

Measure? ← why?

$$\text{Eg: } P[2^{\text{nd}} \text{ year}] = 10\% = \frac{10}{100} \leftarrow \begin{array}{l} \# \text{ of second \\ year student} \\ \text{in all people sitting} \\ \text{in the room} \end{array}$$

You are measuring something.

Axioms

- ① $P[A]$ has to be non-negative
- ② $P[\emptyset] = 0$
- ③ $P[S] = 1$

$$\text{Ex } P[S] = P[\text{uni students}] = 1$$

$$\text{④ } P[\text{Additive}] = P[A_1 \cup A_2 \cup \dots] = P[A_1] + P[A_2] + \dots$$

Eg $A_1 = \text{first year}$ } disjoint because
 $A_2 = \text{second year}$ } nothing in common

$$\begin{aligned} 3 &= HHH \\ 2 &= HHT \\ 2 &= HTH \\ 1 &= HTT \\ 2 &= THT \\ 1 &= THT \\ 1 &= TTH \\ 0 &= TTT \end{aligned} \quad \left. \begin{array}{l} \\ \\ \\ \text{sample space} \\ \end{array} \right\} \quad \begin{aligned} P[H] &= \frac{1}{2} \\ P[T] &= \frac{1}{2} \\ P[3H] &= \frac{1}{2} \times \frac{1}{2} \times \frac{1}{2} = \frac{1}{8} \end{aligned}$$

Random variable

Maps sample space

$$S \rightarrow \mathbb{R} \quad , \quad X = \# \text{ of heads}$$

X_i :	0	1	2	3
$p[X_i]$:	$\frac{1}{8}$	$\frac{3}{8}$	$\frac{3}{8}$	$\frac{1}{8}$

/ or add probabilities

↑

table called pmf or probability mass functions.

$$\text{To find } E(X) = \sum x p[X] \rightarrow \text{discrete}$$

$$\int x p[X] dx \rightarrow \text{continuous}$$

$$\text{To find } E[X^2] = \sum x^2 p[X] \rightarrow \text{discrete}$$

$$E[X^2] = \int_{-\infty}^{\infty} x^2 p[X] dx \rightarrow \text{continuous.}$$

Bernoulli:

$$p_X(x) = \begin{cases} \theta & \\ 1 - \theta & \end{cases}$$

$$\left| \begin{array}{l} E_x / x = \# \text{ of H} \leq 0 \\ P[H] = \theta \end{array} \right.$$

$$P[T] = 1 - \varnothing$$

Poisson mean and variance is exactly the same \Rightarrow ✓

Continuous ↳

Uniform, Exp, gamma, normal, Beta.

Next class review function, mean, cdf, pdf etc...

		Marginal prob example						
		1	2	3	4	5	6	
A	B	$\frac{1}{12}$	$\frac{1}{12}$	$\frac{1}{12}$	$\frac{1}{12}$	$\frac{1}{12}$	$\frac{1}{12}$	\vdots
		$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$= \frac{1}{2}$

$A = H$;
 $B = I$ is $A \perp B$? Yes

Proof $P[\text{Joint } (A \cap B)] = \frac{1}{12}$

$$P(A) = \frac{1}{2}$$

$$P(B) = \frac{1}{6}$$

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

$$P[1|H] = \frac{P[1 \cap H]}{P(H)} = \frac{\frac{1}{12}}{\frac{1}{6}} = \frac{1}{2}$$

x:	0	1	2	3
P[x]:	$\frac{1}{8}$	$\frac{3}{8}$	$\frac{3}{8}$	$\frac{1}{8}$

Treatment Heart Transplant

Control group

P1 - survived 42 days after died

P28 - survived 118 days - but he is alive

P - indicator

P1 - wait time for transplant is 0 days \rightarrow survived 15 days - dead

P52 - wait time 5 days \rightarrow survived 43 days - alive

$$30 \text{ ppl} \rightarrow \text{mean}(t)$$

Treatment

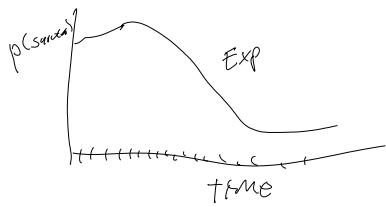
$$\text{Control}$$

P

$$52 \text{ ppl} \rightarrow \text{mean}(c)$$

compare the two values.

Assume SD is coming from a distribution
e.g.



if mean of treatment group is bigger \Rightarrow mean of control group

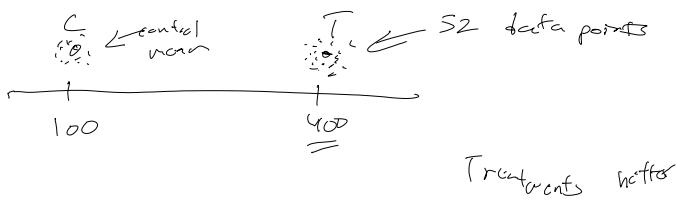
Interpretation about the population:

\Rightarrow if you go through the treatment you are expected to live longer.

$\text{mean}(T) > \text{mean}(c)$ are samples, interpretation we want to make is about the entire population.

assume

- ① $X \sim \text{Exp}(\lambda) \rightarrow$
 ② estimate of λ from these
 fits (parameters)



In real life you never know the distribution

$$\left. \begin{array}{l} \text{Recall} \\ X \sim \text{exp}(x) \\ f_x(x) = \lambda e^{-\lambda x} \end{array} \right\} \text{mean is the center of the distribution}$$

radius also matters.

Data - Circle

mean - center of data

standard deviation - radius

look if they are overlapping or far apart.

$$5.1.1 \quad \text{mean}(c) = 93.2 \\ = \frac{\text{sum (30 numbers)}}{30}$$

$$\text{mean}(t) = 356.2$$

you could just compare the mean, look at SD and then mean.

Ex 5.1.8

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

$$x_1, x_2, \dots, x_n$$

$$E(x) = \int_0^\infty x f(x) dx$$

$$= \int_0^\infty x \lambda e^{-\lambda x} dx$$

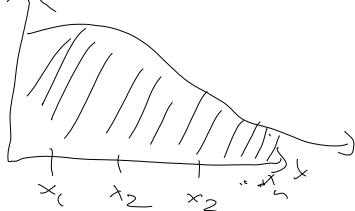
$$= \lambda \int_0^\infty x e^{-\lambda x} dx$$

difference between x and x_i is

$$E(x) - x = 2$$

$$f_{x|>2} = 2e^{-2x}$$

$$f(x)$$



$$= \lambda \int_0^{\infty} x e^{-\lambda x} dx$$

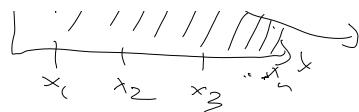
$$= \frac{\lambda}{\Gamma(2)} \int_0^{\infty} x^{2-1} e^{-\lambda x} dx \cdot \frac{\lambda^2}{\Gamma(2)} \leftarrow \text{divide by } \Gamma(2)$$

gamma density = 1

$$= \frac{1}{\lambda} (1) = \frac{1}{\lambda}$$

weak law of large #'s says

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \xrightarrow{\lambda} \frac{x_1 + x_2 + \dots + x_n}{n} \xrightarrow{\text{converge}} \frac{1}{\lambda} \xrightarrow{\lambda \approx 100} \frac{1}{\lambda} \xrightarrow{\text{estimate of mean}} \frac{1}{\bar{x}} \xrightarrow{\text{Estimate of lambda}}$$



can take any value x or y . x is the random variable that can take any value

x_i is sample value
 $x_1 = 100$ days
 $x_2 = 200$ days

Recall: Gamma

$$y \sim G(\alpha, \beta)$$

$$f(y) = \frac{\beta^\alpha}{\Gamma(\alpha)} y^{\alpha-1} e^{-\beta y}, y \geq 0$$

problems

$$\bar{x} = 0.05 \quad \hat{\lambda} = 20 \quad \text{Estimate}$$

$$\bar{x} = 0.6 \quad \hat{\lambda} = 16.66$$

if λ is really big eg 200 to contain it you need a large sample size

R-vector: $c(1, 3, 5) \Rightarrow$

1
3
5

$$c(1, 3, 5) + 2 = \begin{bmatrix} 3 \\ 5 \\ 2 \end{bmatrix}$$

variable: $x = c(5, 7, 9, 10)$

printing: $>x$
 $[1] 5 > 9 10$

$$\log(x) \Rightarrow \log \begin{bmatrix} 5 \\ 7 \end{bmatrix}$$

1 2 3

$$\log(x) \Rightarrow \log \begin{pmatrix} 5 \\ 7 \\ 9 \\ 10 \end{pmatrix}$$

1.60903 1.10510...

