

Random Variable (r.v.)

A r.v. models uncertainty in engineering systems. It typically represents a scalar, whose value is pre-determined.

- ex: i) received signal strength in UEs. $\text{A} \xrightarrow{\text{UE}} \text{UE}$
ii) internet speed b/w two ports (real no.)
iii) number of e-/charge stored in a flash memory cell (discrete)
iv) Signal to interference ratio between a radio transmitter & a receiver (real no.)

X is a r.v. if :-

- 1) $P(X \in (-\infty, \infty)) = 1$, i.e. X is finite with prob 1
- 2) $P(X \in [a, b])$ is well defined for any $-\infty < a < b < \infty$
- 3) $P(X \in \bigcup_{i=1}^{\infty} [a_i, b_i]) = \sum_{i=1}^{\infty} P(X \in [a_i, b_i])$ if the intervals $[a_i, b_i]$ are disjoint.

Ex. Uniform r.v.

A uniform r.v. ($\text{Unif}[0, 1]$) is defined as
 $P(U \in [a, b]) = \frac{(b-a)}{1}$ for $0 \leq a < b \leq 1$

The prob. values for X lying in various intervals can be obtained from a single fⁿ. called as cumulative distribution fⁿ.

c.d.f The function $F(x) = P(X \leq x) = P(X \in (-\infty, x])$ is called the c.d.f of X.
 $\Rightarrow F_x(-\infty) = 0, F_x(\infty) = 1$ & $F_x(x)$ is non-decreasing

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$$\text{if } n_1 < n_2 \Rightarrow F_x(n_1) \leq F_x(n_2)$$

$$\therefore P(X \in (n_1, n_2]) = F_x(n_2) - F_x(n_1)$$

One can show that $F_x(n)$ is right continuous,
ie. $\lim_{\epsilon \downarrow 0} P(X \leq n + \epsilon) = P(X \leq n)$

$$\text{or } \lim_{\epsilon \downarrow 0} P(F_x(n + \epsilon)) = F_x(n)$$

$\hookrightarrow P(X \in [a, b])$ is well defined. Note
that $P(X \in (a, b))$, $P(X \in [a, b))$, $P(X \in a, b)$
are all well defined.

$P(X \in [a, b]) = F_x(b) - F_x(a)$

$$[a, b] \cup (-\infty, a) = (-\infty, b]$$

$$\therefore P(X \in [a, b] \cup (-\infty, a)) = P(X \in (-\infty, b))$$

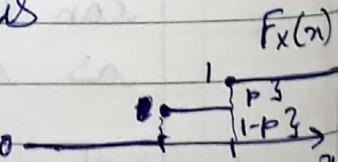
$$\therefore P(X \in [a, b]) + P(X \in (-\infty, a)) = F_x(b)$$

$$\therefore P(X \in [a, b]) = F_x(b) - F_x(a)$$

Example (A switch)

Consider a R.V. X which is

$$\begin{aligned} X &= 1 \text{ w.p. } p \\ &= 0 \text{ w.p. } (1-p) \end{aligned}$$



X represents a switch, X is a Bernoulli(p) R.V. or simply $Ber(p)$

Verify that cdf is right contⁿ. at n=0 & n=1

cdf of r.v \iff A cadlag fⁿ.
starts at 0, ↗

ends in 1, non-decreasing, right contⁿ.

Discrete r.v.

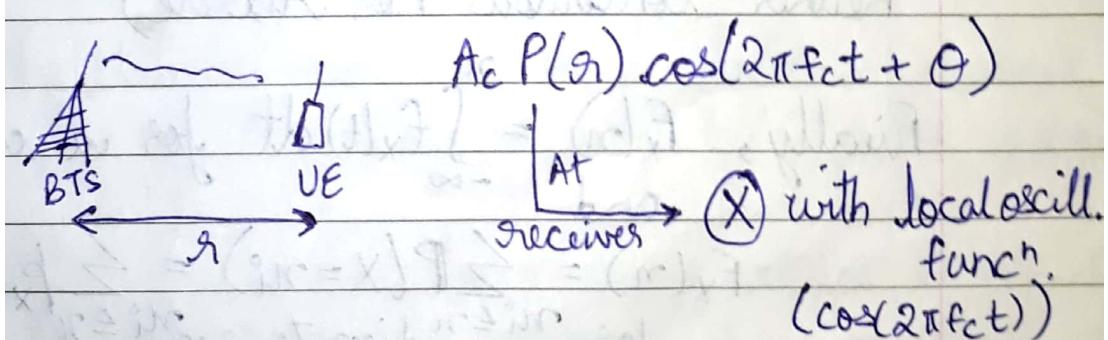
If X takes finite or countable set of values with prob. 1, then X is a discrete r.v.

