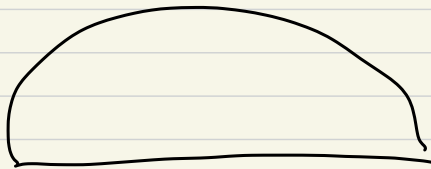
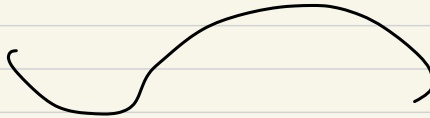
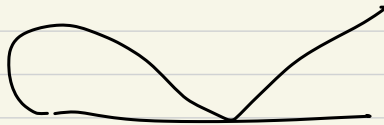
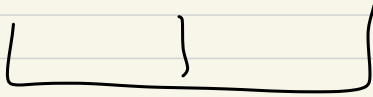
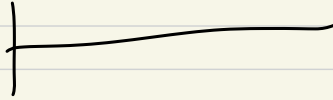
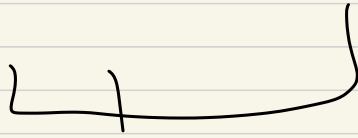



Random Variables

- given a sample space Ω , set of events F , a probability function P , and countable set of real numbers D a discrete random variable is a function with domain Ω and range D
 - \hookrightarrow for any outcome ω , $X(\omega)$ exists
- numbers from coin or dice \rightarrow random variable
- flip a coin 32 times, record 1/0 depending on heads/tails
 - \hookrightarrow 32 bit number \leftarrow also a random variable
- random variable is a function that quantifies the outcome of a random process
- random variables can take on many values with different probabilities and so it makes more sense to talk about the probability of a random variable relative to a certain value.
- for any $X = \underline{x}$ there's a series of values associated with it
 - set of outcomes $= \omega$
 - $X(\omega) = x \approx X = x$
 - $P(\{\omega: X(\omega) = x\}) \approx P(\{X = x\}) \approx P(x)$
 - $P(X(\omega) \leq x)$ can also be calcd. etc.



properties of probability distributions

expected values

- an estimate about what would happen over a large number of events, on a per-event basis.
- a weighted average of the outcomes and their probabilities.
- for outcomes $\{x_1, x_2, \dots, x_n\}$ with respective probabilities $\{p_1, p_2, \dots, p_n\}$

$$E(X) = x_1 p_1 + x_2 p_2 + \dots + x_n p_n = \sum_{i=1}^n x_i p_i = \mu_x$$

↳ can take a value that the random variable doesn't take

f is a f^n on random variables

- $E(0) = 0$
- $E(kf) = kE(f)$
- $E(f \pm g) = E(f) \pm E(g)$
- $E[f(X)] = \sum f(x_i) \cdot p_i$
- $E[XY] = E[X] \cdot E[Y]$

and when $f = \text{identity } f^n$
 $E(X)$ satisfies all these.

so if $f(X) = X^2$, $E[X^2] = \sum x_i^2 p_i$
or $f(X) = (X - \mu)^2$, $E[(X - \mu)^2] = \text{Var}[X] = \sum (x_i - \mu)^2 p_i$

- mean is the same as the expected value
- variance: $\text{Var}[X] = E[(X - E[X])^2] = E[X^2] - (E[X])^2$
- $E(X^2) = \sum x^2 \cdot p(x)$
 $E(Y)$ where $Y = (aX + b)^2 = a^2 E(X^2) + 2abE(X) + b^2$

