Data Mining and Knowledge Discovery
Practice notes: Decision trees

Data Mining and Knowledge Discovery: Practice Notes

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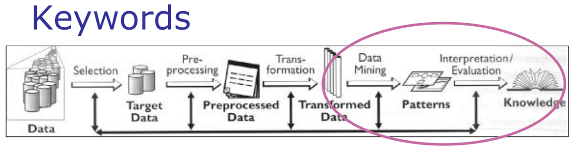
Course

- Prof. Bojan Cestnik
  - Data preparation
- Prof. Nada Lavrač:
  - Data mining overview
  - Advanced topics
- Dr. Petra Kralj Novak
  - Data mining basis
  - Hand on Weka
  - Written exam
  - Reading clubs:
    - Basic: Max Bramer: Principles of Data Mining (2007)
    - Advanced: Charu C. Aggarwal : Data Mining: The Textbook
- Prof. Dunja Mladenić
  - Text mining

6.11.2018	17h-19h	MPS	Nada Lavrač	ICT2 Data and text mining	ICT3 Data Mining and Knowledge Discovery
7.11.2018	16h-19h	MPS	Bojan Cestnik	ICT2 Data and text mining	
8.11.2018	17h-19h	Oranžna	Petra Kralj Novak Exercises and Hands on Weka	ICT2 Data and text mining	ICT3 Data Mining and Knowledge Discovery
13.11.2018	15h-17h	MPS	Nada Lavrač	ICT2 Data and text mining	ICT3 Data Mining and Knowledge Discovery
15.11.2018	15h-18h	Oranžna	Petra Kralj Novak Exercises and Hands on Weka Book club Bramer ch. 1-5	ICT2 Data and text mining	ICT3 Data Mining and Knowledge Discovery
21.11.2018	15h-19h	MPŠ	Dunja Mladenić	ICT2 Data and text mining	
22.11.2018	17h-19h	Oranžna	Nada Lavrač	ICT2 Data and text mining	ICT3 Data Mining and Knowledge Discovery
28.11.2018	16h-18h	Oranžna	Bojan Cestnik	ICT2 Data and text mining	
29.11.2018	15h-18h	Oranžna	Petra Kralj Novak Exercises and Hands on Weka Book club Bramer ch. 6-10	ICT2 Data and text mining	ICT3 Data Mining and Knowledge Discovery
6.12.2018	15h-17h	Oranžna	Petra Kralj Novak Hands on Exercises Book club Bramer ch. 11-15	ICT2 Data and text mining	ICT3 Data Mining and Knowledge Discovery
10.12.2018	16h-18h	Oranžna	Dunja Mladenic	ICT2 Data and text mining	ICT3 Data Mining and Knowledge Discovery
14.12.2018	15h-18h	Oranžna	Martin Žnidaršič	ICT2 Data and text mining	ICT3 Data Mining and Knowledge Discovery
19.12.2018	16h-18h	MPŠ	Petra Kralj Novak Written test Seminar proposals	ICT2 Data and text mining	ICT3 Data Mining and Knowledge Discovery
10.1.2019	15h-17h	Oranžna	Petra Kralj Novak Advanced Hands-on	ICT2 Data and text mining	ICT3 Data Mining and Knowledge Discovery
14.1.2019	17h-19h	MPŠ	Dunja Mladenić	ICT2 Data and text mining	

Keywords

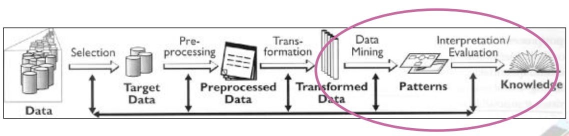


- Data
  - Attribute, example, attribute-value data, target variable, class, discretization
- Algorithms
  - Decision tree induction, entropy, information gain, overfitting, Occam's razor, model pruning, naïve Bayes classifier, KNN, association rules, support, confidence, numeric prediction, regression tree, model tree, heuristics vs. exhaustive search, predictive vs. descriptive DM
- Evaluation
  - Train set, test set, accuracy, confusion matrix, cross validation, true positives, false positives, ROC space, AUC, error, precision, recall

Decision tree induction

Given
- Attribute-value data with nominal target variable

Induce
- A decision tree and estimate its performance



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

Data Mining and Knowledge Discovery
Practice notes: Decision trees

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	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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P10	pre-presbyopic	myope	no	reduced	**NO**
P11	pre-presbyopic	hypermetrope	no	normal	**YES**
P14	pre-presbyopic	myope	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**
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Decision tree induction

Given

- Attribute-value data with nominal target variable

Induce

- A decision tree and estimate its performance

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 S_i

Test the model on the test set T

Quinlan, J. R. 1986. Induction of Decision Trees. Mach. Learn. 1, 1 (Mar. 1986), 81-106

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

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Practice notes: Decision trees

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) =

Entropy

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

- 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

Entropy

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

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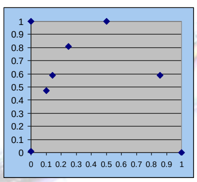

Entropy

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

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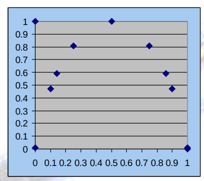
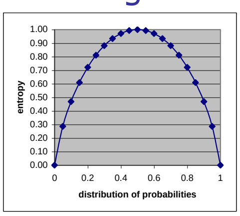


Entropy and information gain

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

Decision tree induction (ID3)

Given:
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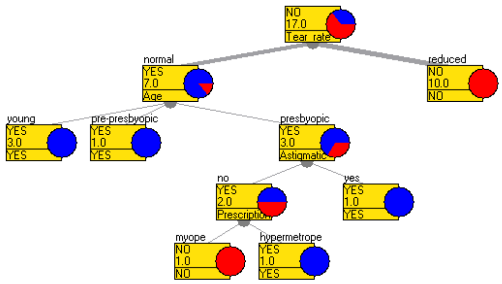
Decision tree



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)

Evaluating decision tree accuracy

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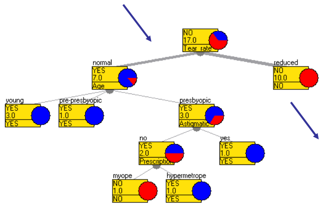

Ca = (3+2)/ (3+2+2+0) = 71%

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

Is 71% good classification accuracy?

- Depends on the dataset!
- Compare to the **majority class classifier** (ZeroR in Weka)
  - Classifies all the data in the most represented class
- In our Lenses example, the majority class is "Lenses=NO".
  - Accuracy on train set = 11/17 = 65%
  - Accuracy on test set = 4/7 = 57%
  - If we had bigger sets, these two numbers would be almost the same
- Since 71% > 57%, there is some improvement from the majority class classifier

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?