Defn. Contn. r.v.

If $F_X(n)$ has a finite derivative as a fⁿ. of n, then X is a contn. r.v & its derivative is called as p.d.f - prob. density funct.

Ex. (phase)

In a wireless system, the trans, rec. are separated.

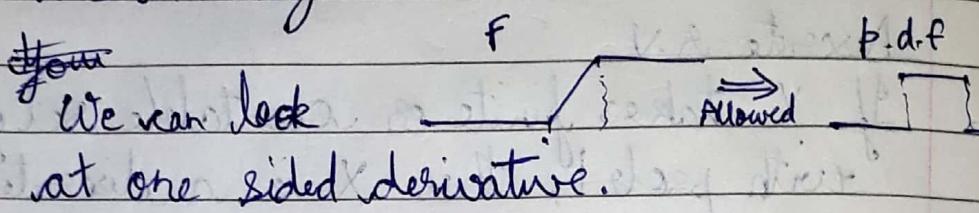


The phase offset is well modelled by a Uniform $[0, 2\pi]$ distribution.

Its pdf is given by, $f_\theta(\theta) = \frac{1}{2\pi}; 0 \leq \theta < 2\pi$
 $= 0 \quad \text{o.w.}$

Its cdf, $F(\theta) = \begin{cases} 0 & \theta < 0 \\ \theta/2\pi & 0 \geq \theta, \theta < 2\pi \\ 1 & \theta \geq 2\pi \end{cases}$

Ques 24/10 For a contn. r.v., its p.d.f may have discontinuity



For a contn. r.v X , p.d.f $f_X(x) = \frac{dF_X(x)}{dx}$

For a discrete r.v., i.e. there are countable set of pts $\{n_i^o, i \in \mathbb{Z}^+\}$ such that

$$P(X=n_i^o) \neq 0 \quad \text{and} \quad \sum_{i=1}^{\infty} P(X=n_i^o) = 1$$

Some r.v. can be of the mixed type (i.e. neither continuous nor discrete)

Finally, $F_X(x) = \int_{-\infty}^x f_X(t) dt$ for a contn. r.v.
and

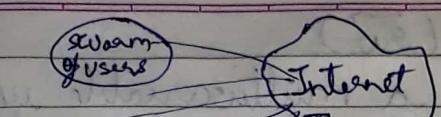
$$F_X(x) = \sum_{n_i^o \leq x} P(X=n_i^o) = \sum_{n_i^o \leq x} f_X(n_i^o)$$

for a discrete r.v.

Poisson distribution

It models the no. of people arrivals in a queue in time $[0, t]$

Let X be the r.v. which models the no. of packets arriving at a switch in time $[0, T]$



The poison model

$$P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}; \lambda > 0, k = 0, 1, 2, \dots$$

where λ is the parameter that models the rate of arrival.

↳ The prob of no arrival in $[0, T]$ is

$$P(X = 0) = e^{-\lambda}$$

↳ This distribution models many counting and arrival process.

↳ The cdf of a Poisson(λ) r.v. is not known in closed form.

Boltzmann distn.

In statistical mechanics or in electronic devices, this distribution is useful (in particle equil.).

Let e_1, e_2, \dots, e_m be m energy states in which the particle can be present. Then,

$$P(X = i) = \frac{e^{-e_i/kT}}{\sum_{j=1}^m e^{-e_j/kT}}, \text{ where } X = i \text{ means particle is in state } i \text{ corresponding to energy } e_i$$

$$\begin{matrix} \frac{1}{2} \times 0.1 & \frac{1}{2} \times 0.7 & \frac{1}{2} \times 0.2 \\ N=10 & & \end{matrix}$$

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Random vectors (\vec{w})

A \vec{w} models a multivariable uncertain parameters in an engineering system.

Let $\vec{X} = (X_1, \dots, X_n)$. Then \vec{X} is a rv.

