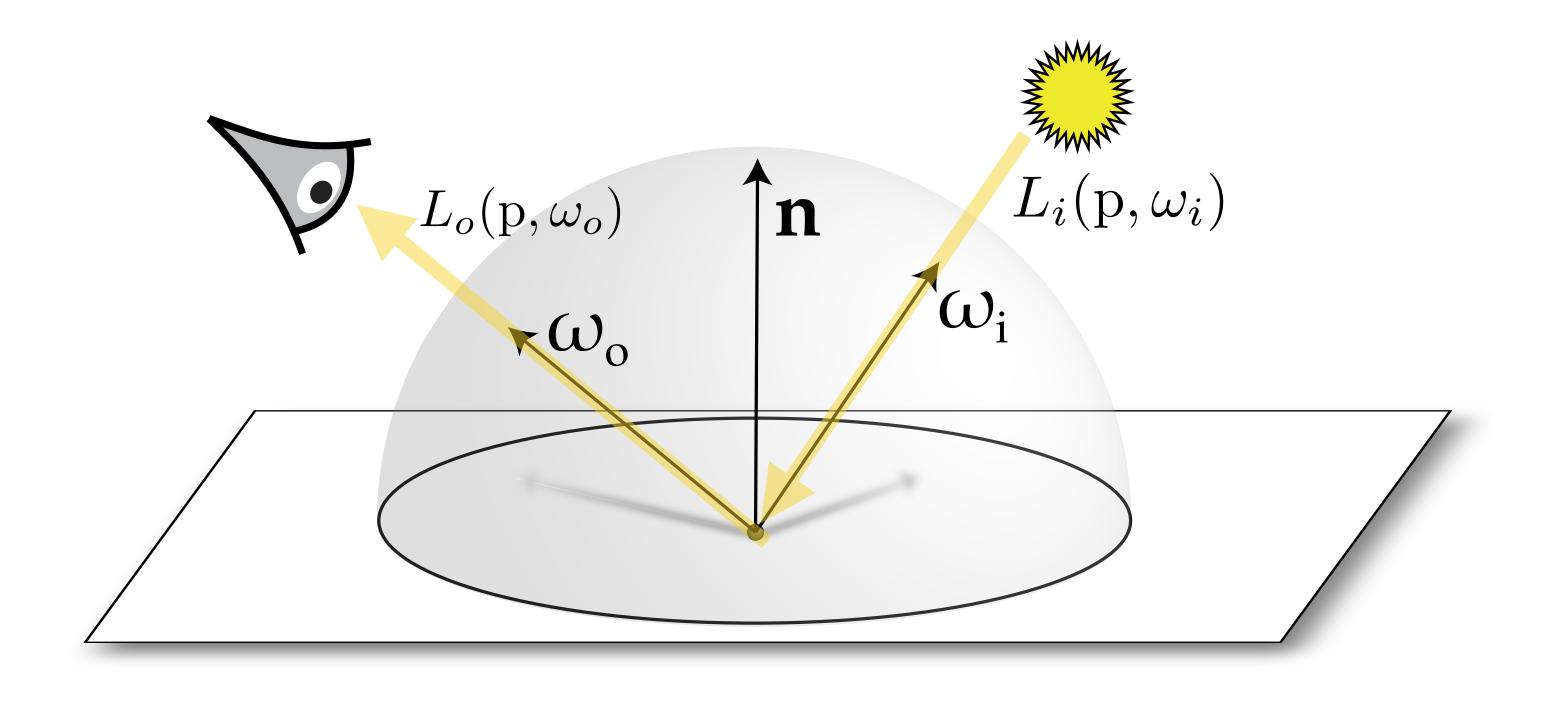
Lecture 11:

Materials (Part 2) + Numerical Integration Basics

Interactive Computer Graphics Stanford CS248A, Winter 2024

Last time: the reflection equation



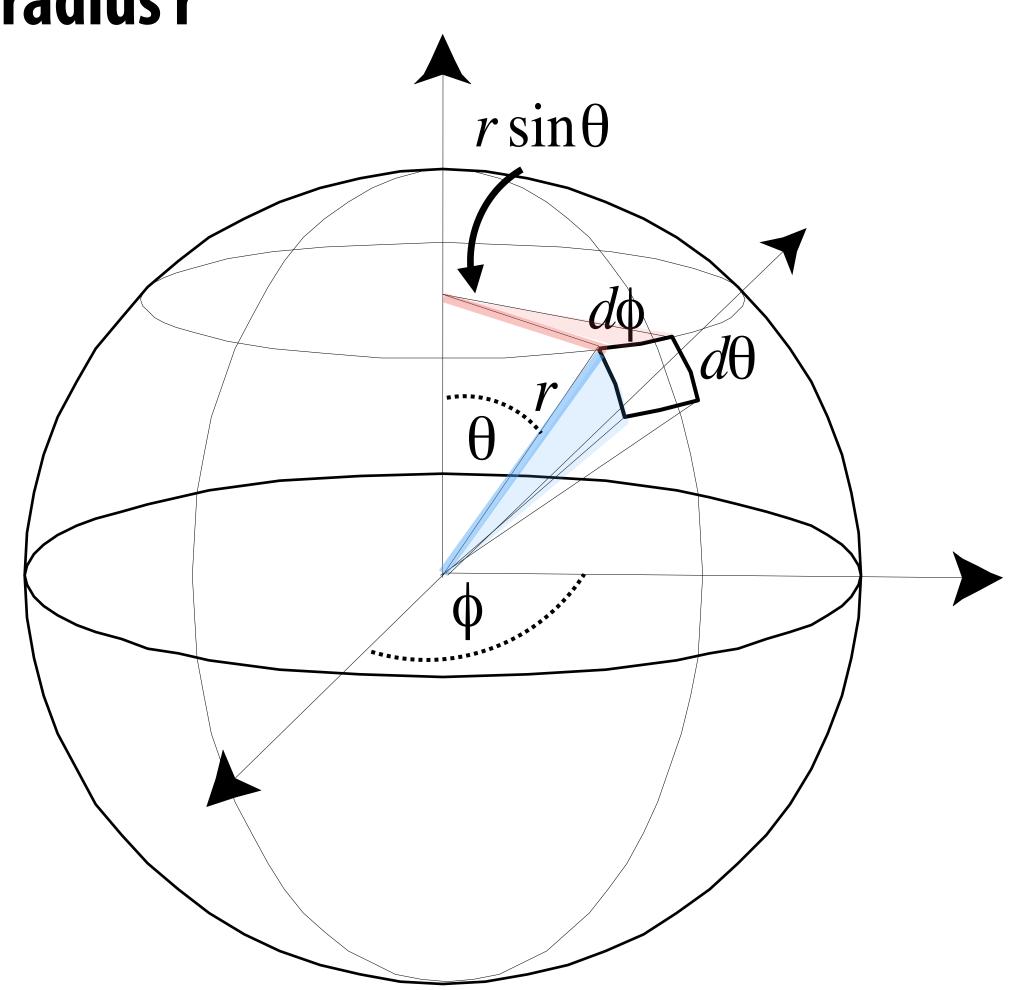
$$L_{\rm o}({
m p},\omega_{
m o}) = \int_{\Omega^2} f_{
m r}({
m p},\omega_{
m i}
ightarrow \omega_{
m o}) L_{
m i}({
m p},\omega_{
m i}) \, \cos heta_{
m i} \, {
m d}\omega_{
m i}$$

BRDF Illumination

Review: radiometry and illumination

Review: differential solid angles

Sphere with radius r

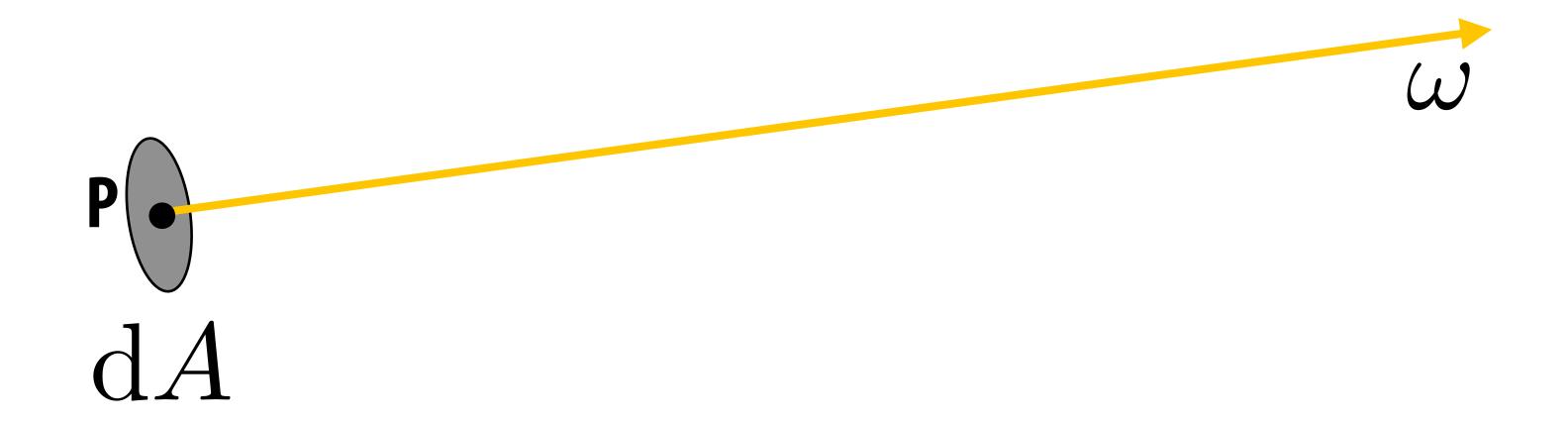


$$dA = (r d\theta)(r \sin\theta d\phi)$$
$$= r^2 \sin\theta d\theta d\phi$$

$$d\omega = \frac{dA}{r^2} = \sin\theta \ d\theta \ d\phi$$

Review: radiance

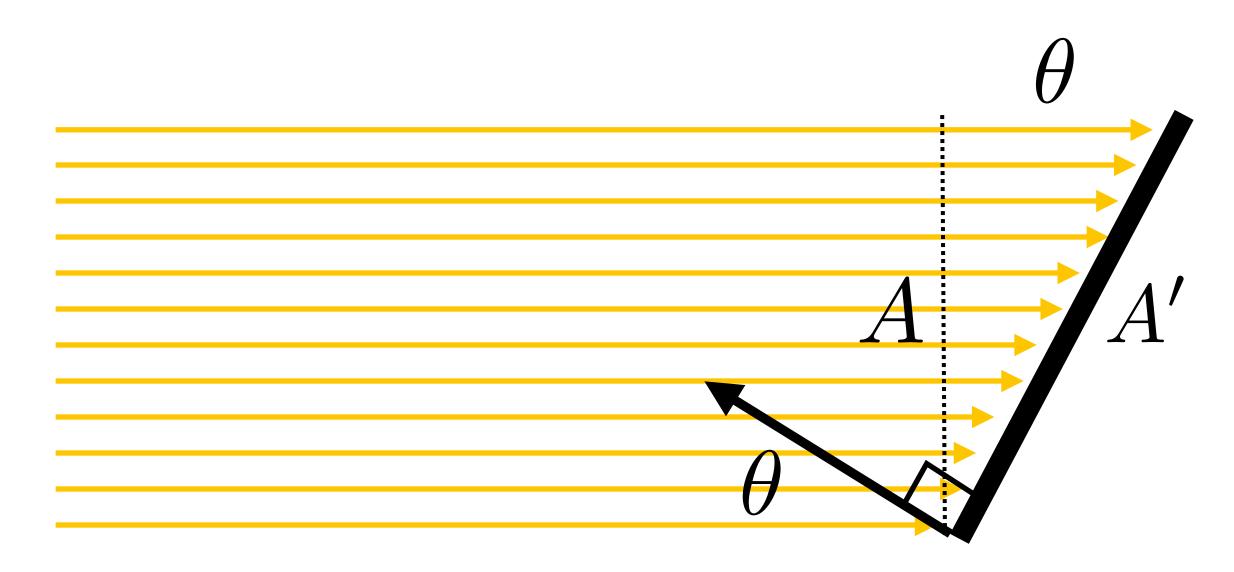
Radiance (L) is energy along a ray defined by origin point ${m p}$ and direction ${m \omega}$



■ Radiance is the solid angle density of irradiance (irradiance per unit direction) where ω denotes that the differential surface area is oriented to face in the direction