- std deviation of random variable X
 $\text{std}(\{X\}) = \sqrt{\text{var}[X]}$

- Variance:

for sample of n independent observations

$$s^2 = \frac{1}{n-1} \left[\sum x^2 - \frac{(\sum x)^2}{n} \right]$$

variance of rv. $X \rightsquigarrow s^2$ the theoretical limit of the sample variance as the sample size n becomes very large

$$\begin{aligned} \text{var}(X) &= p_1(x_1 - \mu)^2 + p_2(x_2 - \mu)^2 + \dots + p_n(x_n - \mu)^2 \\ &\downarrow \text{or } \sigma^2 \\ &= \sum_{i=1}^n p_i (x_i - \mu)^2 = E[(X - \mu)^2] \end{aligned}$$

$$= \sum p_i (x_i^2 - 2x_i\mu + \mu^2)$$

$$= \sum p_i x_i^2 - 2\mu \underbrace{\sum p_i x_i}_{\mu} + \mu^2 \underbrace{\sum p_i}_1$$

$$= E[X^2] - \mu^2$$

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

- if $Y = aX + b \rightarrow E(Y) = aE(X) + b$

$$\text{var}(Y) = a^2 \text{var}(X)$$

$$\sigma_y = \sqrt{a^2 \text{var}(X)} = a \sqrt{\text{var}(X)} = a\sigma_x$$

same as independent case, you can't calc the variance of sum

$$\sigma_{X+Y} = \sqrt{\text{var}(X+Y)}$$

- and if $T = a + bX \pm cY$ (X, Y are uncorrelated)

$$E(T) = a + bE(X) \pm cE(Y)$$

$$\text{var}(T) = b^2 \text{var}(X) + c^2 \text{var}(Y) \leftarrow \text{note: always addition}$$

\hookrightarrow always $> b^2 \text{var}(X)$ or $c^2 \text{var}(Y)$

ex

x	0	1	2
$p(x)$	0.2	0.5	0.3

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

$$E[Y] = ?$$

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

y	1	0	1
-----	---	---	---

$$E[Y] = 1(0.2) + 0 + (0.3)(1)$$

$$E[Y] = 0.5$$

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

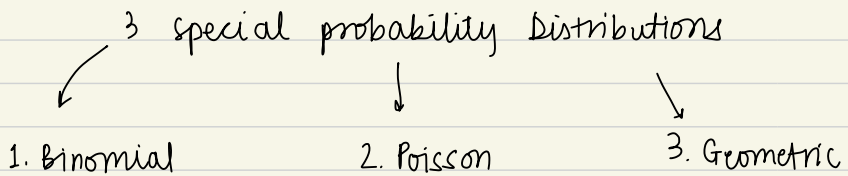
$$\begin{aligned} & \hookrightarrow [1^2(0.2) + 0^2 + 1^2(0.3)] \\ & = 0.5 - (0.5)^2 = \underline{0.25} \end{aligned}$$

empirical quantity (m observed data)	theoretical quantity (mathematical drv)	remarks
relative freq(x_i) = $\frac{f_i}{m}$	$P[X = x_i] = p_i$	$\frac{f_i}{n} \rightarrow p$ if $n \rightarrow \infty$
mean: $\bar{X} = \sum_{i=1}^m \frac{f_i}{m} \cdot x_i$	expectation $E[X] = \sum_{i=1}^n x_i p_i = \mu$	$\bar{X} \rightarrow \mu$ as $n \rightarrow \infty$
variance $s^2 = \sum_{i=1}^m \frac{(x_i - \bar{X})^2 f_i}{m-1}$	$\text{var}[X] :$ $\sigma^2 = \sum_{i=1}^n (x_i - \bar{X})^2 p_i$	$s^2 \rightarrow \sigma^2$ as $n \rightarrow \infty$

Probability Distribution of ^{drv} Discrete Random Variable

list of values of $drv(X)$ and their probabilities is called

or Discrete Probability Distribution
Probability Mass Function (pmf)



1. Binomial

bernoulli trial : each experiment has only 2 possible results

↳ success or failure

$$P(S) = 1 - P(f)$$

- probability of all trials stays the same
- each trial is independent
- finite number of trials

let X be r.v = total number of successes in n trials

$$P(X=x) = \binom{n}{x} \cdot \overset{\substack{\uparrow \\ \text{number of arrangements}}}{p^x} \cdot \overset{\substack{\leftarrow \\ p(\text{failure})}}{(1-p)^{n-x}}$$

\uparrow \leftarrow
 $p(\text{success})$

X	0	1	...	n
$P(X=x)$	$\binom{n}{0} p^0 (1-p)^n$	$\binom{n}{1} p^1 (1-p)^{n-1}$...	