- i) $P(\vec{X} \in (-\infty, \infty)^n) = 1$, that is all the entries of \vec{X} are finite
- ii) $P(\vec{X} \in [a_1, b_1] \times \dots \times [a_n, b_n])$ is well defined for every $-\infty < a_i < b_i < \infty, i=1, \dots, n$.
- iii) $P(\vec{X} \in \bigcup_{i=1}^{\infty} S_i) = \sum_{i=1}^{\infty} P(\vec{X} \in S_i)$ where S_1, \dots, S_∞ are disjoint subsets of \mathbb{R}^n

cdf. of a \vec{w}

The cdf. of a \vec{w} $\vec{X} = (X_1, \dots, X_n)^T$ is defined as:-

$$F_{\vec{X}}(\vec{n}) := P(X_1 \leq n_1, X_2 \leq n_2, \dots, X_n \leq n_n)$$

is defined as

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Properties

joint cdf.

$$1) \lim_{n_i \rightarrow -\infty} F_{\vec{X}}(\vec{n}) = 0 \quad (\text{subset incg})$$

original

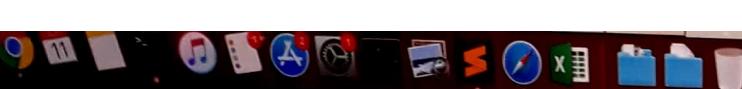
$$2) F_{\vec{X}_i}(n_i) = F_{\vec{X}}(+\infty, \dots, n_i, \dots, +\infty)$$

$$3) P(X \in A) \leq P(X \in B) \text{ for } A \subseteq B \in \mathcal{R}$$

disjoint

$$X \in B = (X \in A) \cup (X \in B \cap A^c)$$

$$P(X \in B) = P(X \in A) + P(X \in B \cap A^c) \geq 0$$



variable uncertain system.

\bar{X} is a r.v. if it is well defined, $b_i < \infty$, $i=1, \dots, n$.
 S_i where $S_i \subset R^n$.

... $X_n \in S_n$)

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$(x_i \leq -\infty) \supseteq (x_1 \leq -\infty, x_2 \leq \dots, x_n \leq \frac{x_n}{n})$

4) $F_{x_1, x_2}(x_1, x_2) = F_{\bar{X}}(x_1, x_2, +\infty, \dots, +\infty)$

5) For a contⁿ. r.v., the pdf is defined as

$$f_{\bar{X}}(\bar{x}) = \frac{1}{2\pi_1 2\pi_2 \dots 2\pi_n} F_{\bar{X}}(\bar{x})$$

6) Independence

~~Two r.v. are statically indep. if~~

$F_{x_1, x_2}(x_1, x_2) = F_{x_1}(x_1) F_{x_2}(x_2)$
 for every $x_1, x_2 \in R$
 i.e. the joint cdf of \bar{X} should be a product of the marginal cdfs
 $F_{\bar{X}}(\bar{x}) = F_{x_1}(x_1) \dots F_{x_n}(x_n)$
 for all $(x_1, \dots, x_n) \in R^n$

Joint indep. \Rightarrow Pair wise indep. & not vice versa.
 (marginal indep.)

For contⁿ. r.v., statically indep holds iff

$$f_{\bar{X}}(\bar{x}) = f_{x_1}(x_1) \dots f_{x_n}(x_n)$$

For discrete r.v. \bar{X} , statically indep. is equivalent to $p_{\bar{X}}(\bar{x}) = p_{x_1}(x_1) \dots p_{x_n}(x_n)$

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$A^c \Rightarrow \geq 0$

Conditional prob. distribution.

There is a pair of r.v. (X, Y) which have the joint cdf. as $F_{X,Y}(x,y)$

The value of Y is revealed after realization (or prob. exp.) but X is not revealed.

The initial distribution of X was $F_X(x)$.

With $Y=y$, can we obtain/compute a better distributn. for X ?

$$P(X=x | Y=y) := \frac{P(X=x, Y=y)}{P(Y=y)}$$

whenever $P(Y=y) > 0$

For cont'. r.v $P(Y=y) = \int_{y^-}^{y^+} f_Y(y) dy = 0$
 \therefore This defn. can't be used for cont'. r.v.

