

#### ENGINEERING RELIABILITY

#### COMBINATORICS

BINOMIAL &

### RANDOM

BAYES' RILLE

### ENGINEERING RELIABILITY FUNDAMENTALS OF PROBABILITY

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### OUTLINE

ENGINEERING RELIABILITY

PRELIMINARY DEFINITIONS

COMBINATORICS

THE PROBABILITY FORMALISM

Events

**Probabilities** 

**COMBINATORICS** 

**Elementary Combinatorics** 

Bernoulli Trials

Binomial & Poisson Distributions

RANDOM VARIABLES

Discrete & Continuous RV's

Normal Distribution

Bayes' Rule Revisited

SUMMARY



### RANDOM VARIABLE

### ENGINEERING RELIABILITY

#### PRELIMINARY DEFINITIONS

THE PROBABILIT FORMALISM

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#### COMBINATORICS

COMBINATORICS

BERNOULLI TRIAL

POISSON DISTRIBUTION:

#### RANDOM VARIABLE

DISCRETE & CONTINUOUS RV

NORMAL.

BAYES' RU

BAYES' RUI REVISITED

SUMMARY

- ► A random variable (denoted by X) is a variable that can assume one or more possible numerical values (denoted by x)
- ▶ The value *x* that *X* assumes is determined by chance
- A random variable may be:
  - discrete

$$x \in \{1, 2, 3\}$$

or continuous

$$x \in \{x \mid 0 \le x < \infty\}$$



# PROBABILITY DISTRIBUTION/PROBABILITY DENSITY

### ENGINEERING RELIABILITY

 for discrete random variables the probability distribution function is the set of probabilites

### PRELIMINARY DEFINITIONS

$$f(x) = P(X = x)$$
, and  $\sum_{x} f(x) = 1$ 

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EVENIS

for continuous random variables the (cumulative) probability function is the function:

#### COMBINATORICS

F(x) = P(X < x)

COMBINATORICS
BERNOULLI TRIALS
BINOMIAL &
POISSON
DISTRIBUTIONS

for continuous random variables the probability distribution or probability density is:

#### RANDOM VARIABLE

$$f(x) = \frac{d}{dx}F(x)$$
, and  $\int_{-\infty}^{\infty} f(x) dx = 1$ 

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CONTINUOUS RV

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SUMMARY



### PROBABILITY OF FAILURE/RELIABILITY

#### ENGINEERING RELIABILITY

#### PRELIMINARY DEFINITIONS

#### COMBINATORICS

### ▶ Let the random variable T denote the time of failure of a product during service. Then the possible values of T are the set $0 < t < \infty$ .

ightharpoonup The associated probability density is f(t), the probability that failure occurs at time t is

$$F(t) = \int_0^t f(\tau) \, d\tau$$

► The reliability function is the probability of survival to time t

$$R(t) = P(T \ge t) = 1 - F(t) = \int_{t}^{\infty} f(\tau) d\tau$$



### SAMPLE SPACE

### ENGINEERING RELIABILITY

PRELIMINARY DEFINITIONS

PROBABILITY FORMALISM

EVENTS
PROBABILITIE

Corenzarimona

#### COMBINATORICS

COMBINATORIC

BERNOULLI TRI

POISSON DISTRIBUTION

#### RANDOM VARIABLE

Continuous

DISTRIBUTION

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SUMMARY

The underlying idea is that there is a well-defined trial and a set of possible outcomes.

EXAMPLE (FLIPPING A COIN 3 TIMES)

Flipping a coin 3 times yields the following set of outcomes:

$$\xi_1 = TTT$$
  $\xi_2 = TTH$   $\xi_3 = THT$   $\xi_4 = THH$   
 $\xi_5 = HTT$   $\xi_6 = HTH$   $\xi_7 = HHT$   $\xi_8 = HHH$ 

- ► Sample space, *S*, the set of all possible outcomes.
- ▶ Elementary outcome,  $\xi$ , the individual elements of S.



