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Data-driven process discovery

Reproduktion und kritische Betrachtung der Ergebnisse von F. Mannhardt et al.(TU/e)

Abschlussarbeit im Hauptseminar - Hot Topics in Data Science
vorgelegt von

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Declaration of Authorship

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HOCHSCHULE DARMSTADT

Abstract

Faculty Name
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Master of Science (M.Sc.)

Data-driven process discovery

by Lisa Stolz

Ziel dieser Seminararbeit ist die kritische Auseinandersetzung mit dem Paper "Data-driven process discovery: revealing conditional infrequent behavior from event logs“ von F. Mannhardt et. al. der Technischen Univerität Eindhoven.
Die Autoren stellen in dieser Arbeit den „Data-aware Heuristic Miner“ (DHM) vor, welcher bisherige heuristische Process Mining Ansätze um ein Maß der bedingten Abhängigkeit erweitert.
Der DHM basiert auf der Idee, dass seltenes - jedoch durch Daten gestütztes - Prozessverhalten nicht als Hintergrundrauschen verworfen werden sollte. Die Autoren erklären in ihrer Arbeit zunächst die theoretischen Hintergründe des DHM und zeigen anschließend die Ergebnisse der Evaluierung in ProM.

In dieser Arbeit wird zunächst ein kurzer Überblick über den DHM und die Erweiterung bisheriger heuristischer Ansätze des Process Mining gegeben.[1] Der Schwerpunkt liegt anschließend auf der praktischen Anwendung des Pakets „DataAwareC-NetMiner“ in ProM, einem interaktiven Tool, das einen schnellen Vergleich mit dem „standard Flexible Heuristic Miner“ erlaubt.
Zunächst werden die im Paper dargestellten Evaluierungen reproduziert und getestet ob die Ergebnisse nachvollzogen werden können.
Die erste Evaluierung basiert auf einem synthetisch generierten Datensatz und die zweite auf realen Event Logs zu Strafzetteln im italienischen Straßenverkehr und Krankenhausrechnungen eines Enterprise Resource Planing Tools.
Wenn die Ergebnisse und das Vorgehen der Autoren reproduziert werden können, werden im Anschluss die Versuchsparameter variiert (z.B. Klassifizierung durch Entscheidungsbäume C3.4 und Objektivitätsmaß Cohens Kappa). Schließlich werden die bis dahin getesteten Mining Methoden auf einen neuen Eventlog Datensatz angewendet und mit den bisherigen Ergebnissen verglichen.

[1] Man17.

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List of Abbreviations

DHM	**D**ata-aware **H**euristic **M**iner
HM	**H**euristic **M**iner
IM	**I**nductive **M**iner

List of Symbols

$C = (\Sigma, s_i, s_o, D, I, O)$	Causal nets (C-nets tuple)
Σ	finite set of activities
$s_i \in \Sigma$	unique start activity
$s_o \in \Sigma$	unique end activity
$D \subseteq \Sigma \times \Sigma$	dependency relation
$B = \{X \subseteq \mathscr{P}(\Sigma) \mid X = \{\varnothing\} \vee \varnothing \notin X\}$	possible bindings
$I \in \Sigma \to B$	set of input bindings per activity
$O \in \Sigma \to B$	set of output bindings per activity
A	attributes
U	values
$L = (E, \Sigma, \#, L)$	event log
E	finite set of unique event identifiers
$\Sigma \subseteq U$	a finite set of activities
$\# : E \to (A \nrightarrow U)$	obtains the attribute values recorded for an event
$\mathscr{L} \subseteq E^*$	the set of traces over E
$\sigma \in L$	one trace - sequence of events for one process instance

Chapter 1

Introduction

Process Models are everywhere - not only in the business world, but they can also be found in social networks, politics and official bodies or Technology. There are two main approaches to a process model. Either they are written in advance to be followed i.e. by employees in a company that introduces new processes to comply with regulatory standard, or they are derived from existing behavior. The latter one describes the field of Process Mining, which relies on digital traces of actions.

The general idea to inspect the data and discover that certain actions follow each other is straight forward, however it becomes more difficult once there are several steps which can follow one action. Are these actions executed in parallel or only one of them exclusively? Do they have to be completed in a certain order?
Even more complex is the question if rare events and actions which can be found in the data are part of the process or just random noise in the sense that they don't belong in the model and can be discarded.

In their paper "Data-driven process discovery: revealing conditional infrequent behavior from event logs", F. Mannhardt et. al. from the Eindhoven University of Technology describe their approach to handle rare events in the data. They introduce the „Data-aware Heuristic Miner" (DHM) which applies classification techniques in order to derive dependencies between activities and thus distinguish between noise and infrequent behavior.

This seminar paper gives an insight into Process Mining following the approach of F. Mannhardt et. al.
In Chapter two the basic concepts of Business Process Mining will be explained - based on concepts applied by the authors. After explaining the theoretical concept of the DHM the results of the empirical evaluation from the paper shall be reproduced and presented in Chapter three.
The free, interactive tool „ProM" was used for evaluating the the DHM approach and for replicating the authors results in this seminar paper, the package „interactive DataAwareCNetMiner" will be applied.
In Chapter four the most important results will be summed up and the main conclusions from this paper presented. In the end an outlook to further research questions and connected fields of interest will be provided.

Chapter 2

Business Process Mining

2.1 Basic Concepts of Process Mining

Before introducing the Data-aware Heuristic Miner, the basic concepts of Process Mining will be introduced in order to provide a good understanding of Business Process Mining beforehand.
The work in the field of Processes can be seen as a process it self. In order to distinguish the focus of this seminar paper from other fields of research, the main steps are displayed in the following figure.

