Data Mining and Knowledge Discovery: Practice Notes

Discussion about decision trees

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Discussion

- How much is the information gain for the “attribute” Person? How would it perform on the test set?
- How do we compute entropy for a target variable that has three values? Lenses = {hard=4, soft=5, none=13}
- What would be the classification accuracy of our decision tree if we pruned it at the node *Astigmatic*?
- What are the stopping criteria for building a decision tree?
- How would you compute the information gain for a numeric attribute?

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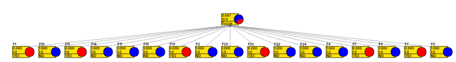
Information gain of the “attribute” Person



On training set
- As many values as there are examples
- Each leaf has exactly one example
- E(1/1, 0/1) = 0 (entropy of each leaf is zero)
- The weighted sum of entropies is zero
- The information gain is maximum (as much as the entropy of the entire training set)

On testing set
- The values from the testing set do not appear in the tree

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Entropy{hard=4, soft=5, none=13}=

= E(4/22, 5/22, 13/22)

= $-\sum p_i * \log_2 p_i$

= $-4/22 * \log_2 4/22 - 5/22 * \log_2 5/22 - 13/22 * \log_2 13/22$

= 1.38

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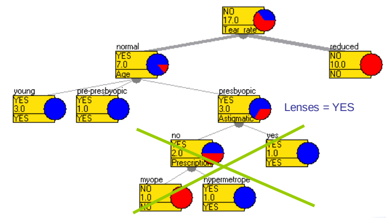
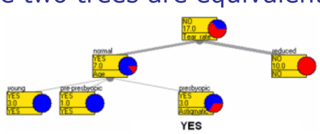
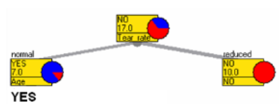
Decision tree pruning



These two trees are equivalent

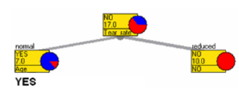




Classification accuracy of the pruned tree

Person	Age	Prescription	Astigmatic	Tear_rate	Lenses
P3	young	hypermetrope	no	normal	YES
P9	pre-presbyopic	myope	no	normal	YES
P12	pre-presbyopic	hypermetrope	no	reduced	NO
P13	pre-presbyopic	myope	yes	normal	YES
P15	pre-presbyopic	hypermetrope	yes	normal	NO
P16	pre-presbyopic	hypermetrope	yes	reduced	NO
P23	presbyopic	hypermetrope	yes	normal	NO

Ca = (3+2)/ (3+2+2+0) = 71%



	Predicted positive	Predicted negative
Actual positive	TP=3	FN=0
Actual negative	FP=2	TN=2

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Stopping criteria for building a decision tree

- ID3
  - "Pure" nodes (entropy =0)
  - Out of attributes
- J48 (C4.5)
  - Minimum number of instances in a leaf constraint

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Information gain of a numeric attribute

Age	Lenses
67	YES
52	YES
63	NO
26	YES
65	NO
23	YES
65	NO
25	YES
26	YES
57	NO
49	NO
23	YES
39	NO
55	NO
53	NO
38	NO
67	YES
54	NO
29	YES
46	NO
44	YES
32	NO
39	NO
45	YES

Information gain of a numeric attribute

Age	Lenses
67	YES
52	YES
63	NO
26	YES
65	NO
23	YES
65	NO
25	YES
26	YES
57	NO
49	NO
23	YES
39	NO
55	NO
53	NO
38	NO
67	YES
54	NO
29	YES
46	NO
44	YES
32	NO
39	NO
45	YES

Sort by Age →

Age	Lenses
23	YES
23	YES
25	YES
26	YES
26	YES
29	YES
32	NO
38	NO
39	NO
39	NO
44	YES
45	YES
46	NO
49	NO
52	YES
53	NO
54	NO
55	NO
57	NO
63	NO
65	NO
65	NO
67	YES
67	YES

Information gain of a numeric attribute

Age	Lenses
67	YES
52	YES
63	NO
26	YES
65	NO
23	YES
65	NO
25	YES
26	YES
57	NO
49	NO
23	YES
39	NO
55	NO
53	NO
38	NO
67	YES
54	NO
29	YES
46	NO
44	YES
32	NO
39	NO
45	YES

Sort by Age →

Age	Lenses
23	YES
23	YES
25	YES
26	YES
26	YES
29	YES
32	NO
38	NO
39	NO
39	NO
44	YES
45	YES
46	NO
49	NO
52	YES
53	NO
54	NO
55	NO
57	NO
63	NO
65	NO
65	NO
67	YES
67	YES

