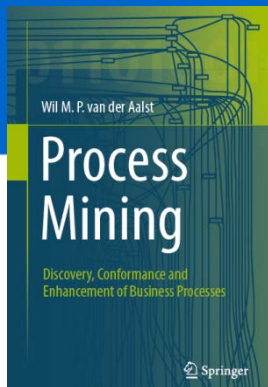


Process Mining: Data Science in Action

Mining Decision Points

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

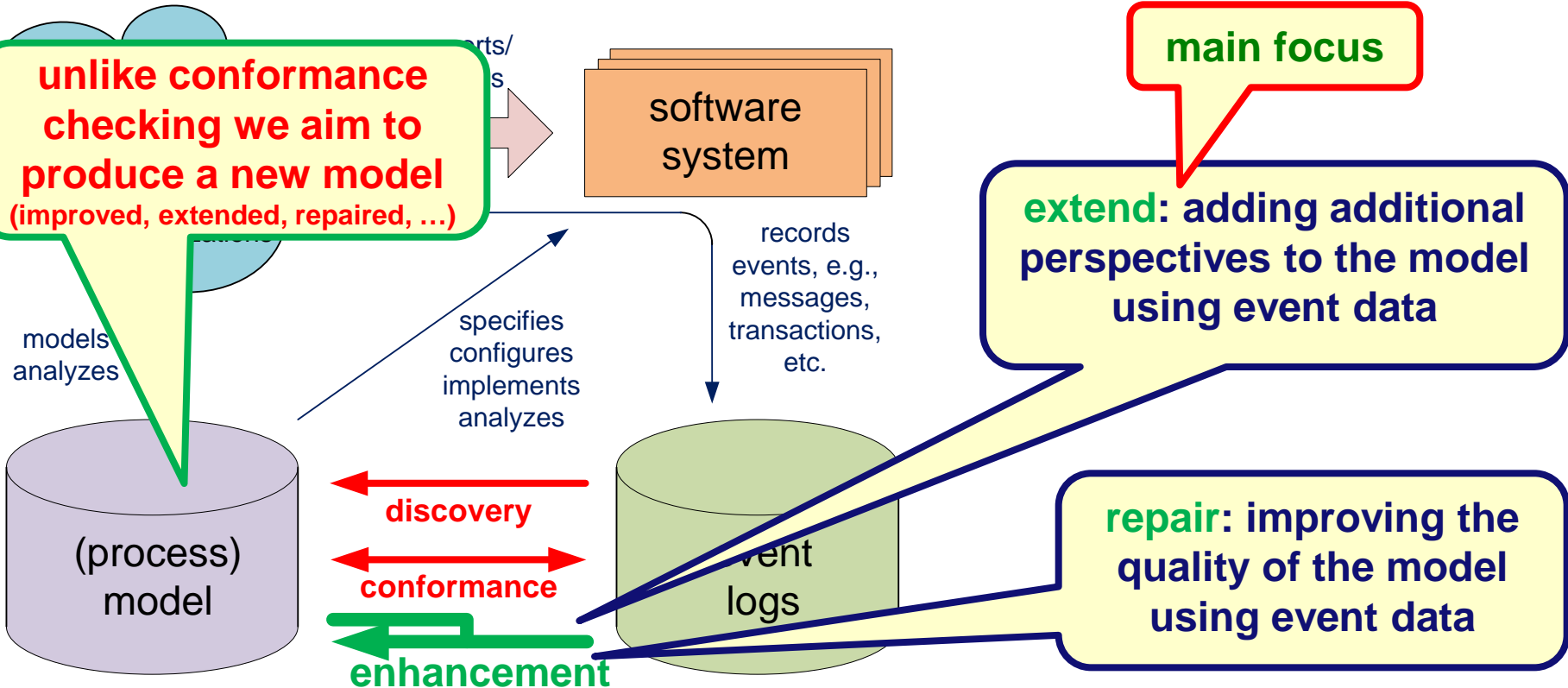


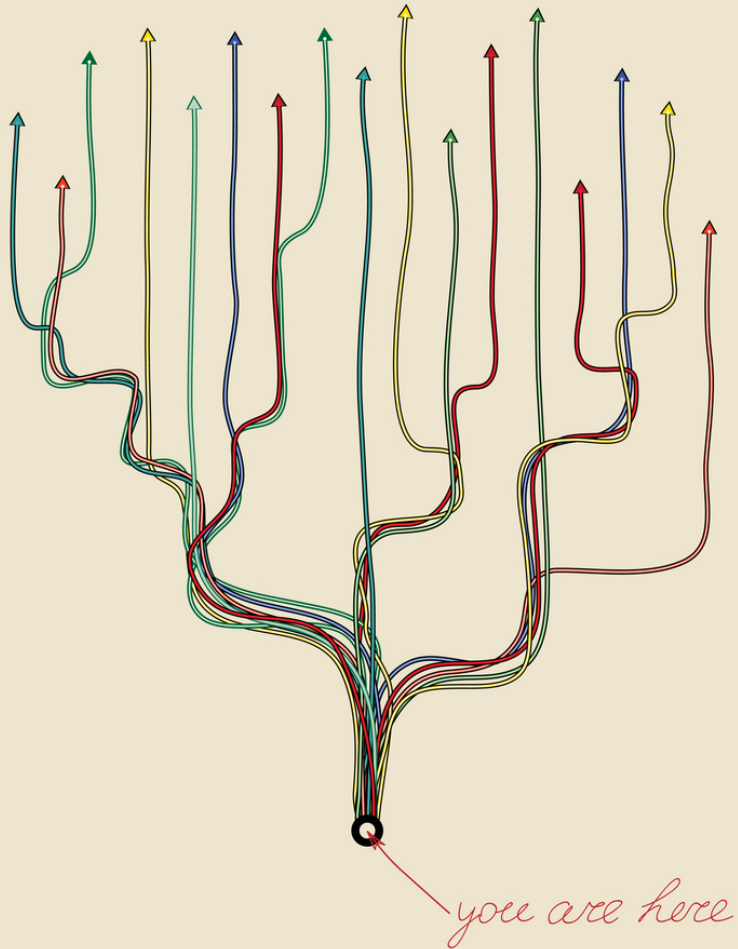
TU/e

Technische Universiteit
Eindhoven
University of Technology

Where innovation starts

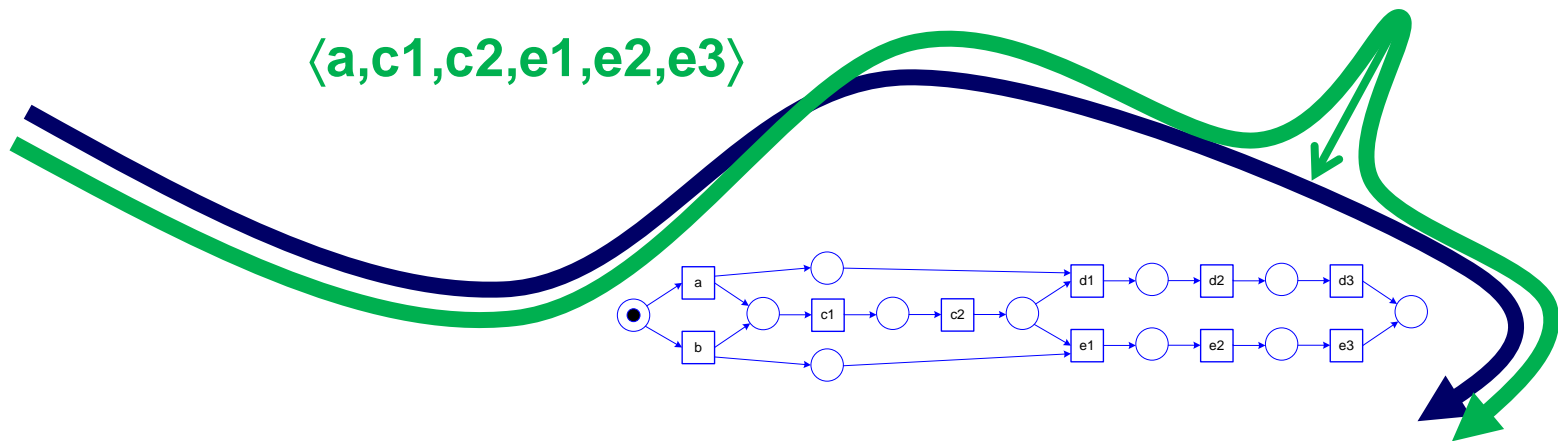
Enhancement: Extension and Repair





Mining Decision Points