The conditional distn. of a contn. rv. can be understood using the conditional pdf defined as :-

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)} \text{ whenever } f_Y(y) > 0$$

Note :- $\int_{-\infty}^{\infty} f_{X|Y}(x|y) dx = 1 = \frac{\int_{-\infty}^{\infty} f_{X,Y}(x,y) dx}{f_Y(y)}$

which have

realization
revealed.

$\bar{x}(n)$.

note a

y)

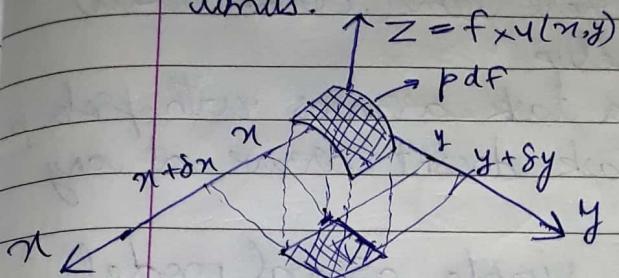
$y = 0$
1. r.v.

g.v.
conditional

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Interpretation

One way to interpret this formula is using limits.



$$\bullet P(X \in [x, x+\delta x], Y \in [y, y+\delta y]) \approx f_{X,Y}(x, y) \cdot \delta x \cdot \delta y$$

$$\begin{aligned} & \bullet P(X \in [x, x+\delta x] | Y \in [y, y+\delta y]) \\ & \quad \times P(Y \in [y, y+\delta y]) \\ & \approx f_Y(y) \delta y \cdot P(X \in [x, x+\delta x] | Y \leq y + \delta y) \end{aligned}$$

Taking ratios,

$$\frac{P(X \in [x, x+\delta x], Y \in [y, y+\delta y])}{P(Y \in [y, y+\delta y])} \approx \frac{f_{X,Y}(x, y) \delta x}{f_Y(y)}$$

Let $\delta y \rightarrow 0$,

$$\therefore P(X \in [x, x+\delta x] | Y = y) \approx \frac{f_{X,Y}(x, y) dx}{f_Y(y)}$$

Thus we can interpret conditional density

Independence

X_1, \dots, X_n are independent if

$$F_{X_1, \dots, X_n}(x_1, \dots, x_n) = F_{X_1}(x_1) \cdots F_{X_n}(x_n)$$

Indep. & identically distributed r.v (IID)

X_1, X_2, \dots, X_n are iid r.v if X_1, \dots, X_n are
indp. & $X_i \sim F_X(x)$ → is distributed as

Example (clocked arrivals)

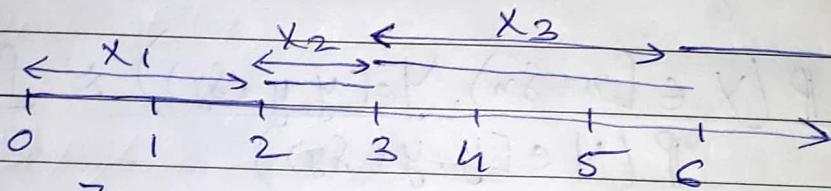
Consider a discrete time (clock-based) task arrival setup

↳ At each time, a task arrives with prob p .
More than one task doesn't arrive at any clock instance

↳ This is a very simple arrival model.
let, $Z_i^o = 1$ if tasks arrives at time i
 $= 0$ if " doesn't arrive "

Then ~~defn~~ let $P(Z_i^o = 1) = p$. Let
 Z_1, \dots, Z_n be iid. Ber(p) r.v.

of arrived
tasks



$$Z_1 = 0 \quad Z_2 = 1 \quad Z_3 = 1 \quad Z_4 = 0 \quad Z_5 = 0 \quad Z_6 = 1$$

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For analysis purposes, we might be interested in

- (i) inter-arrival time - distn.
- (ii) # of tasks arrived till time n .

Let $S_n = \# \text{ of jobs arrived till time } n$

Let X_1, X_2, \dots be the inter-arrival times

Verify that X_1, X_2, X_3, \dots are iid.