Define possible splitting points

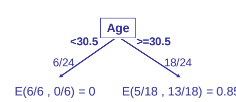
Age	Lenses
23	YES
23	YES
25	YES
26	YES
26	YES
29	YES
32	NO
38	NO
39	NO
39	NO
44	YES
45	YES
46	NO
49	NO
52	YES
53	NO
54	NO
55	NO
57	NO
63	NO
65	NO
65	NO
67	YES
67	YES

Information gain of a numeric attribute

Age	Lenses	
23	YES	
23	YES	
25	YES	
26	YES	
26	YES	
29	YES	→ **30.5**
32	NO	
38	NO	
39	NO	
39	NO	→ **41.5**
44	YES	
45	YES	→ **45.5**
46	NO	
49	NO	→ **50.5**
52	YES	→ **52.5**
53	NO	
54	NO	
55	NO	
57	NO	
63	NO	
65	NO	
65	NO	→ **66**
67	YES	
67	YES	

Information gain of a numeric attribute

Age	Lenses	
23	YES	
23	YES	
25	YES	
26	YES	
26	YES	
29	YES	→ **30.5**
32	NO	
38	NO	
39	NO	
39	NO	→ **41.5**
44	YES	
45	YES	→ **45.5**
46	NO	
49	NO	→ **50.5**
52	YES	→ **52.5**
53	NO	
54	NO	
55	NO	
57	NO	
63	NO	
65	NO	
65	NO	→ **66**
67	YES	
67	YES	



Information gain of a numeric attribute

Age	Lenses
23	YES
23	YES
25	YES
26	YES
26	YES
29	YES
32	NO
38	NO
39	NO
39	NO
44	YES
45	YES
46	NO
49	NO
52	YES
53	NO
54	NO
55	NO
57	NO
63	NO
65	NO
65	NO
67	YES
67	YES

30.5
41.5
45.5
50.5
52.5
66

E(S) = E(11/24 , 13/24) = 0.99

Age
<30.5 >=30.5
6/24 18/24
E(6/6 , 0/6) = 0   E(5/18 , 13/18) = 0.85

InfoGain (S, Age$_{30.5}$)=
= E(S) - $\sum p_v$ E(pv)
= 0.99 – (6/24*0 + 18/24*0.85)
= 0.35

Information gain of a numeric attribute

Age	Lenses
23	YES
23	YES
25	YES
26	YES
26	YES
29	YES
32	NO
38	NO
39	NO
39	NO
44	YES
45	YES
46	NO
49	NO
52	YES
53	NO
54	NO
55	NO
57	NO
63	NO
65	NO
65	NO
67	YES
67	YES

30.5
41.5
45.5
50.5
52.5
66

Age
<30.5 >=30.5
InfoGain (S, Age$_{30.5}$) = 0.35

Age
<41.5 >=41.5
Age
<45.5 >=45.5
Age
<50.5 >=50.5
Age
<52.5 >=52.5
Age
<66 >=66

Decision trees

- Many possible decision trees

$$\sum_{i=0}^{k} 2^i (k-i) = -k + 2^{k+1} - 2$$

  - k is the number of binary attributes
- Heuristic search with information gain
- Information gain is short-sighted

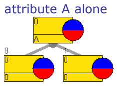
Trees are shortsighted (1)

A	B	C	A xor B
1	1	0	0
0	0	1	0
1	0	0	1
0	0	0	0
0	1	0	1
1	1	1	0
1	0	1	1
0	0	1	0
0	1	0	1
0	1	0	1
1	0	1	1
1	1	1	0

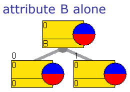
- Three attributes:
  A, B and C
- Target variable is a logical combination attributes A and B
  class = A xor B
- Attribute C is random w.r.t. the target variable

Trees are shortsighted (2)

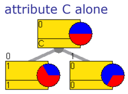
attribute A alone



attribute B alone



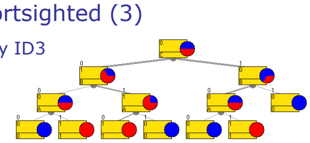
attribute C alone



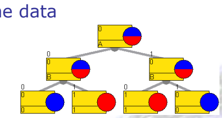
Attribute C has the highest information gain!

Trees are shortsighted (3)

- Decision tree by ID3



- The real model behind the data



Overcoming shortsightedness of decision trees

- Random forests
  (Breinmann & Cutler, 2001)
  - A random forest is a set of decision trees
  - Each tree is induced from a bootstrap sample of examples
  - For each node of the tree, select among a subset of attributes
  - All the trees vote for the classification
  - See also ansemble learning
- ReliefF for attribute estimation
  (Kononenko el al., 1997)

- More on 14.12.2018 by Martin Žnidaršič