

$$\underline{(x, y) \leftarrow 2d \text{ r.v.}}$$

$$\underline{\mathbb{E}_h(t) = E[h(x, y) | x=t]}$$

$$= E[h(t, y) | x=t]$$

$$\rightarrow = \int h(t, y) \frac{f(t, y)}{f_t(t)} dy$$

$$\boxed{E[h(x, y) | x] = \mathbb{E}_h(x)}$$

$$f_{y|x=t}(y)$$

Results:

$$\mathbb{E}[\mathbb{E}[h(x, y) | x]] = \mathbb{E}[h(x, y)]$$

$$= \mathbb{E}[\mathbb{E}_h(x)]$$

$\downarrow$

double integral

$\int =$

as an integral w.r.t density of  $X$

$$\mathbb{E}[w(x) h(x, y) | x] = w(x) \mathbb{E}[h(x, y) | x]$$

Can pull the term just depending on  $X$  outside conditional expectation

## Conditional variance function

Var[h(x, y) | x] → we're going to define this

$$\text{Var}[z] = \mathbb{E}[(z - \mathbb{E}z)^2] = \mathbb{E}z^2 - (\mathbb{E}z)^2$$

starting from this expression, define:

$$\text{Var}[h(x, y) | x] = \frac{\mathbb{E}[h^2(x, y) | x]}{\left[\mathbb{E}(h(x, y) | x)\right]^2}$$

Recall that:

$$\mathbb{E}[h^2(x, y) | x=t] = \int h^2(t, y) \frac{f(t, y)}{f_t(t)} dy$$

etc - - -

Note:

$$\text{Var}[h(x, y) | x]$$

$$= \mathbb{E}\left[\overline{(h(x, y) - \mathbb{E}(h(x, y) | x))^2} | x\right]$$

$$\rightarrow = \mathbb{E}\left[(h(x, y) - \mathbb{E}_h(x))^2 | x\right]$$

$$E[(h(x, y) - \bar{\epsilon}_h(x))^2 | x]$$

$$= E\left[\left\{h^2(x, y) - 2\bar{\epsilon}_h(x)h(x, y) + \bar{\epsilon}_h(x)^2\right\} | x\right]$$

We can take conditional expectations

term by term, and hence:

$$\begin{aligned} &= E[h^2(x, y) | x] - 2 \underbrace{E[\bar{\epsilon}_h(x)h(x, y) | x]}_{+ E[\bar{\epsilon}_h(x)^2 | x]} \\ &= E[h^2(x, y) | x] - 2 \bar{\epsilon}_h(x) \underbrace{E[h(x, y) | x]}_{+ \bar{\epsilon}_h(x)^2} \end{aligned}$$

$$E[h(x, y) | x] = \bar{\epsilon}_h(x)$$

giving us:

$$\begin{aligned} &E[h^2(x, y) | x] - 2 \bar{\epsilon}_h^2(x) + \bar{\epsilon}_h^2(x) \\ &\quad = E[h^2(x, y) | x] - (\underbrace{E[h(x, y) | x]}_{\nearrow})^2 \end{aligned}$$

## Variance decomposition formula:

Before I do this, a digression:

$(X, Y)$  - random vector.  $X$ :  $d$ -dimensional  
 $Y$ : 1 dimensional

$$f(x, y) = f(x_1, \dots, x_d, y)$$

$$x = (x_1, x_2, \dots, x_d)$$

$f_1(x)$ : marginal density of  $x$

$$\begin{array}{c} \xleftarrow{\quad} \xrightarrow{\quad} \\ = \int f(x, y) dy \end{array}$$

function of  $d$  variables.

$$E[h(x, y)|x] = \int_{\mathbb{R}^d} h(t, y) \frac{f(t, y)}{f_1(t)} dt$$

$$t = (t_1, \dots, t_d)$$

$$\boxed{\int dt = (dt_1, dt_2, \dots, dt_d)}$$

Variance decomposition formula:

$$\underline{\text{Var}[h(x, y)]} = \mathbb{E}[\text{Var}(h(x, y) | x)] + \text{Var}[\mathbb{E}(h(x, y) | x)]$$
$$\underline{\text{Var}[v]} = \text{Var}[\mathbb{E}(v | u)] + \mathbb{E}[\text{Var}(v | u)]$$

$\downarrow$        $\downarrow$        $\uparrow$   
 $\downarrow$        $\downarrow$        $\uparrow$   
 $\underline{h(x, y)}$

for any pair of random variables  $(u, v)$   
with a joint distribution.

