

Stochastic Simulation Introduction

Bo Friis Nielsen

Applied Mathematics and Computer Science

Technical University of Denmark

2800 Kgs. Lyngby – Denmark

Email: bfni@imm.dtu.dk

Practicalities



- Notes will be handed out next week, some will be available online
- Course evaluation is: passed/not passed - based on lab reports, report over final project, and possibly oral presentation of project.
- Teachers:
 - ◇ Bo Friis Nielsen, room 205, building 321 ext. 53397, e-mail bfni@imm.dtu.dk
 - ◇ Flavia Dalia Frumosa fdal@dtu.dk, Jesper Fink Andersen jfan@dtu.dk, Oscar Peralta Gutierrez osgu@dtu.dk

Significance



- One of the most (**The most?**)important Operations Research techniques
- Many modern statistical techniques rely on simulation

What is simulation?

DTU

- (From *Concise Oxford Dictionary*): To simulate: To pretend, to act like, to mimic, to imitate.
- Here: *Computer experiments with mathematical model*

- **Stochastic simulation**

To (have a computer) simulate a system which is affected by randomness.

Narrow sense: To generate (pseudo)random numbers from a prescribed distribution (e.g. Gaussian)

- Computer experiments with mathematical model
- General engineering technique
- Analytical/numerical solutions

Why simulate?



- Real system expensive
- Mathematical model to complex
- Get idea of dynamic behaviour

Related areas



- Statistics
- Computer science
- Operations research

Target group



- Methodology course of general interest
- Of special importance for students specialising in
 - ◇ Computer science
 - ◇ Statistics
 - ◇ Operations Research
 - ◇ Planning and management

Course goal



- Topics related to scientific computer experimentation
- Specialised techniques
 - ◇ Variance reduction methods
 - ◇ Random number generation
 - ◇ Random variable generation
 - ◇ The event-by-event principle
- Simulation based statistical techniques
 - ◇ Markov chain Monte Carlo
 - ◇ Bootstrap
- Validation and verification of models
- Model building

02443

Recommended reading

- Sheldon M. Ross: Simulation, fifth edition, Academic Press 2013
- Averill M. Law: Simulation Modeling and Analysis, McGraw-Hill 2015, ISBN 0-07-340132-3
- Jerry Banks, John S. Carson II, Barry L. Nelson, David M. Nicol: Discrete-Event System Simulation, Prentice and Hall 1999, ISBN 0-13-088702-1
- Brian Ripley: Stochastic Simulation, John Wiley & Sons 1987, ISBN 0-471-818884-4.
- Reuven Y. Rubinstein and Benjamin Melamed: Modern Simulation and Modelling, John Wiley & Sons 1998, ISBN 0-471-17077-1
- Jack P. C. Kleijnen: Statistical Tools for Simulation Practitioners, Marcel Dekker 1987, ISBN 0-8247-7333-0

Knowledge/science in simulation



- Modelling skill
- Statistical methods - it is necessary to understand statistical methodology
- OR - Stochastic Processes
- Technical skills
 - ◇ Random number generations
 - ◇ Sampling from distributions
 - ◇ Variance reduction techniques
 - ◇ Statistical techniques bootstrap/MCMC
- General purpose/and specialised simulation software

Discrete versus continuous



- Discrete event simulation
- as opposed to continuous simulation
- mixed models

Probability basics

- $0 \leq P(A) \leq 1$ $P(\Omega) = 1$ $P(\emptyset) = 0$
- $A \cap B = \emptyset \Rightarrow P(A \cup B) = P(A) + P(B)$
- Complement rule $P(A^c) = 1 - P(A)$
- Difference rule for $A \subset B$: $P(B \cap A^c) = P(B) - P(A)$
- Inclusion, exclusion for 2 events
$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$
- Conditional probability: for A given B (partial information): $P(A|B) = \frac{P(A \cap B)}{P(B)}$
- Multiplication rule: $P(A \cap B) = P(B)P(A|B)$
- Law of total probability: (B_i is a partitioning), $P(A) = \sum_i P(B_i)P(A|B_i)$
- Bayes theorem: (B_i is a partitioning): $P(B_i|A) = \frac{P(A|B_i)P(B_i)}{\sum_j P(A|B_j)P(B_j)}$
- independence: $P(A|B) = P(A|B^c)$ ($P(A \cap B) = P(A)P(B)$)

Random variables



- Mapping from sample space to the real line
- Probabilities defined in terms of the preimage
- Most probabilistic calculations are performed with only a slight reference to the underlying sample space

Random variables



- Random variables: *maps* **outcomes** to **real values**

- ◇ Distribution $P(X = x) \quad \sum_x P(X = x) = 1$

- ◇ Joint distribution

$$P(X = x, Y = y) \quad \sum_{x,y} P(X = x, Y = y) = 1$$

- ◇ Marginal distribution $P_X(X = x) = \sum_y P(X = x, Y = y)$

- ◇ Conditional distribution $P(Y = y|X = x) = \frac{P(X=x,Y=y)}{P_X(X=x)}$

- ◇ independence $P(Y = y, X = x) = P_X(X = x)P_Y(Y = y)$

- Mean value $E(X) = \sum x \cdot P(X = x)$

- General expectation $E(g(X)) = \sum g(x) \cdot P(X = x)$

- Linearity $E(aX + bY + c) = aE(X) + bE(Y) + c$

Continuous random variables

- Uniform distribution of two variables: $P((x, y) \in C) = \frac{A(C)}{A(D)}$
- Continuous random variables
 - ◇ Density: $f(x) \geq 0$, $\int f(x)dx = 1$, $P(X \in dx) = f(x)dx$
 - ◇ Mean, variance (moments): $E(X) = \int x f(x)dx$
 $E(g(X)) = \int g(x) f(x)dx$, $E(X^k) = \int x^k f(x)dx$
- Normal distribution: $f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$ $Z = \frac{X-\mu}{\sigma}$
- Joint densities
$$f(x, y)dx dy = P(x \leq X \leq x + dx, y \leq Y \leq y + dy), f(x, y) \geq 0$$
- Joint distribution

$$F(x, y) = P(X \leq x, Y \leq y) = \int_{-\infty}^y \int_{-\infty}^x f(u, v) du dv$$

Continuous random variables continued

- Conditional continuous distributions $f(y|X = x) = \frac{f(x,y)}{f_X(x)}$



- Integral version of law of total probability

$$P(A) = \int P(A|X = x) f_X(x) dx$$

- Conditional expectation $E(Y) = E(E(Y|X))$
- Covariance/correlation

$$Cov(X, Y) = E[(X - E(X))(Y - E(Y))] = E(XY) - E(X)E(Y)$$

$$Corr(X, Y) = \frac{Cov(X, Y)}{SD(X)SD(Y)}$$

- (X, Y) independent $\Rightarrow Corr(X, Y) = 0$
- Variance of sum of variables

$$Var\left(\sum_{k=1}^N X_k\right) = \sum_{k=1}^n Var(X_k) + 2 \sum_{1 \leq j < k \leq n} Cov(X_j, X_k)$$

- Bilinearity of covariance

$$Cov\left(\sum_{i=1}^n a_i X_i, \sum_{j=1}^m b_j Y_j\right) = \sum_{i=1}^n \sum_{j=1}^m a_i b_j Cov(X_i, Y_j)$$