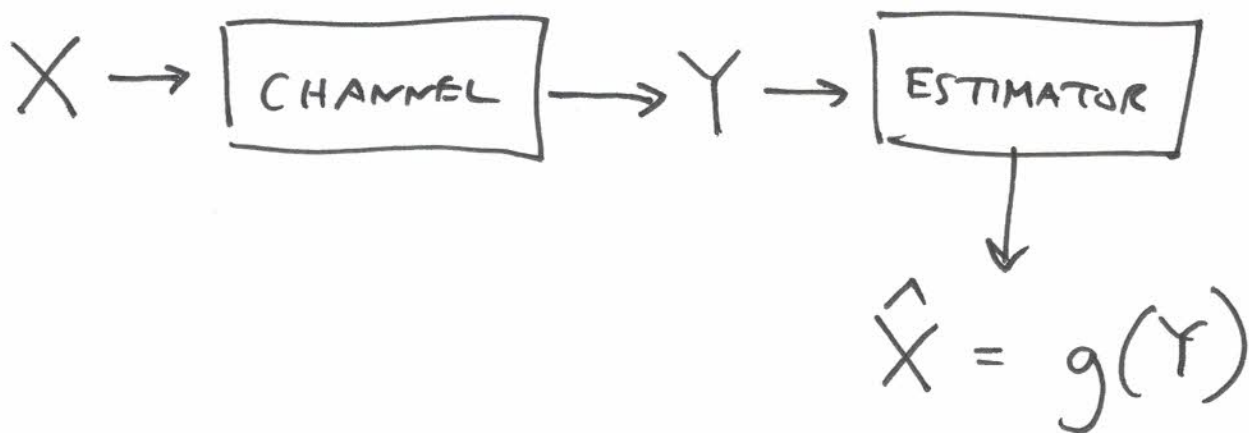


ESTIMATION

①
SETUP: WE OBSERVE THE
VALUE OF A R.V. Y
AND WE WANT TO ESTIMATE
THE VALUE OF A RELATED
R.V. X . (WE DON'T
OBSERVE X DIRECTLY).

WE HAVE INFO LIKE CONDITIONAL/
JOINT PDFS.



WE WANT TO FIND $g(Y)$

SO THAT $g(Y)$ IS "AS

CLOSE AS POSSIBLE TO " OR

"THE BEST ESTIMATE OF" X .

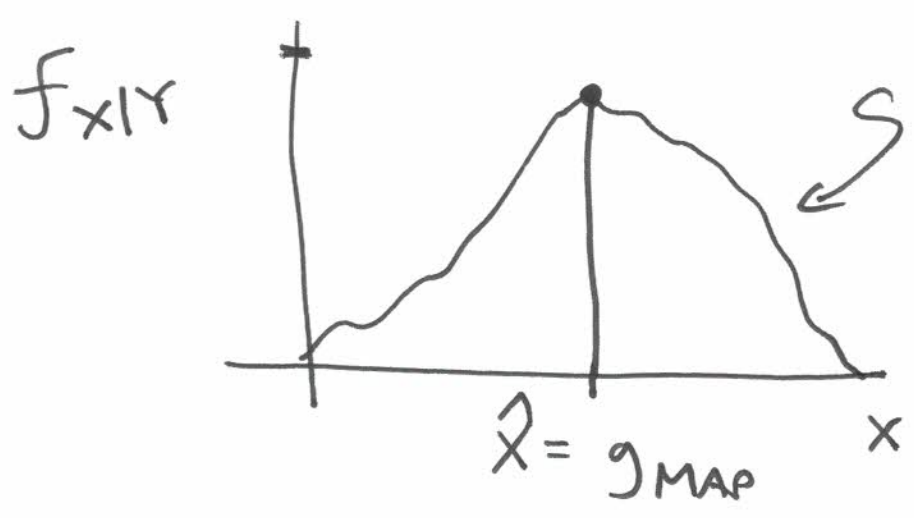
MAP ESTIMATION

MAXIMUM A POSTERIORI
"AFTER THE FACT"

GIVEN THE VALUE OF Y,
WHAT VALUE OF X IS
MOST LIKELY TO HAVE OCCURRED?

$$\hat{X} = g_{MAP}(Y)$$

$$= \arg \max_x f_{X|Y}(x|y)$$



CONDITIONAL
PDF OF
X GIVEN
Y=y.

