introduction to classification

carlos soares

(csoares@fe.up.pt)

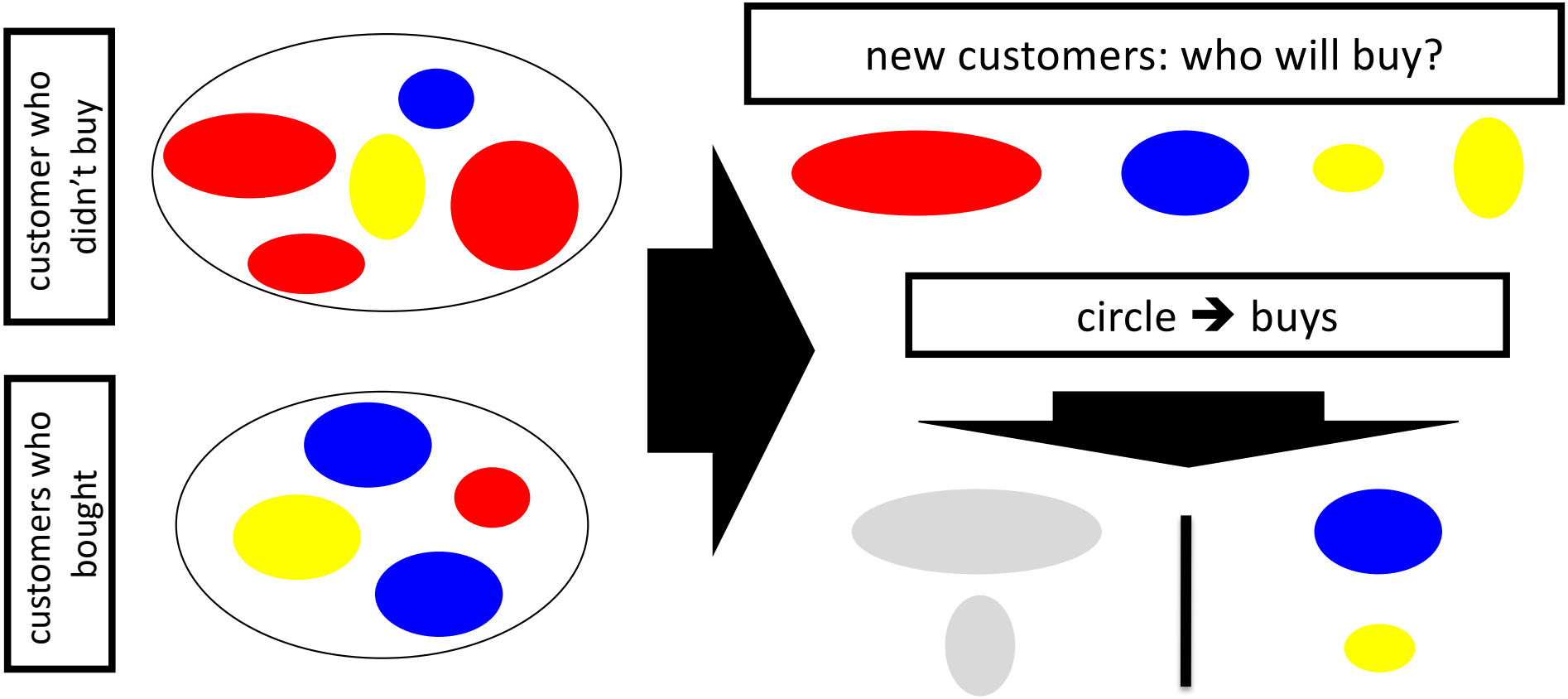
[including materials kindly provided by Alípio Jorge and adapted from David Sontag, Luke Zettlemoyer, Carlos Guestrin and Andrew Moore]

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

http://www.flickr.com/photos/upv cfrontdoor/4642103837/

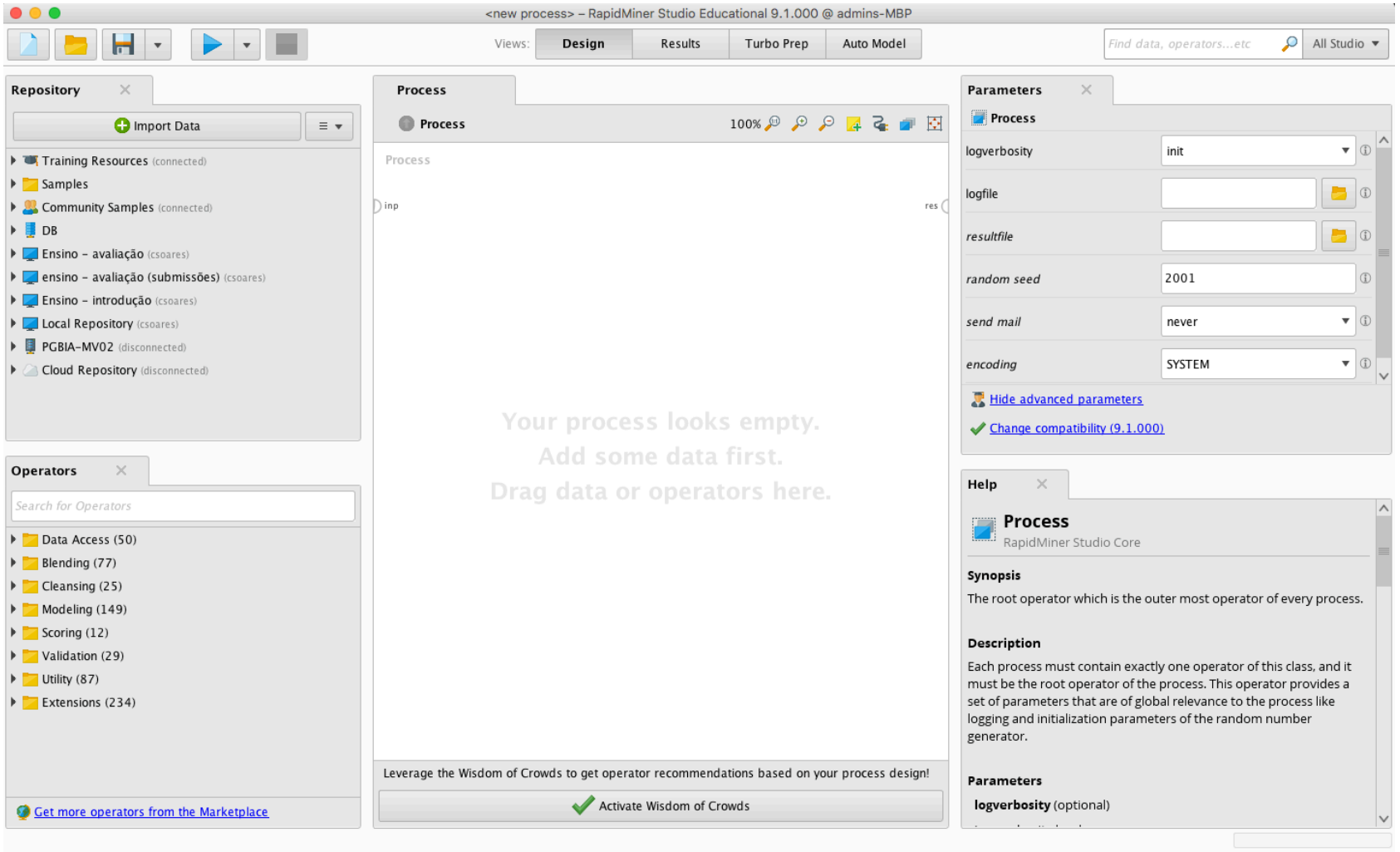
predictive: classification for targeting

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO



but, first, introduction to rapidminer

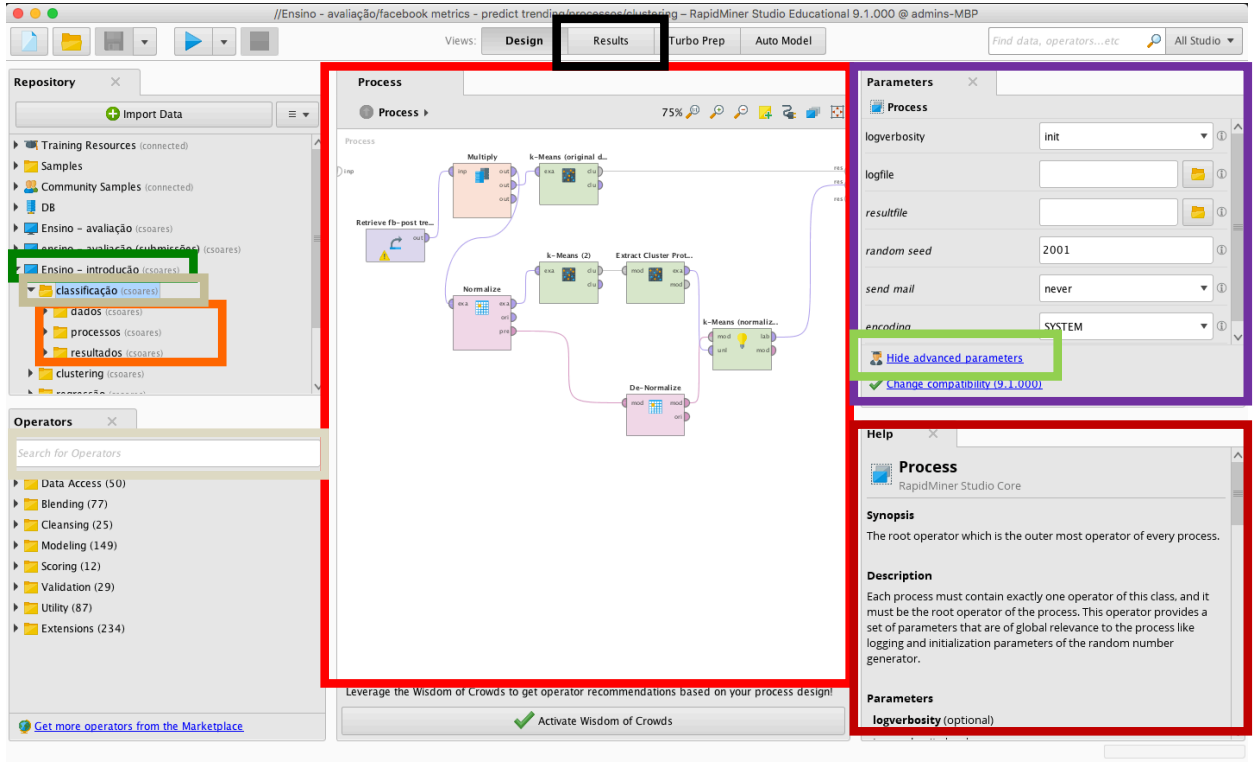
U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO



