

BAYESIAN METHODS FOR DISCRETE EVENT SIMULATION

Stephen E. Chick¹

¹Technology and Operations Management
INSEAD
Fontainebleau, France

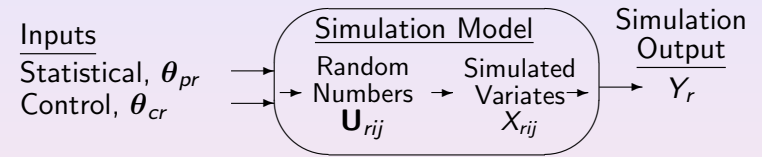
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Bayesian Methods for Simulation

Why Bayesian methods in Simulation?



$$Y_r = g(\theta_p, \theta_c; \mathbf{U}_r)$$

- Example: Single Server Queue (M/M/1): $\theta_p = (\lambda, \mu_i) =$ arrival and service rates (server $i = 1, 2$)
- Output: $Y \approx \lambda / (\mu_i - \lambda) + \text{noise}$
- Simulation: Analyze stochastic processes via sample path generation. Inform decisions: pick design parameter $\theta_c = i$, value $h(E[Y | \theta, \theta_c])$
- Bayesian as alternative to frequentist

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Bayesian Methods for Simulation

Why Bayesian methods?

- Glynn (1986): *Uncertainty analysis*. Not $\alpha = h(E[Y])$, but

$$\alpha(\theta) = h(E[Y | \theta])$$

- Unknown parameters, $p(\theta)$, data from modeled system to update
 - 1 Mean $E[\alpha(\Theta)]$
 - 2 Distribution of $\alpha(\Theta)$ induced by Θ
 - 3 Credible set: θ_{lo}, θ_{hi} so $p([h(\theta_{lo}), h(\theta_{hi})]) = 95\%$

- Chick (1997): Reviewed work to that date.
- Suggested broader range of application.
 - 1 *Ranking and selection*
 - 2 *Response surface modeling*
 - 3 *Experimental design*

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Bayesian Methods for Simulation

The Point of Today

- Review some basic concepts of subjective probability, Bayesian statistics, decision theory.
- Identify several applications to simulation experiments.
- Summarize some implementation issues.
- Identify some areas for future work.

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Bayesian Methods for Simulation

Related work

See the WSC paper for a long (but incomplete) citation list for work over the last 8 years on:

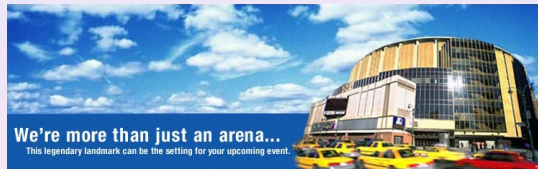
- Formal Bayes or decision theoretic theory
- Applications: scheduling, insurance, finance, traffic modeling, public health, waterway safety, supply chain and other areas
- Bayes and deterministic simulations
- Favorite books on subjective and Bayesian probability and decision theory

Health Economics: increasingly uses simulation (in addition to decision trees, Markov chains), and *increasingly* requires *probabilistic sensitivity analysis*.

Outline

- 1 Getting down to brass tacks
 - Subjective and Bayesian methods
 - Assessing prior probability
 - Asymptotic Theorems
 - Decisions, loss, and value of information
 - Entropy and Kullback-Leibler Discrepancy
- 2 Applications
 - Uncertainty Analysis
 - Selecting from Multiple Candidate Distributions
 - Selecting the Best System
 - Metamodels
- 3 Implementation
- 4 Summary

Getting down to brass tacks



Probability of 7 heads in the first 10 flips?
How to approach the problem...

Getting down to brass tacks

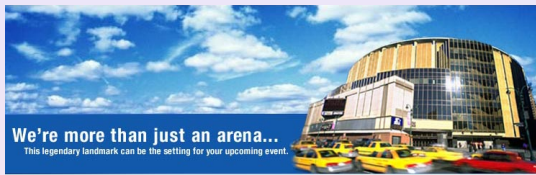


Probability of 7 heads in the first 10 flips?
Comte d'Alembert (18th cent.)

- Indifference says maybe $1/11$?
- But wait, for one flip, probability of heads is $1/2$?

See Savage (1972) and Kreps (1988).

Getting down to brass tacks



Probability of 7 heads in the first 10 flips?

Dwight (an unreconstructed frequentist)

- $\frac{10!}{7!3!} \theta^7 (1 - \theta)^3$, where $\theta = \lim_{n \rightarrow \infty} \frac{X_1 + \dots + X_n}{n}$ (a.e.).
- If we rent Madison Square garden and flip the tack repeatedly, I can estimate θ for you. What confidence and how accurately do you need to know θ ?

Hmmm...

Getting down to brass tacks



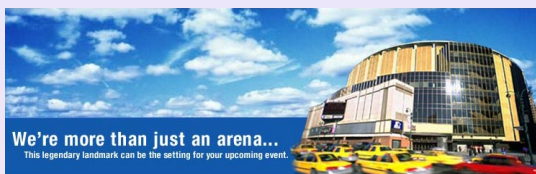
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Let's reformulate the question ...

Why am I a Bayesian?



Will you accept the following bet *now*? You get \$100 if there are 7 heads, but you pay \$5 if not.

more from Dwight

- I can't answer until I have a good idea of what θ is.
- Guessing wouldn't be scientific.

Why am I a Bayesian?



Ralph

Probability of 7 heads in the first 10 flips?

- I'm willing to use probability for personal judgments
- $\int_0^1 \frac{10!}{7!3!} \theta^7 (1 - \theta)^3 \pi(\theta) d\theta$, where $\pi(\theta)$ is a *prior probability*.
- I'll update with *Bayes' rule*, to get *posterior probability*

$$p(\theta | \mathbf{x}_n) = \frac{\pi(\theta) p(\mathbf{x}_n | \theta)}{p(\mathbf{x}_n)} = \frac{\pi(\theta) \prod_{i=1}^n p(x_i | \theta)}{\int p(\mathbf{x}_n | \theta) d\pi(\theta)}$$

Why am I a Bayesian?

