Bayesian Networks and Decision Graphs

Chapter 8

Classification: Text Categorization

The Association for Computing Machinery (ACM) maintains a subject classification scheme for computer science research papers. Part of the subject hierarchy (1998 version):

I. Computing Methodologies
I.2 Artificial Intelligence
I.2.6 Learning
- Analogies
- Concept learning
- Connectionism and neural nets
- Induction
- Knowledge acquisition
- Language acquisition
- Parameter learning

Papers are manually classified by authors or editors.

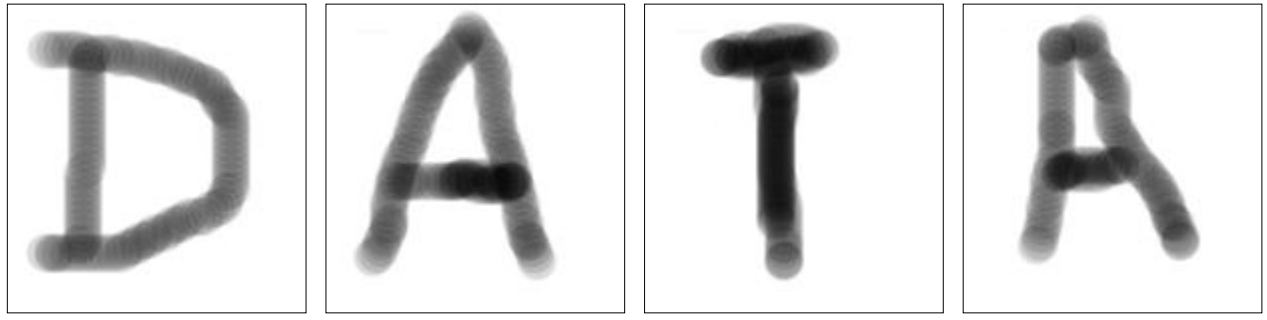
Data: collection of classified papers (full text or abstracts)
Task: build a *classifier* that automatically assigns a subject index to new, unclassified papers.

Classification: Spam Filtering

Spam filtering in Mozilla: user trains the mail reader to recognize spam by manually labeling incoming mails as spam/no spam.

Data: collection of user-classified emails (full text).
Task: build a classifier that automatically categorizes an incoming email as spam/no spam

Classification: Character Recognition



Data: collection of handwritten characters, correctly labeled.

Task: build a classifier that identifies new handwritten characters.

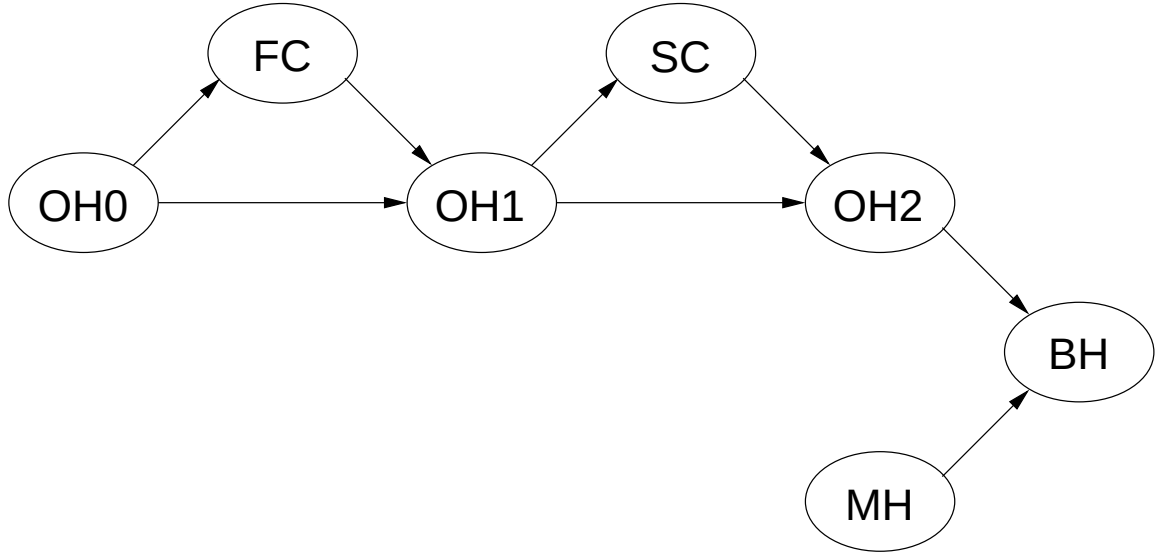
Classification: Credit Rating

From existing customer data predict whether a person applying for a new loan will repay or default on the loan.

