

Advanced Statistics

→ Experiment

→ Deterministic Experiment
 $y = f(n)$

→ Random Experiment

→ Sample space $S = \{ \dots \}$

 └ discrete (countable (finite or infinite))
 └ continuous (ranges, interval)

Discrete (coin toss, dice roll)

Continuous (temperature, height measure)

(5) Event

(subset of a sample space given a constraint / desired output)

"An event where all outputs are even in dice roll"

(6) Probability

(quantification the outcomes of a random experiment)

"Chance" is qualitative "

(7) Axioms of Probability (general rules)

$P(A)$ probability of occurrence of A

"Relative frequency of experimental event"

$$1 * 0 \leq P(A) \leq 1$$

$$2 * P(S) = 1 \quad (\text{sum of all prob is } 1)$$

$$3 * P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

$$P(A_1 \cup A_2 \cup \dots \cup A_{n+1}) = P(A_1) + P(A_2) + \dots + P(A_n)$$

$P(A) = \frac{n(A)}{n(S)}$ if events are equally likely

and sample space discrete

$n(A)$ = number of elements in A (event)

$n(S)$ number of elements in sample space

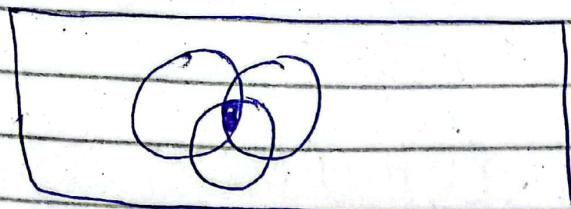
$$\star \boxed{\begin{array}{c} S \\ \cap \\ A \quad B \end{array}} \quad P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

→ We have added the shaded region twice so subtract it once -

$$P(A \cup B \cup C) = P(A) + P(B) + P(C) - P(A \cap B) -$$

$$P(A \cup B \cup C \cup D) = \downarrow \quad P(A \cap C) - P(B \cap C)$$

something as above.



Complement any event

$$P(A) = 1 - P(A^c)$$

$$P(A^c) = 1 - P(A)$$

Additive rules :-

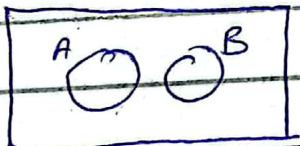
$P(A)$; $P(B)$ known

Conditional Probability

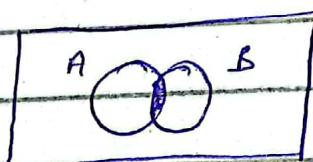
$$P(B|A) = ?$$

→ conditional prob of B over A

→ prob of B given A has occurred already



mutually exclusive



mutually inclusive

$$P(B|A) = \frac{P(A|B)(P(B))}{P(A)}$$

$$P(B|A) = \frac{P(A \cap B)}{P(A)}$$

Joint probability of events :-

Baye's Theorem :-

$$P(B|A) = \frac{P(A \cap B)}{P(A)}$$

$$P(A) = \frac{P(A \cap B)}{P(B|A)}$$

$$P(A) =$$

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

$$P(B) = \frac{P(A \cap B)}{P(A|B)}$$

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

$$P(A|B) = \underline{P(B|A)}$$

if $P(A) \neq 0$

Dependent :-

Occurrence of A effects occurrence of B.

Product Rule

if A and B are independent

then

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

B₁
B₅

and

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

→ division
method

$$\left\{ \begin{array}{l} P\left(\bigcap_{i=1}^n E_i\right) = P(E_1) \cdots P(E_n) \\ = \prod_{i=1}^n P(E_i) \end{array} \right.$$

P(A) =

if E_1, E_2, \dots, E_n are independent
but mutually inclusive.

P(A) =

$$\left\{ \begin{array}{l} P(A_1 \cup A_2 \cup \dots \cup A_n) = P(A_1) + P(A_2) + \dots \\ = \sum_{i=1}^n P(A_i) \end{array} \right.$$

=

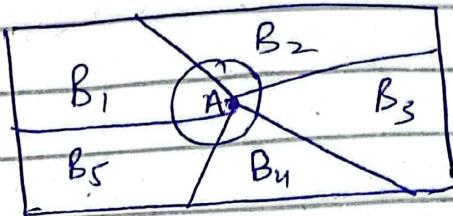
if they are mutually exclusive

P(A) =

P(B)

P(E)

B_a



→ dividing a sample space in N ~~non~~
mutually exclusive (disjoint partition)

$$P(A) = P(A \cap B_1) \cup P(A \cap B_2) \cup \\ P(A \cap B_3) \cup \dots \cup P(A \cap B_n)$$

$$P(A) = P(A \cap B_1) + P(A \cap B_2) + \\ P(A \cap B_3) + \dots + P(A \cap B_n)$$

Because A & B are exclusive.
within themselves.

$$= \sum_{i=1}^N (P(A \cap B_i))$$

$$P(A) = \sum_{i=1}^N P(A|B_i) P(B_i)$$

Total probability

$$P(B_i | A) = \frac{P(A \cap B_i)}{P(A)}$$

$$P(B_i | A) = \frac{P(A | B_i) \cdot P(B_i)}{\sum_{i=1}^N P(A | B_i) P(B_i)}$$

Baye's Theorem

Experiment :-

- a process that generates some data
 - experiment is performed under certain closed conditions that are constant.
 - environment does not change for an experiment
 - If the outcome does not change, we can model the outcome mathematically
- $y = f(x)$
- output ↘
function ↓
 input

Deterministic Experiment :-

- If conditions are fixed, and then the outcomes are variable then we call such an experiment

Random Experiment :-

- all natural processes / experiments are random
- if the experiment generates discrete no. Then the experiment is discrete such as tossing a coin or rolling a dice
- If the experiment is continuous then it will generate ranges and interval as output. Such as measuring height / temp.

Sample Space :-

- Contains all possible outcomes of an experiment
- It is a set $S = \{ \dots \}$
- It can be an interval or a discrete value
- We can have discrete sample space; infinite or finite which is countable
- We can have continuous outputs in sample space that are finite / infinite.

$$S = \{ 1, 2, 3, 4, 5, 6 \}$$

$$E = \{ 2, 4, 6 \}$$

Experiment & Event :-

- A subset of set / sample space is called an event based on certain checks to derive success.

Probability :-

A quantification of the outcomes of a random experiment.

"Chance" is qualitative so we quantify it.

$$P(A) \Rightarrow \text{probability of } A$$

Axioms?

Axioms of Probability

$$① \quad 0 \leq P(A) \leq 1$$

$$② \quad \sum_{i=1}^N P(A_i) = 1, \quad P(S) = 1$$

③ If A and B are mutually exclusive
then $P(A \cup B) = P(A) + P(B)$

If A and B are mutually inclusive

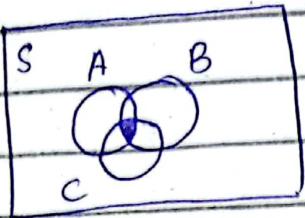
$$\text{then } P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

If $A_1, A_2, A_3, \dots, A_n$ are mutually exclusive then

$$P(A_1 \cup A_2 \cup \dots \cup A_n) = P(A_1) + P(A_2) + \dots + P(A_n)$$

$$P(\bigcup_{i=1}^N A_i) = \sum_{i=1}^N P(A_i)$$

oo



$$(A \cup B \cup C) = (A \cup B) \cup (A \cup C) \cup (B \cup C)$$

$$\begin{aligned} P(A \cup B \cup C) &= P(A \cup B) + P(A \cup C) + P(B \cup C) + \\ &+ P(A \cap B \cap C) - P(A \cap B) - P(A \cap C) - P(B \cap C) \\ &= P \{ \underbrace{A \cup (B \cup C)}_{E_1} \} \\ &= P(E_1 \cup E_2) \end{aligned}$$

$$= P(E_1) + P(E_2) - P(E_1 \cap E_2)$$

$$\begin{aligned} &= P(A) + P(B \cup C) - P \{ A \cap (B \cup C) \} \\ &= P(A) + P(B \cup C) - P(A \cap B \cup A \cap C) \\ &\quad - P \{ A \cap B \cup (A \cap C) \} \end{aligned}$$

$$\begin{aligned} &= P(A) + P(B \cup C) - P \{ A \cap B \cup A \cap C \} \\ &= P(A) + P(B \cup C) - P(A \cap B) - P(A \cap C) \\ &= P(A) + P(B) + P(C) - P(A \cap B) + P(A \cap C) \\ &= P(A) + P(B \cup C) - P(A \cap B) + P(C) - \\ &\quad P[(A \cup B) \cap C] \end{aligned}$$

$$= P(A) + P$$

Conditional Probability

$\& =$ if two events are always independent

$$P(B|A) = \frac{P(A \cap B)}{P(A)}$$

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

\Rightarrow Independent events :-

If occurrence of A does not impact B, then A and B are not dependent i.e. independent

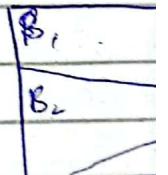
Generalizing Pro

$$P(E_1 \cap E_2 \cap E_N) = P(E_1) P(E_2) \dots P(E_N)$$

$$P(\bigcap_{i=1}^N E_i)$$

Baye's Theor

- * Two mutually exclusive events are not always independent.

