

Lecture 14

$$X \sim \text{Geom}(p) \quad p \in [0, 1]$$

$$M(t) = E[e^{tX}]$$

$$= \sum_{x=1}^{\infty} e^{tx} (1-p)^{x-1} p$$

$$= \sum_{x=0}^{\infty} e^{t(x+1)} (1-p)^x p$$

$$= p e^t \left[\sum_{x=0}^{\infty} \underbrace{\left((1-p) e^t \right)^x}_r \right] = \frac{1}{1-r} \quad \text{for } |r| < 1$$

$$= p e^t \frac{1}{1 - (1-p)e^t} \quad \text{for } (1-p)e^t < 1$$

$$M(t) = \frac{p e^t}{1 - (1-p)e^t} \quad \text{for } t < -\log(1-p)$$

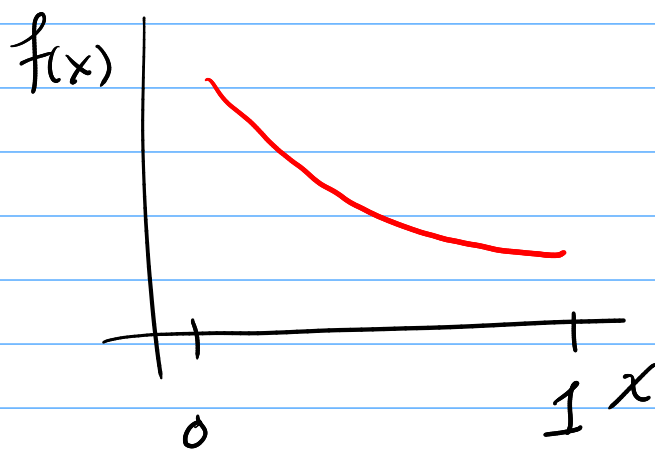
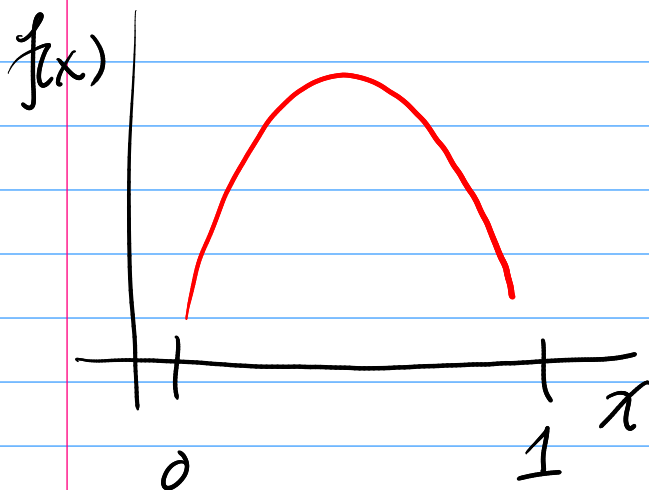
$$E[X] = \left. \frac{dM}{dt} \right|_{t=0} = \dots = \frac{1}{p}$$

$$E[X^2] = \frac{d^2 M}{dt^2} \Big|_{t=0} = \dots = \frac{2-p}{p^2}$$

$$\begin{aligned} \text{Var}(X) &= E[X^2] - E[X]^2 \\ &= \frac{2-p}{p^2} - \left(\frac{1}{p}\right)^2 \\ &= \frac{1-p}{p^2} \end{aligned}$$

Beta Distribution

- cts dist w/ support $[0, 1]$



Beta Function $B: \mathbb{R}_{\geq 0}^2 \rightarrow \mathbb{R}$

$$B(a, b) = \int_0^1 x^{a-1} (1-x)^{b-1} dx = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$$

