Process Discovery and Conformance Checking

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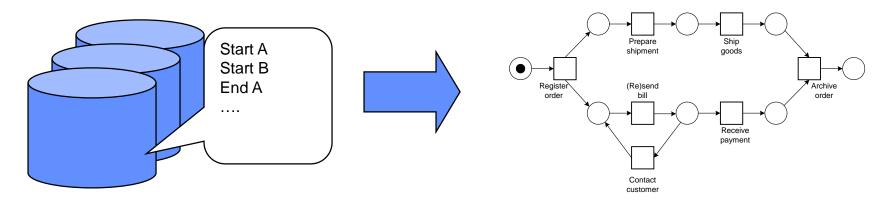
1 Motivation

- 2 Petri Nets in a Nutshell
- 3 The α -Algorithm
- 4 Heuristic and Genetic Miner
- 5 Conformance Checking
- 6 Summary

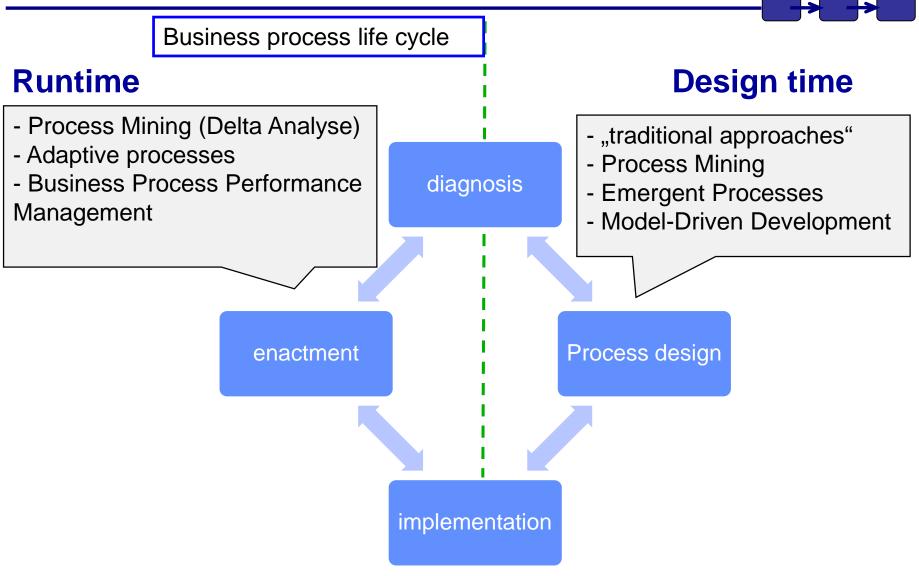
1 Motivation



- Particularly exploration ("finding") process models is often a cumbersome and errorneous task
- Are there alternatives?
- Observation: Processes are often implicitly executed (maybe distributed over different systems)
- Prerequisite: Log data of processes available
- Process / Workflow mining offers techniques to automatically derive process / workflow models from such log data



1 Motivation

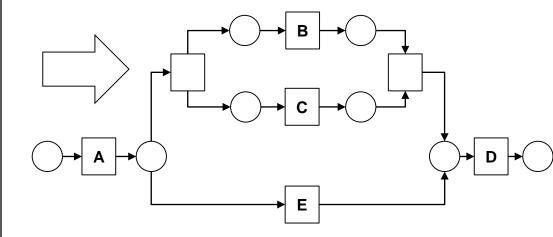


1 Motivation



Workflow Instance	Workflow Task
case 1	task A
case 2	task A
case 3	task A
case 3	task B
case 1	task B
case 1	task C
case 2	task C
case 4	task A
case 2	task B
case 2	task D
case 5	task A
case 4	task C
case 1	task D
case 3	task C
case 3	task D
case 4	task B
case 5	task E
case 5	task D
case 4	task D

Execution log (e.g., Staffware) [ADHM03]



Teaching Objectives



After discussing this chapter it should be clear

- what process discovery means
- what is the basic idea behind process discovery algorithms
- what are typical problems arising with process discovery algorithms
- how these problems can be tackled
- which algorithms exist and how they differ
- □ discovery is one of the process mining tasks (i.e., there are more tasks)

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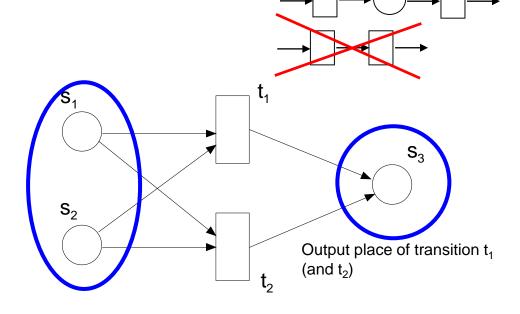
2 Petri Nets in a Nutshell



A Petri Net is a bipartite graph and contains the following (static) elements:

- ➤ Places → Preconditions / States
- ➤ Transitions → Actions / Activities
- > Edges that connect places with transitions and transitions with places
- Example:

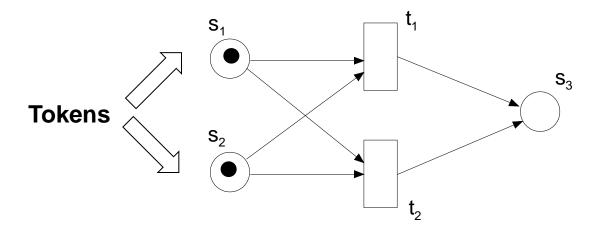
Input places of transition t₁ (and t₂)



2 Petri Nets in a Nutshell



- Dynamic behavior of a Petri Net is represented by tokens and markings respectively.
- > Example:



Interpretation:

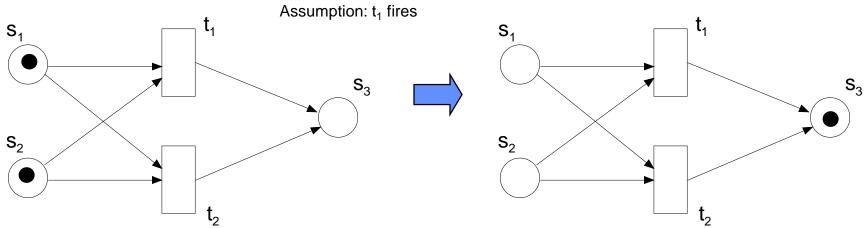
Transitions t_1 and t_2 are activated \rightarrow only one of them can fire

2 Petri Nets in a Nutshell



Dynamic behavior (ctd):

- > Firing rules determine the execution of the Petri Net
- > Example:



Result: all tokens from the input places of t1 are removed and all output places of t2 are marked with tokens

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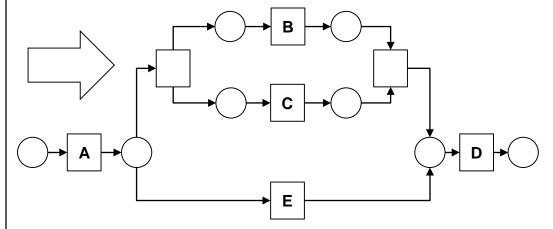
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case 2	task B
case 2	task D
case 5	task A
case 4	task C
case 1	task D
case 3	task C
case 3	task D
case 4	task B
case 5	task E
case 5	task D
case 4	task D

Execution log (e.g., Staffware) [ADHM03]





In general: Basic workflow mining algorithms analyze frequency and order of events within the logs of the different workflow instances.

Workflow Instance	Workflow Task
case 1	task A
case 2	task A
case 3	task A
case 3	task B
case 1	task B
case 1	task C
case 2	task C
case 4	task A
case 2	task B
case 2	task D
case 5	task A
case 4	task C
case 1	task D
case 3	task C
case 3	task D
case 4	task B
case 5	task E
case 5	task D
case 4	task D

1st Step:

Determine traces σ within log W:

Case 1: <A, B, C, D> (

Case 2: <A, C, B, D>

Case 3: <A, B, C, D>

Case 4: <A, C, B, D>

Case 5: <A, E, D>



α -algorithm [ADHM03 AWM04, MDAW04]

Traces σ in log W:

Case 1: <A, B, C, D>

Case 2: <A, C, B, D>

Case 3: <A, B, C, D>

Case 4: <A, C, B, D>

Case 5: <A, E, D>

2nd step:

Analyzing order relations between tasks per each trace:

 \rightarrow a $>_W$ b $\Leftrightarrow \exists$ trace $\sigma = t_1 t_2 t_3 \dots t_{n-1}$, such

that: $\sigma \in W$ and $t_i = a$ and $t_{i+1} = b$

Result of Analysis in 2nd step: Case 1: $A >_W B$, $B >_W C$, $C >_W D$

Case 2: $A >_W C$, $C >_W B$, $B >_W D$

Case 3: $A >_W B$, $B >_W C$, $C >_W D$

Case 4: $A >_W C$, $C >_W B$, $B >_W D$

Case 5: $A >_W E, E >_W D$



α -algorithm [ADHM03 AWM04, MDAW04]

Case 1: $A >_W B$, $B >_W C$, $C >_W D$

Case 2: $A >_W C$, $C >_W B$, $B >_W D$

Case 3: $A >_W B$, $B >_W C$, $C >_W D$

Case 4: $A >_W C$, $C >_W B$, $B >_W D$

Case 5: $A >_W E, E >_W D$

3rd step:

Analysis of order relations over entire workflow log W:

- \Box a \rightarrow_{W} b \Leftrightarrow a $>_{W}$ b and \neg (b $>_{W}$ a)
- \Box a#_wb $\Leftrightarrow \neg$ (a >_w b or b >_w a)
- $\Box a |_{W} b \Leftrightarrow a >_{W} b$ and $b >_{W} a$

Result of analysis step 3:

 $A \rightarrow_W B, A \rightarrow_W C, A \rightarrow_W E$

B ||_w C

 $B \rightarrow_W D, C \rightarrow_W D, E \rightarrow_W D$

E #w B, E#w C



α -algorithm [ADHM03 AWM04, MDAW04]

