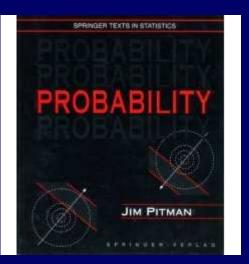
Stat 134 FAll 2005 Berkeley



Lectures prepared by: Elchanan Mossel Yelena Shvets

Introduction to probability

Follows Jim Pitman's book: Probability Section 4.1

Examples of Continuous Random Variables

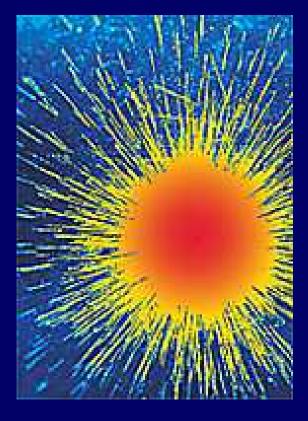
Example 1:

X -- The distance traveled by a golf-ball hit by Tiger Woods is a continuous random variable.



PointedMagazine.com

Examples of Continuous Random Variables

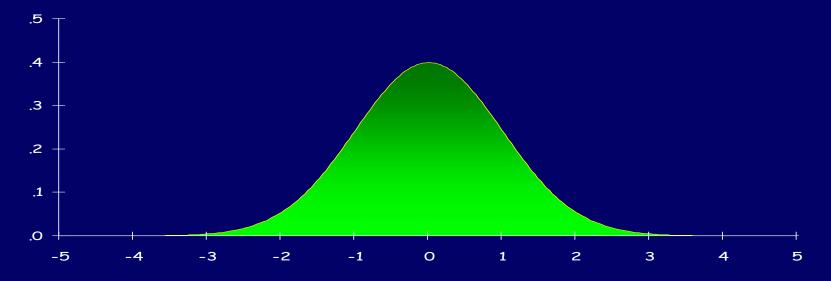


Example 2: Y - The total radioactive emission per time interval is a continuous random variable.

BANGI Colored images of the radioactive emission of a**-particles from radium.** C. POWELL, P. FOWLER & D. PERKINS/SCIENCE PHOTO LIBRARY

Examples of Continuous Random variables

$\frac{\text{Example 3:}}{Z \sim N(0,1)} - Z \sim N(0,1) - Z \text{ approximates (Bin(10000,1/2)-5000)/50} \text{ random variable.}$



How can we specify distributions?

What is P {X_{tiger}=100.1 ft} = ?? P {X_{tiger}=100.0001 ft}=??



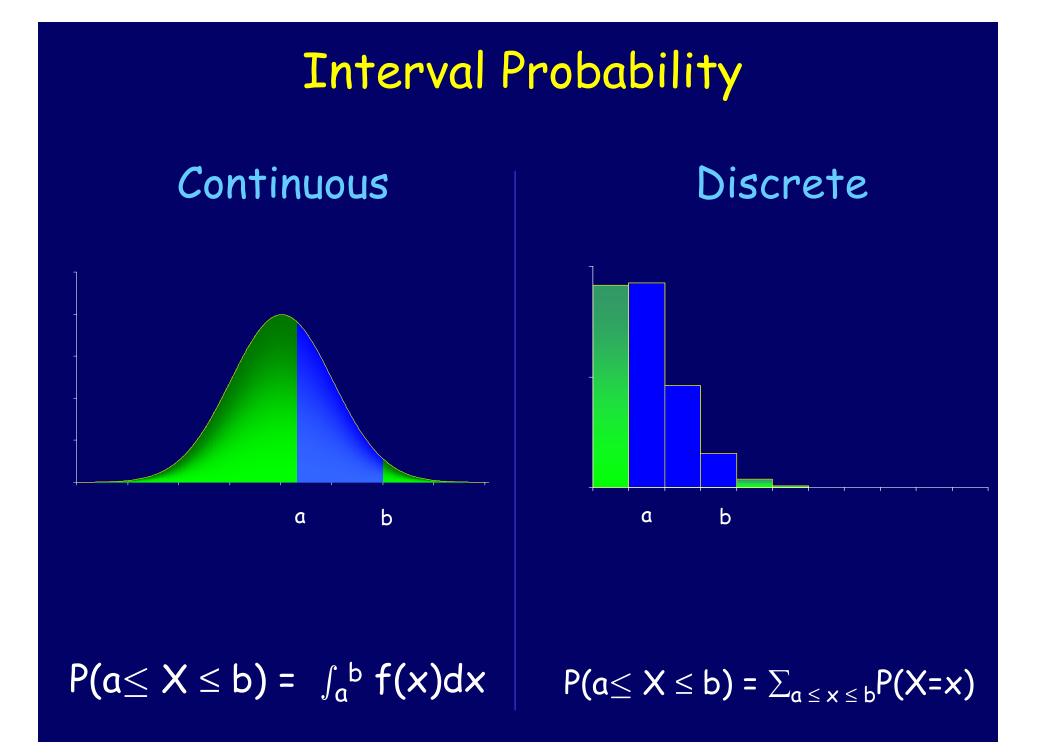
Photo by Allen Eyestone, www.palmbeachpost.com