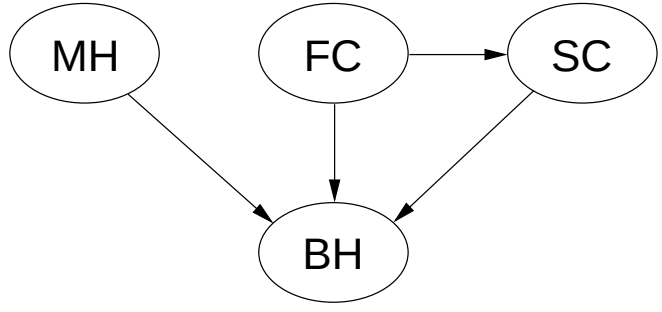
Data: existing customer records with attributes like age, employment type, income, . . . and information on payback history.
Task: build a classifier that predicts whether a new customer will repay the loan.

Classification using Bayesian networks

Consider the poker domain and assume that we want a classifier for predicting BH based on FC, SC, and MH.



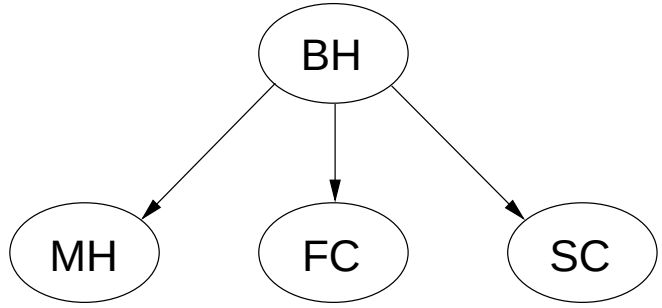
When learning the model from data (over FC, SC, MH, BH), we are likely to get:



This is not a compact model!

Naive Bayes

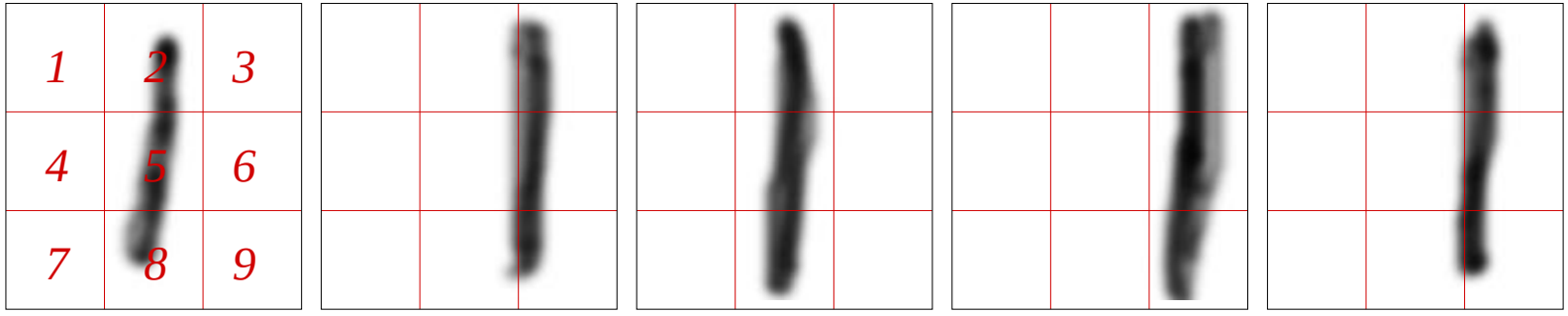
A compact type of model is the naive Bayes model:



Interpretation: Given the true class labels, the different attributes take their value independently.

Naive Bayes

The naive Bayes assumption I



For example:

$$P(\textit{Cell-2} = b \mid \textit{Cell-5} = b, \textit{Symbol} = 1) > P(\textit{Cell-2} = b \mid \textit{Symbol} = 1)$$

Attributes not independent given *Symbol*=1!

Naive Bayes

The naive Bayes assumption II

For spam example e.g.:

$$P(\text{Body'nigeria'=y} \mid \text{Body'confidential'=y}, \text{Spam=y})$$
$$\gg$$
$$P(\text{Body'nigeria'=y} \mid \text{Spam=y})$$

Attributes not independent given *Spam*=yes!

$\rightsquigarrow$ Naive Bayes assumption often not realistic. Nevertheless, Naive Bayes often successful.

