

$$E[g(x)] = \int g(x) f_x(x) dx. \quad \text{LOTUS}.$$

$$x \sim f_x(x).$$

$$y = g(x).$$

$$y \sim \frac{f_x(x)}{\left| \frac{dy}{dx} \right|}$$

Proof.

Find CDF of  $y$ , then take derivatives

$$\begin{aligned} P(y \leq y) &= P(g(x) \leq y) \\ &= P(x \leq g^{-1}(y)) \\ &= F_x(g^{-1}(y)) = F_x(x). \end{aligned}$$

Take derivatives w.r.t  $y$ .

$$f_y(y) = f_x(x) \frac{dx}{dy}.$$

$$\int_a^b f_x(x) dx = f_y(y) dy.$$



$$T = X + Y$$

$$E[T] = E[X] + E[Y]$$

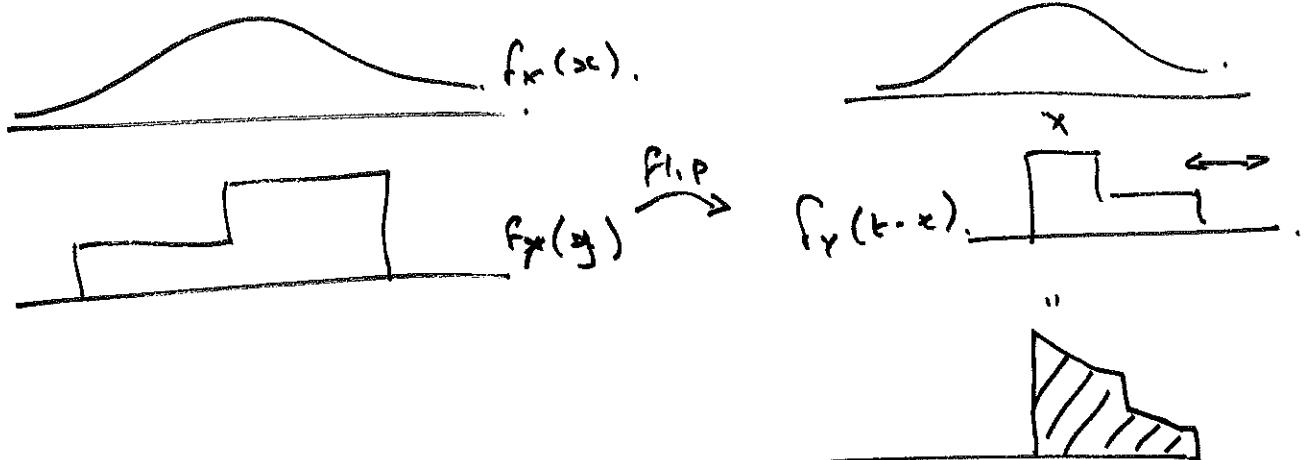
$$f_T(t) = ? \quad \text{Assume } X, Y \text{ independent.}$$

discrete case

$$P(T = t) = \sum_{x=0}^t P(X=x) P(Y=t-x)$$

continuous

$$f_t(t) = \int_{-\infty}^{\infty} f_x(x) f_y(t-x) dx \quad \text{convolution.}$$



$$CDF \quad F_T(t) = P(T \leq t)$$

$$= \int_{-\infty}^{\infty} P(X+Y \leq t | X=x) f_X(x) dx$$

LOTF.

$$= \int_{-\infty}^{\infty} P(Y \leq t-x) f_X(x) dx$$

Substitute  $X=x$  and  
drop the conditioning  
as  $X, Y$  are independent

$$F_T(t) = \int_{-\infty}^{\infty} F_Y(t-x) f_X(x) dx.$$

take derivatives w.r.t  $t$

$$f_T(t) = \int_{-\infty}^{\infty} f_X(x) f_Y(t-x) dx.$$


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Example  $X \sim N(0,1)$

$Y \sim N(0,1)$  independent.

