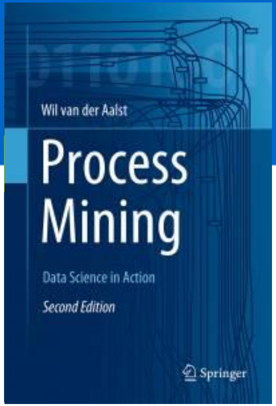
Process Mining: Data Science in Action

Applying Decision Trees

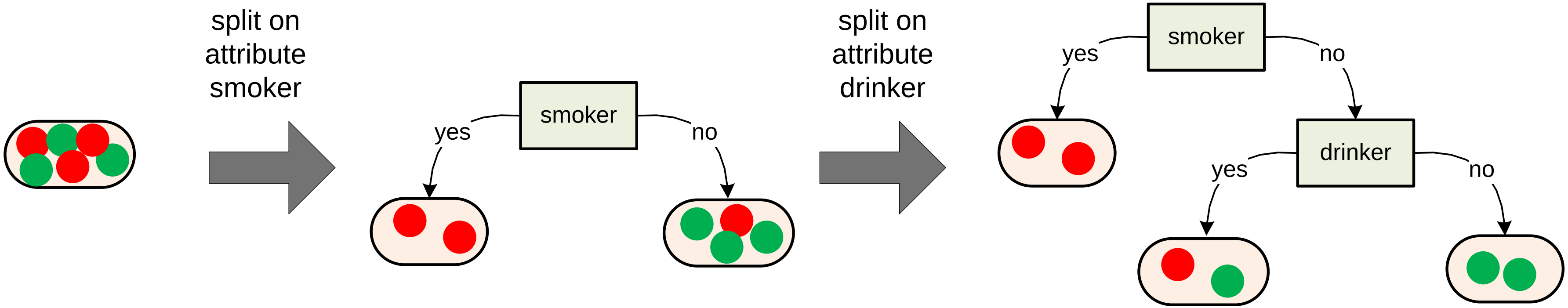
prof.dr.ir. Wil van der Aalst
www.processmining.org



Technische Universiteit Eindhoven University of Technology

Where innovation starts

Decision tree learning



$$E = -\sum_{i=1}^{k} p_i \log_2(p_i)$$

Iteratively reduce the overall level of uncertainty (entropy) using label splitting until no significant information gain is possible.

Example: 160 students (100 pass, 60 fail)

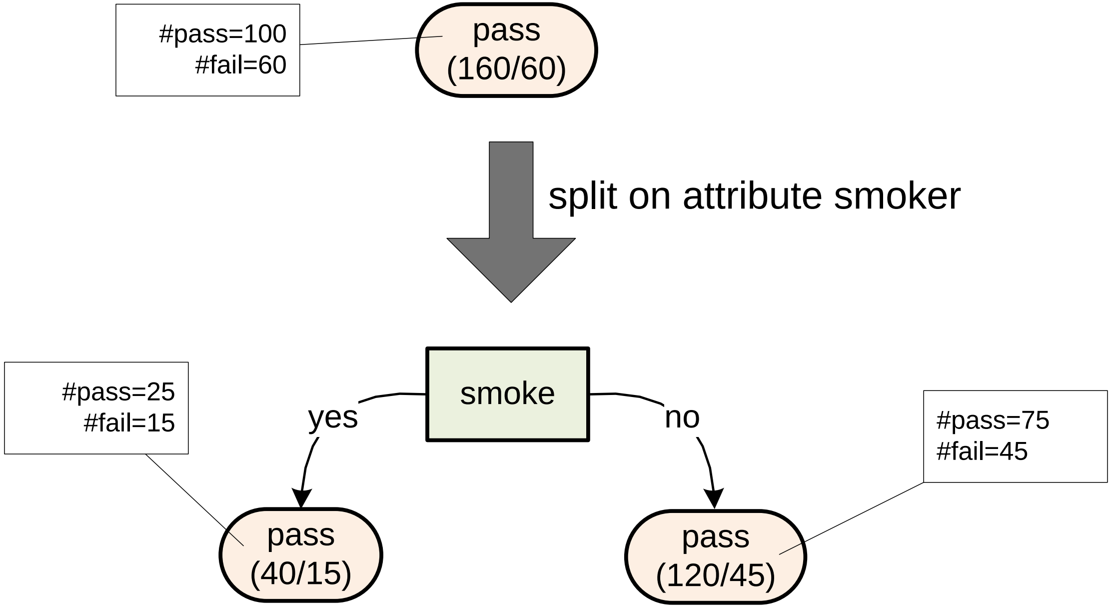
What matters?

attending lectures?

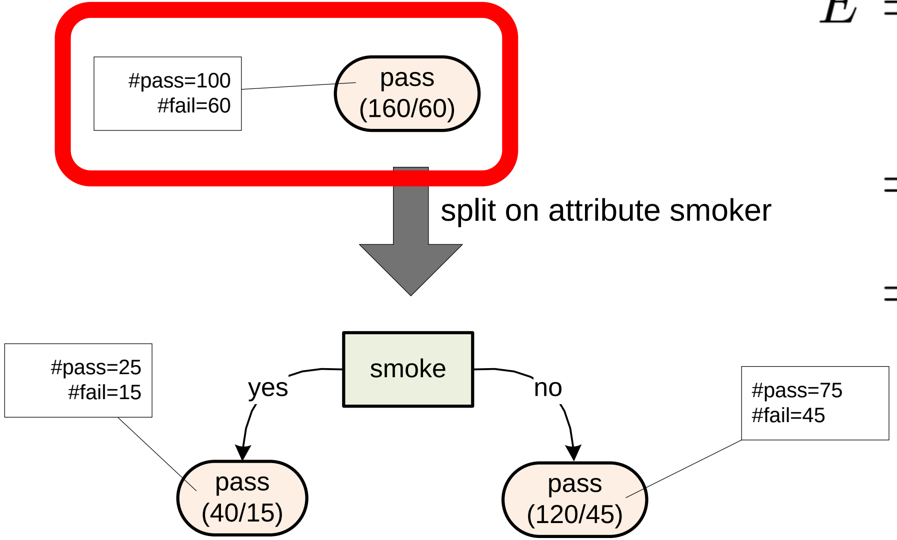
gender?

smoking?

Question: What is the information gain?



Answer: Entropy of root node

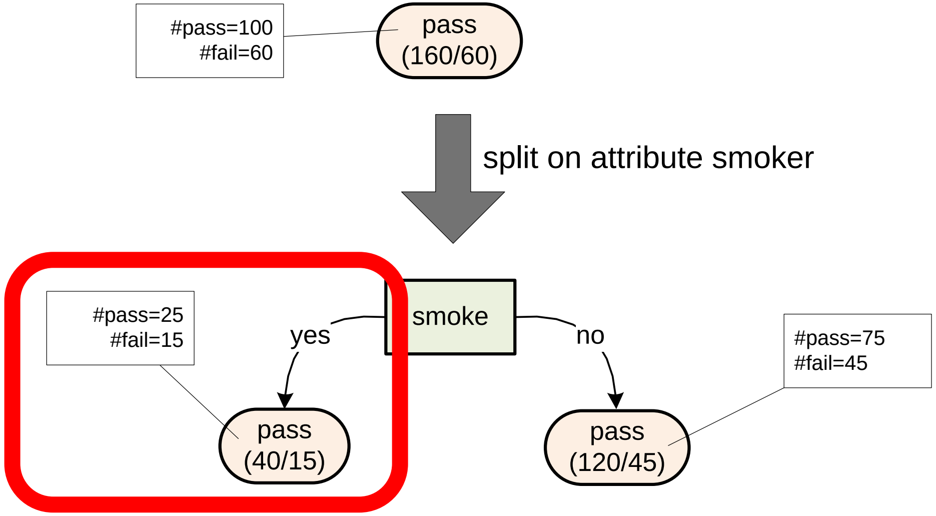


$$E = -\sum_{i=1}^{k} p_i \log_2(p_i)$$

$$= -\left(\frac{100}{160}\log_2\left(\frac{100}{160}\right) + \frac{60}{160}\log_2\left(\frac{60}{160}\right)\right)$$

$$= 0.9544$$

Answer: Entropy of smokers

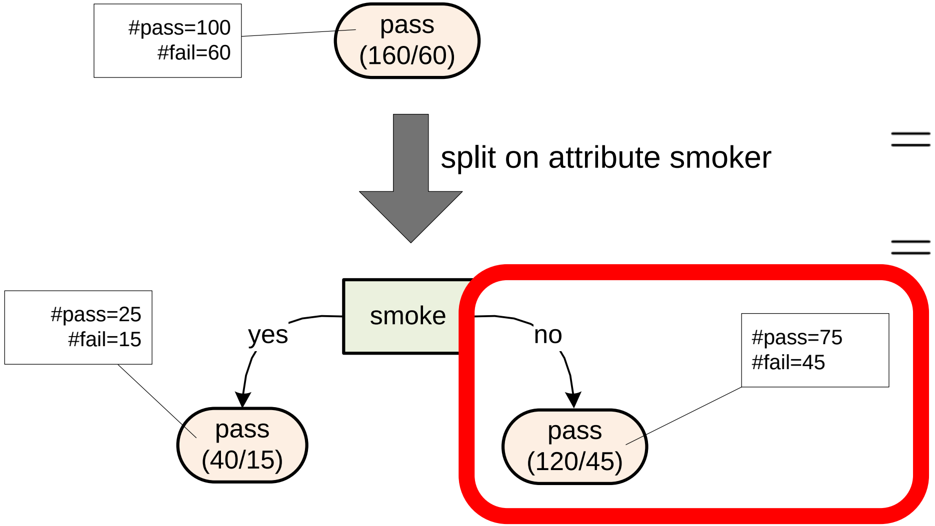


$$E = -\sum_{i=1}^{k} p_i \log_2(p_i)$$

$$= -\left(\frac{25}{40}\log_2\left(\frac{25}{40}\right) + \frac{15}{40}\log_2\left(\frac{15}{40}\right)\right)$$

$$= 0.9544$$

Answer: Entropy of non-smokers

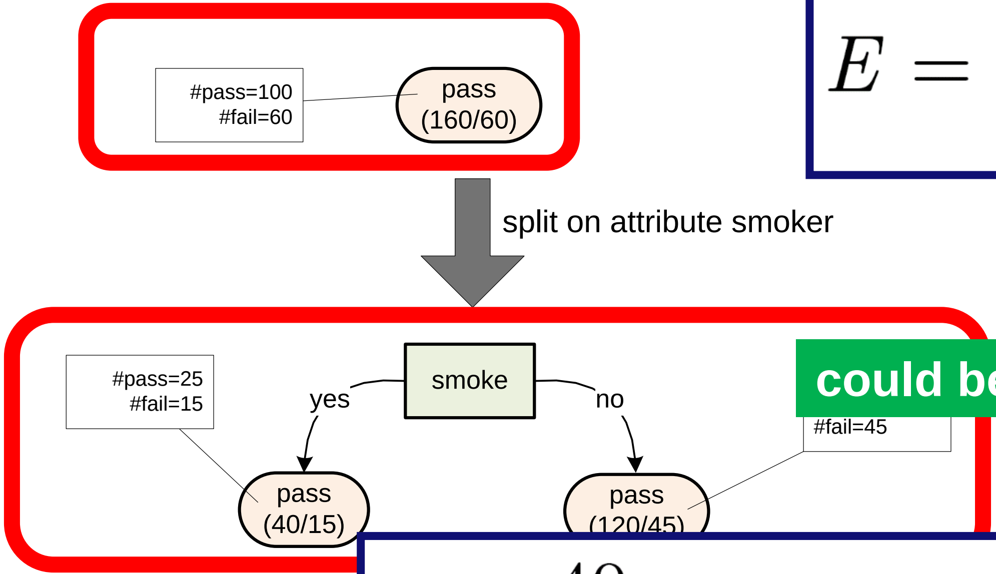


$$E = -\sum_{i=1}^{k} p_i \log_2(p_i)$$

$$= -\left(\frac{75}{120}\log_2\left(\frac{75}{120}\right) + \frac{45}{120}\log_2\left(\frac{45}{120}\right)\right)$$