Naive Bayes

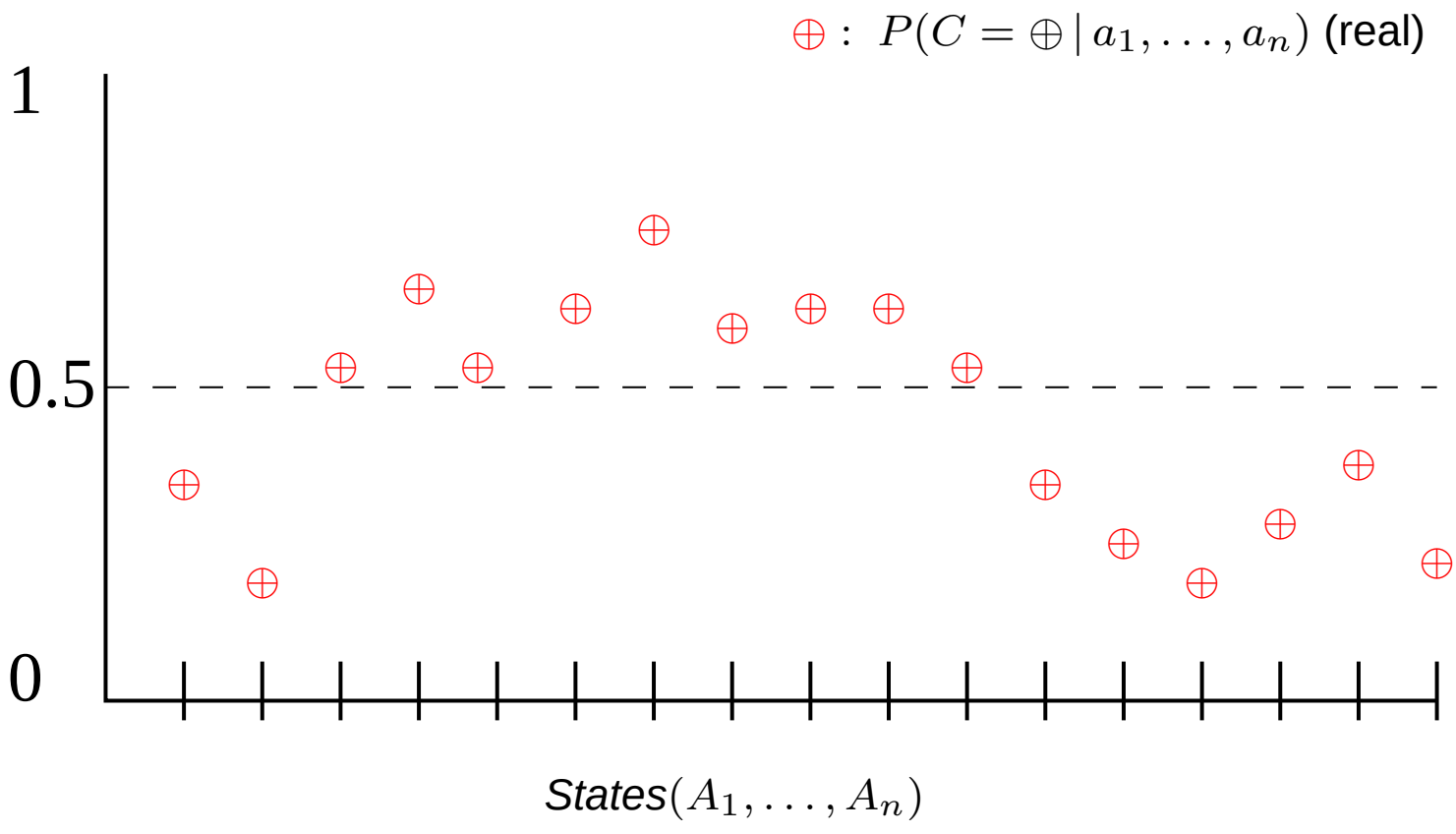
Learning a Naive Bayes Classifier

- Determine parameters $P(a_i \mid c)$ ($a_i \in \mathit{States}(A_i), c \in \mathit{States}(C)$) from empirical counts in the data.
- Missing values are easily handled: instances for which A_i is missing are ignored for $P(a_i \mid c)$.
- Discrete and continuous attributes can be mixed.

