

# **Exact Simulation in a Nutshell**

# Murray Pollock<sup>1</sup>, Adam Johansen & Gareth Roberts





# - Overview

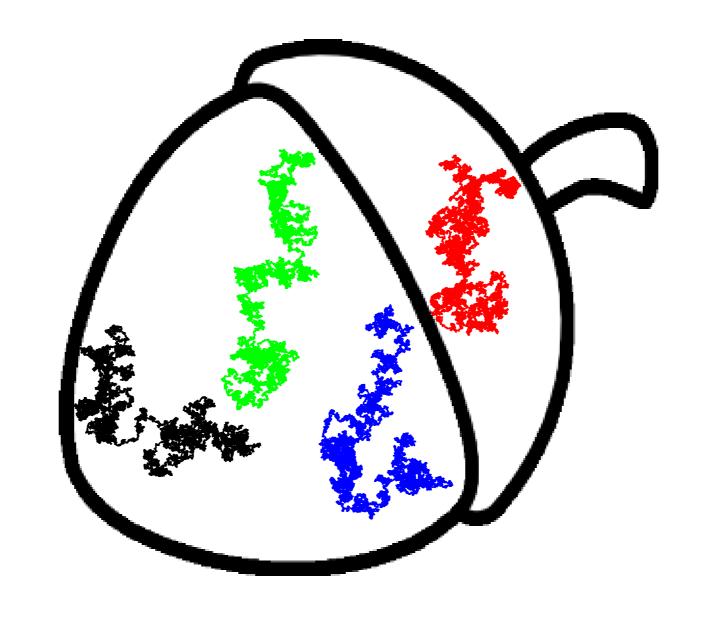
1.1 - The Goal...??? Evaluate with certainty whether or not a given jump diffusion sample path crosses a barrier.

Target Jump Instantaneous Jump Jump Size Initial Value 
$$\mathbb{T}^{x}_{0,T}: \mathrm{d}X_{t} = \beta(X_{t-})\,\mathrm{d}t + \sigma(X_{t-})\,\mathrm{d}W_{t} + \mathrm{d}J^{\lambda,\mu}_{t}, \quad t \in [0,T], \ X_{0} = x.$$
Instantaneous Standard Compound Poisson Mean Brownian Motion Process Interval

1.2 - Main Difficulties...??? Sample paths are infinite dimensional random variables. Discretisation schemes introduce error and don't sufficiently characterise sample paths to determine barrier crossing.

1.3 - Applications... Monte Carlo Integration, Option Pricing, Simulating First Hitting Times, Killed Diffusions, Rare Events...

## ...in a nutshell...



# 2 - Summary of Key Methodology

2.1 - Exact Algorithm (EA)... A diffusion path space retrospective rejection sampler which characterises entire (accepted) sample paths in the form of a finite dimensional skeleton, composed of the sample path at a finite collection of intermediate points and spatial information.

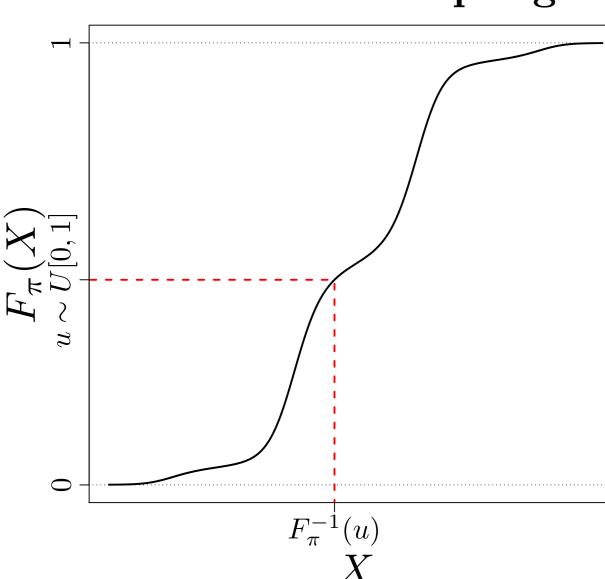
2.2 -  $\epsilon$ -Strong Simulation ( $\epsilon$ SS)... Methodology for constructing upper and lower convergent dominating processes  $(X^{\downarrow})$  and  $X^{\uparrow}$ , which enfold almost surely sample paths over some finite interval.

