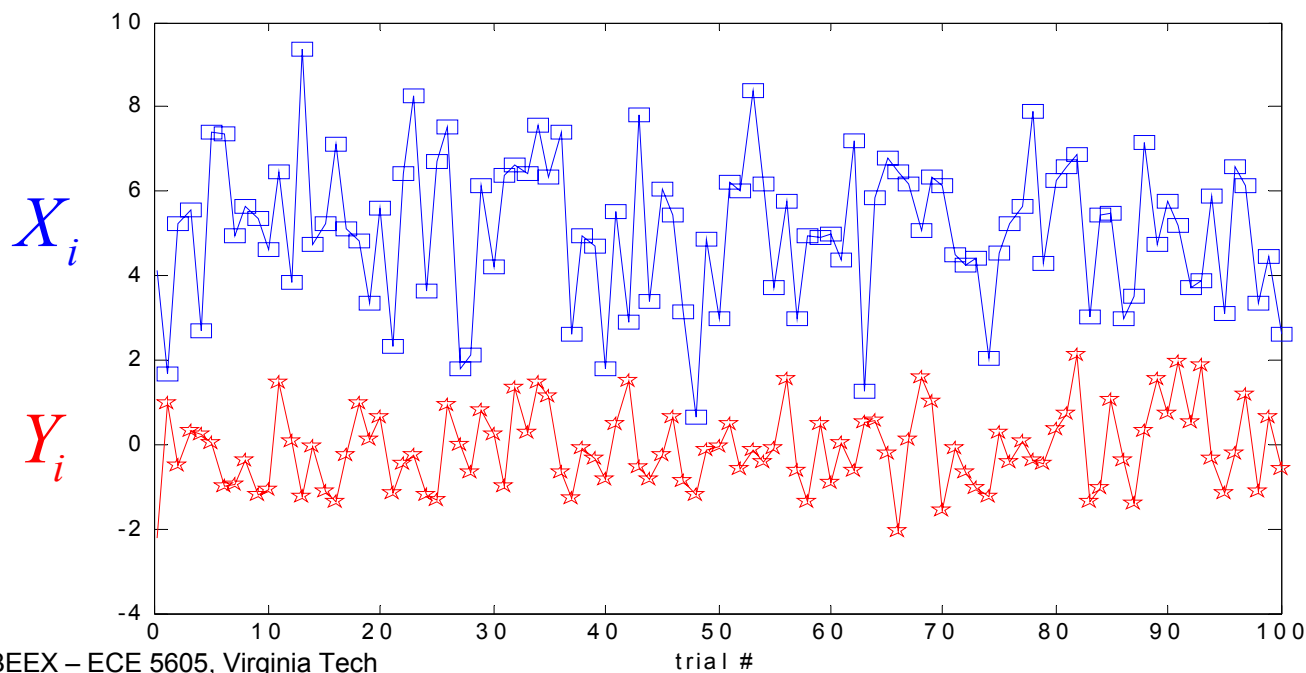


# Expected value of r.v.'s

- CDF or PDF are complete (probabilistic) descriptions of the behavior of a random variable. Sometimes we are interested in less information; in a partial characterization.



different center  
different spread

# Expected value or MEAN

$$E[X] \triangleq \int_{-\infty}^{\infty} t f_X(t) dt$$

$$E[X] \triangleq \sum_k x_k p_X(x_k)$$

defined if integral or sum converges absolutely

$$E[|X|] = \int_{-\infty}^{\infty} |t| f_X(t) dt < \infty$$

$$E[|X|] = \sum_k |x_k| p_X(x_k) < \infty$$

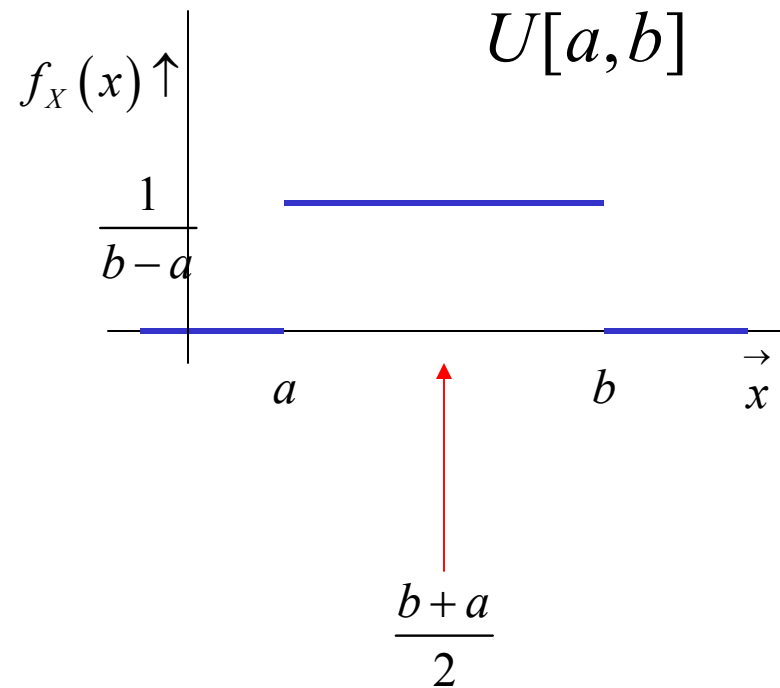
there are random variables for which the above do not converge  
we then say "the mean does not exist"

