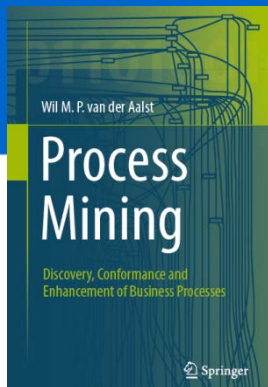


Process Mining: Data Science in Action

How Process Mining Relates to Data Mining

prof.dr.ir. Wil van der Aalst
www.processmining.org

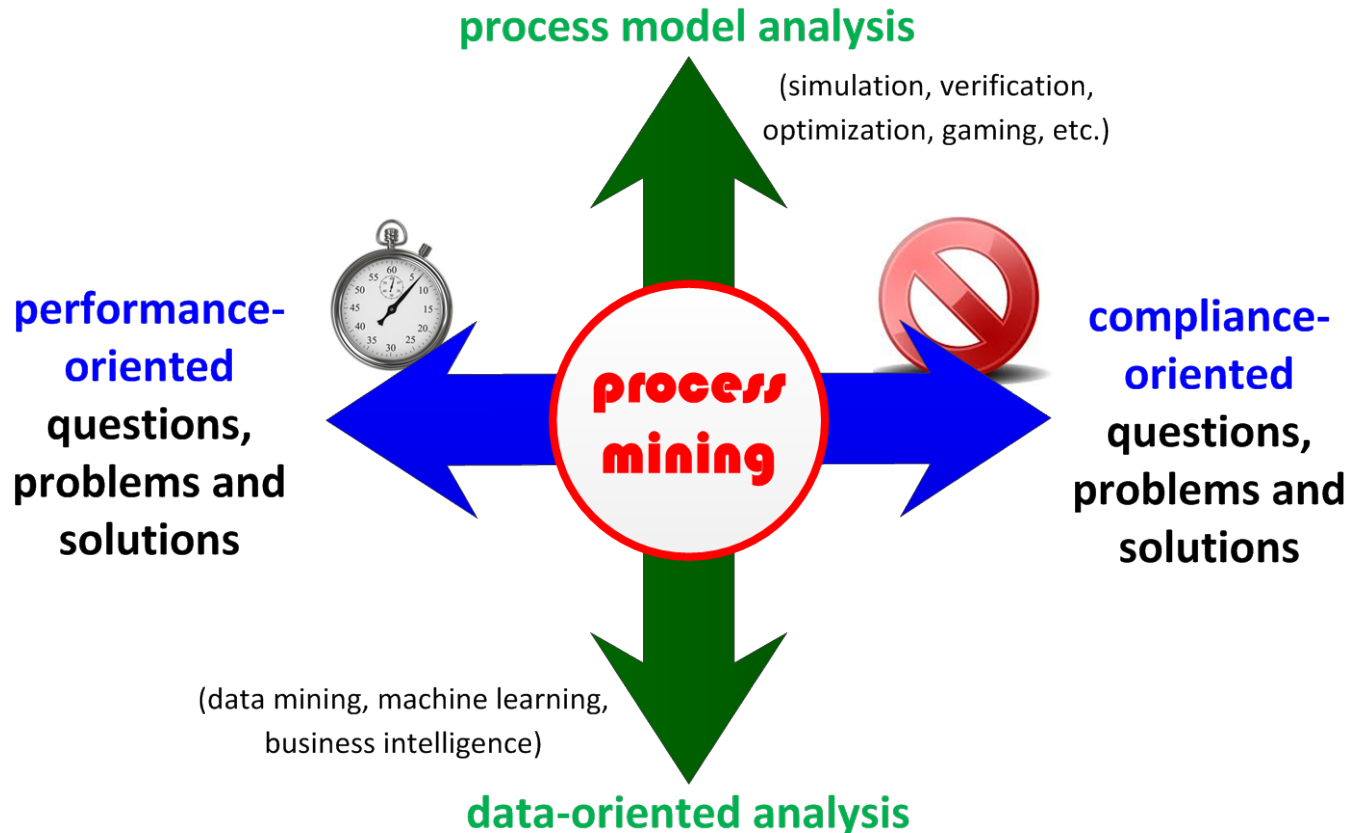


TU/e

Technische Universiteit
Eindhoven
University of Technology

Where innovation starts

Process mining: The missing link

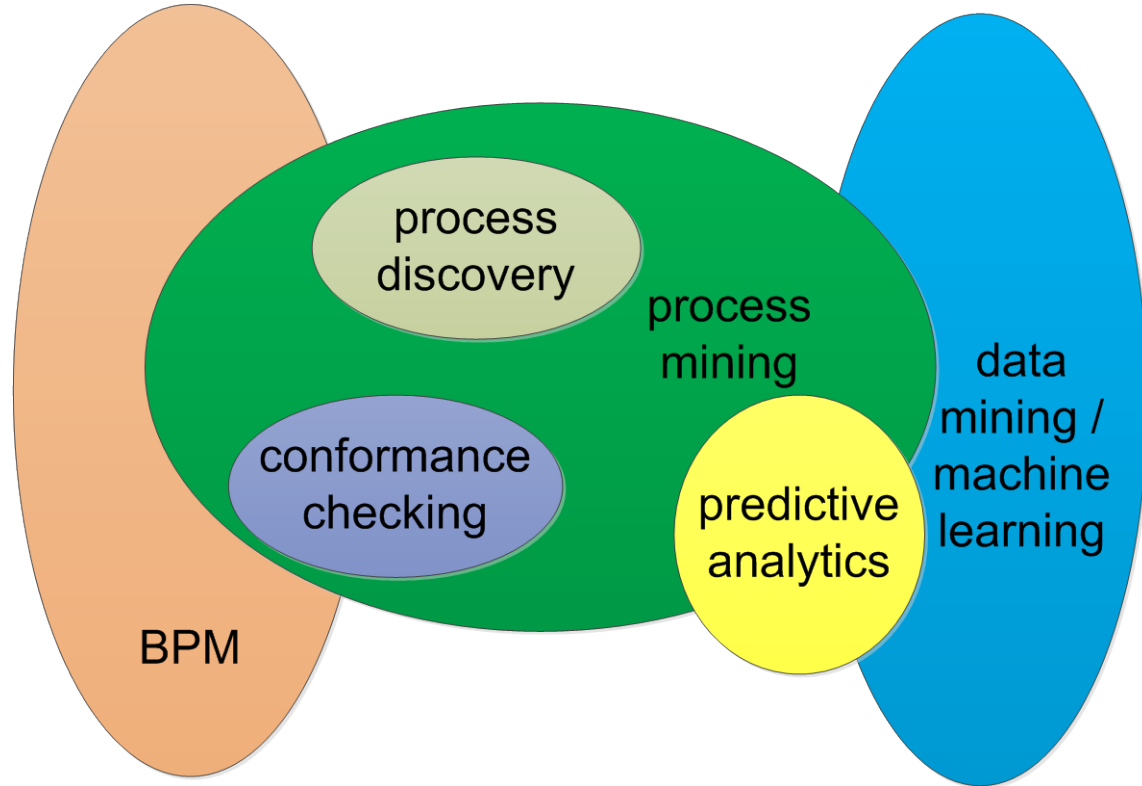


