

MGF of $X \sim U(a, b)$

$$M(t) = \mathbb{E}[e^{tx}] = \int_a^b e^{tx} f(x) dx = \int_a^b e^{tx} \frac{1}{b-a} dx$$

$$= \frac{1}{b-a} \left. \frac{1}{t} e^{tx} \right|_{x=a}^{x=b}$$

$$M(t) = \frac{e^{tb} - e^{ta}}{t(b-a)}$$

Bernoulli Distribution

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

Flip a coin, $X=1$ if H, $X=0$ if T.

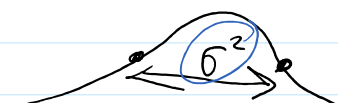
$$X \sim \text{Bin}(n=1, p)$$

Normal / Gaussian Distribution

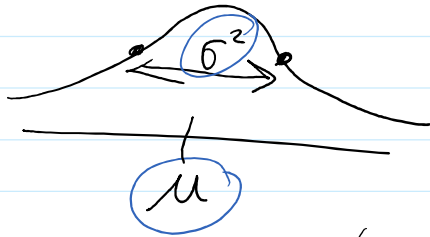
$$X \sim N(\mu, \sigma^2)$$

$\mu \in \mathbb{R}$ $\sigma^2 > 0$

PDF:



PDF:



$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) \quad \text{for } x \in \mathbb{R}$$

special case: $\mu = 0$; $\sigma^2 = 1$

Standard normal, $X \sim N(0, 1)$

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

CDF: no closed form $F(x) = \int_{-\infty}^x f(t) dt$

Claims: $EX = \mu$ and $\text{Var } X = \sigma^2$

MGF:

$$M(t) = \mathbb{E}[e^{tx}] = \int_{\mathbb{R}} e^{tx} f(x) dx$$

$$= \int_{-\infty}^{\infty} e^{tx} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) dx$$

expand

$$e^a e^b = e^{a+b}$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x^2 - 2\mu x + \mu^2 - 2\sigma^2 tx)\right) dx$$

complete the square

$$(a+b)^2 = a^2 + 2ab + b^2$$

$$x^2 - 2\mu x + \mu^2 - 2\sigma^2 t x$$

$$= x^2 - 2x(\sigma^2 t + \mu) + \mu^2$$

$$= (x - (\mu + \sigma^2 t))^2 - (\mu + \sigma^2 t)^2 + \mu^2$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2} \left[(x - (\mu + \sigma^2 t))^2 + \underbrace{\mu^2 - (\mu + \sigma^2 t)^2}_{\text{doesn't depend on } x} \right]\right) dx$$

$$= \exp\left(-(\mu + \sigma^2 t)^2 + \mu^2\right) / -2\sigma^2$$

$$\cdot \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2} (x - (\mu + \sigma^2 t))^2\right) dx$$

PDF of $N(\mu + \sigma^2 t, \sigma^2)$
integrates to 1

$$= \exp\left(-\frac{1}{2\sigma^2} [\mu^2 - (\mu + \sigma^2 t)^2]\right)$$

; algebra

$$\boxed{= \exp\left(\mu t + \frac{\sigma^2 t^2}{2}\right) = M(t)}$$

$$\left. \frac{dM}{dt} \right|_{t=0} = (\mu + \cancel{\sigma^2 t}) \exp\left(\mu \cancel{t} + \frac{\sigma^2 \cancel{t}^2}{2}\right) \Big|_{t=0}$$

$$\left. \frac{dM}{dt} \right|_{t=0} = \left. \mu \cdot \exp\left(\mu t + \frac{\sigma^2}{2} t^2\right) \right|_{t=0}$$

$$= \mu \cdot 1 = \mu = E[X]$$

$$\left. \frac{d^2 M}{dt^2} \right|_{t=0} = \sigma^2 \exp\left(\mu t + \frac{\sigma^2}{2} t^2\right) + (\mu + \sigma^2 t)^2 \exp\left(\mu t + \frac{\sigma^2}{2} t^2\right)$$

$$= \sigma^2 + \mu^2 = E[X^2]$$

so

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

$$= (\sigma^2 + \mu^2) - \mu^2 = \sigma^2 = \text{Var}(X)$$

Theorem: Linear Functions of Normal RV

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

$$Y = aX + b$$

then $Y \sim N(\underline{a\mu + b}, \underline{a^2 \sigma^2})$.

intuition: $E[Y] = aE[X] + b = a\mu + b$

$$\text{Var}(Y) = a^2 \text{Var}(X) = a^2 \sigma^2$$

of. normal L. show

in a r.v. of a r.v. of a r.v.

pf. Need to show

$$M_y(t) = \exp\left((a\mu + b)t + \frac{(a^2\sigma^2)}{2}t^2\right)$$

have this theorem:

$$M_y(t) = e^{bt} M_x(at)$$

$$= e^{bt} \exp\left(\mu(at) + \frac{\sigma^2(at)^2}{2}\right)$$

$$= \exp\left(bt + \mu at + \frac{\sigma^2 a^2 t^2}{2}\right)$$

MGF of $N(\mu, \sigma^2)$ is

$$M(t) = \exp\left(\mu t + \frac{\sigma^2 t^2}{2}\right)$$

Poisson Distribution

- discrete RV
- support of non-neg integers: $\{0, 1, 2, 3, \dots\}$

Canonical experiment:

the count of the number of "events" in some fixed time period

Ex.