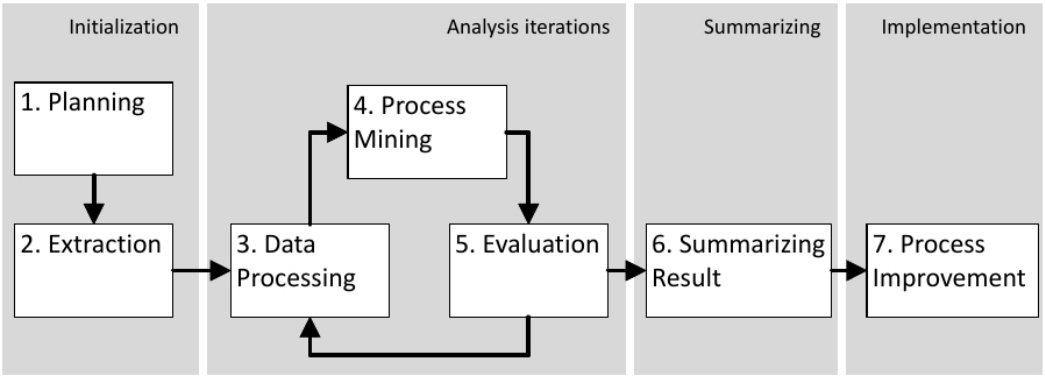


FIGURE 2.1: Steps in Process Mining[Bui16]

The DHM is a new mining method and thus the main focus lies on step 4. and only partly on 3. and 5. when reproducing the results and testing further functionalities in ProM. [Bui16]

2.1.1 Event logs, Petri nets and model criteria

Event logs store information about **activities** and each execution of a process produces a sequence of **events**. Events are stored with attributes A and values U in traces $\sigma \in \mathscr{L}$.
Thus an event log $L = (E, \Sigma, \#, L)$ consists of:

- E - a finite set of unique event identifiers
- $\Sigma \subseteq U$ - a finite set of activities
- $\# : E \to (A \nrightarrow U)$ - attribute values recorded for an event
- $\mathscr{L} \subseteq E^*$ - the set of traces over E

- $\sigma \in \mathscr{L}$ - traces, which record the sequence of events for one process instance - each event occurs only in a single trace

In the following figure this can be seen for three traces with attributes **act**ivity, **p**riority, **n**urse and **t**ype. The emergency ward example will be used throughout this paper and in Chapter three it will be explained in more detail, when reproducing the results for the DHM. [Man17]

(a) Trace $\sigma_1 \in \mathscr{L}$

id	act	p	n	t
e_{11}	Triage	Red		
e_{12}	Register		Joe	
e_{13}	Check			
e_{14}	Check			
e_{15}	Check			
e_{16}	Visit			
e_{17}	X-Ray			
e_{18}	F. Visit			ICU
e_{19}	Prepare			

(b) Trace $\sigma_2 \in \mathscr{L}$

id	act	p	n	t
e_{21}	Triage	Red		
e_{22}	Register		Alice	
e_{23}	Check			
e_{24}	X-Ray			
e_{25}	Visit			
e_{26}	Check			
e_{27}	F. Visit			out
e_{28}	Prepare			
e_{29}	Org. Amb.			

(c) Trace $\sigma_3 \in \mathscr{L}$

id	act	p	n	t
e_{31}	Triage	Red		
e_{32}	Register		Joe	
e_{33}	Check			
e_{34}	Visit			
e_{35}	X-Ray			
e_{36}	Check			
e_{37}	Check			
e_{38}	F. Visit			NC
e_{39}	Prepare			

FIGURE 2.2: Three traces of an example process of the emergency ward data [Man17]

While the data is presented in event logs - consisting of traces, the model derived from it, can be displayed in graphical form (i.e. Petri net, C-net, BPMN). Common patterns, which can be displayed by a Petri net are Sequences, Choice [e, f], Parallelism [b, c, d], and Loops.

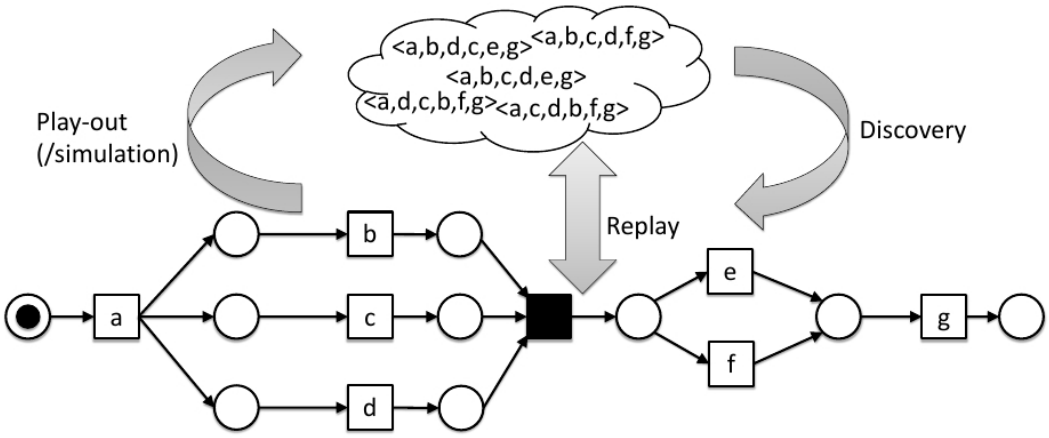


FIGURE 2.3: A Petri net derived from Event logs[Bui16]

Once a model has been discovered the following criteria should be considered:

1. Soundness: Are the criteria for Soundness met?
2. Replay Fitness: Can all traces be represented by the model?
3. Precision: Can the model represent additional cases, not seen in the traces?
4. Generalization: Is the model restrictive or can it be applied in general?

