

PA213

Jan Byška (inspired by Keenan Crane lectures)

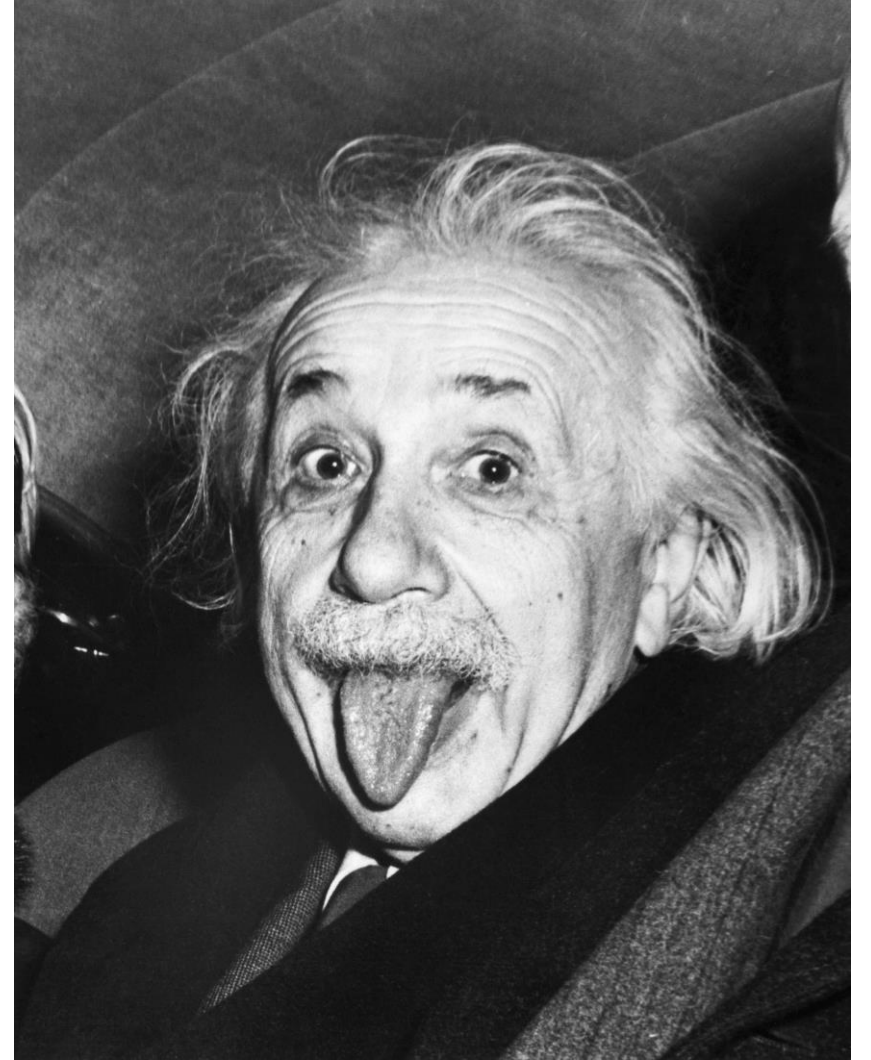
# Monte Carlo Rendering

HCI<sup>LAB</sup>

∴. visitlab

# Mass–Energy Equivalence

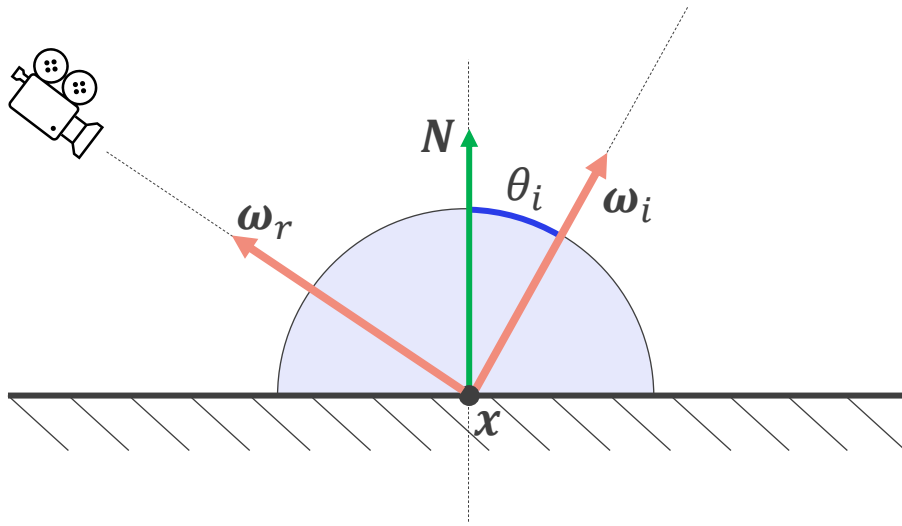
$$E = mc^2$$



Albert Einstein 2

# Rendering Equation

$$L_r(\mathbf{x}, \omega_r) = L_e(\mathbf{x}, \omega_r) + \int_{\Omega} f_r(\mathbf{x}, \omega_i, \omega_r) L_i(\mathbf{x}, \omega_i) \cos \theta_i d\omega_i$$

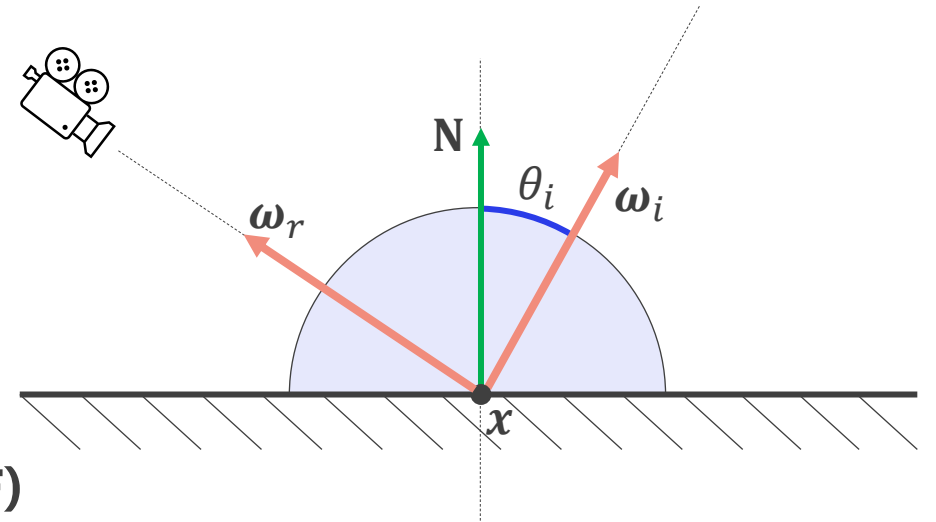


James Kajiya

# Rendering Equation

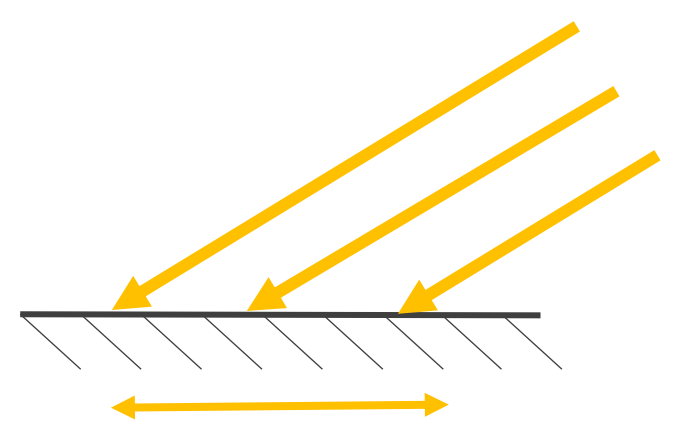
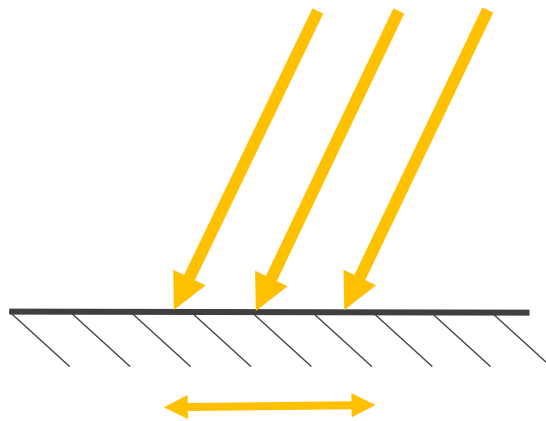
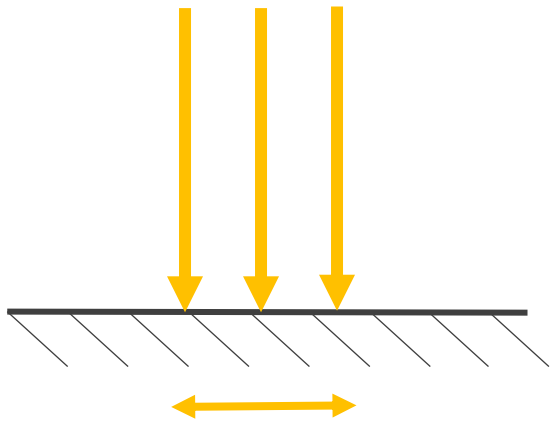
$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \int_{\Omega} f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_i(\mathbf{x}, \boldsymbol{\omega}_i) \cos \theta_i d\boldsymbol{\omega}_i$$

- $L_r$  is **radiance**
  - amount of light emitted from  $\mathbf{x}$  in direction  $\boldsymbol{\omega}_r$
- $L_e$  is **emitted radiance**
  - non-zero, if  $\mathbf{x}$  is a light source
- $L_i$  is **incoming radiance**
  - amount of light arriving to  $\mathbf{x}$  from direction  $\boldsymbol{\omega}_i$
- $f_r$  is **bidirectional reflectance distribution function (BRDF)**
  - material property at  $\mathbf{x}$
  - it is a ratio of the light reflected along  $\boldsymbol{\omega}_r$  to the light incoming from  $\boldsymbol{\omega}_i$
- $\cos \theta_i = \mathbf{N} \cdot \boldsymbol{\omega}_i$ 
  - describes Lambert's cosine law



# Lambert's Cosine Law

$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \int_{\Omega} f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_i(\mathbf{x}, \boldsymbol{\omega}_i) \underline{\cos \theta_i} d\boldsymbol{\omega}_i$$



# Bidirectional Reflectance Distribution Function (BRDF)

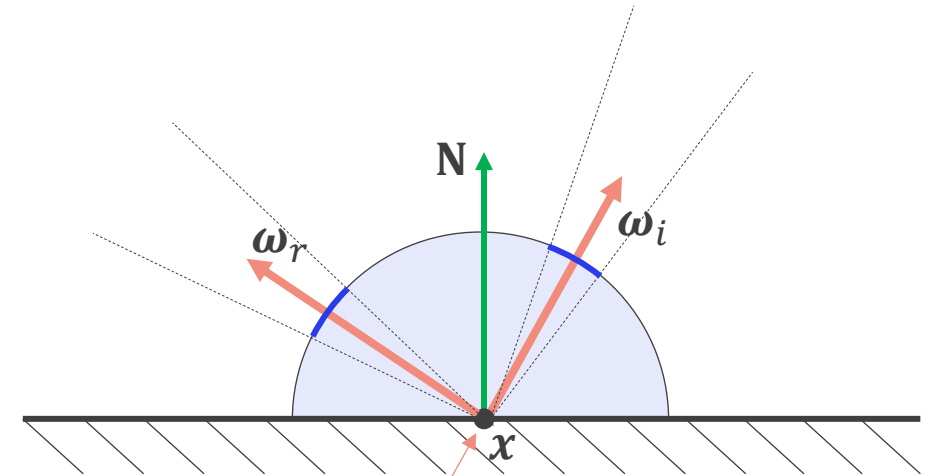
- Light is measured in terms of energy per unit area ( $W/m^2$ )
  - Radiance: amount of light from a single direction ( $W/sr m^2$ )
  - Irradiance: amount of light from possibly all directions ( $W/m^2$ )

$$f_r(x, \omega_i, \omega_r) = \frac{dL_r(\omega_r)}{dE_i(\omega_i)} = \frac{dL_r(\omega_r)}{L_i \cos \theta d\omega_i}$$

partial radiance: light **reflected**  
in the infinitely small cone

partial irradiance: light **incoming**  
from the infinitely small cone

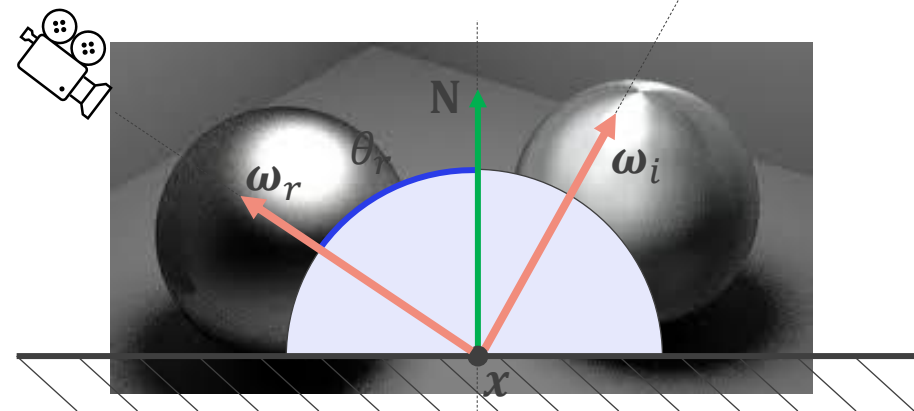
radiance from the solid angle  
projected onto the surface



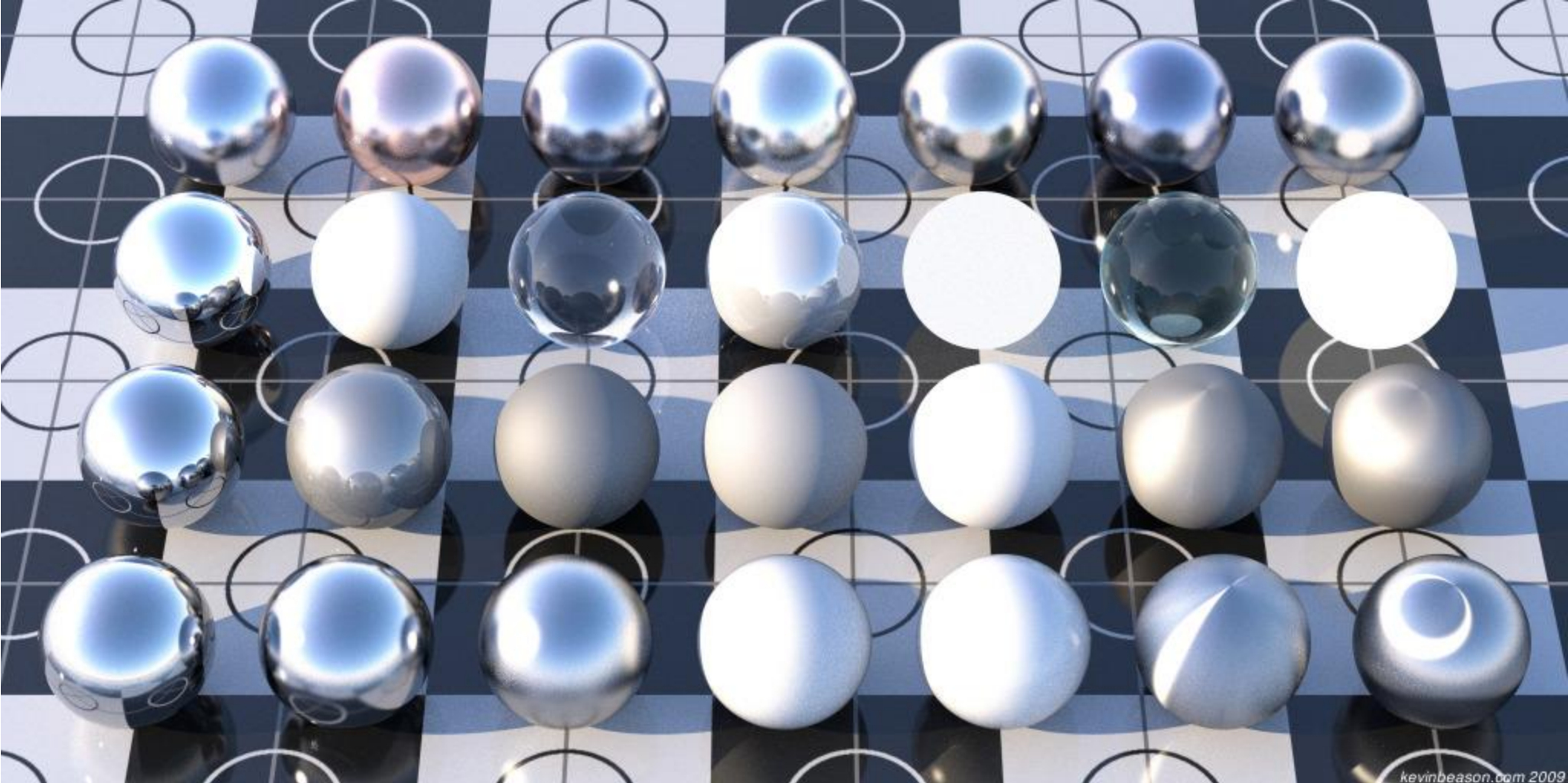
infinitely small  
part of the surface

# Bidirectional Reflectance Distribution Function (BRDF)

- Properties of BRDF  $f_r(\mathbf{x}, \omega_i, \omega_r)$ :
  - **Energy conservation:** A surface cannot reflect more light than falls on it from  $\omega_i$ 
    - For each  $\omega_i$  we have  $\int_{\Omega} f_r(\mathbf{x}, \omega_i, \omega_r) \cos \theta_r d\omega_r \leq 1$
  - **(Helmholtz) Reciprocity principle:**  $f_r(\mathbf{x}, \omega_i, \omega_r) = f_r(\mathbf{x}, \omega_r, \omega_i)$ 
    - The value  $f_r(\mathbf{x}, \omega_i, \omega_r)$  remains the same if we swap  $\omega_i$  and  $\omega_r$
  - **Isotropic:** The value  $f_r(\mathbf{x}, \omega_i, \omega_r)$  remains the same, if we rotate the surface about the normal at  $\mathbf{x}$  by any angle
    - Example: smooth plastic
  - **Anisotropic:** The value  $f_r(\mathbf{x}, \omega_i, \omega_r)$  change, if we rotate the surface about the normal at  $\mathbf{x}$  by some angle
    - Example: Brushed metal, hair



# Surface Appearance

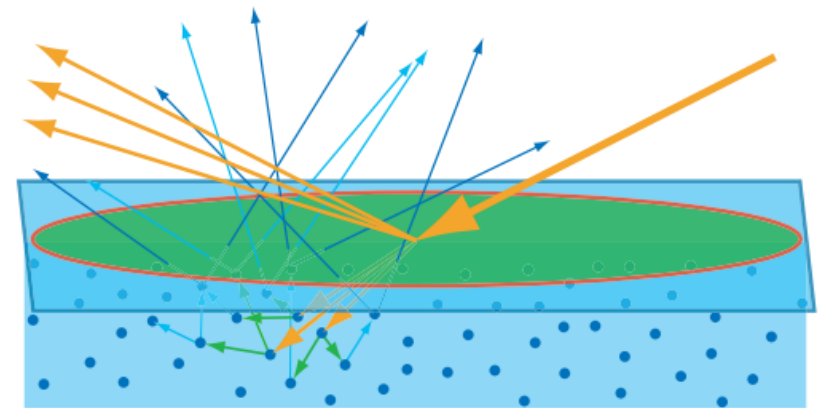
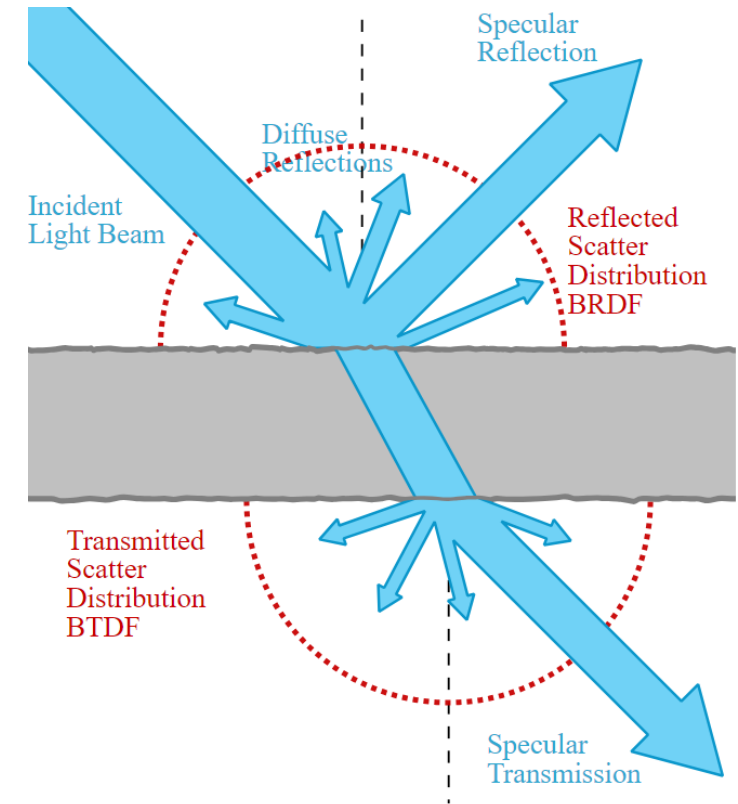


kevinbeason.com 2009



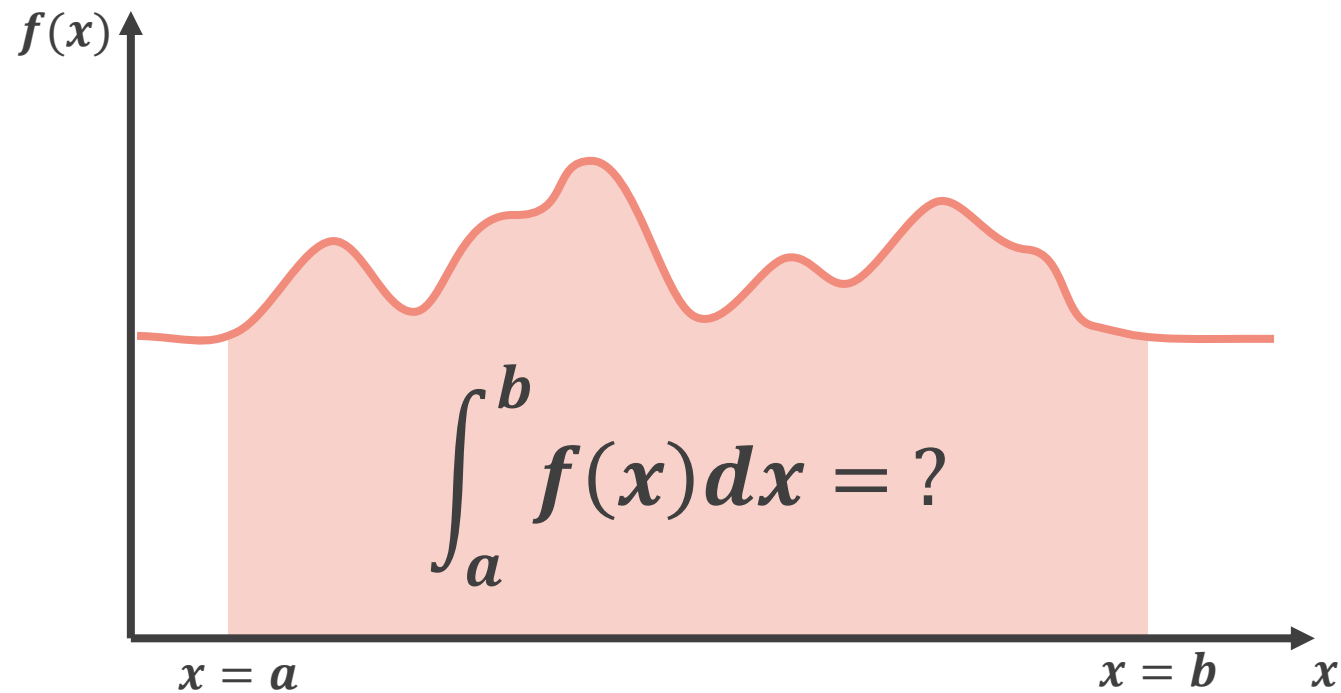
# Distribution Functions

- Bidirectional transmittance distribution function (**BTDF**)
  - Like BRDF but for the opposite side of the surface.
- **BSSRDF + BSSTDF**
  - Like BRDF and BTDF but include subsurface scattering
- Bidirectional Scattering Distribution Function (**BSDF**)
  - Superset and the generalization of the BSSRDF and BSSTDF
  - When subsurface is omitted then  $BSDF = BRDF + BTDF$



# Evaluating Rendering Function

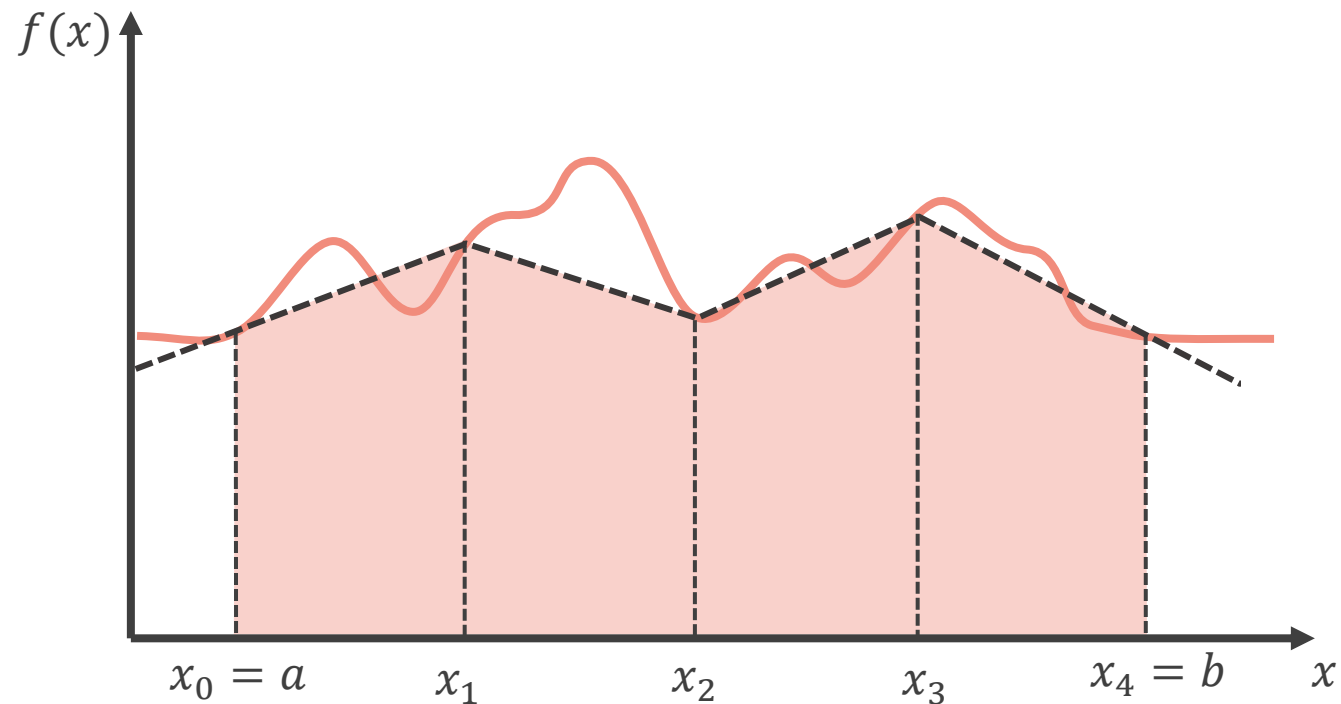
$$L_r(\mathbf{x}, \omega_r) = L_e(\mathbf{x}, \omega_r) + \int_{\Omega} f_r(\mathbf{x}, \omega_i, \omega_r) L_i(\mathbf{x}, \omega_i) \cos \theta_i d\omega_i$$



# Trapezoid Rule

$$\int_a^b f(x) dx \approx \sum_{i=1}^n \left[ \frac{f(x_{i-1}) + f(x_i)}{2} \frac{b-a}{n} \right] = \frac{b-a}{n} \sum_{i=1}^n \left[ \frac{f(x_{i-1}) + f(x_i)}{2} \right]$$

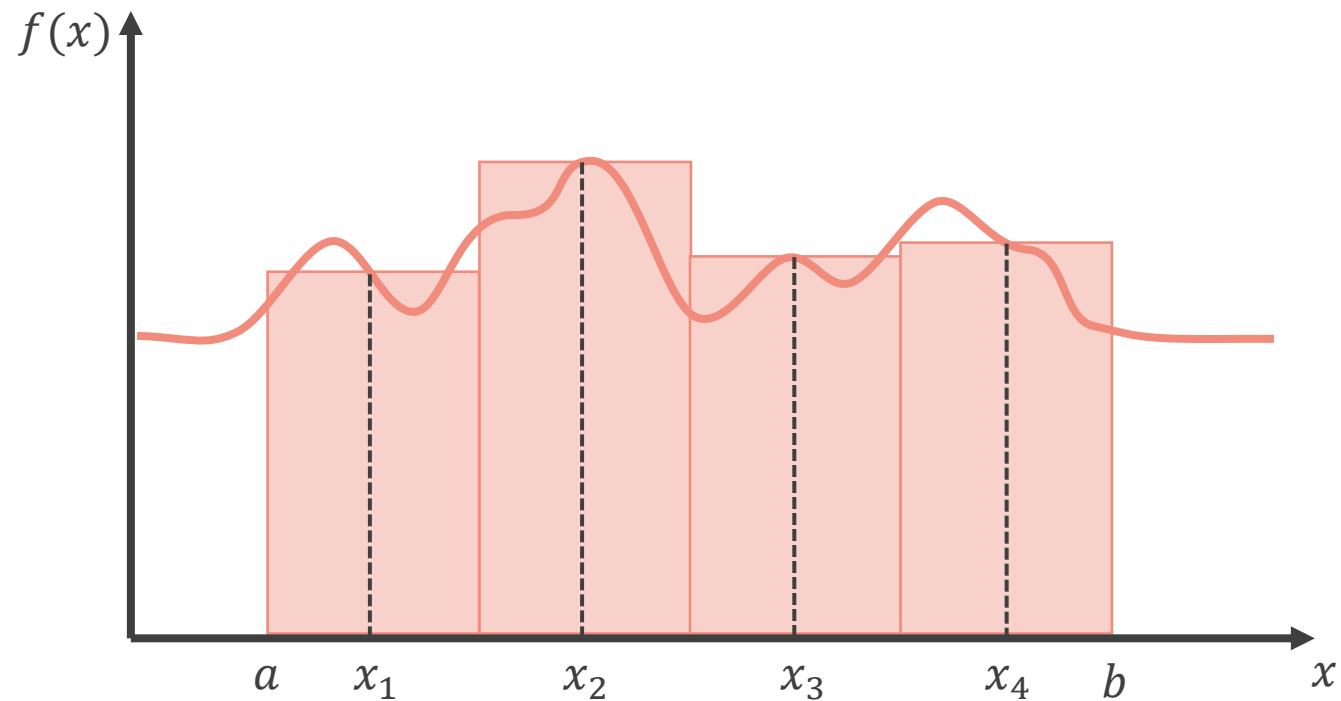
$$\Delta x = \frac{b-a}{n}$$



# Rectangle Rule

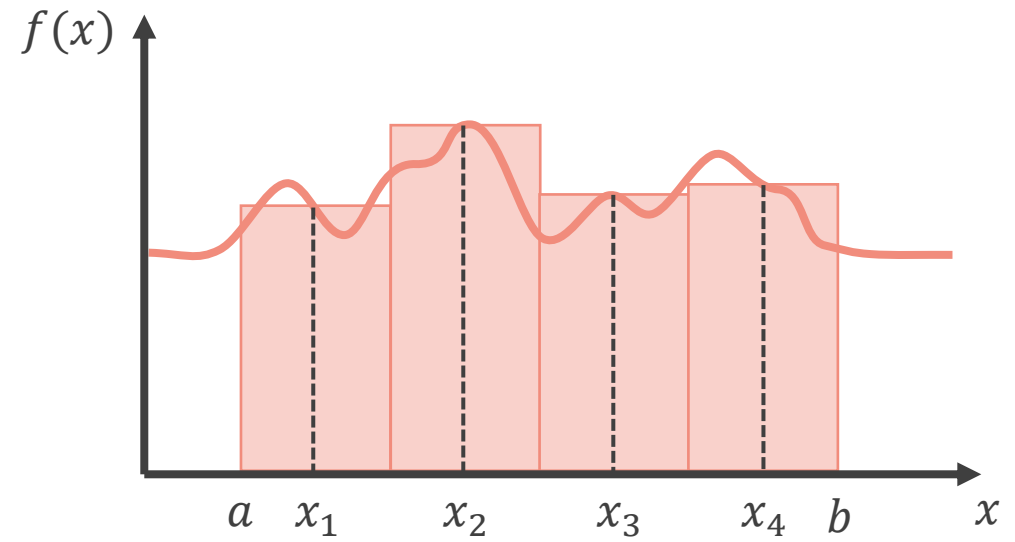
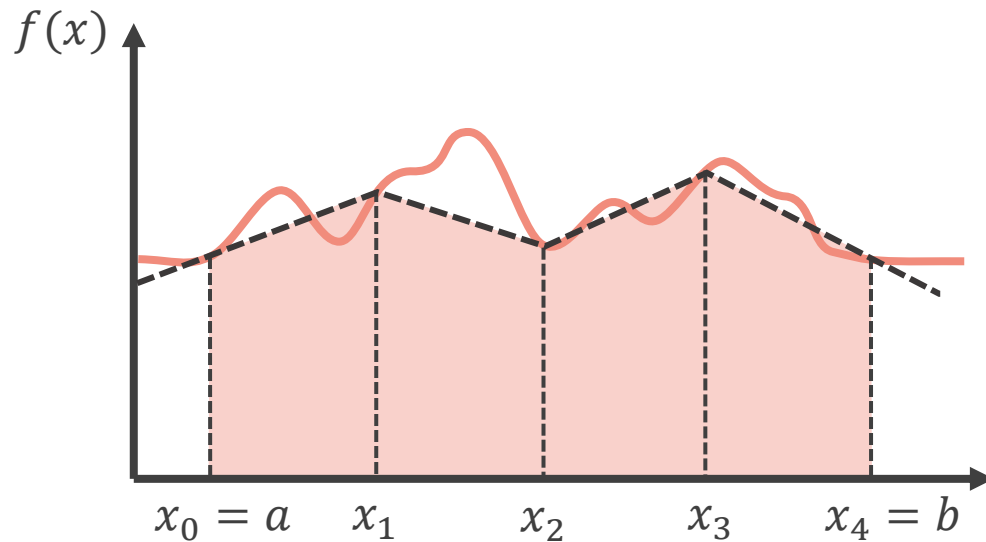
$$\int_a^b f(x) dx \approx \sum_{i=1}^n \left[ f(x_i) \frac{b-a}{n} \right] = \frac{b-a}{n} \sum_{i=1}^n f(x_i)$$

$$\Delta x = \frac{b-a}{n}$$

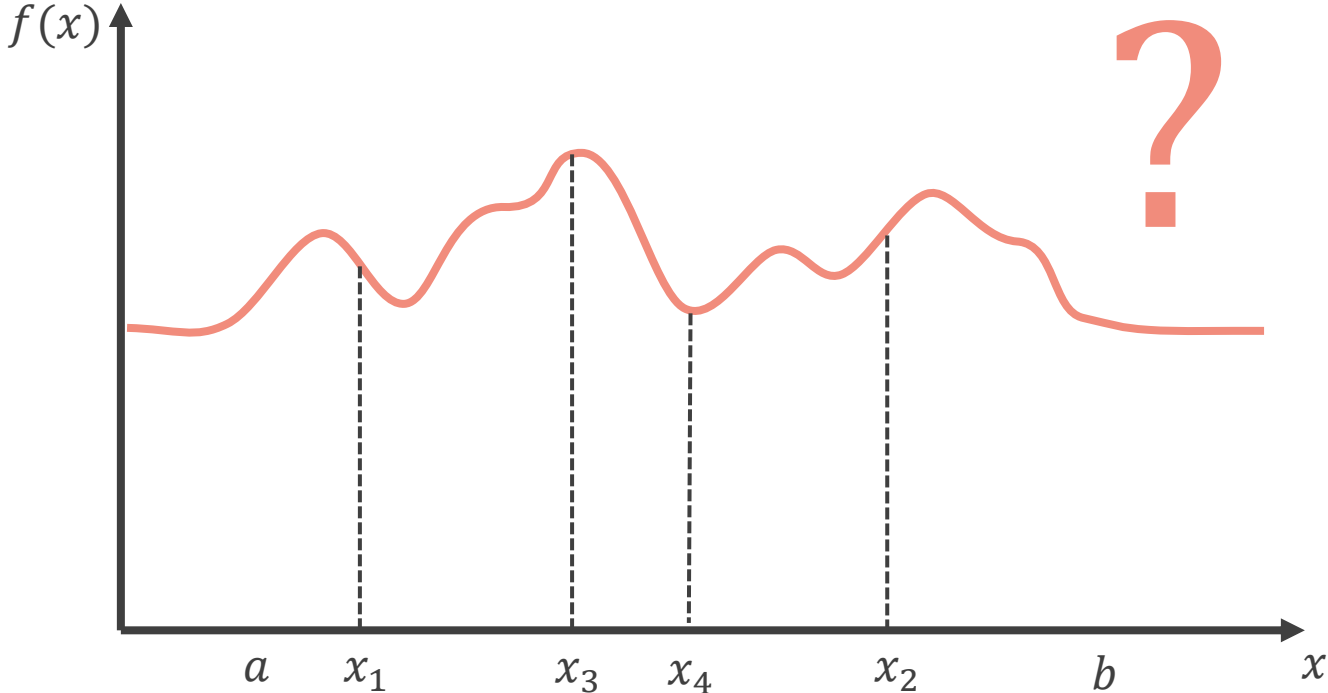


# Disadvantages

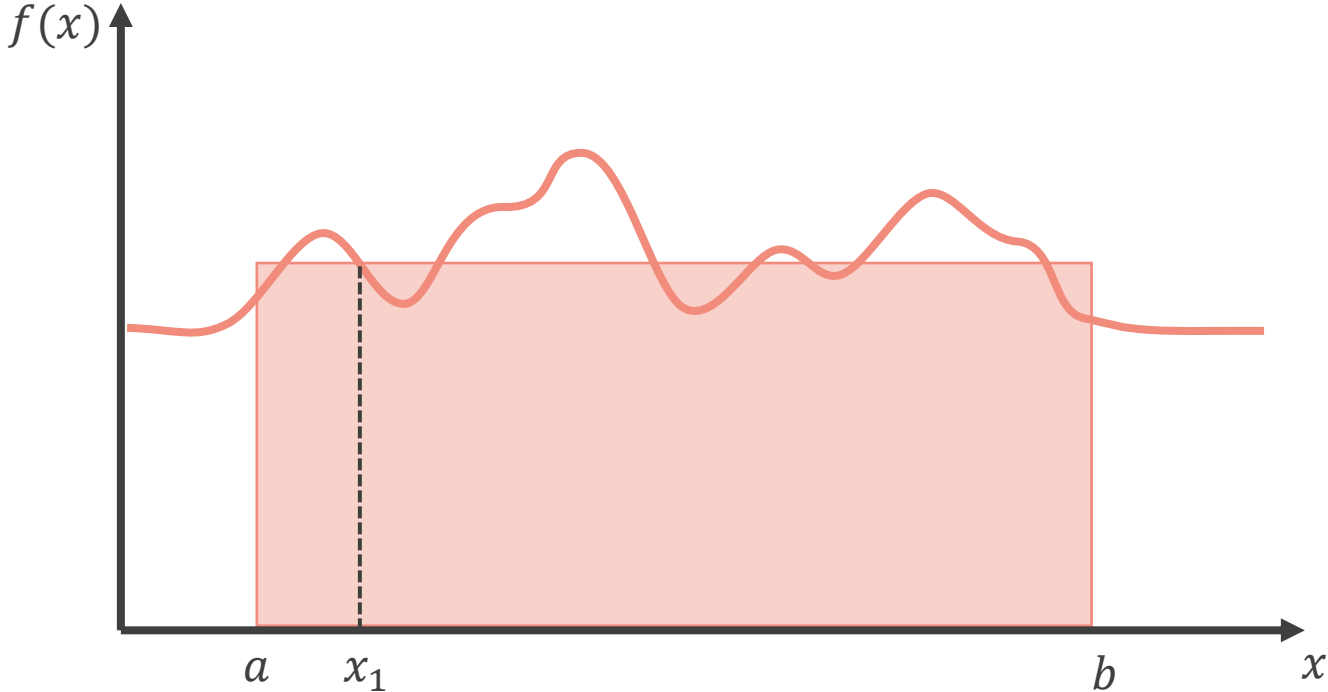
- Computationally expensive and the complexity increases with dimensions