$E[X]$  represents the "center of mass"

arithmetic average of large # independent observations of a r.v.  
will tend to the mean; it's like the "average of  $X$ "

## Ex 3.29 mean of $U[a,b]$

$$\begin{aligned} E[X] &\triangleq \int_{-\infty}^{\infty} t f_X(t) dt \\ &= \int_a^b t \frac{1}{b-a} dt \\ &= \frac{b^2 - a^2}{2(b-a)} = \frac{b+a}{2} \end{aligned}$$



midpoint of interval  $[a,b]$



## Ex 3.31 mean of exponential r.v.

---

- Time  $X$  between customer arrivals at a service station has an exponential PDF with parameter  $\lambda$ . Find the mean inter-arrival time.

$$E[X] = \int_0^{\infty} \underbrace{t \lambda e^{-\lambda t}}_u dv = t e^{-\lambda t} \Big|_0^{\infty} + \int_0^{\infty} e^{-\lambda t} dt$$
$$= \lim_{t \rightarrow \infty} t e^{-\lambda t} - 0 + \frac{e^{-\lambda t}}{-\lambda} \Big|_0^{\infty} = \frac{1}{\lambda}$$

$\int u dv = uv - \int v du$

As  $\lambda$  is customer arrival rate in customers per second, the mean inter-arrival time of  $\lambda^{-1}$  seconds/customer makes sense!



## Ex 3.32 mean of geometric r.v.

- $N$  is the number of times a computer polls a terminal until the terminal has a message ready for transmission. Assuming the terminal produces messages according to a sequence of independent Bernoulli trials,  $N$  has a geometric distribution. Find the mean of  $N$ .

$$E[N] = \sum_{k=1}^{\infty} k p q^{k-1}$$

$$\sum_{k=0}^{\infty} x^k = \frac{1}{1-x} \xrightarrow{d/dx} \sum_{k=0}^{\infty} k x^{k-1} = \frac{1}{(1-x)^2}$$

$$= p \frac{1}{(1-q)^2} = \frac{1}{p}$$

if probability of “success” is  $p$ , then it makes sense that on average it takes  $p^{-1}$  trials to hit “success”

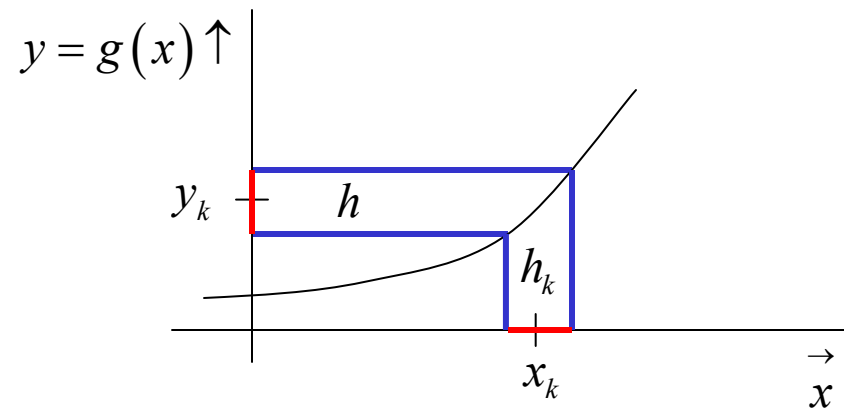
# Expected value of a function of a r.v.

$$E[Y] \triangleq \int_{-\infty}^{\infty} t f_Y(t) dt$$

alternative in terms of  $X$

$$\begin{aligned} E[Y] &\approx \sum_k y_k f_Y(y_k) h \\ &= \sum_k g(x_k) f_X(x_k) h_k \\ &= \int_{-\infty}^{\infty} g(x) f_X(x) dx \end{aligned}$$

limit  $h \rightarrow 0$



$$\Theta \sim U(0, 2\pi]$$

$$Y = a \cos(\omega t + \Theta)$$



## Ex 3.33

- Sampling a sinusoid with random phase. Find the expected value of  $Y$  and of  $Y^2$ , the power of  $Y$ .