 $A \rightarrow_W B, A \rightarrow_W C, A \rightarrow_W E$

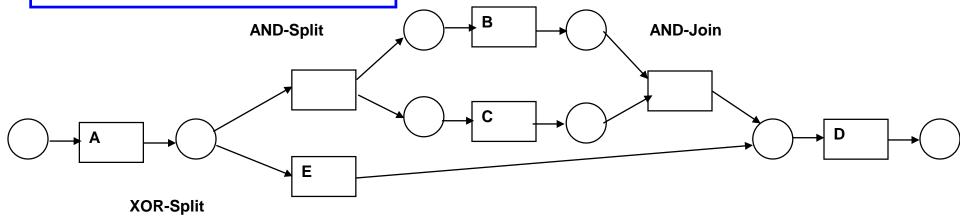
 $B \parallel_W C$

 $B \rightarrow_W D, C \rightarrow_W D, E \rightarrow_W D$

E #_W B, E#_W C

4th step:

Deriving associated Petri net





EXERCISE: For the following log, apply the α -algorithm and derive the corresponding Petri Net:

- Case1: <A, C, D, E, F, G>
- Case2: <A, B, D, E, F, G>
- Case3: <A, C, D, F, E, G>
- Case4: <A, B, D, F, E, G>
- Case5: <A, B, D, E, F, G>



Result:



ProM system:

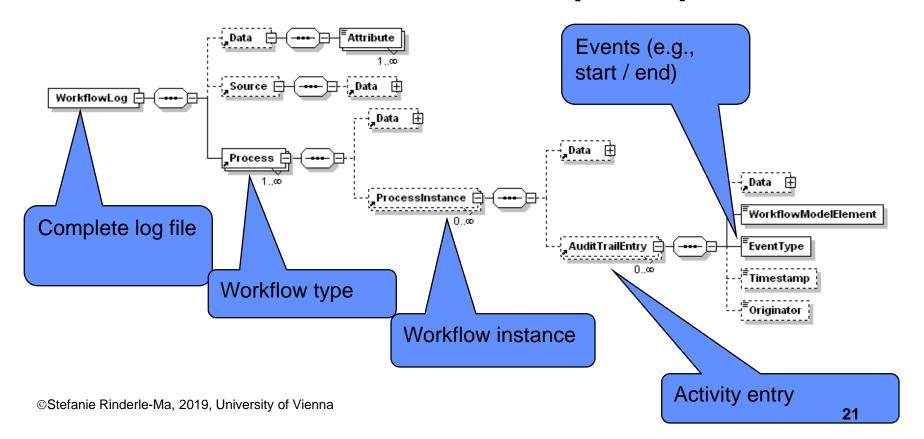
- Alternative approaches for process exploration are highly relevant since "traditional" approaches (e.g., interviews, questionnaires) are often costly
- Process mining offers means to automatically derive process models from log data
- However, existence of log data and its quality are preconditions for applicability of process mining techniques



- Currently: ProM is the most comprehensive mining toolkit
- > open source: http://www.processmining.org/prom/start
- Developed at Technical University of Eindhoven (The Netherlands)
- > ProM comprises:
 - > ProM framework: process analysis, filtering, and mining
 - ProMimport framework: imports and converts log data from different systems into ProM specific format
 - ProM CPN library: simulation environment based on colored Petri Nets
- ➤ Two log formats: MXML and XES (eXtensible Event Stream) → see also chapter on data provisioning



- In the following examples: execution logs are generated in ADEPT and transformed into MXML (ProMimport contains converter from ADEPT to ProM)
- MXML: XML-based data format for ProM [GuAa06]:





MXML-file for example workflow instance:

```
<ProcessInstance id="EXECLOG_OP-Vorbereitung_39">
                      <AuditTrailEntry>
                                  <WorkflowModelElement>0 Start</WorkflowModelElement>
                                  <EventType>start</EventType>
                                  <Timestamp>2006-04-19T14:58:54Z</Timestamp>
                      </AuditTrailEntry>
                      <AuditTrailEntry>
                                  <WorkflowModelElement>0 Start</WorkflowModelElement>
                                  <EventType>complete</EventType>
                                  <Timestamp>2006-04-19T14:58:54Z</Timestamp>
                      </AuditTrailEntry>
                      <AuditTrailEntry>
                                  <WorkflowModelElement>2 Patient aufnehmen</WorkflowModelElement>
                                  <EventType>start</EventType>
                                  <Timestamp>2006-04-19T14:58:54Z</Timestamp>
                      </AuditTrailEntry>
                      <AuditTrailEntry>
                                  <WorkflowModelElement>2 Patient aufnehmen</WorkflowModelElement>
                                  <EventType>complete</EventType>
                                  <Timestamp>2006-04-19T14:58:54Z</Timestamp>
                      </AuditTrailEntry>
                      <AuditTrailEntry>
                                  <WorkflowModelElement>3 Blutentnahme</WorkflowModelElement>
                                  <EventType>complete</EventType>
                                  <Timestamp>2006-04-19T14:58:54Z</Timestamp>
```

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- How to obtain logs?
- Challenges:
 - distributed sources
 - different format
- → information integration problem
- > Minimum requirements
 - case ID
 - events (START / END); order relevant (time stamps or ordered log)
- > Additionally:
 - Performers
 - General data
- Useful tools:
 - ProM Import
 - Commercial: Disco (direct import of csv data)

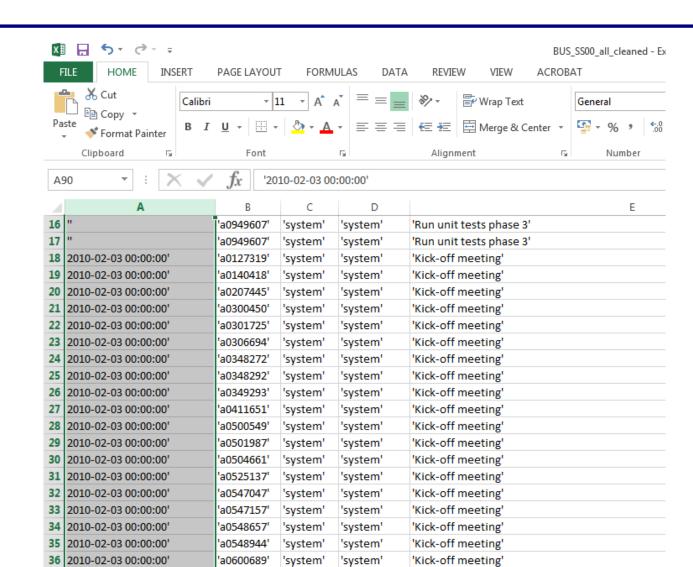
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2010-02-03 00:00:00'

©Stefanie Rin

'a0606549'

'a0608497'



'system'

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'system'

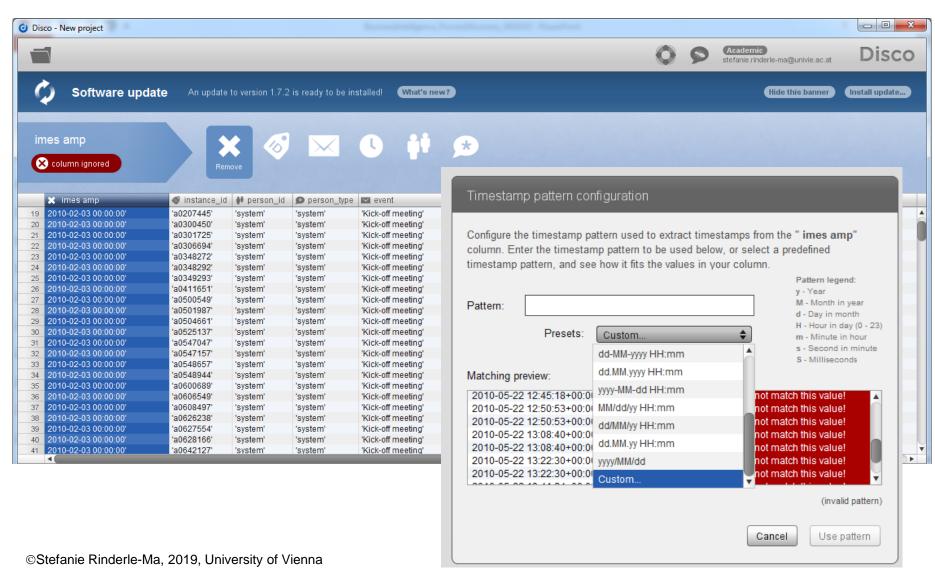
'Kick-off meeting'

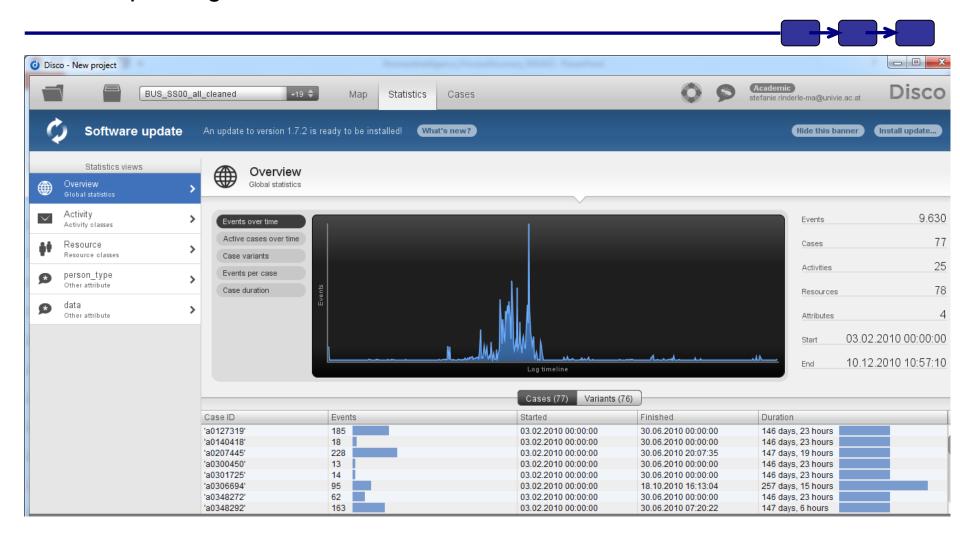
'Kick-off meeting'

