

Lecture 13

Stoch. Meth.

Nov. 8th, 2024

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

$$X \sim \text{Exp}(\lambda)$$

$$X \sim N(\mu, \sigma^2)$$

Exercise:

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

$$Y \sim \text{Beta}(1, 1/2)$$

$$X \perp\!\!\!\perp Y$$

$$W := \max(X, Y)$$

$$\begin{aligned} F_W(w) &= P[W \leq w] = P[\max(X, Y) \leq w] \\ &= P[X \leq w, Y \leq w] = P[X \leq w] \cdot P[Y \leq w] \end{aligned}$$

$$V := \min(X, Y)$$

$$F_V(v) = P[\min(X, Y) \leq v]$$

$$\begin{aligned} &= 1 - P[\min(X, Y) > v] = \\ &= 1 - P[X > v] \cdot P[Y > v] \end{aligned}$$

$$F_V(v) = \begin{cases} 0 & v < 0 \\ 1 - 2v & 0 \leq v < 1 \\ 1 & v \geq 1 \end{cases}$$

④

⑤

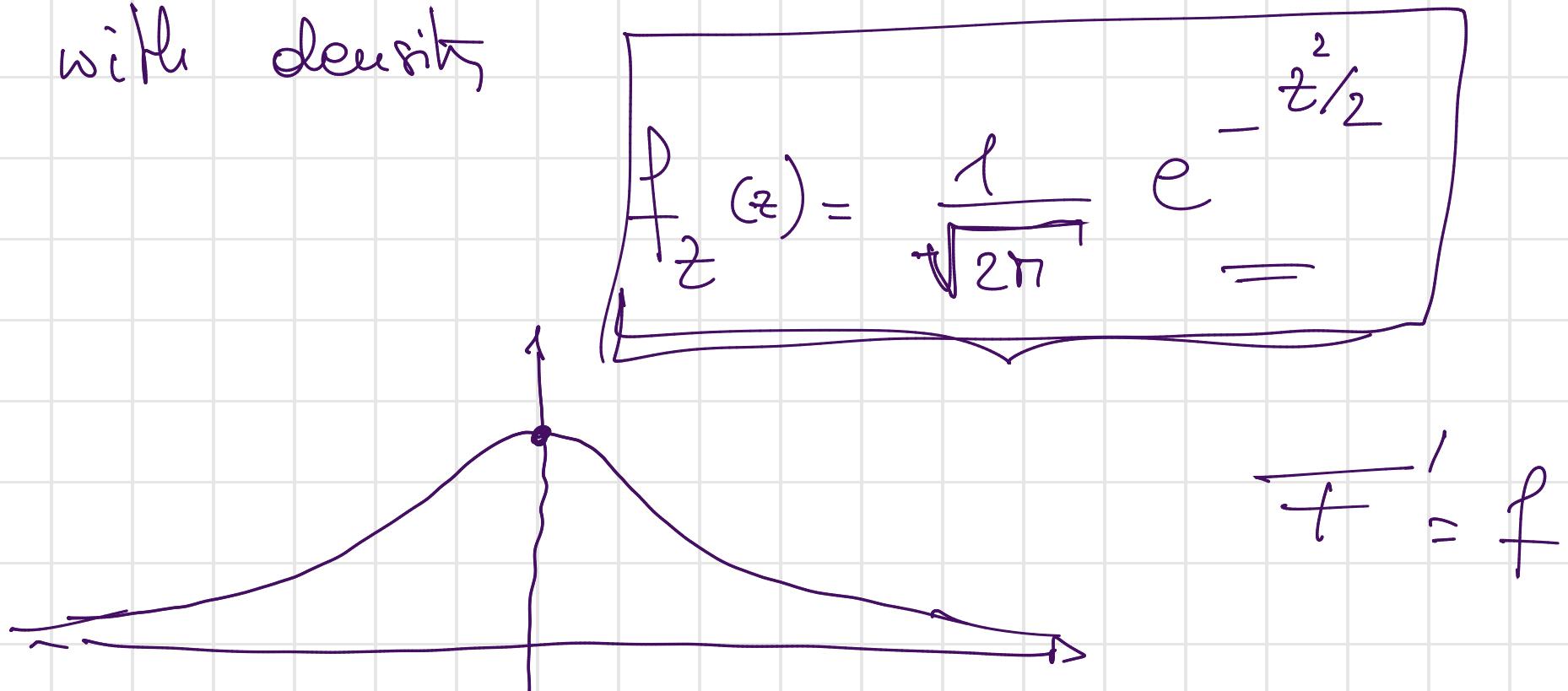
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Normal (Gaussian) distributions