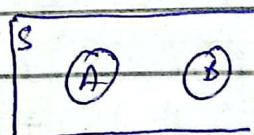


Independent is B of A then

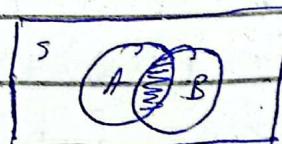
$$* P(B|A) = P(B)$$

$$\text{if } P(A \cap B) = P(A) P(B)$$

then A and B are independent



dependent +
m. exclusive



? + m. inclusive
if

\rightarrow idon't know if dependent
 \rightarrow dependent if $P(A \cap B) \neq P(A) P(B)$

given P
P[E]

Q = If two events occur at the same time, are they always independent?

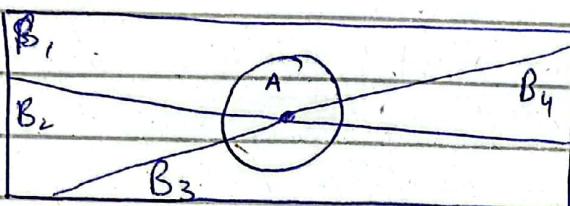
Generalizing Product Rule :-

$$P(E_1 \cap E_2 \cap E_3 \dots \cap E_n) = \text{if } E_i \text{ are independent}$$

$$P(E_1) P(E_2) P(E_3) \dots P(E_n)$$

$$P\left(\bigcap_{i=1}^n E_i\right) = \prod_{i=1}^n P(E_i)$$

Baye's Theorem :-



$$P(B_i)$$

$i = 1, 2, 3, 4$

$$P(A) = ?$$

$$A = (A \cap B_1) \cup (A \cap B_2) \cup$$

$$(A \cap B_3) \cup (A \cap B_4) \dots$$

$$P(A) = P(A \cap B_1) + P(A \cap B_2) +$$

$$P(A \cap B_3) + P(A \cap B_n)$$

Given that B_1, B_2, B_3 are exclusive

$$P[(A \cap B_1) \cup (A \cap B_2) \dots \cup (A \cap B_n)]$$

$$\Rightarrow \sum_{i=1}^N P(A \cap B_i) = P(A)$$

$$= P(A) = \sum_{i=1}^N P(A|B_i) P(B_i)$$

Total Probability Law

$$P(B_i|A) = ? \\ = \frac{P(A \cap B_i)}{P(A)}$$

$$= \frac{P(A|B_i) P(B_i)}{P(A)}$$

$$= \frac{P(A|B_i) P(B_i)}{\sum_{i=1}^N P(A|B_i) P(B_i)} \quad \begin{cases} \text{out of} \\ \text{sum} \end{cases}$$

Advanced Statistics

Random Variable :-

defined by: X

defined over a whole sample space on a \mathbb{R}^+ number line.

(i) $R.V \rightarrow X$

(ii) Range of $X \rightarrow S_X = \{ \dots \}$

$$S = \{ HH, HT, TH, TT \}$$

$$S_X = \{ 0, 1, 2 \}$$

X shows no. of heads when a pair of coins is tossed.

Y shows no. of ..

(iii) Probability assignments to outcomes of Random Variable -

"Probability Mass Function"

PMF $\rightarrow P_X(x)$

$$P_X(x) = P[X = x]$$

Probability that X takes value of x

PMF is used to assign masses of probability to random variable values

Expectation

(ii) $0 \leq P_X(x) \leq 1$

"a prediction"

(iii) $\sum_x P_X(x) = 1$

"also called average"

PMF of $\{0, 1, 2\}$

→ Not all

X = no. of heads when two coins are tossed

$E[X]$

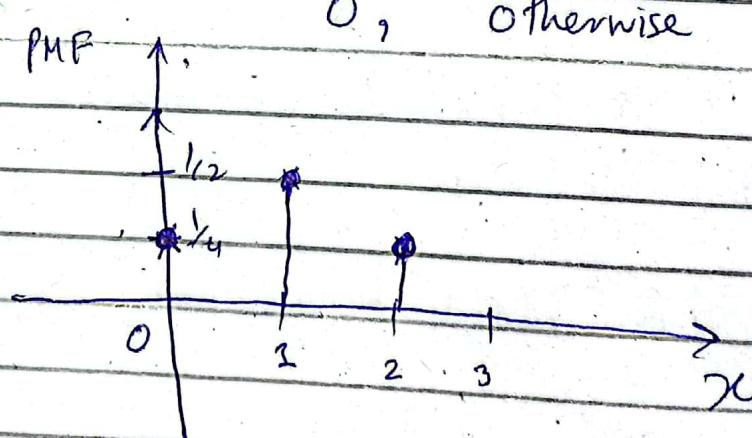
$$S_x = \{0, 1, 2\} \quad S = \{HH, TT, HT, TH\}$$

$$\mu = \frac{1}{2} \times 1$$

$$PMF = \begin{cases} \frac{1}{4}, & x=0 \\ \frac{1}{2}, & x=1 \\ 0, & \text{otherwise} \end{cases}$$

$S_x =$

getting
if it



$$\frac{1}{6} \times 1$$

$$= \frac{1}{6}$$

$$= \frac{1}{6}$$

$$= 3.$$

Expected Value

"a prediction of the trend"

"also called the average of or weighted average"

→ Not always an average.

$$E[X] = \sum_{x} x P_X(x)$$

⇒ statistical inference ↑

$$\mu = \frac{1}{2} \times 1 + \frac{1}{4} \times 2 = \frac{1}{2} + \frac{1}{2} = 1$$

$$S_x = \{0, 1, 2\} \quad S \subseteq \{HH, TT, HT, TH\}$$

Getting 1 head has highest probability if two coins are tossed.

$$\frac{1}{6} \times 1 + \frac{1}{6} \times 2 + \frac{1}{6} \times 2 + \frac{1}{6} \times 4 + \frac{1}{6} \times 5 + \frac{1}{6} \times 6$$

$$= \frac{1}{6} + \frac{1}{3} + \frac{1}{2} + \frac{4}{6} + \frac{5}{6} + 1$$

$$= \frac{1}{6} + \frac{1}{3} + 0,5 + \frac{1}{2} + 1$$

$$= 3,5 \quad S_X = \{1, 2, 3, 4, 5, 6\}$$

* When the probability of each values is same then $E[\sum x_i]$ is not useful. (uniform Random Variable)

* If PMF is constant i.e. in case of tossing a fair die.

See Box VARIANCE :-

Expected variation around its average in tossing two coins.

$$\text{Var}[x] = E[(x - E[x])^2]$$

$$= E[x^2] - (E[x])^2$$

$$= \sum x^2 p_i(x) - (E[x])^2$$

* Variance can never be negative

$$\text{STD}(x) = \sqrt{\text{var}(x)}$$

$$\sigma = \sqrt{\sigma^2}$$

Bernoulli's Trials.

- We divided a sample space in 2
- a success is 1, and failure is 0
- This is a bernoulli trial-
- first trial is not impacting the other trial.