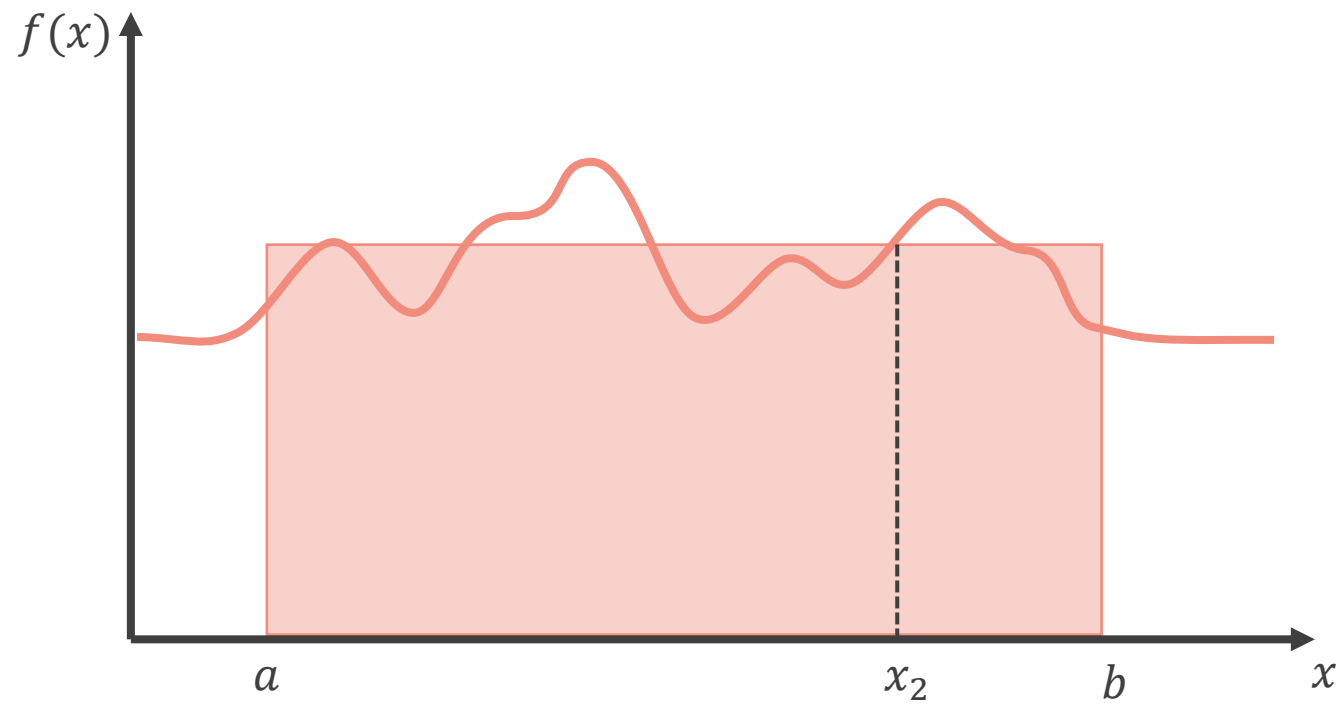
# Random Sampling



# Random Sampling

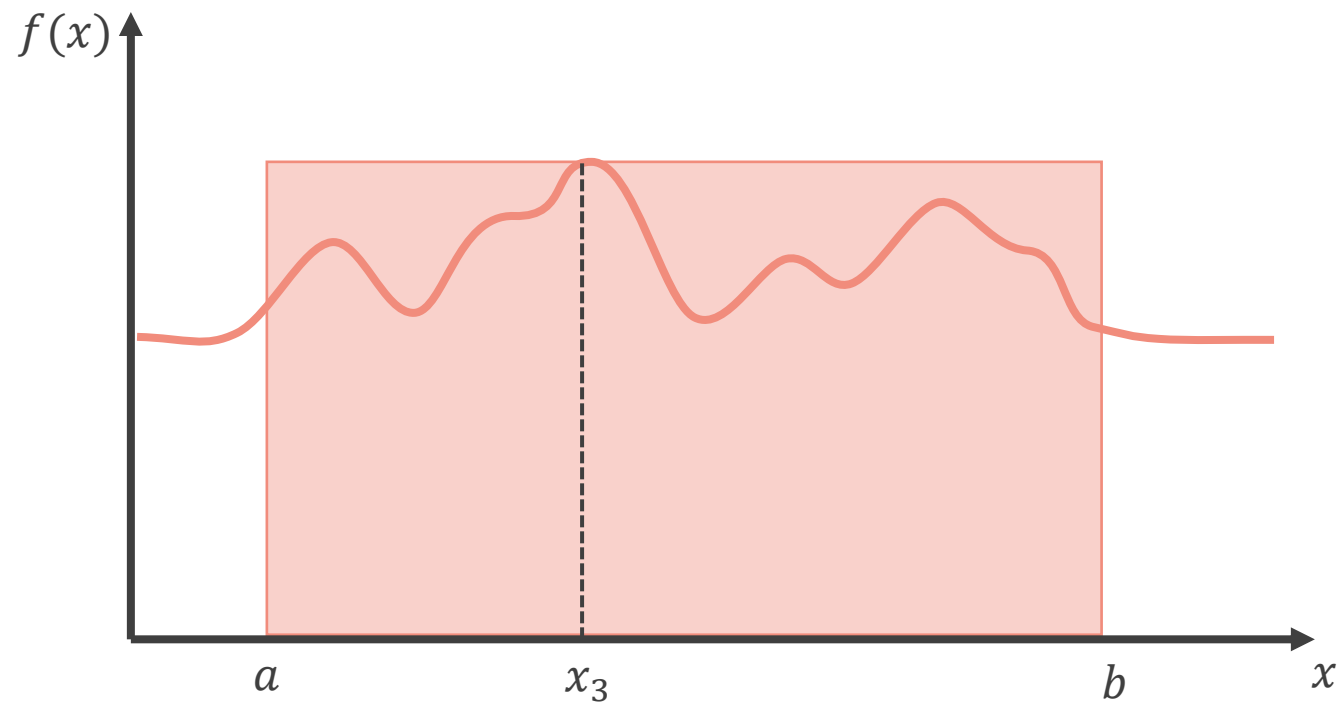
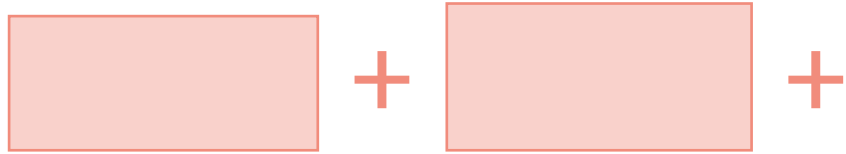


# Random Sampling

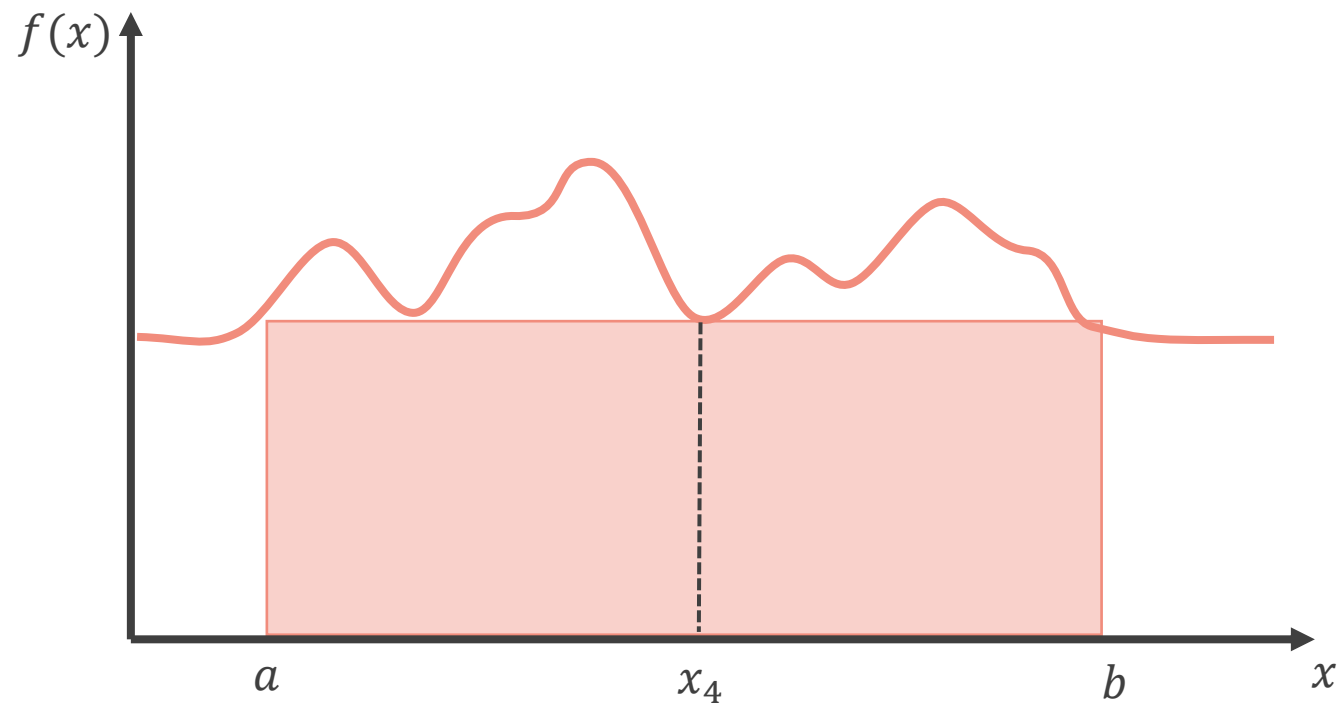




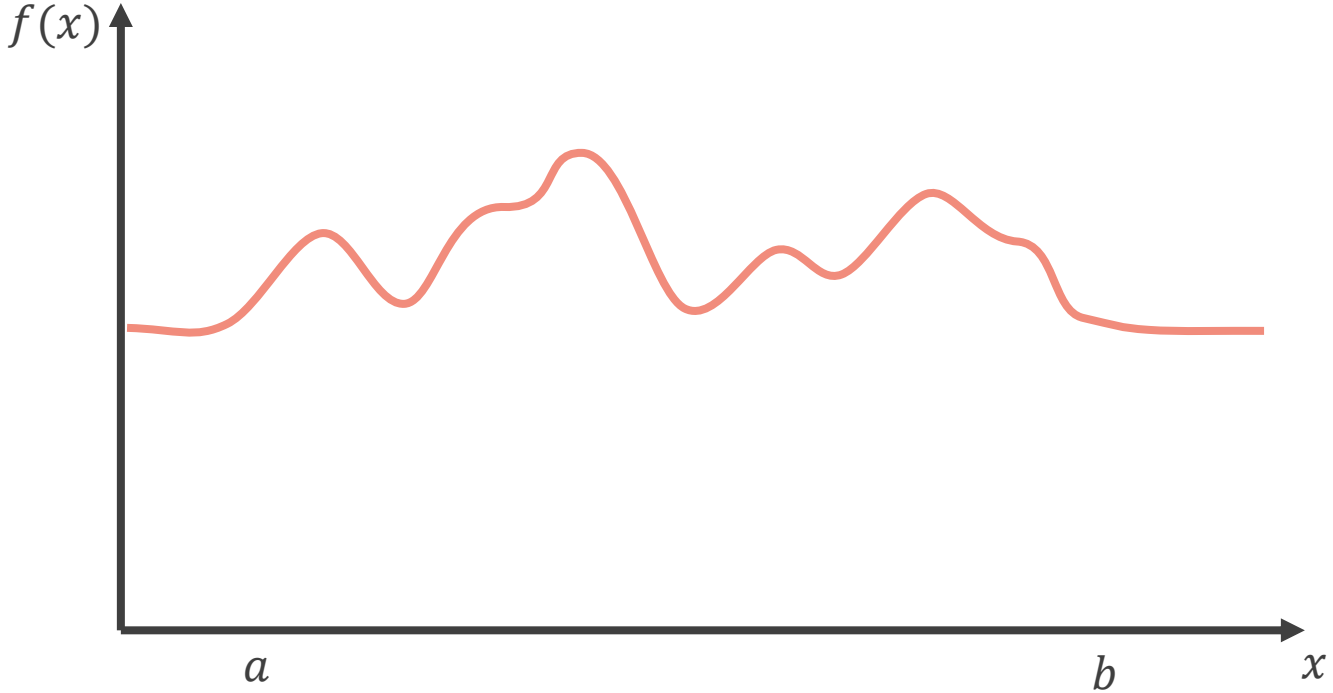
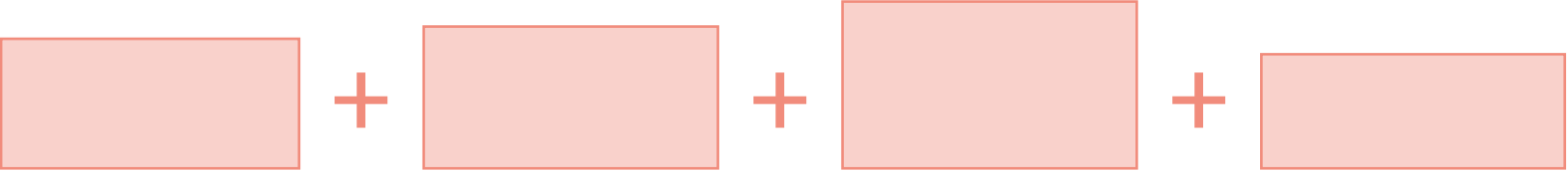
# Random Sampling



# Random Sampling

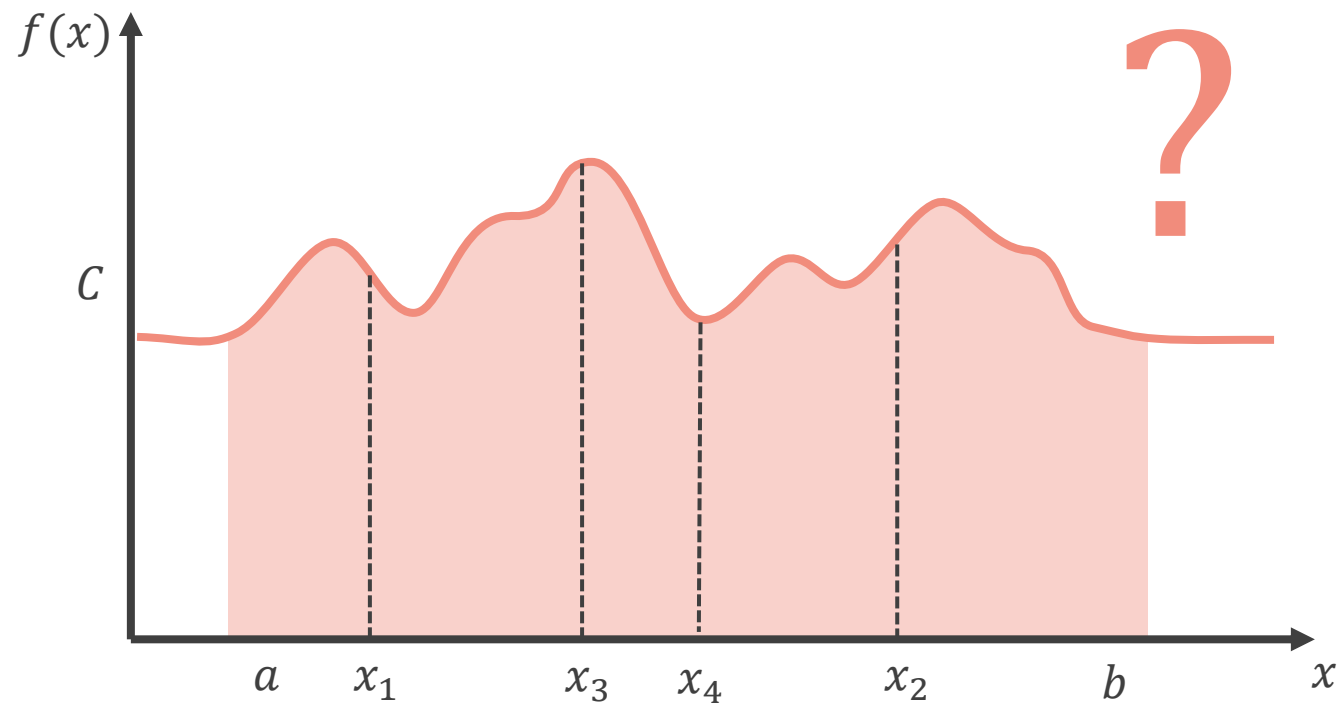


# Random Sampling



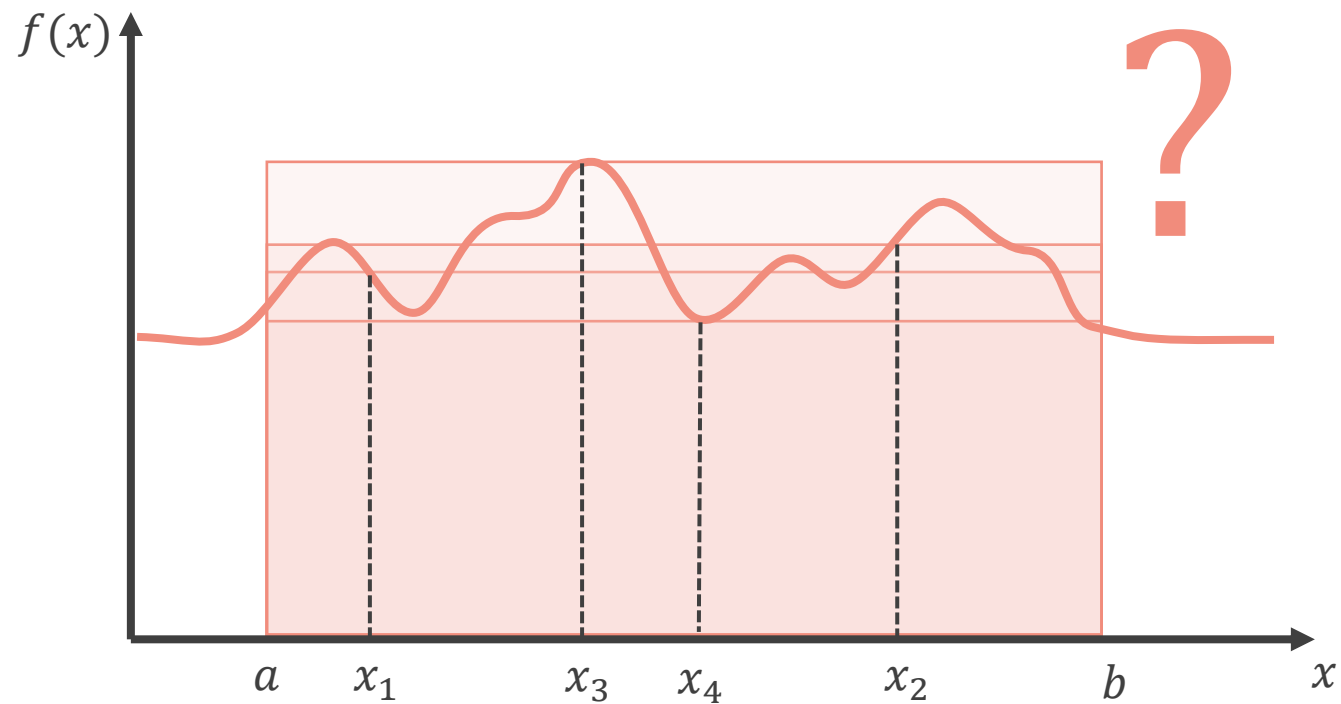
# Random Sampling

$$\left( \text{[red box]} + \text{[red box]} + \text{[red box]} + \text{[red box]} \right) / 4$$



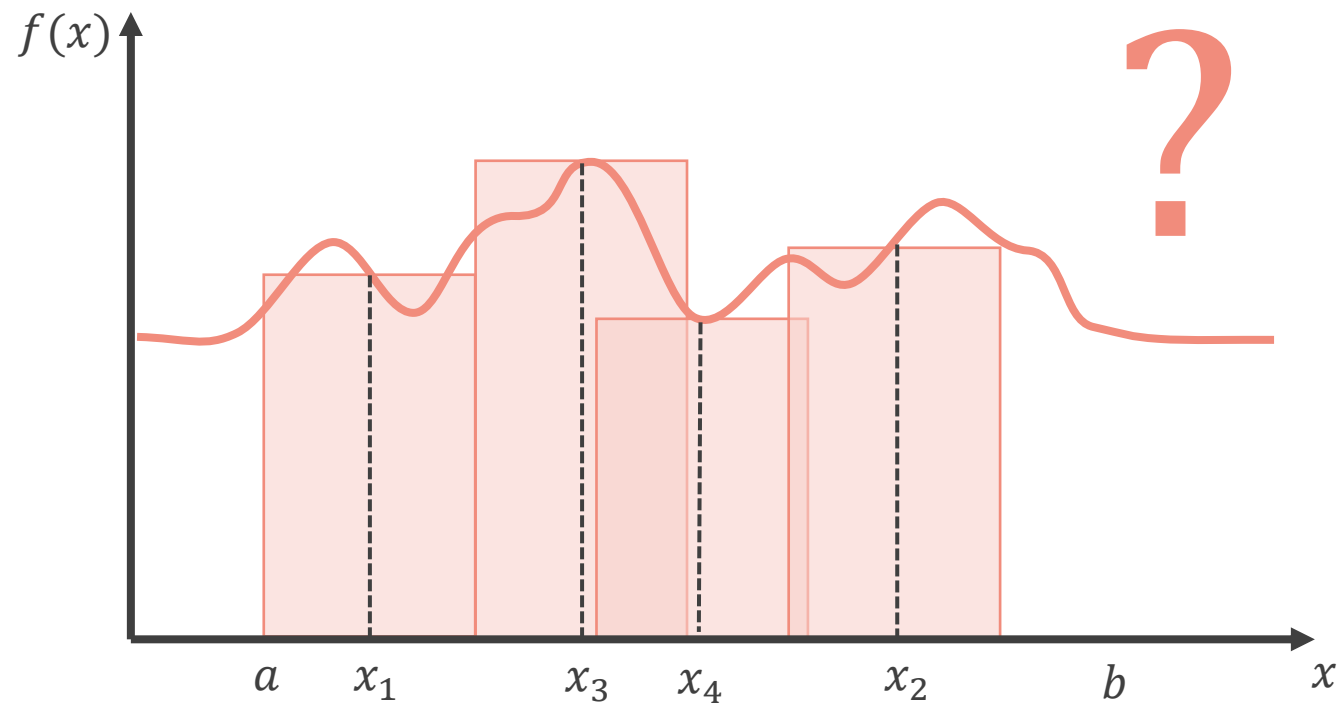
# Monte Carlo Estimator

$$MCE(X) = \frac{1}{n} \sum_{i=1}^n f(X_i)(b - a)$$



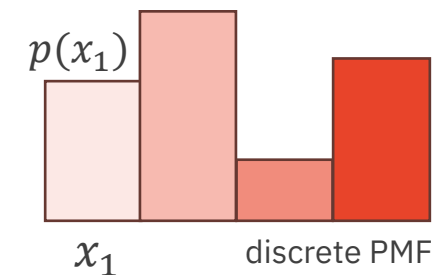
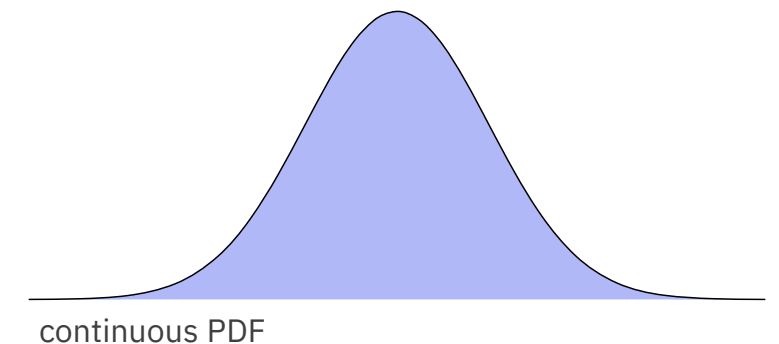
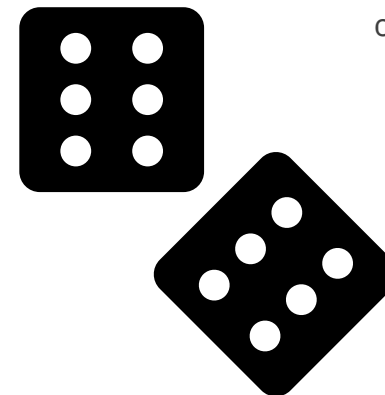
# Monte Carlo Estimator

$$MCE(X) = \frac{1}{n} \sum_{i=1}^n f(X_i)(b - a) = \frac{b - a}{n} \sum_{i=1}^n f(X_i)$$



# Random Variable

- **Intuition: Random variable  $X$  represents potential values for a random process**
  - $X_i$  denotes  $i^{\text{th}}$  realization of the random variable  $X$
  - $x_i$  denotes the actual value of the  $X_i$
- Probability mass/density function (PMF/PDF)  $X \sim p(x)$  describes relative probability that a random process chooses value  $x$ 
  - Example: unbiased die
    - All values are equally likely (uniform PMF)
    - $p(1) = p(2) = p(3) = p(4) = p(5) = p(6) = \frac{1}{6}$
  - Properties PMF:
    - $p(x_i) \geq 0$  and  $\sum_{i=1}^k p(x_i) = 1$
  - Properties PDF:
    - $p(x) \geq 0$  and  $\int_D p(x)dx = 1$



# Expected Value

- **Intuition: what value does a random variable take, on average?**
- Example:
  - coin with heads = 1, tails = 0
  - fair coin with probability  $\frac{1}{2}$  for each outcome
  - expected value:  $\frac{1}{2} * 1 + \frac{1}{2} * 0 = \frac{1}{2}$

expected value of random variable  $X$

number of possible outcomes

$$E[X] = \sum_{i=1}^k x_i p_i$$

value of  $i$ th outcome

probability of  $i$ th outcome

PDF

$$E[X] = \int_D x p(x) dx$$

values of the random variable over domain  $D$



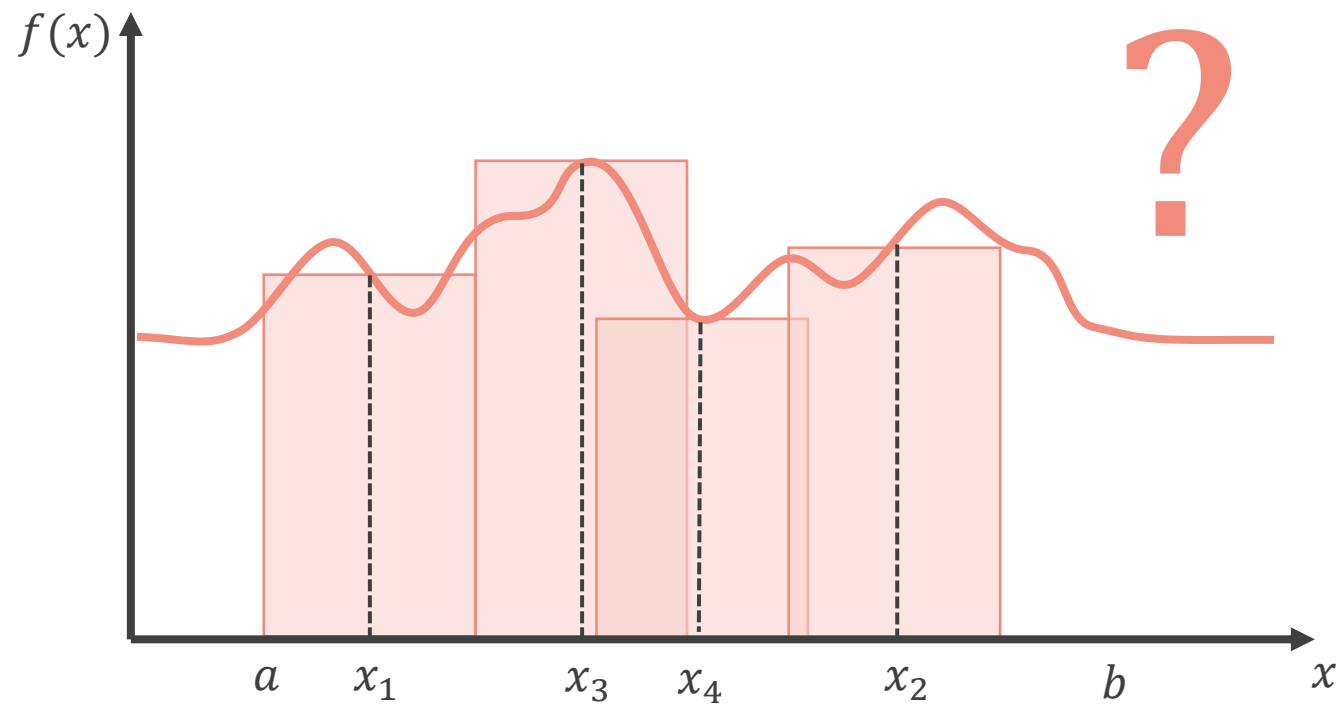
# Expected Value of Function

- Applying a function  $f: \mathbb{R} \rightarrow \mathbb{R}$  to a random variable results in a new random variable

$$E[X] = \int_D x p(x) dx \quad \longrightarrow \quad E[f(X)] = \int_D f(x) p(x) dx$$

# Monte Carlo Estimator

$$MCE(X) = \frac{1}{n} \sum_{i=1}^n f(X_i)(b - a) = \frac{b - a}{n} \sum_{i=1}^n f(X_i)$$



# Monte Carlo Integration

$$MCE(X) = \frac{1}{n} \sum_{i=1}^n f(X_i)(b - a) = \frac{b - a}{n} \sum_{i=1}^n f(X_i)$$

$$E[MCE(X)] = E \left[ \frac{b - a}{n} \sum_{i=1}^n f(X_i) \right]$$

think about this as  $E[f(X)]$   
since in each step we are drawing  
from the same random variable

$$E[aX] = aE[X]$$
$$E \left[ \sum_i X_i \right] = \sum_i E[X_i]$$

$$E[MCE(X)] = \frac{b - a}{n} \sum_{i=1}^n E[f(X_i)]$$

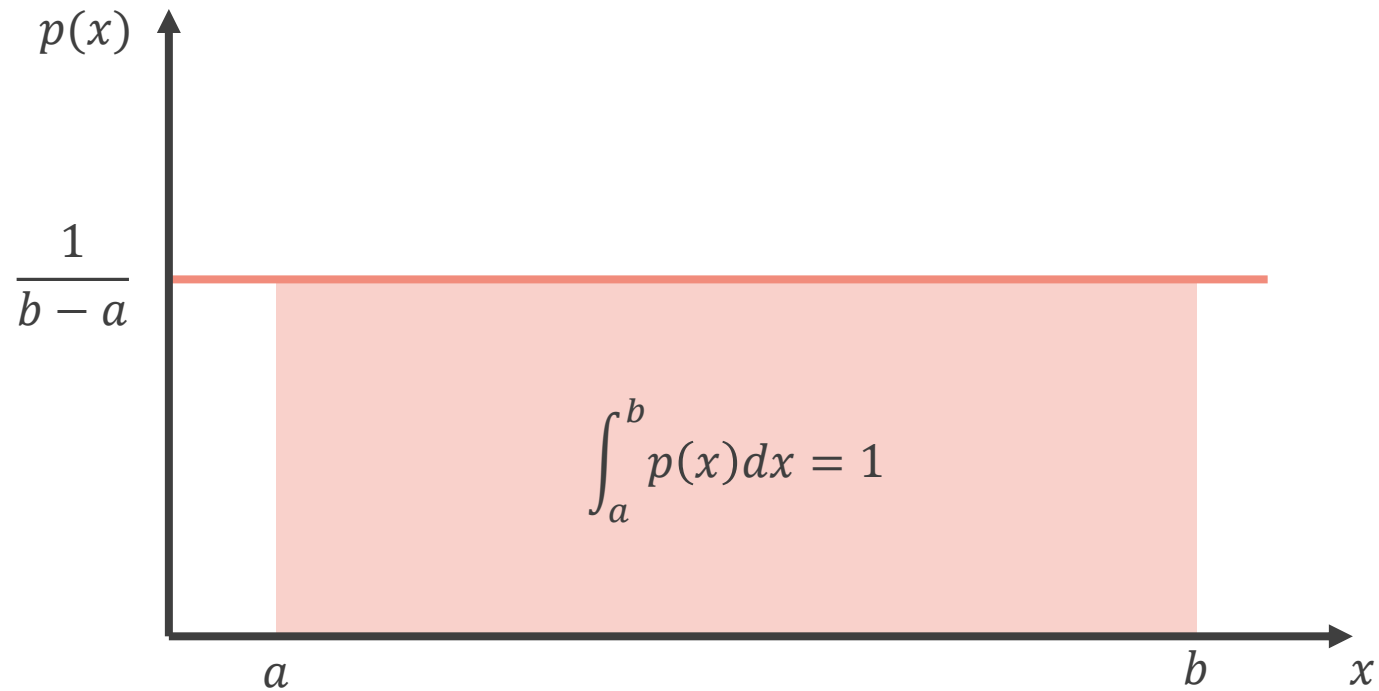
$$E[f(X)] = \int_a^b f(x) p(x) dx$$

$$E[MCE(X)] = \frac{b - a}{n} \sum_{i=1}^n \int_a^b f(x) p(x) dx$$

# Monte Carlo Integration

Assuming uniform distribution  $X \sim p(x)$

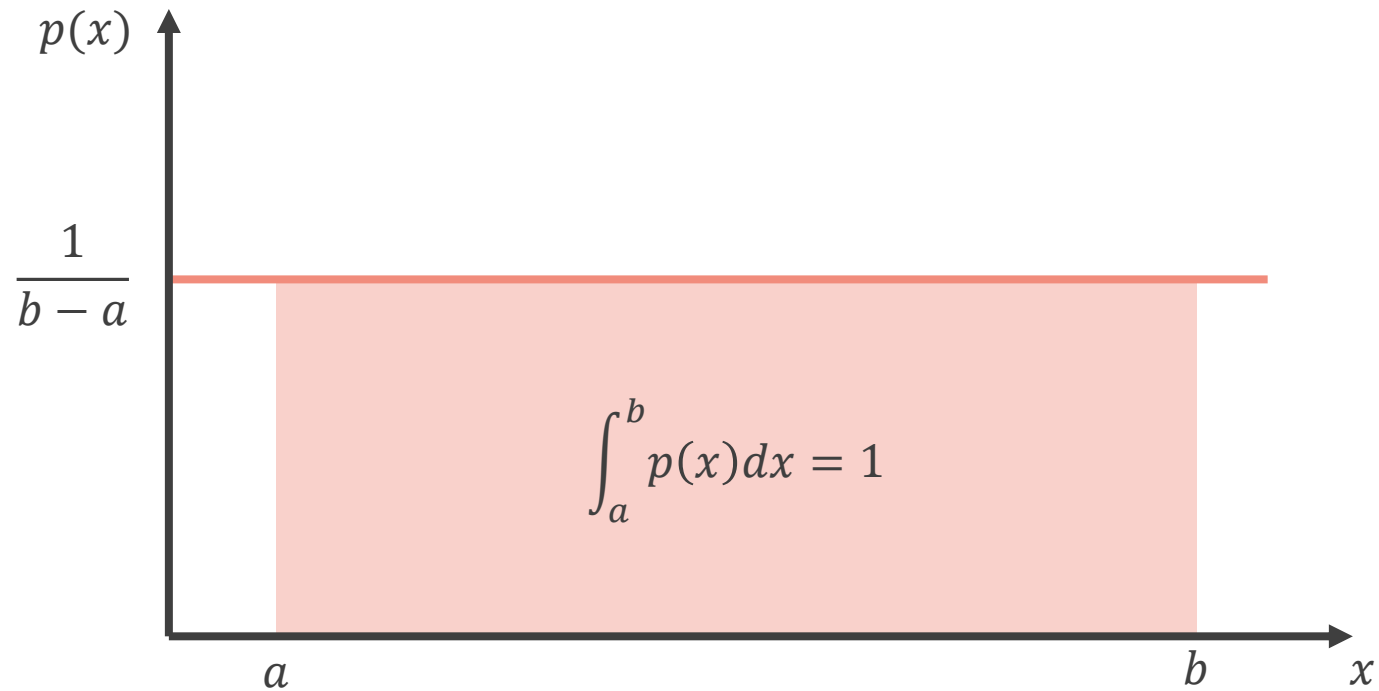
$$E[MCE(X)] = \frac{b-a}{n} \sum_{i=1}^n \int_a^b f(x) p(x) dx$$



# Monte Carlo Integration

Assuming uniform distribution  $X \sim p(x)$

$$E[MCE(X)] = \frac{b-a}{n} \sum_{i=1}^n \int_a^b f(x) \frac{1}{b-a} dx$$



# Monte Carlo Integration

Assuming uniform distribution  $X \sim p(x)$

$$E[MCE(X)] = \frac{b-a}{n} \sum_{i=1}^n \int_a^b f(x) \frac{1}{b-a} dx$$

$$E[MCE(X)] = \frac{1}{n} \sum_{i=1}^n \int_a^b f(x) dx$$

$$\frac{1}{n} \sum_{i=1}^n A = A$$

$$E[MCE(X)] = \int_a^b f(x) dx$$

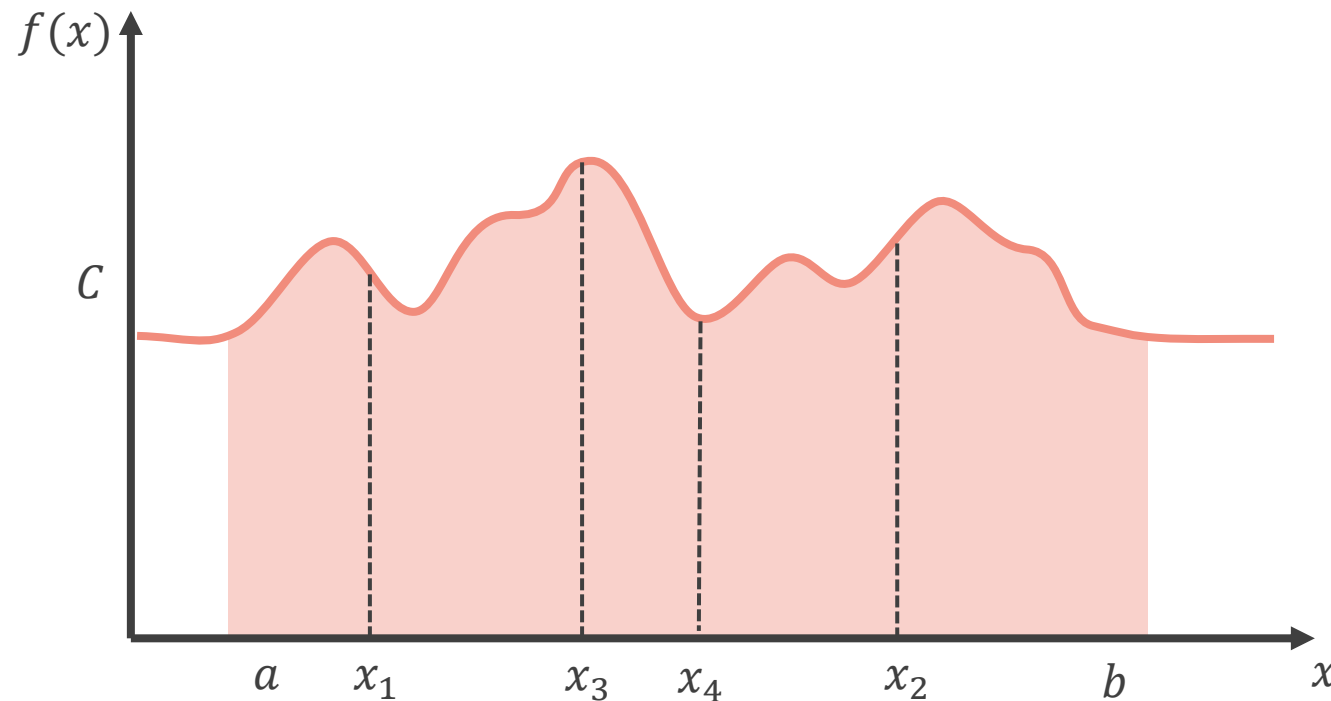
# Monte Carlo Integration

Assuming uniform distribution  $X \sim p(x)$

$$E[f(X)] = \int_a^b f(x)p(x)dx$$

does not really help us


$$\int_a^b f(x)dx = E[MCE(X)] = E\left[\frac{b-a}{n} \sum_{i=1}^n f(X_i)\right] = \frac{b-a}{n} \sum_{i=1}^n E[f(X_i)]$$



# Law of Large Numbers

- For any random variable, the average value of  $n$  trials approaches the expected value as we increase  $n$

$$E[X] = \lim_{n \rightarrow \infty} \left( \frac{1}{n} \sum_{i=1}^n X_i \right)$$

