classification, decision trees and scoring: a reminder

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

http://www.flickr.com/photos/upvcfrontdoor/4642103837/

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reference materials

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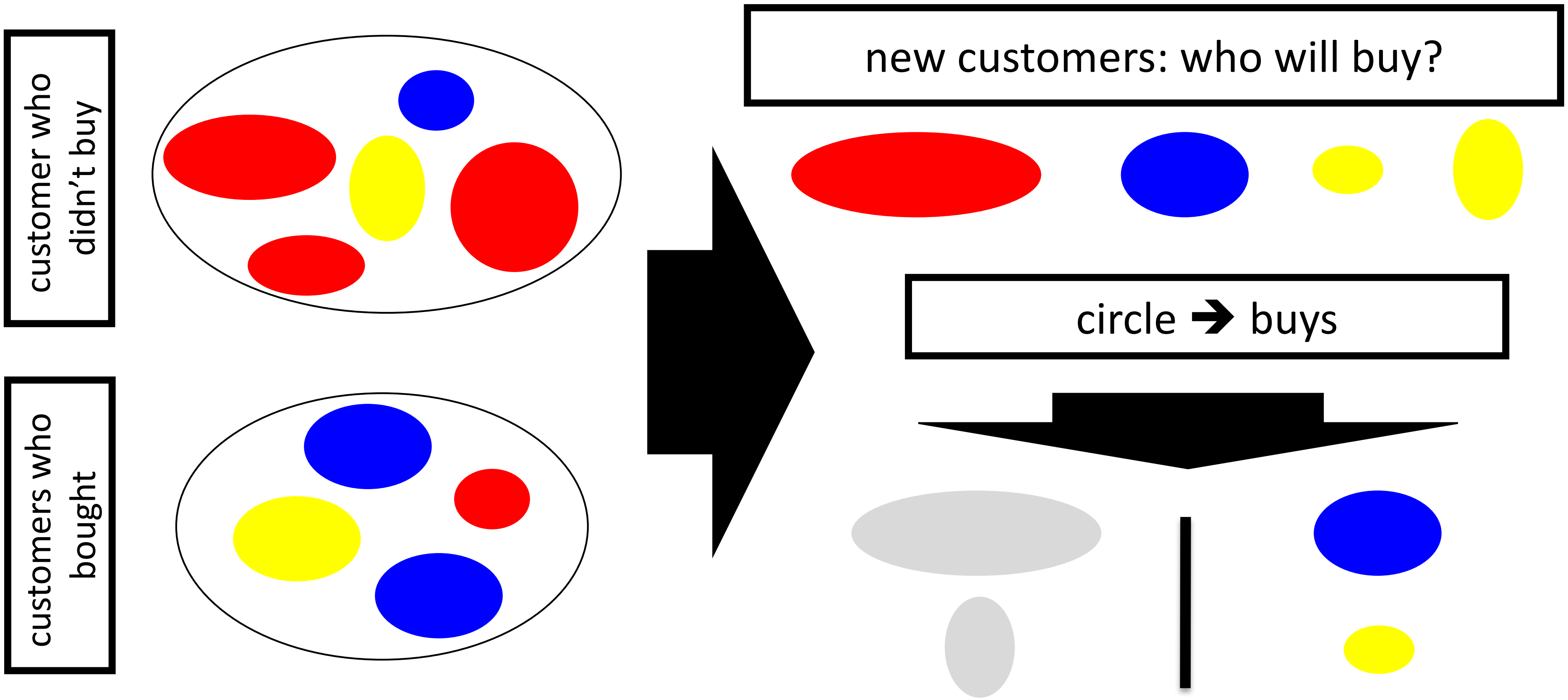
- JMM et al. ch. 4+7

predictive: classification for targeting



data for classification

target (or dependent) variable

independent variable (or attribute)

- prospects
  - customers who didn't buy a car in the last 4 years

would like to predict

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

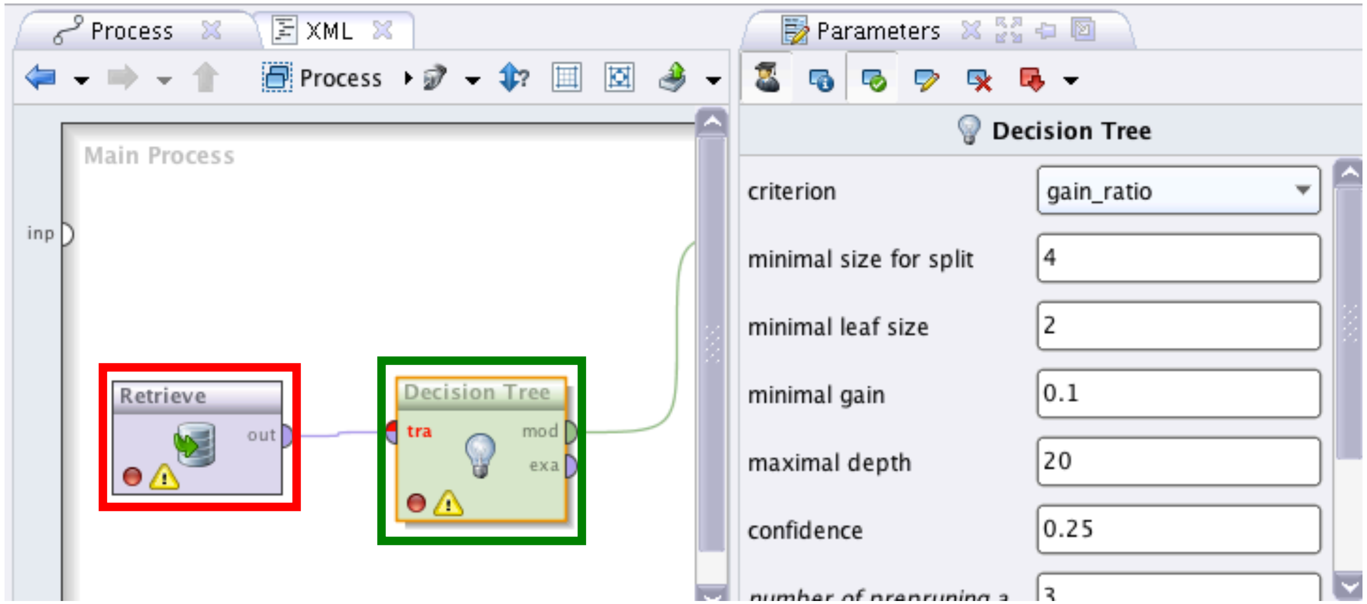
- results from previous campaigns
  - customers who were contacted and their response