⇒ Binomial Random Variable

$$S_n = \{0, 1, 2, 3, \dots, n\}$$

$$P_n(k) = {}^n_C_k p^k (1-p)^{n-k}$$

$$E(X) = np \quad \text{var}(X) = np(1-p)$$

Random Variable $X \geq 0$

- keep performing independent trials until a success comes.

Geometric Random Variable

$$S_n = \{1, 2, 3, \dots\}$$

$$P_X(n) = p(1-p)^{n-1}$$

$$E(X) = \frac{1}{p}; \quad \text{var}(X) = \frac{1-p}{p^2}$$

Negative Binomial Random Variable

(getting r successes in Bernoulli trials)

$$S_x = \{r, r+1, r+2, \dots\}$$

$$P_x(x) = \frac{n-1}{C_{r-1}} p^r (1-p)^{n-r}$$

$$E(X) = \frac{r}{p}; \text{Var}(X) = r\left(\frac{1-p}{p^2}\right)$$

Hyper Geometric Random Variable

$$S_n = \{0, 1, 2, 3, \dots, n\}$$

If $n \leq K$ and $n \leq N-K$

$$P_x(x) = \frac{(K)_x (N-K)_{n-x}}{N_{C_n}}$$

$$E(X) = \frac{nK}{N}$$

$$\text{Var}(X) = \frac{N-n}{N-1} \cdot \frac{nK}{N} \cdot \frac{(1-K)}{N}$$

Poisson Random Variable

$$S_x = \{0, 1, 2, 3, \dots\}$$

$$P(x=k) = \frac{(\lambda t)^k}{k!} \cdot e^{-\lambda t}$$

$$E(x) = \lambda t \quad \text{Var}(x) = \lambda t$$

29 January 2023

Advance Statistics

RV $\rightarrow X$

($S_x = \{ \text{continuous interval} \}$)

$$P = \frac{m}{V}$$

$P(x, y, z)$ density of definite solid body-

$f(v)$

$$m = \iiint_{x y z} P(x, y, z) dx dy dz$$

$$= \int_V f_v dv$$

$$0 \leq X < 1$$

Probability (PDF)

Continuous Density Function

(i) $f_x(x) \geq 0$

(II)

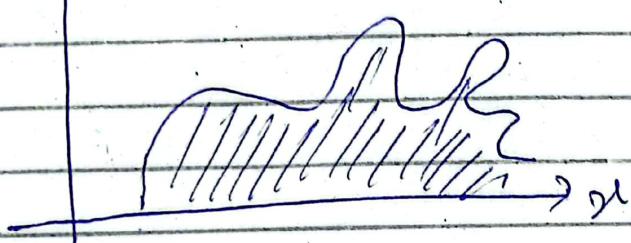
$$P[X \leq a] = \int_{-\infty}^a f_x(x) dx$$

(III) $\int_{-\infty}^{\infty} f_x(x) dx = 1$

$$P[X \leq a \& X \geq b]$$

$$= \int_a^b f_x(x) dx$$

$f(x)$

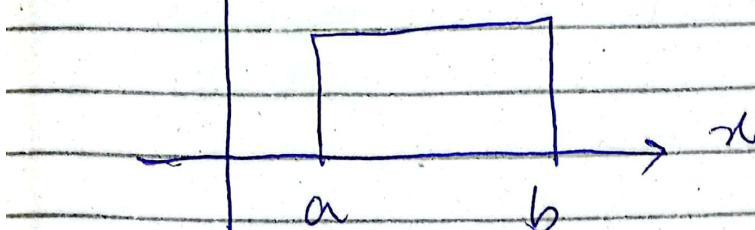


a

$$\frac{1}{b-a} = 1$$

* Uniform RV - $f(x) = \frac{1}{b-a}$

$f(x)$



$$\int_a^b f(x) dx = 1$$

height = $\frac{1}{b-a}$

(I) Uniform RV

$$f_x(x) = \begin{cases} \frac{1}{b-a}, & a \leq x \leq b \\ 0, & \text{otherwise} \end{cases}$$

Inter
waiting
expone
becau
inter

$$E[x] = \int_{-\infty}^{\infty} f(x) \cdot x \, dx$$

E[x]

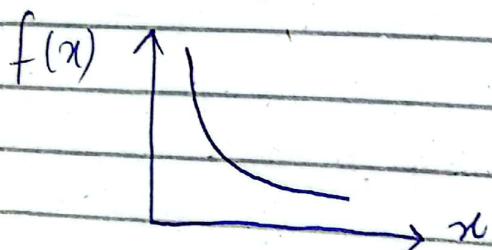
$$E[x] = \frac{a+b}{2}$$

f_x(x)

$$V[x] = \frac{(b-a)^2}{12}$$

Cum.

(II) Exponential RV (continuous)



$$f_x(x) = \begin{cases} \lambda e^{-\lambda x}, & 0 \leq x \\ 0, & \text{otherwise} \end{cases}$$

if con

=

* cum

* →

Inter arrival time in poisson dist. is waiting time and is modeled by exponential random variable because it is used to measure inter arrival time.

$$E[x] = \lambda \quad \text{var}[x] = \frac{\lambda}{\lambda^2}$$

$$f_x(x) = \begin{cases} \lambda e^{-\lambda x}, & 0 \leq x \\ 0, & \text{otherwise} \end{cases}$$

Cumulative distribution Function

CDF F

$$\Pr(X \leq a) = ?$$

$$\text{if discrete, } P(X \leq a) = \sum_{x \leq a} P_x(x)$$

$$\text{if continuous, } P(X \leq a) = \int_{-\infty}^a f_x(u) du$$

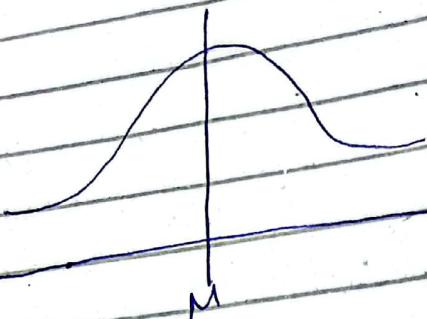
$$= \boxed{F_X(a)}$$

$$\star \text{ axiom 3 8- } \Pr(a \leq X \leq b) = \int_a^b f(x) dx$$

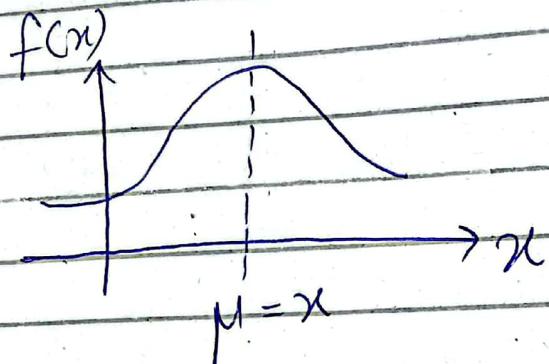
$$\star \rightarrow \Pr(a \leq X \leq b) = F_X(b) - F_X(a)$$

3) Normal Distribution

Gaussian



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



* When $\sigma \uparrow$ width is high
when $\sigma \downarrow$ width is low.

$$E[x] = \mu$$

$$\text{Var}[x] = \sigma^2$$

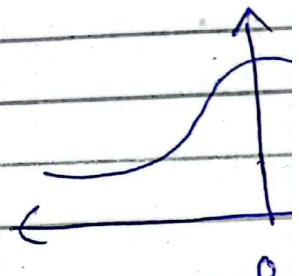
$$P[a \leq x \leq b] = \int_a^b f_x(u) du$$

