

$$\boxed{Y = g(X)}$$

$\uparrow \quad \downarrow$

$g: \mathbb{R} \rightarrow \mathbb{R}$
 $X: S \rightarrow \mathbb{R}$

$Y: S \rightarrow \mathbb{R}$

really mean: $Y = g \circ X$

Formalism: $P(Y \in A) = P(g \circ X \in A)$

$$\begin{aligned} &= P((g \circ X)^{-1}(A)) \\ &= P(X^{-1}(g^{-1}(A))) \\ &= P(X \in g^{-1}(A)) \end{aligned}$$

$$Y = g(X)$$

\hookrightarrow $P(Y \in A) = P(g(X) \in A) = P(X \in g^{-1}(A))$

This lecture:

① Know something about X

② What do I know about $Y = g(X)$?

Discrete R.V.s. X is a discrete r.v.

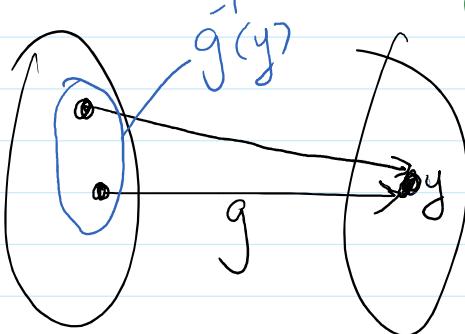
\rightarrow Know f_X \leftarrow PMF of X

\rightarrow how do I get f_Y \leftarrow PMF of $Y = g(X)$?

Notice:

$$f_Y(y) = P(Y=y) = P(g(X)=y)$$

$$= P(X \in g^{-1}(\{y\})) = \sum_{x \in g^{-1}(y)} f_X(x)$$



For $A \subset \mathbb{R}$,

$$P(X \in A) = \sum_{x \in A} f_X(x)$$

Recall:

g^{-1} = inverse image

(typically a set)

conventions:

① $g^{-1}(y)$ denotes $g^{-1}(\{y\})$
when set contains just y

② if g is invertible —
 g^{-1} denotes inverse

①

Theorem: If X is discrete then if $Y=g(X)$

$$f_Y(y) = \sum_{x \in g^{-1}(y)} f_X(x)$$

PMF of Y = sum over
all x s.t.
 $g(x)=y$

of $P(X=x)$

Ex1 Let $X \sim \text{Bin}(n, p)$

and $Y = n - X$

of successes in
 n indep. trials w/
prob. p of success
on each.

failures

$$y = g(x) = n - x$$

↓

$$x = g^{-1}(y) = n - y$$

aside get g^{-1}

1 item

$$f_Y(y) = \sum_{x \in g^{-1}(y)} f_X(x) = \sum_{x=n-y} f_X(x) = f_X(n-y)$$

$$P(Y=y) = f_Y(y) = f_X(n-y) = P(X=n-y)$$

y failures

n-y successes

$$\stackrel{?}{=} \binom{n}{n-y} p^{n-y} (1-p)^{n-(n-y)}$$

why?

$$= \binom{n}{y} p^{n-y} (1-p)^y$$

let $q = 1-p$

$$= \binom{n}{y} q^y (1-q)^{n-y} = f_Y(y)$$

PMF of a $\text{Bin}(n, q=1-p)$

Hence $\boxed{Y \sim \text{Bin}(n, 1-p)}$

(2) Move on to continuous RVs.

Move on to continuous RVs.

(2)

Theorem:

