Data Mining and Knowledge Discovery

Knowledge Discovery and Knowledge Management in e-Science

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Practice, 2007/11/8

Practice plan

- 2007/11/8: Predictive data mining
  - Decision trees
  - Naïve Bayes classifier
  - Evaluating classifiers (confusion matrix, classification accuracy)
  - Predictive data mining in Weka
- 2007/11/15: Regression and Descriptive data mining
  - Regression models
  - Association rules
  - Regression models and evaluation in Weka
  - Descriptive data mining in Weka
  - Discussion about seminars and exam
- 2007/11/29: Written examination and seminar proposal presentations

Decision tree induction (ID3)

Given:

Attribute-value data with nominal target variable

Divide the data into training set (S) and test set (T)

Induce a decision tree on training set S:

1. Compute the entropy E(S) of the set S
2. **IF** E(S) = 0
3. The current set is "clean" and therefore a leaf in our tree
4. **IF** E(S) > 0
5. Compute the information gain of each attribute Gain(S, A)
6. The attribute A with the highest information gain becomes the root
7. Divide the set S into subsets S_i according to the values of A
8. Repeat steps 1-7 on each Si

Test the model on the test set T

Attribute-value data

attributes

target variable

examples

classes = values of the target variable

Person	Age	Prescription	Astigmatic	Tear_rate	Lenses
P1	young	myope	no	normal	YES
P2	young	myope	no	reduced	NO
P3	young	hypermetrope	no	normal	YES
P4	young	hypermetrope	no	reduced	NO
P5	young	myope	yes	normal	YES
P6	young	myope	yes	reduced	NO
P7	young	hypermetrope	yes	normal	YES
P8	young	hypermetrope	yes	reduced	NO
P9	pre-presbyopic	myope	no	normal	YES
P10	pre-presbyopic	myope	no	reduced	NO
P11	pre-presbyopic	hypermetrope	no	normal	YES
P12	pre-presbyopic	hypermetrope	no	reduced	NO
P13	pre-presbyopic	myope	yes	normal	YES
P14	pre-presbyopic	myope	yes	reduced	NO
P15	pre-presbyopic	hypermetrope	yes	normal	NO
P16	pre-presbyopic	hypermetrope	yes	reduced	NO
P17	presbyopic	myope	no	normal	NO
P18	presbyopic	myope	no	reduced	NO
P19	presbyopic	hypermetrope	no	normal	YES
P20	presbyopic	hypermetrope	no	reduced	NO
P21	presbyopic	myope	yes	normal	YES
P22	presbyopic	myope	yes	reduced	NO
P23	presbyopic	hypermetrope	yes	normal	NO
P24	presbyopic	hypermetrope	yes	reduced	NO

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Training and test set

Person	Age	Prescription	Astigmatic	Tear_Rate	**Lenses**
P1	young	myope	no	normal	YES
P2	young	myope	no	reduced	NO
P3	young	hypermetrope	no	normal	YES
P4	young	hypermetrope	no	reduced	NO
P5	young	myope	yes	normal	YES
P6	young	myope	yes	reduced	NO
P7	young	hypermetrope	yes	normal	YES
P8	young	hypermetrope	yes	reduced	NO
P9	pre-presbyopic	myope	no	normal	YES
P10	pre-presbyopic	myope	no	reduced	NO
P11	pre-presbyopic	hypermetrope	no	normal	YES
P12	pre-presbyopic	hypermetrope	no	reduced	NO
P13	pre-presbyopic	myope	yes	normal	YES
P14	pre-presbyopic	myope	yes	reduced	NO
P15	pre-presbyopic	hypermetrope	yes	normal	NO
P16	pre-presbyopic	hypermetrope	yes	reduced	NO
P17	presbyopiceko	myope	no	normal	NO
P18	presbyopiceko	myope	no	reduced	NO
P19	presbyopiceko	hypermetrope	no	normal	YES
P20	presbyopiceko	hypermetrope	no	reduced	NO
P21	presbyopiceko	myope	yes	normal	YES
P22	presbyopiceko	myope	yes	reduced	NO
P23	presbyopiceko	hypermetrope	yes	normal	NO
P24	presbyopiceko	hypermetrope	yes	reduced	NO

Put 30% of examples in a separate test set

Test set

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	presbyopiceko	hypermetrope	yes	normal	**NO**

Put these data away and do not look at it in the training phase!

