University of Pisa MSc in Computer Engineering

PROCESS MINING

http://www.iet.unipi.it/m.cimino/wdis/

Mario G.C.A. Cimino Department of Information Engineering

Process Mining: introduction

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✓ The focus of process mining is to discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs readily available in today's information systems.

✓ Process mining techniques includes:

a) automated **process discovery** (extracting process models from an event log)

b) conformance checking (monitoring deviations by comparing model and log)

c) **model enhancement** (model extension and repairing)



Figure : The three basic types of process mining explained in terms of input and output: (a) discovery, (b) conformance checking, and (c) enhancement. ✓ Drivers: growth of digital world + continuous process changes over time

 ✓ Process models are expressed via process notation: Petri net, causal nets, process trees, EPCs, BPMN, or UML activity diagrams.

✓ BPMN 2.0 is a de-facto standard for modeling.



Process Mining: introduction



Process Mining: introduction

• **Petri net**, a mathematical modeling language for describing distributed systems. It is a bipartite graph in which nodes represents **transitions** and **places**, connected by **arcs**.



• a transition is an event that may occur, and is represented by a bar

• a place is a condition and is represented by a circle

• **arcs** run from a place to a transition (input place) or vice versa (output place), never between places or between transitions

• places may contain a discrete number of marks called **tokens**. A distribution of tokens over the places represents a configuration (marking) of the net

• a transition is fired if it is enabled, i.e., there are sufficient tokens in all of its input places. When the transition fires it consumes the required input tokens and created tokens in its output places. A firing is atomic (single non interruptible step).

• Unless otherwise specified, when multiple transitions are enabled at the same time, any one of them may fire (non determinism).

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• In **pure petri nets** the behavior can be specified with **arc multiplicities**: a transition *t* is enabled at marking *m* if every input place *p* of *t* contains at least as many tokens as the multiplicity of the arc from *p* to *t* is.



A Petri net with an enabled transition.

• Extended Petri exist, e.g, coloured petri nets are a backward compatible extension allowing the distinction between tokens with data values attached.

• Model transformations provide a wide range of techniques for model analysis on business processes used in industry. Process algebra is a family of formal approaches used in computer science to model concurrent systems. It provides algebraic laws to manipulate, analyze and permit formal reasoning about processes, and are at the core of process software engines.



The Petri net that follows after the transition fires (Initial Petri net in the figure above).



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Mapping task, events, and gateways onto Petri-net modules

Process Mining: introduction



A Petri net modeling the handling of compensation requests



The same process modeled in terms of BPMN

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PM is not limited to workflow, it covers different perspectives:

a) **control-flow perspective**: focuses on the ordering of activities, with the purpose of finding a good characterization of all possible paths.

b) **organizational perspective:** focuses on resources, the goal is to either structure the organization by classifying people in terms of roles and organizational units or to show the business network.

c) **case perspective:** focuses on properties of cases: the case path in the process, the actors working on it, the values of the corresponding data objects.

d) **time perspective** is concerned with discovering bottlenecks, measuring service levels, monitoring resources utilization, predicting the remaining processing time of running cases.

	An event log						
case id	activity	id	originator	time stamp			
case 1	activity	Α	John	9-3-2004:15.01			
case 2	activity	Α	John	9-3-2004:15.12			
case 3	activity	Α	Sue	9-3-2004:16.03			
case 3	activity	В	Carol	9-3-2004:16.07			

Process Mining: introduction



Fig. Some mining results for the process perspective (a) and organizational (b and c) perspective based on the event log shown.

Process Mining: introduction

 Starting 	Level	Characterization	Examples
point for PM is a collection of events (events log),	****	Highest level: the event log is of excellent quality (i.e., trustworthy and complete) and events are well-defined. Events are recorded in an automatic, systematic, reliable, and safe manner. Privacy and security considerations are addressed adequately. Moreover, the events recorded (and all of their attributes) have clear semantics. This implies the existence of one or more ontologies. Events and their attributes point to this ontology.	Semantically annotated logs of BPM systems.
stored in database	****	Events are recorded automatically and in a systematic and reliable manner, i.e., logs are trustworthy and complete. Unlike the systems operating at level $\star \star \star$, notions such as process instance (case) and activity are supported in an explicit manner.	Events logs of traditional BPM/ workflow systems.
tables, message logs, mail archives, transaction logs, and	***	Events are recorded automatically, but no systematic approach is followed to record events. However, unlike logs at level $\star\star$, there is some level of guarantee that the events recorded match reality (i.e., the event log is trustworthy but not necessarily complete). Consider, for example, the events recorded by an ERP system. Although events need to be extracted from a variety of tables, the information can be assumed to be correct (e.g., it is safe to assume that a payment recorded by the ERP actually exists and vice versa).	Tables in ERP systems, event logs of CRM systems, transaction logs of messaging systems, event logs of high-tech systems, etc.
other data sources. More important than the	**	Events are recorded automatically, i.e., as a by-product of some information system. Coverage varies, i.e., no systematic approach is followed to decide which events are recorded. Moreover, it is possible to bypass the information system. Hence, events may be missing or not recorded properly.	Event logs of document and product management systems, error logs of embedded systems, worksheets of service engineers, etc.
storage is their quality .	*	Lowest level: event logs are of poor quality. Recorded events may not correspond to reality and events may be missing. Event logs for which events are recorded by hand typically have such characteristics.	Trails left in paper documents routed through the organization ("yellow notes"), paper-based medical records, etc.
		Table: Maturity levels for event logs.	