already known

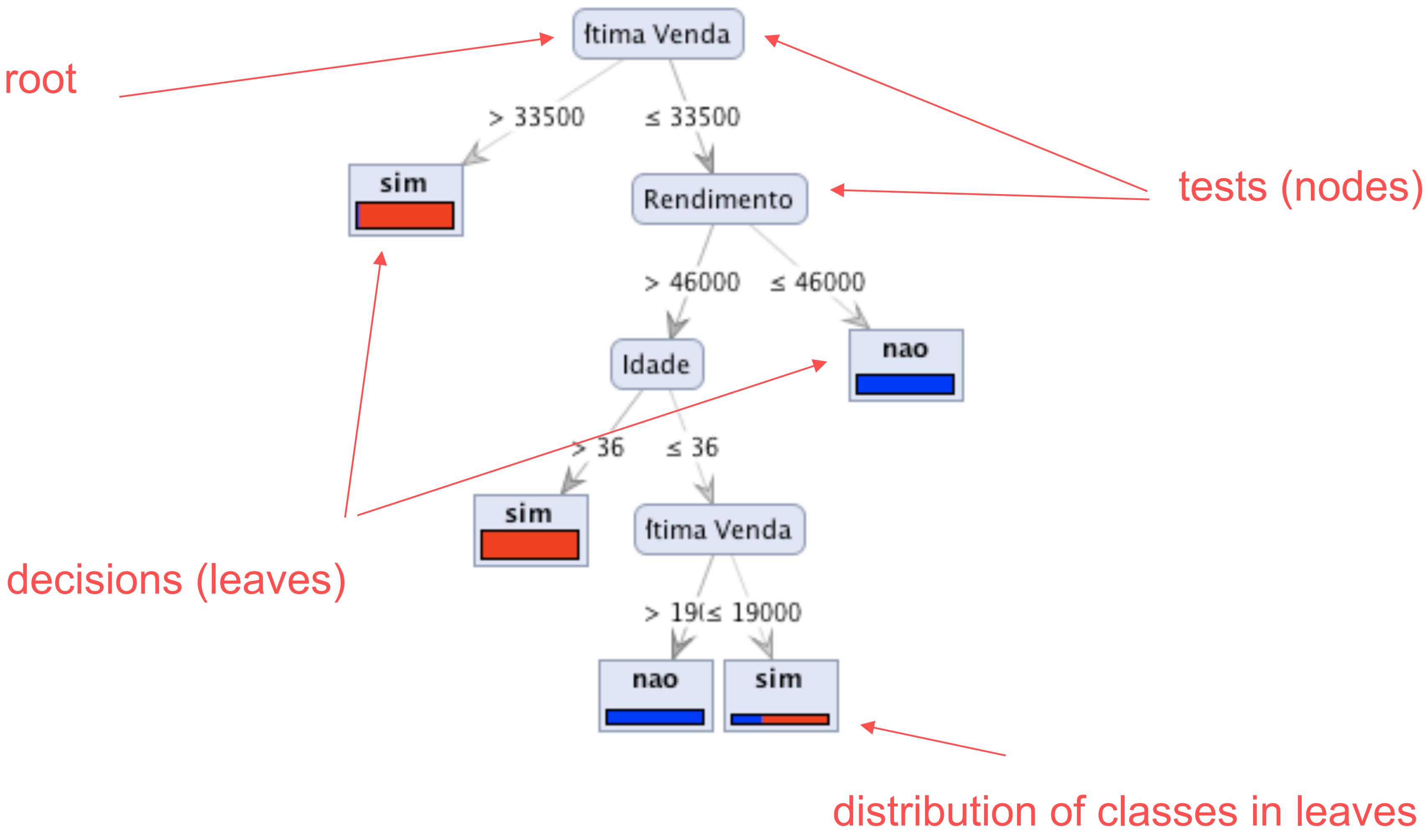
Comprou	Idade	Rendimento	Ag.fam	Vendas anteriores	Última Venda
não	37	49000	2	1	42000
sim	43	68000	3	0	0
sim	42	61000	4	0	0
sim	26	52000	2	0	0
sim	40	64000	1	1	21000
sim	38	52000	1	0	0
sim	45	43000	4	1	47000
sim	35	45000	2	1	34000
não	39	43000	2	0	0
sim	31	55000	3	1	46000
sim	34	57000	3	1	52000
não	38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

learning a model from data

- load data
- apply decision tree algorithm



model: classification tree (or decision tree)

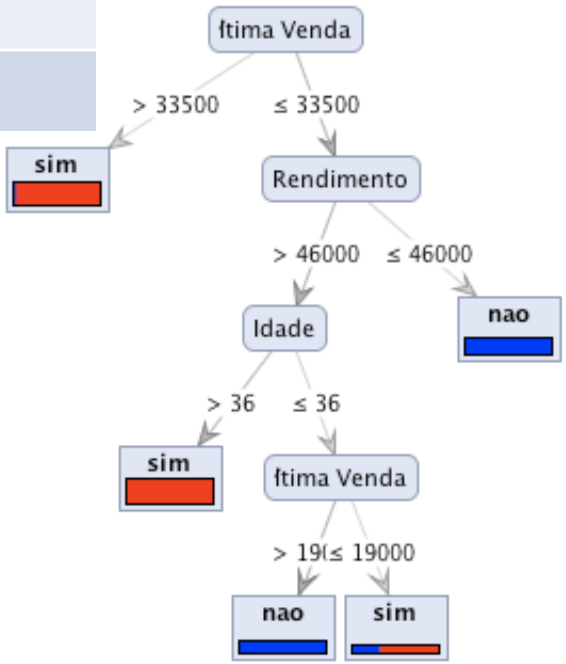


classify new examples

- 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…



classification: are we there yet?

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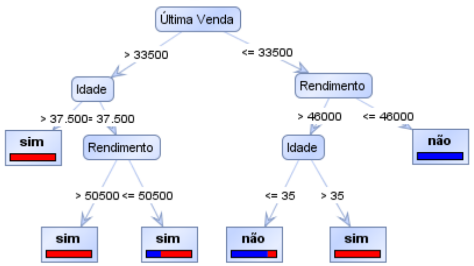
responses to previous campaigns

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

1



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)