Lenny

Probability of 7 heads in the first 10 flips?

- Fair bets: I set $p(E_1) > p(E_2)$ if I prefer the first bet:



- Exchangeability (weaker than i.i.d.)

$$p(x_1, x_2, \dots, x_n) = p(x_{s_1}, x_{s_2}, \dots, x_{s_n})$$

for permutations s on $\{1, 2, \dots, n\}$ for arbitrary n .

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Bayesian Methods for Simulation

Why am I a Bayesian?

Lenny

- Exchangeability plus conceptually infinite N imply

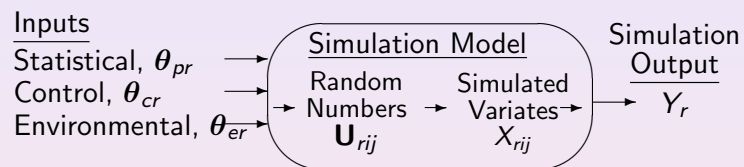
$$\lim_{N \rightarrow \infty} p(7 \text{ heads in first 10 flips}) = \int_0^1 \frac{10!}{7!3!} \theta^7 (1-\theta)^3 dF(\theta)$$

- de Finetti (1990)-like representation
- Ralph assumed conditional i.i.d., Lenny *derives* formula from exchangeability
- Probability defined by bet preferences, not repeated outcomes

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Bayesian Methods for Simulation

Implication for Simulation: $Y_r = g(\theta_p, \theta_e, \theta_c; \mathbf{U}_r)$



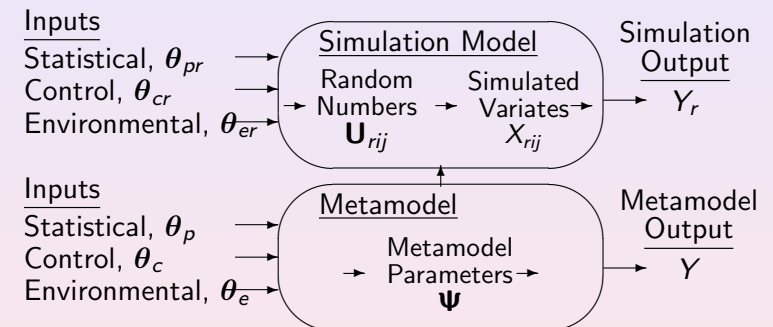
- Input selection: Infinite exchangeable sequence X_{ij} from modeled system to infer Θ_i

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Bayesian Methods for Simulation

Implication for Simulation: $Y_r = g(\theta_p, \theta_e, \theta_c; \mathbf{U}_r)$



- Input selection: Infinite exchangeable sequence X_{ij} from modeled system to infer Θ_i
- Metamodeling: Infinite exchangeable Y_r to infer Ψ .

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Bayesian Methods for Simulation

Part of the process

- Establish exchangeability arguments, posit potential likelihood functions
- Assess prior distributions
- Relevant asymptotic theorems
- Decisions, loss, and value of information
 - ranking and selection,
 - other experimental design issues

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Subjective Methods

We need a prior distribution for unknown parameters.
For a Bernoulli outcome ... de Finetti (1990), Savage (1972) require *You* to assess your personal belief, $\pi(\theta)$ to describe $p(\Theta \leq \theta)$

- Important gain in flexibility
- Consistent with expected value decision theory
- Kahneman, Slovic, and Tversky (1982) describe difficulties with elicitation ...

Some nonetheless seek 'automated' methods ...

Principle of Indifference

For finite exchangeable sequence, set

$$\theta_N = \frac{X_1 + \dots + X_N}{N} \in \{0/N, 1/N, \dots, (N-1)/N, 1\}$$

- Indifference: discrete uniform for finite N
- Limit: $\lim_{N \rightarrow \infty} p(\theta_N) \xrightarrow{D} \text{uniform}[0, 1]$
- Laplace (1812) used $\text{uniform}[0, 1]$ for his prior probability that the sun would come up tomorrow
- Coordinate dependence for continuous r.v. (X_i versus $\log X_i$)



Jeffrey's invariant prior

- $\pi(\theta) \propto |H(\theta)|^{1/2} d\theta$, where H is the expected information in one observation,

$$H(\theta) = E_X \left[-\frac{\partial^2 \log p(X | \theta)}{\partial \theta^2} \Big|_{\theta} \right], \quad (1)$$

'uniform' with respect to the natural metric induced by the likelihood function (Kass 1989)

- *Jeffreys' prior* for Bernoulli sampling is $\text{beta}(1/2, 1/2)$
- For some likelihoods, Jeffreys' prior is improper (doesn't integrate to 1). Might be used formally

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Conjugate prior distribution

Bernoulli sampling

- Set $s_n = \sum_{i=1}^n x_i$
- Likelihood:
 $p(\mathbf{x}_n | \theta) \propto \theta^{s_n} (1 - \theta)^{n - s_n}$
- Prior:
 $\pi(\theta) \propto \theta^{\alpha-1} (1 - \theta)^{\beta-1}$, a $\text{beta}(\alpha, \beta)$ distribution
- Posterior:
 $\propto \theta^{\alpha+s_n-1} (1 - \theta)^{\beta+n-s_n-1}$, a $\text{beta}(\alpha + s_n, \beta + n - s_n)$ (conjugate) distribution

Exponential family

- Likelihood: $p(x | \theta) = a(x) h_0(\theta) \exp \left[\sum_{j=1}^d c_j \phi_j(\theta) h_j(x) \right]$
- Canonical conjugate prior: $p(\theta) = K(\mathbf{t}) [h_0(\theta)]^{n_0} \exp \left[\sum_{j=1}^d c_j \phi_j(\theta) t_j \right]$
- Posterior, given n data points: has parameters $n_0 + n$ and sum of $\mathbf{t} = (t_1, t_2, \dots, t_d)$ and sufficient statistics (Bernardo and Smith 1994)

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'Noninformative'

- The uniform[0, 1] distribution is conjugate for Bernoulli sampling—a beta(1, 1) distribution.
- 'Noninformative' means 'evenly spread'—a heuristic term
- For canonical conjugate prior (for exponential family), the posterior has parameter $n_0 + n$
- Some think of n_0 as an 'effective' number of data points
- Noninformative can imply a small n_0

Others

- Jaynes (1983): maximum entropy methods
- Berger (1994), Kass and Wasserman (1996): Default rules

Useful? Actually informative?

