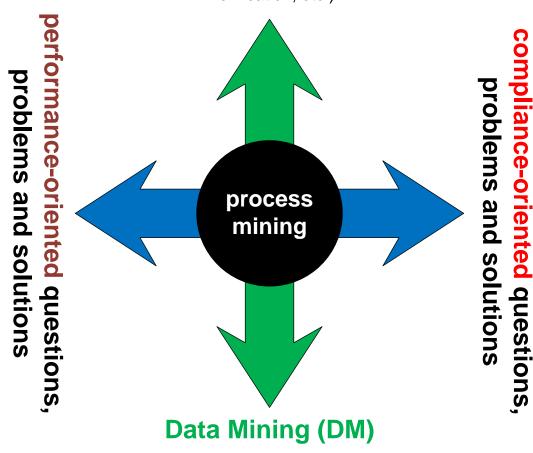


#### **Positioning Process Mining**

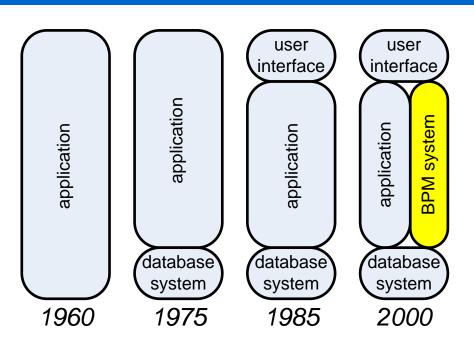
#### **Business Process Management (BPM)**

(process analysis/modeling, enactment, verification, etc.)

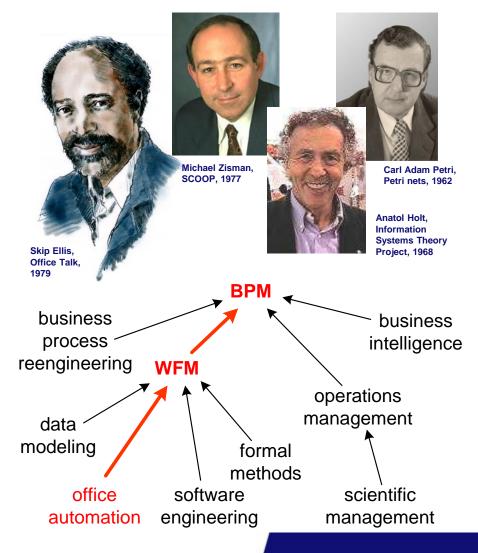


(clustering, classification, rule discovery, etc.)

#### **History and Origins of BPM**

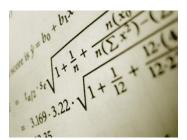




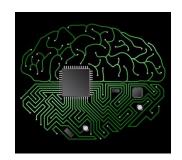


### **History and Origins of Data Mining**

Classical statistics (since 500 BC): descriptive statistics (e.g., sample mean) statistical inference (e.g., confidence interval, regression, hypothesis testing).



data dredging, data fishing, data snooping



Artificial intelligence (since 1950): making intelligent machines by applying human-thought-like processing to statistical problems.

Machine learning (since 1950): construction and study of systems that can learn from data.



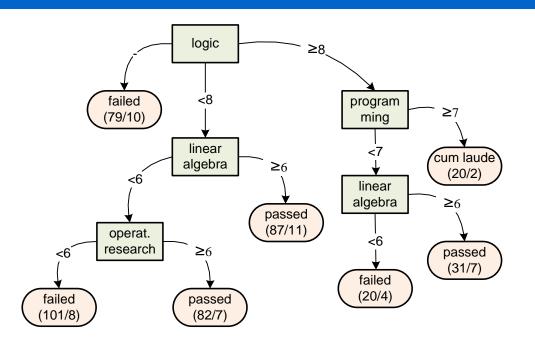
Many other terms: knowledge analytics, ... discovery, (predictive)



#### **Data Mining: 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).
- 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.

### **Example: Decision tree learning**



linear algebra	logic	program- ming	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
6	7	6	-	8		39	passed
9	9	9	9	8		38	cum laude
5	5	-	6	6		52	failed
•••	• • •	• • •	• • •	•••	• • •	• • •	•••

#### **Unsupervised Learning**

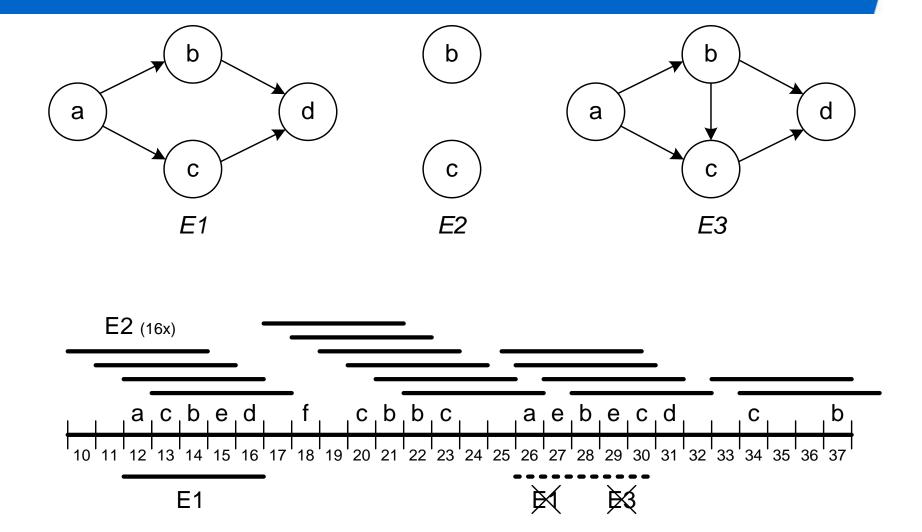
- Unsupervised learning assumes unlabeled data, i.e., the variables are not split into response and predictor variables.
- Examples: clustering (e.g., k-means clustering and agglomerative hierarchical clustering) and pattern discovery (association rules)

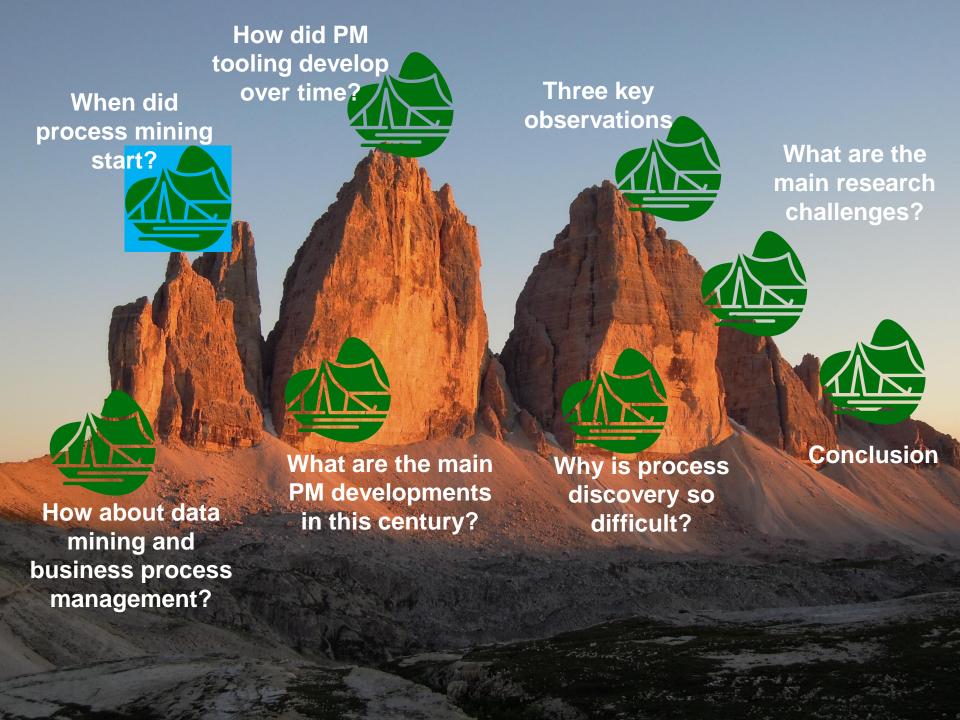
#### **Example: Association rules**

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	O	0
0	0	0	0	0	1	2	0
0	0	0	1	1	0	0	0
•••		•••	•••	•••	•••	•••	