5. Simplicity: Is the model as simple as possible?

Soundness

1. Option to complete
   For each possible state of the process model, it is possible to reach the end state
2. Proper completion
   When the process model reaches the end state, there are no tokens left behind
3. No dead transitions
   Each transition in the process model can be enabled
   [Bui16]

2.1.2 Causal Nets

Conventional model notations like Petri nets and BPMN are often not able to represent observed behavior properly and discovered process models tend to have dead- or livelocks. For this reason C-nets are preferred by the authors as representation for their DHM.
In a Causal-net (C-net) nodes represent activities and arcs represent causal dependencies. Each activity has a set of possible input bindings and a set of possible output bindings. For example in the following Figure the Activity "Register" has one input binding from "Triage" but two sets of output bindings {"Check", "Visit"}, {"Check", "X-Ray"}. This means that "Register" is either followed by "Check" and "Visit" or "Check" and "X-Ray".[Man17][VAV11]

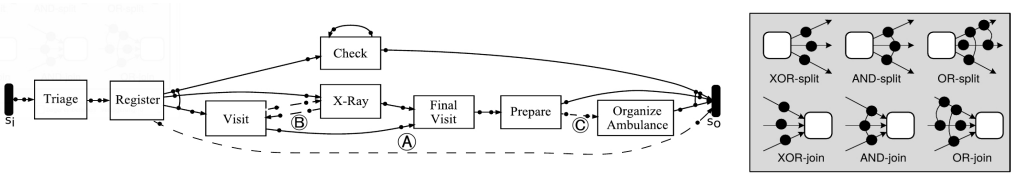


FIGURE 2.4: C-net of the emergency ward example process[Man17][**VanDerAlst11**]

In mathematical notation a C-net is a tuple $C = (\Sigma, s_i, s_o, D, I, O)$, consisting of:

- Σ finite set of activities
- $s_i \in \Sigma$ unique start activity
- $s_o \in \Sigma$ unique end activity
- $D \subseteq \Sigma \times \Sigma$ dependency relation
- $B = \{X \subseteq \mathscr{P}(\Sigma) \mid X = \{\varnothing\} \vee \varnothing \notin X\}$ possible bindings
- $I \in \Sigma \to B$ set of input bindings per activity
- $O \in \Sigma \to B$ set of output bindings per activity
  [Man17]

2.2 Mining Methods

In order to discover an adequate process model the DHM builds on methods, which are applied in several established miners. The concepts of relation notation, footprint- / dependency matrices and classification by decision trees in an event log, will be briefly introduced in connection to the respective miner.

2.2.1 Alpha Miner

This very basic miner was the first to bridge from Event Logs to Petri nets. First a footprint matrix is detected from the event log. By applying the following notation, it can be interpreted from the symmetric matrix, that b follows a, but e, f and g never follow a.

$>$	Directly follows	a $>$ b	a is directly followed by b
$\rightarrow$	Sequence	a $\rightarrow$ b	if $a > b$ and not $b > a$
||	Parallel	a || b	if both a > b and b > a
#	No direct relation	a # b	if neither $a > b$ and $b > a$

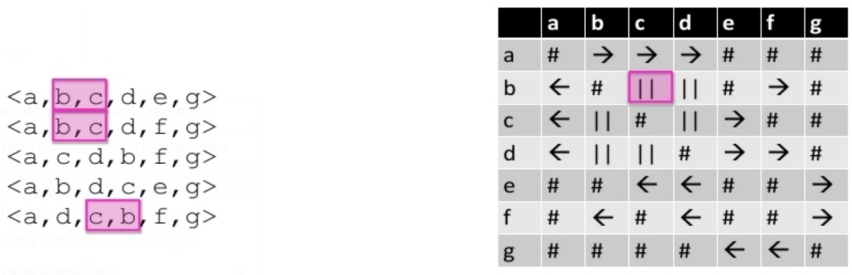


FIGURE 2.5: The Footprint Matrix of the Alpha Miner[Bui16]

From the footprint matrix the following Petri net can be derived. The actions b, c and d, which were marked as parallel in the above Figure, are now displayed as parallel paths.[Bui16]

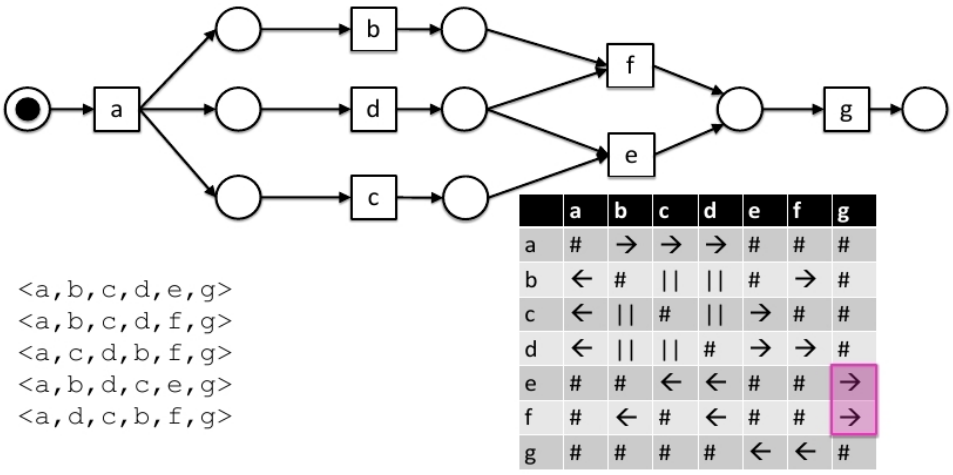


FIGURE 2.6: A derived Petri net of the Footprint Matrix[Bui16]

2.2.2 Heuristics Miner (HM)

The Heuristic Miner is an Improvement of the Alpha miner, as it takes frequencies into account, detects short-loops and can detect skipping activities. However it does not guarantee for sound process models.

The basic idea is, to count the relations in the footprint matrix and calculate relative frequencies which returns a dependency matrix, as depicted in the following Figure.

|=>|	a	b	c	d	e	f	g
a		.98	.67	.80			
b	-.98		.82	.67		.86	
c	-.67	-.82		.90	.92		
d	-.80	-.67	-.90		.95	.97	
e			-.92	-.95			.95
f		-.86		-.97			.98
g					-.95	-.98	

|>|	a	b	c	d	e	f	g
a		56	2	4			
b			44	12		6	
c		4		46	12		
d		2	4		18	38	
e							18
f							44
g							