lization and an extendi

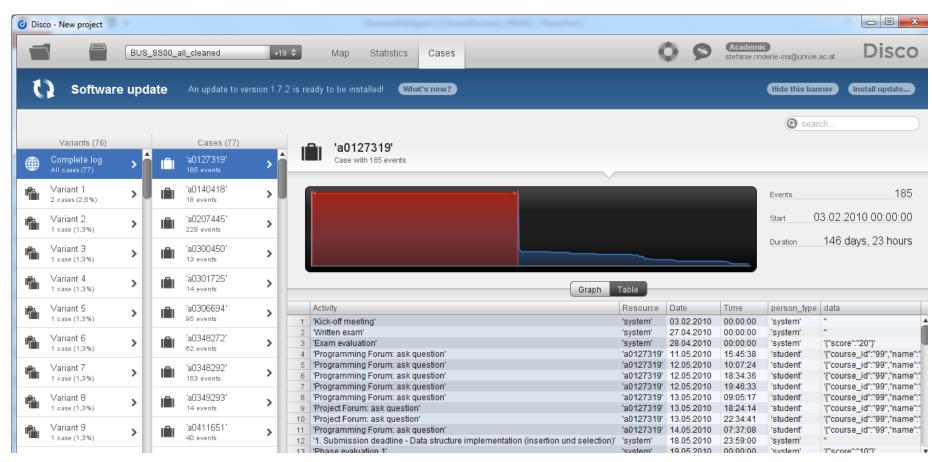




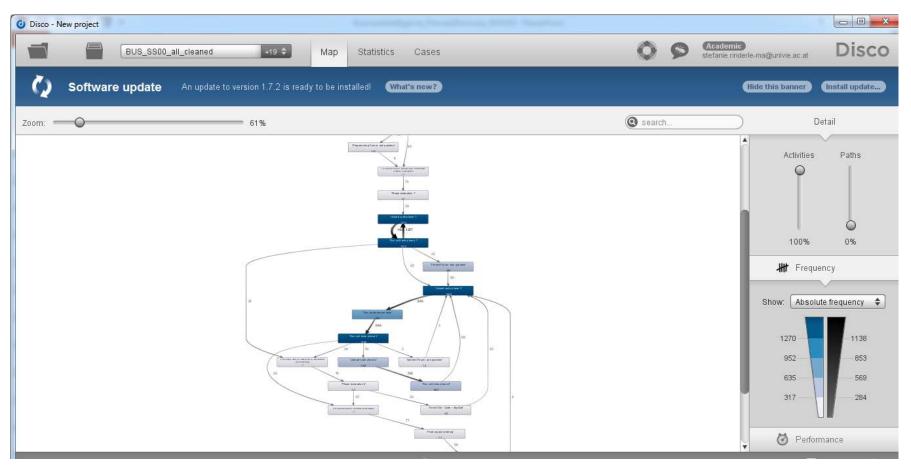




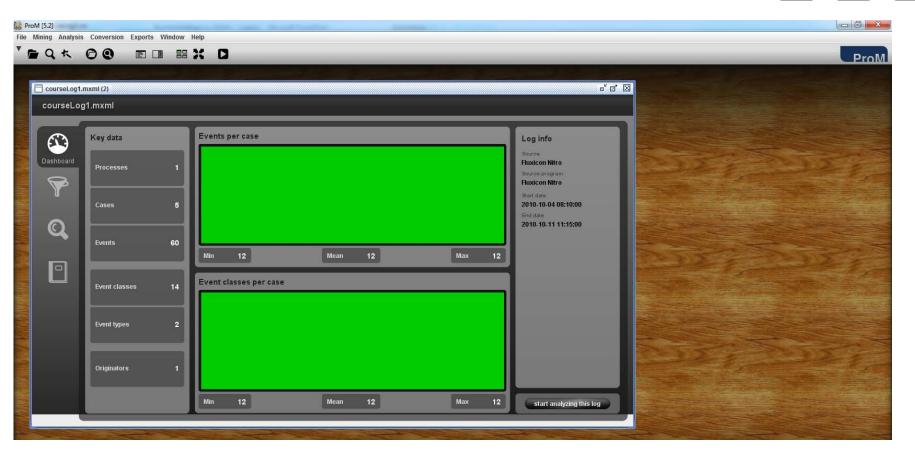








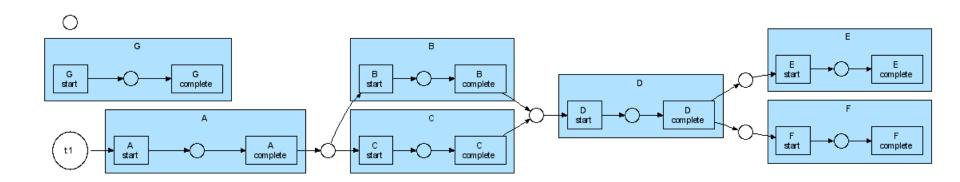




After import to ProM → some first statistics (of course not that interesting for this small example)



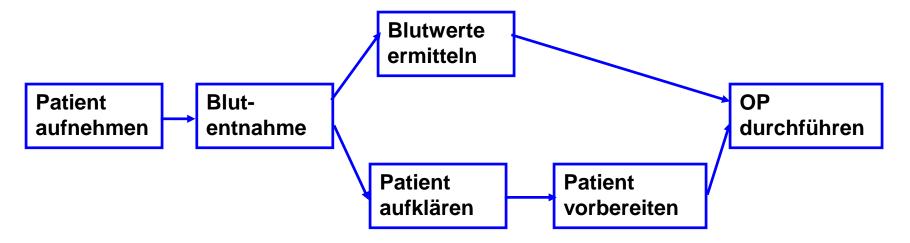
Our exercise example after applying α -algorithm

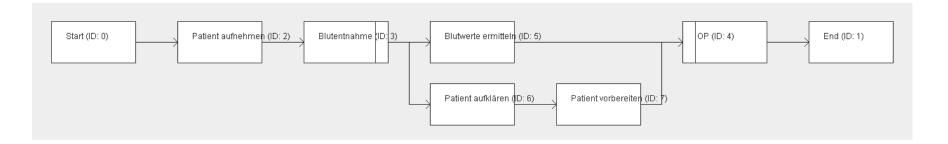


Why does it look different form our hands-on result?



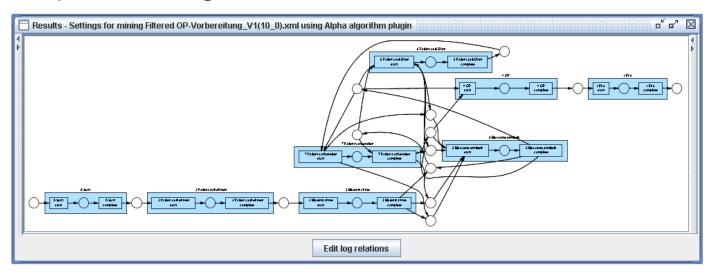
Example process (designed and executed within ADEPT Demonstrator)



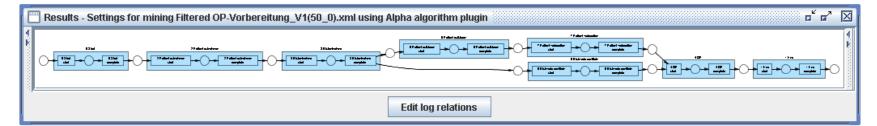




Example 1: α -algorithm for 10 instances



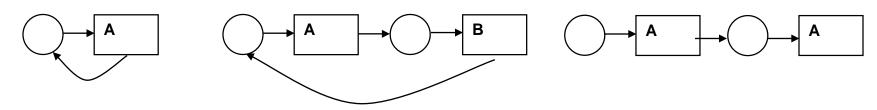
Example 2: α -algorithm for 50 instances



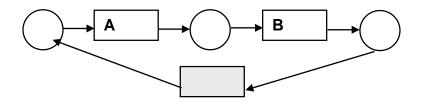


Structural problems (e.g., α -algorithm [ADHM03])

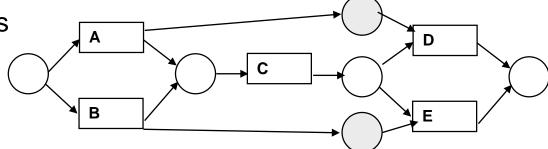
> Short loops and multiple occurrences of activities



Hidden activities (e.g. for structuring purposes)



> Implicit dependencies





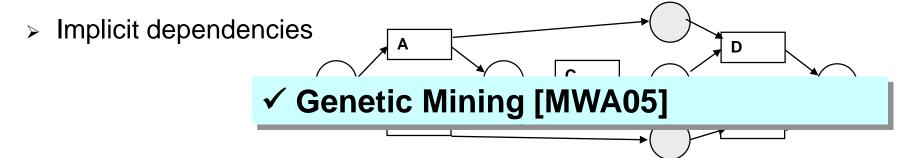
Structural problems (e.g., α -algorithm [ADHM03])

Short loops and multiple occurrences of activities



Still open (WHY?)

- Hidden activities (e.g. for structuring purposes)
 - **✓** Heuristics Miner
 - ✓ Genetic Mining [MWA05]





> Further problems:

- Noise (missing or erroneous log data)
- small/ big number of log data
- Parallel branchings with high number of branches

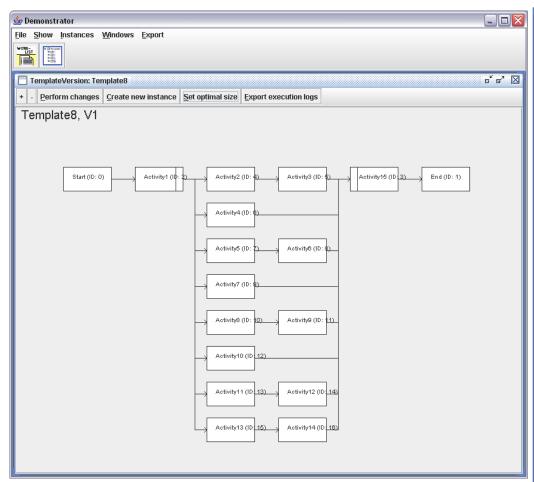
> Algorithms:

- Multi-Phase-Mining [DoAa05]:
 - > For each case a separate graph is generated (Petri Net, EPC)
 - > The case graphs are aggregated afterwards
 - Robust when dealing with noise
- Genetic algorithm [MWA05]:
 - Robust when dealing with noisy log data
 - Not very efficient