rapidminer projects

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

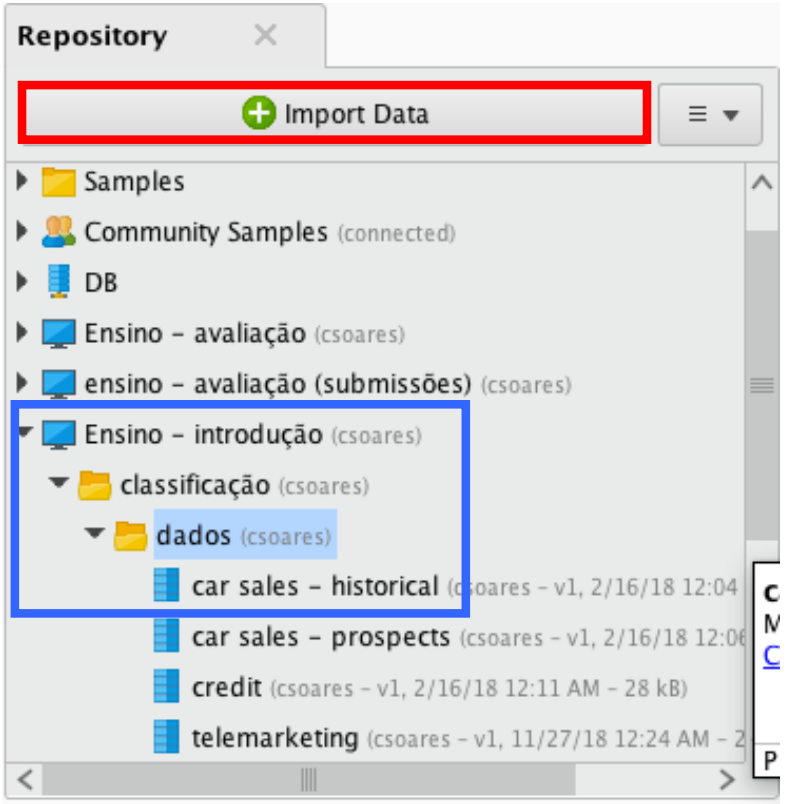
- workflow of operators
  - with parameters
    - including advanced ones
  - and help easily available
  - searchable
- repository of folders
  - e.g. repository = company
  - ... folder = project
- folders also used to organize projects
- results presented in a different view



… need data

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- data are imported to rapidminer
  - many different formats accepted
  - … including databases
- … wizards available
  - use carefully!
- … and stored in a folder



U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

CLASSIFICATION

classification for campaign optimization

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

fonte: ferrari

- campaign to promote new vehicle
  - (large) list of prospects
  - invitations for test-drive
  - gifts
  - free phone line (800) for enquiries/reservations
- goal
  - reduce costs
  - maximize returns

- strategy
  - analyse response to previous campaigns
    - stored in a database
  - build customer relating customer characteristics and response
  - apply model to prospects
  - invite prospects selected by the model
    - [who bought last car more than 4 years ago]

data for classification

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- prospects
  - customers who didn't buy a car in the last 4 years
- results from previous campaigns
  - customers who were contacted and their response

target (or dependent) variable

independent variable (or attribute)

would like to predict

already known

Comprou	Idade	Rendimento	Ag.fam	Vendas anteriores	Última Venda
	41	50000	2	1	0
	39	68000	2	0	30000
	58	61000	4	0	0
	26	25000	3	0	0
	21	50000	1	1	20000
	38	43000	2	0	0
	44	43000	4	1	47000
	27	47000	2	1	21000
	70	23000	2	0	25000

Comprou	Idade	Rendimento	Ag.fam	Vendas anteriores	Última Venda
não	37	49000	2	1	42000
sim	43	68000	3	0	0
sim	42	61000	4	0	0
sim	26	52000	2	0	0
sim	40	64000	1	1	21000
sim	38	52000	1	0	0
sim	45	43000	4	1	47000
sim	35	45000	2	1	34000
não	39	43000	2	0	0
sim	31	55000	3	1	46000
sim	34	57000	3	1	52000
não	38	44000	4	0	0
não	34	68000	2	1	33000

exercise: marketing campaign

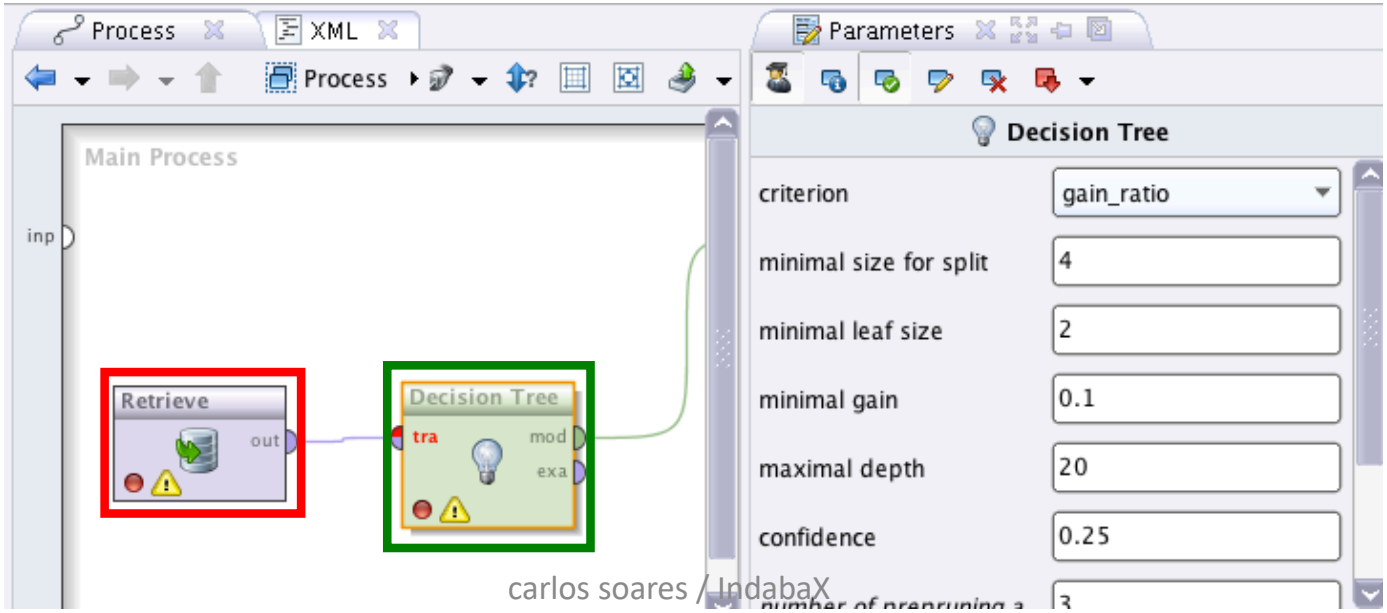
U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- predict which customers will accept invitation for test drive
  - business goal
    - efficient and effective use of sales resources
  - data available at the data.xlsx
    - worksheets
      - “car sales (historical data)”
      - “car sales (prospects)”
  - variables
    - target
      - bought?
    - features
      - age, income, family size, cars bought previouslt and value of last purchase
  - tool
    - RapidMiner

exercise: classification model in rapid miner

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- load data into repository
  - target variable is a *label*!!
- load data from repository into workspace
- apply decision tree algorithm
  - e.g. operators ➔ modeling ➔ classification and regression ➔ tree induction ➔ decision tree
- analyse model



gps

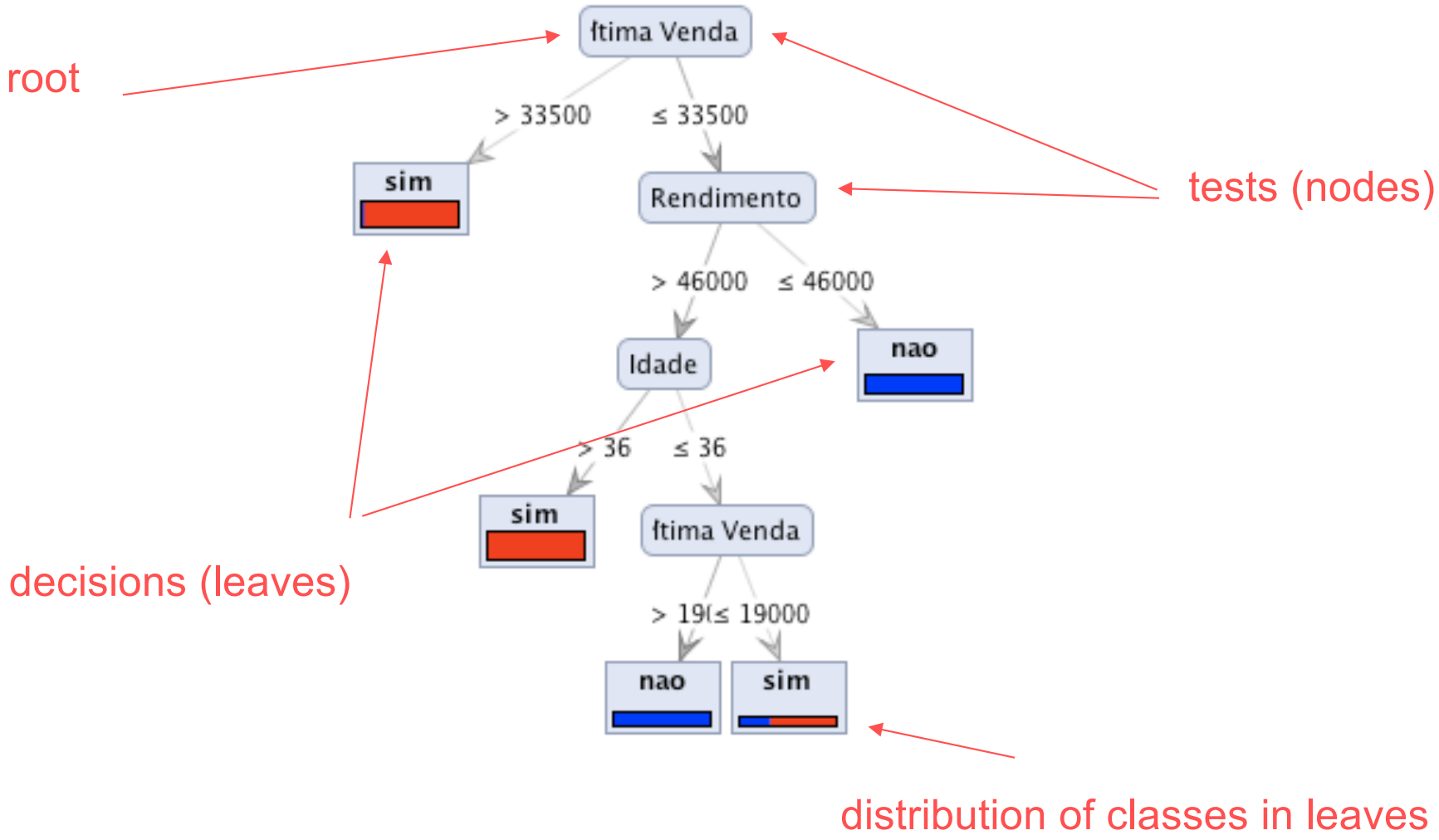
U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- learn decision tree
- use decision tree
  - interpretation
  - application to new examples

fonte: http://www.flickr.com/photos/emina2492/2638248645/

model: classification tree (or decision tree)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO