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Classic Analogs for Infinite Exchangeable Sequences

Classical asymptotic theorems (e.g. Billingsley 1986) ...

- laws of large numbers (LLN)
- central limit theorem (CLT)
- law of iterated logarithm (LIL)

... have Bayesian interpretations if considered conditional on mean and standard deviation of an infinite exchangeable sequence.

Bayesian LLN

A Bayesian extension of the LLN allows for sample averages to converge to random variables rather than to 'true' means.

Theorem (Bayesian LLN)

If \bar{X}_n and \bar{Y}_m are respectively the averages of n and m exchangeable random quantities X_i (the two averages may or may not have some terms in common), the probability that

$$|\bar{X}_n - \bar{Y}_m| > \epsilon$$

may be made arbitrarily small by taking n and m sufficiently large (de Finetti 1990, p. 216 assumes a finite variance).

Theorem (Posterior Normality)

For each n , let $p_n(\cdot)$ be the posterior pdf of the d -dimensional parameter θ_n given $\mathbf{x}_n = (x_1, \dots, x_n)$, let $\tilde{\theta}_n$ be its mode (MAP), and define the $d \times d$ Bayesian observed information matrix Σ_n^{-1} by

$$\Sigma_n^{-1} = - \frac{\partial^2 \log p_n(\theta | \mathbf{x}_n)}{\partial \theta^2} \Big|_{\tilde{\theta}_n}. \quad (2)$$

Then $\phi_n = \Sigma_n^{-1/2}(\theta_n - \tilde{\theta}_n)$ converges in distribution to a standard (multivariate) normal random variable (Bernardo and Smith 1994, Prop 5.14 needs regularity conditions).

Frequentist analog: asserts that MLE is asymptotically normally distributed about a 'true' θ_0 (Law and Kelton 2000), as opposed to describing uncertainty about θ .

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Decisions under uncertainty

- Uncertainty described by probability \Rightarrow modeler can assess *expected value of information* (EVI) of additional data.
- EVI is useful in experimental design.
- EVI : value of resolving uncertainty with respect to a *loss function* $\mathcal{L}(d, \omega)$ that describes losses when a *decision* d is chosen when the state of nature is ω .
- Data from experiment can reduce uncertainty about ω , reduce expected loss.

Example: What is the mean? Setup

Example adapted from de Groot (1970) illustrates key concepts used for VIP procedures (Chick and Inoue 2001a)

- Decide if unknown mean W of normal distribution (known σ^2) is smaller (decision $d = 1$) or larger ($d = 2$) than w_0 .
- Exchangeable samples $\mathbf{X}_n = (X_1, X_2, \dots, X_n)$, with $p(X_i) \sim \text{Normal}(w, \sigma^2)$, given $W = w$, are available
- Goal: design experiment (choose n) to balance sampling cost (cn) and expected opportunity cost if wrong answer chosen

$$\mathcal{L}(1, w) = \begin{cases} 0 & \text{if } w \leq w_0 \\ w - w_0 & \text{if } w > w_0, \end{cases}$$

$$\mathcal{L}(2, w) = \begin{cases} w_0 - w & \text{if } w \leq w_0 \\ 0 & \text{if } w > w_0. \end{cases}$$

Example: What is the mean? If we knew. . .

- Prior: $W \sim \text{Normal}(\mu, 1/\tau)$ is conjugate. NOTE: τ is the *precision* in our uncertainty about unknown mean, W .
- Posterior: Observing $\mathbf{X}_n = \mathbf{x}_n$ would result in

$$p(w | \mathbf{x}_n) \sim \text{Normal}(z, \tau_n^{-1})$$

$$z = \text{posterior mean of } W = E[W | \mathbf{x}_n] = \frac{\tau\mu + \frac{n}{\sigma^2}\bar{X}_n}{\tau + \frac{n}{\sigma^2}}$$

$$\tau_n = \text{posterior precision of } W = \tau + n/\sigma^2.$$

τ_n^{-1} equals the asymptotic posterior variance approximation Σ_n from theorem

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Example: What is the mean? How much to know. . .

- Posterior mean z for unknown w influences the decision, but depends upon n , which is selected before \mathbf{X}_n is seen.
- Conditional distribution of \bar{X}_n given w is $\text{Normal}(w, \sigma^2/n)$
- *Predictive distribution* $p(z)$ of the posterior mean $Z = E[W | \mathbf{X}_n] = (\tau\mu + n\bar{X}_n)/\tau_n$
- Mixing over prior $\pi(w)$ implies a predictive distribution

$$Z \sim \text{Normal}(\mu, \tau_z^{-1})$$

$$\tau_z = \tau(\tau + n/\sigma^2)/(n/\sigma^2)$$

Note: $\tau_z^{-1} \rightarrow 0$ when $n \rightarrow 0$ (no new information).
If $n \rightarrow \infty$, then $\text{Var}[Z] \rightarrow \sigma^2$.

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Example: What is the mean? What is the risk. . .

To minimize risk (sampling cost + expected loss from potentially incorrect decision), pick n to minimize a nested expectation

$$\rho(n) = cn + E_{\mathbf{X}_n}[E_W[\mathcal{L}(d(\mathbf{X}_n), W) | \mathbf{X}_n]].$$

- General technique: set $\mathcal{L}^*(d, w) = \mathcal{L}(d, w) - \mathcal{L}(1, w)$, which is 0 if $d = 1$ and is $w_0 - w$ if $d = 2$. Then

$$E_W[\mathcal{L}^*(d(\mathbf{X}_n), W) | \mathbf{X}_n] = \begin{cases} 0 & \text{if } d = 1 \\ w_0 - Z & \text{if } d = 2. \end{cases} \quad (3)$$

- To minimize loss in Eq. 3, assert $d(\mathbf{X}_n) = 2$ ('bigger') if posterior mean exceeds threshold, $Z > w_0$, and assert $d(\mathbf{X}_n) = 1$ ('smaller') if $Z \leq w_0$.

