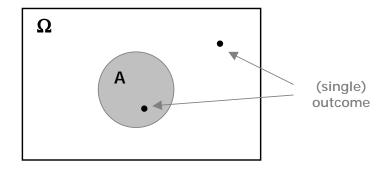
Short Tutorial on Probability and Random Variables

http://www.site.uottawa.ca/~nvlajic/ProbabilityTutorial.pdf

(January 2003, by N. Vlajic)

1. Probability

Let us envision an experiment, for which the result is unknown.



- <u>Def. 1</u> Sample Space (Ω) collection of all possible outcomes.
- <u>Def.2</u> Event (A) set of outcomes i.e. subset of the Sample Space.

Example: experiment "measurement of voltage"

- 1) measured voltage = 1 [V] outcome!
- 2) measured voltage negative- event!

<u>Def. 3</u> Probability Space - three-tuple (Ω , F, Pr), where

- Ω is a sample space
- *F* is a collection of events from the sample space (event space)
- Pr is a probability measure (law) that assigns a number to each event in F

Furthermore, Pr must satisfy, for \forall A, B \in F the following conditions

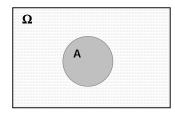
- (1) $Pr(A) \ge 0$ probability is a positive measure
- (2) $Pr(\Omega)=1$ probability is a finite measure
- (3) A, B are disjoint events \Rightarrow Pr(A+B)=Pr(A)+Pr(B) additive property

(1), (2) and (3) are known as axioms of probability measure Pr.

From the above axioms, the following well-known properties of probability measure (Pr) are derived:

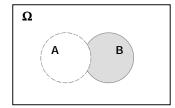
Property 1 $Pr(A^{C}) = 1 - Pr(A)$

Proof:
$$Pr(\Omega) = Pr(A+A^C) = Pr(A^C) + Pr(A) = 1$$



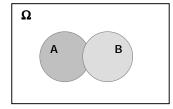
Property 2 Pr(B-A) = Pr(B) - Pr(AB)

Proof:
$$Pr(B) = Pr(B-A+(AB)) = Pr(B-A) + Pr(AB)$$



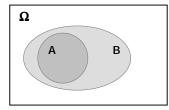
Property 3
$$Pr(A+B) = Pr(A) + Pr(B) - Pr(A-B)$$

Proof:
$$Pr(A+B) = Pr(A+(B-A)) = Pr(A) + Pr(B-A)$$



Property 4 if $A\subseteq B \Rightarrow Pr(A) \leq Pr(B)$

Proof:
$$Pr(B) = Pr((B-A)+A) = Pr(B-A) + Pr(A) \ge Pr(A)$$



Property 5 $Pr(\emptyset) = 0$

Proof:
$$Pr(\emptyset) = Pr(\Omega^{C}) = 1 - Pr(\Omega) \ge 0$$



'Relative Frequency' Definition of Probability

Perform an experiment a number of times/trials (n), counting the occurrences of event A (n_A) . Then the probability P(A) of event A can be found/defined as the limit:

$$P(A) = \lim_{n \to \infty} \frac{n_A}{n}$$

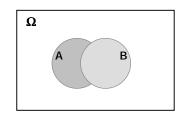
<u>Def. 4</u> Conditional Probability enables us to determine whether two events, A and B, are related in the sense that knowledge about the occurrence of one alters the likelihood of occurrence of the other.

probability of A given B has occurred:

$$Pr(A|B) = \frac{Pr(AB)}{Pr(B)} \bullet A \text{ occurs, in reduced event space, only if } A \cap B \text{ occurs}$$

consequently:

$$Pr(AB) = Pr(A|B) \cdot Pr(B)$$

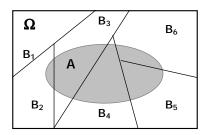


<u>Def. 5</u> Independent Events - two events, A and B, are independent if $Pr(AB)=Pr(A)\cdot Pr(B)$

From Def. 4 and Def. \Rightarrow A and B are independent if Pr(A|B)=Pr(A).

Theorem 1 Total Probability

Let B_1 , ..., B_n be mutually exclusive events whose union equals the sample space Ω .

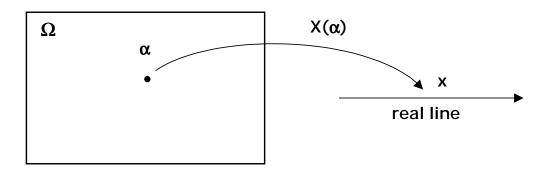


Then, the probability of any given event $A\subseteq \Omega$ can be expressed as

$$Pr(A) = Pr(A|B_1) \cdot Pr(B_1) + Pr(A|B_2) \cdot Pr(B_2) + ... + Pr(A|B_n) \cdot Pr(B_n)$$

Proof: based on $A = A \cap \Omega = A(B_1+B_2+..+B_n) = AB_1 + AB_2 + ... + AB_n$

<u>Def. 6</u> Random Variable (X) is a function that assigns a real number (X(α)) to each outcome α in the sample space.