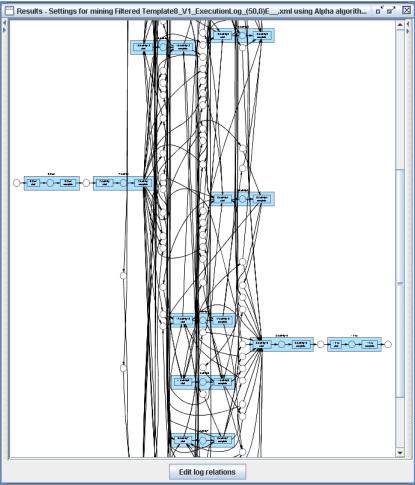


Problem 1: Parallel branches

Start process



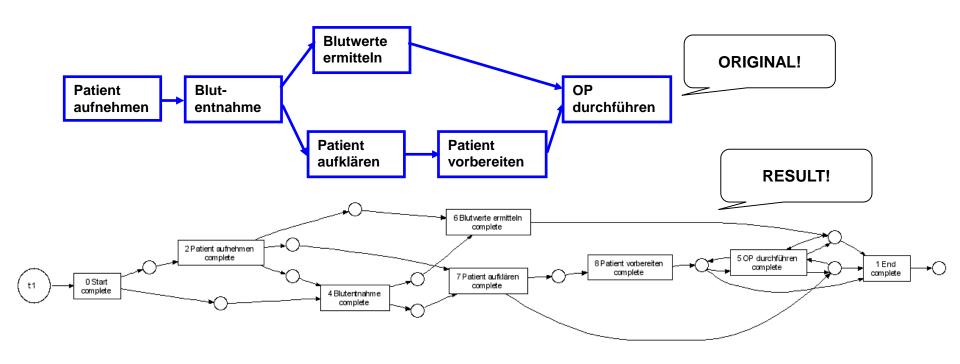
Result α -algorithm



3 The alpha-Algorithm



Problem 2: missing or wrong log data (noise)



 α -algorithm, 100 instances, 5% noise

3 The alpha-Algorithm



- > Further problems:
- **✓** Heuristics Miner
- > Noise (missing or errone
- > small/ big number of log ✓ Genetic Mining [MWA05]
- > Parallel branchings with high number of branches

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Heuristics Miner

- Read a log
- 2. Get the set of tasks
- 3. Infer the ordering relations based on their frequencies
- 4. Build the net based on inferred relations
- 5. Output the net

Weijters, AJMM (Ton), van der WMP (Wil) Aalst, und de AKA (Ana Karla) Medeiros. 2006. *Process mining with the HeuristicsMiner algorithm*. Technische Universiteit Eindhoven. http://repository.tue.nl/615595.



Heuristics Miner:

Let W be an event log over T, and $a, b \in T$:

• $|a>_W b|$ is the number of times $a>_W b$ occurs in W,

•
$$a \Rightarrow_W b = \left(\frac{|a>_W b| - |b>_W a|}{|a>_W b| + |b>_W a| + 1}\right)$$

Insight:

The more frequently a task A directly follows another task B, and the less frequently the opposite occurs, the higher the probability that A causally follows B!

Source: T. Weijters, A. K. de Medeiros: Process Mining course, TU Eindhoven, 2009 (http://prom.win.tue.nl/research/wiki/courses/processmining)

Traces σ in log W:

Case 1: <A, B, C, D>

Case 2: <A, C, B, D>

Case 3: <A, B, C, D>

Case 4: <A, C, B, D>

Case 5: <A, E, D>

Case 1: $A >_W B$, $B >_W C$, $C >_W D$

Case 2: $A >_W C$, $C >_W B$, $B >_W D$

Case 3: $A >_W B$, $B >_W C$, $C >_W D$

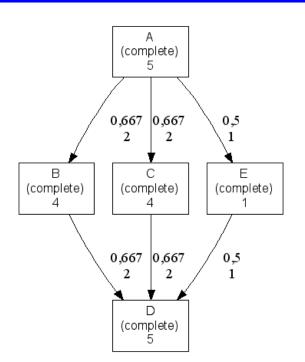
Case 4: $A >_W C$, $C >_W B$, $B >_W D$

Case 5: $A >_W E$, $E >_W D$

Let W be an event log over T, and $a, b \in T$:

• $|a>_W b|$ is the number of times $a>_W b$ occurs in W,

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Traces σ in log W:

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Case 2: <A, C, B, D>

Case 3: <A, B, C, D>

Case 4: <A, C, B, D>

Case 5: <A, E, D>

Case 1 $A >_W B B >_W C, C >_W D$

Case 2: $A >_W C$, $C >_W B$, $B >_W D$

Case 3: $A >_W B$, $B >_W C$, $C >_W D$

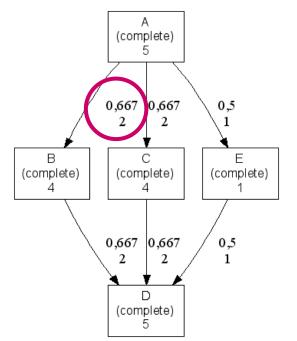
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Case 5: $A >_W E$, $E >_W D$

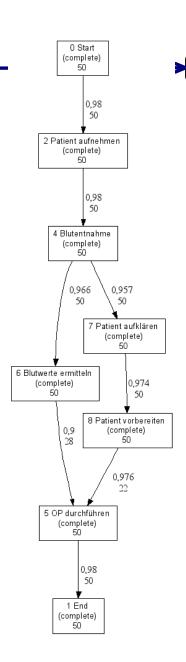
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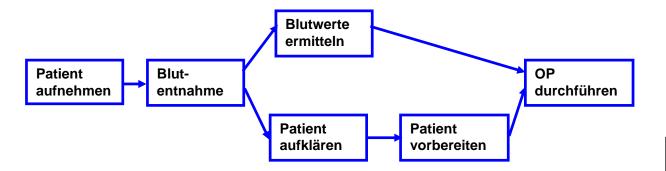
•
$$a \Rightarrow_W b = \left(\frac{|a>_W b| - |b>_W a|}{|a>_W b| + |b>_W a| + 1}\right)$$

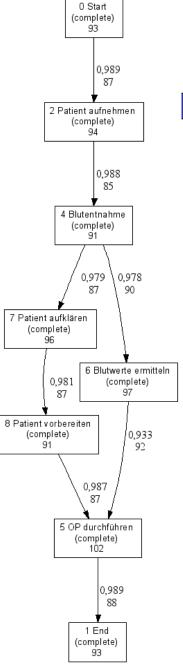


- > Let us have a look at our healthcare example
- Results for 50 workflow logs
- > We learned that Heuristics Miner can better deal with noise than the α -algorithm
- Let us try...



- Healthcare example
- > 1000 workflow logs, 5% noise





Workflow Instance 1

Preparation

Travel by train

Conference

Visit brewery

Dinner

Travel by train

Travel refund

Workflow Instance 2

Preparation

Travel by train

Conference

Presentation

Visit brewery

Dinner

Travel by train

Travel refund

Genetic Mining

Workflow Instance 3

Preparation

Travel by car

Conference

Visit brewery

Dinner

Pay parking

Travel by car

Travel refund

Workflow Instance 4

Preparation

Travel by train

Conference

Presentation

Visit brewery

MISSING

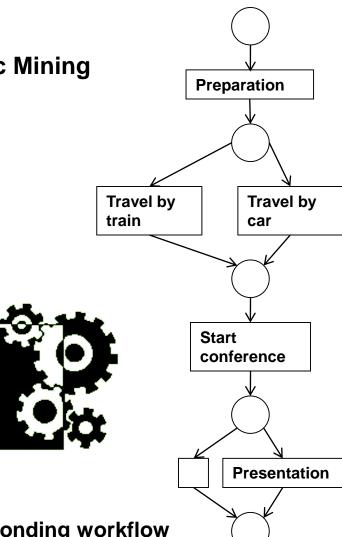
Travel by train

Travel refund

Corresponding workflow model (Petri Net)

Execution logs for a business process

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•Strengths of genetic algorithms:

- Highly complex problems
- Noisy logs

Workflow Instance 3

Preparation

Travel by car

Conference

Visit brewery

Dinner

Pay parking

Travel by car

Travel refund

Workflow Instance 4

Preparation

Travel by train

Conference

Presentation

Visit brewery

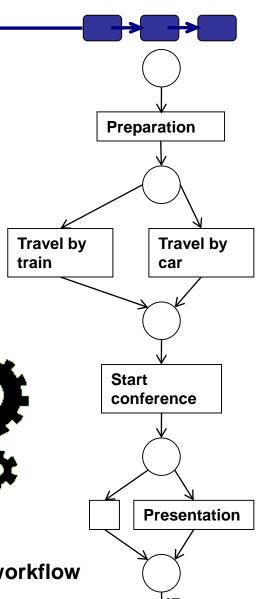
MISSING

Travel by train

Travel refund

Execution logs for a business process

Corresponding workflow model (Petri Net)

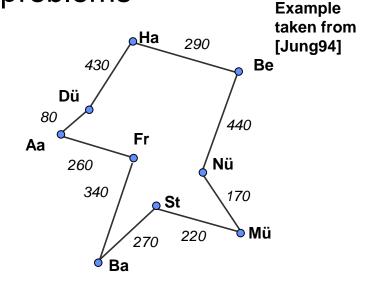




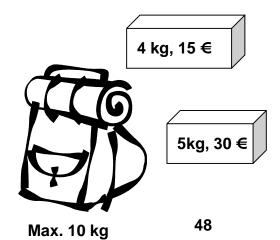
Many "traditional" Computer Science problems

- > Traveling Salesman Problem
 - > Combinatoric optimization
 - Used, for example, in logistics
- Knapsack Problem
 - Combinatoric optimization
 - > Used, for example, for portfolio management

The following introductory slides follow Eiben, Smith: Introduction to Evolutionary Computing, Springer 2003



