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**Software**

# ***COSSAN TRAINING COURSE*** ***on UNCERTAINTY QUANTIFICATION***

## **Bayesian Model Updating: Part II**

Adolphus Lye

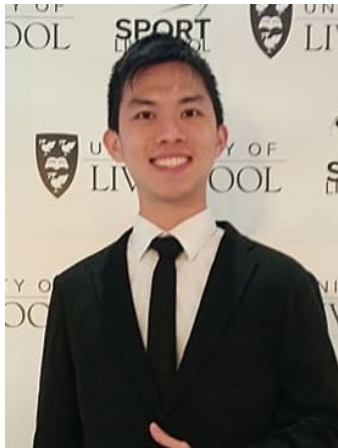
**COSSAN**  
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[info@cossan.co.uk](mailto:info@cossan.co.uk)  
[www.cossan.co.uk](http://www.cossan.co.uk)

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# Introduction

Facilitator



- PhD Student, 2<sup>nd</sup> Year of Study
- Affiliated with Singapore Nuclear Research and Safety Initiatives (SNRSI)
- Research Interests:
  - Bayesian Model Updating;
  - Mathematical Modelling;
  - Nuclear Energy;
  - Predictive Maintenance;
  - Probabilistic Safety Assessment

# Pre-requisites

Participants/Students should have watched/read the following:

- Lecture Note: Bayesian Model Updating [Part I]
- Lecture Video: Bayesian Model Updating [Part I]

- 1 Re-cap of Bayesian Model Updating
- 2 Motivation behind Advanced Sampling Techniques
- 3 Detailed description of Advanced Sampling Techniques:
  - Markov Chain Monte-Carlo (MCMC)
  - Transitional Markov Chain Monte-Carlo (TMCMC)
  - Sequential Monte-Carlo (SMC)
- 4 Tutorials

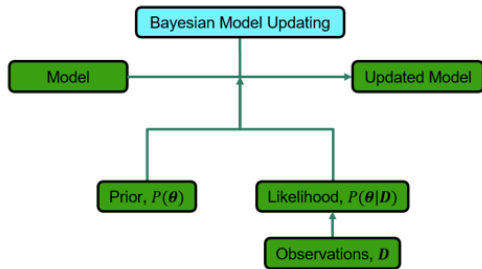
# Bayesian Model Update

## Re-cap

A Probabilistic Model Updating technique based on Bayes' Inference:

$$P(\theta|\mathbf{D}) = \frac{P(\theta) \cdot P(\mathbf{D}|\theta)}{P(\mathbf{D})} \quad (1)$$

where  $P(\theta)$  is the Prior;  $P(\mathbf{D}|\theta)$  is the Likelihood function;  $P(\theta|\mathbf{D})$  is the Posterior;  $P(\mathbf{D})$  is the Evidence.  $\theta$  denotes vector of epistemic parameters;  $\mathbf{D}$  denotes vector of observations.



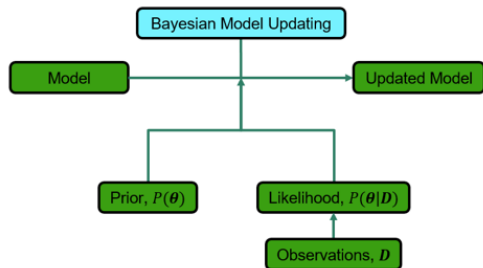
# Bayesian Model Update

## Re-cap

$P(\mathbf{D})$  is a normalisation factor which is independent of  $\theta$  and, thus, a numerical constant.

Equation (1) can therefore be re-expressed as shown below:

$$P(\theta|\mathbf{D}) \propto P(\theta) \cdot P(\mathbf{D}|\theta)$$



# Bayesian Model Update

## Re-cap

- To generate samples from a distribution, a standard tool would be **Monte-Carlo** sampling;
- HOWEVER...recall that:

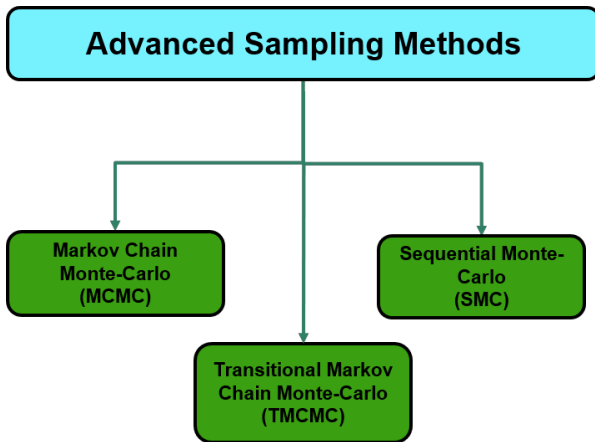
$$P(\theta|\mathbf{D}) \propto P(\theta) \cdot P(\mathbf{D}|\theta)$$

- Standard Monte-Carlo technique is unable to sample from un-normalised distribution function;
- We need advanced sampling techniques to do so ... ..