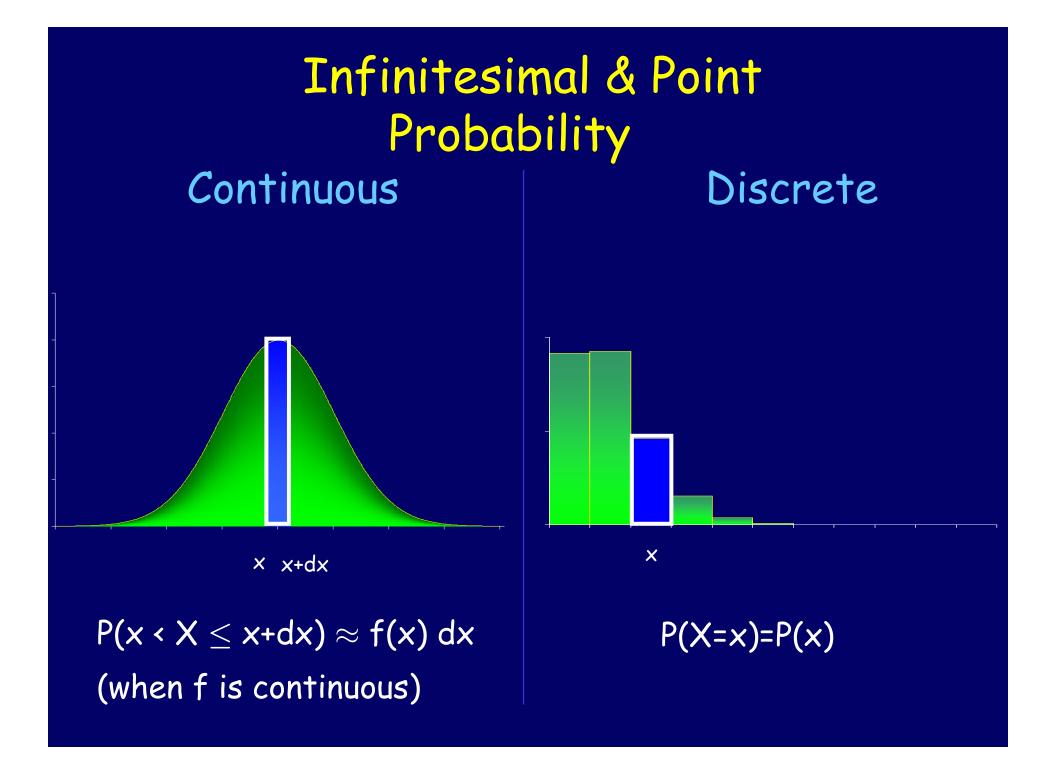
Continuous Distributions

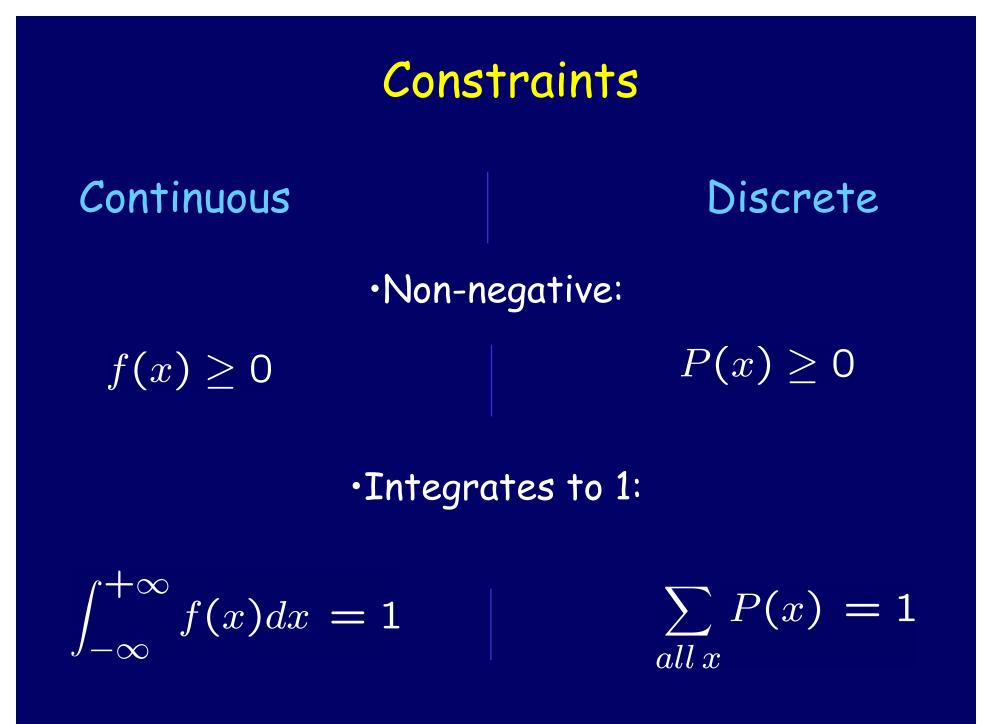
- Continuous distributions are determined by a probability density f.
- Probabilities are defined by areas under the graph of f.
- Example: For the golf hit we will have:

 $P(99.9 < X < 100.1) = \int_{99.9}^{100.1} f_{tiger}(x) dx$

where f_{tiger} is the probability density of X.







Expectations Continuous Discrete •Expectation of a function g(X): $E(g(X)) = \int_{-\infty}^{+\infty} g(x)f(x) \, dx \qquad E(g(X)) = \sum_{x} g(x)P(x)$ all x Variance and SD: $Var(X) = E[(X - E(X))^2]$ $SD(X) = \sqrt{Var(X)}$