Review: irradiance = power per unit area

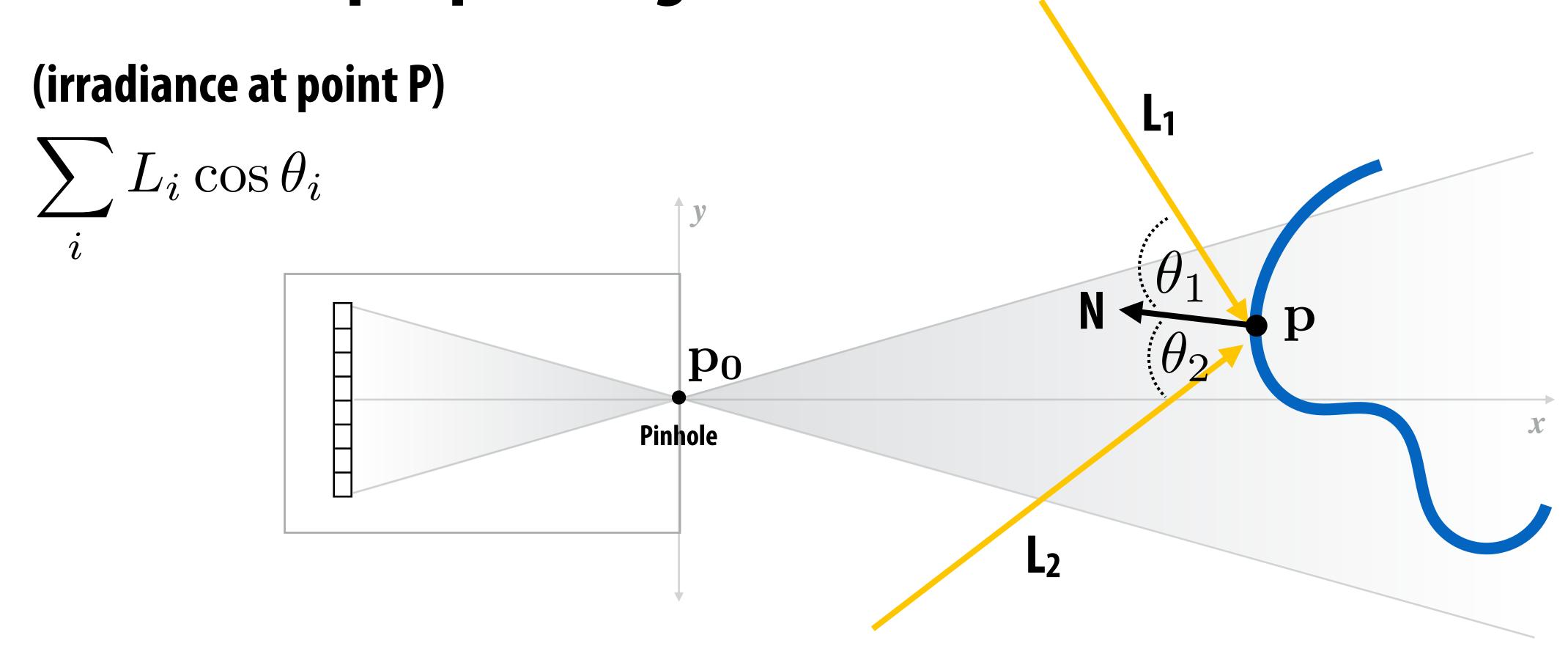
Irradiance at surface is proportional to cosine of angle between light direction and surface normal. (Lambert's Law)



$$A = A' \cos \theta$$

$$E = \frac{\Phi}{A'} = \frac{\Phi \cos \theta}{A}$$

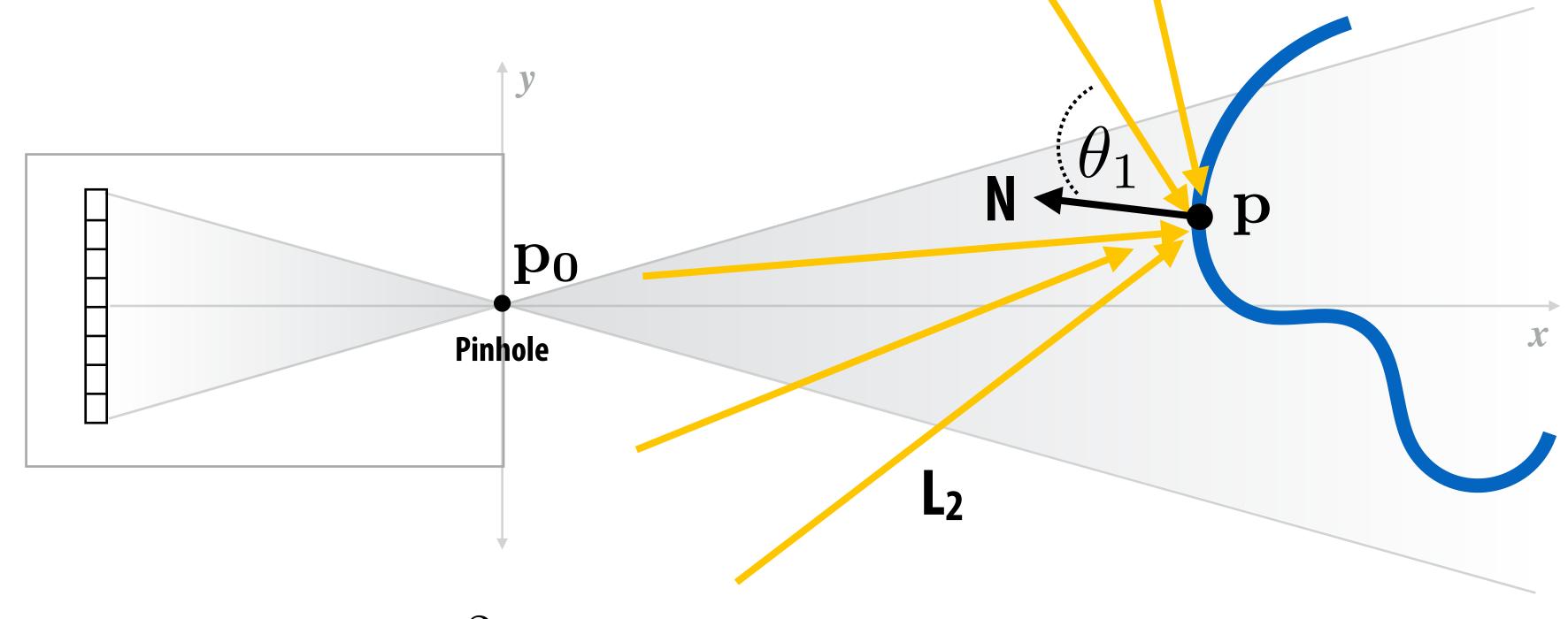
Review: how much light hits the surface at point p? (from multiple point light sources)



How much light hits the surface at point p?

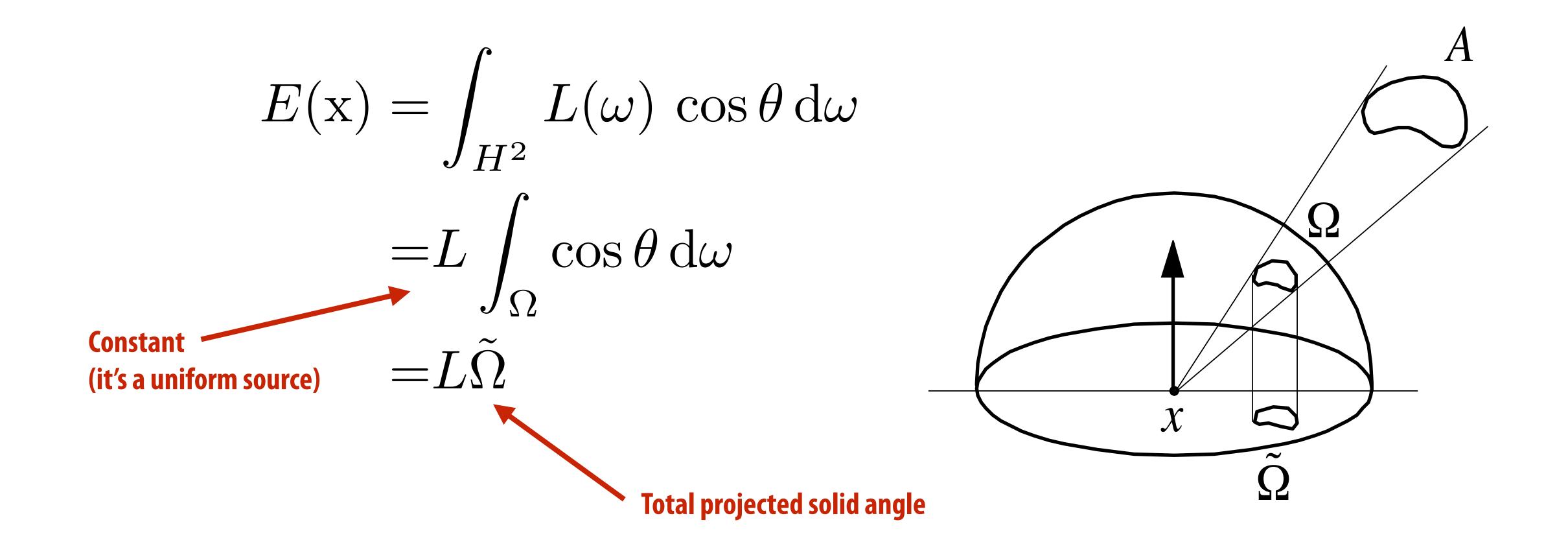
(from light from all directions!)





$$\int_{S^2} L_i(\omega_i) \cos \theta_i d\omega = \int_0^{2\pi} \int_0^{\pi} L_i(\omega_i) \cos \theta_i \sin \theta_i d\theta d\phi$$

Irradiance at point X from a uniform area source



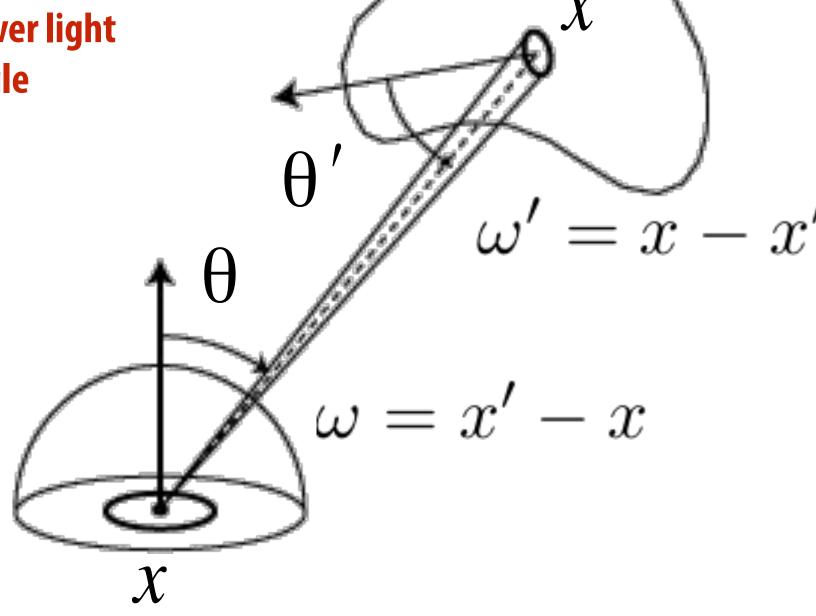
Irradiance at point X from uniform area source

$$E(x) = \int_{H^2} L_i(x,\omega) \cos\theta \, d\omega = \int_{A'} L \frac{\cos\theta \cos\theta'}{|x - x'|^2} dA'$$

Reparameterization: now integrate over light source area, instead of solid angle

Integral reparameterization:

$$d\omega = \frac{\cos \theta'}{|x - x'|^2} dA'$$



Radiance leaving light from x' in direction $\omega' = radiance$ arriving at surface at x from ω . (assuming that ω is pointing at the light)