Naive Bayes

The paradoxical success of Naive Bayes

One explanation for the surprisingly good performance of Naive Bayes in many domains: do not require exact distribution for classification, only the right decision boundaries



Naive Bayes

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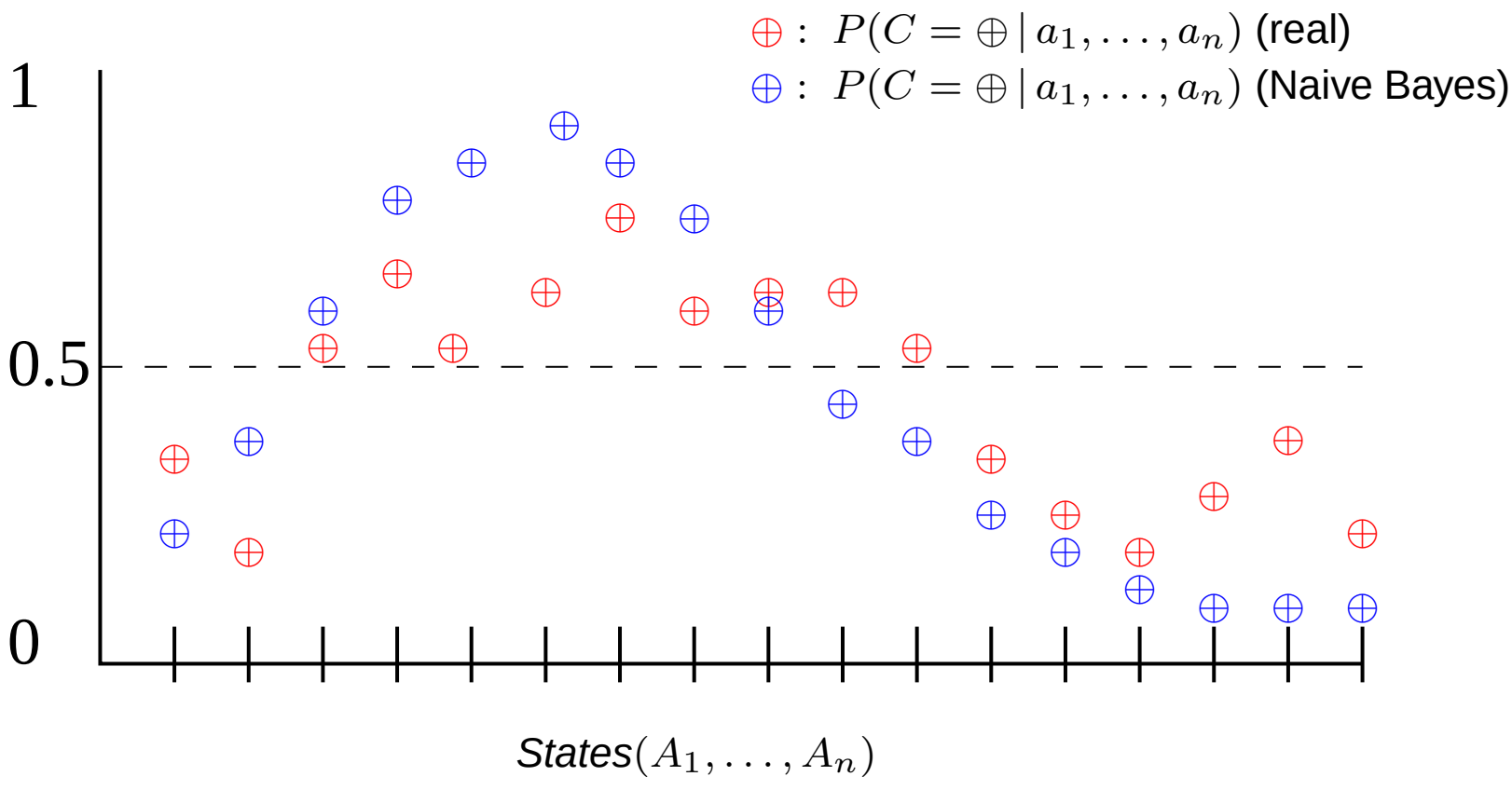


Naive Bayes

When Naive Bayes must fail

No Naive Bayes Classifier can produce the following classification:

A	B	Class
yes	yes	$\oplus$
yes	no	$\ominus$
no	yes	$\ominus$
no	no	$\oplus$

because assume it did, then:

1. $P(A = y \mid \oplus)P(B = y \mid \oplus)P(\oplus) > P(A = y \mid \ominus)P(B = y \mid \ominus)P(\ominus)$
2. $P(A = y \mid \ominus)P(B = n \mid \ominus)P(\ominus) > P(A = y \mid \oplus)P(B = n \mid \oplus)P(\oplus)$
3. $P(A = n \mid \ominus)P(B = y \mid \ominus)P(\ominus) > P(A = n \mid \oplus)P(B = y \mid \oplus)P(\oplus)$
4. $P(A = n \mid \oplus)P(B = n \mid \oplus)P(\oplus) > P(A = n \mid \ominus)P(B = n \mid \ominus)P(\ominus)$