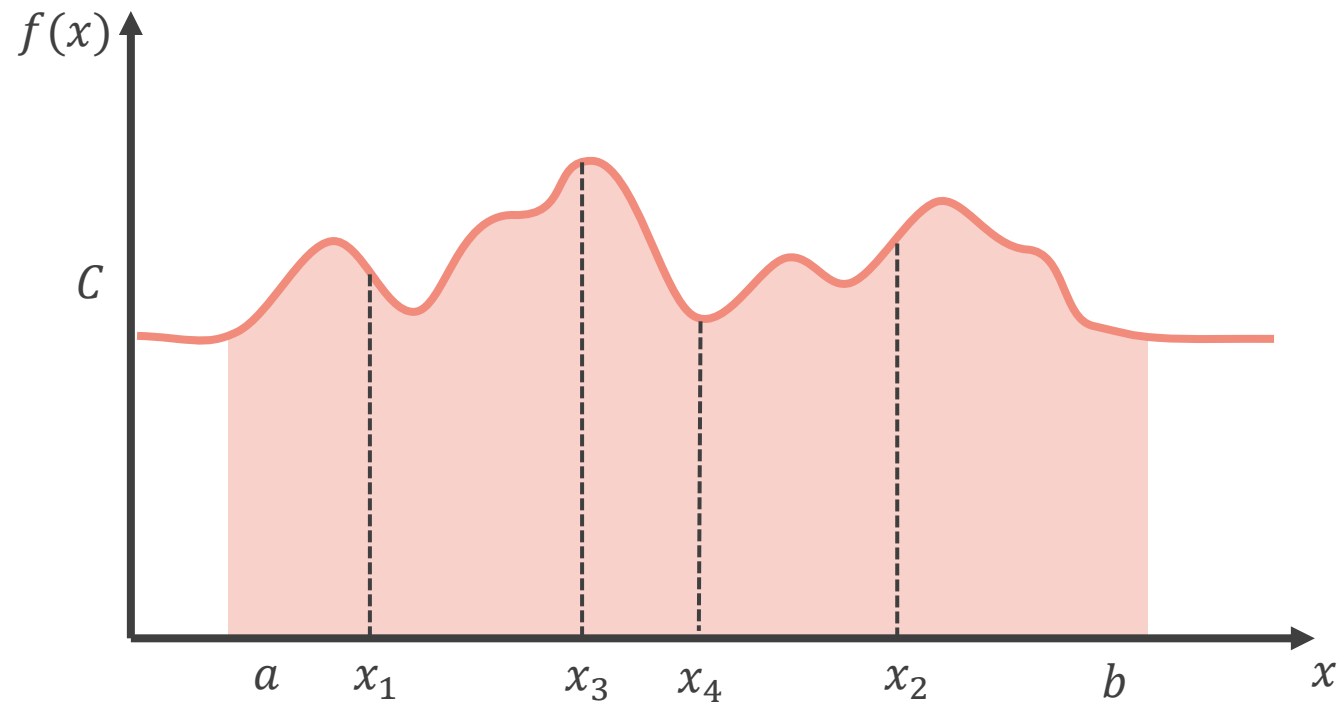
number of trials  




# Monte Carlo Integration

Assuming uniform distribution  $X \sim p(x)$

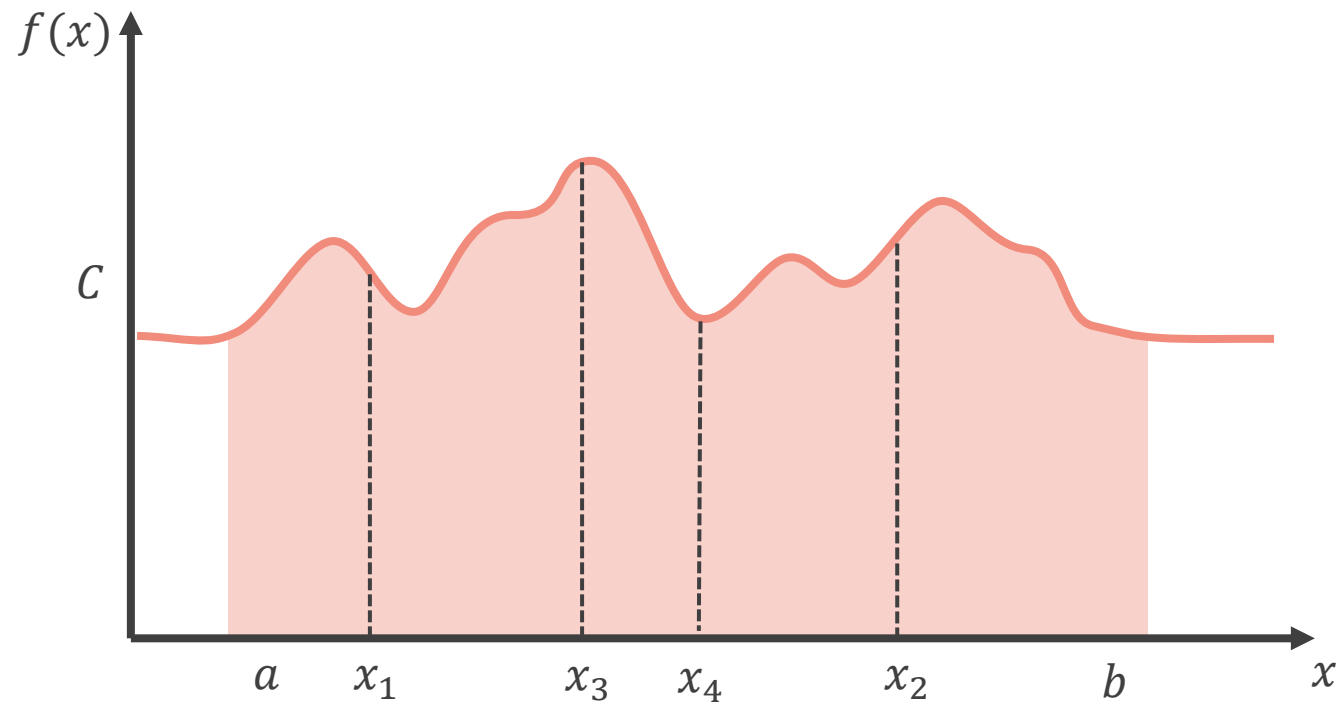
$$\int_a^b f(x) dx \approx \frac{b-a}{n} \sum_{i=1}^n f(X_i)$$



# Monte Carlo Integration

Assuming arbitrary distribution  $X \sim p(x)$

$$\int_a^b f(x) dx = \int_a^b \frac{f(x)}{p(x)} p(x) dx = ?$$



# Monte Carlo Integration

Assuming arbitrary distribution  $X \sim p(x)$

$$\begin{aligned} E[f(X)] &= \int_a^b f(x)p(x)dx \\ &= \int_a^b \frac{f(x)}{p(x)} p(x)dx \\ &= \int_a^b g(x)p(x)dx \\ &= E[g(X)] \\ &= E\left[\frac{f(X)}{p(X)}\right] \end{aligned}$$

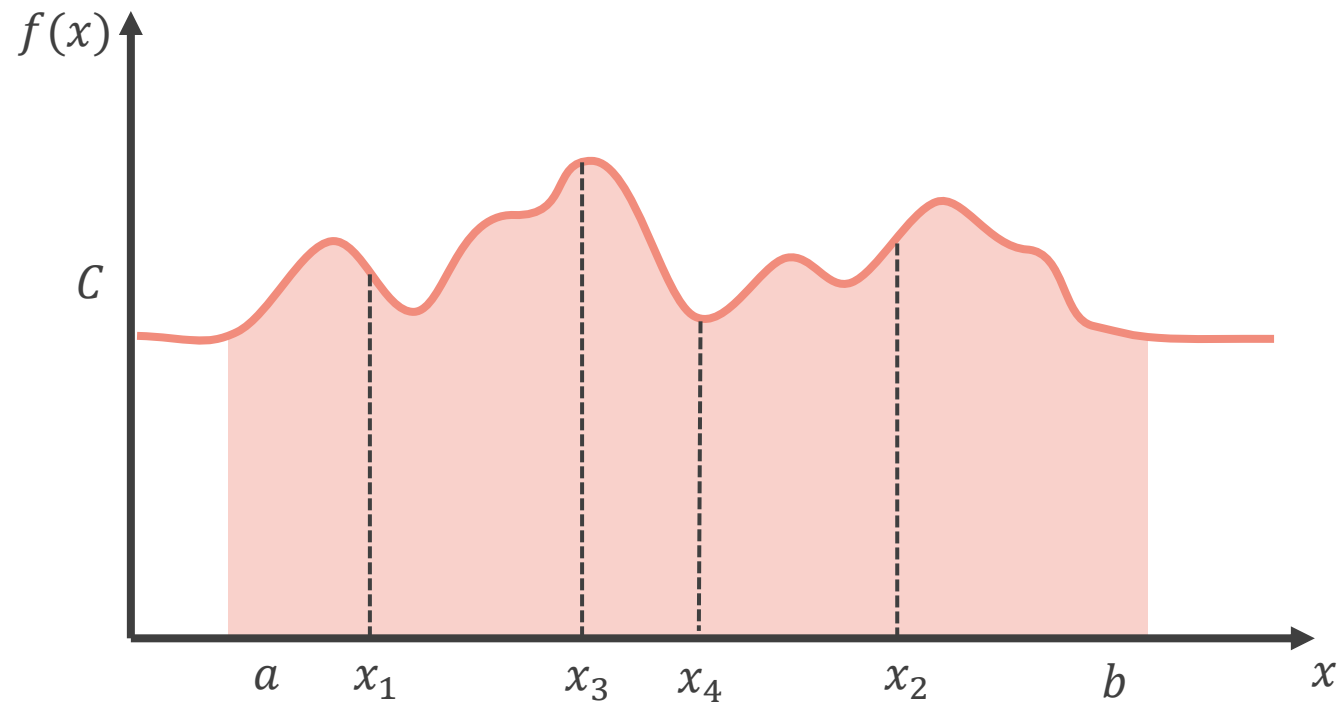
*g(x) = f(x)/p(x)*

*g(x) = f(x)/p(x)*

# Monte Carlo Integration

Assuming arbitrary distribution  $X \sim p(x)$

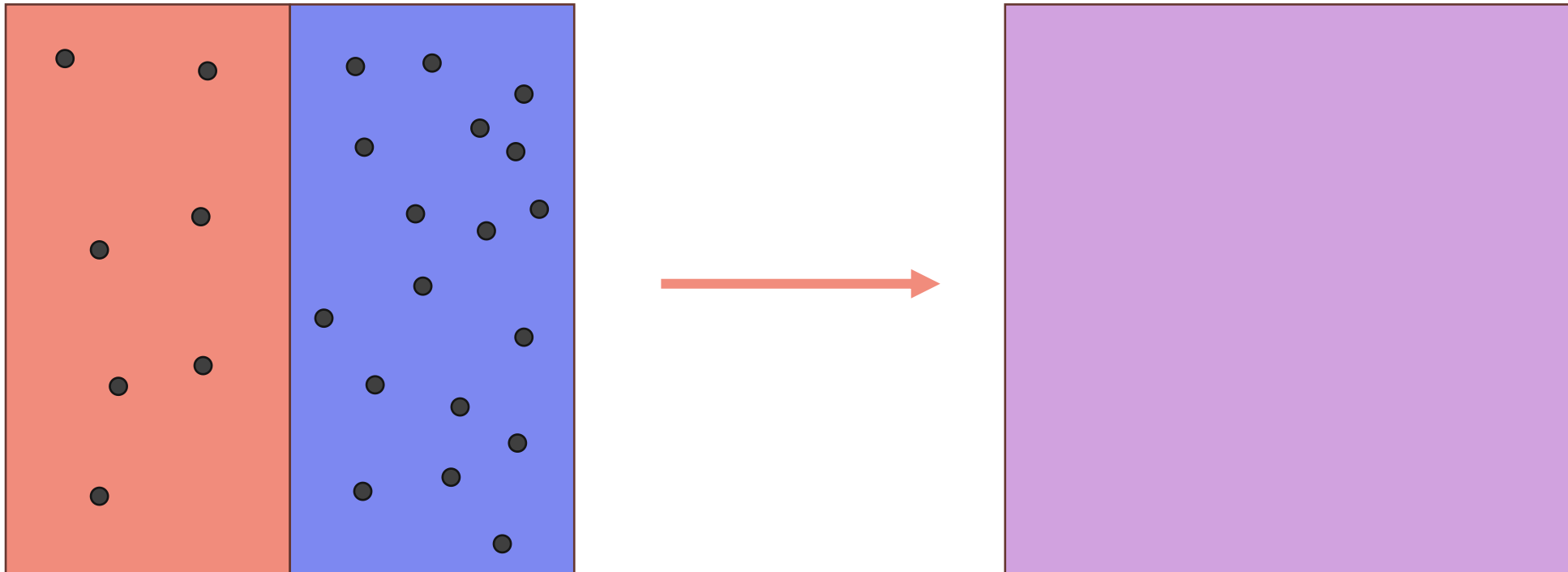
$$\int_a^b f(x) dx \approx \frac{1}{n} \sum_{i=1}^n \frac{f(X_i)}{p(X_i)}$$



# Monte Carlo Integration

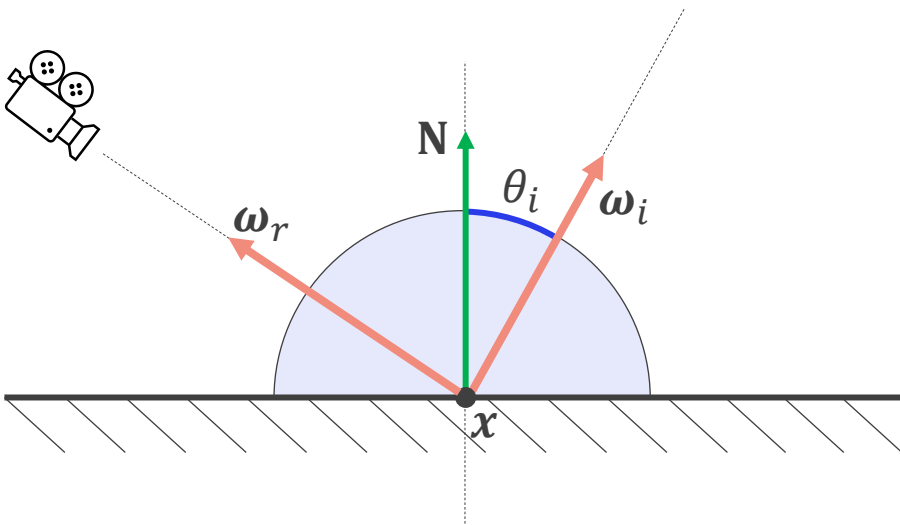
Assuming arbitrary distribution  $X \sim p(x)$

$$\int_a^b f(x) dx \approx \frac{1}{n} \sum_{i=1}^n \frac{f(X_i)}{p(X_i)}$$



# Evaluating Rendering Function

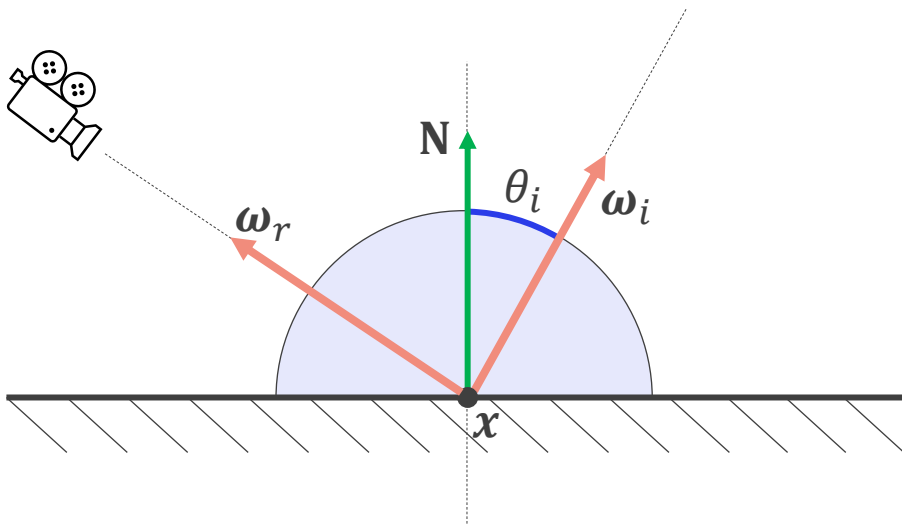
$$L_r(\mathbf{x}, \omega_r) = L_e(\mathbf{x}, \omega_r) + \int_{\Omega} f_r(\mathbf{x}, \omega_i, \omega_r) L_i(\mathbf{x}, \omega_i) \cos \theta_i d\omega_i$$
$$\approx L_e(\mathbf{x}, \omega_r) + \frac{2\pi}{n} \sum_{i=1}^n f_r(\mathbf{x}, \omega_i, \omega_r) L_i(\mathbf{x}, \omega_i) \cos \theta_i$$



$$\int_a^b f(x) dx \approx \frac{b-a}{n} \sum_{i=1}^n f(X_i)$$

# Evaluating Rendering Function

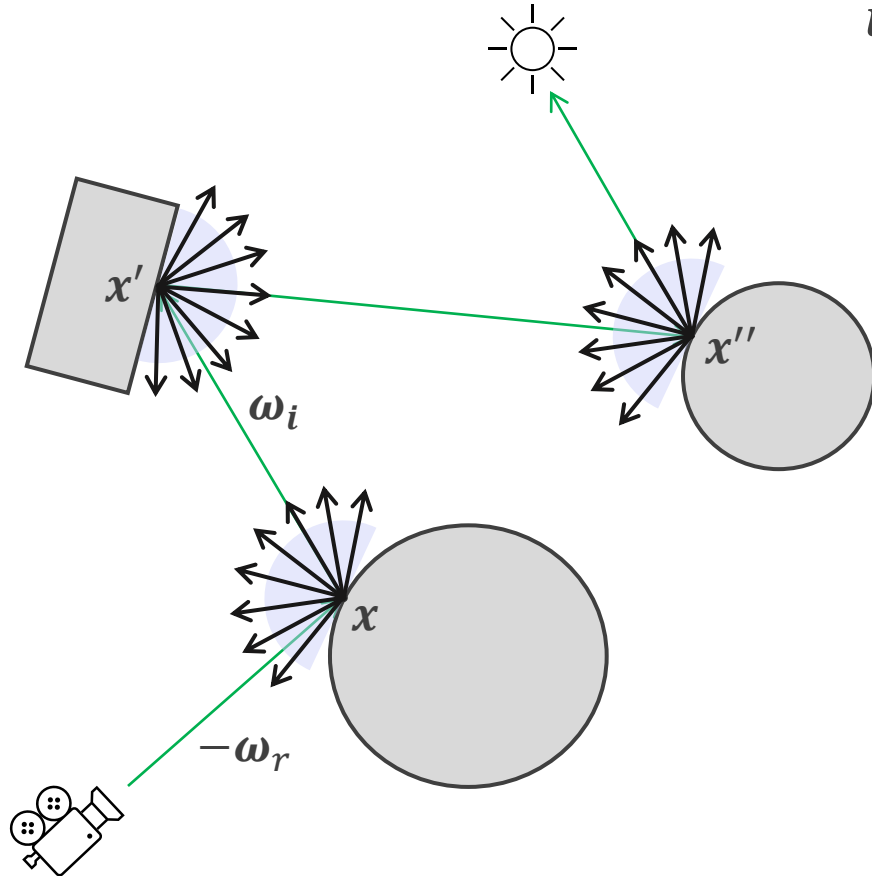
$$L_r(\mathbf{x}, \omega_r) = L_e(\mathbf{x}, \omega_r) + \int_{\Omega} f_r(\mathbf{x}, \omega_i, \omega_r) L_i(\mathbf{x}, \omega_i) \cos \theta_i d\omega_i$$
$$\approx L_e(\mathbf{x}, \omega_r) + \frac{1}{n} \sum_{i=1}^n \frac{f_r(\mathbf{x}, \omega_i, \omega_r) L_i(\mathbf{x}, \omega_i) \cos \theta_i}{p(\omega_i)}$$



$$\int_a^b f(x) dx \approx \frac{1}{n} \sum_{i=1}^n \frac{f(X_i)}{p(X_i)}$$

# Evaluating Rendering Function

$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_i(\mathbf{x}, \boldsymbol{\omega}_i) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$



$$L_r(\mathbf{x}', \boldsymbol{\omega}'_r) = L_e(\mathbf{x}', \boldsymbol{\omega}'_r) + \frac{1}{n} \sum_{i=1}^n f'_r(\mathbf{x}', \boldsymbol{\omega}'_i, \boldsymbol{\omega}'_r) L_i(\mathbf{x}', \boldsymbol{\omega}'_i) \cos \theta'_i d\boldsymbol{\omega}'_i \frac{1}{p(\boldsymbol{\omega}'_i)}$$

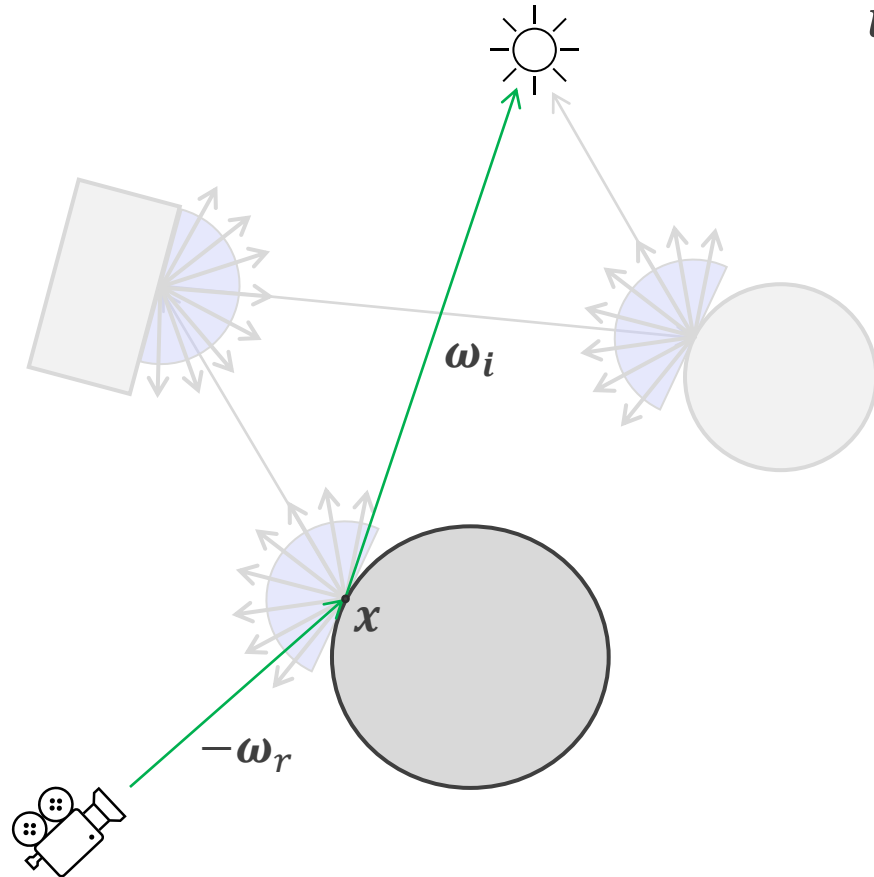
$$L_r(\mathbf{x}'', \boldsymbol{\omega}''_r) = L_e(\mathbf{x}'', \boldsymbol{\omega}''_r) + \frac{1}{n} \sum_{i=1}^n f''_r(\mathbf{x}'', \boldsymbol{\omega}''_i, \boldsymbol{\omega}''_r) L_i(\mathbf{x}'', \boldsymbol{\omega}''_i) \cos \theta''_i d\boldsymbol{\omega}''_i \frac{1}{p(\boldsymbol{\omega}''_i)}$$

$$L_r(\mathbf{x}''', \boldsymbol{\omega}'''_r) = L_e(\mathbf{x}''', \boldsymbol{\omega}'''_r) + \frac{1}{n} \sum_{i=1}^n f'''_r(\mathbf{x}''', \boldsymbol{\omega}'''_i, \boldsymbol{\omega}'''_r) L_i(\mathbf{x}''', \boldsymbol{\omega}'''_i) \cos \theta'''_i d\boldsymbol{\omega}'''_i \frac{1}{p(\boldsymbol{\omega}'''_i)}$$



# Direct Illumination

$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_i(\mathbf{x}, \boldsymbol{\omega}_i) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$



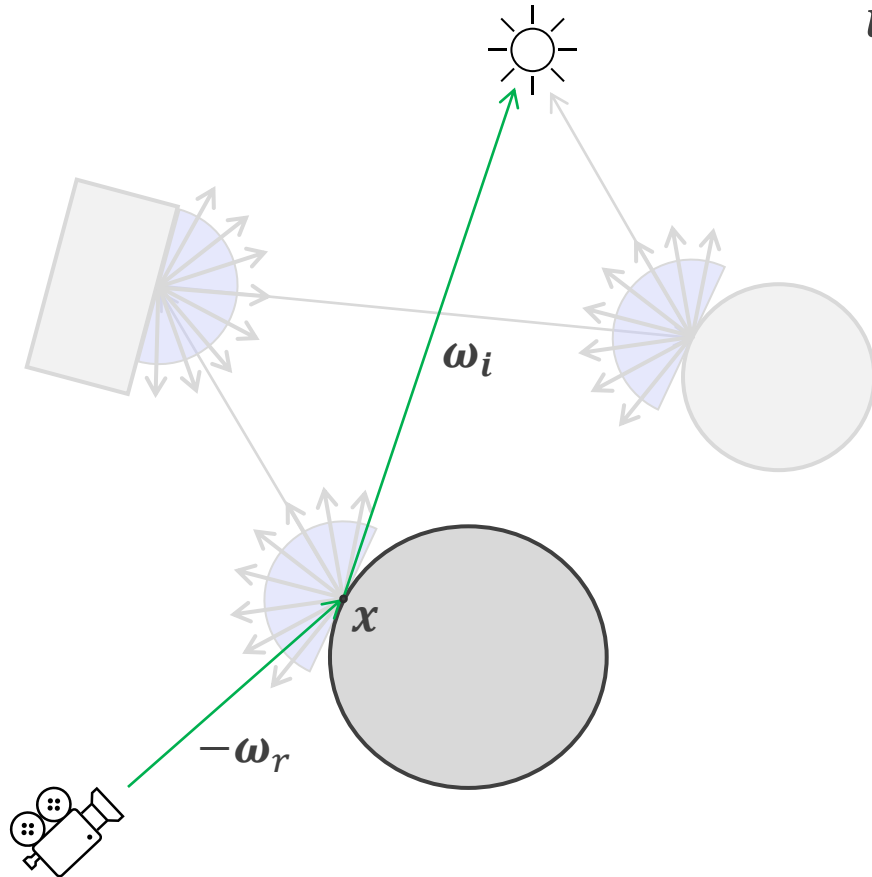
$$L_r(\mathbf{x}', \boldsymbol{\omega}'_r) = L_e(\mathbf{x}', \boldsymbol{\omega}'_r) + \frac{1}{n} \sum_{i=1}^n f'_r(\mathbf{x}', \boldsymbol{\omega}'_i, \boldsymbol{\omega}'_r) L_i(\mathbf{x}', \boldsymbol{\omega}'_i) \cos \theta'_i d\boldsymbol{\omega}'_i \frac{1}{p(\boldsymbol{\omega}'_i)}$$

$$L_r(\mathbf{x}'', \boldsymbol{\omega}''_r) = L_e(\mathbf{x}'', \boldsymbol{\omega}''_r) + \frac{1}{n} \sum_{i=1}^n f''_r(\mathbf{x}'', \boldsymbol{\omega}''_i, \boldsymbol{\omega}''_r) L_i(\mathbf{x}'', \boldsymbol{\omega}''_i) \cos \theta''_i d\boldsymbol{\omega}''_i \frac{1}{p(\boldsymbol{\omega}''_i)}$$

$$L_r(\mathbf{x}''', \boldsymbol{\omega}'''_r) = L_e(\mathbf{x}''', \boldsymbol{\omega}'''_r) + \frac{1}{n} \sum_{i=1}^n f'''_r(\mathbf{x}''', \boldsymbol{\omega}'''_i, \boldsymbol{\omega}'''_r) L_i(\mathbf{x}''', \boldsymbol{\omega}'''_i) \cos \theta'''_i d\boldsymbol{\omega}'''_i \frac{1}{p(\boldsymbol{\omega}'''_i)}$$

# Direct Illumination

$$L_r(\mathbf{x}, \omega_r) = L_e(\mathbf{x}, \omega_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \omega_i, \omega_r) L_i(\mathbf{x}, \omega_i) \cos \theta_i \frac{1}{p(\omega_i)}$$



$$L_r(\mathbf{x}', \omega_r') = L_e(\mathbf{x}', \omega_r') + \frac{1}{n} \sum_{i=1}^n f_r'(\mathbf{x}', \omega_i', \omega_r') L_i(\mathbf{x}', \omega_i') \cos \theta_i' d\omega_i' \frac{1}{p(\omega_i')}$$

$$L_r(\mathbf{x}'', \omega_r'') = L_e(\mathbf{x}'', \omega_r'') + \frac{1}{n} \sum_{i=1}^n f_r''(\mathbf{x}'', \omega_i'', \omega_r'') L_i(\mathbf{x}'', \omega_i'') \cos \theta_i'' d\omega_i'' \frac{1}{p(\omega_i'')}$$

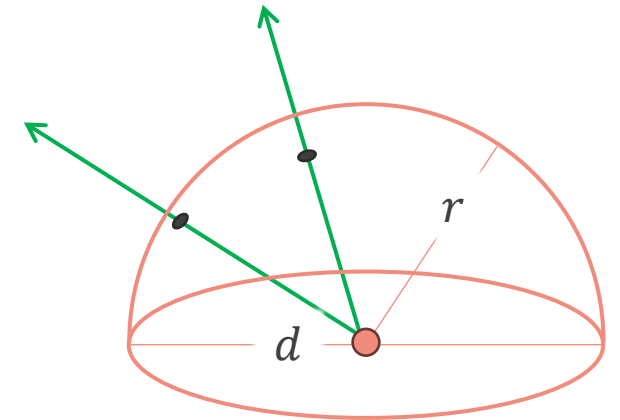
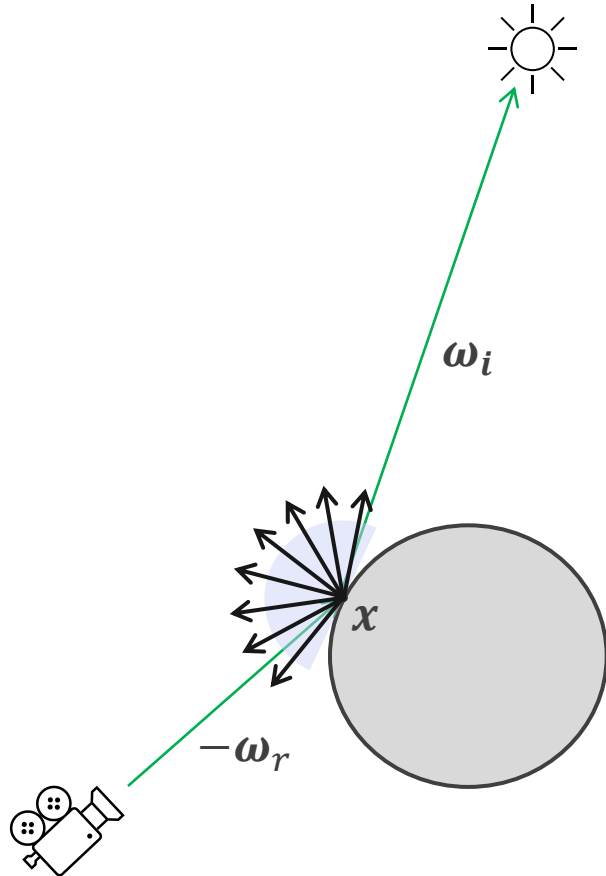
$$L_r(\mathbf{x}''', \omega_r''') = L_e(\mathbf{x}''', \omega_r''') + \frac{1}{n} \sum_{i=1}^n f_r'''(\mathbf{x}''', \omega_i''', \omega_r''') L_i(\mathbf{x}''', \omega_i''') \cos \theta_i''' d\omega_i''' \frac{1}{p(\omega_i''')}$$

# Direct Illumination

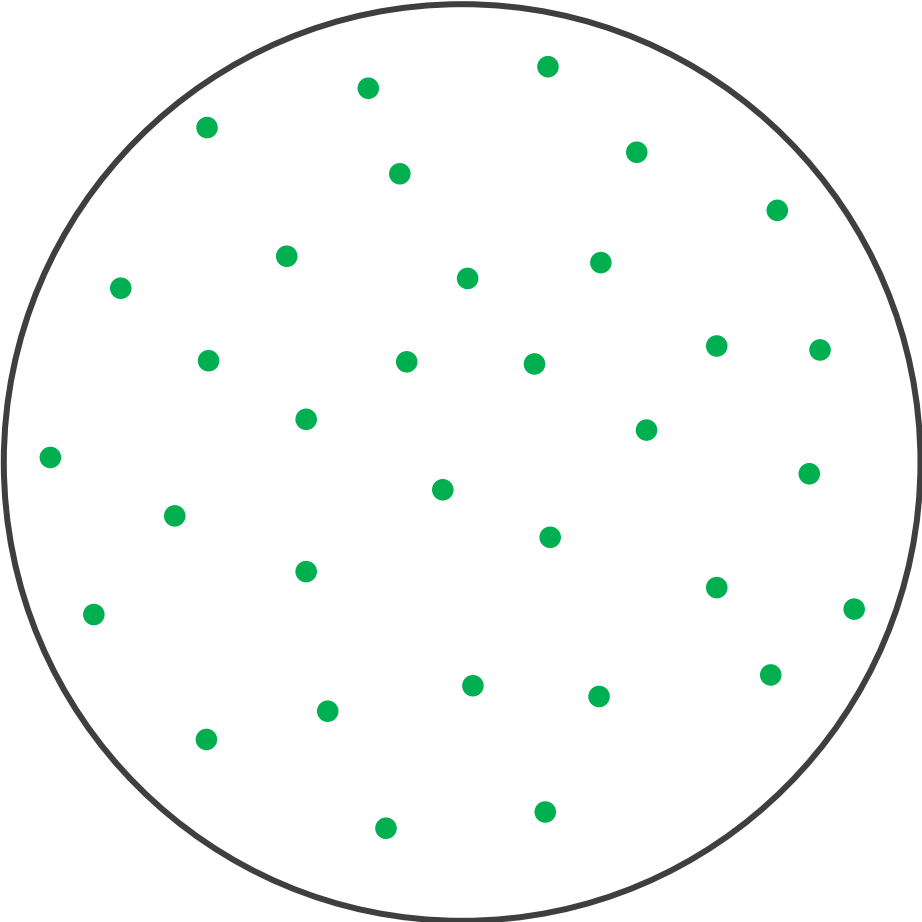
$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_e(\mathbf{x}', \boldsymbol{\omega}'_r) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$

evaluates to 0 for  
non-emissive objects

$\boldsymbol{\omega}'_r = -\boldsymbol{\omega}_i$

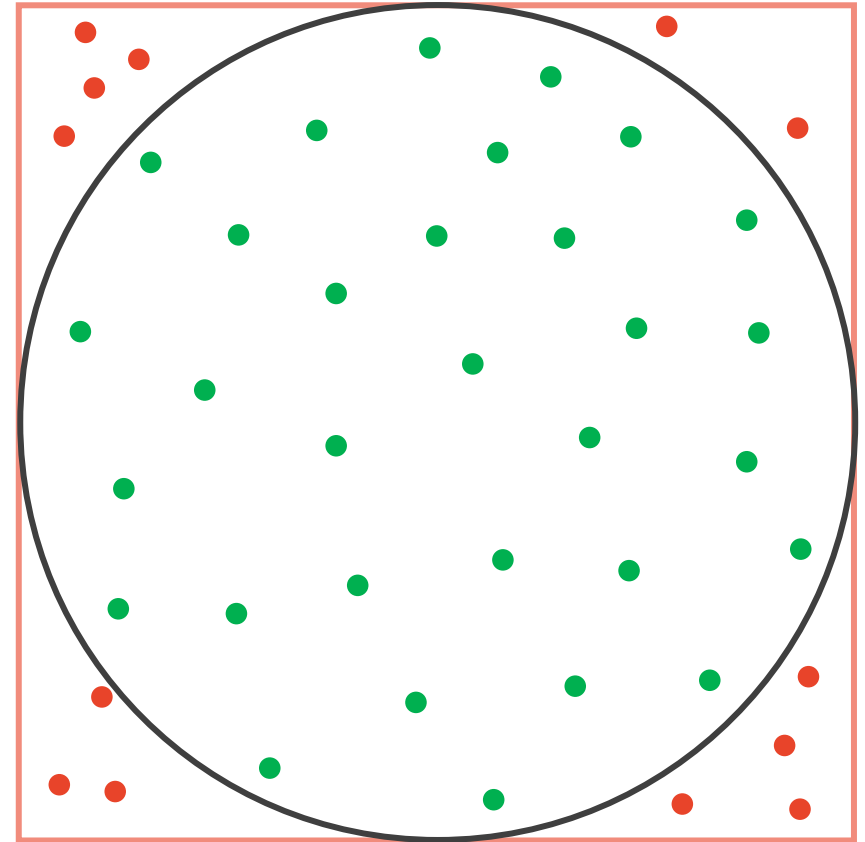


# Uniformly Sample Unit Circle



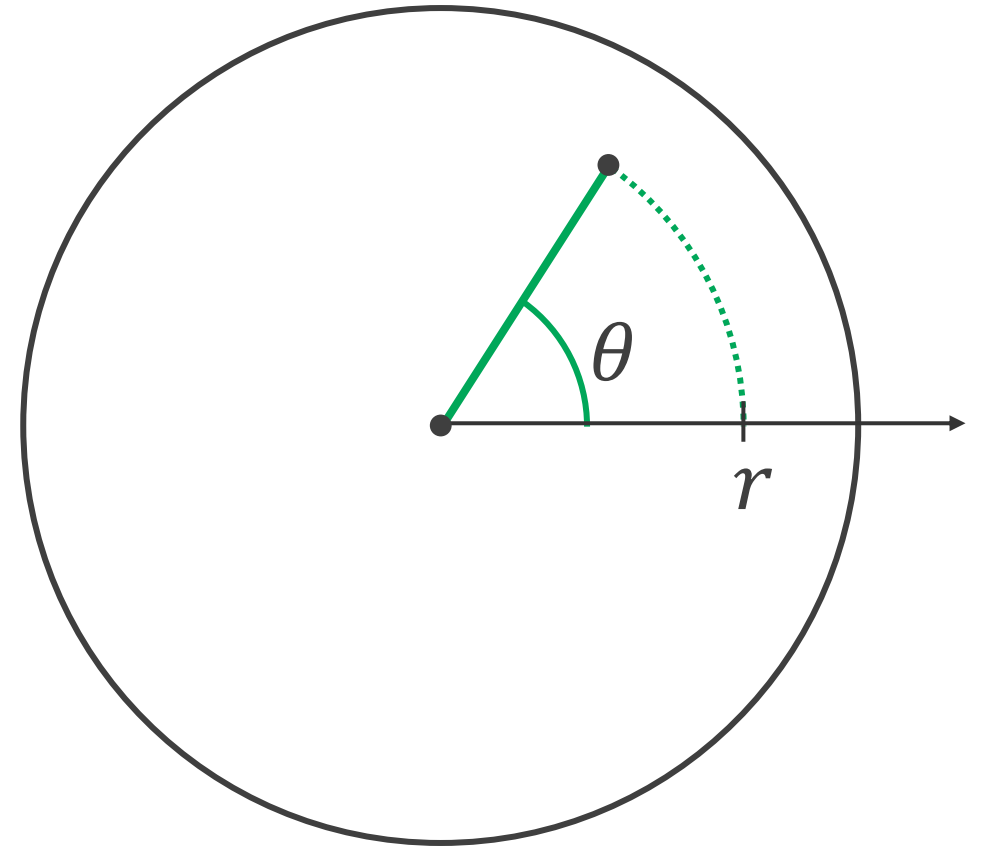
# Rejection Technique

- Randomly generate  $(x, y)$ 
  - $x \in [0,1]$
  - $y \in [0,1]$
  - keep when  $x^2 + y^2 \leq 1$



