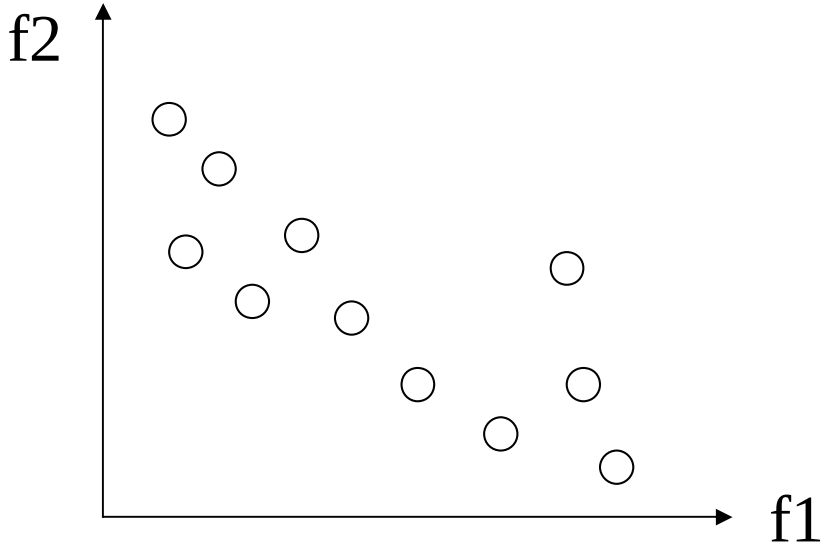
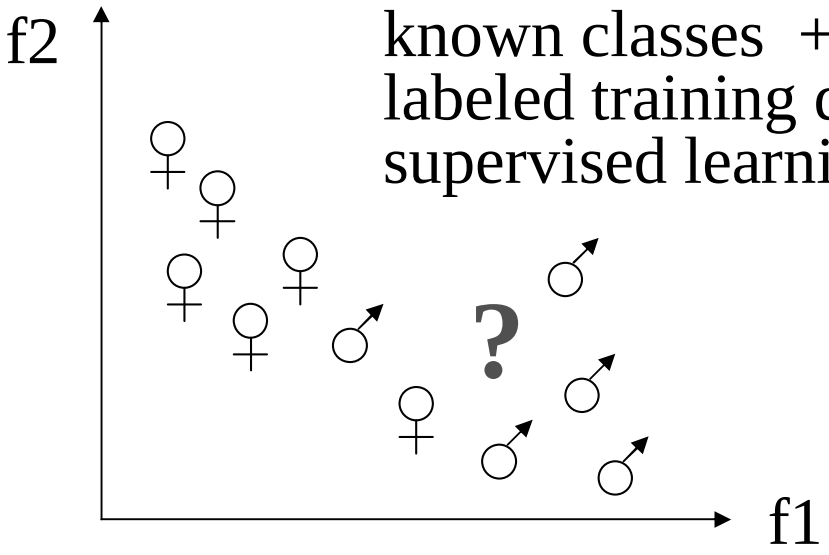
Chapter 6: Automatic Classification (Supervised Data Organization)

Classification Problem (Categorization)

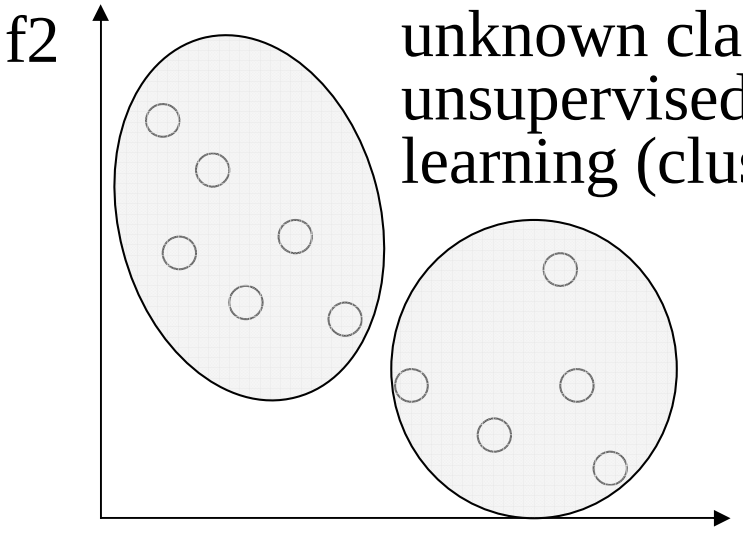
given:
feature vectors



determine class/topic
membership(s)
of feature vectors



known classes +
labeled training data:
supervised learning



unknown classes:
unsupervised
learning (clustering)

Uses of Automatic Classification in IR

- ***Filtering:*** test newly arriving documents (e.g. mail, news) if they belong to a class of interest (stock market news, spam, etc.)
- ***Summary/Overview:*** organize query or crawler results, directories, feeds, etc.
- ***Query expansion:*** assign query to an appropriate class and expand query by class-specific search terms
- ***Relevance feedback:*** classify query results and let the user identify relevant classes for improved query generation
- ***Word sense disambiguation:*** mapping words (in context) to concepts
- ***Query efficiency:*** restrict (index) search to relevant class(es)
- ***(Semi-) Automated portal building*:** automatically generate topic directories such as yahoo.com, dmoz.org, about.com, etc.

Classification variants:

- with terms, term frequencies, link structure, etc. as features
- binary: does a document d belong class c or not?
- many-way: into which of k classes does a document fit best?
- hierarchical: use multiple classifiers to assign a document to node(s) of topic tree

Automatic Classification in Data Mining

Goal:

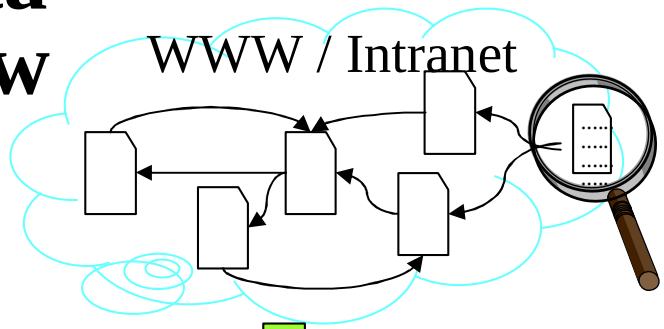
Categorize persons, business entities, or scientific objects
and predict their behavioral patterns

Application examples:

- categorize types of bookstore customers based on purchased books
- categorize movie genres based on title and casting
- categorize opinions on movies, books, political discussions, etc.
- identify high-risk loan applicants based on their financial history
- identify high-risk insurance customers based on
  observed demoscopic, consumer, and health parameters
- predict protein folding structure types based on
  specific properties of amino acid sequences
- predict cancer risk based on genomic, health, and other parameters

...