$$\text{Var}[v] = \mathbb{E}[(v - \mathbb{E}v)^2]$$
$$= \mathbb{E}[(v - \mathbb{E}(v|u) + \mathbb{E}(v|u) - \mathbb{E}v)^2]$$
$$= \mathbb{E}[(v - \mathbb{E}(v|u))^2] \quad \textcircled{I}$$
$$+ \mathbb{E}[(\mathbb{E}(v|u) - \mathbb{E}v)^2] \quad \textcircled{II}$$
$$+ 2 \mathbb{E}[(v - \mathbb{E}(v|u))(\mathbb{E}(v|u) - \mathbb{E}v)]$$

$\rightarrow$        $\textcircled{III}$        $\textcircled{III} = D$ .

$$\textcircled{I} = \mathbb{E} \left[ (\mathbb{V} - \mathbb{E}(\mathbb{V}|u))^2 \right]$$

$$= \mathbb{E} \left[ \mathbb{E} \left[ (\mathbb{V} - \mathbb{E}(\mathbb{V}|u))^2 | u \right] \right]$$

$\mathbb{V} \mathbb{A} \mathbb{R} [\mathbb{V}|u]$

$$= \mathbb{E} [\mathbb{V} \mathbb{A} \mathbb{R} (\mathbb{V}|u)] .$$

$$\textcircled{II} = \mathbb{E} \left[ (\mathbb{E}(\mathbb{V}|u) - \mathbb{E}\mathbb{V})^2 \right]$$

$$\mathbb{E}\mathbb{V} = \mathbb{E}[\mathbb{E}(\mathbb{V}|u)] .$$

$$\Rightarrow \textcircled{II} = \mathbb{E} \left[ (\underbrace{\mathbb{E}(\mathbb{V}|u)}_{\mathbb{K}(u)} - \mathbb{E}(\mathbb{E}(\mathbb{V}|u)))^2 \right]$$

$$= \mathbb{E} [\mathbb{K}(u) - \mathbb{E}(\mathbb{K}(u))]^2$$

$$= \mathbb{V} \mathbb{A} \mathbb{R} [\mathbb{K}(u)]$$

$$= \mathbb{V} \mathbb{A} \mathbb{R} (\mathbb{E}(\mathbb{V}|u))$$

$$\frac{\text{III}}{2} = \mathbb{E} [ (\nu - \mathbb{E}(\nu|u)) (\mathbb{E}(\nu|u) - \mathbb{E}\nu) ]$$

$\swarrow \quad \searrow$   
 $\gamma(u)$

$$= \mathbb{E} [ (\nu - \mathbb{E}(\nu|u)) \gamma(u) ]$$

$$= \mathbb{E} [ \mathbb{E} [ (\nu - \mathbb{E}(\nu|u)) \gamma(u) | u ] ]$$

$$= \mathbb{E} [ \gamma(u) \mathbb{E} [ (\nu - \mathbb{E}(\nu|u)) | u ] ]$$

$$= \mathbb{E} [ \gamma(u) [\mathbb{E}(\nu|u) - \mathbb{E}(\nu|u)] ]$$

$$= 0$$

$$\mathbb{E} [ \mathbb{E}(\nu|u) | u ] = \mathbb{E}(\nu|u)$$

as  $\mathbb{E}(\nu|u)$  is a function of  $u$ .

## Exercise

List of  $n$  symbols.

Computer searches list sequentially to determine if pre-specified object is present in list, and stops as soon as object is discovered. Otherwise whole list is searched.

Object is in the list with prob  $p$ .

What is the expected number of items the program searches to find object?

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B : 1 (Object present in list)

N : # of item searched by computer

Want to find  $\boxed{\text{IENT}}$

$N|B=0$  is degenerate at  $n \cdot w \cdot p - 1$ .

We'll assume that  $N|B=1$  is uniformly distributed over  $\{1, 2, \dots, n\}$

$$\begin{aligned} \text{So: } \mathbb{E}N &= \frac{\mathbb{E}[\mathbb{E}(N|B)]}{\mathbb{P}(B=1)} \\ &= \mathbb{P}(B=1) \frac{\mathbb{E}[N|B=1] + \mathbb{P}(B=0)}{\mathbb{E}[N|B=0]} \\ &\quad \downarrow \\ &= \frac{1}{n} \cdot 1 + \frac{1}{n} \cdot 2 + \dots + \frac{1}{n} \cdot n \end{aligned}$$

$$= \frac{1}{n} \frac{n(n+1)}{2} = \frac{n+1}{2}$$

$$\begin{aligned} \text{So: } \mathbb{E}N &= p \cdot \frac{n+1}{2} + (1-p)n \\ &= n - \frac{np}{2} + \frac{p}{2} \end{aligned}$$

Exercise: Fair coin.

Stage 1: Tossed  $n$  times.  $H$ , the # of Heads is recorded.

Stage 2: Coin tossed again  $H$  times.  $N$ , the # of Heads is recorded

Total number of heads combining the two stages is  $H + N$ .

