2002 Quality & Productivity Research Conference

Tempe, Arizona June 5-7, 2002

Quality of Design for Products and Processes

Service Quality Control using Bayesian Networks

B.M. Colosimo, Q. Semeraro

Dipartimento di Meccanica-Politecnico di Milano (Italy)

e-mail: colosimo@mecc.polimi.it

Why service quality?

– *in manufacturing: large-scale competition (standard): customization through services (logistics, post-sale assistance, etc.)*

one third of the operators in *manufacturing* employed in services functions (finance, logistics, marketing, etc.)

(Maguire 1999)

– *Services industries:*

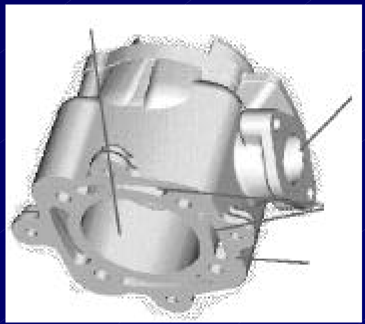
during the last decades use of services for firms in USA increased of about 500%

(Maguire 1999)

services currently account for 58% of the total worldwide GNP

(Cronin et al. 1992)

Service Quality and Customer Satisfaction



Overall satisfaction

Characteristic 1 · *Characteristic 2* ... *Characteristic n*

Direct inquiry: Questionnaires

EPA United States Environmental Protection Agency
"...to protect human health and to safeguard the natural environment..."

Discrete categorical variables

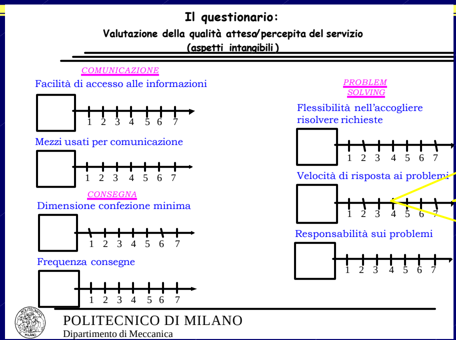
1. How satisfied were you with your overall visit to our site?

☐	☐	☐	☐	☐	☐
Extremely Dissatisfied	Very Dissatisfied	Dissatisfied	Satisfied	Very Satisfied	Extremely Satisfied

5. Please rate your level of satisfaction with the following aspects of our site:

a) Ability to navigate around Web site,b) Time to download information, c) Information is up to date, d) Ability to search for information,e) Usefulness of information, etc.

The Literature vs. firms practice



Il questionario:

Valutazione della qualità attesa/percepita del servizio
(aspetti intangibili)

COMUNICAZIONE

Facilità di accesso alle informazioni
1 2 3 4 5 6 7

Mezzi usati per comunicazione
1 2 3 4 5 6 7

CONSEGNA

Dimensione confezione minima
1 2 3 4 5 6 7

Frequenza consegne
1 2 3 4 5 6 7

PROBLEM SOLVING

Flessibilità nell'accogliere risolvere richieste
1 2 3 4 5 6 7

Velocità di risposta ai problemi
1 2 3 4 5 6 7

Responsabilità sui problemi
1 2 3 4 5 6 7

POLITECNICO DI MILANO
Dipartimento di Meccanica

Population of clients ⇨ *Analyze data*

The Literature

(ServQual, ServPerf, TwoWay, Normqual, Qualitometro):

- general purpose
- Assumptions:
  - continuous variables (scaling)

Companies practice

- customer oriented
- "distortion" of real data

1. How satisfied were you with your overall visit to our site?

The Literature vs. firms practice

The Literature (ServQual, ServPerf, TwoWay, Normqual, Qualitometro):	**Companies practice**

Assumptions:

- independent
- often dependent

5. Please rate your level of satisfaction with the following aspects of our site:

a) Ability to navigate around Web site,b) Time to download information, c) Information is up to date, **d) Ability to search for information**,e) Usefulness of information, etc.

