Data Mining and Knowledge Discovery
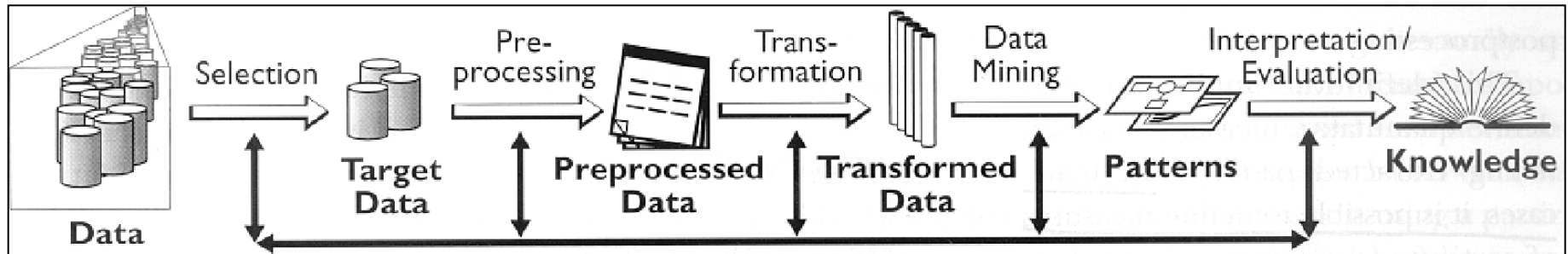
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2010/11/25

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

(the lecture will be repeated on 8.12.2010)

- Dr. Kralj Novak
  - Data mining basis

Keywords

- Data
  - Attribute, example, Attribute-value data, target variable, class, train set, test set
- 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
  - Accuracy, confusion matrix, cross validation, ROC space, error

Practice plan

- 2010/11/25: Predictive data mining
  - Decision trees
  - Naïve Bayes classifier
  - Evaluating classifiers (separate test set, cross validation, confusion matrix, classification accuracy)
  - Predictive data mining in Weka
- 2010/12/2: 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

- 2010/12/16: Written exam, Seminar proposal presentations

- 2011/2/1: deadline for data mining papers (written seminar)
- 2011/2/3: 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

attributes

(nominal) target variable

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)
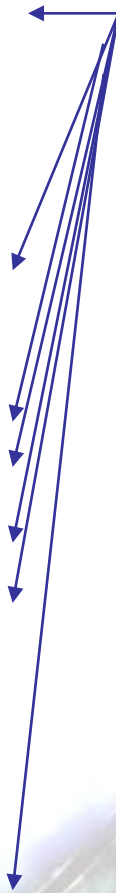
Induce a decision tree on training set S:
1. Compute the entropy E(S) of the set S
2. **IF** E(S) = 0
3.   The current set is "clean" and therefore a leaf in our tree
4. **IF** E(S) > 0
5.   Compute the information gain of each attribute Gain(S, A)
6.   The attribute A with the highest information gain 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**
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

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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**
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	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**
P24	presbyopic	hypermetrope	yes	reduced	**NO**

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) =

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

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

- Calculate the following entropies:
  E (0,1) = 0
  E (1/2 , 1/2) = 1
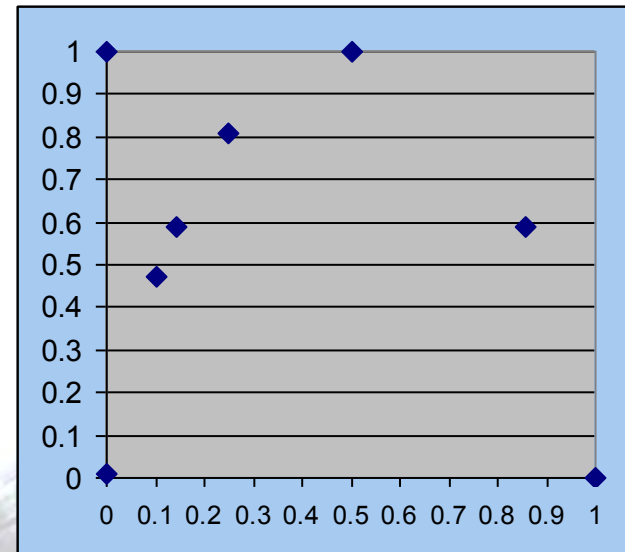 E (1/4 , 3/4) = 0.81
  E (1/7 , 6/7) = 0.59
  E (6/7 , 1/7) = 0.59
  E (0.1 , 0.9) = 0.47
  E (0.001 , 0.999) = 0.01

