

1. Mathematically, continuous and discrete random variables are very different.
2. *Quantitatively* , however, some continuous models are very close to some discrete models.
3. Therefore, which kind of model to use for a given system is a matter of *convenience* .

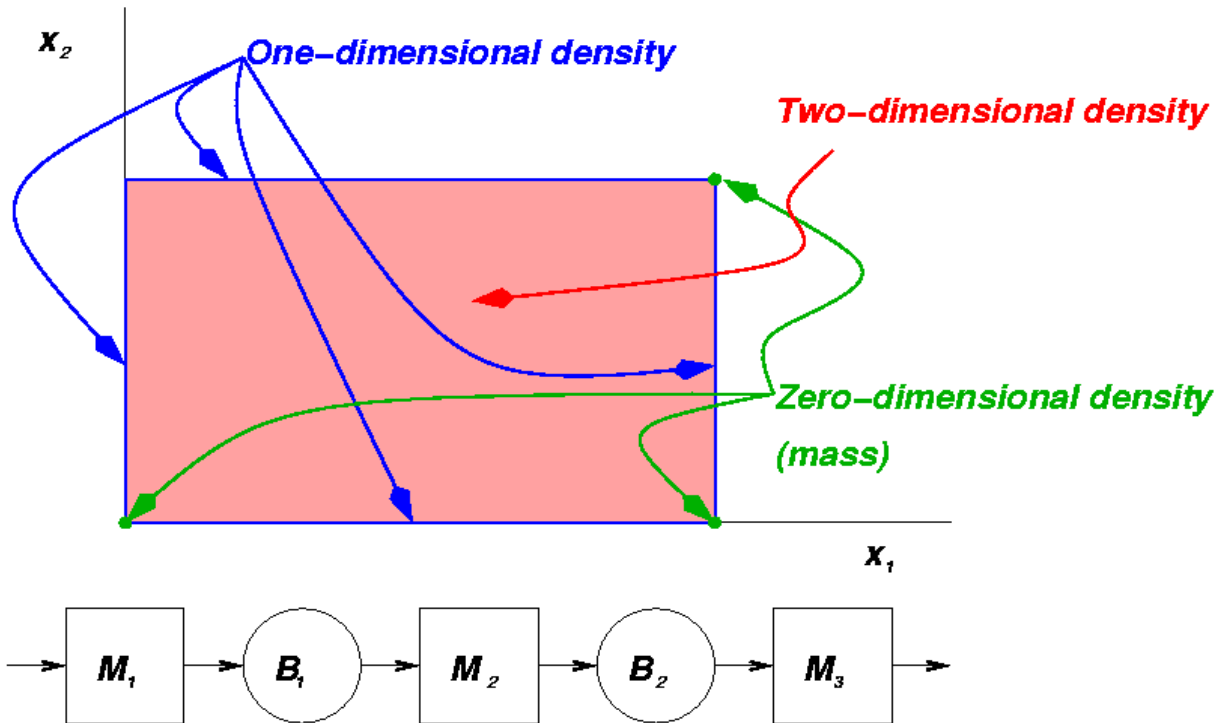
Example: The production process for small metal parts (nuts, bolts, washers, etc.) might better be modeled as a continuous flow than a large number of discrete parts.

- Continuous random variables can be defined
 - ★ in one, two, three, ..., infinite dimensional spaces;
 - ★ in finite or infinite regions of the spaces.
- Continuous random variables can have
 - ★ probability measures with the same dimensionality as the space;
 - ★ lower dimensionality than the space;
 - ★ a mix of dimensions.

