

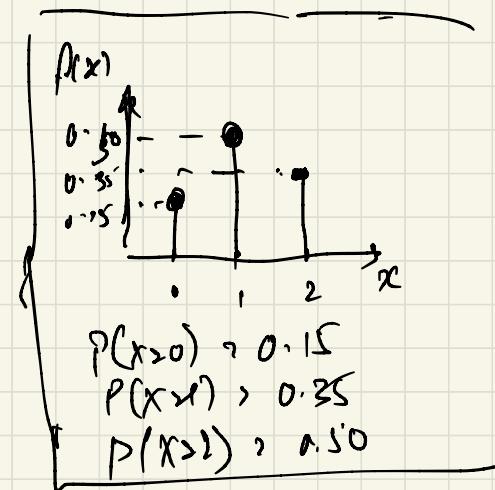

(C) PMF :

for discrete random variable X with possible outcomes x_1, x_2, \dots, x_n , a PMF (Prob. Mass function)

S.F - (i) $f(x_i) \geq 0$

(ii) $\sum_i f(x_i) = 1$

(iii) $f(x_i) > P(X=x_i)$



(2) CDF :

for discrete R.V X , $F(x)$ is,

$$F(x) = \sum_{x_i \leq x} f(x_i)$$

satisfies the properties;

(i) $F(x) \rightarrow P(X \leq x) = \sum_{x_i \leq x} f(x_i)$

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

(iii) If $x \leq y$, then $F(x) \leq F(y)$

② Mean: Central value of probability distribution
 $\mu, E[x], \sum x f(x)$

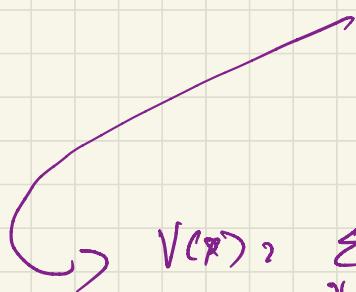
④ Variance: Dispersion or variability in the distribution.

$$\sigma^2, V(X) = E[(x-\mu)^2]$$

$$= \sum (x - \mu)^2 f(x)$$

$$= \sum x^2 f(x) - \mu^2$$

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



$$V(X) = \sum x \cdot (x - \mu)^2 f(x)$$

$$= \sum (x^2 + \mu^2 - 2x\mu) f(x) - (E[X])^2$$

$$= \sum x^2 f(x) + \mu^2 \sum f(x) - 2\mu \sum x f(x)$$

$$= \sum x^2 f(x) + \mu^2 - 2\mu \cdot \mu$$

$$= \sum x^2 f(x) + \mu^2 - 2\mu^2$$

$$= \sum x^2 f(x) - \mu^2$$

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

(5) Expected Value of a function of discrete R.V.

Consider $h(x)$ a function of R.V. x :

$$E[h(x)] = \sum_x h(x) f(x)$$

Interpretation: The E.V. of h is the weighted average of function evaluated at values of the random variable.

Special case: $E[h(x)] \neq h(E[x])$

Consider $h(x) = ax + b$

$$E[ax + b] = aE(x) + b \quad - \textcircled{1}$$

$$\text{Var}(ax + b) = a^2 \text{Var}(x) \quad - \textcircled{2}$$

$$\begin{aligned}
 \textcircled{1} \quad D[ax + b] &= \sum_x h(x) \cdot f(x) \\
 &= \sum_x (ax + b) \cdot f(x) \\
 &\stackrel{x}{=} \sum_x ax \cdot f(x) + b \sum_x f(x) \\
 &\stackrel{x}{=} a \sum_x f(x) + b \\
 &\sim n E[x] + b
 \end{aligned}$$

$$\begin{aligned}
 \textcircled{A} \quad \text{Var}(h(x)) &= \sum_n (h(x_n) - E[h(x)])^2 \cdot f(x_n) \\
 &\Rightarrow \sum_n (ax_n - aE(x))^2 \cdot f(x_n) \\
 &\stackrel{a}{=} \sum_n (ax - aE(x))^2 \cdot f(x_n) \\
 &\Rightarrow \sum_n (a[x - E(x)])^2 \cdot f(x_n) \\
 &\Rightarrow a^2 \sum_n (x - E(x))^2 \cdot f(x_n) \\
 &\qquad\qquad\qquad \underbrace{ = \text{Var}(x)}_{\text{Var}(x)} \\
 &\Rightarrow a^2 \cdot \text{Var}(x)
 \end{aligned}$$

(B) Uniform Distribution :

A random variable has n values in the range \in each with equal probability:
 $f(x_i) = \frac{1}{n}$

Assume interval (a, b) for the sample:

N.W $E(x) = \sum_a^b x_i \cdot f(x_i)$ $\rightarrow p(x_i) = \frac{1}{b-a+1}$

$$\begin{aligned}
 \text{Now } \sum_{k=a}^b k &\rightarrow \frac{b(b+1)}{2} - \frac{a(a+1)}{2} \\
 &= \underline{b(b+1) - a(a+1)}
 \end{aligned}$$