Connecting things: Process mining as super glue

- **Data – Process**
- **Business – IT**
- **Business Intelligence – Business Process Management**
- **Performance – Compliance**
- **Runtime – Design time**
- ...



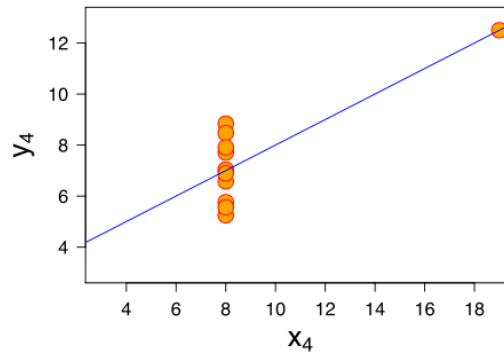
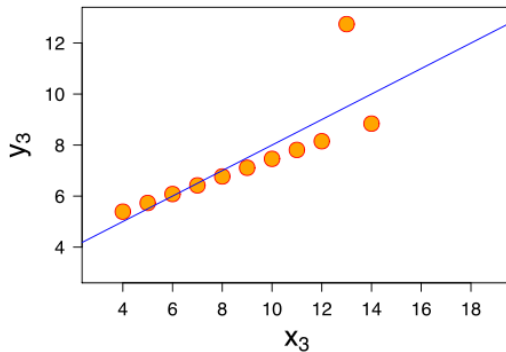
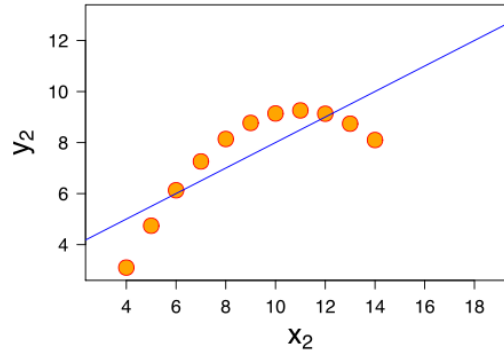
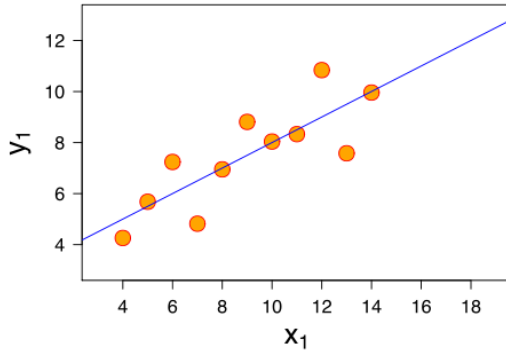
Positioning Process Mining