$$tea \land latte \Rightarrow muffin$$
  
 $tea \Rightarrow muffin \land bagel$ 

#### **Example: Episode Mining**





# Language identification in the limit (Mark Gold 1967)

- Mother uses sentences from some language {aab, ab, abc, ...}.
- "Perfect child" listens to mother and hypothesizes what the full language is like (given all sentences so far).
- Eventually the perfect child's hypothesis is correct and never changes again (without knowing), i.e., only finitely many wrong hypotheses are generated.
- A language is learnable in the limit if such a perfect child exists.



# Language identification in the limit (E. Mark Gold 1967)

- Gold showed that most languages cannot be learned in the limit (including the most simple ones like regular languages (ab\*(c|d)).
- He noted that it matters whether the child gets positive and negative examples (corrections), whether the mother is evil, etc.
- Frequencies matter!
- Representational bias matters!

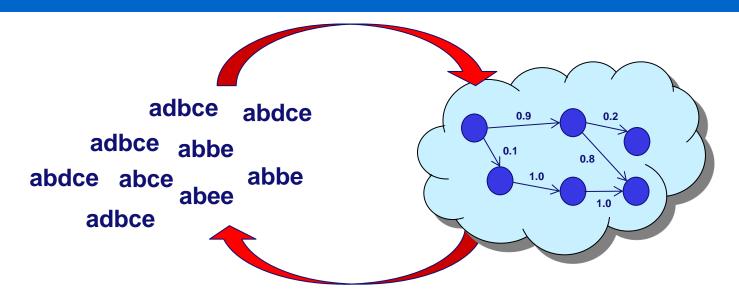


sentence ≅ trace in event log language ≅ process model

## Myhill-Nerode Theorem (1958) and the Biermann/Feldman Algorithm (1972)

- There is a unique minimal deterministic finite automaton recognizing a regular language L (shown by John Myhill and Anil Nerode in 1958).
- Cannot be applied to example traces: overfitting and no generalization.
- Alan W. Biermann and Jerome A. Feldman propose in 1972 techniques to learn finite state machines from examples (e.g., considering k-tails).

# Baum-Welch (1970) and Viterbi (1967) Algorithms to learn Hidden Markov Models



- The Viterbi algorithm finds the most likely sequence of hidden states called the Viterbi path that results in a sequence of observed events (Andrew Viterbi, 1967).
- The Baum-Welch algorithm is an expectationmaximization algorithm that constructs a HMM (Leonard E. Baum and Lloyd R. Welch, 1970).

### Where/when did process mining start?

- Myhill/Nerode(1958)?
- Gold (Acurrence):

  By no concurrence

  Welch
- Bierman, handle noise,?
  Ra unable to handle man (197)
  Ra unable Agrange
- - nded to sequences, episodes, ...
- Raunal Agrawal (moleteness)

   Apriori algorithe incomuent patterns lend to end models

  Jonath to handle kand Alex noticer Wolf (1998)?

   Maria Agrawal (moleteness)

  Jonath to handle kand Alex noticer Wolf (1998)?

   Maria Agrawal (moleteness)

   Apriori algorithe incomuent patterns lend to end models

   Apriori algorithe incomuent patterns lend to end models

   Line Agrawal (moleteness)

   Apriori algorithe incomuent patterns lend to end models

   Line Agrawal (moleteness)

   Apriori algorithe incomuent patterns lend to end models

   Line Agrawal (moleteness)

   Line Agrawal (moleteness) sing techniques similar to Biermann/Feldman (k-tails) and Baum/Welch (Markov models)
- Rakesh Agrawal, Dimitrios Guntics los, Frank Leymann?

   "Mining Process Models from Workflow semantics)

   Flowmark process models without is sering type of splits and joins, no loops, etc.

  Anindya Datta (196 no Precise sering type of splits and joins, no loops, etc.)
- Anindya Datta (194)
  - Automating the of AS-IS Business Process Models
  - Biermann/Feldr style work, embedded in BPM



### How did process mining start at TU/e?

- Paper and research proposal: "Process Design by Discovery: Harvesting Workflow Knowledge from Ad-hoc Executions" (1999)
  - Upcoming move to Technology Management department to lead the IS group (working at CU-Boulder at the time).
  - Collaboration with Ton Weijters stimulated by BETA (linking Petri nets and workflow to Ton's expertise in machine learning).
- First PhDs on process mining (many followed):
  - Laura Maruster
  - Ana Karla Alves de Medeiros
  - Boudewijn van Dongen
- Initial work on alpha algorithm (formal limits) and heuristic and genetic mining (dealing with noise).