- **Input:**
 - event log
 - process model
- **Assumption:** Log and model have been aligned.
 - Mapping of activity names in log and model.
 - Every trace can be related to a path through the model.



a	»	c1	c2	e1	e2	e3
»	b	c1	c2	e1	e2	e3



accept
claim

reject
claim

XOR-split

Which cases go left?

Which cases go right?



book
flight

book
hotel

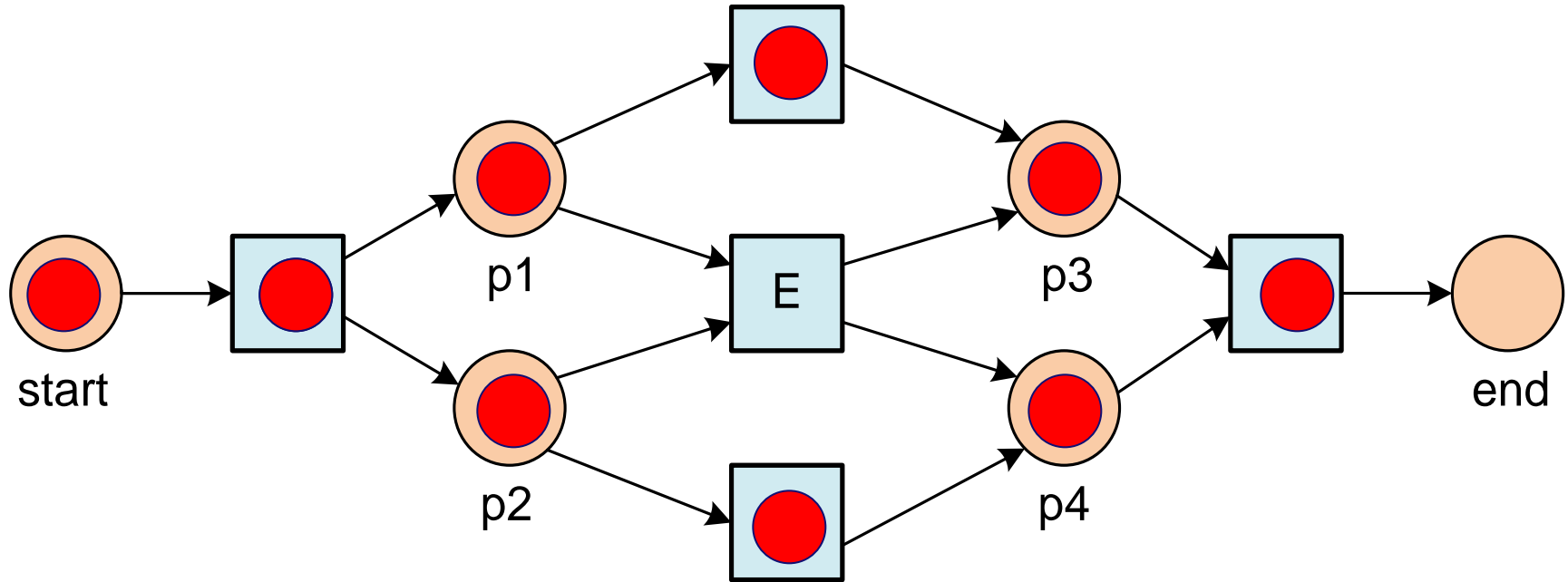
OR-split

Which cases go left?

Which cases go right?