Standard

• special

$$f_z(z) =$$

$$\mu = 0 \\ \text{var}[x]$$



$z \rightarrow$

$P_x[$

$P_x[$

$P[-$

$P_r[$

Standard Normal Random Variable

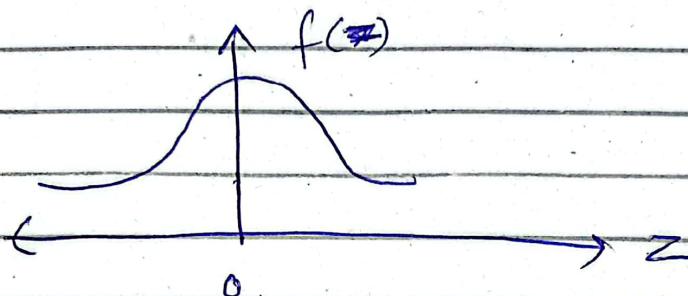
• special

$$f_z(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}$$

$$\mu = 0$$

$$E[x] = 0$$

$$\text{var}[x] = 1$$



$Z \rightarrow$ Standard normal variable

$$P_x[a \leq x \leq b] = P_{\text{std}}[?]$$

$$P_x[x \leq a] = P\left[\frac{x-\mu}{\sigma} \leq \frac{a-\mu}{\sigma}\right]$$

$$P\left[\frac{x-\mu}{\sigma} \leq \frac{a-\mu}{\sigma}\right]$$

$$P\left[\cancel{x-\mu} / \sigma \leq \frac{a-\mu}{\sigma}\right]$$

$$P[X \leq a] = P\left[\frac{X-\mu}{\sigma} < \frac{a-\mu}{\sigma}\right]$$

$$P[X \leq a] = P[Z \leq \frac{a-\mu}{\sigma}]$$

$$P_X(X \leq a) = F_X(a) = F_Z\left(\frac{a-\mu}{\sigma}\right)$$

R.V

$$f_X(x) = \frac{d}{dx} F_X(x)$$

(i) f_{X_1}

f_{X_1}

$$F_X(x) = \int_{-\infty}^x f(x) dx$$

$$z = f_{Y_1}$$

* P.C

$$\int_{-\infty}^{\infty}$$

$\text{cov}(X, Y)$

$$\text{cov}(xy) = E[XY] - E[X]E[Y]$$

$$*\rho = \frac{\text{cov}(X, Y)}{\sqrt{\text{var}[X]\text{var}[Y]}}$$

$$*\rho = -1 \leq \rho \leq 1$$

* Coefficient of
Correlation

31 January 2024

Wednesday

- fundamentals of prob theory
- RV - discrete & continuous
- mean and variance of RV
- Joint discrete & continuous RV

Random variable X & Y

→ If their covariance or correlation coefficient is zero then they are not related to each other

Independent Random Variables :-

$$P_{xy}(x, y) = P_x(x) \cdot P_y(y)$$

Joint density of x and y Probability of x Probability of y

Joint PMF

The above equation holds true if the two variable (random) are Independent.

$$f(x, y) = f(x) \cdot f(y) \text{ if } x \text{ and } y \text{ are continuous random variables.}$$

* if two RV are independent then their covariance is zero but vice versa is not true.

* Independent variables are un-correlated but not vice versa.

Linear Combination of Random Variables

→ let $X_1, X_2, X_3, \dots, X_n$ be random variables and $C_1, C_2, C_3, \dots, C_n$ are constants

A new RV "Y" can be a linear combination of X_i and C_i

$$Z = X + 1$$

$$Z = X + Y$$

• We can generate new RV using present RV with help of some mathematical operations

$$Y = X_1 C_1 + X_2 C_2 + X_3 C_3$$

$$\text{let } \mu_1 = E[X_1] \quad i = 1, 2, 3, \dots, n$$

$$\mu_2 = E[X_2]$$

$$\sigma^2 = \text{Var}[X_i]$$

So, Y is called linear combination of X

$$E[Y] = ?$$

$$= E[C_1 X_1 + C_2 X_2 + \dots + C_n X_n]$$

Ques: $\frac{\text{JPDF}}{\text{JPMF}} = \text{variance}/\mu = ?$

• Linear operator :-

If $f(x_1) = y_1$ and $f(x_2) = y_2$ and
 $f(x_1 + x_2) = (y_1 + y_2)$ then f
 is a linear operator -

• Expectation is a Linear operator

$$E[y] = E[c_1 x_1 + c_2 x_2 + \dots + c_n x_n]$$

$$E[y] = c_1 E[x_1] + c_2 E[x_2] + \dots + c_n E[x_n]$$

$$\mu_x = \sum_{i=1}^n c_i \mu_i$$

$$\mu_y = E[y] = [c_1 + c_2 + c_3 + \dots + c_n] [E[x_1] + x_2]$$

• Variance operator is highly non-linear

IE Variance

If x_i 's are all independent
 Then variance of $E[y]$ is :-

$$\sigma^2 = \text{Var}[y] = \text{Var}[c_1 x_1 + c_2 x_2 + \dots + c_n x_n]$$

$$\text{Var}[y] = c_1^2 \text{Var}[x_1] + c_2^2 [\text{Var}[x_2]] + \\ c_3^2 \text{Var}[x_3] + \dots + c_n^2 [\text{Var}[x_n]]$$

$$* \text{Var}[y] = \sum_{i=1}^n c_i^2 \sigma_i^2 = \sigma_y^2$$

If X_i 's are independent i.e.
not related to each other
And are identically distributed i.e.
their PMF or PDF is same

$$\Rightarrow E[X_i] = \mu \quad \forall i = 1, 2, 3, \dots, n$$

$$\Rightarrow \text{Var}[X_i] = \sigma^2 \quad \forall i = 1, 2, 3, \dots, n$$

because they are identically distributed
 $X_i \sim f(x_i)$



If X_i are IID then

$$Y = \sum_{i=1}^N C_i X_i$$

$$\mu_y = \sum_{i=1}^N E[X_i] = N \sum_{i=1}^N \mu_i$$



$$\mu_y = E\left[\sum_{i=1}^N X_i\right] = \sum_{i=1}^N E[X_i]$$

$$\boxed{\mu_y = \sum_{i=1}^N \mu = N \mu}$$

given that
 C is 1

$$\boxed{\sigma_y^2 = N \sigma_x^2}$$

If constants are different :-

$$Y = \sum_{i=1}^N C_i X_i$$

$$\mu_Y = \mu \cdot \sum_{i=1}^N C_i$$

$$\sigma^2 = \sigma^2 \cdot \sum_{i=1}^N C_i^2$$



If X_i 's are IID with Bernoulli distribution

then

$$Y = \sum_{i=1}^N X_i$$

Y becomes binomial

X can be 0 or 1

$$\mu_Y = np \quad \sigma^2 Y = np(1-p)$$

$$\text{PMF}(Y) = N_C Y \cdot p^y \cdot (1-p)^{N-y}$$



geometric IID X_i 's

$$Y = \sum_{i=1}^N X_i, \text{ PMF}(Y) = \sum_{r=1}^{n-1} \binom{n-1}{r-1} p^r (1-p)^{n-r}$$

Y becomes - negative binomial

$$\Rightarrow \text{var}(Y) = r(1-p)$$

$$\Rightarrow \mu_Y = \frac{r}{p}$$

If X_i 's are Gaussian / Normal
IID

$$Y = \sum_{i=1}^N C_i X_i$$

Y becomes Normal

$$\mu_Y = \mu$$

$$\mu_Y = \sum_{i=1}^N C_i \mu_i$$

$$\sigma_Y^2 = \sum_{i=1}^N C_i^2 \sigma_i^2$$

$$\text{PDF}(Y) = \frac{1}{\sqrt{2\pi\sigma_Y^2}} \cdot \exp\left\{-\frac{1}{2} \left(\frac{Y-\mu}{\sigma_Y}\right)^2\right\}$$



X_i 's are IID Normal Then

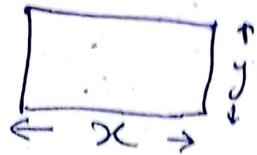
$$\mu_Y = N\mu$$

$$\sigma_Y^2 = N\sigma^2$$

$$f_Y(y) = \frac{1}{\sqrt{2\pi\sigma_Y^2}} \exp\left\{-\frac{1}{2} \left(\frac{y-\mu_Y}{\sigma_Y}\right)^2\right\}$$

pmf

Question



- RV X_1 shows length of component.
- RV X_2 shows width of component.
- Both are independent of each other



$$E[X_1] = 2 \text{ cm} \quad E[X_2] = 5 \text{ cm}$$

$$\text{Var}[X_1] = 0.1^2 \text{ cm}^2 \quad \text{Var}[X_2] = 0.2^2 \text{ cm}^2$$

X_1 and X_2 follow Normal Dist
and are I.I.D.