$\log_{10}(x)$

$\sin(x)$

$\cos(x)$

x^2

does it for all others

$y =$

5.1.1 / $x \sim N(0, 1)$

$$y = x + 2x^3 - 3$$

$p(y \in (1, 2)) \leftarrow$ probability between (1, 2)

$$x^2 \rightarrow \text{hi-sq}$$

$\overbrace{-\infty}^{\infty}$

Ex 5.2.1

x = life length of a machine

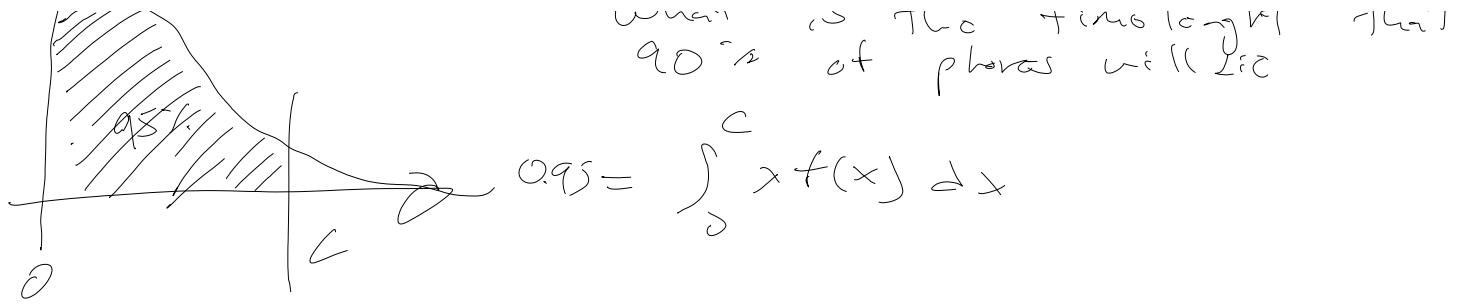
$$x \sim \text{Exp}(1)$$

mean life length \Rightarrow asking for $E(x)$

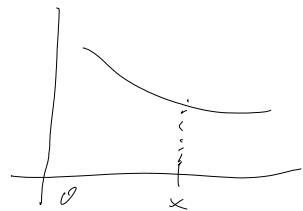
$$\text{Exp}(\lambda) = \frac{1}{\lambda} \Rightarrow \text{Exp}(1) = \frac{1}{1} = 1$$



what is the time length plant 90% of phones will last



$$F(x) = \int_0^x f(x) dx \leftarrow \text{cdf}$$



$$1 - e^{-c} = 0.95$$

$$e^{-c} = \frac{0.95}{1}$$

$$\ln(e^{-c}) = \ln(0.05)$$

$$c = -\ln(0.05)$$

Conditional Distribution

X:	0	1	2	3
$P[X=x]$:	$\frac{1}{8}$	$\frac{3}{8}$	$\frac{3}{8}$	$\frac{1}{8}$

$$\text{mean} = (0)\left(\frac{1}{8}\right) + 1\left(\frac{3}{8}\right) + 2\left(\frac{3}{8}\right) + 3\left(\frac{1}{8}\right) \\ = 1.5$$

Is this valid Probability Distribution?

Yes because

- 1) $0 \leq P(X=x) \leq 1$
- 2) $\sum P[X=x] = 1$

Condition: cell phone survived 6 month then you won't have the same distribution

X:	0	1	2	3
$P[X=x]$:	$\frac{1}{8}$	$\frac{3}{8}$	$\frac{3}{8}$	$\frac{1}{8}$

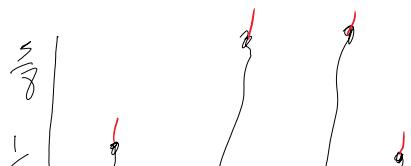
Then 0 isn't an option

This is not a valid probability distribution since it does not add up to 1.

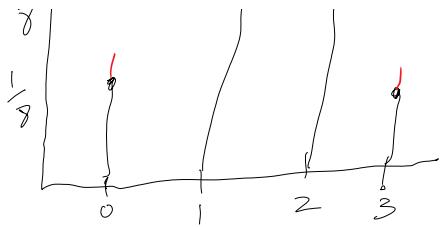
First make it a valid probability distribution

$$P(X=1 | X \geq 0) ?$$

$$\frac{P(X=1 \cap X \geq 0)}{P(X \geq 0)} = \frac{P(X=1)}{P(X \geq 0)} = \frac{\frac{3}{8}}{\frac{7}{8}} = \frac{3}{7}$$



make it a bit bigger
in. down -



makes it a hit bigger
for $\text{PPF} = 1$

if $x \sim \text{Exp}(1)$

PDF: $f_x(x) = e^{-x}$

$$E[x | x > 1] = \int x, \text{ conditional function}$$

$$f_{x|x>1}(x) = \frac{f_x(x)}{P[x > 1]} \leftarrow \begin{array}{l} \text{condition needed} \\ \text{for } \sum \text{ to } = 1 \end{array}$$

$$= \frac{e^{-x}}{\int_1^\infty e^{-x} dx}$$

$$\Rightarrow = \int_1^\infty x e^{-(x-1)} dx$$

Review S.I

Example \rightarrow Samples

\hookrightarrow Distribution

\hookrightarrow Inference \rightarrow commenting on the calculation

* If $x \sim \text{life length}$

what is mean/expected life length?

\hookrightarrow asking for expected value $E(x)$

\hookrightarrow by what time 95% of the machines

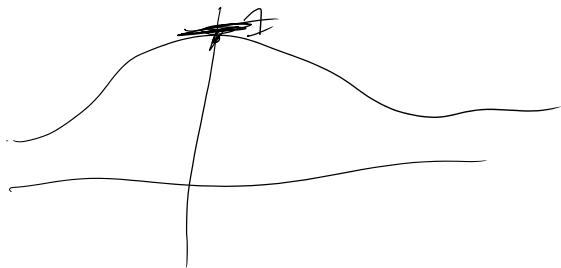
↳ by what time 95% of the machines will fail.

calculate cdf, equal it to 0.95 or value given and solve it.

2nd question: conditional, given $x > 1$
↳ mean / expected life?

$$E(x | x > 1)$$

product life time distribution; mean or mode



mode = highest point

To find # failure derivative
set it = 0

max / min

5.2.7 example where you have to calculate the mode.

5.2.8 $x \sim P(X)$

* Predict the future values?

mean
mode

mode

$$P[X=x] = \frac{\lambda^x e^{-\lambda}}{x!}, \text{ if discrete no derivative}$$

$$P[X=x+1] = \frac{\lambda^{x+1} e^{-\lambda}}{(x+1)!}$$

$$\frac{P[Y=x+1]}{P[X=x]} = \frac{\cancel{\lambda}^{x+1} \cancel{e^{-\lambda}}}{(x+1)!} \div \frac{\cancel{\lambda} \cancel{e^{-\lambda}}}{x!}$$

$$= \lambda \frac{x!}{(x+1)!} = \frac{\lambda}{x+1}$$

$$\Rightarrow \frac{P[Y=x+1]}{P[X=x]} = \frac{1}{x+1}$$

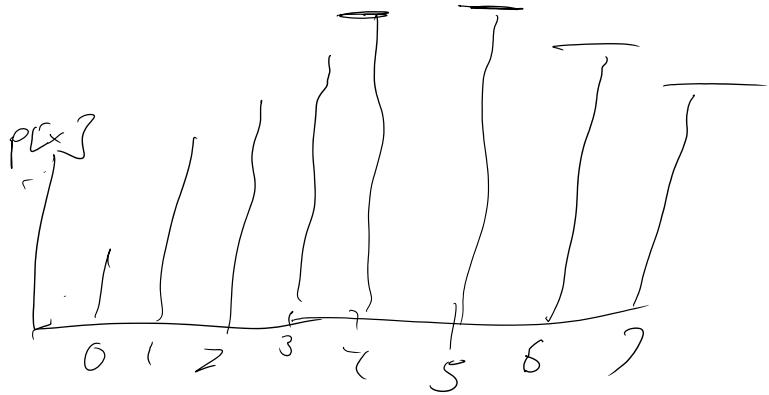
$$X=0 \Rightarrow \frac{P[X=1]}{P[X=0]} = \lambda \rightarrow \text{if } \lambda = 5 \text{ then its Sx ratio}$$

$$X=1 \Rightarrow \frac{P[X=2]}{P[X=1]} = \frac{\lambda}{2} \rightarrow \text{if } \lambda = 5 \text{ then its Sx ratio}$$

$$\frac{P[X=3]}{P[X=2]} = \frac{5}{3} = 1.666$$

$$\frac{P[X=4]}{P[X=3]} = \frac{5}{4} = 1.25$$

$$\frac{P[x=5]}{P[x=4]} = \frac{5}{5}$$



5.3 Statistical Models

① Population: a combination of all the subjects in your subspace. All the outcome.