X is a discrete r.v.

$$P_{X_1}(1) = P(Z_1 = 1) = p$$

$$P_{X_1}(2) = P(Z_1 = 0, Z_2 = 1) = P(Z_1 = 0) \cdot P(Z_2 = 1)$$

In general $P_{X_1}(k) = (1-p)^{k-1} p$ \Rightarrow geometric distribution with parameter $(1-p)$

↳ What about S_n ?

a) Through X_i 's b) Through Z_i 's

Note That,

$$S_n = \sum_{i=1}^n Z_i \Rightarrow S_n \text{ are not indep.}$$

$$S_n = S_{n-1} + Z_n$$

$$P_{S_n}(k) = 0 \text{ if } k < 0 \text{ or } k > n$$

$$= \binom{n}{k} p^k (1-p)^{n-k} \quad 0 \leq k \leq n$$

We say that $S_n \sim \underbrace{\text{Binomial}(n, p)}_{\text{Bin}(n, p)}$

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$$P(\text{Bin}(n, p) \approx np) \approx 1 \Rightarrow \text{conv. in prob.}$$

Expectation of a r.v.

Let X \rightarrow r.v. & let $E(X)$ denote its expectation

If X is discrete,

$$E(X) := \sum_{n_i} n_i p_x(n_i)$$

If X is cont.,

$$E(X) := \int_{-\infty}^{\infty} n f_x(n) d n$$

In both cases, it is assumed that $E(X)$ is well defined.

Existence of $E(X)$

Let X be any rv. Then define

$$X^+ = \begin{cases} X & \text{if } X \geq 0 \\ 0 & \text{if } X \leq 0 \end{cases}$$

$$X^- = \begin{cases} -X & \text{if } X \leq 0 \\ 0 & \text{if } X > 0 \end{cases}$$

Then $X^+ - X^- = X$ and both X^+ & X^- are non-negative rv.

$$\therefore E(X) = E(X^+) - E(X^-)$$

since $E(X)$ is a linear operator

If $E(X^+) < \infty$ & $E(X^-) < \infty$, then $E(X)$ exists
(As a finite real no.)

If $E(X^+) = \infty$ & $E(X^-) < \infty$, then $E(X) = \infty$

$$\begin{array}{ccc} < \infty & = \infty & - \infty \\ = \infty & = \infty & \text{undefined} \end{array}$$

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Finding expectation using cdf

$$\begin{aligned} \text{Let } F_x^c(n) &= 1 - F_x(n) \\ &= P(X > n) \\ &= P(X \in (n, \infty)) \end{aligned}$$

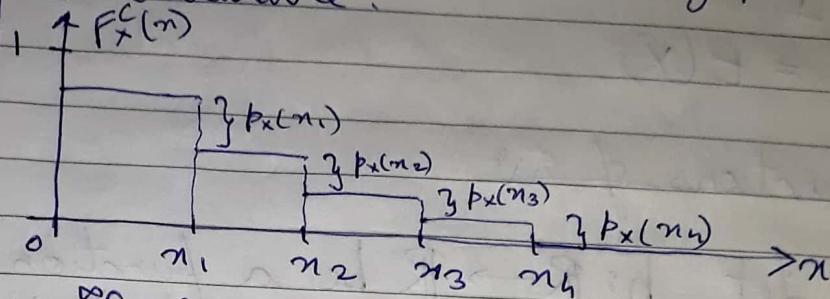
If $X \geq 0$ (i.e. a non-negative rv.)

then,

$$E(X) = \int_0^\infty F_x^c(n) dx = \int_0^\infty P(X > n) dx$$

$\{P(X > n)\}$

For the discrete case, a graphical proof is available.

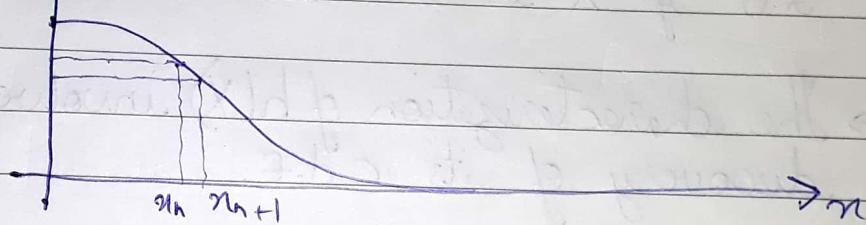


$$\therefore \int_0^\infty F_x^c(n) dn = n_4 p_x(n_4) + n_3 p_x(n_3) + n_2 p_x(n_2) + n_1 p_x(n_1)$$

∴ It's true for discrete.

