STATISTICS CLASS 2

- · Agenda for today
 - Sample V. Population
 - Moments
 - _ Covariance
 - Correlation
- · Sample v. Population

Population includes all data of a specified group. Sample is a subset of the population.

sample is a sussel	5 4 34356		
ι	Population	Sampling	
Avg. Height of people in USA	~330 Mn	select people from each state?	
Avg. Height of people in UCLA	~ 50 k	MFE, MBA, Profs?	
Avg. Weight of people in Japan	~125Mn	Volunteering hooths at diff	

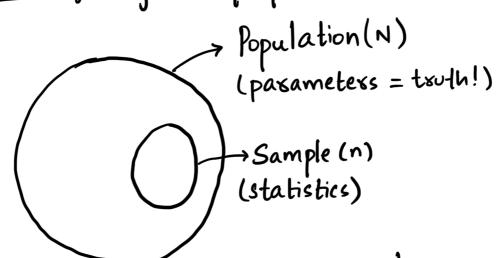
places in Japan?

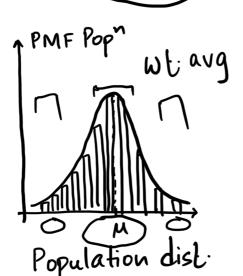
Sampling } → Advertising (ex:3)
bias

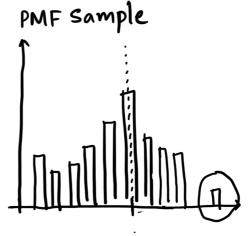
Non-response (ex:1)

Random sample → gold standard (good proxy/less bias)

Ex1: Avg. Height of people in USA

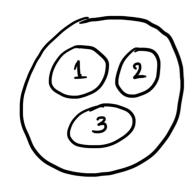






Distribution of sample data

Ex2: Distribution of sample statistic



Population =
$$\mu = \frac{1+2+3}{3} = 2$$

•	Samples	Mean (x)	> proxies for M
	(1,1) (1,2) (1,3) (2,1) (2,2) (2,3) (3,1)	1 1·5 2 1·5 2 2·5 2	PMF(X) 3/8 2/8 1/8 7/8
	(3,2) (3,3)	2·5 3	1 15 2 25 3

Depending on who samples from pop", x changes

Similarly we can) -> Mean (Normal) \
get PDF of other \ -> Variance (\chi^2)
Sample Stats. \ \ > Median/Quantiles

skewness/kustosis

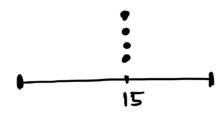
Moments

Robust ways of summarizing data Mean, vax, stdder, Quantile, skew, kust. }

$$X = \left\{ \frac{12}{14}, \frac{14}{14}, \frac{20}{20} \right\}$$

$$\bar{X} = \frac{12 + 14 + 14 + 20}{4} = 15$$

Sample data2



Mean = Avg. distance from D

→ First moment

$$(\frac{1}{n} \leq \chi_{i}^{2}) \frac{|2^{2} + |4^{2} + |4^{2} + 20^{2}}{4} = 234$$

$$\frac{1}{n} \le y_i^2 = 15^2 = 225$$

squared dist from O (increases with mure spread

Alternatively we can compute distifoom mean

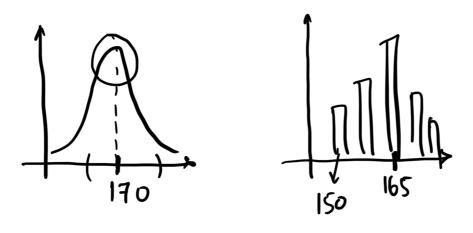
$$\frac{1}{n} \leq (x_{1} - \overline{x})^{2} = \frac{(-3)^{2} + 2 \cdot (-1)^{2} + (5)^{2}}{4} = q \qquad \frac{1}{n} \leq (y_{1} - \overline{y})^{2} = 0$$

centered

2nd moment

in data

Remove effect of 1^{st} moment (\bar{x}) to capture any additional info in the dataset.



Moment	Population (param)	Sample (statistic)	
(1) Mean	$M = E[X] = \int_{X} f_{X}(x) dx$ $M = \sum_{i=1}^{n} \lambda_{i} / N$	$\bar{X} = m = \sum_{i=1}^{n} x_i / n /$	
	M = 2 1/N	n!	