Sample: A small subset of the population
 $\text{Sample} \subseteq \text{Population}$

Parameter: Any characteristic of a population is a parameter
 Statistic: summary of sample

populations are too big, samples are easier to work with.

Study sample \Rightarrow make inference about population. That is statistics

$$\text{Eg } f_{\lambda}(x) \quad , \quad p_{\theta}(x)$$

$$f(x) = \frac{e^{-\lambda} \lambda^x}{x!} \quad x \text{ is r.v., } \lambda \text{ is the parameter.}$$

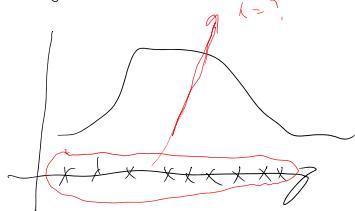
Statistical model

$\left\{ \begin{array}{l} p_{\theta} : \theta \in \Omega \\ \text{function} \\ \text{e.g. poisson} \\ \text{normal} \end{array} \right.$	θ can take any value in the sample space parameter space
--	--

$$\frac{e^{-5} 5^x}{x!} \sim p_5(x)$$

$$\frac{e^{-100} 100^x}{x!} \sim p_{100}(x)$$

$$\text{Eg } x \sim p_{\lambda}(\lambda = ?)$$



$$\bar{x} \rightarrow \frac{1}{\lambda}$$

We use \bar{x} to estimate $\frac{1}{\lambda}$. This is an example of point estimation.

Interval estimation - Review

Example: Pg 264

Ex 5.3.2

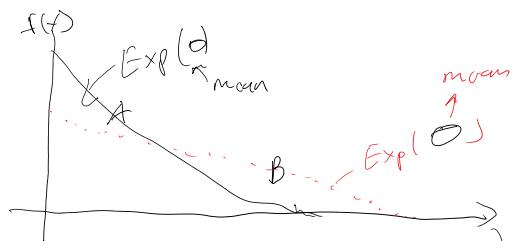


$$P_\theta(x) = f_\theta(x)$$

\curvearrowleft discrete continuous

Sample (x_1, x_2, \dots, x_5)

In this case, we know the parameters as the mean is already there.



\curvearrowleft we should be able to distinguish between if a function has a mean of 2 or 1.5.

$$\textcircled{1} (x_1, \dots, x_5) = (5.0, 3.5, 3.3, 4.1, 2.8)$$

$$\textcircled{2} (x_1, \dots, x_5) = (2.0, 2.5, 3.0, 3.1, 3.0)$$

\curvearrowleft which one belongs with which sample?

$$\textcircled{1} \Rightarrow \text{Exp}(1.5)$$

$$\textcircled{2} \Rightarrow \text{Exp}(1)$$

Parameter space in this case is

$$\Pi = \{1, 1.5\}$$

$$\Pi = \{A, B\}$$

Ex 5.3.1

- \curvearrowleft
- ① Exp \curvearrowleft know function
 - ② $\Pi = \{1, 1.5\}$ \curvearrowleft know parameter space
 - ③ Sample \curvearrowleft select sample and pick

Real life

- ① observe sample
- ② find the distribution
- known or assumed

② Sample \leftarrow select sample and pick θ - known or assumed

③ Parameter - Use sample to make inference about parameter

5.3.7 parameter

θ	$P_\theta(x=1)$	$P_\theta(x=2)$	$P_\theta(x=3)$
A	0.5	0.5	0
B	0	0.5	0.5

\rightarrow space $\{A, B\}$

b) if we observe $x=1$ then x is coming from A

if we observe $x=3$ then x is coming from B

if we observe $x=2$ then either A or B.

parameter

θ	$P_\theta(x=1)$	$P_\theta(x=2)$	$P_\theta(x=3)$
A	λ_1	λ_2	0
B	0	0.5	0.5

what if $x=2$?

probably A

Notation

$$\{f_\theta : \theta \in \Omega\}$$

for one ^{sample} value what is the statistic model

$$\text{Ex: } \hat{P}_{\text{obs}}(x)$$

$$\text{Ex: } x \sim \text{Exp}(\theta)$$

$$x = L$$

$$\sum \frac{\hat{P}_{\text{obs}}(x)}{2!}$$

$$f_\theta(x) = \theta e^{-\theta x}$$

$$x=5 = \theta e^{-\theta(5)} \leftarrow \text{statistical model of one sample.}$$

Joint density of sample

$$\text{Ex: } p[x_1, x_2, x_3, \dots, x_n] \text{ if I break it down}$$

$$\Rightarrow f_\theta(x_1) f_\theta(x_2) \dots f_\theta(x_n)$$

I is an assumption

$$x = \{2, 4, 9\}$$

$$X = \{2, 4, 9\}$$

$$\theta e^{-2\theta} \times \theta e^{-k\theta} \times \theta e^{-q\theta}$$

Ex 5.3.3

$$x \sim B(n, \theta)$$

$$p_X(x) = \begin{cases} 1 & , \theta \\ 0 & , 1-\theta \end{cases}$$

$$p_X(x) = \theta^x (1-\theta)^{n-x}$$

$$\begin{aligned} & x_1, x_2, \dots, x_n \\ & \downarrow \\ \theta^x & (1-\theta)^{1-x_1} * (\theta)^{x_2} (1-\theta)^{1-x_2} * \dots * \theta^{x_n} (1-\theta)^{1-x_n} \\ & = \theta^{x_1+x_2+\dots+x_n} (1-\theta)^{n-(x_1+x_2+\dots+x_n)} \\ & = \theta^{\sum_{i=1}^n x_i} (1-\theta)^{n-\sum_{i=1}^n x_i} \end{aligned}$$

Ex 5.3.4

$$(x_1, \dots, x_n) \sim N(\mu, \sigma^2)$$

$$\theta = (\mu, \sigma^2) \in \mathbb{R}^1 \times \mathbb{R}^+, \quad \mathbb{R}^+ = (0, \infty)$$

$$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} \cdot \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x_1-\mu)^2} \cdot \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x_2-\mu)^2} \cdot \dots \cdot \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x_n-\mu)^2}$$

$$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\left[\frac{1}{2\sigma^2} \sum (x_i - \mu)^2\right]}$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}}$$

$$\begin{aligned}
 &= \sum_{i=1}^n (x_i - \mu)^2 \quad \begin{matrix} a-b \\ a-c+c-b \end{matrix} \\
 &= \sum_{i=1}^n (x_i - \bar{x} + \bar{x} - \mu)^2 \\
 &= \sum_{i=1}^n (x_i - \bar{x})^2 + 2(\bar{x} - \mu) \sum_{i=1}^n (x_i - \bar{x}) + \sum_{i=1}^n (\bar{x} - \mu)^2 \\
 &\quad \begin{matrix} \cancel{\sum_{i=1}^n (x_i - \bar{x})} \\ = \sum x_i - \sum \bar{x} \end{matrix} \quad \text{sum of deviations from mean} = 0 \\
 &= n\bar{x} - n\bar{x} = 0
 \end{aligned}$$

$$\sum_{i=1}^n (\bar{x} - \mu)^2 = n(\bar{x} - \mu)^2$$

$$s^2 = \frac{\sum (x_i - \bar{x})^2}{n-1} \sim \text{sample variance}$$

x_i	\bar{x}	$x_i - \bar{x}$	$(x_i - \bar{x})^2$
2	-2	4	16
4	0	4	16
6	2	0	0
	0	8	8

$$\begin{aligned}
 s^2 &= \frac{\sum (x_i - \bar{x})^2}{n-1} \\
 &= \frac{8}{2} = 4
 \end{aligned}$$

$\frac{1}{\text{Var}} = \text{precision}$

$$\lambda = \frac{1}{6^2}$$

precision

$$\begin{aligned}
 &(2\pi\sigma^2)^{-\frac{1}{2}} \exp\left[-\frac{1}{2\sigma^2} (x-\mu)^2\right] \\
 &= (2\pi)^{-\frac{1}{2}} (\lambda)^{\frac{1}{2}} \exp\left[-\frac{1}{2} \lambda (x-\mu)^2\right] \quad \leftarrow \text{still normal but in precision instead of variance}
 \end{aligned}$$

Reparameterization :- only do it if it's a one to one function. Precision is \perp variance. The change old parameter to new parameter has to be one to one.

old param $\xrightarrow{\text{func}}$ new param.