$$T = X + Y$$

$$f_T(t) = \int_{-\infty}^{\infty} f_X(x) f_Y(t-x) dx$$

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

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2} \left[ x^2 + t^2 - 2tx + x^2 \right] \right)$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2} \left[ 2x^2 - 2tx + t^2 \right] \right) dx$$

$$2x^2 - 2tx + t^2$$

$$2 \left( x^2 - tx + \frac{t^2}{2} \right).$$

$$2 \left( (x - \frac{t}{2})^2 - \frac{t^2}{4} + \frac{t^2}{2} \right)$$

$$2 \left[ (x - \frac{t}{2})^2 + \frac{t^2}{4} \right]$$

$$f_F(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2} \times 2 \left[ (x - \frac{t}{2})^2 + \frac{t^2}{4} \right]\right) dx$$

$$= \frac{1}{2\pi} \exp\left(-\frac{t^2}{4}\right) \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2} \times 2 \left( x - \frac{t}{2} \right)^2\right) dx$$

this looks like the

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

$$\mu = \frac{t}{2}$$

$$\sigma^2 = \frac{1}{2}$$

$$\text{so } \int_{-\infty}^{\infty} \exp\left(-\frac{1}{2} \times 2 \left(x - \frac{t}{2}\right)^2\right) dx$$

$$= \frac{1}{\sqrt{2}} \sqrt{2\pi} = \sqrt{\pi}$$

$$f_T(t) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{4}\right) \times \frac{\sqrt{2\pi}}{\sqrt{2}}$$

$$= \frac{1}{\sqrt{2} \sqrt{2\pi}} \exp\left(-\frac{1}{2} \frac{t^2}{2}\right) = N(0, 2)$$

Hence the sum of two independent  $N(0, 1)$  RVs is an  $N(0, 2)$  RV.

In general, any linear combination of Normal RVs will be Normal.

$$\begin{cases} x \sim N(\mu_1, \sigma_1^2) \\ y \sim N(\mu_2, \sigma_2^2) \end{cases} \rightarrow x+y \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

variance >

Poisson.

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

$$\text{Mean} = \lambda$$

$$\text{Variance} = \lambda$$

$$E[X^2] = \sum_{k=0}^{\infty} k^2 P(X=k)$$

$$= \sum_{k=0}^{\infty} k^2 \frac{e^{-\lambda} \lambda^k}{k!}$$

left as  
exercise  
the reader

$$= \lambda^2 + \lambda$$

Binomial.

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

$$E[X^2] = \sum_{k=0}^n k^2 \binom{n}{k} p^k (1-p)^{n-k}.$$

$X$  is sum of  $n$  iid Bernoulli( $p$ ) RVs

Var of a sum of independent RVs = sum of variances of the RVs.

(Proof later)

$$X = X_1 + X_2 + X_3 + \dots + X_n$$

$$= I_1 + I_2 + I_3 + \dots + I_n \quad \begin{matrix} I_i \sim \text{iid} \\ \text{Bernoulli} \end{matrix}$$

$$X^2 = (I_1 + I_2 + \dots + I_n)(I_1 + I_2 + \dots + I_n)$$

$$= I_1^2 + I_2^2 + \dots + I_n^2$$

$$+ 2I_1I_2 + 2I_1I_3 + \dots + 2I_{n-1}I_n$$

$$E[X^2] = n E[I_i^2] + 2 \binom{n}{2} E[I_i I_j]$$

|  $\binom{n}{2}$  cross terms.  
 each  
 $I_j^2$  has  
 the same distribution

$I_i$  - indicator variable of success on 1st trial.

$I_i^2$  - takes the values 0, 1 with the same probabilities that  $I_i$  does

Expected value of an indicator RV

- prob. of the event that it is an indicator for.

$$E[I] = 0 \cdot P(I=0) + 1 \cdot P(I=1)$$

$$\Rightarrow E[I_i^2] = P$$

$$E[I_1 I_2]$$

This is an indicator for both trials being successful

- which happens with prob  $p^2$

$$E[I_1 I_2] = p^2$$

$$E[X^2] = np + n(n-1)p^2$$

$$= np + n^2p^2 - np^2$$

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

$$= np + \cancel{n^2p^2} - np^2 - \cancel{np^2}$$

$$= np - np^2$$

$$= p np(1-p)$$

$$= npq.$$

—.

What can we predict about the store based on what we have observed so far?

