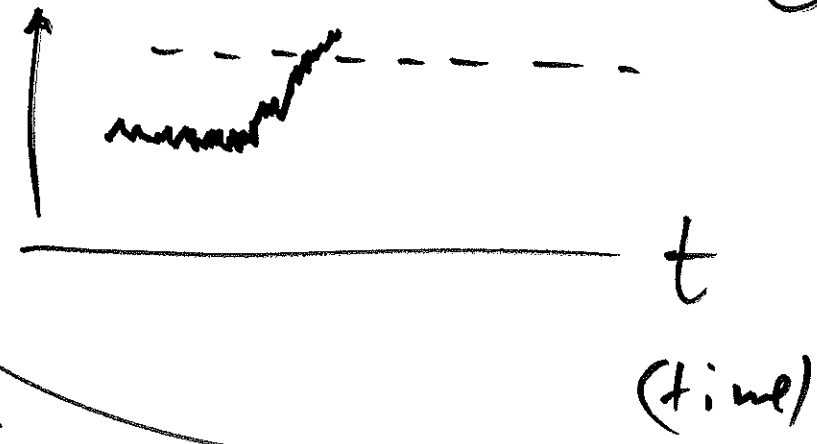


this multivariate
time: distributions

(9.51)

next
time:

more realistic



goal $(B_i | \theta_i) \stackrel{I}{\sim} \text{Bernoulli}(\theta_i)$
 $(i = 1, \dots, n)$

but this is unattainable:

n data points, n unknowns (too many unknowns)

$$\prod_{i=1}^n \theta^{b_i} (1-\theta)^{1-b_i} =$$

$$\left[\theta^{b_1} (1-\theta)^{1-b_1} \right] \left[\theta^{b_2} (1-\theta)^{1-b_2} \right] \dots$$

$$= \theta^{b_1 + \dots + b_n} (1-\theta)^{n - (b_1 + \dots + b_n)}$$

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

$S = \sum_{i=1}^n b_i$
 # pts. in \mathbb{T} w/ good outcome

\underline{Y} continuous RV ($n=1$) with CDF $F_{\underline{Y}}$ $\textcircled{3}$

$F_{\underline{Y}}(y)$ and PDF $f_{\underline{Y}}(y)$, then

$$f_{\underline{Y}}(y) = \frac{d}{dy} F_{\underline{Y}}(y)$$

$\underline{Y} = (Y_1, Y_2)$ continuous random vector

($n=2$) with CDF $F_{\underline{Y}}(z)$ and

PDF $f_{\underline{Y}}(z)$, then

$$F_{Y_1, Y_2}(y_1, y_2)$$

$$f_{\underline{Y}}(z) = \frac{d}{dy_1} \frac{d}{dy_2} F_{Y_1, Y_2}(y_1, y_2)$$

$$= \frac{d}{dy_2} \frac{d}{dy_1} F_{Y_1, Y_2}(y_1, y_2)$$

$I_i = \begin{cases} 1 & \text{with prob } \theta \\ 0 & \text{with prob } 1-\theta \end{cases}$

$n = 7$
 θ unknown

machine outcome
 $y = (0, 1, 1, 1, 0, 1, 1)$
 $n = 7$

θ known = 0.75 ←

$y = (0, 1, 1, 1, 0, 1, 1)$

the I_i are conditionally independent
 $J_i | \theta$

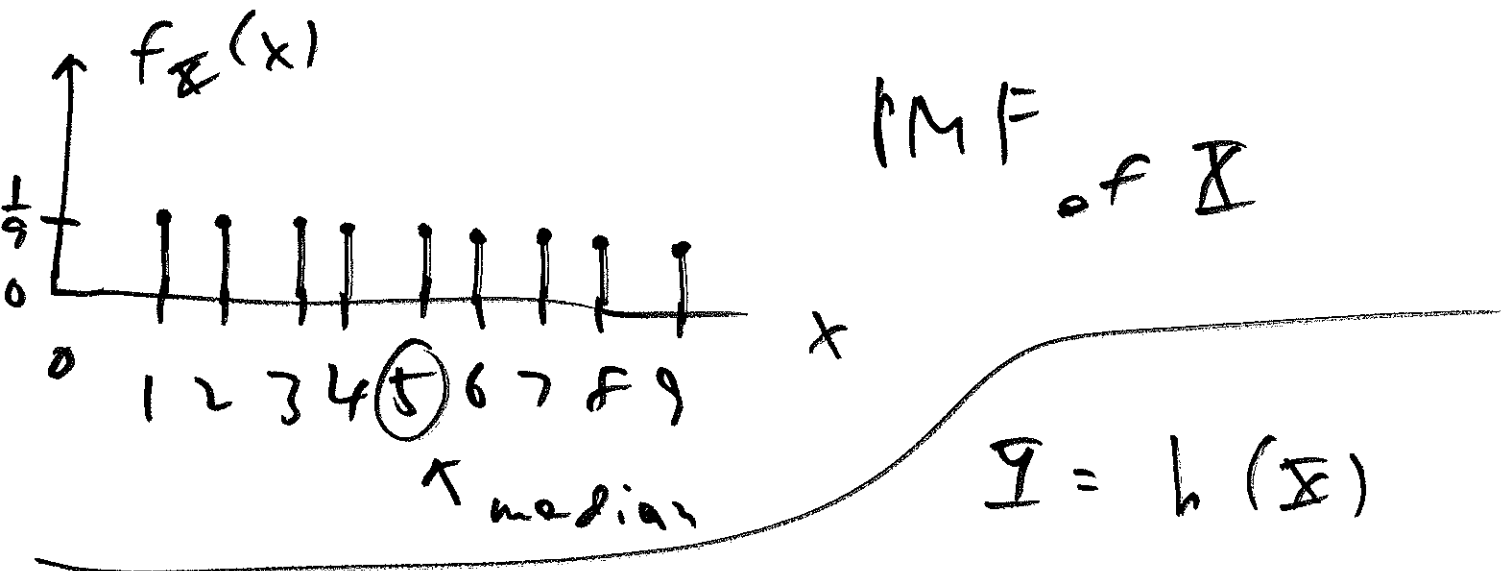
data

$\underline{I} = (I_1, \dots, I_n)$ $(I_i | \theta)$ are cond. indep.

unknown

then $f_{\underline{I}}(y | \theta) = \prod_{i=1}^n f_{I_i}(y_i | \theta)$

crucial ingredient in statistical inference



possible values y for Z	$X = x$ such that $Z = X - 5 = y$	prob. $P(Z = y)$
0	5	$\frac{1}{9}$
1	4 or 6	$\frac{2}{9}$
⋮	⋮	⋮