Entropy

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

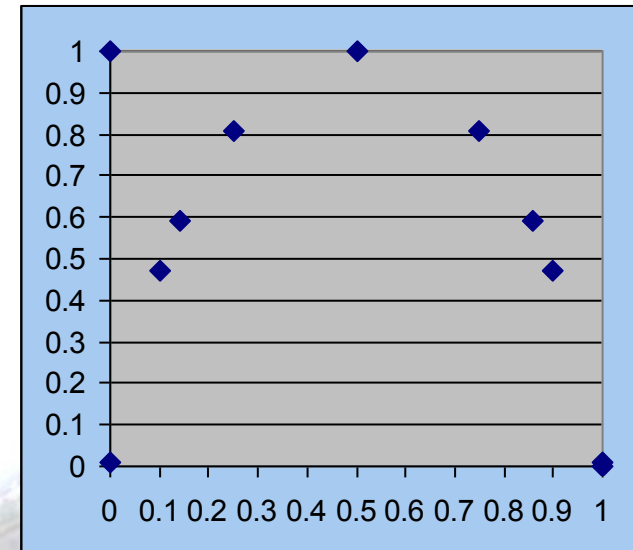- Calculate the following entropies:
  E (0,1) = 0
  E (1/2 , 1/2) = 1
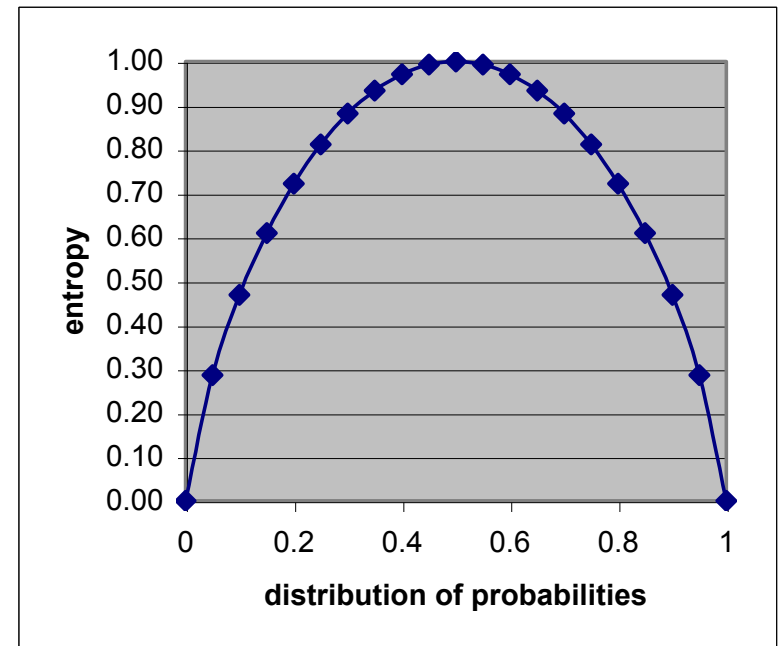 E (1/4 , 3/4) = 0.81
  E (1/7 , 6/7) = 0.59
  E (6/7 , 1/7) = 0.59
  E (0.1 , 0.9) = 0.47
  E (0.001 , 0.999) = 0.01

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Entropy and information gain

probability of class 1	probability of class 2	entropy E(p₁, p₂) =
p_1	$p_2 = 1-p_1$	$-p_1 * \log_2(p_1) - p_2 * \log_2(p_2)$
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