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Example: What is the mean? Expected loss

- Decision depends on \mathbf{X}_n via Z ; Z has normal distribution
- Expected loss found with standard normal loss for newsboy

$$L_N[s] = \int_s^\infty (t - s)\phi(t)dt = \phi(s) - s(1 - \Phi(s))$$

$$E[\mathcal{L}^*(d(\mathbf{X}_n), W)] = E_{\mathbf{X}_n}[E_W[\mathcal{L}^*(d(\mathbf{X}_n), W) | \mathbf{X}_n]]$$

$$= -\tau_z^{-1} L_N[\tau_z^{-1/2}(w_0 - \mu)]$$

- Add back $E[\mathcal{L}(1, W)]$, use prior for W

$$E[\mathcal{L}(d(\mathbf{X}_n), W)] = \tau^{-1/2} L_N[\tau^{1/2}(w_0 - \mu)] - \tau_z^{-1/2} L_N[\tau_z^{1/2}(w_0 - \mu)]$$

- EVI and EVPI

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Example: What is the mean? What is the risk...

- First-order optimality condition

$$\frac{\partial \rho}{\partial n} = \frac{1}{2} \tau_z^{-\frac{3}{2}} \phi[\tau_z^{\frac{1}{2}}(w_0 - \mu)] \cdot \frac{-\tau_z^2 \sigma^2}{n} + c = 0$$

- For small costs $c \rightarrow 0$, the sample size is large. Since $\tau_z \rightarrow \tau$ as $n \rightarrow \infty$, the optimal sample size n is asymptotically

$$n^* \approx \left(\tau^{\frac{1}{2}} \sigma^2 \phi[\tau_z^{\frac{1}{2}}(w_0 - \mu)] / (2c) \right)^{1/2}.$$

- Asymptotic approximations are a second useful tool to identify criteria-based sampling plans.
- Extensions of these ideas used to derive VIP procedures (Chick and Inoue 2001a).

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Bayesian Methods for Simulation

Alternate approximation

- Regular exponential family: asymptotic variance approximation Σ_n from theorem simplifies to

$$H^{-1}(\theta) / (n_0 + n),$$

where H is the expected information from one observation (Eq. 1), if canonical conjugate prior distribution is used

- Approximate effect of m new samples is to change posterior to

$$\text{Normal} \left(\tilde{\theta}_n, \Sigma_n \frac{n_0 + n}{n_0 + n + m} \right).$$

- Used for OCBA (Chen 1996), sampling plans for field data (Ng and Chick 2001). Frequentist result to obtain CI of desired size (Law and Kelton 2000)

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Bayesian Methods for Simulation

Another loss function: discrepancy

- Kullback-Leibler discrepancy: difference between distributions
- Discrete distributions \tilde{p} and p ,

$$\delta(p \parallel \tilde{p}) = \sum \tilde{p}_i \log(\tilde{p}_i / q_i).$$

- Continuous r.v. X with densities \tilde{f} and $f_\theta = f(x \mid \theta)$,

$$\delta(f_\theta \parallel \tilde{f}) = \int \tilde{f}(x) \log \frac{\tilde{f}(x)}{f(x \mid \theta)} dx.$$

- One use: loss function for eliciting probability. If you believe the distribution is \tilde{f} , and you lose $\delta(f \parallel \tilde{f})$ if you provide a distribution f , then you should honestly report \tilde{f} (Bernardo 1979)

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Bayesian Methods for Simulation

Discrepancy: Other uses

- Select design matrix \mathbf{d}_Θ of r vectors of inputs $(\theta_{pi}, \theta_{ei}, \theta_{ci})$ for $i = 1, 2, \dots, r$ with output \mathbf{Y} in order to best differentiate the posterior distribution of the response parameters ψ from the prior distribution for ψ (Bayesian D-optimal, Bernardo 1979; Smith and Verdinelli 1980; Ng and Chick 2002)

$$\int p(\mathbf{Y} | \mathbf{d}_\Theta) \left(\int p(\psi | \mathbf{Y}) \log \frac{p(\psi | \mathbf{Y})}{p(\psi)} d\psi \right) d\mathbf{Y}$$

- Select maximum entropy prior distribution (Jaynes 1983)
- More later: input distribution selection ...

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Why Uncertainty Analysis?

- Simple Example

$$\mu_j \rightarrow \text{Simulation} \rightarrow Y_j = 2\mu_j + e_j$$

- Input model: $X_\ell \sim \text{Normal}(\mu, \sigma_x^2)$, known σ_x^2
- Data: X_ℓ observed ($\ell = 1, 2, \dots, n_0$)
- Run r replications with \bar{X}_{n_0} input for μ
- Construct 90% CI:

$$\bar{Y}_r \pm z_{0.95} \frac{\hat{\sigma}_y}{\sqrt{r}}$$

Coverage?

If μ is known, expect coverage to be 90%. But μ is *not* known.

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$$\bar{Y}_r \pm z_{0.95} \frac{\bar{Y}_r}{\sqrt{V_{tot}}} \sqrt{V_{tot}}$$

Account for parameter uncertainty

$$V_{tot} = \frac{\sigma_y^2}{r} + \frac{4\sigma_x^2}{n_0}, \text{ so try } \bar{Y}_r \pm z_{0.95} \sqrt{V_{tot}}$$

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- Run r replications with \bar{X}_{n_0} input for μ
- Construct 90% CI:

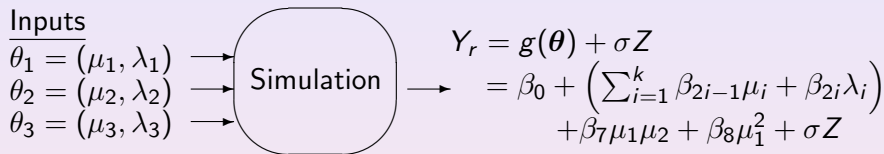
$$\bar{Y}_r \pm z_{0.95} \frac{\bar{Y}_r}{\sqrt{V_{tot}}} \sqrt{V_{tot}}$$