$$\begin{aligned} E[Y] &= E[a \cos(\omega t + \Theta)] \\ &= \int_0^{2\pi} a \cos(\omega t + \theta) \frac{1}{2\pi} d\theta \\ &= \frac{-a}{2\pi} \sin(\omega t + \theta) \Big|_0^{2\pi} \\ &= \frac{-a}{2\pi} [\sin(\omega t + 2\pi) - \sin(\omega t)] = 0 \end{aligned}$$

$$\begin{aligned} E[Y^2] &= E[a^2 \cos^2(\omega t + \Theta)] \\ &= \frac{a^2}{2} E[1 + \cos(2\omega t + 2\Theta)] \\ &= \frac{a^2}{2} \left[ 1 + \int_0^{2\pi} \cos(2\omega t + 2\theta) \frac{1}{2\pi} d\theta \right] \\ &= \frac{a^2}{2} \end{aligned}$$

agreement with time-averages: "DC" value of 0, power  $a^2/2$



## Variance of $X$

- Provides information about a random variable – in addition to its mean value – regarding its deviations from the mean

$$D \triangleq X - E[X] \quad \text{deviation from the mean}$$

$$VAR[X] \triangleq E\left[\left(X - E[X]\right)^2\right]$$

$$STD[X] \triangleq \sqrt{VAR[X]}$$

measures of “width/spread”

variance of r.v.

standard deviation of r.v.

$$\begin{aligned} VAR[X] &= E\left[X^2 - 2E[X]X + E^2[X]\right] \\ &= E\left[X^2\right] - 2E[X]E[X] + E^2[X] \\ &= E\left[X^2\right] - E^2[X] \end{aligned}$$





## Ex 3.36 variance of $X \sim U[a, b]$

$$E[X] = \frac{b+a}{2}$$

$$VAR[X] = \frac{1}{b-a} \int_a^b \left( x - \frac{b+a}{2} \right)^2 dx$$

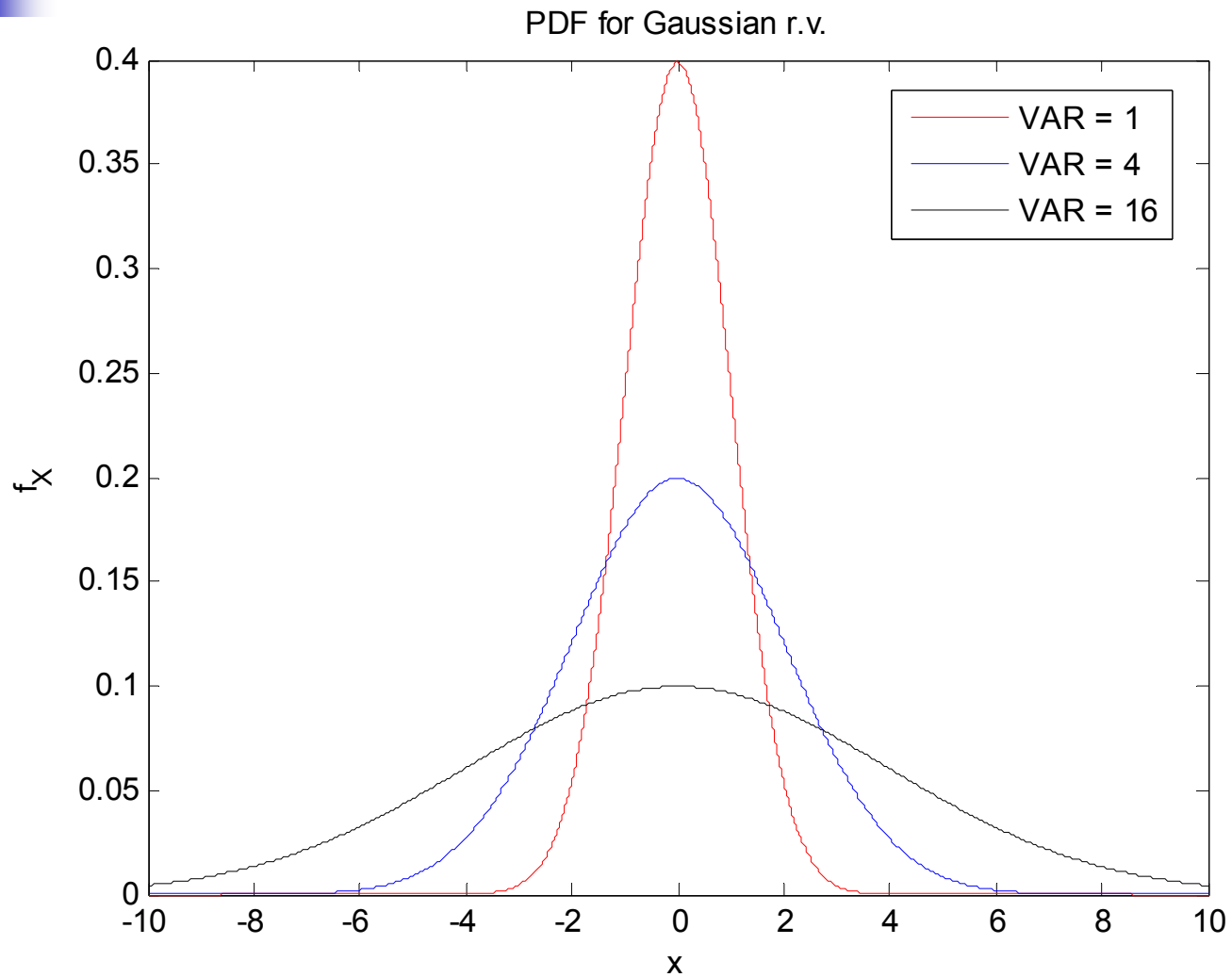
$$= \frac{1}{b-a} \int_{-(b-a)/2}^{(b-a)/2} y^2 dy = \frac{y^3}{3(b-a)} \Big|_{-(b-a)/2}^{(b-a)/2} = \frac{(b-a)^2}{12}$$