Process Discovery: introduction

• Starting PM need to be driven by **questions**. Without concrete questions it is very difficult to extract meaningful events from tables of a database.

• As event logs contain only sample behavior, they should not be assumed to be complete. **Open world assumption**: the fact that something did not happen does not mean that it cannot happen.

• The simplest model that can explain the behavior seen in the log is the best model (Occam's Razor principle)

Consider an event log L = {
A, B, C, D, E>,
A, B, D, C, E>,
A, C, B, D, E>,
A, C, D, B, E>,
A, D, B, C, E>,
A, D, C, B, E> }



Process Discovery: introduction

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 But cases such as
 A, B, B, B, B, E> are possible according to the model but are not likely according to the event log.

• Noise and incompleteness make process discovery a challenging problem. There are four competing model quality dimensions:

(a) fitness: to allow for most of the behavior seen in the event log,

(b) **simplicity:** to allow for the most compact representation of the log

(c) precision: it does not allow for too much extra behavior w.r.t the log

(d) generalization: it does not restrict behavior to just the log

• A model that is not precise is "underfitting". A model that does not generalize is "overfitting".

• Balancing fitness, simplicity, precision and generalization is challenging. This is the reason that most of the more powerful process discovery techniques provide various parameters.

Process Discovery: introduction

• Three important categories of mining algorithms:

i) **Deterministic** mining algorithm: it always delivers the same result for the same input. e.g. the alpha-algorithm (Van der Aalst et al. 2002).

ii) **Heuristic** mining algorithm: it also uses deterministic algorithms but they incorporate frequencies of events and traces for reconstructing a process model, disregarding infrequent paths in order to manage complexity.

iii) **Genetic** mining algorithm: it uses an evolutionary approach to find a satisfactory solution by iteratively selecting individuals and reproducing them by crossover and mutation over different generations.

E.g. Heuristic Fuzzy Miner algorithm (Günther and Van der Aalst 2007), which does not follow the BPMN notation but uses a **dependency graph:**



Process Mining tools

• **ProM:** a major academic tool providing many different mining algorithms, analysis, conversion and export modules.

• **Disco:** intuitive and usabile application. It provides integrated

Process Mining Tools Product Name Type⁶ Link **ARIS Process Performance Manager** С www.softwareag.com celonis business intelligence (SAP) С www.celonis.de Disco С www.fluxicom.com Genet/Petrify 0 www.lsi.upc.edu Interstage Business Process Manager С www.fujitsu.com **QPR** ProcessAnalysizer С www.gqr.com ProM 0 www.processmining.org ProcessGold С www.processgold.de Rbminer/Dbminer 0 www.lsi.upc.edu ReflectOne С www.pallas-athena.com **ServiceMosaic** 0 soc.cse.unsw.edu.au C = commercial, O = open source

functionality for filtering and loading of event logs. It is especially suited for novel users. Non-commercial license is for academic institutions.

• Most used formats: CSV(comma separated values), MXML (Mining eXtensible Markup Language) and its successor, XES (eXtensible Event Stream)

• No support for the extraction of event data from source systems: data has to be extracted with specialized data extraction software or by using export functionalities of the source systems.

Process Discovery: introduction

• Event logs contain a set of events. A single event has a unique event ID, it refers to one individual case, it has a timestamp, and it shows which resources executed which task. It is a minimum requirement that the events refer to (i) one case, (ii) one task, and (iii) a point in time.

