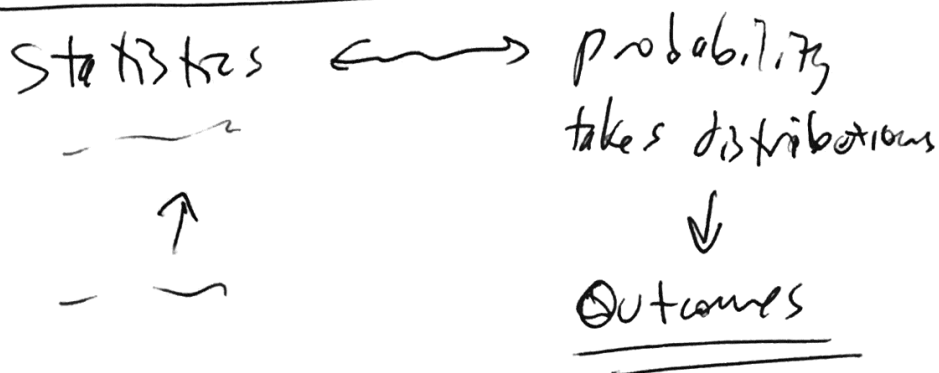


Regression / Correlation Analysis

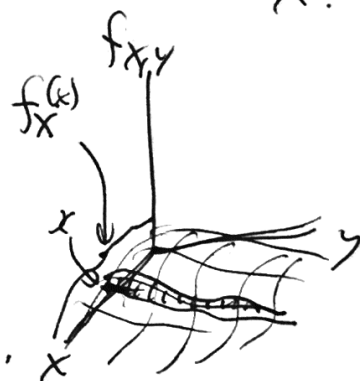
Interdependence of variables



Recall: $f_Y(y, X=x) =$ conditional density
 of Y knowing value of X .

$f_{X,Y}(x,y) \equiv$ joint
 prob density

$$\frac{f_{X,Y}(x,y)}{f_X(x)}$$



marginal density $f_X(x) = \int_Y f_{X,Y}(x,y) dy$

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

Conditional expectation $\mathbb{E}(Y|X=x) = \int_Y y f_Y(y|X=x) dy$

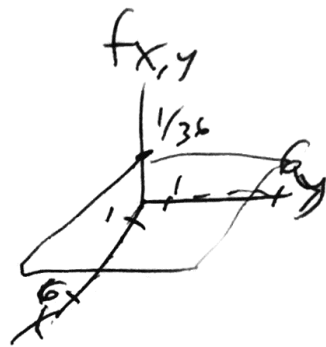
E.g.: X, Y iid dice

(1)

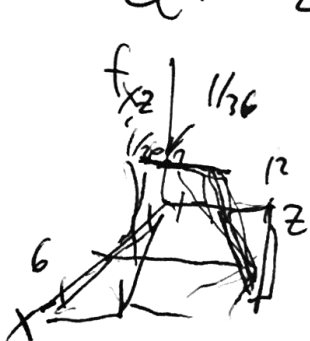
If X & Y independent,
 $\mathbb{E}(Y|X=x) = \mathbb{E}(Y)$.

$f_{X,Y}$
 $E(X) = 3.5$

X \ Y	1	2	3	4	5	6
1	$1/36$
2
3
4
5
6



Let $Z = X + Y$ Look at $f_{X,Z}(x,z)$.



X \ Z	2	3	4	5	6	7	8	9	10	11	12	$f_X(x)$
1	$1/36$	$1/36$	$1/6$
2	0	$1/6$
3	0	0	$1/6$
4	0	0	$1/6$
5	0	0	$1/6$
6	0	0	$1/6$
$f_Z(z)$	$1/36$	$2/36$	$3/36$	$4/36$	$5/36$	$6/36$	$5/36$	$4/36$	$3/36$	$2/36$	$1/36$	

$$E(X|Z=z) = \int_X x \cdot \frac{f_{X,Z}(x,z)}{f_Z(z)} dx = \frac{z}{2}$$

Z	2	3	4	5	6	7	8	9	10	11	12	z
$E(X Z=z)$	1	$\frac{1+2}{2}$	2	2.5	3	3.5					6	$\frac{z}{2}$

~~$E(X|Z=2)$~~

$$1 \cdot \frac{1}{36} + 2 \cdot \frac{2}{36} + 3 \cdot \frac{1}{36}$$

②

$E(Z | X=x)$ Exercise: work this out explicitly.

|| " $E(X+Y | X=x) = \underbrace{E(X | X=x)}_x + \underbrace{E(Y | X=x)}_{3.5}$

Note: Conditional expectation is a RV!

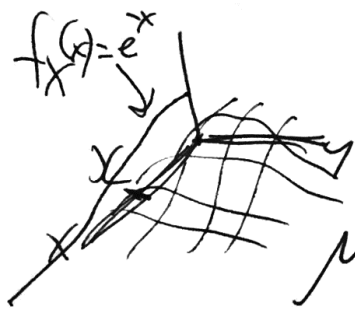
$E(Z | X) = X + 3.5.$

Def: ~~RVS~~ A regression (i.e. conditional expectation) is linear if $E(Y | X=x) = \alpha + \beta x.$

Find Bivariate regression equation for Y of X for

$$f_{X,Y}(x,y) = \begin{cases} x e^{-x(1+y)} & , x, y > 0 \\ 0 & \text{else.} \end{cases}$$

$x e^{-x} \cdot e^{-xy}$ Not indep.