2

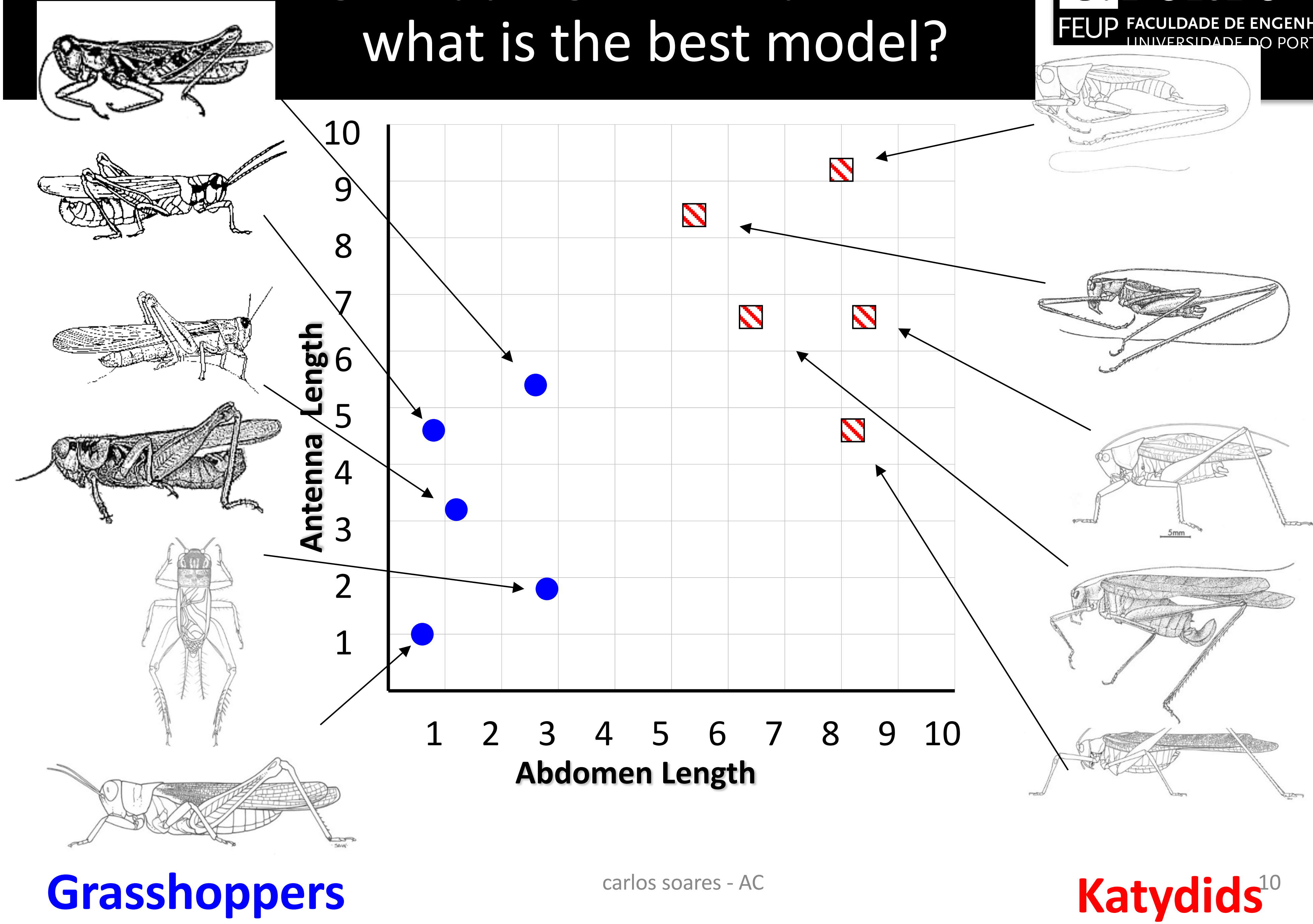
3

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?

running (hopping?) example: what is the best model?



how decision tree algorithms see data…

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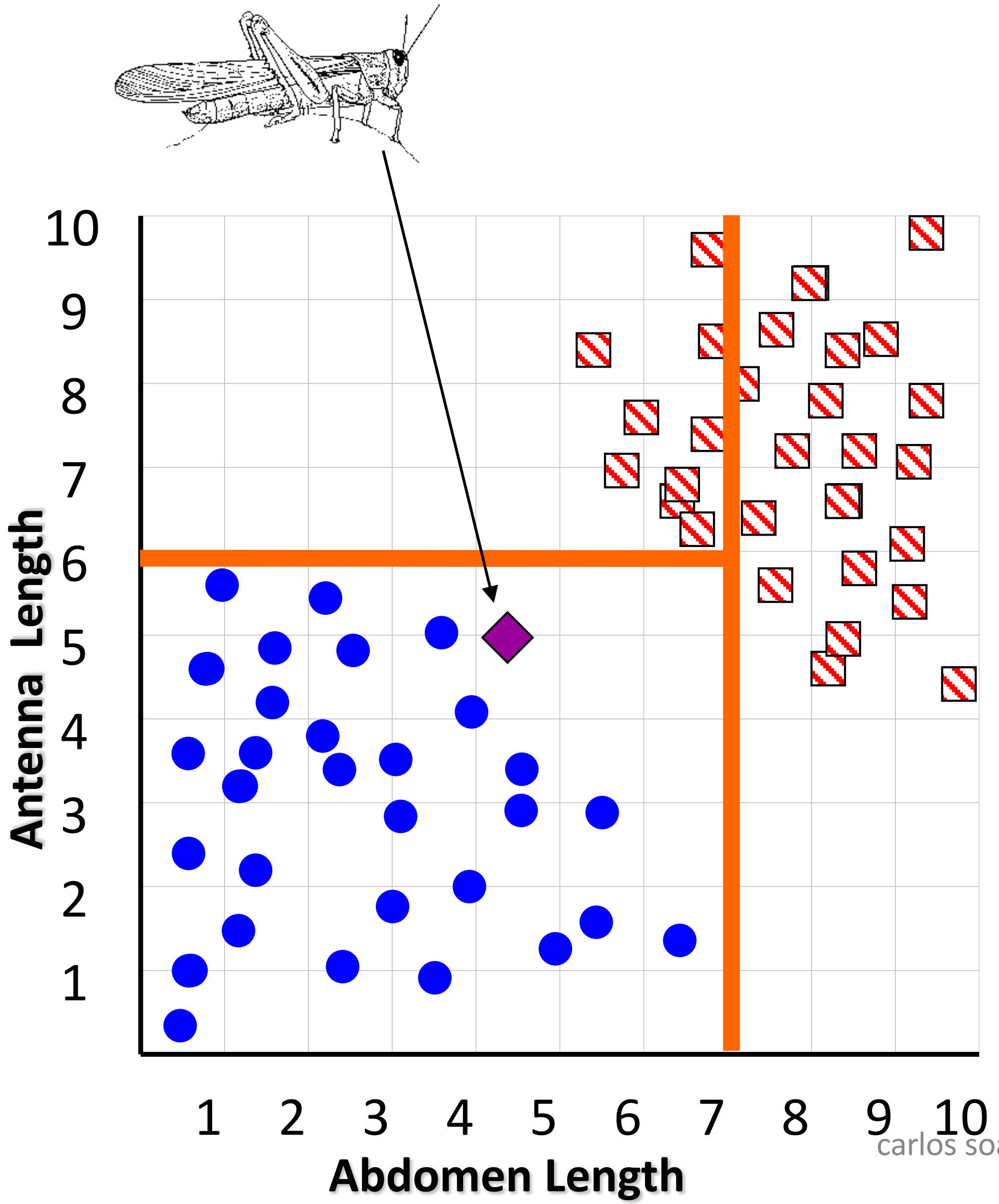
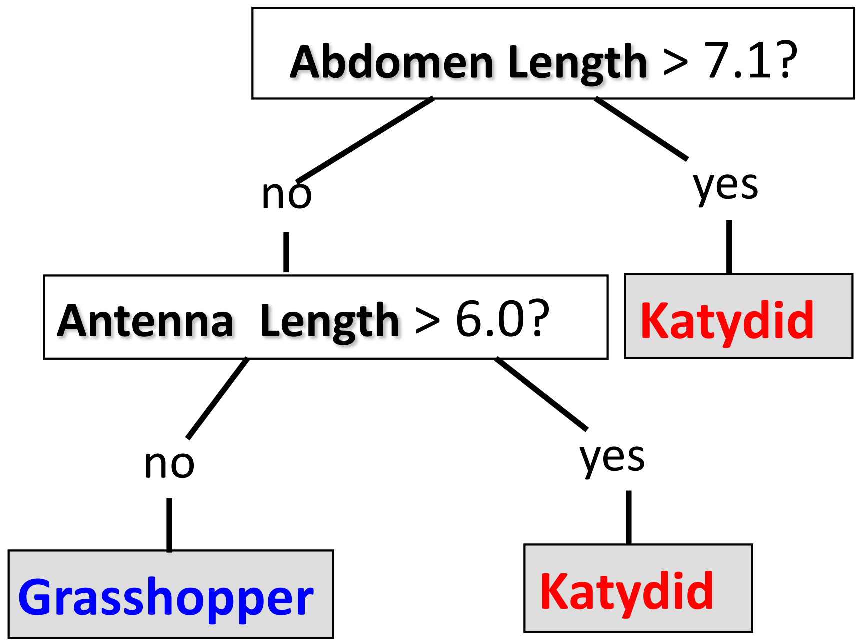