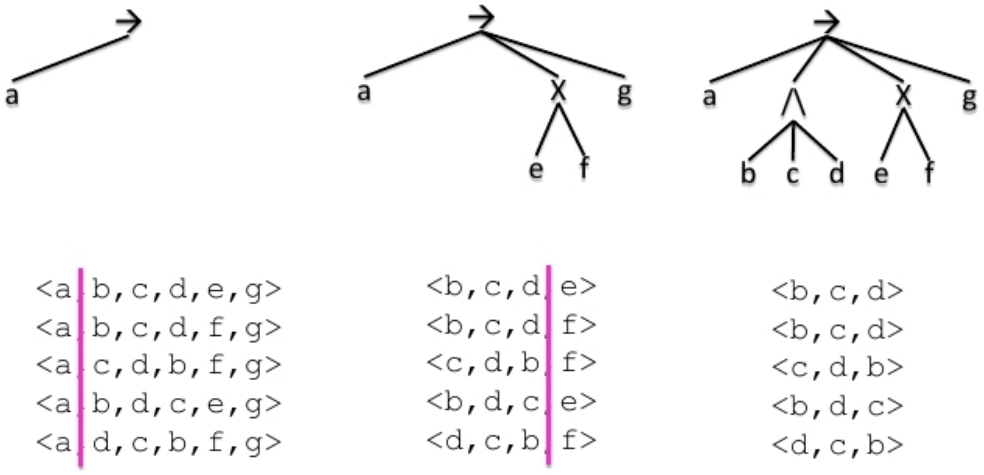
FIGURE 2.7: Dependency Matrix des Heuristic Miners[Bui16]

$$a => b = \frac{|a > b| - |b > a|}{|a > b| - |b > a| + 1}$$

It can be seen that the frequency of |a>b| - meaning a was followed by b - is 56. The opposite |b>a| never occurred and for this reason, by applying the formula above, the relative frequency or "significance of the dependency" of 0.98 can be calculated. The opposing relative frequency of -0.98 can be derived from the first result and is inserted in the matrix as well.[Bui16]

2.2.3 Inductive Miner (IM)

With the Inductive Miner the idea of classification by decision trees is introduced to process mining and because it doesn't use Petri nets, it guarantees sound process models. The IM repeatedly finds the most prominent splits in the event log, then detects the operator (e.g. X) and afterwards continues on both sublogs.
In the following Figure the example event log from this chapter is first split into the most prominent activities a (start) and g (end). Afterwards the OR operator is applied for e and f and finally b,c and d are split with and the parallel operator detected for this split.[Bui16]



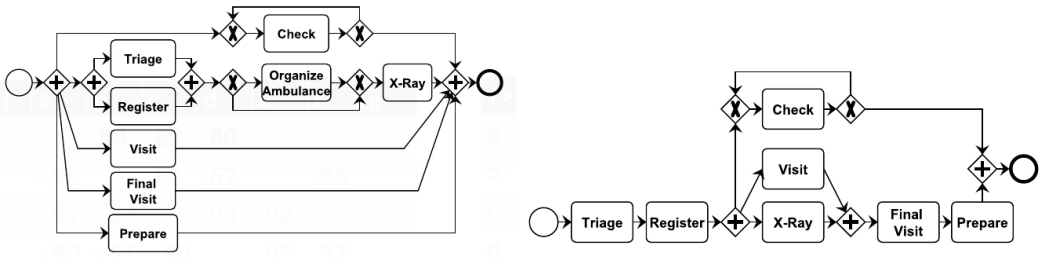
(a) Always a (b) Always e OR f (c) Parallelism b,c,d

FIGURE 2.8: Inductive Miner - Repeatedly Split Event Log[Bui16]

2.3 The Data-aware Heuristic Miner (DHM)

2.3.1 Data-aware Dependency Measures

In contrast to the miners which have been shortly presented in this chapter, the DHM is supposed to also consider and evaluate infrequent but data-dependent process behavior. Rare events are either vastly disregarded as noise e.g. by the HM or not properly filtered e.g. by the IM.



(a) Inductive Miner (b) Heuristic Miner

FIGURE 2.9: Discovered models by the IM and HM in BPMN [Man17]

The approach of Mannhardt et. al is to extend the HM with a measure for conditional dependency. Binary classifiers are applied to predict directly-follows relations based on attribute values recorded in the event log.
Those classifiers are denoted as **Dependency Conditions**:

$$C_{a,b}(x) = (C(a,b))(x)$$

This binary classifier predicts whether an event of activity a is directly followed by an event of activity b for the attribute values x. This means that $C_{a,b}(x) = 1$ when b is predicted to directly follow a and $C_{a,b}(x) = 0$ when a different activity is predicted.

Given $a, b \in \Sigma$ and dependency conditions C, the frequency with which b is observed to directly follow a is derived from the event log. This relation is denoted as:
Conditional directly follows relation

$$a >^{C,L} b$$

An execution of activity a with the latest attribute values x is directly followed by an execution of activity b under dependency condition $C_{a,b}(x)$.
The **Conditional dependency measure** is calculated analogous to the dependency measure described for the HM earlier. The authors define $a =>^{C,L} b : \Sigma \times \Sigma \rightarrow [-1, 1]$ as the strength of the causal dependency from a to b under condition $C_{a,b}$ in the event log:

$$a =>^{C,L} b = \begin{cases} \frac{|a>^{C,L}b| - |b>^{C,L}a|}{|a>^{C,L}b| - |b>^{C,L}a| + 1} & \text{for a} \neq b, \\ \frac{|a>^{C,L}b|}{|a>^{C,L}b| + 1} & \text{otherwise.} \end{cases}$$

The difference to the earlier measure is the data-aware dependency condition. If a relation (a, b) is clearly characterized by a certain dependency condition $C_{a,b}$ it should be included in the dependency relations of the discovered causal net.