We'd like to find  $E(H + N)$ ,  $\text{Var}(H + N)$

$$\begin{aligned} H &\sim \text{Bin}(n, \frac{1}{2}) \\ N|H &\sim \text{Bin}(H, \frac{1}{2}) \end{aligned}$$

Solve by conditioning on  $H$ .

alternative: find joint of  $(H, N)$  and

then compute the quantities.

try this

$$E(H + N) = E H + E N$$

$$= \frac{n}{2} + \text{EN}$$

$$EN = E [E(N|H)] = E(H/2)$$

$$\begin{aligned} \text{So: } E(N|H) &= \frac{3n}{4} \\ &= \frac{1}{2} \cdot EH \\ &= \frac{n}{4}. \end{aligned}$$

Variance:

$$\text{Var}(N+H) = \mathbb{E}[\text{Var}(N+H|H)] + \text{Var}[\mathbb{E}(N+H|H)]$$

Consider:  $\mathbb{E}[\text{Var}(N+H|H)] \leftarrow$

$$= \mathbb{E}[\text{Var}(N|H)] \\ = \mathbb{E}[H/4] = \frac{n}{8}$$

$$\text{Var}[\mathbb{E}(N+H|H)]$$

$$= \text{Var}[\mathbb{E}(N|H) + H]$$

$$= \text{Var}\left[\frac{H}{2} + H\right] = \frac{9}{4} \cdot \frac{\text{Var}(H)}{4} \\ = \frac{9}{4} \times \frac{n}{4} = \frac{9}{16} n.$$

$$\text{So: } \text{Var}(N+H) = \frac{9n}{16} + \frac{n}{8} = \frac{11n}{16}$$

Mixed joint-distribution arising  
 via multistage random experiments  
 (Bayesian Inference)

Example: Generate a discrete R.V  
 at Stage 1.

Depending on its value generate continuous  
 random variable at stage 2.

$$X \sim f(x) \cdot \text{p.m.f}$$

$X$  assumes value in countable set  $\mathcal{R}$ .

$$\text{So } \sum_{x \in \mathcal{R}} f(x) = 1$$

$$Y | X = x \sim g_x(y) \quad \text{p.d.f}$$

$$f(x, y) = f(x) \cdot g_x(y)$$

can't think of this guy as a pure  
 p.d.f or a pure p.m.f

The marginal density of  $y$ :

$$f_y(y) = \sum_{x \in X} f(x) g_x(y)$$

proper p.d.f.

Conditional of  $X$  given  $y = y$ :

$$f_{X|Y=y}(x) = \frac{f(x, y)}{f_y(y)}$$

Example:  $\begin{array}{c} X \sim \text{continuous distribution} \\ Y | X=x \sim \text{discrete} \end{array}$

Suppose  $X \sim \text{Exp}(\lambda)$   
 $Y | X=x \sim \underline{\text{Poi}(x)}$

$(X, Y)$

$$f_{X,Y}(x, y) = \lambda e^{-\lambda x} \mathbf{1}\{x > 0\} \cdot \frac{e^{-x} x^y}{y!} \mathbf{1}\{y \in \mathbb{Z}_+^*\}$$

$$f_{x,y}(x,y) = \frac{\lambda e^{-\lambda(x+1)} x^y}{y!} \times \mathbf{1}_{\{x>0, y \in \mathbb{Z}^+\}}$$

Marginal of  $y$ :

Conditional of  $x | y=y$

$$f_{x|y=y}(x) = \frac{\lambda e^{-\lambda(x+1)} x^y}{y!} \mathbf{1}_{\{x>0\}}$$

$\left( \int_{[0,\infty)} \frac{\lambda e^{-\lambda(x+1)} x^y}{y!} dx \right)$

$f_y(y) \rightarrow$  is a valid p.m.f

$X | y=y$

$\sim \text{gamma}(y+1, \lambda+1)$

So:

$$f_{x|y=y}(x) = \frac{1}{\psi(\lambda, y)} e^{-\lambda(x+1)} x^{y+1-1} \mathbf{1}_{\{x>0\}}$$

non-constant of  
a gamma  $(y+1, \lambda+1)$

$$\begin{aligned}
 f_Y(y) &= \int_0^\infty \frac{\lambda e^{-x(\lambda+1)} x^y}{y!} dx \\
 &= \frac{\lambda}{y!} \int_0^\infty e^{-x(\lambda+1)} x^{y+1-1} dx \\
 &= \frac{\lambda}{y!} \frac{\Gamma(y+1)}{(\lambda+1)^{y+1}} = \frac{\lambda}{(\lambda+1)^{y+1}}, \\
 &\quad y \geq 0.
 \end{aligned}$$

Check that this is a valid  
p.m.f.