↑ Binomial Distribution w/ parameters n and p

$$P(X=x) = X \sim B(n, p)$$

mean

$$E[X] = \sum x_i p_i = \sum x_i \binom{n}{x_i} p^{x_i} (1-p)^{n-x_i} = np$$

$$\text{proof: } \sum_{x=1}^n x \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x}$$

$$\text{let } y = x-1, \quad n = m+1$$

$$E[X] = \sum_{y=0}^m \frac{(m+1)!}{y!(m-y)!} p^{y+1} (1-p)^{m-y}$$

$$= (m+1)p \sum_{y=0}^m \frac{m!}{y!(m-y)!} p^y (1-p)^{m-y}$$

$$= (m+1)p \sum_{y=0}^m \binom{m}{y} p^y (1-p)^{m-y}$$

$$= np \quad (p + (1-p))^m = np$$

variance

$$\text{Var}[X] = \sigma_x^2 = E[X^2] - (E[X])^2 = np(1-p) = npq$$

proof
↓

didn't
get it.

$$= E[X(X-1)] + E[X] - (E[X])^2$$

Binomial Random Variable :

- outcome can be success or failure
- each trial is independent of the others
- fixed number of trials
- probability p of success remains constant on each trial

- is the discrete probability distribution of the number of events occurring in a given time period, given the average number of times the event occurs over that time period

2. Poisson

- rv. X is no of successes in a ~~given time interval~~

$$P(X=x) = \frac{e^{-\mu} \mu^x}{x!} \quad X \sim \text{Pois}(\mu)$$

$$0 < x < \infty$$

$$\mu = E[X] \quad (\text{avg no of successes})$$

$$e = 2.71828...$$

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

→ in the time interval we are calculating for

- can use when :

- event can occur any number of times : $0 < x < \infty$
- events occur independently
- rate of occurrence is constant
- $P(\text{event}) \propto \text{length of time}$

use when :

$$n \geq 100$$

$$p \leq 0.01$$

$$\mu = np$$

Poisson as approximating Binomial

$$P(X=k) : \lim_{n \rightarrow \infty} \binom{n}{k} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k}$$

$$\lim_{n \rightarrow \infty} \frac{n!}{(n-k)!k!} \frac{\lambda^k}{n^k} \left(1 - \frac{\lambda}{n}\right)^n \cdot \left(1 - \frac{\lambda}{n}\right)^{-k}$$

$$\lim_{n \rightarrow \infty} \frac{\underset{1 \downarrow}{n} \underset{1 \downarrow}{(n-1)} \cdots \underset{1 \downarrow}{(n-k+1)}}{n^k} \times \frac{\lambda^k}{k!} \left(1 - \frac{\lambda}{n}\right)^n \left(1 - \frac{\lambda}{n}\right)^{-k}$$

$\Rightarrow e^{-\lambda}$ $\Rightarrow 1$

$$= \frac{\lambda^k \cdot e^{-\lambda}}{k!}$$

$$\begin{matrix} n \rightarrow \infty \\ p \rightarrow 0 \\ np = \mu \end{matrix}$$

3 Geometric

- $P(M \geq 5) \rightarrow 5 \text{ or more for success to occur}$
 $= P(\bar{M} \text{ for } 4) \rightarrow \text{prob of failure for first four}$

- $$P(M \leq 2)$$
$$= 1 - \underbrace{P(\bar{M} \text{ for } 2)}_{= P(\bar{M} \geq 3)}$$
$$P(X \leq 3)$$
$$= 1 - P(\bar{X} \text{ for } 3)$$
$$= 1 - (0.1)^3$$

$$\begin{aligned} \geq & \rightarrow -1 \\ 1 - & \rightarrow = \end{aligned}$$

- for a sequence of independent Bernoulli trials, where each trial is an 'experiment' with exactly 2 possible outcomes
- with no cap, the experiments are performed consecutively until the first success is obtained.