Continuous random variables

Spaces

Dimensionality

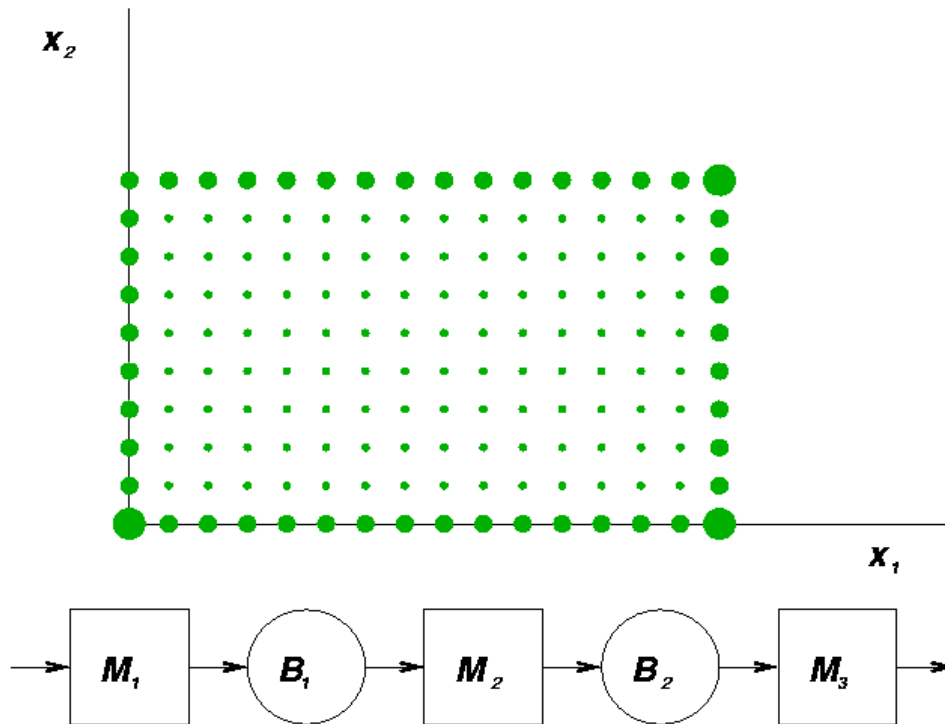


Probability distribution of the amount of material in each of the two buffers.

Continuous random variables

Spaces

Discrete approximation



Probability distribution of the amount of material in each of the two buffers.

Continuous Random Variables

cumulative distribution function (cdf) is

$$F(t) = P(X \leq t) \text{ for all } t$$

probability density function (pdf) is

$$f(t) = \frac{dF(t)}{dt}$$

$$\Pr(a \leq X \leq b) = \int_a^b f(t) dt = F(b) - F(a)$$

$E[X]$ and $VAR(X)$ are similar to discrete case, except you replace sums by integrals

$$E(X) = \int xf(x)dx$$

Example:

IQ test scores are normally distributed with $\mu = 100$ and $\sigma = 10$

What is $P(X > 125)$?

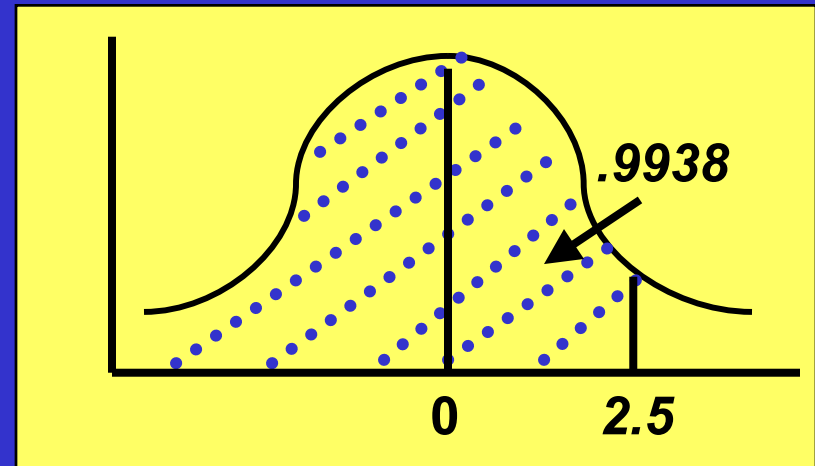
$$= P\left(\frac{X - 100}{10} > \frac{125 - 100}{10}\right)$$

$$= P(Z > 2.5)$$

$$= 1 - P(Z \leq 2.5)$$

$$= 1 - .9938$$

$$= .0062$$



Example:

Manufacturing cycle times are normal with $\mu = 100$ days and $\sigma = 10$ days

You want to quote delivery lead times (= delivery date - current date) so that you achieve 90% on-time delivery

Q: What delivery lead time should you quote?