3 kg, 20 €





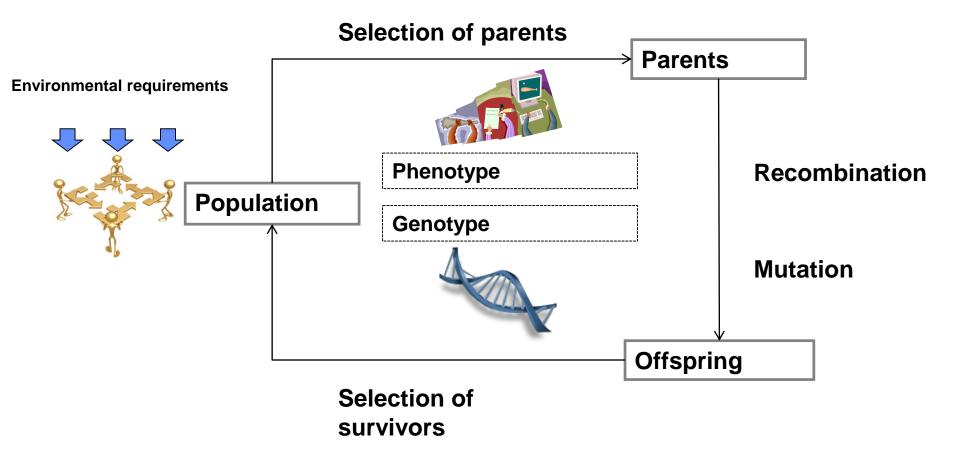
Observation of natural problem solvers

Evolutionary processes

Evolution	Problem solving
Environment	Search space
Individual	Solution candidate
Fitness	Quality

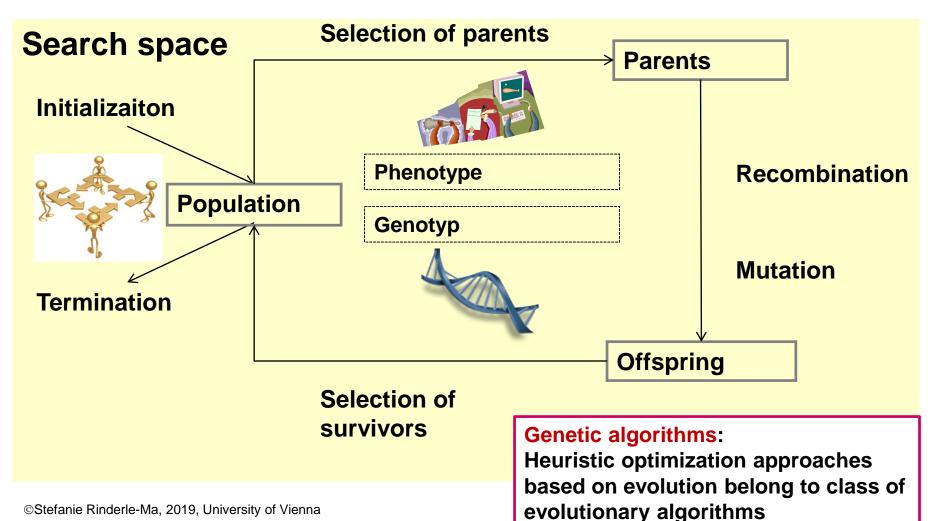


Basic idea:



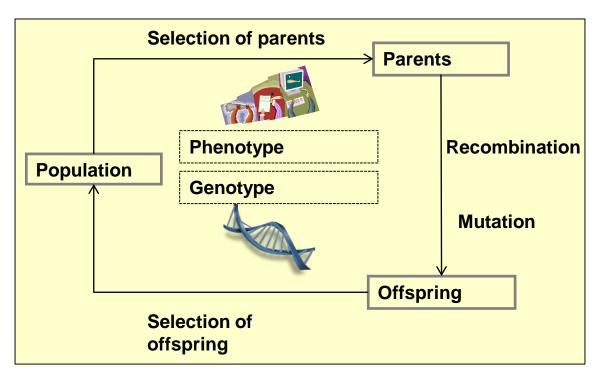


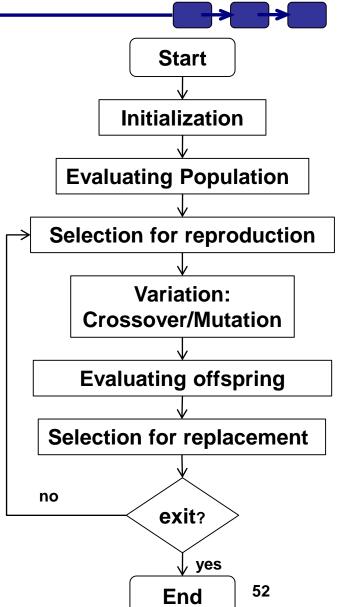
Basic idea:

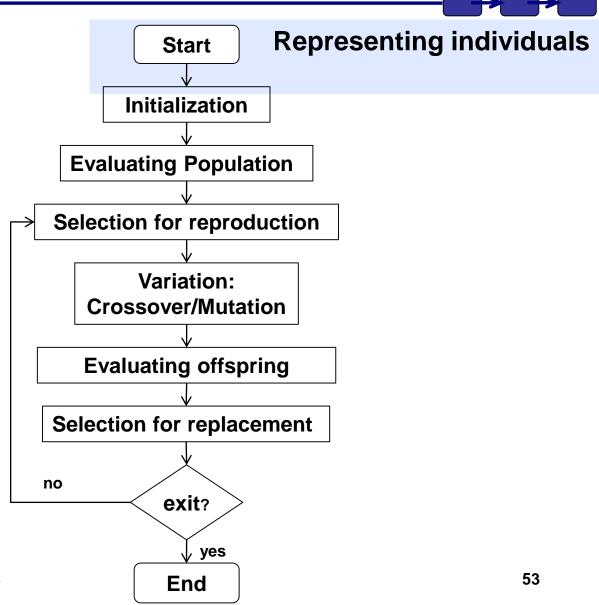


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Basic structure:



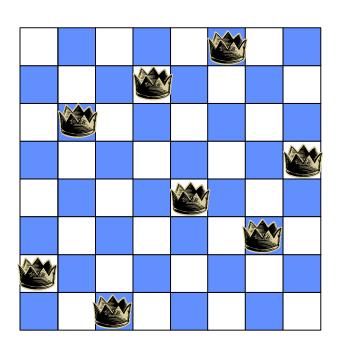


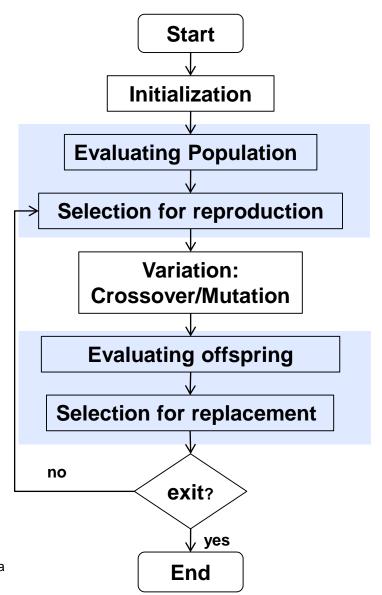




Representing individuals

- "good" coding of individuals
- > example: 8-Dames-Problem
 - Phenotype: one specific constellation
 - Coding genotype:
 - > Matrix representation
 - > Can we do it better?
 - \Rightarrow g = $\langle i_1, ..., i_8 \rangle$:
 - > n-th column, dame on position i_n
 - \rightarrow example: g = <2, 6, 1, 7, 4, 8, 3, 5>



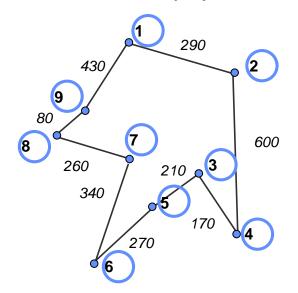




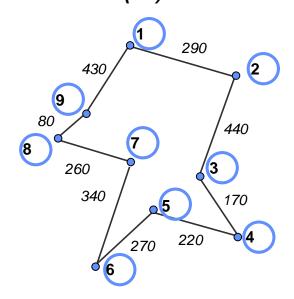
Selection criterion:

- Fitness function
- Determines quality of individuals
- Example: length of a trip with Traveling Salesman Problem

Tour T1: Fitness f(T1) = 2650



Tour T2: Fitness f(T2) = 2500



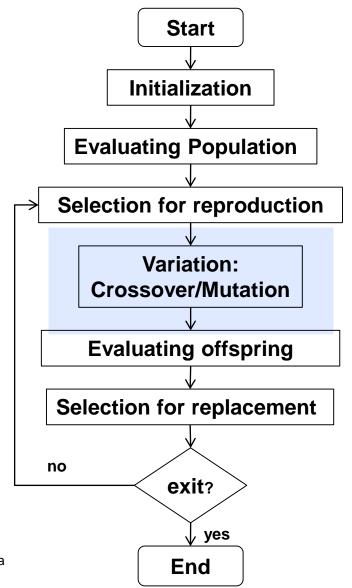


Selection of parents:

- Parents: creating offspring
- Goal: increased quality (fitness)
- "Better" individuals are selected with higher priority
- ➤ However, also individuals with lower fitness values are selected with some probability → diversity

Selection of offspring:

- Population size constant
- Selection based on fitness







Variation operators:

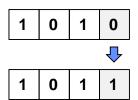
> Creating offspring

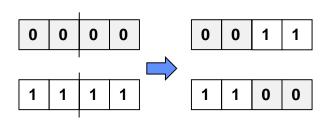
Mutation:

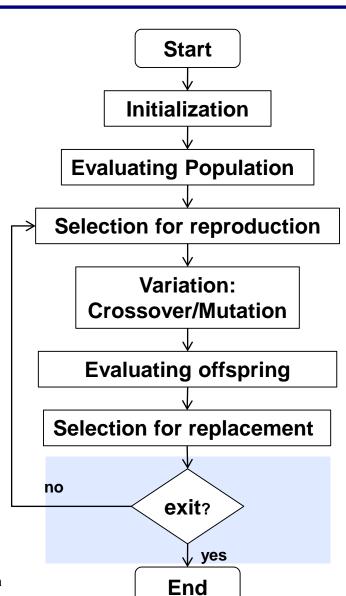
- > Example: Sphynx cat
- Unary operation

Recombination (Crossover):

- > Example: human being
- > In nature: binary operations











Termination

- ➤ If optimal fitness value known → termination with optimal solution
- However not sufficient (WHY??):
 - > Time limit
 - Upper bound for fitness evaluations



Representation of individuals:

- Finding an adequate genotype (coding)
- Often the most difficult part
- Depends on application
- Rules of thumb:
 - Data structure should corresponds as much as possible to natural representation
 - > If possible: genotypes represent valid solutions
 - If possible: variation operators do not destroy validity



Possible representations:

- First possibility: Bit-Strings s ∈ {0,1}ⁿ
- > Example:
 - MAXONE: Fitness function f counts number of "1" entries in bit string
 - \Rightarrow $s_1 = 1111010101$ $f(s_1) = 7$
- > Evaluation:
 - > Well suited for analytical purposes
 - > Representation of integer values:
 - \rightarrow Integer value corresponds to phenotype (e.g. x = 12)
 - > Bit String corresponds to geno type (e.g., s = 01100, $s \in \{0,1\}^5$)