# Bayesian Model Update

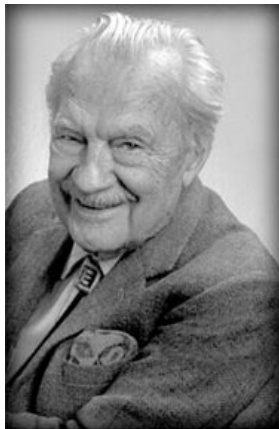
Re-cap



# MCMC Sampler

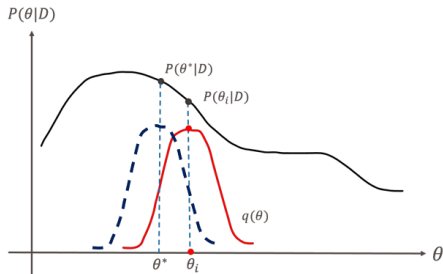
## Conceptual Introduction

- Conceptualised by Nicholas Metropolis;
- Adopts the use of Markov Chains to generate samples;
- New samples are generated based on current sample via a Proposal distribution;
- The chain will run until it approaches stationary distribution (Posterior);
- Accept-Reject algorithm: Metropolis-Hastings.

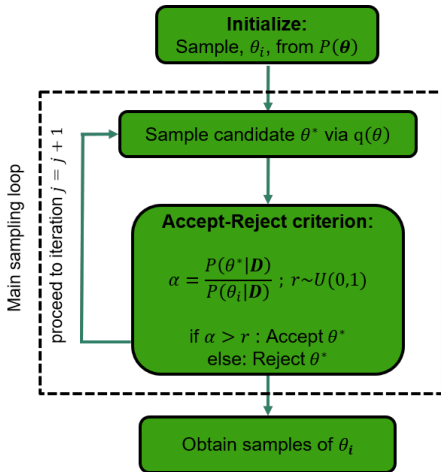


# MCMC Sampler

## Work-flow of the MCMC sampler



Note: Should  $\theta^*$  be accepted, the Proposal distribution will shift from its current location (in red), to the new one represented by the blue dotted curve. Otherwise, the Proposal distribution remains in its current location.



# TMCMC Sampler

## Conceptual Introduction

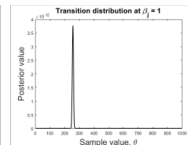
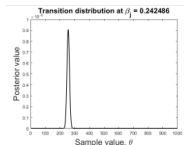
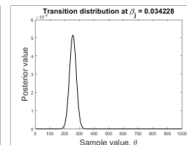
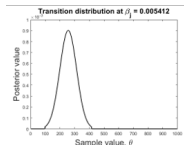
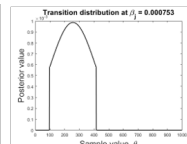
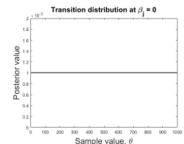
- Based on Adaptive Metropolis-Hastings (AMH) algorithm;
- Adopts the use “transitional” distributions,  $P^j$ :

$$P^j = P(\mathbf{D}|\theta)^{\beta_j} \cdot P(\theta)$$

where  $j = 1, \dots, m$  denotes the iteration number, and  $\beta_j$  is such that

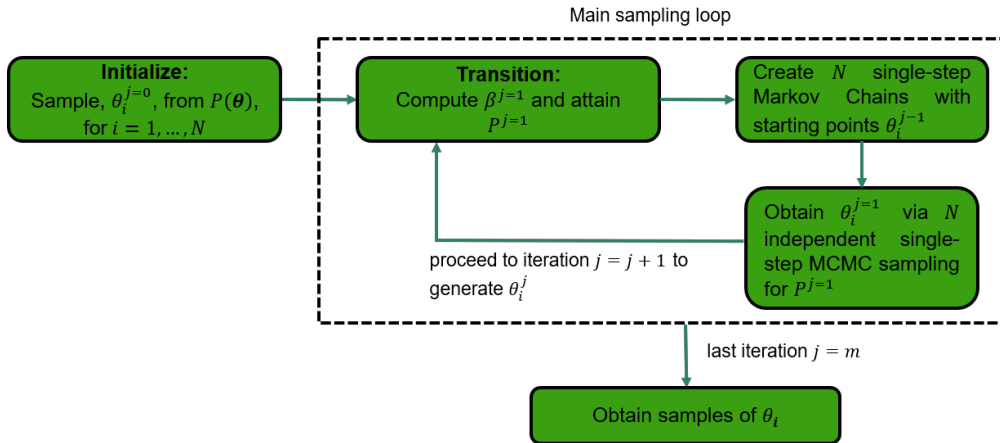
$$\beta_0 = 0 < \beta_1 < \dots < \beta_{m-1} < \beta_m = 1$$

- Change in  $\beta_j$  has to be small to ensure smooth, gradual transition;
- Performs parallel sampling:  $N$  samples obtained per iteration.