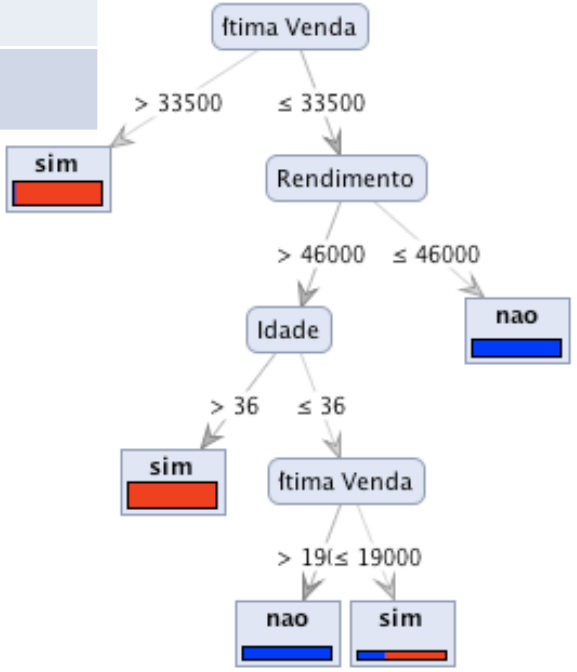
classify new examples

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- prospects list

age	income	family size	previous sales	last sale
28	39.000	2	0	0
39	52.000	4	1	17.000
29	42.000	4	1	40.000

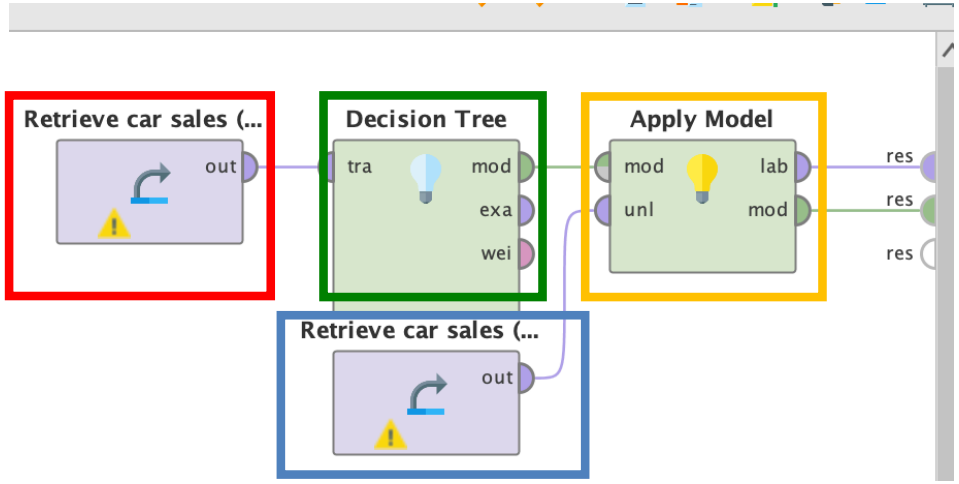
- class of the leaf each example is assigned by the tree?
  - i.e. predict…



classify new examples with rapidminer

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- load new data into repository
  - target variable is a label!!
  - ... even for the new data
- load labelled data from repository into workspace
  - just drag it!
- apply decision tree algorithm
  - operator: decision tree
- load unlabelled data from repository into workspace
- apply decision tree model to the new data
  - operator: Apply Model



predictions

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- predictions made by the model
- … and probability of each class

Row No.	Bought?	prediction(...	confidence(...	confidence(...	Age	Income	Family size	Cars boug...	Value of la...
1	?	nao	0.642	0.358	41	50000	2	1	0
2	?	sim	0.283	0.717	39	68000	2	0	30000
3	?	nao	0.524	0.476	58	61000	4	0	0
4	?	nao	0.935	0.065	26	25000	3	0	0
5	?	nao	0.869	0.131	21	50000	1	1	20000
6	?	nao	0.758	0.242	38	43000	2	0	0
7	?	sim	0.067	0.933	44	43000	4	1	47000
8	?	nao	0.704	0.296	27	47000	2	1	21000
9	?	nao	0.847	0.153	70	23000	2	0	25000

classification: applying a model to new cases

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

responses to previous campaigns

known responses (class)

Comprou	Idade	Rendimento	Ag.fam	Vendas anteriores	Última Venda
não	37	49000	2	1	42000
sim	43	68000	3	0	0
sim	42	61000	4	0	0
sim	26	52000	2	0	0
sim	40	64000	1	1	21000
sim	38	52000	1	0	0
sim	45	43000	4	1	47000
sim	35	45000	2	1	34000
não	39	43000	2	0	0

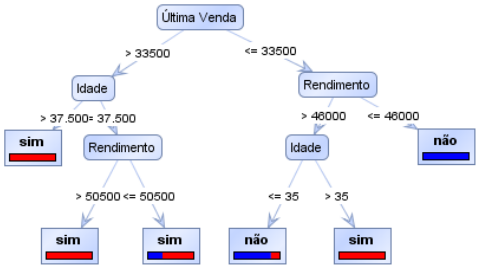
prospects

	A	B	C	D	
1	Comprou	Idade	Rendimento	Ag.fam	Vendas
2		41	50000	2	
3		39	68000	2	
4		58	61000	4	
5		26	25000	3	
6		21	50000	1	
7		38	43000	2	
8		44	43000	4	
9		27	47000	2	
10		70	23000	2	

unknown responses (class)

1

2



3

row no.	Comprou	prediction(...	confidence(...	confidence(...	Ida
1	?	sim	0	1	41
2	?	sim	0	1	39
3	?	sim	0	1	58
4	?	não	1	0	26
5	?	não	0.818	0.182	21
6	?	não	1	0	38
7	?	sim	0	1	44
8	?	não	0.818	0.182	27
9	?	não	1	0	70

predictions by the model

would you use the decisions proposed by this model?

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

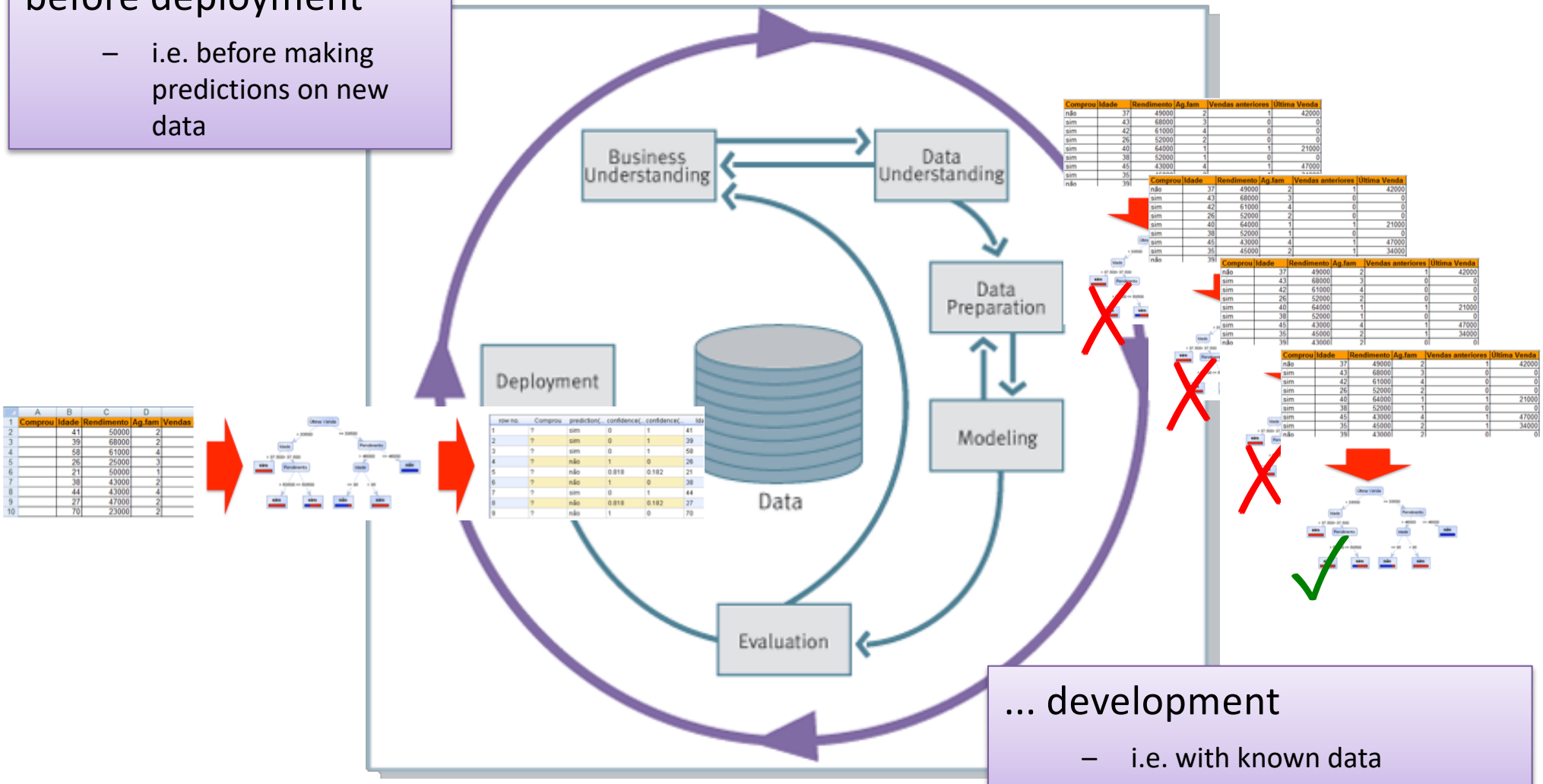
CLASSIFIER EVALUATION

model development

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

before deployment

- i.e. before making predictions on new data



... development

- i.e. with known data

how good are the predictions?