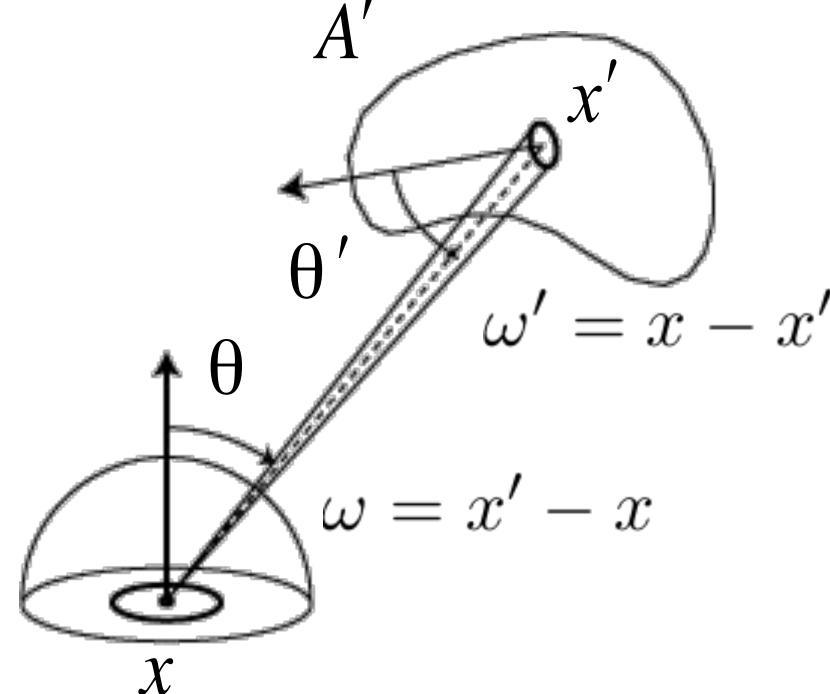
$$L_i(x,\omega) = L_o(x',\omega') = L$$

Materials (Back to slides from last lecture)

Numerical Integration

Many examples of needing to compute integrals already in this lecture

$$E(x) = \int_{H^2} L \cos\theta \, d\omega = \int_{A'} L \frac{\cos\theta \cos\theta'}{|x - x'|^2} dA'$$



Review: fundamental theorem of calculus

$$\int_{a}^{b} f(x)dx = F(b) - F(a)$$

$$f(x) = \frac{d}{dx}F(x)$$

$$F(x)$$

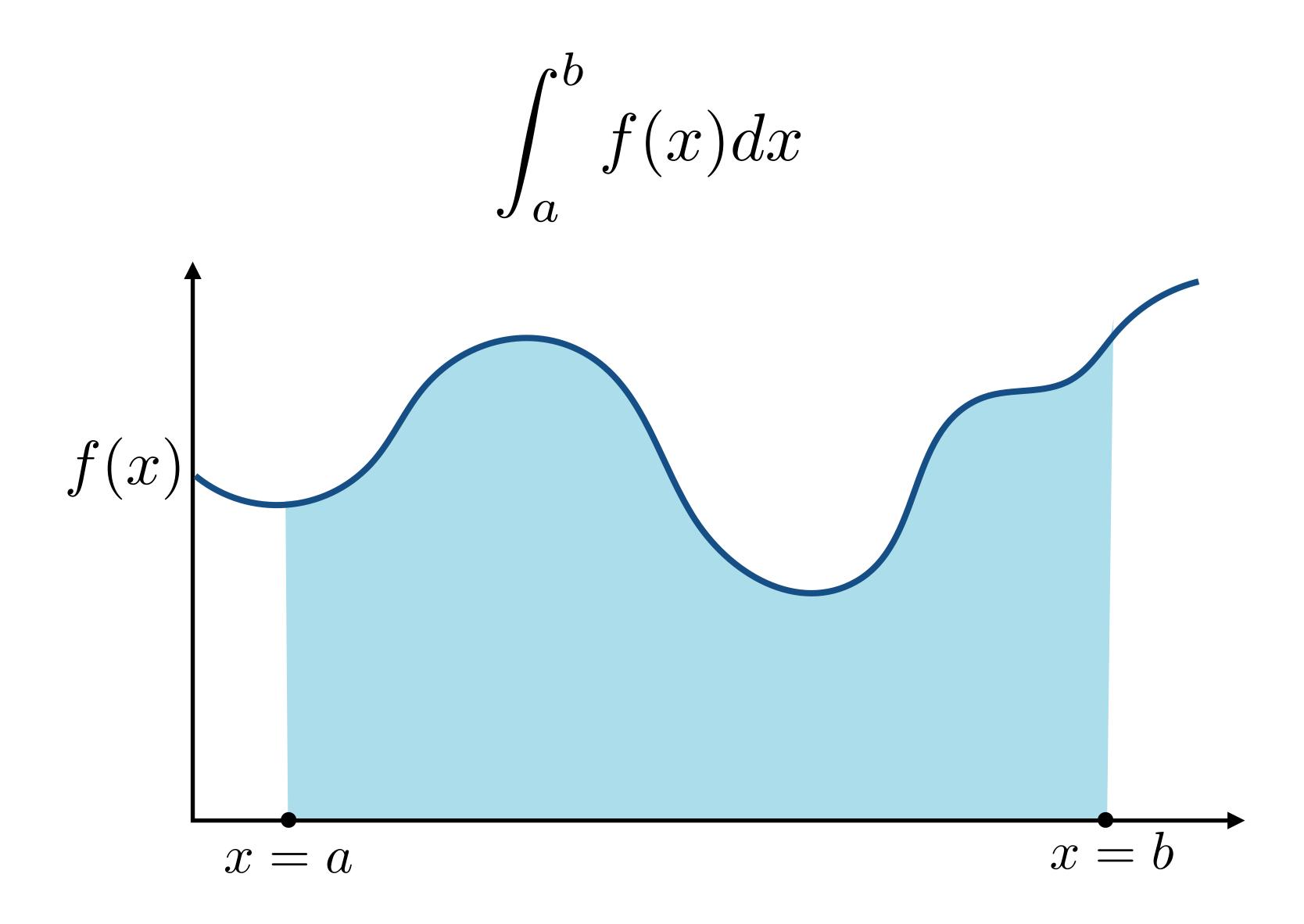
$$F(x)$$

$$F(a)$$

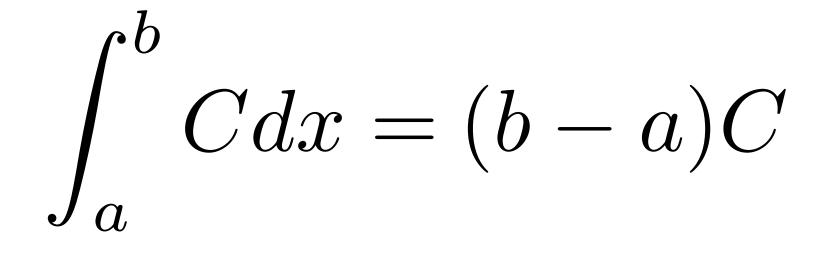
$$F(a)$$

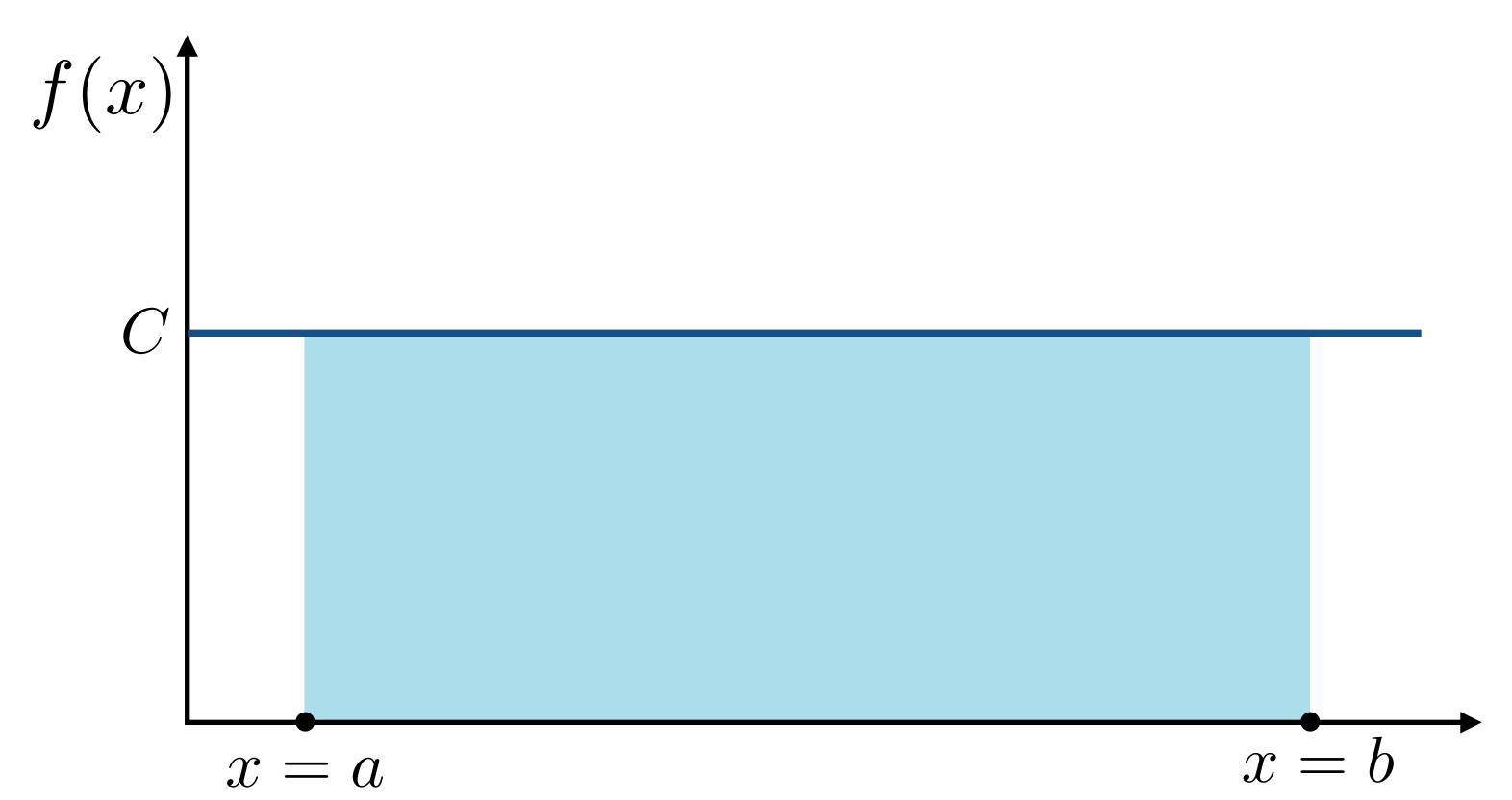
$$x = a$$

Definite integral as "area under curve"



Simple case: constant function

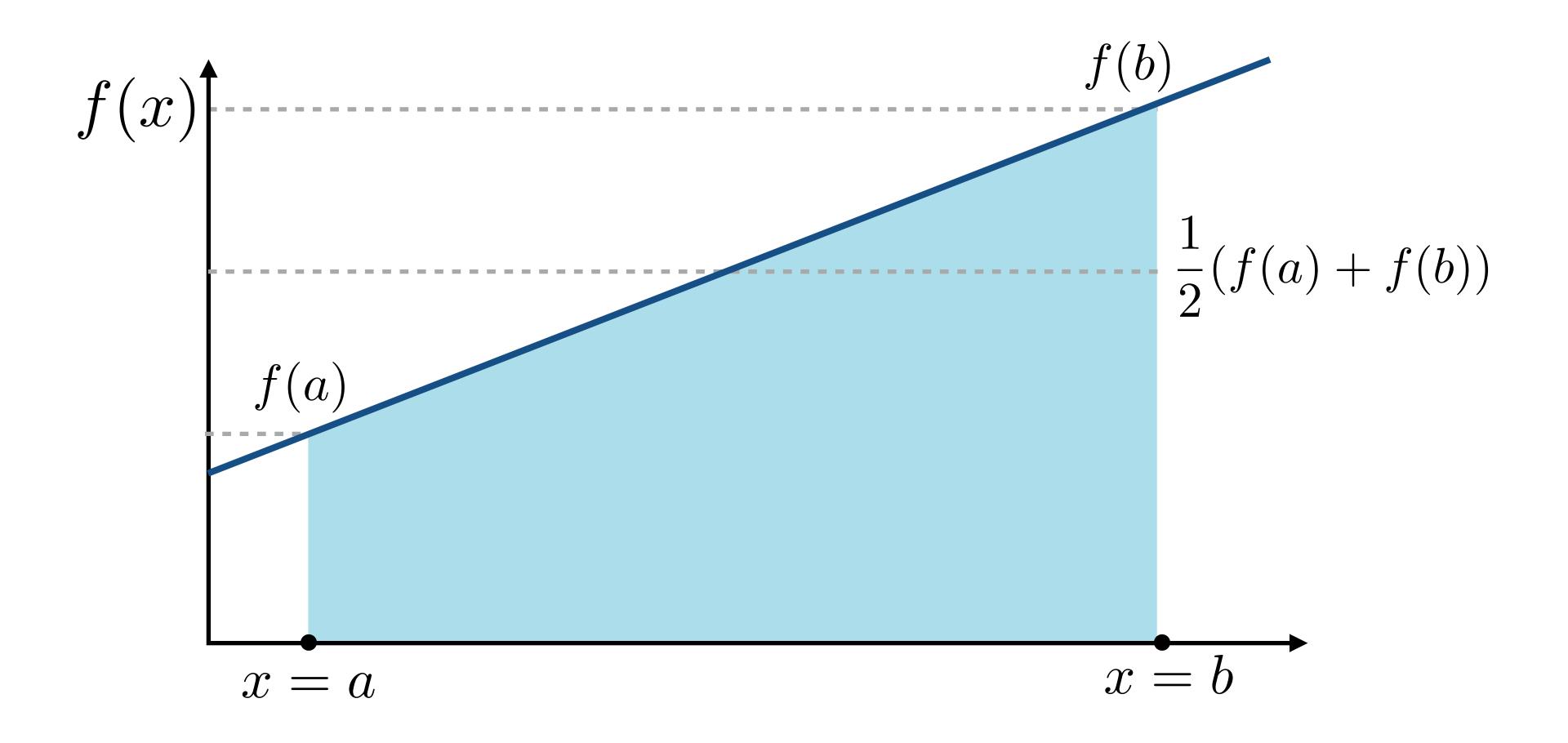




Affine function:

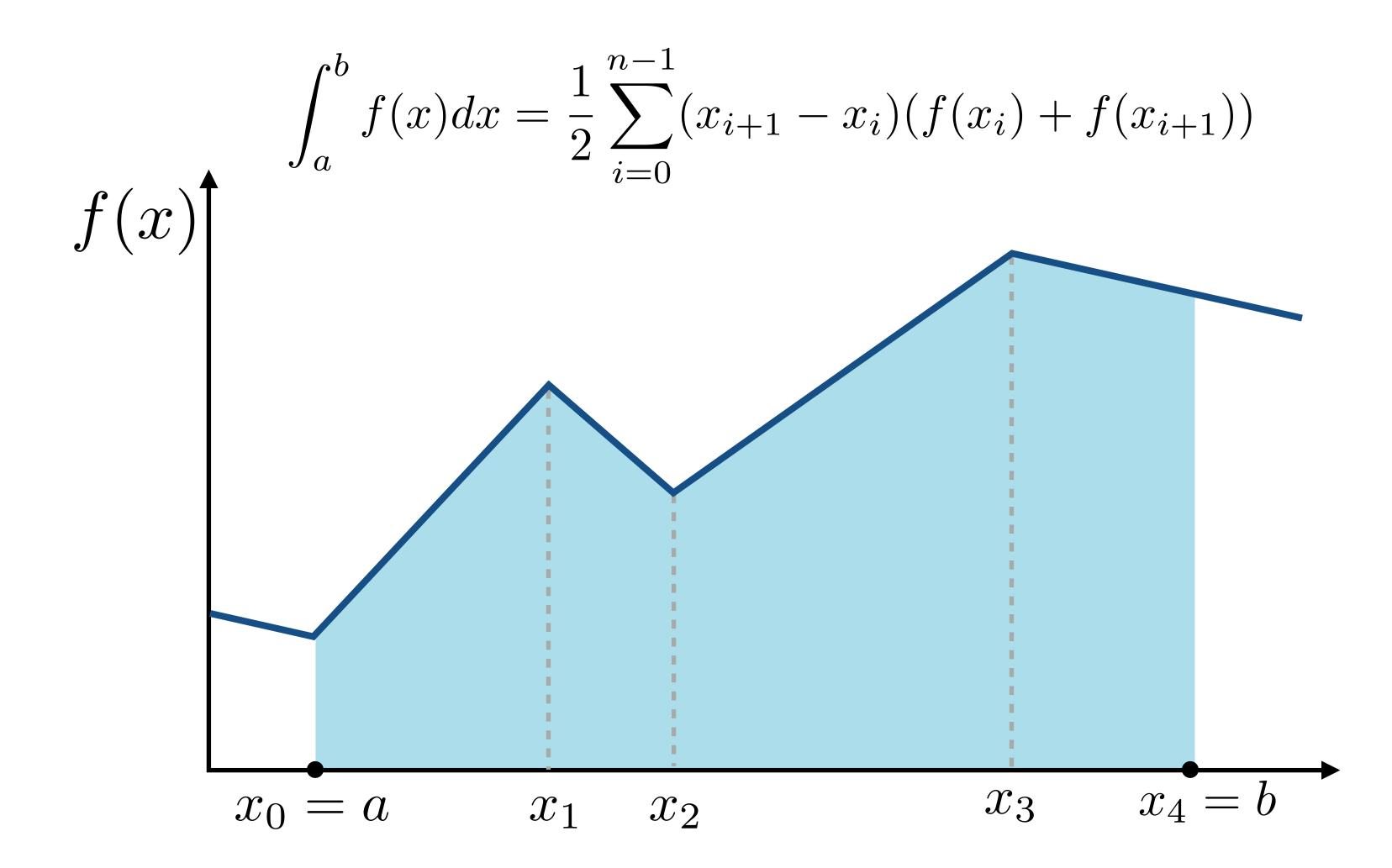
$$f(x) = cx + d$$

$$\int_{a}^{b} f(x)dx = \frac{1}{2}(f(a) + f(b))(b - a)$$



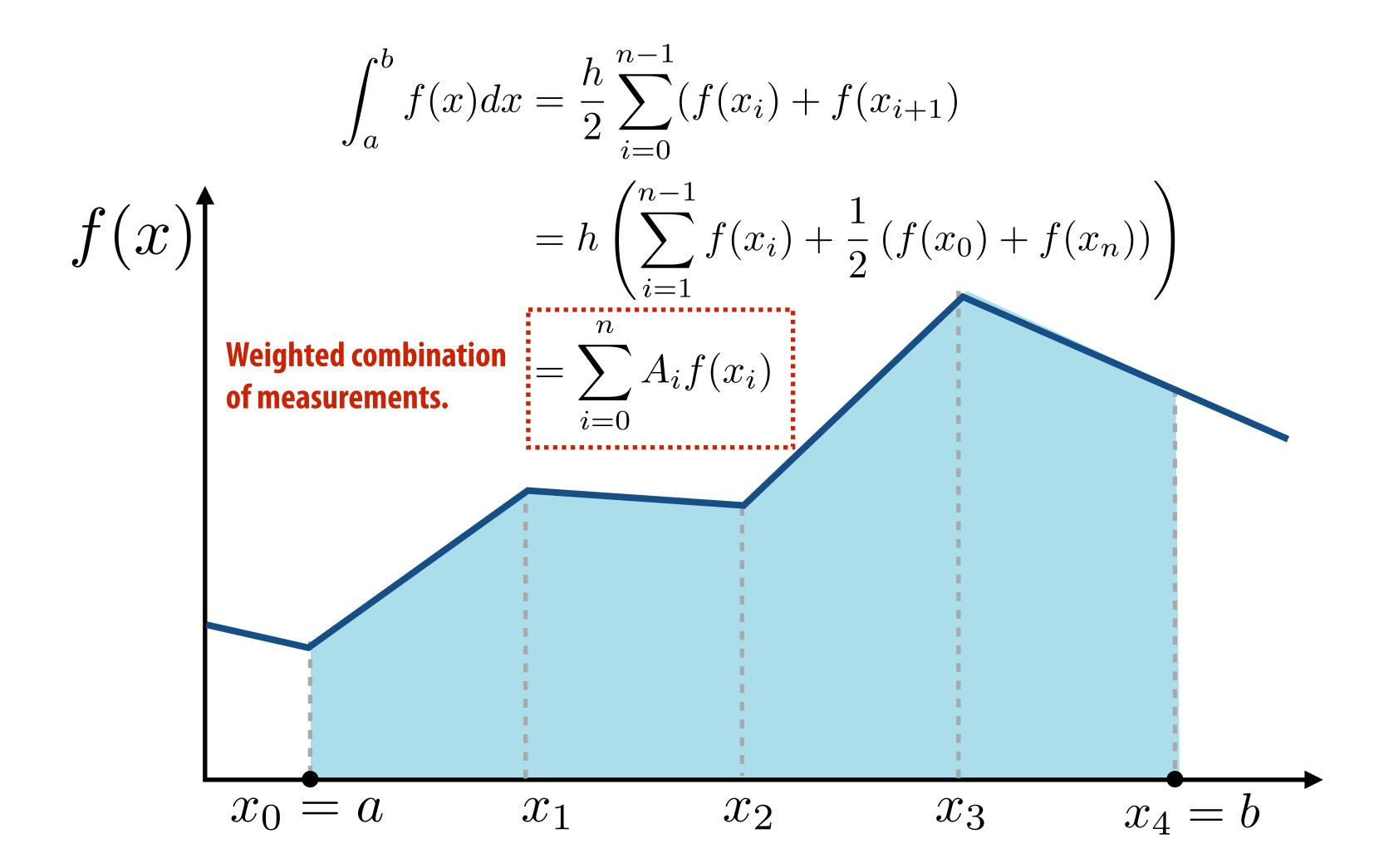
Piecewise affine function

Sum of integrals of individual affine components

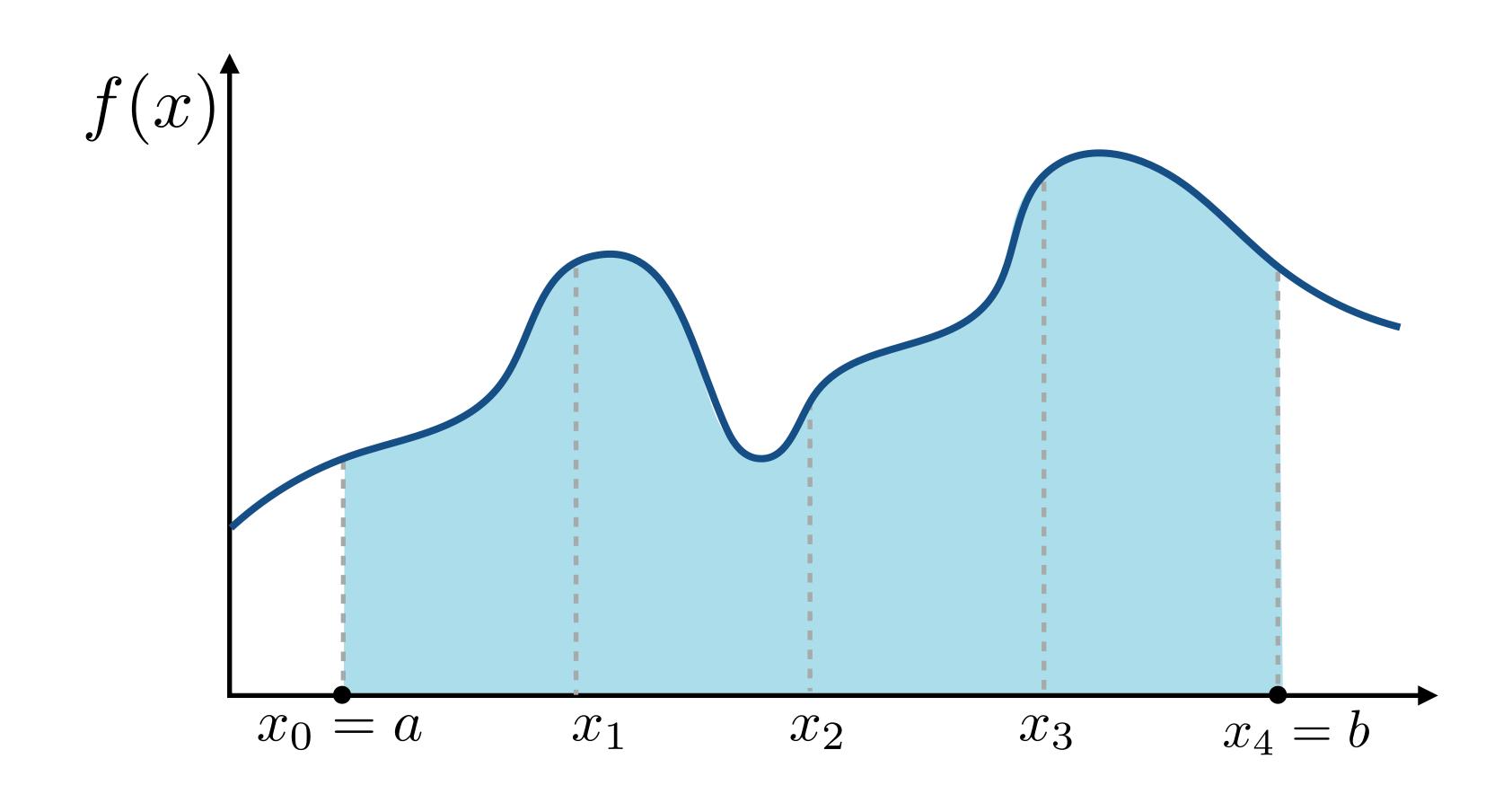


Piecewise affine function

If N-1 segments are of equal length: $h = \frac{b-a}{n-1}$



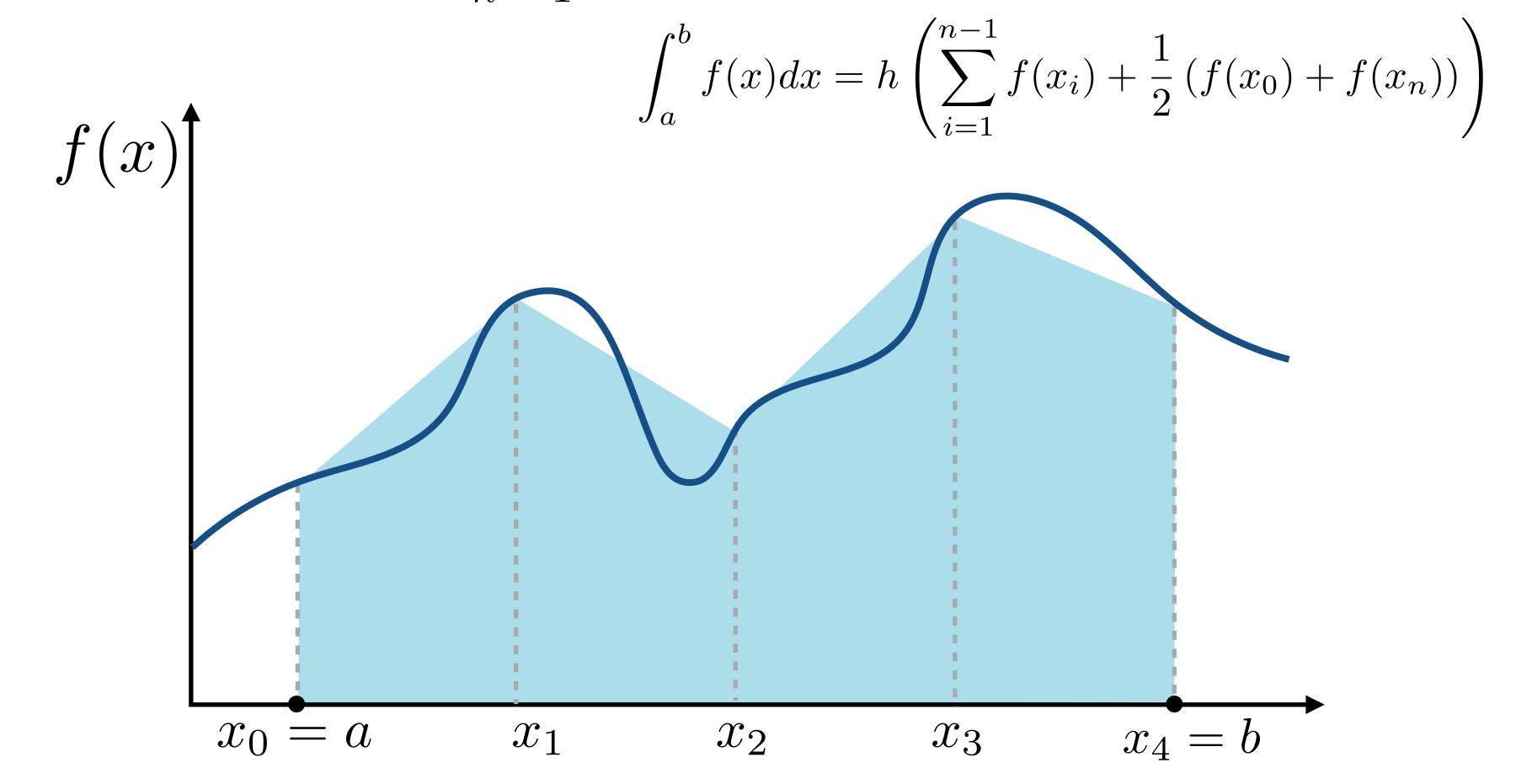
Arbitrary function f(x)?



Trapezoidal rule

Approximate integral of f(x) by assuming function is piecewise linear

For equal length segments: $h = \frac{b-a}{n-1}$

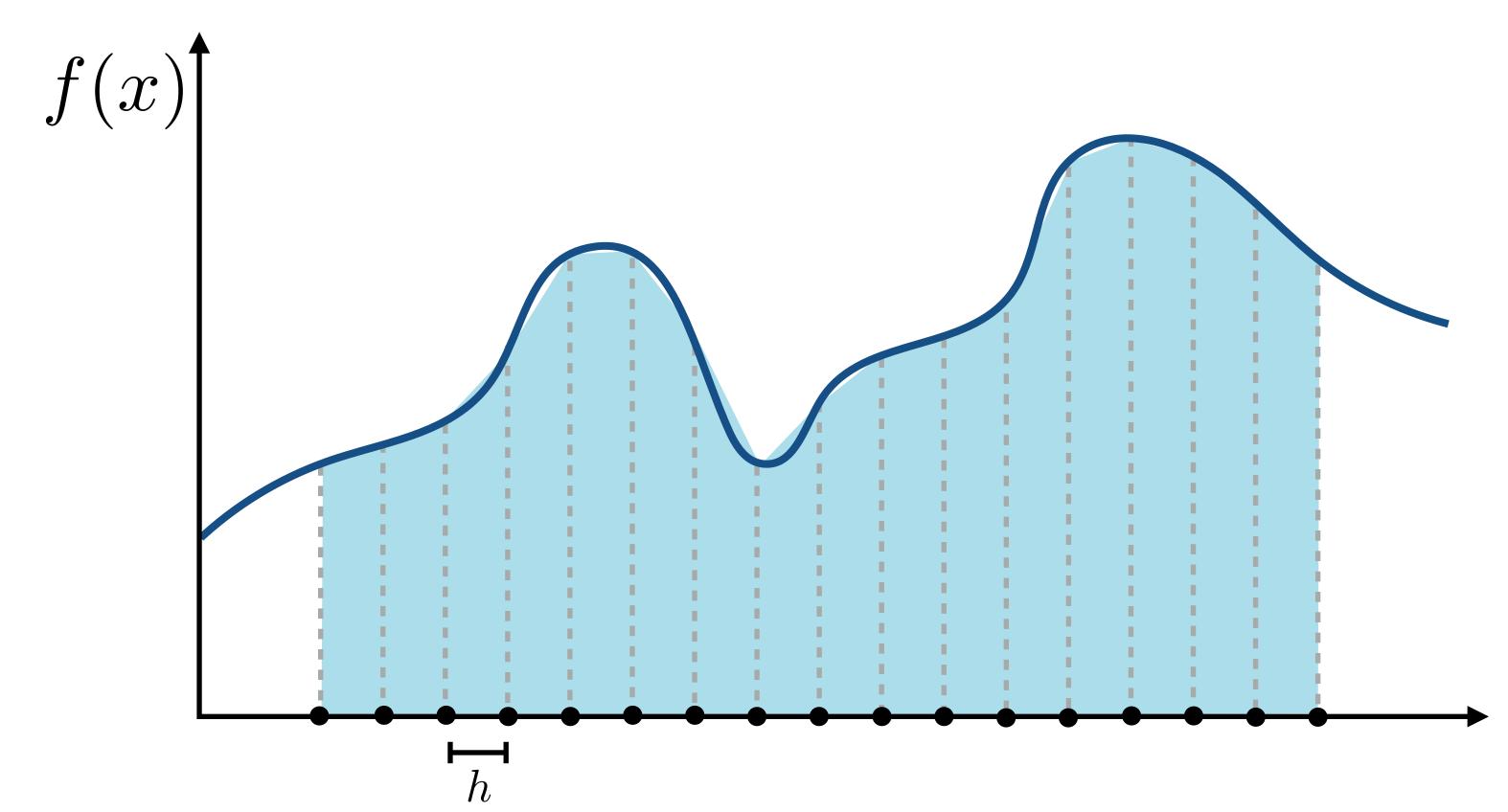


Trapezoidal rule

Consider cost and accuracy of estimate as $n \to \infty$ (or $h \to 0$)

Work: O(n)

Error can be shown to be: $O(h^2) = O(\frac{1}{n^2})$ (for f(x) with continuous second derivative)



Integration in 2D

Consider integrating f(x, y) using the trapezoidal rule (apply rule twice: when integrating in x and in y)

$$\int_{a_y}^{b_y} \int_{a_x}^{b_x} f(x,y) dx dy = \int_{a_y}^{b_y} \left(O(h^2) + \sum_{i=0}^n A_i f(x_i,y)\right) dy$$
 First application of rule
$$= O(h^2) + \sum_{i=0}^n A_i \int_{a_y}^{b_y} f(x_i,y) dy$$

$$= O(h^2) + \sum_{i=0}^n A_i \left(O(h^2) + \sum_{j=0}^n A_j f(x_i,y_j)\right)$$
 Second application
$$= O(h^2) + \sum_{i=0}^n \sum_{j=0}^n A_i A_j f(x_i,y_j)$$

Errors add, so error still: $O(h^2)$

But work is now: $O(n^2)$

(n x n set of measurements)

Must perform much more work in 2D to get same error bound on integral!

In K-D, let
$$N=n^k$$

Error goes as:
$$O\left(\frac{1}{N^{2/k}}\right)$$

Monte Carlo integration

Monte Carlo numerical integration

- Estimate value of integral using random sampling of function