$$= 0.9544$$

Answer: No information gain



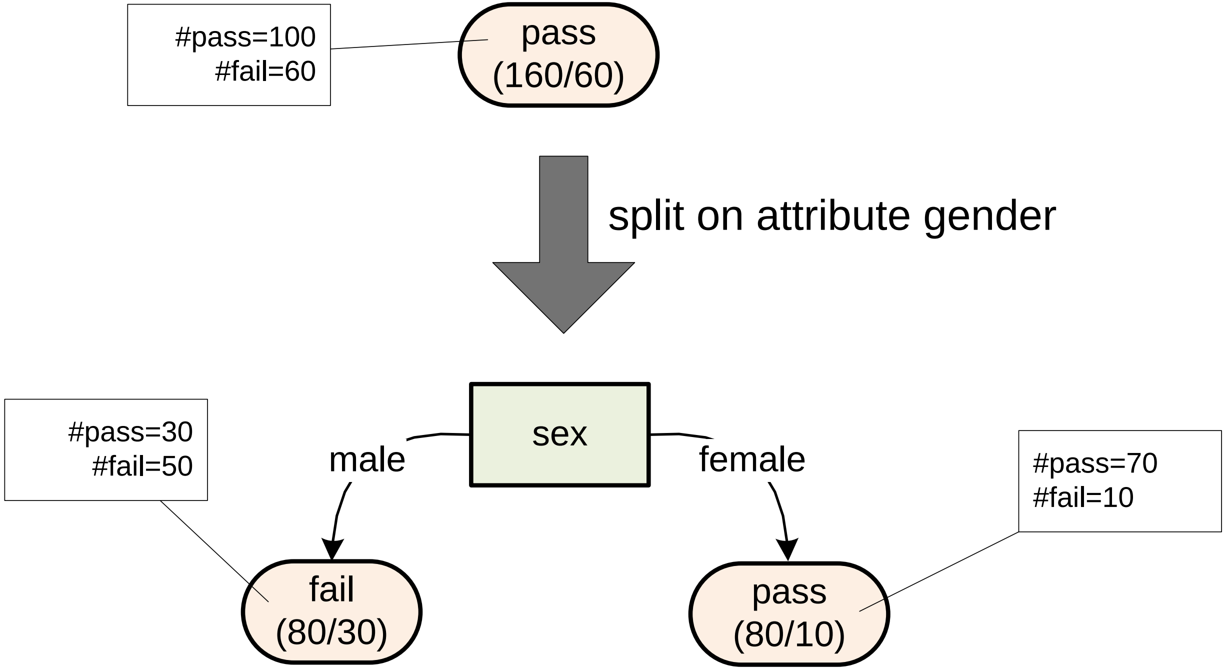
$$E = \frac{160}{160} \times 0.9544 = 0.9544$$

information gain = 0

could be seen without computation

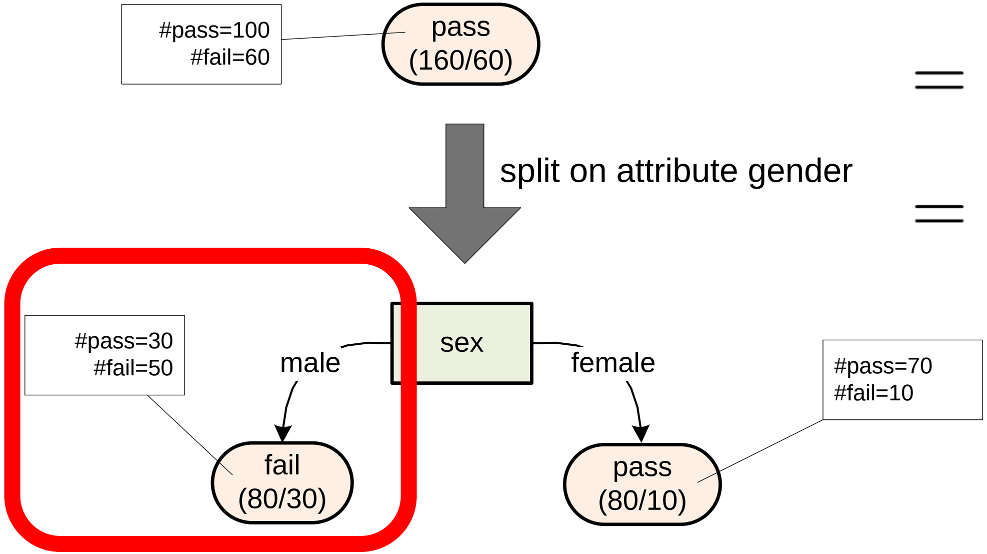
$$E = \frac{40}{160} \times 0.9544 + \frac{120}{160} \times 0.9544 = 0.9544$$

Question: What is the information gain?



Answer: Entropy of male students

$$E = -\sum_{i=1}^{k} p_i \log_2(p_i)$$
$$= -(\frac{100}{160}\log_2(\frac{100}{160}) + \frac{60}{160}\log_2(\frac{60}{160}))$$
$$= 0.9544$$

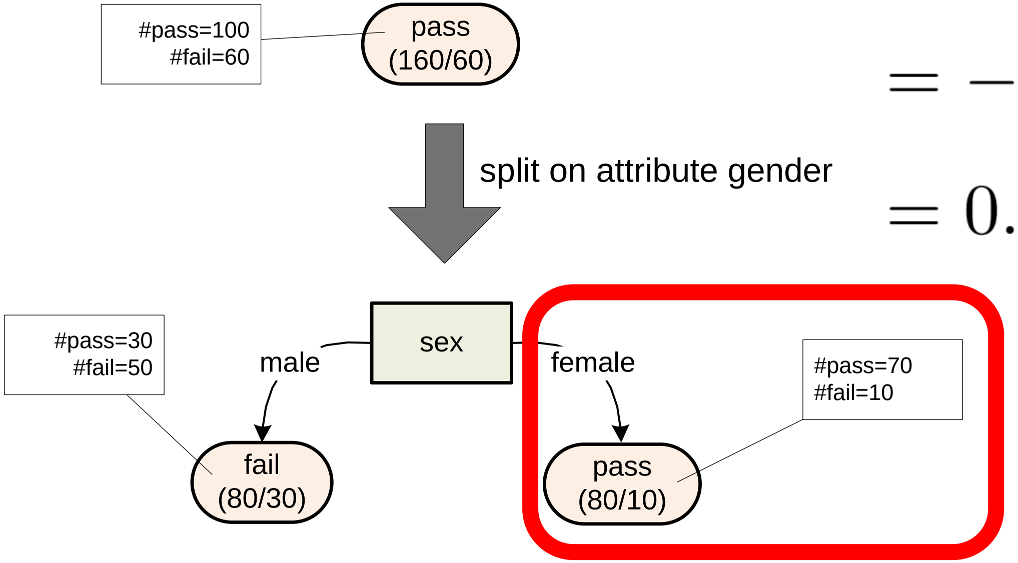


$$E = -\sum_{i=1}^{k} p_i \log_2(p_i)$$
$$= -(\frac{30}{80}\log_2(\frac{30}{80}) + \frac{50}{80}\log_2(\frac{50}{80}))$$
$$= 0.9544$$

Answer: Entropy of female students

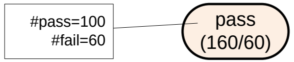
$$
\begin{aligned}
E &= -\sum_{i=1}^{k} p_i \, \log_2(p_i) \\
&= -(\frac{100}{160}\log_2(\frac{100}{160}) + \frac{60}{160}\log_2(\frac{60}{160})) \\
&= 0.9544
\end{aligned}
$$

$$
\begin{aligned}
E &= -\sum_{i=1}^{k} p_i \, \log_2(p_i) \\
&= -(\frac{70}{80}\log_2(\frac{70}{80}) + \frac{10}{80}\log_2(\frac{10}{80})) \\
&= 0.5436
\end{aligned}
$$

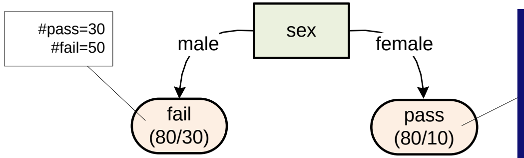


Answer: Information gain

$$
\begin{aligned}
E &= -\sum_{i=1}^{k} p_i \, \log_2(p_i) \\
&= -(\frac{100}{160}\log_2(\frac{100}{160}) + \frac{60}{160}\log_2(\frac{60}{160})) \\
&= 0.9544
\end{aligned}
$$



split on attribute gender



$$
\begin{aligned}
E &= -\sum_{i=1}^{k} p_i \, \log_2(p_i) \\
&= -(\frac{30}{80}\log_2(\frac{30}{80}) + \frac{50}{80}\log_2(\frac{50}{80})) \\
&= 0.9544
\end{aligned}
$$