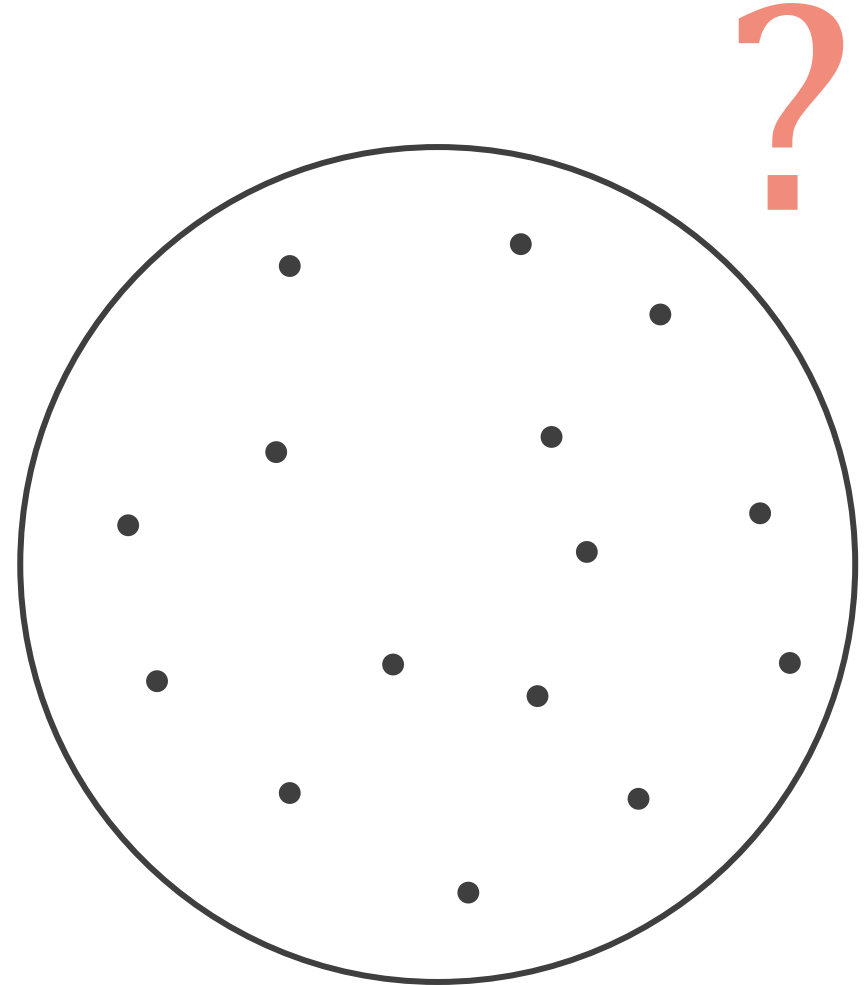
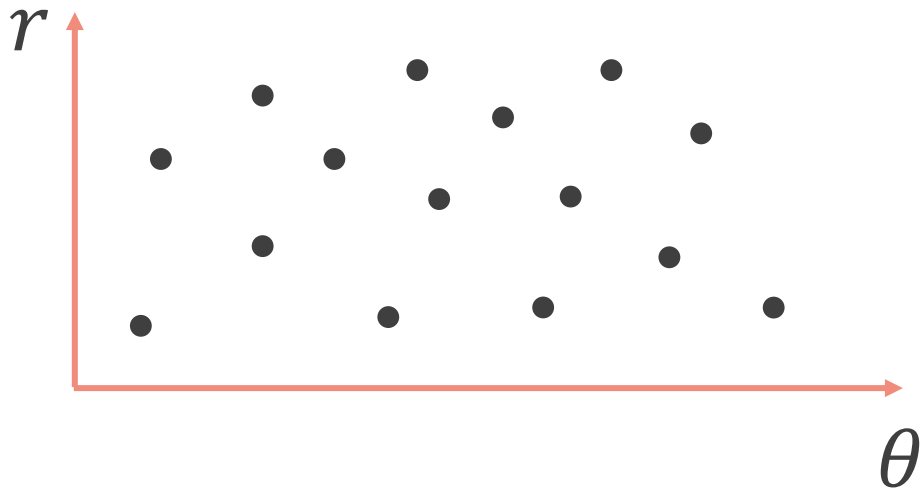
# Polar Coordinates

- $\theta$  uniform random angle between 0 and  $2\pi$
- $r$  uniform random angle between 0 and 1



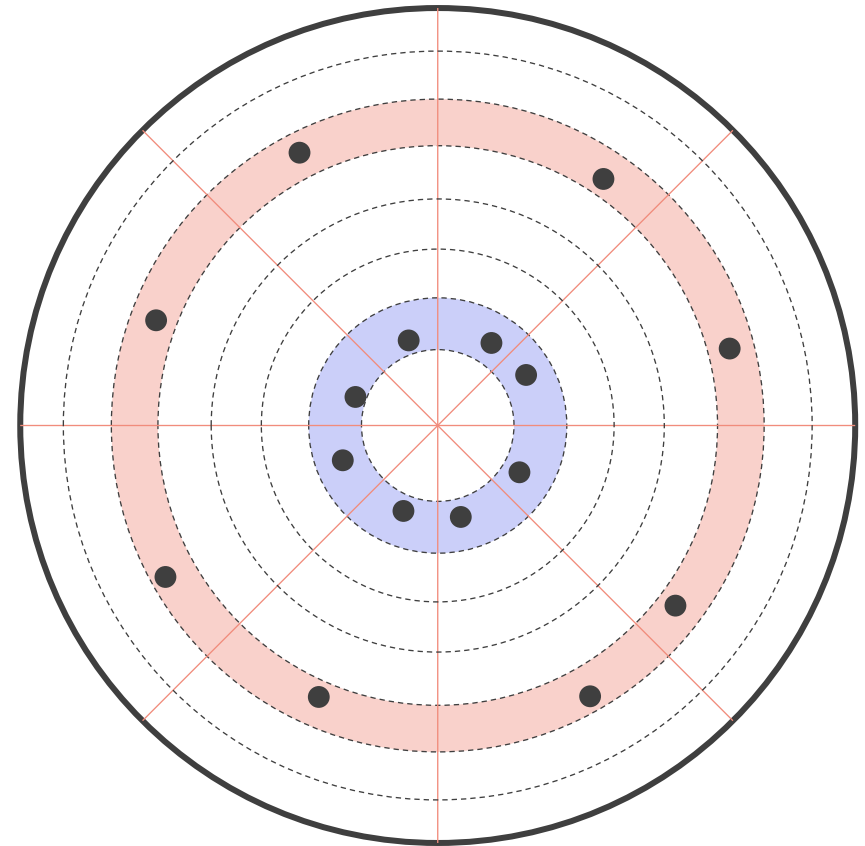
# Polar Coordinates

- $\theta$  uniform random angle between 0 and  $2\pi$
- $r$  uniform random angle between 0 and 1



# Sampling is NOT Uniform in Area!

- Samples closer to the center are more likely to be chosen

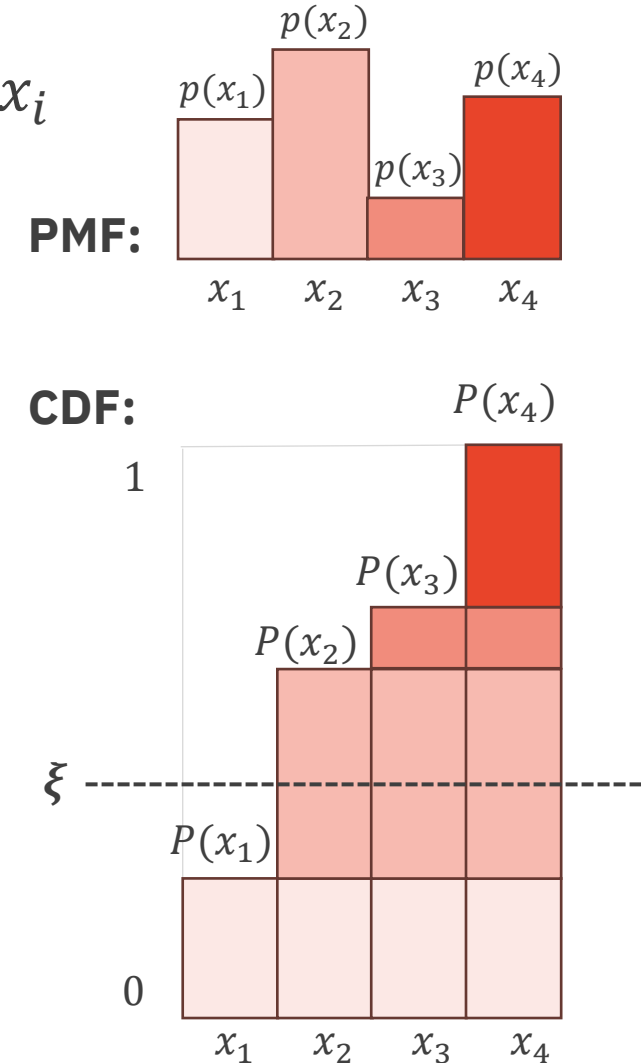




# Cumulative Distribution Function (CDF)

- Probability that random variable  $X$  will take a value  $\leq x_i$
- **For PMF:**  $P(x_i) = \sum_{j=1}^i p(x_j)$
- For PDF:  $P(x) = \int_0^x p(x) dx$
- Properties
  - $0 < P(x) < 1$
  - $P(n) = 1$
- Sampling probability distributions
  - Select  $x_i$  if  $P(x_{i-1}) < \xi < P(x_i)$

canonical uniform random variable  $\in [0,1)$

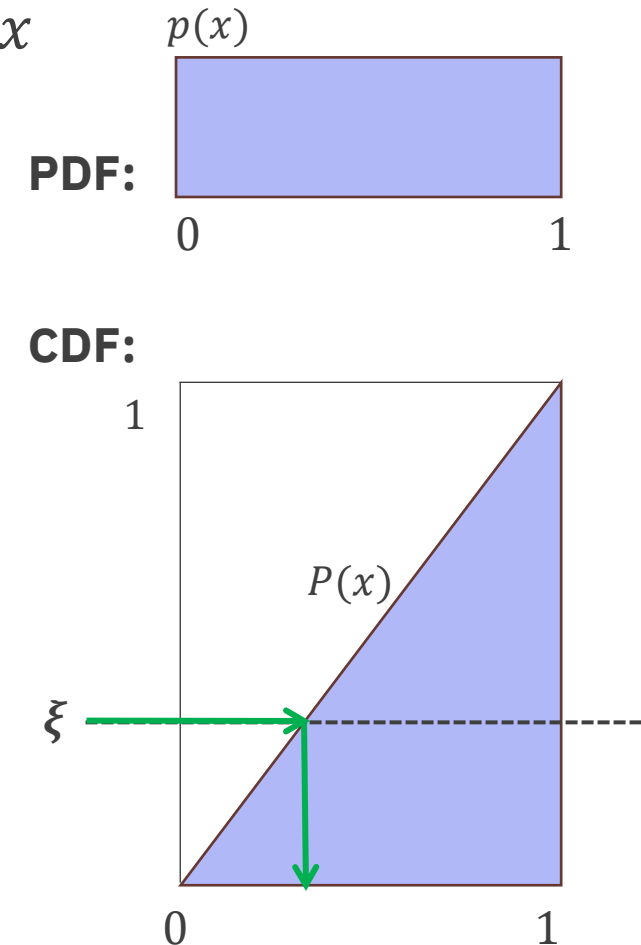


# Cumulative Distribution Function (CDF)

- Probability that random variable  $X$  will take a value  $\leq x$
- For PMF:  $P(x_i) = \sum_{j=1}^i p(x_j)$
- **For PDF:**  $P(x) = \int_0^x p(x) dx$
- Properties
  - $0 < P(x) < 1$
  - $P(n) = 1$
- Sampling probability distributions
  - **Select  $x = P^{-1}(\xi)$**



canonical uniform random variable  $\in [0,1)$



# Better Sampling Using Inversion Method

[https://www.pbr-book.org/3ed-2018/Monte\\_Carlo\\_Integration/Transforming\\_between\\_Distributions](https://www.pbr-book.org/3ed-2018/Monte_Carlo_Integration/Transforming_between_Distributions)

[https://www.pbr-book.org/3ed-2018/Monte\\_Carlo\\_Integration/2D\\_Sampling\\_with\\_Multidimensional\\_Transformations](https://www.pbr-book.org/3ed-2018/Monte_Carlo_Integration/2D_Sampling_with_Multidimensional_Transformations)

- Area of the **unit** disk:  $\pi$

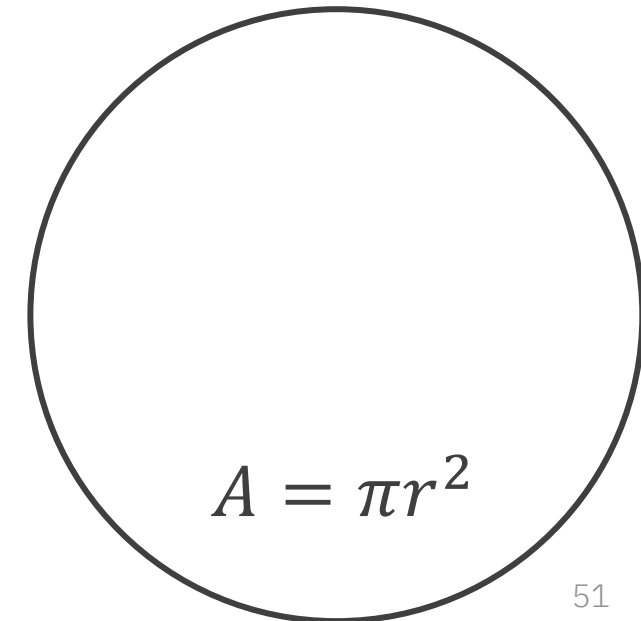
- Since we want uniform distribution over the disk and  $\int_D p(x, y) = 1$

$$p(x, y) = \frac{1}{\pi} \longrightarrow p(r, \theta) = \frac{r}{\pi} \quad p(x, y) = \frac{p(r, \theta)}{r} \rightarrow p(r, \theta) = r p(x, y)$$

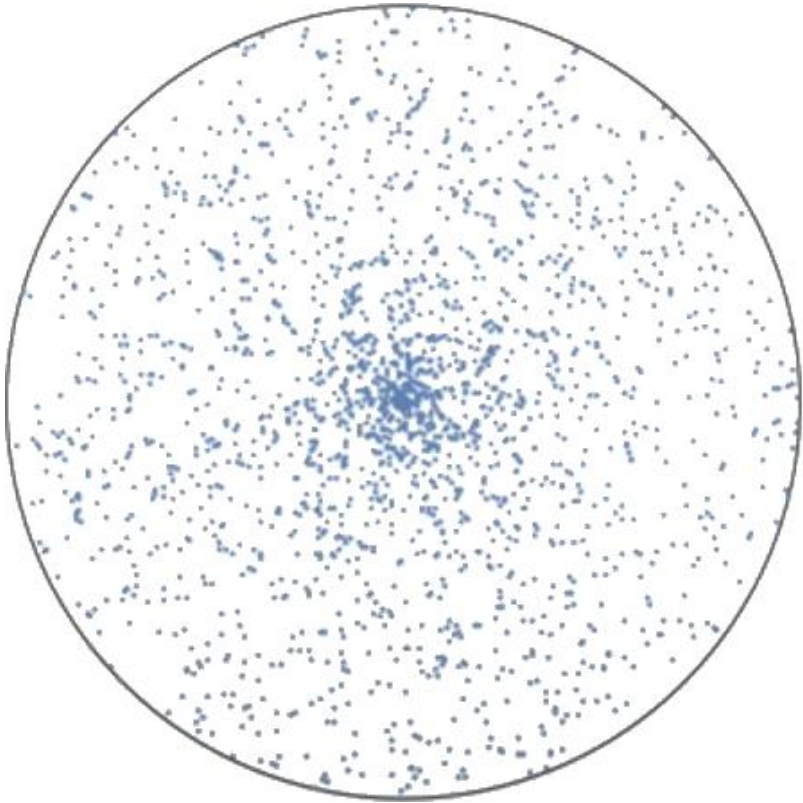
- $r, \theta$  are independent  $\rightarrow p(r, \theta) = p(r)p(\theta)$

$$p(\theta) = \frac{1}{2\pi} \longrightarrow P(\theta) = \frac{\theta}{2\pi} \longrightarrow P^{-1}(\xi_1) = 2\pi\xi_1$$

$$p(r) = 2r \longrightarrow P(r) = r^2 \longrightarrow P^{-1}(\xi_2) = \sqrt{\xi_2}$$

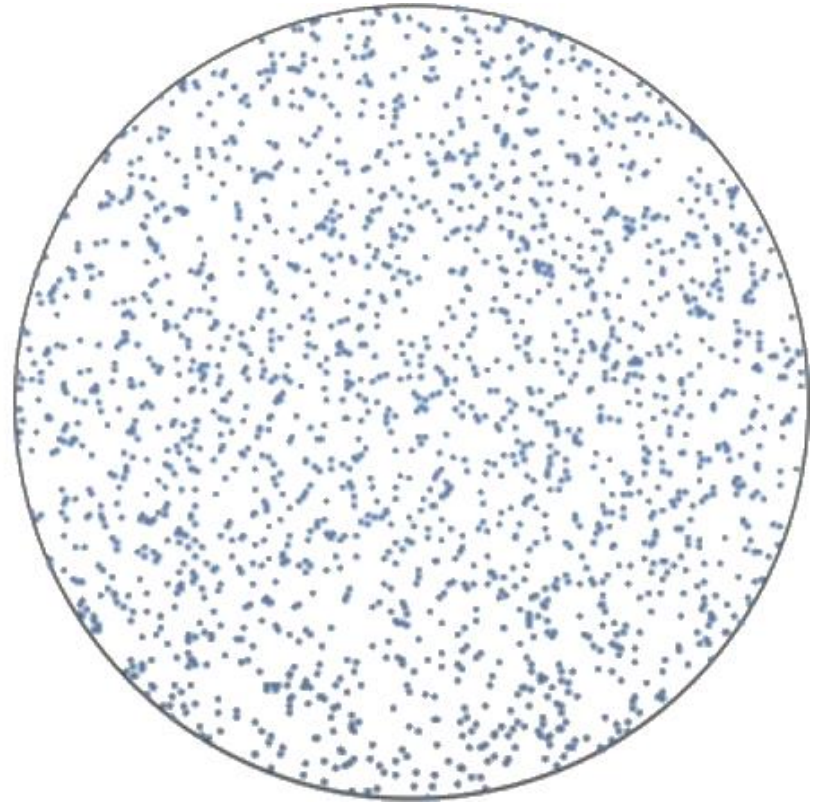


# Better Sampling Using Inversion Method



$$\theta = 2\pi\xi_1$$

$$r = \xi_2$$



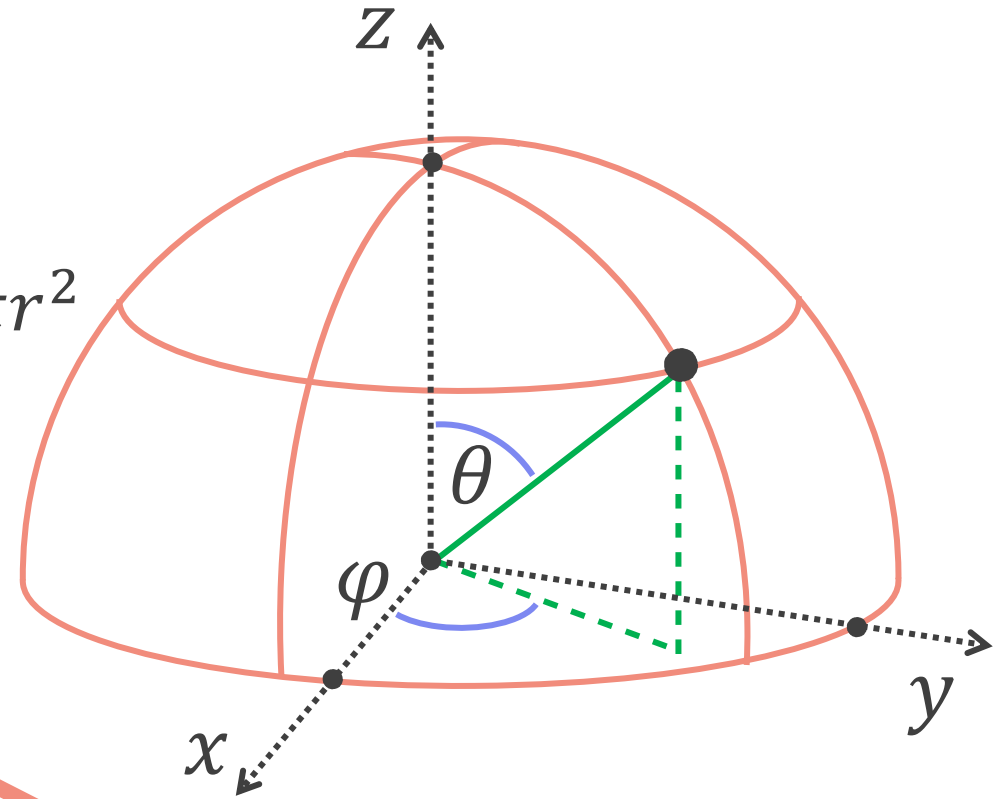
$$\theta = 2\pi\xi_1$$

$$r = \sqrt{\xi_2}$$

# Uniform Hemisphere Sampling

$$\begin{aligned}x &= r \sin \theta \cos \varphi \\y &= r \sin \theta \sin \varphi \\z &= r \cos \theta\end{aligned}$$

$$A = 2\pi r^2$$



$$p(r, \theta, \varphi) = r^2 \sin \theta p(x, y, z)$$

$$p(\omega) = \frac{1}{2\pi}$$



$$p(\theta, \varphi) = \frac{\sin \theta}{2\pi}$$

note that we ignore  $r$

$$p(\theta) = \sin \theta$$



$$P(\theta) = 1 - \cos \theta$$



$$P^{-1}(\xi_1) = \cos^{-1}(1 - \xi_1) \longrightarrow \cos^{-1}(\xi_1)$$

$$p(\varphi) = \frac{1}{2\pi}$$



$$P(\varphi) = \frac{\varphi}{2\pi}$$

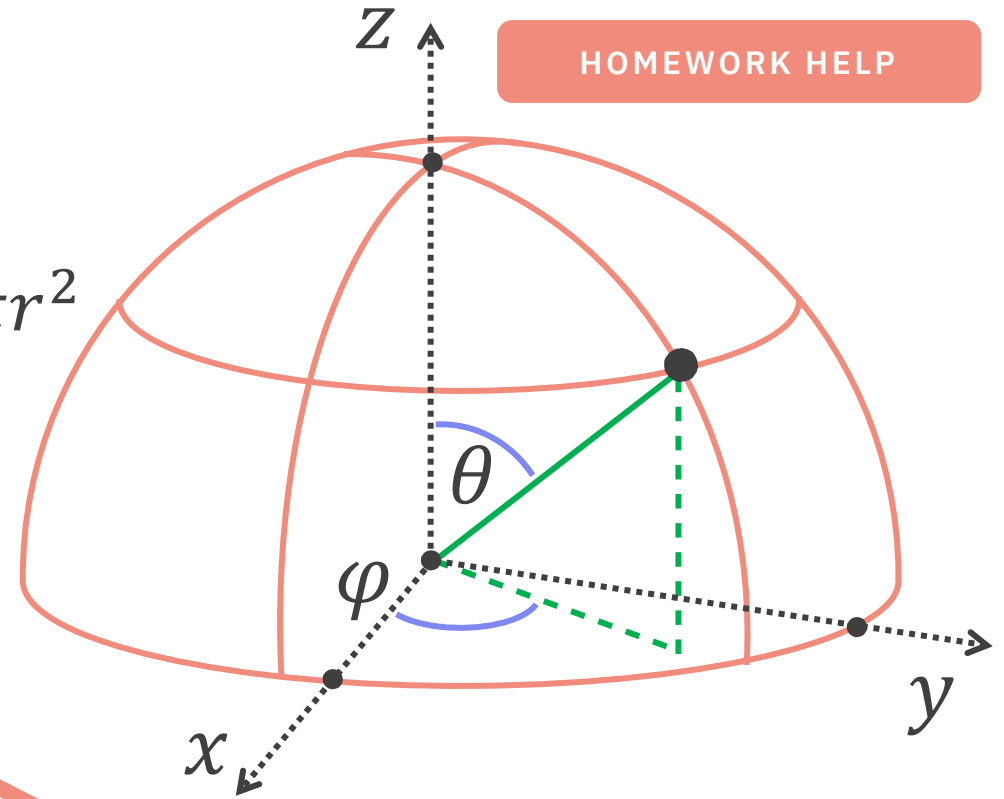


$$P^{-1}(\xi_2) = 2\pi \xi_2$$

# Uniform Hemisphere Sampling

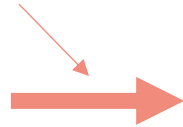
$$\begin{aligned}
 x &= r \sin \theta \cos \varphi = \sqrt{1 - \xi_1^2} \cos(2\pi\xi_2) \\
 y &= r \sin \theta \sin \varphi = \sqrt{1 - \xi_1^2} \sin(2\pi\xi_2) \\
 z &= r \cos \theta = \xi_1
 \end{aligned}$$

$$A = 2\pi r^2$$



$$p(r, \theta, \varphi) = r^2 \sin \theta p(x, y, z)$$

$$p(\omega) = \frac{1}{2\pi}$$



$$p(\theta, \varphi) = \frac{\sin \theta}{2\pi}$$

note that we ignore  $r$

$$p(\theta) = \sin \theta$$



$$P(\theta) = 1 - \cos \theta$$



$$P^{-1}(\xi_1) = \cos^{-1}(1 - \xi_1) \longrightarrow \cos^{-1}(\xi_1)$$

$$p(\varphi) = \frac{1}{2\pi}$$

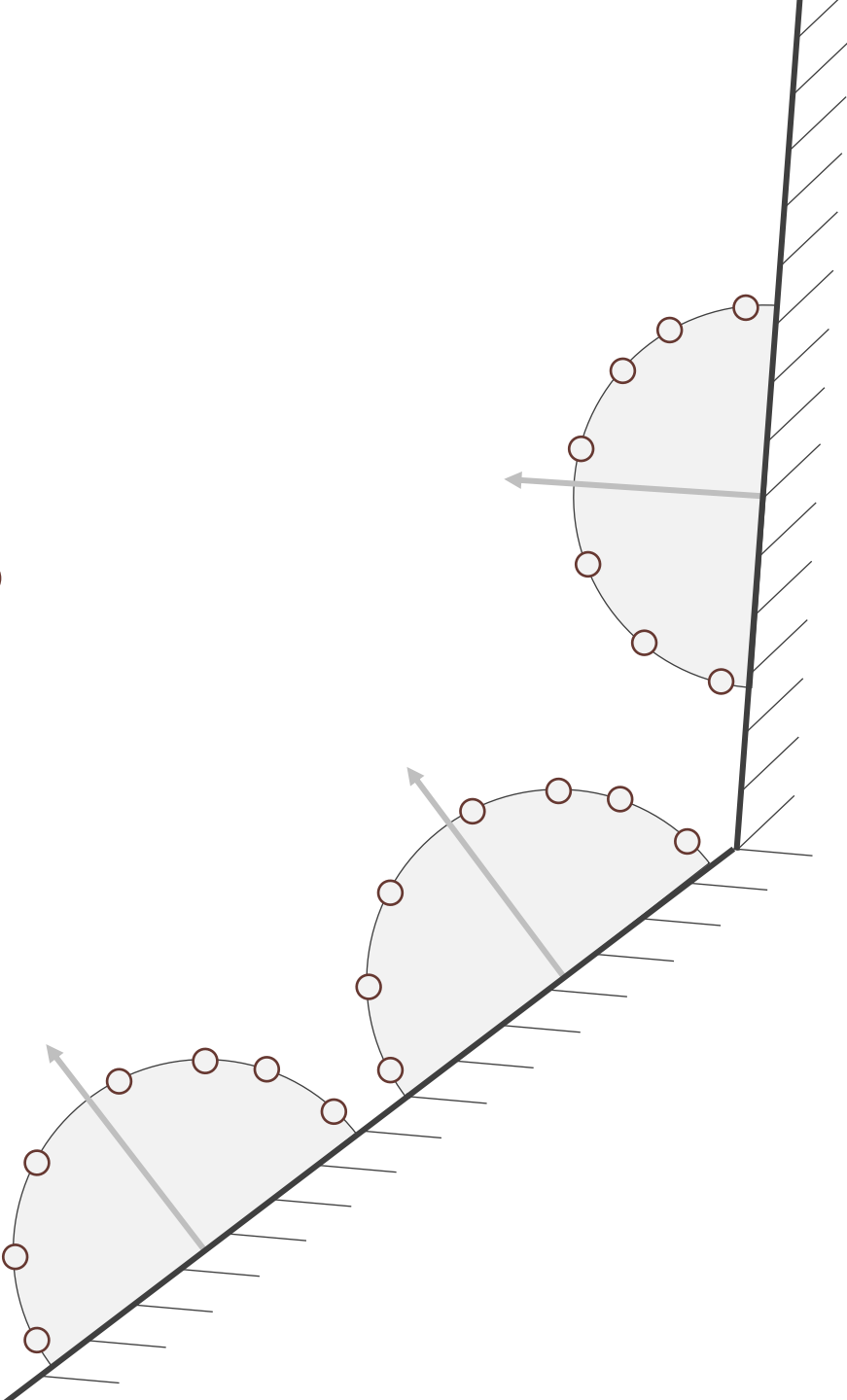
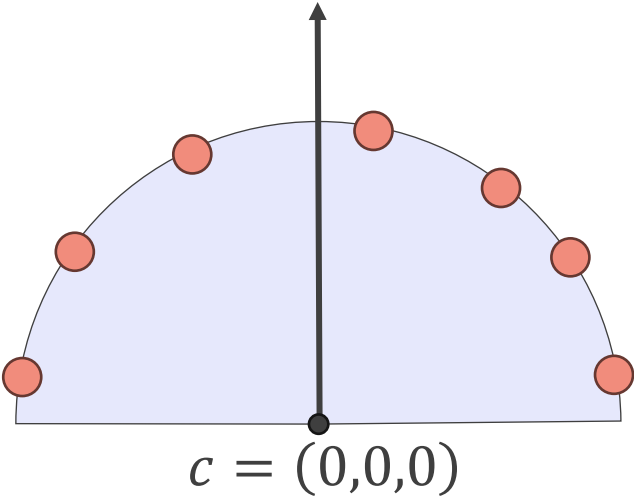


$$P(\varphi) = \frac{\varphi}{2\pi}$$



$$P^{-1}(\xi_2) = 2\pi\xi_2$$

# Transforming Samples



# Transforming Samples

- We do not care about hemisphere rotation
- So for a local sample  $(x, y, z)$  and surface normal  $N$

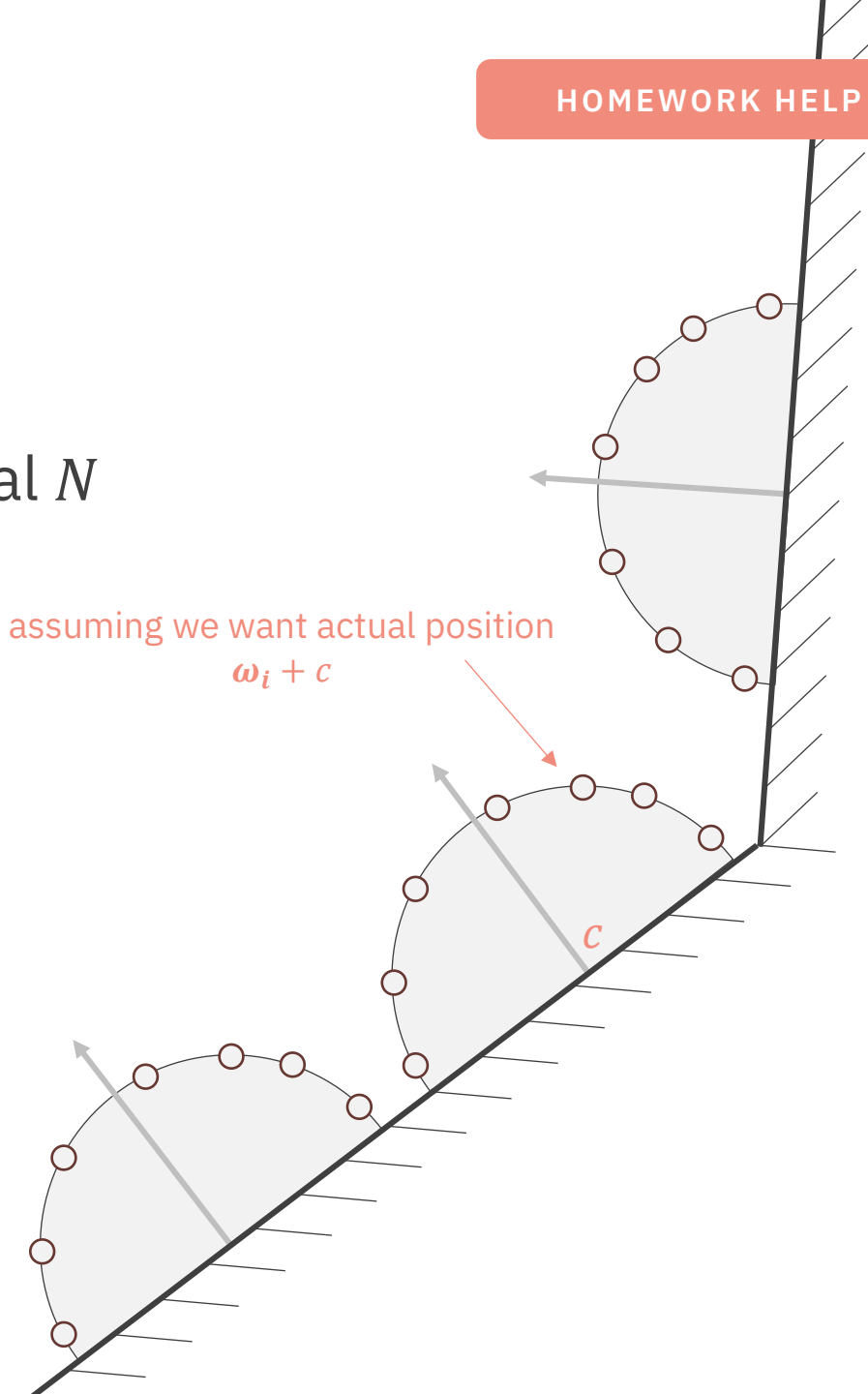
- $U = \begin{cases} (0, 0, 1) & \text{when } |N \cdot z| < 0.999 \\ (0, 1, 0) & \text{otherwise} \end{cases}$

- $T = U \times N$  ← cross products, order is important, do not forget to normalize

- $B = N \times T$  ←

- $\omega_i = Tx + By + Nz$

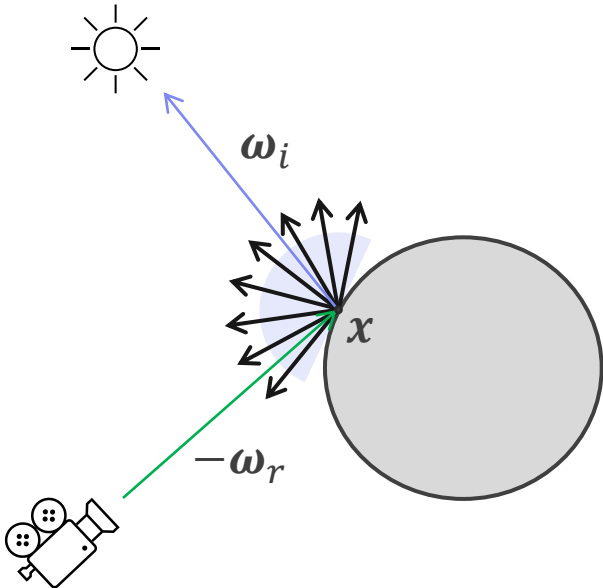
sample local coordinates





# Direct Illumination

$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_e(\mathbf{x}', \boldsymbol{\omega}'_r) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$



```
Trace(ray) {
  radiance ← (0,0,0)
  hit ← ClosestHit(ray)
  if(hit == miss) return radiance

  Le = hit.material.emission

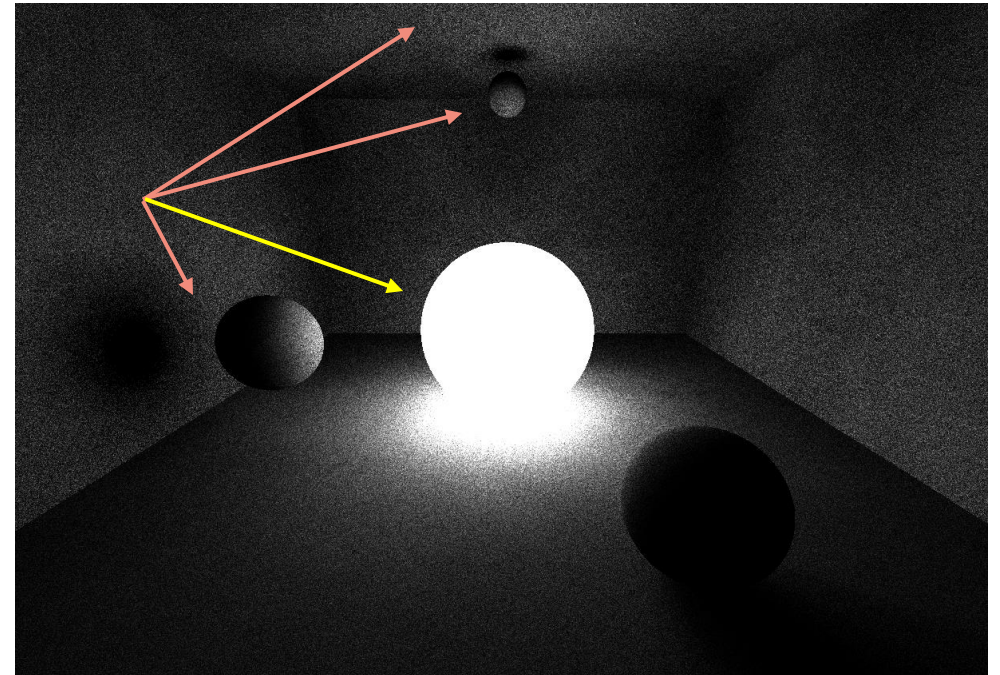
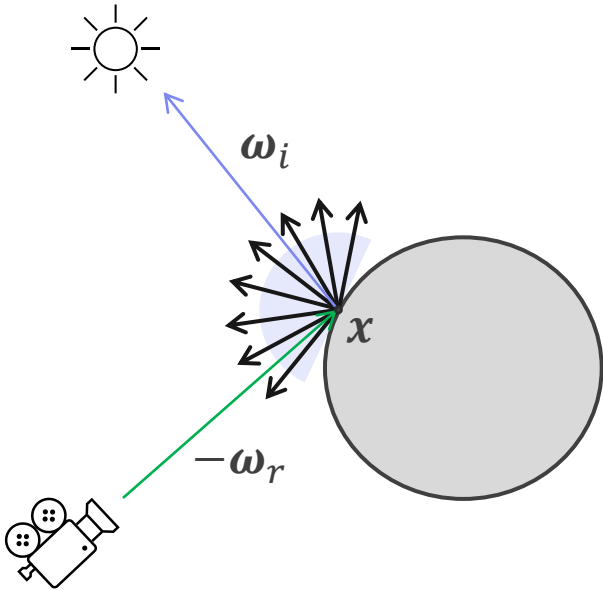
  for(i=0; i < samples; i++) {
    sample ← GetNextSample(hit, ray)
    next_ray ← Ray(hit.intersection + epsilon * hit.normal, sample.direction)
    next_hit ← ClosestHit(next_ray);
    if(next_hit == miss || sample.pdf == 0) continue //i.e., skip this sample

    brdf ← ComputeBRDF(hit, next_ray.direction, -ray.direction)
    emission ← next_hit.material.emission
    radiance += brdf * emission * dot(hit.normal, next_ray.direction) / sample.pdf
  }
  return Le + radiance / samples
}
```

# Direct Illumination

$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_e(\mathbf{x}', \boldsymbol{\omega}'_r) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$

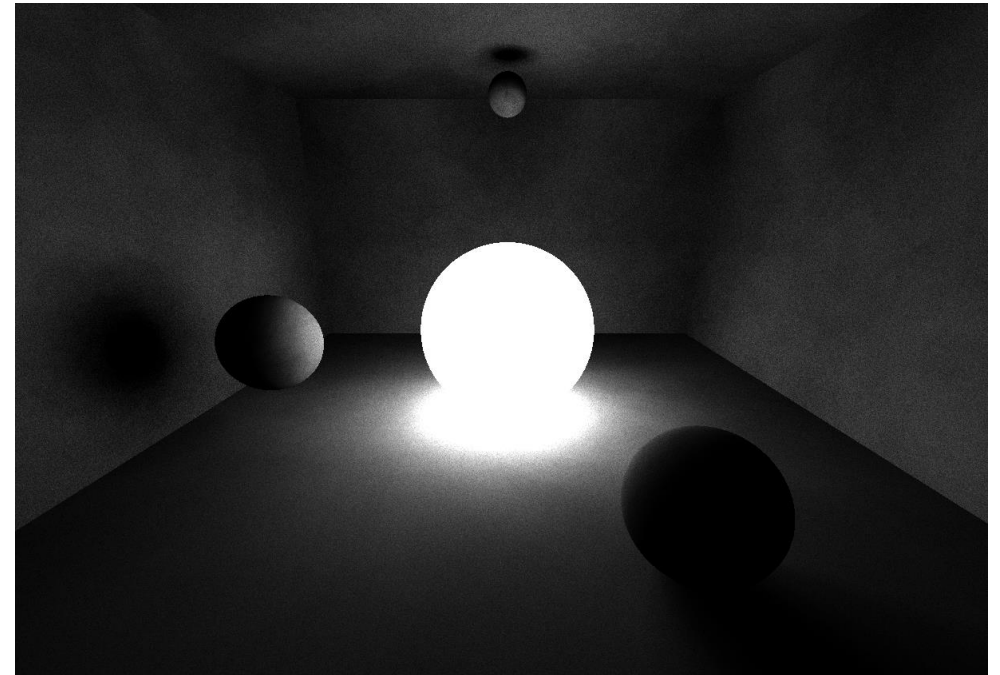
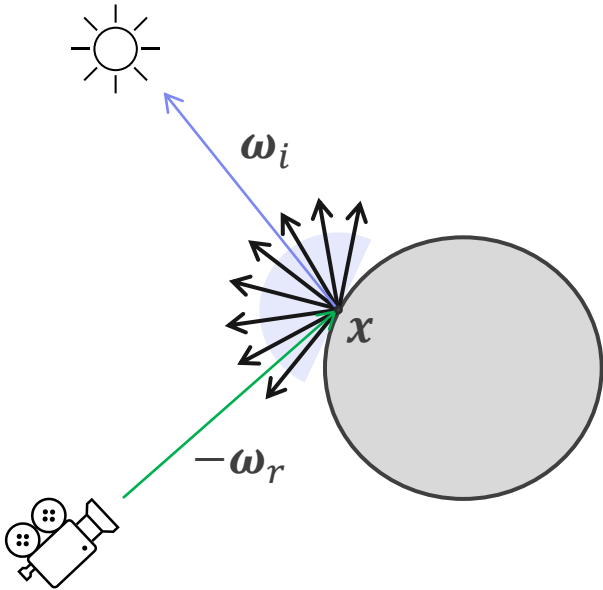
$$f_r = 1.0, n = 100, p(\boldsymbol{\omega}_i) = \frac{1}{2\pi}$$