Independence

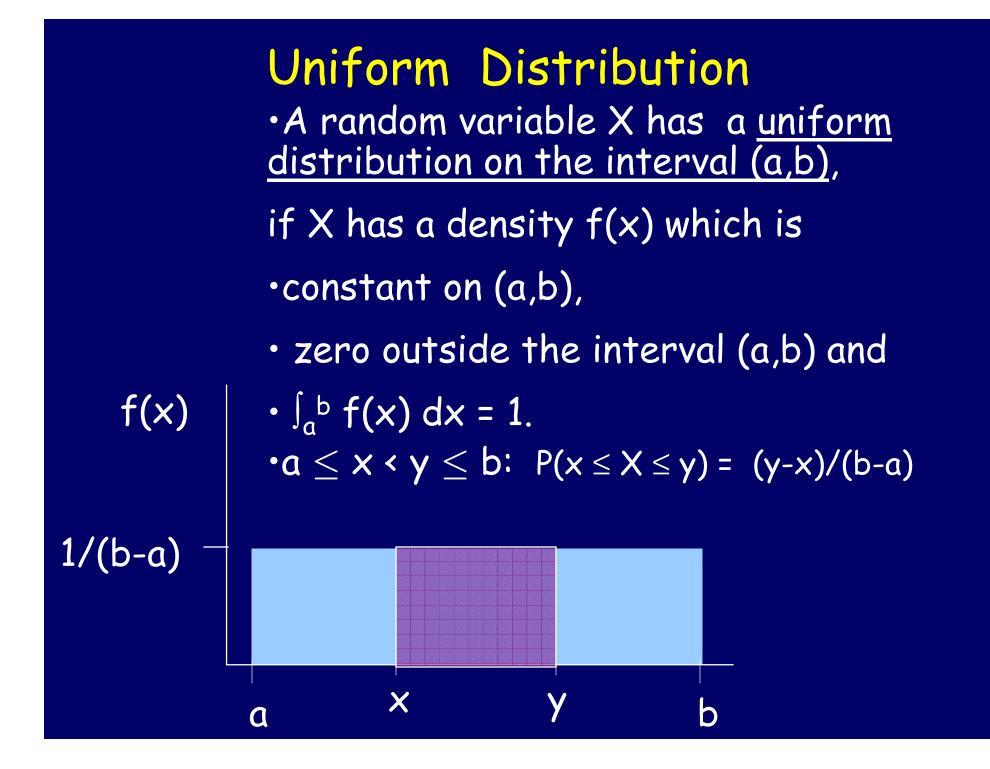
Continuous Discrete

Random Variables X and Y are independent

• For all intervals A and B: $P[X \in A, Y \in B] =$ $P[X \in A] P[Y \in B].$

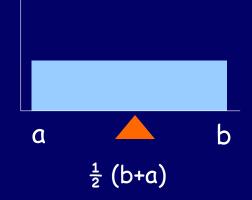
. This is equivalent to saying that for all sets A and B: $P[X \in A, Y \in B] =$ $P[X \in A] P[Y \in B].$ For all x and y:
P[X = x, Y = y] =
P[X=x] P[Y=y].

• This is equivalent to saying that for all sets A and B: $P[X \in A, Y \in B] =$ $P[X \in A] P[Y \in B].$



Expectation and Variance of Uniform Distribution