## **Initial team**





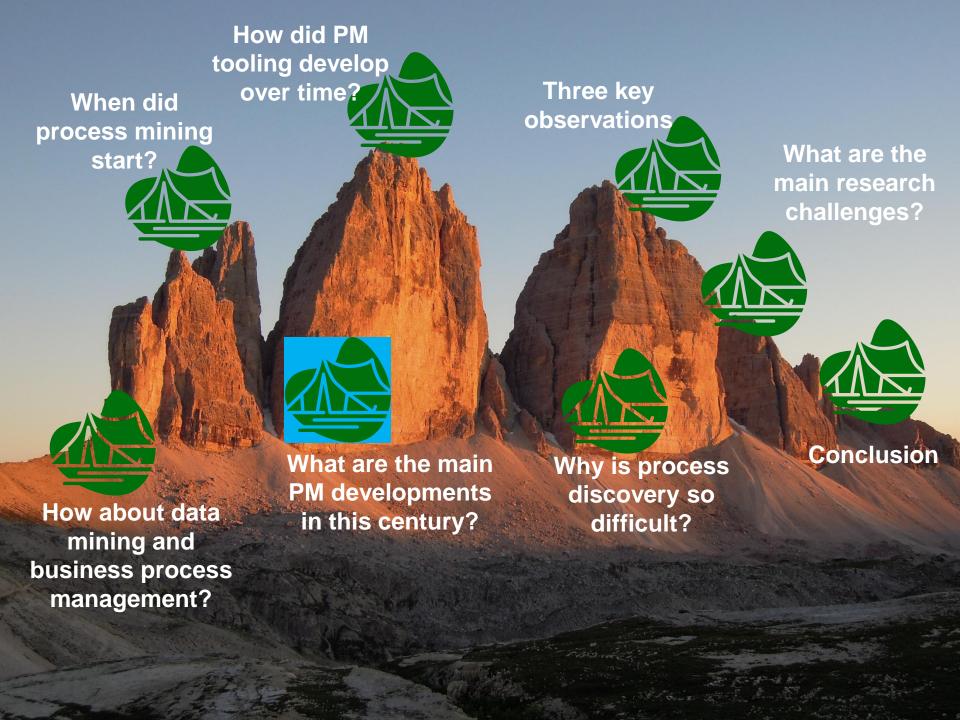


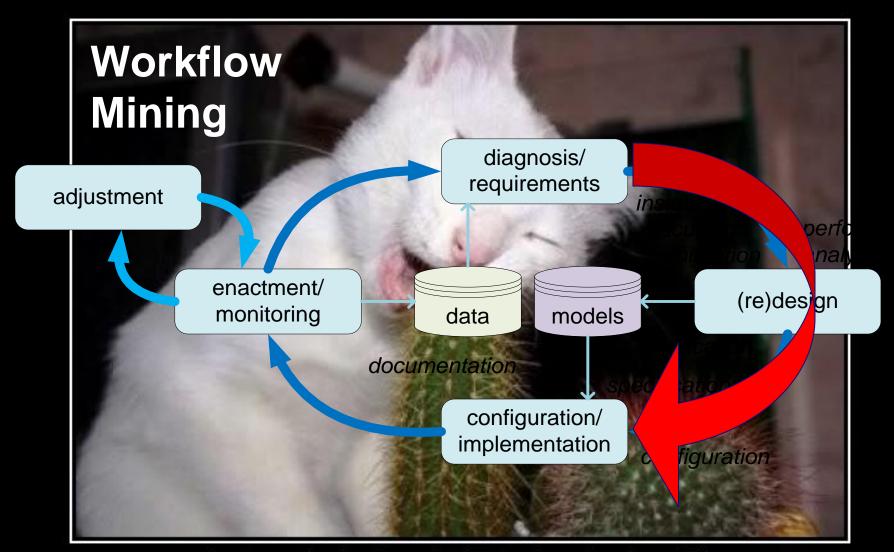








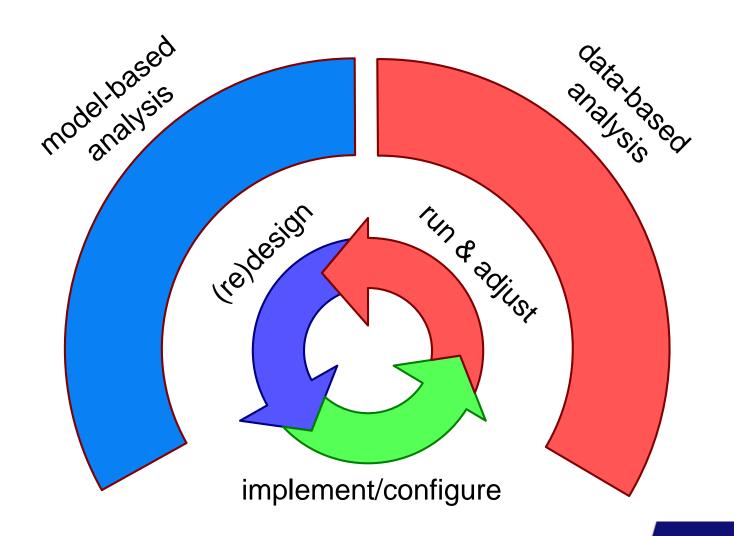




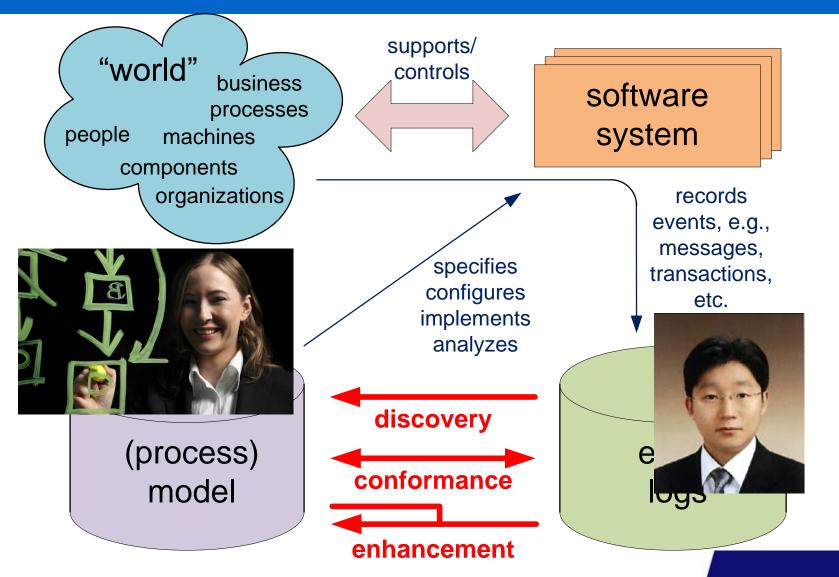
## BAD IDEAS

We All Have Them

### Models, data, and systems coexist



# Process mining spectrum in 2007: Beyond control-flow discovery



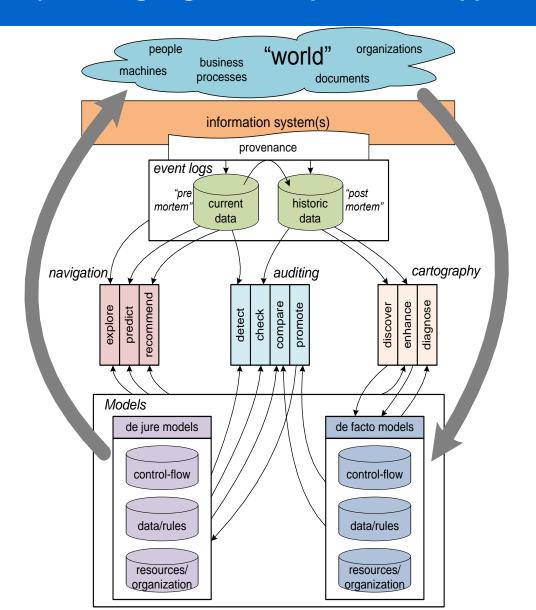
#### **Team in November 2007**



Some people are missing, e.g., Peter van den Brand.

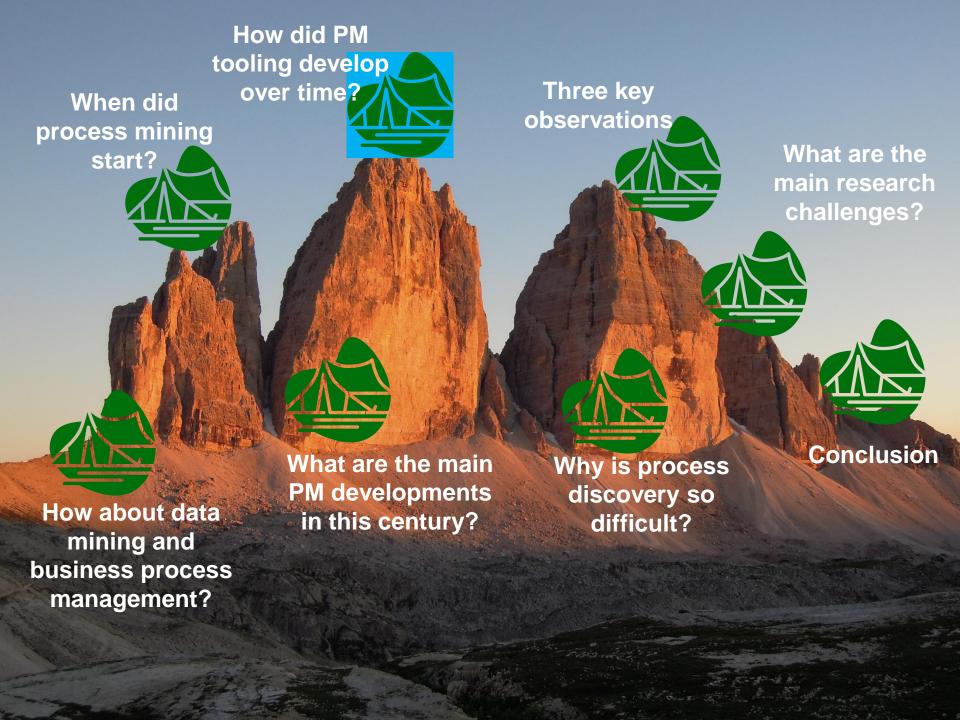
#### **Current process mining spectrum**