- let X be number till first success
so $X-1$ = no of failure

$$P(X = x) = (1-p)^{x-1} p$$

$$X \sim G(p) \quad \begin{matrix} \nearrow p(\text{success}) \end{matrix}$$

- $E[X] = \frac{1}{p}$

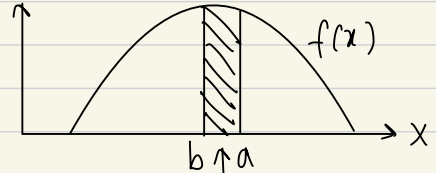
- $\text{Var}[X] = \frac{1-p}{p^2}$

NOON

Probability Distribution of a Continuous R.V.

Probability density function (pdf)

$$f(x) \geq 0 \quad \forall x$$



and area under the curve = 1

$$P(a > x > b) = \int_a^b f(x) dx$$

area of

$P(X < x) \rightarrow$ cumulative distribution function (CDF)

$$\text{cdf of } X = \int_{-\infty}^x f(x) dx$$

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

$$\text{Var}[X] = E[X^2] - E[X]^2 = \int_{-\infty}^{\infty} (x - \mu)^2 f(x) dx$$

\downarrow

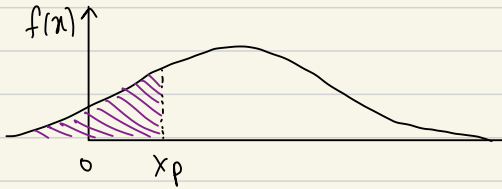
$$\int_{-\infty}^{\infty} x^2 f(x) dx$$

example!

$$f(x) = \begin{cases} \cos x & 0 \leq x \leq \pi/2 \\ 0 & \text{else.} \end{cases}$$

$$\begin{aligned} E[X] &= \int_{-\infty}^{\infty} x f(x) dx = \int_{-\infty}^0 x f(x) dx + \int_0^{\pi/2} x f(x) dx \\ &\quad + \int_{\pi/2}^{\infty} x f(x) dx \\ &= \int_0^{\pi/2} x \cos x dx = [x \sin x]_0^{\pi/2} - \int_0^{\pi/2} \sin x dx \\ &= \frac{\pi}{2} \sin(90) + [\cos x]_0^{\pi/2} \\ &= \frac{\pi}{2} - 1 \end{aligned}$$

Percentile



p^{th} percentile = value x_p
: $P(X < x_p) = p\%$

\Rightarrow  = $p\%$

$$\int_{-\infty}^{x_p} f(x) dx = \frac{p}{100}$$

eg.

$$f(x) = e^{-x} \quad x > 0$$

$$\int_0^{x_p} e^{-x} dx = 0.25$$

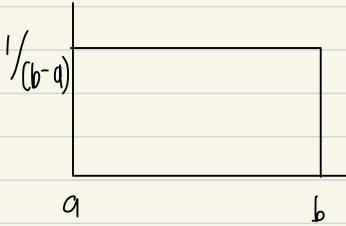
$$\left[-e^{-x} \right]_0^{x_p} = 0.25$$

$$1 - e^{-x_p} = 0.25$$

$$1 - e^{-x_p} = 0.25$$

$$\ln(0.75) = -x_p$$

Uniform Distribution



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

↖ uniform probability over this dis.