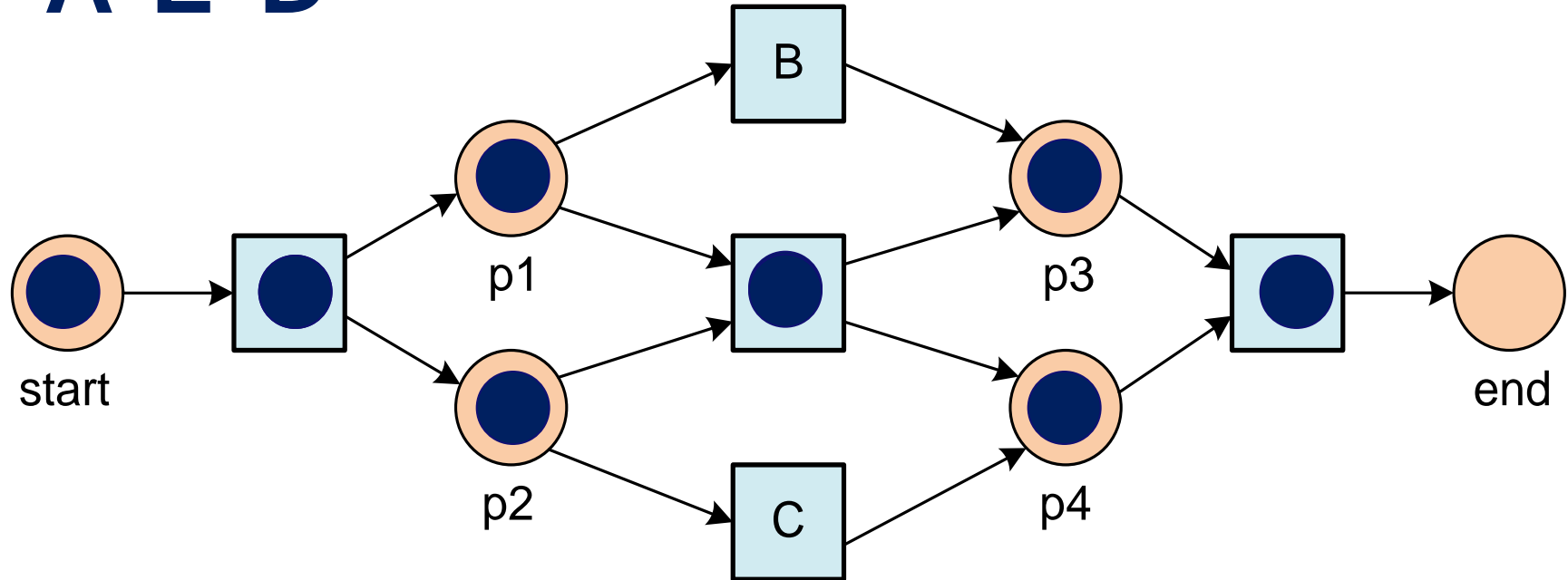
Decision mining: “Red” cases

A B C D



Decision mining: “Blue” cases

A E D

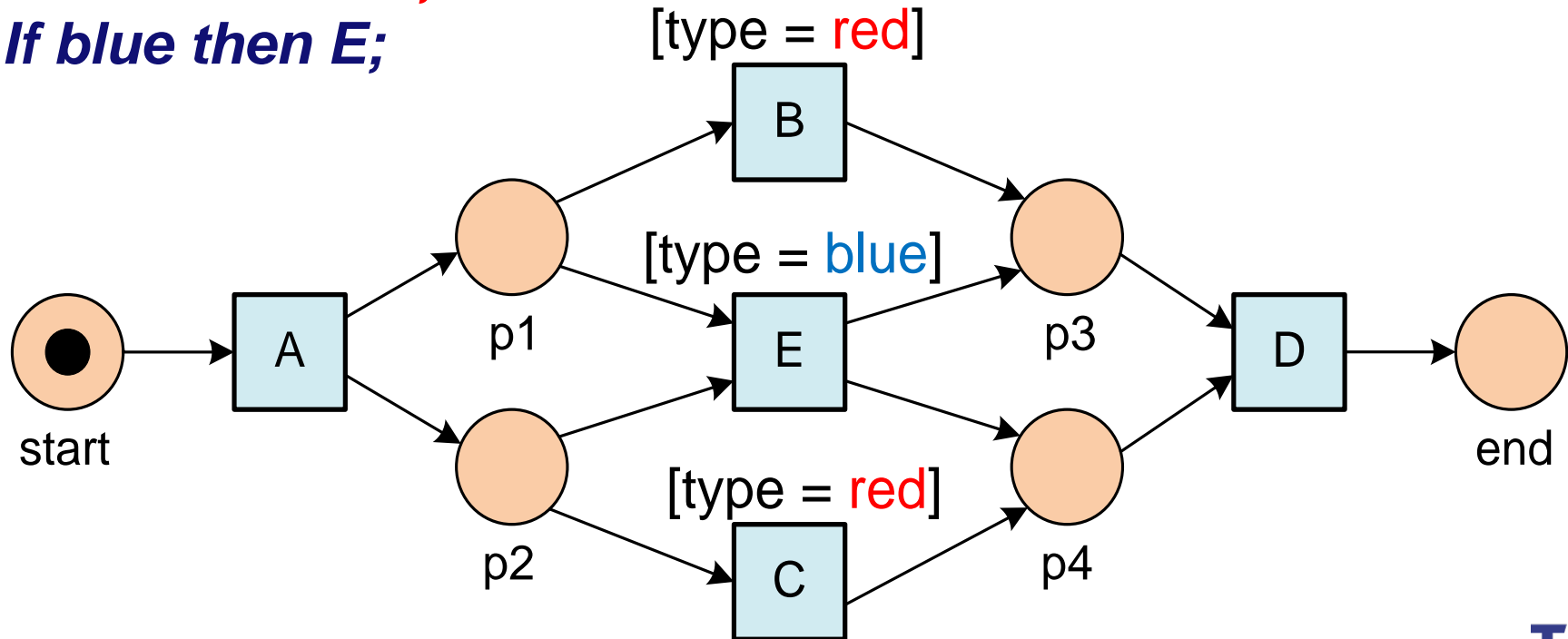


Guards ensure that the right path is taken

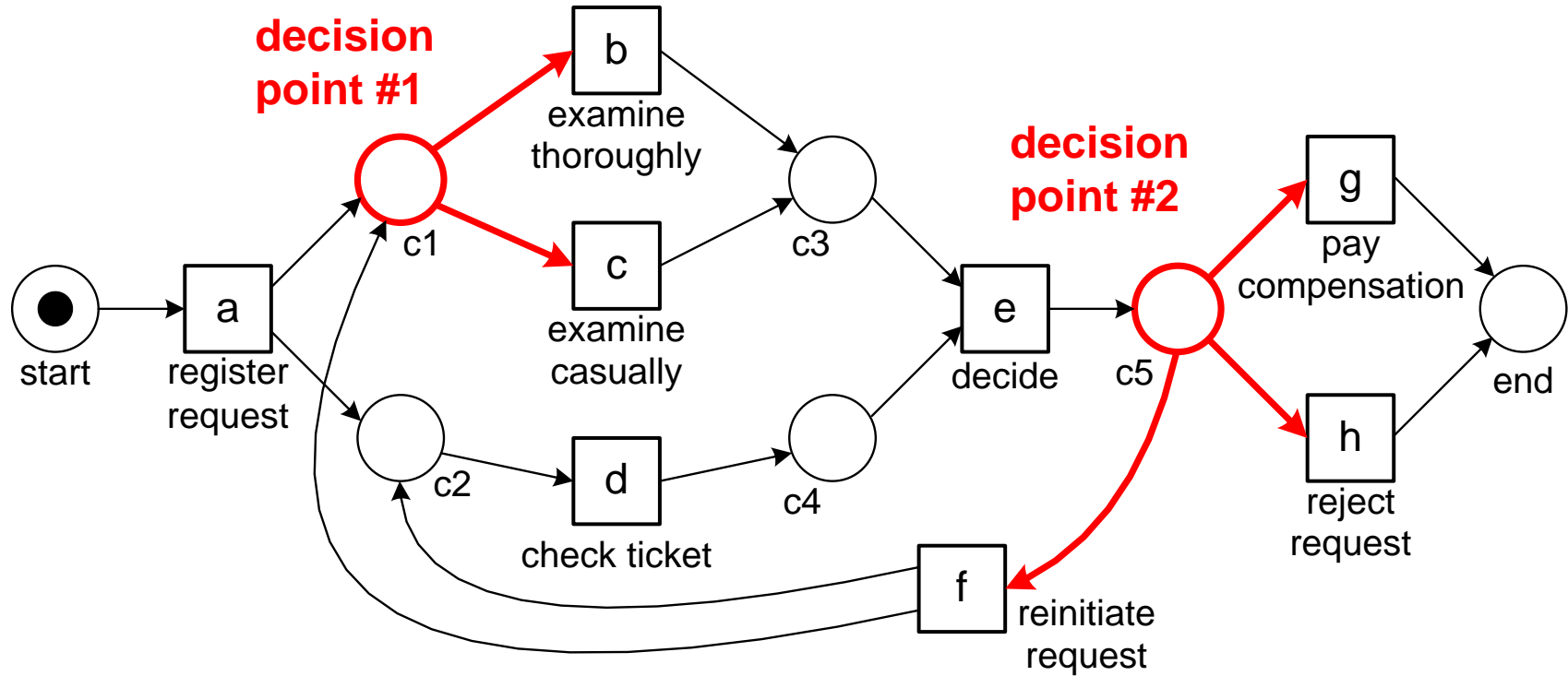
(assuming cases have a data attribute *type* having value blue or red)

If red then B+C;

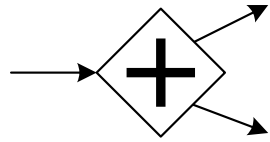
If blue then E;



Places with multiple output arcs form decision points

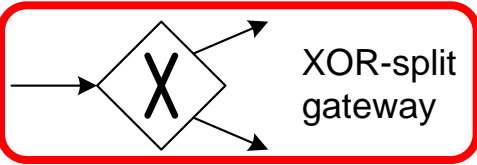
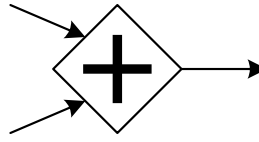


Decision points in BPMN



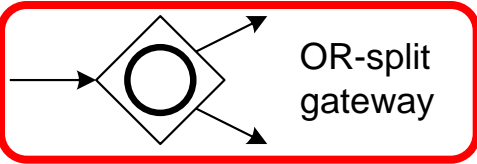