Training set

Person	Age	Prescription	Astigmatic	Tear_Rate	**Lenses**
P1	young	myope	no	normal	**YES**
P2	young	myope	no	reduced	**NO**
P4	young	hypermetrope	no	reduced	**NO**
P5	young	myope	yes	normal	**YES**
P6	young	myope	yes	reduced	**NO**
P7	young	hypermetrope	yes	normal	**YES**
P8	young	hypermetrope	yes	reduced	**NO**
P10	pre-presbyopic	myope	no	reduced	**NO**
P11	pre-presbyopic	hypermetrope	no	normal	**YES**
P14	pre-presbyopic	myope	yes	reduced	**NO**
P17	presbyopiceko	myope	no	normal	**NO**
P18	presbyopiceko	myope	no	reduced	**NO**
P19	presbyopiceko	hypermetrope	no	normal	**YES**
P20	presbyopiceko	hypermetrope	no	reduced	**NO**
P21	presbyopiceko	myope	yes	normal	**YES**
P22	presbyopiceko	myope	yes	reduced	**NO**
P24	presbyopiceko	hypermetrope	yes	reduced	**NO**

Entropy

$$E(S) = -\sum_{c=1}^{N} p_c . \log_2 p_c$$

- Calculate the following entropies:
  - E (1/2 , 1/2) =
  - E (1/4 , 3/4) =
  - E (1/7 , 6/7) =
  - E (6/7 , 1/7) =
  - E (0.1 , 0.9) =
  - E (0.001 , 0.999) =

Entropy

$$E(S) = -\sum_{c=1}^{N} p_c . \log_2 p_c$$

- Calculate the following entropies:

  E (1/2 , 1/2) = 1

  E (1/4 , 3/4) = 0.81

  E (1/7 , 6/7) = 0.59

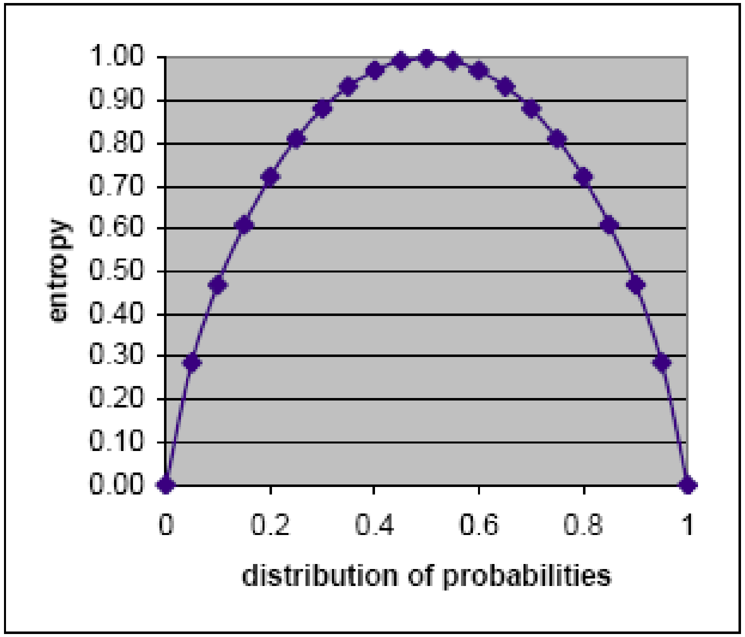
  E (6/7 , 1/7) = 0.59

  E (0.1 , 0.9) = 0.47

  E (0.001 , 0.999) = 0.01

Entropy and information gain

probability of class 1	probability of class 2	
p_1	$p_2 = 1-p_1$	**entropy $E(p_1, p_2) =$** $-p_1 * \log_2(p_1) - p_2 * \log_2(p_2)$
0	1	0.00
0.05	0.95	0.29
0.10	0.90	0.47
0.15	0.85	0.61
0.20	0.80	0.72
0.25	0.75	0.81
0.30	0.70	0.88
0.35	0.65	0.93
0.40	0.60	0.97
0.45	0.55	0.99
0.50	0.50	1.00
0.55	0.45	0.99
0.60	0.40	0.97
0.65	0.35	0.93
0.70	0.30	0.88
0.75	0.25	0.81
0.80	0.20	0.72
0.85	0.15	0.61
0.90	0.10	0.47
0.95	0.05	0.29
1	0	0.00



number of examples in the subset

probability of the "branch"