For known mean response g , input parameters $\theta = (\theta_1, \dots, \theta_k)$

$$V_{tot} \approx \frac{\sigma_y^2}{r} + \sum_{i=1}^k \frac{\beta_i H(\tilde{\theta}_i)^{-1} \beta_i^T}{n_i} \text{ where gradient } \beta_i = \frac{\partial g(\tilde{\theta})^T}{\partial \theta_i} \Big|_{\tilde{\theta}}$$

(asymptotics. Cheng & Holland; Ng & Chick; Wilson & Zouaoui)

Why Uncertainty Analysis? Estimate response



- Assess $X_{j\ell} \sim \text{Normal}(\mu_j, \lambda_j^{-1})$
- Observe data $X_{j\ell}$ are observed ($j = 1, 2, k; \ell = 1, 2, \dots, n_0$)
- Estimate unknown β with r_0 runs (e.g. CCD from DOE)

$$V_{tot} = \frac{\hat{\sigma}_y^2}{r_0} + \sum_{i=1}^k \underbrace{\frac{\partial g(\tilde{\theta}_n, \tilde{\beta}_{r_0})}{\partial \theta_i} \Sigma_{n_i} \frac{\partial g(\tilde{\theta}_n, \tilde{\beta}_{r_0})^T}{\partial \theta_i}}_{V_{par} = O(n_i^{-1})} + \underbrace{\Sigma_{\beta} \otimes \Sigma_{\theta}}_{V_{resp} = O(n_i^{-1} r)}$$

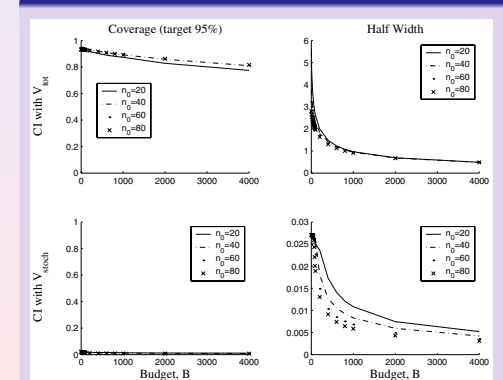
Uncertainty Analysis: Uncertainty Reduction

- Goal: Reduce uncertainty, not just quantify
 - r more replications
 - m_i more samples from source of randomness i
- Optimization:

$$\min_{r, m_i} \frac{\hat{\sigma}_y^2}{r_0 + r} + \sum_{i=1}^k \frac{\xi_i}{n_i + m_i} + \frac{\zeta_i}{(r_0 + r)(n_i + m_i)}$$

$$r, m_i \geq 0$$

CI Coverage (Chick and Ng 2004)



Uncertainty Analysis

- Sensitivity analysis: $E[g(\theta)]$ as a function of θ (average out stochastic uncertainty from \mathbf{u})
- Uncertainty analysis: $E[Y | \mathcal{E}]$, with both stochastic and parameter uncertainty, given all information \mathcal{E}
- Bayesian Model Average (BMA) estimates $E_Y[Y | \mathcal{E}]$

for $r = 1, \dots, R$ replications

sample parameter $\theta_r \sim p(\theta | \mathcal{E})$

for $i = 1, 2, \dots, n$

generate output y_{ri} given input θ_r

end loop

end loop

Generate estimate $\bar{y} = \sum_{r=1}^R \frac{1}{R} \sum_{i=1}^n \frac{y_{ri}}{n}$.

Variations on Estimating $E[Y | \mathcal{E}]$

- Zouaoui and Wilson (2003): decouple stochastic, parameter uncertainty; update estimate as new data becomes available with variations on BMA
- Andradóttir and Glynn (2004): biased estimates of $E[Y | \theta]$; quasi-random numbers; quadrature to select inputs θ_i
- Estimate distribution of conditional expectation $E[Y | \Theta, \mathcal{E}]$. Steckley and Henderson (2003) derive asymptotically optimal ways selecting r and n in BMA to produce a kernel density estimator (some conditions apply)

Outline

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Basic Problem

- Which distribution/parameter to pick?
- 'Usual':
 - 1 Pick q candidate input distributions (e.g. exponential, gamma, Weibull, lognormal)
 - 2 Find MLE $\hat{\theta}_i$ for candidates $i = 1, \dots, q$
 - 3 Goodness-of-fit (χ -squared, K-S, A-D) tests
- Concerns:
 - 1 CI coverage if MLE/best distribution selected
 - 2 How to select among unrejected models? ... (Lindley 1957; Berger and Pericchi 1996; Chick 2001)

Bayesian Input Selection

- BMA applies without change for q candidates
 - 1 Put prior on $(M = m, \theta_m)$, where $m \in \{1, 2, \dots, q\}$
 - 2 Compute posterior $p(m, \Theta_m | \mathcal{E})$, sample from it in BMA
- Chick (2001): stochastic process simulation context; moment matching method for commensurate prior distributions
- Zouaoui and Wilson (2001): decouple stochastic uncertainty from two types of structural uncertainty (candidate model & parameters); variance reduction for BMA; numerical analysis
- Model selected closest to the true model in sense of Kullback-Leibler divergence (Berk 1966; Bernardo and Smith 1994; Dmochowski 1999).

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Ranking and selection procedures differ?