### **EVENTS**

ENGINEERING RELIABILITY

PRELIMINARY DEFINITIONS

PROBABILIT FORMALISM

EVENTS
PROBABILITIES

COMBINATORICS

COMBINATORICS
BERNOULLI TRIAI
BINOMIAL &

BINOMIAL & POISSON DISTRIBUTIONS

RANDOM VARIABLE

DISCRETE & CONTINUOUS RV'S

DISTRIBUTION
BAYES' RULE
REVISITED

SUMMARY

Event *A*: a subset of the sample space. In general, an event is defined by a proposition about the elements in it.

EXAMPLE (FLIPPING A COIN 3 TIMES)

A is the event that a tail shows up on the second toss

$$A = \{\xi_1, \xi_2, \xi_5, \xi_6\}$$

Elementary event:  $\{\xi\}$ , where  $\xi$  is an elementary outcome.

Sure event: the entire sample space, S.

Impossible event: the empty set,  $\emptyset$ .

Complementary event:  $A^c$  consists of all events not in A. Mutually Exclusive events: events that have pairwise empty intersections



### **PROBABILITY**

### ENGINEERING RELIABILITY

PRELIMINARY DEFINITIONS

PROBABILITY FORMALISM

PROBABILITIES

#### COMBINATORICS

ELEMENTARY

BERNOULLI TRIAL

BINOMIAL & POISSON DISTRIBUTIONS

#### RANDOM VARIABLE

DISCRETE & CONTINUOUS R

NORMAL DISTRIBUTION

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SHMMARY

A probability measure is a function that assigns a 'likelihood' of occurrence to each subset of S (to each event)

A Probability Measure *P* is a function on the set of subsets of *S* that has the following properties:

- ▶ P(S) = 1
- ▶  $P(A) \ge 0$  for each  $A \subset S$
- For any sequence of mutually exclusive events A<sub>1</sub>, A<sub>2</sub>,...

$$P\left(\cup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P\left(A_i\right)$$



### VENN DIAGRAMS

#### ENGINEERING RELIABILITY

PROBABILITIES

COMBINATORICS

The Venn diagram is an aid in visualizing basic properties of sets. It can also serve as a simple visual representation of the probability model.

- ► The sample space S is visualized as a rectangular set of points in the plane.
- ▶ The elementary outcomes are the points in S.
- The probability is associated with a the (non-uniform) distribution of a unit mass over the set S. In the case of a finite number of outcomes, the mass is concentrated at a finite number of points.



### VENN DIAGRAMS

#### BASIC SET OPERATIONS

### ENGINEERING RELIABILITY

PRELIMINARY DEFINITIONS

THE PROBABILIT FORMALISM

PROBABILITIES

#### COMBINATORICS

ELEMENTARY

BERNOULLI TRI

BINOMIAL & POISSON

#### RANDOM VARIABLES

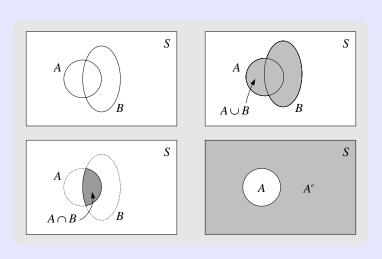
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NORMAL

BAYES' RULE

REVISITED

SUMMARY





# CONDITIONAL PROBABILITY & INDEPENDENT EVENTS

ENGINEERING RELIABILITY

PRELIMINARY DEFINITIONS

PROBABILIT FORMALISM

PROBABILITIES

#### COMBINATORICS

COMBINATORICS
BERNOULLI TRI
BINOMIAL &

POISSON
DISTRIBUTIONS

#### RANDOM VARIABLE

DISCRETE &
CONTINUOUS R
NORMAL

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SUMMARY

The probability that an event A occurs, given the occurrence of an event B is called the conditional probability of A given B. It is denoted P(A|B). From the Venn diagram we see that,