$$\mu_{Y|X} = E(Y|X) = \int_Y y \frac{f_{X,Y}(x,y)}{f_X(x)} dy.$$

Step 1: compute marginal density $f_X(x).$

$$f_X(x) = \int_Y f_{X,Y}(x,y) dy = \int_0^{\infty} x e^{-x} e^{-xy} dy =$$

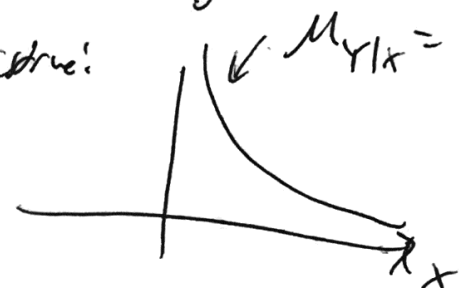
(B) 0

$$= x e^{-x} \frac{e^{-xy}}{-x} \Big|_0^{\infty} = + x e^{-x} \frac{1}{x} = e^{-x} \quad (x > 0)$$

$$M_{Y|X} = \int_0^{\infty} y \cdot \frac{x e^{-x} e^{-xy}}{e^{-x}} dy = x \int_0^{\infty} y e^{-xy} dy$$

$$= \frac{1}{x}$$

Regression curve:



E.g.: Find multiple regression of X_2 on X_1, X_3
 where $f_{X_1, X_2, X_3}(x_1, x_2, x_3) = \begin{cases} (x_1 + x_2) e^{-x_3} & 0 < x_1, x_2 < 1 \\ 0 & x_3 > 0 \\ \text{else.} & \end{cases}$

$$M_{X_2|X_1, X_3} = \int_{X_2} x_2 \frac{f_{X_1, X_2, X_3}(x_1, x_2, x_3)}{f_{X_1, X_3}(x_1, x_3)} dx_2$$

joint marginal $f_{X_1, X_3}(x_1, x_3) = \int_{X_2} f_{X_1, X_2, X_3}(x_1, x_2, x_3) dx_2 =$

$$= \int_0^1 (x_1 + x_2) e^{-x_3} dx_2 = e^{-x_3} \left[x_1 x_2 + \frac{x_2^2}{2} \right]_0^1 = e^{-x_3} \left[x_1 + \frac{1}{2} \right]$$

$$\text{So } M_{X_2|X_1, X_3} = \int_0^1 x_2 \frac{(x_1 + x_2) e^{-x_3}}{e^{-x_3} (x_1 + \frac{1}{2})} dx_2$$

$$= \frac{1}{x_1 + \frac{1}{2}} \int_0^1 (x_1 x_2 + x_2^2) dx_2$$

$$= \frac{1}{x_1 + \frac{1}{2}} \left[x_1 \cdot \frac{x_2^2}{2} + \frac{x_2^3}{3} \right]_{x_2=0}^1 = \frac{x_1 \cdot \frac{1}{2} + \frac{1}{3}}{x_1 + \frac{1}{2}}$$

$$= \frac{x_1 + \frac{2}{3}}{2x_1 + 1} \leftarrow \text{indep of } X_3. \quad \boxed{\text{for } x_1 < 1}$$

If $M_{X_2|X_1, X_3}$ is indep of $X_3 \Rightarrow X_2$ & X_3 indep.

Thm: Suppose $M_{Y|X} = \alpha + \beta x$ is linear.

Then we know α & β as a function of:

$$\mathbb{E}(X) = \mu, \mathbb{E}(Y) = \nu, \text{Var}(X) = \sigma^2, \text{Var}(Y) = \tau^2,$$

$$\text{Cov}(X, Y) = c.$$

$$Pf: \int_X \mu_{Y|X} f_X(x) dx = \int_X \int_Y y \frac{f_{X,Y}(x,y)}{f_X(x)} dy f_X(x) dx = \int_X (\alpha + \beta x) f_X(x) dx$$

$$\int_X \int_Y y \frac{f_{X,Y}(x,y)}{f_X(x)} dy \cdot f_X(x) dx = \int_X (\alpha + \beta x) f_X(x) dx$$

$$v = E(y) = \alpha + \beta E(x) = \alpha + \beta \mu$$

$$\int_X x \int_Y y \frac{f_{X,Y}(x,y)}{f_X(x)} dy f_X(x) dx = \int_X x (\alpha + \beta x) f_X(x) dx$$

$$E(X \cdot Y) = c + \mu v = \alpha \mu + \beta E(X^2) (\sigma^2 + \mu^2)$$

$$c = \text{Cov}(X, Y) = E((X - \mu)(Y - v)) = E(XY) - \mu v$$

$$\sigma^2 = \text{Var}(X) = E((X - \mu)^2) = E(X^2) - E(X)^2 = E(X^2) - \mu^2$$

(6)

$$\alpha + \beta \mu = \nu \Rightarrow -\mu \alpha - \mu^2 \beta = -\mu \nu$$

$$\mu \alpha + (\sigma^2 + \mu^2) \beta = C + \mu \nu$$

$$\Rightarrow \sigma^2 \beta = C \Rightarrow \boxed{\beta = \frac{C}{\sigma^2}}$$

$$\alpha = \nu - \mu \beta = \boxed{\nu - \frac{\mu C}{\sigma^2} = \alpha}$$

Thm: If $M_{Y|X}$ = linear, then,

$$M_{Y|X} = \nu - \frac{\mu C}{\sigma^2} + \frac{C}{\sigma^2} x.$$

$$\Leftrightarrow M_{Y|X} - \nu = \frac{C}{\sigma^2} (x - \mu).$$