- What is it for?
 - Select the 'best' of a finite set
 - Best identified by mean simulation response
- What are the approaches?
 - IZ, Indifference zone: $P(CS) \geq 1 - \alpha, \delta^*$, repeated applications of procedure
 - VIP, Bayesian value of information procedures: Like selection of mean bigger or smaller than threshold, Bayesian inference, loss, EVI
 - OCBA, Chen et al.: Heuristic, allocates samples to improve Bayesian PCS using 'thought experiment' $\sigma^2/r_0 \rightarrow \sigma^2/(r_0 + r)$

VIP procedures

- Motivated by 'statistical conservativeness' of IZ approaches
- Two-stage: Unknown means of several systems.
 - Opportunity cost and 0-1 loss ($P(CS)$)
 - Variances also unknown, different (conjugate prior, student marginal for mean)
 - Optimal solution unknown except special cases
 - Asymptotic approximation, Bonferroni bound for loss
- Sequential:
 - In theory, should improve things
 - Behrens-Fisher
 - Seems to work quite well

Procedure $\mathcal{LL}(\mathcal{B})$, for opportunity cost (linear loss)

- Specify the first-stage sample size r_0 . Take independent replications y_{i1}, \dots, y_{ir_0} , for each system, $i = 1, \dots, k$
- Compute all first-stage sample means $\bar{x}_i = \sum_{j=1}^{r_0} y_{ij} / r_0$ and sample variances $\hat{\sigma}_i^2 = \frac{\sum_{j=1}^{r_0} (y_{ij} - \bar{x}_i)^2}{r_0 - 1}$, order statistics $\bar{x}_{[1]} \leq \dots \leq \bar{x}_{[k]}$, and $\lambda_{i,k} = r_0 / (\hat{\sigma}_{[k]}^2 + \hat{\sigma}_{[i]}^2)$
- If sampling budget is B , run r_i more independent replications,

$$r_{[i]} = \frac{B + \sum_{j \in \mathcal{S}} r_0 c_j}{\sum_{j \in \mathcal{S}} \left(\frac{c_j c_{[j]} \hat{\sigma}_j^2 \eta_j}{\hat{\sigma}_{[i]}^2 \eta_{[i]}} \right)^{1/2}} - r_0$$

$$\eta_{[i]} = (\lambda_{i,k})^{1/2} \frac{(r_0 - 1) + \lambda_{i,k} (\bar{x}_{[k]} - \bar{x}_{[i]})^2}{(r_0 - 1) - 1} \phi_{r_0 - 1} [(\lambda_{i,k})^{1/2} (\bar{x}_{[k]} - \bar{x}_{[i]})]$$

if $[i] \neq [k]$ and $\eta_{[k]} = \sum_{j=1}^{k-1} \eta_{[j]}$

- Select system with largest $\bar{x}_{\bar{i}} = \sum_{j=1}^{r_0 + r_i} y_{ij} / (r_0 + r_i)$

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Bayesian Methods for Simulation

Sample Comparison with Combined Procedure, \mathcal{C} (MDM)

Figure of merit	Proc.	Number of systems, k			
		2	5	10	100
ANR	All	738	3,429	8,784	42,862
Empirical P(CS)	\mathcal{C}	0.8363	0.9140	0.9323	0.9763
	0-1(\mathcal{B}) $\mathcal{LL}(\mathcal{B})$	0.8527*	0.9117	0.9480*	0.9937*
Empirical frac. 'good' selections	\mathcal{C}	1.0000	0.9943	0.9990	1.0000
	0-1(\mathcal{B}) $\mathcal{LL}(\mathcal{B})$	1.0000	0.9953	0.9977	0.9997
Expected posterior PCS	\mathcal{C}	0.8336	0.8379	0.8649	0.9318
	0-1(\mathcal{B}) $\mathcal{LL}(\mathcal{B})$	0.8446*	0.8339	0.8821*	0.9717*
Expected bound, opp. cost	\mathcal{C}	0.0176	0.0138	0.0104	0.0037
	0-1(\mathcal{B}) $\mathcal{LL}(\mathcal{B})$	0.0157*	0.0128*	0.0075*	0.0012*
		0.0154*	0.0110*	0.0055*	0.0005*

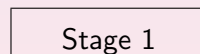
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Bayesian Methods for Simulation

VIP: Common Random Numbers

- Common random numbers (CRN) can sharpen contrasts between systems (e.g. same simulated demand pattern)
- Two-stage with screening (Chick and Inoue 2001b)
 - Run subset of systems in stage 2
 - Use 'missing data' formulas to update
 - Select from even screened systems
- Matrix intensive, heuristic provided



1 2 3 4 5 ... k

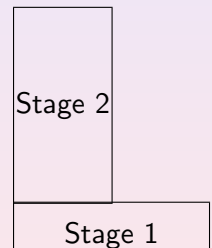
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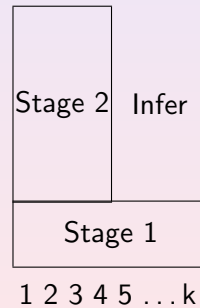
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Summaries

- VIP procedures have solid basis, perform numerically quite well (Chick and Inoue 2001a; Chick and Inoue 2002; Chick and Inoue 2001a; Inoue et al. 1999).
 - Matlab: All procedures (0-1 or opportunity cost loss; two-stage or independent sequential; two-stage CRN)
 - C: Independent replications, two-stage or sequential, both loss functions, *plus* variants (work in progress) to achieve Bayesian predictive targets for PCS and EOC
- OCBA has seen strong empirical performance. Connection?
- Have started to look at comparison of VIP with KN++ from Kim and Nelson (2001) (results not yet done)

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Metamodels

- Normal linear model

$$Y = \sum_{\ell=1}^p g_{\ell}(\boldsymbol{\theta})\beta_{\ell} + Z(\boldsymbol{\theta}; \mathbf{U}) = \mathbf{g}^T(\boldsymbol{\theta})\boldsymbol{\beta} + Z(\boldsymbol{\theta}; \mathbf{U}), \quad (4)$$

- Gaussian random function (GRF) - kriging

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Normal linear model

$$Y = \sum_{\ell=1}^P g_{\ell}(\boldsymbol{\theta})\beta_{\ell} + Z(\boldsymbol{\theta}; \mathbf{U}) = \mathbf{g}^T(\boldsymbol{\theta})\boldsymbol{\beta} + Z(\boldsymbol{\theta}; \mathbf{U}), \quad (5)$$

- Model
 - Known: regression functions g_1, \dots, g_p
 - Unknown: coefficients $\boldsymbol{\beta}$, variance of zero-mean noise $Z(\cdot)$
- Conjugate prior $p(\boldsymbol{\beta}, \sigma^2)$ (if all factors active)
 - Inverted gamma distribution for unknown variance σ^2
 - Multivariate normal distribution for $\boldsymbol{\beta}$ given σ^2 ,
 - Raftery, Madigan, and Hoeting (1997) describe a relatively 'uninformative' prior distribution, 'good' results
- Identifying important factors like input distribution selection
 - 2^P candidate models
 - KL discrepancy-based design criterion balances factor identification and parameter estimation (Ng and Chick 2004a)