(including alignments, operational support, and multiple perspectives)





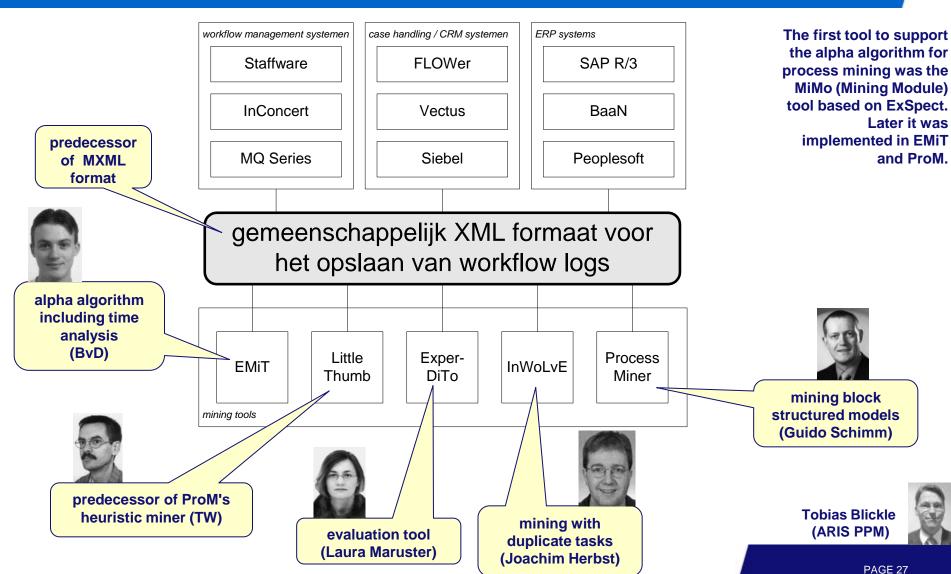


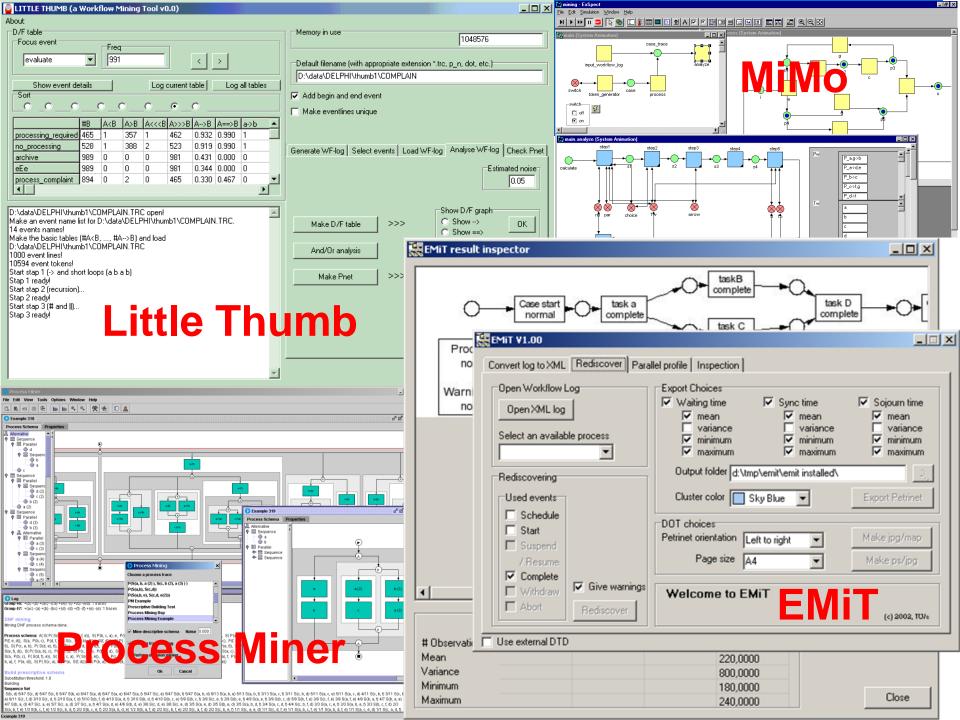


#### Pre-ProM

(figure from March 2002!)