A real valued r.v. Z is called standard

Normal if it is absolutely continuous

with density



$$\Rightarrow f_z \geq 0$$

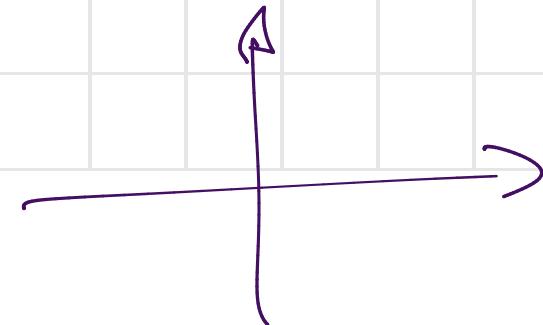
$$\int_{-\infty}^{+\infty} f_z(z) dz = 1$$

\Leftrightarrow

$$\int_{-\infty}^{+\infty} e^{-z^2/2} dz = \sqrt{2\pi}$$

$$\int_{R^2} e^{-x^2/\lambda^2} \cdot e^{-y^2/\lambda^2} dx dy$$

2π



$$z \in L^1(\Omega)$$

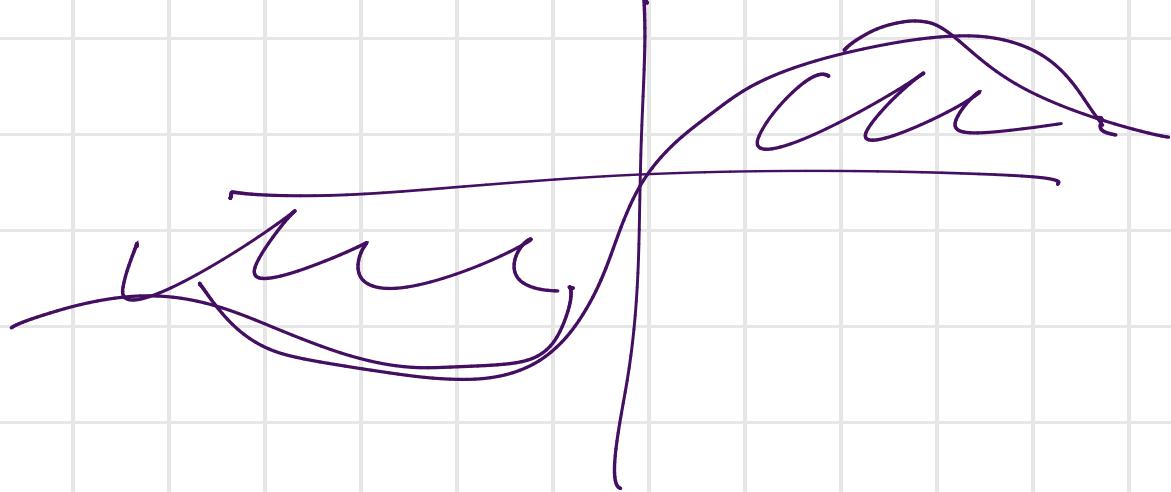
$$\int_{-\infty}^{\infty} |z| \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz < \infty$$

$$E[z] = \int_{-\infty}^{\infty} z \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz = \left[\frac{z}{\sqrt{2\pi}} e^{-z^2/2} \right]_{-\infty}^{+\infty} = 0$$

$$f(z) = z e^{-z^2/2}$$

$$f(-z) = -f(z)$$

$(0, z)$



$$E[z^2] = \text{Var}[z] = \int_{-\infty}^{+\infty} z^2 \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz$$

$$= \int_{-\infty}^{+\infty} z \cdot$$

$$\frac{z}{\sqrt{2\pi}} e^{-z^2/2} dz =$$

$$= \frac{1}{\sqrt{2\pi}} \left[z \cdot \left(-e^{-z^2/2} \right) \right]_{-\infty}^{+\infty}$$

$$+ \left[-\frac{1}{\sqrt{2\pi}} \cdot (-e^{-z^2/2}) \right]_{-\infty}^{+\infty}$$

$$1 \cdot \left(-e^{-z^2/2} \right) dz$$

$$E[Z^2] = \text{Var}[Z] = \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt = 1$$