↑
beta function

Beta dist

PDF: $X \sim \text{Beta}(a, b)$, $a > 0, b > 0$

$$f(x) = \frac{x^{a-1} (1-x)^{b-1}}{B(a, b)} \quad \text{for } 0 < x < 1$$

$$E[X^r] = \int_0^1 x^{\overset{r}{a}} \frac{x^{\overset{a}{a-1}} (1-x)^{b-1}}{B(a, b)} dx$$

$$= \frac{B(a+r, b)}{B(a, b)} \int_0^1 \frac{x^{a+r-1} (1-x)^{b-1}}{B(a+r, b)} dx$$

looks like $\text{Beta}(a+r, b)$

$\frac{x^{a+r-1} (1-x)^{b-1}}{B(a+r, b)}$

1

$$\Rightarrow E[X^r] = \frac{B(a+r, b)}{B(a, b)}$$

$$E[X] = \frac{B(a+1, b)}{B(a, b)} = \frac{\frac{P(a+1)P(b)}{P(a+b+1)}}{\frac{P(a)P(b)}{P(a+b)}}$$

$$= \frac{P(a+1)}{P(a)} \frac{P(a+b)}{P(a+b+1)}$$

$$= \frac{a \cancel{P(a)}}{\cancel{P(a)}} \frac{\cancel{P(a+b)}}{(a+b) \cancel{P(a+b)}}$$

$$= \frac{a}{a+b}$$

$$E[X^2] = \frac{B(a+2, b)}{B(a, b)} = \frac{\frac{P(a+2) \cancel{P(b)}}{P(a+b+2)}}{\frac{P(a) \cancel{P(b)}}{P(a+b)}}$$

$$= \frac{P(a+2)}{P(a)} \frac{P(a+b)}{P(a+b+2)}$$

$$= \frac{(a+1) a \cancel{P(a)}}{\cancel{P(a)}} \frac{\cancel{P(a+b)}}{(a+b+1)(a+b) \cancel{P(a+b)}}$$

$$= \boxed{\frac{a(a+1)}{(a+b)(a+b+1)} = E[X^2]}$$

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

$$= \frac{a(a+1)}{(a+b)(a+b+1)} - \left(\frac{a}{a+b} \right)^2$$

$$= \dots$$

$$= \frac{ab}{(a+b)^2(a+b+1)}$$

EXAM 2

Transformations

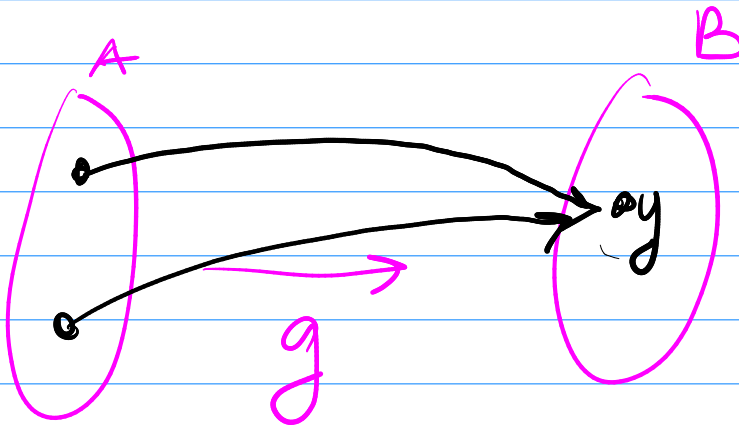
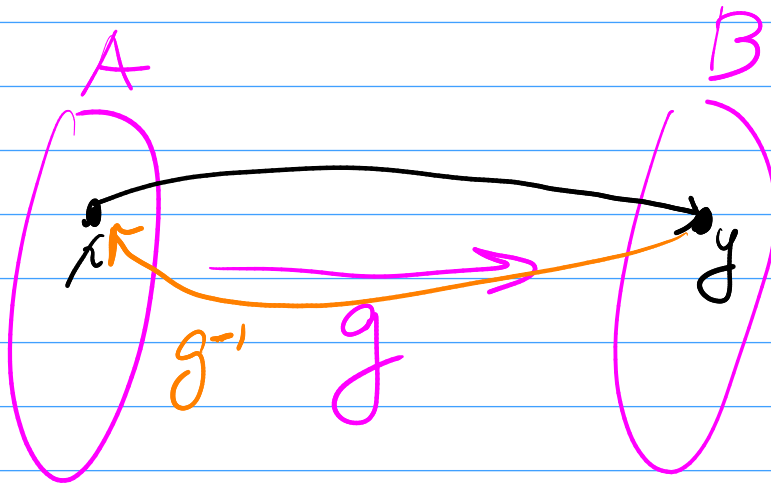
If I know something about X
what do I know about $Y = g(X)$?

