dividing each row by the sum of the row. We then filter out the results by a certain threshold p and add the entries surviving the threshold to each event trace. This algorithm can serve as baseline for further extensions.
- Furthermore, we can utilitze a deep-learning based black-box approach. The issue with implementing supervised learning algorithms is that we need a labeled training dataset. In our case, this would be a preexisting translucent event log, which is unavailable in our setting due to missing enabled activities data. We can cirucmvent the problem by training the model using the next activity information as label, as this information is available in every event log. Since most learning algorithms would not return a single value but an underlying probability distribution of possible outcomes, we can substitute the final *argmax* operation with selecting a threshold p and returning all labels lying above it.

Note that this is not the final list as we are still in the process of selecting new methods. The final list of methods will be updated in the final version of the thesis paper.

Chapter 5

Implementation

- The program should accept an event log and an optional process model, e.g. a Petri net, as inputs and should return a corresponding translucent event log as output. Users should have the option to select from various methods of log generation, will will be specified below. Mainly, these methods can be classified in two categories: top-down approaches which require a Petri net, and bottom-up approaches which solely need the event log.

Chapter 6

Evaluation

- Limitations: Using real-life translucent event logs is often implausible for our scenario due to the fact that most real-life logs do not contain the set of enabled activities. Therefore, direct evaluation by receiving a real-life translucent event log as input, stripping away the enabled activities column, inserting the log in our algorithm as input then comparing the result with the original translucent event log is not possible.
- Instead, we can use artificial process models. The evaluation process works like the following:
    1. We generate random process models, e.g. data Petri nets.
    2. We then play-out the model randomly and extract 1. a normal log and 2. a translucent event log.
    3. We then use the normal log as input to our TLG program and compare the result with the original translucent log.
- On top of that, we can also evaluate its versatility by directly comparing models generated using translucent event logs and the usual state-of-the-art process discovery algorithms. The evaluation process works like the following:
    1. Given a normal process log, we use state-of-the-art process discovery algorithms to generate process models.
    2. We use the log as input to our program and generate a translucent event log.
    3. We then generate a process model based on translucent-log based process discovery algorithms.
    4. We then compare the models based on their performance measures.
- In the model annotation setting, we can evaluate the performance of the model extension algorithm by comparing the stochastic precision of the annotated model with the original model. The evaluation process works like the following:
    1. We iterate over each trace and replay it on two models: The original model received as input and the annotated model.

2. For each transition, we calculate the stochastic precision by computing the product of the transition probabilities in each transition step.
3. We then add up the stochastic precision score for each trace and divide it by the total number of traces to get the average stochastic precision score.

Note that this is different from the translucent precision score defined in [9], since we need a precision measure comparable and applicable to both of the original log-model-pair and the translucent-log-annotated-model pair.

- As we are not presenting a single generation method, it will be necessary to compare and evaluate each method separately using the process described above.

Chapter 7

Discussion

Chapter 8

Conclusion

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