**2.3** - Sufficient Conditions...  $\beta \in C^1$ ,  $\sigma \in C^2$  and strictly positive,  $\lambda$ locally bounded, linear growth and Lipschitz continuity coefficient conditions.

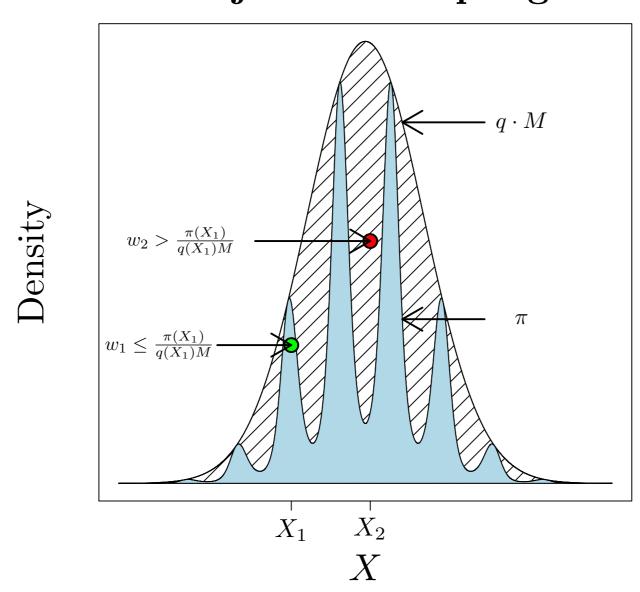
**2.4** - Further Details... arXiv 1302.6964 or scan QR code!

### 3 - Key Ideas

**Inversion Sampling** 



Rejection Sampling



Key Idea: Find and simulate some finite dimensional

auxiliary random variable  $F := F(X) \sim \mathbb{F}$ , such that an

unbiased estimator of the acceptance probability can be

constructed which can be evaluated using only a finite

4 – With probability  $P_{\mathbb{P}_{0,T}^{x}|F}(X)$  accept, else reject and

 $5 - *** Simulate X^c \sim \mathbb{P}_{0,T}^{x,y} | (X^f, F) \text{ as required. } ***$ 

dimensional subset of the proposal sample path...

Implementable Exact Algorithm

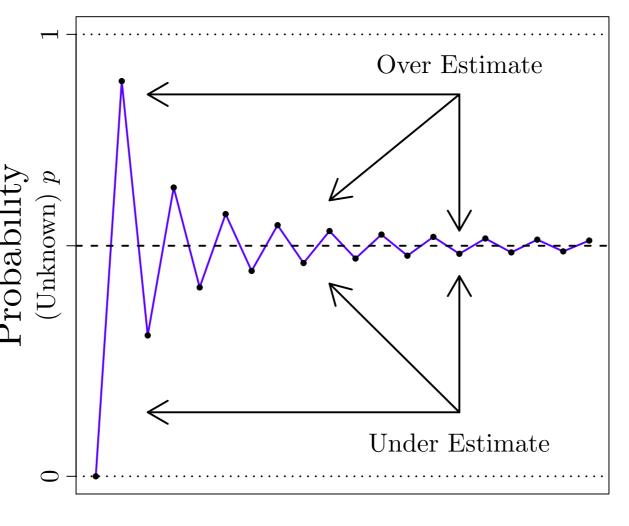
1 – Simulate  $X_T := y \sim h$ .

3 – Simulate  $X^f \sim \mathbb{P}_{0,T}^{x,y} | F$ .

2 – Simulate  $F \sim \mathbb{F}$ .

