

Considering $Y=g(X)$ when Oct 4, 2022
 X is cont. and Y is discrete
(case ②)

We can let $\mathcal{R}_Y = g(\mathbb{R})$

Find the pmf of Y .

We know that

$$P_Y(y) = P(g(X)=y) = P(X \in D_y)$$

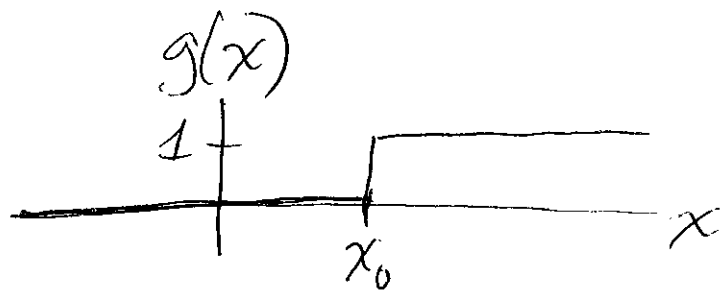
where $D_y = \{x \in \mathbb{R} : g(x)=y\}$, $\forall y \in \mathcal{R}_Y$

So we need to find
 D_y such that

$$\{g(X)=y\} = \{X \in D_y\} \text{ for each } y \in \mathcal{R}_Y$$

$$\text{Then } P_Y(y) = \int_{D_y} f_X(x) dx$$

Example. Let $g(x) = \underset{\substack{\text{indicator} \\ \text{function}}}{I_{(x_0, \infty)}(x)}$



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Can see that $R_y = \{0, 1\}$

For ~~$x < x_0$~~ ~~$y = 0$~~ $y = 0$:

$$D_0 = \{x \in \mathbb{R} : g(x) = 0\} = (-\infty, x_0)$$

For $y = 1$:

$$D_1 = \{x \in \mathbb{R} : g(x) = 1\} = [x_0, \infty)$$

$$\text{So } P_Y(0) = \int_{-\infty}^{x_0} f_X(x) dx$$

$$P_Y(1) = \int_{x_0}^{\infty} f_X(x) dx$$

$$P_Y(y) = \begin{cases} \int_{-\infty}^{x_0} f_X(x) dx & \text{if } y=0 \\ \int_{x_0}^{\infty} f_X(x) dx & \text{if } y=1 \end{cases}$$

Case (3) X, Y are both discrete
 Can let $R_y = g(\mathbb{R})$ or
 $R_y = g(R_x)$

If you know \mathcal{R}_X , ⁽³⁾
use $g(\mathcal{R}_X)$, if not,
use $g(\mathbb{R})$

For this case

$$\begin{aligned} P_Y(y) &= P(g(X)=y) \\ &= P(\{x \in \mathcal{R}_X : g(x)=y\}) \\ &\quad (\text{or } x \in \mathbb{R} \text{ if } \\ &\quad \mathcal{R}_X \text{ is not} \\ &\quad \text{known}) \end{aligned}$$

So

$$P_Y(y) = \sum_{\substack{x \in \mathcal{R}_X : \\ g(x)=y}} P_X(x), \quad \forall y \in \mathcal{R}_Y$$

(can write
 $D_y = \{x \in \mathcal{R}_X : g(x)=y\}$)

Example. Let X be the
value rolled on a die, and
 $Y = \begin{cases} 1 & \text{if } X \text{ is odd} \\ 0 & \text{if } X \text{ is even} \end{cases}$

We have

$$\mathcal{R}_x = \{1, 2, 3, 4, 5, 6\}$$

$$\mathcal{R}_y = \{0, 1\}$$

Note that $g(x) = x \% 2$

We then have

$$P_Y(y) = \sum_{\substack{x \in \mathcal{R}_x: \\ x \% 2 = y}} P_X(x), \quad y \in \{0, 1\}$$

or

$$P_Y(0) = P_X(2) + P_X(4) + P_X(6)$$

$$P_Y(1) = P_X(1) + P_X(3) + P_X(5)$$

Expectations

Expectation is often used in probability for:

- characterizing a rv (or a collection of rvs) when there is insufficient data to find histograms
- finding the parameters

for many types of (5)
rvs (e.g., μ, σ for a Gaussian)

Defn. The expected value of a
rv X is defined as

$$E[X] = \int_{-\infty}^{\infty} x f_X(x) dx \in \mathbb{R}$$

Also called the mean of X

Other notation: μ, μ_X, EX, \bar{X}

It can be shown (using
the sifting property) that

$$E[X] = \sum_{x \in \mathcal{R}_X} x p_X(x) \quad \text{if } X \text{ is discrete}$$

Example. Let X be exponential
with parameter λ , so

$$f_X(x) = \lambda e^{-\lambda x} u(x), \quad \lambda > 0$$

$$\text{So } E[X] = \int_{-\infty}^{\infty} x f_X(x) dx = \lambda \int_0^{\infty} x e^{-\lambda x} dx$$

which gives

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$$E[X] = \frac{1}{\lambda}$$

Letting this value be denoted μ gives

$$f_X(x) = \frac{1}{\mu} e^{-x/\mu} u(x)$$