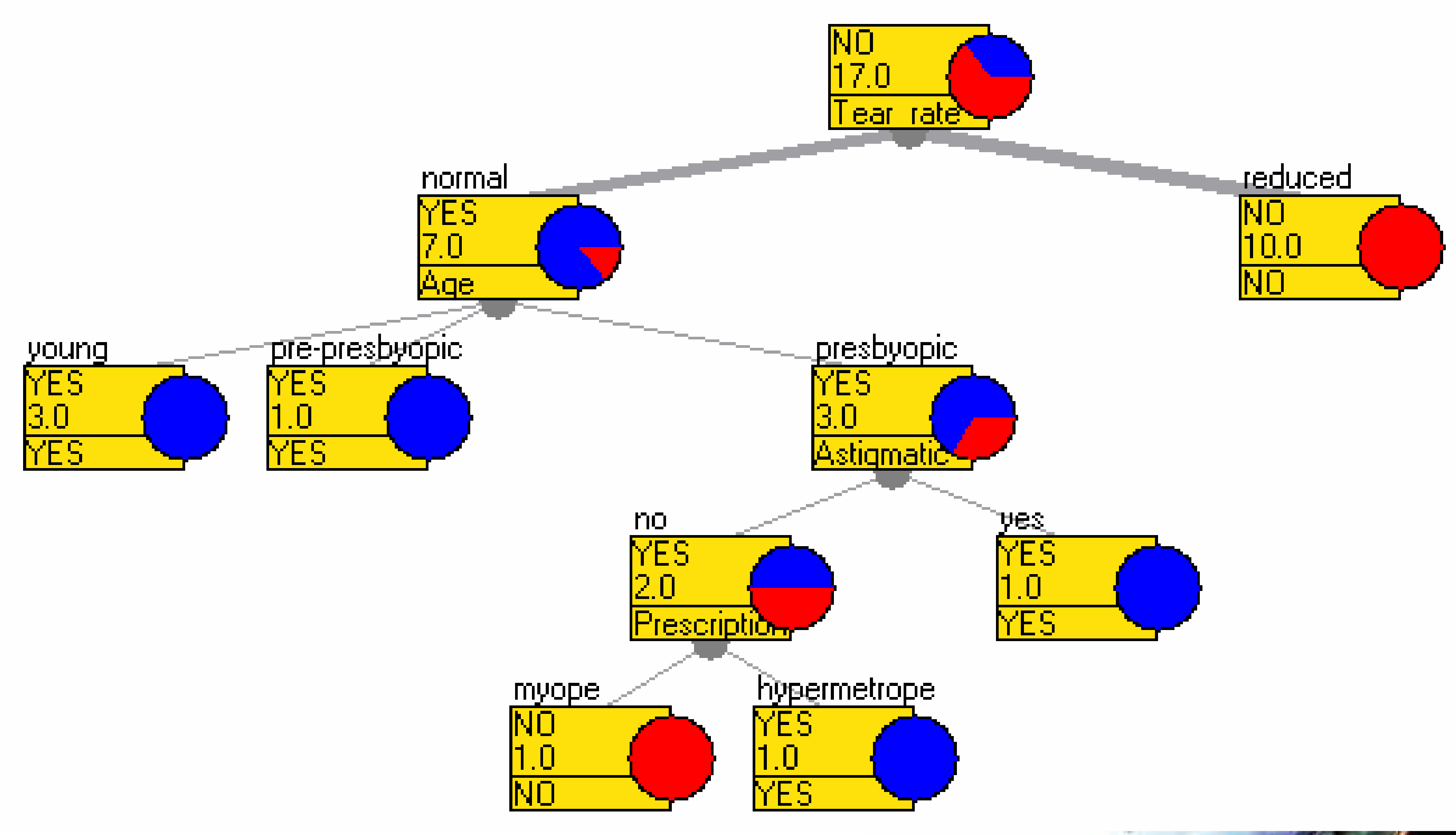
attribut A

$$Gain(S, A) = E(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} \cdot E(S_v)$$

set S

number of example in the set S

Decision tree



Confusion matrix

predicted

actual

	Predicted positive	Predicted negative
Actual positive	TP	FN
Actual negative	FP	TN