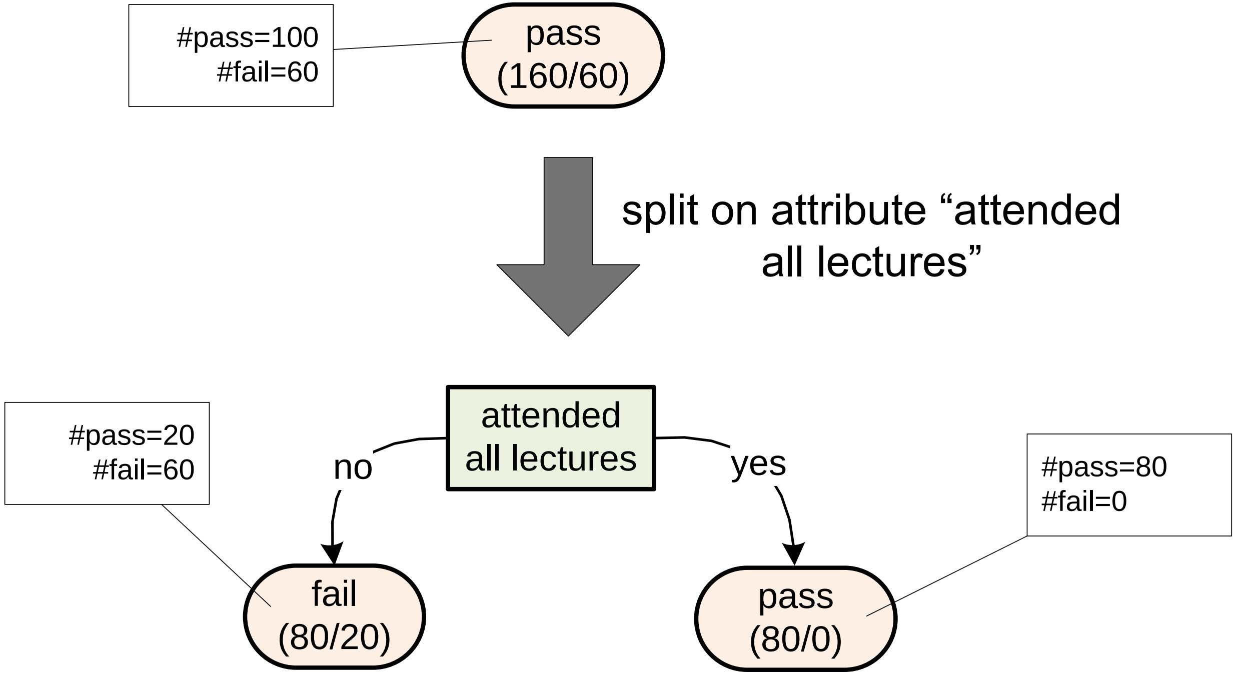
$$
\begin{aligned}
E &= -\sum_{i=1}^{k} p_i \, \log_2(p_i) \\
&= -(\frac{70}{80}\log_2(\frac{70}{80}) + \frac{10}{80}\log_2(\frac{10}{80})) \\
&= 0.5436
\end{aligned}
$$

$$E = \frac{160}{160} \times 0.9544 = 0.9544$$

information gain = 0.2054

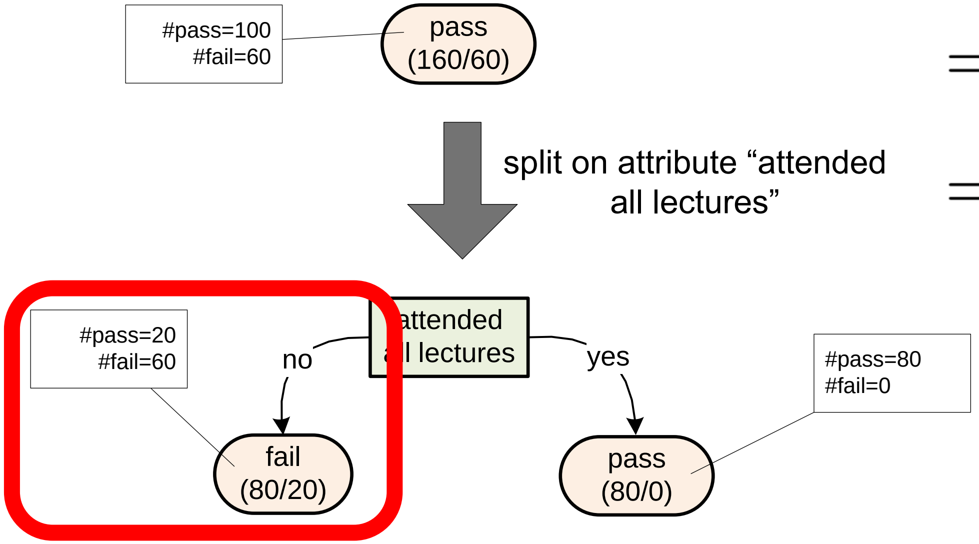
$$E = \frac{80}{160} \times 0.9544 + \frac{80}{160} \times 0.5436 = 0.7490$$

Question: What is the information gain?



Answer: Entropy of missing students

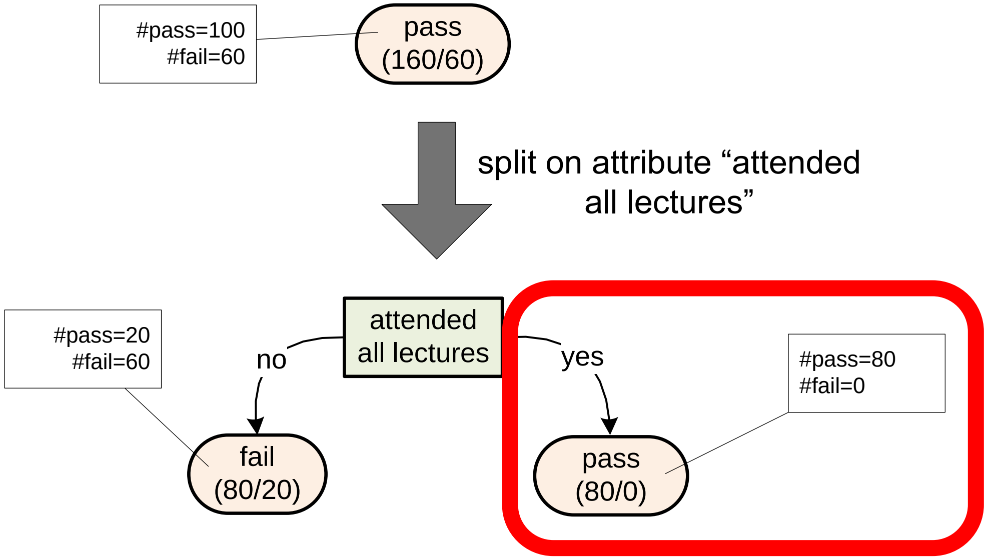
$$E = -\sum_{i=1}^{k} p_i \log_2(p_i)$$
$$= -(\frac{100}{160}\log_2(\frac{100}{160}) + \frac{60}{160}\log_2(\frac{60}{160}))$$
$$= 0.9544$$



$$E = -\sum_{i=1}^{k} p_i \log_2(p_i)$$
$$= -(\frac{20}{80}\log_2(\frac{20}{80}) + \frac{60}{80}\log_2(\frac{60}{80}))$$
$$= 0.8113$$

Answer: Entropy of attending students

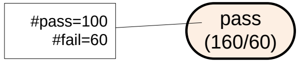
$$E = -\sum_{i=1}^{k} p_i \, \log_2(p_i)$$
$$= -(\frac{100}{160}\log_2(\frac{100}{160}) + \frac{60}{160}\log_2(\frac{60}{160}))$$
$$= 0.9544$$



$$E = -\sum_{i=1}^{k} p_i \, \log_2(p_i)$$
$$= -(\frac{80}{80}\log_2(\frac{80}{80}))$$
$$= 0$$

Answer

$$
\begin{aligned}
E &= -\sum_{i=1}^{k} p_i \log_2(p_i) \\
&= -(\frac{100}{160}\log_2(\frac{100}{160}) + \frac{60}{160}\log_2(\frac{60}{160})) \\
&= 0.9544
\end{aligned}
$$

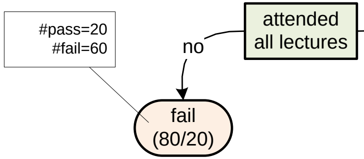


$$E = \frac{160}{160} \times 0.9544 = 0.9544$$

information gain = 0.5488

split on attribute "attended all lectures"

$$E = \frac{80}{160} \times 0.8113 + \frac{80}{160} \times 0 = 0.4056$$



$$
\begin{aligned}
E &= -\sum_{i=1}^{k} p_i \log_2(p_i) \\
&= -(\frac{20}{80}\log_2(\frac{20}{80}) + \frac{60}{80}\log_2(\frac{60}{80})) \\
&= 0.8113
\end{aligned}
$$

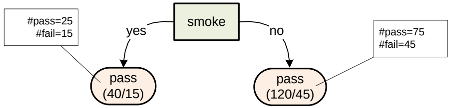
$$
\begin{aligned}
E &= -\sum_{i=1}^{k} p_i \log_2(p_i) \\
&= -(\frac{80}{80}\log_2(\frac{80}{80})) \\
&= 0
\end{aligned}
$$

Comparing information gains

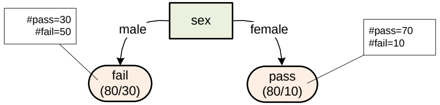
So we should split the root node on the attribute "attend all lectures"!

#pass=100
#fail=60

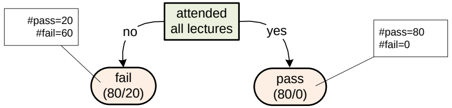
split on attribute smoker



split on attribute gender



split on attribute “attended all lectures”