# TMCMC Sampler

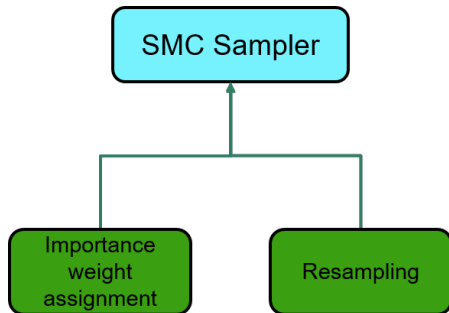
## Work-flow of the TMCMC sampler



# SMC Sampler

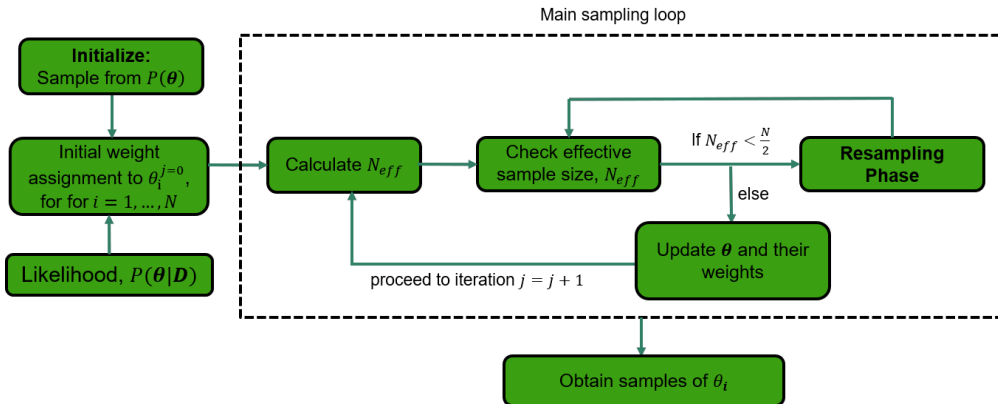
## Conceptual Introduction

- Based on the Sequential Importance Resampling (SIR) Particle-Filter algorithm;
- Adopted for systems identification and to sample from dynamic posteriors in a sequential manner;
- Recursive algorithm.



# SMC Sampler

## Work-flow of the SMC sampler



# Relevant References

For More Information

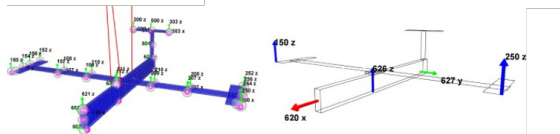
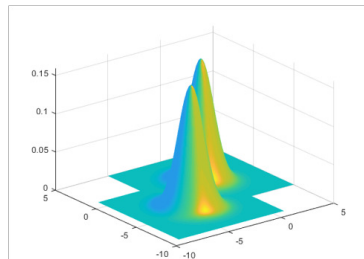
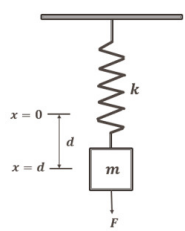
Technique:	References:
MCMC	W. K. Hastings (1970). Monte Carlo Sampling Methods using Markov Chains and their Applications, <i>Biometrika</i> <b>57</b> , 97-109. doi: 10.1093/biomet/57.1.97
TMCMC	J. Y. Ching, and Y. C. Chen (2007). Transitional Markov Chain Monte Carlo Method for Bayesian Model Updating, Model Class Selection, and Model Averaging, <i>Journal of Engineering Mechanics</i> <b>133</b> . doi: 10.1061/(ASCE)0733-9399(2007)133:7(816)
SMC	<p>P. D. Moral, A. Doucet, and A. Jasra (2006). Sequential Monte Carlo Samplers, <i>Journal of the Royal Statistical Society. Series B (Statistical Methodology)</i> <b>68</b>, 411-436.</p> <p>N. Chopin (2002). A Sequential Particle Filter Method for Static Models, <i>Biometrika</i> <b>89</b>, 539-552. doi: 10.1093/biomet/89.3.539</p>



# Bayesian Model Update Tutorial Problems

Tutorials on the use of Advanced Monte Carlo Sampling methods

- 4 sets of tutorials are available on OpenCOSSAN:
  - 1-D Linear Static Spring-Mass System
  - 1-D Simple Harmonic Oscillator System
  - 2-D Inverse Eigen-value Problem
  - 18-D DLR-AIRMOD
- Each tutorial presents the implementation of 3 advanced sampling techniques:
  - MCMC Sampler
  - TMCMC Sampler
  - SMC Sampler



# Conclusion

## Summary

- Overview of the different Advanced Sampling Techniques;
- Detailed description of the workings of each Advanced Sampling Technique
- Understanding of the difference between each Advanced Sampling Technique;

# Conclusion

Follow-up

## What's next

- Read up / watch lecture series on the implementation of Bayesian Model Updating on OpenCOSSAN.