Ross Quinlan



model development

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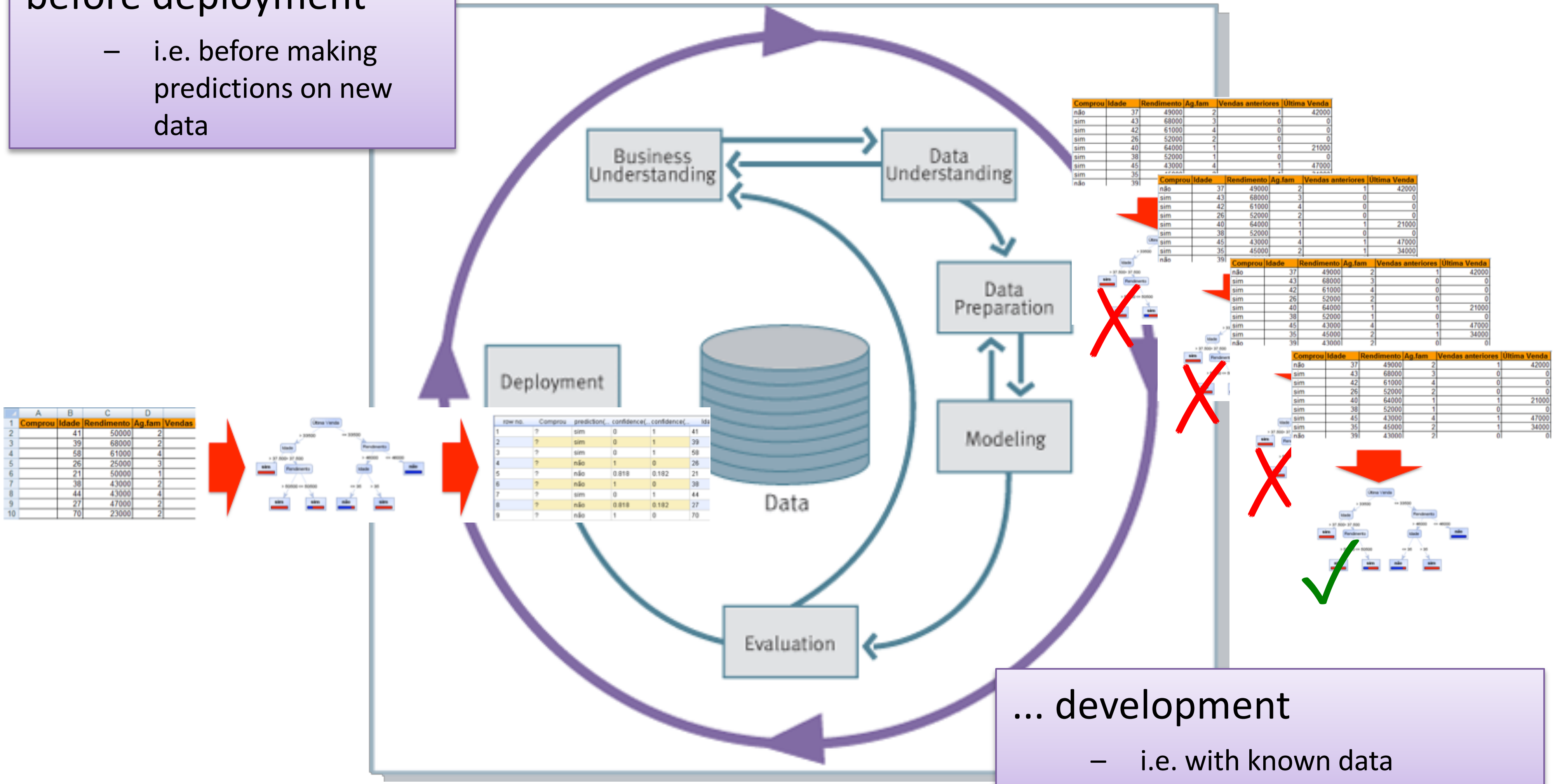
before deployment

- i.e. before making predictions on new data



... development

- i.e. with known data

how good are the predictions?

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- 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**

not all errors are born equal...

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- e.g. targetting campaign
  - is contacting a non-buyer or missing a buyer equally important?
- the focus is on one class
  - ... usually
- the positive class
  - ... positive not necessarily good
- a new perpective on the confusion matrix

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

evaluation measures

- 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	$\boxed{\frac{TP}{TP+FP}}$	Positive predictive value (PPV), also known as precision
$\frac{FN}{TP+FN}$	False negative rate (FNR) = 1-TPR	$\boxed{\frac{TN}{TN+FN}}$	Negative predictive value (NPV)
$\boxed{\frac{TP}{TP+FN}}$	True positive rate (TPR), also known as recall or sensitivity	$\frac{TP+TN}{TP+TN+FP+FN}$	Accuracy
$\boxed{\frac{TN}{TN+FP}}$	True negative rate (TNR), also known as specificity	$\frac{2}{1/\,precision+1/\,recall}$	F1-measure

is the model any good at all?