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- confusion matrix
  - prediction vs reality
  - number of right answers on the main diagonal
  - sum of the array is the total number of examples
- error rate
  - percentage/proportion of cases where the model misses
  - e.g. (2 + 1)/(5 + 1 + 2 + 29) = 8.1%

	truth: no	truth: yes
prediction: no	5	1
prediction: yes	2	29

evaluation measures

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- multiple measures can be computed from the confusion matrix, including...

	truth: no	truth: yes
prediction: no	TN	FN
prediction: yes	FP	TP

$\frac{FP}{FP+TN}$ False positive rate (FPR) = 1-TNR

$\frac{FN}{TP+FN}$ False negative rate (FNR) = 1-TPR

$\frac{TP}{TP+FP}$ Positive predictive value (PPV), also known as precision

$\frac{TN}{TN+FN}$ Negative predictive value (NPV)

$\frac{TP}{TP+FN}$ True positive rate (TPR), also known as recall or sensitivity

$\frac{TN}{TN+FP}$ True negative rate (TNR), also known as specificity

$\frac{TP+TN}{TP+TN+FP+FN}$ Accuracy

$\frac{2}{1/precision+1/recall}$ F1-measure

is the model any good at all?

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

	truth: no	truth: yes
prediction: no	5	1
prediction: yes	2	29

- model error: 3/37 = 8.1%
- **baseline**
  - simplest model that can be obtained from the data

	truth: no	truth: yes
class distribution	7	30

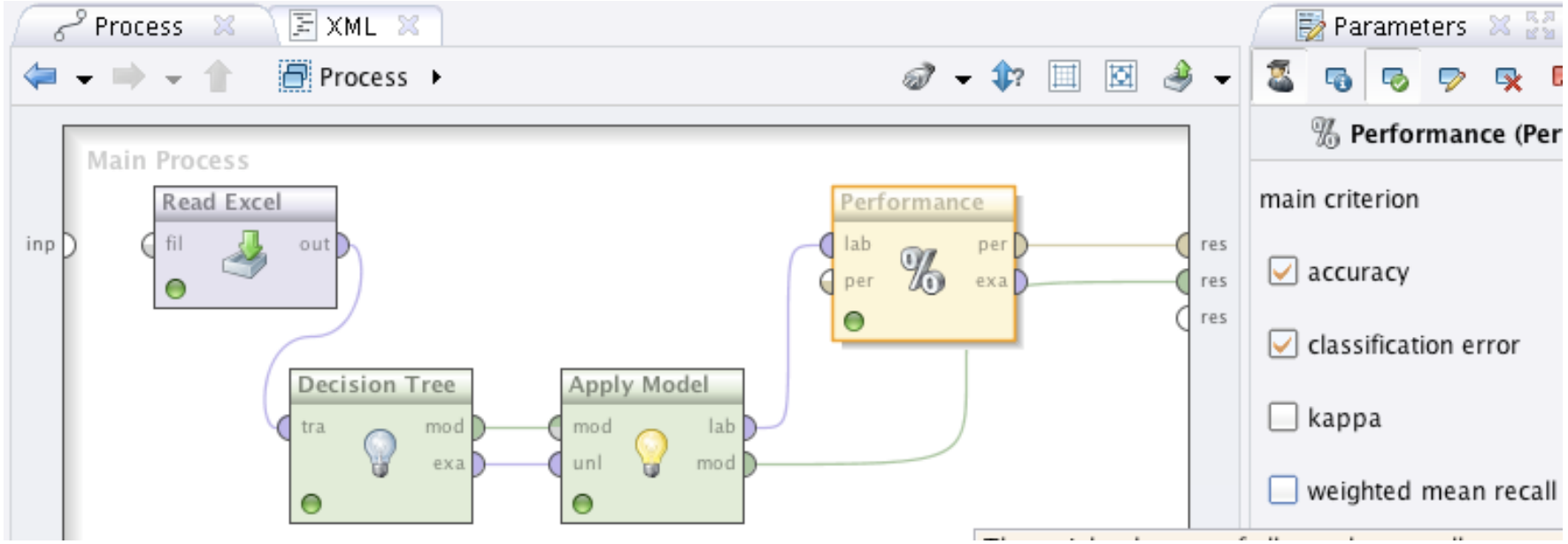
most “popular” choice

  - ... with error: 7/37 = 18,9%
- so, should we use the model?

exercise I: marketing campaign

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- evaluate decision tree
  - operator: performance (classification)

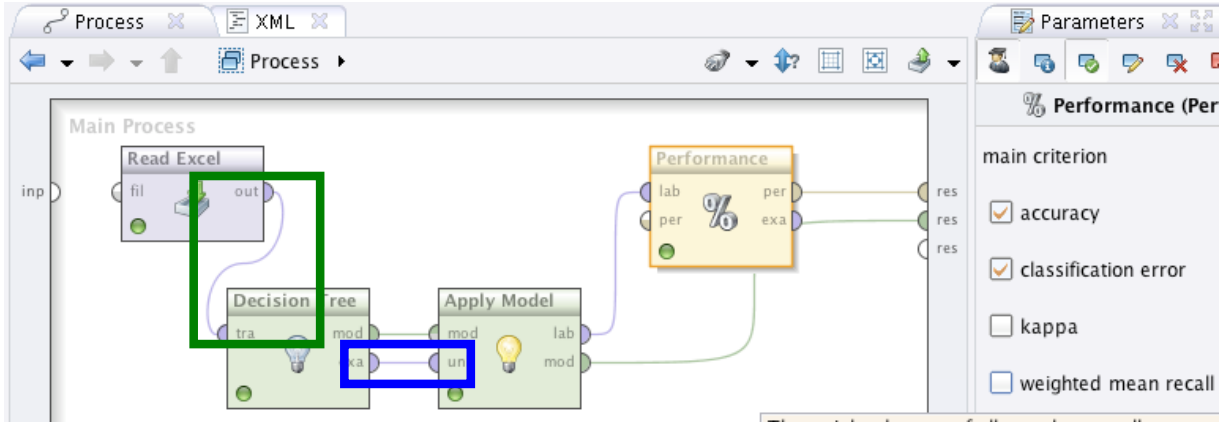


- doesn't this feel strange?

what is the value of the model?

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

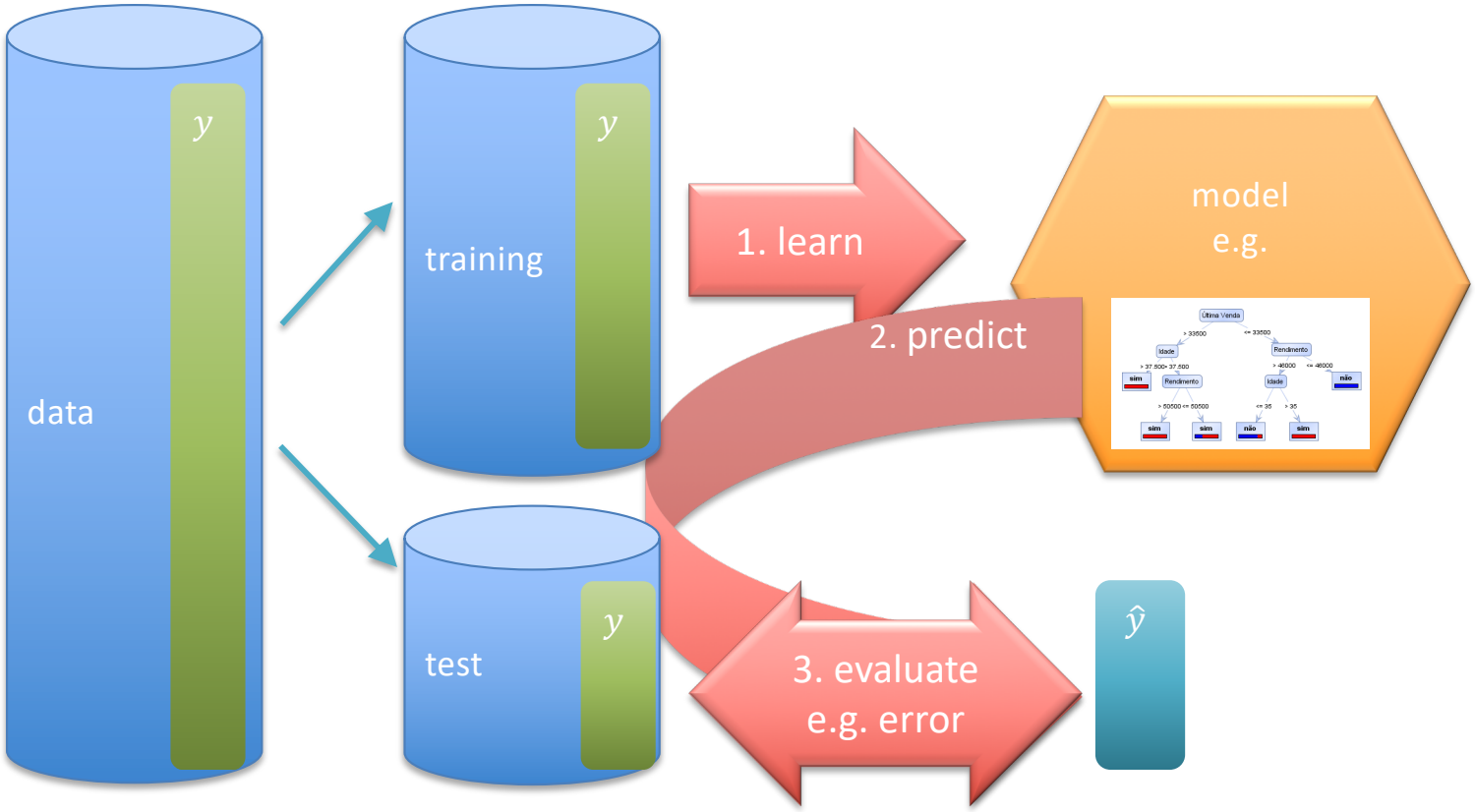
- goal: apply the model to **new** cases
- but, so far, same data to
  - **train** model
  - ... and evaluate it



- evaluation with training data
  - it's easy(ier) to make predictions in cases you already observed
  - assumes that future cases will be equal to those of training
    - similar to giving an exam with the same problems that were solved in the last class
  - unreliable estimator of model behavior in new examples

evaluation methodology: do not forget!