Tues Oct 3. 3. 5.

Population

Population CDF

$$F_X(x) = \frac{\text{Count of } X \leq x}{N}$$

Ex 5.4.1

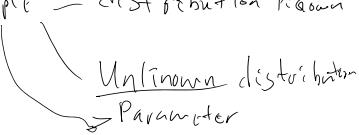
$$N = 20$$

$$\underline{\text{min}} = 3$$

$$P(X < 3) = 0$$

$$P(X < 4) = \frac{3}{20}$$

$$P(X < 4) - P(X < 3) = P(X=3)$$

5.4 = Population = finite
= Sample — distribution known

Parameter

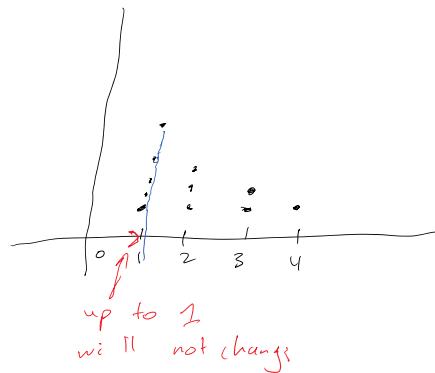
If a population is finite, do you need money/time to study them?

Ex

i	1	2	3	4	5	6	7	8	9	10
$X(\pi_i)$	1	1	2	1	2	3	3	1	2	4

Sort

i	1	1	2	1	2	3	3	1	2	4
$X(\pi_i)$	1	1	1	1	2	2	3	3	4	



$$P[X \leq 0] = 0$$

$$P[X \leq 0.999] = 0$$

$$P[X \leq 1] = \frac{4}{10} = 0.4$$

$$P[X \leq 1.999] = \frac{4}{10} = 0.4$$

$$P[X \leq 2] = \frac{7}{10} = 0.7$$

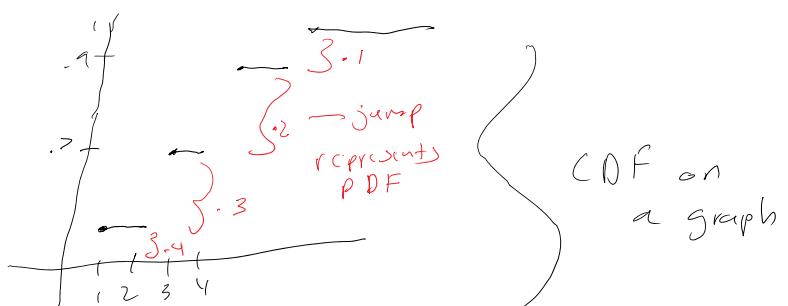
$$P[X \leq 2.99] = \frac{7}{10} = 0.7$$

$$P[X \leq 3] = \frac{9}{10} = 0.9$$

$$P[X \leq 3.99] = 0.9$$

$$P[X \leq 4] = 1$$

$$CDF = F_x(x) = \begin{cases} 0 & x < 1 \\ 0.4 & 1 \leq x \\ 0.7 & 2 \leq x < 3 \\ 0.9 & 3 \leq x \leq 4 \\ 1 & x > 4 \end{cases}$$



PMF:

$$f_x(x) = \begin{cases} 0.4, & x=1 \\ 0.3, & x=2 \\ 0.2, & x=3 \\ 0.1, & x=4 \\ 0, & otherwise \end{cases} \Rightarrow$$

x	1	2	3	4
$p[x]$	0.4	0.3	0.2	0.1

To calculate small f, pdf just calculate the proportion.

$$\text{CDF} = F_x(x) = \begin{cases} 0 & x < 1 \\ .4 & 1 \leq x \\ .7 & 2 \leq x < 3 \\ .9 & 3 \leq x \leq 4 \\ 1 & x \geq 4 \end{cases}$$

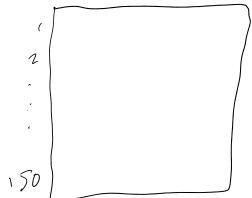
Same calculation but if it's sampled it's called Empirical distribution function

Empirical distribution: Same calculation but put $\hat{F}_x(x)$

g.4.1 ex/ do it on your own drug.

Simple random Sampling:

Ex, in a class, blindly picking #'s



To do it in R: `sample(1:150, size=1)`

for a random sample between 1-150

A, B, C, D, E, Z

$N=5$ - draw 2 samples $n=2$

$$P(A) = \frac{1}{5}$$

$$P(A \text{ being selected}) = \frac{1}{N} = \frac{1}{5}$$

$$P(A \text{ being selected} | b \text{ is selected}) = \frac{1}{N-1} = \frac{1}{4} = 0.25$$

Samples are not \perp because one being in the sample changes prob of the other one.

After picking with replacement — pick and put it back \rightarrow samples are \perp

$$\frac{1}{N} \quad \frac{1}{N-1}$$

$$N=100,000$$

0.2

0.25

0.00000 | \approx next numbers
 are closer.
 something
 like that

large sample even though they are dependent because N is large change is insignificant, so we treat as 1

Conditions

$N \rightarrow$ large

$n \rightarrow$ small relative to N

$$\therefore \hat{F}_x(x) \rightarrow F_x(x)$$

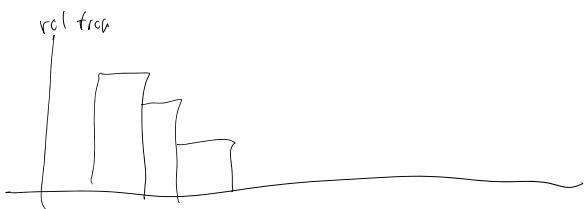
$\hat{F}_x(x)$
 cdf
 calculated
 based on
 sample

Histogram

Ex height

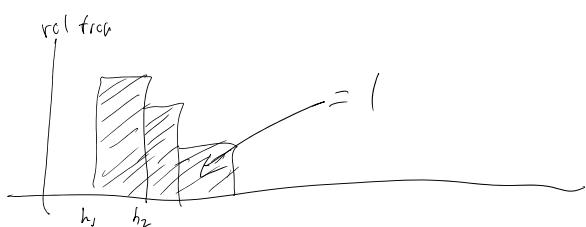
$$(h_1, h_2] \quad (h_2, h_3] \quad (h_3, h_4] \quad \dots \dots$$

5 5:6 5:6 6 6:5



relative frequency = proportion

Density histogram

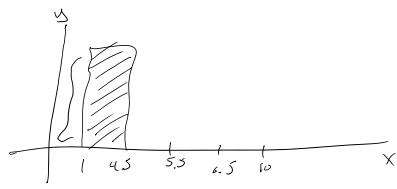


$$h_x(x) = \frac{\text{proportion}}{\text{length}}$$

5.4.5

$$\begin{aligned} & n \{ 1.2 \ 1.8 \ 2.3 \ 2.5 \ 3.1 \ 3.4 \ 3.7 \ 3.2 \ 3.9 \ 4.3 \ 4.4 \ 4.5 \ 4.5 \} \\ & (4.8 \ 4.8] (5.6 \ 5.8] (6.9 \ 7.2 \ 8.5] \end{aligned}$$

$$h_x(x) = \frac{\frac{13}{20}}{(4.5 - 1)} \quad (1, 4.5]$$



$$h_x(x) = \frac{\frac{13}{20}}{(4.5 - 1)} \quad , (1, 4.5)$$

$$= \frac{13}{20}$$

Question on
Midterm on this.

$$(4.5, 5.5] \quad , (4.5, 5.5]$$

$$h_x(x) = \frac{\frac{2}{20}}{(5.5 - 4.5)}$$

Ex

$$f_x(x) = \begin{cases} .4 & / x = 1 \\ .3 & / x = 2 \\ .2 & / x = 3 \\ .1 & / x = 4 \\ 0 & / \text{o/w} \end{cases}$$

from this list make the table

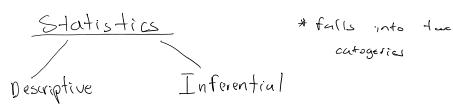
look for unique numbers

① 2, 3, 4

count pop by total + get proportion

loop

Prof uploaded w code. look at the table.