Z standard Normal, $E[Z] = 0$, $\text{Var}[Z] = 1$

 $Z \sim N(0, 1)$ and $X \sim N(\mu, \sigma^2)$

$$\mu \in \mathbb{R}, \sigma > 0$$

$$X = \mu + \sigma Z$$

$$\begin{aligned}\Phi'(t) &= f_Z \\ \Phi(t) &= P[Z \leq t]\end{aligned}$$

$$F_X(x) = P[X \leq x] = P[\mu + \sigma Z \leq x]$$

$$= P[\sigma Z \leq x - \mu] = P[Z \leq \frac{x - \mu}{\sigma}]$$

$$= \Phi\left(\frac{x - \mu}{\sigma}\right)$$

$$\phi'(t) = \frac{1}{\sqrt{2\pi}} \cdot e^{-t^2/2}$$

$$\frac{\partial}{\partial x} F_X(x) = \frac{\partial}{\partial x} \Phi\left(\frac{x - \mu}{\sigma}\right) = \Phi'\left(\frac{x - \mu}{\sigma}\right) \cdot \frac{1}{\sigma}$$

$$f_X(x)$$

$X \sim N(\mu, \sigma^2)$

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

X Normal (Gaußsche) r.v.

$$X = \mu + \sigma Z$$

$$\boxed{\mathbb{E}[X]} = \mathbb{E}[\mu + \sigma Z]$$

$$= \mathbb{E}[\mu] + \mathbb{E}[\sigma \cdot Z]$$

$$= \mu + \sigma \mathbb{E}[Z] \stackrel{\text{def}}{=} \mu$$

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

$$X = \mu + \sigma Z$$

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$$\text{Var}[\mu + \sigma Z] = \text{Var}[\mu] + \text{Var}[\sigma Z] = \underbrace{\sigma^2}_{=\sigma^2} \text{Var}[Z]$$

1
||

Remarks :

(a) If $X \sim N(\mu, \sigma^2)$, then

$$Z = \frac{X - \mu}{\sigma} \sim N(0, 1) \quad \text{standard Normal}$$

(b) If $X \sim N(\mu, \sigma^2)$, $a, b \in \mathbb{R}$, $b \neq 0$

then $a + bX \sim N(\underbrace{a + b\mu}_{\text{mean}}, \underbrace{b^2 \sigma^2}_{\text{variance}})$

Exercise : $X, Y \sim \text{Exp}(1)$ $X \perp\!\!\! \perp Y$

$$Z = \min(X, Y)$$

$$\mathbb{E}[Z]$$

$$Z \sim \text{Exp}(2)$$

$$W = \max(X, Y)$$

$$\mathbb{E}[W]$$

$$\begin{aligned}
 F_Z(z) &= P[Z \leq z] = P[\min(X, Y) \leq z] = \\
 &= 1 - P[\underbrace{\min(X, Y) > z}_{\text{ND.}}] = 1 - P[X > z, Y > z] \\
 &= 1 - P[X > z] \cdot P[Y > z] = 1 - e^{-z} \cdot e^{-z} \\
 &= 1 - e^{-2z}
 \end{aligned}$$

$$\mathbb{E}[Z] = \frac{1}{2}$$

Remark : $X \perp\!\!\!\perp Y$, $X \sim \text{Exp}(\lambda)$, $Y \sim \text{Exp}(\mu)$

$$\min(X, Y) \sim \text{Exp}(\lambda + \mu)$$

$$W = \max(X, Y)$$

$$\begin{aligned} F_W(w) &= P[W \leq w] = P[\max(X, Y) \leq w] \\ &= P[X \leq w, Y \leq w] \stackrel{\text{IND.}}{=} \underbrace{P[X \leq w]}_{=} \cdot \underbrace{P[Y \leq w]}_{=} \end{aligned}$$

$$\Rightarrow F_W(w) = \begin{cases} 0 & w < 0 \\ (1 - e^{-\lambda w})(1 - e^{-\mu w}) = (1 - e^{-\lambda w})^2 & w \geq 0 \end{cases}$$

$$\mathbb{E}[W] = \frac{\int_0^\infty (1 - F_W(w)) dw}{\int_0^\infty F_W(w) dw}$$

$$= \int_0^{+\infty} (1 - (1 - e^{-\lambda w})^2) dw = \int_0^{+\infty} (1 - 1 + e^{-2\lambda w} + 2e^{-\lambda w}) dw$$

$$= \int_0^{+\infty} (2e^{-\lambda w} - e^{-2\lambda w}) dw = 2 \left[\frac{e^{-\lambda w}}{-\lambda} \right]_0^{+\infty} - \left[\frac{e^{-2\lambda w}}{-2\lambda} \right]_0^{+\infty}$$

$$= 2 \left[\frac{e^{-\lambda \omega}}{-\lambda} \right]_0^{+\infty} - \left[\frac{e^{-2\lambda \omega}}{-2\lambda} \right]_0^{+\infty}$$