$$P(A \cap B) = P(A|B)P(B)$$
  
 $P(A|B) = \frac{P(A \cap B)}{B}, \quad \text{if } P(B) \neq 0$ 

$$P(A|B) = \frac{P(A \cap B)}{P(B)}, \quad \text{if } P(B) \neq 0$$

Two events *A* and *B* are independent if the occurrence of one does not 'condition' the occurrence of the other, i.e.,

$$P(A|B) = P(A)$$
 and  $P(B|A) = P(B)$ 

Thus, for independent events

$$P(A \cap B) = P(A) P(B)$$



### INDEPENDENT EVENTS

#### ENGINEERING RELIABILITY

### EXAMPLE (FLIPPING A COIN 3 TIMES)

- reconsider the coin flipping experiment with sample space *S* shown below.
- let *A* be the event that a *T* occurs on the third toss.
- let B be the event that an H occurs on the second toss.

$$P(A) = \frac{1}{2}, \quad P(B) = \frac{1}{2}, \quad P(A|B) = \frac{1}{2}, \quad P(B|A) = \frac{1}{2}$$

Notice that the events are independent, but not mutually exclusive.

DEFINITIONS

PROBABILITY FORMALISM

PROBABILITIES

#### COMBINATORICS

COMBINATORICS

BINOMIAL &

POISSON DISTRIBUTION

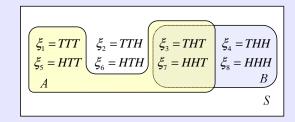
#### RANDOM VARIABLE

DISCRETE & CONTINUOUS RV

NORMAL DISTRIBUTION

BAYES' RU REVISITED

SHMMARY





### BAYES' RULE

#### ENGINEERING RELIABILITY

PRELIMINAR DEFINITIONS

PROBABILITY FORMALISM

PROBABILITIES

#### COMBINATORICS

ELEMENTARY

D------

BINOMIAL &

Poisson Distribution

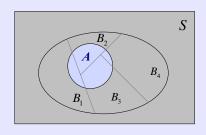
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DISCRETE & CONTINUOUS RV

DISTRIBUTI

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SUMMARY



▶ expansion rule:  $A \subset \bigcup_{i \in J} B_i$ , events  $B_i$  mutually exclusive

$$P(A) = \sum_{i \in J} P(A|B_i) P(B_i)$$

▶ Bayes' rule:  $A \subset \bigcup_{i \in J} B_i$ , events  $B_i$  mutually exclusive

$$P(B_i|A) = \frac{P(B_i \cap A)}{P(A)} = \frac{P(A|B_i) P(B_i)}{\sum_{i \in J} P(A|B_i) P(B_i)}$$



### **ELEMENTARY COMBINATORICS**

ENGINEERING RELIABILITY

PRELIMINARY DEFINITIONS

PROBABILITY FORMALISM

PROBABILITIE

COMBINATORICS

ELEMENTARY COMBINATORICS

BINOMIAL & POISSON

RANDOM VARIABLES

CONTINUOU

DISTRIBUTIO

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SHMMARY

A *population of size* n is a set of n distinguishable elements.

Consider a population of size n from which we obtain an 'ordered' sample of size r.

- ▶ Sampling with replacement there are n<sup>r</sup> possible samples.
- Sampling without replacement there are  $(n)_r = n (n-1) \cdots (n-r+1)$  possible samples.
- Set n = r to find that there are n! different orderings of n elements.



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### ENGINEERING RELIABILITY

PRELIMINAR DEFINITIONS

THE PROBABILIT FORMALISM

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COMBINATORIC:

#### FLEMENTARY

### COMBINATORICS

BINOMIAL & POISSON

#### RANDOM VARIABLE

DISCRETE & CONTINUOUS RV

DISTRIBUTE

BAYES' RUI

SUMMARY

We want to choose a subpopulation of size r from a population of size n. How many different such subpopulations are there?