If X is a continuous random variable, then

① If g is an increasing function and $\boxed{Y=g(X)}$

then

$$\textcircled{*} \quad \boxed{F_Y(y) = F_X(g^{-1}(y))}$$

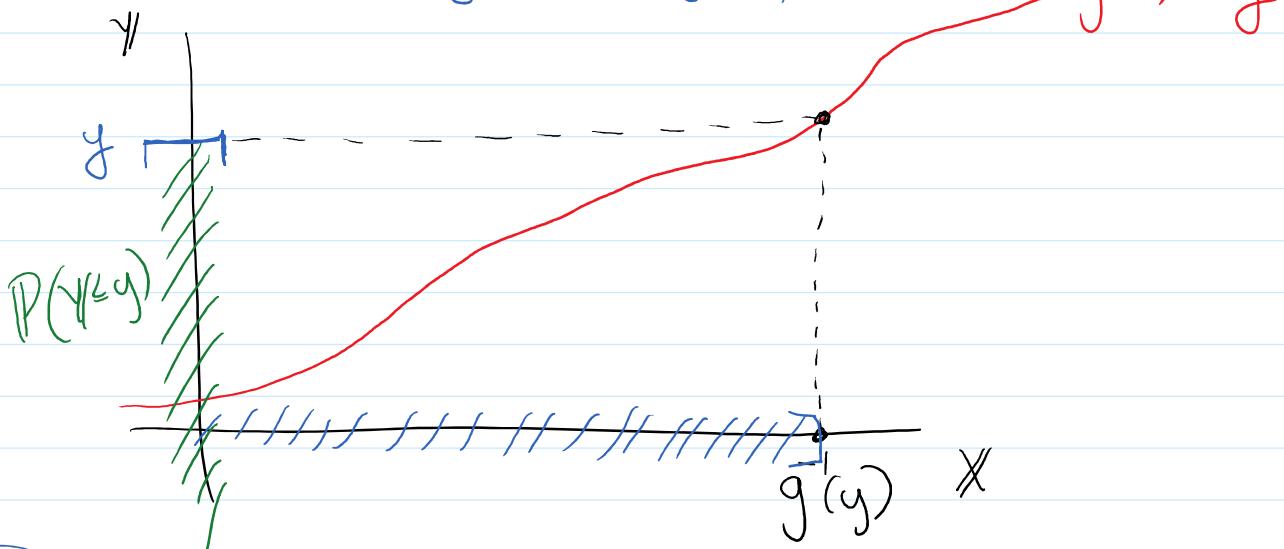
↓ if g strictly increasing then it is invertible

② If g is a decreasing function and $\boxed{Y=g(X)}$

then

$$\boxed{F_Y(y) = 1 - F_X(g^{-1}(y))}$$

Pf. Case I: strictly increasing fn.

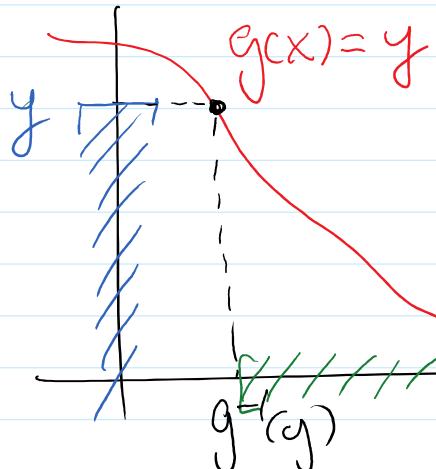


$$F_Y(y) = P(Y \leq y) = P(g(X) \leq y) = P(X \leq g^{-1}(y))$$

$$\text{Case 1: } Y(g) \neq \Gamma(X=y) = \Gamma(g(x) \leq y) = \Gamma(X = g^{-1}(y))$$

$$= F_X(g^{-1}(y))$$

Case 2: Decreasing g



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

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

$$= P(X \geq g^{-1}(y)) \quad \begin{matrix} \text{reg.} \\ \times \end{matrix} \quad \begin{matrix} \text{continuous} \end{matrix}$$

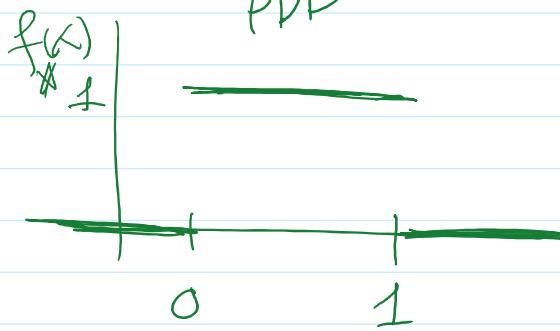
$$= 1 - P(X \leq g^{-1}(y))$$

$$= 1 - F_X(g^{-1}(y))$$

Ex.

