Data Mining and Knowledge Discovery
Practice notes – 10.11.2009

Data Mining and Knowledge Discovery

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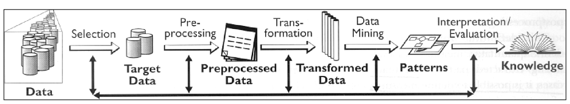
2009/11/10

- Prof. Lavrač:
  - Data mining overview
  - Advanced topics

(the lecture will be repeated on 18.11.2009)

- Dr. Kralj Novak
  - Data mining basis

Keywords



- Data
  - Attribute-value data, attribute, target variable, class, example, train set, test set
- Mata mining
  - Heuristics vs. exhaustive search, decision tree induction, entropy, information gain, overfitting, Occam's razor, model pruning, association rules, support, confidence, predictive vs. descriptive DM, numeric prediction
- Evaluation
  - Accuracy, confusion matrix, cross validation, ROC space, error

Practice plan

- 2009/11/10: Predictive data mining
  - Decision trees
  - Naïve Bayes classifier
  - Evaluating classifiers (separate test set, cross validation, confusion matrix, classification accuracy)
  - Predictive data mining in Weka
- 2009/11/24: Numeric prediction and descriptive data mining
  - Regression models
  - Association rules
  - Regression models and evaluation in Weka
  - Descriptive data mining in Weka
  - Discussion about seminars and exam

- 2009/12/8: Written exam

- 2010/1/26: Seminar proposal presentations
- 2009/3/1: deadline for data mining papers (written seminar)
- 2009/3/3: Data mining seminar presentations

Decision tree induction

Given

- Attribute-value data with nominal target variable

Induce

- A decision tree and estimate its performance on new data

Attribute-value data

(nominal) target variable

attributes

examples

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**

classes = values of the (nominal) target variable

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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

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**
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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**

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	presbyopic	hypermetrope	yes	normal	**NO**

Put these data away and do not look at them 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**
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Information gain

number of examples in the subset S_v

(probability of the branch)

set S

attribute A

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

number of examples in set S

Entropy

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

- Calculate the following entropies:
  - E (0,1) =
  - 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) =

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Entropy

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- Calculate the following entropies:
  - E (0,1) = 0
  - 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

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Entropy

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

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  - E (0,1) = 0
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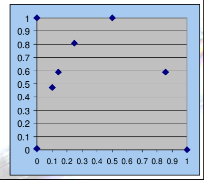

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Entropy

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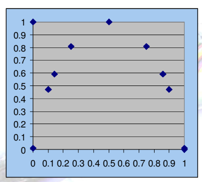

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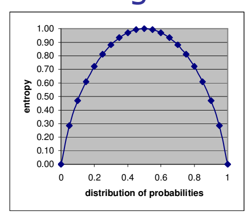
Entropy and information gain

probability of class 1 p_1	probability of class 2 $p_2 = 1-p_1$	entropy $E(p_1, p_2) = -p_1 \cdot \log_2(p_1) - p_2 \cdot \log_2(p_2)$
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

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

set S

number of examples in set S

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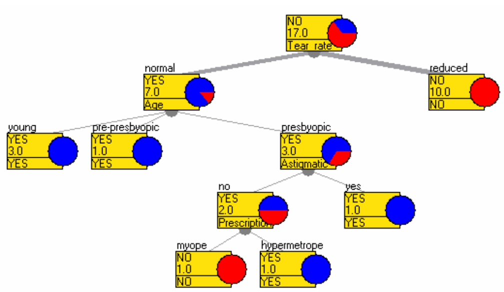
Decision tree



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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**
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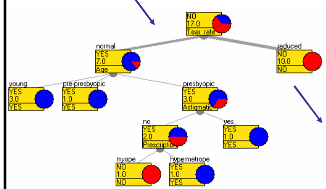

Ca = (3+2)/ (3+2+2+0) = 0,71%

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

Predicting with Naïve Bayes

Given

- Attribute-value data with nominal target variable

Induce

- Build a Naïve Bayes classifier and estimate its performance on new data

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**

$v_1 =$ "$Color = white$"

$v_2 =$ "$Time = night$"

$c_1 = YES$

$c_2 = NO$

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

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

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

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

Discussion

- List evaluation methods for classification.
- How 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}
- How would you compute the information gain for a numeric attribute?
- What would be the classification accuracy of our decision tree if we pruned it at the node *Astigmatic*?
- Compare the naïve Bayes classifier and decision trees regarding
  - the handling of missing values
  - numeric attributes
  - interpretability of the model