

continuous Bayes' rule:

$$f_{X|Y}(x|y) = \frac{f_{Y|X}(y|x) \cdot f_X(x)}{\int_{-\infty}^{\infty} f_{Y|X}(y|t) \cdot f_X(t) dt}$$

Ex.

Let Y be a normal r.v. with
s.d. 1 and mean X , another r.v.

X is uniform on $[1, 3]$

Q.) find $f_Y(y)$

Solu.

we are given

$$f_X(x) = \begin{cases} \frac{1}{2} & 1 \leq x \leq 3 \\ 0 & \text{otherwise} \end{cases}$$

and

$$f_{Y|X}(y|x) = \begin{cases} \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{(y-x)^2}{2}} & 1 \leq x \leq 3 \\ & y \in \mathbb{R} \\ 0 & \text{otherwise} \end{cases}$$

so

$$f_Y(y) = \int_{-\infty}^{\infty} f_{Y|X}(y|x) \cdot f_X(x) dx$$

$$= \frac{1}{2} \int_1^3 \frac{1}{\sqrt{2\pi}} \cdot e^{-(x-y)^2/2} dx \quad \begin{array}{l} u = x - y \\ du = dx \end{array}$$

$$= \frac{1}{2} \int_{1-y}^{3-y} \frac{1}{\sqrt{2\pi}} \cdot e^{-u^2/2} du$$

$$= \frac{1}{2} \left(\Phi(3-y) - \Phi(1-y) \right)$$

b.) find $f_{X|Y}(x|y)$

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

$$= \begin{cases} \frac{\frac{1}{\sqrt{2\pi}} e^{-(y-x)^2/2}}{\Phi(3-y) - \Phi(1-y)} & 1 \leq x \leq 3 \\ & y \in \mathbb{R} \\ 0 & \text{otherwise} \end{cases}$$

c.) Suppose we sample Y and get $y=3$. What is the probability that $X \leq 2$?

$$\begin{aligned} P(X \leq 2 | Y=3) &= \int_1^2 f_{X|Y}(x|3) dx \\ &= \frac{\int_1^2 \frac{1}{\sqrt{2\pi}} e^{-(x-3)^2/2} dx}{\Phi(0) - \Phi(-2)} \end{aligned}$$

$$\begin{aligned}
 &= \frac{\int_{-2}^{-1} \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du}{\Phi(0) - \Phi(-2)} \\
 &= \frac{\Phi(-1) - \Phi(-2)}{\Phi(0) - \Phi(-2)} \\
 &= \boxed{.2848}
 \end{aligned}$$

d.) find $E[Y]$

$$\begin{aligned}
 E[Y] &= \int_{-\infty}^{\infty} y \cdot f_Y(y) dy \\
 &= \int_{-\infty}^{\infty} y \cdot \frac{1}{2} \cdot \int_1^3 \frac{1}{\sqrt{2\pi}} e^{-(x-y)^2/2} dx dy
 \end{aligned}$$

$$= \frac{1}{2} \int_1^3 \int_{-\infty}^{\infty} y \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{(y-x)^2}{2}} dy dx$$

$$= \frac{1}{2} \int_1^3 x dx = \frac{1}{2} \frac{x^2}{2} \Big|_1^3 = \frac{1}{4} (9-1) = \boxed{2}$$

4.1 Derived distributions

If $Y = g(X)$, how can we find

$$f_Y(y)$$

from

$$f_X(x)$$

We call $f_Y(y)$ a derived dist.

2-step process

1.) find CDF: $F_Y(y)$

$$F_Y(y) = P(g(X) \leq y)$$

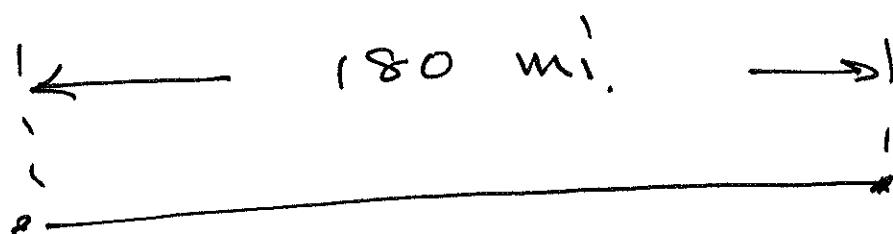
$$= \int_{\{x \mid g(x) \leq y\}} f_X(x) dx$$

2.) differentiate!

$$f_Y(y) = \frac{d}{dy} F_Y(y).$$

Ex.