Descriptive: describes ^{any summary}
eg mean of sample
standard deviation
median

Inferential: moment you use these #'s to make a inference about the data.

Recall: $f_x(x)$ is the proportion of the population members whose X measurements equal x .

$$\Rightarrow f_x(x) = P[X=x]$$

$F_x(x)$ is the proportion of population members whose X measurements is less than or equal to x

$$Ex \quad \{1.2, -2.1, 0.4, 3.3, -2.1, 4.0, -0.3, 2.2, 1.5, 5.0\}$$

put in ascending order

$$\{-2.1, -0.3, 0.4, 1.2, 1.5, 2.1, 2.2, 3.3, 4.0, 5.0\}$$

$$\begin{aligned} &\# flag in each data point \\ &\text{to get pdf} \\ f_x(x) &= P[X=x] \\ f_x(-3) &= P[X=-3] = 0 \\ f_x(-2.1) &= P[X=-2.1] = \frac{1}{10} \\ f_x(-0.3) &= P[X=-0.3] = \frac{1}{10} \\ &\vdots \\ f_x(5) &= P[X=5] = \frac{1}{10} \end{aligned}$$

CDF same thing but everything up to the point

$$F_x(-2.1) = P[X \leq -2.1] = \frac{1}{10}$$

$$F_x(-0.3) = P[X \leq 0.3] = \frac{2}{10} = \frac{1}{5}$$

A natural estimate of $F_x(x)$ is given by $\hat{F}_x(x)$

$$\hat{F}_x(x) = \frac{1}{n} \sum_{i=1}^n I_{(-\infty, x]}(x_i) \quad \text{that's the formal definition for what we did above}$$

This is also called empirical distribution function of x
↳ means sample.

Calculating Population Quantiles

Given value calculate percentile.

$x(60)$

p-quantile

Note .75 quantile = 75th percentile

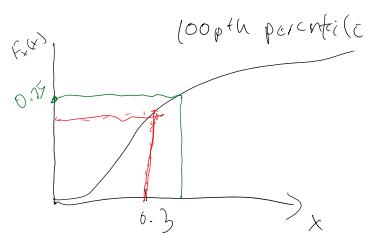


↳ more values between quantiles.

↳

$$p\text{-quantile} \quad N_{100} \cdot 75 \text{ quantile} = \overset{\text{100}}{\underset{1}{\text{75}}} \text{ percentile}$$

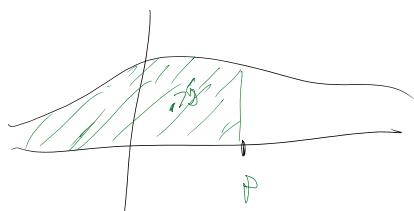
$$80^{\text{th}} \text{ percentile} = 0.8 \text{ quantile}$$



$$f_x(0.3) = P[x \leq 0.3]$$

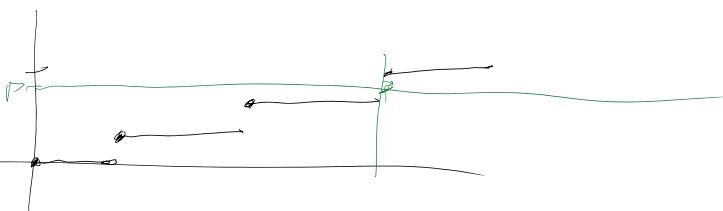
Percentile is opposite

$$f_x(x) = P[x \leq x] = 0.75$$



$$F(x_p) = p$$

$x_p = ?$ if continuous
cdf



$$\{1.2, 2.1, 0.4, 3.3, -2.1, 4.0, -0.3, 2.2, 1.5, 5.0\}$$

put in ascending order

$$\begin{array}{ccccccccc} x(1) & x(2) & & & & & & & x(n) \\ \downarrow & \downarrow & & & & & & & \downarrow \\ -2.1 & -0.3 & 0.4 & 1.2 & 1.5 & 2.1 & 2.2 & 3.3 & 4.0 & 5.0 \end{array}$$

70th percentile? 2.2

$$P[x \leq 2.2] = 0.7$$

* if you don't have equal then go to the next one

its a # between 2.2 - 3.3
 $2.2 \left(\frac{70}{100}\right) \text{ or } 2.2 + \frac{1}{10} = 2.3$
 $2.2 \left(\frac{10}{100}\right) \text{ or } 2.2 + \frac{3}{10} = 2.5$

← interpolation

$$2.2 \left(\frac{5}{10}\right) \text{ or } 2.2 + \frac{(3.3-2.2)}{2} = 2.2 + \frac{1.1}{2} = 2.2 + 0.55 = 2.75$$

$$\frac{i-1}{n} \leq p \leq \frac{i}{n}$$

$$\frac{i-1}{n} \leq p \leq \frac{i}{n}$$



Continuous one always a solution, if discrete no solution. Some times?

$$x = x_{(i-1)} + (x_i - x_{i-1}) n \left(p - \frac{i-1}{n} \right) \stackrel{\text{in this case}}{\Rightarrow} 2.2 + (3.3 - 2.2) 10 (0.75 - 0.7) \\ \approx 2.2 + (1.1)(0.5) \\ = 2.75$$

25th percentile ← mid term / final question

$$\frac{i-1}{n} < p \leq \frac{i}{n} \\ 0.2 < p \leq 0.3, i=3$$

$$x = x_{(i-1)} + (x_i - x_{i-1}) n \left(p - \frac{i-1}{n} \right) \cancel{\text{uncorrected}} \\ \approx -0.3 + (0.4 + 0.3) 10 (0.25 - 0.2) \\ \approx 0.05$$

25th percentile = Q_1 = 1st quartile

75th percentile = Q_3 = 3rd quartile

$$P[X \leq 1.5] = 0.5$$

$$P[X \geq 1.5] = 0.6$$

$$\{1.2, 2.1, 0.4, 3.3, -2.1, 4.0, -0.3, 2.2, 1.5, 5.0\}$$

put in ascending order

$$\{-2.1, -0.3, 0.4, 1.2, \textcircled{1.5}, 2.1, 2.2, 3.3, 4.0, 5.0\}$$

\uparrow
median

If calculate percentile use this formula.

on mid term and final

In one definition

$P[X \leq 1.5] = 0.5$ is enough to call it a median but in another definition

$P[X \geq 1.5] = 0.6$ will not suffice if $\neq 0.5$.

Result if n is odd $\rightarrow \frac{n+1}{2}$ th term

$$\text{even} \rightarrow \frac{n}{2} \text{th} + \frac{n+1}{2} \text{th term}$$

$$P(X \geq 1.8) = 0.5 \quad \checkmark$$

$$\begin{array}{c|cc} 1.5 & & 2.1 \\ \hline 1.8 & & \end{array}$$

Two definition of median, also easiest one.

$$1, 3, \textcircled{5} \text{ median is } \frac{n+1}{2} = \frac{3+1}{2} = 2 \text{nd terms}$$

7

011

Interquartile range: (width of data)

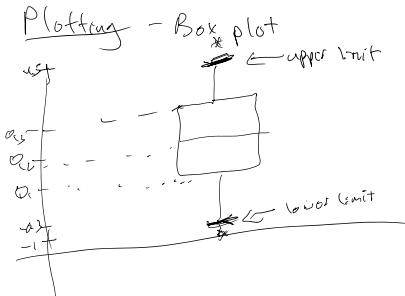
$$IQR = Q_3 - Q_1$$

replacement of SD.



extreme outliers median doesn't suffer

Skew \rightarrow median
symmetric \rightarrow mean.



$$\text{lower limit} = Q_1 - 1.5 \times IQR$$

$$\text{upper limit} = Q_3 + 1.5 \times IQR$$

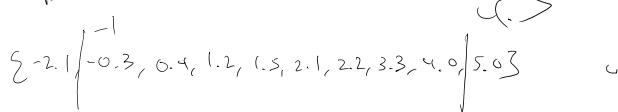
* Box plot
also for continuous cases.

