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# Computational solutions

Bayes Theorem ⇒ *posterior* distribution

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#### Computational solutions

Bayes Theorem ⇒ *posterior* distribution

 $\wedge$  in pratice:

- analytical form rarely available (very particular cases)
- integral to the denominator often very hard to compute

C B. Hejblum

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### Computational solutions

Bayes Theorem  $\Rightarrow$  *posterior* distribution

 $\underline{\wedge}$  in pratice:

- analytical form rarely available (very particular cases)
- integral to the denominator often very hard to compute

How can one estimate the *posteriori* distribution ?

- $\Rightarrow$  sample according to this posterior distribution
  - direct sampling
  - Markov chain Monte Carlo (MCMC)

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# Monte Carlo method

Monte Carlo : von Neumann & Ulam

(Los Alamos Scientific Laboratory - 1955)

 $\Rightarrow$  use random numbers to compute quantities whose analytical computation is hard (or impossible)

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 $\Rightarrow$  use random numbers to compute quantities whose analytical computation is hard (or impossible)

• Law of Large Numbers (LLN)

so-called "Monte Carlo sample"

⇒ compute various functions from that sample distribution

**Example :** One wants to compute 
$$\mathbb{E}[f(X)] = \int f(x)p_X(x)dx$$
  
If  $x_i \stackrel{iid}{\sim} p_X$ ,  $\mathbb{E}[f(X)] = \frac{1}{N} \sum_{i=1}^N f(x_i)$  (LLN)  
 $\Rightarrow$  if one knows how to sample from  $p_X$ , one can then estimate  $\mathbb{E}[f(X)]$ 

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# Monte Carlo method: illustration

#### $\pi$ estimation:





A casino roulette (in Monte Carlo ?)

A 36×36 grid

- 1 The probability of being inside the disk while in the square:  $p_C = \frac{\pi R^2}{(2R)^2} = \frac{\pi}{4}$
- 2 n points {(x<sub>11</sub>, x<sub>21</sub>),..., (x<sub>1n</sub>, x<sub>2n</sub>)} = {P<sub>1</sub>,..., P<sub>n</sub>} on the 36 × 36 grid (generated with the *roulette*)
- 3 Count the number of points inside the disk
- ⇒ Compute the ratio (estimated probability of being inside the disk while in the square):  $\hat{p}_C = \frac{\sum P_i \in circle}{n}$

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If n = 1000 and 786 points are inside the disk :  $\hat{\pi} = 4 \times \frac{786}{1000} = 3.144$ 

One can improve the estimate by increasing:

- the grid resolution, and also
- the number of points sampled *n*:  $\lim_{n \to +\infty} \hat{p}_C = p_C = \pi/4$  (LLN)

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**Monte Carlo** sample  $\Rightarrow$  compute various functions e.g.  $\pi = 4 \times$  the probability of being inside the disk

Direct sampling

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#### Your turn !



Practical: exercise 2