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

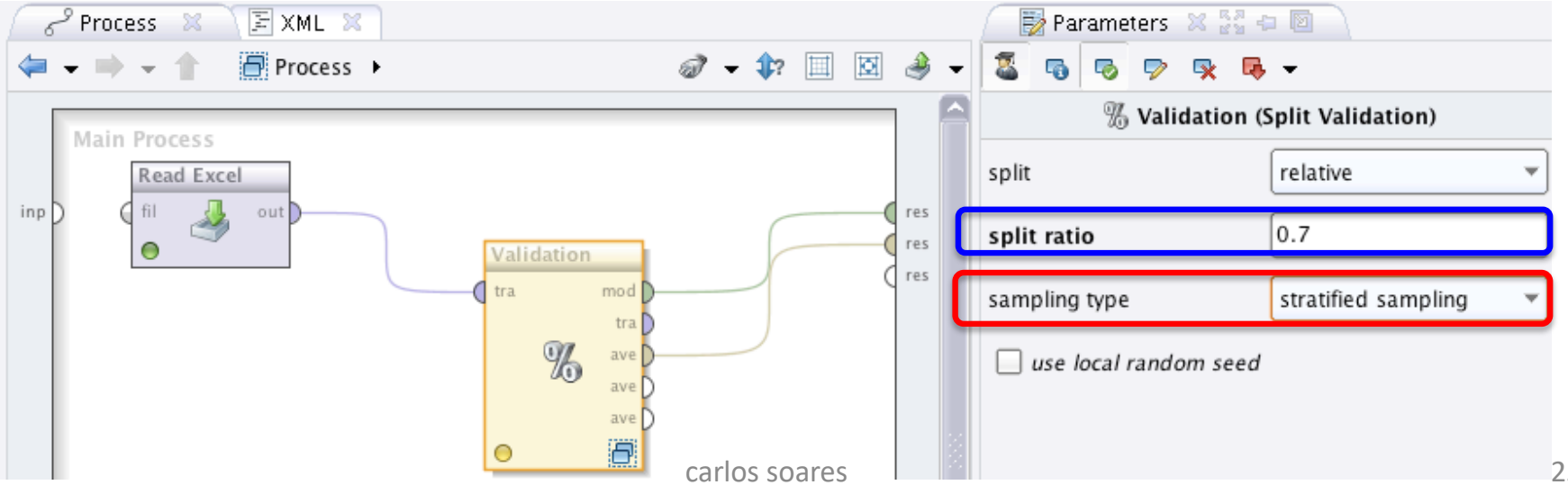


exercise II: marketing campaign (1/2)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- operator split validation
- sub-process
  - operator that groups operators

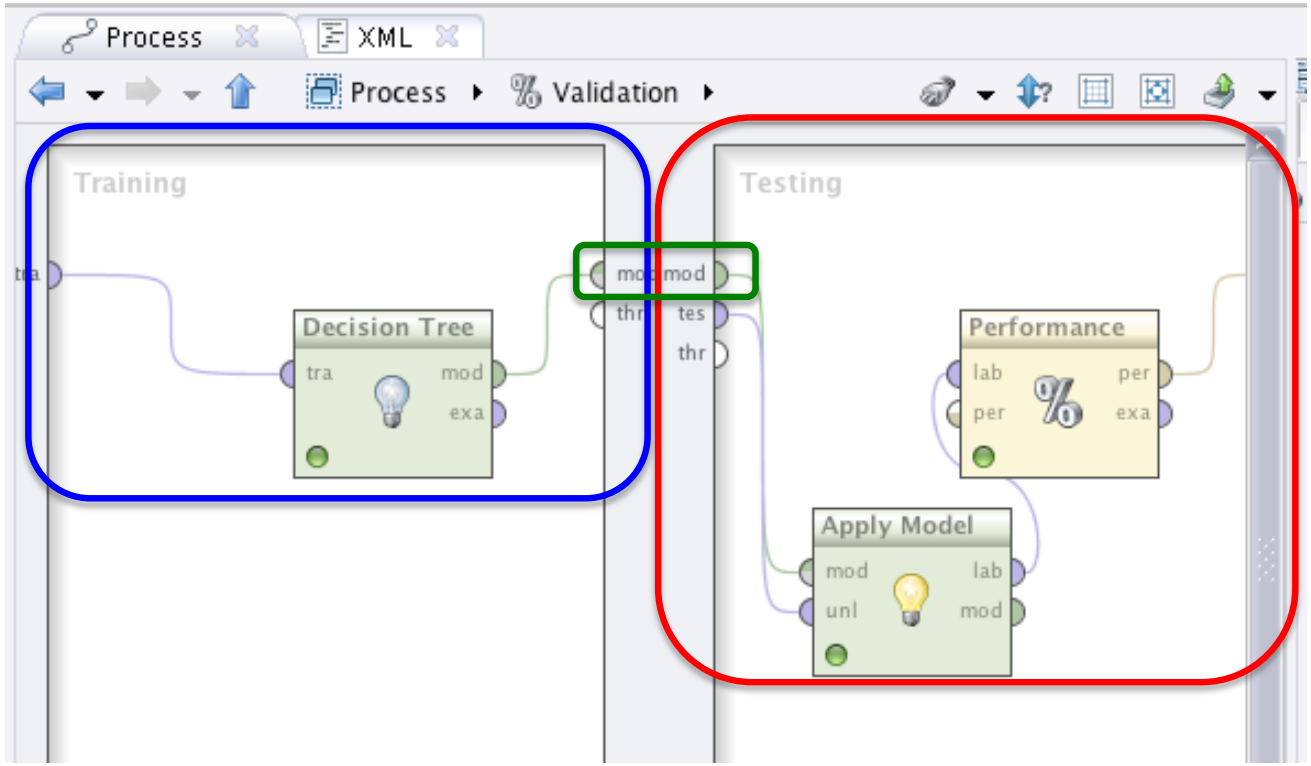
- distribute data randomly between the training and test sets
  - ensuring the same class proportion
- proportion
  - 70% of the cases for training
  - 30% of the cases for testing



exercise II: marketing campaign (2/2)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- split validation
  - different operations for training data and for test data
  - model obtained on the train side is passed on to the test side



U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

DECISION TREES

gps

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- how the algorithm for induction of decision trees works
- overfitting

learning a decision tree (1 and 2/5)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

x1	x2	class
a	p	yes
a	q	no
a	p	yes
b	q	no
c	p	no
a	p	yes
c	p	yes
b	p	no

yes= 4
no= 4

1. we have a set of labelled examples
   - the target variable indicates the class of each case (e.g. yes, no)
   - on the root knot we have all the cases
2. if all the examples are of the same class, we stop

learning a decision tree (3/5)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

x1	x2	class
a	p	yes
a	q	no
a	p	yes
b	q	no
c	p	no
a	p	yes
c	p	yes
b	p	no

yes= 4
no= 4

test	true (yes/no)	false (yes/no)
x1=a	3/1	1/3

3. otherwise, we will divide (split) the examples in the root
   - so that the classes are well separated
   - each test is of variable type = value, or variable > value

learning a decision tree (3/5 – cont'd)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

x1	x2	class
a	p	yes
a	q	no
a	p	yes
b	q	no
c	p	no
a	p	yes
c	p	yes
b	p	no

yes= 4
no= 4

test	true (yes/no)	false (yes/no)
x1=a	3/1	1/3
x1=b	0/2	4/2
x1=c	1/1	3/3
x2=p	4/2	0/2
x2=q		

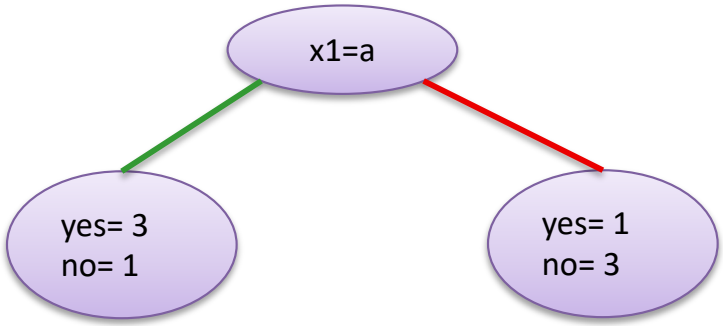
3. otherwise, we will divide (split) the examples in the root
   - so that the classes are well separated
   - each test is of variable type = value, or variable > value

unnecessary

learning a decision tree (4/5)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

x1	x2	class
a	p	yes
a	q	no
a	p	yes
b	q	no
c	p	no
a	p	yes
c	p	yes
b	p	no



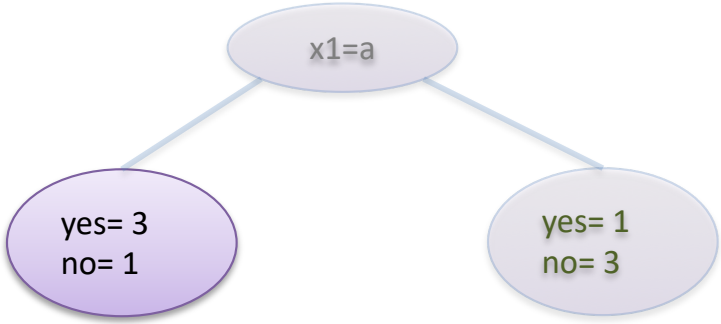
4. create to descendant nodes according to the selected test

test	true (yes/no)	false (yes/no)
x1=a	3/1	1/3

learning a decision tree (5/5)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

x1	x2	class
a	p	yes
a	q	no
a	p	yes
b	q	no
c	p	no
a	p	yes
c	p	yes
b	p	no



test	true (yes/no)	false (yes/no)
x1=a	3/1	1/3
x2=p	3/0	0/1

unnecessary

5. We repeat the process for the set of examples in each of these descendant nodes

splits: the good, the bad and the ugly

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

x1	x2	class
a	p	yes
a	q	no
a	p	yes
b	q	no
c	p	no
a	p	yes
c	p	yes
b	p	no

too good to be true?

good or bad?...