Classification with Training Data (Supervised Learning): Overview



Science

Mathematics

Algebra

Probability and Statistics

Hypotheses Testing

Large Deviation

classes

$c_k \in \left(R_0^+\right)^m$

feature space:

term frequencies f_i (i = 1, ..., m)

new documents

automatic assignment

estimate $P[d \in c_k \mid \vec{f}]$ and assign document to the class with the highest probability

e.g. with Bayesian method:

$$P[d \in c_k \mid \vec{f}] = \frac{P[\vec{f} \mid d \in c_k] \, P[d \in c_k]}{P[\vec{f}]}$$

intellectual assignment

training data

Assessment of Classification Quality

empirical by automatic classification of documents that
do not belong to the training data
(but in benchmarks class labels of test data are usually known)

For **binary classification** with regard to class C:

a = #docs that are classified into C and do belong to C
b = #docs that are classified into C but do not belong to C
c = #docs that are not classified into C but do belong to C
d = #docs that are not classified into C and do not belong to C

$$\text{Acccuracy (Genauigkeit)} = \frac{a+d}{a+b+c+d} \qquad \text{Error (Fehler)} = 1 - \text{accuracy}$$

$$\text{Precision (Präzision)} = \frac{a}{a+b} \qquad \text{Recall (Ausbeute)} = \frac{a}{a+c}$$

$$\text{F1 (harmonic mean of precision and recall)} = \left(\frac{1}{precision} + \frac{1}{recall} \right)^{-1}$$

For **manyway classification** with regard to classes C_1, ..., C_k:

- macro average over k classes or
- micro average over k classes

Estimation of Classifier Quality

use benchmark collection of completely labeled documents
(e.g., Reuters newswire data from TREC benchmark)

cross-validation (with held-out training data):
- partition training data into k equally sized (randomized) parts,
- for every possible choice of k-1 partitions
  - train with k-1 partitions and apply classifier to k^{th} partition
  - determine precision, recall, etc.
- compute micro-averaged quality measures

leave-one-out validation/estimation:
variant of cross-validation with two partitions of unequal size:
use n-1 documents for training and classify the n^{th} document

6. 1 Distance-based Classifiers: k-Nearest-Neighbor Method (kNN)

Step 1:
find among the training documents of all classes the k (e.g. 10-100) most similar documents (e.g., based on cosine similarity):
the k nearest neighbors of $\vec{d}$

Step 2:
Assign $\vec{d}$ to class Cj for which the function value

$$f(\vec{d}, C_j) = \sum_{\vec{v} \in kNN(\vec{d})} sim(\vec{d}, \vec{v}) * \begin{cases} 1 \text{ if } \vec{v} \in C_j \\ 0 \text{ otherwise} \end{cases}$$

is maximized

With binary classification assign $\vec{d}$ to class C if
$f(\vec{d}, C)$ is above some threshold δ ($\delta > 0.5$)

Distance-based Classifiers: Rocchio Method

Step 1:
Represent the training documents for class Cj
by a **prototype vector** with tf*idf-based vector components

$$\vec{c}_j := \alpha \frac{1}{|C_j|} \sum_{\vec{d} \in C_j} \frac{\vec{d}}{\|\vec{d}\|} - \beta \frac{1}{|D - C_j|} \sum_{\vec{d} \in D - C_j} \frac{\vec{d}}{\|\vec{d}\|}$$

with appropriate coefficients α and β (e.g. α=16, β=4)

Step 2:
Assign a new document $\vec{d}$ to the class Cj for which
the cosine similarity $cos(\vec{c}_j, \vec{d})$ is maximized.

6.2 Feature Selection

For *efficiency* of the classifier and to *suppress noise*
choose subset of all possible features.
→ Selected features should be

- frequent to *avoid overfitting* the classifier to the training data,
- but not too frequent in order to be characteristic.

Features should be good ***discriminators*** between classes
(i.e. frequent/characteristic in one class but infrequent in other classes).

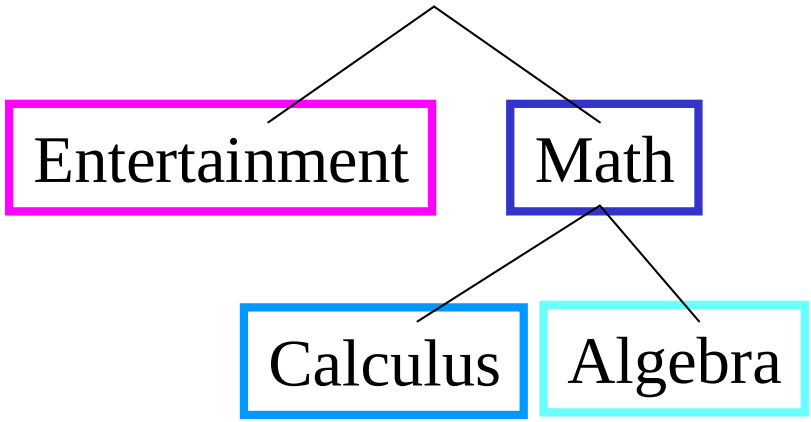
Approach:
- compute measure of discrimination for each feature
- select the top k most discriminative features in greedy manner

tf*idf is usually not a good discrimination measure,
and may give undue weight to terms with high idf value
(leading to the danger of overfitting)

Example for Feature Selection

	film	hit	chart	theorem	limit	integral	group	vector
	f1	f2	f3	f4	f5	f6	f7	f8
d1:	1	1	0	0	0	0	0	0
d2:	0	1	1	0	0	0	1	0
d3:	1	0	1	0	0	0	0	0
d4:	0	1	1	0	0	0	0	0
d5:	0	0	0	1	1	1	0	0
d6:	0	0	0	1	0	1	0	0
d7:	0	0	0	0	1	0	0	0
d8:	0	0	0	1	0	1	0	0
d9:	0	0	0	0	0	0	1	1
d10:	0	0	0	1	0	0	1	1
d11:	0	0	0	1	0	1	0	1
d12:	0	0	1	1	1	0	1	0

Class Tree:



training docs:

d1, d2, d3, d4
→ Entertainment

d5, d6, d7, d8
→ Calculus

d9, d10, d11, d12
→ Algebra

Simple (Class-unspecific) Criteria for Feature Selection

Document Frequency Thresholding:
Consider for class Cj only terms ti that occur in at least δ training documents of Cj.

Term Strength:
For decision between classes C1, ..., Ck select (binary) features Xi with the highest value of

$$s(X_i) := P[X_i \text{ occurs in doc } d \mid X_i \text{ occurs in similar doc } d']$$

To this end the set of similar doc pairs (d, d‘) is obtained
- by thresholding on pairwise similarity or
- by clustering/grouping the training docs.

+ further possible criteria along these lines

Feature Selection Based on χ^2 Test

For class Cj select those terms for which the χ^2 test (performed on the training data) gives the highest confidence that Cj and ti are *not* independent.