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

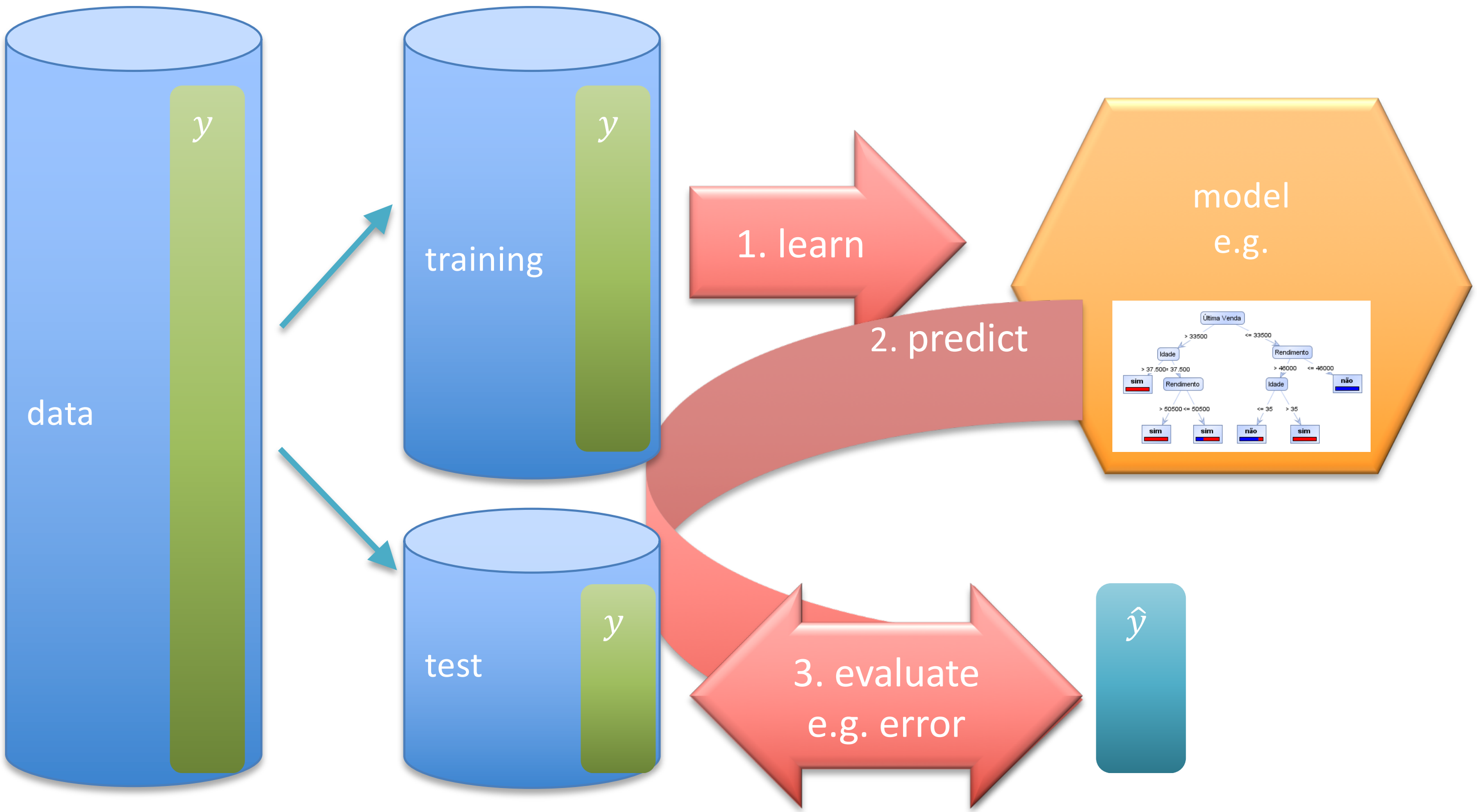
- model error: 3/37 = 8.1%
- **baseline**
  - simplest model that can be obtained from the data

	truth: no	truth: yes
class distribution	7	30

most "popular" choice

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

evaluation methodology: do not forget!



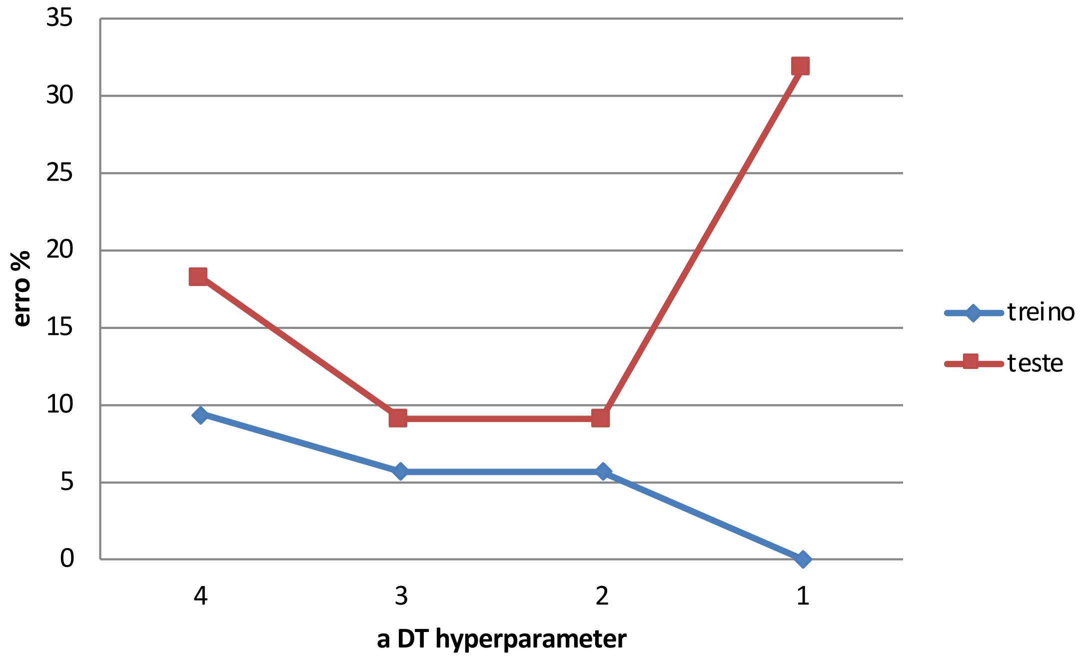
DECISION TREES

gps

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

overfitting

- algorithms can be controlled to adjust to the data more or less



- good reason to
  - design your experimental setup carefully
  - understand how algorithms work

learning a decision tree (1 and 2/5)

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)

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)

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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)

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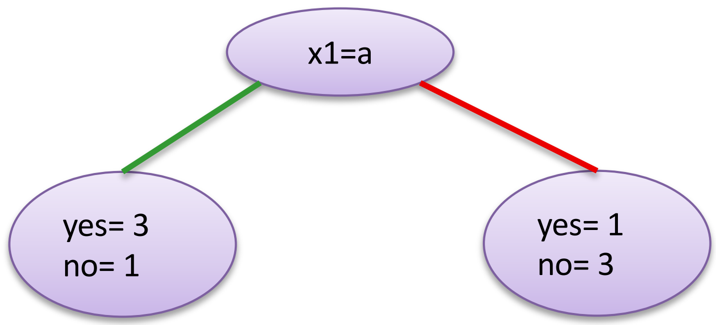
x1	x2	class
a	p	yes
a	q	no
a	p	yes
b	q	no
c	p	no
a	p	yes
c	p	yes
b	p	no

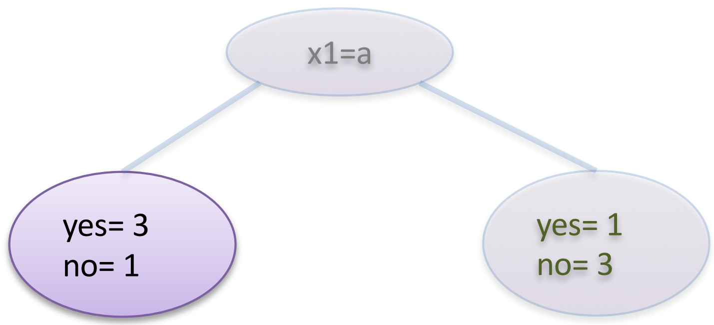


4. create to descendant nodes according to the selected test

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

learning a decision tree (5/5)

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

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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?...