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Gaussian random functions (GRF)

- Well-known in deterministic simulations, particularly in geostatistics (Cressie 1993; Santner et al. 2003)
- Provide flexibility that the linear model does not, and are useful when g takes a long time to compute.
- GRF for unknown nonstochastic g (no random numbers \mathbf{u}) is

$$Y(\boldsymbol{\theta}) = \sum_{\ell=1}^P g_{\ell}(\boldsymbol{\theta})\beta_{\ell} + Z(\boldsymbol{\theta}) = \mathbf{g}^T(\boldsymbol{\theta})\boldsymbol{\beta} + Z(\boldsymbol{\theta}) \quad (6)$$

for *known* regression functions g_1, \dots, g_p of \mathbb{R}^d , unknown regression coefficients $\boldsymbol{\beta}$, and a *zero-mean random second-order process* so that for any distinct inputs $\boldsymbol{\theta}_1, \dots, \boldsymbol{\theta}_m$, the vector (Y_1, \dots, Y_m) has (nonindependent) multivariate normal distribution, conditional on $\boldsymbol{\beta}$.

Inference with GRFs

- GRF: Determined by mean $\mathbf{g}^T(\boldsymbol{\theta})\boldsymbol{\beta}$ and covariance function

$$C^*(\boldsymbol{\theta}_1, \boldsymbol{\theta}_2) = \text{Cov}(Y(\boldsymbol{\theta}_1), Y(\boldsymbol{\theta}_2))$$

- Common to assume strong stationarity, so

$$C^*(\boldsymbol{\theta}_1, \boldsymbol{\theta}_2) = C(\boldsymbol{\theta}_1 - \boldsymbol{\theta}_2)$$

- Inference for $g(\boldsymbol{\theta})$ at $\boldsymbol{\theta}_{r+1}$ not yet input to simulation model with correlation function $R(\mathbf{h}) = C(\mathbf{h})/C(0)$ for $\mathbf{h} \in \mathbb{R}^d$.
Example: power exponential $R(\mathbf{h}) = \prod \exp[-|h_i/\gamma_i|^{p_i}]$ for $p_i \in [0, 2]$.
- Kriging (geostatistics) is best linear unbiased prediction (BLUP) for $g(\boldsymbol{\theta}_{r+1})$

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More GRF

- Assessment of uncertainty in $g(\boldsymbol{\theta}_{r+1}) \Rightarrow$ experimental design technique to choose inputs to reduce response uncertainty (Santner et al. 2003)
- Also see tutorial by van Beers and Kleijnen (2004) in this year's WSC
- Deterministic simulation: (Sacks et al. 1989; O'Hagan et al. 1999; Kennedy and O'Hagan 2001; Santner et al. 2003; van Beers and Kleijnen 2003).
- More work is needed for GRFs in the stochastic simulation context.

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Implementation

Issues:

- Maximize (MLE $\hat{\theta}$ or MAP $\tilde{\theta}$)
- Integrate (marginal distribution $p(\theta_1 | \mathbf{x}_n)$ from $p(\theta_1, \theta_2 | \mathbf{x}_n)$, or proportionality constant $c^{-1} = \int f(\mathbf{x}_n | \theta) d\pi(\theta)$)
- Simulate (sample from $p(\theta | \mathbf{x}_n)$ to estimate $E[\alpha(\Theta)]$)

Tools:

- Newton-Raphson, Nelder-Mead, expectation-maximization (EM) algorithm, ...
- Quadrature, normal approximation, data augmentation (IP algorithm), importance sampling (IS)
- Inversion, importance sampling (IS), Markov Chain Monte Carlo (MCMC)

Evans and Swartz 1995; Tanner 1996; Gilks et al. 1996; Devroye 2004, ...

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Metropolis-Hastings: An MCMC Algorithm

Target: Sample from $p(\theta | \mathcal{E})$

Capable: Easily sample from $q(\cdot | \theta_{t-1})$

Initialize $t = 0, \theta_0$

for $t = 1, 2, \dots$

sample a candidate $\theta \sim q(\cdot | \theta_{t-1})$

compute acceptance probability

$$\alpha(\theta_{t-1}, \theta) = \min \left\{ 1, \frac{p(\theta | \mathcal{E}) \cdot q(\theta_{t-1} | \theta)}{p(\theta_{t-1} | \mathcal{E}) \cdot q(\theta | \theta_{t-1})} \right\}$$

generate an independent $u \sim \text{uniform}[0, 1]$

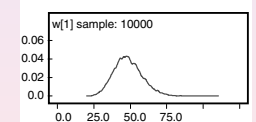
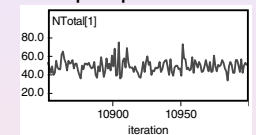
if $u \leq \alpha(\theta_{t-1}, \theta)$ then set $\theta_t \leftarrow \theta$

otherwise set $\theta_t \leftarrow \theta_{t-1}$

set $t \leftarrow t + 1$

end loop

Sample path



Density Estimate

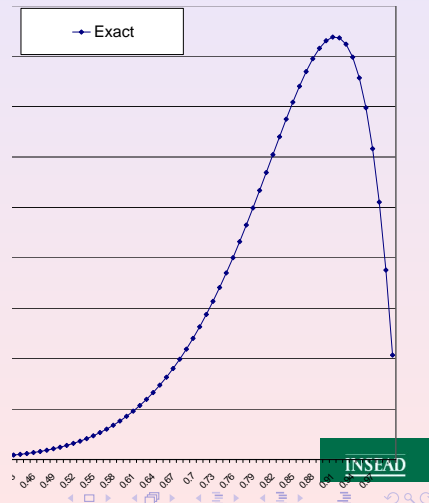
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Approximating Posterior Distributions: Pros and Cons

Exact Posterior

- Exact
- Good if simple closed form known
- May be hard in general (mixtures, missing data, marginal distribution, curse of dimensionality?)