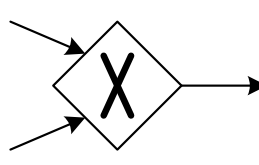
AND-split gateway

AND-join gateway



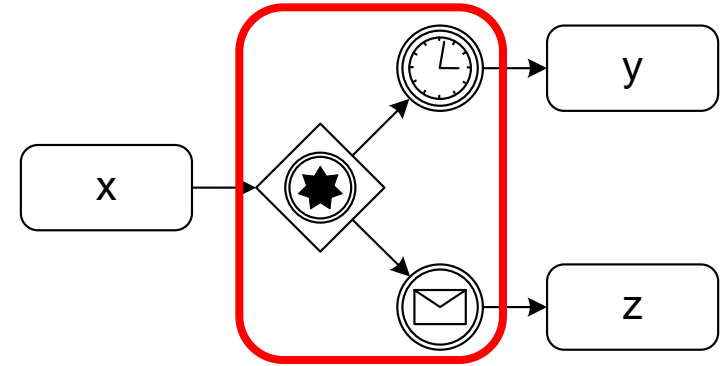
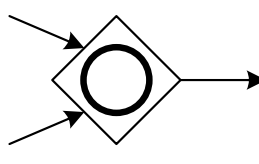
XOR-split gateway

XOR-join gateway



OR-split gateway

OR-join gateway



event-based XOR-split gateway
(deferred choice pattern)

A silhouette of a person in mid-jump, bridging a gap between two dark, jagged rock formations. The background is a bright blue sky with a large, radiant sunburst effect emanating from behind the person. A small, white, fluffy cloud is visible in the upper left corner. The overall image conveys a sense of achievement and overcoming challenges.

