Speeding up Monte Carlo methods

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- Reliability analysis
  - → estimating small probabilities

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- Reliability analysis
  - → estimating small probabilities
- Estimating properties
  - → if you can define them as an expectation

$$X \sim P(X)$$

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$$p_{fail} = \mathcal{P}(g(X) < 0)$$

$$egin{aligned} X &\sim P(X) \ &p_{fail} = \mathcal{P}(g(X) < 0) \ &= \mathbb{E}_{X \sim P} \left[ \mathbb{1}_{g(X) < 0} 
ight] \end{aligned}$$

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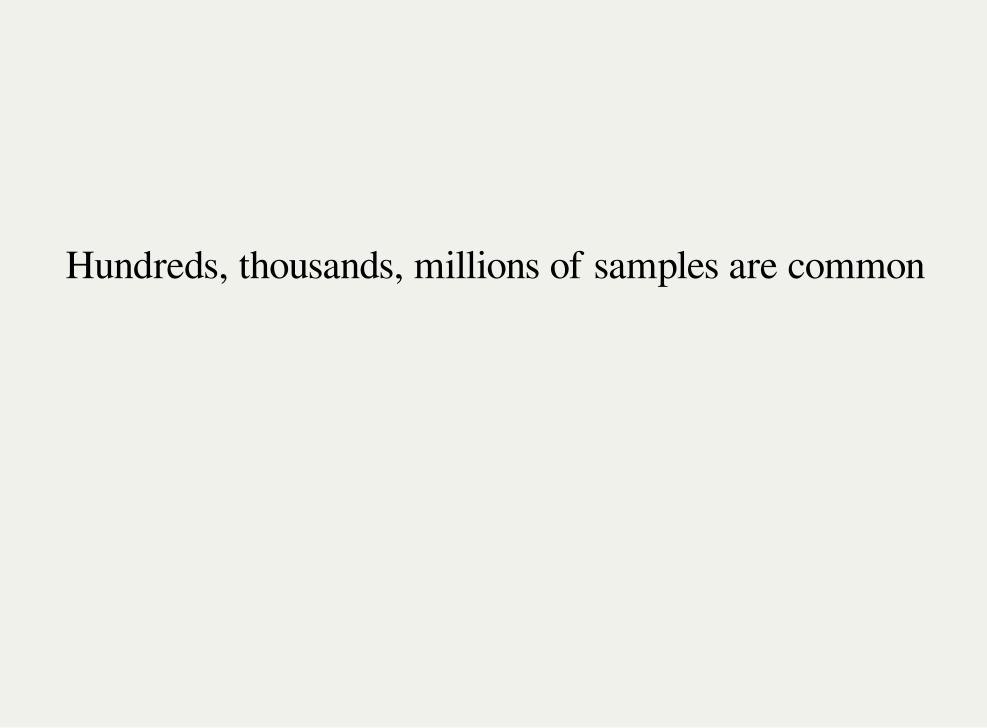
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...and the law of large numbers gives us convergence, i.e.

$$\mathbb{E}_{X\sim P}[f(X)] = \lim_{N o\infty}rac{1}{N}\sum_{i=1}^N f(x_i)$$

when  $x_i \sim P$ 



Hundreds, thousands, millions of samples are common When f(x) is expensive to evaluate, this can get out of hand quickly

→ for example, when it means solving a PDE

$$\mathbb{E}_{X\sim P}\left[f(X)
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$$\rightarrow \frac{p(x)}{q(x)}$$
 are called importance weights

**Key concept:** rewrite an expectation w.r.t. a probability distribution as another expectation w.r.t. a new probability distribution

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Why though?