• importance weights (comparing heterogeneous characteristics: AHP, Saaty)	• no importance weights (to avoid *idiosyncratic effect*)
• no missing data	• missing data

Objective

To design an approach to analyze and control service quality in real cases

- categorical variables: multinomial

(i.e. a natural generalization of binomial variables when possible outcomes are more than two)

$$
X_i \rightarrow
\begin{array}{ll}
1 & q_{i1} = 1 - \sum_k q_{ik} \\
2 & q_{i2} \\
\vdots & \\
k & q_{ik} \\
\vdots & \\
c_i & q_{ic_i}
\end{array}
$$

- importance weights ⇒ *conditional probability*

Conditional distribution :

X_1={1, 2, 3} overall satisfaction

X_i= {1, 2, 3} satisfaction on the i^{th} characteristic

$P(X_1|X_i)$

- missing data ⇒

Bayesian Networks

Medical diagnosis (S.L. Lauritzen, D.J. Spiegelhalter, D. Heckerman)

Microsoft (http://research.microsoft.com/)

Compaq: (http://www.crl.research.digital.com)

Bayesian Network (M^h, P)

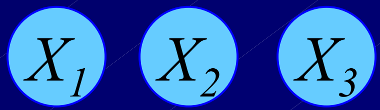
1) a model M^h (Direct Acyclic Graph)

Example: three categorical variables X_1, X_2, X_3 with c_i=2

$P(X_1 = 1) = q_1$

$P(X_1 = 2) = 1 - q_1$

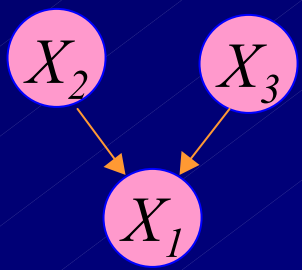
M^1



Variables	X_1	X_2	X_3
Parents	$\varnothing$	$\varnothing$	$\varnothing$

q_1, q_2, q_3

M^2



Variables	X_1	X_2	X_3
Parents	X_2, X_3	$\varnothing$	$\varnothing$

X2	X3	pa_1	
1	1	1	q_{11}
2	2	2	q_{12}
1	2	3	q_{13}
2	2	4	q_{14}

è $_2$,è $_3$

2) a set of local probabilities P

M^1 q_1, q_2, q_3

M^2 è $_1 = (q_{11}, q_{12}, q_{13}, q_{14})$, q_2, q_3

***Factorization of the joint probability distribution for* X**

$$p(\boldsymbol{x_k}) = \prod_{i=1}^{n} p(x_{ik} \mid pa_{ij})$$

where pa_{ij} denotes the configuration of states of pa_i in $\boldsymbol{x_k}$

Bayesian Networks

1. Model identification:

- *score criterion: Maximum posterior probability $p(M^h \mid D)$*

$$\underbrace{\log p(D,M^h)}_{\text{log relative posterior probability}} = \underbrace{\log p(M^h)}_{\text{log prior}} + \underbrace{\boxed{\log p(D \mid M^h)}}_{\text{log marginal likelihood}}$$

- Best sequential predictor of the data (Dawid, 1984)
- for large N -> Bayesian Information Criterion (Schwartz)

- *search procedure (greedy search with random permutation of the order)*

2. Parameters estimation:

$X_i \mid pa_i$ multinomial

$X_i|pa_i=j$

- $1 \quad q_{ij1} = 1 - \sum_k q_{ijk}$
- $2 \quad q_{ij2}$
- $\vdots$
- $k \quad q_{ijk}$
- $\vdots$
- $c_i \quad q_{ijc_i}$

conjugate analysis

Parameters estimation

Prior selection:

conjugate analysis : Dirichlet distribution

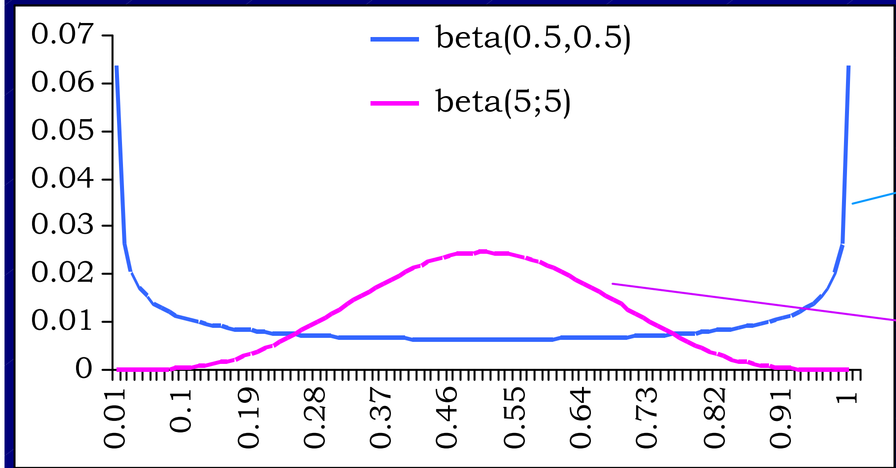
$$p(\mathbf{q}_{ij} \mid M^h) = Dir(\mathbf{q}_{ij} \mid a_{ij1},\ldots,a_{ijc_i}) = \frac{\Gamma(a_{ij})}{\prod_{k=1}^{c_i}\Gamma(a_{ijk})}\prod_{k=1}^{c_i} q_{ijk}^{a_{ijk}-1}$$

c_i=2: $p(q_{1j} \mid M^h) = beta(a_{ij1}, a_{ij2})$

$$a_{ij1} = a_{ij2}$$

$$a_{ij1} + a_{ij2} = a_{ij}$$

Prior precision (imaginary cases)



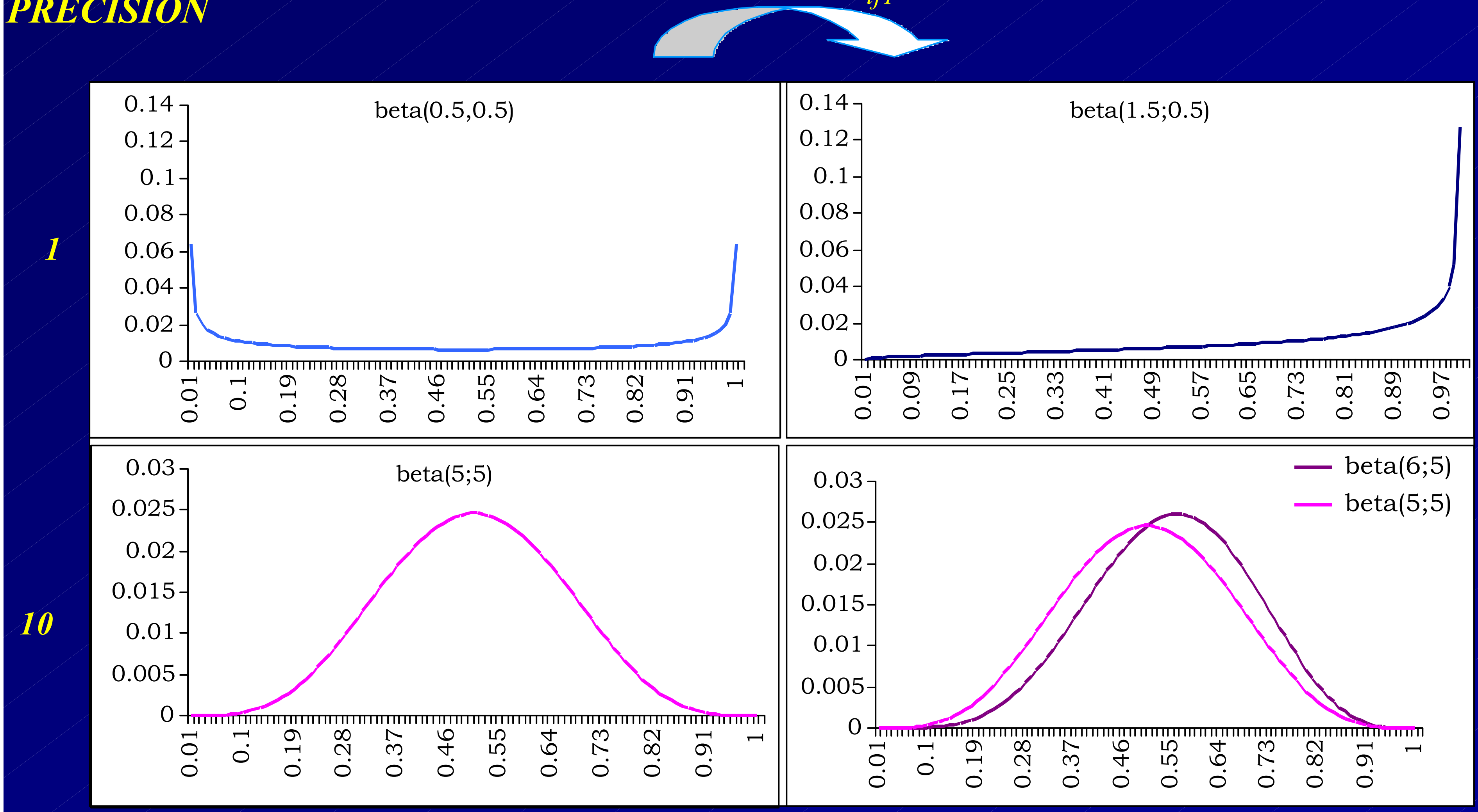
precision=1 ➡ **No *prior* information**

