

Random Variable  $\rightarrow$  One particular choice.

Distribution  $\rightarrow$  Maps for different choices

Poisson Distribution  
(Important)

$$P(X=k) = e^{-\lambda} \lambda^k / k!$$

$$k \geq 0; k \in \mathbb{N} \cap \mathbb{I} \text{ (Integer)}$$

$\lambda$  is the scale parameter.  $\lambda > 0$

$$\text{PMF} = \sum_{k=0}^{\infty} P(X=k) = 1$$

$$= \sum_{k=0}^{\infty} \frac{e^{-\lambda} \lambda^k}{k!} = e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{k!}$$

$$= e^{-\lambda} (e^{\lambda}) \rightarrow \text{from Taylor series}$$

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Taylor series of a function  $f(x)$  at  $a$  is

$$f(a) + \frac{f'(a)(x-a)}{1!} + \frac{f''(a)(x-a)^2}{2!} + \dots$$

if  $f(x) = e^x$ ;  $a=0$ , then:

$$\frac{1}{0!} + \frac{x}{1!} + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots = e^x$$
$$\sum_{k=0}^{\infty} \frac{x^k}{k!} = e^x$$

$$E[X] = \sum k \frac{e^{-\lambda} \lambda^k}{k!}$$

$$= e^{-\lambda} \sum_{k=0}^{\infty} k \frac{\lambda^k}{k!}$$

$$= e^{-\lambda} \sum_{k=1}^{\infty} \frac{\lambda^k}{(k-1)!}$$

$$= e^{-\lambda} \times \lambda \sum_{k=1}^{\infty} \frac{\lambda^{k-1}}{(k-1)!}$$

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

|                                  |
|----------------------------------|
| $k-1 = j$<br>$j = 0$<br>$\infty$ |
|----------------------------------|

This distribution is

Used to count # of "success" where each success has a small probability of success.

e.g. no. of emails

no. of insects in your food.



no. of earthquakes.

no. of ~~hacking~~ attacks

Say we have  $j$  events

$A_1, A_2, \dots, A_n$   $P(A_j) = p_j$  and  $n$  is very large

# of  $A_j$ 's that occur is approximately

$\text{Pois}(\lambda)$

$$\lambda = E[X] \quad X \sim \text{Pois}(\lambda)$$

$$= \sum p_j$$

Example

↳ Hospital 1.8 births/hour

$$D) P(X=4) = \frac{e^{-\lambda} \lambda^k}{k!} = \frac{e^{-1.8} (1.8)^4}{4!} = 0.07$$

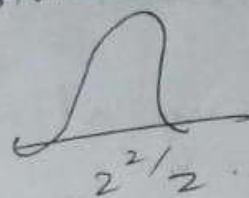
$$2) P(X \geq 2) = P(X=2) + P(X=3) + \dots$$
$$= 1 - P(X < 2)$$

$$= 1 - P(X=0) - P(X=1)$$

$$= 1 - \frac{e^{-1.8} (1.8)^0}{0!} - \frac{e^{-1.8} (1.8)^1}{1}$$

Normal Distribution.

$N(0,1)$



$$f(z) = c e^{-z^2/2}$$

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

Normalizing constant.

$$\int_{-\infty}^{\infty} e^{-z^2/2} dz = \int_{-\infty}^{\infty} f(z) dz = 1.$$

$$I^2 = \int_{-\infty}^{\infty} e^{-z^2/2} dz \int_{-\infty}^{\infty} e^{-z^2/2} dz$$

$$= \int_{-\infty}^{\infty} e^{-x^2/2} dx \int_{-\infty}^{\infty} e^{-y^2/2} dy$$

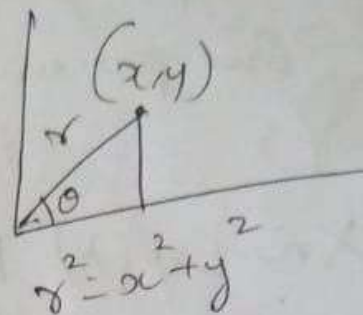
(Notation change)

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-x^2/2} e^{-y^2/2} dx dy$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-(x^2+y^2)/2} dx dy$$



$$= \int_0^{2\pi} \int_0^{\infty} e^{-r^2/2} \times \underbrace{r}_{\text{Jacobian}} dr d\theta$$



$$= 2\pi$$

$$\Rightarrow I = \sqrt{2\pi}$$

CDT

$$\phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-t^2/2} dt$$

Easy to compute  
on computer  
systems

Exponential Distribution.  
→ One parameter  $\lambda$  (Rate at which some events occur)

$X \sim \text{Exp}(\lambda)$  has PDF  $\lambda e^{-\lambda x}$ ,  $x > 0$ .  
otherwise 0.