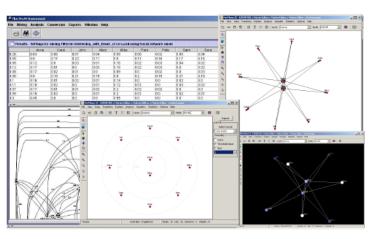


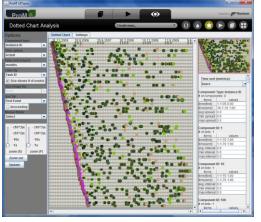


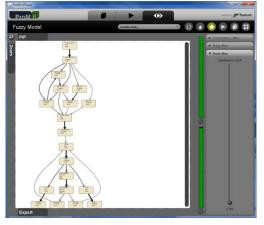
## **ProM (2004 – now)**



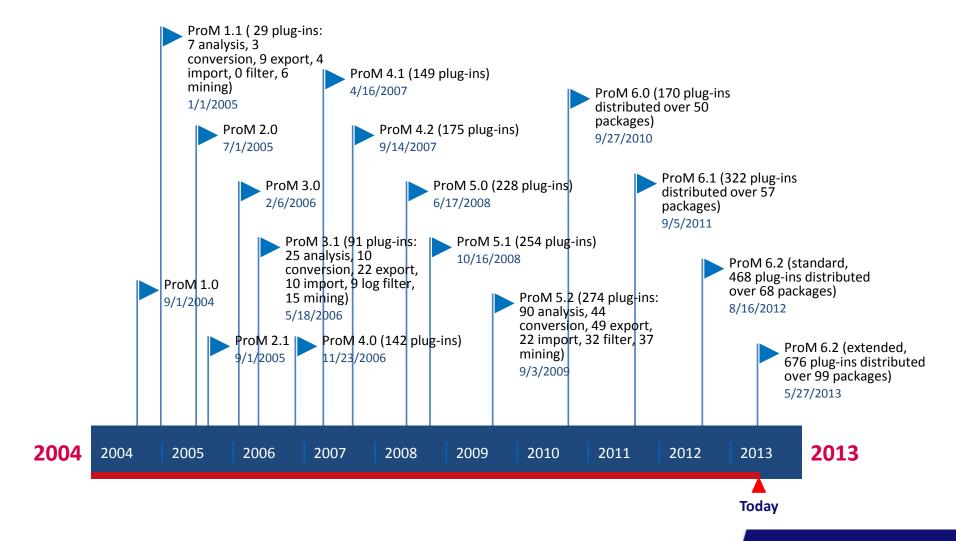






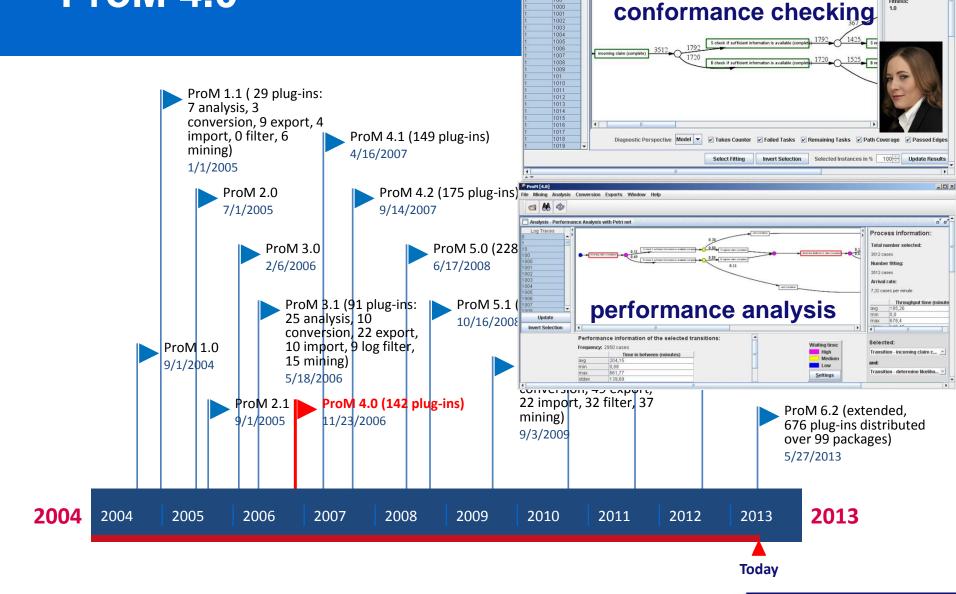


#### Overview of ProM releases



#### **ProM 1.1 ProM 1.1 (29 plug-ins:** 7 analysis, 3 conversion, 9 export, 4 **SNA** import, 0 filter, 6 ProM 4.1 (149 plug-ins) mining) 4/16/2007 1/1/2005 ProM 2.0 ProM 4.2 (17 **MFM** 7/1/2005 9/14/2007 าร ProM 3.0 ProN 2/6/2006 6/17 ProM 3.1 (91 plug-ins: 25 analysis, 10 conversion, 22 export, 10 import, 9 log filter, (standard, ns distributed ProM 1.0 ackages) 15 mining) 9/1/2004 5/18/2006 ProM 4.0 (142 plug-ins ProM 2.1 11/23/2006 mining 9/1/2005 **AlphaM** 9/3/2009 activity B complete activity Di complete activity E activity A 2004 2004 2005 2006 2007 2008 2009 2010 2011 activity C complete

#### **ProM 4.0**



ProM [4.0]

File Mining Analysis Conversion Exports Window Help

Fitness Precision Structure

Analysis - Conformance Checker

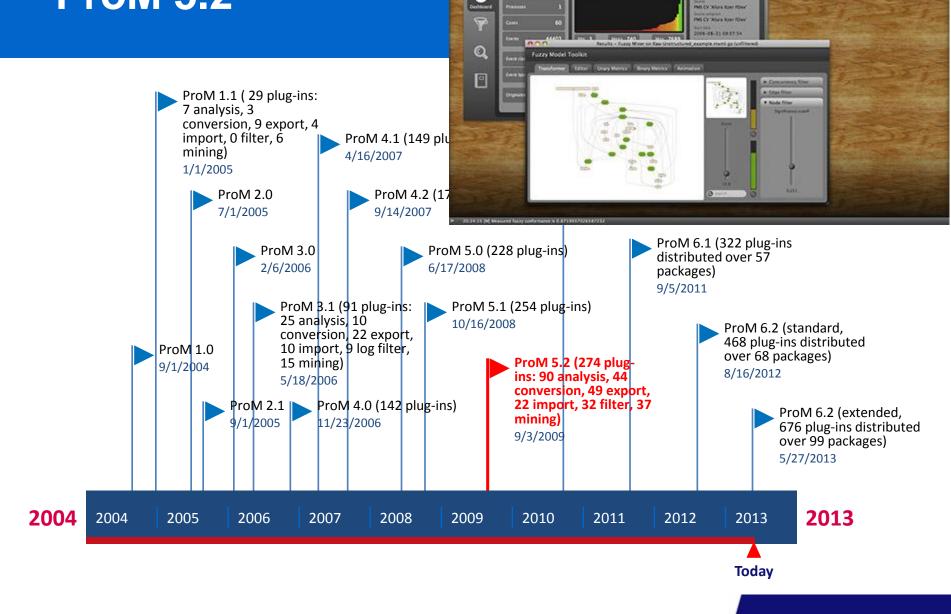
100

o" o" |

Model-related Measure

Fitness:

#### **ProM 5.2**

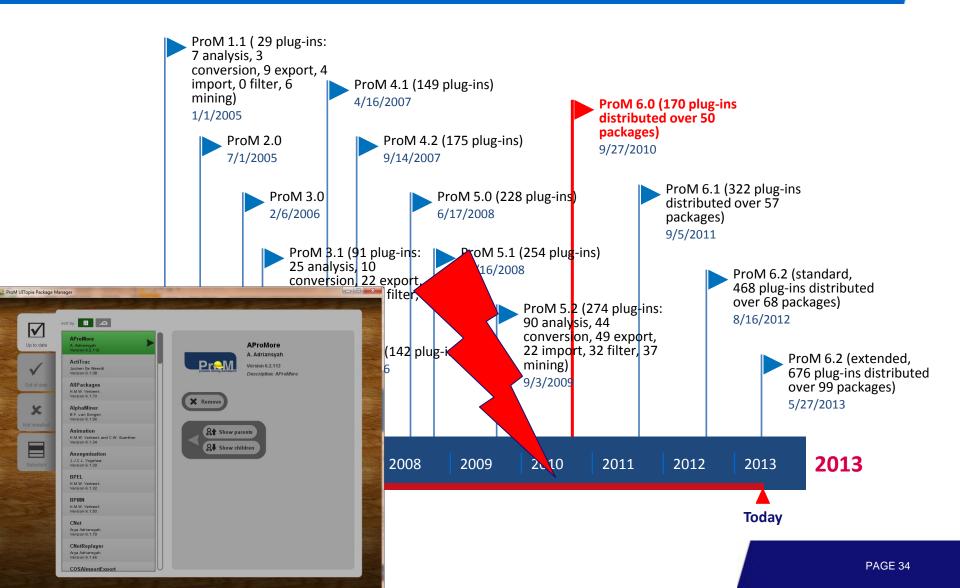


\* Q K 00 E E E E

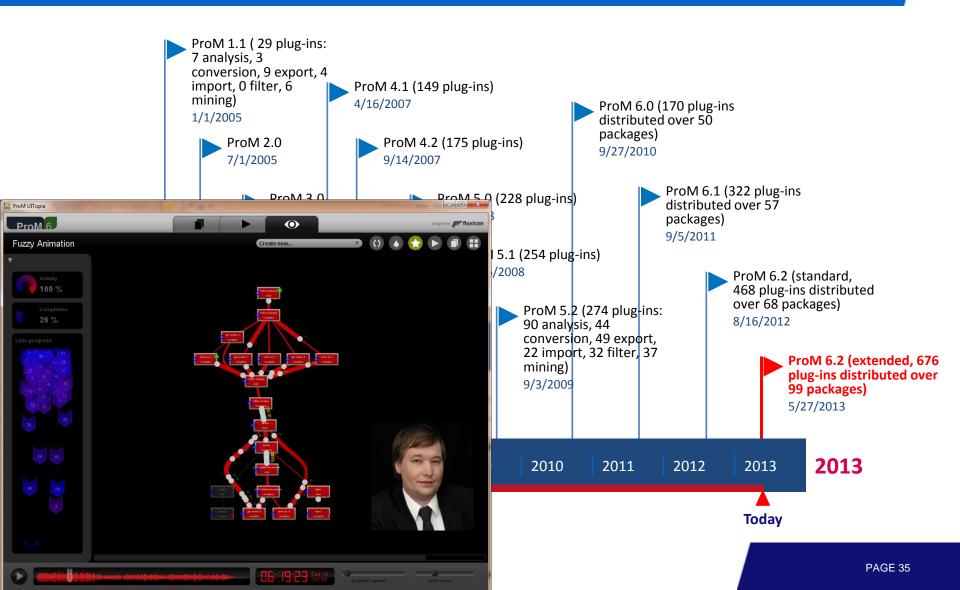
Events per case

ProM

#### ProM 6.0: A new start ...



### **ProM Today**

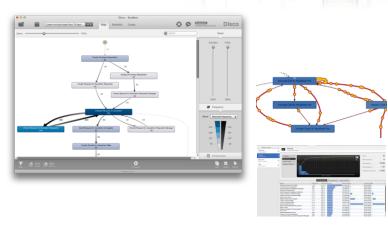


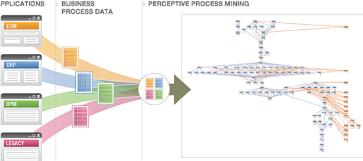
### **Commercial PM tools**

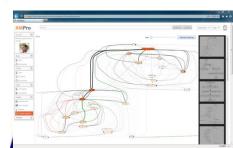
Process Mining has arrived.
Finally.

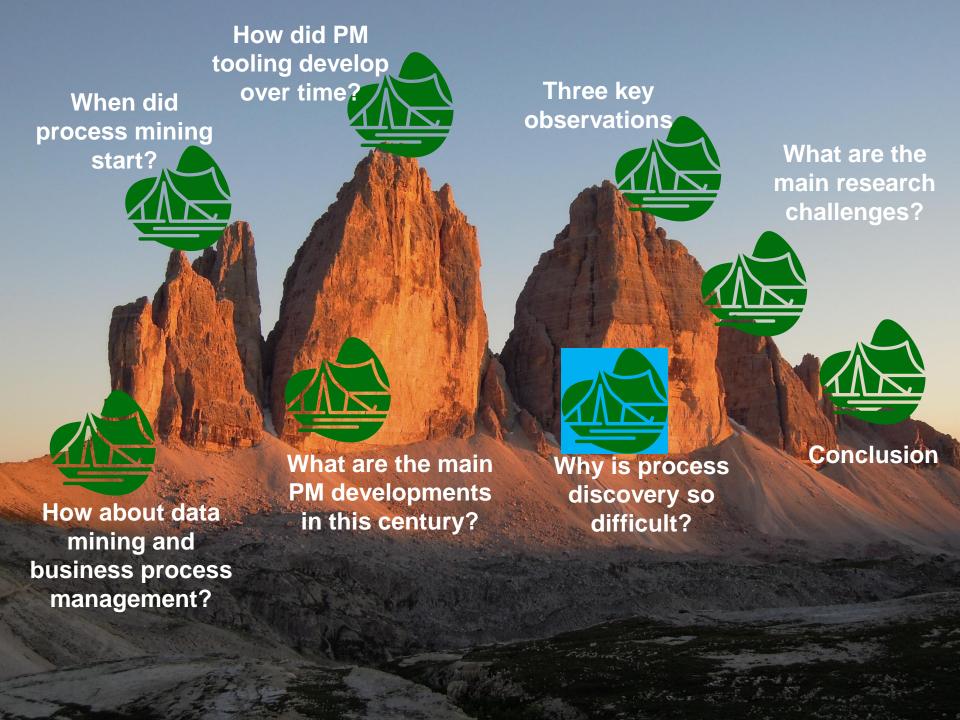
- Disco (Fluxicon)
- Perceptive Process Mining (before Futura Reflect and BPM|one)
- ARIS Process Performance Manager
- QPR ProcessAnalyzer
- Interstage Process Discovery (Fujitsu)
- Discovery Analyst (StereoLOGIC)
- XMAnalyzer (XMPro)