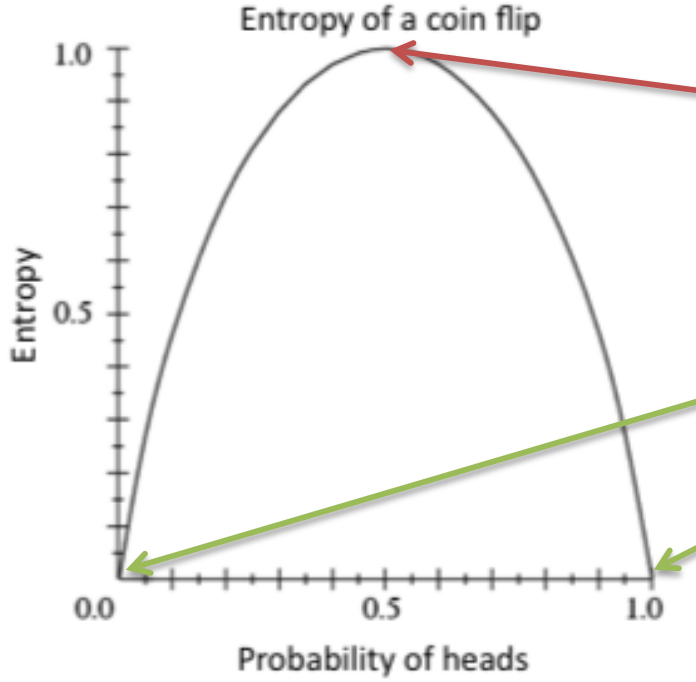
test	true (yes/no)	false (yes/no)
x1=a	3/1	1/3
x1=b	0/2	4/2
x1=c	1/1	3/3
x2=p	4/2	0/2
x2=q		

is this always bad?

entropy as diversity

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- Entropy *H(Y)* of a random variable *Y*



test	true (yes/no)	false (yes/no)
x1=a	3/1	1/3
x1=b	0/2	4/2
x1=c	1/1	3/3
x2=p	4/2	0/2
x2=q		

$$H(Y) = -\sum_{i=1}^{k} P(Y = y_i) \log_2 P(Y = y_i)$$

… the bigger the decrease in diversity, the better

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

x1	x2	class
a	p	yes
a	q	no
a	p	yes
b	q	no
c	p	no
a	p	yes
c	p	yes
b	p	no

test	true (yes/no)	false (yes/no)
x1=a	3/1	1/3

i.e. d(current set) >> d(left branch) + d(right branch)

e.g. information gain

$$IG(X) = H(Y) - H(Y \mid X)$$

numerical attributes

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

... x3	class
1	yes
3	no
2	yes
3	no
9	no
5	yes
5	yes
3	no

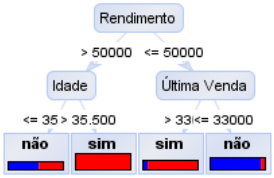
... x3	class
1	yes
2	yes
3	no
3	no
3	no
5	yes
5	yes
9	no

test	true (yes/no)	false (yes/no)
x3<1.5	1/0	3/4
x3<2.5	2/0	2/4
x3<4	2/3	2/1
x3<7	4/3	0/1

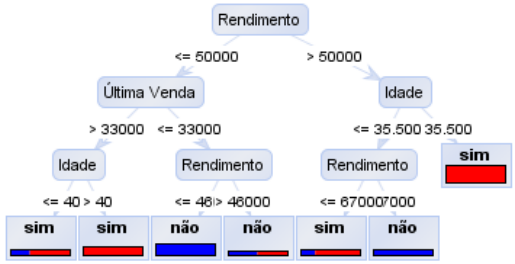
- only splits between examples of different classes should be considered
  - x3 < 1.5 cannot be better than x3 < 2.5

overfitting

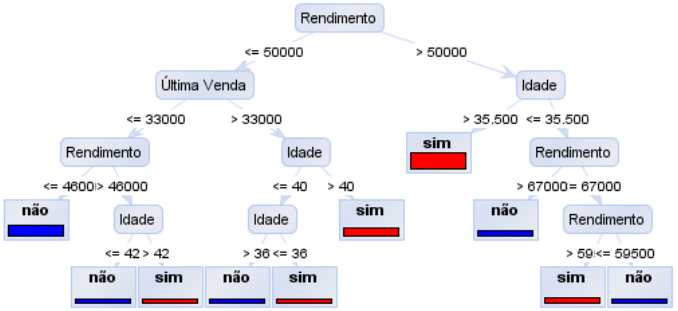
- trees obtained with different values of “minimum leaf size”
  - 4, 2 and 1



error (train)=18,18



error (train)=9,09%



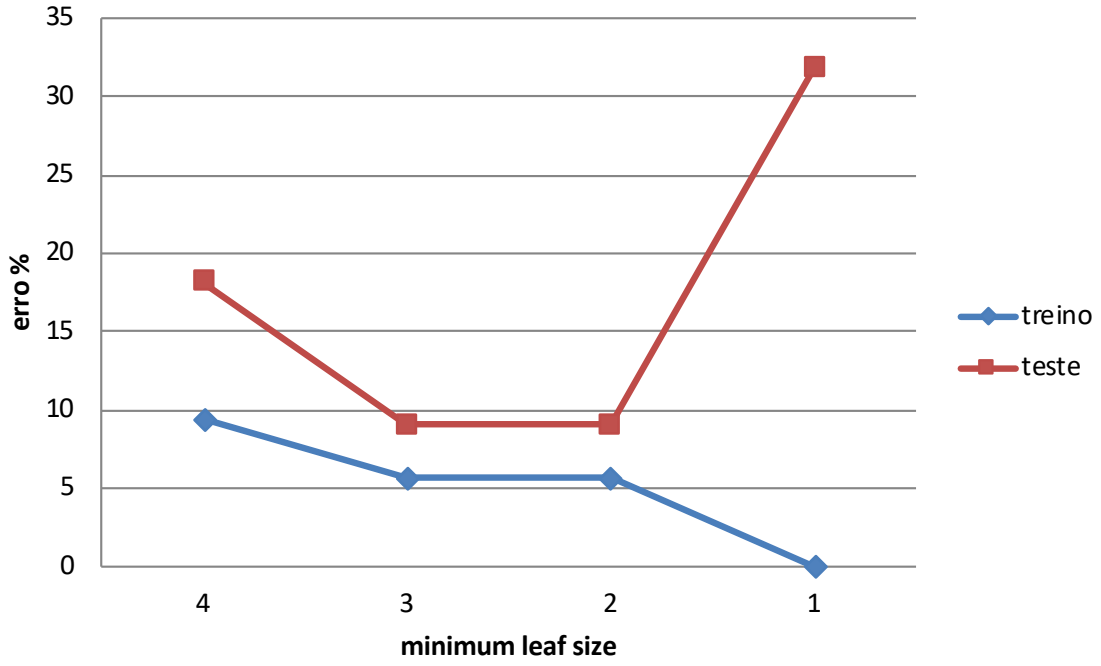
error (train)=0,00%

- However
  - decreasing the training error does not mean that the model is better on new cases
  - a model too adjusted to training cases is overfitted
  - an overfitted model generalizes poorly

overfitting: experiment

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- how does the error of the DT vary in test data?
  - vary the minimum leaf size between 4 and 1



- training error always goes down
- test error begins by descending but then rises again
  - an overadjusted AD generalizes poorly

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

CLASSIFICATION FOR SCORING

plan

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- binary classification
- evaluation in binary classification

classification: b&w or gray?

U.PORTO
FEUP FACULDADE DE ENGENHARIA UNIVERSIDADE DO PORTO

- direct application of the model splits examples into classes
  - eg. good and bad customers/buys or doesn't buy
- not suitable for all problems
  - list of 1000 prospects but send only to the 200 with the highest probability of buying
  - ... what if model selects only 30
  - ... or 300?
- *scoring*: use estimated probability of buying to order cases
  - select 200 with the highest probability ... or score
- score also provides information about (um)certainty of prediction

fonte: http://www.flickr.com/photos/backpackphotography/3354435787/

where to cut?

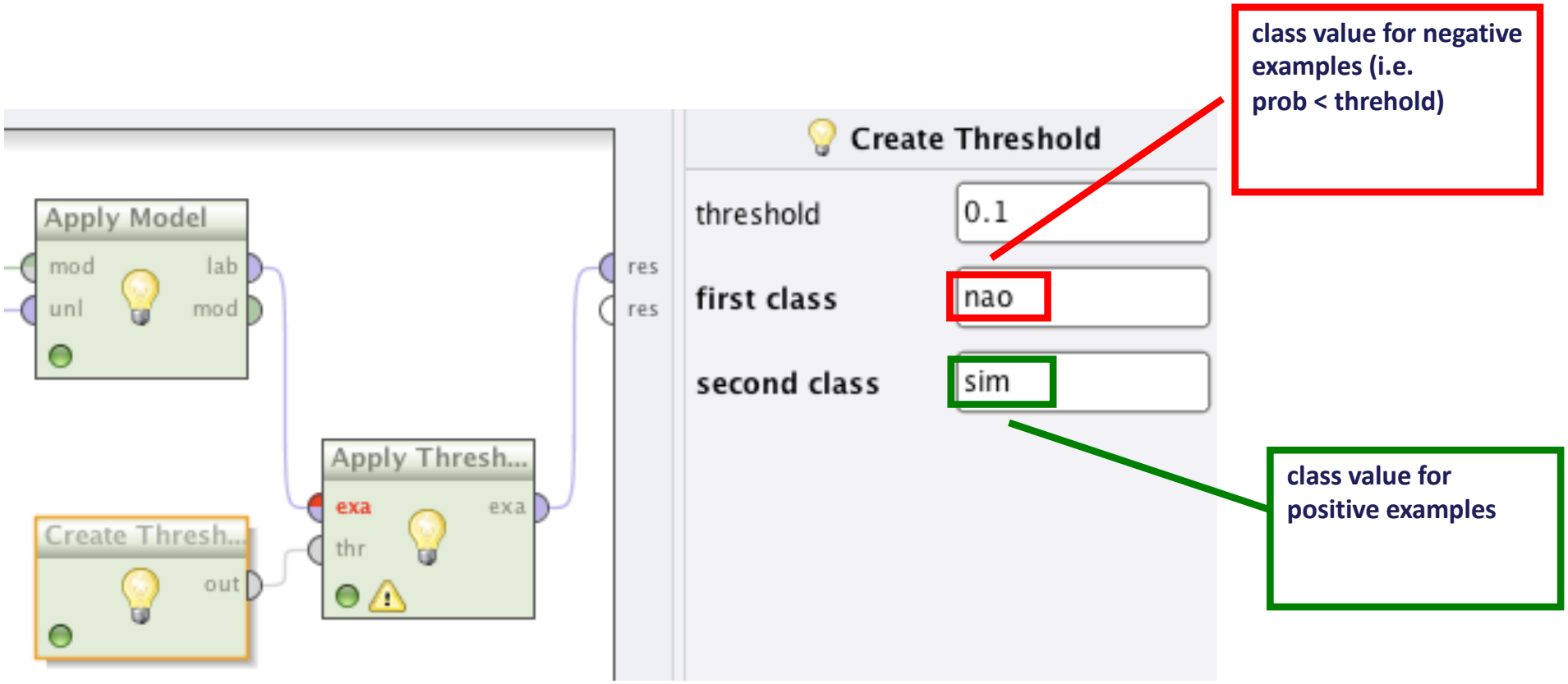
U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- imposed by available resources
  - *n* cases

- is *n* a suitable number?
  - maybe too many “bad” customers...