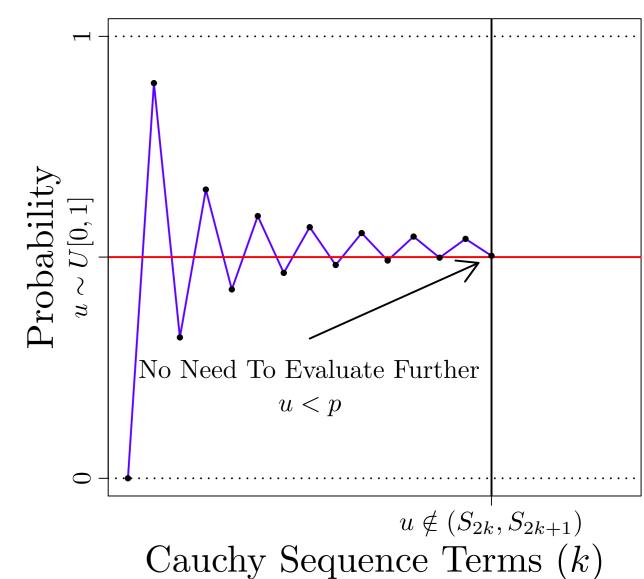
return to 1.

Bernoulli Sampling



Cauchy Sequence Terms (k)

Retro. Bernoulli Sampling



### 4 - The Exact Algorithm

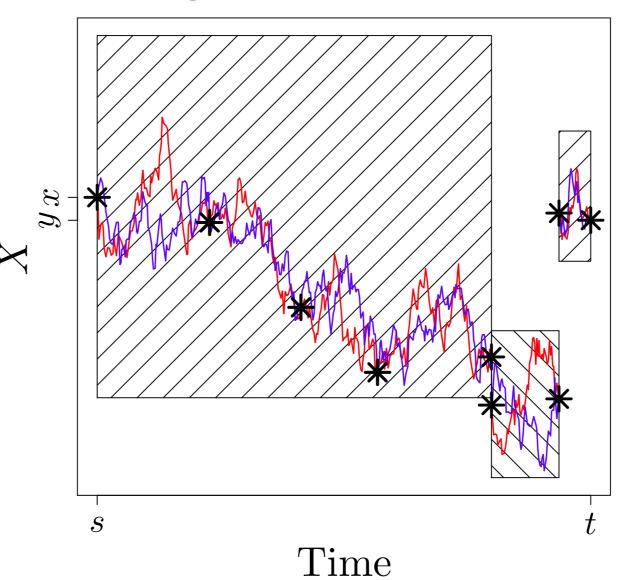
#### **Idealised Exact Algorithm**

- 1 Simulate  $X \sim \mathbb{P}_{0,T}^{x}$ .
- 2 With probability  $P_{\mathbb{P}_{0,T}^x}(X) := \frac{1}{M} \frac{\mathrm{d}' \mathbb{F}_{0,T}^x}{\mathrm{d} \mathbb{P}_{0,T}^x}(X) \in [0,1]$ set I = 1.
- $3 X | (I = 1) \sim \mathbb{T}_{0,T}^{x}$