# Direct Illumination

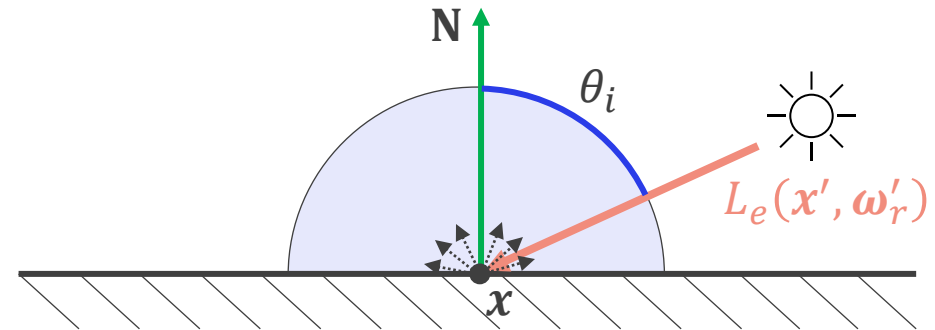
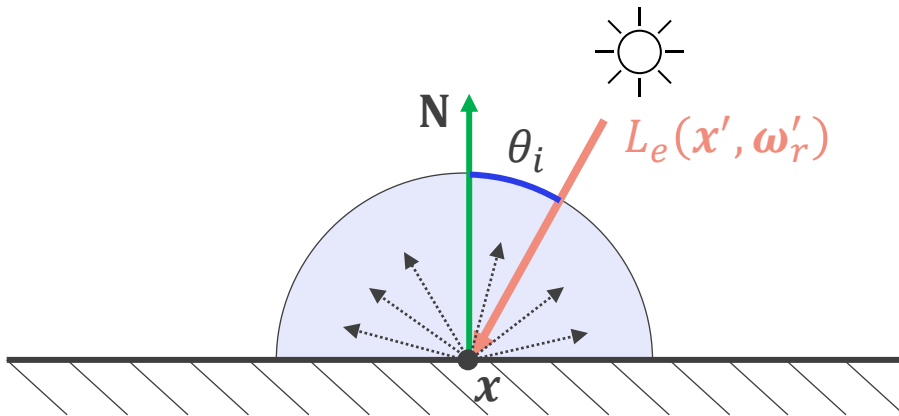
$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_e(\mathbf{x}', \boldsymbol{\omega}'_r) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$

$$f_r = 1.0, n = 1000, p(\boldsymbol{\omega}_i) = \frac{1}{2\pi}$$



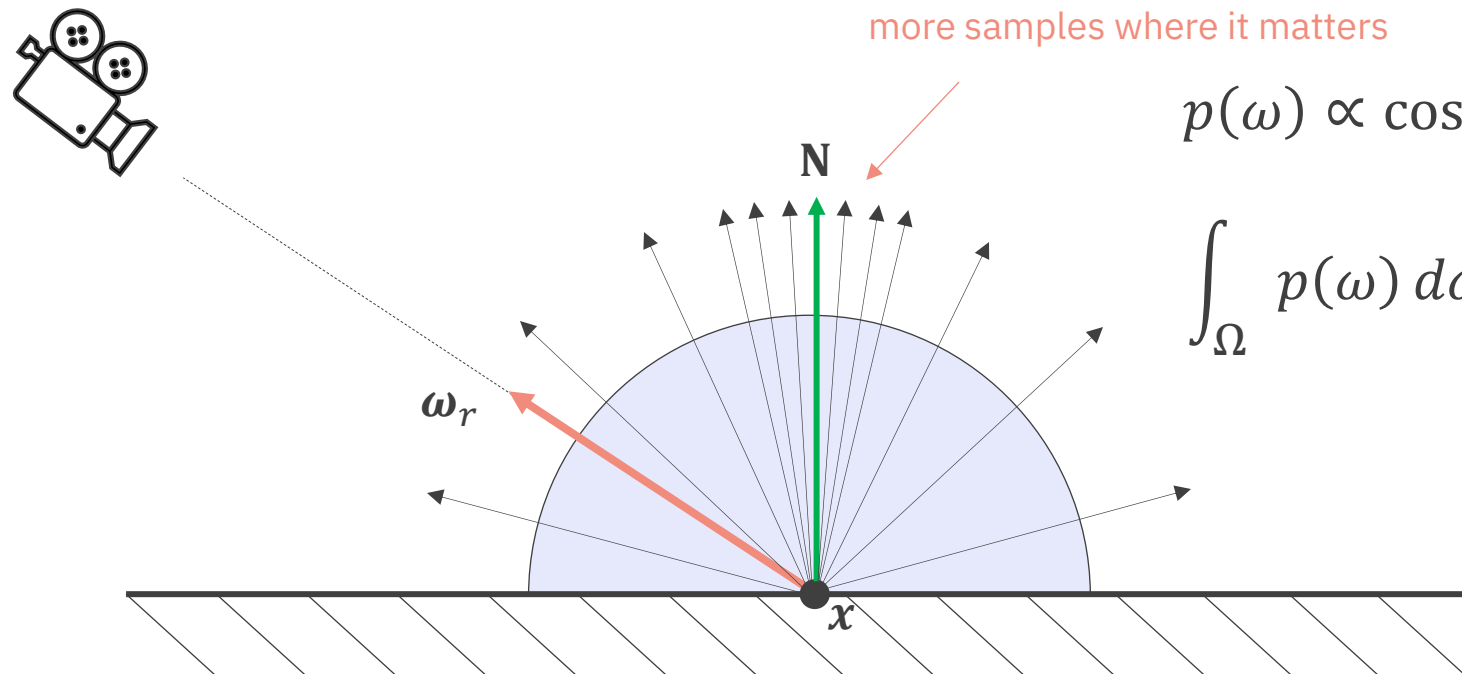
# Lambert's Cosine Law

$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_e(\mathbf{x}', \boldsymbol{\omega}'_r) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$



# Cosine-Weighted Sampling

$$L_r(\mathbf{x}, \omega_r) = L_e(\mathbf{x}, \omega_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \omega_i, \omega_r) L_e(\mathbf{x}', \omega'_i) \cos \theta_i \frac{1}{p(\omega_i)}$$



$$p(\omega) \propto \cos \theta$$

$$\int_{\Omega} p(\omega) d\omega = 1 \rightarrow p(\omega) = \frac{\cos \theta}{\pi}$$

# Cosine-Weighted Sampling

$$x = r \sin \theta \cos \varphi$$

$$y = r \sin \theta \sin \varphi$$

$$z = r \cos \theta$$

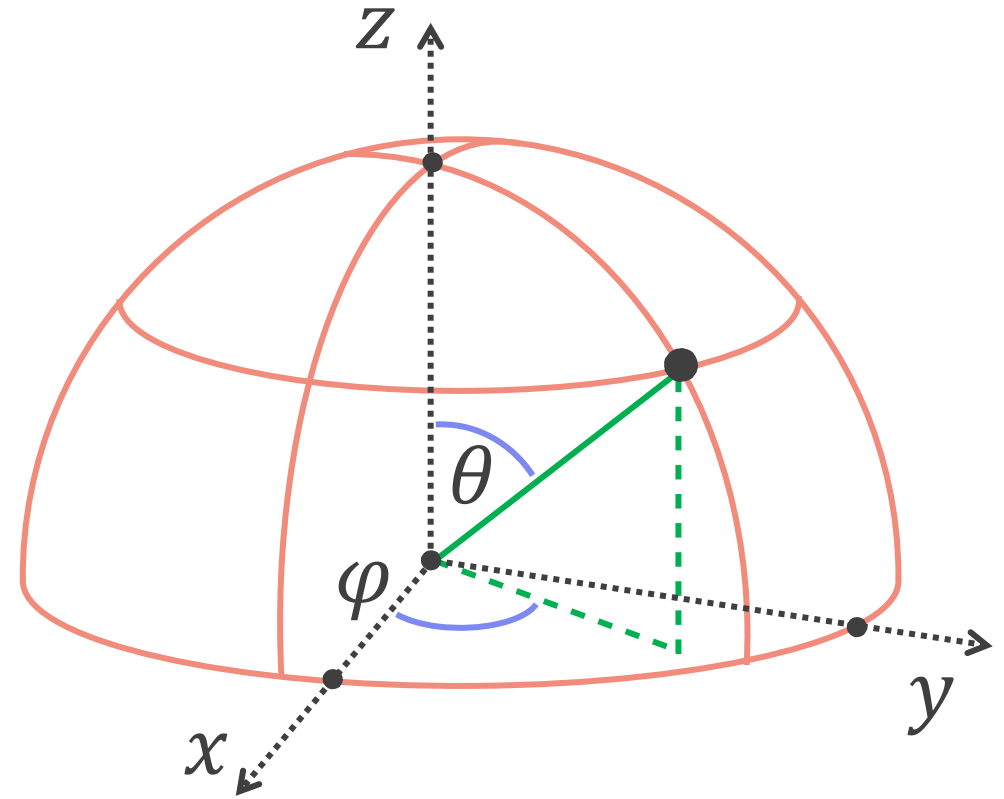
$$p(r, \theta, \varphi) = r^2 \sin \theta p(x, y, z)$$

$$p(\omega) = \frac{\cos \theta}{\pi} \longrightarrow p(\theta, \varphi) = \frac{\cos \theta \sin \theta}{\pi}$$

note that we ignore  $r$

$$p(\theta) = 2 \cos \theta \sin \theta \longrightarrow P(\theta) = 1 - \cos^2 \theta \longrightarrow P^{-1}(\xi_1) = \cos^{-1} \sqrt{1 - \xi_1}$$

$$p(\varphi) = \frac{1}{2\pi} \longrightarrow P(\varphi) = \frac{\varphi}{2\pi} \longrightarrow P^{-1}(\xi_2) = 2\pi \xi_2$$



# Cosine-Weighted Sampling

$$x = r \sin \theta \cos \varphi = \sqrt{\xi_1} \cos(2\pi\xi_2)$$

$$y = r \sin \theta \sin \varphi = \sqrt{\xi_1} \sin(2\pi\xi_2)$$

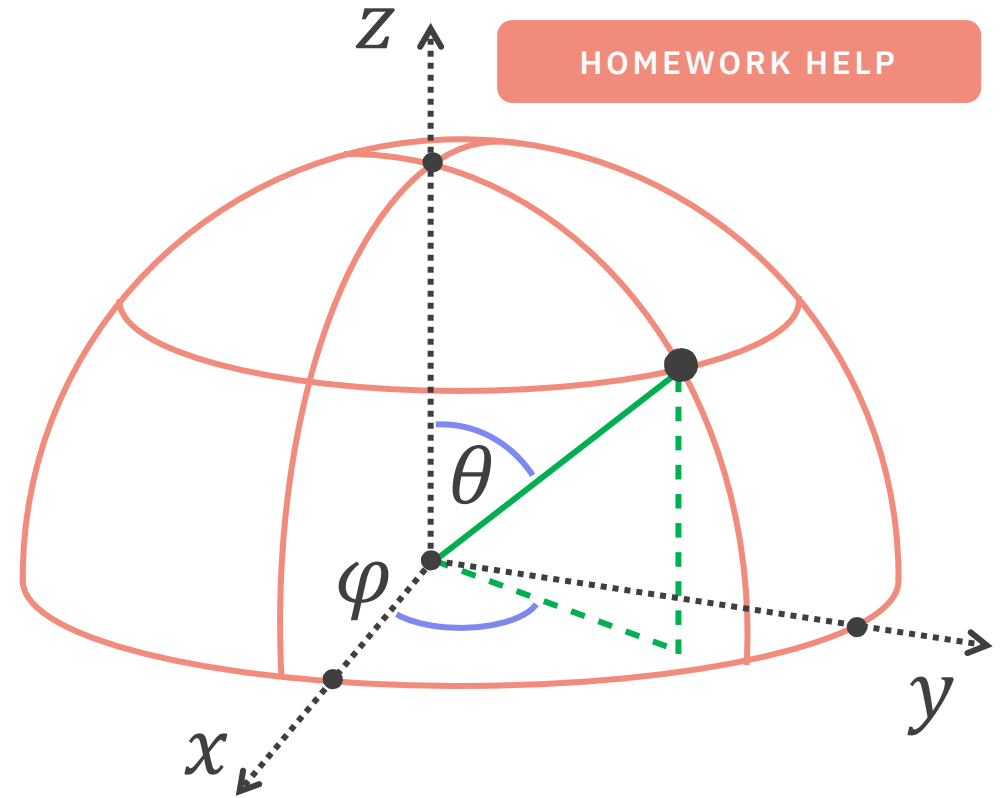
$$z = r \cos \theta = \sqrt{1 - \xi_1} = \sqrt{1 - x^2 - y^2}$$

Malley's method

$$p(r, \theta, \varphi) = r^2 \sin \theta p(x, y, z)$$

$$p(\omega) = \frac{\cos \theta}{\pi} \longrightarrow p(\theta, \varphi) = \frac{\cos \theta \sin \theta}{\pi}$$

note that we ignore  $r$



$$p(\theta) = 2 \cos \theta \sin \theta \longrightarrow P(\theta) = 1 - \cos^2 \theta \longrightarrow P^{-1}(\xi_1) = \cos^{-1} \sqrt{1 - \xi_1}$$

$$p(\varphi) = \frac{1}{2\pi} \longrightarrow P(\varphi) = \frac{\varphi}{2\pi} \longrightarrow P^{-1}(\xi_2) = 2\pi\xi_2$$

# Cosine-Weighted Sampling

$$p(\omega_i) = \frac{\cos \theta_i}{\pi}$$

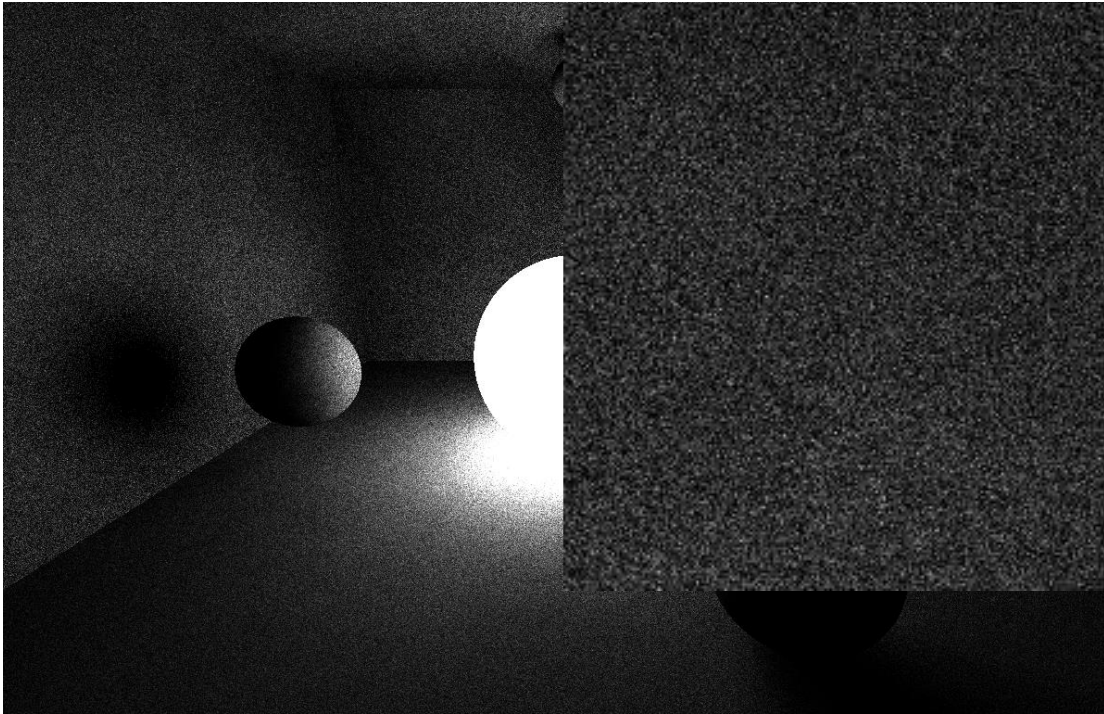
$$\begin{aligned} L_r(\mathbf{x}, \omega_r) &= L_e(\mathbf{x}, \omega_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \omega_i, \omega_r) L_e(\mathbf{x}', \omega'_r) \cos \theta_i \frac{1}{p(\omega_i)} \\ &= L_e(\mathbf{x}, \omega_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \omega_i, \omega_r) L_e(\mathbf{x}', \omega'_r) \cos \theta_i \frac{\pi}{\cos \theta_i} \\ &= L_e(\mathbf{x}, \omega_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \omega_i, \omega_r) L_e(\mathbf{x}', \omega'_r) \pi \end{aligned}$$

**Observation:** We no longer care about the light direction, because we have more samples around the normal, thus the contribution will be stronger from there

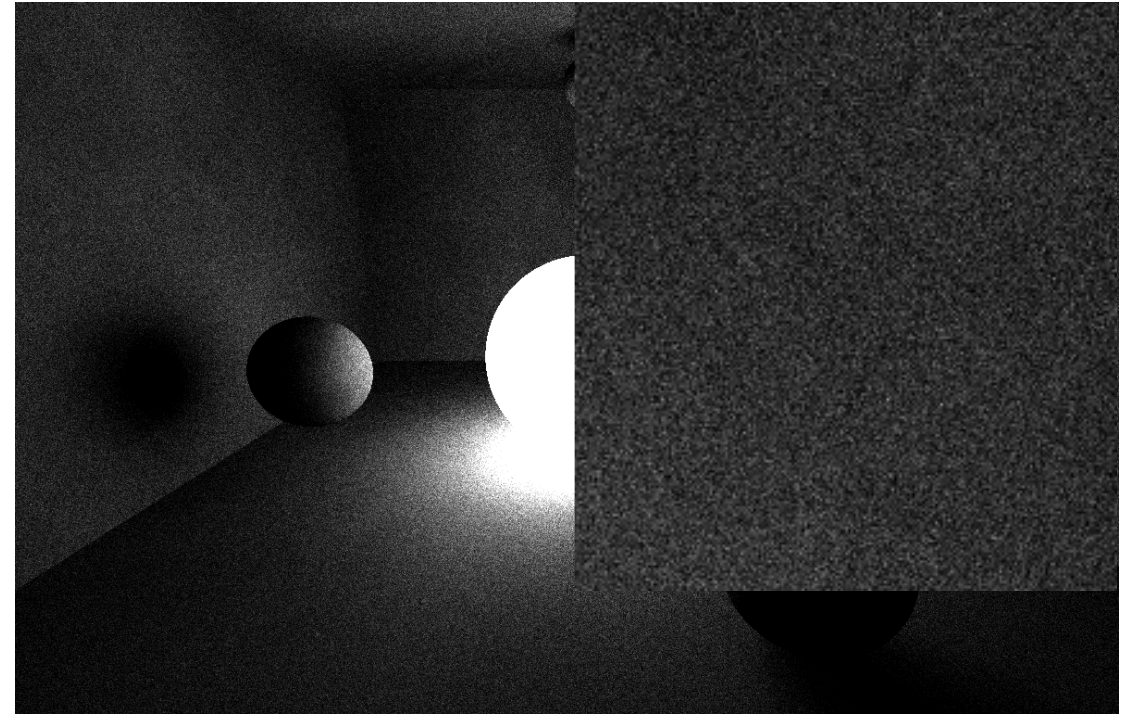


# Comparison

$$f_r = 1.0, n = 100, p(\omega_i) = \frac{1}{2\pi}$$



$$f_r = 1.0, n = 100, p(\omega_i) = \frac{\cos \theta}{\pi}$$



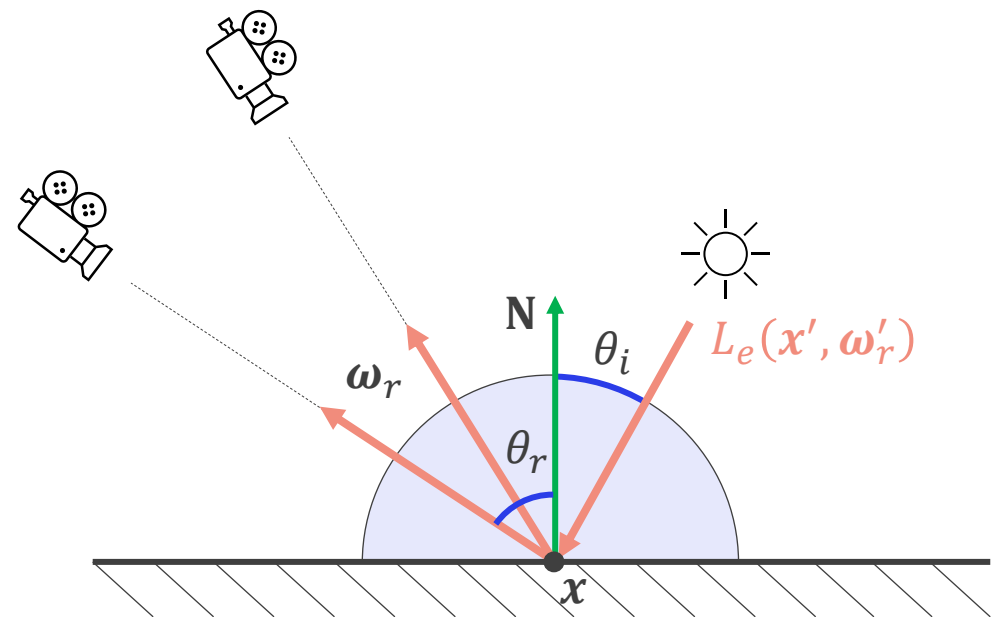
# Energy Non-Conserving BRDF

$$f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) = 1$$

$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n 1 L_e(\mathbf{x}', \boldsymbol{\omega}'_r) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$

- Sum of energy reflected in all directions:

$$\int_{\Omega} f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) \cos \theta_r d\boldsymbol{\omega}_r > 1$$



# Lambertian BRDF

$$f_r(\mathbf{x}, \omega_i, \omega_r) = \frac{\rho}{\pi}$$

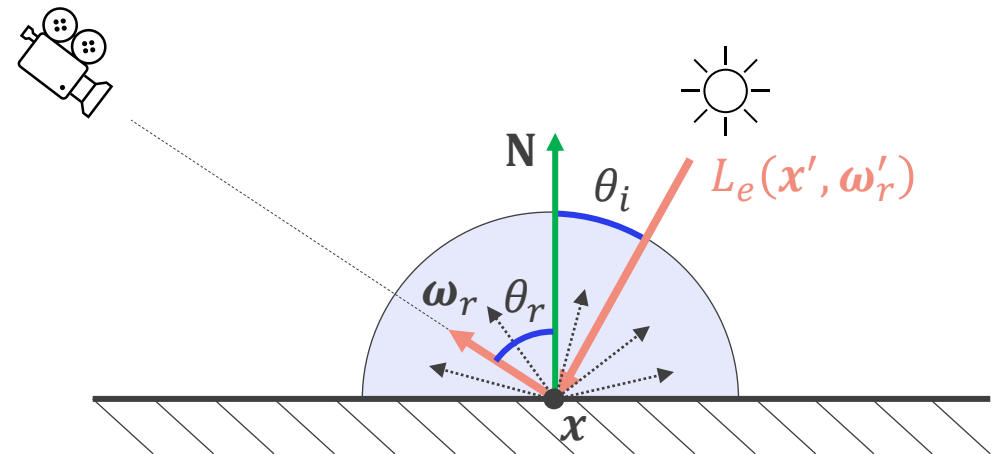
$$L_r(\mathbf{x}, \omega_r) = L_e(\mathbf{x}, \omega_r) + \frac{1}{n} \sum_{i=1}^n \frac{\rho}{\pi} L_e(\mathbf{x}', \omega'_r) \cos \theta_i \frac{1}{p(\omega_i)}$$

- Sum of energy reflected in all directions:

$$\int_{\Omega} f_r(\mathbf{x}, \omega_i, \omega_r) \cos \theta_r d\omega_r \leq 1$$

$$f_r(\mathbf{x}, \omega_i, \omega_r) \leq \frac{1}{\int_{\Omega} \cos \theta_r d\omega_r}$$

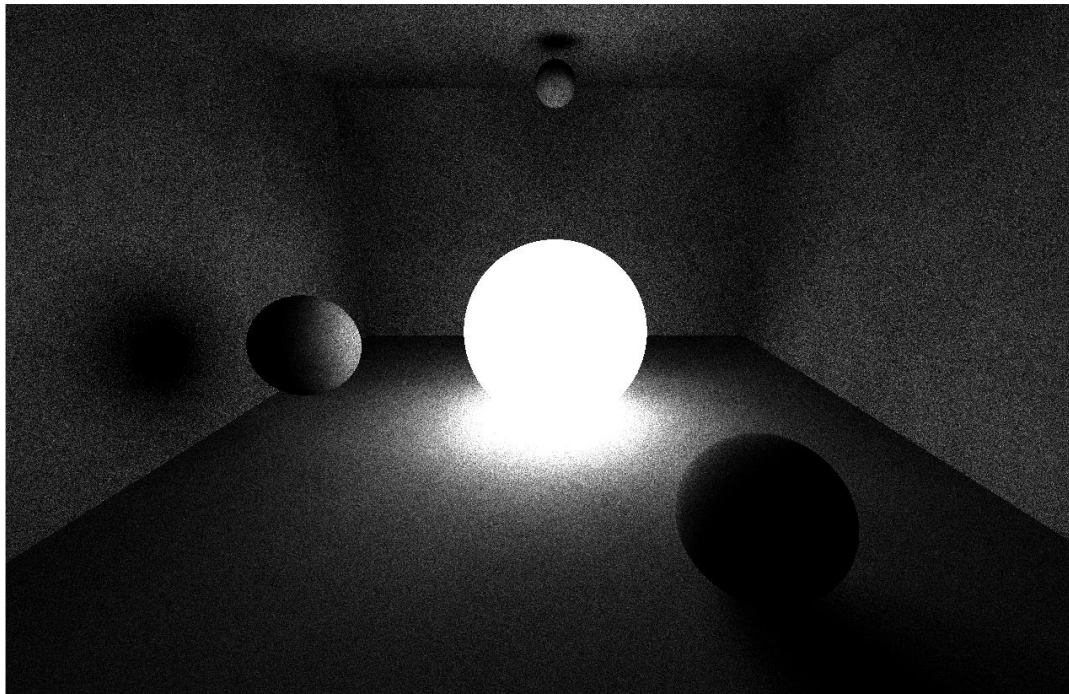
$$f_r(\mathbf{x}, \omega_i, \omega_r) \leq \frac{1}{\pi}$$



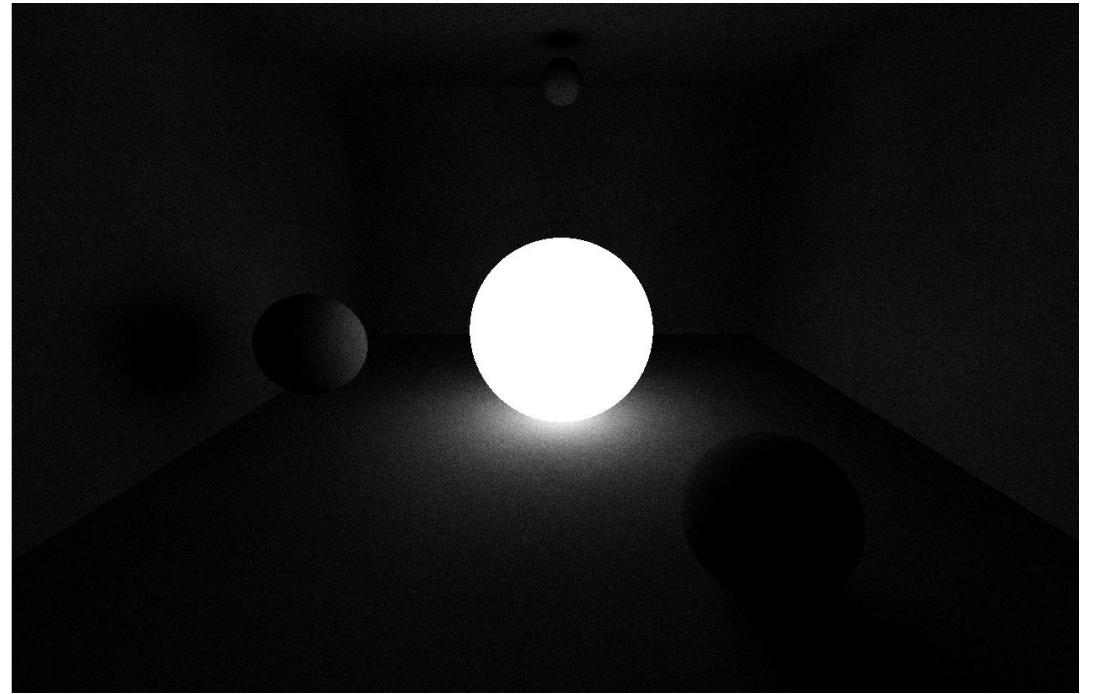
$\rho$  – albedo  $[0,1]$  – defines how much light is absorbed by the surface

# Lambertian BRDF Comparison

$$f_r = 1, n = 100, p(\omega_i) = \frac{\cos\theta}{\pi}$$

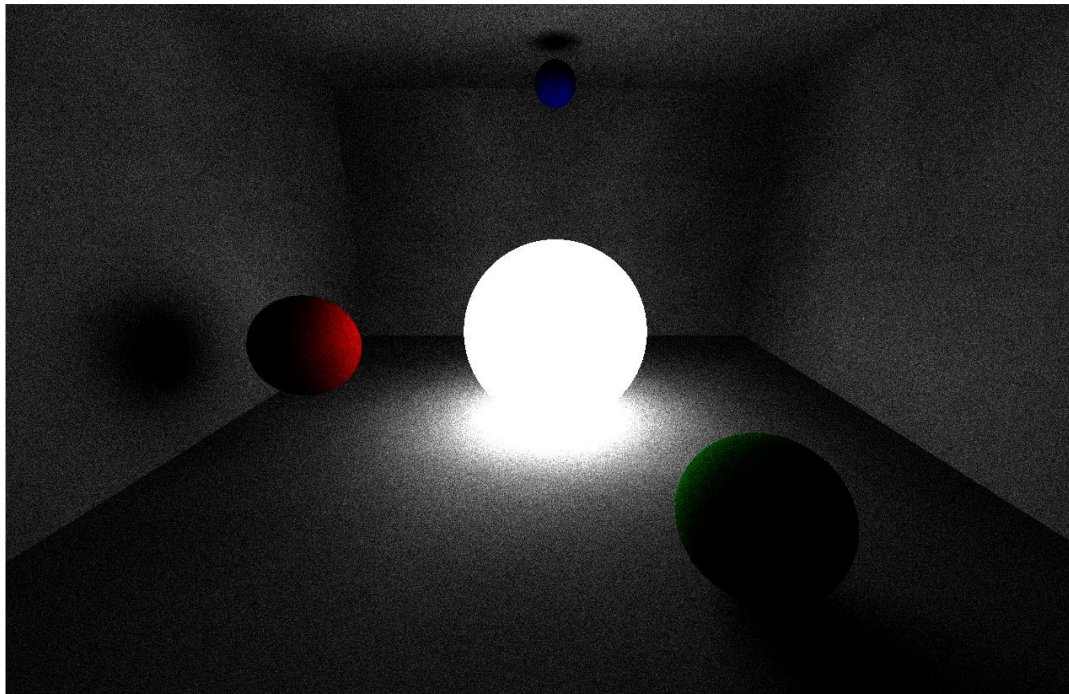


$$f_r = \frac{1}{\pi}, n = 100, p(\omega_i) = \frac{\cos\theta}{\pi}$$

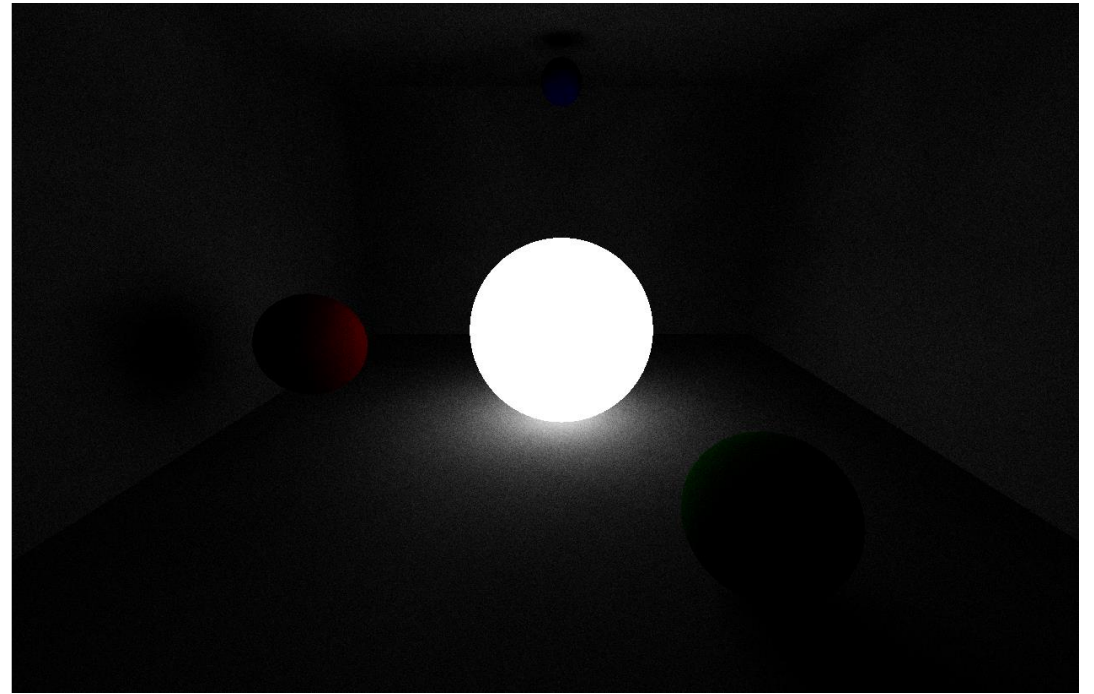


# Lambertian BRDF Comparison

$$f_r = \rho, n = 100, p(\omega_i) = \frac{\cos\theta}{\pi}$$

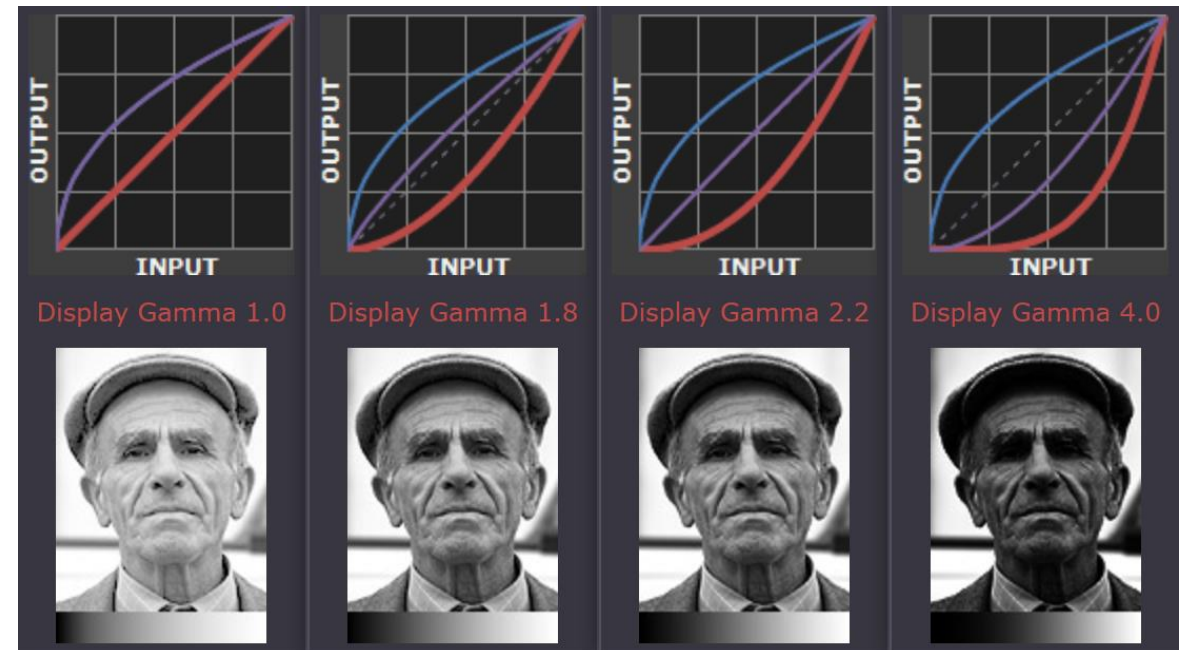


$$f_r = \frac{\rho}{\pi}, n = 100, p(\omega_i) = \frac{\cos\theta}{\pi}$$



# Gamma Correction

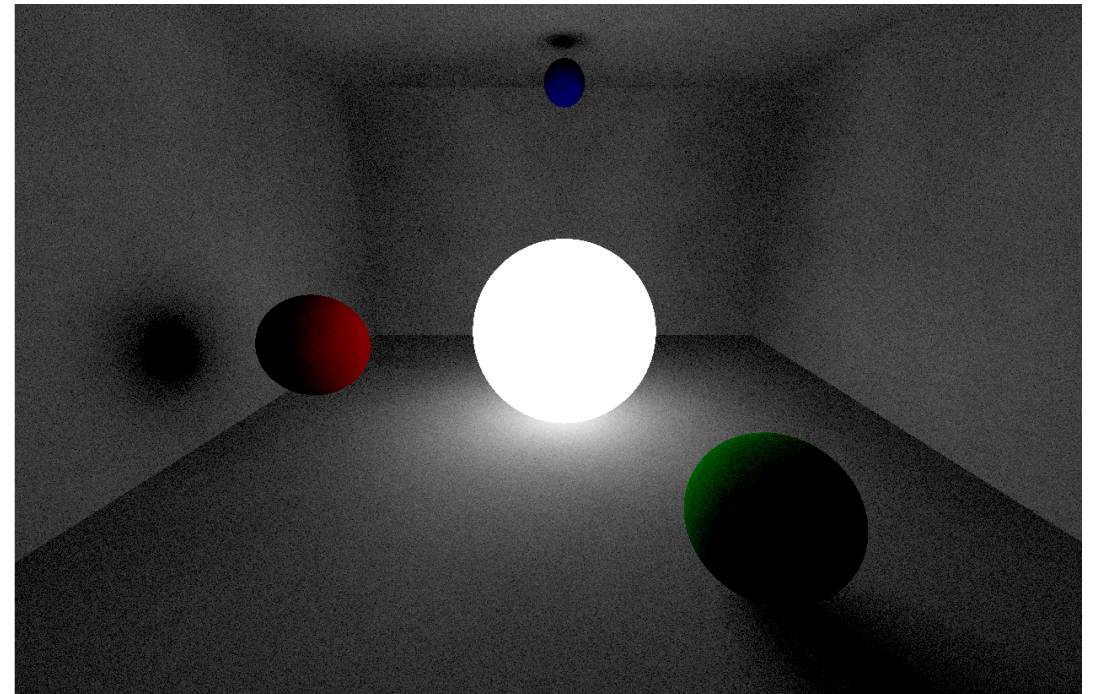
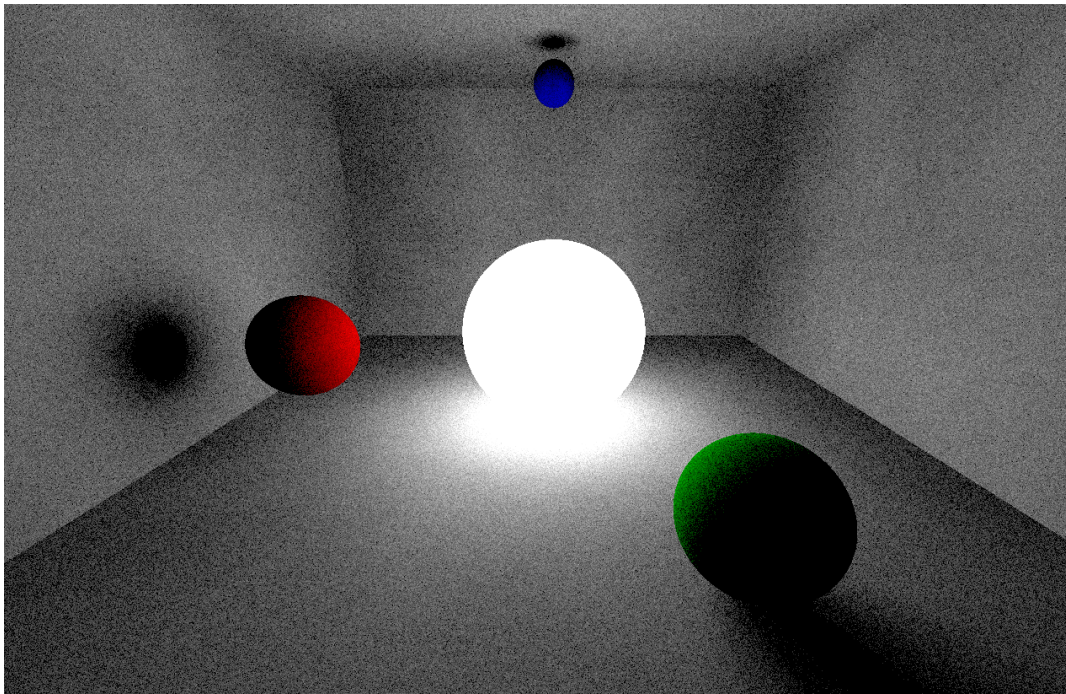
- Humans do not perceive luminance linearly
  - much more sensitive to changes in dark tones
- We can use gamma correction to fix that
  - Nonlinear operation used to encode and decode luminance
  - $output = input^\gamma$