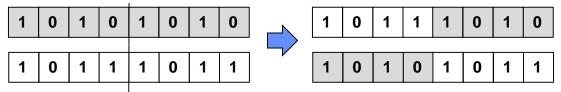


Variation operators for Bit Strings:

Mutation: Bit Flip with probabilities p_m per Bit



- Recombination:
 - One-Point Crossover



> N-Point Crossover (e.g. n = 2)

1	0	1	0	1	0	1	0	_	1	0	1	0	0	0	1	0
1	0	1	1	0	0	1	1		1	0	1	1	1	0	1	1

4 Genetic Mining

Workflow Instance 1

Preparation

Travel by train

Conference

Visit brewery

Dinner

Travel by train

Travel refund

Workflow Instance 2

Preparation

Travel by train

Conference

Presentation

Visit brewery

Dinner

Travel by train

Travel refund

Workflow Instance 3

Preparation

Travel by car

Conference

Visit brewery

Dinner

Pay parking

Travel by car

Travel refund

Workflow Instance 4

Preparation

Travel by train

Conference

Presentation

Visit brewery

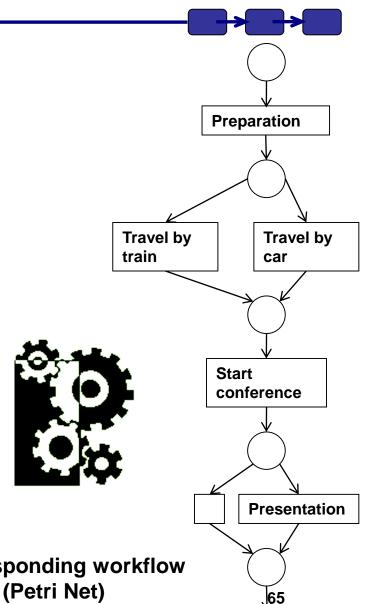
MISSING

Travel by train

Travel refund

Execution logs for a business process

Corresponding workflow model (Petri Net)



•Strengths of genetic algorithms:

- Highly complex problems
- Noisy logs

Workflow Instance 3

Preparation

Travel by car

Conference

Visit brewery

Dinner

Pay parking

Travel by car

Travel refund

Workflow Instance 4

Preparation

Travel by train

Conference

Presentation

Visit brewery

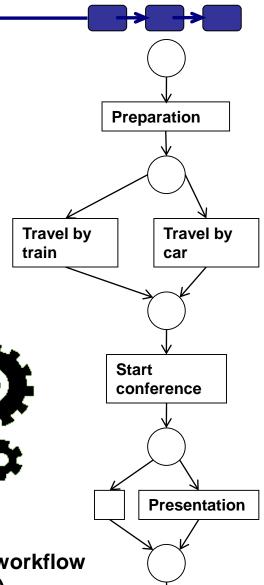
MISSING

Travel by train

Travel refund

Execution logs for a business process

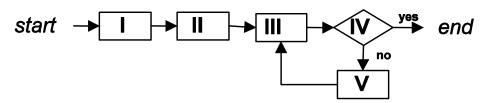
Corresponding workflow model (Petri Net)



©Stefanie Rinderle-Ma, 2019, University of Vienna



Genetic Mining Algorithm:



Source: T. Weijters, A. K. de Medeiros: Process Mining course, TU Eindhoven, 2009 (http://prom.win.tue.nl/research/wiki/courses/processmining)

Internal Representation Fitness Measure Genetic Operators

Step	Description
1	Read event log
	Build the initial population •
III	Calculate fitness of the
	individuals in the population
IV	Stop and return the fittest
	individuals? •
V	Create next population – use
	elitism and genetic operators ••



Internal Representation:

- ➤ Abstraction from Petri Nets → WHY?
- However, no information should be lost!
- Representation as causal matrix:

Genetic Mining

A.K.A. Medeiros, A.J.M.M. Weijters, und W.M.P.

evaluation," *Data Mining and Knowledge Discovery*, vol. 14, 2007, S. 245-304.

Aalst, "Genetic process mining: an experimental

DEFINITION (CAUSAL MATRIX): A Causal Matrix is a tuple CM = (A, C, I, O), where

- A is a finite set of activities,
- $C \subseteq A \times A$ is the causality relation,
- I: A $\rightarrow \mathscr{A}(A)$) is the input condition function
- O: A $\rightarrow \mathscr{P}(\mathscr{P}(A))$ is the output condition function,

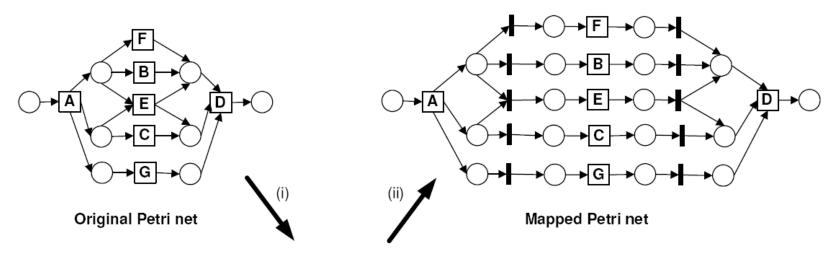
such that

- C = $\{(a_1, a_2) \in A \times A \mid a_1 \in \cup I(a_2)\}$
- C = $\{(a_1, a_2) \in A \times A \mid a_2 \in \cup O(a_1)\}$
- C \cup {(a_o, a_i) \in A \times A | a_o \bullet = $\emptyset \land \bullet$ a_i = \emptyset } is a strongly connected graph,



Genetic Mining Example:

Source: A.K.A. Medeiros, A.J.M.M. Weijters, und W.M.P. Aalst, "Genetic process mining: an experimental evaluation," *Data Mining and Knowledge Discovery*, vol. 14, 2007, S. 245-304.



ACTIVITY	I(ACTIVITY)	O(ACTIVITY)
Α	{}	{{F,B,E},{E,C},{G}}
В	{{ A }}	{{D}}}
С	{{ A }}	{{D}}}
D	$\{\{F,B,E\},\{E,C\},\{G\}\}$	{}
E	{{ A }}	{{D}}}
F	{{ A }}	{{D}}
G	{{ A }}	{{D}}

Causal Matrix



Mapping between Petri Net and Causal Matrix

Genetic Mining

Definition $\Pi_{PN\to CM}$ Let PN=(P,T,F) be a Petri net. The mapping of PN is a tuple $\Pi_{PN\to CM}(PN)=(A,C,I,O)$, where

- A = T.
- $-C = \{(t_1, t_2) \in T \times T \mid t_1 \bullet \cap \bullet t_2 \neq \emptyset\},\$
- $I \in T \to \mathcal{P}(\mathcal{P}(T))$ such that $\forall_{t \in T} I(t) = \{ \bullet p \mid p \in \bullet t \},$
- $O \in T \to \mathcal{P}(\mathcal{P}(T))$ such that $\forall_{t \in T} O(t) = \{p \bullet \mid p \in t \bullet \}.$

Source: A.K.A. Medeiros, A.J.M.M. Weijters, und W.M.P. Aalst, "Genetic process mining: an experimental evaluation," *Data Mining and Knowledge Discovery*, vol. 14, 2007, S. 245-304.



Genetic Mining - Initial Population:

- Individuals are causal matrices
- Given a log, all individuals in any population of the genetic algorithm have the same set of activities (or tasks) A. This set contains the tasks that appear in the log.
- The setting of the causality relation C can be done via a completely random approach or a heuristic one.
- The random approach uses 50% probability for establishing (or not) a causality relation between two task in A
- The heuristic approach uses the information in the log to determine the probability that two tasks are going to have a causality relation set:
- "The more often a task t_1 is directly followed by a task t_2 (i.e. the subtrace " t_1 , t_2 " appears in traces in the log), the higher the probability that individuals are built with a causality relation from t_1 to t_2 (i.e., $(t_1, t_2) \in C$)"

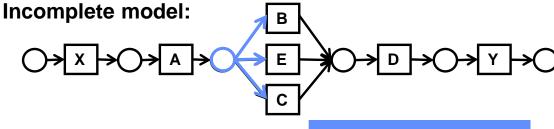
Source: A.K.A. Medeiros, A.J.M.M. Weijters, und W.M.P. Aalst, "Genetic process mining: an experimental evaluation," *Data Mining and Knowledge Discovery*, vol. 14, 2007, S. 245-304.

t of non

Gentic Mining - Fitness function

Punish for the amount of non producable traces

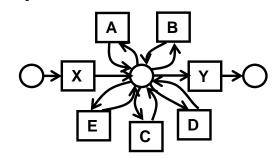
Process instance	Execution logs
1	X, A, C, D, Y
2	X, B, C, E, Y
3	X, A, C, D, Y
4	X, B, C, E, Y
5	X, B, C, E, Y
6	X, A, C, D, Y



Not producable

X, B, C, E, Y

Imprecise model:



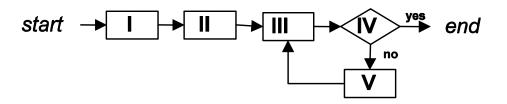
Additionally producable, e.g.,

X, A, A, A, B, Y

Punish for the amount of enabled tasks during the parsing!