 - Value of estimate depends on random samples used
 - But algorithm gives the correct value of integral "on average"
- Only requires function to be evaluated at random points on its domain
 - Applicable to functions with discontinuities, functions that are impossible to integrate directly
- Error of estimate is independent of the dimensionality of the integrand
 - Depends on the number of random samples used: $O(n^{1/2})$

Monte Carlo algorithms

Advantages

- Easy to implement
- Easy to think about (but be careful of subtleties)
- Robust when used with complex integrands (lights, BRDFs) and domains (shapes)
- Efficient for high-dimensional integrals
- Efficient when only need solution at a few points

Disadvantages

- Noisy
- Slow (many samples needed for convergence)

Review: random variables

 $X \hspace{1cm}$ random variable. Represents a distribution of potential values

 $X \sim p(x)$ probability density function (PDF). Describes relative probability of a random process choosing value x

Uniform PDF: all values over a domain are equally likely

e.g., for an unbiased die

X takes on values 1,2,3,4,5,6

$$p(1) = p(2) = p(3) = p(4) = p(5) = p(6)$$



Discrete probability distributions

n discrete values x_i

With probability p_i

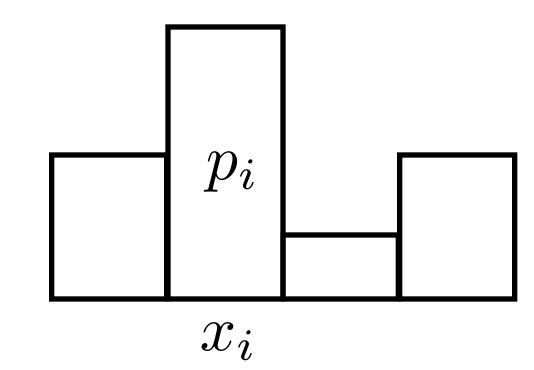
Requirements of a PDF:

$$p_i \ge 0$$

$$\sum_{i=1}^{n} p_i = 1$$

Six-sided die example:
$$p_i = \frac{1}{6}$$

Think: p_i is the probability that a random measurement of X takes on the value x_i with probability p_i



will yield the value \boldsymbol{x}_i

Cumulative distribution function (CDF)

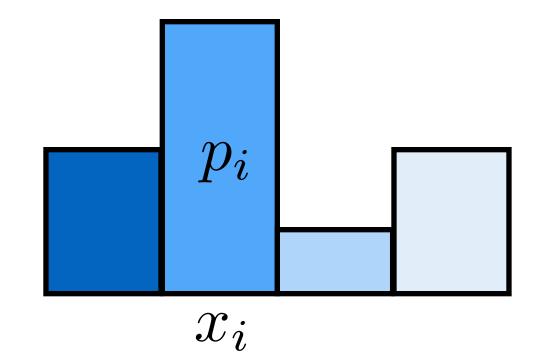
(For a discrete probability distribution)