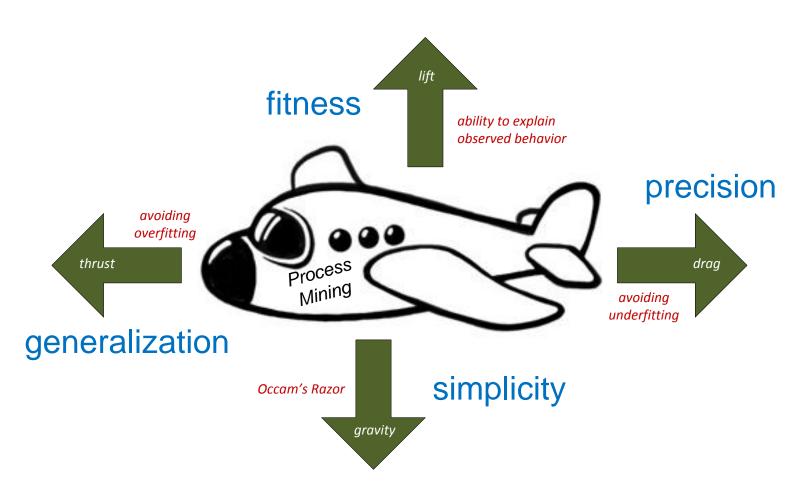






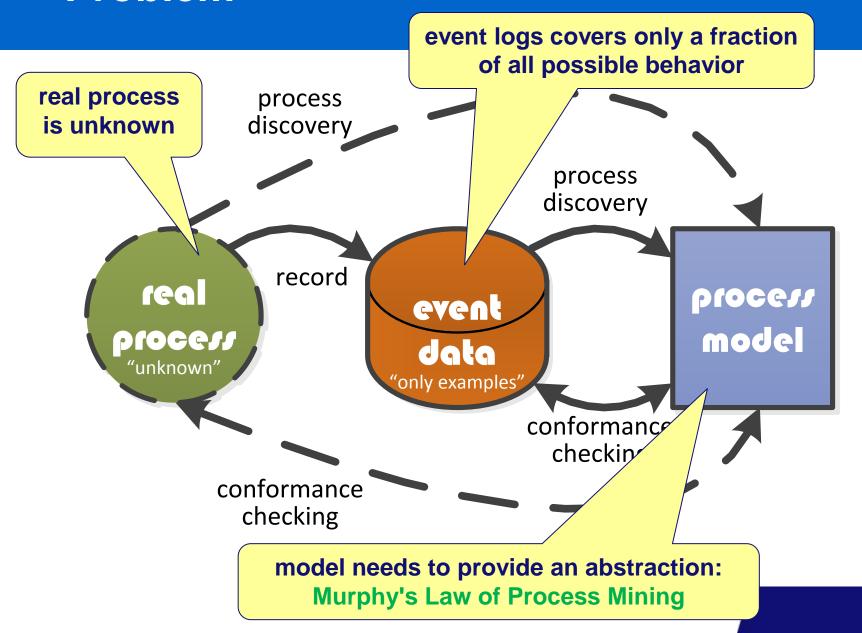


## How good is my model: Four forces

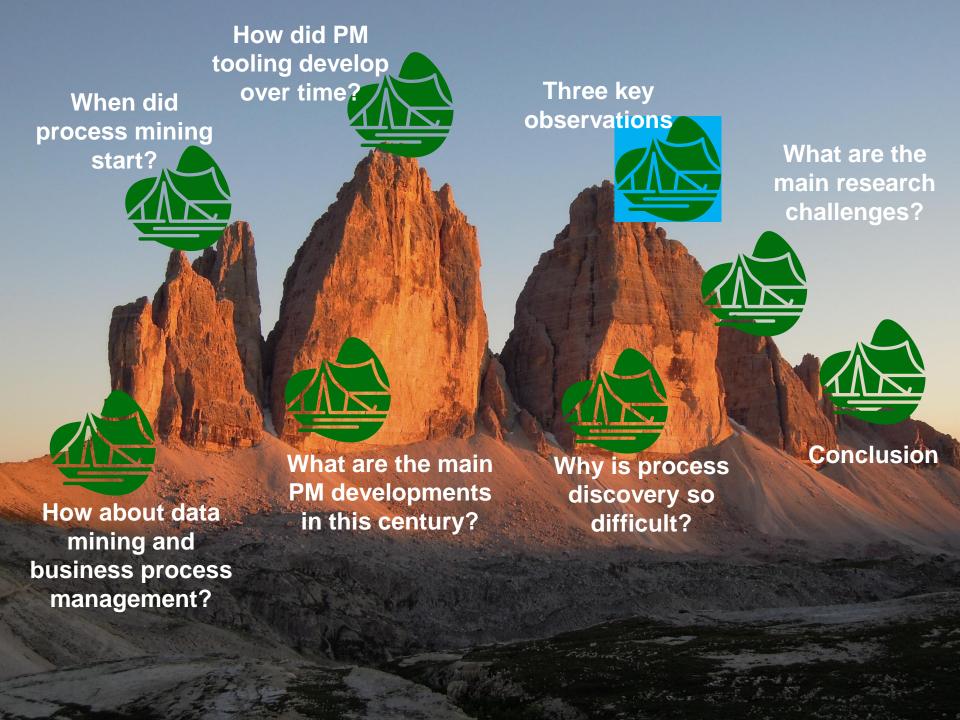


Leaving out one of these dimensions during discovery will lead to degenerate cases!