Genetic Mining Algorithm:



Source: T. Weijters, A. K. de Medeiros: Process Mining course, TU Eindhoven, 2009 (http://prom.win.tue.nl/research/wiki/courses/processmining)

Internal Representation Fitness Measure Genetic Operators



Step	Description
1	Read event log
11	Build the initial population •
III	Calculate fitness of the individuals in the population
IV	Stop and return the fittest individuals?
V	Create next population — use elitism and genetic operators ● ●



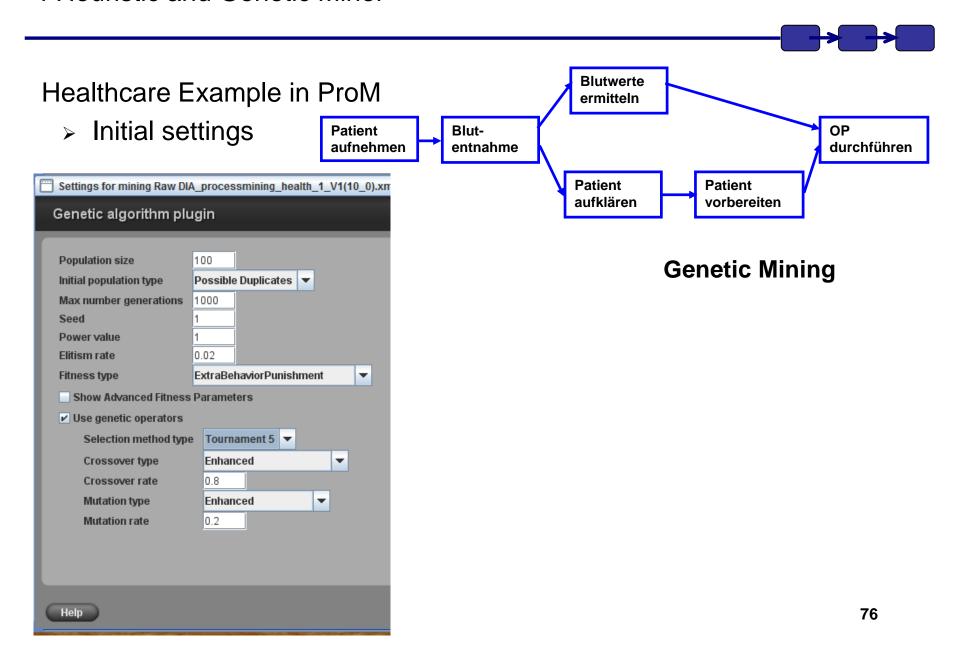
Genetic Operators:

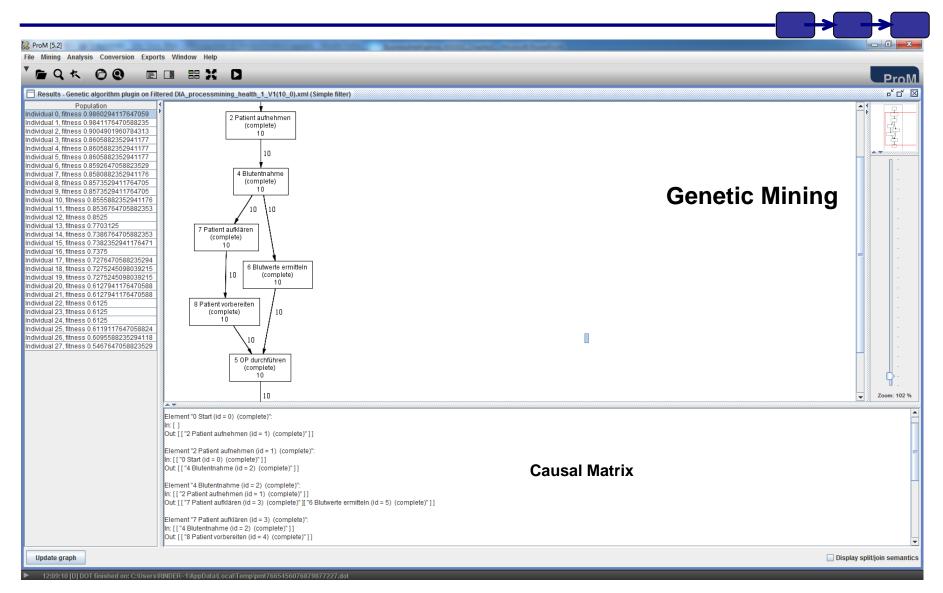
- Elitism: certain percentage of the best individuals is copied into next population
- > Crossover.
 - two parents produce two offsprings
 - > Selection of parents: tournament
- > Mutation: Insertion of new material into current population
 - ➤ Randomly choose subset and add a task (∈ A) into subset
 - Randomly choose subset and remove task
 - Randomly redistribute elements in the subsets of I/O into new subsets
 - Example for Mutation: I(D) = {{F, B, E}, {E, C}, {G}}
 - Mutation by adding tasks: {{F, B, E}, {E, C}, {G, D}}
 - > Mutation by removing tasks: {{F, B, E}, **{C}**, {G}}
 - Mutation by redistribution: {{F}, {E, C, B}, {G}, {E}}

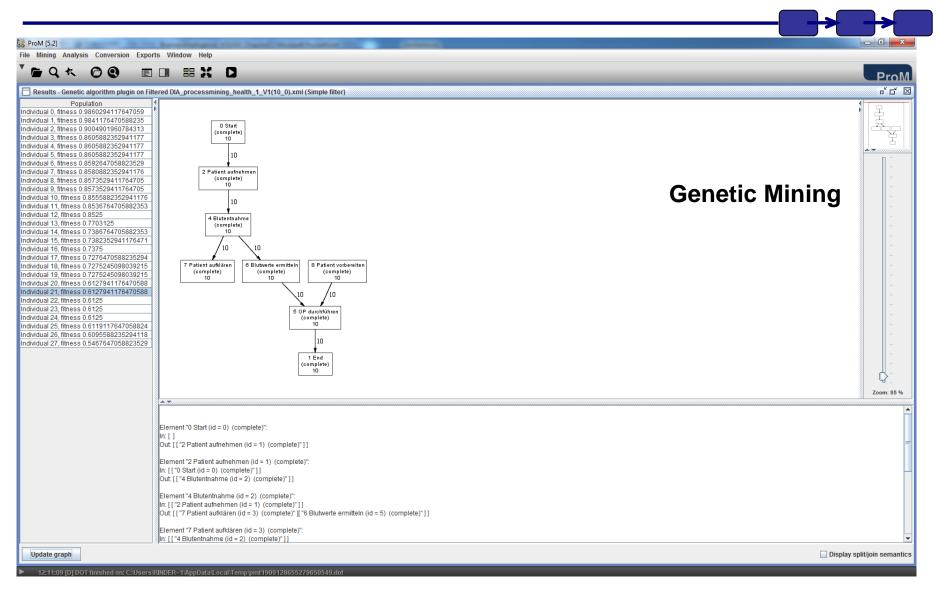


Genetic Mining - Stop Criteria:

- > n generations allowed
- > Fittest individual has not changed for n/2 generations in a row



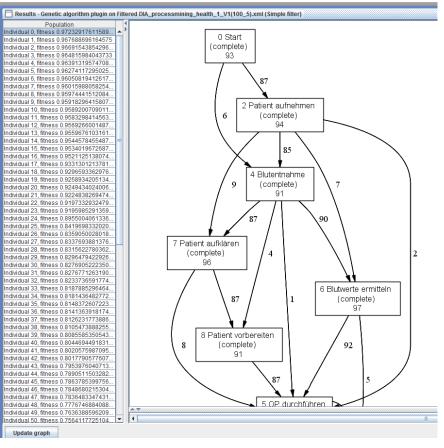


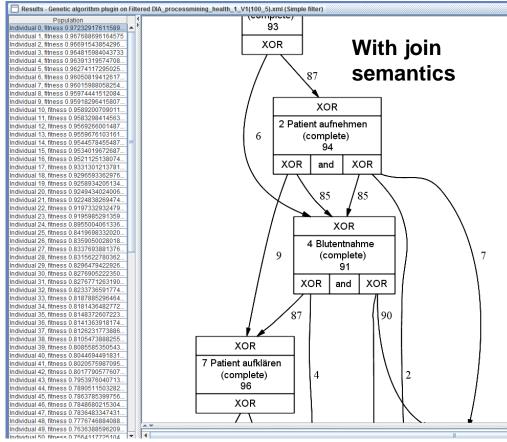




100 instances, 5% noise

Genetic Mining

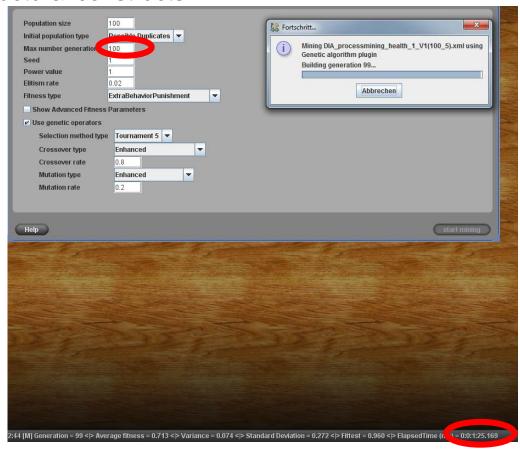






Genetic Mining - Discussion:

- Advantages
 - Tackles all common structural constructs
 - > Robust to noise
- Disadvantages
 - Computational Time
 - > Example:



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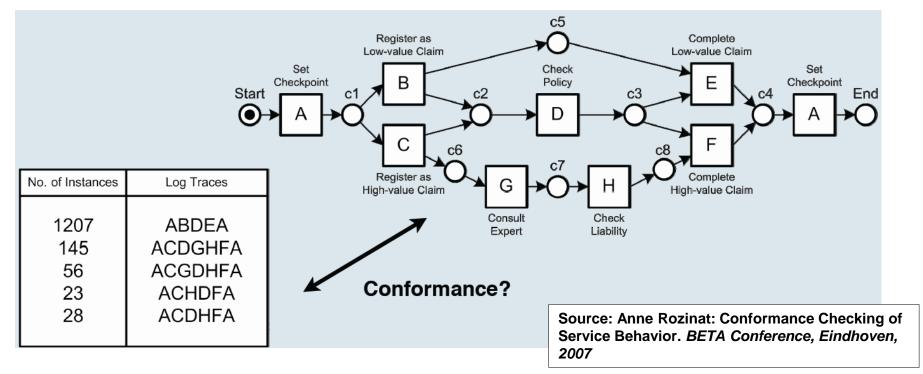


- 1 Motivation
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- **5 Conformance Checking**
- 6 Summary



Objectives:

- Compare process models and event data (e.g., for auditing)
- quantitatively measure conformance (i.e., metrics)
- locate deviations