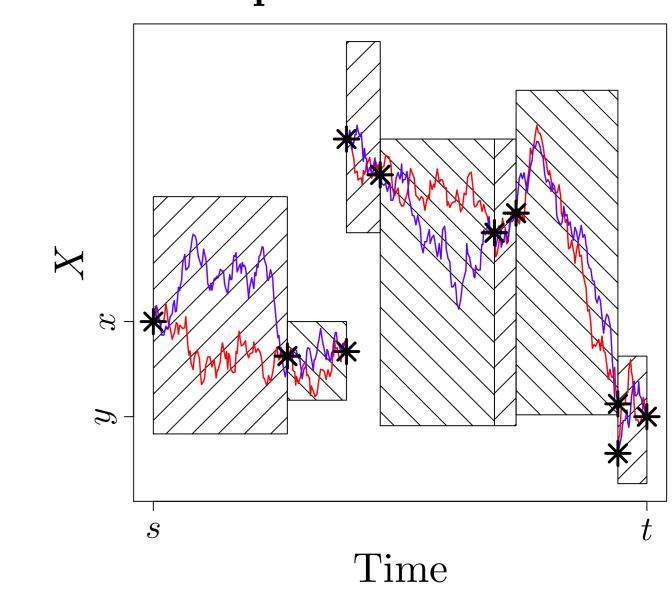
#### **Key Points**

- $1 \mathbb{T}_{0,T}^{x}$  target law.
- $2 \mathbb{P}_{0,T}^{x}$  equivalent (+ tractable) proposal law.
- $3 \frac{\mathrm{d}\mathbb{T}_{0,T}^x}{\mathrm{d}\mathbb{P}_{0,T}^x}(X)$  bounded (by  $M < \infty$ ).