•E(X) = $\int_{a}^{b} x/(b-a) dx = \frac{1}{2} (b+a)$



$$\cdot E(X^2) = \int_a^b x^2/(b-a) dx = 1/3 (b^2+ba+a^2)$$

Var(X) = $E(X^2) - E(X)^2 = 1/3 (b^2+ba+a^2) - \frac{1}{4}(b^2+2ba+a^2)$ = $1/12 (b-a)^2$

Uniform (0,1) Distribution:

f(x)

1

•If X is uniform(a,b) then U = (X-a)/(b-a) is uniform(0,1). So:

•E(U) = $\frac{1}{2}$, E(U²) = $\int_0^1 x^2 dx = 1/3$

Var(U) = $1/3 - (\frac{1}{2})^2 = 1/12$

Using X = U(b-a) + a: E(X) = E[U(b-a) + a] = (b-a) E[U] + a= (b-a)/2 + a = (b+a)/2

1

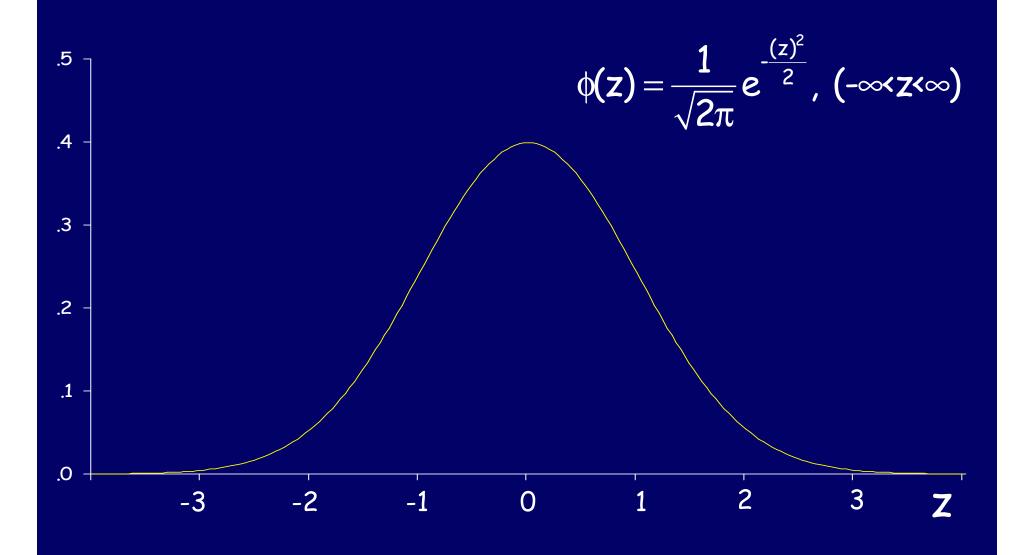
 $Var(X) = Var[U (b-a) + a] = (b-a)^2 Var[U] = (b-a)^2 / 12^3$