For continuous case,

$$F_x^c(n) = P(X > n)$$



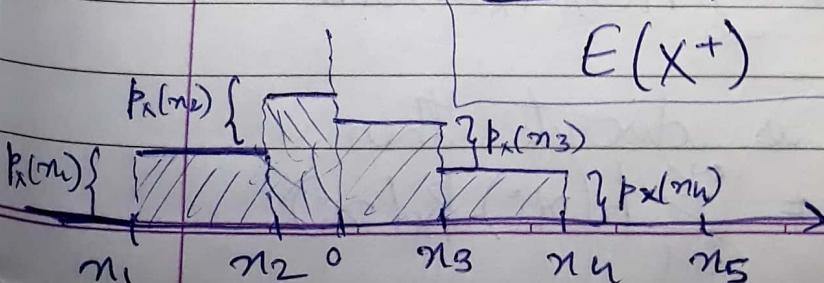
$$\therefore n P(X \in [n_n, n_{n+1}]) \leq \int_{n_n}^{n_{n+1}} F_x^c(n) dn \leq n_{n+1} P(X \in [n_n, n_{n+1}])$$

~~2/08~~ # $X \geq 0$,

$$E(X) = \int_0^\infty F_x^c(n) dn$$

For a two sided rv.,

$$E(X) = \underbrace{\int_0^\infty F_x^c(n) dn}_{E(X^+)} - \underbrace{\int_{-\infty}^0 F_x(n) dn}_{E(X^-)}$$



$$[P_x(n_1) n_1 + P_x(n_2) n_2] - (-n_1 P_x(n_1) - n_2 P_x(n_2))$$

$$= E(X)$$

Functions of r.v.

Let $h: \mathbb{R} \rightarrow \mathbb{R}$ be a function. Then we want to examine if $h(X)$ is a r.v. i.e. we will need to ensure ^{the} 3 properties of r.v.

If $h(\cdot)$ is continuous, then $h(X)$ is a r.v if X is a r.v.

The characterization of $h(X)$ involves the discovery of its c.d.f.

The simplest characterization of $h(X)$ is finding its expectation

$E(h(X)) \rightarrow$ Find the distribution of $h(X)$ from X , & evaluate $E(h(X))$

easier way using the distⁿ. of X^2 .

If X is continuous, then

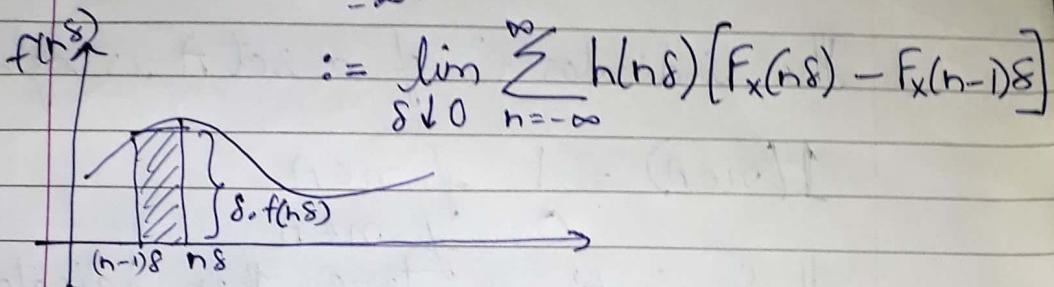
$$E(h(X)) = \int_{-\infty}^{\infty} h(n) f_X(n) dn$$

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$E(h(x)) \rightarrow$ Find the cdf of $Y = h(x)$
 Find $E(Y)$

$\hookrightarrow E(h(x))$ can also be found using
 the cdf of X .

$$E(h(x)) = \int_{-\infty}^{\infty} h(n) dF_X(n)$$



If X is continuous, then

$$E(h(x)) = \int_{-\infty}^{\infty} h(n) f_X(n) dn$$

If X is discrete, then

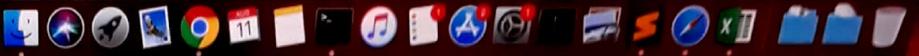
$$E(h(x)) = \sum_{i=1}^{\infty} h(x_i) p_X(x_i)$$

Example (mean & variance)

Recall that the mean is $E(X)$. Often we denote $\mu = E(X)$

Let $Y = X - \mu$ (centered r.v.) be another r.v. One measure of "closeness" of X to μ is $\sigma_X^2 = E((X - \mu)^2)$

$$\begin{aligned}\sigma_X^2 &= E(X^2 - 2\mu X + \mu^2) \\ &= E(X^2) - 2\mu E(X) + \mu^2 \\ &= E(X^2) - \mu^2 = E(X^2) - (E(X))^2\end{aligned}$$