#### "Regular" EA Skeleton

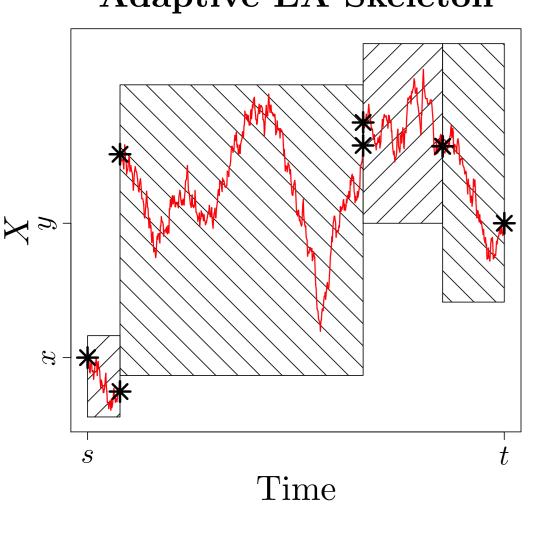


Adaptive EA Skeleton

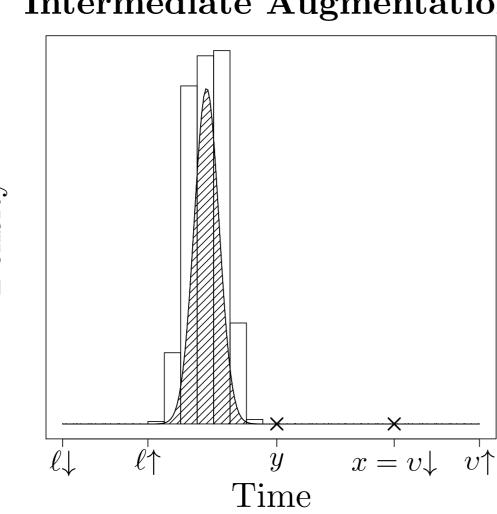


# **5** - $\epsilon$ -Strong Simulation

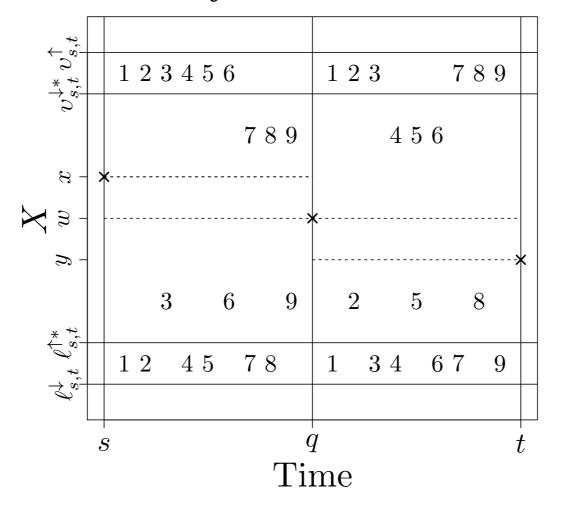
Adaptive EA Skeleton



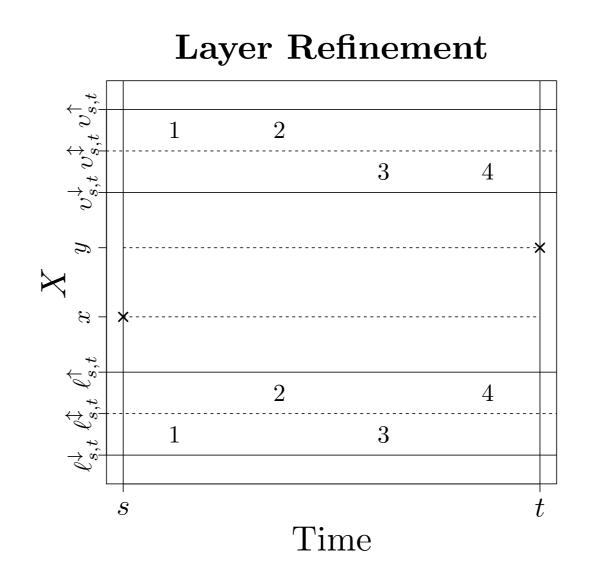