$\omega \rightarrow +\infty$

$$= \frac{2}{\lambda} - \frac{1}{2\lambda} = \frac{3}{2\lambda}$$

$\omega = 0$

$$\mathbb{E}[\max(X, Y)] = \frac{3}{2} \cdot \frac{1}{\lambda}$$



Two generating functions

X_A

- Moment generating function

$\boxed{\frac{M}{A}}$

- Characteristic function

Scalar case (R) $X: \Omega \rightarrow \mathbb{R}$

Define

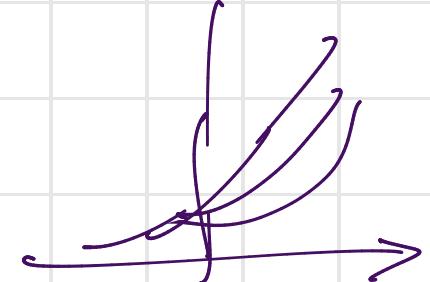
$m_X : \mathbb{R} \rightarrow [0, +\infty] = [0, +\infty) \cup \{\infty\}$

$m_X(t) := \mathbb{E}[e^{tX}]$

$\mathbb{E}[X]$
 $\mathbb{E}[X^2]$
 \vdots
 $\mathbb{E}[X^n]$

$$\mathbb{E}[g(x)] = \int_{-\infty}^{+\infty} g(x) f(x) dx$$

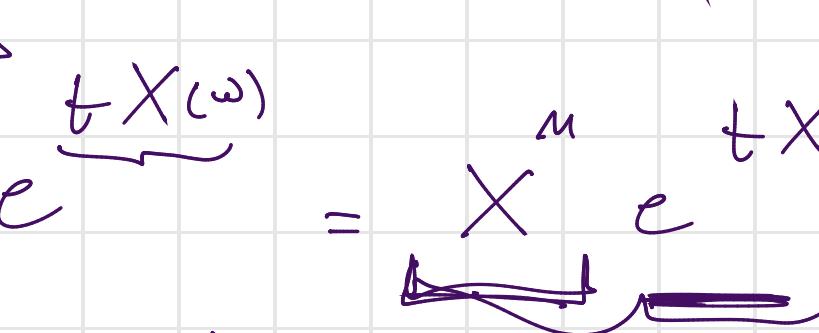
$g(x) = x$
 $g(x) = x^2$
 x^n



$$\mathbb{E}[e^{tX}]$$

m_x is called the moment generating function

Fix ω

$$\frac{d^n}{dt^n} e^{tX(\omega)} = X^n e^{tX}$$


$$m_x(t) = \frac{d^n}{dt^n} \mathbb{E}[e^{tX}] =$$

$$= \mathbb{E}\left[\frac{d^n}{dt^n} e^{tX}\right] = \mathbb{E}[X^n e^{tX}]$$

$$\left. \frac{d^n}{dt^n} m_x(t) \right|_{t=0} = \mathbb{E}[X^n]$$

$t \in \mathbb{N}$

If can be proven that this last identity is true

when are

$\exists \varepsilon > 0$ s.t.