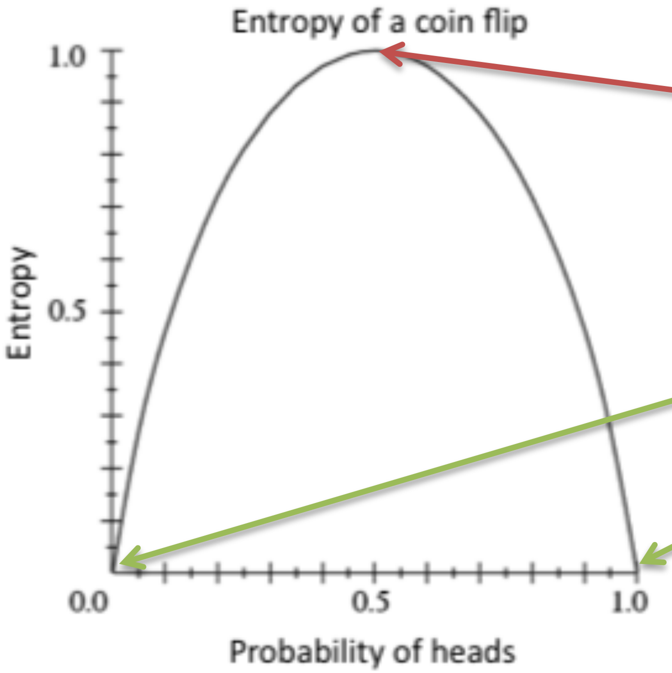
test	true (yes/no)	false (yes/no)
x1=a	3/1	1/3
x1=b	0/2	4/2
x1=c	1/1	3/3
x2=p	4/2	0/2
x2=q		

is this always bad?

entropy as diversity

- 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

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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

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

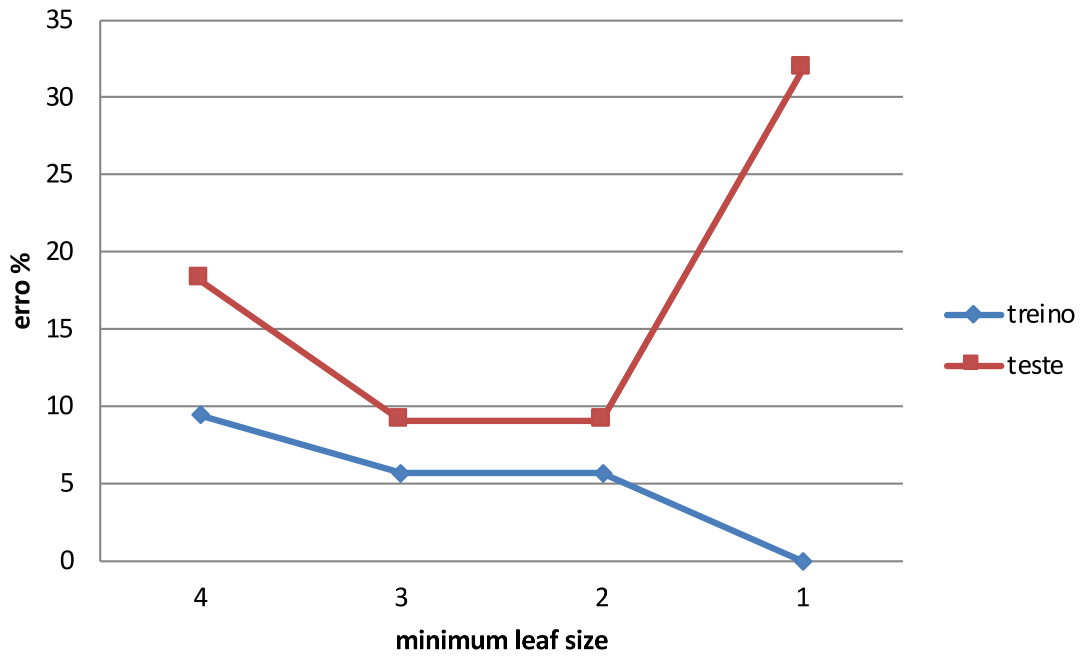
… x3	class
1	yes
2	yes
3	no
3	no
3	no
5	yes
5	yes
9	no

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

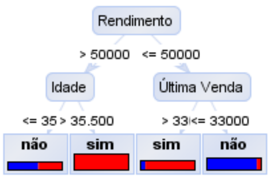
overfitting in DTs

- smaller leaves
  - eg. minimum leaf size hyperparameter

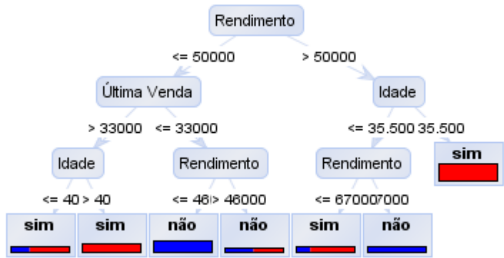


overfitting

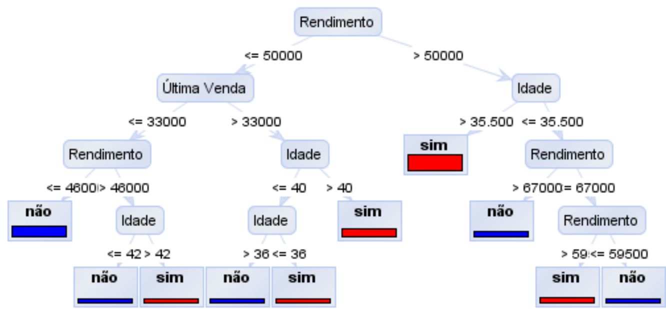
- trees obtained with different values of "minimum leaf size"
  - 4, 2 and 1



error (train)=18,18



error (train)=9,09%



error (train)=0,00%

CLASSIFICATION FOR SCORING

plan

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- binary classification
- evaluation in binary classification

classification: b&w or gray?

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- 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

