

Artificial Intelligence

Decision Trees

Nilsson - briefly mentioned in Chapter 3
(Russell and Norvig - Chapter 18)

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credit card application (1)

information from your application:

how long have you lived at your current address?
what is your salary?
do you have a savings account?
how old are you?

information from the credit bureau:

have you ever defaulted on a loan? when?
how many other credit cards do you have already?
have you ever declared bankruptcy?

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credit card application (2)

information from your application:

F1: how long have you lived at your current address? 5 years
F2: what is your salary? \$25,000
F3: do you have a savings account? no
F4: how old are you? 28

information from the credit bureau:

F5: have you ever defaulted on a loan? when? yes, 8 years ago
F6: how many other credit cards do you already have? none
F7: have you ever declared bankruptcy? no

Do we issue a credit card to this person?
If yes, a regular or a gold card?

classification problem

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credit card application (3) inductive learning problem

features					class
F1	F2	F3	F4	...	was it a good idea to issue a credit card to this person?
5	\$100,000	yes	52	...	yes
3	\$50,000	yes	40	...	no
2	\$12,000	no	20	...	yes
9	\$60,000	yes	31	...	yes
5	\$25,000	no	28	...	???
a	b	c	d		f(a,b,c,d)

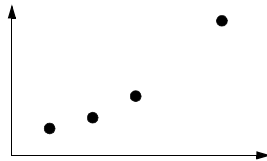
training examples

find a function that is consistent with all training examples
and that we believe will make the fewest mistakes
on the examples with unknown classes

note: we need bias!

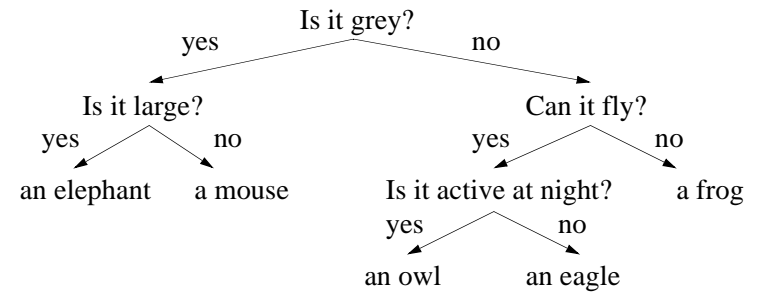
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credit card application (4)
bias



decision trees (1)
= one particular inductive learning method

learning takes time, classification is fast



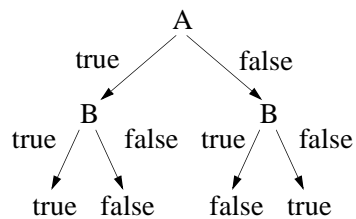
in the following: binary values only
(not multi-valued, not continuous, not missing)

decision trees (2)

every prop formula corresponds to a decision tree with binary variable
every decision tree with binary variables corresponds to a prop formula

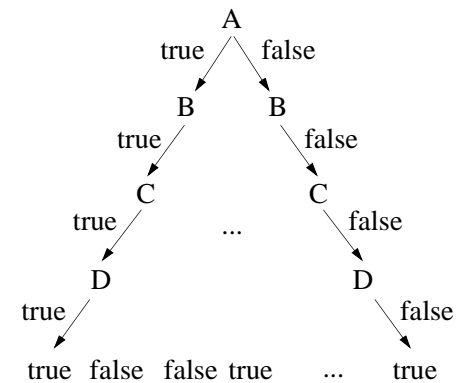
convert into disjunctive normal form

(A AND B) OR (NOT A AND NOT B)



decision trees (3)

decision trees are often much more compact than tables
however, some simple concepts have large decision trees
for example: even parity



inductive bias of decision trees

small is beautiful (number of tests, depth)

Occams Razor

there are fewer small decision trees than large ones

thus, there is only a small chance
that ANY small decision tree
that is completely incorrect

will be consistent with all training examples

problem:
finding the smallest decision tree
that is consistent with all training examples
is NP hard

example

put the most discriminating feature first (= at the root)

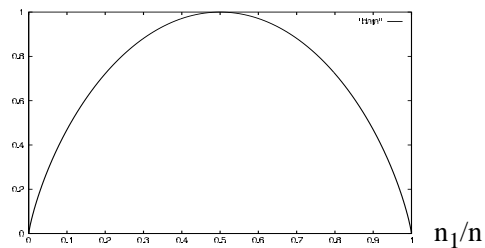
	F1	F2	F3	F4	class
E1:	true	true	false	true	true
E2:	true	false	false	false	true
E3:	true	true	true	true	false
E4:	true	true	true	false	false

entropy

assume that there are n examples total
 n_i examples have class i

$$-\sum_i (n_i/n) \log_2 (n_i/n)$$

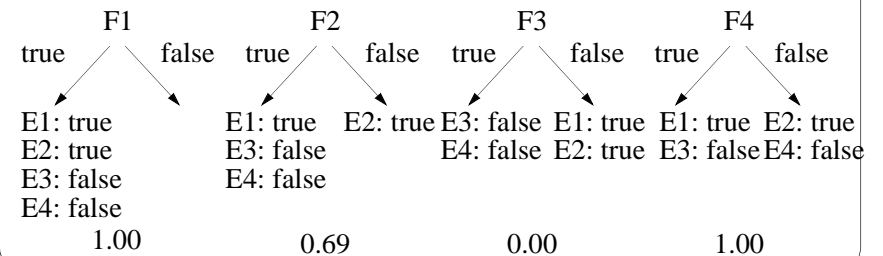
assume two classes



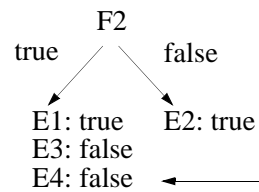
example (1)

put the feature first that results in the smallest average entropy

	F1	F2	F3	F4	class
E1:	true	true	false	true	true
E2:	true	false	false	false	true
E3:	true	true	true	true	false
E4:	true	true	true	false	false



example (2)



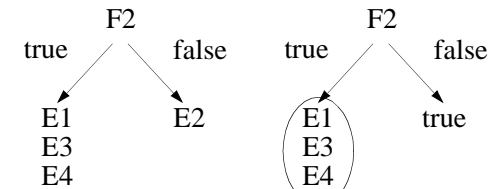
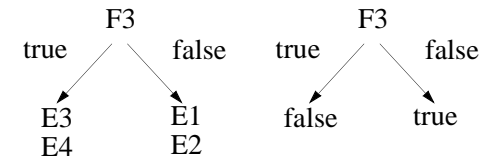
why do we want to minimize these entropies?
because they are a measure of the remaining work and this work must be small for the tree to be small

left branch: 3 out of 4 examples
entropy is 0.9182

right branch: 1 out of 4 examples
entropy is 0.0000

average entropy is $\frac{3}{4} 0.9182 + \frac{1}{4} 0.0000 = 0.6887$

example (3)



continue to split
no examples?
no attributes left for splitting?
probabilities or majority?