$$\boxed{\begin{array}{l} m_X(t) < \infty \\ H(t) < \varepsilon \end{array}}$$

$$(1) \quad -\varepsilon < t < \varepsilon$$

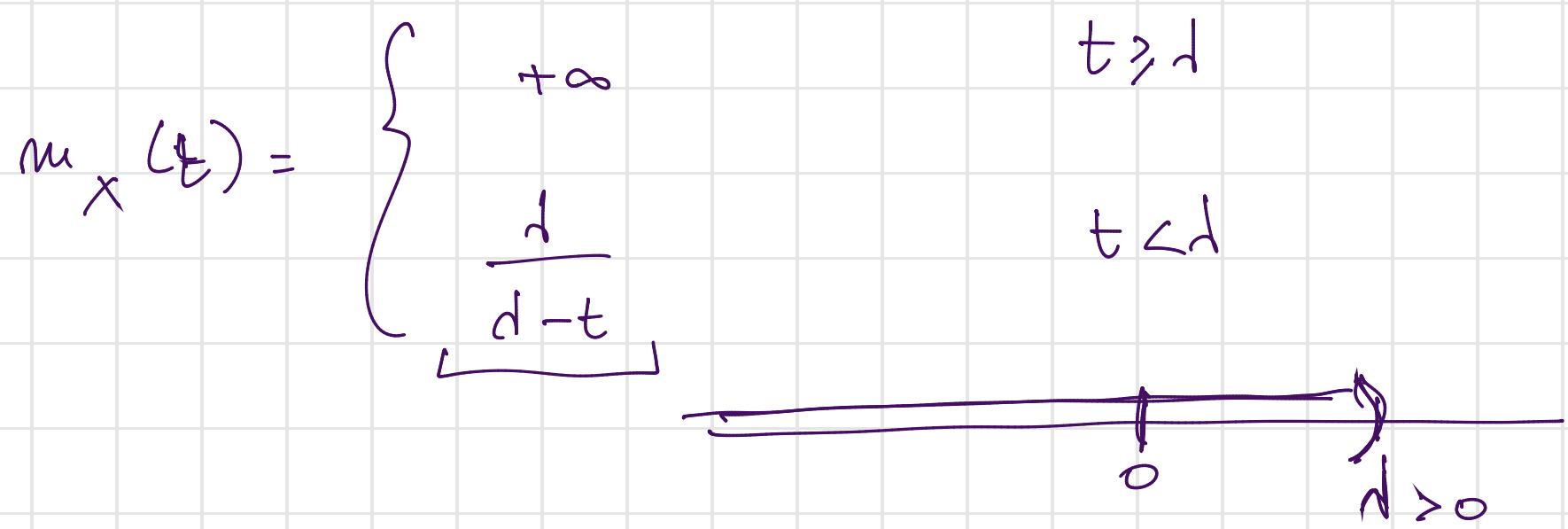
$$\frac{d^n}{dt^n} m_X(t) \Big|_{t=0} = E[X^n]$$

Example

$$X \sim \text{Exp}(d)$$

$$f_X(x) = \begin{cases} 0 & x < 0 \\ de^{-dx} & x > 0 \end{cases}$$

$$\begin{aligned} m_X(t) &= E[e^{tx}] = \int_{\mathbb{R}} e^{tx} \cdot f_X(x) dx \\ &= \int_0^{+\infty} e^{tx} \cdot d e^{-dx} dx = \int_0^{+\infty} d e^{-(d-t)x} dx \\ &= \begin{cases} +\infty & d-t \leq 0 \\ \int_0^{+\infty} d e^{-(d-t)x} dt = \frac{d}{d-t} & d-t > 0 \end{cases} \end{aligned}$$



$$m_x(t) \leftarrow \infty \quad \text{in } (-\varepsilon, \varepsilon)$$

$$\frac{d}{dt} m_x(t) \Big|_{t=0} = \mathbb{E}[X]$$

$$\frac{d}{dt} m_x(t) = \frac{d}{dt} \left(\frac{1}{d-t} \right) = (-1) \frac{d}{(d-t)^2} (-1) = \frac{1}{d^2}$$

$$\frac{d}{dt} m_x(t) \Big|_{t=0} = \frac{1}{d^2} = \frac{1}{d^2} = \mathbb{E}[X]$$

Exercise: Compute $\mathbb{E}[X^2], \mathbb{E}[X^3]$ and

prove

$$\boxed{\mathbb{E}[X^n] = \frac{n!}{d^n}}$$

If $m_x(t) < +\infty$ for $t \in (-\varepsilon, \varepsilon)$, then

$\mathbb{E}[X^n] < +\infty$ if n and $\frac{d^n}{dt^n} m_x(t) \Big|_{t=0} = \mathbb{E}[X^n]$

Exercise

Log normal distribution

$$Y \sim N(\mu, \sigma^2)$$

$$\boxed{X = e^Y}$$

$\mathbb{E}[X^n] < +\infty$ but $m_x(t) \not< +\infty$ for $t \in (-\varepsilon, \varepsilon)$

$$\mathbb{E}[X^n], m_x(t)$$

$$X \sim \text{Bin}(1, p)$$

$$X = \begin{cases} 0 & 1-p \\ 1 & p \end{cases}$$

$$m_x(t) = \mathbb{E}[e^{tX}]$$

$$\begin{aligned} m_x(t) &= e^{t \cdot 0} \cdot P[X=0] + e^{t \cdot 1} \cdot P[X=1] \\ &= 1-p + e^t \cdot p < +\infty \quad \forall t \in \mathbb{R} \end{aligned}$$

Exer.

$X \sim \text{Geo}(p)$

$m_X(t)$

$X \sim \text{Poisson}(\lambda)$

$m_X(t)$