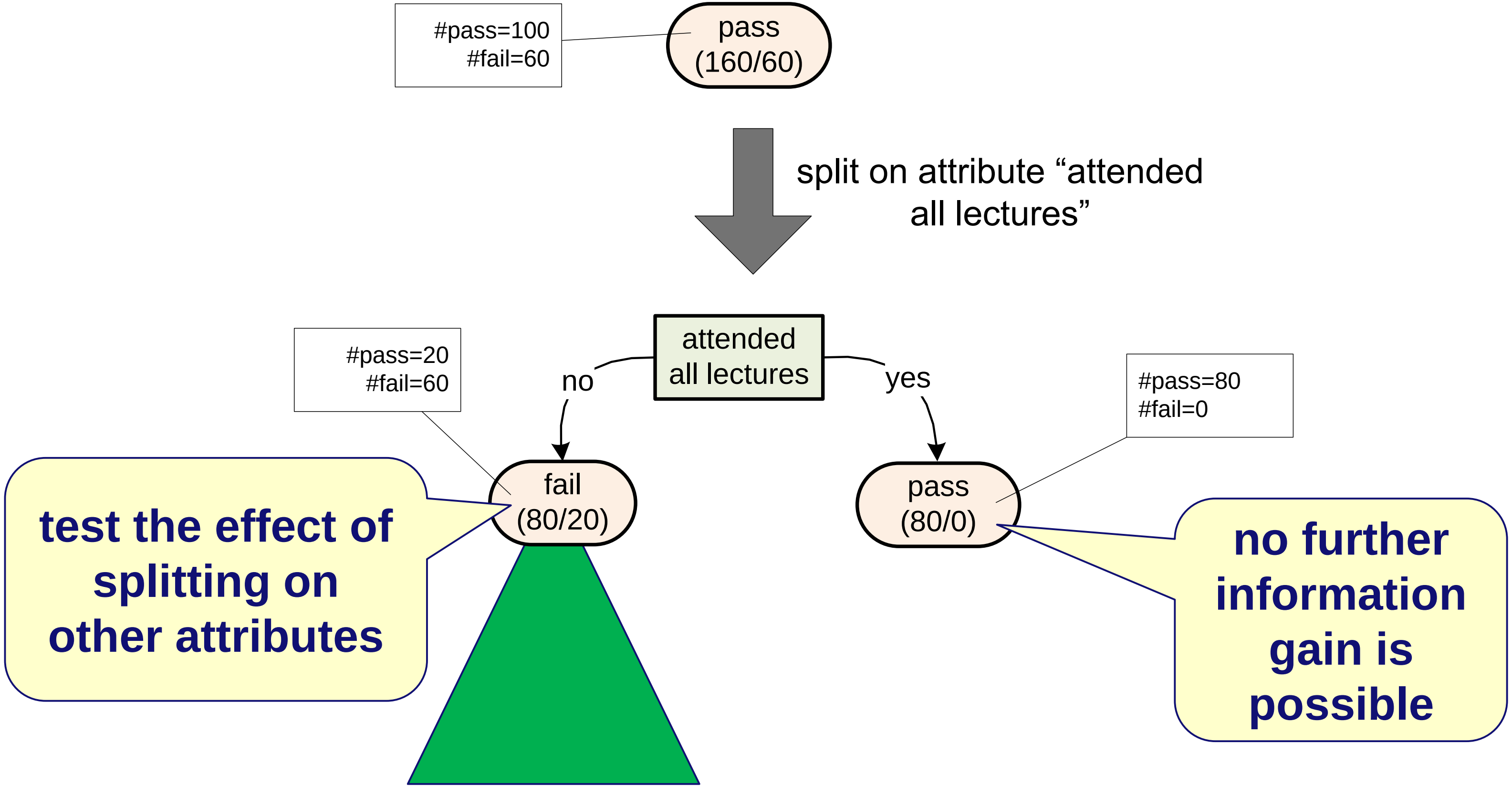


information gain = 0

information gain = 0.2054

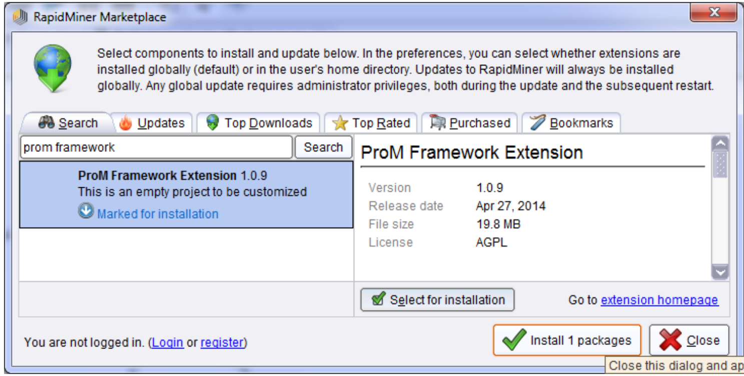
information gain = 0.5488

Iterate until no significant gain is possible



RapidMiner
(installation is optional)

- An integrated extendible environment for machine learning, data mining, text mining, and predictive analytics.
- RapidMiner Marketplace also provides a ProM extension for process mining.
- Commercial and open-source versions of the software.



Decision trees in RapidMiner

gender	age	smoker	car brand	claim
female	47	yes	Volvo	no
male	31	no	Alfa Romeo	yes
ma				
ma				
male	44	no	BMW	no
fema				
ma				
…	…	..	…	…

CSV file contains information about 999 customers of an insurance company.

The company wants to know which customers claim insurance.

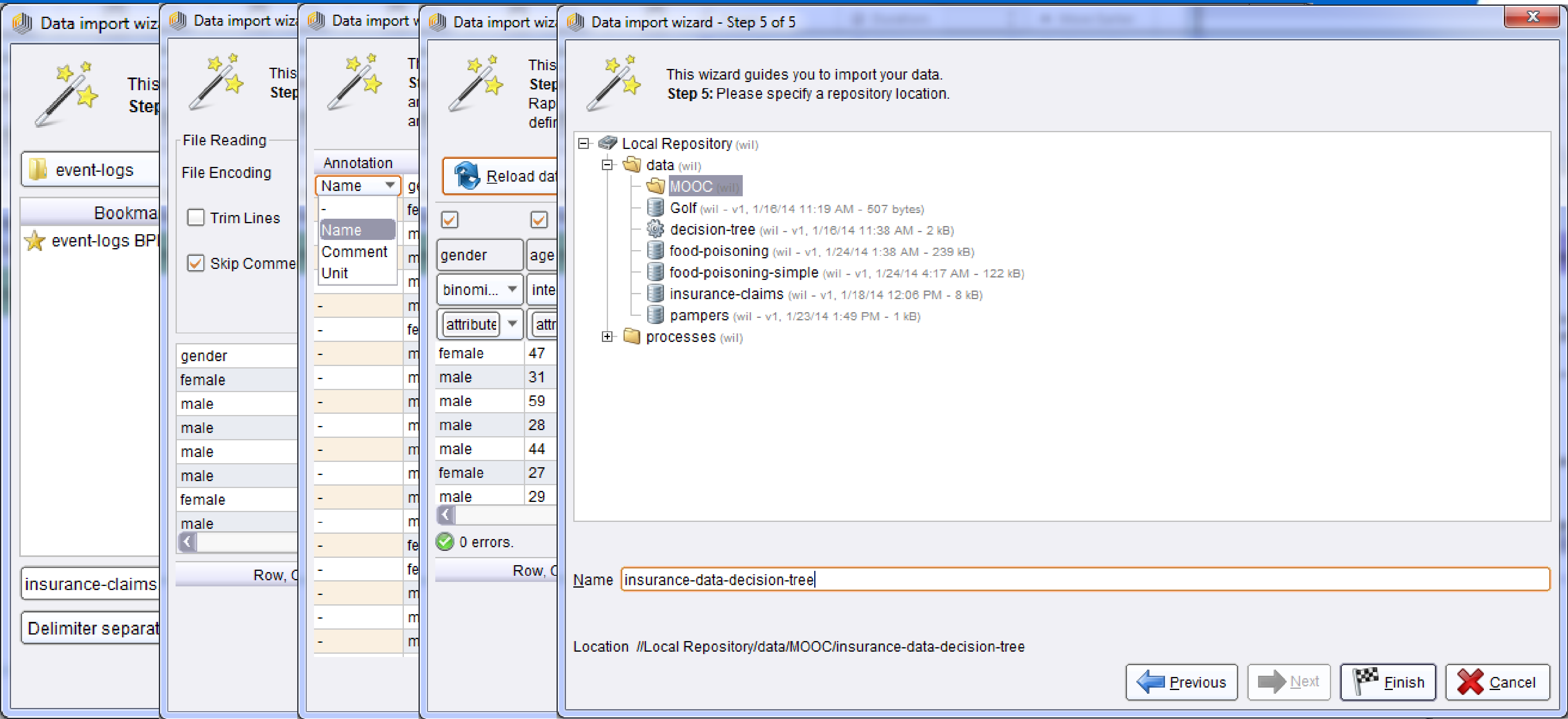
Decision trees in RapidMiner

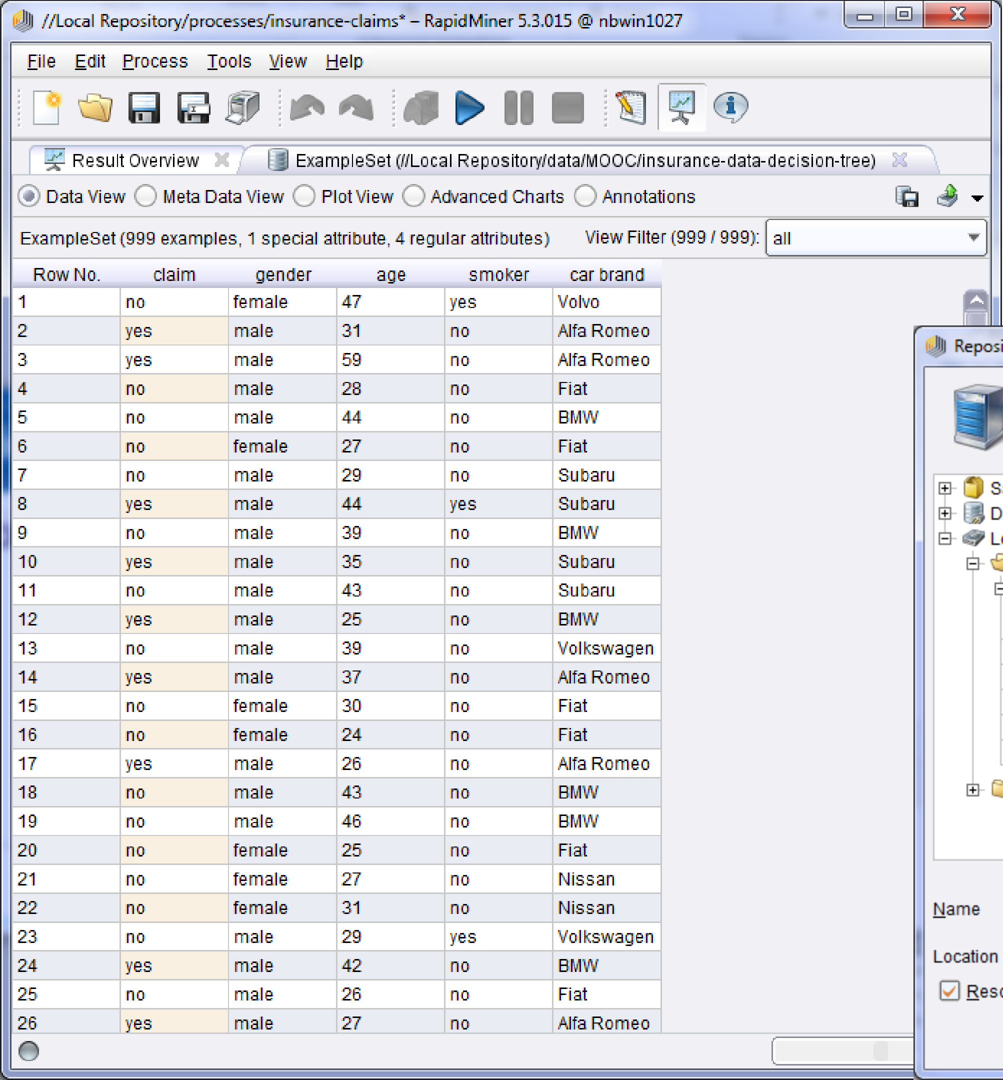
gender	age	smoker	car brand	claim
female	47	yes	Volvo	no
male	31	no	Alfa Romeo	yes
male	59	no	Alfa Romeo	yes
male	28	no	Fiat	no

Response variable (dependent variable): claim.

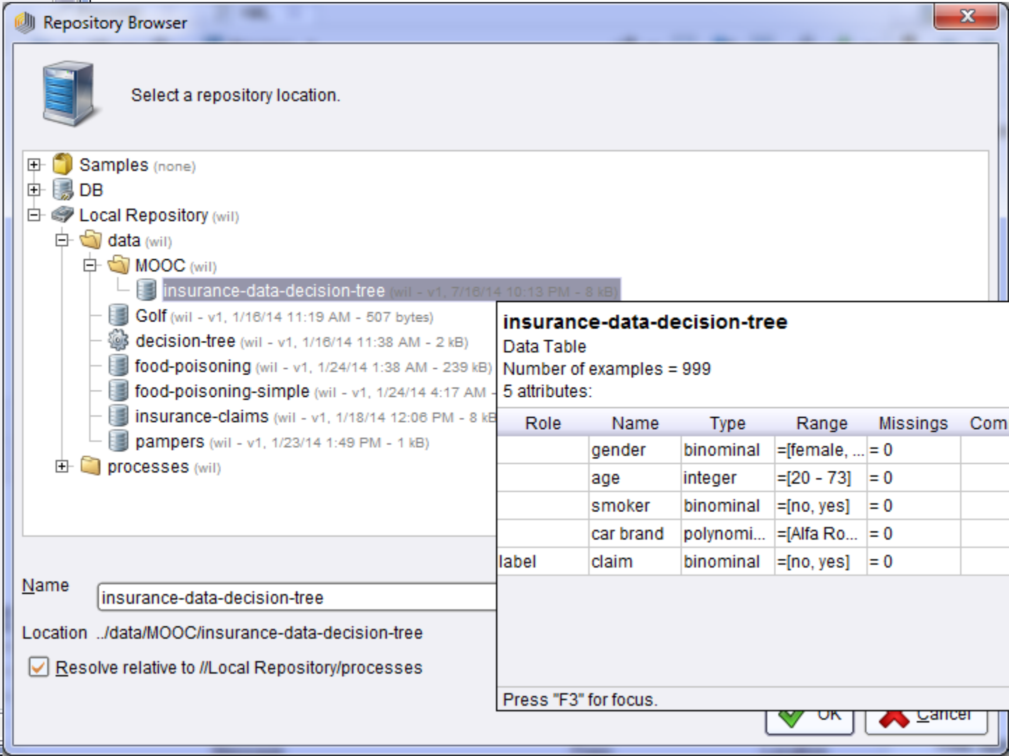
Predictor variables (independent variables): gender, age, smoker, car brand.