PDF  $P(X=x) = \lambda e^{-\lambda x}$ .

CDF  $F(x) = \int_0^x \lambda e^{-\lambda x} dx = 1 - e^{-\lambda x}$ .

We know  $\frac{dF(x)}{dx} = f(x)$ .

One good thing

if  $Y = \lambda X$

$X \sim \text{Exp}(1)$

$$P(Y \leq y) = P(\lambda X \leq y) = P(X \leq y/\lambda)$$

$$= 1 - e^{-\lambda \times y/\lambda}$$

$$= 1 - e^{-y}$$

$$\Rightarrow \lambda = 1$$



Say  $Y \sim \text{Exp}(1)$

$$E[Y] = \int_0^{\infty} y e^{-y} dy$$

$$= \underbrace{y(-e^{-y})}_0^{\infty} + \int_0^{\infty} e^{-y} dy$$

$$= 0 + (-e^{-y})_0^{\infty}$$

$$= 0 + 1 = 1$$

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

$$= \int_0^{\infty} y^2 e^{-y} dy - (1)^2$$

$$= y^2(-e^{-y})_0^{\infty} + 2 \left[ \int_0^{\infty} y e^{-y} dy \right] - 1$$

$$= 0 + 2 - 1 = 1$$

$$E[X] = \frac{1}{\lambda}$$

$$\text{Var}(X) = \frac{1}{\lambda^2}$$

Since  $X = \frac{Y}{\lambda}$

$$\text{and } E[Y] = 1$$

$$\text{Var}(Y) = 1$$

$\therefore$  using properties of  
linearity of expectation and  
variance, we get  
the result.

Memoryless property -

$$P(X > t+s | X > s) = P(X > t)$$

we have  
like  
waited  
minutes

$$P(X > s) = 1 - P(X \leq s) \\ = e^{-\lambda s}$$

just undo

$$P(X > t+s | X > s) = \frac{P(X > t+s, X > s)}{P(X > s)}$$

coz if we're waiting for  $t+s$ ,  
we have already waited for  $s$  minutes  
-  $X(t+s)$   
= 0

$$= \frac{e^{-\lambda(t+s)}}{e^{-\lambda s}}$$

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

$$= P(X > t)$$

$$\Rightarrow P(X > s+t | X > s) = P(X > t)$$

Standard

$$Z \sim N$$

$$-Z \sim N$$

$$E[Z] = 0$$

$$E[Z^2] = 1$$

$$E[Z^k] = 0$$

let  $X = \mu$

$\sigma$

then  $X \sim N$

$$E[X] = \mu$$

$$= \mu$$

$$= \mu$$

$$\text{Var}(X) = \sigma^2$$

Note

$$\text{Var}(X+Y)$$

Var if  $X$

$$\text{Var}(X+Y)$$



Standard Normal

$$Z \sim N(0, 1).$$

$$-Z \sim N(0, 1). \text{ (Symmetry).}$$

$$E[Z] = 0$$

$$E[Z^2] = 1$$

$$E[Z^k] = \begin{cases} 0 & k = \text{odd} \\ 1 & k = \text{even} \end{cases}$$

Let  $X = \mu + \sigma Z$ ,  $\mu \in \mathbb{R}$  (mean)

$\sigma > 0$  (S.D.)  $\Rightarrow$  This is the scale.

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

$$\begin{aligned} E[X] &= E[\mu + \sigma Z] \\ &= E[\mu] + \sigma E[Z] \\ &= \mu \end{aligned}$$

$$\text{Var}(\mu + \sigma Z) =$$

Note

$$\text{Var}[X+Y] \neq \text{Var}[X] + \text{Var}[Y]$$

Var if  $X, Y$  are independent

$$\text{Var}[X+Y] = \text{Var}[X] + \text{Var}[Y].$$

$$\text{Var}(\mu + \sigma Z) = \text{Var}(\sigma Z) \\ = \sigma^2 \text{Var}[Z].$$

$$\text{or } Z = \frac{X - \mu}{\sigma} \cdot [\text{standardization}].$$

Find PDF of  $N(\mu, \sigma^2)$ .