Here, gene linkage example (Tanner 1996)



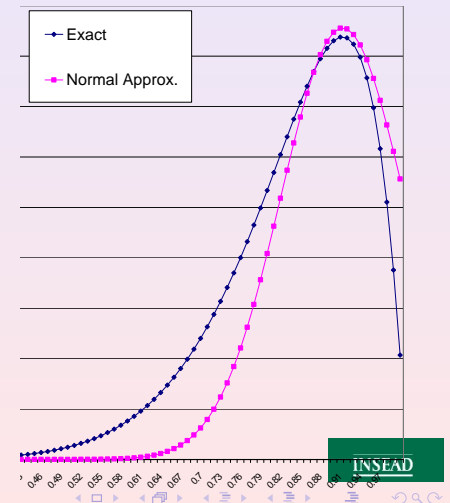
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Bayesian Methods for Simulation

Approximating Posterior Distributions: Pros and Cons

Asymptotic normality (from theorem)

- Normal $(\tilde{\theta}_n, \Sigma_n)$
- Relatively easy to compute
- Requires many data points ($n > 20d$)
- Does not model skew, etc.



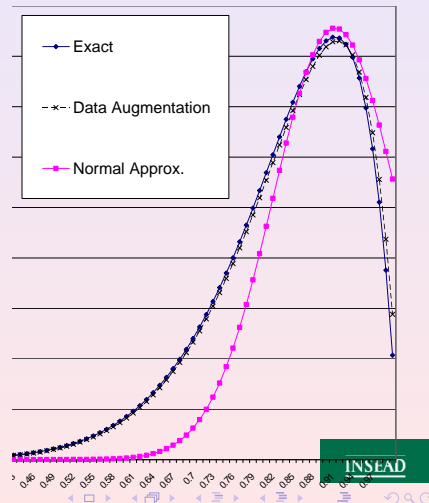
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Bayesian Methods for Simulation

Approximating Posterior Distributions: Pros and Cons

Data Augmentation (IP algorithm)

- $p(\theta|\mathcal{E}) = \int p(\theta|Z, \mathcal{E})p(Z|\mathcal{E})$, average over $Z =$ 'missing data'
- 1 Set $i = 0$; $g_0(\theta) =$ current estimate of $p(\theta|\mathcal{E})$
- 2 Generate z_1, z_2, \dots, z_m from $g_i(\theta)$ by
 - 1 Sample $\theta_1, \dots, \theta_m$ from $g_i(\theta)$
 - 2 Sample z_1, \dots, z_m from $p(Z|\theta_i, \mathcal{E})$
- 3 $g_{i+1}(\theta) = \sum_{j=1}^m p(\theta|z_j, \mathcal{E})$



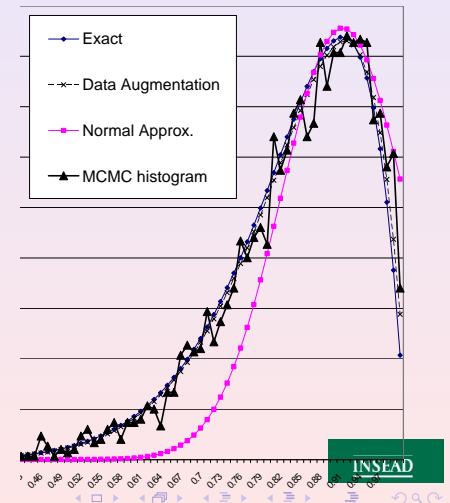
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Bayesian Methods for Simulation

Approximating Posterior Distributions: Pros and Cons

MCMC with histogram

- General tool to sample (approximately) from posterior
- Complicated models possible
- Output analysis issues (convergence)
- Time-average (IP was average of distributions)
- MCMC can average distributions, too

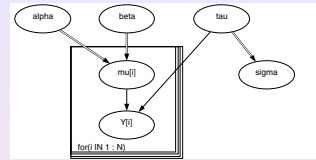


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Bayesian Methods for Simulation

Some Tools

- Handcode: Matlab, C, Gauss
- WinBUGS (Spiegelhalter et al. 1996) (<http://www.mrc-bsu.cam.ac.uk/bugs/welcome.shtml>)
- R (<http://www.r-project.org/>), S-PLUS packages, BOA add-on (<http://www.public-health.uiowa.edu/boa/>)
- Uncertainty analysis in spreadsheet Monte Carlo applications are available (e.g. Winston 2000).
- Most DEDS Commercial Tools: cumbersome to implement BMA



```

model
{
  for( i in 1 : N ) {
    Y[i] ~ dnorm(mu[i],tau)
    mu[i] <- alpha + beta * (x[i] - xbar)
  }
  tau ~ dgamma(0.001,0.001) sigma <- 1 / sqrt(tau)
  alpha ~ dnorm(0.0,1.0E-6)
  beta ~ dnorm(0.0,1.0E-6)
}

```

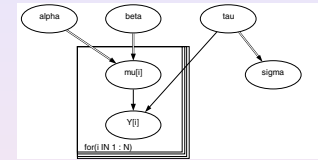


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```



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Bayesian Methods for Simulation

Bayesian Methods for Stochastic Process Simulation

- Themes:
 - Represent *all* uncertainty with probability, update with Bayes' rule, expected value of information for sampling decisions
 - Use simulation to efficiently estimate quantities of interest for a Bayesian analysis
- Applications: input distribution selection, uncertainty analysis, experimental design, ranking and selection
- Asymptotic approximations helpful when exact optimal solutions are hard to find

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Bayesian Methods for Simulation

Research opportunities include

- Input modeling and uncertainty analysis (kernel estimation of conditional means; the effect of different candidate distributions on uncertainty; prior distributions elicitation; calibration/inverse problem)
- Response modeling (extend the Gaussian random field work for stochastic simulation; nonasymptotic sampling plans for input parameter inference to optimally reduce output uncertainty; reasoning about models; calibration. . .)
- Experimental design (quantiles, non-expected value goals; CRN for unknown input parameters for ranking and selection; non-Gaussian output for ranking and selection, GRFs)
- Improved computational tools (e.g. MCMC, software interop)

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Bayesian Methods for Simulation