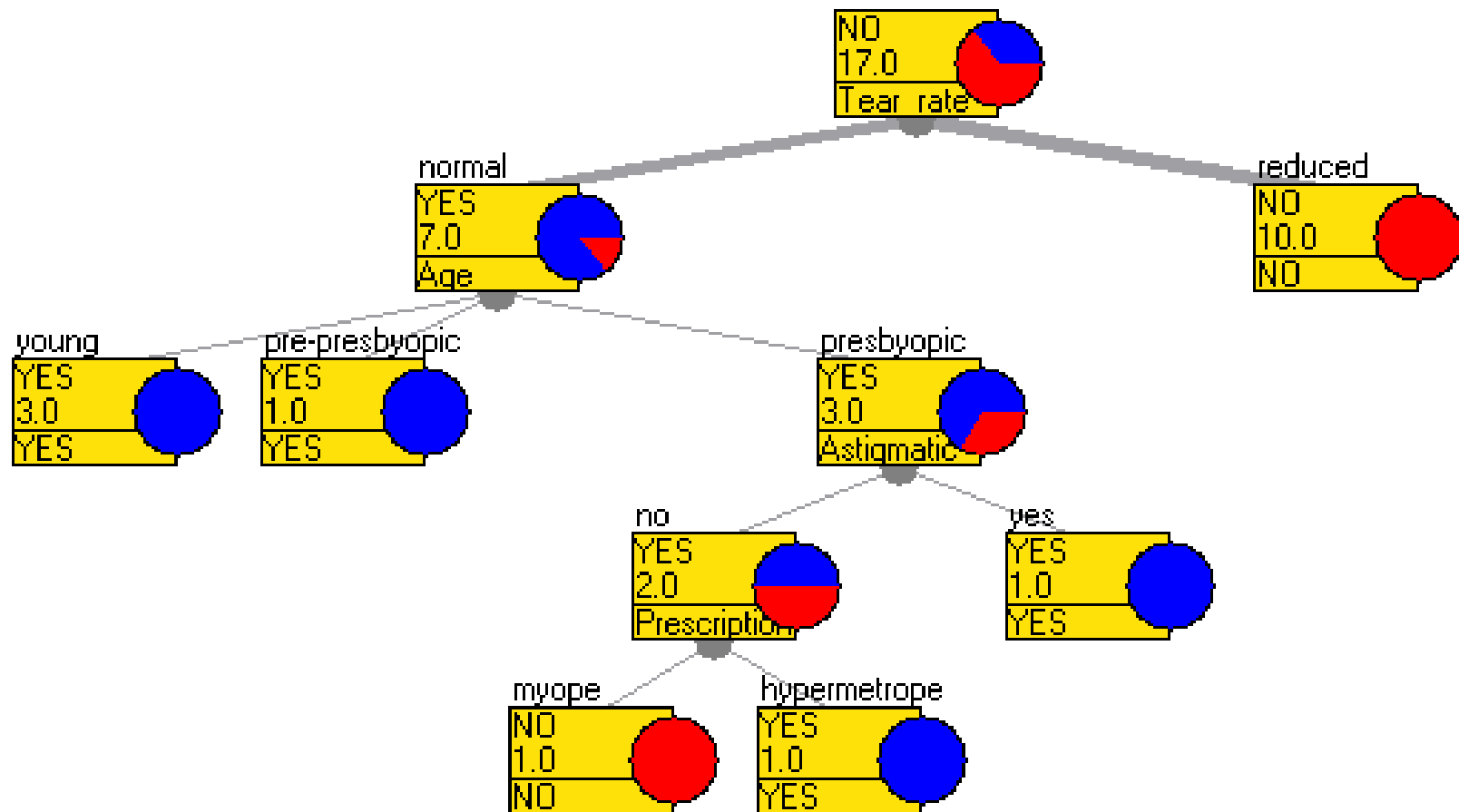entropy vs distribution of probabilities

attribut A

number of examples in the subset

probability of the "branch"

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

set S

number of examples in set S

Decision tree

Confusion matrix

predicted

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

actual

- 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

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**

$Ca = (3+2)/ (3+2+2+0) = 71\%$
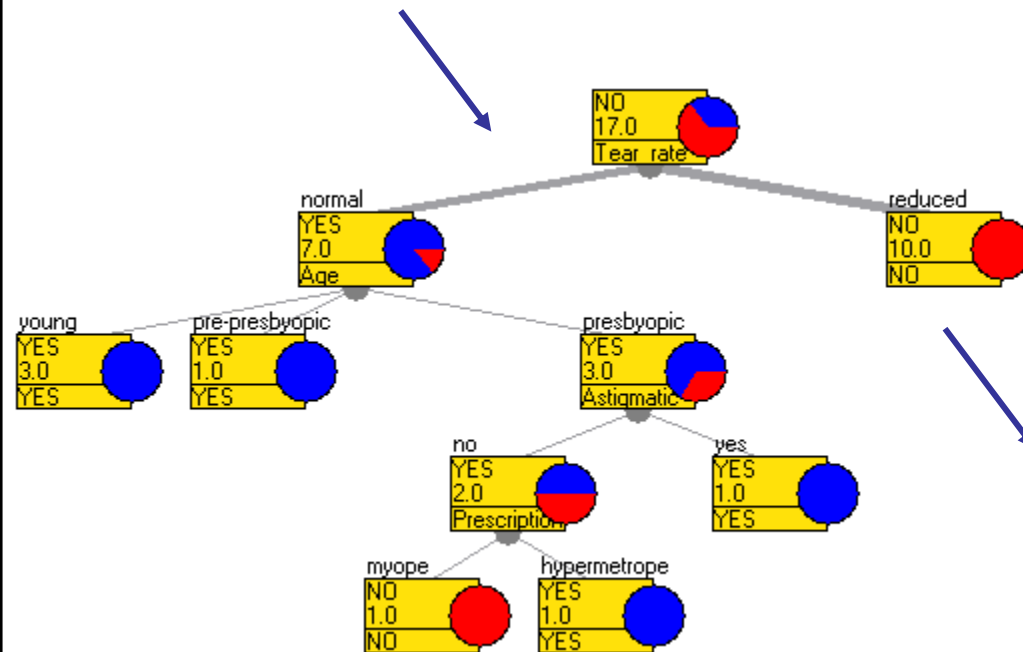
	Predicted positive	Predicted negative
Actual positive	TP=3	FN=0
Actual negative	FP=2	TN=2

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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

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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 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