constant



$$P(X = c) = 0$$

$$X \sim U(a, b)$$

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

$$\text{Var}[X] = \frac{(a-b)^2}{12}$$

Exponential Distribution

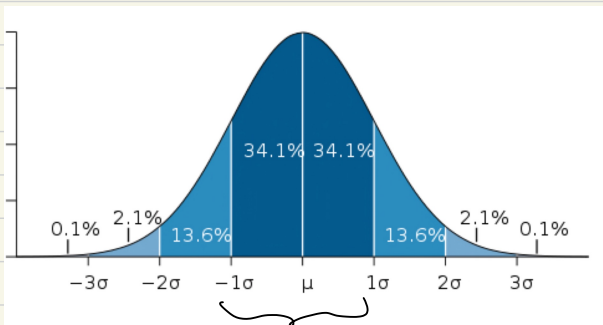
- no of success in time $T \rightarrow$ poisson dist
then
inter-success time $X \rightarrow$ exponential dist
- $f(x) = \lambda e^{-\lambda x} \quad x > 0$
- $\lambda =$ mean success
 $\frac{1}{\lambda} =$ mean inter-success time
- $X \sim \text{Exp}(\lambda)$
- $E[X] = 1/\lambda$
- $\text{Var}[X] = 1/\lambda^2$

Normal Distribution

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad \leftarrow \text{no need to remember}$$

$$-\infty < x < \infty$$

$$X \sim N(\mu, \sigma^2) \quad (\text{mean, var})$$



$$X = \mu + z\sigma$$

$$z = \frac{x - \mu}{\sigma}$$

$$\begin{aligned} & \underbrace{\hspace{10em}}_{68\%} \\ & \underbrace{\hspace{15em}}_{95\%} \\ & \underbrace{\hspace{20em}}_{99.7\%} \end{aligned}$$

$$\begin{aligned} E[Z] &= 0 \\ \text{Var}[Z] &= 1 \end{aligned}$$

$$E(\text{constant}) = \text{constant}$$

$$Z \sim N(0, 1) \quad \leftarrow \text{standard normal distribution}$$

↓
because all bell curves can be transformed into such bell curves

$$m+n = 80$$

$$3(80-n) + 8(n) = 490$$

$$240 - 3n + 8n = 490$$

$$5n = 250$$

3R 7G

odd: 1, 3, 5, 7 \rightarrow 6

even: 4

even green: 2, 4, 6

odd red: 2

$$\begin{array}{ccc} 10 & \text{even} & \text{else} \\ (2)(4) & (2)(3) & (1)(4) \\ 8 & 3 & + (1)(3) \end{array} \left. \vphantom{\begin{array}{ccc} 10 & \text{even} & \text{else} \\ (2)(4) & (2)(3) & (1)(4) \\ 8 & 3 & + (1)(3) \end{array}} \right\} 7$$

odd r odd odd r even

9 9

$$\left(\frac{6}{10}\right)\left(\frac{5}{9}\right)\left(\frac{4}{8}\right) = \frac{1}{6} (500)$$

$$0.09 \times 50 \rightarrow 4.5$$

$$0.42 \times 20 \rightarrow 8.4$$

$$0.49 \times 0$$

$$\frac{6}{10} - \frac{1}{6} = \frac{13}{30} (100)$$

$$1 - \frac{1}{6} - \frac{13}{30} = \frac{2}{5} (0)$$

$$\begin{array}{ccc} 5 & 3 & -10 \\ 0.5 & 0.12 & 0.36 \end{array}$$

small

$$10 \text{ mil} \quad -1 \text{ mil} \\ (0.4)^5 \quad 1 - (0.4)^5$$

$$102400 = 989760 \\ 0$$

large

$$15 \text{ mil} \quad -5 \text{ mil} \\ (0.3)^3 \quad 1 - (0.3)^3$$

$$405000 \quad 486500$$

$$\mu = 3$$

$$P(X=0) = \frac{e^{-3} \cdot 3^0}{0!} = e^{-3} \quad \leftarrow$$

$$\text{ans} = 1 - e^{-3}$$

$$\mu_{hr} = \frac{3}{8}$$

$$P(X=1) = \frac{e^{-3/8} (3/8)^1}{1!}$$

$$\mu_w = 3 \quad \mu_{\text{month}} = 12$$

$$P(X \geq x) = 0.5$$

$$P(X \geq 12) = P(X=0) + P(X=1) + P(X=2) \dots$$

$$e^{-12} \left(\frac{12^0}{0!} + \frac{12^1}{1!} + \frac{12^2}{2!} + \frac{12^3}{3!} + \frac{12^4}{4!} \dots \right)$$