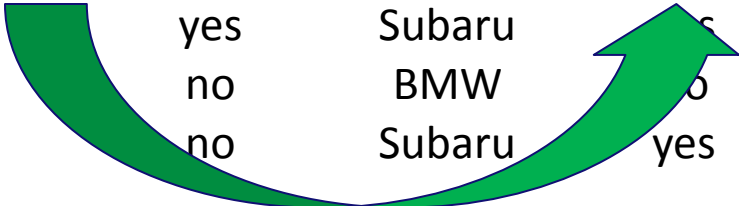
**data
mining**

**process
mining**

Remember:

Classification using decision trees

gender	age	smoker	car brand	claim
female	47	yes	Volvo	no
male	31	no	Alfa Romeo	yes
male	59	no	Alfa Romeo	yes
male	28	no	Fiat	no
male	44	no	BMW	no
female	27	no	Fiat	no
male	29	no	Subaru	no
male	44	yes	Subaru	no
male	39	no	BMW	no
male	35	no	Subaru	yes



- Response variable (dependent variable): **claim** (yes/no).
- Predictor variables (independent variables): **gender**, **age**, **smoker**, **car brand**.

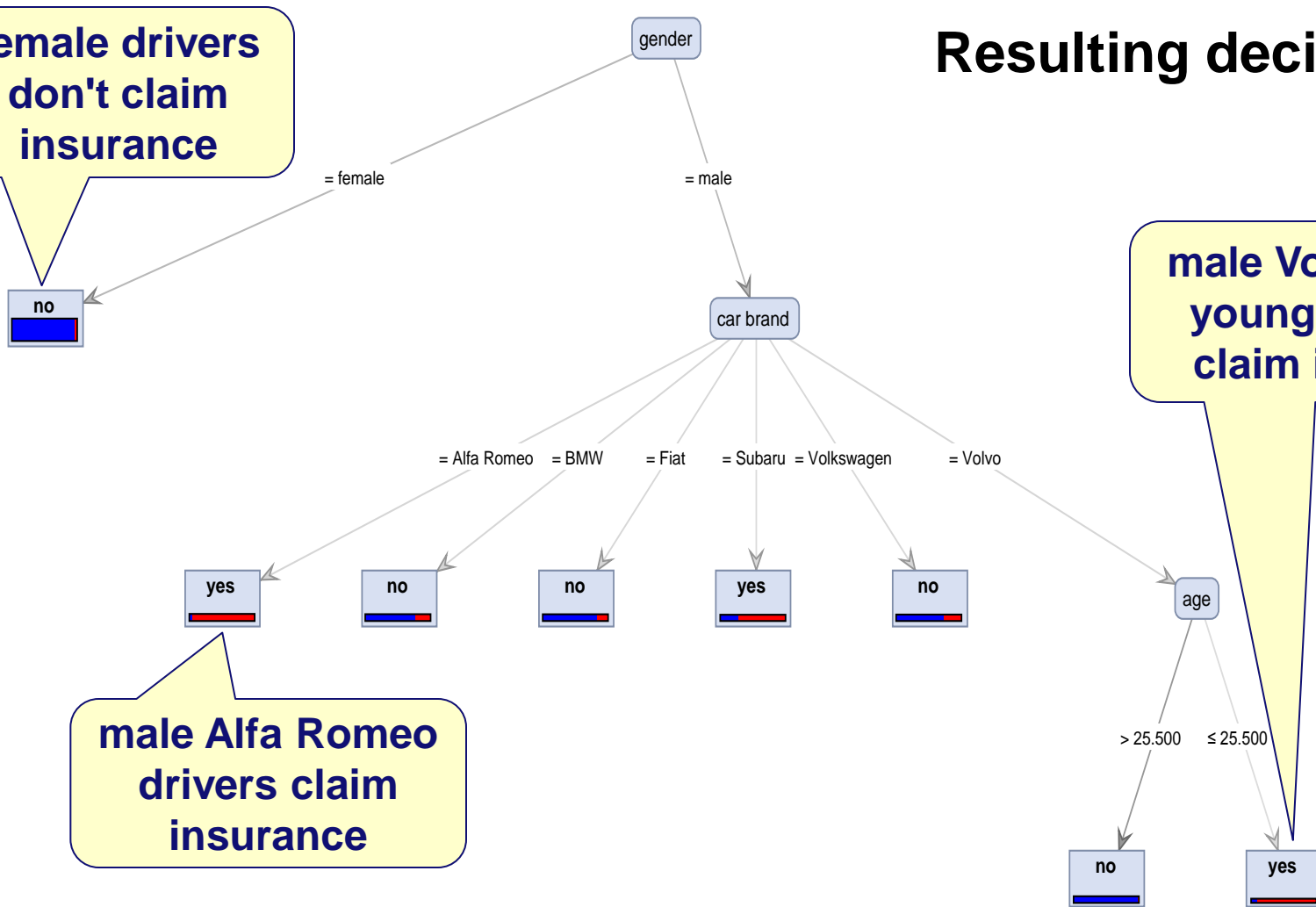
Goal: explain response variable in terms of relevant predictor variables.