$$\text{Peri} = 2x + 2y$$

$$= 2X_1 + 2X_2$$

R.V shows perimeter

$$\text{R.V. } Y = 2X_1 + 2X_2$$

X is perimeter of component -

What is probability that a selected
compo exceeds 14.5 cm in perimeter

$$\mu_Y = \sum_{i=1}^N C_i \mu_i \quad \text{because } 2 \text{ R.V.}$$

$$= 2 \cdot 2 + 5 = 7 \times 2 = 14 \text{ cm}$$

$$\sigma^2_Y = N \cdot \sigma^2 = 2^2 \cdot (0.1 + 0.2) =$$

$$M_y = 14 \text{ cm}$$

$$= 2 \times (0.5 + 0.2) =$$
$$= 2 \times (7) = 14 \text{ cm}$$

$$\text{Var}(y) = 2^2 \times (0.1)^2 +$$
$$2^2 \times (0.2)^2$$

$$= 4 \times 0.1 + 4 \times 0.04$$
$$= 0.4 + 0.04 + 0.16$$
$$= 0.2 \text{ cm}$$

$$P[X > 14.5 \text{ cm}] = ?$$

$$P(X < 14.5) = 1 - P(X > 14.5)$$

$$P(X \leq 14.5) = 1 - F_Y(14.5)$$

$$= 1 - F_Z\left(\frac{14.5 - 14}{\sqrt{0.2}}\right)$$

$$= 1 - F_Z(1.136)$$

$$= 1 - 0.8708$$

$$= 0.1292$$

Profit in year
Probability

loss
probability

expected gain

E[X]

f(n) =

$$\int_0^1$$

$$= \int_0^1 \left(\frac{2}{x}\right)$$

$$\text{Profit in year} = 4000$$
$$\text{Probability} = 0.3$$

$$\text{Loss} = 1000$$
$$\text{Probability} = 0.7$$

$$\text{Expected gain} = 0.3 \times 4000 + (-1000 \times 0.7)$$
$$= \$500$$

$$E[X] = x P(x)$$

$$f(x) = \begin{cases} \frac{2(x+2)}{5} & 0 < x < 1 \\ 0 & \text{elsewhere} \end{cases}$$

$$f(x) = \frac{2(x+2)}{5} = \frac{2x+4}{5} \quad 0 < x < 1$$

$$\int_0^1 \frac{2(x+2)}{5} dx$$

$$= \int \left(\frac{2x^2}{2} \right) + \frac{4x}{5} dx = \left[\frac{x^2}{5} + \frac{4x}{5} \right]_0^1$$

$$= \frac{1}{5} + \frac{4}{5} - \left(\frac{1}{5} - \frac{4}{5} \right)$$

$$2x+4$$

$$g(x) = (2x+1)^2$$

$$E[X]_g = g(n) P(n)$$

$$= (2(-3)+1)^2 \cdot \frac{1}{6} +$$

$$(2(6)+1)^2 \cdot \frac{1}{2} +$$

$$(2(9)+1)^2 \cdot \frac{1}{3}$$

$$= 25 \cdot \frac{1}{6} +$$

$$13^2 \cdot \frac{1}{2} +$$

$$19^2 \cdot \frac{1}{3}$$

$$= 209$$

$$f(u) = 3u^{-4} \quad u > 0$$

$$f(u) = 3u^{-4}$$

$$F(u) = \int_1^\infty 3u^{-4} du$$

$$= 3 \int_1^\infty x^{-4} dx$$

$$= 3 \left[\frac{x^{-3}}{-3} \right]_1^\infty$$

$$= 3 \left[-x^{-3} \right]_1^\infty$$

$$= -1 - \left(-\frac{1}{\infty} \right) = \textcircled{-1}$$

$$F(u) = \int_1^t$$

$$= 3t$$

$$= -x$$

$$= -t^{-3}$$

$$P(X > 3)$$

$$E[X] =$$

$$E[X]$$

$$\begin{aligned}
 F(u) &= \int_1^t f(u) du = \int_1^t 3u^{-4} du \\
 &= 3 \int_1^t u^{-4} du = 3 \cdot \left[\frac{u^{-3}}{-3} \right]_1^t \\
 &= \left[-u^{-3} \right]_1^t = -t^{-3} - (-1) \\
 &= -t^{-3} + 1
 \end{aligned}$$

$$\begin{aligned}
 P(X > 3) &= 1 - P(X < 3) \\
 &= 1 - (-t^{-3} + 1) \\
 &= 1 - (-u^{-3} + 1) \\
 &= 1 - \left(-\frac{1}{64} \right) + 1 \\
 &= 1 - \left(\frac{63}{64} \right) = \frac{1}{64}
 \end{aligned}$$

$$\begin{aligned}
 E[X] &= \frac{1}{64} \cdot (3x^{-4}) \\
 &= \frac{1}{64} \cdot (3x^{-4})
 \end{aligned}$$

$$\begin{aligned}
 E[X] &= \int_{-\infty}^{\infty} x f(x) dx \\
 &= \int_{-\infty}^{\infty} (3x^{-4})(x) dx \\
 &= \int_1^{\infty} 3x^{-3} dx \\
 &= \left[\frac{3x^{-2}}{-2} \right]_1^{\infty} = \frac{3}{-2} \left[\frac{1}{x^2} - \frac{1}{1^2} \right] \\
 &= \frac{3}{-2} \left(0 - \frac{1}{1^2} \right) = \frac{3}{2}
 \end{aligned}$$

$$f(y) = \begin{cases} 5(1-y)^4, & 0 \leq y \leq 1 \\ 0, & \text{else} \end{cases}$$

$$(a) \left(\int_0^1 (5-5y)(1-y)^4 dy \right)$$

$$= 5 \int_0^1 (1-y)^4 dy$$

$$= 5 \int_0^1 (1-y)^2 \cdot (1-y)^2 dy$$

$$= 5 \int_0^1 (1+y^2-2y)(1+y^2-2y) dy$$

$$= 5 \int_0^1 (1+y^2-2y) + (y^2+y^4-2y^3) -$$

$$(2y-2y^3+4y^2) dy$$

$$= 5 \int_0^1 1 + 6y^2 - 4y + y^4 dy$$

$$= 5 \int_0^1 6y^2 + y^4 dy$$

$$= 5 \int_0^1 y^4 + 6y^2 - 4y + 1 dy$$

$$= 5 \left[\frac{y^5}{5} \right]_0^1 + 6 \left[\frac{y^3}{3} \right]_0^1 - 4 \left[\frac{y^2}{2} \right]_0^1 + y \Big|_0^1$$

$$= 5 \left[\frac{1}{5} \right] + \left[6 \cdot \frac{1}{3} \right] - 4 \left[\frac{1}{2} \right] + 1$$

$$= 5 \left[\frac{1}{5} + 2 - 2 + 1 \right]$$

$$= \frac{1}{5} \times 5 + 1 \times 5 = 6$$

$$= (1-y)^2 (1+y^2-2y)$$

$$= (1+y^2-2y)$$

$$= (1+y^2-2y)$$

$$= 1+y^2+$$

$$-2y^3$$

$$1+6y$$

$$\int_0^1 (1+6y) dy$$

$$5 \left[y \right]$$

$$5 \left[1 - \frac{y^5}{5} \right]$$

$$+ 6 \left[\frac{y^3}{3} \right] - 4 \left[\frac{y^2}{2} \right] + y \Big|_0^1$$