$$\text{lower limit} = Q_1 - 1.5 \times (Q_3 - Q_1) = 1 \quad (\leftarrow \text{means line goes down to } 1)$$

stop at -0.3 * - outliers

$$\begin{aligned} \text{upper limit} &= Q_3 + 1.5 \times (Q_3 - Q_1) \\ &= 4.5 \end{aligned}$$

stop at 4.5



4.5 is also an outlier.

whiskers = *

adjacent values: 4.5, -1

Ex/

- (1) car 0.42
- (2) Van 0.28
- (3) BS 0.22
- (4) St 0.08

} categorical variable has no order.

if categorical stuff above does not apply

Do this instead

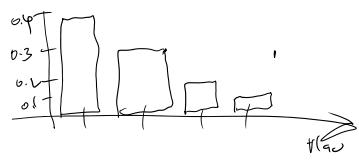


\rightarrow CP

put shift in order

determine region





cover

determine region

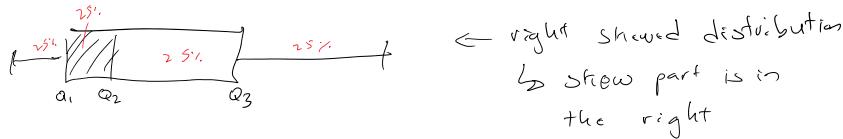
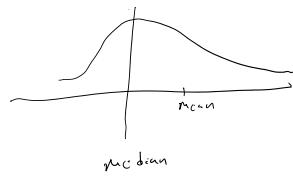
calculate percentile



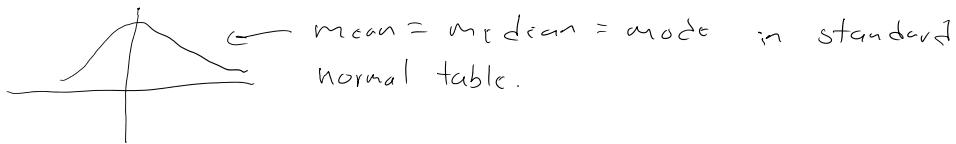
Recap

$$\tilde{x}_p = x_{(i-1)} + (x_{(i)} - x_{(i-1)}) n \left(p - \frac{i-1}{n}\right)$$

odd	$\left(\frac{n+1}{2}\right)$ th term
even	$\frac{n}{2}$ th + $\left(\frac{n}{2}+1\right)$ th

skewness:

if skewed use median and not the mean



5.2 $X \sim \text{Exp}(1)$

- ① Predict future value
 - ② $P[X > 5]$
 - ③ $P[X \leq a] = 0.95$
- These are inferences about the future X . (observation)

5.3 inference is about distribution

In this chapter $\text{Exp}(\theta) \rightarrow$ estimate θ

Chi

$$\psi(\theta) = \frac{1}{\theta} \quad \text{mean} = \frac{1}{\theta} \quad \text{var}(\theta) = \frac{1}{\theta^2}$$

$$\psi'(\theta) = \frac{1}{\theta^2} \quad \text{median} = \int_0^M f_\theta(x) dx = 0.5$$

$$\Rightarrow F(m) = 0.5 \\ \Rightarrow m = F^{-1}(0.5)$$

$\boxed{\psi(\theta) = F_\theta^{-1}(0.5)}$

median

25th percentile: $\psi(\theta) = F_\theta^{-1}(0.25)$

Inverse or Exp(1)

$$f_\theta(x) = e^{-x}$$

$$F_\theta(x) = \int_0^x e^{-r} dr = 1 - e^{-x}$$

$$\begin{aligned} F_\theta(m) &= 1 - e^{-m} = 0.5 \\ e^{-m} &= 0.5 \\ -m &= \ln(0.5) \\ \Rightarrow m &= -\ln(0.5) \\ \Rightarrow F_\theta^{-1}(0.5) & \end{aligned}$$

$$f_\theta(x) \rightarrow \text{Normal}(\mu, \sigma^2)$$

$\psi(\theta) \leftarrow$ Parameter of interest

$$\psi(\theta) = \mu$$

$x_1, x_2, \dots, x_n \leftarrow$ can you use this to get mean?

yes $\rightarrow \bar{x}$ use sample mean

$$T(s) = \frac{1}{n} \sum x_i$$

$T(s)$ is an estimate of $\psi(\theta)$

Variance: $\psi(\theta) = \sigma^2$

$$T(s) = \frac{\sum (x_i - \bar{x})^2}{n-1} \rightarrow \text{an estimate of } \frac{\sigma^2}{\psi(\theta)}$$

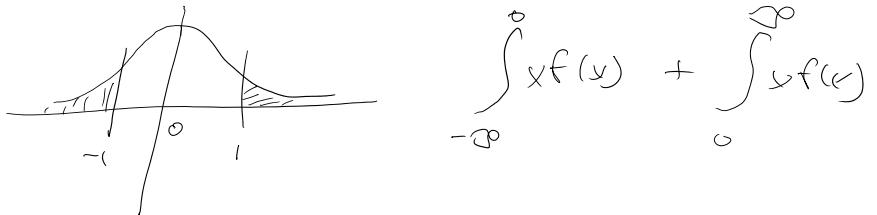
$$\bar{x} \rightarrow E(x)$$
$$n \rightarrow$$

5.5.8

3rd moment $N(\mu_0, \sigma_0^2)$

$$\begin{aligned}
 \text{Var}(x) &= E(x^2) - \mu^2 = E[(x-\mu)^2] \\
 &= E[(x-\mu)^3 + 3(x-\mu)^2\mu + 3(x-\mu)\mu^2 + \mu^3] \\
 &= E[(x-\mu)^3] + E[3(x-\mu)^2\mu] + E[3(x-\mu)\mu^2] + E[\mu^3] \\
 &= E[(x-\mu)^3] + 3\mu E[(x-\mu)^2] + 3\mu^2 E[(x-\mu)] + \mu^3
 \end{aligned}$$

↓ ↓ ↓
 3rd central moment var(x)
 moment σ²



$$x \leq 1 = x \geq 1$$

if the distribution is symmetric around (μ)

$$E[(x-\mu)^1] = 0$$

$$E[(x-\mu)^3] = 0$$

$$E[(x-\mu)^5] = 0$$

$$\begin{aligned}
 E[(x-\mu)^3] + 3\mu E[(x-\mu)^2] + 3\mu^2 E[(x-\mu)] + \mu^3 \\
 \downarrow \quad \downarrow \quad \downarrow \quad \downarrow \\
 3^{\text{rd}} \text{ central} \quad \text{moment} \quad \text{var}(x) \quad 0 \\
 \parallel \quad 0 \quad \parallel \quad 0
 \end{aligned}$$

$$= 3\mu\sigma^2 + \mu^3$$

if $N(\mu, \sigma^2)$, what's Θ ? $\Theta = \{\mu, \sigma^2\}$

↑
means all first of parameter

$$G(a, b) \Rightarrow \Theta = \{a, b\}$$

Section: 5.2

- Predicting future value

- $X \sim (\theta)$
 - mean
 - mode: predicting \hat{x}
 - $P[X > S], P[X < S]$
 - $E[X | X > S]$

Section 5.3

$\sum_{i=1}^n x_i = x_1, x_2, x_3, \dots, x_n$ (Let's say you have a sample,
 $f_\theta(s) = f_\theta(x_1), f_\theta(x_2), \dots, f_\theta(x_n)$ what is $f_\theta(s)$ ← probability function
 at the sample)

- reparameterization: $\theta = \theta(r)$ one to one then we can reparameterize

Section: 5.4

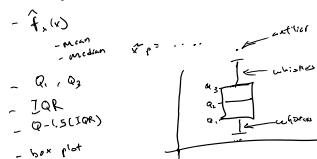
$$F_\theta(x) \rightarrow f_\theta(x)$$

population CDF

- Once you know the sample f_i , can calculate everything.

- $\hat{F}_s(x) \leftarrow$ empirical distribution function

- histogram



- $\hat{\theta} = \hat{M}_1 G^L$
 $E(\hat{\theta}) = \dots$ (refer to last class notes)

6.1 Likelihood Function

$$X \sim \text{Bern}(\theta) \quad \theta \in [0, 1]$$

$$S = \{x_1, x_2, \dots, x_n\}$$

$$f_\theta(S) = f_\theta(x_1) \times f_\theta(x_2) \times \dots \times f_\theta(x_n)$$

Toss coins S times:

$$\begin{bmatrix} x_1 \\ 1, 0, 1, 1, 0 \end{bmatrix} = S$$

$$f_\theta(S) = \theta^{x_1} (1-\theta)^{1-x_1} \quad \text{likelihood of } \theta$$

$$L(\theta|S) = \theta^S (1-\theta)^{n-S}$$

likelihood function
of theta given
the sample.