A car travels a dist. of 180 miles at const. rate R . Also R is itself a random variable, uniform cont. on $30 \leq R \leq 60$ (mph)



let T be the time of travel.

find $f_T(t)$.

Solu.

have : $180 = R \cdot T$

$$\therefore T = \frac{180}{R}$$

$$\textcircled{1} \quad F_T(t) = P(T \leq t)$$

$$= P\left(\frac{180}{R} \leq t\right)$$

$$= P\left(R \geq \frac{180}{t}\right)$$

$$= 1 - P\left(R < \frac{180}{t}\right)$$

$$= 1 - F_R\left(\frac{180}{t}\right)$$

We are given

$$f_R = \begin{cases} \frac{1}{30} \\ 0 \end{cases}$$

$$30 \leq r \leq 60$$

otherwise

$$\therefore F_R(r) = \int_{-\infty}^r f_R(s) ds$$

$$= \int_{30}^r \frac{1}{30} ds$$

$$= \frac{1}{30} \cdot s \Big|_{30}^r = \frac{r-30}{30}$$

$$= \begin{cases} 0 & r < 30 \\ \frac{r-30}{30} & 30 \leq r \leq 60 \\ 1 & r > 60 \end{cases}$$

hence

$$F_T(t) = 1 - F_R\left(\frac{180}{t}\right)$$

$$= \begin{cases} 0 & t < 3 \\ 2 - \frac{6}{t} & 3 \leq t \leq 6 \\ 1 & t > 6 \end{cases}$$

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$$f_T(t) = \begin{cases} \frac{6}{t^2} & 3 \leq t \leq 6 \\ 0 & \text{otherwise} \end{cases}$$

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If $Y = aX + b$, then

$$f_Y(y) = \frac{1}{|a|} f_X\left(\frac{y-b}{a}\right) \quad (a \neq 0)$$

Proof:

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$$F_Y(y) = P(Y \leq y)$$

$$= P(aX + b \leq y)$$

$$= \begin{cases} P\left(X \leq \frac{y-b}{a}\right) & a > 0 \\ P\left(X \geq \frac{y-b}{a}\right) & a < 0 \end{cases}$$

$$= \begin{cases} P\left(X \leq \frac{y-b}{a}\right) & a > 0 \\ 1 - P\left(X < \frac{y-b}{a}\right) & a < 0 \end{cases}$$

$$= \begin{cases} F_X\left(\frac{y-b}{a}\right) & a > 0 \\ 1 - F_X\left(\frac{y-b}{a}\right) & a < 0 \end{cases}$$

(2) diff w.r.t. x

$$f_Y(y) = \begin{cases} f_X\left(\frac{y-b}{a}\right) \cdot \frac{1}{a} & a > 0 \\ -f_X\left(\frac{y-b}{a}\right) \cdot \frac{1}{a} & a < 0 \end{cases}$$

$$= \frac{1}{|a|} f_X\left(\frac{y-b}{a}\right)$$

~~□~~

Ex.

Let X be normal with mean μ
and var. σ^2 . Then

$$Y = aX + b$$

is also normal with mean $a\mu + b$
and var. $a^2\sigma^2$

Proof: we have

$$f_X(x) = \frac{1}{\sqrt{2\pi} \cdot \sigma} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Thus

$$f_Y(y) = \frac{1}{|a|} \cdot f_X\left(\frac{y-b}{a}\right)$$

$$= \frac{1}{|a|} \cdot \frac{1}{\sqrt{2\pi}\sigma} \cdot e^{-\left(\frac{y-b}{a} - \mu\right)^2 / 2\sigma^2}$$

$$= \frac{1}{\sqrt{2\pi} \cdot |a|\sigma} \cdot e^{-\left(\frac{y-b-a\mu}{a}\right)^2 / 2\sigma^2}$$

$$= \frac{1}{\sqrt{2\pi} \cdot |a|\sigma} \cdot e^{-\left(y - (a\mu + b)\right)^2 / 2(a\sigma)^2}$$

which is normal.



Defn

A function $g: \mathbb{R} \rightarrow \mathbb{R}$ is called strictly monotonic iff for all $x_1, x_2 \in \mathbb{R}$, either

$$(1) \ x_1 < x_2 \Rightarrow g(x_1) < g(x_2) \quad (\text{increasing})$$

or

$$(2) \ x_1 < x_2 \Rightarrow g(x_1) > g(x_2) \quad (\text{decreasing})$$

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