14

①

$$= (1-y)^2 (1-y)^2$$

$$= (1+y^2 - 2(y))(1+y^2 - 2y)$$

$$= (1+y^2 - 2y) + (y^2 + y^4 - 2y^3) + \\ (-2y - 2y^3 + 4y^2)$$

$$= 1 + y^2 + y^2 + 4y^2 - 2y - 2y + y^4 - 2y^3 \cancel{+}$$

$$= 1 + 6y^2 - 4y - 4y^3 + y^4$$

$$= 5 \int_0^1 (1 + 6y^2 - 4y - 4y^3 + y^4) dy$$

$$= 5 \left[y + \frac{6y^3}{3} - \frac{4y^2}{2} - \frac{4y^4}{4} + \frac{y^5}{5} \right]_0^1$$

$$= 5 \left[1 + \frac{6}{3} - \frac{4}{2} - 1 + \frac{1}{5} \right]$$

$$= \cancel{5} + \frac{30}{3} - \frac{20}{2} - \cancel{5} + 1$$

$$= 10 - 10 \cancel{+ 1}$$

$$= \textcircled{1} \quad \checkmark$$

$$P(X < 0.1) = ?$$

$$F(x) = \int_0^x 1 + 6y - 4y^2 - 4y^3 + y^4 dy$$

$$= \left[y + \frac{6y^2}{2} - \frac{4y^3}{3} - \frac{4y^4}{4} + \frac{y^5}{5} \right]_0$$

$$= \left[t + \frac{6t^2}{2} - \frac{2t^3}{3} - \frac{t^4}{4} + \frac{t^5}{5} \right]$$

$$P(X < 0.1) =$$

$$\frac{0.1}{5} = \left[t + \frac{6t^2}{2} - \frac{2t^3}{3} - \frac{t^4}{4} + \frac{t^5}{5} \right]$$

$$P(X < 0.1) = \frac{1}{5} \left(0.1 + (0.1)^2 \cdot 2 - \frac{2(0.1)^3}{3} - \frac{(0.1)^4}{4} + \frac{(0.1)^5}{5} \right)$$

$$= 0.00099$$

$$= 0.4095$$

$$1 - P(X < 0.5)$$

$$= 1 - (1-y)^5$$

$$= 1 - (1-0.5)^5 =$$

(707)

$$0.3125$$

$$E(X) = \int_0^1 x f(x) dx$$

$$= \int_0^1 y \cdot (1-y)^4 dy$$

$$= \int_0^1 y \cdot$$

$$= \textcircled{y} \cdot$$

$$= y \cdot [5y + 10y^3 - 10y^2 - 5y^4 + y^5]$$

$$= 5y^2 + 10y^4 - 10y^3 - 5y^5 + y^6$$

$$= \cancel{5} + \cancel{10} - \cancel{10} - \cancel{5} + T$$

= $\textcircled{1}$

$$= \int_0^1 (y + 6y^3 - 4y^2 - 4y^4 + y^5) dy$$

$$= \left[\frac{y^2}{2} + 6\frac{y^4}{4} - 4\frac{y^3}{3} - 4\frac{y^5}{5} + \frac{y^6}{6} \right]_0^1$$

$$= \left[\frac{1}{2} + 6\frac{1}{4} - 4\frac{1}{3} - 4\frac{1}{5} + \frac{1}{6} \right] \cancel{5}$$

$$= \frac{5}{2} + 15\frac{1}{2} - 20\frac{1}{3} - 20\frac{1}{5} + 5\frac{1}{6}$$

$$= 5\frac{1}{2} + 15\frac{1}{2} - 20\frac{1}{3} - 4 + 5\frac{1}{6} =$$

$$= \frac{1}{6} \quad \begin{aligned} P(X > 1.6) &= 1 - P(X < 1.6) \\ &= 1 - (1 - \frac{1}{6})^5 \\ &= 0.40187 \end{aligned}$$

$\mu = 3$
exponential dist-

(λt)

$$f(x) = \lambda e^{-\lambda x} \quad 0 \leq x$$
$$= 3$$

$$E[x] = \frac{1}{\lambda} \quad \left(\frac{1}{3}\right)$$

$$\text{var}[x] = \frac{1}{\lambda^2}$$

$$3 = \frac{1}{\lambda}$$

$$\boxed{\lambda = \frac{1}{3}}$$

$$\frac{(\lambda t)^k}{k!} e^{-\lambda t}$$

(λt)

3.

$\mu = 3/1$

(λt)^k

K

f

F

$$\mu = 3/\text{hour}$$

$$\frac{(\lambda t)^k e^{-\lambda t}}{k!} = \frac{(3 \cdot 60)^{10} \cdot e^{-3 \cdot 60}}{10!}$$
$$= \mu = \frac{1}{k} \quad k = 3$$

$$\frac{60^2}{2!} = 20$$

$$= 1 - e^{-\frac{\lambda \mu}{3}}$$
$$= 1 - e^{-4/3}$$

$$\mu = 3 \text{ minutes}$$

$$f(x) = \frac{x e^{-\lambda x}}{3 \cdot e^{-x/3}(4)}$$

=

$$F(x) = \int_1^x \lambda e^{-\lambda x} \cdot x$$

$$= \int \lambda e^{-\lambda x}$$

$$= \int 3 e^{-3x} \cdot x$$

$$= 3 \int e^{-3x} \cdot x$$

$$= 3 \int e^{-3x} x (-3x)$$

$$= \boxed{\frac{e^{-3x} \cdot 3x + 1}{3}}$$

Known even
Independent

PDF for
exponential dist.

$$= \lambda e^{-\lambda x}$$

CDF for exponential function

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

$$= 1 - e^{-(x/0.3)}$$

0

so much ti
between on
mother (

λ (rate
units = 1/
1/

Q6 One man completes reservation
with mean time of 3 minutes.

It is an exponential distribution.

Out of 5 people ; what is

probability that at-least 4

will complete their reservation

in 3 minutes

is expo
Gauss

It is
dish

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at o
a b

ii

- known events i.e constant time b/w events
- independent of each other (memoryless)

6.45 ask

Exponential	Poisson (Poisson)
→ how much time passes between one event and another (continuous)	→ how many events occur in a given period of time (discrete)
→ λ (rate of occurrence)	→ μ (expected no. of occurrence)
→ units = $1/\text{time}$ or $1/\text{area}$	→ units \Rightarrow counts

- Exponential is a special case of Gamma distribution when $\alpha = 1$ and $\beta = 1$
- It is continuous analogy of geometric distribution.
- The probability of occurrence of an event at a particular exact time will be a bernoulli trial (0 or 1)

11

$$W = 2X + 3Y$$

$$E(X) = 5 \quad \text{Var}(X) = 4$$

$$E(Y) = 10 \quad \text{Var}(Y) = 9$$

$$\text{Var}(Y) = (c)$$

$$E(W) = 2 \times 5 + 3 \times 10$$

$$= 10 + 30 = 40$$

$$\text{Var}(W) = 4^2 \times 2^2 +$$

$$9^2 \times 3^2$$

$$= 16 \times 4 + 81 \times 9$$

$$= 793 \text{ (a7)}$$

$$P(W < 30) = P\left(Z < \frac{30 - 40}{\sqrt{793}}\right)$$

$$c = 2$$

$$c = 0$$

$$P(z <$$

$$P(\bar{X} < -0.335)$$

$$= 0.3707 \quad 0.1562 *$$

$$x($$

$$\bar{x} =$$

$$\sigma(x) =$$

(Q2)

$$\mu(x) = 2$$

$$\sigma(x) = 0.1$$

$$\bar{y} =$$

$$\sigma =$$

$$\mu(y) = 0.2 \quad P(X > 4.3)$$

$$P(y) = 0.1 \quad = 1 - P(X < 4.3)$$

$$y = x + y \quad = 1 - P(X < \frac{4.3 - 4}{0.2})$$

$$\mu(y) = 2 + 2 =$$

$$= 4 \text{ mm}$$

$$\epsilon(y) = 0.1^2 + 0.12$$

$$= 0.01 + 0.12$$

$$= 0.02$$

$$V(X) = (0.1^2)^2 + (0.1)^2$$

$$= 2 \times 10^{-4}$$

$$\sigma = 0.0141$$

$$P(Z < 4.3) = \frac{0.3}{0.0141}$$

=

X(

$$\bar{x} = 0.2$$

$$\sigma(x) = 0.1$$

$$\bar{y} = 0.2$$

$$\sigma = 0.1$$

$$w = x + y$$

$$\bar{w} = 2 + 2$$

$$= 4 \text{ mm}$$

$$\begin{aligned} V(w) &= (0.1^2) + (0.1)^2 \\ &= 0.01 + 0.01 \\ &= 0.02 \end{aligned}$$

$$P(W > 4.3) = 1 - P(W < 4.3)$$

$$= 1 - P(Z < 2.12)$$

$$= 1 - 0.9830$$

$$= 0.017$$

7 February 2

$$\bar{X} = 0.1$$

$$\sigma_x = 0.00031$$

$$\bar{Y} = 0.23$$

$$\sigma_y = 0.00017$$

$$W = X + Y$$

$$\bar{W} (= \bar{X} + \bar{Y}) \\ = 0.1 + 0.23$$

$$= 0.33$$

$$\sigma_W = \sqrt{(0.00031)^2 + (0.00017)^2}$$

$$=$$

$$= 3.535 \times 10^{-4}$$

$$P(W < 0.2337)$$

$$= P(z <$$

$$= 0.9967$$

$$Y = \sum_{i=1}^n$$

$$E[Y] = ?$$

$$\text{Var}[Y]$$

X

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2. Bern

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3. Gau

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E

Y

17 February 2023

Monday.

$$Y = \sum_{i=1}^N C_i Y_i$$

$$E[Y] = ?$$

$$\text{Var}[Y] = ?$$

1. gaussian
independent
non-identical
2. Bernoulli
independent
identical
3. Gaussian
Independent
Identical.