Case ID	Event ID	Timestamp	Activity	Resource
1	Ch-4680555556-1	2012-07-30 11:14	Check stock availability	SYS1
1	Re-5972222222-1	2012-07-30 14:20	Retrieve product from warehouse	Rick
1	Co-6319444444-1	2012-07-30 15:10	Confirm order	Chuck
1	Ge-6402777778-1	2012-07-30 15:22	Get shipping address	SYS2
1	Em-6555555556-1	2012-07-30 15:44	Emit invoice	SYS2
1	Re-4180555556-1	2012-08-04 10:02	Receive payment	SYS2
1	Sh-4659722222-1	2012-08-05 11:11	Ship product	Susi
1	Ar-38333333333-1	2012-08-06 09:12	Archive order	DMS
2	Ch-4055555556-2	2012-08-01 09:44	Check stock availability	SYS1
2	Ch-42083333333-2	2012-08-01 10:06	Check materials availability	SYS1
2	Re-4666666667-2	2012-08-01 11:12	Request raw materials	Ringo
2	Ob-3263888889-2	2012-08-03 07:50	Obtain raw materials	Olaf
2	Ma-6131944444-2	2012-08-04 14:43	Manufacture product	SYS1
2	Co-6187615741-2	2012-08-04 14:51	Confirm order	Conny
2	Em-6388888889-2	2012-08-04 15:20	Emit invoice	SYS2
2	Ge-6439814815-2	2012-08-04 15:27	Get shipping address	SYS2
2	Sh-727777778-2	2012-08-04 17:28	Ship product	Sara
2	Re-3611111111-2	2012-08-07 08:40	Receive payment	SYS2
2	Ar-3680555556-2	2012-08-07 08:50	Archive order	DMS
3	Ch-4208333333-3	2012-08-02 10:06	Check stock availability	SYS1
3	Ch-4243055556-3	2012-08-02 10:11	Check materials availability	SYS1

Process Discovery: the α -algorithm

- It is a basic deterministic mining algorithm. Assumptions:
- (1) the events in the log are chronologically ordered.
- (2) each event refers to a single case.
- (3) each event relates to a specific activity of the process.
- (4) each activity of the process is included in the log.
- (5) the log is behaviorally complete in the sense that if an activity *a* can be

directly	Case ID	Event ID Timestamp	Activity	Letter	Actvities
followed	1	Ch-468 2012-07-30 11:14	Check stock availability	a	Check stock availability
human	1	Re-597 2012-07-30 14:20	Retrieve product from warehouse	b	Retrieve product from warehouse
by an	1	Co-631 2012-07-30 15:10	Confirm order	с	Check materials availability
activity b,	1	Ge-640 2012-07-30 15:22	Get shipping address	d	Request raw materials
thon thoro	1	Em-655 2012-07-30 15:44	Emit invoice	e	Obtain raw materials
then there	1	Re-418 2012-08-04 10:02	Receive payment	f	Manufacture product
is at least	1	Sh-465 2012-08-05 11:11	Ship product	g	Confirm order
000 0200	1	Ar-383 2012-08-06 09:12	Archive order	h	Get shipping address
Une case	2	Ch-405 2012-08-01 09:44	Check stock availability	i	Ship product
in the log	2	Ch-420 2012-08-01 10:06	Check materials availability	j	Emit invoice
where we	2	Re-466 2012-08-01 11:12	Request raw materials	k	Receive payment
	2	Ob-326 2012-08-03 07:50	Obtain raw materials	1	Archive order
observe	2	Ma-613 2012-08-04 14:43	Manufacture product		Workflow Log
ab	2	Co-618 2012-08-04 14:51	Confirm order		a,b,g,h,j,k,i,l
u <i>b</i> .	2	Em-638 2012-08-04 15:20	Emit invoice		a,c,d,e,f,g,j,h,i,k,l
	2	Ge-643 2012-08-04 15:27	Get shipping address		
	2	Sh-727 2012-08-04 17:28	Ship product	 The 	starting point is to
	2	Re-361 2012-08-07 08:40	Receive payment	h. ala	the workflow lar
	2	Ar-368 2012-08-07 08:50	Archive order	Duild	the workflow log

Process Discovery: the α -algorithm

• A workflow log is a collection of all unique execution sequences observed in the log. The α -algorithm does not distinguish how often a specific execution sequence was observed in a workflow log.

- 1st phase: extract three order relations from the workflow of L:
- i) causality: $a \rightarrow b$ ("a then b") holds if we observe ab and not ba

ii) (potential) **parallelism:** *a*||*b* ("*a parallel b*")

holds if we observe both *ab* and *ba* iii) **non-succession**: *a#b* ("*a* hash *b*") holds if we observe neither *ab* nor *ba* (b)

- 2nd **phase**: map combinations of order relations to control flow patterns:
- a) sequence: if $a \rightarrow b$
- b) *xor-split*: if $a \rightarrow b \land a \rightarrow c \land b \# c$
- c) xor-join: if $b \rightarrow d \land c \rightarrow d \land b \# c$
- d) parallel-split:
- if $a \rightarrow b \land a \rightarrow c \land b \parallel c$ e) parallel-join:
 - if $b \rightarrow d \land c \rightarrow d \land b \parallel c$



Process Discovery: the α -algorithm

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• Order relations are easily derived by using the footprint matrix of the log:

 Fig. Footprint represented as a matrix of the workflow log L=[(a,b,g,h,j,k,i,l) (a,c,d,e,f,g,j,h,i,k,l)];

	a	b	с	d	e	f	g	h	i	j	k	l
a	#	\rightarrow				0	0			5		
b	←											
С												
d												
e												
$\int f$												
g												
h												
i												
j												
k												
l												