The **emergency ward example** will provide a better understanding of the described measures. An event log L with 50 traces for each of the three σ_{1-3} was introduced earlier and will be used in the following steps:

1. Determine the conditional dependency measure $X =>^{C,L} V$ from activity X-Ray (X) to activity Visit (V)
   => Assumtion that condition $C_{X,V}(v) = 1$ only if attribute Nurse = Alice
2. Obtain the number of times X is directly followed by V under condition $C_{X,V}$
   => $|X >^{C,L} V|$ = 50
3. Obtain the number of times V is directly followed by X under conditions C
   => $|V >^{C,L} X|$ = 0
4. Derive the conditional dependency measure under C
   => $X =>^{C,L} V = \frac{50-0}{50+0+1} \approx 0.98$

This indicates a strong dependency relation from activity X to activity V under condition $C_{X,V}$. By contrast, if we consider the unconditional dependency measure $X =>^{1,L} V$, then we obtain $\frac{50-100}{50+100+1} \approx -0.33$. Thus, when disregarding the data perspective, both activities appear to be executed in parallel.[Man17]

2.3.2 Training a classifier for the dependency condition

The **dependency condition** which was introduced above, is the basis of the other two definitions and thus the first step when applying the DHM in order to decide which relations should be included in the C-net.
A set of training instances is built for every combination of activities $(a, b) \in \Sigma \times \Sigma$.
Training Instances are defined by:

- $a \in \Sigma$ the given source activity
- $b \in \Sigma$ the candidate activity
- $\theta_{dep} \in [0, 1]$ the dependency threshold

Then $a\bullet \subseteq \Sigma$ is the set of activities s that directly follow a in the event log with an unconditional dependency measure above the threshold θ_{dep} , i.e.,

$$a\bullet = s \in \Sigma | a =>^{1,L} s \geq \theta_{dep}$$

We collect those events $X_{L,a,b} \subseteq E$ that directly follow an execution of a in the event log, and refer to activities in $a\bullet$, or to the candidate activity b, i.e.,

$$X_{L,a,b} = e \in E | \bullet(e) = a \wedge \#_{act}(e) \in a\bullet \cup \{b\}$$

Function $T_{L,\theta_{dep}} \in (\Sigma \times \Sigma) \rightarrow B((A \nrightarrow U) \times 1, 0)$ returns the multi-set of training instances:

$$T_{L,\theta_{dep}}(a,b) = \biguplus_{e \in X_{L,a,b}} [(val(e), cl(e))] with cl(e) = \begin{cases} 1, & for \#_{act}(e) = b, \\ 0, & for \#_{act}(e) \neq b \end{cases}$$

This method is conceptually independent of the used classification algorithm. The authors employed **decision trees (C4.5)** as they are efficient and provide results in human interpretable conditions.
To build the **dependency conditions C**:

1. A set of training instances $T_{L,\theta_{dep}}(a,b)$ is assembled.
2. A decision tree for each possible relation $(a,b) \in \Sigma \times \Sigma$ is trained.
3. A score $q(C_{a,b}) \in [0,1]$ is used to determine the quality of a condition $C_{a,b}$.

As a performance measure the authors opted for Cohen's kappa (κ), which indicates whether the prediction was better than a prediction by chance (i.e., for κ > 0).

Again the **emergency ward example** with an event log of 150 traces will provide a better understanding of the just described methods.
The dependency threshold shall be $\theta_{dep} = 0.9$ and the classifier for the dependency condition $C_{X,V}$, i.e., the dependency relation from X-Ray (X) to Visit (V) will be trained:

1. The training instances are $T_{L,\theta_{dep}}(X,V) = [(v1, FinalVisit)^{50}, (v2, Visit)^{50}]$
2. The attribute value functions are $v1(P) = Red$, $v1(N) = Joe$ and $v2(P) = Red$, $v2(N) = Alice$
3. A C4.5 decision tree is trained and the dependency condition $C_{X,V}$ with $C_{X,V}(v2) = 1$ and $C_{X,V}(v1) = 0$ is obtained

There is no instance with the activity Check (C) since the unconditional dependency measure $X =>^{1,L} C$ is below the threshold of 0.9. So the instances based on trace $\sigma 3$ are not included because activity C is in parallel to X.[Man17]

2.3.3 Tuning noise filtering capabilities and discovering C-nets

In order to filter the noise from rare events the DHM supports four user-specified thresholds which range between 0 and 1:

- θ_{obs}, observation threshold - controlling the relative frequency of relations

- θ_{dep}, dependency threshold - controlling the strength of causal dependencies
- θ_{bin}, binding threshold - controlling the number of bindings
- θ_{con}, condition threshold - controlling the quality of data dependencies

A C-net tuple $C = (\Sigma, s_i, s_o, D, I, O)$ is derived from an event log $L = (E, \Sigma, \#, L)$ and the thresholds θ_{obs}, θ_{dep}, θ_{bin}, θ_{con}, in the following steps.

1. Add artificial start and end events to all traces to ensure unique start and end activities s_i and s_0
2. Build the set of standard dependency relations
3. Discover the dependency conditions C by training the classifiers for each pair (a, b), using the training instances $T_{L,\theta_{dep}}(a, b)$.
4. Add the conditional dependency relations C to D, using θ_{con} instead of θ_{obs} to obtain infrequent, high-quality data conditions
5. Handle activities $s \in \Sigma$ which don't have a predecessor or successor in the directed graph induced by D. As all tasks in the C-net should be connected, two alternative heuristics are proposed by the authors: **all-task-connected** and **accepted-task-connected**. The latter one connects repeatedly only those activities that are already part of the dependency graph using their best neighboring activities until all activities have a cause and an effect.
   $\bar{D}$ denotes the set of relations necessary to connect all activities accepted so far. Afterwards the dependency relations with the new relations, i.e., $D = D \cup \bar{D}$ is extended. As now there might be new, unconnected activities in $\bar{D}$ the steps are repeated i.e. the best neighboring activities are added until set $\bar{D}$ is empty.
6. The input and output binding functions of the C-net are discovered. We discover the input (I) and output (O) binding functions of the C-net. To find $O(a)$ it has to be determined which of the executions of b were caused by an execution of activity a. Using the same heuristic like before activity a only is considered to have caused b if it is the nearest activity. Any other activity s executed in between a and b should not be a possible cause of b. $\bar{O}$ denotes the set of activities that were caused by event e_i.