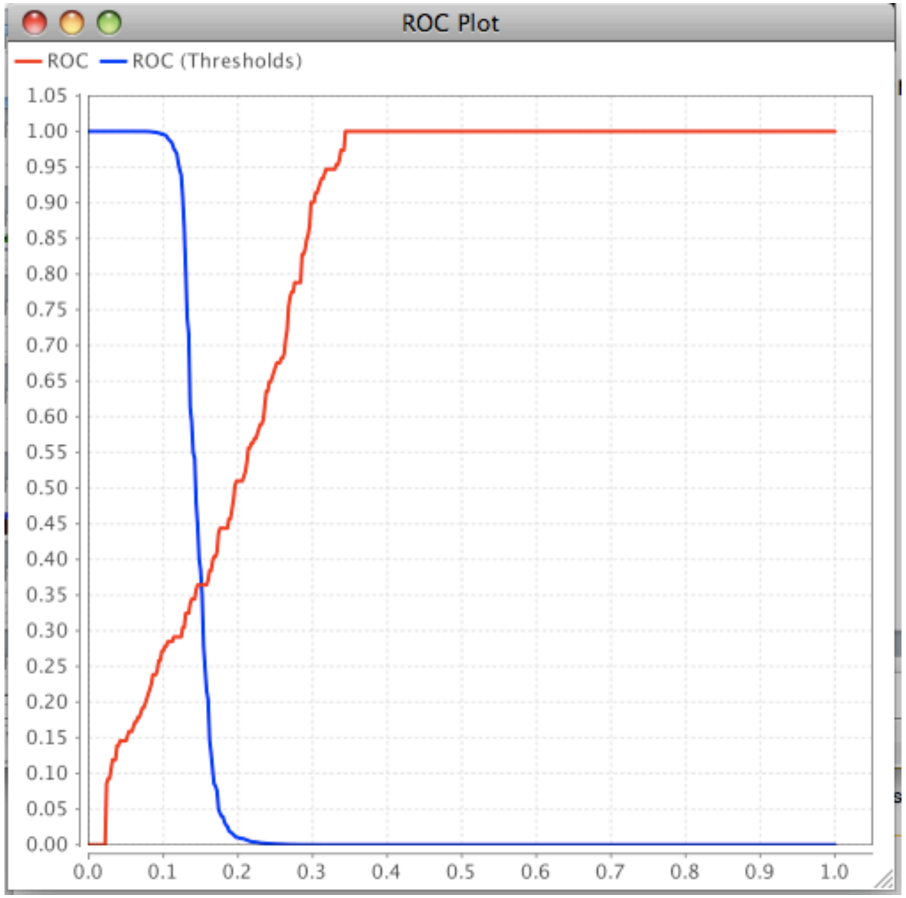
fonte: http://www.flickr.com/photos/backpackphotography/3354435787/

where to cut?

- 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

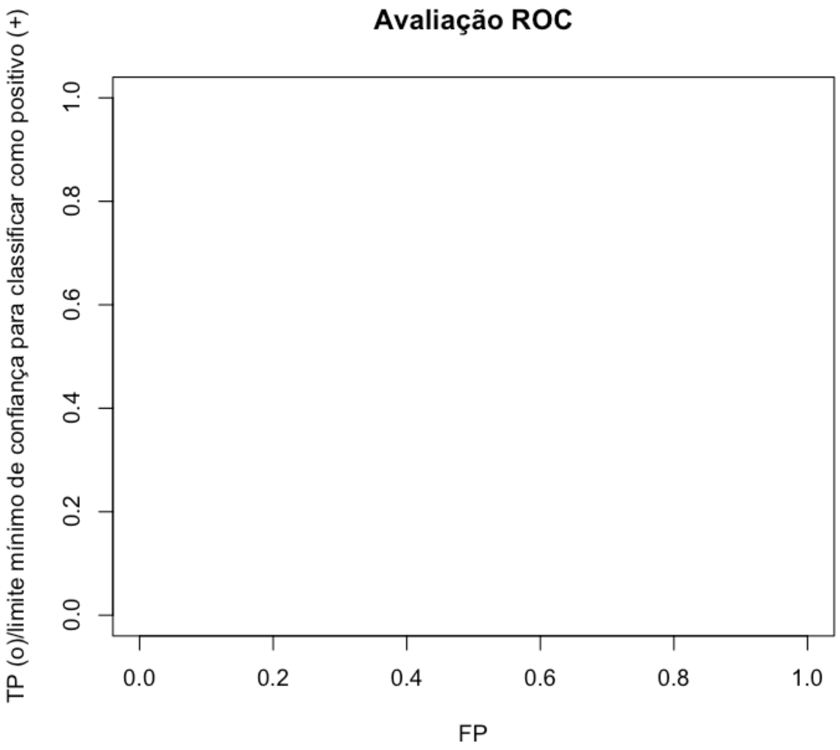
evaluate scoring models

- 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)

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)

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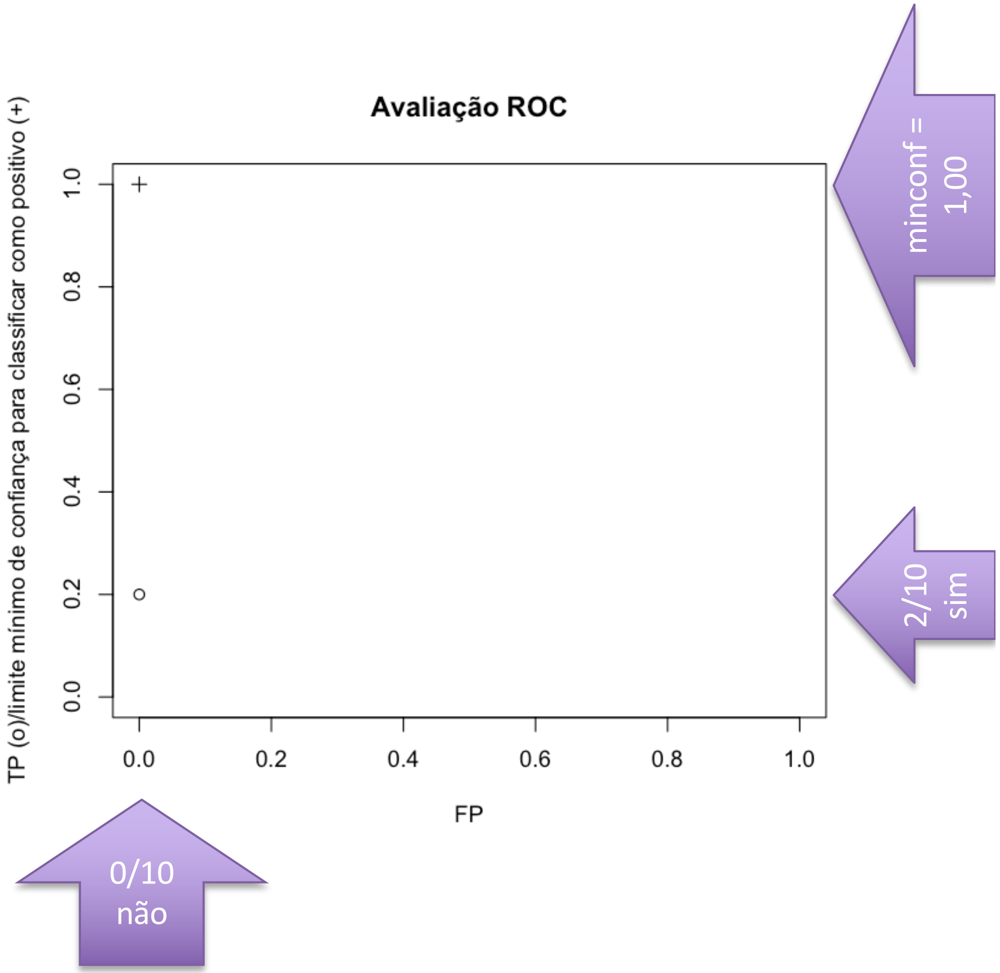
min conf

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)