**How about BI
(Business
Intelligence)?**

Don't try to capture reality in a simple KPI!

(Like BI tools do)



4 data sets of
11 elements

**Anscombe's
Quartet**

mean $x = 9$
variance $x = 11$
mean $y = 7.5$
variance $y = 4.12$
correlation = 0.816
same linear regression

**process
model**

event data

0100110011010101010

0100110011010101010





event data

A photograph of a dirt path with a large, diagonal watermark reading "0100110101010100" overlaid on it. The path is surrounded by grass and some small plants. A blue arrow points to the first '0' of the watermark.



**process model or
information
system**

Picture by Koen Olsthoorn

The image features a vibrant blue background with a faint world map. A network of white lines with glowing nodes connects various points across the globe. Numerous white-outlined rectangles of different sizes are scattered throughout the scene, some appearing to float. In the center, a large, prominent white-outlined rectangle contains the word "Demo" in a bold, white, sans-serif font. A human hand is shown from the bottom right, with the index finger touching the bottom edge of this central rectangle, suggesting an interactive element or a selection process.

Demo

Process discovery is like learning a language: By example



sentence \cong trace in event log

...

language \cong process model

Conformance checking is like spell checking

an activity that should not happen happened

an activity was executed by the wrong person

an activity was executed too late

an activity that should happen did not happen

two activities were swapped

Recent breakthroughs in process mining research makes it possible to discover, analyze, and improve business processes based on event data from people, machines, and software. Leaf-tracing logs. Events such as entering a customer order into SAP, checking in for a flight, changing dosage for a patient, and rejecting a building are common that they seem. Over the last decade, a lot of data. Moreover, the digital universe and the physical universe has becoming more and more aligned.

Data Mining

Straight Ahead



Data mining

- The growth of the “digital universe” is the main driver for the popularity of data mining.
- Initially, the term “data mining” had a negative connotation (“data snooping”, “fishing”, and “data dredging”).
- Now a mature discipline.
- Data-centric, **not** process-centric.

Data set 1

Data about 860 recently deceased persons to study the effects of drinking, smoking, and body weight on the life expectancy.

drinker	smoker	weight	age
yes	yes	120	44
no	no	70	96
yes	no	72	88
yes	yes	55	52
no	yes	94	56

Questions:

- What is the effect of smoking and drinking on a person's bodyweight?
- Do people that smoke also drink?
- What factors influence a person's life expectancy the most?
- Can one identify groups of people having a similar lifestyle?

Data set 2

Data about 420 students to investigate relationships among course grades and the student's overall performance in the Bachelor program.

linear algebra	logic	programming	operations research	workflow systems	...	duration	result
9	8	8	9	9	...	36	cum laude
7	6	-	8	8	...	42	passed
-	-	5	4	6	...	54	failed
8	6	6	6	5	...	38	passed

Questions:

- Are the marks of certain courses highly correlated?
- Which electives do excellent students (cum laude) take?
- Which courses significantly delay the moment of graduation?
- Why do students drop out?
- Can one identify groups of students having a similar study behavior?

Data set 3

Data on 240 customer orders in a coffee bar recorded by the cash register.

cappuccino	latte	espresso	americano	ristretto	tea	muffin	bagel
1	0	0	0	0	0	1	0
0	2	0	0	0	0	1	1
0	0	1	0	0	0	0	0
1	0	0	0	0	0	0	0
0	0	0	0	0	1	2	0
0	0	0	1	1	0	0	0
							...