* Not the probability of observing θ
It is the probability of observing
the sample for a given true θ .

$\theta \rightarrow$ fixed true value, $\theta \in \Omega$

θ any other member from Ω

below $f_{\theta_1}(S) > f_{\theta_2}(S)$

The more data the smaller the likelihood.

Ex/ 6.1.1

Suppose $S = \{1, 2, \dots, 3\}$ and that the statistical model is $\{\theta : \theta \in \{1, 2\}\}$,

where P_1 is the uniform distribution on the integers $\{1, \dots, 10^3\}$ and

P_2 is the uniform distribution on $\{1, \dots, 10^6\}$

Dist 1 $\rightarrow f_{\theta_1} \rightarrow$ Unif $\{1, 2, 3, \dots, 1000\}$
 \sim Unif $\{1, 2, 3, \dots, 1000000\}$

$\text{Dist 1} \rightarrow 10$
 $\text{Dist 2} \rightarrow \text{for } S = \{1, 2, 3, \dots, 1000\}$

$S = \{100\} \rightarrow$ comes from distribution 2. Since distribution 2 stops at 1000.

$S = \{10\} \rightarrow$ # calculate likelihood for both and compare

$L(\theta_1 | S) = \frac{1}{1000} \Rightarrow$ sample 10 is in 1000 x more likely to come from θ_1
 $L(\theta_2 | S) = \frac{1}{1000000} \Rightarrow$ sample 10 is in 1000000 x more likely to come from θ_2

Example ^{6.1.4} $x \sim N(\theta, \sigma^2)$, σ^2 known?

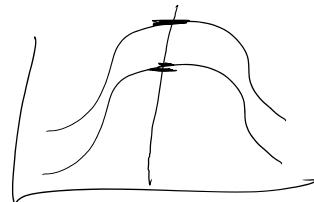
1 unknown parameter θ , mean

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

$$\begin{aligned} f_{\theta}(x) &= \prod_{i=1}^n \underbrace{(2\pi\sigma^2)^{-\frac{1}{2}}}_{\text{constant}} \exp\left[-\frac{1}{2\sigma^2}(x_i - \theta)^2\right] \\ &= (2\pi\sigma^2)^{-\frac{n}{2}} \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \theta)^2\right] \quad \begin{array}{l} \text{Recognize this!} \\ \text{expand it. Do it yourself.} \end{array} \\ &= (2\pi\sigma^2)^{-\frac{n}{2}} \exp\left[-\frac{n}{2\sigma^2} (\bar{x} - \theta)^2\right] \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^{n-1} (x_i - \bar{x})^2\right] \\ &\quad \begin{array}{l} \text{constant} \\ \text{sample variance} \end{array} \end{aligned}$$

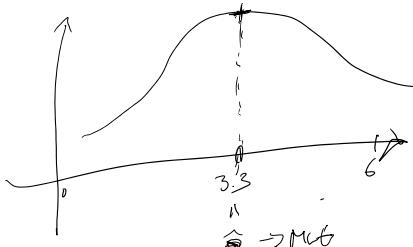
Since constant re write

$$L(\theta | S) \propto \exp\left[-\frac{n}{2\sigma^2} (\bar{x} - \theta)^2\right] \quad \Rightarrow$$



$$n = 25, \sigma^2 = 1, \bar{x} = 3.3$$

$$L(\theta | S) \propto \exp\left[-\frac{25}{2}(3.3 - \theta)^2\right]$$



$$\begin{aligned} &\text{vertical} \\ &y = \bar{x} \quad \text{proportional to } x \end{aligned}$$

Same graph but just stretched as a result you can make inference about mean

① Point of estimate of θ

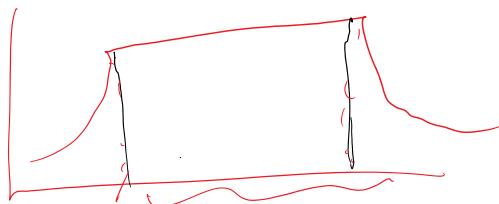
$$\hat{\theta} \rightarrow \theta$$

estimate

MLE \Rightarrow maximum likelihood estimator of θ

$$L(\hat{\theta} | S) \geq L(\theta | S)$$

Note you can have multiple MLE for σ^2



this whole
thing is MLE

Ex 6.2.1

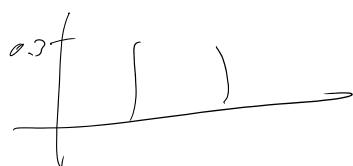
	$s=1$	$s=2$	$s=3$
f_1	0.3	0.4	0.3
f_2	0.1	0.7	0.2

$\{s=1\} \Rightarrow$ probably came from 1^{st} one

$\{s=2\} \Rightarrow$ probably came from 2^{nd} one

$\{s=3\} \Rightarrow$ probably came from 3^{rd} one

	$s=1$	$s=2$	$s=3$
f_1	0.3	0.4	0.3
f_2	0	0.7	0.3

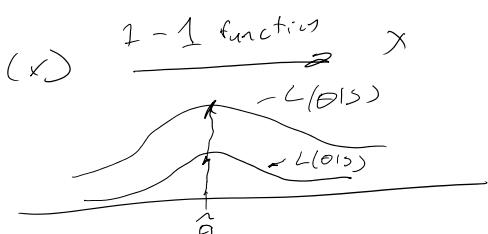


$\{s=3\} \Rightarrow$ MLE is probably
 Θ_1 or Θ_2

$$L(\Theta(s)) = \prod_{i=1}^n f_{\Theta}(x_i)$$

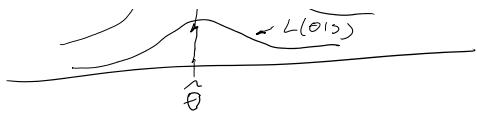
taking the ln
allows us to
change to
summation

$$\ln(L(\Theta(s)))$$



$$\ln(L(\theta|s)) \quad \text{summ.}$$

$$= \sum_{i=1}^n \ln f_\theta(x_i)$$



Now maximize

$$L(\theta|s) \propto \exp\left[\frac{-n}{2\sigma^2} (\bar{x} - \theta)^2\right]$$

proportional

$$(1) \quad l(\theta|s) = \frac{-n}{2\sigma^2} (\bar{x} - \theta)^2 \quad \leftarrow \text{ln likelihood of } \theta$$

Differentiate

$$(2) \quad \text{Score function} = \frac{\partial l(\theta|s)}{\partial \theta}$$

$$(3) \quad \text{Score equation} = \frac{\partial l(\theta|s)}{\partial \theta} = 0$$

$\downarrow \hat{\theta} = \boxed{\text{something}}$

To check if max or min, second derivative.

$$\frac{\partial^2 l(\theta|s)}{\partial \theta^2} \Big|_{\theta = \hat{\theta}} < 0$$

$$l(\theta|s) = \frac{-n}{2\sigma^2} (\bar{x} - \theta)^2$$

$$\begin{aligned} \frac{\partial l(\theta|s)}{\partial \theta} &= -\frac{2n}{2\sigma^2} (\bar{x} - \theta)(-1) \\ &= \frac{n}{\sigma^2} (\bar{x} - \theta) \quad \leftarrow \text{score} \end{aligned}$$

$$\Rightarrow \frac{n}{\sigma^2} (\bar{x} - \theta) = 0$$

$$\theta = \bar{x}$$

check MLE

$$\begin{aligned} \text{Score} &= \frac{n}{\sigma^2} (\bar{x} - \theta) \quad \sim \text{sample size} \\ \frac{\partial^2 l(\theta|s)}{\partial \theta^2} &= -\frac{n}{\sigma^2} \quad \leftarrow \text{positive} \\ \frac{\partial^2 l(\theta|s)}{\partial \theta^2} &= n, 0 \end{aligned}$$

or (a)

$$\therefore -\frac{n}{\theta^2} \leq 0$$

$\therefore \bar{x}$ is the MLE of θ

Do it for exp distribution

Question midterm or final or both, learn to calculate
MLE of anything distribution we know.