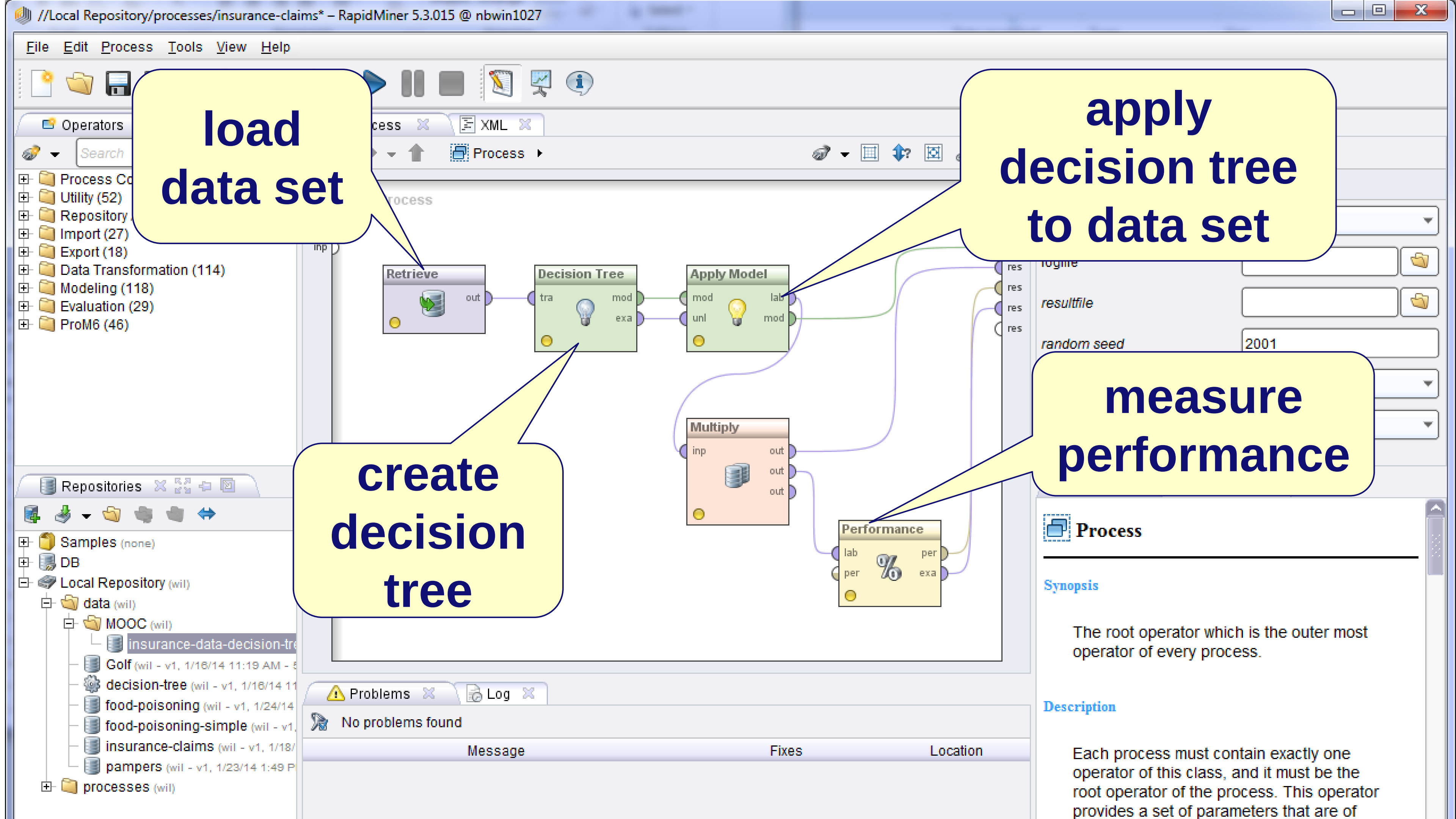
Data in RapidMiner





Data is stored in repository. Now we can apply an analysis workflow to it.




//Local Repository/processes/insurance-claims* – RapidMiner 5.3.015 @ nbwin1027
File
Edit
Process
Tools
View
Help
load data set
apply decision tree to data set
create decision tree
measure performance
Operators
Search
Process Co
Utility (52)
Repository
Import (27)
Export (18)
Data Transformation (114)
Modeling (118)
Evaluation (29)
ProM6 (46)
XML
Process
Retrieve
out
Decision Tree
tra
mod
exa
Apply Model
mod
unl
lab
mod
Multiply
inp
out
out
out
Performance
lab
per
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resultfile
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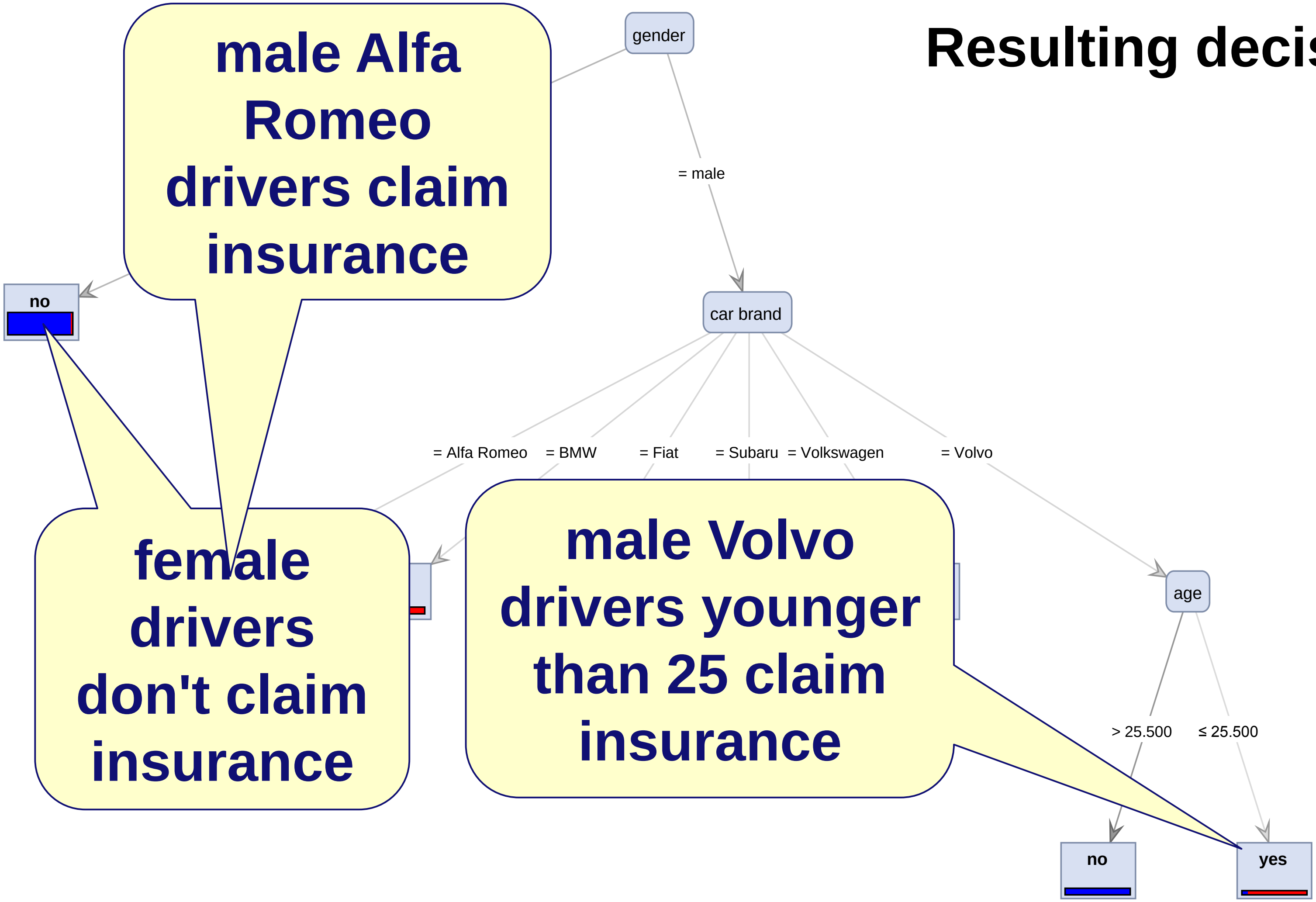
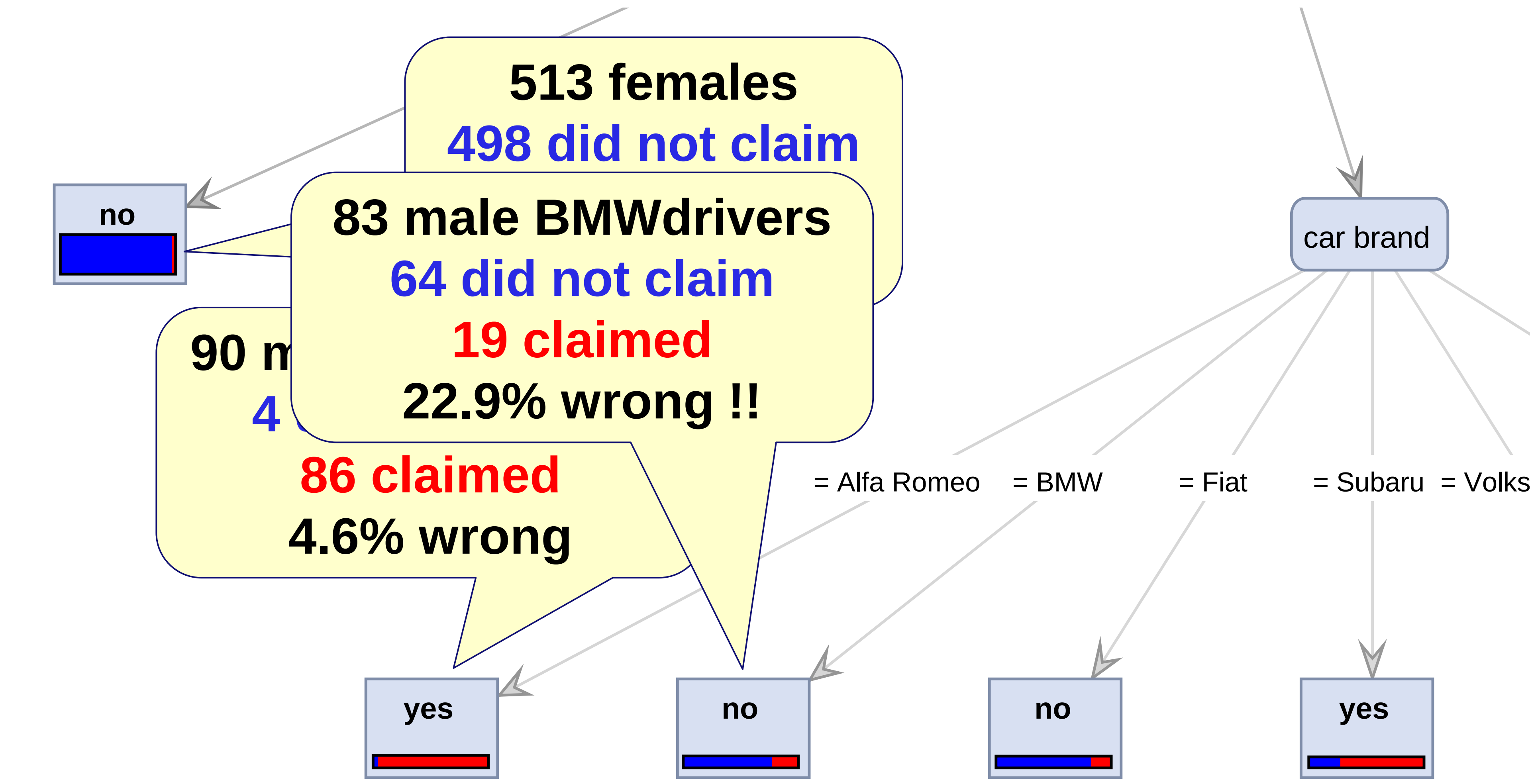
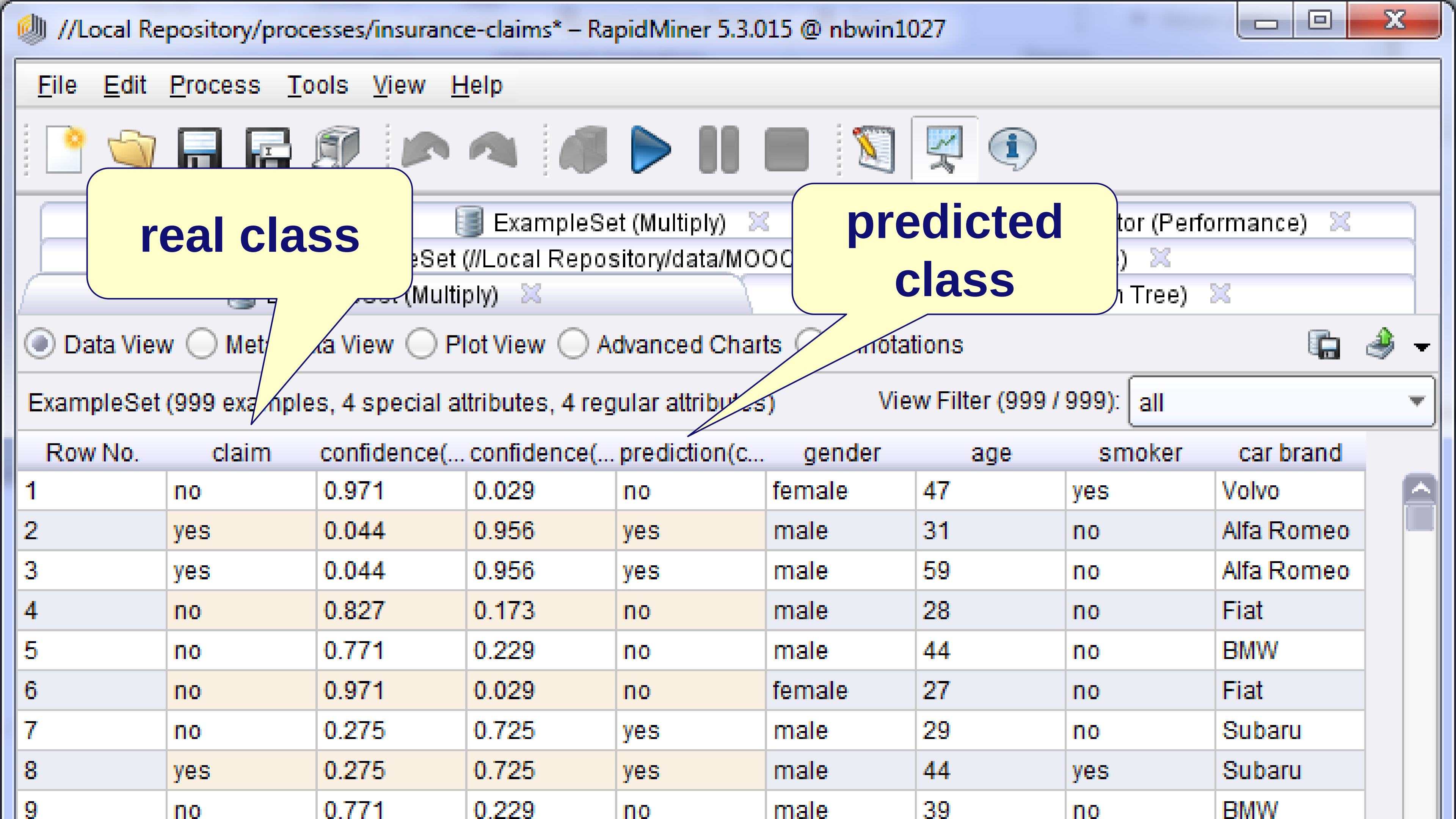
Repositories
Samples (none)
DB
Local Repository (wil)
data (wil)
MOOC (wil)
insurance-data-decision-tre
Golf (wil - v1, 1/16/14 11:19 AM -
decision-tree (wil - v1, 1/16/14 11
food-poisoning (wil - v1, 1/24/14
food-poisoning-simple (wil - v1,
insurance-claims (wil - v1, 1/18/
pampers (wil - v1, 1/23/14 1:49 P
processes (wil)
Problems
Log
No problems found
Message
Fixes
Location
Process
Synopsis
The root operator which is the outer most operator of every process.
Description
Each process must contain exactly one operator of this class, and it must be the root operator of the process. This operator provides a set of parameters that are of