As a discrimination measure compute for each class Cj and term ti:

$$\chi^2(X_i, c_j) = \sum_{X \in \{X_i, \bar{X}_i\}} \sum_{C \in \{C_j, \bar{C}_j\}} \left(\frac{(freq(X \wedge C) - freq(X)\, freq(C)/n)^2}{freq(X)\, freq(C)/n} \right.$$

with absolute frequencies *freq*

Feature Selection Based on Information Gain

Information gain:
For discriminating classes c1, ..., ck select the binary features Xi (term occurrence) with the largest gain in entropy

$$G(Xi) = \sum_{j=1}^{k} P[c_j] \log_2 \frac{1}{P[c_j]}$$

$$- P[X_i] \sum_{j=1}^{k} P[c_j \mid X_i] \log_2 \frac{1}{P[c_j \mid X_i]}$$

$$- P[\overline{X}_i] \sum_{j=1}^{k} P[c_j \mid \overline{X}_i] \log_2 \frac{1}{P[c_j \mid \overline{X}_i]}$$

can be computed in time O(n)+O(mk)
for n training documents, m terms, and k classes

Feature Selection Based on Mutual Information

Mutual information (Kullback-Leibler distance, relative entropy): for class cj select those binary features Xi (term occurrence) with the largest value of

$$MI(X_i, c_j) = \sum_{X \in \{X_i, \bar{X}_i\}} \sum_{C \in \{c_j, \bar{c}_j\}} P[X \wedge C] \log \frac{P[X \wedge C]}{P[X]\,P[C]}$$

and for discriminating classes c1, ..., ck:

$$MI(X_i) = \sum_{j=1}^{k} P[c_j] MI(X_i, c_j)$$

can be computed in time O(n)+O(mk) for n training documents, m terms, and k classes

Example for Feature Selection Based on χ^2, G, and MI

assess goodness of term „chart (c)“ for
discriminating classes „Entertainment (E)“ vs. „Math (M)“

base statistics:
n=12 training docs; f(E) = 4 docs in E; f(M)=8 docs in M;
f(c)=4 docs contain c; f($\overline{c}$)=8 docs don‘t contain c;
f(cE)=3 docs in E contain c; f(cM)=1 doc in M contains c;
f($\overline{c}$ E)=1 doc in E doesn‘t contain c; f($\overline{c}$ M)=7 docs in M don‘t contain c;
p(c)=4/12=prob. of random doc containing c
p(cE)=3/12=prob. of random doc containing c and being in E etc.

χ^2(chart) = (f(cE)-f(c)f(E)/n)^2) / (f(c)f(E)/n) + ... (altogether four cases)
= (3 – 4*4/12)^2 / (4*4/12) + (1 – 4*8/12)^2 / (4*8/12) +
(1 – 8*4/12)^2 / (8*4/12) + (7 – 8*8/12)^2 / (8*8/12)

G(chart) = p(E) log 1/p(E) + p(M) log 1/p(M)
– p(c) (p(cE) log 1/p(cE) + p(cM log 1/p(cM)) – p($\overline{c}$) (analogously for $\overline{c}$)
= 1/3 log3 + 2/3 log3/2 – 4/12 (3/4 log4/3 + 1/4 log4) – 8/12 (1/8 log 8 + 7/8 log 8/7)

MI(chart) = p(cE) log (p(cE) / (p(c)p(E))) + ... (altogether four cases)
= 3/12 log (3/12 / (4*4/144)) + 1/12 log (1/12 / (4*8/144)) +
1/12 log (1/12 / (8*4/144)) + 7/12 log (7/12 / (8*8/144))

Feature Selection Based on Fisher Index

For document sets X in class C and Y not in class C find m-dimensional vector α that maximizes

$$\frac{(\alpha^T(\mu_X - \mu_Y))^2}{\alpha^T(S_X + S_Y)\alpha}$$

Fisher's discriminant
(finds projection α that maximizes ratio of projected centroid distance to variance)

with covariance matrix: $S_X = \frac{1}{card(X)} \sum_{x \in X} (x - \mu_X)(x - \mu_X)^T$

solution requires inversion of $S = (S_X + S_Y)/2$

For feature selection consider vectors α_j = (0 ... 0 1 0 ... 0) with 1 at the position of the j-th term and compute

$$FI(X,Y) = \frac{(\alpha_j{}^T(\mu_X - \mu_Y))^2}{\alpha_j{}^T S \alpha_j}$$

Fisher's index (FI)
(indicates feature contribution to good discrimination vector)

Select features with highest FI values

Feature Space Truncation Using Markov Blankets

Idea:

start with all features F and a drop feature X if there is an approximate Markov blanket M for X in F-{X}:

M is a **Markov blanket** for X in F if X is conditionally independent of F – (M∪{X}) given M.

Algorithm:

F‘ := F

while distribution $P[C_k \mid F']$ is close enough to original $P[C_k \mid F]$ do

for each X in F‘ do

identify candidate Markov blanket M for X

(e.g. the k most correlated features)

compute KL distance between

distributions $P[C_k \mid M \cup \{X\}]$ and $P[C_k \mid M]$ over classes C_k

end

eliminate feature X with smallest KL distance: F‘ := F – {X}

end

Advantage over greedy feature selection: considers feature combinations

6.3 Distribution-based Classifiers: Naives Bayes with Binary Features Xi

estimate: $P[\, d \in c_k \,|\, d \text{ has } \vec{X}\,] = \dfrac{P[\, d \text{ has } \vec{X} \,|\, d \in c_k\,]\, P[\, d \in c_k\,]}{P[\, d \text{ has } \vec{X}\,]}$

$\sim P[\, X \,|\, d \in c_k\,]\, P[\, d \in c_k\,]$

$= \Pi_{i=1}^{m} P[\, X_i \,|\, d \in c_k\,]\, P[\, d \in c_k\,]$

with feature independence or linked dependence:

$$\frac{P[\, X \,|\, d \in c_k\,]}{P[\, X \,|\, d \notin c_k\,]} = \Pi_i \frac{P[\, X_i \,|\, d \in c_k\,]}{P[\, X_i \,|\, d \notin c_k\,]}$$

$= \Pi_{i=1}^{m} p_{ik}^{\,Xi} (1 - p_{ik})^{1-Xi}\, p_k$

with empirically estimated $p_{ik}=P[X_i=1|c_k]$, $p_k=P[c_k]$

$$\Rightarrow \log P[c_k \,|\, d] \sim \sum_{i=1}^{m} X_i \log \frac{p_{ik}}{(1-p_{ik})} + \sum_{i=1}^{m} \log(1-p_{ik}) + \log p_k$$

for binary classification with odds rather than probs for simplification

Naive Bayes with Binomial Bag-of-Words Model

estimate: $P[\, d \in c_k \,|\, d \text{ has } \vec{f}\,] \sim P[\, \vec{f} \,|\, d \in c_k\,]\, P[\, d \in c_k\,]$

with term frequency vector $\vec{f}$

$= \Pi_{i=1}^{m} P[\, f_i \,|\, d \in c_k\,]\, P[\, d \in c_k\,]$ with feature independence