- Confusion matrix is a matrix showing actual and predicted classifications
- Classification measures can be calculated from it, like classification accuracy
  - = #(correctly classified examples) / #(all examples)
  - = (TP+TN) / (TP+TN+FP+FN)

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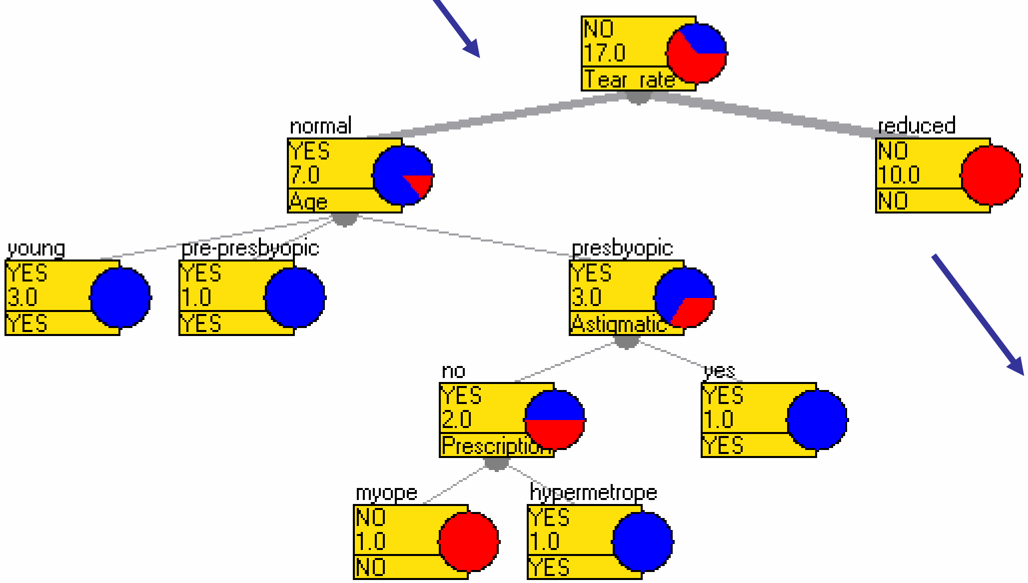
Evaluating decision tree accuracy

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) = 0,71%

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

Naïve Bayes classifier

$$P(c \mid a_1, a_2, \ldots. a_n) = P(c) \prod_i \frac{P(c \mid a_i)}{P(c)}$$

Assumption: conditional independence of attributes given the class.

Will the spider catch these two ants?

- Color = white, Time = night
- Color = black, Size = large, Time = day

Color	Size	Time	Caught
black	large	day	YES
white	small	night	YES
black	small	day	YES
red	large	night	NO
black	large	night	NO
white	large	night	NO

Naïve Bayes classifier -example

Color	Size	Time	Caught
black	large	day	YES
white	small	night	YES
black	small	day	YES
red	large	night	NO
black	large	night	NO
white	large	night	NO

$$v_1 = \text{“}Color = white\text{”}$$

$$v_2 = \text{“}Time = night\text{”}$$

$$c_1 = YES$$

$$c_2 = NO$$

$$p(c_1|v_1, v_2) =$$

$$p(Caught = YES|Color = white, Time = night) =$$

$$p(Caught = YES) * \frac{p(Caught = YES|Color = white)}{p(Caught = YES)} * \frac{p(Caught = YES|Time = night)}{p(Caught = YES)} =$$

$$\frac{1}{2} * \frac{\frac{1}{2}}{\frac{1}{2}} * \frac{\frac{1}{4}}{\frac{1}{2}} = \frac{1}{4}$$

Discussion

- List evaluation methods for classification.
- How do we compute entropy for a target variable that has three values? Lenses = {hard=4, soft=5, none=13}
- How would you compute the information gain for a numeric attribute?
- What would be the classification accuracy of our decision tree if we would have pruned it at he node *Astigmatic*?
- Compare the naïve Bayes classifier and decision trees regarding the handling of missing values.
- Compare the naïve Bayes classifier and decision trees regarding numeric attributes.

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