$$U[-2, 4] \rightarrow E[X] = \frac{4+(-2)}{2} = 1; VAR[X] = \frac{(4-(-2))^2}{12} = 3$$

## 3.38 variance of Gaussian r.v.

$$\begin{aligned} f_X(x) &= \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-m)^2}{2\sigma^2}} \quad -\infty < x < \infty \\ \int_{-\infty}^{\infty} f_X(x) dx &= \int_{-\infty}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-m)^2}{2\sigma^2}} dx = 1 \\ \sigma\sqrt{2\pi} &= \int_{-\infty}^{\infty} e^{-\frac{(x-m)^2}{2\sigma^2}} dx \\ \frac{d}{d\sigma} \sigma\sqrt{2\pi} &= \frac{d}{d\sigma} \int_{-\infty}^{\infty} e^{-\frac{(x-m)^2}{2\sigma^2}} dx \\ \sqrt{2\pi} &= \int_{-\infty}^{\infty} \frac{(x-m)^2}{\sigma^3} e^{-\frac{(x-m)^2}{2\sigma^2}} dx \\ \text{VAR}[X] &= \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} (x-m)^2 e^{-\frac{(x-m)^2}{2\sigma^2}} dx = \sigma^2 \end{aligned}$$

# Effect of VAR on the PDF of a Gaussian r.v.





# Mean & variance

- Are the two most important parameters for (partially) characterizing the PDF of a r.v.

- Others are sometimes used, e.g.

$$\text{skewness} \triangleq \frac{E\left[\left(X - E[X]\right)^3\right]}{\sigma^3}$$

which measures the degree of asymmetry about the mean

- *Skewness is zero for a symmetric PDF*

- Each involves  $n^{\text{th}}$  moment of r.v.  $X$ :  $E[X^n] = \int_{-\infty}^{\infty} x^n f_X(x) dx$
- $VAR[X] = E[X^2] - E^2[X]$
- Under certain conditions, a PDF is completely specified if all moments are known (more on that later)

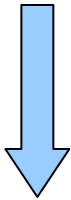
$$VAR[c] = 0 \quad VAR[X + c] = VAR[X] \quad VAR[cX] = c^2 VAR[X]$$



# Multiple r.v.'s

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- Several r.v.'s at a time
  - *Measuring different quantities simultaneously*
    - Engine oil pressure, RPM, generator voltage
  - *Repeated measurement of the same quantity*
    - Sampling a waveform, such as EEG, speech



- Joint behavior of two or more r.v.'s
  - *Independence of sets of r.v.'s*
  - *Correlation if not independent*



## Ex 4.1

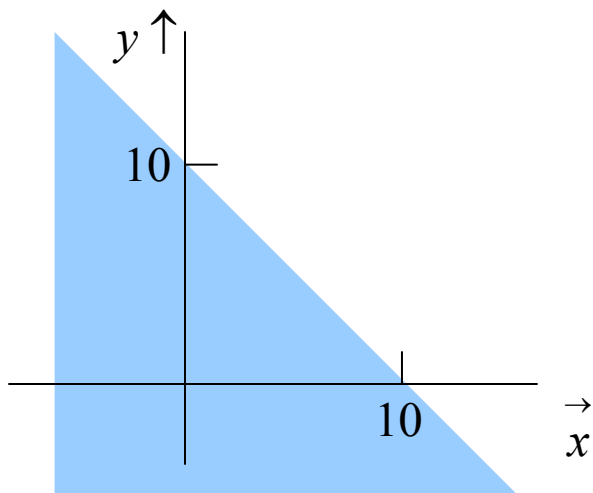
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- Let a random experiment be the selection of a student's name from an urn: outcome  $\zeta$ .
- Define the following three functions:
  - $H(\zeta) = \text{student's height, in inches}$
  - $W(\zeta) = \text{student's weight, in pounds}$
  - $A(\zeta) = \text{student's age, in years}$
- $(H(\zeta), W(\zeta), A(\zeta))$  is a vector r.v.