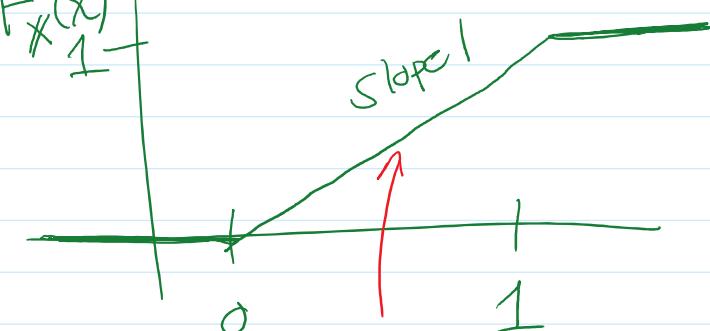
$$X \sim U(0,1)$$

PDF



$$F_X(x)$$

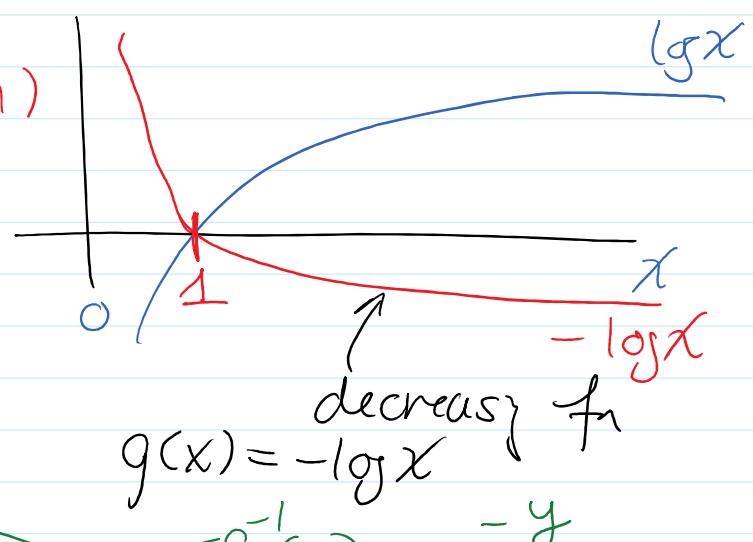
CDF



$$\text{Let } Y = -\log X \stackrel{?}{=} U(0,1)$$

CDF of Y ?

$$F_Y(y) = 1 - F_X(g^{-1}(y))$$



$$y(x) = -\log x$$

$$= 1 - F_X(e^{-y})$$

$$= 1 - e^{-y}$$

$0 < e^{-y} < 1$
for $y > 0$

Show,

$$F_Y(y) = 1 - e^{-y}$$

is the CDF of $\text{Exp}(\lambda=1)$

hence $Y \sim \text{Exp}(\lambda=1)$

What about PDFs?

③ Theorem: If X is

① a continuous RV.

and $Y = g(X)$, and

② g is continuous, monotone (dec or inc.)

→ ③ g^{-1} is differentiable

then,

$$f_Y(y) = f_X(g^{-1}(y)) \left| \frac{dg^{-1}}{dy} \right|$$

P.F. Case 1: g increasing then $\frac{dg^{-1}}{dy} > 0$

Pf Case 1: g increasing then $\frac{dg^{-1}}{dy} > 0$

$$f_Y(y) = \frac{d}{dy} F_Y(y) = \frac{d}{dy} F_X(g^{-1}(y)) \quad \text{chain-rule}$$

$$= f_X(g^{-1}(y)) \left| \frac{dg^{-1}}{dy} \right| \leftarrow$$

Case 2: g decreasing so $\frac{dg^{-1}}{dy} < 0$

$$f_Y(y) = \frac{d}{dy} F_Y(y) = \frac{d}{dy} [1 - F_X(g^{-1}(y))]$$

$$= -f_X(g^{-1}(y)) \frac{dg^{-1}}{dy} \leftarrow \frac{dg^{-1}}{dy} < 0$$

$$= f_X(g^{-1}(y)) \left| \frac{dg^{-1}}{dy} \right| \leftarrow$$

Ex: $X \sim \text{Gamma}(\alpha = n, \lambda = \beta)$

¹
integer

some number > 0

$$\Gamma(n) = (n-1)!$$

means:

$$\rightarrow f_X(x) = \frac{1}{(n-1)! \beta^n} x^{n-1} e^{-x/\beta}, \text{ for } x > 0$$

let $Y = \frac{1}{X}$ equiv. $g(x) = \frac{1}{x}$.

What is the PDF of Y ?

Hence

$$n \cdot n \cdot \dots \sim 1 da^{-1}$$

- ① X continuous
- ② g decreasing
- ③ $g^{-1}(y) = \frac{1}{y}$

Hence

$$f_Y(y) = f_X(g^{-1}(y)) \left| \frac{dg^{-1}}{dy} \right|$$

$$= f_X(\frac{1}{y}) \frac{1}{y^2}$$

$$= \frac{1}{(n-1)! \beta^n} \left(\frac{1}{y}\right)^{n-1} e^{-\frac{1}{y\beta}} \frac{1}{y^2}$$

$$= \boxed{\frac{1}{(n-1)! \beta^n} \left(\frac{1}{y}\right)^{n+1} e^{-\frac{1}{y\beta}}} \quad \text{for } y > 0$$

$Y \sim \text{Inverse Gamma}(n, \beta)$

What about non-monotone transformations?