Intermediate Augmentation

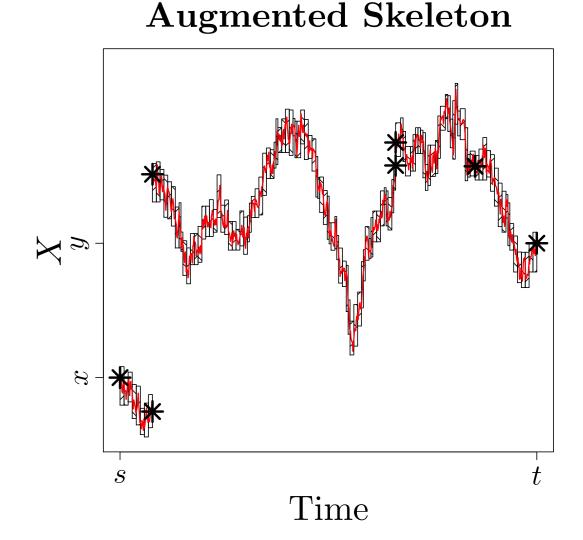


Layer Dissection

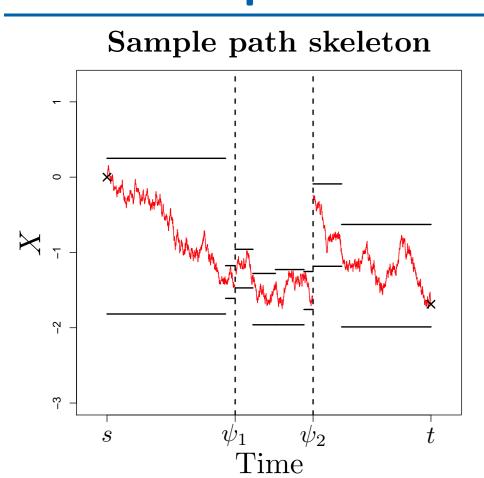


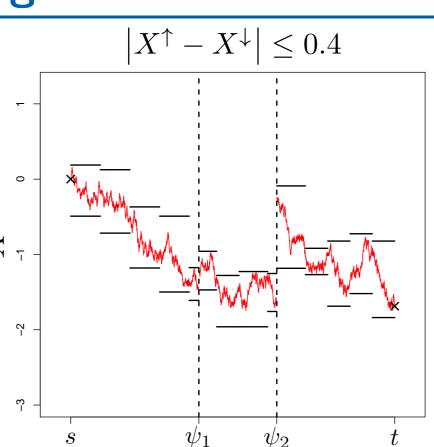
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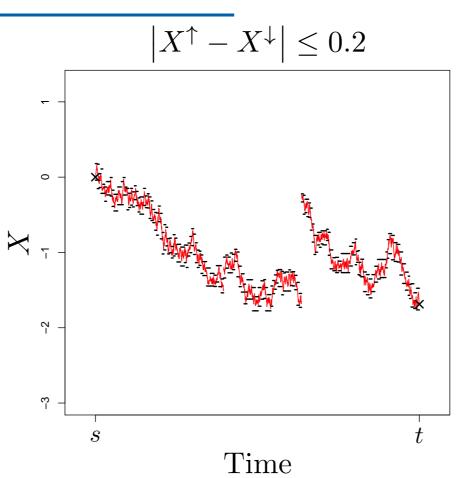