$$\mu_{\text{candle}} = 500$$

$$\sigma_c = 15g$$

$$\mu_s = 200$$

$$\sigma_s = 8g$$

$$\mu_T = 700$$

$$\sigma_T = 17$$

$$P(S) = 0.4$$

$$n = 4$$

$$P(X=3) = \binom{n}{x} p^x (1-p)^{n-x}$$

$${}^4C_3 (0.4)^3 (0.6)$$

$$\text{var}[X] = (0.75)^2(0.5) + 0.015625 + 0.390625$$

$$0.2815 = 0.6875$$

$$\sigma_X = \sqrt{0.6875} = 0.83$$

0	0.4	0
700	0.2	500
1000	0.15	500
1000	0.15	500
1000	0.1	500

0 10 20 30

$$P = 10X - 1$$

$$\sigma = 10\sigma_X$$

$$P(D \geq 4)$$

$$= P(\bar{D} \text{ for } 3)$$

D = forgets

\bar{D} = rem: 0.3

$$\begin{array}{l} \text{81} \\ = \rightarrow \frac{81}{1000} \\ 1 \rightarrow \frac{81}{10000} \\ 0.0081 \end{array}$$

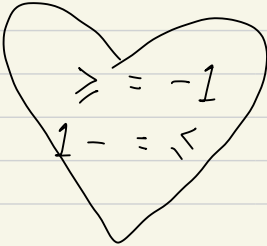
$$1. \quad P(X = 19) = \binom{20}{19} (0.95)^{19} (0.05)^5$$

$$2. \quad \begin{array}{cc} +15 & -10 \\ 0.3 & 0.7 \end{array}$$

$$3. \quad \begin{array}{cc} 100 & 10 \\ 0.1 & 0.9 \end{array} \quad (81)^2 (0.1) + (9)^2 (0.9)$$

$$4. \quad \begin{array}{r} 1819 \\ 1497 \\ \hline 322 \end{array}$$

$$\begin{aligned} 5. \quad P(V \leq 3) &= 1 - P(\bar{V} \text{ for } 3) \\ &= 1 - (0.94)^3 \\ &= \end{aligned}$$



$$\begin{aligned} &\geq = -1 \\ &1 - = .5 \end{aligned}$$

6. binomial

- success / failure
- trials are independent
- fixed no of trials
- $p(\text{succ})$ doesn't change

8. $E[X] = 3.37$

$a + b = 150$

$$\frac{1160 + a + 6b}{500} = 3.37$$

$a + 6b = 525$

$5b = 375$

$b = 75$

9. $P' = P + 10$

10

B	NB
0.3	0.7

binomial var

$n = 15$

$p = 0.3$

$q = 0.7$

$E[X] = np$
 $\sigma_x = \sqrt{npq}$

11

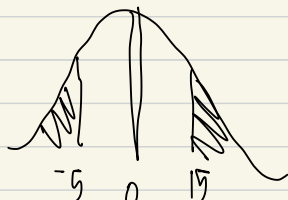
no	w	c	m
0	10	15	25
0.4	0.6	0.3	0.12

$1 - 0.6 \leftarrow \text{Un.}$

$0.6 \times 0.5 \leftarrow w, c'$

$0.6 \times 0.5 \times 0.6 \leftarrow w, c, m'$

$0.6 \times 0.5 \times 0.4 \leftarrow w, c, m$



$\sigma_x + \sigma_y = 12.7779$

0.121×2

$p = 0.7$

$n = 3$

1000	0	-1000
0.5^2	2×0.5^2	$(0.5)^2$
0.25	0.5	0.25

$P(X=2) = \binom{3}{2} (0.7)^2 (0.3)$

$P(X=6) = p(f)^5 p(x)$
 $\quad \quad \quad \searrow \quad \quad \quad \swarrow$
 $\quad \quad \quad 7/8 \quad \quad \quad 1/8$