# Lambertian BRDF Comparison (with Gamma Correction)

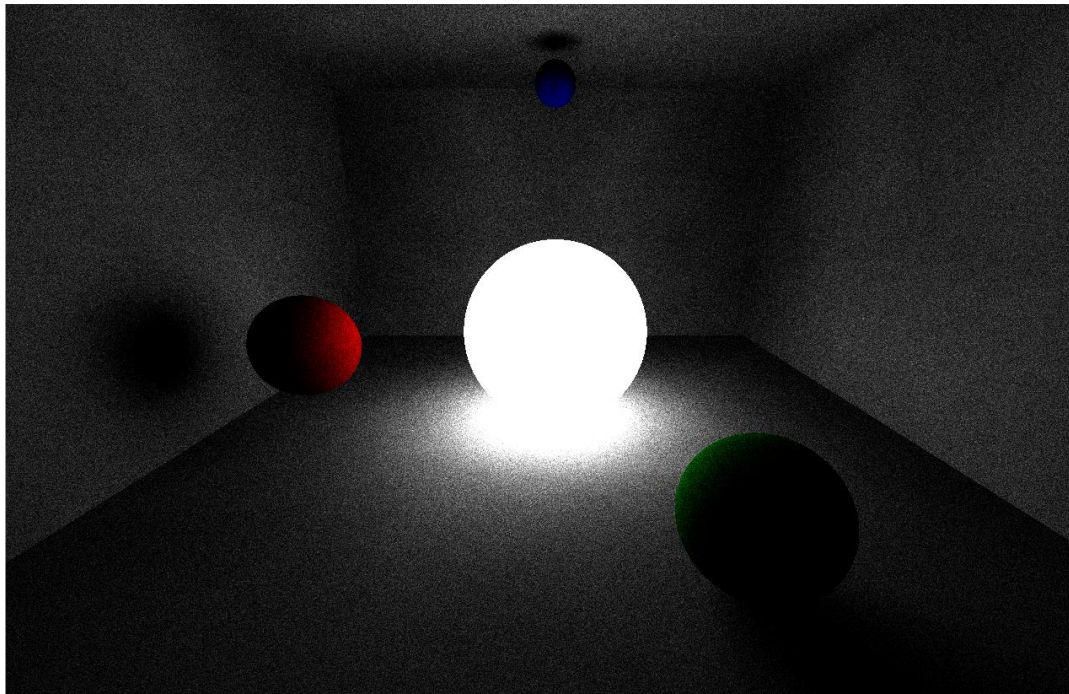
$$f_r = \rho, n = 100, p(\omega_i) = \frac{\cos\theta}{\pi}$$

$$f_r = \frac{\rho}{\pi}, n = 100, p(\omega_i) = \frac{\cos\theta}{\pi}$$

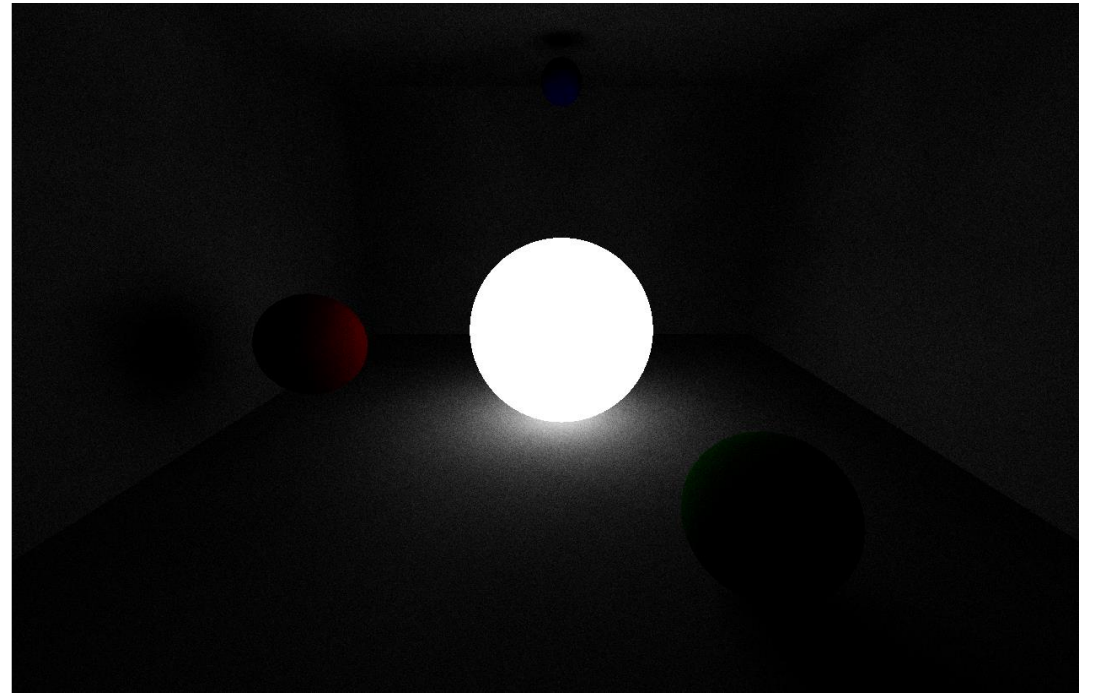


# Lambertian BRDF Comparison

$$f_r = \rho, n = 100, p(\omega_i) = \frac{\cos\theta}{\pi}$$



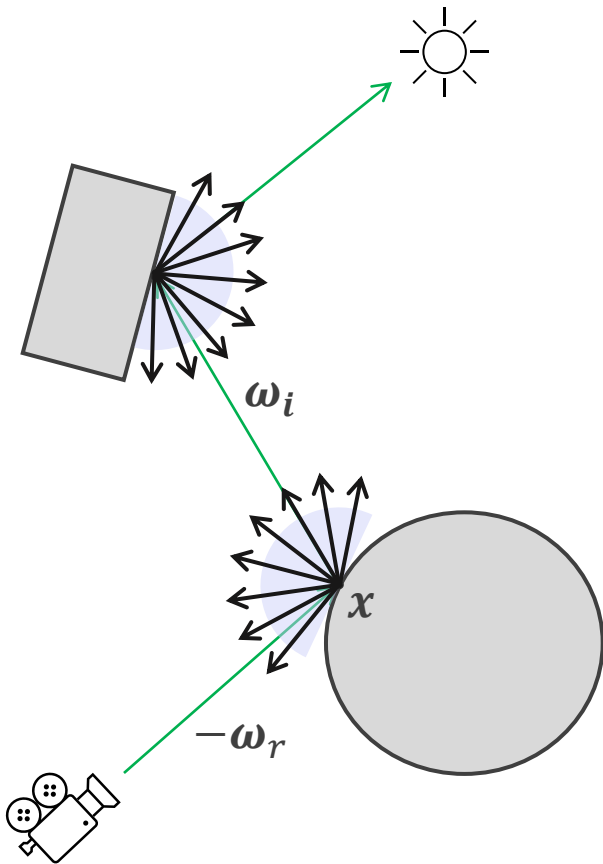
$$f_r = \frac{\rho}{\pi}, n = 100, p(\omega_i) = \frac{\cos\theta}{\pi}$$





# Evaluating Rendering Function

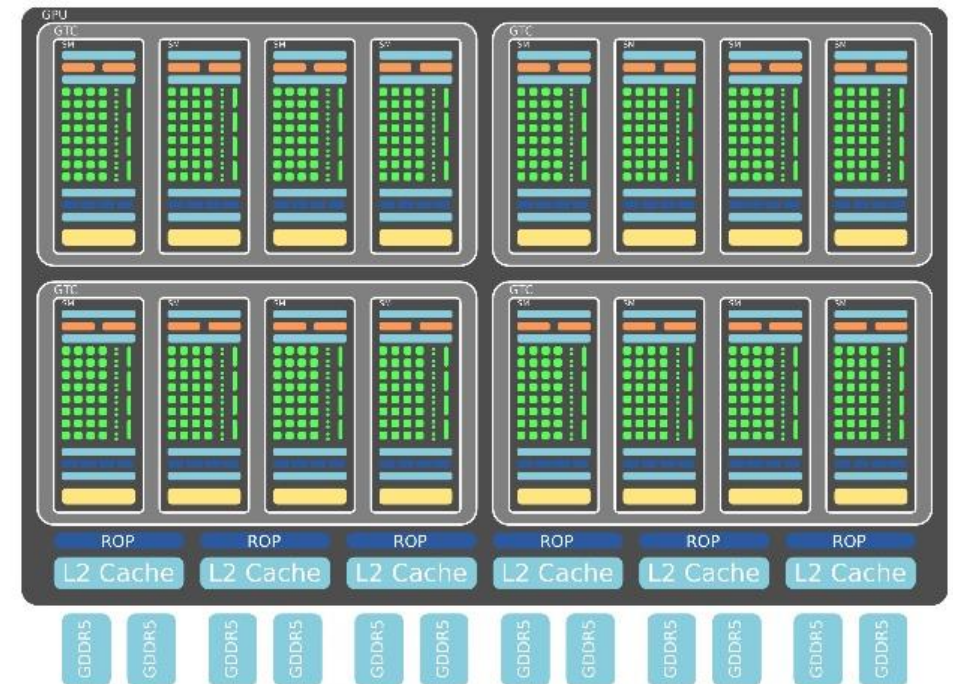
$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_i(\mathbf{x}, \boldsymbol{\omega}_i) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$



```
Trace(ray) {  
  radiance ← (0,0,0)  
  hit ← ClosestHit(ray)  
  if(hit == miss) return radiance  
  
  Le = hit.material.emission  
  
  for(i=0; i < samples; i++) {  
    sample ← GetNextSample(hit, ray)  
    next_ray ← Ray(hit.intersection + epsilon * hit.normal, sample.direction)  
    next_hit ← ClosestHit(next_ray);  
    if(next_hit == miss || sample.pdf == 0) continue //i.e., skip this sample  
  
    brdf ← ComputeBRDF(hit, next_ray.direction, -ray.direction)  
    emission ← next_hit.material.emission  
    radiance += brdf * Trace(next_ray) * dot(hit.normal, next_ray.direction) / sample.pdf  
  }  
  return Le + radiance / samples  
}
```

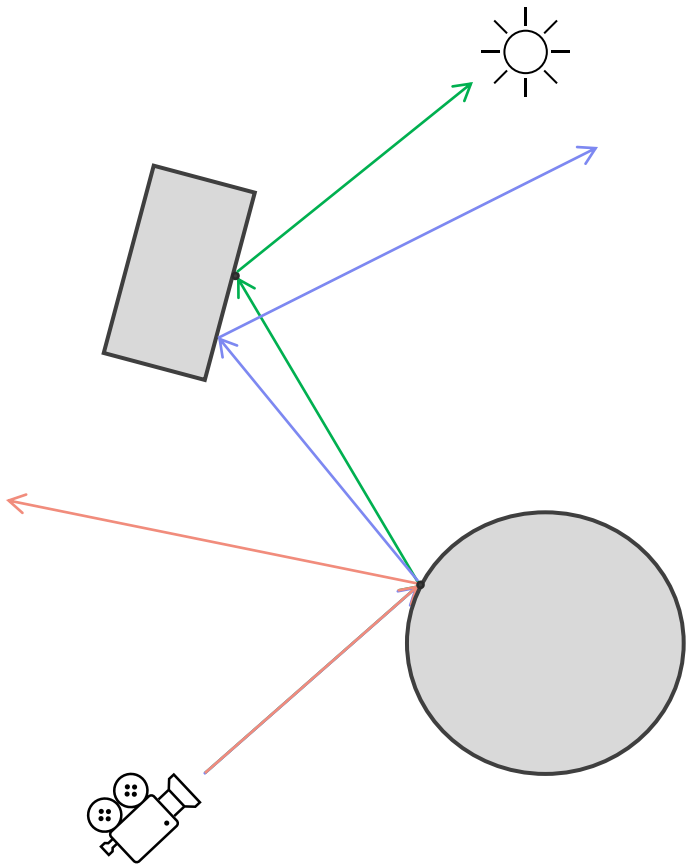
# Recursion on GPU

- Not a good idea as GPU is heavy SIMD architecture
  - Cache divergence
  - Flow divergence
- OpenGL/GLSL does not support/allow it
- Solution:
  - Rewrite using custom stack/queue
    - Pain but it works (no dynamic allocation)
  - Utilize properties of Monte Carlo integration
    - Random samples can be accumulated over time



# Path Tracing

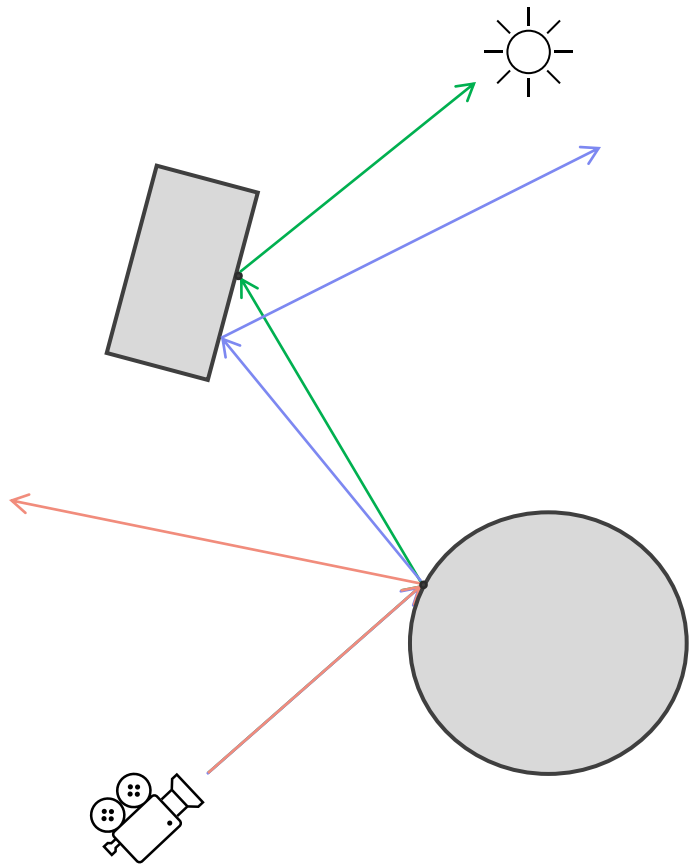
$$L_r(\mathbf{x}, \omega_r) = L_e(\mathbf{x}, \omega_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \omega_i, \omega_r) L_i(\mathbf{x}, \omega_i) \cos \theta_i \frac{1}{p(\omega_i)}$$



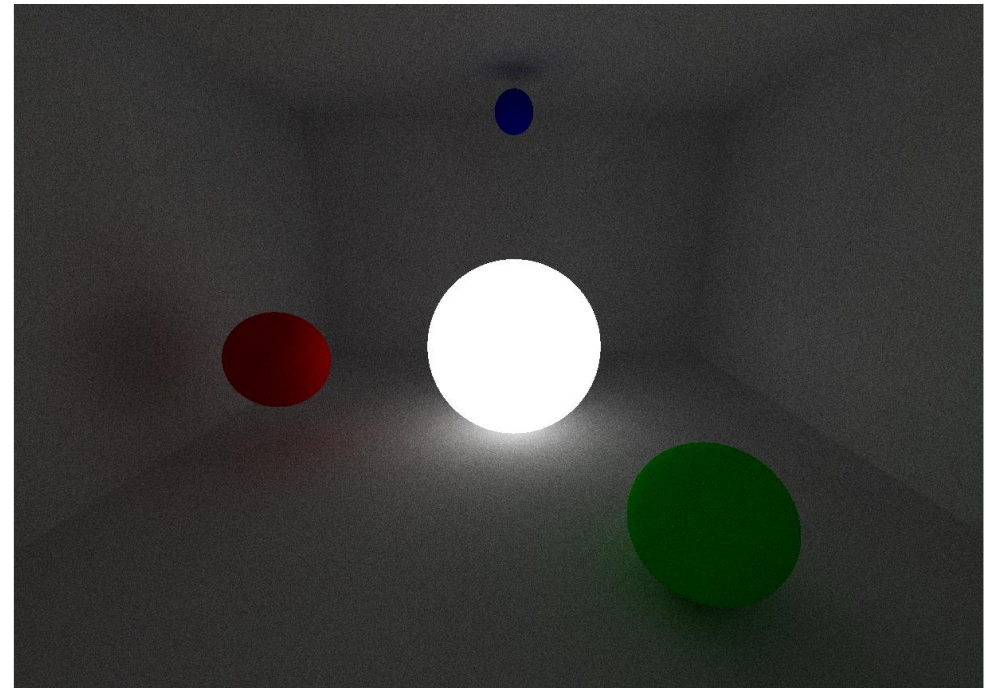
```
Trace(ray) {  
    radiance ← (0,0,0)  
    throughput ← (1,1,1)  
  
    for(i=0; i < bounces; i++) {  
        hit ← ClosestHit(ray)  
        if(hit == miss) return radiance  
        if(hit.emissive){  
            radiance += hit.material.emission * throughput  
            return radiance  
        }  
        sample ← GetNextSample(hit, ray)  
        brdf ← ComputeBRDF(hit, sample.direction, -ray.direction)  
  
        throughput *= brdf * dot(hit.normal, sample.direction) / sample.pdf  
  
        ray ← Ray(hit.intersection + epsilon * hit.normal, sample.direction)  
    }  
    return radiance  
}
```

# Path Tracing

$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_i(\mathbf{x}, \boldsymbol{\omega}_i) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$

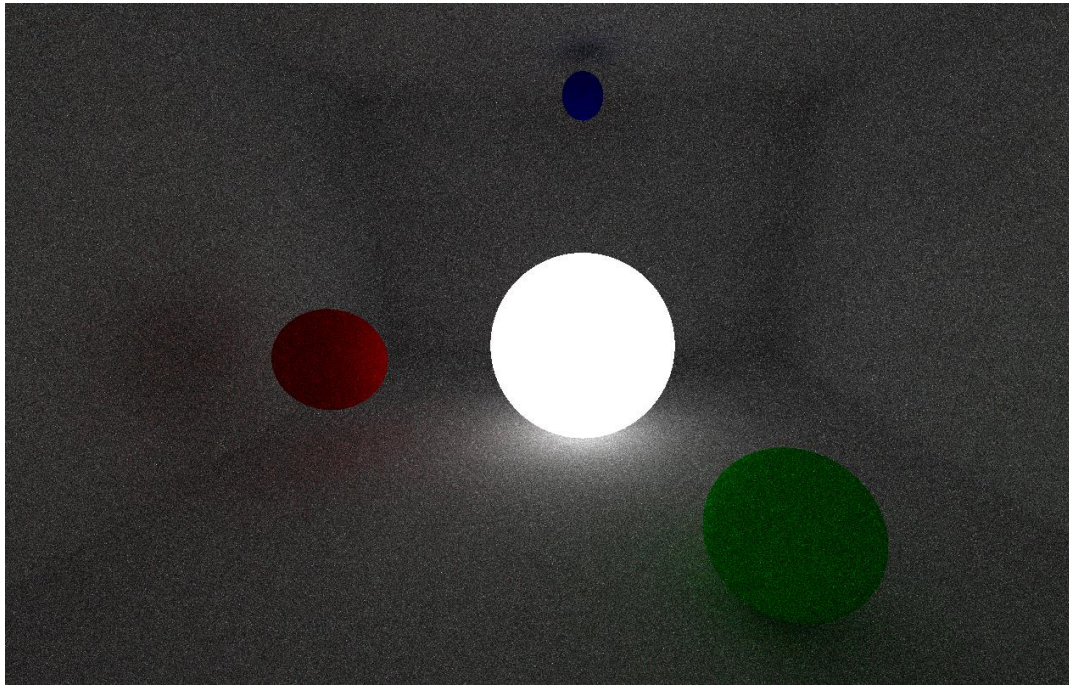


$$f_r = \frac{\rho}{\pi}, n = 100, p(\boldsymbol{\omega}_i) = \frac{\cos \theta}{\pi}, \text{bounces} = 10$$

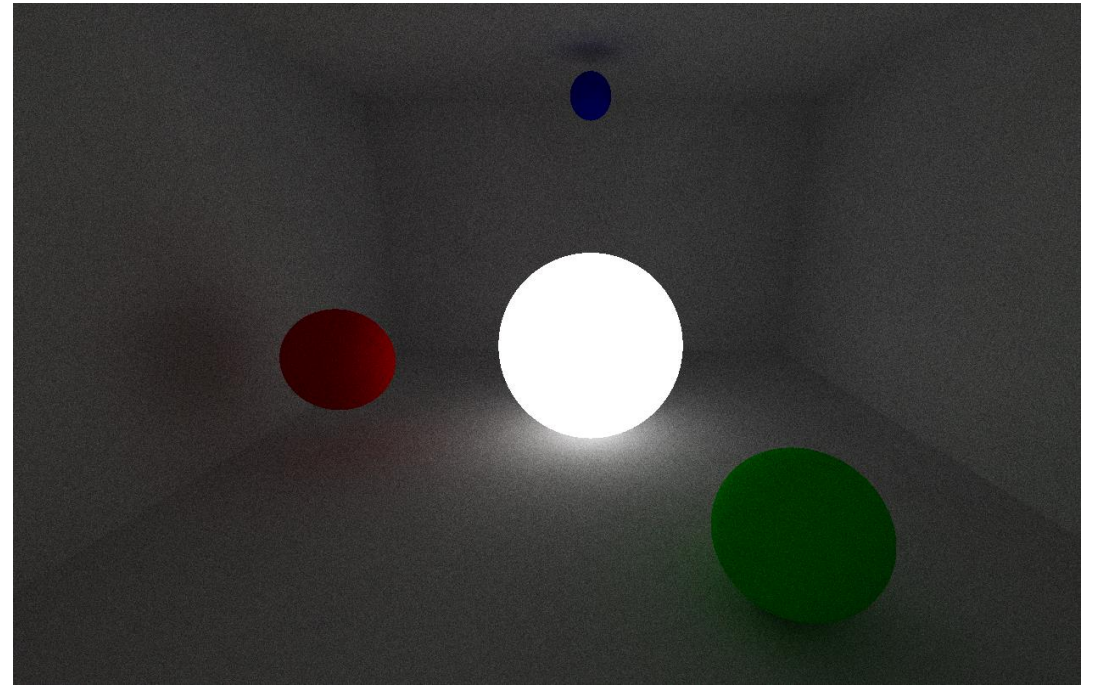


# Comparison

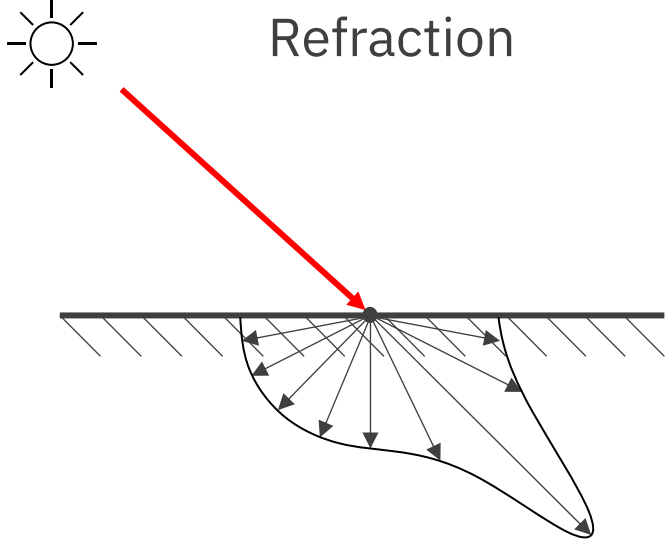
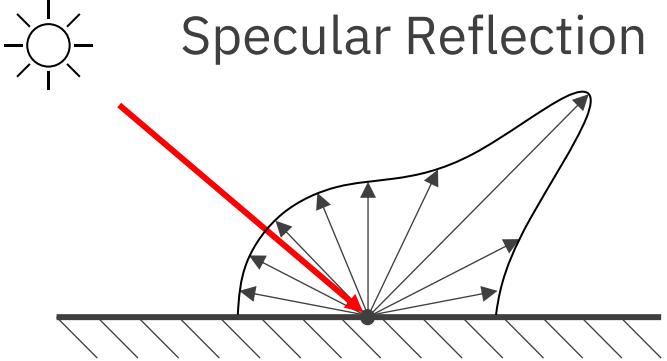
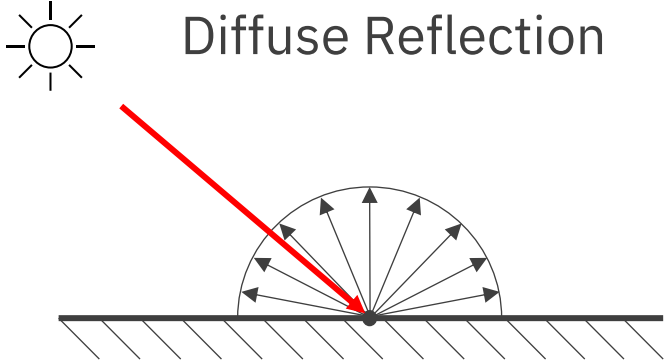
$$f_r = \frac{\rho}{\pi}, n = 100, p(\omega_i) = \frac{1}{2\pi}, \text{bounces} = 10$$



$$f_r = \frac{\rho}{\pi}, n = 100, p(\omega_i) = \frac{\cos\theta}{\pi}, \text{bounces} = 10$$



# Surface Lighting Effects



# Reflection & Refraction

- Described by Fresnel equations (S,P polarizations)

$$R_s = \left| \frac{(\eta_1 * \cos(\theta_i) - \eta_2 * \cos(\theta_t))}{(\eta_1 * \cos(\theta_i) + \eta_2 * \cos(\theta_t))} \right|^2$$

$$R_p = \left| \frac{(\eta_1 * \cos(\theta_t) - \eta_2 * \cos(\theta_i))}{(\eta_1 * \cos(\theta_t) + \eta_2 * \cos(\theta_i))} \right|^2$$

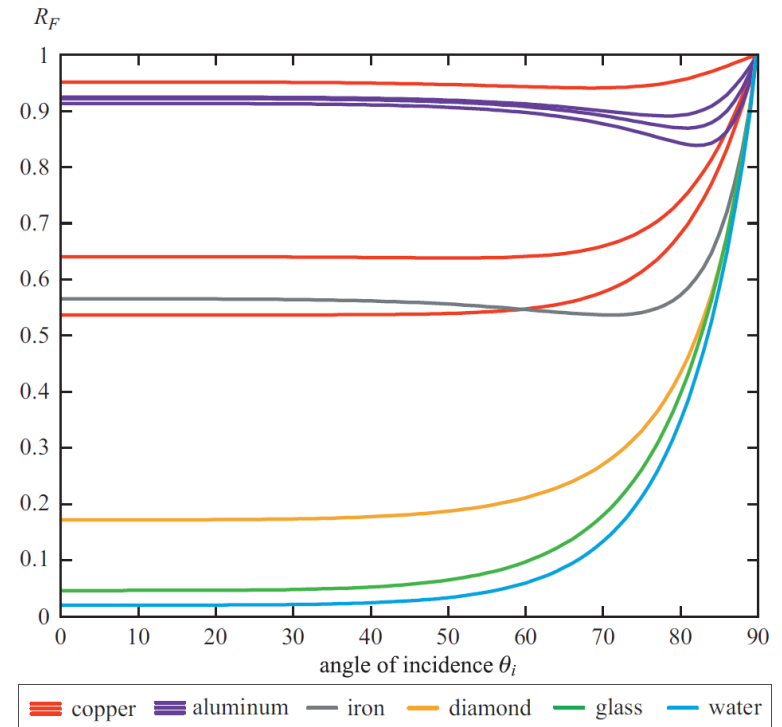
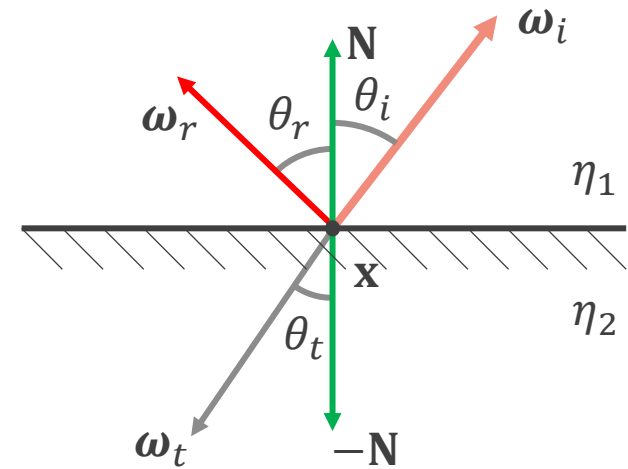
$$R_{eff} = \frac{1}{2} (R_s + R_p)$$

$\eta_1, \eta_2$  – Indices of refraction

- Schlick's approximation:

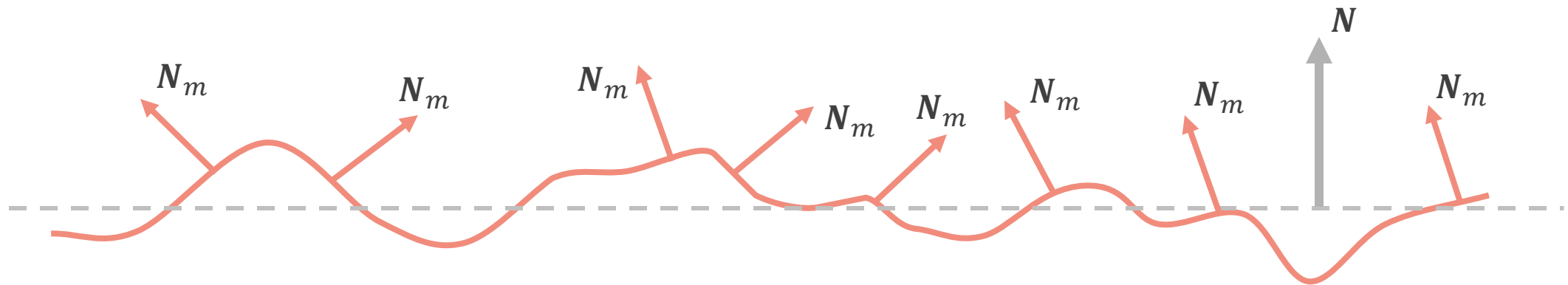
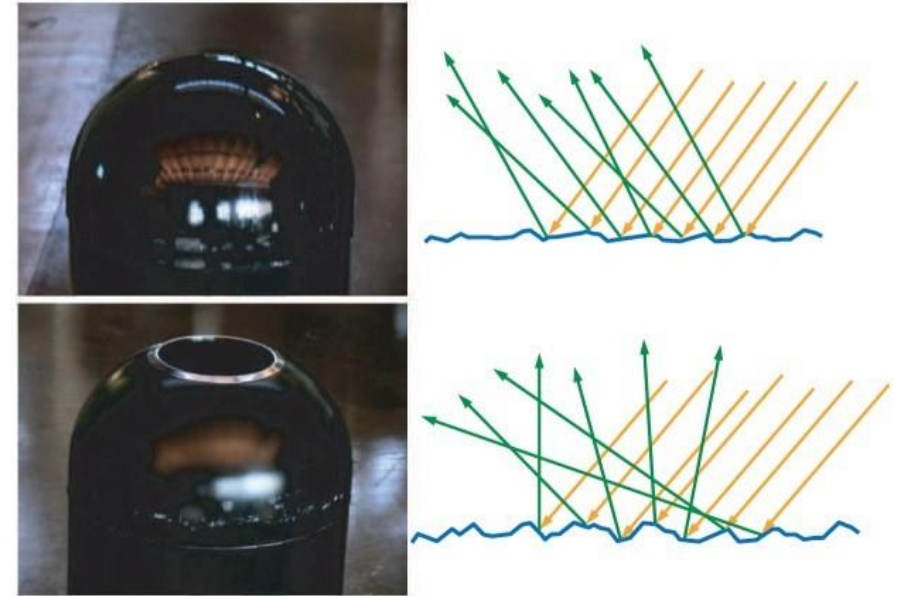
$$F_{Schlick}(R_0, \omega_i, N) = R_0 + (1 - R_0)(1 - \omega_i \cdot N)^5$$

in GLSL you may want to clamp this to [0,1]



# Microfacet Model

- Macrosurface (actual geometry)
- Microsurface (used for illumination)
  - Mirrors smaller than 'pixel'
  - Not for displacement in geometry
  - Not for normal mapping
- Multiple models exist



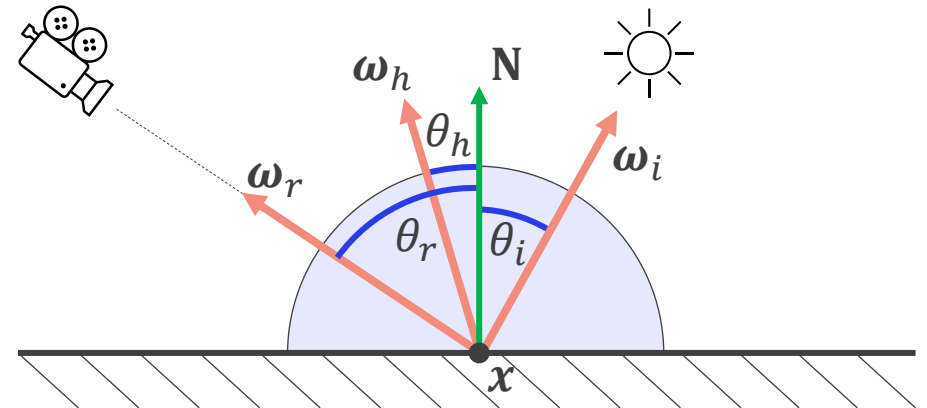


# Microfacet Model BRDF

Torrance–Sparrow Model

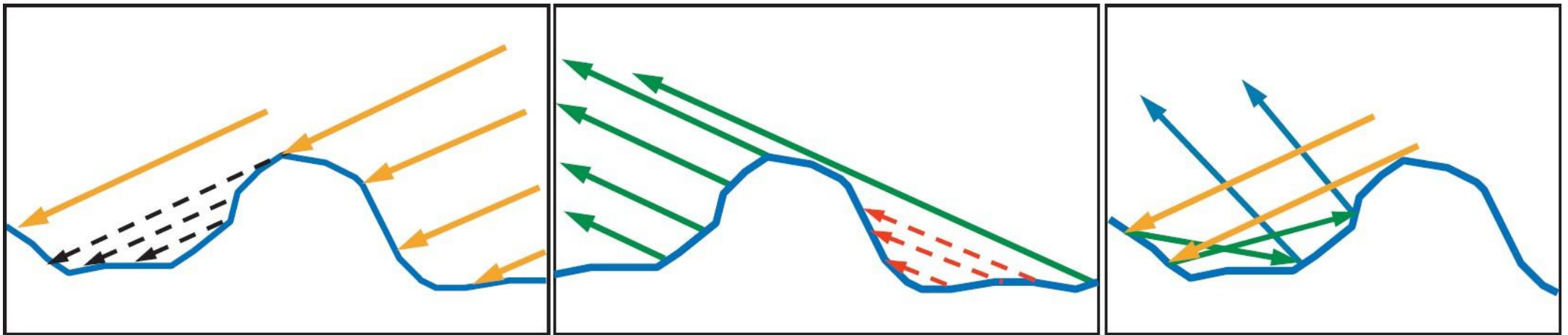
$$f_r(\mathbf{x}, \omega_i, \omega_r) = \frac{F(\omega_i, \omega_h) G(\omega_i, \omega_r) D(\omega_h)}{4 \cos \theta_i \cos \theta_r}$$

Fresnel  $\omega_h = \frac{\omega_r + \omega_i}{|\omega_r + \omega_i|}$  Geometric Attenuation Normal Distribution Function  
 Normalization



# Geometric Attenuation

- Shadowing: Facets occlude the light for other facets
- Masking: Facets cannot be seen due to other facets
- Interreflection: Facets reflect the light to other facets, and then the light is reflected to the viewer



# Geometric Attenuation

- Multiple models for geometric attenuation exist ( $\alpha$  stands for roughness)

- E.g., Smith GGX

- $$G(\omega_i, \omega_r) = \frac{2 \cos \theta_i \cos \theta_r}{\left(\cos \theta_r \sqrt{\alpha^2 + (1 - \alpha^2) \cos^2 \theta_i}\right) + \left(\cos \theta_i \sqrt{\alpha^2 + (1 - \alpha^2) \cos^2 \theta_r}\right)}$$

# Normal Distribution Function

- Multiple NDFs exist  $\alpha$  stands for roughness of the material

- Smith GGX

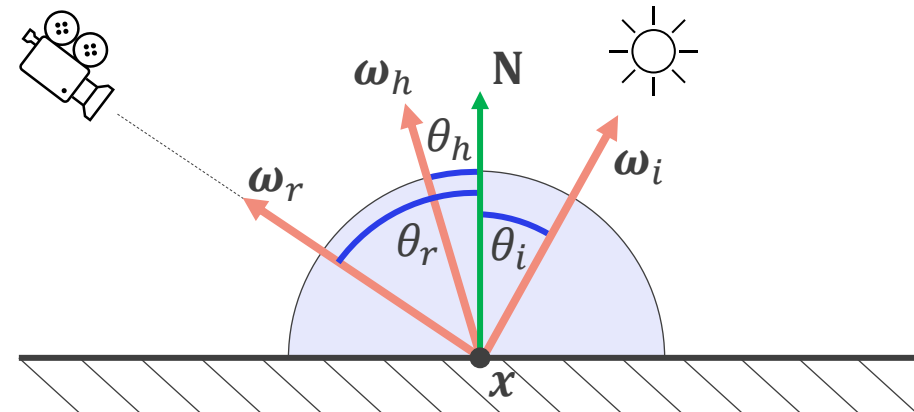
$$D(\omega_h) = \frac{\alpha^2}{\pi((\alpha^2 - 1) \cos^2 \theta_h + 1)^2}$$

- Beckmann

$$D(\omega_h) = \frac{\sin \theta_h}{\pi \alpha^2 \cos^3 \theta_h} e^{-\frac{\tan^2 \theta_h}{\alpha^2}}$$

- Blinn

$$D(\omega_h) = \frac{\alpha + 2}{2\pi} \cos^{\alpha + 1} \theta_h \sin \theta_h$$