precision=10

Prior as a headstart suddenly “cancelled” by data

Just one case: $X_{ij1}=1$

PRECISION



Parameter estimation

posterior

Dirichlet (conjugate analysis)

$$p(q|\tilde{x}) = \frac{f(\tilde{x}|q)\,p(q)}{m(\tilde{x})}$$

$$p(\grave{e}_{ij} \mid D, M^{h}) = Dir(\grave{e}_{ij} \mid a_{ij1} + N_{ij1}, \ldots, a_{ijc_i} + N_{ijc_i})$$

Number of cases in which X_i=k and pa_i=j

marginal likelihood

$$\boxed{p(D \mid M^{h}) = \prod_{i=1}^{I} \prod_{j=1}^{q_i} \frac{\Gamma(a_{ij})}{\Gamma(a_{ij} + N_{ij})} \prod_{k=1}^{c_i} \frac{\Gamma(a_{ijk} + N_{ijk})}{\Gamma(a_{ijk})}}$$

hyperparameters

Missing data:

*Missing At Random**

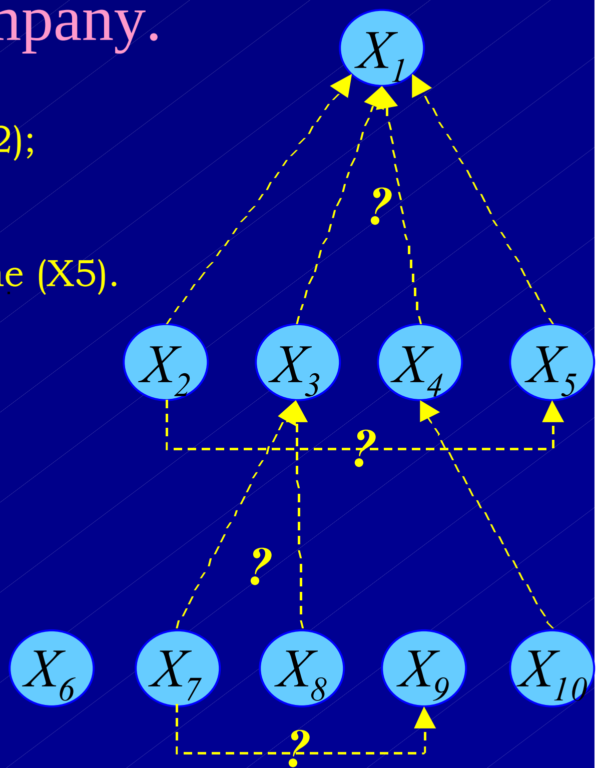
*Algorithms: EM, Gibbs Sampling, <u>Bound and Collapse</u>***