$= \Pi_{i=1}^{m} \binom{length(d)}{f_i} p_{ik}^{\,f_i} (1 - p_{ik})^{length(d) - f_i}\; p_k$

with binomial distribution for each feature

using ML estimator: $p_{ik} = \sum_{d \in c_k} tf(t_i, d) \,/\, \sum_{d \in c_k} length(d)$

satisfying $\sum_i p_{ik} = 1$

or with Laplace smoothing: $p_{ik} = \left(1 + \sum_{d \in c_k} tf(f_i, d)\right) / \left(m + \sum_{d \in c_k} length(d)\right)$

Naive Bayes with Multinomial Bag-of-Words Model

estimate: $P[\, d \in c_k \,|\, d \text{ has } \vec{f}\,] \sim P[\, \vec{f} \,|\, d \in c_k\,]\, P[\, d \in c_k\,]$

with term frequency vector $\vec{f}$

$= \Pi_{i=1}^{m} P[\, f_i \,|\, d \in c_k\,]\, P[\, d \in c_k\,]$ with feature independence

$$= \binom{length(d)}{f_1\, f_2 \ldots f_m}\, p_{1k}^{f_1}\, p_{2k}^{f_2} \ldots p_{mk}^{f_m}\; p_k$$

with $\binom{n}{k_1\, k_2 \ldots k_m} := \frac{n!}{k_1!\, k_2! \ldots k_m!}$ with multinomial distribution of features and constraint

$$\sum_{i=1}^{m} f_i = length(d)$$

Example for Naive Bayes

3 classes: c1 – Algebra, c2 – Calculus, c3 – Stochastics

8 terms, 6 training docs d1, ..., d6: 2 for each class

$\Rightarrow$ p1=2/6, p2=2/6, p3=2/6

	group	homomorphism	vector	integral	limit	variance	probability	dice
	f1	f2	f3	f4	f5	f6	f7	f8
d1:	3	2	0	0	0	0	0	1
d2:	1	2	3	0	0	0	0	0
d3:	0	0	0	3	3	0	0	0
d4:	0	0	1	2	2	0	1	0
d5:	0	0	0	1	1	2	2	0
d6:	1	0	1	0	0	0	2	2

	Algebra	Calculus	Stochastics
	k=1	k=2	k=3
p1k	4/12	0	1/12
p2k	4/12	0	0
p3k	3/12	1/12	1/12
p4k	0	5/12	1/12
p5k	0	5/12	1/12
p6k	0	0	2/12
p7k	0	1/12	4/12
p8k	1/12	0	2/12

without smoothing
for simple calculation

Example of Naive Bayes (2)

classification of d7: (0 0 1 2 0 0 3 0)

$$P[\,\vec{f}\,|d\in c_k\,]\,P[\,d\in c_k\,] = \binom{length(d)}{f_1\ f_2 \dots f_m}\, p_{1k}^{\,f_1}\ p_{2k}^{\,f_2} \dots p_{mk}^{\,f_m}\quad p_k$$

for k=1 (Algebra): $= \binom{6}{1\ 2\ 3}\left(\frac{3}{12}\right)^1 0^2\, 0^3 \quad \frac{2}{6} \qquad = 0$

for k=2 (Calculus): $= \binom{6}{1\ 2\ 3}\left(\frac{1}{12}\right)^1\left(\frac{5}{12}\right)^2\left(\frac{1}{12}\right)^3 \quad \frac{2}{6} \qquad = 20 * \frac{25}{12^6}$

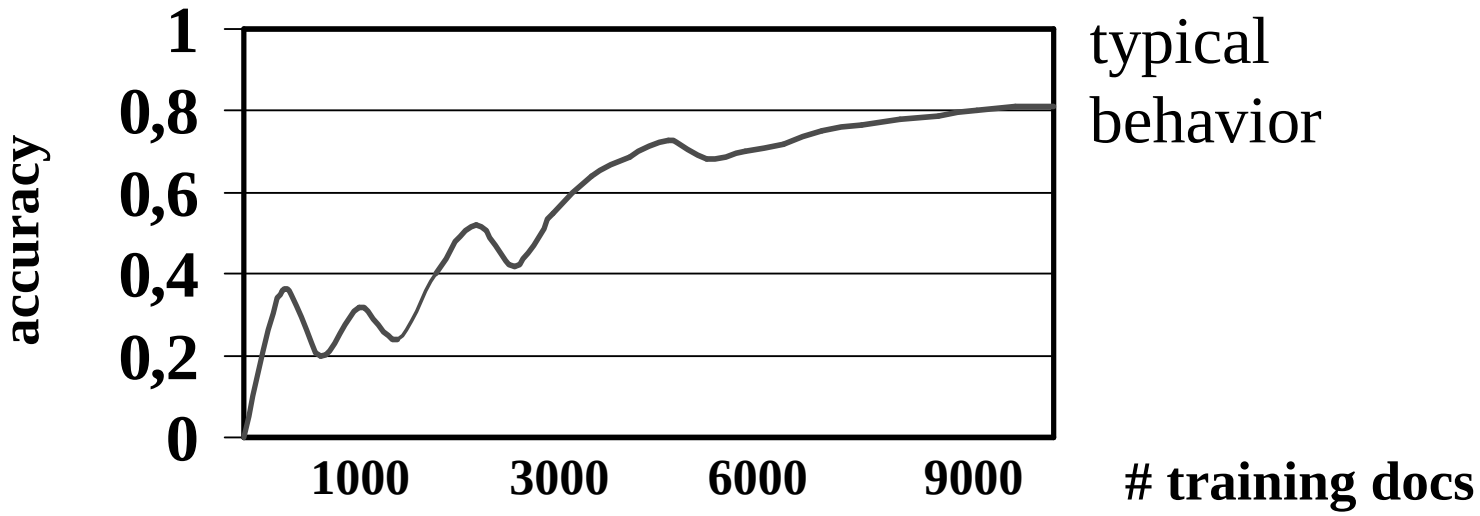
for k=3 (Stochastics): $= \binom{6}{1\ 2\ 3}\left(\frac{1}{12}\right)^1\left(\frac{1}{12}\right)^2\left(\frac{4}{12}\right)^3 \quad \frac{2}{6} \qquad = 20 * \frac{64}{12^6}$

Result: assign d7 to class C3 (Stochastics)

Typical Behavior of the Naive Bayes Method

Reuters Benchmark (see trec.nist.gov):
12902 short newswire articles (business news)
from 90 categories (acq, corn, earn, grain, interest, money-fx, ship, ...)