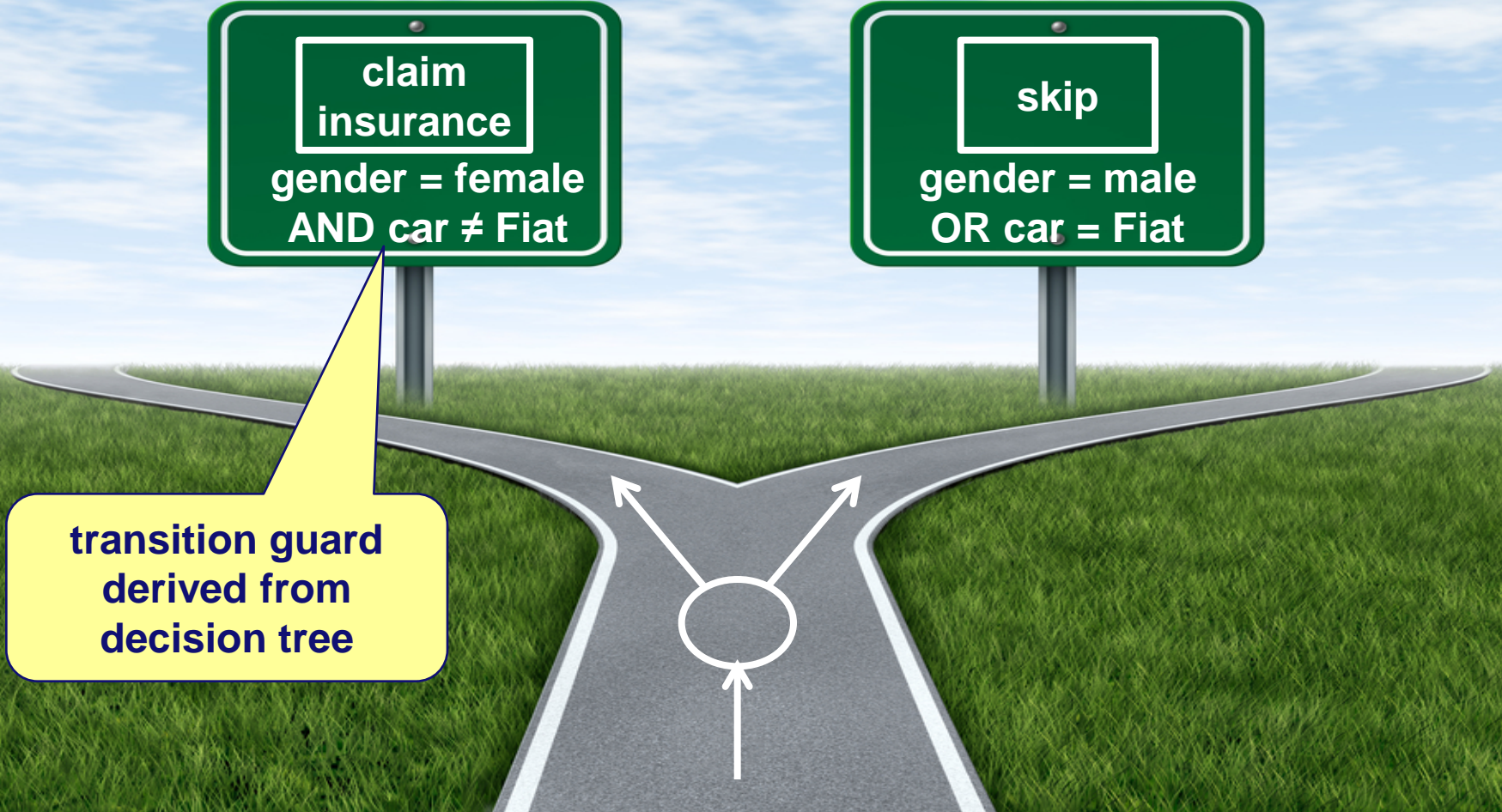
**female drivers
don't claim
insurance**

Resulting decision tree

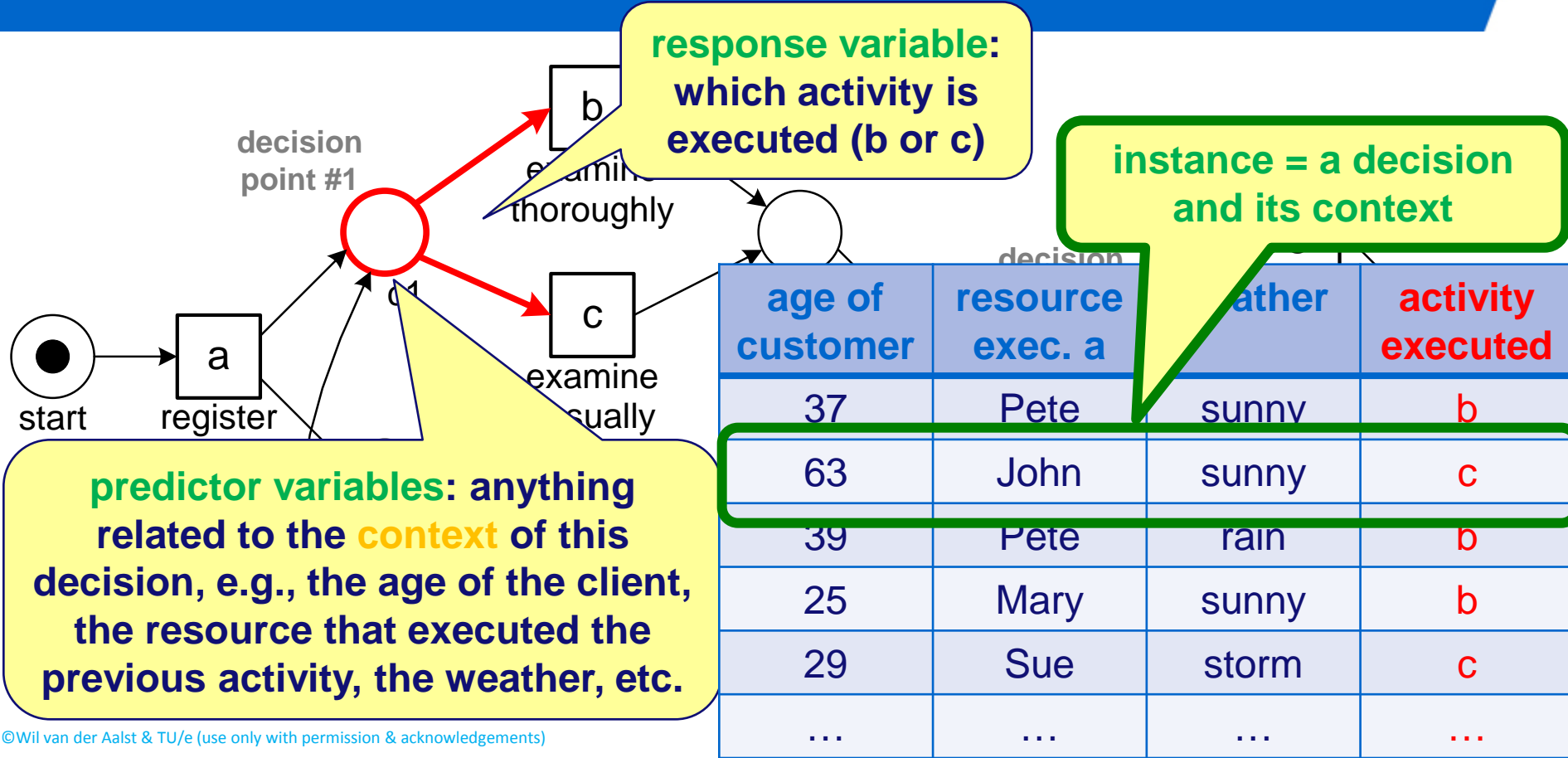
**male Volvo drivers
younger than 25
claim insurance**