The Standard Normal Distribution

<u>Def:</u> A continuous random variable Z has a <u>standard normal distribution</u> if Z has a probability density of the following form:

$$\phi(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(z)^2}{2}}, \ (-\infty < z < \infty)$$

The Standard Normal Distribution



Standard Normal Integrals

 $\int_{-\infty}^{+\infty} \phi(z) dz = 1$

 $E(Z) = \int_{-\infty}^{+\infty} z\phi(z)dz = 0$

 $Var(Z) = \int_{-\infty}^{+\infty} z^2 \phi(z) dz = 1$

Standard Normal Cumulative Distribution Function:

 $\Phi(z) = \int_{-\infty}^{\infty} \phi(x) dx$

 $P(a \le Z \le b) = \Phi(b) - \Phi(a);$

The value of Φ are tabulated in the standard normal table.

The Normal Distribution

<u>Def:</u> If Z has a standard normal distribution and μ and $\sigma > 0$ are constants then X = σ Z + μ has a <u>Normal(μ , σ^2) distribution</u>

<u>Claim</u>: X has the following density:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \ (-\infty < x < \infty)$$

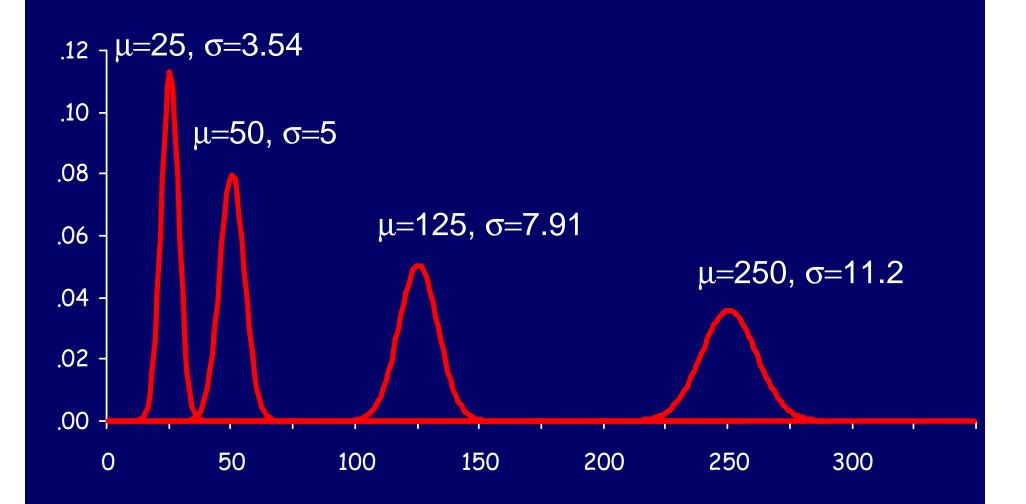
We'll see a proof of this claim later

The Normal Distribution •Suppose X = σ Z + μ has a normal(μ , σ^2) distribution, Then: P(c \leq X \leq d) = P(c $\leq \sigma$ Z + $\mu \leq$ d) = P((c- μ)/ $\sigma \leq$ Z \leq (d- μ)/ σ) = $\Phi((c-\mu)/\sigma) - \Phi((d-\mu)/\sigma)$,

And:

 $E(X) = E(\sigma Z + \mu) = \sigma E(Z) + \mu = \mu$ $Var(X) = Var(\sigma Z + \mu) = \sigma^2 E(Z) = \sigma^2$

Normal(μ, σ^2);



Example: Radial Distance

•A dart is thrown at a circular target of radius 1 by a novice dart thrower. The point of contact is uniformly distributed over the entire target.

• Let R be the distance of the hit from the center. Find the probability density of R.

- Find $P(a \le R \le b)$.
- Find the mean and variance of R.