Example: experiment "measurement of voltage"

 α = (measured voltage = x [V]) - outcome!

 $X(\alpha) = x$ - r.v. associated with experiment!

<u>Def. 7</u> Continuous Random Variable - takes on an uncountablely infinite number of distinct values.

<u>Def. 8</u> <u>Discrete Random Variable</u> - takes on a finite or countably infinite number of distinct values.

<u>Def. 9</u> Cumulative Distribution Function (cdf) $F_X(x)$ of a random variable X is defined as the probability of the event $\{X \le x\}$.

$$F_X(x) = Pr[X \le x]$$

consequently:

$$Pr[a < X \le b] = F_X(b) - F_X(a)$$

$$\Pr[X > x] = 1 - F_X(x)$$

<u>Def. 10</u> Probability Density Function (pdf) $f_X(x)$, if it exists, is defined as a derivative of $F_X(x)$.

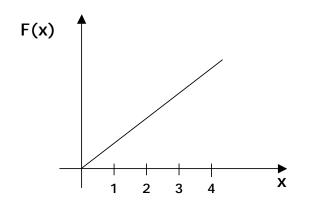
$$f_X(x) = \frac{dF_X(x)}{dx}$$

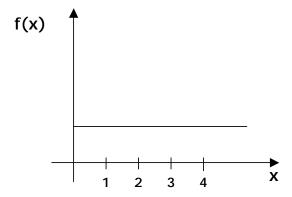
consequently:

$$\Pr[X \le a] = F_X(a) = \int_{-\infty}^a f_X(x) dx$$

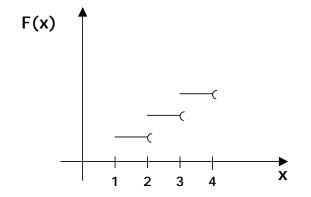
Note: $f_X(x)$ is called "density of probability" at point x, since the probability that X is in a small interval in the vicinity of x is approximately $f_X(x) \cdot x$.

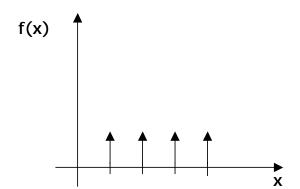
example: cdf & pdf of a continuous r.v.





example: cdf & pmf (prob. mass func.) of a discrete r.v.





We are often concerned with some characteristic of a random variable rather than the entire distribution:

Def. 11 mean of continuous r.v.

$$E[X] = \mu_X = \int_{-\infty}^{\infty} x \cdot f_X(x) dx$$

mean of discrete r.v. Def. 12

$$E[X] = \sum_{\text{all } k} k \cdot Pr(x = k)$$

important properties:

$$E[a \cdot X] = a \cdot E[X]$$

$$E[a \cdot X] = a \cdot E[X]$$
 and $E[X + Y] = E[X] + E[Y]$

<u>Def. 13</u> variance (dispersion around mean) $Var[X] = E[(X - \mu_x)^2] = E[X^2] - \mu_x^2$

$$Var[X] = E[(X - \mu_X)^2] = E[X^2] - \mu_X^2$$

Def. 14 standard deviation

$$\sigma_{x} = \sqrt{\text{Var}[X]}$$

important properties:

$$Var[a \cdot X] = a^2 \cdot Var[X]$$

Exponential Distribution - important in queueing theory because we often assume that the service/waiting time is exp. Distributed.

$$f_x(x) = 1 - e^{-\mu x}$$

 $f_x(x) = \mu e^{-\mu x}$

$$f_x(x) = \mu e^{-\mu x}$$

$$E[X] = \mu$$

properties: 1) 'random distribution'

> for service time with exp. distributed duration – each time at which service may finish is equally likely

memoriless property 2)

> for waiting time with exp distributed duration – the probability of waiting additional h [sec] is the same regardless of how long one has already been waiting

Proof: what is the prob. of waiting another h [sec], given H [sec] already waiting

$$Pr[X \geq h + H \mid X \geq H] = \frac{Pr[X \geq h + H \cap X \geq H]}{Pr[X \geq H]} = \frac{Pr[X \geq h + H]}{Pr[X \geq H]} = \dots = Pr[X \geq h]$$

Poisson Process - important in queueing theory because we often assume that users/packets arrive according to a Poisson process.

$$Pr[N(t)] = \frac{(\lambda t)^{k}}{k!} e^{-\lambda t}$$
 (\lambda - expected # of arrivals per time unit)

$$E[N(t)] = \lambda t$$

properties: 1) exp. distributed inter arrival times

interarrival times in a Poisson process form an iid sequence of exponential random variables with mean $1/\lambda$