- arbitrary threshold
  - by default, class = yes if Prob(yes) > 0.5
- ... but which is the right value?
  - eg. important to find all “yes”
  - ... send if Prob(sim) > 0.3

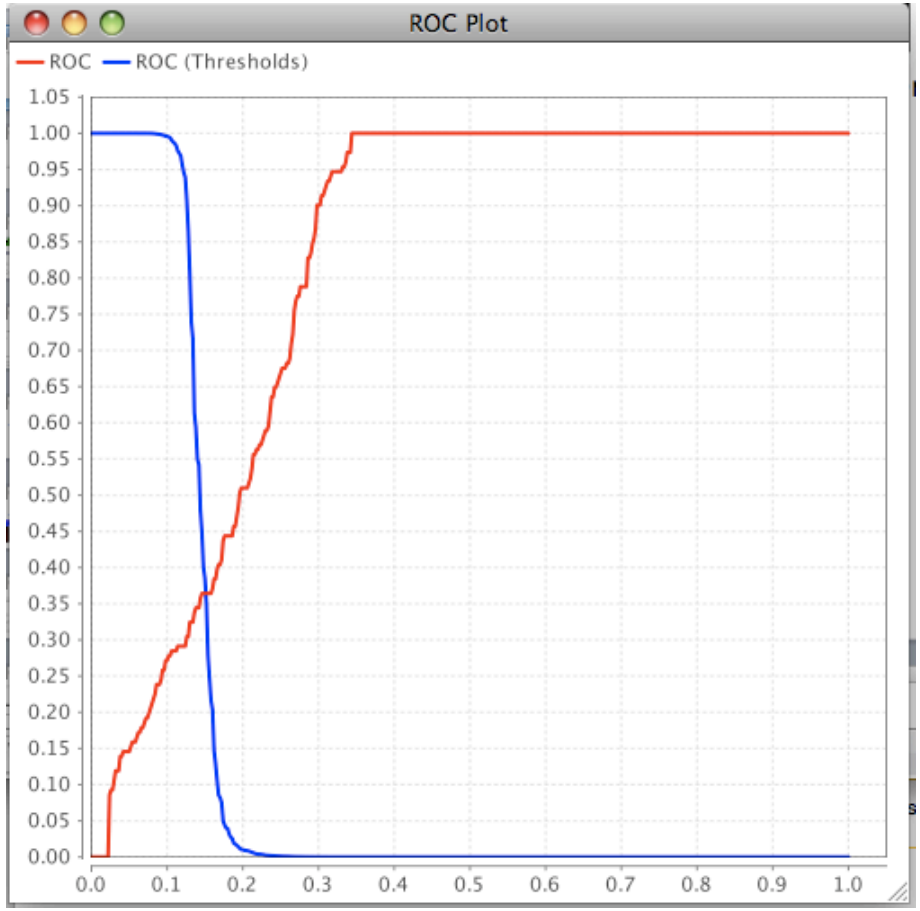
… in RM


Apply Model
mod
unl
lab
mod
Create Thresh...
out
Apply Thresh...
exa
thr
exa
res
res
Create Threshold
threshold
0.1
first class
nao
second class
sim
class value for negative examples (i.e. prob < threhold)
class value for positive examples

evaluate scoring models

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

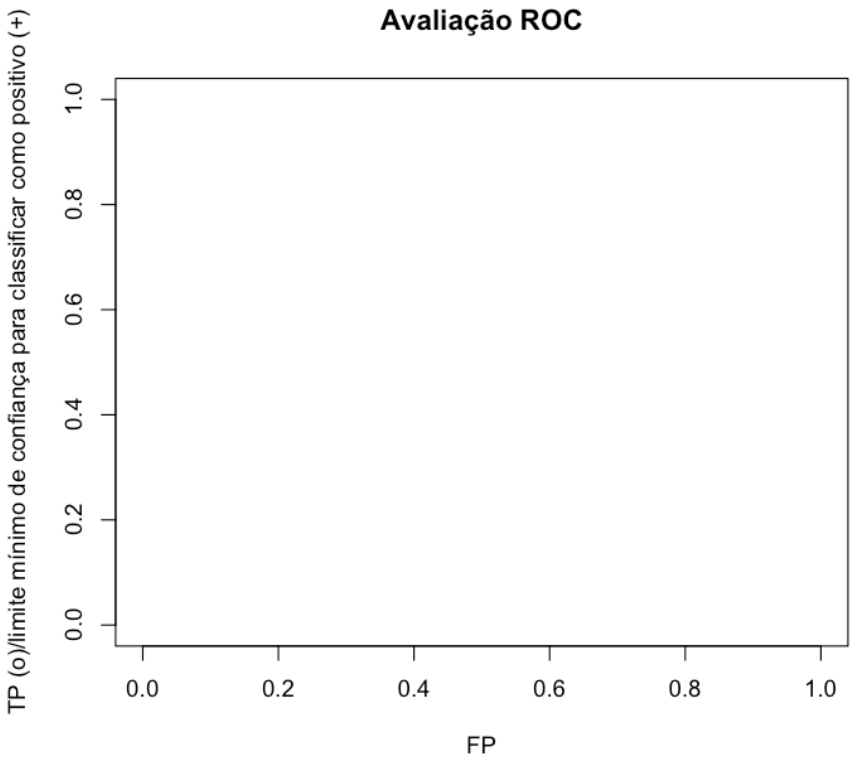
- sort prediction by increasing order of belonging to positive class
  - P(sim | features)
- ROC analysis
  - *Receiver Operating Characteristic*
  - visualize proportion TP vs. FP
    - ... threshold
      - only rapidminer
  - ... to find best compromise



build ROC curve (1/5)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

P(sim)	classe
1,00	sim
1,00	sim
0,90	sim
0,90	não
0,90	sim
0,85	não
0,83	sim
0,76	sim
0,75	não
0,73	sim
… (20 exemplos)	**… 10 × sim/10 × não**

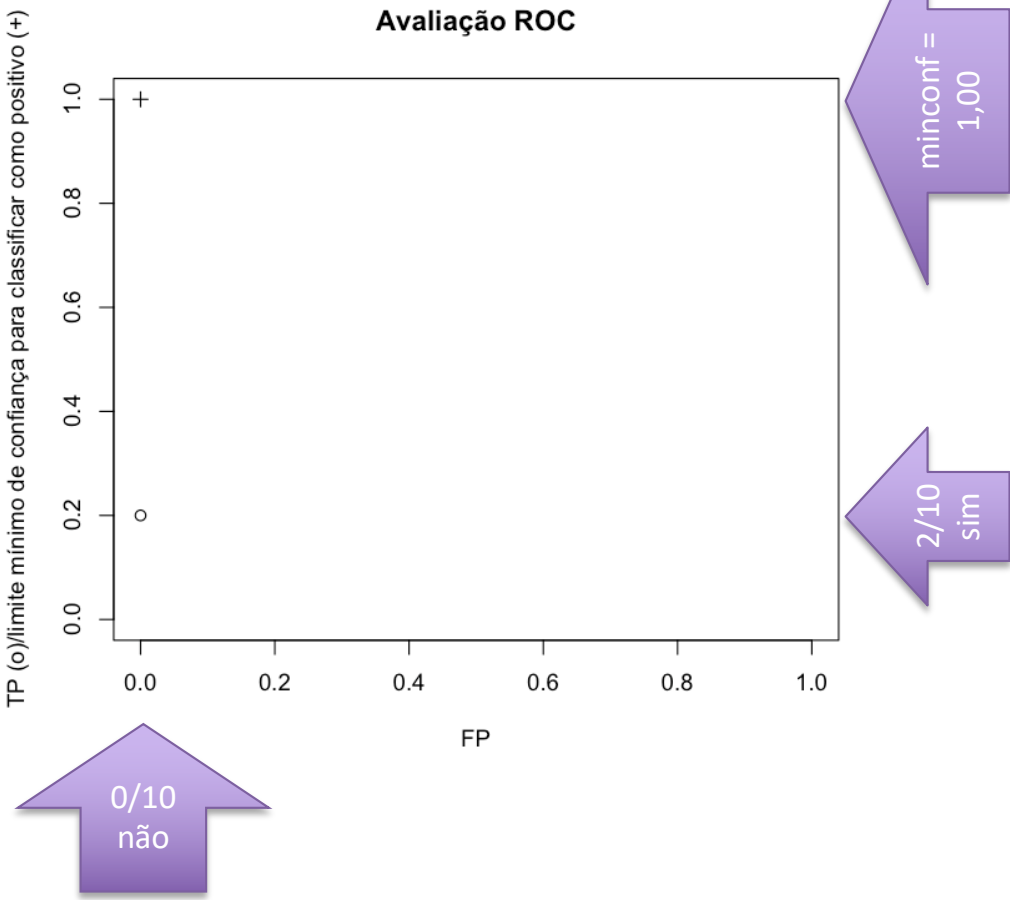


build ROC curve (2/5)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

min conf

P(sim)	classe
1,00	sim
1,00	sim
0,90	sim
0,90	não
0,90	sim
0,85	não
0,83	sim
0,76	sim
0,75	não
0,73	sim
… (20 exemplos)	**… 10 × sim/10 × não**

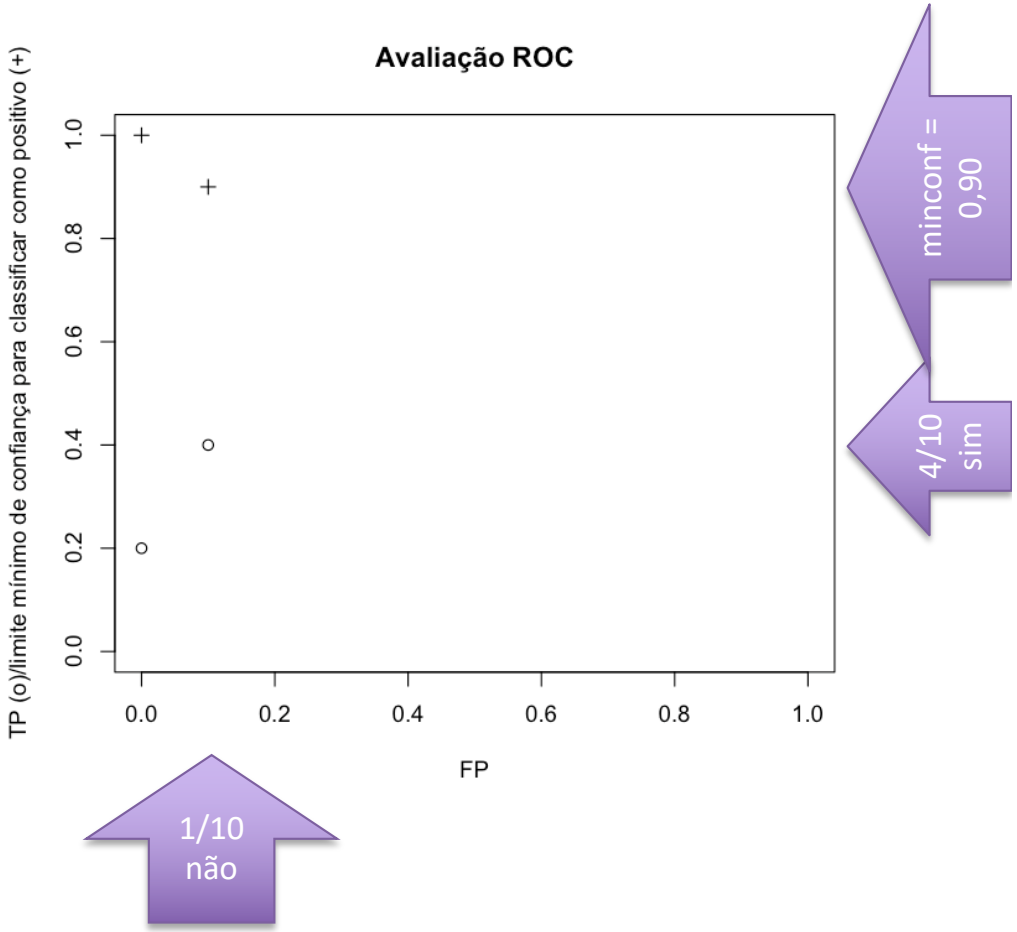


build ROC curve (3/5)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

min conf

P(sim)	classe
1,00	sim
1,00	sim
0,90	sim
0,90	não
0,90	sim
0,85	não
0,83	sim
0,76	sim
0,75	não
0,73	sim
… (20 exemplos)	**… 10 × sim/10 × não**