   The frequency $|o|_{L,a} \in N$ of an output binding $o \subseteq \Sigma$ for activity $a \in \Sigma$ in the event log L is determined as:

$$O(a) = \{o \subseteq \Sigma | \frac{|o|_{L,a}}{max_{\bar{o} \subseteq \Sigma}(|\bar{o}|_{L,a})} \geq \theta_{bin}\}$$

   The input binding function I is obtained by reversing the same approach.[Man17]

Chapter 3

Result Reproduction of the iDHM

3.1 Methodical approach in this paper

3.1.1 Introduced Process Mining Concepts

In the beginning of this paper a few, very basic concepts of process mining where explained, followed by an introduction to the IM and HM. Both miners are used in the paper of Mannhardt et. al. in order to show the main advantages of the HDM, which extends the idea of the HM with the concept of conditional dependencies.
This Seminar paper provides more background information on process mining concepts than the original work of Mannhardt et. al., in order to build a foundation of knowledge before introducing the theoretical basis of the HDM in part two of the second chapter.
Explaining the mathematical concepts and parameters of this method is a necessary step before the evaluation in this section, because adjustments to several parameters are undertaken in order to evaluate the results.

3.1.2 Focus of the evaluation and result comparison

The evaluation approaches from the paper with three different event logs will be presented in this section and each of the three section follows the same order. At first the chosen parameters of the iDHM are summarized and then modified in order to receive the same results, which were presented in the paper. The following step will be to evaluate how the results change when minor adjustments are made to the parameters.

During the evaluation of each event log the following questions are of interest:

1. Can the HDM model for all three evaluation approaches be reproduced?
2. What kind of differences can be discovered between the evaluation in the paper and in this seminar paper?
3. How can possible differences be explained?
4. Do -seemingly minor changes of parameters- result in vastly different results?

3.1.3 ProM - Version and iDHM Package

In order to reproduce the results from the evaluation of the HDM, the free software ProM, which is mainly developed by researchers and associates of the Technical University Eindhoven will be used.
The original package which is cited in the paper is not available within ProM6 or

any of the accessible "Nightly-build versions", because it was replaced within the same year by a package called "interactive Data-aware Heuristic Miner" (iDHM). There are no fundamental differences between the two versions - only a few more options. However after ProM 6.8 it is possible that a few changes are made to the iDHM package.[MDR17]

3.2 Synthetic Data Logs

3.2.1 Evaluation design and set-up

The authors generated an event log with 100,000 traces and approximately 900,000 events. In the following table the main parameters are summarized, which where used to configure the iHDM in ProM when working with the Synthetic Event Logs. The authors injected noise into an increasing number of traces by randomly adding one additional even.
The approach of the DHM is to use conditional dependencies based on attribute values to discover relations which would be discarded as noise otherwise. The attributes in the following table where introduced with relatively few occurrences in order to prove this advantage of the DHM over other methods like the HM.

Attributes	Methods	Thresholds
• Priority (P) white 1.4% • Nurse (N) Alice 19.1% • Type (T) out 4.3%	• DHM • HM - frequency filter (HMF) • HM - no frequency filter (HMA)	• θ_{obs} = 0.06 • θ_{dep} = 0.9 • θ_{bin} = 0.1 • θ_{con} = 0.5

Furthermore the **accepted-task-connected heuristic** was used, the **C4.5** applied as the classifier and its performance was estimated using **10 times 10-fold cross validation**.[Man18]

3.2.2 Result comparison

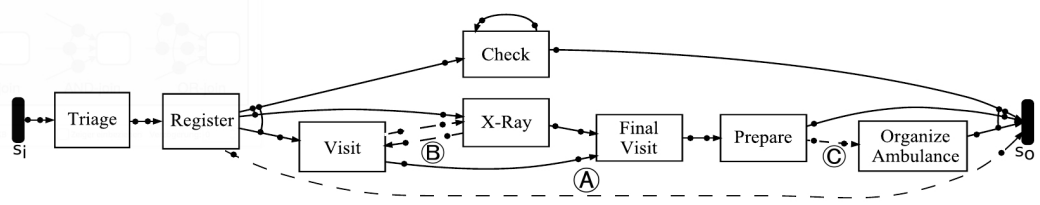


FIGURE 3.1: Synthetic Event Logs with 0% Noise added[Man17]

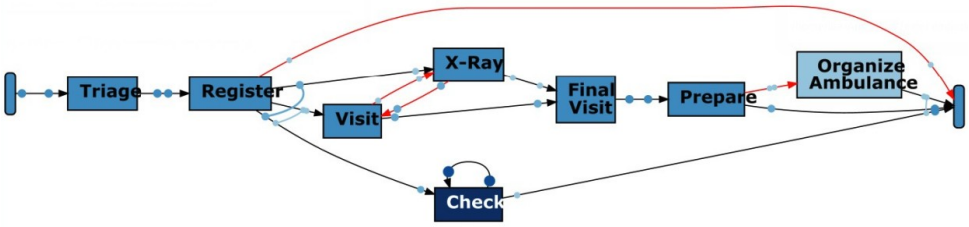


FIGURE 3.2: Reproduction - Synthetic Event Logs with 0% Noise

3.3 Hospital Billing

3.3.1 Evaluation design and set-up

The Hospital Billing (HB) event log contains 100,000 cases with 550,000 events and 38 data attributes related to the billing of medical services.

Attributes			Methods	Thresholds
• CaseType	• msgCode	• blocked	• DHM	• $\theta_{obs} = 0.04$
• CloseCode	• msgType	• flagA	• HMF	• $\theta_{dep} = 0.9$
• isClosed	• isCancelled	• flagB	• IM	• $\theta_{bin} = 0.001$
• Speciality	• version	• flagC		• $\theta_{con} \geqslant 0.6$

Again the **accepted-task-connected heuristic** was used because not all of the 21 attributes are likely to be of interest. The **C4.5** was applied to 13 attributes and its performance was estimated using **10 times 10-fold cross validation**.[Man18]