- ▶ There are  $(n)_r$  samples of size r without replacement,
- ► Each *r*-sample can be ordered in *r*! ways,
- ▶ Thus, there are  $(n)_r/r!$  subpopulations of size r.

$$\binom{n}{r} = \frac{(n)_r}{r!} = \frac{n(n-1)\cdots(n-r+1)}{r(r-1)\cdots1} = \frac{n!}{r!(n-r)!} = C_r^n$$



### BERNOULLI TRIALS

ENGINEERING RELIABILITY

PRELIMINAR DEFINITIONS

THE
PROBABILIT
FORMALISM
EVENTS

COMBINATORICS

COMBINATORICS

REPNOLITI TRIALS

BINOMIAL & POISSON

RANDOM VARIABLE

DISCRETE & CONTINUOUS RV'S NORMAL DISTRIBUTION

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SUMMARY

- By a Bernoulli trial we mean an experiment consisting of a sequence of independent trials with two possible outcomes, *success* and *failure*, having probability of failure p and probability of success q = 1 p.
  - ► Fundamental Problem: Consider a Bernoulli trial of Length *n*. What is the probability of exactly *k* failures?
- ▶ The event 'n trials results in k failures and n k successes' can happen in as many ways as k letters F can be distributed among n places.
- ▶ In other words, i.e., how many subpopulations of size k can be constructed from a population of size n? The event consists of:

 $C_k^n$  points, each with probability  $p^k q^{n-k}$ 



### BINOMIAL DISTRIBUTION

ENGINEERING RELIABILITY

PRELIMINAR DEFINITIONS

PROBABILIT FORMALISM

PROBABILITI

#### COMBINATORICS

ELEMENTARY COMBINATORIC

BINOMIAL &

POISSON DISTRIBUTIONS

### VARIABLES

DISCRETE & CONTINUOUS RV'S

NORMAL.

BAYES' RU

REVISITED

SUMMARY

The probability that n Bernoulli trials with probability p for failure and q = 1 - p for success results in k failures and n - k successes is given by the *Binomial distribution*:

$$b(k; n, p) = \binom{n}{k} p^{k} q^{n-k}, \ 0 \le k \le n$$



### POISSON APPROXIMATION

#### ENGINEERING RELIABILITY

PRELIMINAR' DEFINITIONS

PROBABILIT FORMALISM

PROBABILITIE

#### G -----

ELEMENTARY

COMBINATORICS

BERNOULLI TRIA

BINOMIAL &
POISSON

RANDOM VADIABLE

DISCRETE & CONTINUOUS RV'S

NORMAL

BAYES' RUI

SHMMADV

If

- the probability of failure p is small,
- ▶ the number of trials n is large, so that  $np = \lambda$ , a constant then a good approximation to the Binomial distribution is the *Poisson distribution*:

$$p(k;\lambda) = e^{-\lambda} \frac{\lambda^k}{k!}, \ \lambda = np$$



### RANDOM VARIABLES

ENGINEERING RELIABILITY

PRELIMINARY DEFINITIONS

THE PROBABILIT FORMALISM

PROBABILITIES

#### COMBINATORICS

COMBINATORICS

BERNOULLI TRIALS

BINOMIAL &

POISSON DISTRIBUTION:

VARIABLE

DISCRETE & CONTINUOUS RV'S

DISTRIBUTION
BAYES' RUL

SUMMARY

A function  $X(\cdot)$  that maps a sample space S to the real numbers R is called a (real valued) random variable if it has the property:

$$\{\xi \in S | X(\xi) \le x\}$$
 is an event  $\forall x \in R$ 

All elementary outcomes that result in  $X(\xi) \le x$  is a valid subset of S, for all real x.