**X_i=?* Is assumed to depend on parents pa_i configuration

**Sebastiani, P. and Ramoni M., (2000), *Journal of Computational and Graphical Statistics*

Call Center

A national insurance company has recently installed a Call Center to improve the service offered to the agents of the company.



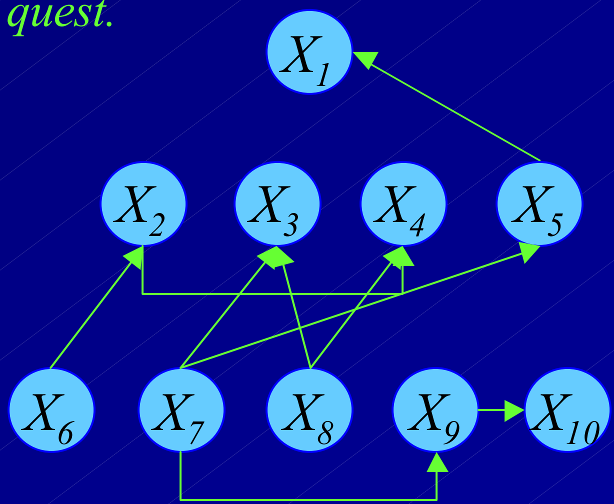
- the overall satisfaction (X_1)
  - the satisfaction for the new interface provided by the Call Center (X2);
  - the satisfaction regarding the duration of the new service (X3);
  - the evaluation of the skill of the front-end operators (X4);
  - the satisfaction for the new service compared with the traditional one (X5).
    - the number of phone calls required to close the dossier (X6);
    - the time required to close the dossier, i.e., to communicate all
    - the data (X7);
    - the efficiency in the process of collecting data (X8);
    - the satisfaction for the office hours, i.e., the timetable in which the new service is available (X9);
    - the operator availability (X10).

***10 categorical variables** organized in **three** levels. **44** cases*

***missing data:** 17 **(38%)** quest.*

with some (1-2)

missing answers



Other models

BN -252.791

Comments:

1. No independent variables

2.Network propagation:

- *new service vs old one (X_5)*
- *time required to communicate all the data (X_7)*

Validation and control chart

Idea in (Box, 1980) and then extended for multinomial sampling in (Wood, 1986) and (Spiegelhalter et al., 1994): using the predictive distribution to check an identified model

Predictive distribution

number of outcomes such that $X_i=x_i^k$ *observed in N cases*

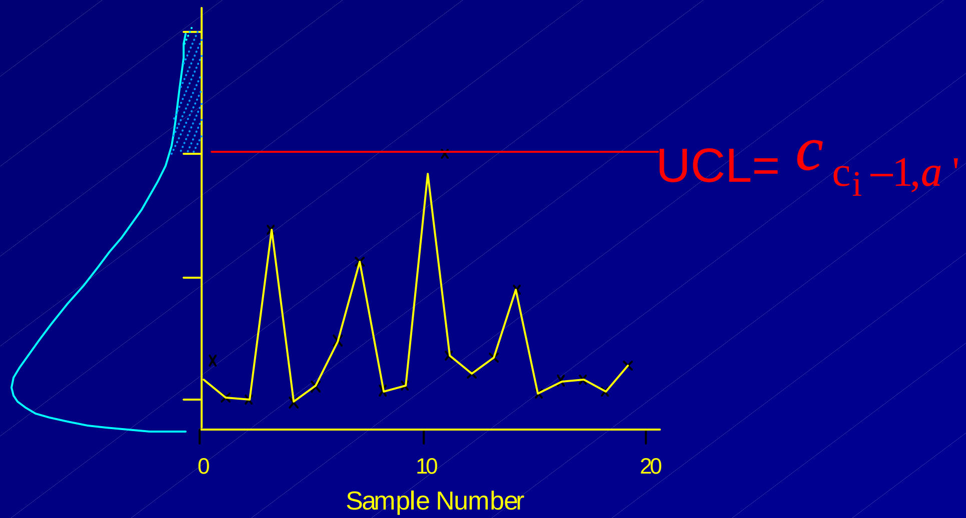
$$g_i = \frac{a+1}{a+N}\sum_{k=1}^{c_i}\frac{(N_{i\bullet k}-p_{i\bullet k}N)^2}{p_{i\bullet k}N} \sim c_{c_i-1}$$