- radioactive decay (in a day)
- number of fish I capture in a trap (in a day)

count the number of mRNA in a cell

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

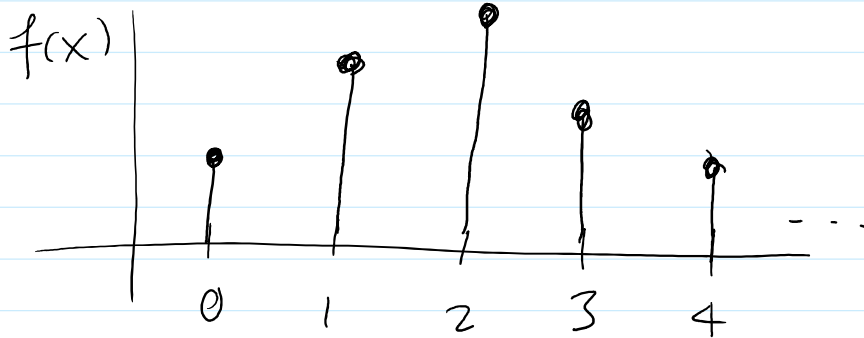
λ is the rate of events occurring

of λ in a ...

of events in a time period

PMF:

$$f(x) = \frac{e^{-\lambda} \lambda^x}{x!} \quad \text{for } x=0, 1, 2, 3, \dots$$



Expected Value:

$$E[X] = \sum_{x=0}^{\infty} x \frac{e^{-\lambda} \lambda^x}{x!} = \sum_{x=1}^{\infty} \frac{e^{-\lambda} \lambda^x}{(x-1)!}$$

$$\frac{\lambda}{x!} = \frac{\lambda}{x(x-1)!} = \frac{1}{(x-1)!}$$

$$e^x = \sum_{i=0}^{\infty} \frac{x^i}{i!}$$

$$= e^{-\lambda} \lambda \sum_{x=1}^{\infty} \frac{\lambda^{x-1}}{(x-1)!}$$

$$= e^{-\lambda} \lambda \left(\sum_{x=0}^{\infty} \frac{\lambda^x}{x!} \right) e^{\lambda}$$

$$= e^{-\lambda} \lambda e^{\lambda} = \lambda = E[X]$$

$$E[X(X-1)] = \sum_{x=0}^{\infty} x(x-1) \frac{e^{-\lambda} \lambda^x}{x!} = \sum_{x=2}^{\infty} \frac{e^{-\lambda} \lambda^x}{(x-2)!}$$

$$\begin{aligned}
 &= e^{-\lambda} \lambda^2 \sum_{x=2}^{\infty} \frac{\lambda^{x-2}}{(x-2)!} \\
 &= e^{-\lambda} \lambda^2 \left(\sum_{x=0}^{\infty} \frac{\lambda^x}{x!} \right) e^{\lambda} \\
 &= e^{-\lambda} \lambda^2 e^{\lambda} = \lambda^2 = E[X(X-1)] \\
 &= E[X^2 - X] \\
 &= E[X^2] - E[X]
 \end{aligned}$$

So

$$\begin{aligned}
 E[X^2] &= \underbrace{E[X^2] - E[X]}_{\lambda^2} + \underbrace{E[X]}_{\lambda} \\
 &= \lambda^2 + \lambda
 \end{aligned}$$

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

MGF:

$$\begin{aligned}
 M(t) &= E[e^{tx}] = \sum_{x=0}^{\infty} e^{tx} \frac{e^{-\lambda} \lambda^x}{x!} \\
 &= e^{-\lambda} \sum_{x=0}^{\infty} \frac{(\lambda e^t)^x}{x!} e^{\lambda e^t} \\
 &= e^{-\lambda} e^{\lambda e^t}
 \end{aligned}$$

$$= e^{-\lambda} e^{\lambda t}$$

$$= \exp(\lambda(e^t - 1))$$

Gamma Distribution: generalize exponential dist

Let's talk about the Gamma Function

the Gamma function
is extension of $x!$
to pos real
numbers.

$$\Gamma: \mathbb{R}^+ \rightarrow \mathbb{R}^+$$

$$\Gamma(a) = \int_0^{\infty} x^{a-1} e^{-x} dx \quad \text{for } a > 0$$