• Suppose 100 different novices each throw a dart. What's the probability that their mean distance from the center is at least 0.7.



Radial Distance

Let R be the distance of the hit from the center.
 Find the probability density of R.

P(R \in (r,r+dr)) = Area of annulus/ total area = $(\pi(r+dr)^2 - \pi r^2)/\pi$ = 2rdr

r+d

$$f(r) = \begin{cases} 2r, \text{ if } 0 \le r \le 1\\ 0, \text{ otherwise.} \end{cases}$$

Radial DistanceWith $f(r) = \begin{cases} 2r, & \text{if } 0 \leq r \leq 1 \\ 0, & \text{otherwise.} \end{cases}$

• Find $P(a \le R \le b)$.

$$P(a \le R \le b) = \int_{a}^{b} 2r \, dr = b^2 - a^2$$

Find the mean and variance of R.

$$E(R) = \int_0^1 2r^2 dr = \frac{2}{3}$$

$$Var(R) = E(R^2) - E(R)^2 = \int_0^1 2r^3 dr - E(R)^2$$

$$= \frac{2}{4} - \left(\frac{2}{3}\right)^2 = \frac{1}{18}$$

Radial Distance

 Suppose 100 different novices each throw a dart. What's the probability that their mean distance from the center is at least 0.7.

•Let R_i = distance of the i'th hit from the center, then R_i 's i.i.d. with $E(R_i)=2/3$ and $Var(R_i)=1/18$.

•The average $A_{100} = (R_1 + R_2 + ... + R_{100})/100$ is approximately normal with

$$E(A_{100}) = E(R) = \frac{2}{3}$$

$$SD(A_{100}) = \frac{SD(R)}{\sqrt{100}} = \frac{1}{\sqrt{1800}} \approx 0.0236$$

So: $P(A_{100} \ge 0.7) = 1 - \Phi\left(\frac{0.7 - 0.667}{0.0236}\right) = 1 - \Phi(1.40) = 8.7\%$

Fitting Discrete distributions by Continuous distributions

•Suppose $(x_1, x_2, ..., x_n)$ are sampled from a continuous distribution defined by a density f(x).

- •We expect that the empirical histogram of the data will be close to the density function.
- •In particular, the proportion P_n of observations that fall between a_i and a_j should be well approximated by

 $a_8 a_9$

 $a_{10}a_{11}a_{12}$

a₆

 a_7

as

a

a₁

a₂

az

 $P_n(a_i, a_j) \approx \int_{a_i}^{a_j} \overline{f(x)} \, dx.$

Fitting Discrete distributions by Continuous distributions

More formally, letting

$$I_{(a_i,a_j)}(x) = \begin{cases} 1, & \text{if } a_i \leq x \leq a_j \\ 0, & \text{otherwise.} \end{cases}$$

•We expect that:

$$\frac{1}{n}\sum_{i=1}^{n}I_{(a_i,a_j)}(x_i) = P_n(a_i,a_j) \approx \int_{a_i}^{a_j}f(x)\,dx = \int_{-\infty}^{\infty}I_{(a_i,a_j)}(x)f(x)\,dx.$$

And more generally for functions g we expect:

$$\frac{1}{n}\sum_{i=1}^n g(x_i) \approx \int_{-\infty}^\infty g(x)f(x)\,dx.$$

Fitting Discrete distributions by Continuous distributions

<u>Claim</u>: if $(X_1, X_2, ..., X_n)$ is a sequence of independent random variables each with density f(x) then:

$$P\left(\left|\frac{1}{n}\sum_{i=1}^{n}g(X_i) - \int_{-\infty}^{\infty}g(x)f(x)\,dx\right| > \epsilon\right) \le \frac{Var[g(X)]}{n\epsilon^2}$$

The claim follows from Chebyshev inequality.

Monte Carlo Method

In the Mote-Carlo method the approximation: $\int g(x)f(x) dx \approx 1/n \sum_{i} g(x_{i})$ is used in order to approximate difficult integrals. <u>Example:</u> $\int_{0}^{1} e^{-\cos(x^{3})} dx$ take the density to be Uniform(0,1) and $g(x) = e^{-\cos(x^{3})}$.