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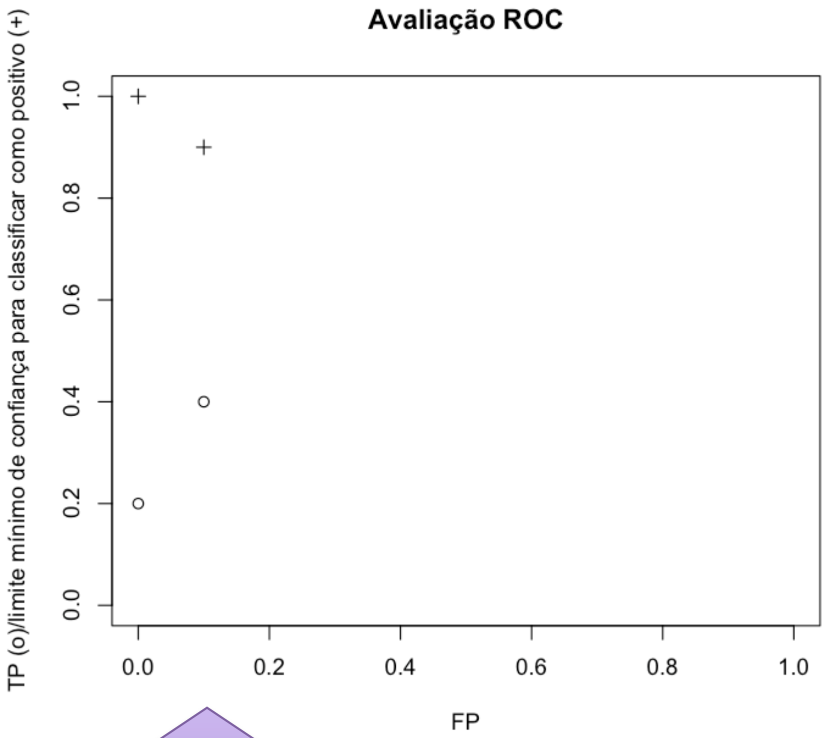
min conf

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**



minconf = 0,90

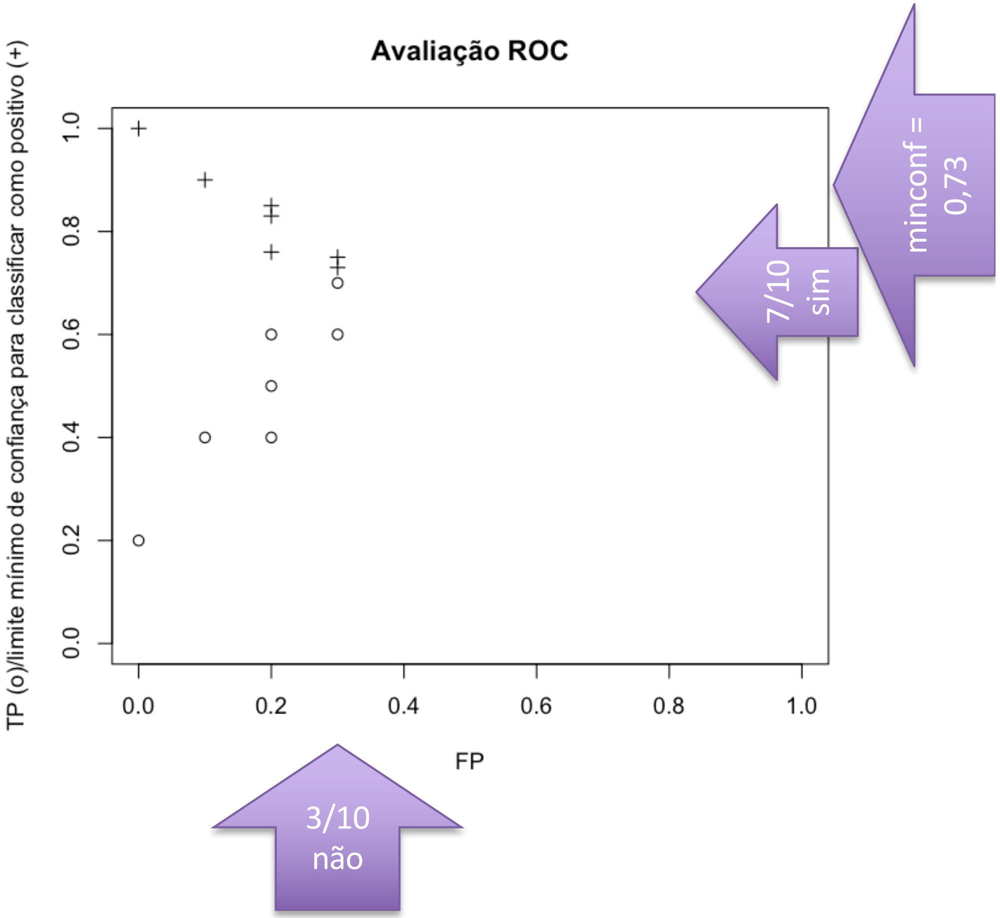
4/10 sim

1/10 não

build ROC curve (4/5)

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**

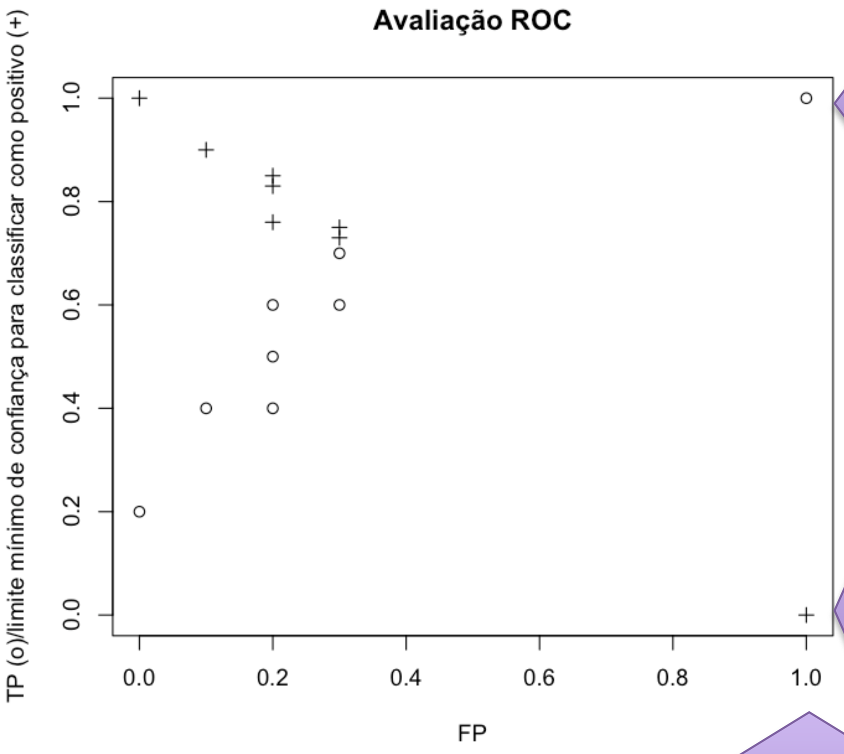
min conf



build ROC curve (5/5)

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



10/10 sim

minconf = 0

10/10 não

are we there yet?

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- 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