$\therefore E[X] \approx M = \sum_{i=1}^n m_i \cdot f(x_i)$
 $\Rightarrow \frac{1}{(b-a+1)} \sum_{i=1}^n x_i$
 $\Rightarrow \frac{1}{(b-a+1)} (b-a+1) \frac{(a+b)}{2}$
 $\Rightarrow \frac{a+b}{2}$

Antecedent series
 whose sum is M
 (F.T. term of $f(x)$)

$$\text{Var}(X) = \frac{(b-a+1)^2}{12} \quad \text{when } (b-a+1)=n$$

Assume any n , then $E[X] = \sum a_i \cdot P(x_i)$

$$\begin{aligned}
 \text{Var}(X) &= E[X^2] - (E[X])^2 \\
 &= \sum x_i^2 f(x_i) - \left(\frac{(n+1)(2n+1)}{6} \right)^2 \\
 &= \frac{n+1}{2} \sum x_i^2 - \frac{(n+1)^2}{6} \\
 &= \frac{n+1}{2} \left[\frac{2n^2 + 2n + n + 1}{12} - \frac{n^2 + 2n + 1}{6} \right] \\
 &= \frac{n+1}{2} \left[\frac{n^2 - 1}{12} \right] \quad \boxed{\text{Lrb for any } n}
 \end{aligned}$$

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Binomial distribution:

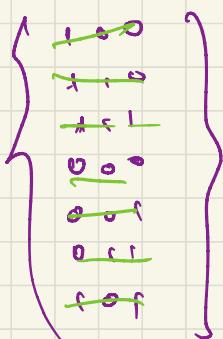
A random experiment consists of n Bernoulli trials.

- (i) Trials are independent
- (ii) Each trial results in only 2 outcomes - success and failure
- (iii) The prob. of success is p and is constant.

$$f(x) = \binom{n}{x} p^x (1-p)^{n-x}; n = 0, 1, \dots, m$$

Assume you run 3 independent trials:

where you may only have success/failure outcomes:



You can have 0, 1, 2, 3 successes
in any of the given orders (sequences)

1 → success 0 → failure

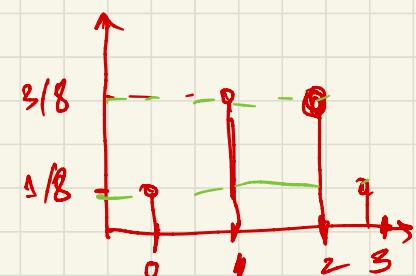
Now $x = 0, 1, 2, 3$

$$0 \rightarrow 000 \rightarrow 3 \text{ cat}$$

$$1 \rightarrow 010, 0=1, 100 \rightarrow 3 \text{ cat}$$

$$2 \rightarrow 011, 110, 101 \rightarrow 3 \text{ cat}$$

$$3 \rightarrow 111 \rightarrow 1 \text{ cat}$$



$$\begin{aligned} & \leq f(n) = \\ & = \frac{1}{8} + \frac{3}{8} + \frac{3}{8} + \frac{1}{8} = \frac{1}{2} \end{aligned}$$

$$\text{Note: } (a+b)^n = \sum_{k=0}^n \binom{n}{k} a^{n-k} b^k$$

$$E(X) = \sum_{k=0}^n k \binom{n}{k} p^k q^{n-k}$$

$$= \sum_{k=1}^n k \binom{n}{k} p^k q^{n-k} \quad \begin{matrix} k \binom{n}{k} = n(n-1) \\ \text{since 1 factor of coefficient} \end{matrix}$$

$$= \sum_{k=1}^n n \binom{n-1}{k-1} p^k q^{n-k} \rightarrow \text{Take out } np$$

$$= \sum_{k=1}^n (np) \binom{n-1}{k-1} p^{k-1} q^{n-1-k} \rightarrow n-1 \geq (n-1)-(k-1)$$

$$\Rightarrow np \sum_{k=1}^n \binom{n-1}{k-1} p^{k-1} q^{(n-1)-(k-1)} \quad \boxed{u = np}$$

Binomial expansion of $(p+q)^{n-1}$

Alternatively consider that each Bernoulli trial is independent and can be treated as a

sequence of R.V's.

$$x_i = x_1, x_2, \dots, x_n$$

$$E[x_i] = 1(p) + 0(1-p) = p$$

$$V[x_i] = (1-p)^2 \cdot p + (0-p)^2 \cdot (1-p) = p(1-p)$$

$$\therefore E[x] = np \quad \text{Var}(x) = np(1-p)$$

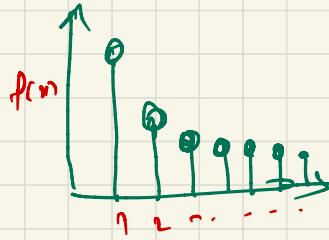


Geometric distribution!