precision after learning

unconditional probability that $X_i=x_i^k$ $(\forall pa_i)$

New set of 15 cases

$$\Pr\{c_2^2 \geq 0.150\} = 0.928$$



Out of control:

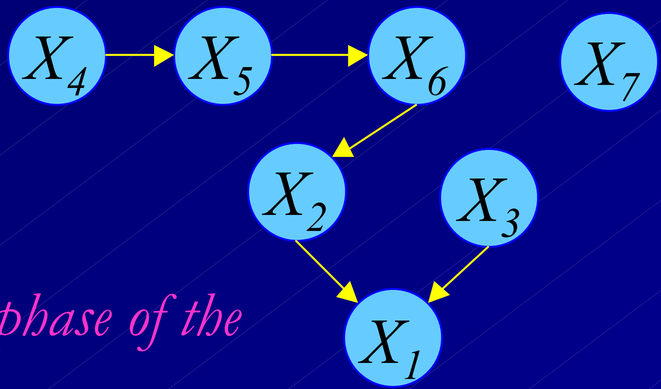
predictive function $\boxed{g_i \quad i=1,\ldots,I}$

diagnostic tool

identifying variables (i.e., quality service characteristics) that are not accurately predicted by the model

Conclusions

- Advantages of the proposed approach:
  – *no scaling (multinomial sample)*
  – *importance weights estimated by data*
  – *conditional dependence*
  – *missing data*
  – *control chart*



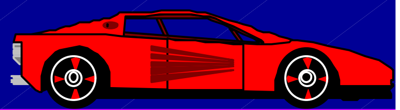
- Future :
  – *improve learning phase of the model (greedy)*

Training
modifying the questionnaire (e.g. to eliminate redundant questions)

Monitoring with time:
control chart

Improving:
by focusing on characteristics that showed to be more important

Products quality:



ISO 9000:2000 Principle 1: Customer focus

Organizations depend on their customers and therefore should understand current and future customer needs, should meet customer requirements and strive to exceed ***customer expectations****.*

intangible quality characteristics (esthetic, comfort)

References

Box, G.E.P. (1980) Sampling and Bayes' Inference in Scientific Modelling and Robustness, *Journal of the Royal Statistical Society, Series A*, 143(4), 383-430.

Dawid, A.P.(1984) Statistical Theory: The Prequential Approach, *Journal of the Royal Statistical Society, Series A*, 147 (2), 278-292.

Heckerman, D.(1998) A Tutorial on Learning with Bayesian Networks in *Learning Graphical models*, edited by M.J. Jordan, Kluwer Academic Publishers, 301-354.

Rubin, D.B. (1976) Inference and missing data, *Biometrika*, 63, 581-592.

Sebastiani, P. and Ramoni M., (2000) Bayesian Inference with Missing Data Using Bound and Collapse, *Journal of Computational and Graphical Statistics*, 9(4).

Spiegelhalter D.J., Dawid, A. P., Lauritzen L. and Cowell R.G. (1993) Bayesian Analysis in Expert Systems, *Statistical Science*, 8(3).

Wood, J.B., (1986) An Application of predictive Checks in the Bayesian Analysis of Multinomial Data, *Statistician*, 35(1), 65-72.