# 6.1 - Example 1: $\epsilon$ -Strong Simulation of Jump Diffusions

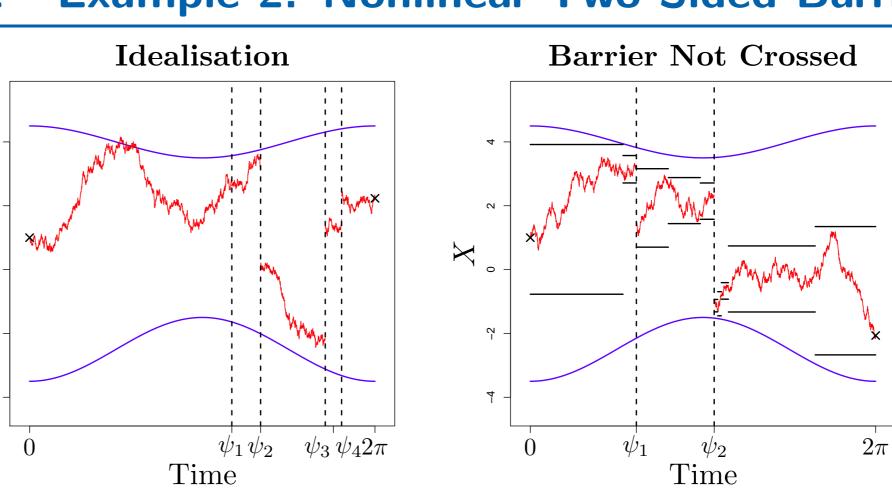


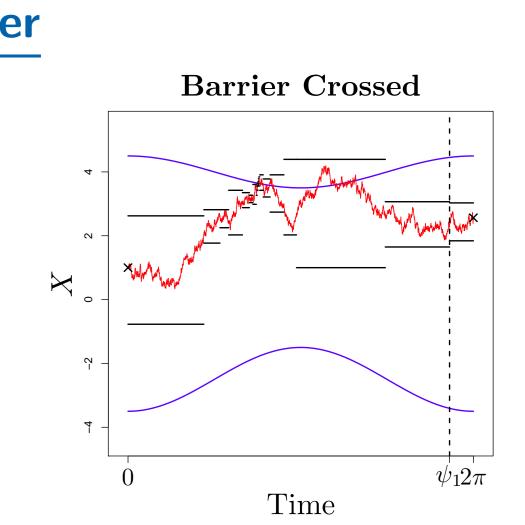


Time

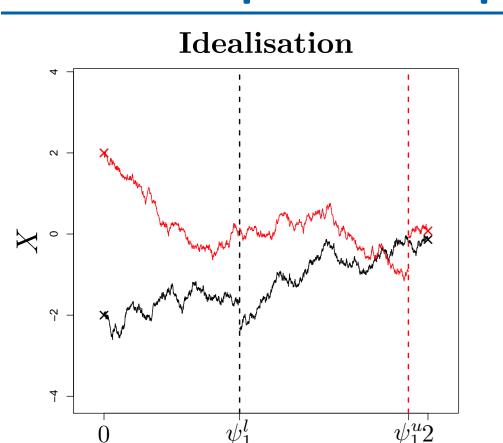


# 6.2 - Example 2: Nonlinear Two Sided Barrier

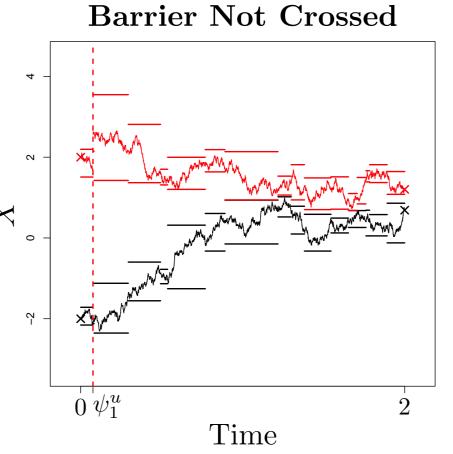


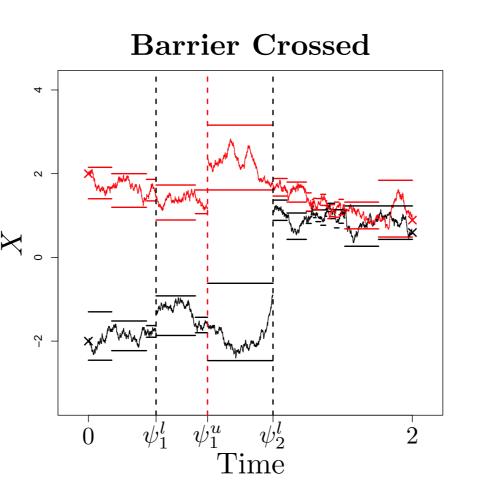


### 6.3 - Example 3: Jump Diffusion Intersection

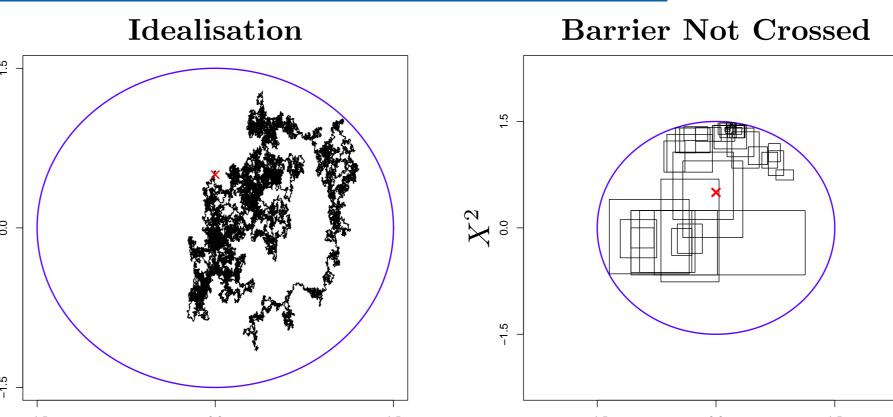


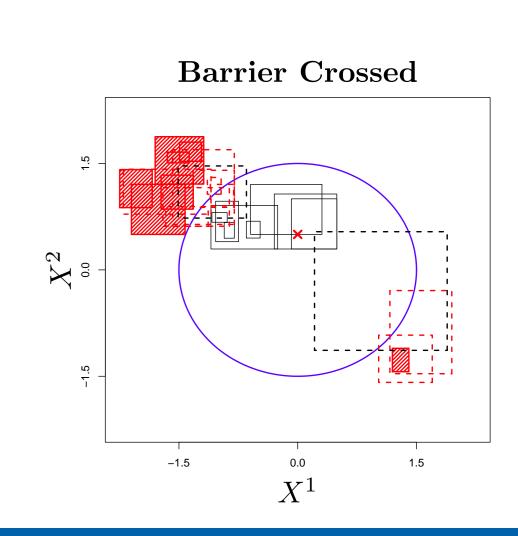
Time





# 6.4 - Example 4: Circular Barrier





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