RECALL: FLIP COIN 3 TIMES

X = # HEADS

Y = POS FIRST HEAD

		0	1	2	3	Y	
X	0	$\frac{1}{8}$					
	1		$\frac{1}{8}$	$\frac{1}{8}$	$\frac{1}{8}$		JOINT PMF
	2		$\frac{1}{4}$	$\frac{1}{8}$			
	3		$\frac{1}{8}$				
		$\frac{1}{8}$	$\frac{1}{2}$	$\frac{1}{4}$	$\frac{1}{8}$		

$F_{X Y}$		0	1	2	3
0		1	0	0	0
1		0	$\frac{1}{4}$	$\frac{1}{2}$	1
2		0	$\frac{1}{2}$	$\frac{1}{2}$	0
3		0	$\frac{1}{4}$	0	0

(Y=2
can choose
X=1
or 2)

$$g_{\text{MAP}}(Y) = \begin{cases} 0 & Y=0 \\ 2 & Y=1 \\ 1 \text{ or } 2 & Y=2 \\ \underline{1} & Y=3 \end{cases}$$

PROBABILITY OF ERROR:

$$P_E = \sum_{k=0}^3 P(\text{ERROR} \mid Y=k) P(Y=k)$$

$$= 0 \cdot \frac{1}{8} + \frac{1}{2} \cdot \frac{1}{2} + \frac{1}{2} \cdot \frac{1}{4} + 0 \cdot \frac{1}{8}$$

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

OR JUST ADD UP ENTRIES OF
JOINT PMF.

EX X AND Y ARE JOINTLY

GAUSSIAN, $\mu_x = \mu_y = 0$

$\sigma_x = \sigma_y = 1$

$\rho = \text{CORR. COEFF} \in [-1, 1]$

WE SHOWED

THAT

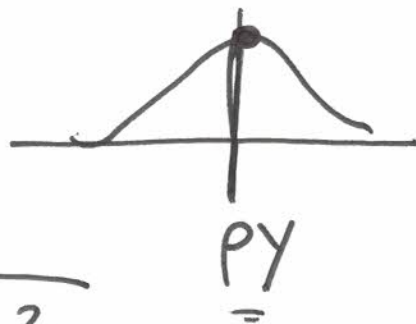
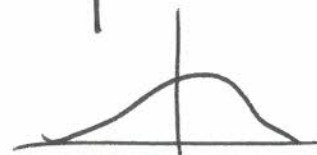
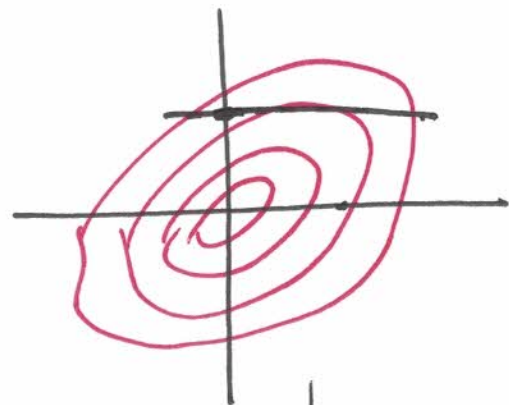
$f_{X|Y}(x|y)$

WAS ALSO GAUSSIAN

WITH MEAN

VARIANCE

$$\frac{\rho y}{\sqrt{1-\rho^2}}$$



So $\hat{X}_{MAP} = g_{MAP}(y) = \rho y.$

IN REAL LIFE, WE MAY
NOT KNOW / BE ABLE TO
ESTIMATE $f_{X|Y}(x|y)$.

IT'S OFTEN MUCH EASIER TO
OBTAIN $f_{Y|X}(y|x)$.

E.G., PUT A LOT OF X
VALUES INTO THE CHANNEL,
BUILD $f_{Y|X}$.

KNOW
DURING TEST

OBSERVED

$$f_{X|Y}(x|y) = \frac{f_{Y|X}(y|x) f_X(x)}{f_Y(y)}$$

OBSERVE.

MAXIMUM LIKELIHOOD ESTIMATION

GIVEN THE VALUE OF Y,
WHAT VALUE OF X IS
MOST LIKELY TO HAVE
PRODUCED IT?

$$\hat{X} = g_{ML}(Y) = \arg \max_x f_{Y|X}(y|x)$$

DISTINCTION B/W MAP AND ML:

MAP ESTIMATE TAKES INTO
ACCOUNT UNDERLYING PROBABILITY
OF X. ML DOESN'T TAKE
THIS INTO ACCOUNT.
"UNINFORMATIVE PRIOR"

COIN FLIP EXAMPLE:

		Y			
f _{Y X}		0	1	2	3
X	0	1	0	0	0
	1	0	1/3	1/3	1/3
	2	0	2/3	1/3	0
	3	0	1	0	0

$$g_{ML}(Y) = \begin{cases} 0 & Y=0 \\ 3 & Y=1 \\ 2 & Y=2 \\ 1 & Y=3 \end{cases}$$

P_{Err} IN THIS CASE:

$$0 \cdot \frac{1}{8} + \frac{3}{4} \cdot \frac{1}{2} + \frac{1}{2} \cdot \frac{1}{4} + 0 \cdot \frac{1}{8}$$

$$= \frac{4}{8} = \frac{1}{2} > \frac{3}{8} \text{ FROM MAP ESTIMATE.}$$

DIFFERENT DEFINITION OF "BEST":

MINIMUM MEAN-SQUARE ESTIMATION:
(MMSE)

$$\min E \left((g(Y) - X)^2 \right)$$

i.p. MINIMIZE DEVIATION BETWEEN

X AND $g(Y) = \hat{X}$ OVER

ALL POSSIBLE FUNCTIONS $g(Y)$.

EASIER PROBLEM: WHAT IS

THE CONSTANT C THAT

MINIMIZES

$$E \left((c - X)^2 \right) ?$$

$$\begin{aligned} \min_c E((c-x)^2) \\ &= E(c^2 - 2cx + x^2) \\ &= c^2 - 2cE(x) + E(x^2) \end{aligned}$$

$$\frac{d}{dc} = 0 \Rightarrow 2c - 2E(x) = 0.$$

$$c = E(x).$$

MAKES SENSE; MEAN VALUE
MINIMIZES THE ERROR.

NOW CONSIDER

$$E((g(Y) - x)^2)$$

$$= E(E((g(Y) - x)^2 | Y = y))$$

[LAW OF ITERATED EXPECTATION]

$$\int_{-\infty}^{\infty} E((g(Y) - x)^2 | Y = y) f_Y(y) dy$$

THIS INTEGRAL WILL BE MINIMIZED IF WE MINIMIZE

$$E((g(Y) - x)^2 | Y = y) \text{ FOR}$$

EACH POSSIBLE VALUE OF y .

(15)
FOR FIXED $Y=y$, $g(Y)$ IS
JUST A CONSTANT.

FROM PREVIOUS RESULT, THIS
CONSTANT SHOULD BE

$$E(X | Y=y)$$

$$g_{\text{MMSE}}(Y) = E(X | Y)$$

IN PRACTICE, THIS COULD BE
MESSY (SOME WEIRD FUNCTION
OF Y).

COMPROMISE: TAKE TIME

BEST LINEAR FUNCTION OF

Y, $g(Y) = aY + b,$

To MINIMIZE THE MEAN-SQUARED ERROR

min $E((aY + b) - X)^2$
a, b

$E(\underset{\substack{\uparrow \\ \text{CONSTANT}}}{b} - (X - aY))^2$

$b^* = E(X - aY)$ FROM BEFORE
 $= E(X) - aE(Y)$

$$a^* = \arg \min_a$$

$$E\left(\left(E(x) - aE(Y) - X + aY\right)^2\right)$$

$$= E\left(\left(a(Y - E(Y)) - (X - E(x))\right)^2\right)$$

$$= E\left(a^2(Y - E(Y))^2 - 2a(Y - E(Y))(X - E(x)) + (X - E(x))^2 \right)$$

$$= a^2 \text{Var}(Y) - 2a \text{Cov}(X, Y) + \text{Var}(X)$$

$$\frac{d}{da} = 0 \Rightarrow 2a \text{Var}(Y) - 2 \text{Cov}(X, Y) = 0$$

$$a^* = \frac{\text{Cov}(X, Y)}{\text{Var}(Y)} = \frac{\rho_{XY} \sigma_X \sigma_Y}{\sigma_Y^2} = \rho_{XY} \frac{\sigma_X}{\sigma_Y}$$

THUS THE MMSE LINEAR
ESTIMATOR FOR X IS:

$$\hat{X} = g_{LMSE}(Y)$$

$$= \rho_{XY} \frac{\sigma_X}{\sigma_Y} Y + \left(\mu_X - \rho_{XY} \frac{\sigma_X}{\sigma_Y} \mu_Y \right)$$

$$= \rho_{XY} \frac{\sigma_X}{\sigma_Y} (Y - \mu_Y) + \mu_X$$

$$g_{LMSE} = \rho_{XY} \frac{\sigma_X}{\sigma_Y} (Y - \mu_Y) + \mu_X$$