(2) Variance
$$\left[\sigma^{2} = E[x^{2}] - E[x]\right] S^{2} = \sum_{i=1}^{2} \frac{(x_{i} - m)^{2}/n - 1}{\sigma^{2}}$$
(3) Skewness

- (4) kurtosis
- · Degrees of freedom

$$\frac{1}{2} = \frac{1}{x=5} = \frac{1}{8}$$

$$\mu = 10$$

$$\frac{1}{n-1} \leq (\chi; -\bar{\chi})^2 = (2-5)^2 + (8-5)^2 = 18$$

$$\frac{1}{n} \leq (x_i - \mu)^2 = (2-4)^2 + (8-4)^2 = 20/1$$

$$\leq (\chi_i - 6)^2 = (2-6)^2 + (8-6)^2 = 20/4$$

Squared deviation at mean is smallest at X

(s² computes vasiance centered at X

[62 computes variance centered at M

If
$$S^2(\bar{X}) = \frac{1}{n} \leq (x_i - (\bar{X}))^2$$
 Function that takes \bar{X} as input

then
$$S^{2}(\mu) > S^{2}(\bar{x})$$
 lower bound

Division by n-1 $\uparrow S^{r}(\bar{x})$ to be closer to $S^{r}(\mu)$

- Intuition 2:

[Sample]:
$$\frac{X}{1.5}$$
 $\frac{\overline{X} - \overline{X}}{1.3}$ | - If we know \overline{X} , one data point is xedundant $\overline{X} = \frac{x_1 + x_2 + x_3}{3}$ $\overline{X} = \frac{x_1 + x_2 + x_3}{3}$ $\overline{X} = \frac{x_1 + x_2 + x_3}{3}$

 $\overline{X} = 0.2$ O after computing the mean!

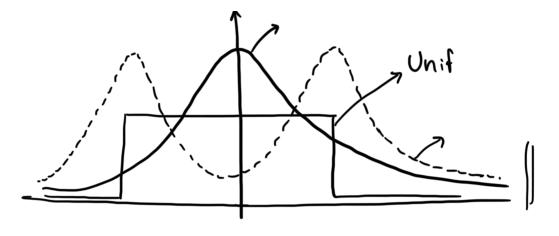
[DF]: No: of data points available to compute sample statistics

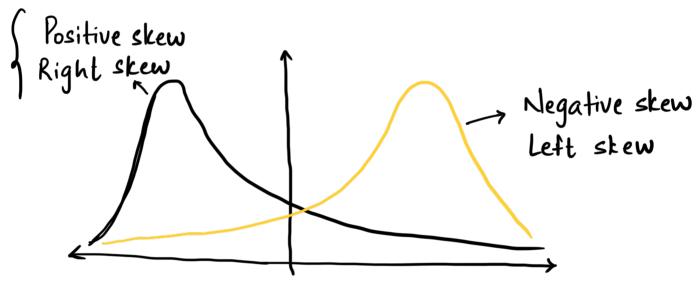
 $x = \{44\}$ sample

(a)
$$\overline{X} = 44$$

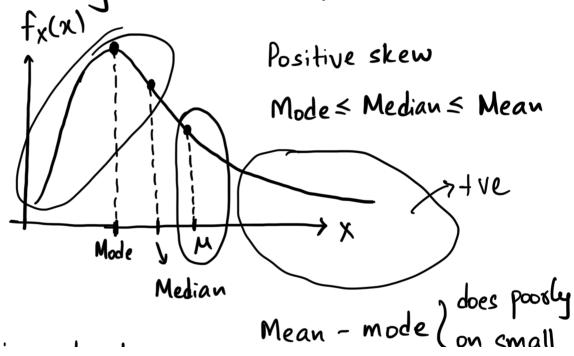
(b)
$$s^2 = \frac{(44-44)}{n-1} = NaN$$

Skewness





which way does the tail point?

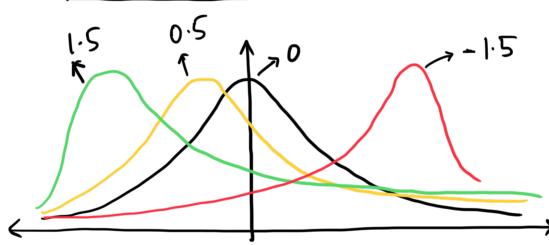


reassons mode skewness =

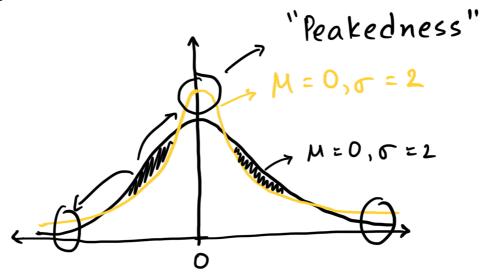
Std. dev | samples

Moment estim. skew =
$$\frac{1}{N} \left[\frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} \right] = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum (x_i - \mu)^3}{\sigma^3 / 1} = \frac{1}{N} \sum_{n=$$