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Variance of X

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$$\therefore \sigma_x^2 = E(X^2) - [E(X)]^2$$

σ_x small $\Rightarrow X$ is "closer" to its avg. value $E(X)$

Example (Indicator functions)

The indicator f_A of a set A is defined as $f_A(x)$ has

$$f_A(x) = 1 \text{ if } x \in A \\ 0 \text{ if } x \notin A$$

If $x \in A$ is true, then indicator is 1.

All cont. maps are measurable but vice-versa not true, ex: Indicator f_A .

$$E(f_A(x)) = F_x(b)$$

$$= \int_{-\infty}^{\infty} f_A(x) dF_x(m)$$

$$= \int_{-\infty}^b 1 dF_x(m)$$

$$= F_x(b)$$

$$E(f_A(x)) = P(X \in A)$$

of a 1-1

cont. r.v.
n). $\rightarrow R$ where
that is $b'(x)$ $P(Y \leq y) =$

derivative

$$= \frac{f_y(y)}{h'(t)}$$

$$\frac{d h^{-1}(y)}{dy} =$$

is assumed
at denom

ple [Sum

 $X \& Y$ be
 $(x) & F_Y(y)$

ep. implies

Example (pdf of a 1-1 function of contn. r.v.)

Let X be a contn. r.v. with pdf $f_X(x)$ & cdf $F_X(x)$.

Let $h: \mathbb{R} \rightarrow \mathbb{R}$ where $h(x)$ is increasing/one-to-one function. That is $h^{-1}(x)$ is well defined.

Then, $Y = h(X)$ has a cdf as below:-

$$\begin{aligned} F_Y(y) &= P(Y \leq y) = P(h(X) \leq y) \\ &= P(X \leq h^{-1}(y)) \\ &= F_X(h^{-1}(y)) \end{aligned}$$

Taking derivative w.r.t. y ,

$$f_Y(y) = \frac{f_X(h^{-1}(y))}{h'(h^{-1}(y))}$$

$$\left(\text{As } \frac{d}{dy} h^{-1}(y) = \frac{1}{h'(h^{-1}(y))}\right)$$

$h(x)$ is assumed to be monotonically \uparrow or \downarrow so that $\text{denom} \neq 0$.

Example (Sum of indep. r.v.)

Let X & Y be 2 indep. r.v. with cdf $F_X(x)$ & $F_Y(y)$.

* Indep. implies that $P(Y \leq y | X \in A) = P(Y \leq y)$ where $P(X \in A) \neq 0$

∴ Let $Z = X + Y$, then,

$$F_Z(z) = P(X+Y \leq z)$$

$$= \int_{-\infty}^{\infty} P(X \leq z-y | Y=y) dF_Y(y)$$

Total prob. rule
(law/theorem)

$$\left. \begin{array}{l} x \\ \text{are} \\ p^n \end{array} \right\} = \int_{-\infty}^{\infty} P(X \leq z-y) dF_Y(y)$$

$$\left. \begin{array}{l} \text{from.} \\ \times Y. \end{array} \right\} = \int_{-\infty}^{\infty} F_X(z-y) dF_Y(y) \quad \left. \begin{array}{l} \text{Like} \\ \text{convolution.} \end{array} \right\}$$

For the continuous case, this results in,

$$f_Z(z) = \frac{dF_Z(z)}{dz} = \int_{-\infty}^{\infty} f_X(z-y) f_Y(y) dy$$

$$f_Z(z) = f_X(z) * f_Y(z)$$

For the discrete case, when pmf. of X & Y are non-zero only on \mathbb{Z} , then

$$p_Z(z) = \sum_{n \in \mathbb{Z}} p_X(n) p_Y(z-n)$$

$$\therefore \frac{d}{dn} \int_0^{g(n)} f(m) dm = f(g(n)) g'(n)$$

↳ For any r.v. X , the expectation of $h(X)$ is understood as

$$E(h(X)) := \int_{-\infty}^{\infty} h(x) dF_X(x)$$

$$:= \lim_{\delta \downarrow 0} \sum_{n=-\infty}^{\infty} h(n\delta) [F_X(n\delta) - F_X((n-1)\delta)]$$