3.3.2 Result comparison

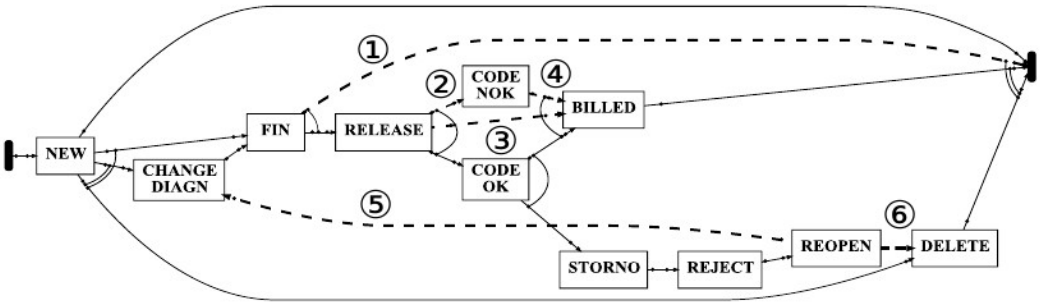


FIGURE 3.3: Process model discovered by the authors [Man17]

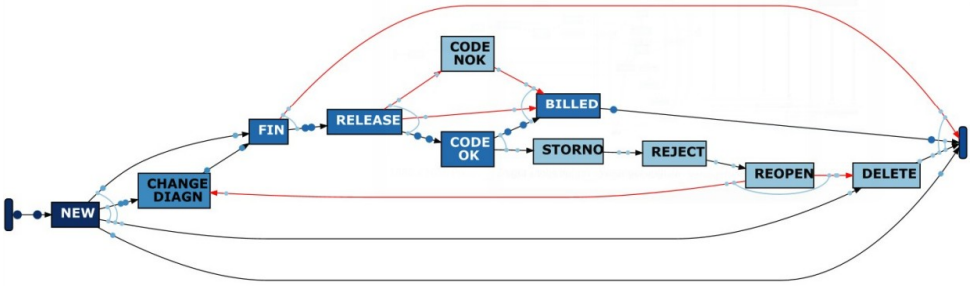


FIGURE 3.4: Reproduced Process Model for the HB Event Logs

3.4 Road Fines

3.4.1 Evaluation design and set-up

The Road Fines (RF) event log contains about 150,000 cases, 500,000 events, and 9 data attributes.

Attributes		Methods	Thresholds
• isPaid	• amount	• DHM	• θ_{obs} = 0.01
• dismissal	• points	• HMF	• θ_{dep} = 0.8
• paymentAmount	• article	• IM	• θ_{bin} = 0.001
• totalPaymentAmount	• expense		• $\theta_{con} \geqslant 0.5$

The **accepted-task-connected heuristic** was used and the **C4.5** was applied. Its performance was again estimated by the **10 times 10-fold cross validation**.

3.4.2 Result comparison

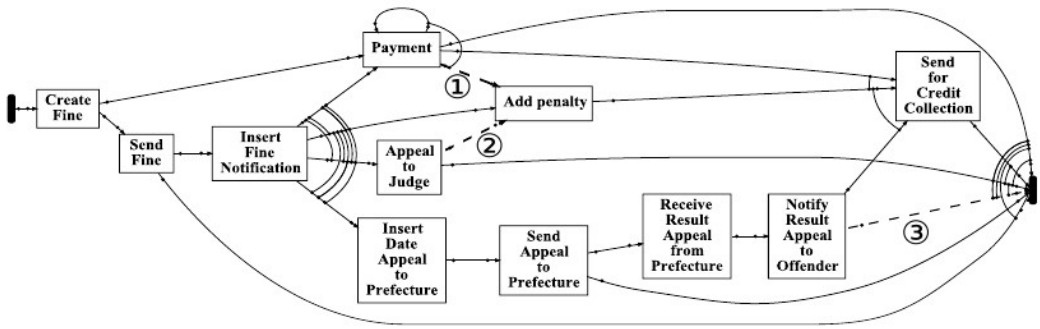


FIGURE 3.5: Process model discovered for the RF Event Logs[Man17]