Naive Bayes

Multiplying the four left sides and the four right sides of these inequalities:

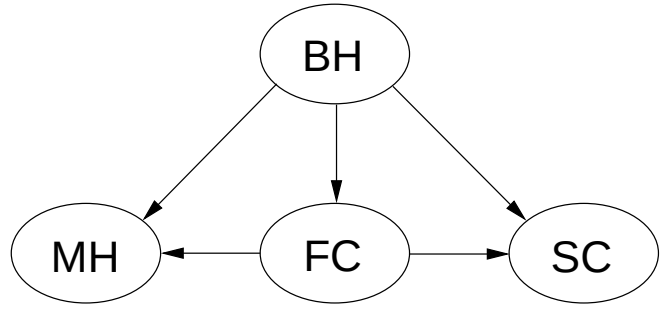
$$\prod_{i=1}^{4}(\textit{left side of } i.) > \prod_{i=1}^{4}(\textit{right side of } i.)$$

But this is false, because both products are actually equal.

Tree Augmented Naive Bayes

Model: all Bayesian network structures where

- The class node is a parent of each attribute node
- The substructure on the attribute nodes is a tree



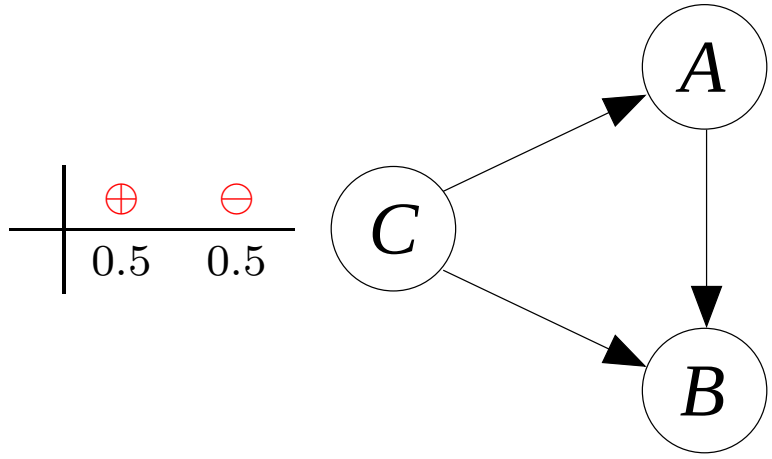
Learning TAN classifier: learning the tree structure and parameters. Optimal tree structure can be found efficiently.

Tree Augmented Naive Bayes

TAN classifier for

A	B	Class
yes	yes	$\oplus$
yes	no	$\ominus$
no	yes	$\ominus$
no	no	$\oplus$

:



$\oplus$	$\ominus$
0.5	0.5

C	yes	no
$\oplus$	0.5	0.5
$\ominus$	0.5	0.5

C	A	yes	no
$\oplus$	yes	1.0	0.0
$\oplus$	no	0.0	1.0
$\ominus$	yes	0.0	1.0
$\ominus$	no	1.0	0.0

Evaluating Classifiers

Validation

Evaluation: estimate of the performance of a classifier on future data. Estimate obtained by measuring performance on *validation set* (distinct from test set used for parameter tuning!); or by cross-validation.

Classification Error

Classifier $\mathcal{C}$ is used to classify instances $\mathbf{a}_1, \ldots, \mathbf{a}_N$ with true class labels $c_1, \ldots, c_N$. Class labels assigned by $\mathcal{C}$: $c'_1, \ldots, c'_N$. Classification error:

$$|\{i \in 1, \ldots, N \mid c_i \neq c'_i\}|/N$$

Evaluating Classifiers

Expected Loss

A more detailed picture is provided by the *confusion matrix* and a *cost function*:

		Pred		
		me	draw	op
True	me	0.25	0.05	0.1
	draw	0.05	0.1	0.05
	op	0.05	0.1	0.25

Confusion matrix

		Pred		
		me	draw	op
True	me	0	0	-1
	draw	0	0	-1
	op	-3	-1	0

Loss matrix

Expected Loss:

$$\sum_{\text{True,Pred.}} \textit{Confusion}(\text{True}, \text{Pred}) \cdot \textit{Loss}(\text{True}, \text{Pred}) = -0.4.$$

When cost function given, try to minimize expected loss (minimizing classification error is special case for *0-1 loss*: $\textit{Loss}(x, x) = 0$ and $\textit{Loss}(x, y) = 1$ for $x \neq y$)!