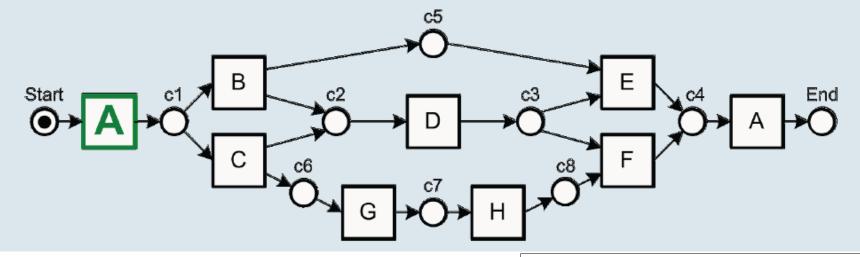


Measuring fitness: Log replay analysis

No. of Instances	Log Traces
1207 145 56 23 28	ABDEA ACDGHFA ACGDHFA ACHDFA ACDHFA

$$f = \frac{1}{2} \left(1 - \frac{\sum_{i=1}^{k} n_i m_i}{\sum_{i=1}^{k} n_i c_i} \right) + \frac{1}{2} \left(1 - \frac{\sum_{i=1}^{k} n_i r_i}{\sum_{i=1}^{k} n_i p_i} \right)$$

missing tokens = 0 consumed tokens = 0 remaining tokens = 0 produced tokens = 1

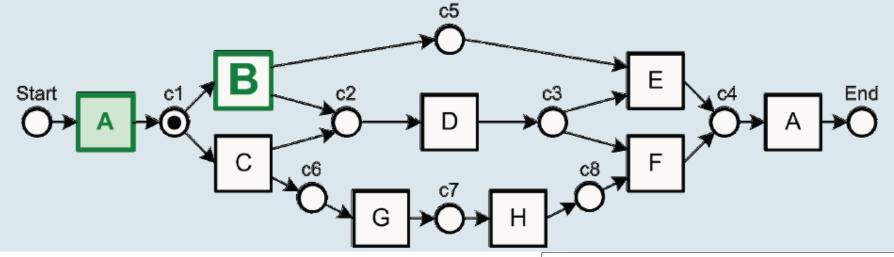




No. of Instances	Log Traces
1207 145 56 23 28	ABDEA ACDGHFA ACGDHFA ACHDFA ACDHFA

$$f = \frac{1}{2} \left(1 - \frac{\sum_{i=1}^{k} n_i m_i}{\sum_{i=1}^{k} n_i c_i} \right) + \frac{1}{2} \left(1 - \frac{\sum_{i=1}^{k} n_i r_i}{\sum_{i=1}^{k} n_i p_i} \right)$$

missing tokens = 0 consumed tokens = 1 remaining tokens = 0 produced tokens = 2



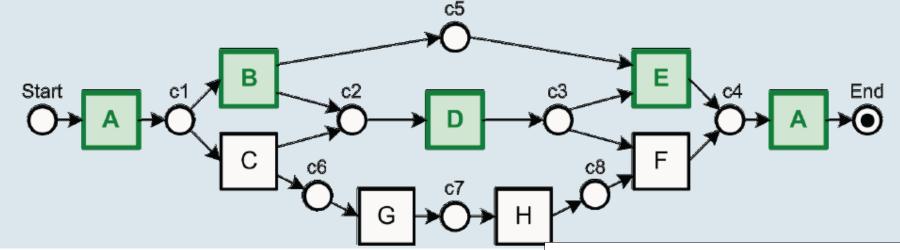


No. of Instances	Log Traces
1207	→ ABDEA
145	ACDGHFA
56	ACGDHFA
23	ACHDFA
28	ACDHFA

$$f = \frac{1}{2} \left(1 - \frac{\sum_{i=1}^{k} n_i m_i}{\sum_{i=1}^{k} n_i c_i} \right) + \frac{1}{2} \left(1 - \frac{\sum_{i=1}^{k} n_i r_i}{\sum_{i=1}^{k} n_i p_i} \right)$$

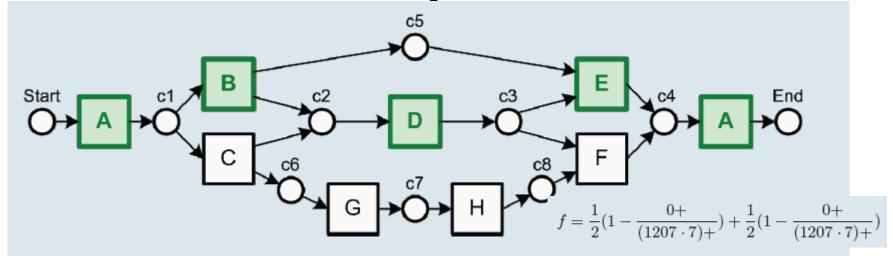
missing tokens = 0remaining tokens = 0 consumed tokens = 6

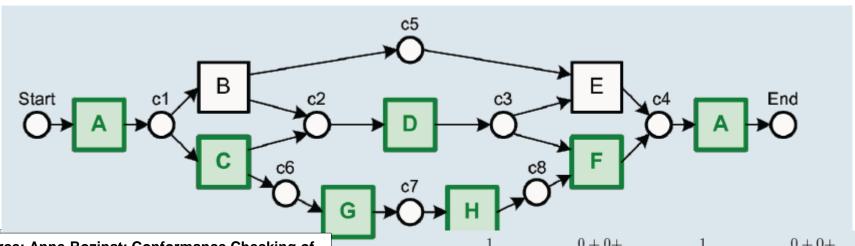
produced tokens = 7





Exercise: Calculate f for the following traces:





Source: Anne Rozinat: Conformance Checking of Service Behavior. *BETA Conference, Eindhoven,*

 $f = \frac{1}{2} \left(1 - \frac{0+0+}{(1207\cdot7) + (145\cdot9)+} \right) + \frac{1}{2} \left(1 - \frac{0+0+}{(1207\cdot7) + (145\cdot9)+} \right)$



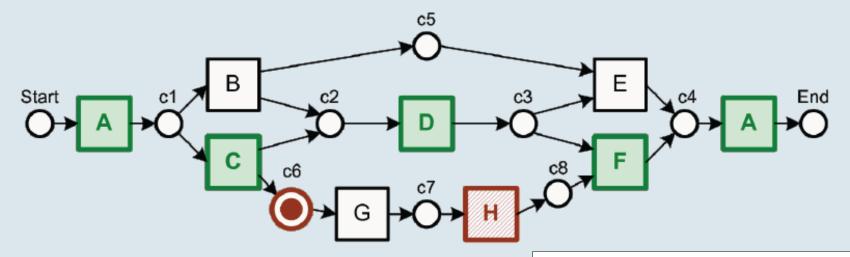
No. of Instances	Log Traces	$f = \frac{1}{2} \left(1 - \frac{0 + 0 + 0 + 0}{(1207 \cdot 7) + ((145 + 56) \cdot 9) + 1}\right)$
1207 145 56	ABDEA ACDGHFA ACGDHFA	$+\frac{1}{2}\left(1 - \frac{0+0+0+}{(1207\cdot7) + ((145+56)\cdot9)+}\right)$
23 28	→ ACHDFA ACDHFA	missing tokens = 1 consumed tokens = 7 remaining tokens = 0 produced tokens = 8
Start A	B C C C C	c5 $c2$ D $c3$ E $c4$ A E $C4$ A $C7$ $C8$ $C7$



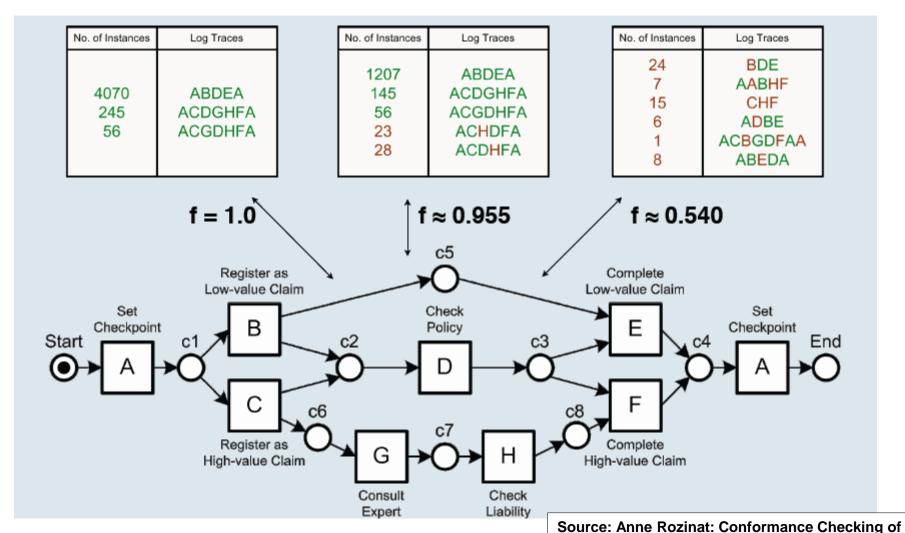
No. of Instances	Log Traces
1207	ABDEA
145	ACDGHFA
56	ACGDHFA
23	→ ACHDFA
28	ACDHFA

$$f = \frac{1}{2} \left(1 - \frac{0 + 0 + 0 + (23 \cdot 1) +}{(1207 \cdot 7) + ((145 + 56) \cdot 9) + (23 \cdot 8) +}\right) + \frac{1}{2} \left(1 - \frac{0 + 0 + 0 + (23 \cdot 1) +}{(1207 \cdot 7) + ((145 + 56) \cdot 9) + (23 \cdot 8) +}\right)$$

missing tokens = 1 consumed tokens = 8 remaining tokens = 1 produced tokens = 8







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Service Behavior. BETA Conference, Eindhoven,

2007

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6 Summary



- So far only discovery of control flow aspects
- Development of approaches for discovery of other important aspects, for example:
 - Organizational structures:
 - Social Network Mining [AaSo04] (e.g., who is working with whom)?
 - Access rules / staff assignment rules [LRRD05] (e.g., step A is executed by an actor having role "physician" and belonging to organizational unit "ward 1")
 - ➤ Decision Mining [RoAa06]: Mining of transition conditions determining routing in alternative branchnings (e.g., age > 20) → combines process mining and data mining (decision trees9 → combined approaches

6 Summary



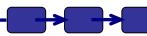
- Process disovery is one task of process mining
- A selection of further tasks is [Aalst11]:
 - > Enhance: connect process models to event logs for, e.g., repair
 - Check: for auditing reasons, process models can be checked against log data
 - Explore: event data can be used on top of process models to explore the performance of processes during runtime
- ➤ Comparing event data and process models is based on → conformance checking

References



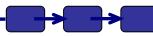
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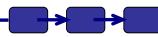
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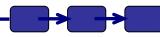
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References (ctd.)



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