- ▶ A random variable is discrete if it can assume a finite set of distinct values, say  $x_i$ ,  $i = 1, ..., n < \infty$
- A random variable is continuous if the values it can assume are continuously distributed over its range, say

$$-\infty < x < \infty$$



### DISCRETE RANDOM VARIABLES

### ENGINEERING RELIABILITY

### PRELIMINAR DEFINITIONS

#### PROBABILIT FORMALISM

PROBABILITIE

#### COMBINATORICS

ELEMENTARY

BERNOULLI TRI

POISSON

### VARIABLE

#### DISCRETE & CONTINUOUS RV'S

DISTRIBUTION
BAYES' RUL

SUMMARY

# ▶ $f(x_i) = P(X = x_i)$ is called the probability distribution, note: $\sum_i f(x_i) = 1$

the (cumulative) probability function is:

$$F(x_k) = \sum_{i=1}^k f(x_i)$$

note: 
$$F(x_k) = P(X \le x_k)$$

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 mean:  $\mu = \sum_{i=1}^n x_i f(x_i)$ 

• variance: 
$$\sigma^2 = \sum_{i=1}^n (x_i - \mu)^2 f(x_i)$$

standard deviation: σ



### COIN FLIPPING EXAMPLE

#### ENGINEERING RELIABILITY

### PRELIMINAR' DEFINITIONS

PROBABILITY FORMALISM

PROBABILITIE

#### COMBINATORICS

ELEMENTARY

BERNOULLI TRIALS

POISSON DISTRIBUTION

#### RANDOM VARIABLE

### DISCRETE &

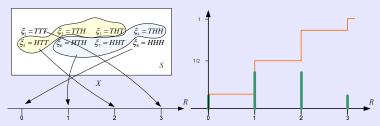
NORMAL

BAYES' RU

SHMMADV

### EXAMPLE (FLIPPING A COIN 3 TIMES)

- ► Flipping a coin 3 times yields a set of 8 outcomes.
- ► Assume: on a single toss, P(H) = P(T) = 1/2.
- Define: X = number of tails in 3 tosses.





### CONTINUOUS RANDOM VARIABLES

### ENGINEERING RELIABILITY

### PRELIMINAR DEFINITIONS

### PROBABILI' FORMALISM

PROBABILITIE

#### Combinatoric

ELEMENTARY

D----------

BINOMIAL &

POISSON DISTRIBUTIONS

### VARIABLE

#### DISCRETE & CONTINUOUS RV'S

DISTRIBUTION BAYES' RUL

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## ► the (cumulative) probability function is: F(x) = P(X < x)</p>

the probability distribution (density) is:

$$f(x) = \frac{d}{dx}F(x) \Rightarrow \int_{-\infty}^{\infty} f(x)dx = 1$$

- mean:  $\mu = \int_{-\infty}^{\infty} x f(x) dx$
- variance:  $\sigma^2 = \int_{-\infty}^{\infty} (x \mu)^2 f(x) dx$
- $\blacktriangleright$  standard deviation:  $\sigma$



### CONTINUOUS RANDOM VARIABLES, CONT'D

#### ENGINEERING RELIABILITY

### PRELIMINAR DEFINITIONS

### PROBABILITY FORMALISM

EVENTS

PROBABI

PROBABILITIE

#### COMBINATORICS

COMBINATORICS

BERNOULLI TR BINOMIAL &

POISSON DISTRIBUTIONS

### VARIABLE

#### DISCRETE & CONTINUOUS RV'S

DISTRIBUTION
BAYES' RUL

BAYES' RULE REVISITED

SUMMARY

### ▶ median: $x_m$ , $F(x_m) = \int_{-\infty}^{x_m} f(x) dx = \frac{1}{2}$

▶ mode:  $x_{\text{mode}}$ ,  $f(x_{\text{mode}}) \ge f(x)$ 

► skewness:  $sk = \frac{1}{\sigma^3} \int_{-\infty}^{\infty} (x - \mu)^3 f(x) dx$ 