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• Order relations are easily derived by using the footprint matrix of the log:

 Fig. Footprint represented as a matrix of the workflow log L=[(a,b,g,h,j,k,i,l) (a,c,d,e,f,g,j,h,i,k,l)],

	a	b	С	d	e	f	g	h	i	j	k	l
а	# (\bigcirc	(\rightarrow)	#	#	#	#	#	#	#	#	#
b	←	#	#	#	#	#	\rightarrow	#	#	#	#	#
С	←	#	#	\rightarrow	#	#	#	#	#	#	#	#
d	#	#	←	#	\rightarrow	#	#	#	#	#	#	#
е	#	#	#	←	#	\rightarrow	#	#	#	#	#	#
f	#	#	#	#	~	#	\rightarrow	#	#	#	#	#
g	#	Ð	#	#	#	Ĵ	#	\bigcirc	#	\bigcirc	#	#
h	#	#	#	#	#	#	←	#	\rightarrow		#	#
i	#	#	#	#	#	#	#	\leftarrow	#	#		\rightarrow
j	#	#	#	#	#	#	←		#	#	\rightarrow	#
k	#	#	#	#	#	#	#	#) ←	#	\rightarrow
l	#	#	#	#	#	#	#	#	Œ	#	(-)	#

Process Discovery: the α -algorithm







Fig. Examples of two short loops, which are problematic for the α -algorithm

- All three models above can produce the workflow logs that yield b||c, because both *bc* and *cb* can be observed.
- To distinguish (I) and (II), in the α +algorithm extension b||c is only included if there is no sequence bcb in the logs. Preprocessing can be also used to collapse repetitions (like *aa* and *bb*) to a single execution.
- Further problems for the α -algorithm are *incompleteness* and *noise*. E.g. to determine potential parallelism in 10 concurrent tasks, the number of required different cases to observe is 10! = 3,268,800. Moreover, event logs often include cases with missing head, tail, intermediate episode, logging errors with events being swapped or recorded twice.

Conformance checking

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 \checkmark Conformance checking is concerned with the question whether or not the execution of a process (i.e., event logs) follows constraints.

 \checkmark We focus on constraints expressed as a *normative process model*. If a particular constraint does not hold, we speak of a *violation*.

 \checkmark The idea is to *replay* each trace of the log recording at each step whether an activity is allowed to be executed according to the model.

✓ For example replay the case (a,b,g,I,j,k,l) on the model shown in figure.



Fig. BPMN model with token on start event for replaying the case $\langle a, b, g, i, j, k, l \rangle$

Conformance checking



Fig. BPMN model with token on start event for replaying the case $\langle a, b, g, i, j, k, l \rangle$

✓ In the initial state the process has a token on the start event, which leads to activity *a*. Then, the XOR-split is activated, which allows to either continue with *b* or with *f*. For the considered case, we can continue with *b*. Then, we can continue with *g*, after which the AND-split enables both *i* and *j*. These activities are concurrent. In order to replay the case, we first execute *i* and *j* afterwards. Once *i* and later *k* is completed, the AND-join is allowed to proceed. One token on each its input arcs is required for that. Since both of these tokens are consumed, a single token can be created to enable *l*, which can be finally executed. Thus, the case can be totally replayed on the model.



 \checkmark Based on the concept of token replay, we can also assess the conformance of a trace to a process model.

✓ The idea is to compare at each step the number of tokens that are required for replaying an activity with the actually available tokens.
 ✓ At each step, we might observe situations of conformance and non-conformance. In case of conformance, we count the following four facts:

- p: # of output tokens correctly produced by a model element
- c: # of input tokens correctly consumed by a model element
- m: # of missing (unproduced) output tokens, e.g. because something did not occur
- r: # of input tokens remaining unconsumed, e.g. because something did not occur although the model expected it to happen

Conformance checking



correctly produce the output tokens: both are correctly consumed in the log

Conformance checking

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✓ We calculate the *fitness* of the case by using the fractions *missing-to-consumed* and *remaining-to-produced*:

$$fitness = \frac{1}{2} \left(1 - \frac{m}{c} \right) + \frac{1}{2} \left(1 - \frac{r}{p} \right)$$

- *p*: # of output tokens correctly *produced*
- c: # of input tokens correctly consumed
- *m*: # of *missing* (unproduced) output tokens
- r: # of input tokens remaining unconsumed

$$p+m = c+r$$

✓ With *m*=1 and *r*=1, *c*=12 and *p*=12, *fitness*=(1-1/12)/2 + (1-1/12)/2 = 0.9166

 \checkmark With a set of cases: after replaying a case, continue counting c,p,m,r by replaying the next case in the process model. Once all cases have been replayed, get the resulting fitness with the same formula. Example in figure



