Data Mining and Knowledge Discovery Practice notes: Predictive data mining

Data Mining and Knowledge Discovery: Practice Notes

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- Prof. Nada Lavrač:
  - Data mining overview
  - Advanced topics
- Dr. Petra Kralj Novak
  - Data mining basis

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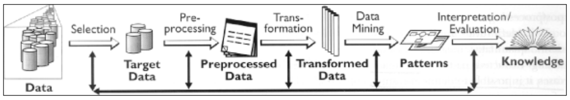
Keywords



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

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Practice plan

- 2014/11/11: Predictive data mining
  - Decision trees
  - Naïve Bayes classifier
  - Evaluating classifiers 1: separate test set, confusion matrix, classification accuracy
  - Hands on Weka: Predictive data mining
- 2014/12/9: Numeric prediction and descriptive data mining
  - Discussion on classification
  - Numeric prediction and evaluation in Weka
  - Association rules
  - Hands on Weka: Numeric prediction
  - Hands on Weka: Descriptive data mining
  - Discussion about seminars and exam
- 2014/12/16: Written exam, seminar proposal discussion
- 2014/1/21: Clowdflows platform and data mining seminar presentations

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Decision tree induction

Given
- Attribute-value data with nominal target variable

Induce
- A decision tree and estimate its performance on new data

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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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Practice notes: Predictive data mining

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**
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P15	pre-presbyopic	hypermetrope	yes	normal	**NO**
P16	pre-presbyopic	hypermetrope	yes	reduced	**NO**
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P18	presbyopic	myope	no	reduced	**NO**
P19	presbyopic	hypermetrope	no	normal	**YES**
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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**
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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

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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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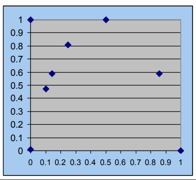

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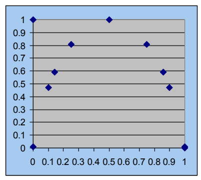
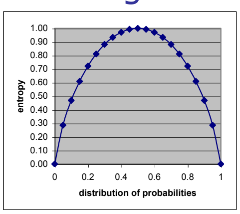


Entropy and information gain

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

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

set S

number of examples in set S

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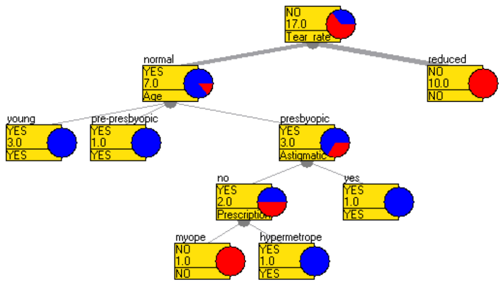
Decision tree



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:
  - Classification accuracy = (TP+TN) / (TP + TN + FP + FN)
  - Precision = TP / (TP + FP)
  - Recall = TP / (TP + FN)
  - …

Evaluating decision tree accuracy

Person	Age	Prescription	Astigmatic	Tear_Rate	Lenses
P3	young	hypermetrope	no	normal	**YES**
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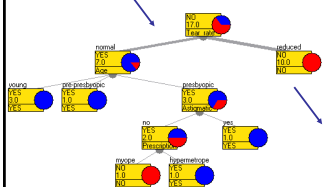

Ca = (3+2)/ (3+2+2+0) = 71%

	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

$v_1 =$ "$Color = white$"

$v_2 =$ "$Time = night$"

$c_1 = YES$

$c_2 = NO$

$$p(c_1|v_1, v_2) =$$
$$p(Caught = YES|Color = white, Time = night) =$$
$$p(Caught = YES) * \frac{p(Caught = YES|Color = white)}{p(Caught = YES)} * \frac{p(Caught = YES|Time = night)}{p(Caught = YES)} =$$
$$\frac{1}{2} * \frac{\frac{1}{2}}{\frac{1}{2}} * \frac{\frac{1}{4}}{\frac{1}{2}} = \frac{1}{4}$$

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K-fold cross validation

1. The sample set is partitioned into K subsets ("folds") of about equal size
2. A single subset is retained as the validation data for testing the model (this subset is called the "testset"), and the remaining K - 1 subsets together are used as training data ("trainset").
3. A model is trained on the trainset and its performance (accuracy or other performance measure) is evaluated on the testset
4. Model training and evaluation is repeated K times, with each of the K subsets used exactly once as the testset.
5. The average of all the accuracy estimations obtained after each iteration is the resulting accuracy estimation.

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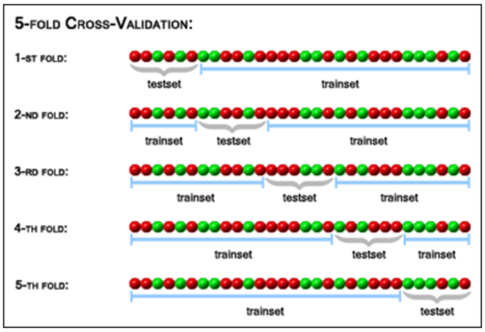

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Discussion

1. How much is the information gain for the “attribute” Person? How would it perform on the test set?
2. How do we compute entropy for a target variable that has three values? Lenses = {hard=4, soft=5, none=13}
3. What would be the classification accuracy of our decision tree if we pruned it at the node *Astigmatic*?
4. What are the stopping criteria for building a decision tree?
5. Why do we prune decision trees?
6. How would you compute the information gain for a numeric attribute?
7. Compare naïve Bayes and decision trees (similarities and differences) .
8. Can KNN be used for classification tasks?
9. Compare KNN and Naïve Bayes.
10. Compare cross validation and testing on a separate test set.
11. List 3 numeric prediction methods.
12. What is discretization.

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