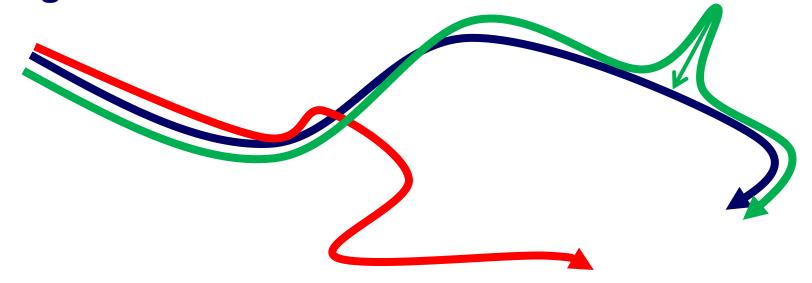
#### **Problem**







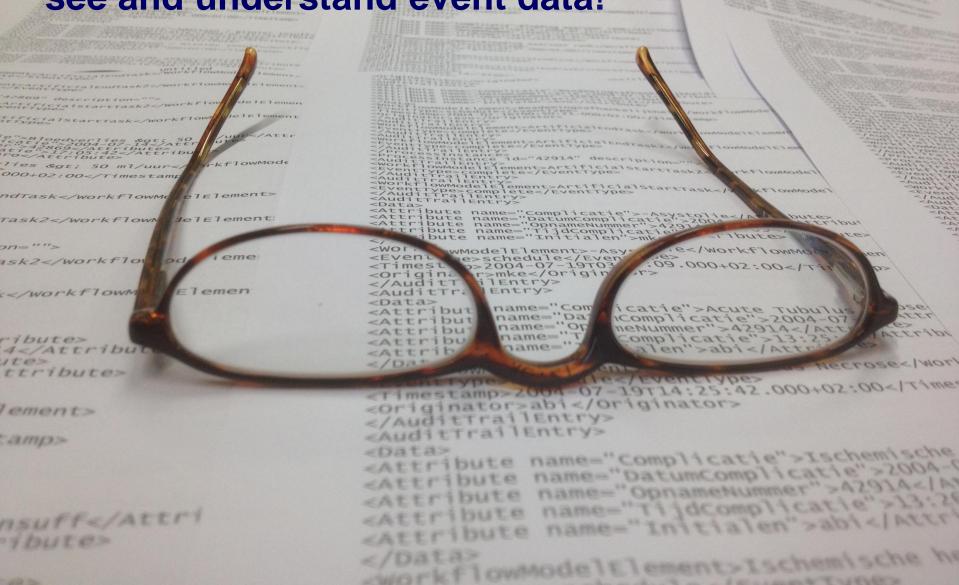
#### **#1 Alignments are essential!**

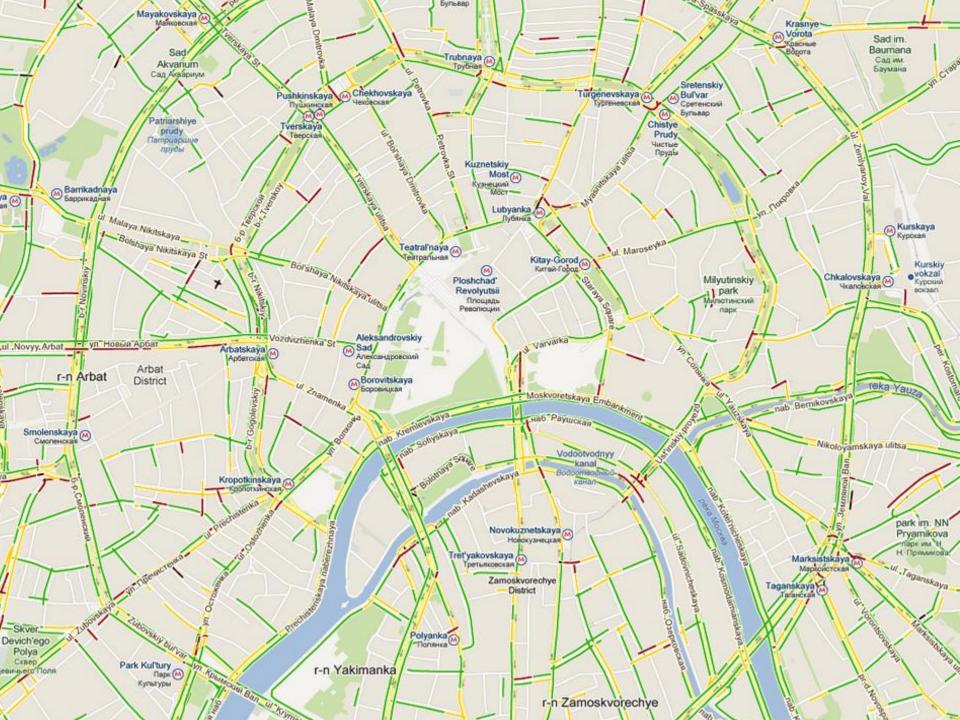


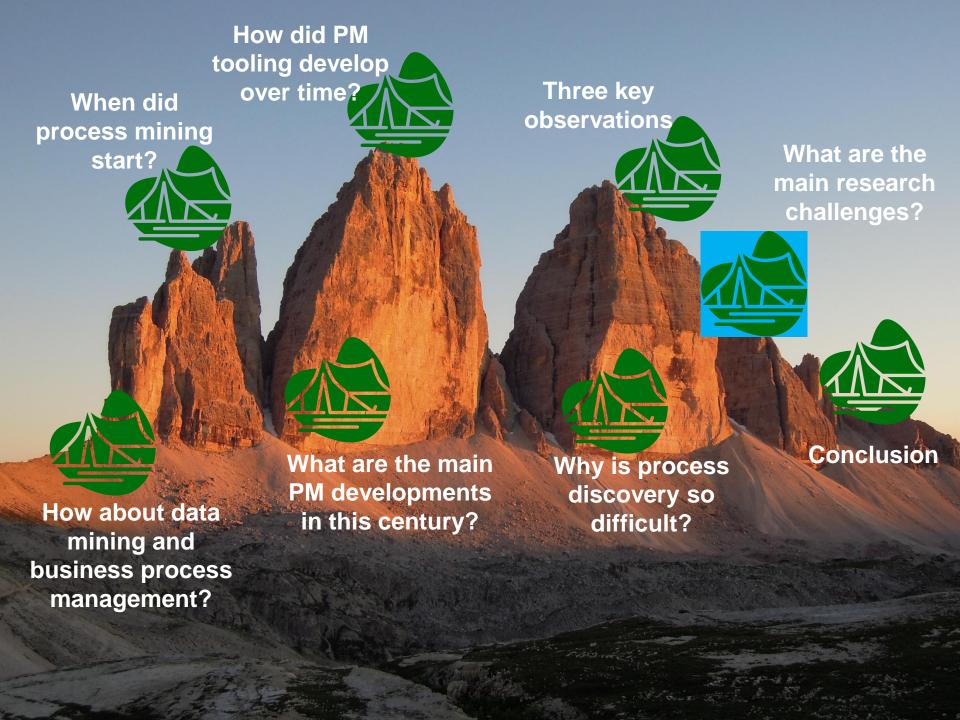
- conformance checking to diagnose deviations
- squeezing reality into the model to do model-based analysis

a	c	>>	d	<b>&gt;&gt;</b>	f	>>
$\overline{a}$	c	b	d	au	<b>&gt;&gt;</b>	h
t1	t4	t3	t5	t7		t10

# #2 Models are like the glasses required to see and understand event data!











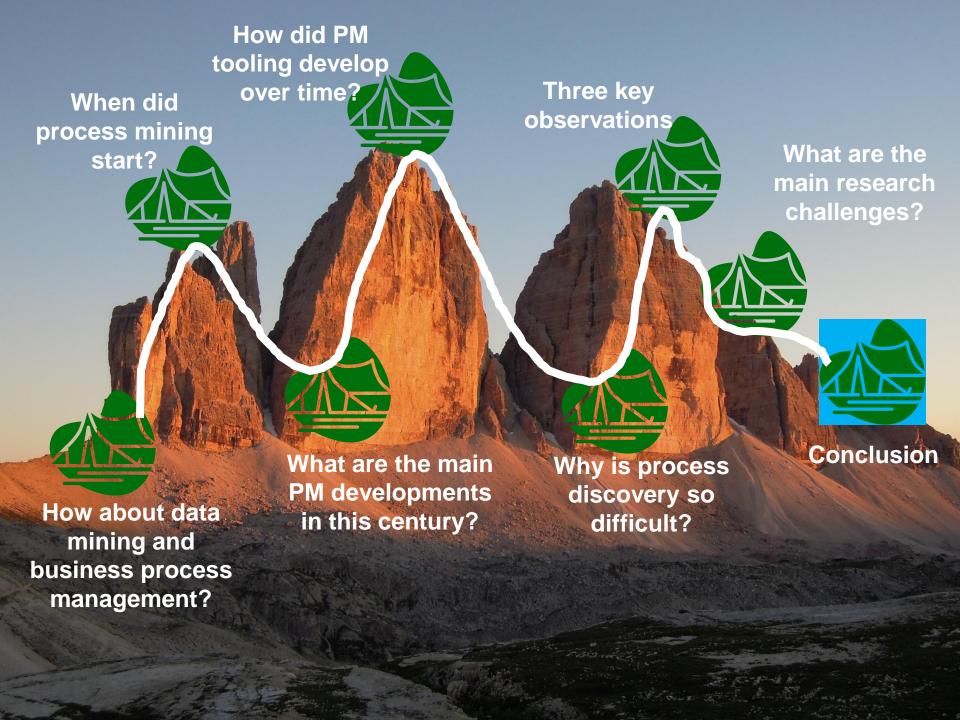




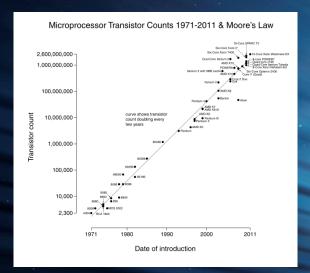


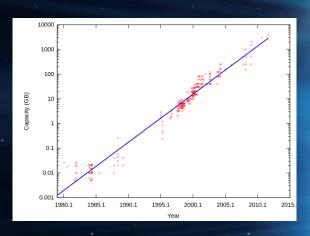


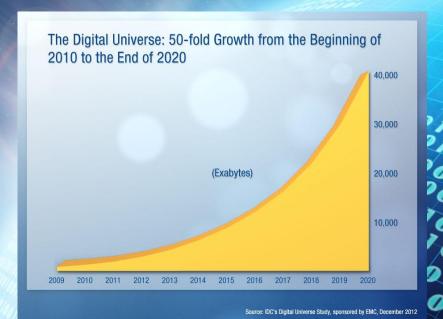




## **Moore's Law**







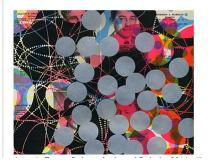


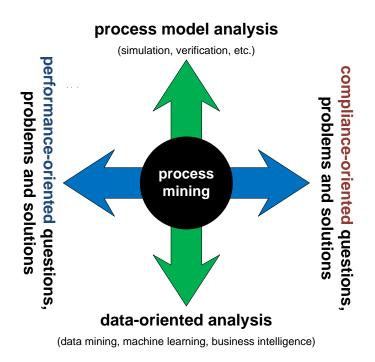
## **Turning Event Data into Real Value**



Data Scientist: The Sexiest Job of the 21st Century

by Thomas H. Davenport and D.J. Patil





Wil M. P. van der Aalst Process Oscovery, Conformance and ethincement of Business Processes. 2 Springer

processmining.org



http://www.win.tue.nl/ieeetfpm/