- Use (a part of) the oldest 9603 articles for training the classifier
- Use the most recent 3299 articles for testing the classifier



max. accuracy is between 50 and 90 percent (depending on category)

Improvements of the Naive Bayes Method

1) smoothed estimation of the p_{ik} values (e.g. Laplace smoothing)

2) classify unlabeled documents and use their terms
for better estimation of p_{ik} values (i.e., the model parameters)
possibly using different weights for term frequencies in
real training docs vs. automatically classified docs

$\rightarrow$ Section 6.7 on semisupervised classification

3) consider most important correlations between features
by extending the approach to a Bayesian net

Framework for Bayes Optimal Classifiers

Use any suitable parametric model for
the joint distribution of features and classes,
with parameters θ for (assumed) prior distribution (e.g. Gaussian)

A classifier for class c that maximizes

$$P[c \mid d] = \sum_{\theta} P[c \mid d, \theta] \, P[\theta \mid D]$$

$$= \sum_{\theta} \frac{P[c \mid \theta] \, P[d \mid c, \theta]}{\sum_{\gamma} P[\gamma \mid \theta] \, P[d \mid \gamma, \theta]} P[\theta \mid D]$$

for given test document d and training data D is called Bayes optimal

Maximum Entropy Classifier

Approach for estimating $P[\, d \in C_k \;\; and \;\; d \;\; has \;\; \vec{f}\,]$:
estimate parameters of probability distribution such that

- the expectations E_{ik} for all features f_i and classes C_k match the empirical mean values M_{ik} (derived from n training vectors) and
- have maximum entropy (i.e. postulate uniform distribution unless the training data indicate a different distribution)

  → distribution has loglinear form

  with normalization constant Z: $P\,[\, C_k\,, \vec{f}\,] \;=\; \frac{1}{Z}\, \Pi_i\, \alpha_i^{\,f_{ik}}$

Compute parameters α_i by iterative procedure
(generalized iterative scaling),
which is guaranteed to converge under specific conditions

6.4 Discriminative Classifiers: Decision Trees

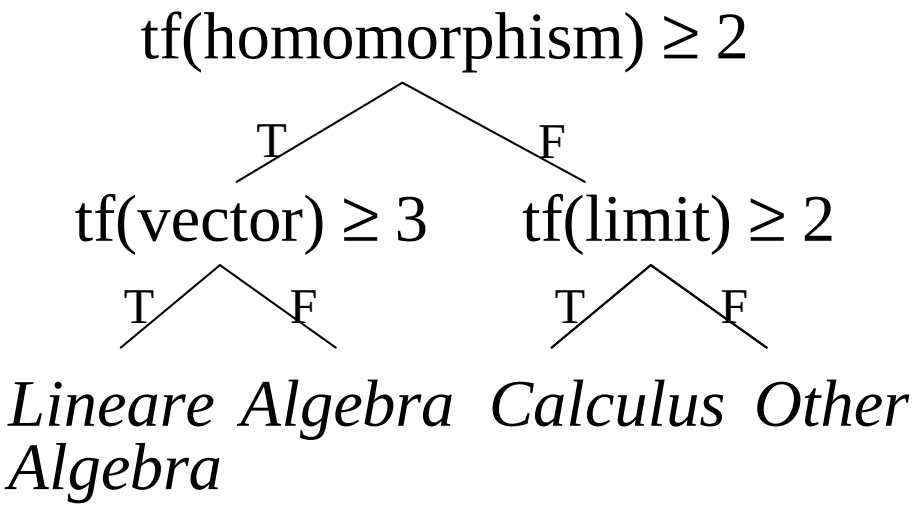
given: a multiset of **m-dimensional training data records** $\subseteq \text{dom}(A1) \times ... \times \text{dom}(Am)$ with numerical, ordinal, or categorial attributes Ai (e.g. term occurrence frequencies $\subseteq N_0 \times ... \times N_0$) and with **class labels**

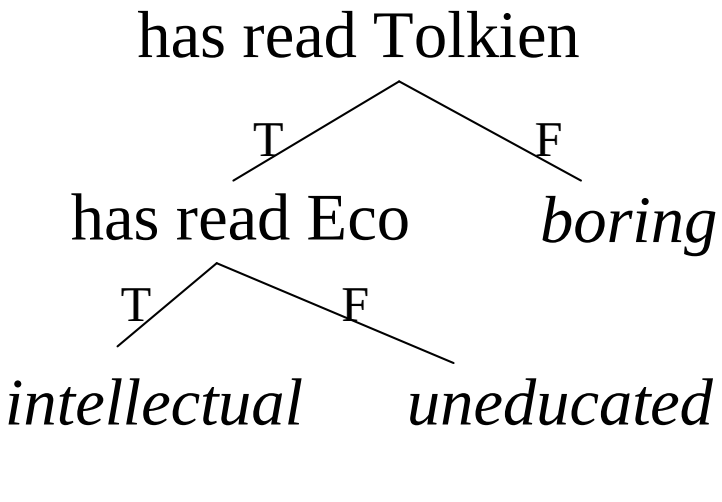
wanted: a **tree** with

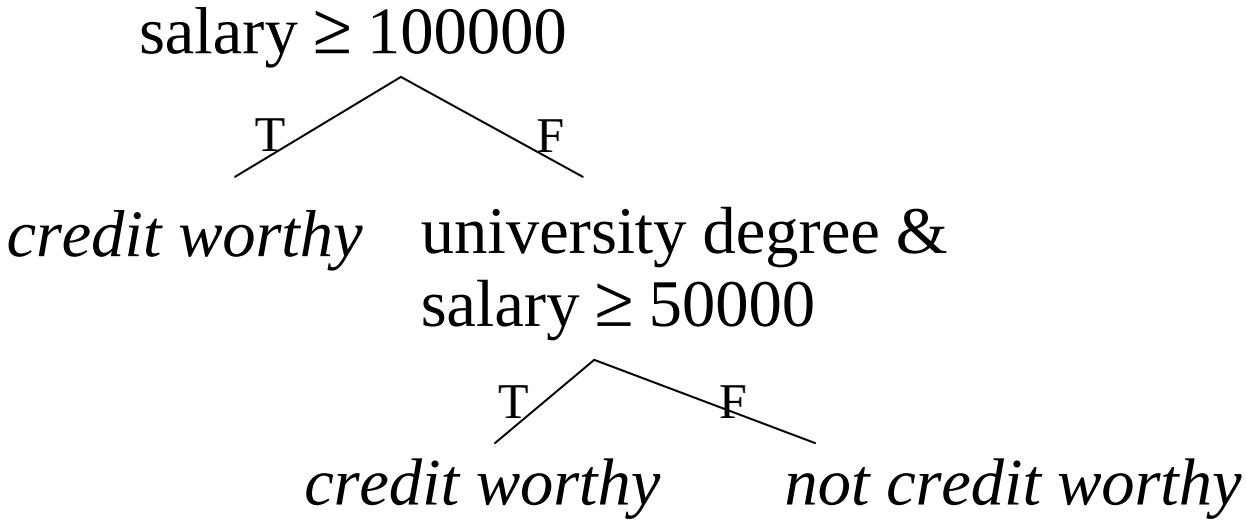
- **attribute value conditions** of the form
  - Ai ≤ value for numerical or ordinal attributes
    or
  - Ai ∈ value set or Ai ∩ value set = ∅
    for categorial attributes
    or
  - linear combinations of this type $\sum k_i A_i \leq value$
    for several numerical attributes