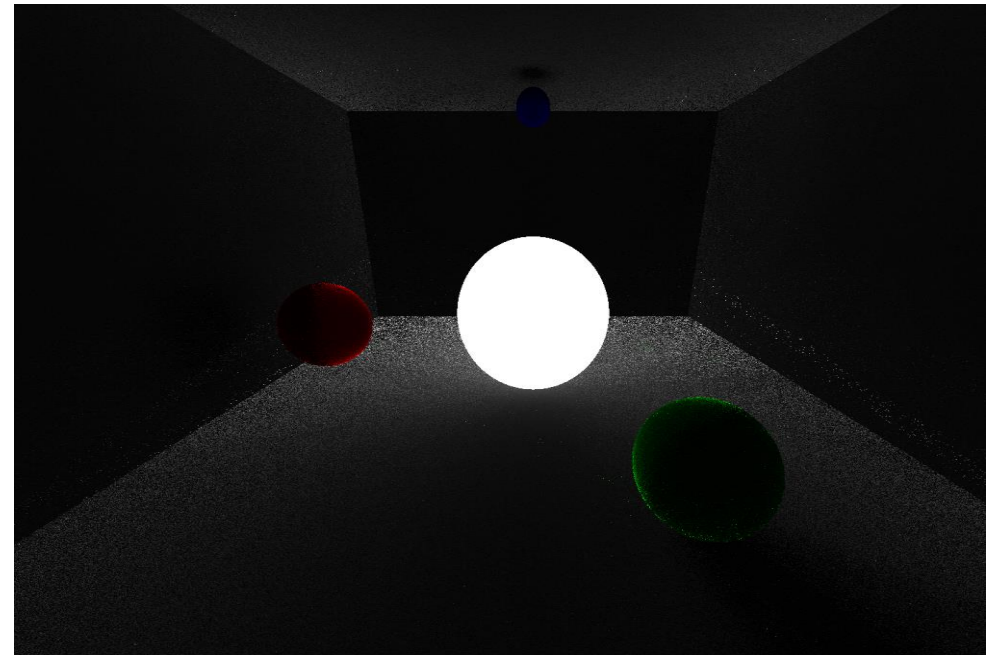
# Microfacet Model BRDF

$$L_r(\mathbf{x}, \omega_r) = L_e(\mathbf{x}, \omega_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \omega_i, \omega_r) L_i(\mathbf{x}, \omega_i) \cos \theta_i \frac{1}{p(\omega_i)}$$

$$f_r(\mathbf{x}, \omega_i, \omega_r) = \frac{F(\omega_i, \omega_h) G(\omega_i, \omega_r) D(\omega_h)}{4 \cos \theta_i \cos \theta_r}$$

$$p(\omega_i) = \frac{\cos \theta_i}{\pi}$$

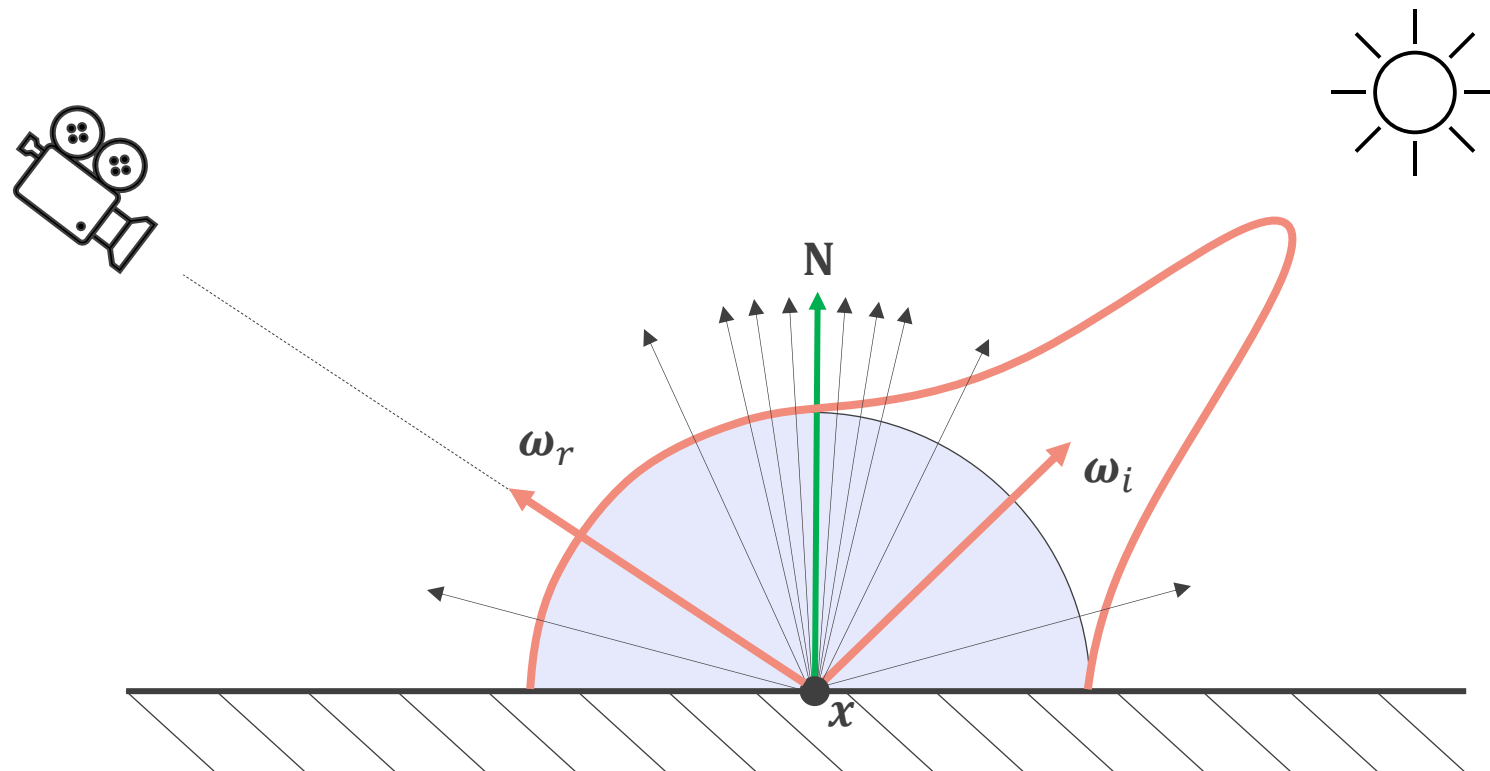
$n = 100, \text{roughness} = 0.2, \text{gama} = 0N$



# Sampling BRDF

$$f_r(\mathbf{x}, \omega_i, \omega_r) = \frac{F(\omega_i, \omega_h)G(\omega_i, \omega_r)D(\omega_h)}{4 \cos \theta_i \cos \theta_r}$$

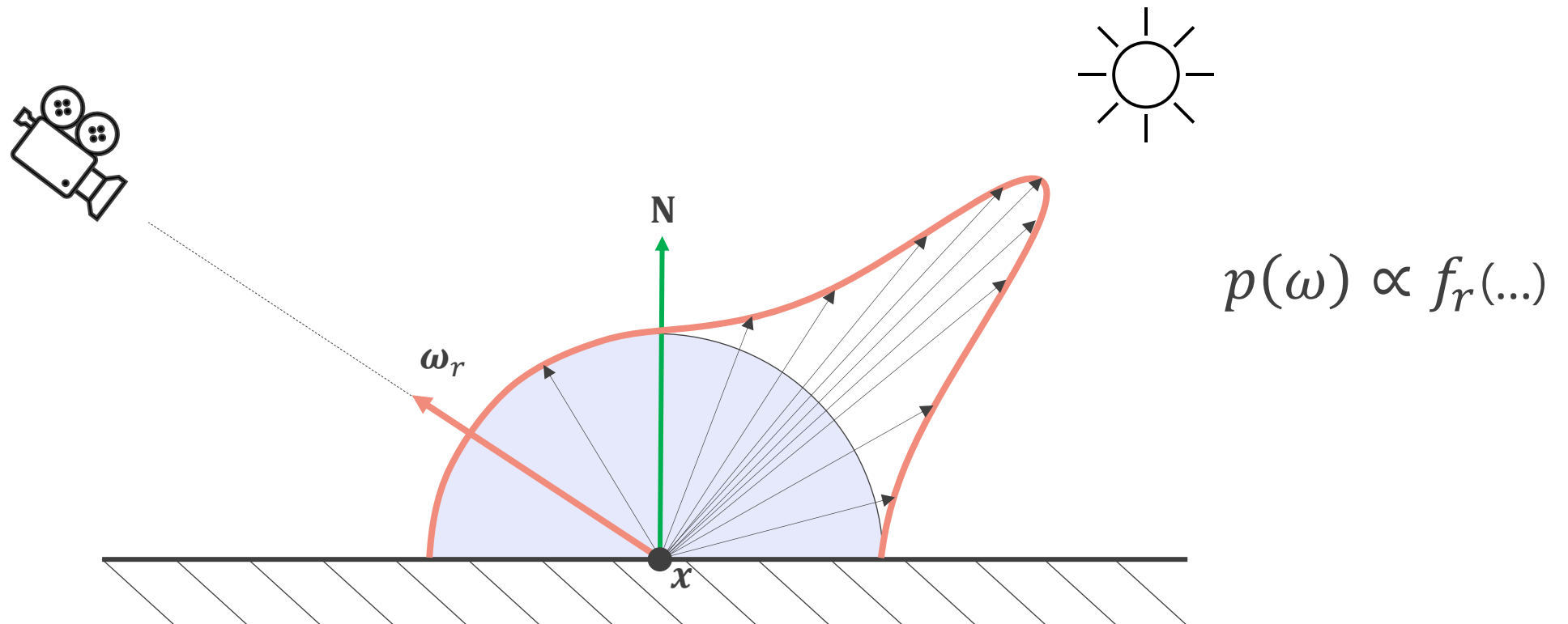
$$L_r(\mathbf{x}, \omega_r) = L_e(\mathbf{x}, \omega_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \omega_i, \omega_r) L_i(\mathbf{x}, \omega_i) \cos \theta_i \frac{1}{p(\omega_i)}$$



# Sampling BRDF

$$f_r(\mathbf{x}, \omega_i, \omega_r) = \frac{F(\omega_i, \omega_h)G(\omega_i, \omega_r)D(\omega_h)}{4 \cos \theta_i \cos \theta_r}$$

$$L_r(\mathbf{x}, \omega_r) = L_e(\mathbf{x}, \omega_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \omega_i, \omega_r) L_i(\mathbf{x}, \omega_i) \cos \theta_i \frac{1}{p(\omega_i)}$$

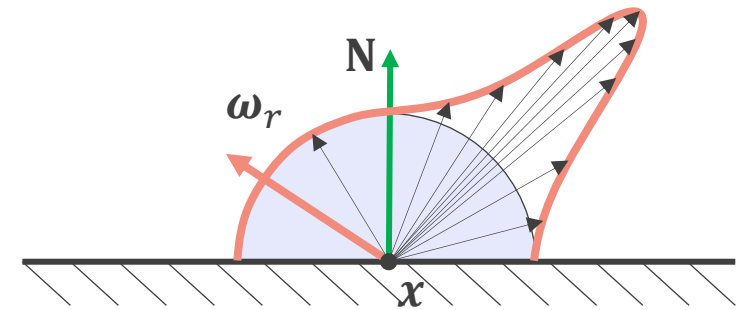


# Sampling Microfacet BRDF

- The  $D(\omega_h)$  has the largest influence on the result

$$f_r(\mathbf{x}, \omega_i, \omega_r) = \frac{F(\omega_i, \omega_h)G(\omega_i, \omega_r)D(\omega_h)}{4 \cos \theta_i \cos \theta_r}$$

- We can use the inversion method to compute sampling according to  $D(\omega_h)$ 
  1. Express  $p(\omega) \propto D(\omega_h)$
  2. Convert  $p(\omega)$  to  $p(\theta, \varphi)$  and separate to  $p(\theta) p(\varphi)$
  3. Compute  $P(\theta)$  and  $P(\varphi)$  by integrating  $p(\theta)$  and  $p(\varphi)$ , respectively
  4. Compute  $P^{-1}(\theta)$  and  $P^{-1}(\varphi)$
  5. Use canonical uniform distribution to sample hemisphere
  6. Convert back to Cartesian coordinates





# Example GGX

[https://agraphicsguynotes.com/posts/sample\\_microfacet\\_brdf](https://agraphicsguynotes.com/posts/sample_microfacet_brdf)

$$D(\omega_h) = \frac{\alpha^2}{\pi((\alpha^2 - 1) \cos^2 \theta_h + 1)^2}$$

PDF respecting solid angle

$$p(\omega_h) = \frac{\alpha^2 \cos \theta_h}{\pi((\alpha^2 - 1) \cos^2 \theta_h + 1)^2}$$



$$p(\theta_h, \varphi_h) = \frac{\alpha^2 \cos \theta_h \sin \theta_h}{\pi((\alpha^2 - 1) \cos^2 \theta_h + 1)^2}$$

$$\theta_h = \arccos \sqrt{\frac{1 - \xi_1}{\xi_1(\alpha^2 - 1) + 1}}$$

$$\varphi_h = 2\pi\xi_2$$



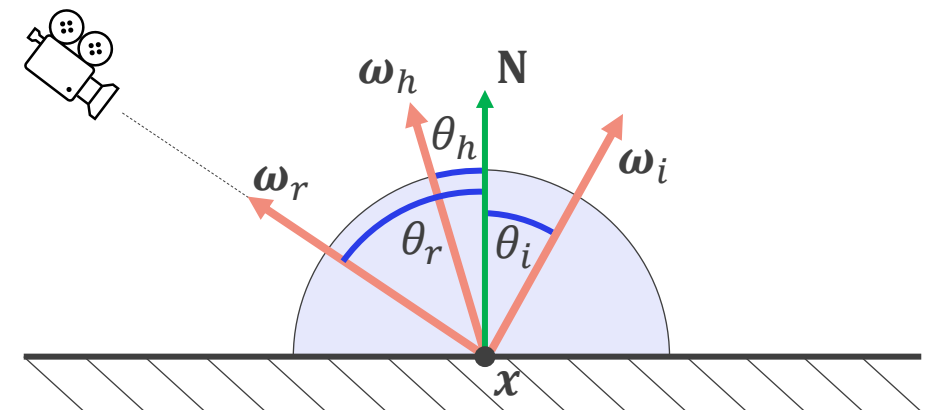
$$\begin{aligned} x_h &= r \sin \theta_h \cos \varphi_h \\ y_h &= r \sin \theta_h \sin \varphi_h \\ z_h &= r \cos \theta_h \end{aligned}$$

do not forget to convert the sample to world coordinates

# Example GGX

[https://agraphicsguynotes.com/posts/sample\\_microfacet\\_brdf](https://agraphicsguynotes.com/posts/sample_microfacet_brdf)

- To compute  $\omega_i$  we need to reflect  $-\omega_r$  along  $\omega_h$
- Assuming  $\omega_r' = -\omega_r$ 
  - $\omega_i = \omega_r' - 2\omega_h(\omega_r' \cdot \omega_h)$  ← in GLSL you may want to use **reflect** ( $\omega_r', \omega_h$ )
- We need to express the probability with respect to  $\omega_i$ 
  - $p(\omega_i) = \frac{D(\omega_h) \cos \theta_h}{4(\omega_r \cdot \omega_h)}$



# Microfacet Model BRDF

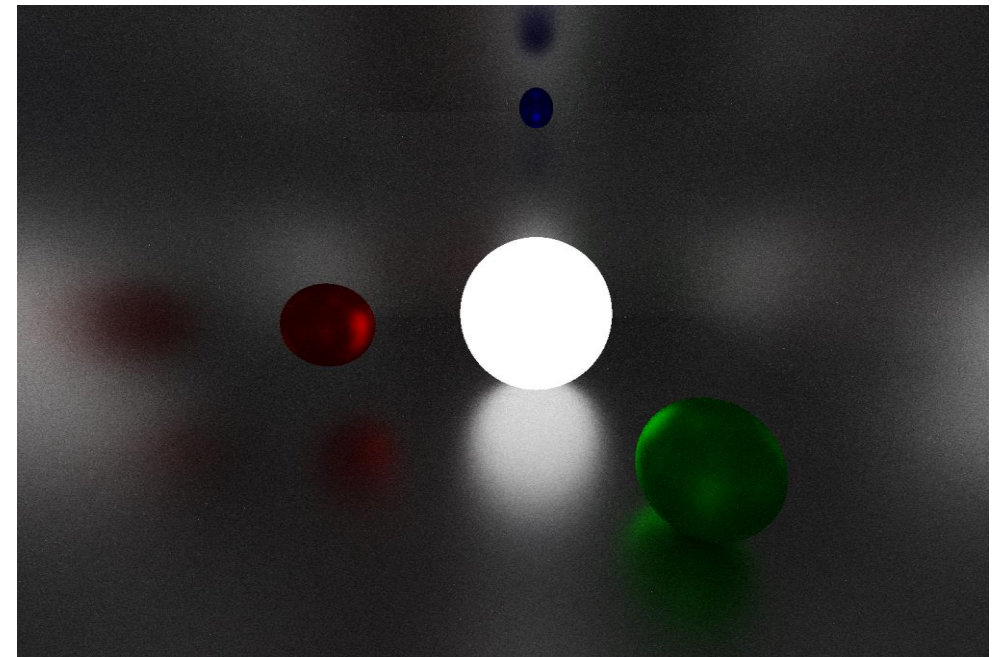
[https://agraphicsguynotes.com/posts/sample\\_microfacet\\_brdf](https://agraphicsguynotes.com/posts/sample_microfacet_brdf)

$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_i(\mathbf{x}, \boldsymbol{\omega}_i) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$

$$f_r = \frac{F(\boldsymbol{\omega}_i, \boldsymbol{\omega}_h) G(\boldsymbol{\omega}_i, \boldsymbol{\omega}_r) D(\boldsymbol{\omega}_h)}{4 \cos \theta_i \cos \theta_r}$$

$$p(\boldsymbol{\omega}_i) = \frac{D(\boldsymbol{\omega}_h) \cos \theta_h}{4(\boldsymbol{\omega}_r \cdot \boldsymbol{\omega}_h)}$$

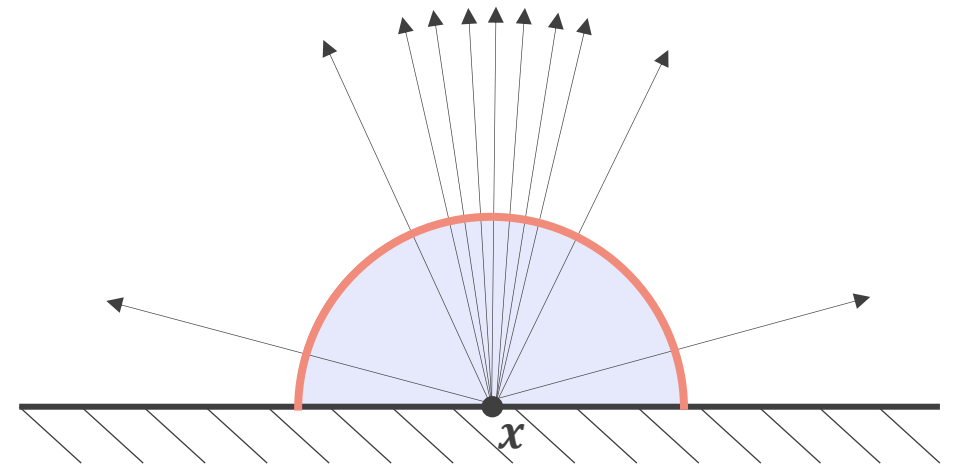
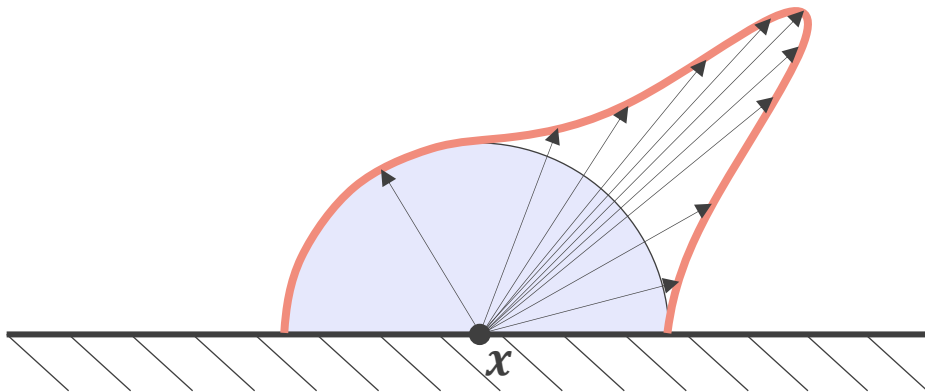
$n = 100, \text{roughness} = 0.2, \text{gama} = \text{OFF}$



# Combining BRDFs

$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_i(\mathbf{x}, \boldsymbol{\omega}_i) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$

- Sampling BRDF converges faster for specular surfaces
- Sampling according to  $\cos \theta_i$  converges faster for diffuse surfaces

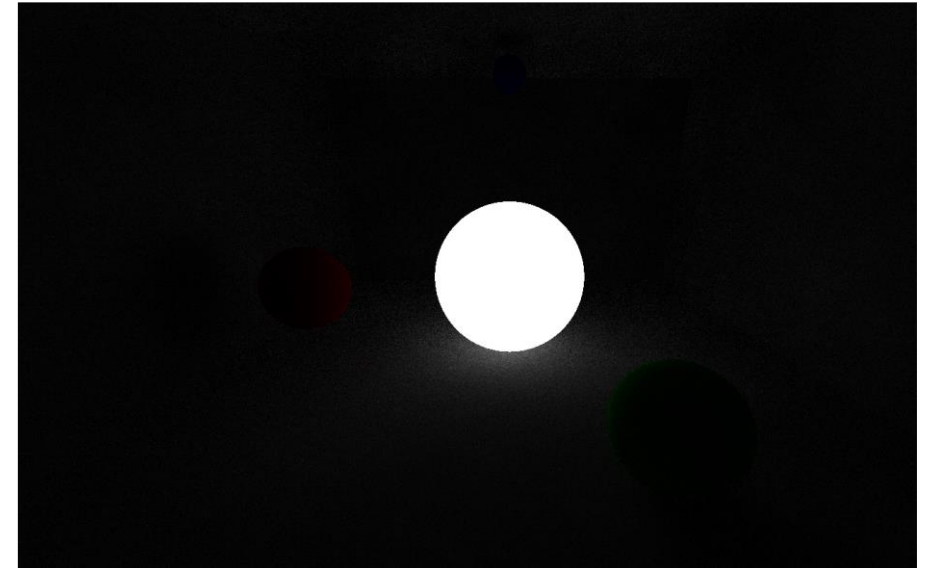
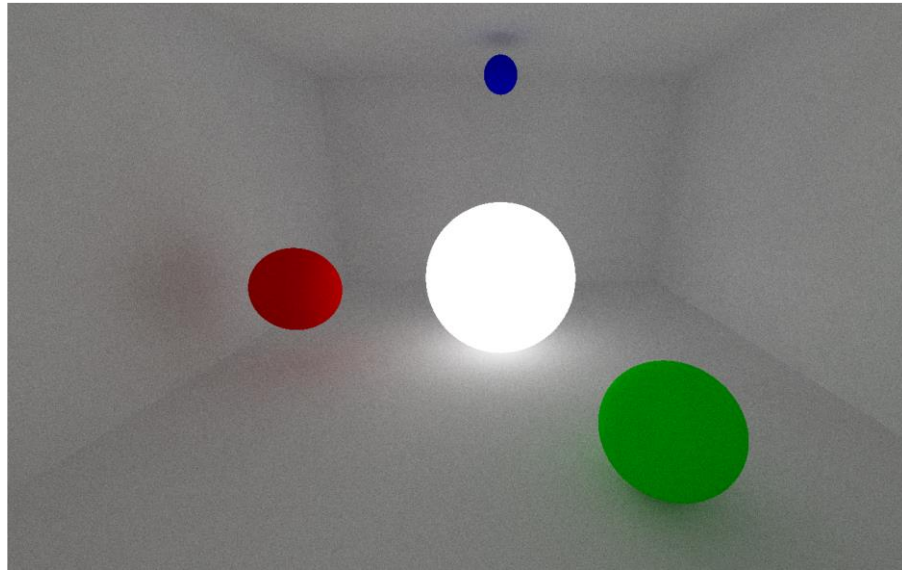


# Comparison

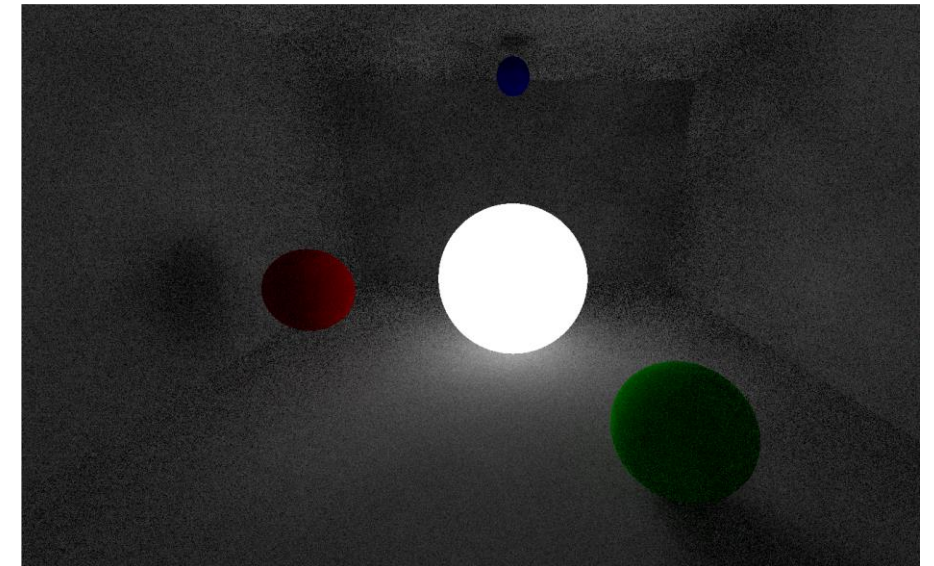
$n = 100, b = 10, \text{roughness} = 1.0, \text{gama} = OFF$

$$f_r = \frac{F(\omega_i, \omega_h)G(\omega_i, \omega_r)D(\omega_h)}{4 \cos \theta_i \cos \theta_r}$$

$$p(\omega_i) = \frac{D(\omega_h) \cos \theta_h}{4(\omega_r \cdot \omega_h)}$$



$n = 100, b = 10, \text{roughness} = 1.0, \text{gama} = OFF$

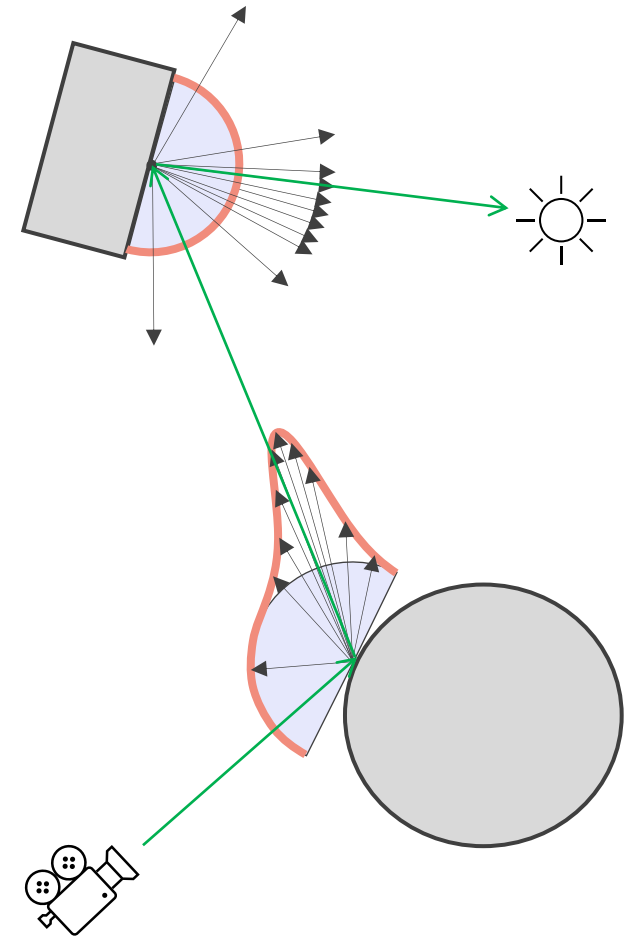
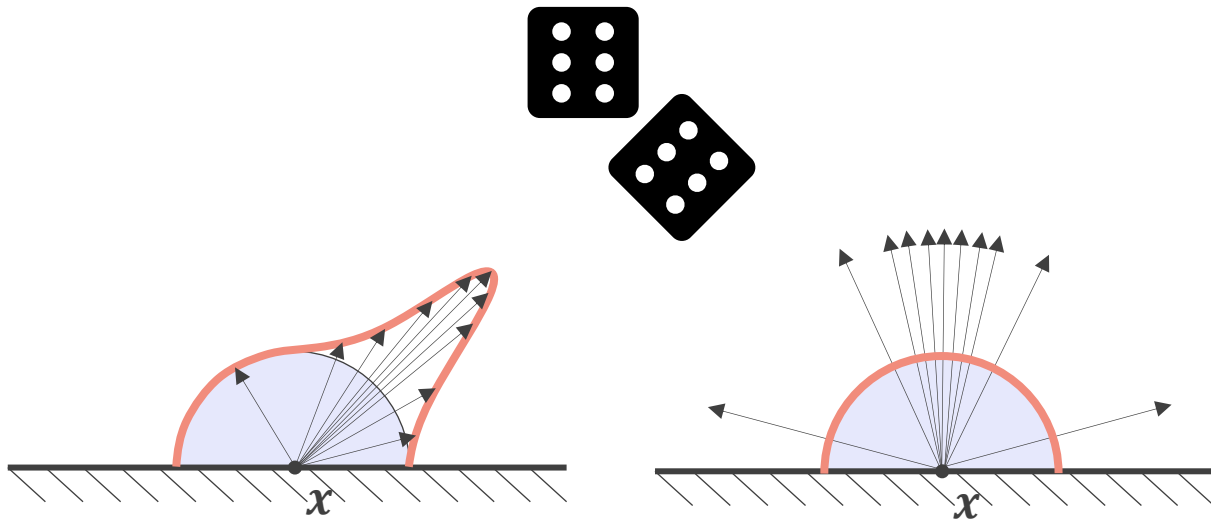


$$f_r = \frac{\rho}{\pi}, p(\omega_i) = \frac{\cos \theta}{\pi}, n = 100, b = 10, \text{gama} = ON$$

# Combining BRDFs

- Mixing two unbiased estimators produces unbiased estimator

$$E \left[ \sum_i X_i \right] = \sum_i E[X_i]$$



# Combining BRDFs

- Mixing two unbiased estimators produces unbiased estimator

$$E \left[ \sum_i X_i \right] = \sum_i E[X_i]$$

## Algorithm

Draw random number  $\xi$  from uniform distribution

If *roughness* >  $\xi$

    Compute diffuse *sample* and corresponding  $PDF_d$

    Set specular  $PDF_s = 1$

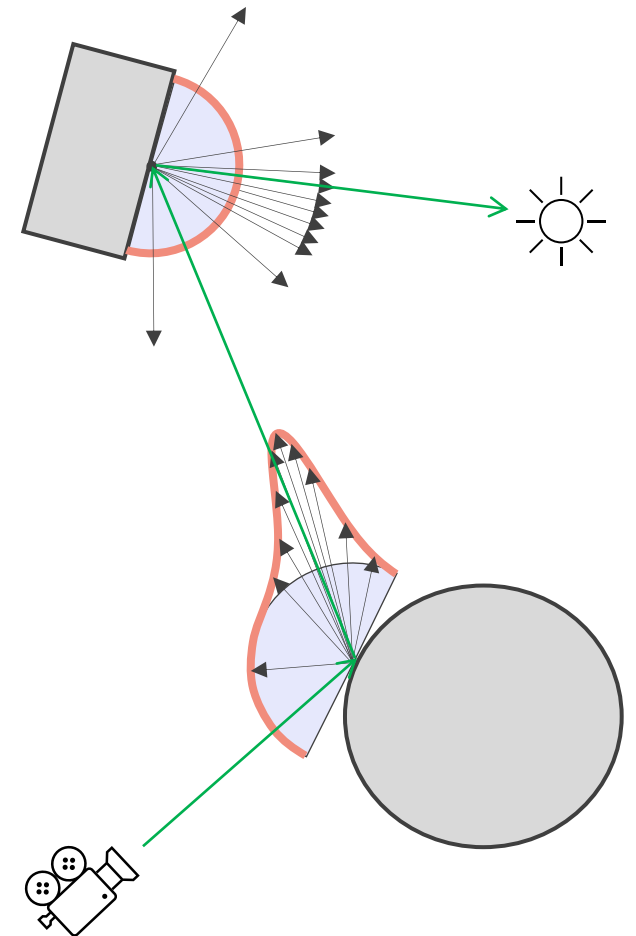
Else

    Compute specular (e.g, GGX) *sample* and corresponding  $PDF_s$

    Set diffuse  $PDF_d = 1$

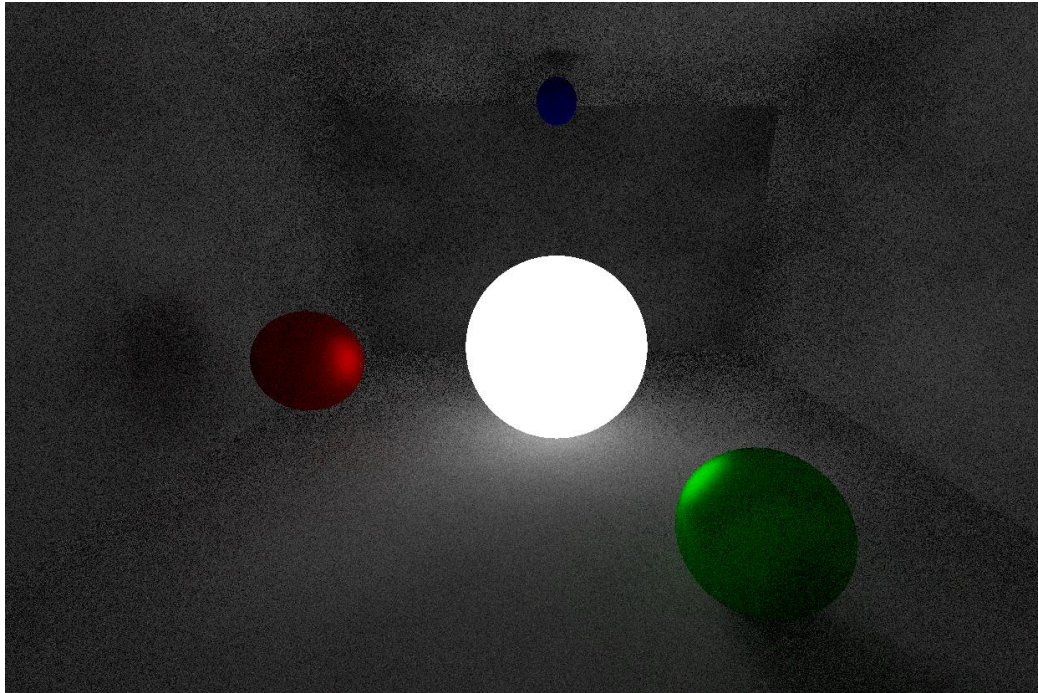
Mix the PDFs based on *roughness*

$$p(\omega) = (\textit{roughness})PDF_d + (1 - \textit{roughness})PDF_s$$

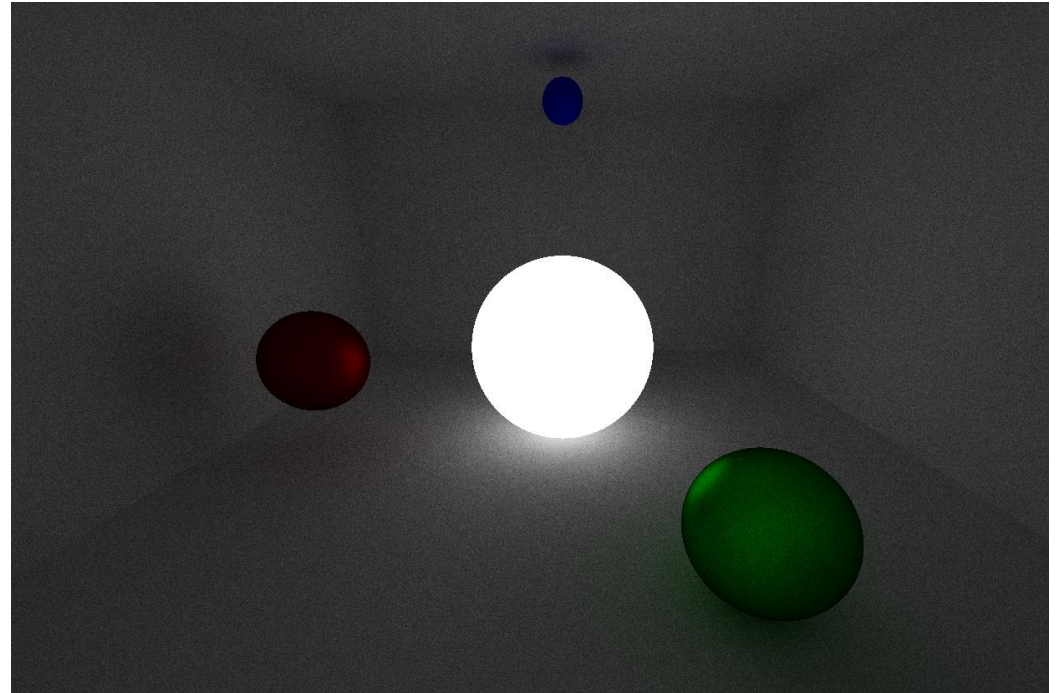


# Comparison

GGX Only ,  $n = 100, b = 10, g = ON$



GGX + Cosine,  $n = 100, b = 10, g = OFF$

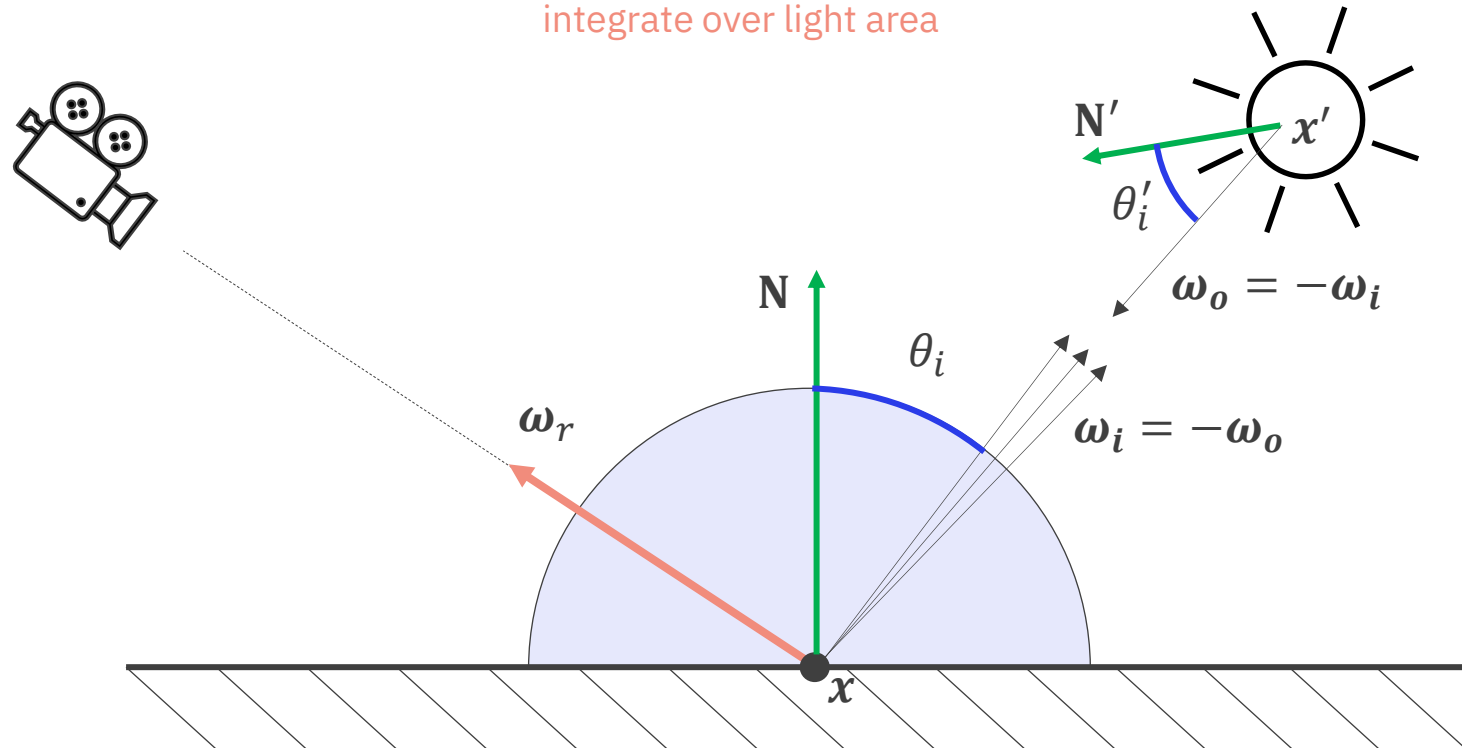




# Light Importance Sampling

$$\int_{\Omega} f_r(x, \omega_i, \omega_r) L_i(x, \omega_i) \cos \theta_i d\omega_i \quad \longrightarrow \quad \int_A L_o(x', \omega_o) V(x, x') \frac{\cos \theta_i \cos \theta'_i}{|x - x'|^2} dA$$

outgoing radiance  $L_o(x', \omega_o)$   
 visibility term  $V(x, x')$   
 light orientation  $\cos \theta_i \cos \theta'_i$   
 distance from light  $|x - x'|^2$   
 integrate over light area  $\int_A$



$$p(\omega) \propto \frac{1}{A}$$

# Uniform Sphere Sampling

$$x = r \sin \theta \cos \varphi$$

$$y = r \sin \theta \sin \varphi$$

$$z = r \cos \theta$$

$$p(r, \theta, \varphi) = r^2 \sin \theta p(x, y, z)$$

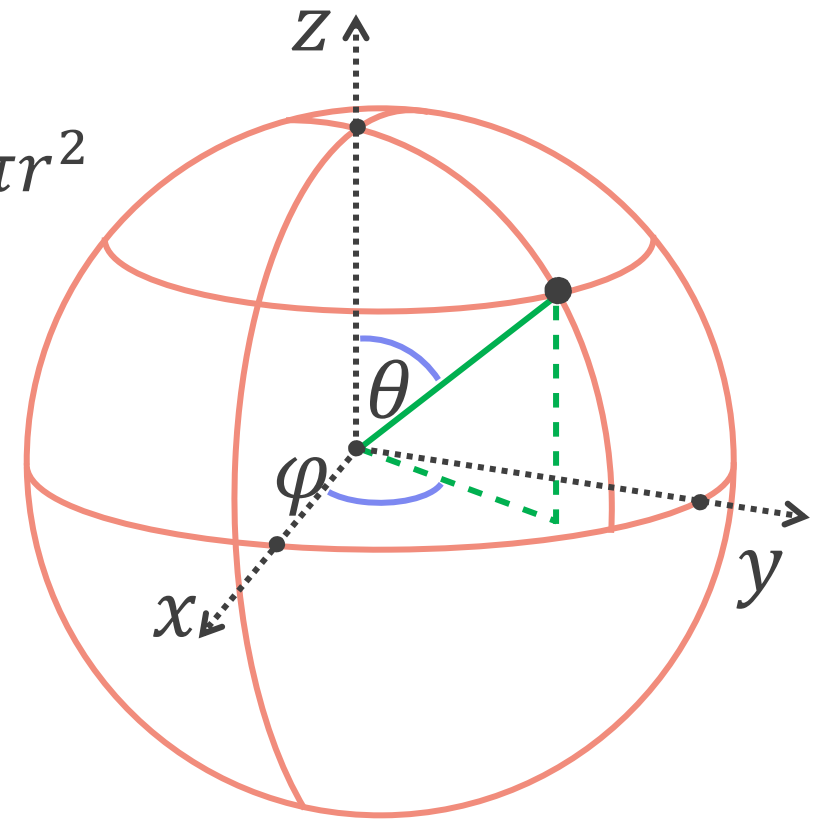
$$p(\omega) = \frac{1}{4\pi} \longrightarrow p(\theta, \varphi) = \frac{\sin \theta}{4\pi}$$

note that we ignore  $r$

$$p(\theta) = \sin \theta \longrightarrow P(\theta) = 1 - \cos \theta \longrightarrow P^{-1}(\xi_1) = \cos^{-1}(1 - \xi_1) \longrightarrow \cos^{-1}(\xi_1)$$

$$p(\varphi) = \frac{1}{4\pi} \longrightarrow P(\varphi) = \frac{\varphi}{4\pi} \longrightarrow P^{-1}(\xi_2) = 4\pi \xi_2$$