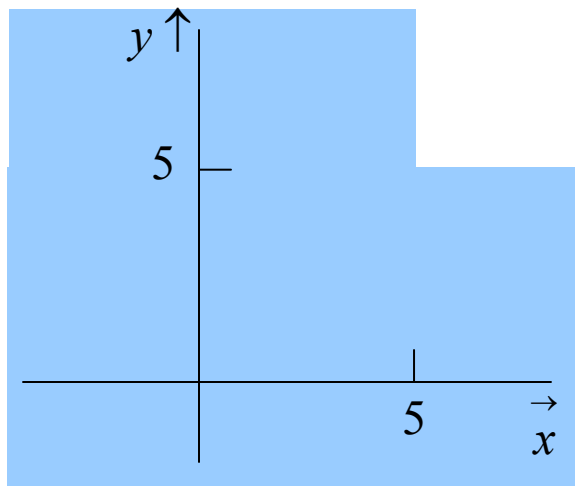
# Events & probabilities

- Each event involving an  $n$ -dimensional r.v.  $\mathbf{X}=(X_1, X_2, \dots, X_n)$  has a corresponding region in an  $n$ -dimensional real space
  - E.g. 2-D r.v.  $\mathbf{X}=(X, Y)$*

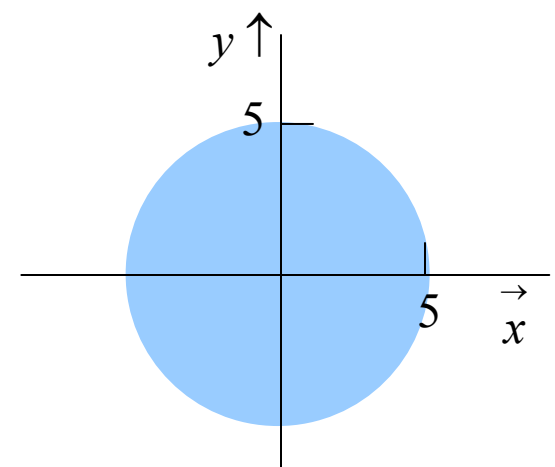
$$A = \{X + Y \leq 10\}$$



$$B = \{\min(X, Y) \leq 5\}$$



$$C = \{X^2 + Y^2 \leq 25\}$$





# Independence

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- Intuitively, if r.v.'s  $X$  and  $Y$  are “independent,” then events that involve only  $X$  should be independent of events that involve only  $Y$ . In other words, if  $A_1$  is any event that involves  $X$  only and  $A_2$  is any event that involves  $Y$  only, then

$$P[X \in A_1, Y \in A_2] = P[X \in A_1]P[Y \in A_2]$$

- In general,  $n$  r.v.'s are independent if

$$P[X_1 \in A_1, \dots, X_n \in A_n] = P[X_1 \in A_1] \cdots P[X_n \in A_n]$$

where  $A_k$  is an event that involves  $X_k$  only

if r.v.'s are independent, knowing the probabilities of the r.v.'s in isolation suffices to specify probabilities of joint events





## Pairs of discrete r.v.'s

vector r.v.  $\mathbf{X} = (X, Y)$

$$S = \left\{ (x_j, y_k), j = 1, 2, \dots, k = 1, 2, \dots \right\}$$

joint probability mass function:

$$p_{X,Y}(x_j, y_k) = P\left[\{X = x_j\} \cap \{Y = y_k\}\right]$$

$$\triangleq P\left[X = x_j, Y = y_k\right] \quad j = 1, 2, \dots \quad k = 1, 2, \dots$$

gives probability of occurrence of pairs  $(x_j, y_k)$

For any event  $A$ : 
$$P[\mathbf{X} \in A] = \sum_{(x_j, y_k) \in A} \sum p_{X,Y}(x_j, y_k)$$

$$\sum_{j=1}^{\infty} \sum_{k=1}^{\infty} p_{X,Y}(x_j, y_k) = P[S] = 1$$



# Marginal PMF's

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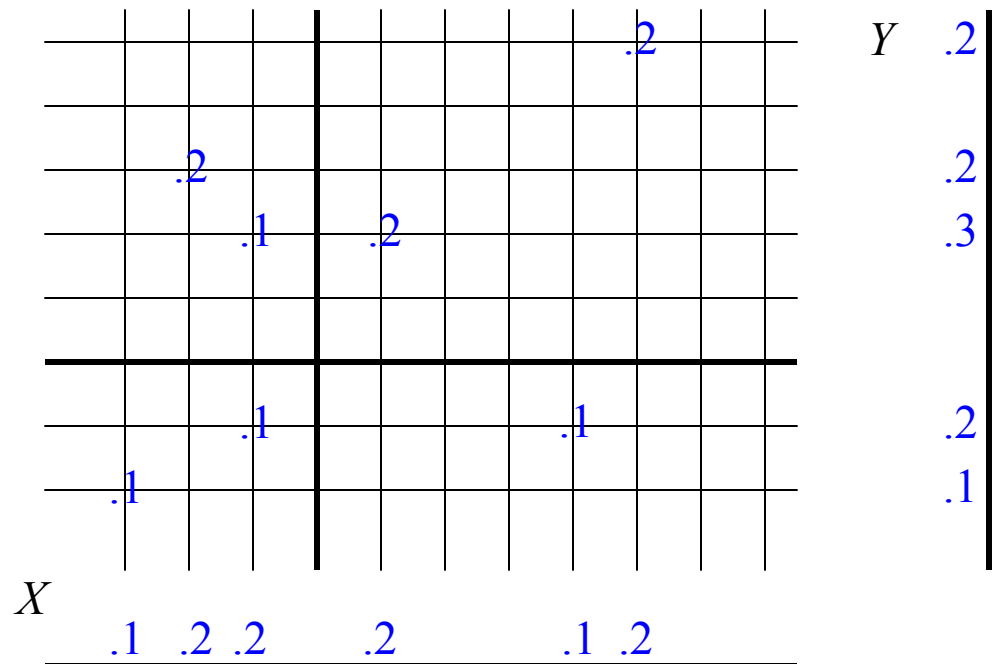
$$p_X(x_j) = p_{X,Y}(x_j, \text{any } y_k)$$