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Total probability rule

Let (X, Y) be a pair of RV.

$$F_x(n) = \frac{P(X \leq n)}{F_{x,y}(n, \infty)} = \frac{P(X \leq n, Y \leq \infty)}{F_{x,y}(n, \infty)}$$

Break $Y \leq \infty$ into } $= \int P(X \leq n, Y \leq y) dy$
into small intervals dy . } y x
 $\frac{dy}{dy} dy dy \rightarrow y$ $\approx Y=y$.

$$F_x(n) = \int_{-\infty}^{\infty} P(X \leq n | Y=y) f_Y(y) dy$$

If Y is continuous, then,

$$F_x(n) = \int_{-\infty}^{\infty} P(X \leq n | Y=y) f_Y(y) dy$$

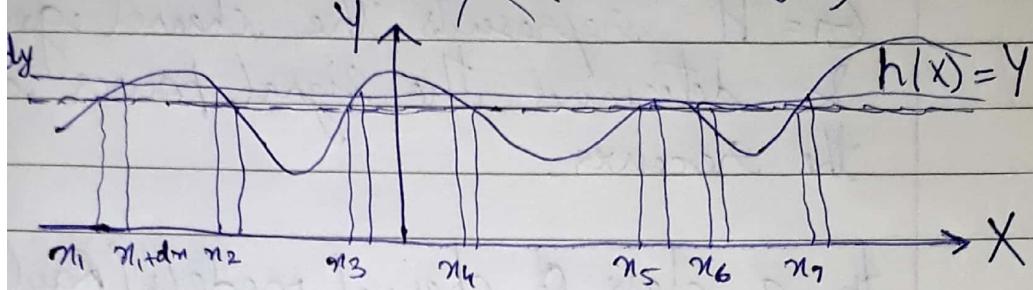
and if Y is discrete, then,

$$F_x(n) = \sum_{i \in \mathbb{Z}} P(X \leq n | Y=y_i) h_Y(y_i)$$

If $h: \mathbb{R} \rightarrow \mathbb{R}$ is strictly increasing, then
 $f_y(y) = \frac{f_x(h^{-1}(y))}{h'(h^{-1}(y))}$

When $h: \mathbb{R} \rightarrow \mathbb{R}$ is not one to one,
then

$$(h(x) \leq y) \Leftrightarrow (n \leq h^{-1}(y))$$



$$\begin{aligned} P(Y \in (y, y+dy)) &= P(X \in (n_1, n_1 + d_n)) \\ &\approx f_y(y) dy \\ &\quad + P(X \in (n_2, n_2 + d_n)) \end{aligned}$$

$$= \sum_{i=1}^{\infty} P(X \in (n_i, n_i + d_n))$$

$$= \sum_{i=1}^{\infty} f_x(n_i) |d_n| \quad \left| \begin{array}{l} n_i \text{ are all} \\ \text{the solns of} \\ y = h(x) \end{array} \right.$$

$$\therefore f_y(y) = \sum_{i=1}^{\infty} \frac{f_x(n_i)}{|\frac{dy}{dn_i}|}$$

$$\Rightarrow f_y(y) = \frac{f_x(n_1)}{|h'(n_1)|} + \frac{f_x(n_2)}{|h'(n_2)|} + \dots$$

(At max. & min, we use $h'(n_i)$)

In a wireless channel, we encounter,

$$Y_t = HX + W \rightarrow \text{noise}$$

channel gain (fading coeff)

received symbol \rightarrow transmitted symbols

$G_t = H^2$ represents the channel gain
 $\&$ determines the signal power at the receiver.

In a class of channel models (Rayleigh channels),

$$f_n(n) = \frac{n}{6^2} e^{-\frac{n^2}{26^2}} ; n \geq 0$$

Note that $G_t = h(H)$; then $h(n) = n^2$

$$\& h'(n) = 2n$$

Since $n \geq 0$ & $h(n)$ is monotonic in \mathbb{R}^+ ,

$$f_{G_t}(y) = \frac{\sqrt{y}}{6^2} \cdot \frac{e^{(-y/26^2)}}{2\sqrt{y}} = \frac{1}{26^2} e^{\frac{-y}{26^2}},$$

$y \geq 0$

$\therefore G_t$ has an exponential distrib'.