Resulting decision tree





513 females
498 did not claim
83 male BMWdrivers
64 did not claim
19 claimed
22.9% wrong !!
90 m
4
86 claimed
4.6% wrong
no
car brand
= Alfa Romeo
= BMW
= Fiat
= Subaru
= Volks
yes
no
no
yes



Row No.	claim	confidence(...	confidence(...	prediction(c...	gender	age	smoker	car brand
1	no	0.971	0.029	no	female	47	yes	Volvo
2	yes	0.044	0.956	yes	male	31	no	Alfa Romeo
3	yes	0.044	0.956	yes	male	59	no	Alfa Romeo
4	no	0.827	0.173	no	male	28	no	Fiat
5	no	0.771	0.229	no	male	44	no	BMW
6	no	0.971	0.029	no	female	27	no	Fiat
7	no	0.275	0.725	yes	male	29	no	Subaru
8	yes	0.275	0.725	yes	male	44	yes	Subaru
9	no	0.771	0.229	no	male	39	no	BMW

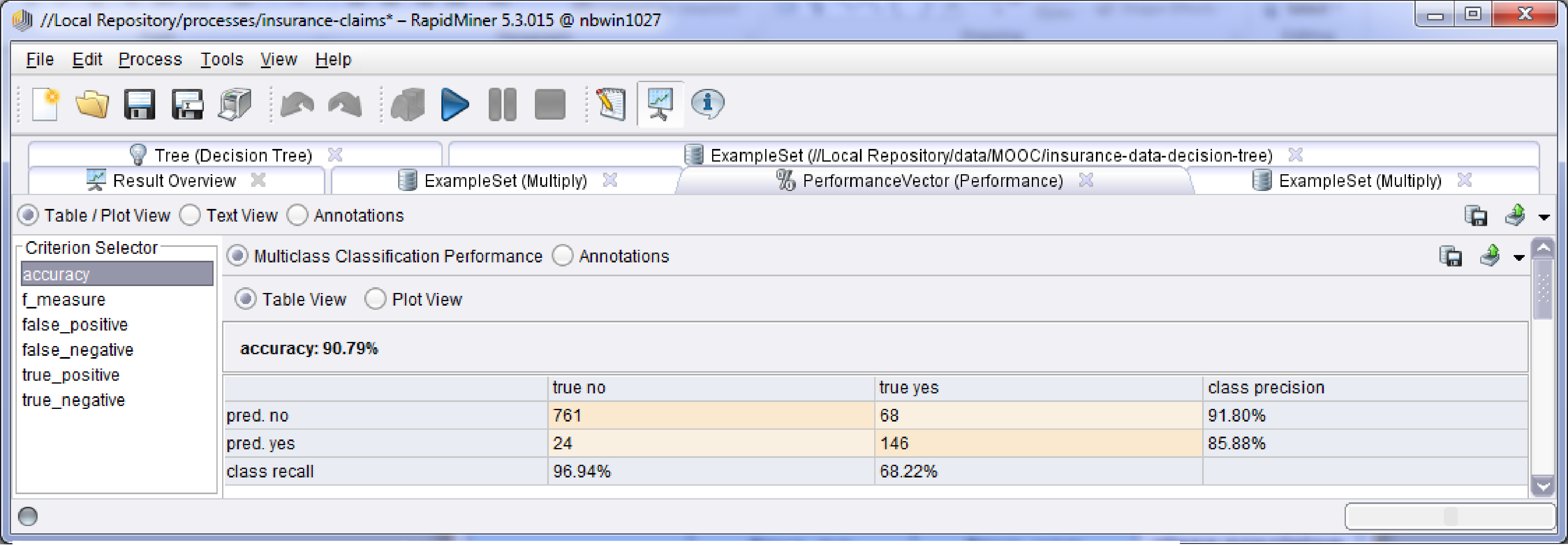
ExampleSet (999 examples, 4 special attributes, 4 regular attributes) View Filter (999 / 999

Row No.	claim	confidence(...	confidence(...	prediction(c...	gender	age	smoker	car brand
9	no	0.771	0.229	no	male	39	no	BMW
10	yes	0.275	0.725	yes	male	35	no	Subaru
11	no	0.275	0.725	yes	male	43	no	Subaru
12	yes	0.771	0.229	no	male	25	no	BMW
13	no	0.740	0.260	no	male	39	no	Volkswagen
14	yes	0.044	0.956	yes	male	37	no	Alfa Romeo

Which instances are classified incorrectly?

11: A male 43-year old non-smoking Subaru driver was predicted to claim but did not.

12: A male 25-year old non-smoking BMW driver was predicted to not claim, but actually did claim insurance.



	true no	true yes	class precision
pred. no	761	68	91.80%
pred. yes	24	146	85.88%
class recall	96.94%	68.22%	

5000 parties ate at an Italian restaurant.

Menu includes: pizza margherita, pizza romana, pizza marinara, pizza capricciosa, pizza siciliana, lasagna, spaghetti carbonara, spaghetti alla diavola, vino rosso,vino bianco, birra, and espresso.