Process Mining tools: ProM 6.x

the input of l)

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conformance measures (like fitness) and local diagnostics

ActionTab for executing algorithms
 Enter "BPMN" to select BPMN-based plugins
 Select "BPMN Analysis (using Causal Net Miner)" and press "Start"

✓ BPMN Analysis using Causal (C-) Net Miner

It is an advanced algorithm. How it works (in brief):

• A **C-net** is a representation of a process model as a graph, where nodes represent activities and arcs represent causal dependencies;

• **Cost-based fitness** is measured based on finding skipped/inserted activities giving minimal costs (highest possible fitness value), using A* algorithm (heuristic variant of Dijkstra's algorithm) to find shortest paths between two nodes in a directed graph with arc costs;

• The cost function is provided with options to specify the relative costs of skipped / inserted activities

• A **projection** method is used to split the log into pieces: it selects groups of events tightly related in the log projecting the log on these events. Leave default values and click on "Continue".

BPMN Analysis Settings	
Projection Details	
Number of Most Frequent Path :	3
Number of Most Time Consuming Path :	3
Number of Least Frequent Path :	3
Number of Least Time Consuming Path :	3
Cancel	Continue

Introduction to Process Mining tools

• A wizard procedure configure the replay process.





• Check the label match between node of the net and event classes. There can be additional nodes in the net, causing mismatch.

• Some algorithms are grounded on the theory of regions, which maps a model in the state based domain (automata) into the event-based domain (e.g Petri net). Leave default values and click "Next"



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- Finally, a threshold can be set to discover also swimlanes
- Leave the default values and press "Finish"/"Continue".

X Cancel	Previous I Finish							
Swimlan	Swimlane Threshold Settings							
Swin	nlane Threshold Selection							
Number of Executions by Users Threshold :	%0 @%0	> %100						
Cancel		Continue						

Introduction to Process Mining tools

- A B C D A C B D A E D 1x Case1 • Exercise 1 BPMN Analysis (Using causal net miner) 1x Case2 1x Case3 С жO D в E 1x Case1 ACD • Exercise 2 Tasks BCE 1x Case2 BPMN Analysis (using Causal Net Miner) X • The log cannot be processed, because it has multiple start events Failure During Log Filtering ×
- To add the Start/End events, you can use either DISCO or TEXTPAD





Introduction to Process Mining tools







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• Exercise 4

1x 1x 1x 1x 1x 1x	Case1 Case2 Case3 Case4 Case5	a a a a	b u b u d a	C b d d e d	d d c b f f	f f f
1x	Case6	а	е	d	f	



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SENIOR log	Case ID	Timestamp	Activity	4	05/02/2015 00.00	start
(Software	0	05/02/2015 00.00	start	4	05/02/2015 01.00 🔎	analyse
	0	05/02/2015 01.00	report	4	05/02/2015 02.00	prototype
Engineering for	0	05/02/2015 02.00	analyse	4	05/02/2015 03.00	integrate
Input/Output	0	05/02/2015 03.00	prototype	4	05/02/2015 04.00	test
	0	05/02/2015 04.00	integrate	4	05/02/2015 05.00	report
pRoblems)	0	05/02/2015 05.00	test	4	05/07/2015 05.00	ena
	0	05/02/2015 06.00	end	5		start
• It contains	1	05/02/2015 00.00	start	5	05/02/2017 01.00	prototype
different cases of	1	05/02/2015 01.00	analyse		05/02/2015 03 00	integrate
	1	05/02/2015 02.00	report	5	05/02/2015 04.00	test
problem solving.	1	05/02/2015 03.00	prototype	5	05/02/2015 05.00	report
Fach case involves	1	05/02/2015 04.00	integrate	5	05/02/2015 07.00	analyse
	1	05/02/2015 05.00	test	5	05/02/2015 08.00	report
a worker improving	1	05/02/2015 06.00	end	5	05/02/2015 09.00	prototype
the input/output	2	05/02/2015 00.00	start	5	05/02/2015 10.00	integrate
	2	05/02/2015 01.00	analyse	5	05/02/2015 11.00	test
(1/o) of a Java-	2	05/92/2015 02.90	prototype	5	05/02/2015 12.00	end
based software	2	05/02/2015/03.00	report	6	05/02/2015 00.00	start
based soleware	2	05/02/2015 04:00	integrate	6	05/02/2015 01.00	analyse
application	2 /	05/02/2015 05.00	test	6	05/02/2015 02.00	report
Curath attic large age	2	05/02/2015 06.00	end	6	05/02/2015 03.00	intograto
• Synthetic log: cases	3	05/02/2015 00.00	start	6	05/02/2015 04.00	tost
without violations: the	3	05/02/2015 01.00	analyse	6	05/02/2015 06 00	analyse
	3	05/02/2015 02.00	prototype	6	05/02/2015 07.00	prototype
base partern, iterated	3	05/02/2015 03.00	Integrate	6	05/02/2015 08.00	report
one or many times is	2	05/02/2015 04.00	tost	6	05/02/2015 09.00	integrate
	3	05/02/2015 05.00	end	6	05/02/2015 10.00	test
$(u \rightarrow p \rightarrow i \rightarrow i) \parallel i$	5	05/02/2013 00.00	citu	6	05/02/2015 11.00	end