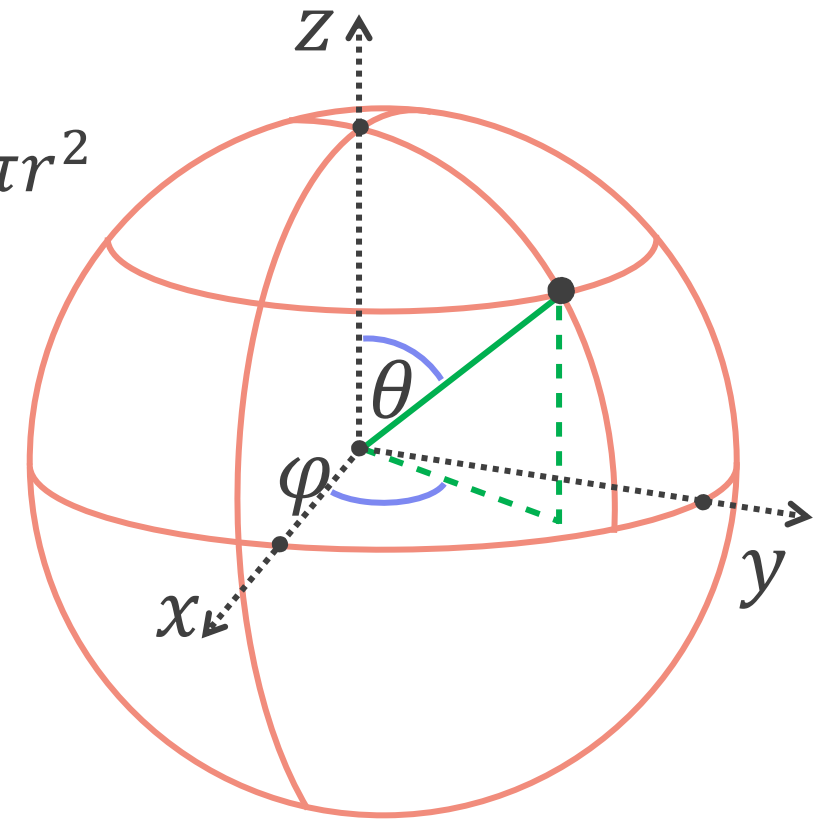
$$A = 4\pi r^2$$



# Uniform Sphere Sampling

$$A = 4\pi r^2$$

$$\begin{aligned} x &= r \sin \theta \cos \varphi = \sqrt{1 - \xi_1^2} \cos(4\pi\xi_2) = \sqrt{1 - \xi_1^2} \cos(2\pi\xi_2) \\ y &= r \sin \theta \sin \varphi = \sqrt{1 - \xi_1^2} \sin(4\pi\xi_2) = \sqrt{1 - \xi_1^2} \sin(2\pi\xi_2) \\ z &= r \cos \theta = \xi_1 \end{aligned}$$



$$p(r, \theta, \varphi) = r^2 \sin \theta p(x, y, z)$$

$$p(\omega) = \frac{1}{4\pi} \longrightarrow p(\theta, \varphi) = \frac{\sin \theta}{4\pi}$$

note that we ignore  $r$

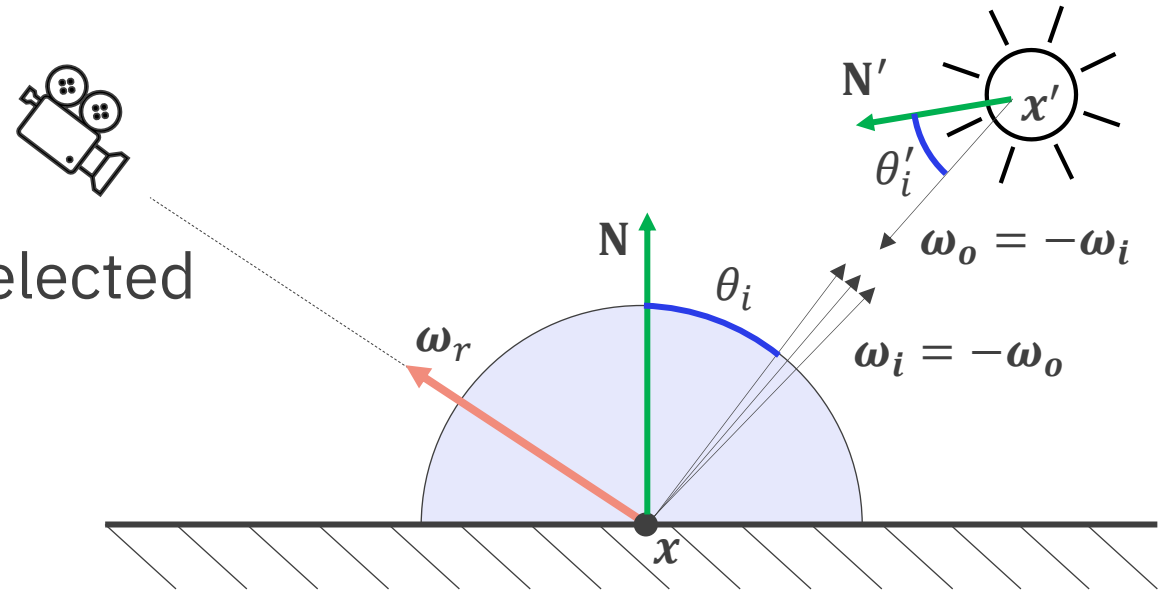
$$p(\theta) = \sin \theta \longrightarrow P(\theta) = 1 - \cos \theta \longrightarrow P^{-1}(\xi_1) = \cos^{-1}(1 - \xi_1) \longrightarrow \cos^{-1}(\xi_1)$$

$$p(\varphi) = \frac{1}{4\pi} \longrightarrow P(\varphi) = \frac{\varphi}{4\pi} \longrightarrow P^{-1}(\xi_2) = 4\pi\xi_2$$

# Sampling Spherical Lights

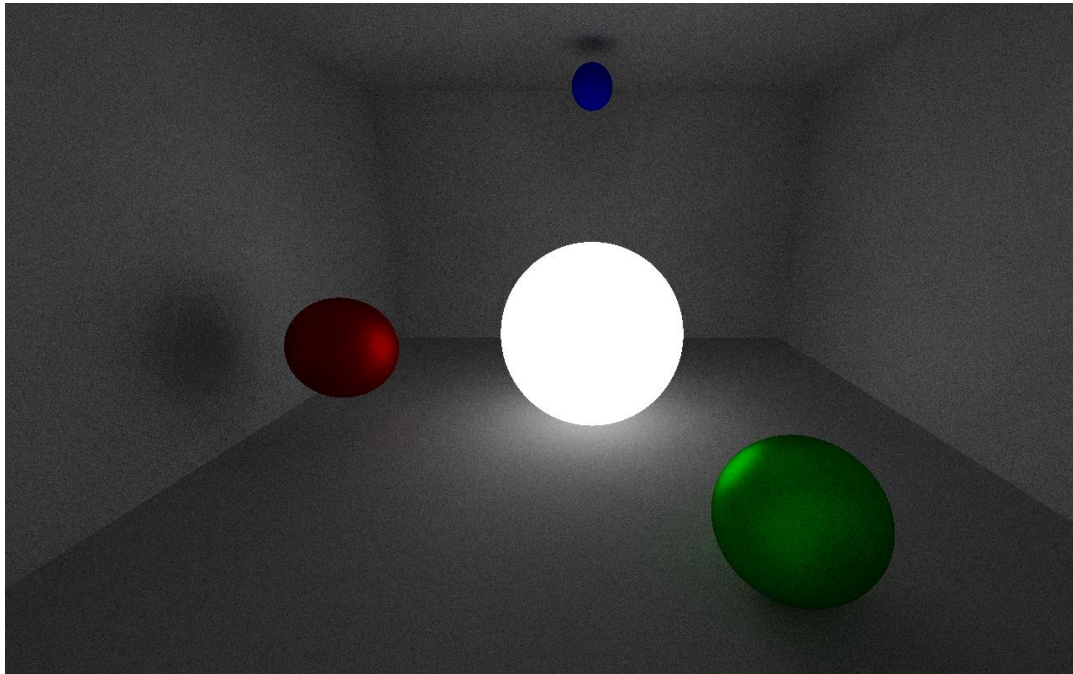
- Pick a random light and obtain its [position, radius] with some probability  $p(l)$ 
  - $[p, r] \leftarrow \text{PickRandomLight}()$
- Compute a random sample on a sphere using canonical uniform distribution
  - $s \leftarrow \text{UniformSampleSphere}(\xi_1, \xi_2)$
- Compute a sample ray  $\omega_i$  to integrate
  - $x' = p + s * r$
  - $\omega_i = x' - x$
- Compute probability the given ray to be selected
  - $p(\omega_i) = \frac{|x-x'|^2}{4\pi r^2} p(l)$

when lights are picked uniformly  
 $p(l) = \frac{1}{\text{number of lights}}$

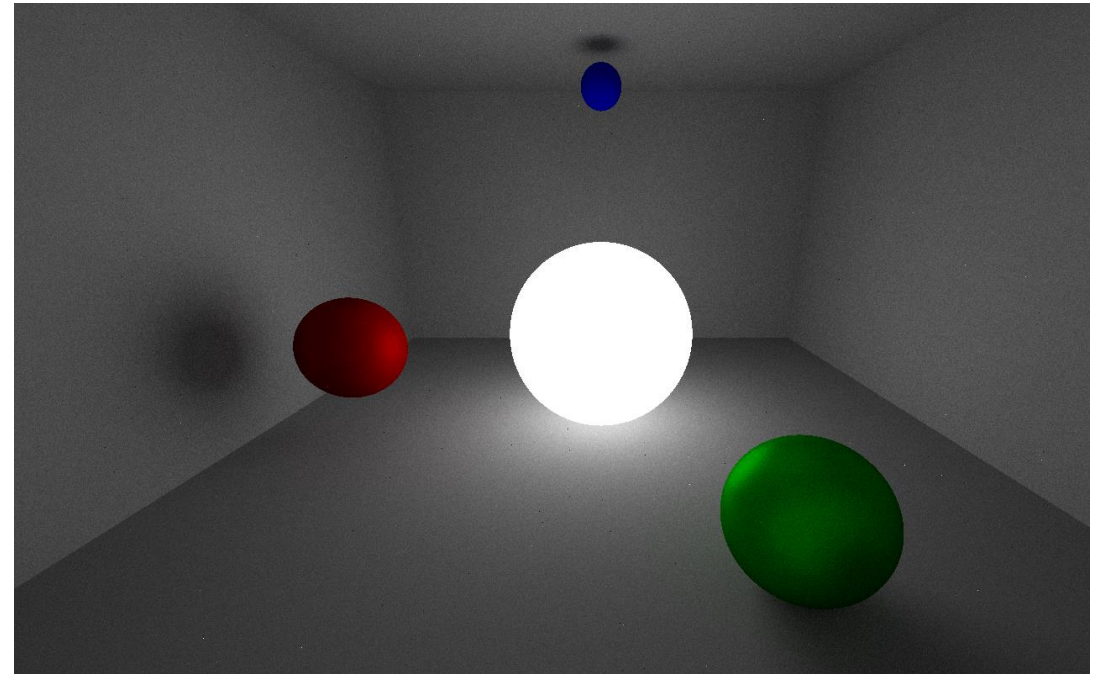


# Comparison

GGX + Cosine ,  $n = 100, b = 10, g = ON$

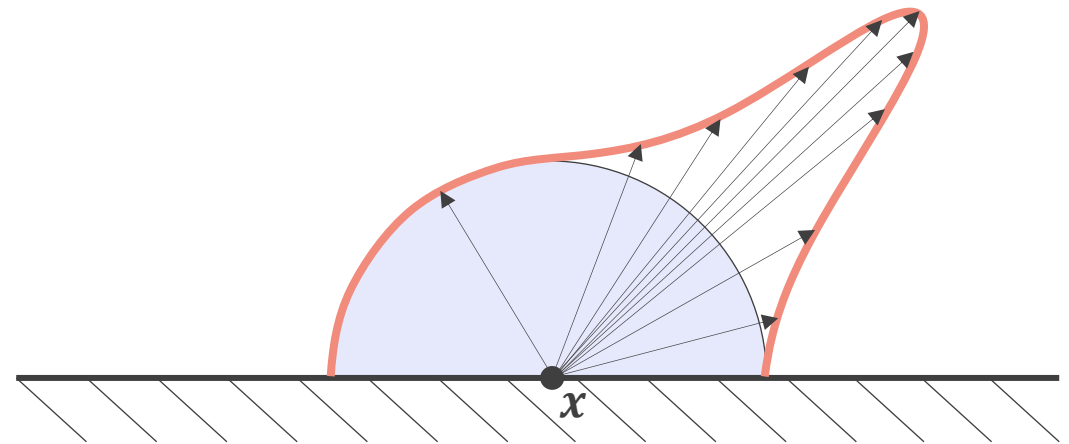
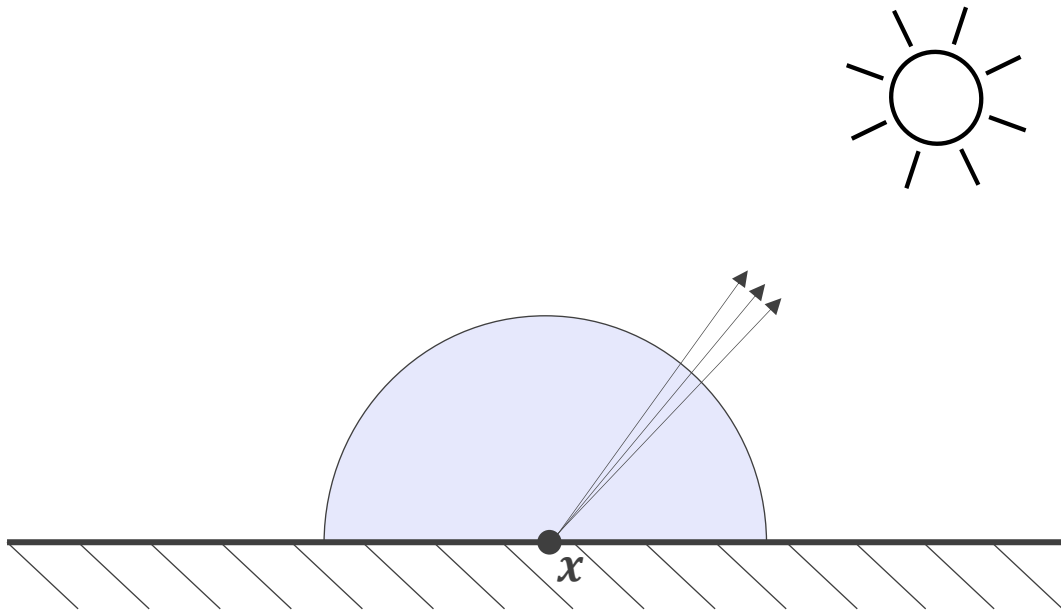


GGX+Cosine+Lights,  $n = 100, b = 10, g = OFF$



# Light Importance Sampling

- In each step, we can sample both towards the light and BRDF spikes
  - Sample light to get direct illumination
  - Sample BRDF to get indirect illumination

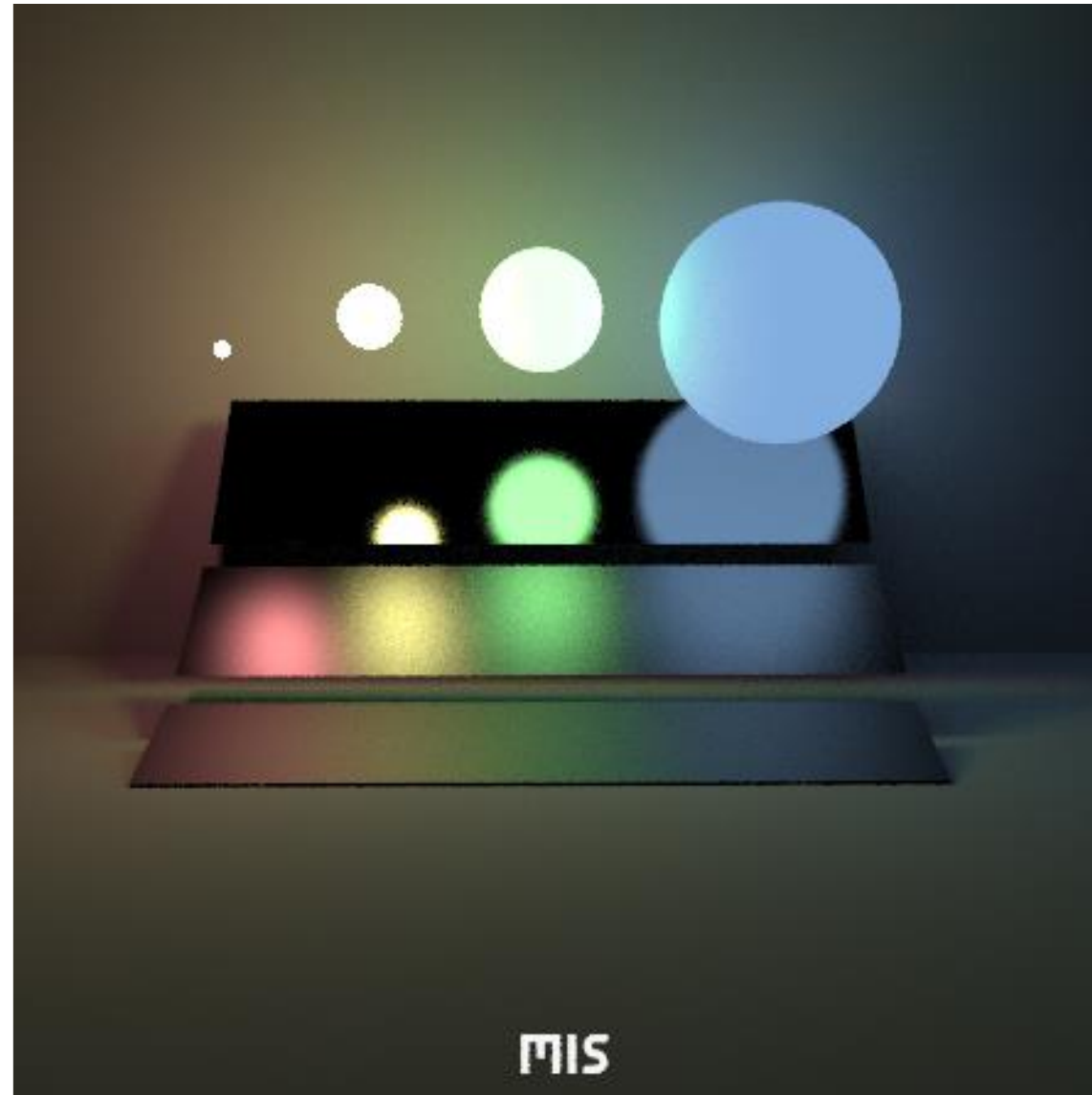


# Example

<https://www.shadertoy.com/view/4sSXWt>



# Combining BRDFs





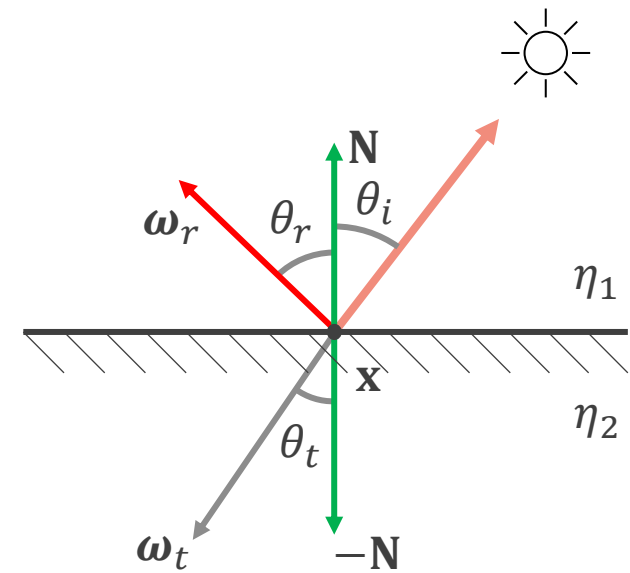
# Snell's Law

$$N_{ff} = \begin{cases} N & \text{when } N \cdot -\omega_r \leq 0 \\ -N & \text{otherwise} \end{cases}$$

$$\eta = \begin{cases} \frac{\eta_1}{\eta_2} & \text{when } N \equiv N_{ff} \\ \frac{\eta_2}{\eta_1} & \text{otherwise} \end{cases}$$

$$\omega_t = -\eta\omega_r + \left( \eta(N \cdot \omega_r) - \sqrt{1 - \eta^2(1 - (N \cdot \omega_r)^2)} \right) N$$

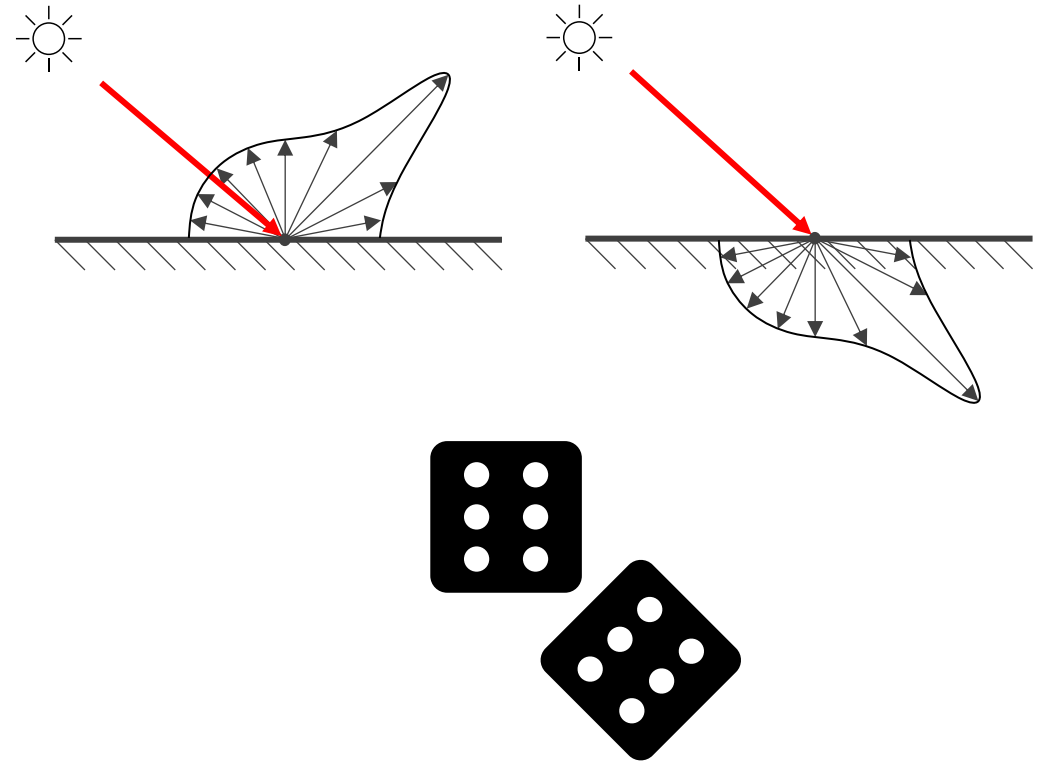
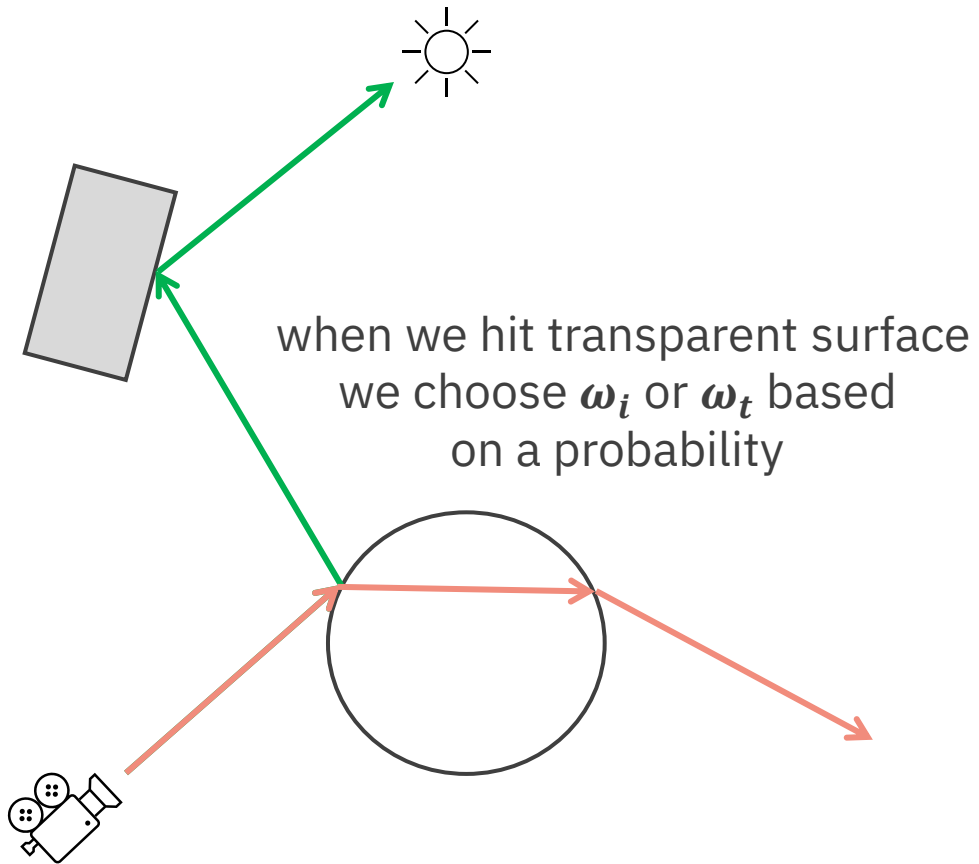
in GLSL you may use `refract(- $\omega_r$ ,  $N_{ff}$ ,  $\eta$ )`



$$\frac{\sin \theta_t}{\sin \theta_i} = \frac{\eta_1}{\eta_2} = \eta \quad \eta_1, \eta_2 \text{ - Indices of refraction}$$

<https://pixelandpoly.com/ior.html>

# Transmission



# Transmission

A bit hacky solution.

```
if (K < 0.0 || prob > ξ){
    return SampleReflection(hit, ray)
} else {
    dir ← normalize(refract(-ωr, Nff, η))
    pdf ← 1.0
    return BSDFSample(dir, pdf)
}
```

$$N_{ff} = \begin{cases} N & \text{when } N \cdot -\omega_r \leq 0 \\ -N & \text{otherwise} \end{cases}$$

$$\eta = \begin{cases} \frac{\eta_1}{\eta_2} & \text{when } N \equiv N_{ff} \\ \frac{\eta_2}{\eta_1} & \text{otherwise} \end{cases}$$

$$F(R_0) = R_0 + (1 - R_0)(1 - (\omega_r \cdot N_{ff}))^5$$

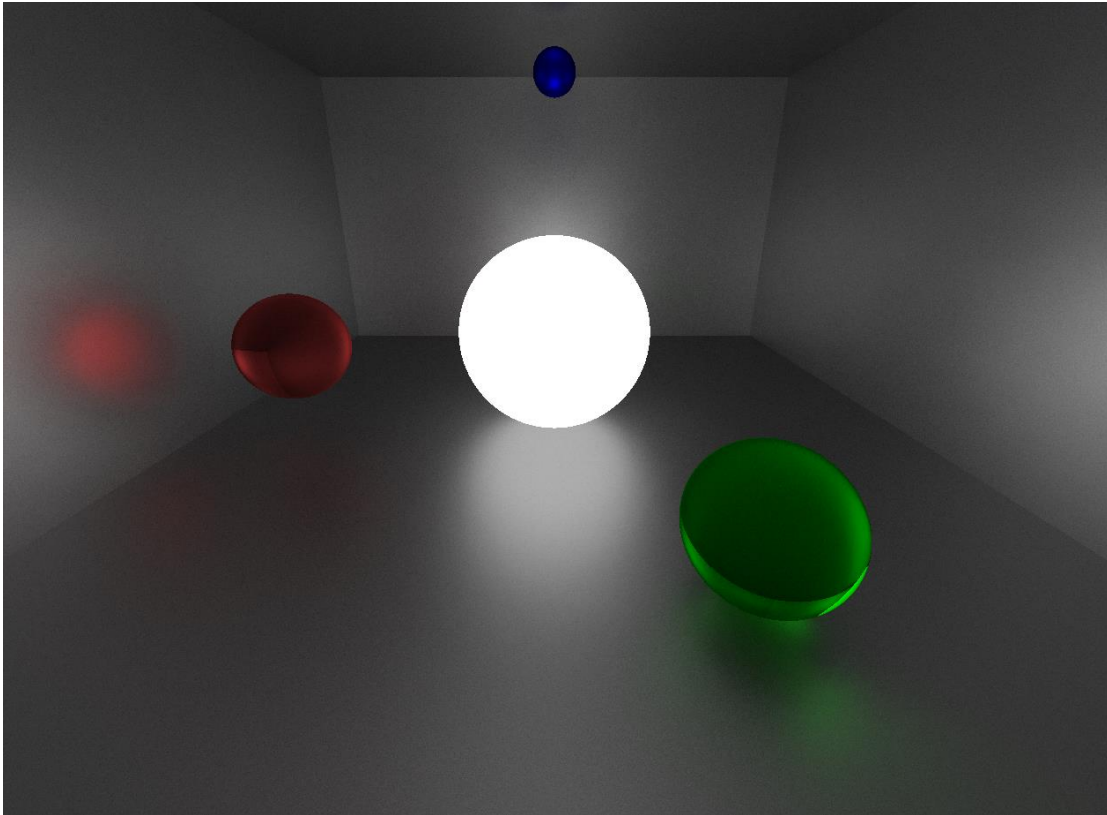
$$prob = F\left(\left(\frac{\eta_1 - \eta_2}{\eta_1 + \eta_2}\right)^2\right)$$

$$K = 1.0 - \eta^2 * (1.0 - (-\omega_r \cdot N_{ff})^2)$$

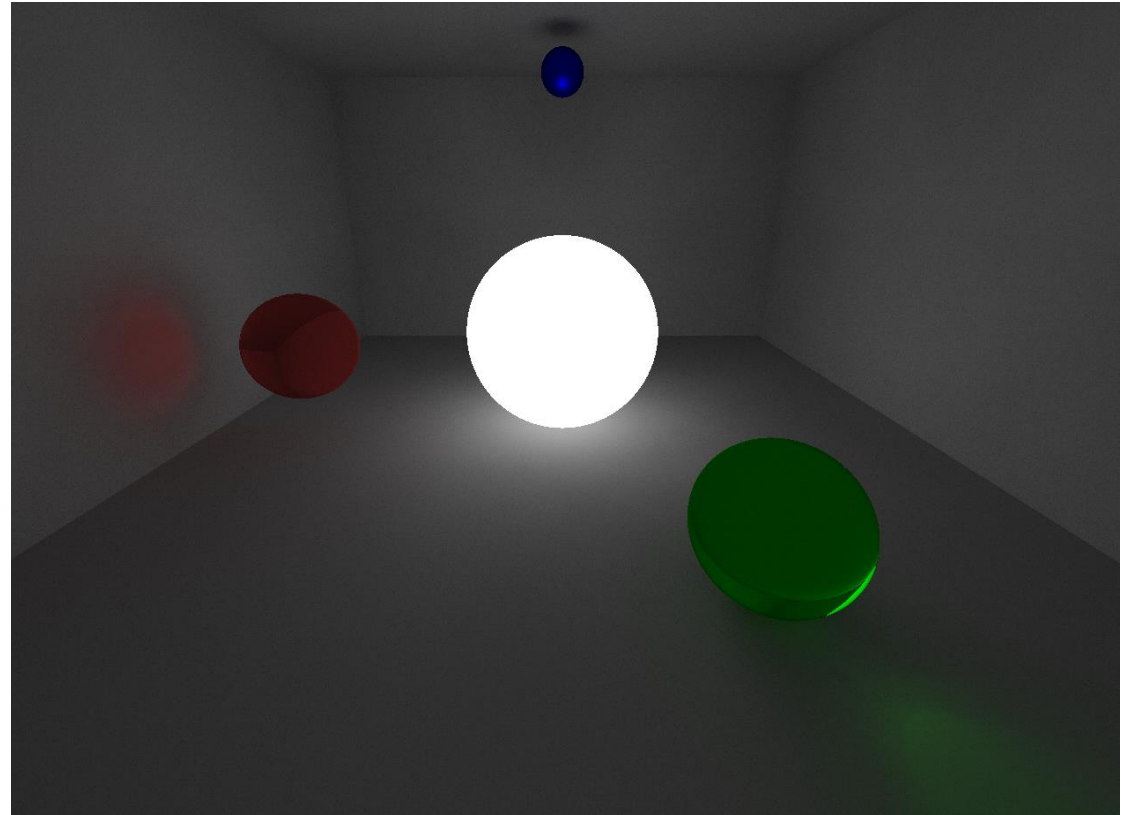
$$\xi = \text{random number } [0 - 1]$$

# Result

GGX+Cosine,  $n = 1000, r = 0.2, b = 10, \text{gama} = ON$



GGX+Cosine,  $n = 1000, b = 10, r = 0.8, \text{gama} = ON$



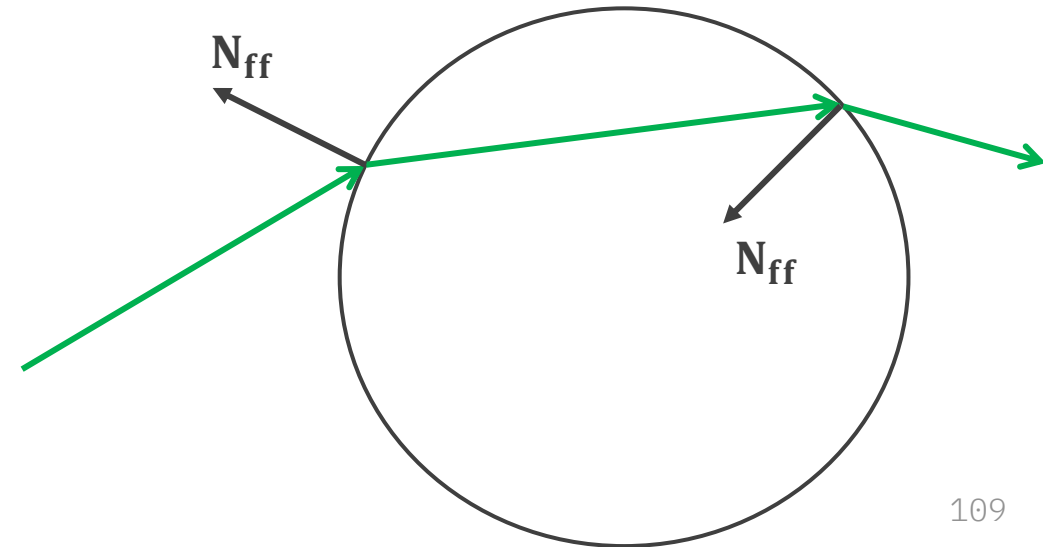
# Problems with Transmission

$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_i(\mathbf{x}, \boldsymbol{\omega}_i) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$

- When computing new ray, we need to correctly offset the origin

```
ray = Ray(hit.intersection + (hit.glass ? -EPSILON * hit.ffnormal : EPSILON * hit.ffnormal), sample.direction)
```

- Rendering equation is not really build for BTDF
  - $\cos \theta_i = N \cdot \boldsymbol{\omega}_i$  will be always negative
  - you may invert  $\boldsymbol{\omega}_i$  or better ignore it completely



# Problems with Transmission

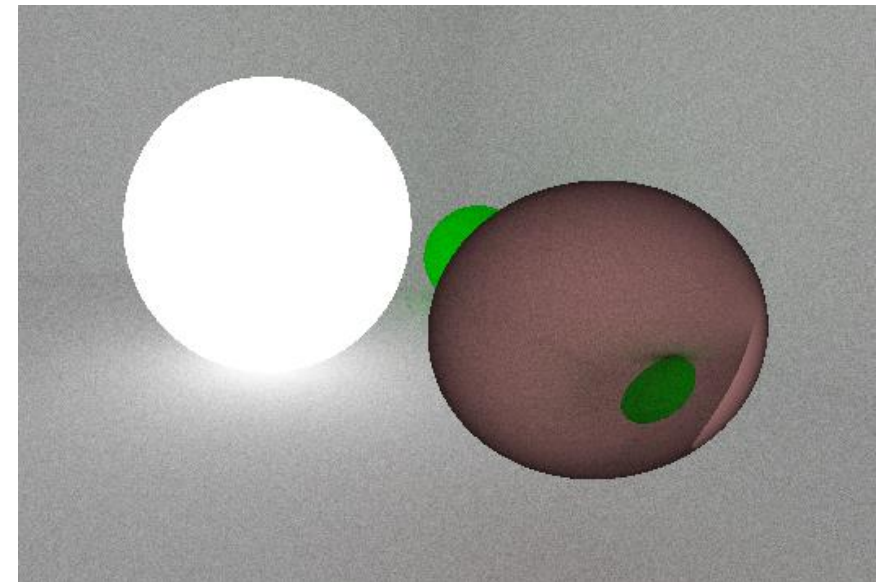
$$L_r(\mathbf{x}, \boldsymbol{\omega}_r) = L_e(\mathbf{x}, \boldsymbol{\omega}_r) + \frac{1}{n} \sum_{i=1}^n f_r(\mathbf{x}, \boldsymbol{\omega}_i, \boldsymbol{\omega}_r) L_i(\mathbf{x}, \boldsymbol{\omega}_i) \cos \theta_i \frac{1}{p(\boldsymbol{\omega}_i)}$$

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```
ray = Ray(hit.intersection + (hit.glass ? -EPSILON * hit.ffnormal : EPSILON * hit.ffnormal), sample.direction)
```

- Rendering equation is not really designed for BTDF

- $\cos \theta_i = N \cdot \boldsymbol{\omega}_i$  will be always negative
- Solution:
  - you may invert  $\boldsymbol{\omega}_i$  (produces dark edges)
  - better ignore it completely



# More Reading

[www.pbr-book.org/3ed-2018/contents](http://www.pbr-book.org/3ed-2018/contents)



[docs.unrealengine.com](http://docs.unrealengine.com)