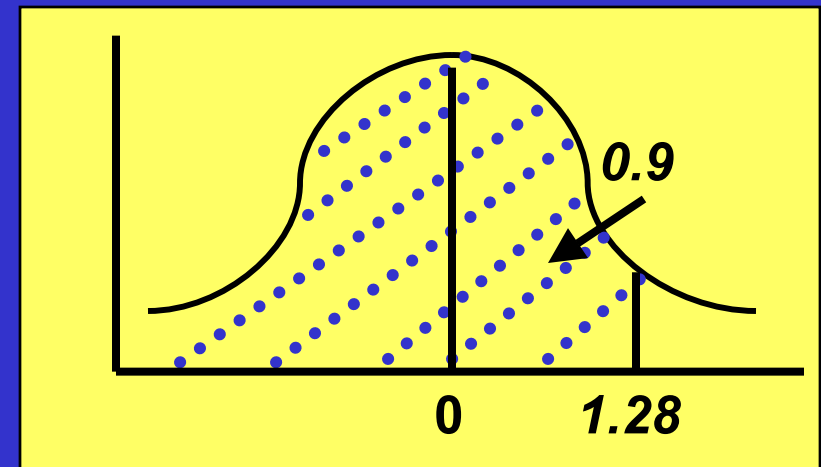
Choose x so that $P(X > x) = .1$

or

$$P\left(\frac{X - 100}{10} > \frac{x - 100}{10}\right) = .1$$
$$P\left(Z > \frac{x - 100}{10}\right) = .1$$

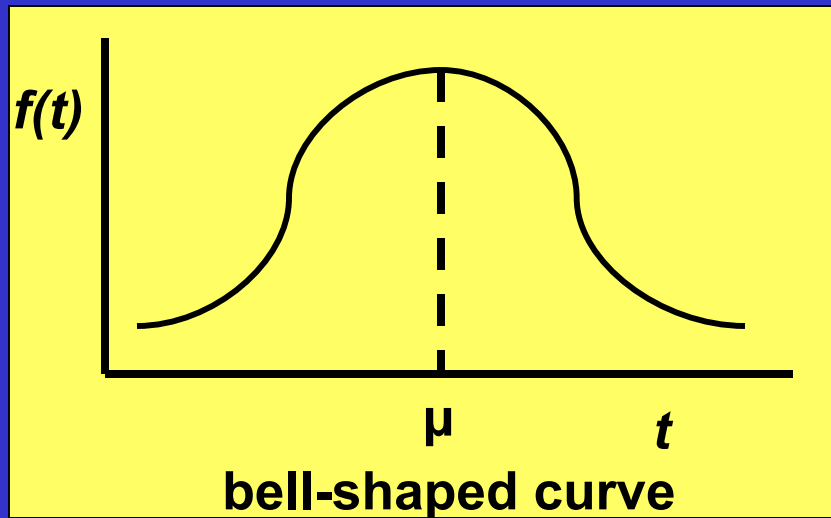
or

$$P\left(Z \leq \frac{x - 100}{10}\right) = .9$$



$$P(Z \leq 1.28) = .9 \quad \text{so} \quad \frac{x - 100}{10} = 1.28 \quad X = 112.8$$