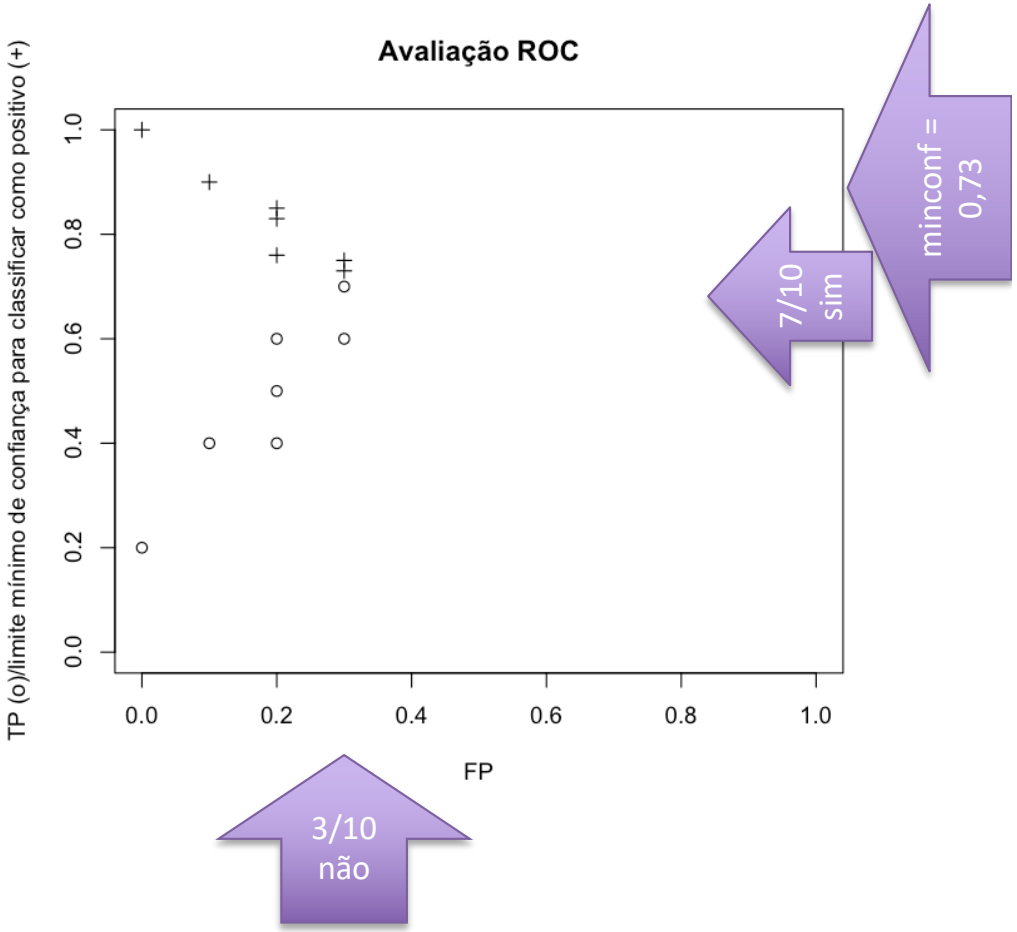


build ROC curve (4/5)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

P(sim)	classe
1,00	sim
1,00	sim
0,90	sim
0,90	não
0,90	sim
0,85	não
0,83	sim
0,76	sim
0,75	não
0,73	sim
… (20 exemplos)	**… 10 × sim/10 × não**

min conf

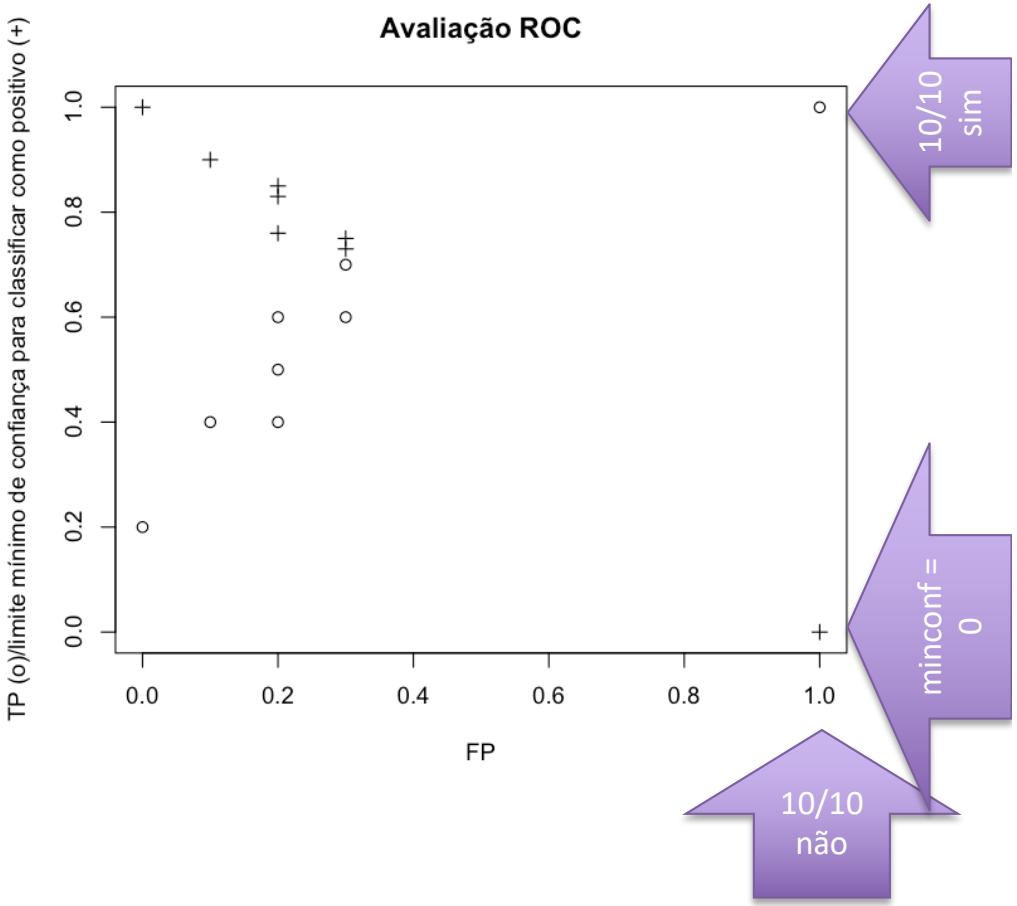


build ROC curve (5/5)

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

P(sim)	classe
1,00	sim
1,00	sim
0,90	sim
0,90	não
0,90	sim
0,85	não
0,83	sim
0,76	sim
0,75	não
0,73	sim
… (20 exemplos)	**… 10 × sim/10 × não**

min conf

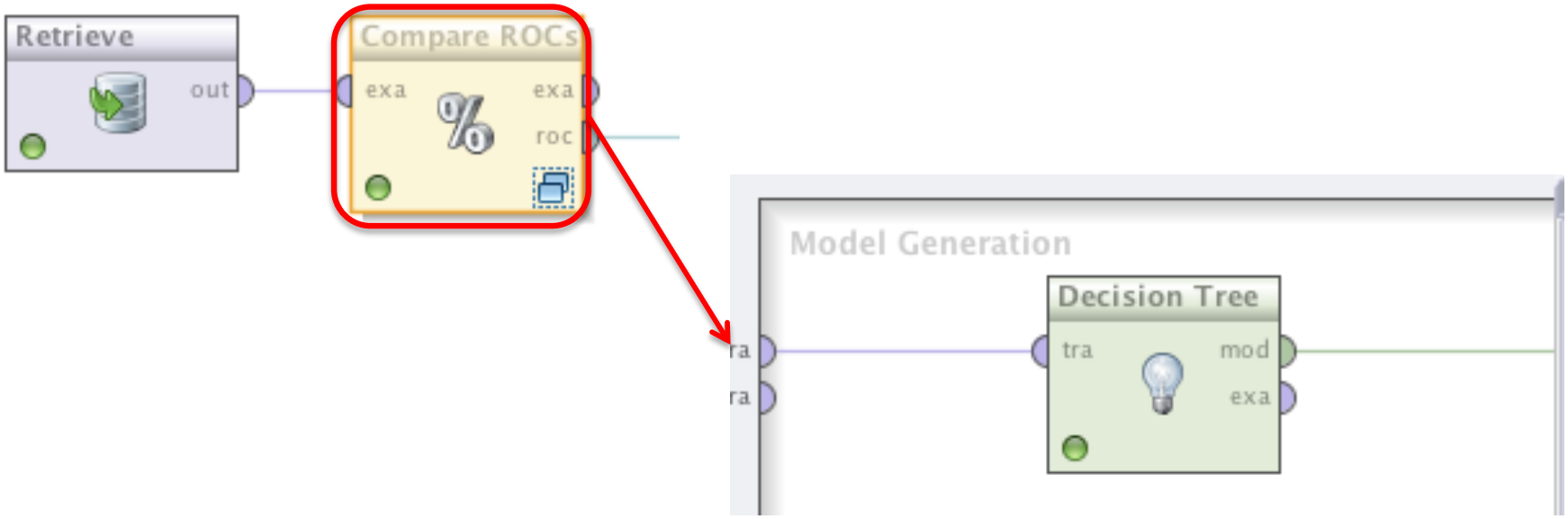


exercício V: sales campaign

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- evaluate decision tree
  - **IMPORTANT NOTE: first example in the training data should belong to positive class**

- not very interesting
  - why?



are we there yet?

U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

- identify problems where classification is useful
- identify relevant data
- know how to analyze and use a decision tree
- know the most common evaluation measures of classification models
- understand the need to use different data for modelling and evaluation
- understand how to evaluate the results of a classification model
- superficially understand the algorithm for induction of decision trees
- understand how to use and evaluate a classification model for scoring
- address a classification problem using RapidMiner algorithms