Questions:

- Which products are frequently purchased together?
- When do people buy a particular product?
- Is it possible to characterize typical customer groups?
- How to promote the sales of products with a higher margin?

Variables

- Data set (sample or table) consists of **instances** (individuals, entities, cases, objects, or records).
- **Variables** are often referred to as attributes, features, or data elements.
- Two types:
 - **categorical variables:**
 - ordinal (high-med-low, cum laude-passed-failed) or
 - nominal (true-false, red-pink-green)
 - **numerical variables**
(ordered, cannot be enumerated easily)

Question

drinker	smoker	weight	age
yes	yes	120	44
no	no	70	96
yes	no	72	88
yes	yes	55	52
no	yes	94	56

There are four variables:

- **Which ones are ordinal categorical variables?**
- **Which ones are nominal categorical variables?**
- **Which ones are numerical variables?**

Answer

drinker	smoker	weight	age
yes	yes	120	44
no	no	70	96
yes	no	72	88
yes	yes	55	52
no	yes	94	56
no	no	62	93

- There are two categorical variables: drinker and smoker. Both are nominal.
- There are two numerical variables: weight and age.

Supervised Learning

- Labeled data, i.e., there is a **response variable** that labels each instance.
- Goal: explain **response variable** (dependent variable) in terms of **predictor variables** (independent variables).

Supervised Learning

- **Classification techniques** (e.g., decision tree learning) assume a categorical response variable and the goal is to classify instances based on the predictor variables.
- **Regression techniques** assume a numerical response variable. The goal is to find a function that fits the data with the least error.

Question

drinker	smoker	weight
yes	yes	120
no	no	70
yes	no	72
yes	yes	55
no	yes	94
no	no	62
...

We would like to learn the influence of drinking and smoking on someone's body weight. What are the response and predictor variables?

Answer

drinker	smoker	weight
yes	yes	120
no	no	70
yes	no	72
no	yes	94
no	no	62
...

predictor variable

predictor variable

response variable

Unsupervised Learning

- Unsupervised learning assumes **unlabeled** data, i.e., the variables are not split into response and predictor variables.
- Examples: **clustering** (e.g., k-means clustering and agglomerative hierarchical clustering) and **pattern discovery** (association rules)

Data Mining Tools

- **RapidMiner** (rapidminer.com, partly commercial)



- **R** (r-project.org, free)



- **Weka** (www.cs.waikato.ac.nz/ml/weka/, GNU)



- **KNIME** (knime.org, partly commercial)



- **SAS** (sas.com, commercial)

- **IBM**
 - **IBM**
- We will use RapidMiner to illustrate classical data mining techniques.**

- **QlikView** (qlikview.com, commercial)

- **SAP BusinessObjects/HANA** (www.sap.com/pc/analytics/, commercial)

Process Mining Versus Data Mining

- Both start from **data**.
- Data mining techniques are typically **not process-centric**.
- Topics such as **process discovery, conformance checking, and bottleneck analysis** are **not** addressed by traditional data mining techniques.

Process Mining Versus Data Mining

- **End-to-end** process models and **concurrency** are essential for process mining.
- Process mining assumes event logs where events have **timestamps** and refer to **cases** (process instances).
- Process mining and data mining need to be **combined** for more advanced questions.

Part I: Preliminaries

Chapter 1
Introduction

Chapter 2
Process Modeling and
Analysis

Chapter 3
Data Mining

Part III: Beyond Process Discovery

Chapter 7
Conformance
Checking

Chapter 8
Mining Additional
Perspectives

Chapter 9
Operational Support

Part II: From Event Logs to Process Models

Chapter 4
Getting the Data

Chapter 5
Process Discovery: An
Introduction

Chapter 6
Advanced Process
Discovery Techniques

Part IV: Putting Process Mining to Work

Chapter 10
Tool Support

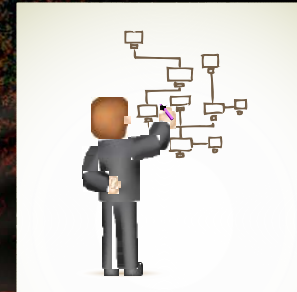
Chapter 11
Analyzing “Lasagna
Processes”

Chapter 12
Analyzing “Spaghetti
Processes”

Part V: Reflection

Chapter 13
Cartography and
Navigation

Chapter 14
Epilogue



Wil M. P. van der Aalst

Process Mining

Discovery, Conformance and
Enhancement of Business Processes

 Springer