### Comments on skewness:

►  $sk > 0 \Rightarrow left - skewed : x_{mode} < x_m < \mu$ 

►  $sk < 0 \Rightarrow right - skewed : x_{mode} > x_m > \mu$ 

► sk = 0 ⇒ symmetric :  $x_{\text{mode}} = x_m = \mu$ 



### EXAMPLE – POISSON DISTRIBUTION

ENGINEERING RELIABILITY

PRELIMINAR'
DEFINITIONS

PROBABILIT FORMALISM

PROBABILITIES

#### COMBINATORICS

BERNOULLI TRIA BINOMIAL & POISSON

RANDOM VARIABLES

DISCRETE &

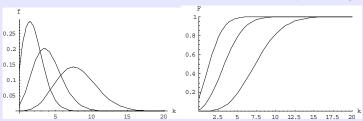
NORMAL DISTRIBUTION

BAYES' RULE REVISITED

SUMMARY

# $f(k) = e^{-\lambda} \frac{\lambda^k}{k!}$ $F(k) = \sum_{i=1}^k e^{-\lambda} \frac{\lambda^i}{i!} = \frac{(1+k)\Gamma(1+k,\lambda)}{\Gamma(2+k)}$

Here is the Poisson distribution for  $\lambda=2,4,8$  (left to right)





### EXAMPLE - POISSON DISTRIBUTION, CONT'D

#### ENGINEERING RELIABILITY

PRELIMINARY DEFINITIONS

THE PROBABILIT

FURMALI

PROBABILITIE

#### COMBINATORIC

ELEMENTARY

COMBINATORIC

DEKNOULLI IKD

POISSON

RANDOM

#### DISCRETE &

CONTINUOUS RV'S

DISTRIBUTION BAYES' RULE

REVISITED

SUMMARY

$$\mu = \sum_{k=0}^{\infty} k \left( e^{-\lambda} \frac{\lambda^k}{k!} \right) = \lambda$$

$$\sigma^2 = \sum_{k=0}^{\infty} (k - \mu)^2 \left( e^{-\lambda} \frac{\lambda^k}{k!} \right) = \lambda$$

$$sk = \frac{1}{\sigma^3} \sum_{k=0}^{\infty} (k - \mu)^3 \left( e^{-\lambda} \frac{\lambda^k}{k!} \right) = \frac{1}{\sqrt{\lambda}}$$



### THE NORMAL DISTRIBUTION

ENGINEERING RELIABILITY

PRELIMINARY DEFINITIONS

THE PROBABILITY FORMALISM

PROBABILITIES

#### Combinatoric

ELEMENTARY COMBINATORICS

BINOMIAL & POISSON

RANDOM VARIABLE

DISCRETE & CONTINUOUS RV

NORMAL DISTRIBUTION BAYES' RULE

BAYES' RULE REVISITED

SUMMARY

The normal distribution has two key applications in reliability:

- ▶ It is a good model for the variability of parameters in batch-manufactured parts.
- It is a good approximation to the 'wear-out' time to failure distribution.

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

where  $\mu$  is the mean time to failure and  $\sigma$  is the standard deviation of the time to failure.





### STANDARD NORMAL DISTRIBUTION

ENGINEERING RELIABILITY

PRELIMINARY DEFINITIONS

PROBABILITY FORMALISM

PROBABILITIES

COMBINATORICS

COMBINATORICS
BERNOULLI TRIA

BINOMIAL & POISSON DISTRIBUTION

RANDOM VARIABLES

CONTINUOI NORMAL

DISTRIBUTION BAYES' RULE

SHMMARY

The normal distribution is commonly used that the standard normal distribution has been introduced to facilitate computations. Suppose X is a normally distributed random variable with mean  $\mu$  and standard deviation  $\sigma$ . Consider a new random variable Z, related to X, by the relation

$$Z = (X - \mu)/\sigma$$

Clearly,

$$P(X \le x) = P(Z \le (x - \mu)/\sigma)$$

Equivalently,

$$F(x) = \Phi\left((x - \mu)/\sigma\right)$$

where F(x) is the probability function for X and  $\Phi(z)$  is that of Z. Thus,

$$f(x) = \frac{dF(x)}{dx} = \frac{d\Phi(z)}{dz}\frac{dz}{dx} = \phi(z)\frac{dz}{dx}$$