$$\text{CDF } P(X \leq x) = P\left(\frac{X - \mu}{\sigma} \leq \frac{x - \mu}{\sigma}\right) \\ = P\left(\frac{X - \mu}{\sigma} \leq \frac{x - \mu}{\sigma}\right) \\ = \Phi\left(\frac{x - \mu}{\sigma}\right).$$

$$= F\left(\frac{x - \mu}{\sigma}\right)$$

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

$$f(x) = \frac{dF(x)}{dx}$$

$$-X = -\mu + \sigma(-Z) \sim N(-\mu, \sigma^2).$$

If  $X_j \sim N(\mu_j, \sigma_j^2)$  independent

then  $X_1 + X_2 \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$

$X_1 - X_2 \sim N(\mu_1 - \mu_2, \sigma_1^2 + \sigma_2^2)$

Rule of

$$P(X = \mu)$$

$$P(X = \mu)$$

$$P(X = \mu)$$

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

$$\sum_{k=0}^{\infty} \frac{\lambda^k}{k!}$$

Diff.

$$\sum_{k=0}^{\infty} \frac{k \lambda^{k-1}}{(k-1)!}$$

Mult.

$$\sum_{k=0}^{\infty} \frac{\lambda^k}{k!}$$

$$k=0$$

$$\sum_{k=1}^{\infty} \frac{\lambda^k}{k!}$$



Rule of thumb  $\Rightarrow$  We cannot evaluate  $F(x)$  for normal.

$$P(|x - \mu| \leq \sigma) \approx 0.65$$

$$P(|x - \mu| \leq 2\sigma) \approx 0.95$$

$$P(|x - \mu| \leq 3\sigma) \approx 0.97$$

Var[x] if  $X \sim \text{pois}(\lambda)$ .