Y
gaussian
independent

binomial

Normal
IID

let $X_1, X_2, X_3 \dots, X_n$ are

independent Normal Random Variables
and their RMF & PDF is same i.e
they are identical.

$$E[X_i] = \mu \quad \text{Var}[X_i] = \sigma^2$$

$$Y = \sum_{i=1}^N X_i$$



• Let $X_1, X_2, X_3, \dots, X_n$ are
IDDs

• $E[X_i] = \mu$ $\text{Var}[X_i] = \sigma^2$

• $E[X] = N\mu$ $\text{Var}[X] = n\sigma^2$

• $Y = \frac{X - n\mu}{\sqrt{n}\sigma}$

$$\begin{aligned} F_Y(y) &= \Pr(Y \leq y) \\ &= \Pr\left(\frac{X - n\mu}{\sqrt{n}\sigma} \leq y\right) \end{aligned}$$

CENTRAL LIMIT THEOREM

$$\lim_{N \rightarrow \infty} F_Y(y) = F_Z(z) \text{ where } z \text{ is}$$

Standard Normal
Variable

$$\lim_{N \rightarrow \infty} F_Y(y) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz$$

Let Y_i

$N = 10$

$i =$

X

P_r

E

V

Thus, probability

$X(C)$

Norm

when n

X

Example:

"We have
Independent
distribu
is the
(con
di

total
of

Y_i

$N = 10$

$i =$

X

P_r

C

Thus, probability distribution of
 X (capital) approaches
 Normal Random Variable
 When N is large

$$X \sim N(N\mu, N\sigma^2)$$

Example :-

"We load 100 packs they are independent and they are distributed normally 5 to 50 kg is the variation for each pack (continuous range) It is uniformly distributed. What is prob that total weight exceeds 3000 kg-

Let Y_i show the weight of i^{th} pack.

$$N = 100$$

$$i = 1 \text{ to } 100$$

X shows total weight

$$\Pr(X > 3000) = ?$$

$$E[X_i] = \frac{a+b}{2} = \frac{50+50}{2} = \frac{50}{2} = 27.5$$

$$\text{var}[X_i] = \frac{(b-a)^2}{12} = \frac{(50-50)^2}{12} = \frac{225}{12}$$

$$= 168.75$$

$$X = \sum_{i=1}^N X_i$$

$$E[X] = n \mu = 100 \times 27.5^n \\ = 2750$$

Using CLD, $\text{Var}[X] = 168.75 \times 100$
 $= 16875$

$$X \sim N(100 \cdot \mu, 100 \sigma^2)$$

$$P(X > 3000) = 1 - P(X \leq 3000)$$

$$\begin{aligned} &= 1 - F_X(3000) \\ &= 1 - F_Z \left(\frac{3000 - 100\mu}{\sqrt{100}\sigma} \right) \\ &= 1 - F_Z(1.92) \\ &= 1 - 0.9728 \\ &= 0.0274 \end{aligned}$$

Statistics

Population

Sample

We also

(not

⇒ independent

choice

with

⇒ each
of

→ probability

• Success

Statistical Analysis

Population \Rightarrow totality of all observations

Sample \Rightarrow subset of population

We always take a random sample
(not sample space)

\Rightarrow independently & randomly
choosing points / observations
without any bias -

\Rightarrow each observation is an outcome
of random variable that
are independent -

\Rightarrow point estimation.

\rightarrow to guess a single point for
parameters that build the
distribution of population -

• Sample mean :-

Let X_1, X_2, X_3, \dots are Random Va-

$$\bar{X} = \frac{1}{N} \cdot \sum_{i=1}^N X_i$$

• Sample variance :-

$$S^2 = \frac{1}{N-1} \sum_{i=1}^N (X_i - \bar{X})^2$$

→ mean of sample is also a
P.V like variance of sample
mean

→ This is because mean is not
constant and is based on
random observations.

Statistics :- Outcome of
mathematical operations
applied on the Random Samples

$$\text{Let } Y = \bar{X} - \sigma^2$$

according to

when N is
normal as

Example :-

$X_1, X_2, X_3, \dots, X_n$ are IID

$$\bar{X} \sim$$

CDF(\bar{X})

$$\bar{X} = \frac{1}{N} \cdot \sum_{i=1}^N X_i ; E[X_i] = \mu \\ \text{Var}[X_i] = \sigma^2$$

$$E[\bar{X}] = \frac{1}{N} \cdot N \cdot \sum_{i=1}^N X_i \\ = \mu$$

$$\text{Var}[\bar{X}] = N \cdot \sigma^2 \\ = N \cdot \frac{1}{N-1} \sum_{i=1}^N (X_i - \bar{X})^2 \\ = N \cdot \frac{1}{N^2} \sigma^2 = \frac{\sigma^2}{N}$$

$$\text{Let } Y = \frac{\bar{X} - \mu}{\sigma/\sqrt{N}}$$

$$\sqrt{\sigma^2/N}$$

according to CLD, Y becomes normal
(standard)

when N is large, therefore, \bar{X} becomes
normal as well when N is large.

$$\bar{X} \sim N(\mu, \frac{\sigma^2}{N})$$

$$\text{CDF}(\bar{X}) = P(\bar{X} \leq x)$$

$$= F_Z \left(Z < \frac{\bar{X} - \mu}{\sqrt{\sigma^2/N}} \right)$$

Note: we can
to make

$$\text{Var}[\hat{\mu}] = \text{Var}[\bar{x}] = \frac{\sigma^2}{N}$$

when N is large, variance decreases

Strong Law of Large Numbers :-

$$\lim_{N \rightarrow \infty} \left(\frac{\sum_{i=1}^N X_i}{N} \right) = \mu$$

$$\Pr \left[\lim_{n \rightarrow \infty} \left(\frac{\sum_{i=1}^n X_i}{n} \right) = \mu \right] = 1$$

$$\hat{\sigma}^2 = S^2 =$$

$$E[\hat{\sigma}^2] =$$

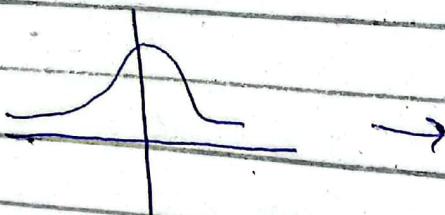
$$E[S^2] =$$

$$= \\ n$$

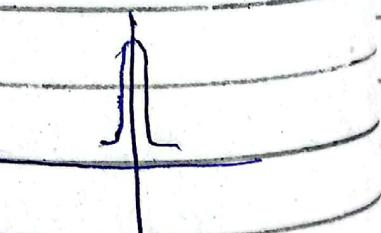
$$E[(X_i - \bar{X})]$$

When using CLT, when N is
large,

$$\bar{X} \sim N(\mu, \frac{\sigma^2}{N})$$



$$\text{Var}[X] \approx 1$$



$$\text{Var}[\bar{X}] \leq 1$$

$$E[$$

$$= E[$$

$$= E[(X_i)]$$

$$E[\bar{X}]$$

$$= \sigma^2 +$$

$$= \sigma^2 + \underline{\sigma^2}$$

Note: we can subtract bias from estimator
to make it fair.