Normal (or Gaussian) Distribution



$$f(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(t-\mu)^2}{2\sigma^2}}$$

mean = μ

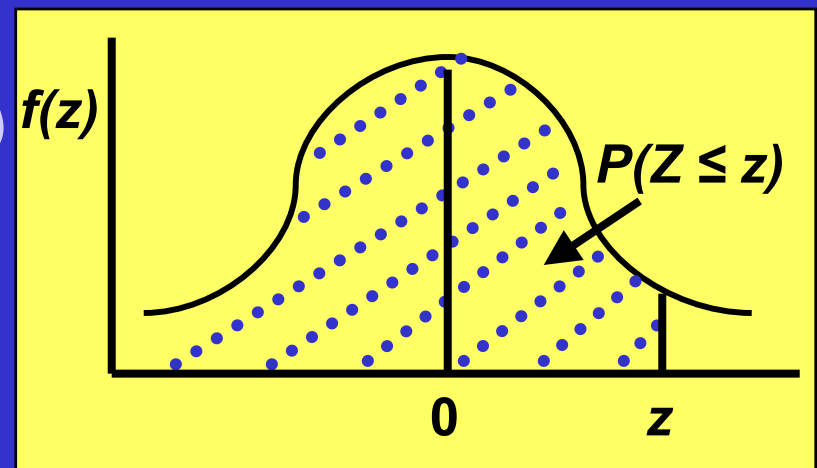
variance = σ^2

X is a $N(\mu, \sigma)$ random variable

Fact: if X and Y are normal,
so is $aX+bY+c$

Statistics books have tables for $Z = N(0,1)$

Fact: if X is $N(\mu, \sigma)$,
then $\frac{X - \mu}{\sigma}$ is $N(0,1)$



Central Limit Theorem

X_1, \dots, X_n are independent and identically distributed with
 $E[X_i] = \mu$ $VAR(X_i) = \sigma^2$

X_i 's are not normal!

Let $S_n = X_1 + \dots + X_n$

Central Limit Theorem for sum: if n is large, then S_n is approximately normal with mean $n\mu$ and standard deviation $\sigma\sqrt{n}$

Let $m_n = \frac{X_1 + \dots + X_n}{n}$

Central Limit Theorem for mean: if n is large, then m_n is approximately normal with mean μ and standard deviation $\frac{\sigma}{\sqrt{n}}$