$$\sum_{k=0}^{\infty} \frac{\lambda^k}{k!} = e^{\lambda}$$

Diff. b/s

$$\sum_{k=0}^{\infty} \frac{k \lambda^{k-1}}{k!} = e^{\lambda}$$

Mult. b/s by  $\lambda$

$$\sum_{k=0}^{\infty} \frac{k \lambda^k}{k!} = \lambda e^{\lambda}$$

Diff. b/s

$$\sum_{k=1}^{\infty} \frac{k^2 \lambda^{k-1}}{k!} = \lambda e^{\lambda}$$

$$+ e^{\lambda} = e^{\lambda}(\lambda + 1)$$

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

$$= \sum_{k=0}^{\infty} \frac{k^2 e^{-\lambda} \lambda^k}{k!}$$

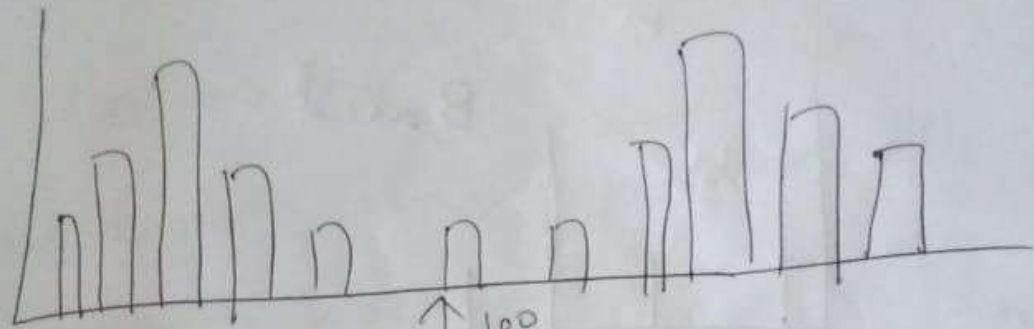
$$- \lambda^2$$

$$= \cancel{\lambda^2} + \lambda - \cancel{\lambda^2}$$

$$= \lambda$$

# Central Limit theorem.

Say we have a distribution of data as

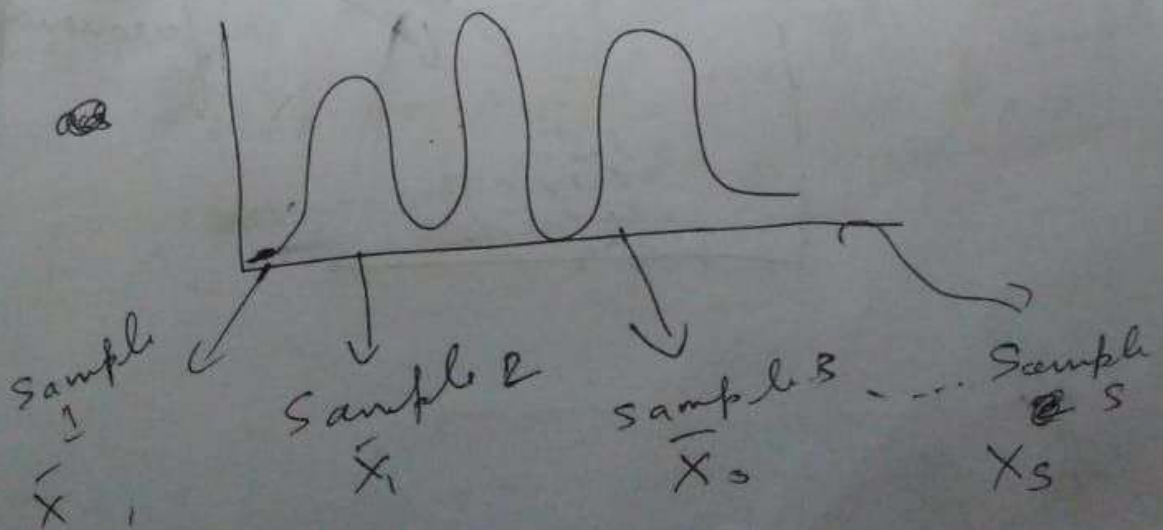
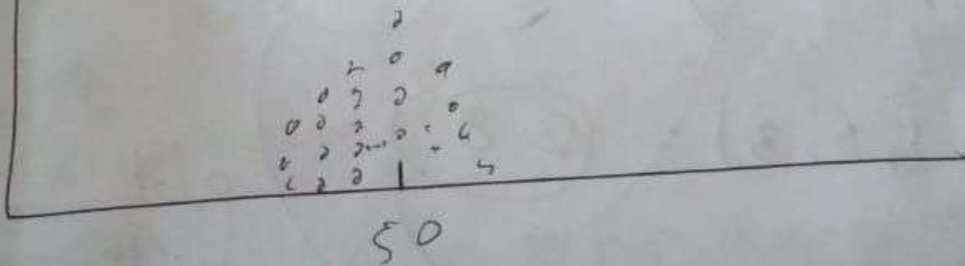


sample  
of  
size  $(n)$

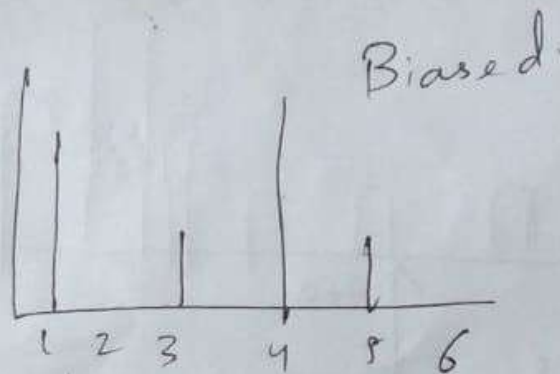
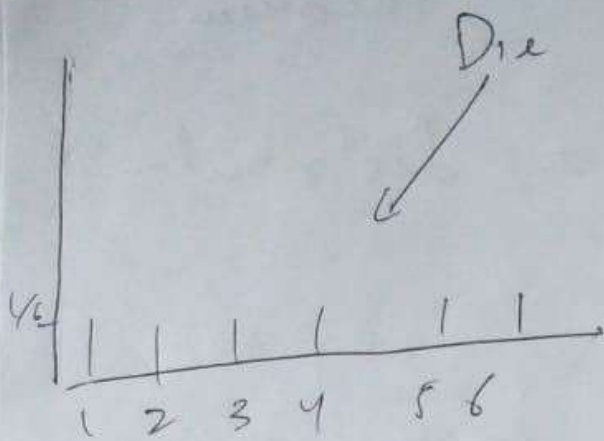
Assume this is the  
mean

plot of  $n$ .

gly  
wavy





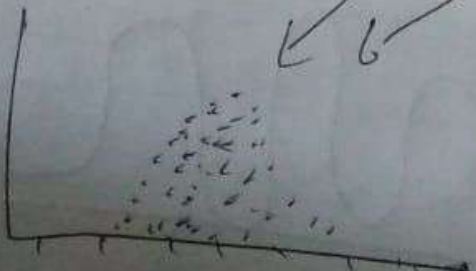


Draw Samples  
or  
roll the die mean

$$(1, 1, 1, 5, 4) = \cancel{2.3} \cdot (2.4)$$

$$(1, 4, 1, 5, 3) = (2.8)$$

plot  
with  
frequency



As the  
the p  
6

norm

5

the

conve

Note 2

Note 2

$\frac{\sigma}{\sqrt{n}}$  is the std. dev of the sample.

distribution of <sup>the</sup> sample ~~the~~ mean

Also called as the stand error of means.