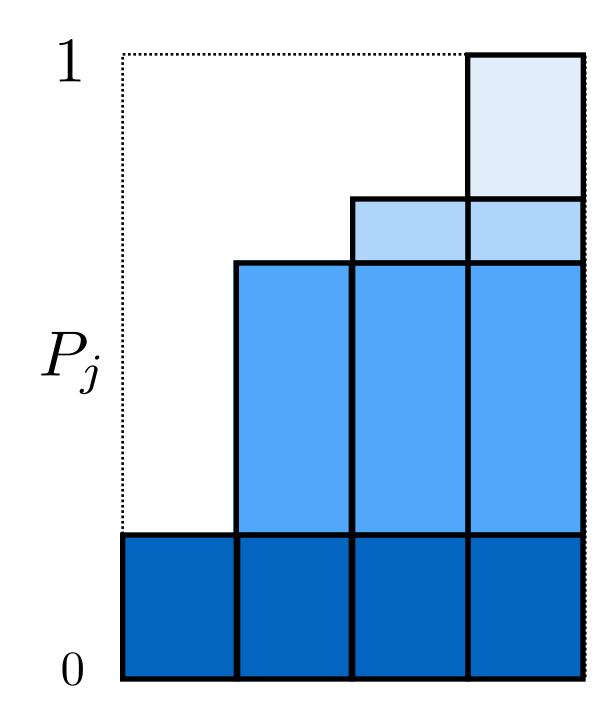
Cumulative PDF:
$$P_j = \sum_{i=1}^{J} p_i$$

where:

$$0 \le P_i \le 1$$

$$P_n = 1$$





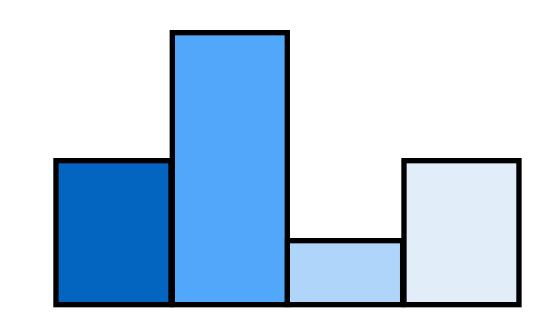
Sampling from discrete probability distributions

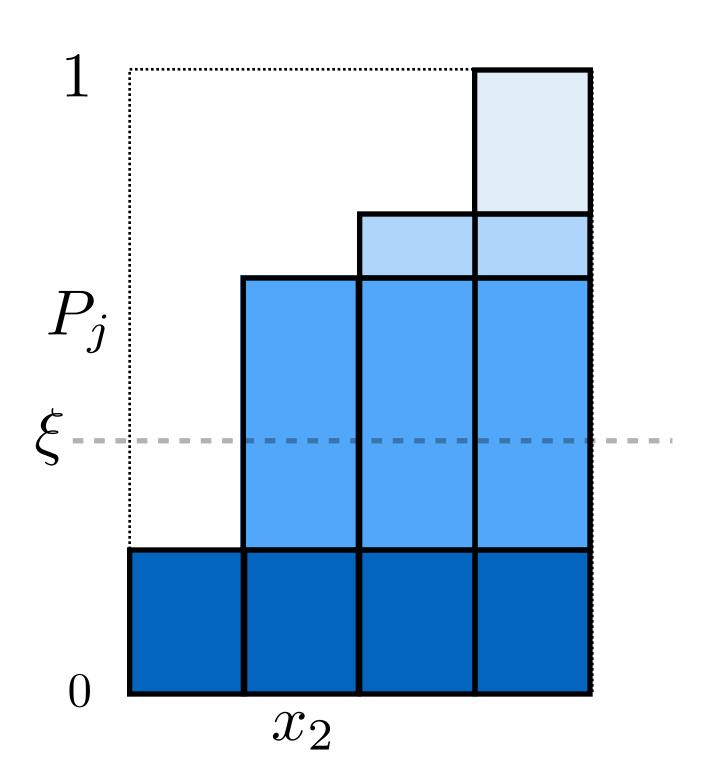
How do we generate samples of a discrete random variable (with a known PDF?)

To randomly select an event, select x_i if

$$P_{i-1} < \xi \le P_i$$

Uniform random variable $\in [0,1)$





Continuous probability distributions

PDF
$$p(x)$$

$$p(x) \ge 0$$

$\mathsf{CDF}\ P(x)$

$$P(x) = \int_0^x p(x) \, \mathrm{d}x$$

$$P(x) = \Pr(X < x)$$

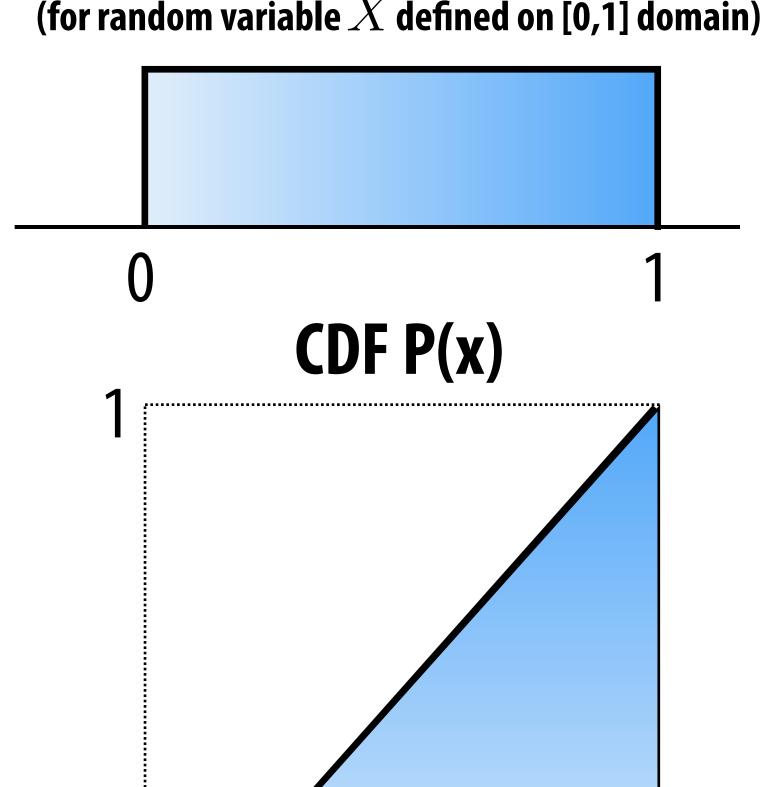
$$P(1) = 1$$

$$\Pr(a \le X \le b) = \int_a^b p(x) \, \mathrm{d}x$$

$$= P(b) - P(a)$$

Uniform distribution: p(x) = c

(for random variable X defined on [0,1] domain)



Sampling continuous random variables using the inversion method

Cumulative probability distribution function

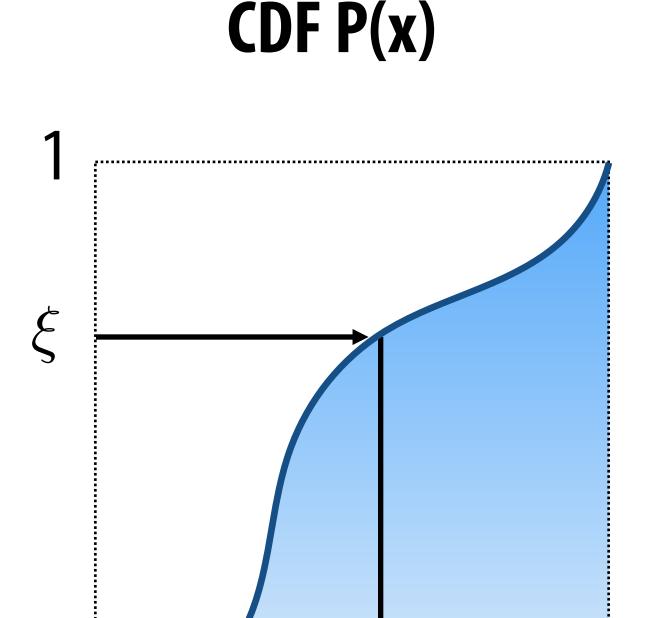
$$P(x) = \Pr(X < x)$$

Construction of samples:

Solve for
$$x = P^{-1}(\xi)$$

Must know the formula for:

- 1. The integral of p(x)
- 2. The inverse function $P^{-1}(x)$

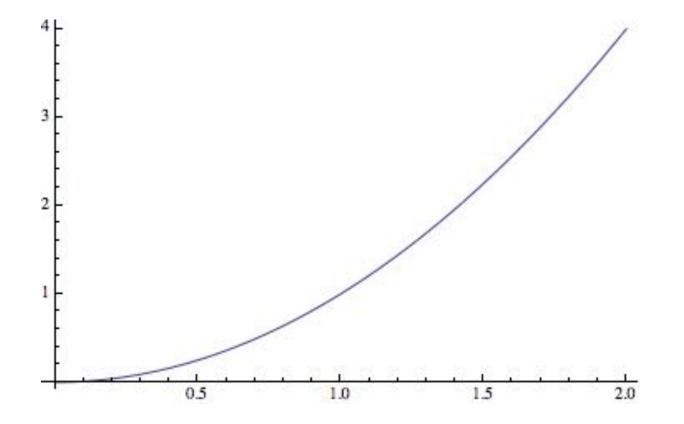


Example: applying the inversion method

Relative density of probability Given: of random variable taking on value *x* over [0,2] domain

$$f(x) = x^2$$
 $x \in [0, 2]$

$$x \in [0, 2]$$



Compute PDF from f(x):

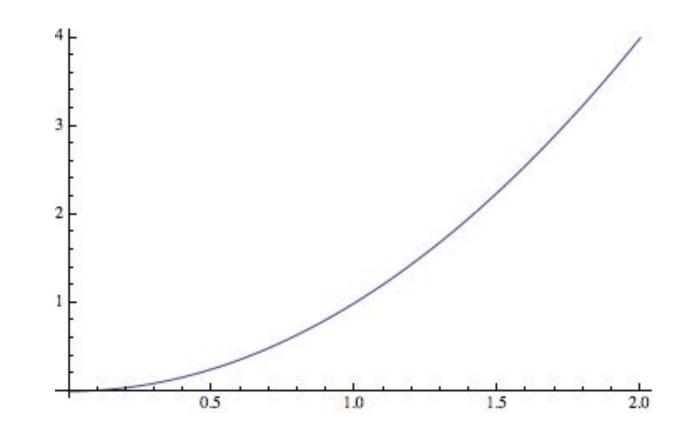
$$\begin{split} 1 &= \int_0^2 c \, f(x) \, \mathrm{d}x \\ &= c(F(2) - F(0)) \qquad F(x) = \frac{1}{3} x^3 \\ &= c \frac{1}{3} 2^3 \\ &= \frac{8c}{3} \longrightarrow c = \frac{3}{8}, \quad p(x) = \frac{3}{8} x^2 \longleftarrow \text{ Probability density function (integrates to 1)} \end{split}$$

Example: applying the inversion method

Given:

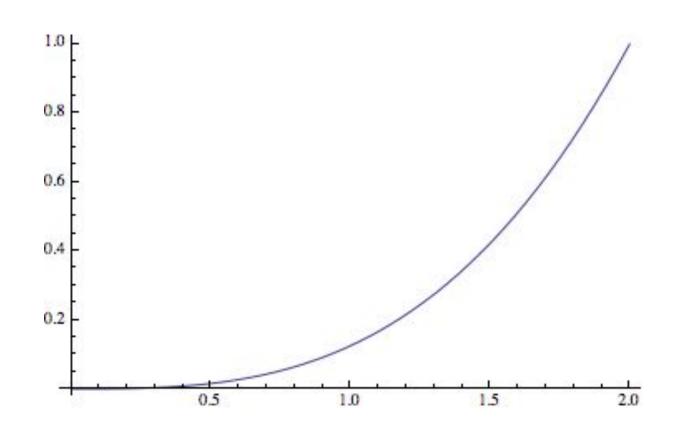
$$f(x) = x^2 \quad x \in [0, 2]$$

 $p(x) = \frac{3}{8}x^2$



Compute CDF:

$$P(x) = \int_0^x p(x) dx$$
$$= \frac{x^3}{8}$$



Example: applying the inversion method

Given:

$$f(x) = x^2 \quad x \in [0, 2]$$

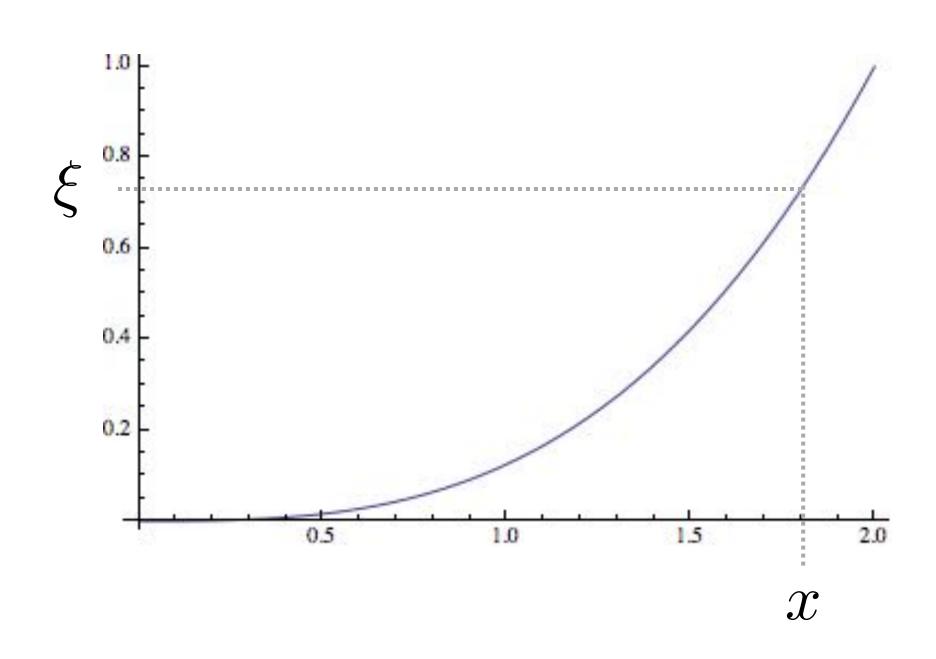
$$p(x) = \frac{3}{8}x^2$$

$$P(x) = \frac{x^3}{8}$$

Sample from p(x)

$$\xi = P(x) = \frac{x^3}{8}$$

$$x = \sqrt[3]{8\xi}$$



How do we uniformly sample the unit circle?

(Choose any point P=(px, py) in circle with equal probability)

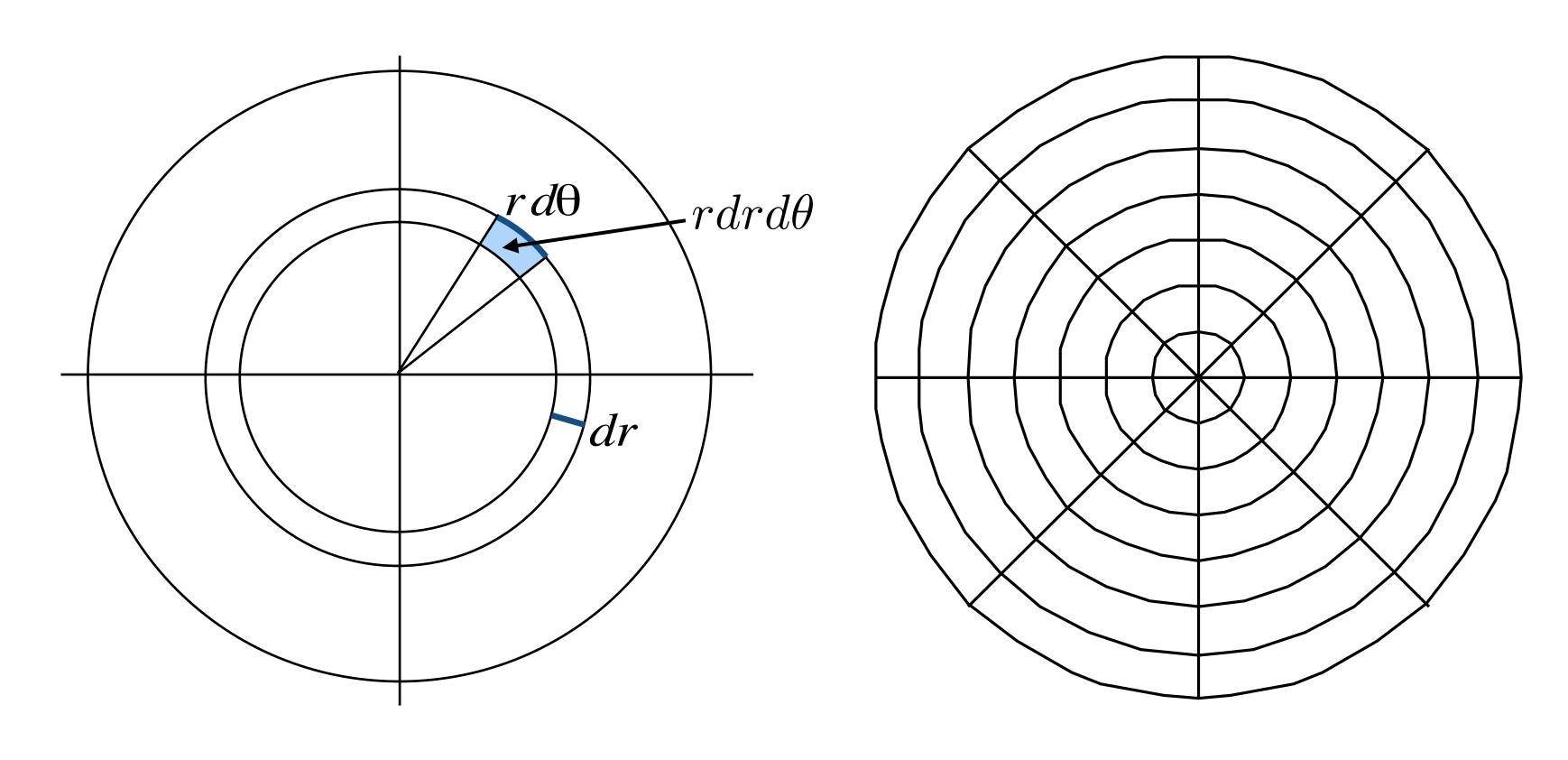
Uniformly sampling unit circle: first try

- lacksquare = uniform random angle between 0 and 2π
- \blacksquare r = uniform random radius between 0 and 1
- Return point: $(r \cos \theta, r \sin \theta)$

This algorithm <u>does not</u> produce the desired uniform sampling of the area of a circle. Why?

Because sampling is not uniform in area!

Points farther from center of circle are less likely to be chosen



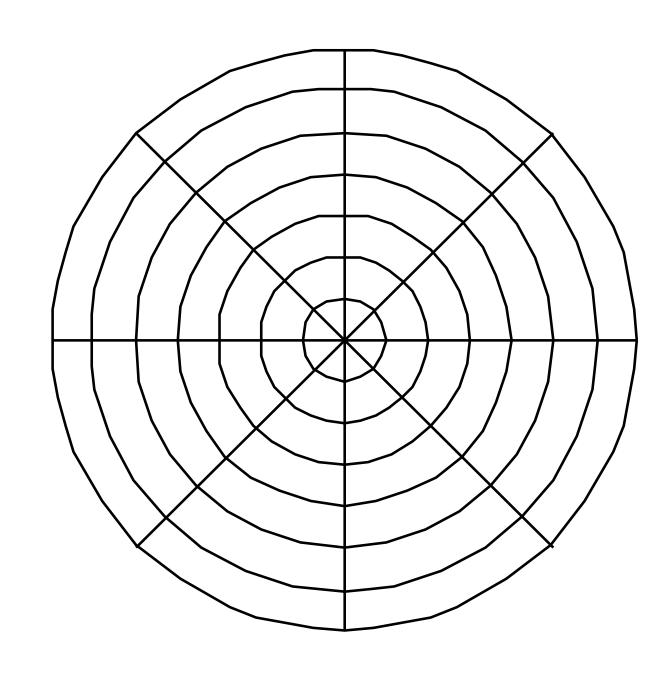
$$\theta = 2\pi \xi_1 \qquad r = \xi_2$$

$$r=\xi_2$$

$$p(r,\theta)drd\theta \sim rdrd\theta$$
 $p(r,\theta) \sim r$

Uniform area sampling of a circle

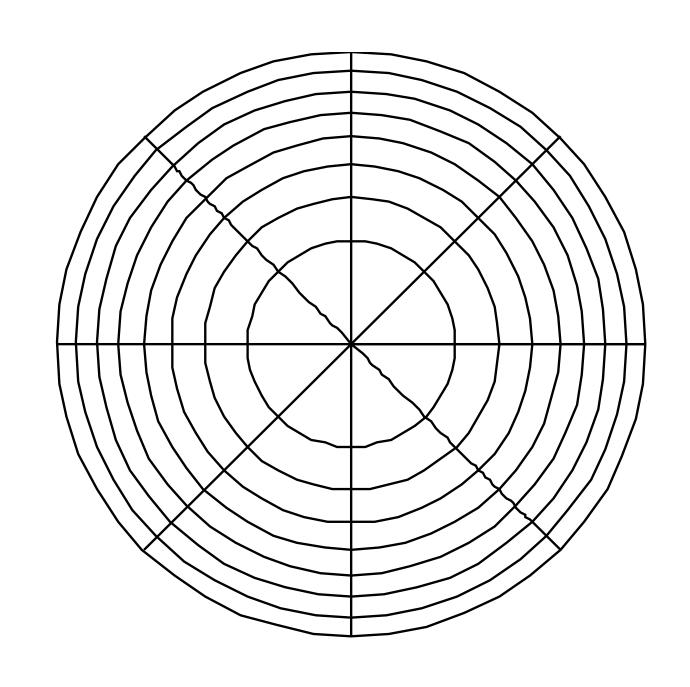
WRONG Not Equi-areal



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

$$r=\xi_2$$

RIGHT Equi-areal



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

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

Sampling a circle (via inversion in 2D)

$$A = \int_0^{2\pi} \int_0^1 r \, dr \, d\theta = \int_0^1 r \, dr \int_0^{2\pi} d\theta = \left(\frac{r^2}{2}\right) \Big|_0^1 \theta \Big|_0^{2\pi} = \pi$$

$$p(r, \theta) dr d\theta = \frac{1}{\pi} r dr d\theta \rightarrow p(r, \theta) = \frac{r}{\pi}$$