  as inner nodes and
- **labeled classes as leaf nodes**

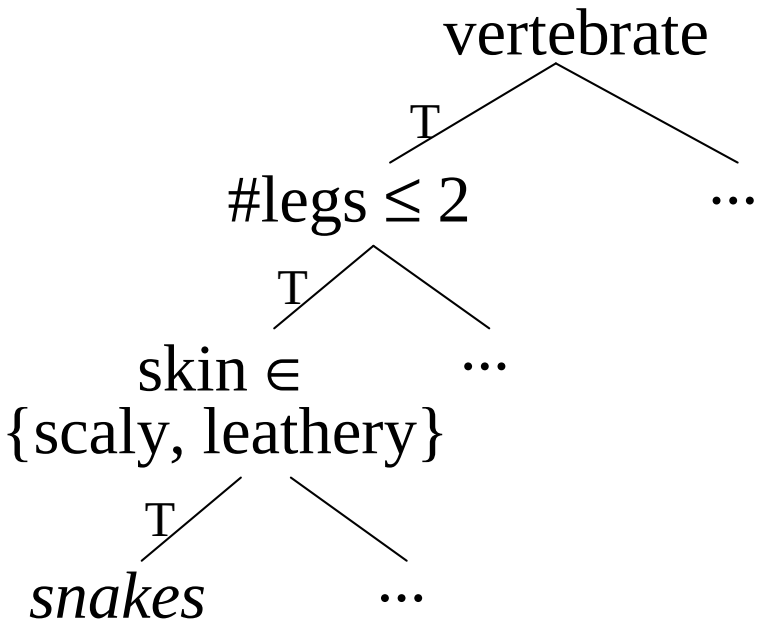
Examples for Decision Trees (1)

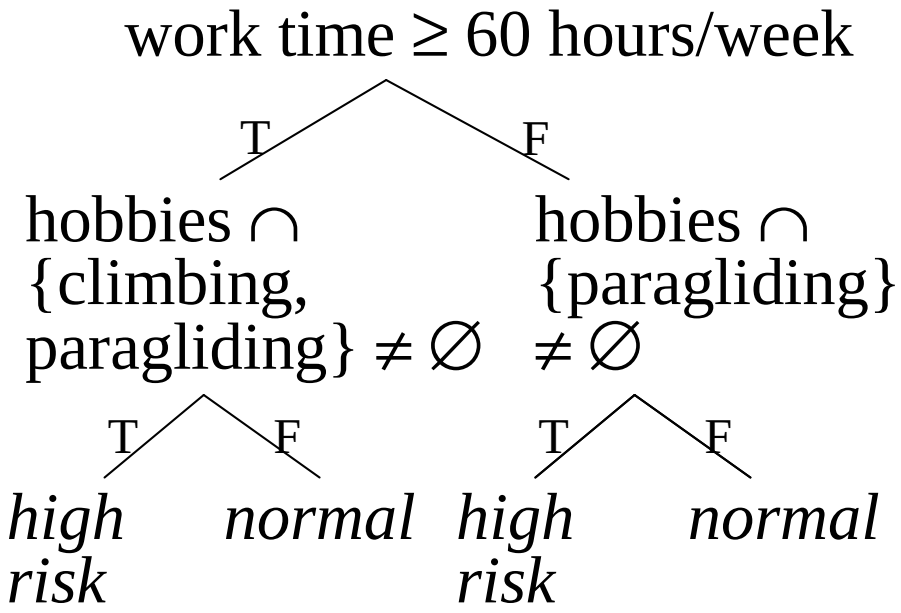


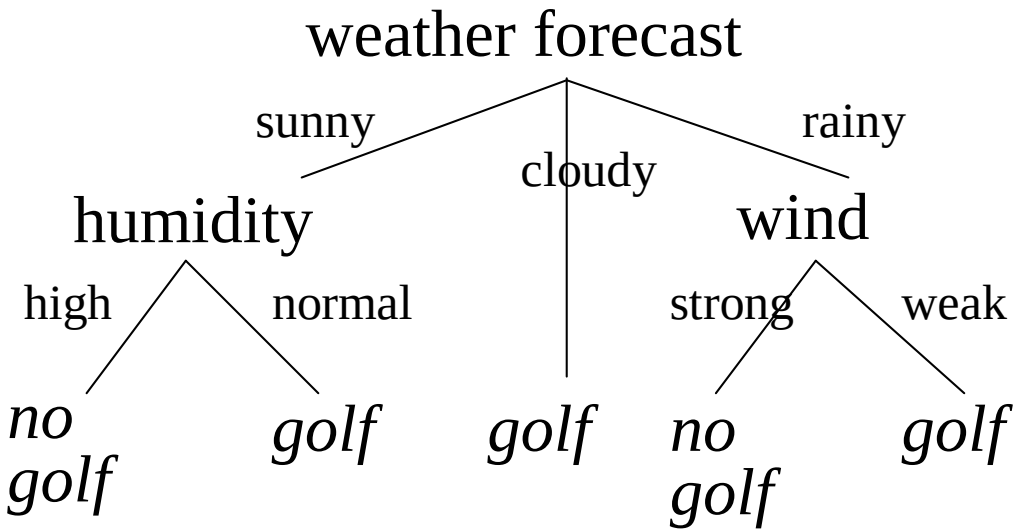




Examples for Decision Trees (2)







Top-Down Construction of Decision Tree

Input: decision tree node k that represents one partition D of $dom(A1) \times ... \times dom(Am)$

Output: decision tree with root k

1) BuildTree (root, $dom(A1) \times ... \times dom(Am)$)
2) PruneTree: reduce tree to appropriate size

with:

procedure BuildTree (k, D):

if k contains only training data of the same class then terminate;
determine split dimension Ai;
determine split value x for most suitable partitioning of D into
$D1 = D \cap \{d \mid d.Ai \leq x\}$ and $D2 = D \cap \{d \mid d.Ai > x\}$;
create children k1 and k2 of k;
BuildTree (k1, D1); BuildTree (k2, D2);

Split Criterion Information Gain

Goal is to split current node such that the resulting partitions are as pure as possible w.r.t. class labels of the corresponding training data. Thus we aim to minimize the **impurity** of the partitions.