$$= P\left[\left\{\{X = x_j\} \cap \{Y = y_1\}\right\} \cup \left\{\{X = x_j\} \cap \{Y = y_2\}\right\} \cup \dots\right]$$

$$= \sum_{k=1}^{\infty} p_{X,Y}(x_j, y_k)$$

$$p_Y(y_k) = \sum_{j=1}^{\infty} p_{X,Y}(x_j, y_k)$$

**marginal PMF's are  
insufficient – in general -  
for specifying joint PMF**



# Ex 4.6 tossing loaded dice

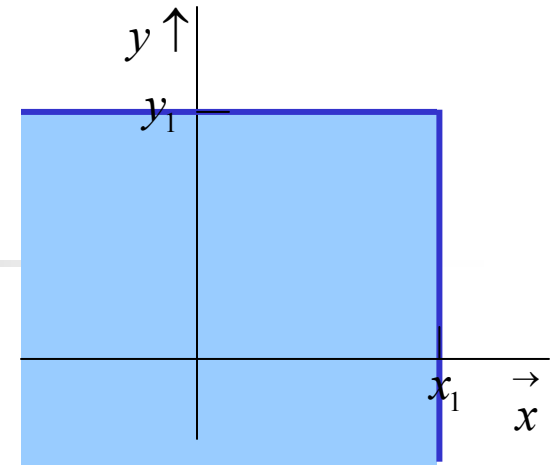
joint PMF in units of  $\frac{1}{42}$

$j \backslash k$	1	2	3	4	5	6			
1	2	1	1	1	1	1	}	7	1
2	1	2	1	1	1	1		7	1
3	1	1	2	1	1	1		7	1
4	1	1	1	2	1	1		7	1
5	1	1	1	1	2	1		7	1
6	1	1	1	1	1	2		7	1
	}							7	1
	7	7	7	7	7	7		42	6
	1	1	1	1	1	1			

marginals give no clue

# Joint CDF of $X$ and $Y$

- Basic building block:



semi-infinite rectangle:  $\{(x, y) : \{x \leq x_1\} \cap \{y \leq y_1\}\}$

joint cumulative distribution function of  $X$  and  $Y$ :

$$\begin{aligned} F_{X,Y}(x_1, y_1) &= P[\{x \leq x_1\} \cap \{y \leq y_1\}] && \text{product-form event} \\ &= P[X \leq x_1, Y \leq y_1] \end{aligned}$$

long-term proportion of times in which the outcome  $(x, y)$  falls in the blue rectangle, or the probability mass in it



# properties of the joint CDF

i.  $F_{X,Y}(x_1, y_1) \leq F_{X,Y}(x_2, y_2) \quad x_1 \leq x_2, y_1 \leq y_2$   
non-decreasing in NE direction

ii.  $F_{X,Y}(-\infty, y_1) = F_{X,Y}(x_2, -\infty) = 0$   
neither  $X$  nor  $Y$  takes on values  $< -\infty$

iii.  $F_{X,Y}(\infty, \infty) = 1$   
 $X$  and  $Y$  can take on only values  $< \infty$

iv.  $F_X(x) = F_{X,Y}(x, \infty) = P[X \leq x, Y < \infty] = P[X \leq x]$

$$F_Y(y) = F_{X,Y}(\infty, y) = P[X < \infty, Y \leq y] = P[Y \leq y]$$

marginal cumulative distribution functions

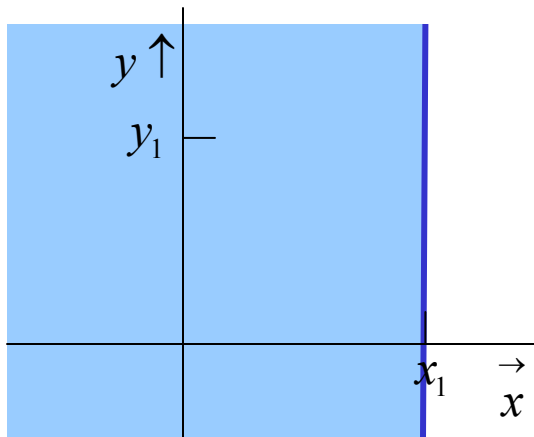
v.  $\lim_{x \rightarrow a^+} F_{X,Y}(x, y) = F_{X,Y}(a, y)$