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→ Importance sampling is a *variance reduction* technique

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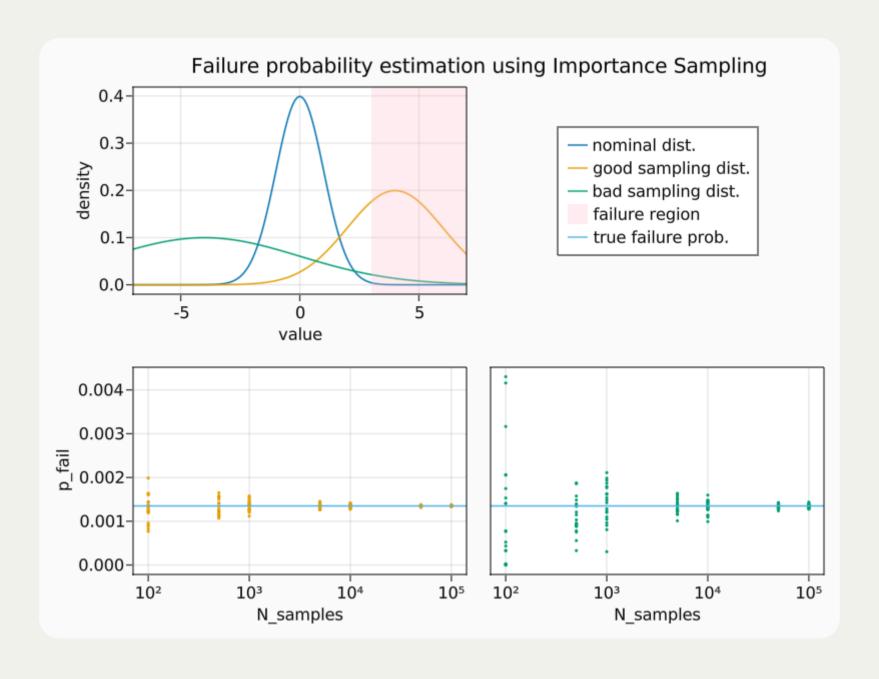
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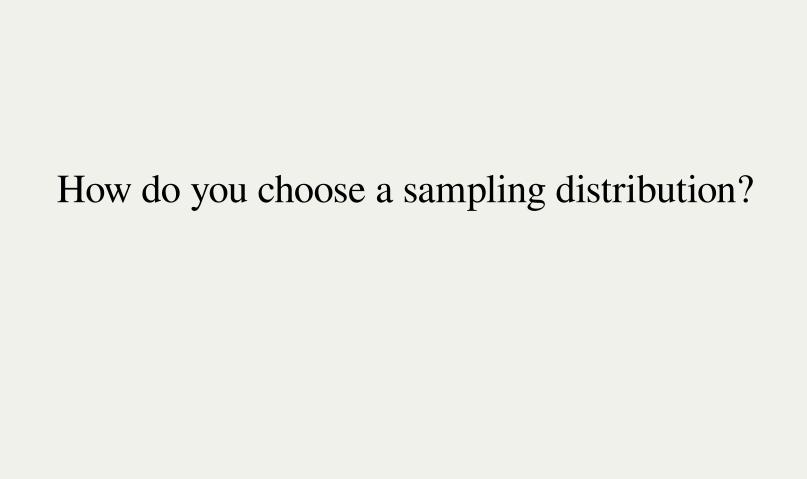
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Sampling from P may not be what you want to do then...

...so you should sample from a different distribution!





# How do you choose a sampling distribution? Multifidelity Importance Sampling by Peherstorfer et al. (2016)

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→ Use a Reduced Order Model

• Generate a surrogate model

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- Find examples of failures (using the surrogate)
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- Evaluate the high-fidelity model  $(X \sim Q)$

**Failure mode:** MFIS and Importance Sampling can *slow* down convergence

#### In conclusion, IS and MFIS can

- reduce computational requirements
- reduce usage of resources like electricity
- save you time



# Open source implementation will be available soon! github.com/RickDW/MFIS

- → Includes *fully automatic* surrogate generation from PDEs and more
  - → Fits right into the scientific ML ecosystem of Julia!