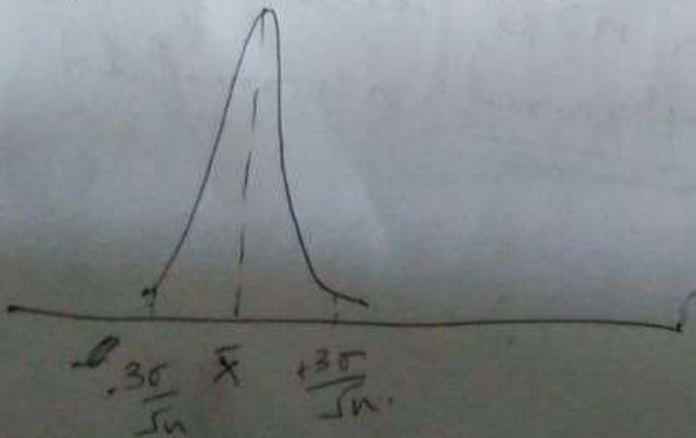
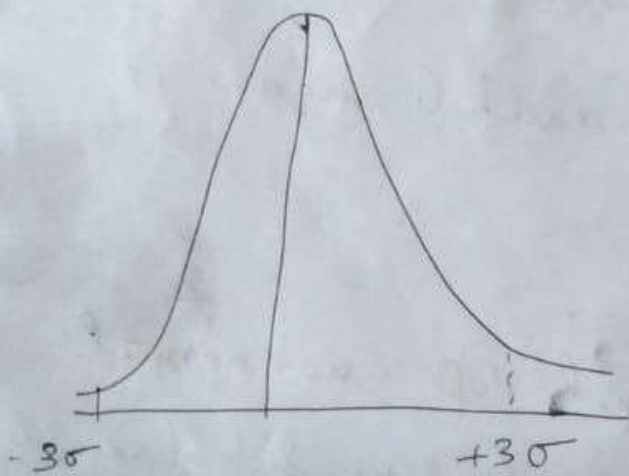


$$\bar{X}_1, \bar{X}_2, \bar{X}_3 \dots \bar{X}_n$$

$$\bar{X} = \frac{\bar{X}_1 + \bar{X}_2 + \dots + \bar{X}_n}{n}$$

$$\bar{X} \approx \mu$$

$$\sigma_{\bar{X}} = \frac{\sigma}{\sqrt{n}} \rightarrow \text{sample size}$$



$$\frac{\sigma}{\sqrt{n}}$$

distribution

Also called  
means

As the number of samples increase  
the plot will approximate the  
frequency  
normal distribution.

$n \rightarrow \infty$   
the distribution of <sup>sample</sup> means will  
converge to normal distribution.

Note 1: If original population  
dist is normal, then the  
dist. of sample mean is  
normal.

Note 2: If original pop is not normal,  
then for  $n > 30$ , the dist. of sample  
means approximate a normal dist.



$$\sum_{k=0}^{\infty} \frac{k^2 \lambda^k}{k!} = \lambda e^{\lambda} (\lambda + 1)$$

$$\sum_{k=0}^{\infty} \frac{k^2 e^{-\lambda} \lambda^k}{k!} = \lambda e^{-\lambda} e^{\lambda} (\lambda + 1)$$

$$\Rightarrow \sum_{k=0}^{\infty} \frac{k^2 e^{-\lambda} \lambda^k}{k!} = \lambda + \lambda.$$

Strong Law of large numbers

Assume we have  $X_1, X_2, X_3 \dots X_j$   
iid ~~samples~~ with mean  $\mu$  and  
Var  $\sigma^2$ .

$$\bar{X}_n = \frac{\sum_{i=1}^n X_i}{n}$$

SLLN says as  $n \rightarrow \infty$

$$\bar{X}_n \rightarrow \mu$$

with prob 1.

E.g.  $X_j \sim \text{Bern}(p)$

$$\frac{X_1 + X_2 + \dots + X_n}{n} \rightarrow p \text{ with prob 1.}$$