1	2	3	4
0.2	(0.8×0.2)	$(0.8 \times 0.8 \times 0.2)$	1 - rest
			$(0.8 \times 0.8 \times 0.8)$

geometric.

↪ $P(\text{succ})$ is const
no of trial undef.

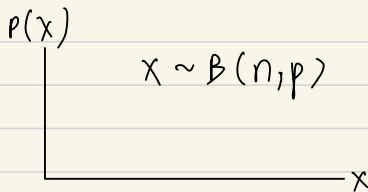
$$P(P < 3) = 1 - P(\bar{X} \text{ for } 2) = 1 - 0.512$$

is the set of numbers $P(\{X = x\})$ for each value x that X can take

probability distribution of discrete rv

X = total no of successes in n trials
prob of x successes

$$P(X = x) = \binom{n}{x} \cdot p^x \cdot (1-p)^{n-x}$$



binomial
distribution
(n, p) parameters
 $X \sim B(n, p)$

mean and variance

proof on mulearn

mean

$$E[X] = np$$

$$(E[X] = \sum x p(x))$$

var.

$$\text{Var}[X] = E[X^2] - E[X]^2 = npq \quad (q = (1-p))$$

$$ab \quad \bar{a}\bar{b} \quad a\bar{b} + b\bar{a}$$

$$\left(\frac{1}{2} \times \frac{1}{2}\right) \quad \left(\frac{1}{2} \times \frac{1}{2}\right) \quad 2\left(\frac{1}{2} \times \frac{1}{2}\right)$$

$$\frac{1}{4} \quad \frac{1}{4} \quad \frac{1}{2}$$

$$2^3 \rightarrow 8$$

- 1 HHH
- 2 HHT, HTH, THH
- 3 HTT, THT, TTH
- 4 TTT

$$n=3, p=0.5$$

$$P(X=x) : X \sim B(3, 0.5) \quad ; \quad \binom{3}{2} p^2 (1-p)^{3-2}$$

$$x=2$$

$$= 3 \cdot 0.5^2 \cdot 0.5$$

$$= 3(0.125)$$

$$= 0.375$$

$$10B, 30G \quad P(B) = 1/4 = 0.25$$

$$n=10$$

$$E[X] = np = 10(0.25) = 2.5$$

$$\text{Var}[X] = npq = 10(0.25)(0.75)$$

$$= 1.875$$

\therefore only 2 outcomes:
bernoulli.

$$P(X=2) = \binom{10}{2} p^2 (1-p)^8$$

$$P(\text{rej}) = P(X \geq 2) = 1 - P(X < 2)$$

at least
1 telephone
order in
first 4

$$P(C < 5) = 1 - P(C \geq 5)$$

$$\rightarrow P(C=1) + P(C=2) + P(C=3) + P(C=4)$$

$$0.1 + (0.9)(0.1) + (0.9)^2(0.1) + (0.9)^3(0.1)$$

$$\cancel{(0.1)} \frac{(1)(0.9^4 - 1)}{0.9 - 1}$$

$$\rightarrow 1 - P(\text{no telephone orders in first 4}) \rightarrow 1 - (0.9)^4$$

p

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- $E(X \pm Y) = \mu_X \pm \mu_Y$

- $\sigma_{X \pm Y} = \sqrt{\text{var}(X) + \text{var}(Y)}$

- $Y = AX + b \Rightarrow E[Y] = A E[X], \text{Var}[Y] =$