<new process> – RapidMiner 5.3.015 @ nbwin1027

File Edit Process Tools View Help

rapidminer

Result Overview | ExampleSet (//Local Repository/data/food-poisoning)

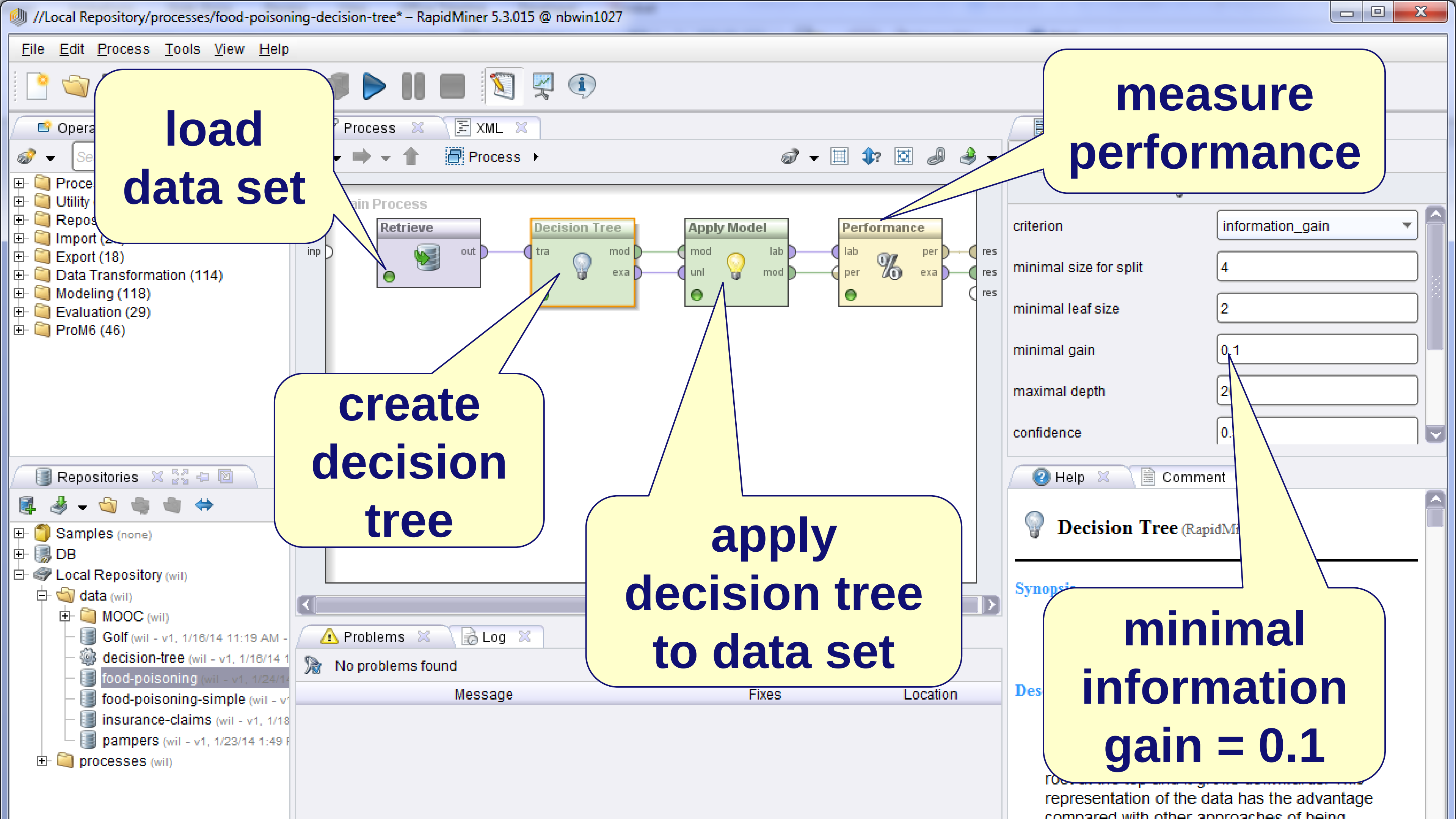
Data View | Meta Data View | Plot View | Advanced Charts | Annotations

csv file loaded into the repository

ExampleSet (5000 examples, 1 special attribute, 12 regular attributes)

View Filter (5000 / 5000): all

Row No.	class	pizza margh...	pizza romana	pizza marin...	pizza capric...	pizza sicilia...	lasagna	spaghetti c...	spaghetti al...	vino rosso	vino bianco	birra	espresso
1	not sick	2	0	0	0	1	1	0	0	0	0	3	1
2	not sick	1	3	1	0	4	0	1	1	2	1	0	2
3	not sick	0	3	0	0	4	1	0	3	0	1	1	1
4	not sick	0	0	0	0	0	0	0	0	0	0	3	0
5	not sick	2	0	1	1	0	3	0	0	0	0	3	0
6	not sick	0	2	0	1	3	0	0	1	0	2	1	4
7	not sick	0	0	0	0	0	2	1	2	1	1	0	0
8	not sick	2	0	1	0	0	3	0	0	0	0	2	0
9	nauseous	0	1	0	0	4	1	0	1	1	1	1	2
10	not sick	0	0	0	0	0	0	0	0	0	0	1	0
11	not sick	0	1	0	0	0	3	3	1	1	0	3	0
12	not sick	0	0	0	0	0	2	2	2	1	1	1	0
13	very sick	3	0	3	0	0	1	0	0	0	0	3	1
14	not sick	1	2	0	0	3	1	0	2	2	1	0	0
15	nauseous	1	3	0	0	4	0	0	4	3	0	0	2
16	not sick	0	2	0	0	4	0	1	1	2	2	0	2
17	not sick	0	0	0	0	0	3	3	2	0	0	1	1
18	not sick	0	1	0	2	4	1	1	2	1	2	1	2
19	not sick	3	0	0	0	0	1	1	0	0	0	2	0
20	not sick	0	0	0	0	0	3	3	2	0	0	2	2


//Local Repository/processes/food-poisoning-decision-tree* – RapidMiner 5.3.015 @ nbwin1027
File Edit Process Tools View Help
load data set
create decision tree
apply decision tree to data set
measure performance
minimal information gain = 0.1
Process
XML
Main Process
Retrieve
Decision Tree
Apply Model
Performance
inp
out
tra
mod
exa
unl
lab
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Utility
Repos
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Data Transformation (114)
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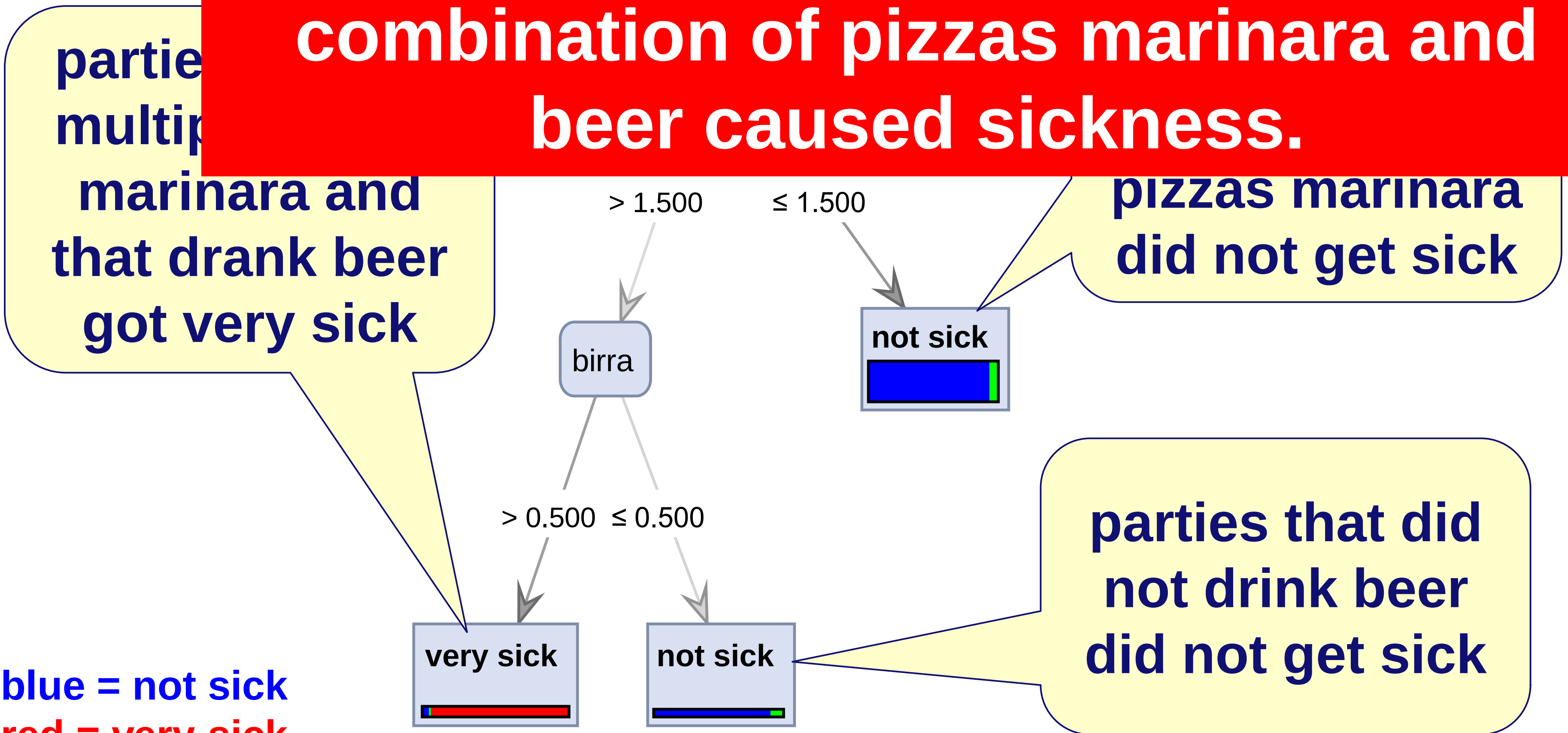
Evaluation (29)
ProM6 (46)
Repositories
Samples (none)
DB
Local Repository (wil)
data (wil)
MOOC (wil)
Golf (wil - v1, 1/16/14 11:19 AM -
decision-tree (wil - v1, 1/16/14 1
food-poisoning (wil - v1, 1/24/14
food-poisoning-simple (wil - v
insurance-claims (wil - v1, 1/18
pampers (wil - v1, 1/23/14 1:49
processes (wil)
Problems
Log
No problems found
Message
Fixes
Location
criterion
information_gain
minimal size for split
4
minimal leaf size
2
minimal gain
0.1
maximal depth
20
confidence
Help
Comment
Decision Tree (RapidMi
Synopsis
representation of the data has the advantage

Decision tree indicates that a combination of pizzas marinara and beer caused sickness.



blue = not sick
red = very sick
green = nauseous

al information gain = 0.1

307 of the 313 parties that were nauseous were classified as "not sick"

accuracy: 93.26%

	true not sick	true nauseous	true very sick	class precision
pred. not sick	4193	307		
pred. nauseous	0	0		
pred. very sick	24	6		
class recall	99.43%	0.00%		

6 of the 313 parties that were nauseous were classified as "very sick"