OK so long as piecewise-monotone.

④ Theorem

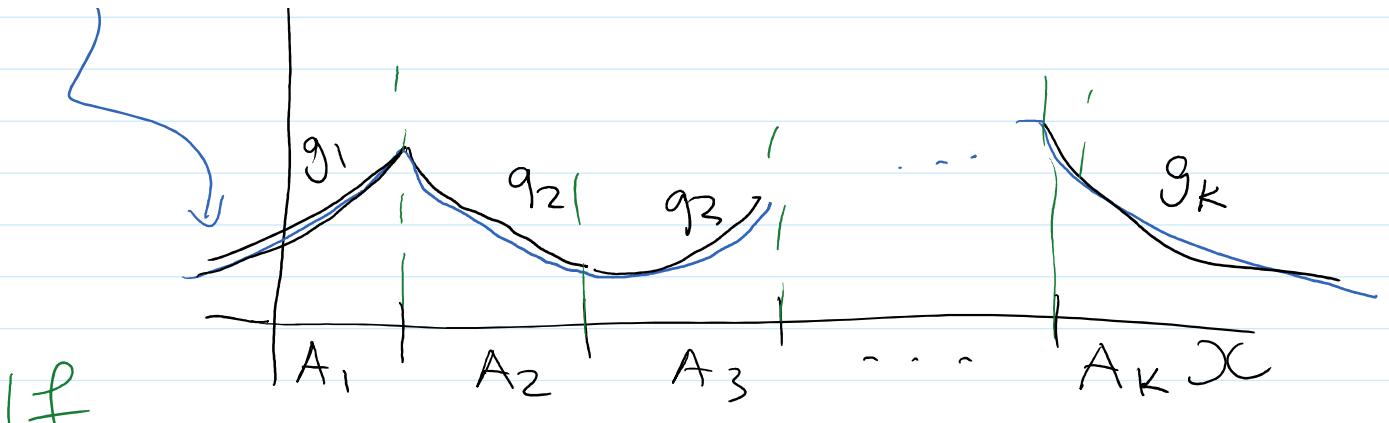
Let X be continuous w/ support \mathcal{X}

and f_X for $i=1, \dots, K$ let $\{A_i\}_{i=1}^K$ partition \mathcal{X} ,

g monotone on each part
of partition

let g_i be g on A_i

③ $\underline{\dot{g}'(y) = \frac{1}{y}}$
is differentiable,
 $\frac{d\dot{g}^{-1}}{dy} = -\frac{1}{y^2}$.



If

(1)

the prev. theorem is satisfied
for each g_i on A_i

(2)

the image of A_i under g_i is
the same H_i

then

if $Y = g(X)$ then

$$f_Y(y) = \sum_{i=1}^K f_X(g_i^{-1}(y)) \left(\frac{dg_i^{-1}}{dy} \right)$$

prev. theorem
applied to g_i

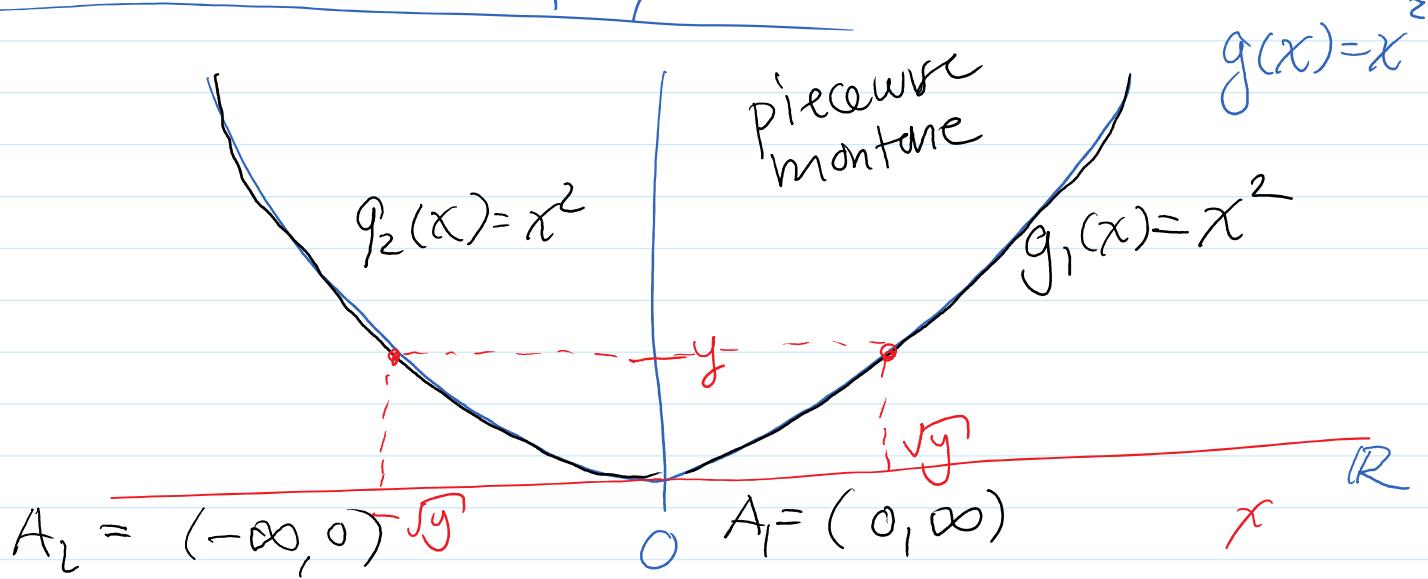
Ex. Chi-Squared Distribution.