An approach to define impurity is via the entropy-based (statistical) **information gain**
(referring to the distribution of class labels within a partition)

$$G(k, k1, k2) = H(k) - (p1*H(k1) + p2*H(k2))$$

where:

n_k: # training data records in k

$n_{k,j}$: # training data records in k that belong to class j

$p1 = n_{k1} / n_k$ and $p2 = n_{k2} / n_k$

$$H(k) = -\sum_j \frac{n_{k,j}}{n_k} log_2 \frac{n_{k,j}}{n_k}$$

Alternative Split Criteria

1) split such that the ***entropy*** of k1 and k2 is minimized:

p1*H(k1) + p2*H(k2)

2) split such that GI(k1)+GI(k2) is minimized
with the ***„Gini index“*:**

$$GI(k) = 1 - \sum_j \left(\frac{n_{k,j}}{n_k} \right)^2$$

3) The information gain criterion prefers branching by attributes with large domains (many different values)
Alternative:
split criterion ***information gain ratio***

$$G(k, k1, k2) / H(k)$$

Criteria for Tree Pruning

Problem: complete decision trees with absolutely pure leaf nodes tend to **overfitting** – branching even in the presence of rather insignificant training data („noise“):

this minimizes the classification error on the training data, but may not generalize well to new test data

Solution: remove leaf nodes until only significant branching nodes are left, using the principle of

Minimum Description Length (MDL):

describe the class labels of all training data records with minimal length (in bits)

- K bits per tree node (attribute, attribute value, pointers)
- n_k*H(k) bits for explicit class labels of all n_k training data records of a leaf node k with

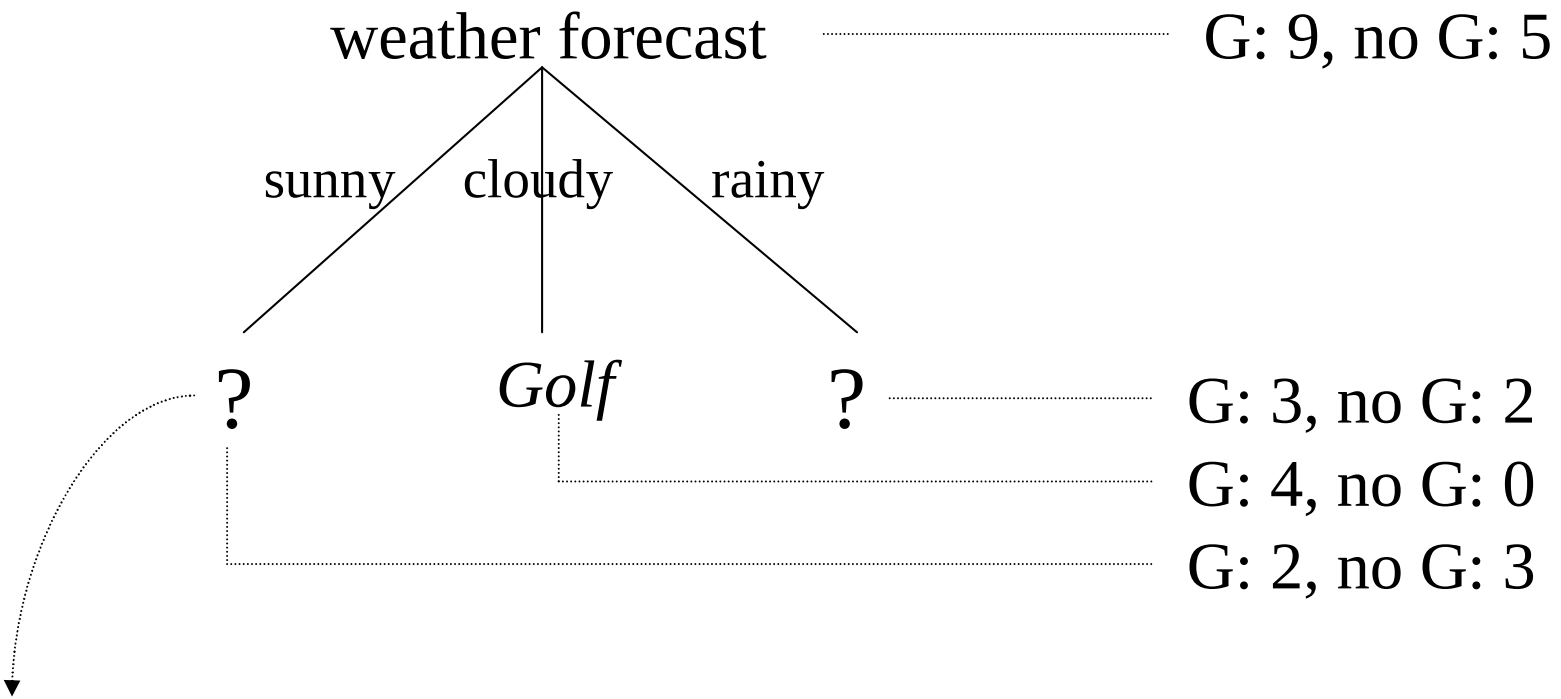
$$H(k) = -\sum_j \frac{n_{k,j}}{n_k} log_2 \frac{n_{k,j}}{n_k}$$

Example for Decision Tree Construction (1)

Training data:

	weather forecast	temperature	humidity	wind	golf
1)	sunny	hot	high	weak	no
2)	sunny	hot	high	strong	no
3)	cloudy	hot	high	weak	yes
4)	rainy	mild	high	weak	yes
5)	rainy	cold	normal	weak	yes
6)	rainy	cold	normal	strong	no
7)	cloudy	cold	normal	strong	yes
8)	sunny	mild	high	weak	no
9)	sunny	cold	normal	weak	yes
10)	rainy	mild	normal	weak	yes
11)	sunny	mild	normal	strong	yes
12)	cloudy	mild	high	strong	yes
13)	cloudy	hot	normal	weak	yes
14)	rainy	mild	high	strong	no

Example for Decision Tree Construction (2)



data records: 1, 2, 8, 9, 11

entropy H(k): $2/5*\log_2 5/2 + 3/5*\log_2 5/3 \approx 2/5*1.32 + 3/5*0.73 \approx 0.970$

choice of split attribute:

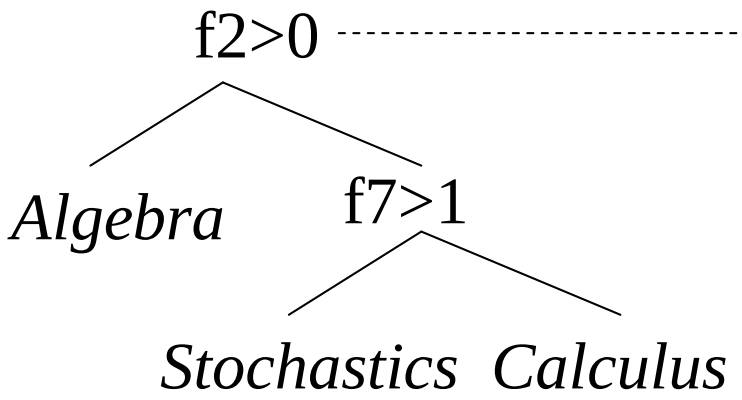
G(humidity): $0.970 - 3/5*0 - 2/5*0 = 0.970$