Introduction to Process Mining tools

Academic mario.cimino@unipi.it senior log ideal Disco ÷ -Statistics Мар Cases • See Zoom: Detail statistics and Cases • Hide less frequent transitions Path between activities to avoid "spaghetti" process map 100% 100% ₩ Frequency • Export Show: Absolute frequency data in a number of • Process map generated by Disco formats (based on Fuzzy Miner), showing the Add secondary metrics frequency of paths between activities 🖉 Performance Γ. × Animation

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Introduction to Process Mining tools

• In ProM, apply "BPMN Miner"



• Model generated by the inductive miner algorithm



• Since there is no violation in the event log, the generated model is very similar to the normative process:



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• In brief: the **Inductive Miner** aims to discover block-structured process models fitting the behavior represented in event log. IM partitions the activities, select the most important process constructs, splits the log and recurses until a base case is encountered.

• A process tree is the hierarchical representation of a block-structured workflow net. The leaves of the tree are activities, representing transitions. The nodes of the tree, *operators*, describe how their children are combined: exclusive choice (×), sequential composition (\rightarrow), parallel composition (\wedge), and loop (\circlearrowright).



Figure: A block-structured workflow net M_E ; filled regions denote the blockstructure; process tree $\rightarrow (\times(\wedge(a,b),c), \times(\bigcirc(\rightarrow(d,e),f),g))$ corresponds to this net.

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• Conformance checking: to check the real log against the normative process



- Steps on ProM:
- 1: Import both the normative model (senior bpmn.xml) and the real log (senior log real.mxml)
- 2: In the action tab, click on "Select BPMN Diagram"; the normative process model appears.
- 3: Select the BPMN Diagram in the workspace tab, and click the action button; then select "Convert BPMN Diagram to Petri net (controlflow)"; a Petri net appears: you do not need to inspect it.
- 4: In the workspace tab, select the Petri net, and click the action button; then click to add input object and select "senior log real.mxml"
- 5: In the action tab, select "Replay Log on Petri Net for Conformance Analysis"

Introduction to Process Mining tools

11.11.11 11 11/ Actions Input Output DO () () Q sear Petrinet log replay result Petri net from play a Log on Petri Net for All Optimal Alignme senior log real.mxml Replay a Log on Petri Net for Conformance Ana Replay a Log on Petri Net for Performance/Confe Simplify Mined Model Using Uma

6: Answer YES to the question "No final marking is foud on this model. Do you want to create one?"; select "p_end_end" as a candidate final

Click on	Select mapping			
"Add —	List of Places		Candidate Final Marking	
place".	Continue report?_null_NO g_xor_null integrate_test_ null_Next iteration?_ null_analyse_ null_null_ null_report_ p_end_end p_start_start	Add Place >>	p_end_end	

7: Select "Event Name" as a classifier

Map Transitions to Ever	it Class	
First, select a classifier. Unmapped transitions wil	I be mapped to a dummy event class.	
Choose classifier	Event Name	
Continue report?_merge_null	NONE	•
report_split_null	NONE	
start_merge_null	NONE	
t_act_analyse	analyse	
t_act_integrate	integrate	T
t_act_prototype	prototype	
t_act_report	report	
t_act_test	test	•
t_end_end	ent	v)
t_start_start	start	

8: Select NONE for all transitions, except for those with "t_act", "t_end", "t_start" as a name prefix, whose mapping must be accurately checked

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- 9: Select "YES, set them to invisible" in the dialog windows on the visibility of unmapped transitions
- 10: Wait the processing for abut a half a mninute



11: Leave the default algorithm for measuring fitness

12: Leave the default parameters, and click on "Finish". Wait some seconds

eplay Parameter General Settings R	eplacement Cost	Swapping Cost	
Set parameters			
ouble click costs on table to change their values. U	se only non-negative ir	ntegers.	
# Maximum explored states (in hundreds). Set i	max for unlimited. 🗲		2000
Transition		Move on Model Cost	
t_start_start t end end	1 1		
t_act_report	1		
t_act_test t_act_integrate	1		
t_act_prototype	1		
t_act_analyse	1		
null_split_Continue report?	0		
null enlit Continue report?	0		
Set all co	osts above to 🚺	Set	
Event Class		Move on Log Cost	
integrate start	1		
test	1		
report	1		
DUMMY	1		
end	1		
analyse			

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13: A Petri Net appears, together with an "Inspector" popup windows



replayed in the discovered Petri Net.