Invariance

$f_\theta(x) \xrightarrow{\theta} \hat{\theta}$ is MLE

$\psi(\theta)$
function
of θ

how do you find MLE?

$$\psi(\theta) \xrightarrow{\theta} \psi(\hat{\theta})$$

b. 2.2 If (x_1, \dots, x_n) is a sample from $\text{Bin}(\theta)$ distribution
where $\theta \in [0, 1]$ is unknown, then determine the MLE of θ

$x_i \sim \text{Bin}(\theta) \leftarrow \text{MLE?}$

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

write the distribution plug x_1, x_2, \dots, x_n

$$\begin{aligned} \text{Likelihood } L(\theta | S) &= \theta^{x_1} (1-\theta)^{1-x_1} \cdot \theta^{x_2} (1-\theta)^{1-x_2} \cdots \cdots \cdot \theta^{x_n} (1-\theta)^{1-x_n} \\ &= \theta^{\sum_{i=1}^n x_i} (1-\theta)^{n - \sum_{i=1}^n x_i} \end{aligned}$$

get in likelihood $\therefore \dots$

likelihood

$$\begin{aligned} \ln L(\theta | s) &= \ln \left(\theta^{\sum_i x_i} (1-\theta)^{n-\sum_i x_i} \right) \\ &= \sum_{i=1}^n x_i \ln \theta + (n - \sum_{i=1}^n x_i) \ln (1-\theta) \end{aligned}$$

get first derivative

$$\frac{\partial \ln L(\theta | s)}{\partial \theta} = \sum_{i=1}^n x_i \cdot \frac{1}{\theta} - (n - \sum_{i=1}^n x_i) \cdot \frac{1}{1-\theta} \quad \left. \right\} \text{score}$$

set it to zero to get score equation

$$\frac{\partial \ln L(\theta | s)}{\partial \theta} = \sum_{i=1}^n x_i \cdot \frac{1}{\theta} - (n - \sum_{i=1}^n x_i) \cdot \frac{1}{1-\theta} = 0$$

$$\Rightarrow \frac{\sum x_i}{\theta} = \frac{n - \sum x_i}{1-\theta}$$

$$\Rightarrow \frac{1-\theta}{\theta} = \frac{n - \sum x_i}{\sum x_i}$$

$$\Rightarrow \frac{1}{\theta} - 1 = \frac{n}{\sum x_i} - 1$$

$$\Rightarrow \frac{1}{\theta} = \frac{n}{\sum x_i}$$

$$\sum x_i = n \theta$$

$$\hat{\theta} = \frac{\sum x_i}{n} = \bar{x}$$

check second derivative then you can say its MLE

Ex/
 $\theta \rightarrow \bar{x}$ MLE } since one to one
 $\sigma^2 \rightarrow \bar{x}^2$ or $\text{Bin}(\theta), [0, 1]$

$$\Theta^2 \sim \bar{X}^2$$

6.2.5 Suppose (x_1, \dots, x_n)

$$x \sim \text{Uniform}[0, \theta]$$

$$f_\theta(x) = \frac{1}{\theta} \mathbb{I}(x \in [0, \theta])$$

$$x_1, x_2, \dots, x_n$$

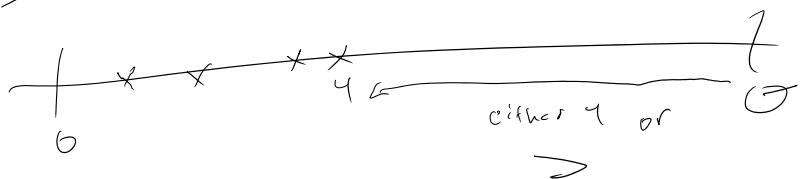
$$\begin{aligned} L(\theta | s) &= \frac{1}{\theta} \cdot \frac{1}{\theta} \cdots \frac{1}{\theta} \\ &= \frac{1}{\theta^n} \end{aligned}$$

Differentiation part doesn't work

$\frac{1}{\theta^n} \rightarrow$ this is maximized when bottom is minimized.

\therefore when $\theta \rightarrow$ minimum $L(\theta)$ is maximum

Ex assume 1, 2, 3, 4



minimum $\theta = \max$ value in sample

$$\hat{\theta} = \max(s)$$

Midterm: November 3rd

1-4 pm

IC #130

Recap:

$$\text{MLE} \quad \frac{\partial}{\partial \theta} = 0 \Rightarrow \hat{\theta}$$

$\frac{\partial^2 L}{\partial \theta^2} < 0$

$$\begin{aligned} \exists x \sim \text{Bern}(\theta) \\ s_1 = (1, 0, 1, 1, 0, 0, 1) \\ s_2 = (0, 1, 0, 1, 0, 1, 1) \end{aligned}$$

$$L(\theta | s) = \theta^{(1-\theta)} \theta^{(1-\theta)(1-\theta)s} = (1-\theta)^2 \theta^4$$

$$L(\theta, s) = (1-\theta)\theta(1-\theta)\theta(1-\theta)\theta = (1-\theta)^3 \theta^4$$

Ex/ $n = 7$
of heads = 4

$$\text{sel } (\underline{\underline{?}}) \Theta \underbrace{(-\Theta)^3}_{L(\Theta|S)}$$

All 3 give you the same likelihood functions, because $\sum x_i = n$, sum of random variables is n .

Sufficient statistics	<u>Transposed shift</u>
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following from sample
 $T(s_1) = T(s_2)$
 $\Rightarrow L(s_1) = L(s_2)$

may or may not have constant in the front. Constant doesn't matter when multiplying it.

$T = \text{sum of all your sample.}$

$$f_0(s) = \ln(s) * g_0(T(s))$$

↓ ↗
 free of θ
 only function
 w.r.t. sample
 sufficient stat

$$\begin{array}{c} \text{Ex} \\ \hline (\underbrace{\square}_N) \overset{u}{\ominus} (\underbrace{(-o)}^3) \\ \text{Ns} \\ \hline \text{In general} \\ \theta^{\sum x} (\underbrace{(-o)}_{\text{Ns}})^{u = \sum x} \\ \qquad \qquad \qquad \text{NB} \end{array}$$

Ex $x \sim \text{Exp}(0)$

x_1, x_2, \dots, x_n

$$\begin{aligned} f_{\theta}(s) &= \theta e^{-\theta x_1} \cdot \theta e^{-\theta x_2} \cdots \cdots \theta e^{-\theta x_n} \\ &= \theta^n e^{-\theta \sum x_i} \end{aligned}$$

$\Rightarrow h(s) = 1$ because both terms are of Θ

$$= \sum x_i \quad \begin{matrix} \text{sufficient} \\ \text{statistic} \end{matrix}$$

$$= (-\hat{O})^n e^{-\Omega t}$$

Ex $x \sim \text{Pois}(\theta)$

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

$$f_\theta(s) = \frac{e^{-\theta} \theta^{x_1}}{x_1!} \times \frac{e^{-\theta} \theta^{x_2}}{x_2!} \times \dots \times \frac{e^{-\theta} \theta^{x_n}}{x_n!}$$

likelihood function

$$= \frac{e^{-n\theta} \theta^{\sum x_i}}{\prod_{i=1}^n x_i!}$$

$$L(s) = \frac{1}{\prod_{i=1}^n x_i!}$$

$$f_\theta = (e^{-n\theta} \theta^{\sum x_i})$$

$$T(s) = \sum x_i$$

if $[2, 3, 4, 2, 1]$ is # of accidents on ^{the} road
and follows $\text{Pois}(\theta)$ then

$$\frac{e^{-n\theta} \theta^{\sum x_i}}{\prod_{i=1}^n x_i} = e^{-5\theta} \theta^{12}$$

take ln

, don't need to know 5 different #'s, you just need the sum

, sum is sufficient for
of data

If from likelihood you can get summation of x but
not sample.

$T(s)$ can be reconst. back from your likelihood
is called a sufficient statistic.

Sufficient means data reduction.

$T(>)$

\nearrow
minimal in direction
that means you can't reduce further

$$\text{if } s_1 = [x_1, x_2, \dots, x_n]$$
$$s_2 = [y_1, y_2, \dots, y_n]$$
$$\frac{\partial E}{\partial x} = \frac{\partial E}{\partial y}$$
$$\Rightarrow \sum (E_x - E_y) \Rightarrow \sum x = \sum y$$

if A

$$\Rightarrow \text{minimal state}$$