G(temperature): $0.970 - 2/5*0 - 2/5*1 - 1/5*0 = 0.570$

G(wind): $0.970 - 2/5*1 - 3/5*0.918 = 0.019$

Example for Decision Tree for Text Classification

		group	homomorphism	vector	integral	limit	variance	probability.	dice
		f1	f2	f3	f4	f5	f6	f7	f8
C1: Algebra	d1:	3	2	0	0	0	0	0	1
	d2:	1	2	3	0	0	0	0	0
C2: Calculus	d3:	0	0	0	3	3	0	0	0
	d4:	0	0	1	2	2	0	1	0
C3: Stochastics	d5:	0	0	0	1	1	2	2	0
	d6:	1	0	1	0	0	0	2	2



$G = H(k) - (2/6*H(k1) + 4/6*H(k2))$

$H(k) = 1/3 \log 3 + 1/3 \log 3 + 1/3 \log 3$

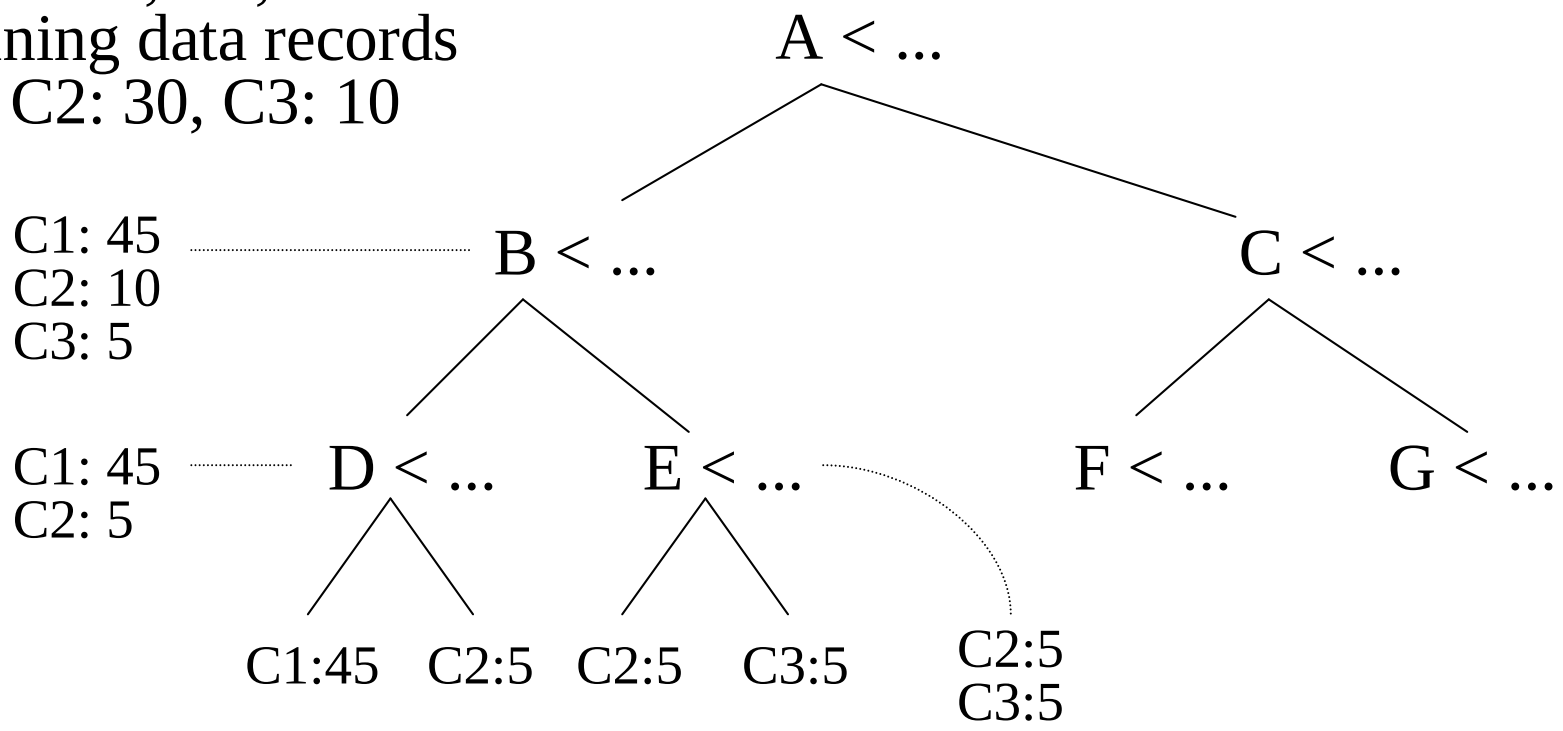
$H(k1) = 1 \log 1 + 0 + 0$

$H(k2) = 0 + 1/2 \log 2 + 1/2 \log 2$

$G = \log 3 - 0 - 2/3*1 \approx 1,6 - 0,66 = 0,94$

Example for Decision Tree Pruning

3 classes: C1, C2, C3
100 training data records
C1: 60, C2: 30, C3: 10



Assumption: coding cost of a tree node is K=30 bits

coding cost of D subtree: $50*(0.9 \log_2 10/9 + 0.1 \log_2 10) \approx$
$50*(0.9*0.15 + 0.1*3.3) \approx 50*0.465 < 30$

coding cost of E subtree: $10*(0.5*\log_2 2 + 0.5*\log_2 2) = 10 < 30$

coding cost of B subtree: $60*(9/12*\log_2 12/9 + 1/6*\log_2 6 + 1/12*\log_2 12) \approx$
$60*(0.75*0.4 + 0.166*2.6 + 0.083*3.6) > 30$

Problems of Decisison Tree Methods for Classification of Text Documents

- Computational cost for training is very high.
- With very high dimensional, sparsely populated feature spaces training could easily lead to overfitting.

Rule Induction (Inductive Logic Programming)

represents training data as simple logic formulas such as:

faculty (doc id ...)
student (doc id ...)
contains (doc id ..., term ...)
...

aims to generate rules for predicates such as:

contains (X, „Professor“) $\Rightarrow$ faculty (X)
contains (X, „Hobbies“) & contains (X, „Jokes“) $\Rightarrow$ student (X)

and possibly generalizing to rules about relationships such as:

link(X,Y) & link(X,Z) & course(Y) & publication(Z) $\Rightarrow$ faculty(X)

generates rules with highest confidence
driven by frequency of variable bindings that satisfy a rule

Problem: high complexity and susceptible to overfitting

Additional Literature for Chapter 6

Classification and Feature-Selection Models and Algorithms:

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- D. Hand, H. Mannila, P. Smyth: Principles of Data Mining, MIT Press, 2001, Chapter 10: Predictive Modeling for Classification
- M.H. Dunham, Data Mining, Prentice Hall, 2003, Chapter 4: Classification
- M. Ester, J. Sander, Knowledge Discovery in Databases, Springer, 2000, Kapitel 4: Klassifikation
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- S.T. Dumais, J. Platt, D. Heckerman, M. Sahami: Inductive Learning Algorithms and Representations for Text Categorization, CIKM Conf. 1998