(X_i 's are IID)

True Variance of Population (σ^2)
which is unknown

$\hat{\sigma}^2$ shows the estimated value of σ^2

$$\hat{\sigma}^2 = S^2 = \frac{1}{N-1} \sum_{i=1}^N [X_i - \bar{X}]^2$$

$$E[\hat{\sigma}^2] = E[S^2]$$

$$\begin{aligned} E[S^2] &= E\left[\frac{1}{N-1} \sum_{i=1}^N (X_i - \bar{X})^2\right] \\ &= \frac{1}{N-1} \sum_{i=1}^N E[(X_i - \bar{X})^2] \end{aligned}$$

$$E[(X_i - \bar{X})^2] =$$

$$E\left[\{(X_i - \mu) - (\bar{X} - \mu)\}^2\right]$$

$$= E[(X_i - \mu)^2 + (\bar{X} - \mu)^2 -$$

$$2(X_i - \mu)(\bar{X} - \mu)]$$

$$= E[(X_i - \mu)^2] +$$

$$E[(\bar{X} - \mu)^2] - 2E[(X_i - \mu)(\bar{X} - \mu)]$$

$$= \sigma^2 + \frac{\sigma^2}{N} - 2E\left[(X_i - \mu)\left(\frac{1}{N} \sum_{i=1}^N X_i - \mu\right)\right]$$

$$= \sigma^2 + \frac{\sigma^2}{N} - \frac{2}{N} E\left[(X_i - \mu)[E[X_i] - N\mu]\right]$$

$$E[(X_i - \bar{X})^2] = \sigma^2 + \frac{\sigma^2}{N} - \frac{2}{N} E\left[\left(X_i - \mu\right) \left\{ \begin{array}{l} (X_1 - \mu)_+ \\ (X_2 - \mu)_+ \\ (X_3 - \mu)_- \end{array} \right.\right]$$

$$= \sigma^2 + \frac{\sigma^2}{N} - \frac{2}{N} E[(X_i - \mu)^2]$$

$$= \sigma^2 + \frac{\sigma^2}{N} - \frac{2}{N} \sigma^2$$

$$= \sigma^2 - \frac{1}{N} \sigma^2$$

$$= \sigma^2 \cdot \left(\frac{N-1}{N} \right)$$

$$E[(X_i - \bar{X})^2] = \sigma^2 \cdot \left(\frac{N-1}{N} \right)$$

$$E[S^2] = \frac{1}{N-1} \sum_{i=1}^N X_i^2 - \sigma^2 \cdot \left(\frac{N-1}{N} \right)$$

$$= \frac{1}{N-1} \cdot N \cdot \sigma^2 \cdot \left(\frac{N-1}{N} \right) \cdot f_x(x) =$$

$$E[S^2] = \sigma^2$$

$$E[\hat{\sigma}^2] = \sigma^2$$

Chi

of
substitute

$$S^2 = \frac{1}{N-1} \sum_{i=1}^N$$

$$(N-1)S^2 = \frac{1}{1} \sum_{i=1}^N$$

$$N-1 = S^{-2}$$

$$\left(\frac{N-1}{\sigma^2} \right) S^2$$

$$\left(\frac{N-1}{\sigma^2} \right) S^2$$

This distri

Chi-

degree

$$S^2 = \frac{1}{N-1} \sum_{i=1}^N (X_i - \bar{x})^2$$

$$(N-1)S^2 = \sum_{i=1}^N (X_i - \bar{x})^2$$

$$N-1 = S^{-2} \sum_{i=1}^N (X_i - \bar{x})^2$$

$$\left(\frac{N-1}{\sigma^2}\right) S^2 = \frac{\sum_{i=1}^N (X_i - \bar{x})^2}{\sigma^2}$$

$$\left(\frac{N-1}{\sigma^2}\right) S^2 = \frac{\sum_{i=1}^N (X_i - \bar{x})^2}{\sigma^2} \quad (i)$$

This distribution follows a

Chi-square PDF with $(N-1)$

degree of freedom

$$f_x(x) = \frac{1}{2^{v/2} \Gamma(v/2)} \chi^{(v-1)} e^{-x/v}$$

Chi square PDF with v degree

of freedom

substitute v with $N-1$ to get (i)

$$E[X] = \nu \quad \text{var}[X] = 2\nu$$

Where $\Gamma(\alpha) \int_0^\infty x^{\alpha-1} e^{-x} dx$

explain

$$\text{let } z = \frac{x}{\sqrt{v}} \rightarrow N(0, 1)$$

$$\text{let } z = \frac{X}{\sqrt{v}} \rightarrow X^2 \sim \chi^2(v)$$

(A)
T₁
(B)
T₂

where T₁

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follows Student-t distribution

$$T = \frac{\bar{X} - \mu}{\sigma/\sqrt{N}} \rightarrow N(0, 1) \quad N=16, \mu=$$

$$\Pr(\mu_{\bar{X}} = 1.0)$$

$$\sqrt{\frac{(N-1)S^2}{N-1}}$$

$$\mu_{\bar{X}} = E[\bar{X}]$$

Chi-square with $N-1$ degree of freedom

$$\Pr(Y_{D.S} <$$

$$\Pr(Z >$$

$$T = \frac{\bar{X} - \mu}{S/\sqrt{N}}$$

$$f_r(\bar{X})$$

follows t-distribution with $(N-1)$ freedom

$$\begin{array}{c} (A \oplus B) \\ T_1 \\ T_2(B) \\ \text{where } T_1 \cdot A^{-1} = 2 \end{array}$$

B	A
9	2
9	3
2	2

1)

2) 3

3) R, A, A

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Monday

Advanced Statistics

(Q)

$$N = 16, \quad \mu = 50, \quad \sigma^2 = 5^2 = 25$$

$$\Pr(\mu_{\bar{x}} - 1.9 \sigma_{\bar{x}} \text{ to } \mu_{\bar{x}} + 0.4 \sigma_{\bar{x}})$$

$$\mu_{\bar{x}} = E[\bar{x}]$$

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

$$\Pr(40.5 < \bar{x} < 48)$$

$$\Pr(\bar{x} > 40.5) = 1 - \Pr(\bar{x} < 40.5)$$

$$\Pr(\bar{x} <$$

$N = 16$

$\mu = 50$

$\sigma = 5$

$\sigma^2 = 25$

$P(M_{\bar{X}} - 1.9 \sigma < \bar{X} < \bar{\mu}_x - 0.4 \sigma \bar{x})$

$P(\bar{\mu}_x - 1.9 \sigma < \bar{X} < \bar{\mu}_x - 0.4 \sigma \bar{x})$

$= F_x(M_{\bar{X}} - 0.4 \sigma \bar{x}) -$

$F_x(\bar{\mu}_x - 1.9 \sigma \bar{x}) \quad (ii)$

$= CDF(i) - CDF(ii)$

= Using central limit theorem

$F_z(\frac{\bar{\mu}_x - 0.4 \sigma \bar{x} - \bar{\mu}_{\bar{x}}}{\sigma \bar{x}}) -$

$F_z(\frac{\bar{\mu}_x - 1.9 \sigma \bar{x} - \bar{\mu}_{\bar{x}}}{\sigma \bar{x}})$

∴ we are subtracting CDF of ~~upper~~ lower bound lower bound from upper bound by mapping into "z" standard normal

$= F_z(-0.4) - F_z(-1.9)$

$= 0.3446 - 0.0287$

$= 0.3159$

$N = 36$

$N = 3$

$r = 2$

if std = 1.2

$\lim_{n \rightarrow \infty} \left(\dots \right)$

$N = 36, \sigma_{\bar{x}} =$

$\text{Var}[\bar{x}] =$

$\sigma^2 = 1$

$= 3$

$= 14$

TRUE MEAN & TRUE VARIANCE

$$\bar{M} = 36 \quad N = 36$$

$$\sigma = 2$$

if std $\sigma = 1.2$.

$$\lim_{n \rightarrow \infty} \left(\dots \right) \frac{1}{N}$$

$$N = 36, \quad \sigma_{\bar{x}} = 2, \quad N' = ?$$

$$\sigma_x' = 1.2$$

$$\text{Var}[\bar{x}] = \frac{\sigma^2}{N}$$

$$\sigma^2 = N \sigma_{\bar{x}}^2$$

$$= 36 \times 2^2$$

$$= 144$$

$$\sigma^2 = \frac{\sigma^2}{N}$$

$$N' = \frac{\sigma^2}{\sigma_{\bar{x}}^2} = \frac{144}{1.2^2}$$

$$N' = 100$$