Removes effect of mean and vasiance



· Kurtosis



Oxange curve has fatter tails

Kuxtosis measures weight on tails

Moment estim. kurtosis = $\left(\frac{1}{N} \frac{\sum (x_i - \mu)^4}{\sqrt{\sigma^4}}\right)$

| kustosis (N(0,1)) = 3, kust ε [1, 00)

If kurtosis > 3 (leptokurtic)

Kuxtosis < 3 (platykuxtic)

· Covariance

Captures joint variation of 2 RVs X, Y

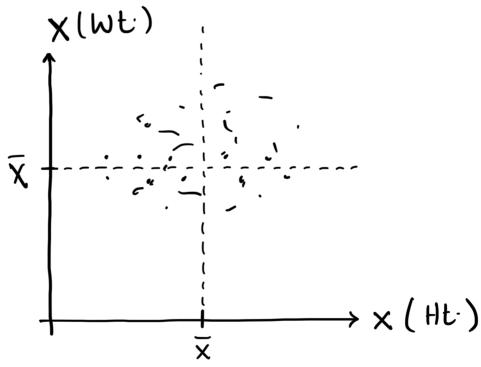
×	У	$\sqrt{x-x}$	$\sqrt{\lambda - \lambda}$	$(x-\overline{x})(y-\overline{x})$	γ) —
100	lo	0	0	0	
102	9	2	-1/	-2	(
98	11	-2	l	-2	
110	14	10	4	40	
90	6	-lo	-4	40	-
X = 100	- γ= 10				

$$COU(X,y) = \frac{1}{-} \leq (x_i - \overline{x})(y_i - \overline{y})$$

COV(X,Y)>0: X,Y are above or below the mean together

COU(x,y) < 0: If x is above its mean,
Y is below (vice-vexsa)

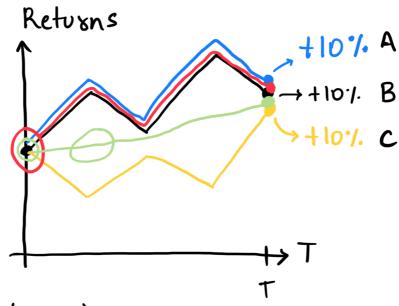




(d)
$$cov = 0$$

(c) cov(x,x)

Ex 2:



COV (A,B) > 0

cov (A,c) <0

cov (B,c) >0

"Maskowitz" 1952

Postfolio 1: 50% A, 50% B

Postfolio 2: 251.A, 251.B, 501.C

Properties of covariance

(a)
$$cov(x,y) = E[(x-\overline{x})(y-\overline{y})]_{y=0}^{\infty}$$

$$= E[(x-\overline{x}) \cdot Y] - E[\overline{y}(x-\overline{x})]$$

$$= E[(x-\overline{x}) \cdot Y]$$

$$= E[(x-\overline{x}) \cdot Y]$$

$$= E[xy-\overline{x}y-x\overline{y}+\overline{x}\overline{y}]$$

$$= E[xy] - E[x] \cdot E[y]$$

$$\Rightarrow E[xy] = E[x] \cdot E[y] + cov(x,y)$$

$$= cov(x,x) = Vax(x)$$

$$= cov(x,x) = 0$$

$$= cov(x,x) = 0$$

$$= cov(x,y) = cov(x,y)$$

$$= E[z(xy - E[xy])$$

$$+ cov(x_1z) \cdot cov(y_1z)$$

(d)
$$Vax(X+Y) = E[(X+Y-X-Y)^2]$$

$$= E[(X+Y)^2+(X+Y)^2-\lambda(X+Y)$$

$$= V[X]+v[Y]+\lambda\cdot cov(X,Y)$$

· Correlation and Causation

$$f_{xy} = coss(x,y) = \frac{cov(x,y)}{\sigma_x \cdot \sigma_y}$$
 | Scaled covariance

Properties of correlation

(c)
$$COXY(X+c,Y) = COXY(X,Y)$$

Causality is the fundamental problem of econometric inference.