$$\lim_{y \rightarrow b^+} F_{X,Y}(x, y) = F_{X,Y}(x, b)$$

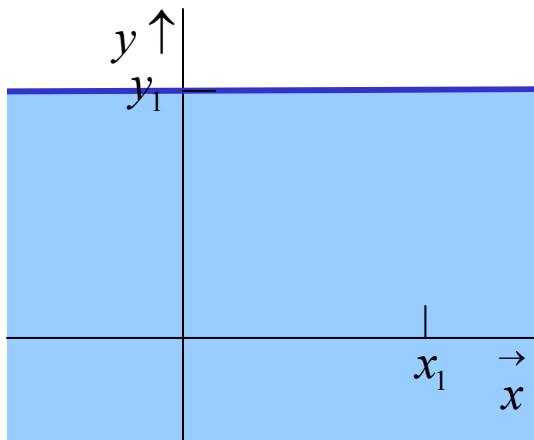
continuous from N & E

## Ex 4.8 marginals for continuous joint r.v.'s

$$\text{Given } F_{X,Y}(x, y) = (1 - e^{-\alpha x})(1 - e^{-\beta y})u(x)u(y)$$



$$F_X(x) = \lim_{y \rightarrow \infty} F_{X,Y}(x, y) = (1 - e^{-\alpha x})u(x)$$



$$F_Y(y) = \lim_{x \rightarrow \infty} F_{X,Y}(x, y) = (1 - e^{-\beta y})u(y)$$

marginal CDFs are exponential distributions with parameters  $\alpha$  and  $\beta$  respectively

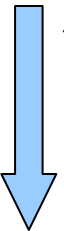


# Joint CDF in terms of joint PDF & v.v.

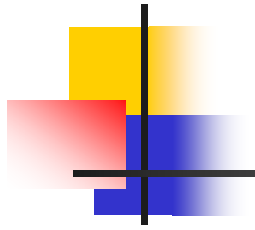
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$$F_{X,Y}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{X,Y}(x', y') dx' dy'$$

if jointly continuous r.v.'s


$$f_{X,Y}(x, y) = \frac{\partial^2 F_{X,Y}(x, y)}{\partial x \partial y}$$

if the CDF is discontinuous  
- or the partial derivatives are discontinuous -  
then the joint PDF does not exist



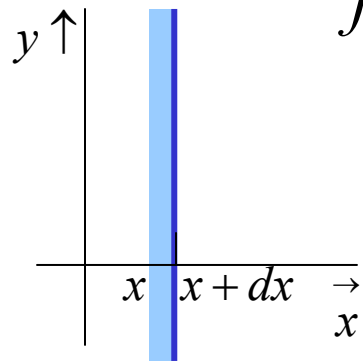
$$A = \{(x, y) : a_1 < x \leq b_1 ; a_2 < y \leq b_2\}$$

$$P[a_1 < X \leq b_1, a_2 < Y \leq b_2] = \int_{a_1}^{b_1} \int_{a_2}^{b_2} f_{X,Y}(x', y') dx' dy'$$

$$P[x < X \leq x + dx, y < Y \leq y + dy] = \int_x^{x+dx} \int_y^{y+dy} f_{X,Y}(x', y') dx' dy'$$
$$\approx f_{X,Y}(x, y) dx dy$$

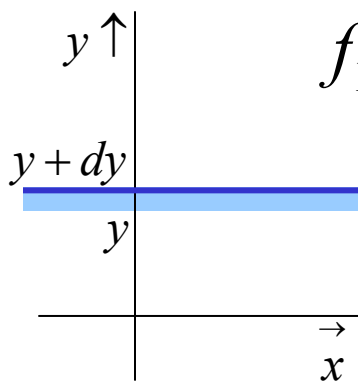


# Marginal PDF's from joint PDF



$$f_X(x) = \frac{d}{dx} F_{X,Y}(x, \infty) = \frac{d}{dx} \int_{-\infty}^x \left\{ \int_{-\infty}^{\infty} f_{X,Y}(x', y') dy' \right\} dx'$$

$$= \int_{-\infty}^{\infty} f_{X,Y}(x, y') dy' \quad \text{concentrating mass on x-axis}$$



$$f_Y(y) = \frac{d}{dy} F_{X,Y}(\infty, y) = \int_{-\infty}^{\infty} f_{X,Y}(x', y) dx'$$

concentrating mass on y-axis

marginal PDF's are obtained by integrating out the other variable(s)

$$f_{X,Y}(x,y) \equiv \begin{cases} 1 & (x,y) \in [0,1] \times [0,1] \\ 0 & \text{o.w.} \end{cases}$$