**male Alfa Romeo
drivers claim
insurance**





Creating a classification problem



type	region	amount	activity
...	...	687.70	...

predictor variables:

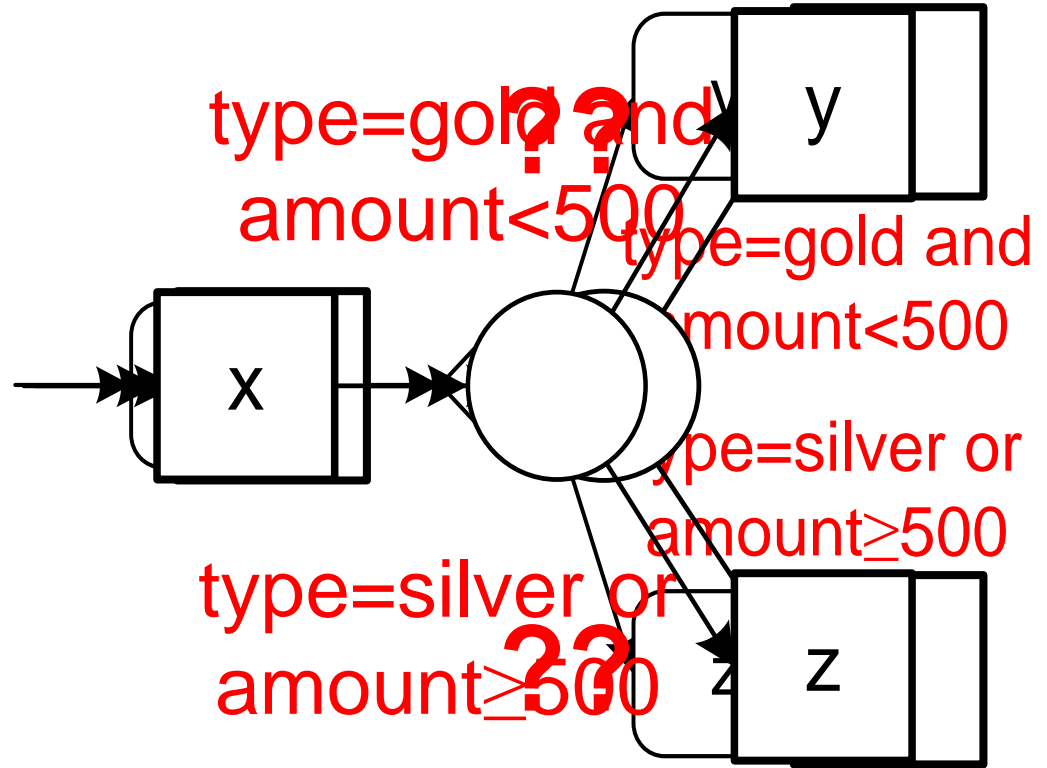
- type = silver
- region = south
- amount = 687.70

response variable

- activity = z

gold	west	413.30	y
silver	south	687.70	z
gold	south	987.30	z
silver	north	378.80	z
gold	south	314.50	y
silver	north	537.70	z
silver	west	158.70	z
gold	east	344.50	y
...

Learning an XOR-split



For any process notation, e.g.,
learning a BPMN XOR-split gateway.

type	region	amount	activity
gold	south	987.30	y and z
silver	west	443.20	y and z
gold	west	500.00	y
silver	west	400.00	z
silver	west	450.00	y and z
silver	west	450.00	y and z
gold	north	488.50	just y
silver	west	443.20	y and z
silver	south	673.70	just z
...

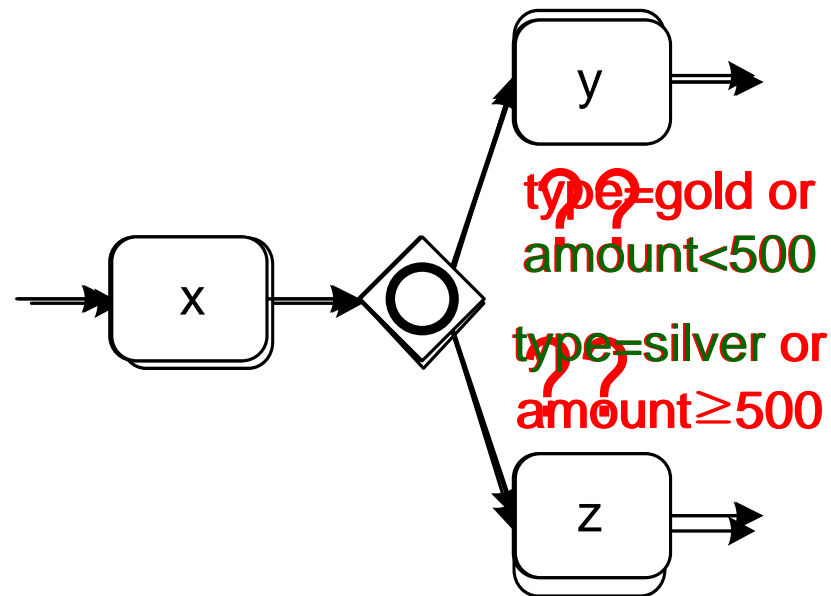
predictor variables:

- type = silver
- region = west
- amount = 443.20

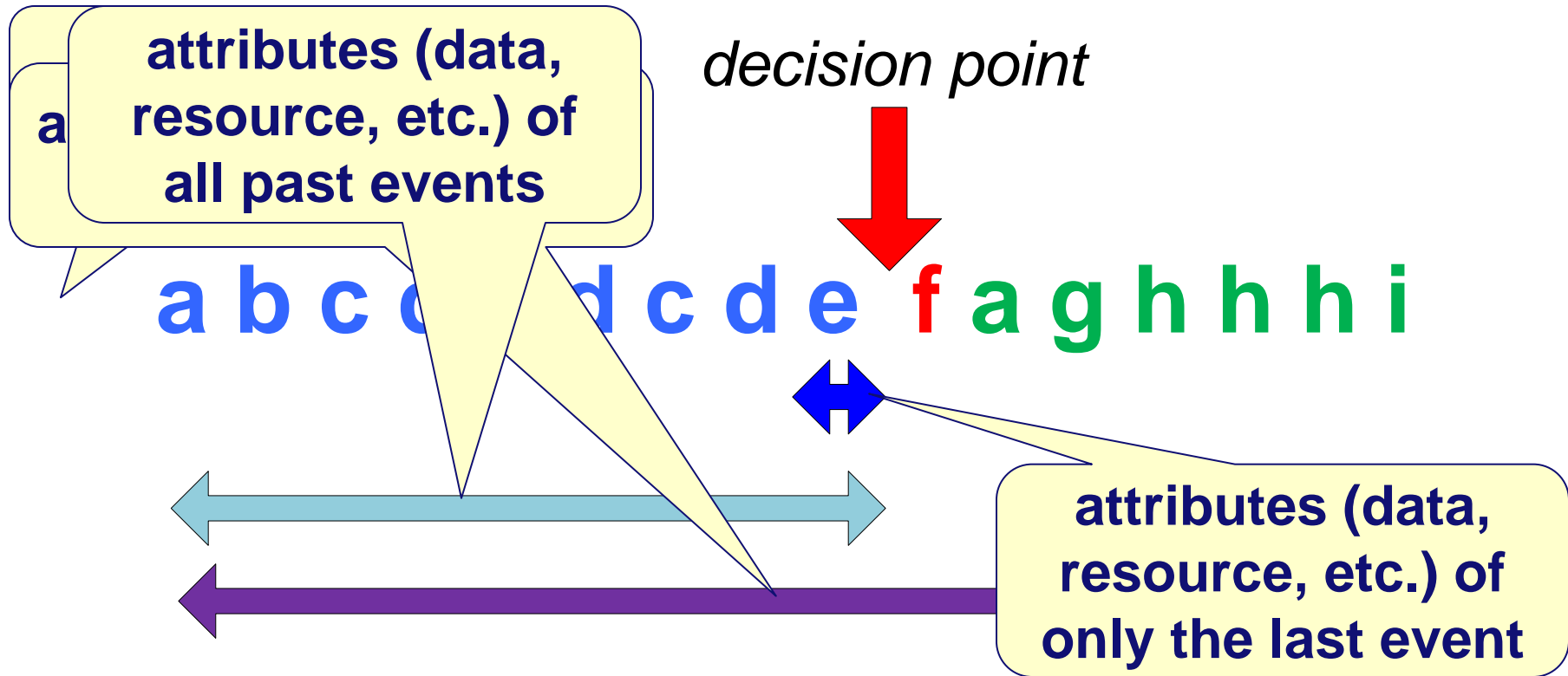
response variable

- activity = y and z

Learning an OR-split

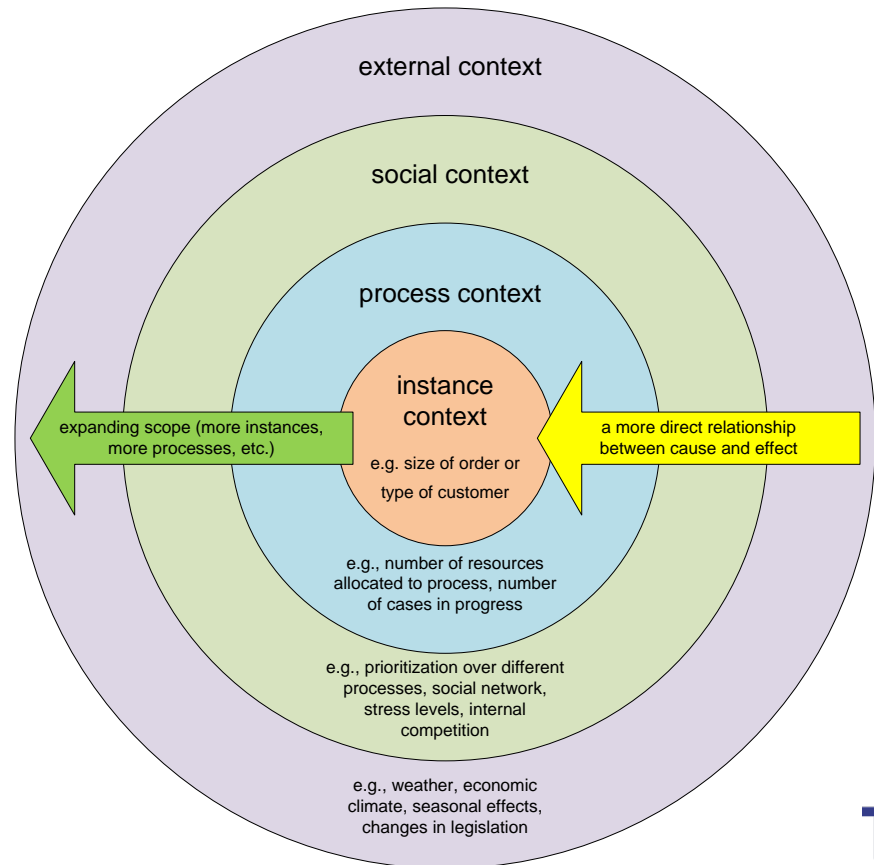


Where do the predictor variables come from?



Predictor variables may also be based on the **context** of the process instance

- Number of cases running (e.g. skip check if busy).
- Number of resources present.
- Workload of resource.
- Day of the week.
- Weather.



curse of dimensionality

more variables,
more combinations,
data gets sparser
(less instances per
combination),
danger of overfitting,

...





remaining
flow time

service levels

costs

incidents

risks

fraud

**"next activity" is
just one of many
possible response
variables !!!**

**operational
support:
predictive
analytics for
processes**



Part I: Preliminaries

Chapter 1
Introduction

Chapter 2
Process Modeling and
Analysis

Chapter 3
Data Mining

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 III: Beyond Process Discovery

Chapter 7
Conformance
Checking

Chapter 8
Mining Additional
Perspectives

Chapter 9
Operational Support

Part IV: Putting Process Mining to

Chapter 10
Tool Support

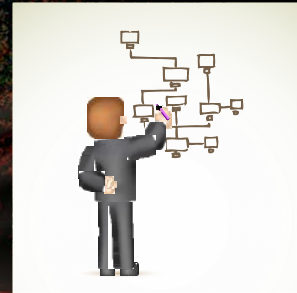
Chapter 11
Analyzing “Lasagna
Processes”

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