Dice Graphs

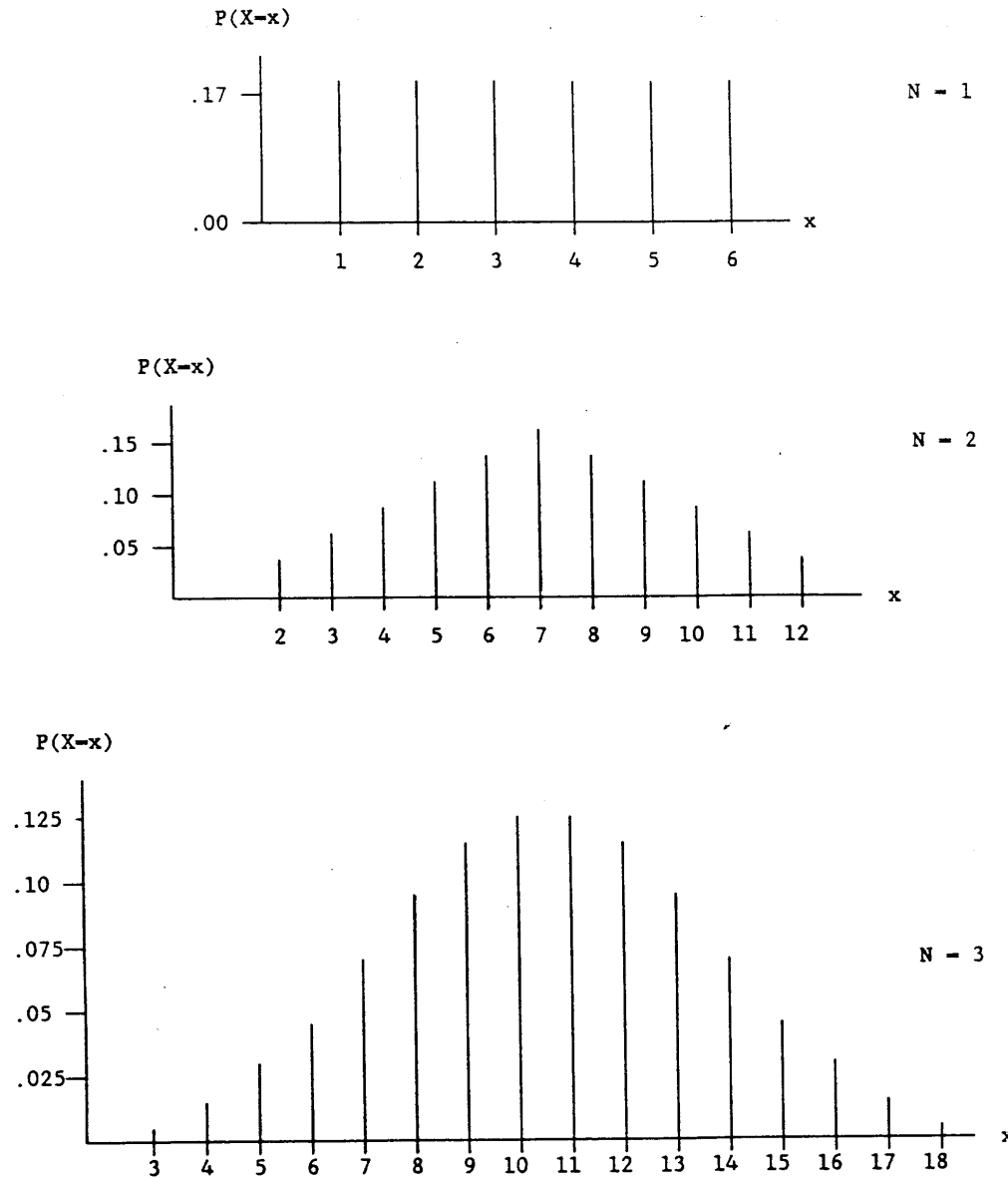
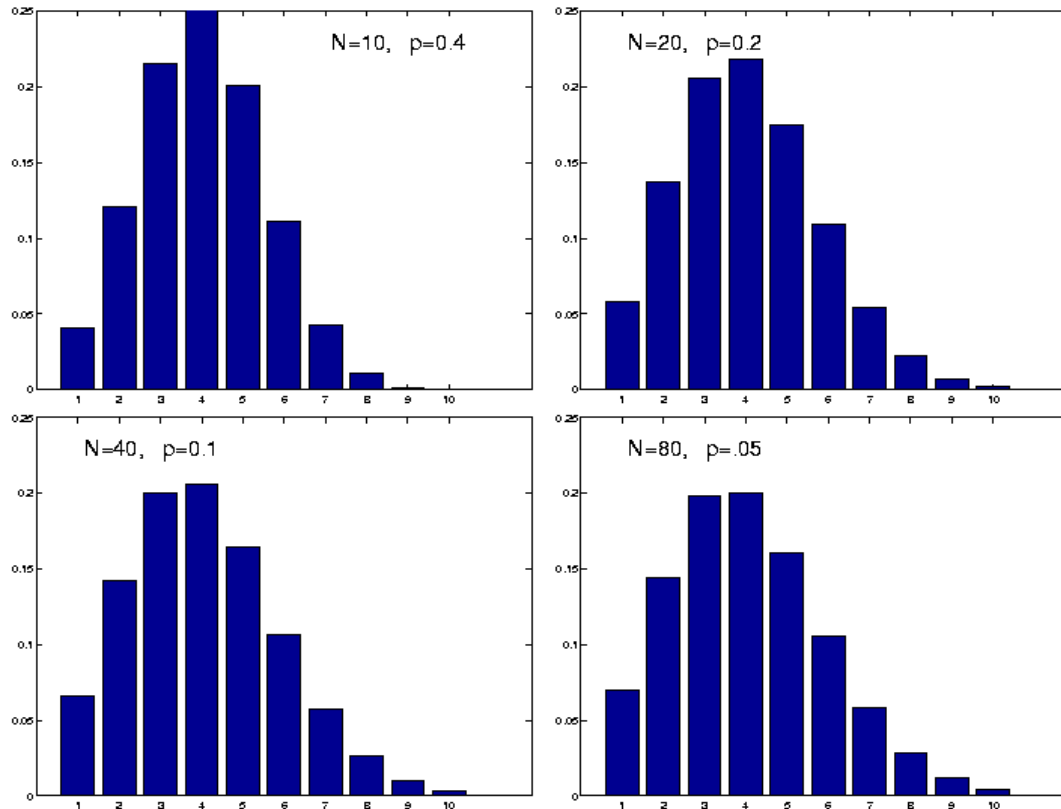