### STANDARD NORMAL DISTRIBUTION – 2

ENGINEERING RELIABILITY

It follows that

### RANDOM

### NORMAL DISTRIBUTION

$$\phi(z) = \left[ f(x) \left( \frac{dz}{dx} \right)^{-1} \right]_{x \to \sigma z + \mu} = \left[ \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2} \left( \frac{x - \mu}{\sigma} \right)^2} \sigma \right]_{x \to \sigma z + \mu}$$

So.

$$\phi\left(z\right) = \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}z^2}$$

and

$$\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{-\frac{1}{2}\zeta^{2}} d\zeta$$

The standard normal is the normal distribution wit zero mean and unit variance. It's usefulness follows from the fact that

$$F(x) = \Phi((x - \mu)/\sigma), \quad f(x) = \phi((x - \mu)/\sigma)$$



# DETERMINING DISTRIBUTION PARAMETERS FROM DATA

ENGINEERING RELIABILITY

PRELIMINARY DEFINITIONS

PROBABILIT FORMALISM

PROBABILITIES

COMBINATORICS

ELEMENTARY

BERNOULLI TRIALS

POISSON DISTRIBUTION

RANDOM VARIABLE

DISCRETE & CONTINUOUS RV':

NORMAL DISTRIBUTION

BAYES' RULE REVISITED

SUMMARY

### EXAMPLE (FLAT PANEL MONITOR)

A flat pane computer monitor is designed to operate for 10,000 hours. Data shows that 2% fail within 1000 hours and 3.8% fail before 2000 hours. Assuming a normal time to failure distribution, determine the mean time to failure.

$$F(t) = \int_{-\infty}^{t} f(\tau) d\tau = \frac{1}{2} \left( 1 + \operatorname{Erf} \left[ \frac{t - \mu}{\sqrt{2} \sigma} \right] \right)$$

We can obtain the unknown parameters  $\mu, \sigma$  from the two relations

$$F(1000) = 0.02, F(2000) = 0.038 \Rightarrow \mu = 8351, \sigma = 3580$$



# BAYES' RULE – CONTINUOUS RANDOM VARIABLES

### ENGINEERING RELIABILITY

Suppose *X* and *Y* are random variables. The following quantities are defined:

PRELIMINAR DEFINITIONS

joint probability distribution is

$$F\left(x,y\right) = P\left(X \le x\right) \cap P\left(Y \le y\right)$$

FORMALISM

joint probability density function is

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$$f(x,y) = \frac{\partial^2}{\partial x \partial y} F(x,y)$$

#### COMBINATORIC

conditional density function for X given Y

BINOMIAL & POISSON DISTRIBUTIONS

$$f(x|y) = \frac{f(x,y)}{f(y)}$$

#### RANDOM VARIABLE

Bayes rule for densities

NORMAL DISTRIBUTION

 $f(x|y) = \frac{f(y|x)f(x)}{\int_{-\infty}^{\infty} f(y|x)f(x) dx}$ 

BAYES' RULE REVISITED

SUMMARY



### **SUMMARY**

#### ENGINEERING RELIABILITY

PRELIMINAR DEFINITIONS

PROBABILIT FORMALISM

PROBABILITIE

#### COMBINATORICS

ELEMENTARY COMBINATORICS BERNOULLI TRIALS

BINOMIAL & POISSON DISTRIBUTIONS

#### RANDOM VARIABLE

DISCRETE & CONTINUOUS

NORMAL DISTRIBUTIO

BAYES' RUL REVISITED

SUMMARY

- Random variable, probability, reliability
- Sample space, events
- Conditional probability, Bayes' rule
- Combinatorics, Bernoulli trials
- Discrete random variables Binomial and Poisson distributions
- Continuous random variables Normal distribution
- Mean, variance skewness, median, mode