$$p(r,\theta) = p(r)p(\theta) \longleftarrow r, \theta$$
 independent

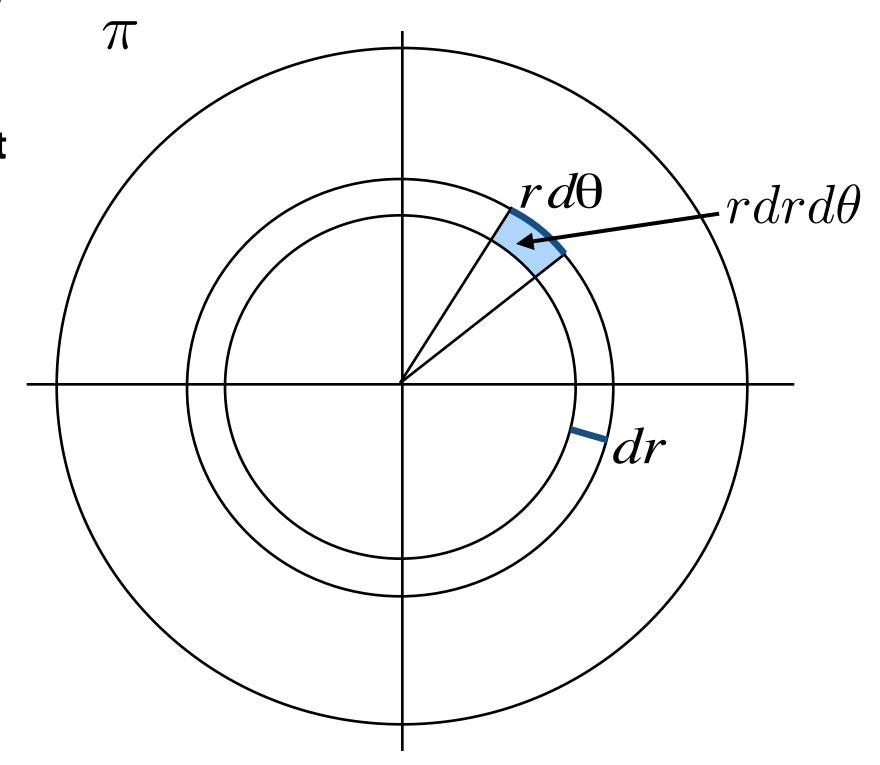
$$p(\theta) = \frac{1}{2\pi}$$

$$P(\theta) = \frac{1}{2\pi}\theta \qquad \theta = 2\pi\xi_1$$

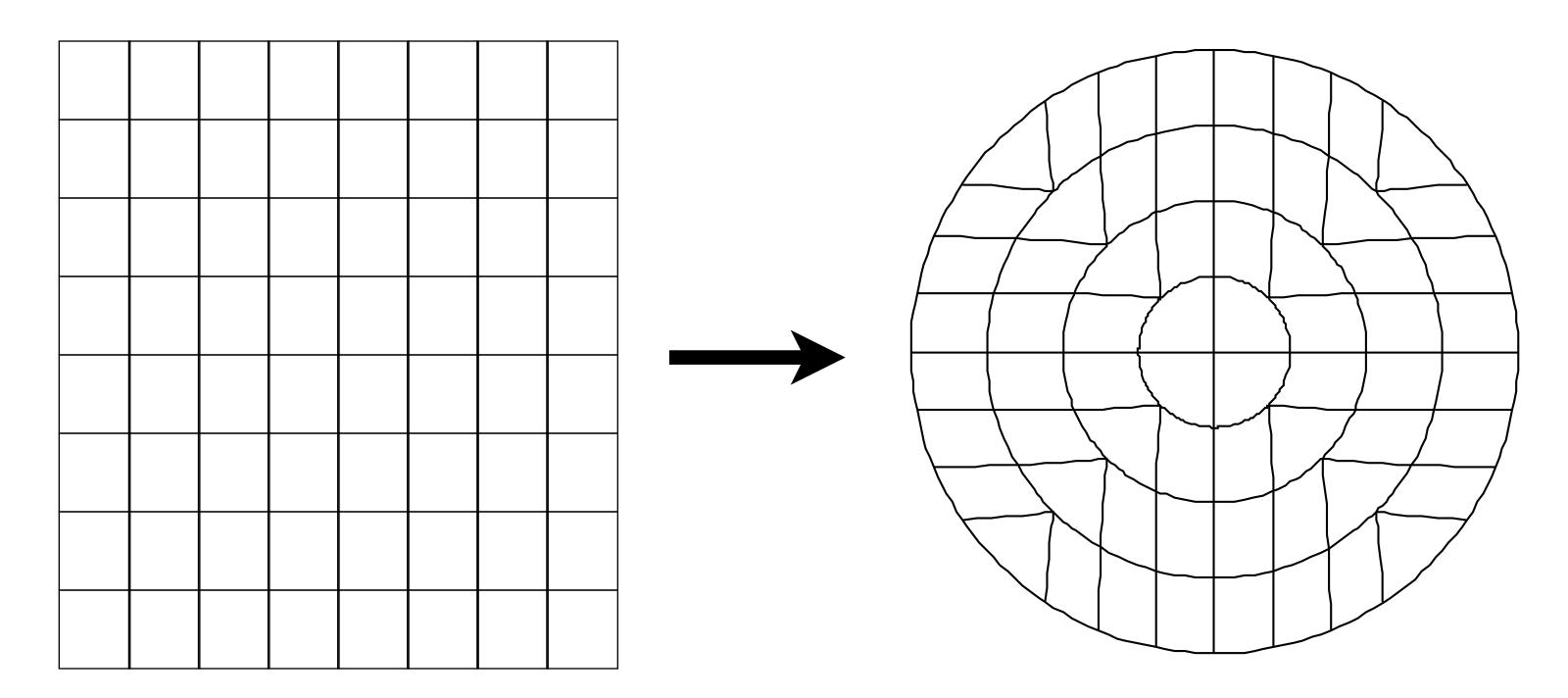
$$p(r) = 2r$$

$$P(r) = r^2$$

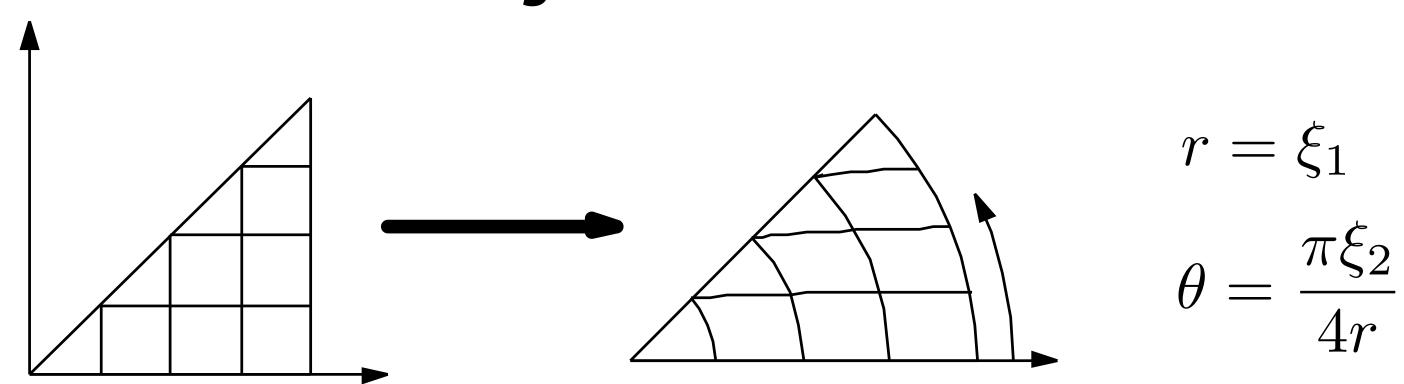
$$r = \sqrt{\xi_2}$$



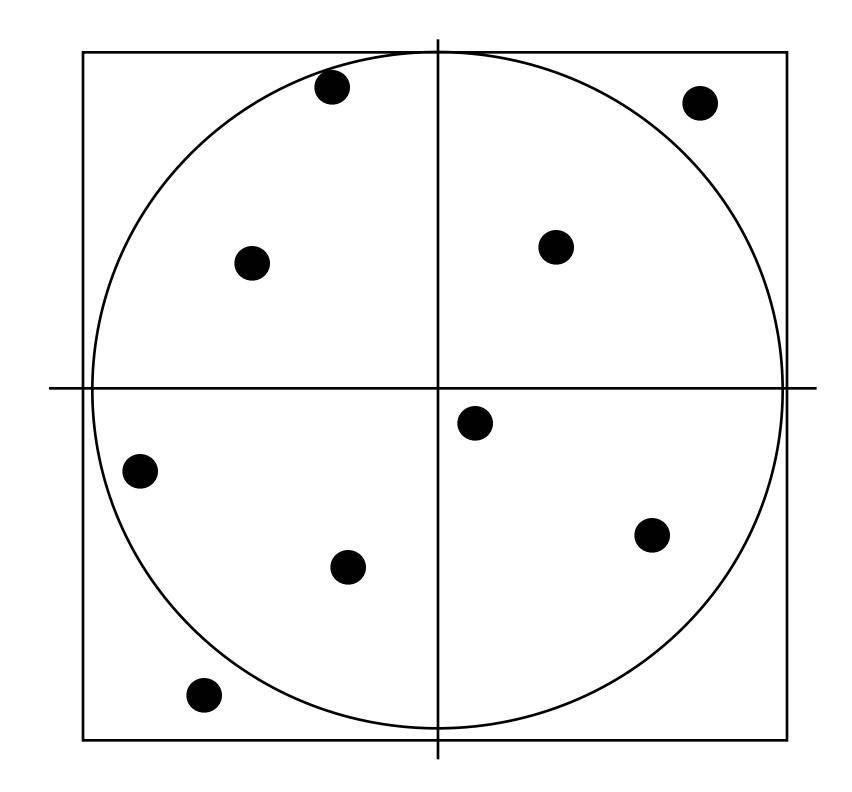
Shirley's mapping



Distinct cases for eight octants



Uniform sampling via rejection sampling

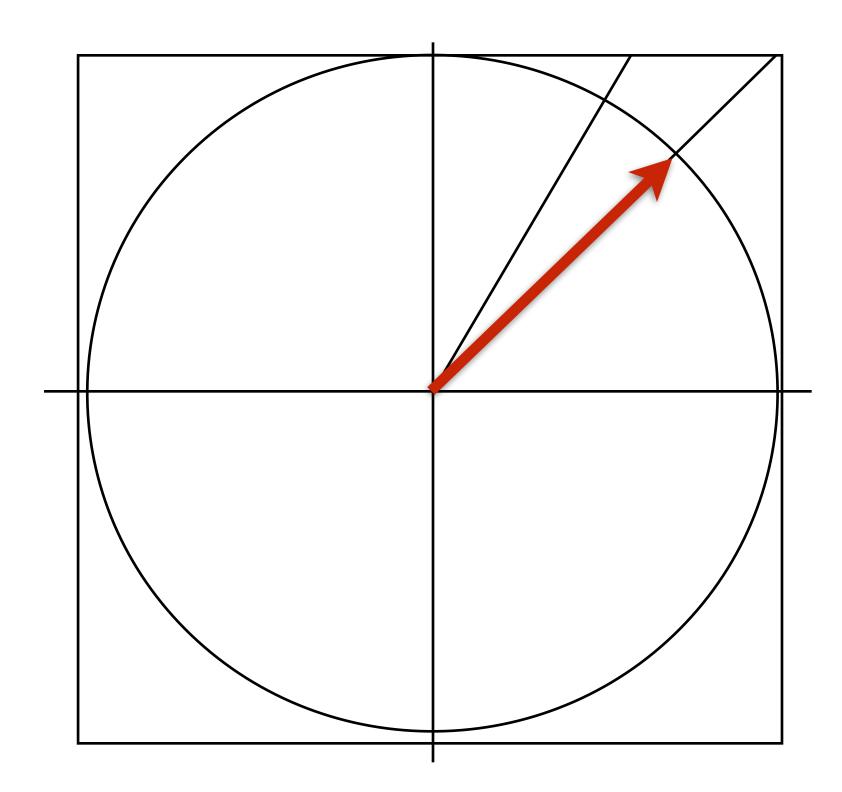


Generate random point within unit circle

```
do {
   x = uniform(-1,1);
   y = uniform(-1,1);
} while (x*x + y*y > 1.);
```

Efficiency of technique: area of circle / area of square

Rejection sampling to generate 2D directions



Goal: generate random directions in 2D with uniform probability

```
x = uniform(-1,1);
y = uniform(-1,1);

r = sqrt(x*x+y*y);
x_dir = x/r;
y_dir = y/r;
```

This algorithm is not correct! What is wrong? What's a better algorithm?

Monte Carlo integration

Definite integral

What we seek to estimate

Random variables

 X_i is the value of a random sample drawn from the distribution $\,p(x)\,$ Y_i is also a random variable.

Expectation of f

Estimator

Monte Carlo estimate of $\int_{a}^{b} f(x) dx$

Assuming samples X_i drawn from uniform pdf. I will provide estimator for arbitrary PDFs later in lecture.

$$\int_{a}^{b} f(x)dx$$

$$X_i \sim p(x)$$
$$Y_i = f(X_i)$$

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

$$F_N = \frac{b - a}{N} \sum_{i=1}^{N} Y_i$$

Basic unbiased Monte Carlo estimator

Unbiased estimator:
Expected value of estimator is the integral we wish to evaluate.

Properties of expectation:

$$E\left[\sum_{i} Y_{i}\right] = \sum_{i} E[Y_{i}]$$

$$E[aY] = aE[Y]$$

$$\begin{split} E[F_N] = & E\left[\frac{b-a}{N}\sum_{i=1}^N Y_i\right] \\ = & \frac{b-a}{N}\sum_{i=1}^N E[Y_i] = \frac{b-a}{N}\sum_{i=1}^N E[f(X_i)] \\ = & \frac{b-a}{N}\sum_{i=1}^N \int_a^b f(x)\,p(x)\mathrm{d}x \\ = & \frac{1}{N}\sum_{i=1}^N \int_a^b f(x)\,\mathrm{d}x \quad \text{probability density for now} \\ = & \int_a^b f(x)\,\mathrm{d}x \quad p(x) = \frac{1}{b-a} \end{split}$$

Acknowledgements

■ Thanks to Keenan Crane, Ren Ng, Pat Hanrahan and Matt Pharr for presentation resources