If $X \sim N(0, 1)$ and $Y = X^2$ ($g(x) = x^2$)

then we say Y has a Chi-Squared distribution

σ (w/ 1 degree of freedom)

What is the PDF of $\chi^2(1)$?



$$\begin{cases} A_1 = (0, \infty); g_1(x) = x^2; g_1^{-1}(y) = \sqrt{x}; \frac{dg_1^{-1}}{dy} = \frac{1}{2\sqrt{y}} \\ A_2 = (-\infty, 0); g_2(x) = x^2; g_2^{-1}(y) = -\sqrt{x}; \frac{dg_2^{-1}}{dy} = \frac{-1}{2\sqrt{y}} \end{cases}$$

$$f_X(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}x^2\right)$$

Normal PDF
w/ $\mu=0$, $\sigma^2=1$.

$$f_Y(y) = \sum_{i=1,2} f_X(g_i^{-1}(y)) \left| \frac{dg_i^{-1}}{dy} \right|$$

$$= f_X(g_1^{-1}(y)) \left| \frac{dg_1^{-1}}{dy} \right| + f_X(g_2^{-1}(y)) \left| \frac{dg_2^{-1}}{dy} \right|$$

$$= f_X(\sqrt{y}) \frac{1}{2\sqrt{y}} + f_X(-\sqrt{y}) \frac{1}{2\sqrt{y}}$$

$$= \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} y^2\right) + \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} (-y)^2\right) \frac{1}{2\sqrt{y}}$$

$|y| = y > 0$

$$= \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{y}} \exp\left(-\frac{1}{2} y\right)$$

(PDF of a $\chi^2(1)$.)

Probability Integral Transformation

If X is a cts r.v. w/ CDF F_X , then

$$\underline{Y} = \underline{F_X}(\underline{X}) \sim U(0,1).$$

(is just same g.)

Pf. Assume that F_X is strictly increasing

so let F_X is invertible.

Then $\underline{Y} = \underline{F_X}(\underline{X})$ and so by our CDF theorem

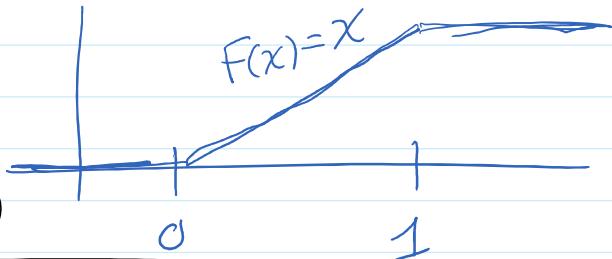
(g)

$$F_Y(y) = F_X(\tilde{g}^{-1}(y)) = F_X(F_X^{-1}(y)) = y$$

So the CDF of CDF of a uniform:

Y is the CDF
of a $U(0,1)$

hence $Y \sim U(0,1)$.



IFF $g(X) \sim U(0,1) \Leftrightarrow g = F_X$. ←

Can use to generate RVs-

idea: Want to generate $X \sim F_X$

① generate $Y \sim U(0,1)$

② let $X = F_X^{-1}(Y)$

then $X \sim F_X$.

why? $F_X(x) = P(X \leq x)$

$$= P(F_X^{-1}(Y) \leq x)$$

$$= P(Y \leq F_X(x)) \quad U(0,1)$$

$$= F_Y(F_X(x))$$

$$= F_X(x)$$