• A fitness value of 1 means that the log can be successfully replayed, whereas a value of 0 means that this is completely not the case.







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Separate cases into clusters according to fitness https://tinyurl.com/pdis-k-means

http://scistatcalc.blogspot.it/2014/01/k-means-clustering-calculator.html

					Trace
Choose File	Perform k-means cli	Isterina	Index	Case ID F	itness
0110000011110		dotorning	1	491381	1
Input	Output:-	Centroid values:-	2	477447	1
1	# Sample value,	#Centroid index,	3	493534	0,67
1	Centroid index	Centroid value	4	490259	0,61
0.67	1,1	1,0.936	5	492746	0,67
0.67	0.67,3	3,0.671	6	493724	0,75
0.75	0.61,3		7	483505	0.41
0.65	0.75,3		8	476904	0.65
0.71	0.41,2		9	479570	0.71
0.56	0.65,3		10	492998	0,56
0.67	Enter number of c	lusters (k value):-	11	490756	0,64
U.88 0.88	3		12	475754	0,67
0.78	F		13	485552	0,88
0.92	Enter number of it	erations:-	14	490875	0.88
	100		15	456762	0.78
Clear Input			16	477089	0,92

Separate cases into clusters according to fitness



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Separate cases into clusters according to fitness https://tinyurl.com/pdis-fcm https://aydos.com/fcm/

FUZZY Clustering Index Case ID Fitness Fuzzy logic c-means clustering 1 491381 1 2 477447 1 3 493534 0,67 4 490259 0,61 5 492746 0,67 1 0 483505 0,41 5 492746 0,67 6 493724 0,75 7 483505 0,41 8 476904 0,655 9 479570 0,71 10 492998 0,56 11 490756 0,64 12 475754 0,67 13 485552 0,88 14 490875 0,88 15 456762 0,78 13 485552 0,88 14 490875 0,88 15 456762 0,78 16 477089 0,92	-				Trace
Fuzzy logic c-means clustering 1 491381 1 2 477447 1 3 493534 0,67 4 490259 0,61 5 492746 0,67 6 493724 0,75 0.6700000 0.6700000 0.4100000 6 0.7500000 0.4100000 0.4100000 9 0.4700000 0.5600000 0.5600000 0.6400000 0.5600000 0.5600000 Use () for decimals and semicolons, tabs, commas or spaces to separate coloums. After entering data click 'Accept Data' 11 490875 0,888 10 492998 0,560 11 490875 0,888 11 490875 0,888 14 490875 0,888 14 490875 0,888 14 490875 0,888 15 456762 0,78 16 477089 0,92	Fuzzy Clu	stering	Index	Case ID F	itness
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Fuzzy Clustering and Data Analysis - v2.3 3 493534 0,67 Image: Data Options Calculation Results 4 490259 0,61 Image: Data Options Calculation Results 5 492746 0,67 Image: Data Options Calculation Results 5 492746 0,67 Image: Data Options Data dimension 1 5 493534 0,67 Image: Data Options Calculation Results 5 492746 0,67 Image: Data Options Data count 16 7 483505 0,41 Image: Data Options Options Options 0,67 6 493724 0,75 Image: Data Options Options Options 0,65 0,41 8 476904 0,65 Image: Data Options Options Max data size is 8x2000. 10 492998 0,56 Image: Data Options Options Options Image: Data 11 490756 0,64 Image: Data			2	477447	1
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Data Options Calculation Results 5 492746 0,67 1.0000000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.6700000 0.68000000 0.6700000 0.6700000 0.68000000 0.64000000 0.64000000 0.64000000 0.64000000 0.64000000 0.64000000 0.68000000 0.68000000 0.64000000 0.64000000 0.64000000 0.64000000 0.64000000 0.64000000 0.64000000 0.64000000 0.64000000 10 492998 0.560 0.640000000 0.68000000 0.68000000 0.68000000 11 490756 0.640 0.78000000 0.92000000 0.92000000 0.46000000 13 485552 0	Puzzy Clustering and Data Analysis - vz.3		4	490259	0,61
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© aydos.com, see terms of usage 16 477089 0,92		Accept Data See Graphs	15	456762	0,78
	© aydos.com, see terms of usage		16	477089	0,92

Accept data > Options > Cluster centers: 0.93 0.67 0.44 Memberships 	> Calculation > Results Fuzzy Clustering and Data Analysis - v2.3 Data Options Calculation Options Calculation Options Clusters 3 - + Fuzziness coefficient 2 - + Separate coloums with tabs + Maximum iteration 100 Epsilon 0.01 +		
Fuzzy Clustering and Data Analysis - v2.3 Data Options Calcula Clustering Fuzzy c-means (FCM) Gustafson-Kessel	tion Results		
Analysis Method Fuzzy Least Square Estimation Improved Fuzzy Functions Calculate Finished.	Data Options Calculation Results Current Previous Results (ready to copy paste) Data size 1x16 - Train data 16 - Validation data 0 - Clusters 3 - Clusters 3 - Fuzziness coefficient 2 - Normalization No - Clustering method FCM - Analysis method FLSE -		

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Exercise: Simplified map transitions to event classes

- a) Import the senior bpmn.xml file in Visual Paradigm and remove the pool
- b) Export the new BPMN as senior bpmn nopool.xml
- c) Convert the model to Petri Net via "Convert BPMN to Petrinet" the resulting Petri Net is more compact
- d) Carry out the "Replay a Log on Petri Net for Conformance Analysis" The map transitions to event classes is simplified.

