

## Langevin's Dynamics

$$m \frac{d^2}{dt^2} \mathbf{r} = -\nabla V(\mathbf{r}) - m\gamma \frac{d}{dt} \mathbf{r} + \mathbf{R}(t)$$

- Other numerical solutions (assume interpart. interactions nearly constant within  $\Delta t$  [i.e.  $\Delta t$  is small]) by Ermak and Buckholtz (1980):

$$\mathbf{r}(t + \delta t) = \mathbf{r}(t) + c_1 \left( \frac{d\mathbf{r}}{dt} \right)_t \Delta t + c_2 \left( \frac{d^2\mathbf{r}}{dt^2} \right)_t \Delta t^2 + \Delta \mathbf{r}^G$$

$$\mathbf{v}(t + \delta t) = c_0 \left( \frac{d\mathbf{r}}{dt} \right)_t + c_1 \left( \frac{d^2\mathbf{r}}{dt^2} \right)_t \Delta t + \Delta \mathbf{v}^G$$

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## Langevin's Dynamics

- Where the vector gaussian random noise:

$$\Delta \mathbf{r}^G \quad \Delta \mathbf{v}^G$$

- Have variance

$$\sigma_r^2 = \Delta t^2 \left( \frac{k_B T}{m} \right) \frac{1}{\gamma \Delta t} \left( 2 - \frac{1}{\gamma \Delta t} (3 - 4 \exp(-\gamma \Delta t) + \exp(-2\gamma \Delta t)) \right)$$

$$\sigma_v^2 = \left( \frac{k_B T}{m} \right) (1 - \exp(-\gamma \Delta t))$$

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## Langevin's Dynamics

- And numerical coefficients:

$$c_0 = \exp(-\gamma \Delta t)$$

$$c_1 = \frac{1 - c_0}{\gamma \Delta t}$$

$$c_2 = \frac{1 - c_1}{\gamma \Delta t}$$

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## Langevin's Dynamics

$$m \frac{d^2}{dt^2} \mathbf{r} = -\nabla V(\mathbf{r}) - m\gamma \frac{d}{dt} \mathbf{r} + \mathbf{R}(t)$$

- More “accurate” solutions for low  $\gamma$  (and interparticle forces linearly dependent on time):

$$\mathbf{r}(t + \delta t) = \mathbf{r}(t) + c_1 \left( \frac{d\mathbf{r}}{dt} \right)_t \Delta t + c_2 \left( \frac{d^2\mathbf{r}}{dt^2} \right)_t \Delta t^2 + \Delta \mathbf{r}^G$$

$$\mathbf{v}(t + \delta t) = c_0 \left( \frac{d\mathbf{r}}{dt} \right)_t + (c_1 - c_2) \left( \frac{d^2\mathbf{r}}{dt^2} \right)_t \Delta t + c_2 \left( \frac{d^2\mathbf{r}}{dt^2} \right)_{t+\Delta t} \Delta t + \Delta \mathbf{v}^G$$

As  $\gamma \rightarrow 0$ , recover velocity Verlet

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## Monte Carlo Simulations

- An experiment?
  - It “samples” by generating large numbers of random numbers
- Usually two types:
  - “Simple” Monte Carlo: **estimates values of integrals by generating uniform sampling of the integrand and adding it up**
  - Metropolis Monte Carlo: **generates a trajectory in phase space. Good for thermodynamics.**

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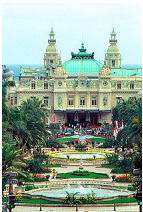
## Early Sampling Methods

- Some deterministic mathematical problems can be treated by finding a probabilistic analogue
- Then solve this analogue by a stochastic sampling experiment
- Early developments:
  - eighteenth-century French “naturalist.” Buffon's Needle problem and geometric probability,  $2l/\pi d$
  - Italian mathematician Lazzerini (1901): needle exp. 3408 times, estimated  $\pi$  to accuracy of  $10^{-7}$

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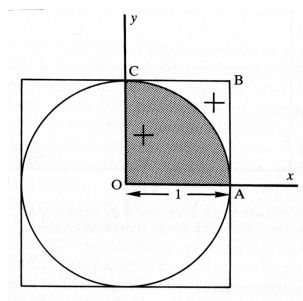
## Simple Monte Carlo

- Estimate value of  $\pi$  by determining the area of one quadrant of the circle using random numbers



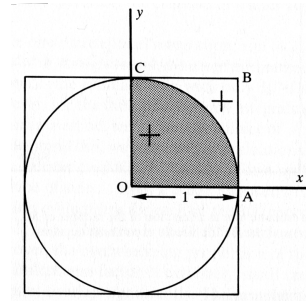
Neumann, Ulam, and Metropolis (1947)

Named for the Monte Carlo Casino



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## Simple Monte Carlo



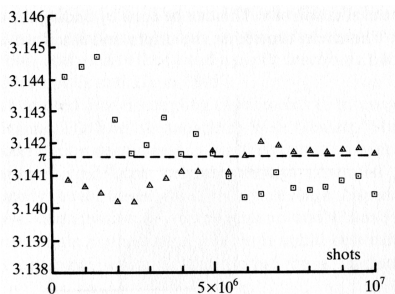
- Generate 2 random numbers and create (x,y)
- If  $x^2+y^2 \leq 1$  count it inside as a “hit”

$$\pi \approx \frac{4 \times \text{area under the curve } AC}{\text{area of the square } OABC} = \frac{4\tau_{hit}}{\tau_{shots}}$$

demo

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## Simple Monte Carlo



- After 107 trials, the value is still 3.14173
- Another decimal will require an order of magnitude more random numbers

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