Figure 1. Probability distribution function for the sum of numbers, X , obtained when rolling N dice [$N = 1, 2, 3$].

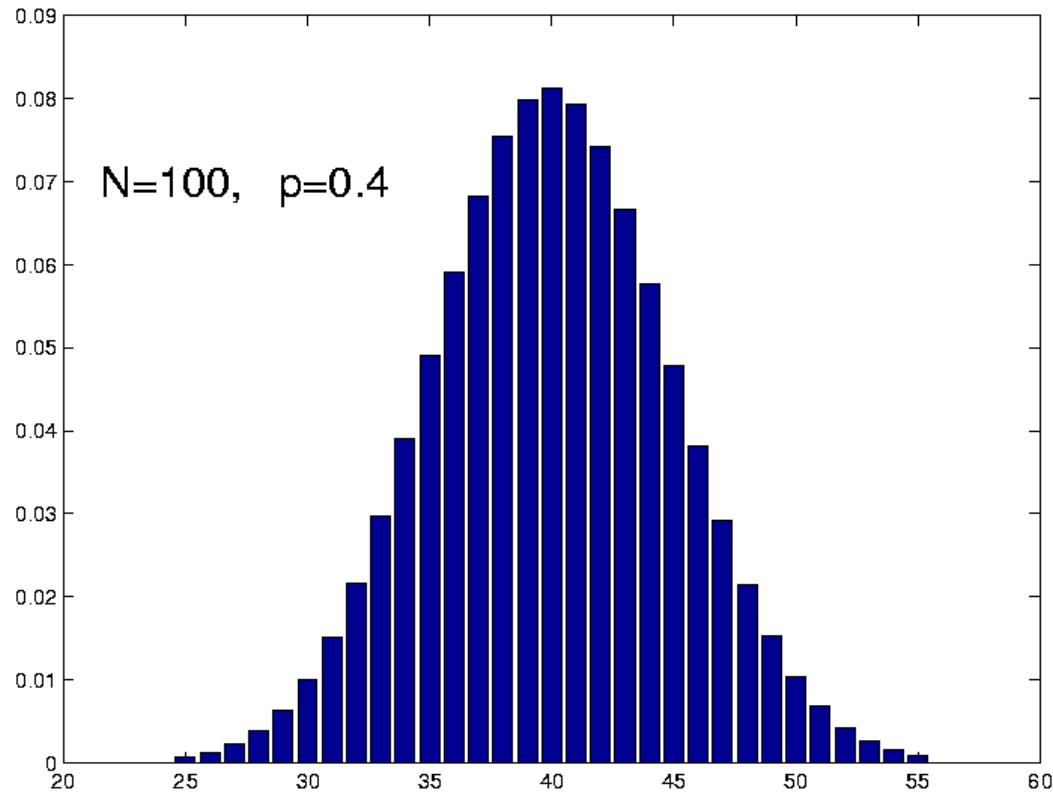
Binomial distributions

Why are these distributions so similar?



Binomial distributions

Binomial for large N approaches normal.



Normal distribution has 3 uses

- 1) Models many physical processes
- 2) Sum of normal random variables
- 3) Sum or mean of many iid random variables