		No Initial Marking
		i No initial marking is found for this model. Do you want to create one?
Select mapping		Yes No
List of Places Continue report? END Next iteration? START p1 p2 p3 p4 p5	Add Place >> << Remove Place	Candidate Initial Marking <empty marking=""></empty>

The transition name may not appear due to label errors in the BPMN

Mapping Petrinet - Event Class of L	og
Map Transitions to Event Class	
First, select a classifier, onmapped transitions will be mapped to	a dummy event class.
Choose classifier	Event Name
	stan
anatyse	anaryse
integrate	integrate v
prototype	prototype 🔻
report	report
10	NONE
u	NONE
13	NONE
t4	NONE
test	(test v)
Cancel	Previous 🗹 Finish

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Inspect individual cases, compare the trace fitness w.r.t. the other Petri Net



The four quality dimensions for process discovery



The **Fitness** of a mined Model (M_m) meaures how much of the observed behavior in the log (L) is captured by the process model. Good fitness (close to 1) allows the replay of (most of) the behavior seen in the event log

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

E.g. the fraction of event patterns represented by kthe model, the n_i fraction of cases m_i that can be r_i replayed in the c_i model) p_i

- # of different traces.
- # of traces of type k in log L.
- $m_i \# of missing tokens (artificially added) parsing i.$
- \mathbf{r}_{i} # of remaining tokens parsing *i*.
- $c_i \# of consumed tokens parsing i.$

 $p_i \# of produced tokens parsing i.$

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• **Simplicity** is measured by comparing the number of elements (i.e., **#gateways + #sequence flows + #activities**) of the model M with the number of activities (cardinality of) in the log.

In general it is measured by complexity metrics for process models such as model size or degree of structuredness.

• Fitness and simplicity are not enough to judge the quality of a discovered process model, as clearly shown in the following exercise.

• Exercise: Draw a model in BPMN with which you can replay any execution sequence that includes tasks a, b, c, d, e. Furthermore, discuss the fitness, simplicity, precision, and generalization of such a model for the trace $\langle a, b, c, d, e \rangle$.

• Solution:



- Fitness: it is perfect to the execution sequence as it is able to replay the occurrence of *a* to *e*
- Simplicity: the model is not completely simple as it includes four gateways for characterizing the behavior of five activities.
- **Precision:** The discovered model should not allow for behavior very different from what was seen in the event log. The solution is not very precise because it does not introduce specific constraints on the behavior: any occurrence of *a* to *e* is allowed at any stage.
- A simplified formula for the precision of a mined model (M), assuming that {enL} is included in {enM}:

if the enM >> enL then the P is low (too much extra behavior)

ε

$$\mathbf{P}(L, M) = \frac{1}{|\varepsilon|} \sum_{e \in \varepsilon} \frac{|\mathbf{en}_{\mathbf{L}}(e)|}{|\mathbf{en}_{\mathbf{M}}(e)|}$$

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- collection of *unique events* in a context of the log.
- $en_M(e)$ enabled activities in the model M.
- $en_L(e)$ observed activities actually executed in a similar context in L.

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- Generalization: as opposed to precision, this criterion focus on avoiding overly precise models, since event logs are often far from complete.
- It refers to the ability of the model to abstract. The solution model does not constrain the behavior, and then there is hardly any general insight that we can learn from it.
- To calculate precision and generalization with ProM: after the Replay result generated by conformance cheking, in the workspace select Replay Result, Petri net and the Log Then select "Measure Precision/Generalization" and continue with default settings



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Other useful ProM plugins (alternative to Disco)

a) Log filtering

- "CSV File (XES Conversion with Log package)": to import csv logs
- "Convert CSV to XES": to transform the csv log into a XES log
- "Move trace level attributes from events to trace (In Place)": to set trace attributes in the XES
- "Filter Log on Trace Attribute Values": to filter trace attributes
- "Filter Log using Simple Heuristic": to remove cases on the basis of the activities frequency
- Add Artificial Events, to add start/end tasks when missing

b) Model miners

- "Mine for a Fuzzy Model": it generates a transition map
- "BPMN Miner" > "Heuristics Miner ProM6": it extracts compact models