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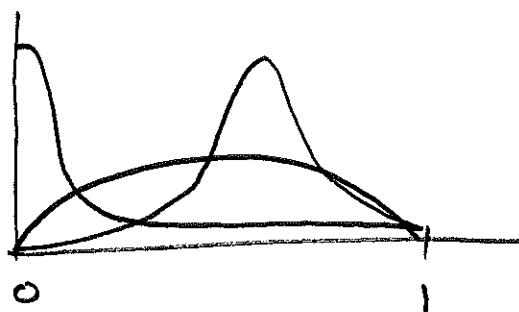
What's the probability that the sun will rise tomorrow?

Sun has risen for the last  $n$  days.

Model:  $X_1, X_2, \dots, X_n \sim \text{iid Bernoulli}(\theta)$ .

What I'm interested in is the unknown success probability  $\theta$

$\theta$  is a Random Variable  
it has a distribution  $f_\theta(\theta)$



$f_\theta(\theta)$  encodes our knowledge of the success prob. of the Bernoulli distribution

$$f_{\theta|D}(\theta | D = d)$$

parameters  
of the  
model

data that  
we have  
observed

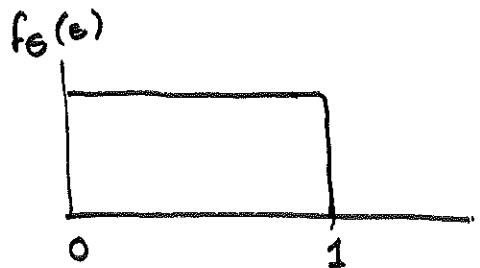
$$f_{\theta|D}(\theta | d) = \frac{f_{D|\theta}(d|\theta) f_\theta(\theta)}{f_D(d)}$$

Continuous form  
of Bayes  
theorem

$$f_D(d) = \int f_{D|\theta}(d|\theta) f_\theta(\theta) d\theta. \text{ LOTP.}$$

- thus is not a function of  $\theta$ .
  - Sometimes we ignore it, if we're interested in the shape of  $f_{\theta|D}$ .
  - sometimes we can recognize the numerator as a distribution we know about, and so we know directly how it is normalized.

Before we collect data.



$U(0,1)$  - we have no idea what values of  $\Theta$  (success probability) are likely before collecting data.

~~Ex~~  $f_{D|\theta}(d|\theta)$ .

Assume a value for the success prob.  $\Theta$ .  
what's the probability of observing the data?

$n$  successes in  $n$  trials

$$P(\text{data} | \theta) = \theta^n$$

$$P(\theta | \text{data}) \propto \theta^n = c\theta^n$$

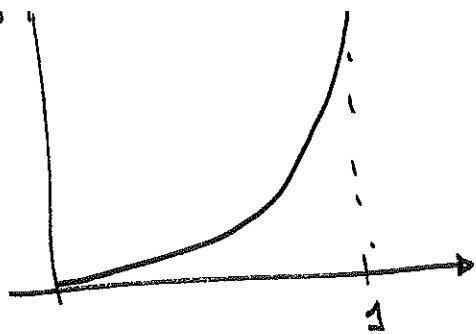
Hence  $\int_0^1 c\theta^n d\theta = 1$ .

$$c \frac{\theta^{n+1}}{n+1} \Big|_0^1 = 1$$

$$\therefore \quad \quad \quad c = n+1$$

$$p(\theta | \text{data}) = (n+1) \theta^n$$

$$f_{\theta|D}(\theta | d) = (n+1) \theta^n$$



This summarizes our knowledge of the success prob. after having observed the data.

What's the prob. that the sun will rise tomorrow?

- prob. of success on  $(n+1)^{\text{th}}$  trial, given data for 1<sup>st</sup>  $n$  trials.

$$P(X_{n+1} = 1 | X_1, X_2, \dots, X_n)$$

$$= \int_0^1 P(X_{n+1} = 1 | \theta) * f_{\theta|D}(\theta | d). d\theta.$$

LOTP.

$$= \int_0^1 \theta (n+1) \theta^n d\theta.$$

$$= \frac{n+1}{n+2}.$$

← Predictive probability.

(prob. of some unobserved events based on the event .. .. .. observed)