Discrete RVs

Q: If I know f_X can I get f_Y ?

Inverses / Inverse Images

Invertible



Inverse Image: $g^{-1}(y) = \{x : g(x) = y\}$

Notice: $f_Y(y) = P(Y=y)$

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

If g is invertible

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

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

If g isn't invertible

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

inverse image

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

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

$$= \sum_{x: g(x)=y} f_X(x)$$

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

$$f_Y(y) = \sum_{x: g(x)=y} f_X(x)$$

Ex. $X \sim \text{Bin}(n, p)$

$$Y = n - X$$

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

$$f_Y(y) = \sum_{x: g(x)=y} f_X(x) \quad \xrightarrow{x=n-y}$$

$$= \sum_{x=n-y} f_X(x)$$

$$= f_X(n-y)$$

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

for $x=0, \dots, n$

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

for $n-y=0, \dots, n$

$$= \binom{n}{y} p^{n-y} (1-p)^y \text{ for } y=0, \dots, n$$

$$q = 1-p$$

$$f_Y(y) = \binom{n}{y} q^y (1-q)^{n-y} \text{ for } y=0, \dots, n$$

$$\text{Bin}(n, q)$$

Continuous RVs and CDF

Theorem: If X is cts and $Y = g(X)$ and g is invertible, then

① If g is increasing then

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

② If g is decreasing then

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

pf. Case 1:

$$\begin{aligned} F_Y(y) &= P(Y \leq y) \\ &= P(g(X) \leq y) \\ &= P(X \leq g^{-1}(y)) \\ &= F_X(g^{-1}(y)) \end{aligned}$$

$$\begin{array}{l} x < y \\ \log x < \log y \\ \hline x < y \\ \frac{1}{x} > \frac{1}{y} \end{array}$$

Case 2:

$$\begin{aligned} F_Y(y) &= P(Y \leq y) = P(g(X) \leq y) \\ &= P(X \geq g^{-1}(y)) \\ &= 1 - P(X < g^{-1}(y)) \\ &= 1 - F_X(g^{-1}(y)). \end{aligned}$$

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

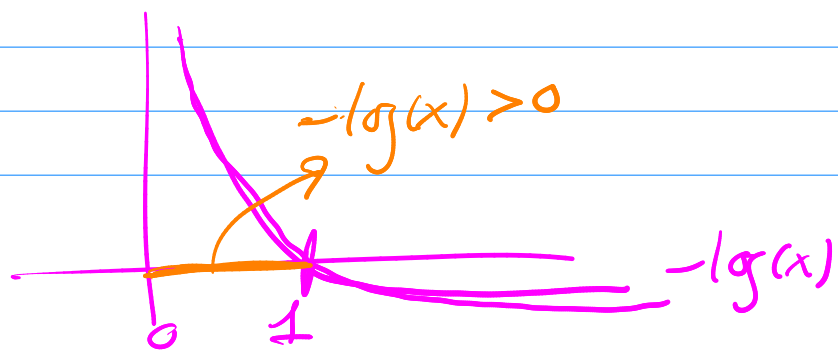
$$\underline{F_X(x) = x \text{ for } 0 < x < 1}$$

$Y = -\log X$, support of Y is $(0, \infty)$

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

$$\Rightarrow e^{-y} = x = g^{-1}(y)$$

Apply theorem:



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

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

btwn 0 and 1

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

CDF of $\text{Exp}(1)$

$$e^{-y} > 0$$

$$y > 0 \text{ then } e^{-y} = \frac{1}{e^y} \leq 1$$

i.e.

$$Y \sim \text{Exp}(1).$$

CDF of $Z \sim \text{Exp}(\lambda)$

$$1 - e^{-\lambda z} \text{ for } z > 0$$

What about PDFs?

Theorem: If X is cts and $Y = g(X)$

and

① g is invertible

② g^{-1} is differentiable

then

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