In a series of Bernoulli trials on R.V. X
 χ equals the # of trials before the first
 success is a geometric random variable with
 parameter $0 < p < 1$

$$f(n) = (1-p)^{n-1} p \quad \text{for } n = 1, 2, \dots, \infty$$

The probability / height of the line at x
 is $(1-p)$ times height at $n-1$



Lack of memory:

The trials are independent, the
 count of # of trials until next success
 can be started at any total no. of
 trials, which defines
 the probability distribution for the R.V.

$$\underline{E[X] = \mu = 1/p} \quad \underline{\sigma^2 = \text{Var}(X) = \frac{1-p}{p^2}}$$

Alternatively, one could be looking at the
 number of failures before hitting 1st success:

$$\underline{E[X] = \mu = \frac{1-p}{p}} \quad \underline{\sigma^2 = \text{Var}(X) = \frac{1-p}{p^2}}$$

Q) Negative binomial :-

A generalization of geometric distribution in which R.V. is the # of Bernoulli trials required to obtain r successes is negative binomial.

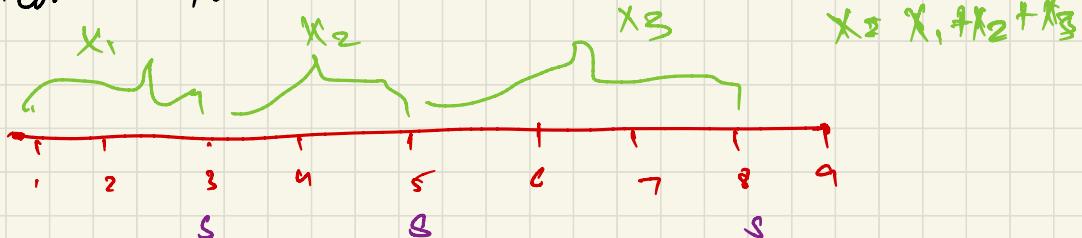
$$f(n) = \binom{n-1}{r-1} p^r q^{n-r}$$

Now, we assume that there are $r-1$ successes in the first $n-1$ trials and r^{th} success is obtained on the n^{th} trial.



$$\begin{aligned} r &= 4 & p &= 0.9 \\ r &= 4 & p &= 0.4 \\ r &= 16 & p &= 0.4 \end{aligned}$$

N.B can also be represented as a sum of Geometric random Variable.



Furthermore if X = Negative Binomial with p
 it can also be represented as $X = X_1 + X_2 + X_3$
 where X_1, X_2, X_3 are geometric with param p

$$\underline{D[X] = 1/p}$$

$$\underline{\sigma^2 = \text{Var}(X) = r(1-p)/p^2}$$

⑩ Hypergeometric distribution:

A set of N objects

$\hookrightarrow k$ are classified as successes
 $\hookrightarrow N-k$ are "failures"

A sample of n objects is selected at random from N objects where $n \leq N$ and $k \leq N$.
w/o replacement

The R.V. X that equals # of successes is a hypergeometric random variable and

$$f(x) = \frac{\binom{k}{x} \binom{N-k}{n-x}}{\binom{N}{n}}$$

$$x^2 \max \{0, n+k-N\} \text{ to min } \{k, n\}$$

$$\mathbb{E}[X] = q > np \quad \text{Var}(X) = \sigma^2 = np(1-p) \left(\frac{N-n}{N-1} \right)$$

where $q = k/N$

N = total # objects

k = # of successes

n = # of objects sampled

finite population
correction factor

Sampling is done w/o replacement from an infinite set in binomial trials and thus the success probability hypergeometric R.V. without replacement would have mean and variance equal to $\mu = R \cdot p$.

Without replacement changes the probability of success and thus the variance is lower since we are drawing from a finite set.

Poisson distribution!

Events occur randomly in a given interval.

The r.v. of interest is the count of events that occur within that interval.

$$f(x) = \frac{e^{-\lambda T} (\lambda T)^x}{x!} \quad \text{where } x = 0, 1, \dots$$

$$\mathbb{E}[x] = \lambda T \quad \text{Var}(x) = \sigma^2 = \lambda T$$

Imagine partitioning the interval into n subintervals $\Delta t = T/n$.

Furthermore, assume that probability of the flow occurring is the same across all subintervals. Our variable can now be treated as a Binomial Random Variable.

$$\mathbb{E}[x] = \lambda T = np \quad p = \frac{\lambda T}{n}$$

$$P(x=k) = \binom{n}{k} p^k (1-p)^{n-k} \quad \text{for small subintervals}$$

$$\binom{n}{k} \left(\frac{\lambda T}{n}\right)^k \rightarrow \frac{\lambda T^k}{k!} \left(1 - \frac{\lambda T}{n}\right)^{n-k} \rightarrow 1 \left(1 - \frac{\lambda T}{n}\right)^n \rightarrow e^{-\lambda T}$$

$$\lim_{n \rightarrow \infty} P(x=k) = \frac{e^{-\lambda T} (\lambda T)^k}{k!}; \quad k=0, 1, 2, \dots$$