> 0.500 ≤ 0.500

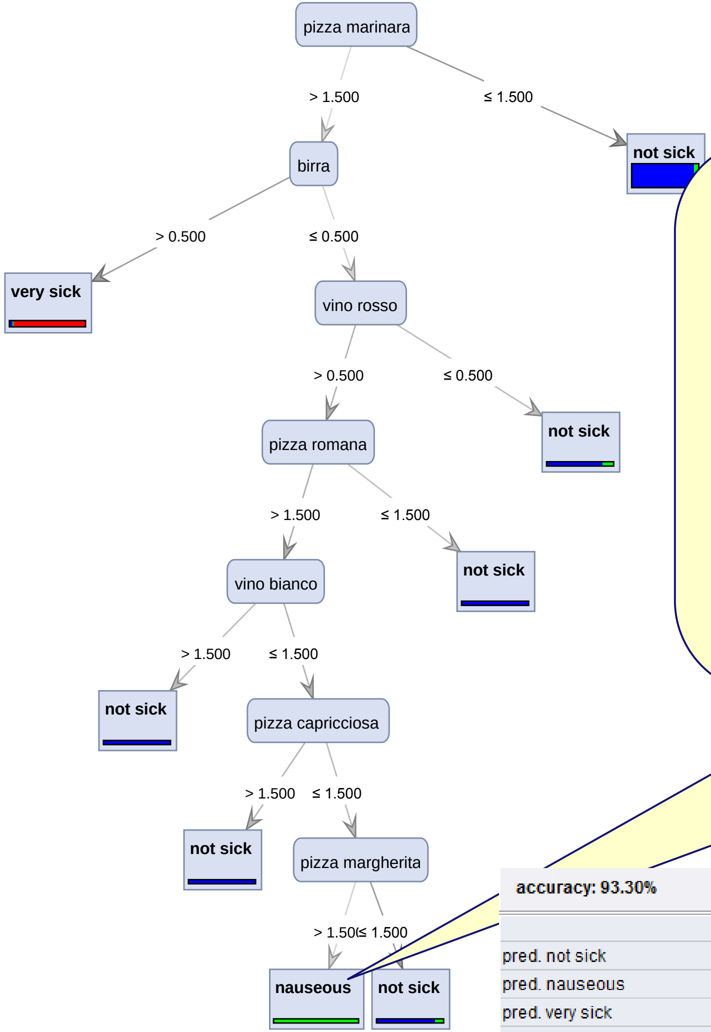
The decision tree does not explain why some parties were nauseous.

blue

red =

green = nauseous

minimal information gain = 0.05



people that ate multiple pizzas marinara, pizzas romana, pizzas margherita, but at most one pizza capricciosa, and drank red wine but not multiple glasses of white wine and did not drink any beer got nauseous.

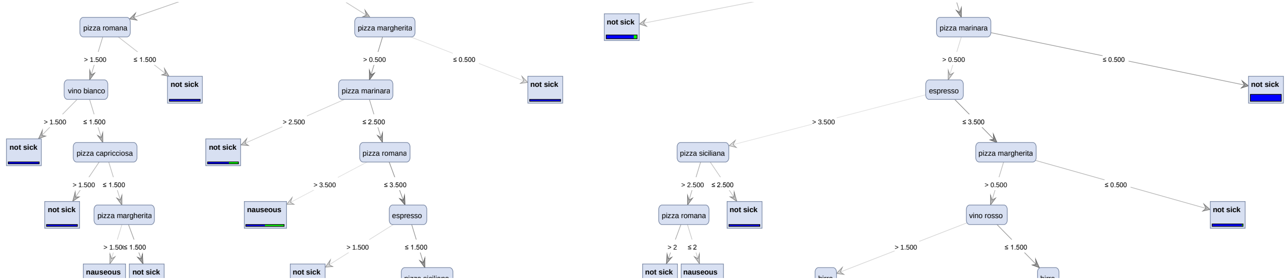
Extremely small improvement at the cost of overfitting.

accuracy: 93.30%

	true not sick	true nauseous	true very sick	class precision
pred. not sick	4193	305	0	93.22%
pred. nauseous	0	2	0	100.00%
pred. very sick	24	6	470	94.00%
class recall	99.43%	0.64%	100.00%	

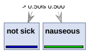
underfitting

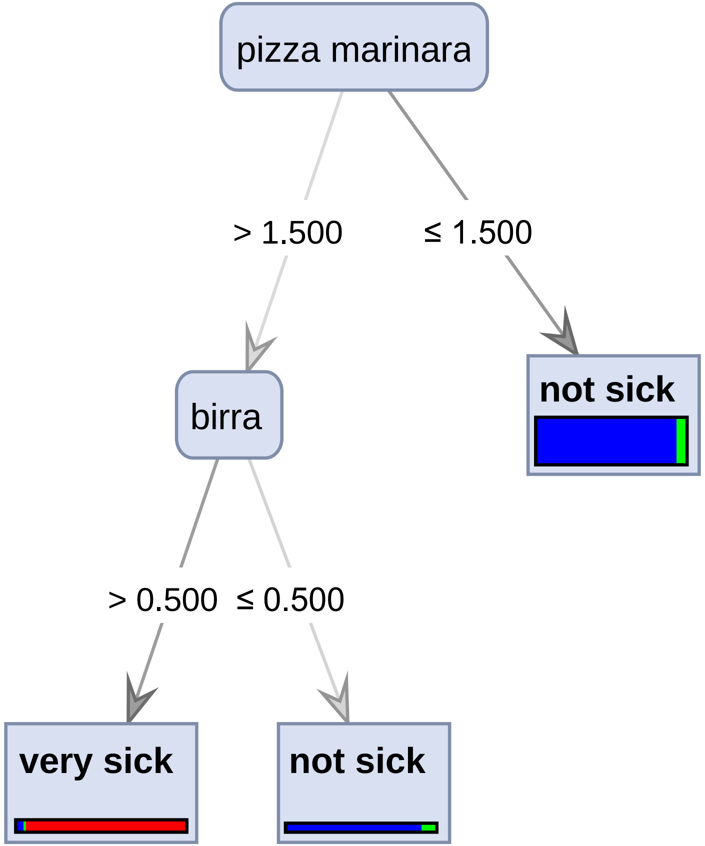
accuracy: 84.34%				
	true not sick	true nauseous	true very sick	class precision
pred. not sick	4217	313	470	84.34%
pred. nauseous	0	0	0	0.00%
pred. very sick	0	0	0	0.00%
class recall	100.00%	0.00%	0.00%	



overfitting

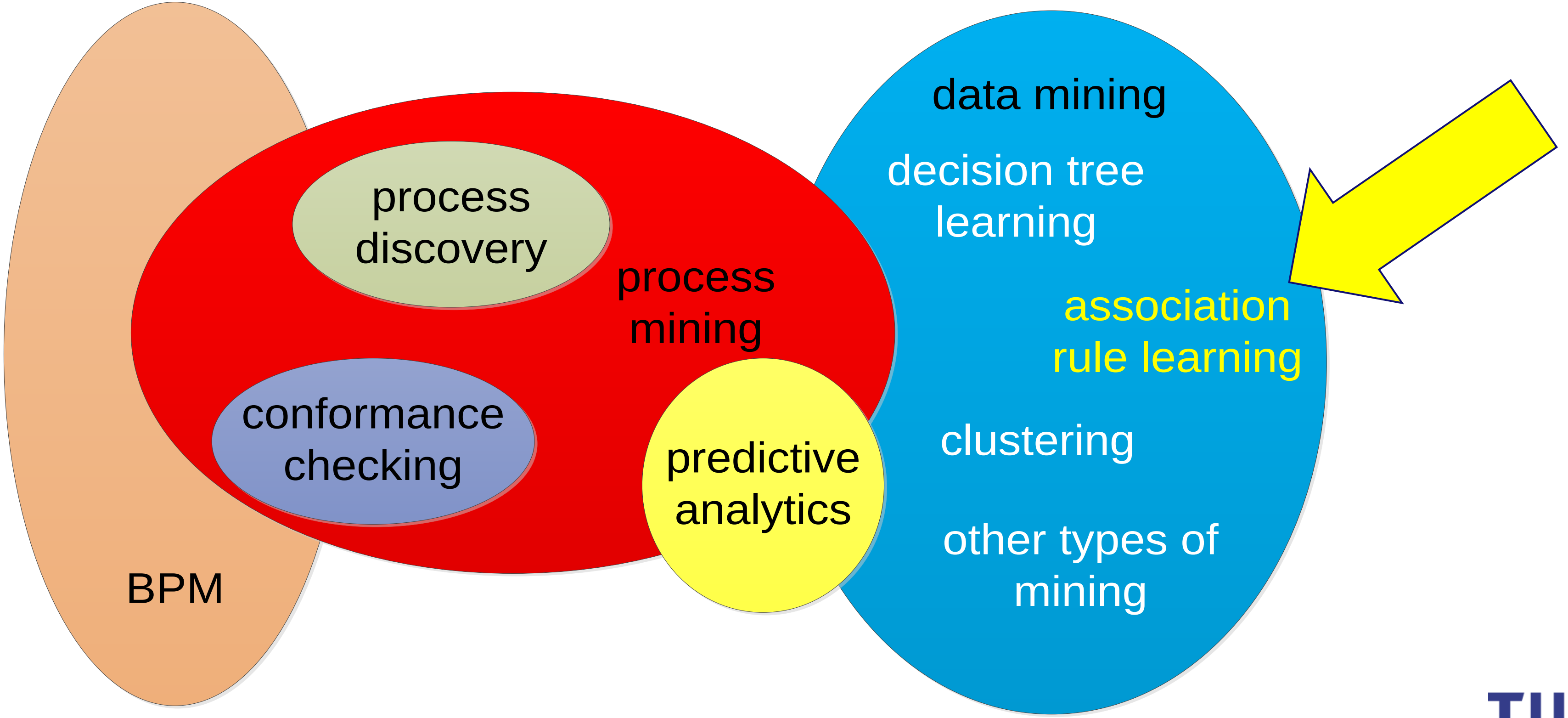
accuracy: 93.48%				
	true not sick	true nauseous	true very sick	class precision
pred. not sick	4190	293	0	93.46%
pred. nauseous	3	14	0	82.35%
pred. very sick	24	6	470	94.00%
class recall	99.36%	4.47%	100.00%	





- Reasonable balance between underfitting and overfitting.
- Can be used to understand what is happening.
- Can be used for predictions and recommendations.

Next


data mining
decision tree learning
association rule learning
clustering
other types of mining
process discovery
process mining
conformance checking
predictive analytics
BPM

Part I: Introduction

Chapter 1
Data Science in Action

Chapter 2
Process Mining: The Missing Link

Part II: Preliminaries

Chapter 3
Process Modeling and Analysis

Chapter 4
Data Mining

Part III: From Event Logs to Process Models

Chapter 5
Getting the Data

Chapter 6
Process Discovery: An Introduction

Chapter 7
Advanced Process Discovery Techniques

Part IV: Beyond Process Discovery

Chapter 8
Conformance Checking

Chapter 9
Mining Additional Perspectives

Chapter 10
Operational Support

Part V: Putting Process Mining to Work

Chapter 11
Process Mining Software

Chapter 12
Process Mining in the Large

Chapter 13
Analyzing “Lasagna Processes”

Chapter 14
Analyzing “Spaghetti Processes”

Part VI: Reflection

Chapter 15
Cartography and Navigation

Chapter 16
Epilogue