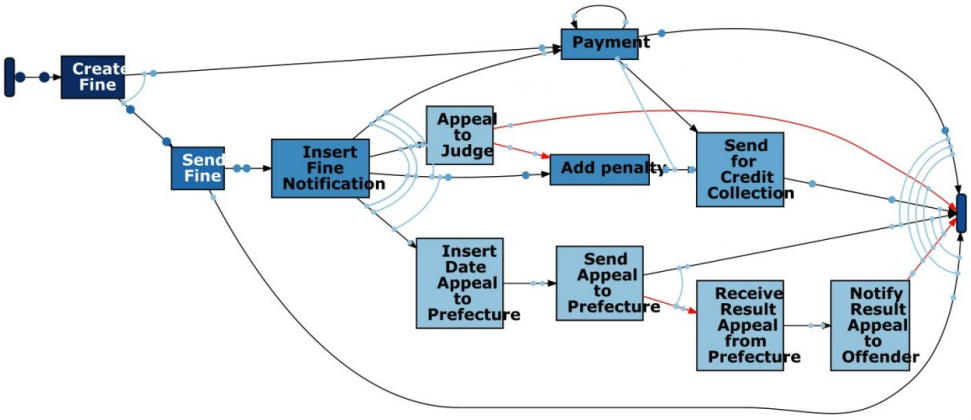


FIGURE 3.6: Result reproduction for the RF Event Logs

3.5 Critical evaluation of the iDHM

.1 Appendix - Synthetic Event Log Evaluation

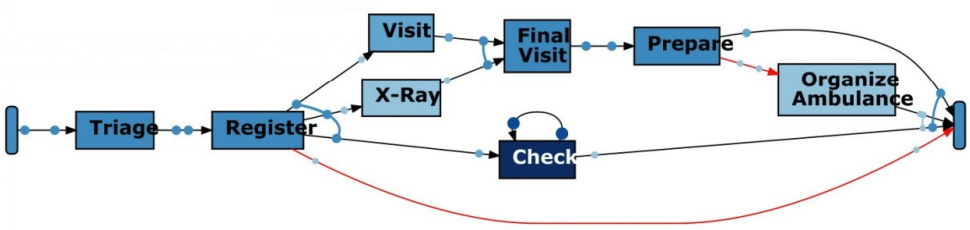


FIGURE 7: Reproduction - Synthetic Event Logs with 20% Noise

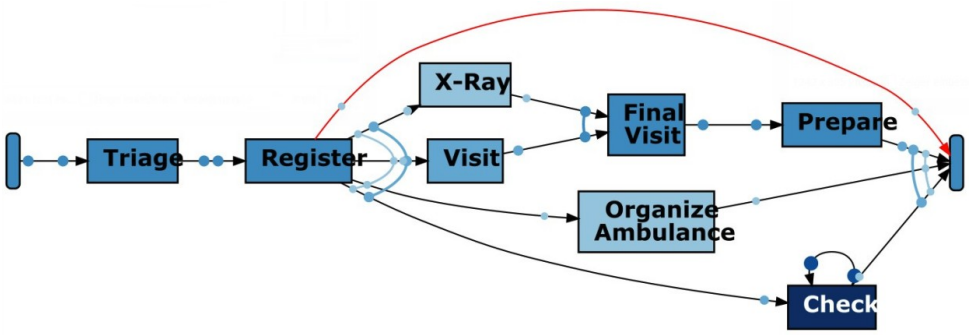


FIGURE 8: Reproduction - Synthetic Event Logs with 30% Noise

.2 Appendix - Hospital Billing Evaluation

Attribute	Domain	Description
actOrange	boolean	A flag that is used in connected with services that may not be covered by the standard health insurance.
actRed	boolean	A flag that is used in connected with services that may not be covered by the standard health insurance.
blocked	boolean	A flag that is used when the billing may not proceeed (i. e., is blocked).
caseType	literal	A code for the type of the billing package, which may influence it's handling.
closeCode	literal	There may be several reasons to close a billing package, this attribute stores the code used.
diagnosis	literal	A code for the diagnosis used in the billing package.
flagA	literal	An anonymized flag.
flagB	literal	An anonymized flag.
flagC	literal	An anonymized flag.
flagD	literal	An anonymized flag.
isCancelled	boolean	A flag that indicates whether the billing package was eventually cancelled.
isClosed	boolean	A flag that indicates whether the billing package was eventually closed.
msgCode	literal	The code returned by activity CODE NOK.
msgCount	discrete	The number of messages returned by activity CODE NOK.
msgType	literal	The type of messages returned by activity CODE NOK.
speciality	literal	A code for the medical speciality involved.
state	literal	Stores the current state of the billing package.
version	literal	A code for the version of the rules used.

TABLE 1: Attributes recorded in the HB event log

Activity	Frequency	Description
NEW	101,289	A new billing package is created.
FIN	74,738	The billing package is closed, i. e., it may not be changed anymore.
RELEASE	70,926	The billing package is released to be sent to the insurance company.
CODE OK	68,006	A declaration code was successfully obtained.
BILLED	67,448	The billing package has been billed, i. e., the invoice is sent out.
CHANGE DIAGN	45,451	The diagnosis that the billing package is based on was changed.
DELETE	8,225	The billing package was deleted.
REOPEN	4,669	The billing package was reopened, i. e., additional medical services may be added or existing services removed.
CODE NOK	3,620	The declaration code was obtained with an error message.
STORNO	2,973	The billing package was canceled.
REJECT	2,016	The invoice sent to the insurance company was rejected.
SET STATUS	705	The status (i. e., new, closed, etc.) was manually changed.
EMPTY	449	The status (i. e., new, closed, etc.) was manually changed.
MANUAL	372	The billing package was manually changed from a non-standard system.
JOIN-PAT	358	Two billing packages are joined together since they refer to the same patient.
CODE ERROR	75	The declaration code could not be obtained.
CHANGE END	38	The projected end date of the billing package was changed.

TABLE 2: Activities recorded in the HB event log

.3 Appendix - Road Fines Evaluation

Attribute	Shorthand	Domain	Description
amount	am	continuous	The amount due to be paid for the fine.
article	ar	discrete	The number of the article of the Italian road-traffic law that is violated by the offender.
dismissal	di	literal	A flag indicating whether and how the fine is dismissed. Several values are possible: G encodes a dismissal by the judge, # encodes that the fine was dismissed by the prefecture, and NIL encodes that the fine was not dismissed. There are several other values used for which we cannot reveal the semantics.
expense	ex	continuous	The additional amount due to be paid for postal expenses.
notificationType	nt	literal	A code indicating to whom the fine refers. The codes used in the event log are P (the owner of the car) or C (the driver that committed the offense). When the actual offender is unknown (e. g., was not stopped), a fine is created for the owner of the car.
org:resource	or	literal	A code indicating the employee who handled the case. We cannot disclose more information regarding these codes.
paymentAmount	py	continuous	The amount paid by the offender in one transaction.
points	po	discrete	The penalty points deducted from the offender's license. In Italy each driver starts with 20 points on their license and may loose point for each offence. Drivers who loose all their points need to take a new driving test.
totalPaymentAmount (**payment**)	pa	continuous	The cumulative amount paid by the offender.
vehicleClass	vc	literal	The kind of vehicle used by the offender.

TABLE 3: Attributes recorded in the RF event log

Activity	Frequency	Description
Create Fine	150,370	The initial creation of the fine in the information system.
Send Fine	103.087	A notification about the fine is sent by post to the offender.
Insert Fine Notification (**Notification**)	79,860	The notification is received by the offender.
Add Penalty	79,860	An additional penalty is applied.
Payment	77,601	A payment made by the offender is registered.
Send For Credit Collection	59,013	A separate credit collection process is started for unpaid fines.
Insert Date Appeal to Prefecture (**Appeal to Prefecture**)	4,188	The offender appeals against the fine to the prefecture.
Send Appeal to Prefecture (**Send Appeal**)	4,141	The appeal is sent to the prefecture by the local police.
Receive Result Appeal from Prefecture (**Receive Result**)	999	The local police receives the result of the appeal.
Notify Result Appeal to Offender (**Notify Result**)	896	The local police informs the offender of the appeal result.
Appeal to Judge	555	The offender appeals against the fine to a judge.

TABLE 4: Activities recorded in the RF event log

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