## Ex 4.10 CDF for jointly uniform r.v.'s

$$F_{X,Y}(x,y) = \int_{-\infty}^x \int_{-\infty}^y f_{X,Y}(x',y') dx' dy'$$

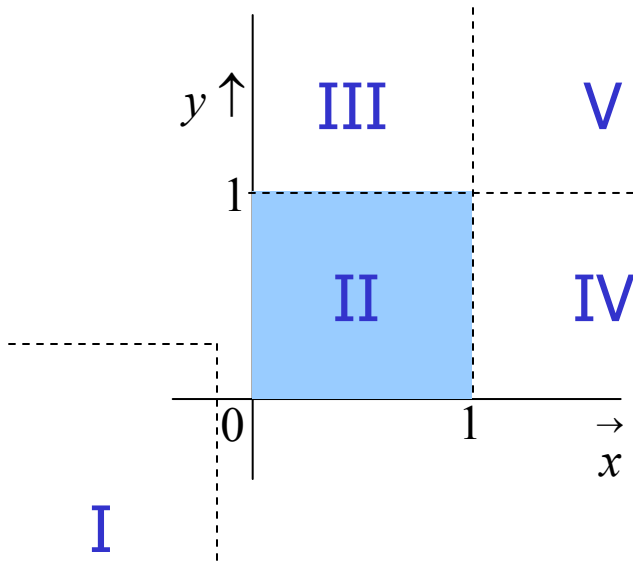
$$= 0 \quad \text{for } (x,y) \in I$$

$$= \int_0^x \int_0^y 1 dx' dy' = xy \quad \text{for } (x,y) \in II$$

$$= \int_0^x \int_0^1 1 dx' dy' = x \quad \text{for } (x,y) \in III$$

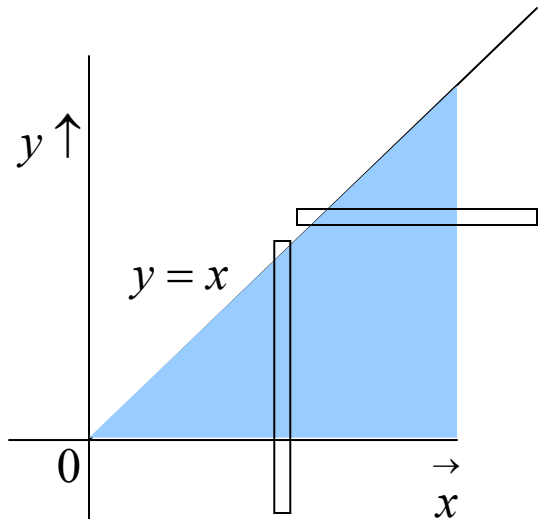
$$= \int_0^1 \int_0^y 1 dx' dy' = y \quad \text{for } (x,y) \in IV$$

$$= \int_0^1 \int_0^1 1 dx' dy' = 1 \quad \text{for } (x,y) \in V$$



## Ex 4.11 finding marginal PDF's

$$f_{X,Y}(x,y) = \begin{cases} ce^{-x}e^{-y} & 0 \leq y \leq x < \infty \\ 0 & \text{o.w.} \end{cases}$$



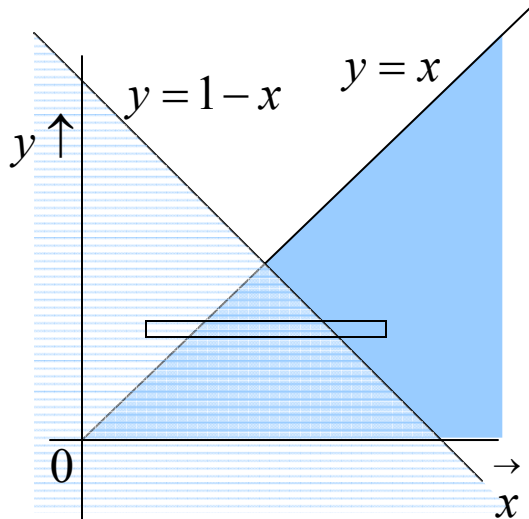
$$\begin{aligned} 1 &= \int_0^{\infty} \int_0^x ce^{-x}e^{-y} dy dx = \int_0^{\infty} ce^{-x} \int_0^x e^{-y} dy dx \\ &= \int_0^{\infty} ce^{-x} \frac{e^{-x} - 1}{-1} dx = \frac{c}{2} \Rightarrow c = 2 \end{aligned}$$

$$f_X(x) = \int_0^x 2e^{-x}e^{-y} dy = 2e^{-x}(1 - e^{-x}) \quad 0 \leq x < \infty$$

$$f_Y(y) = \int_y^{\infty} 2e^{-x}e^{-y} dx = 2e^{-y}(e^{-y}) = 2e^{-2y} \quad 0 \leq y < \infty$$

are these PDF's?

## Ex 4.12 Find $P[X + Y \leq 1]$ in EX 4.11



$$\begin{aligned} P[X + Y \leq 1] &= \int_0^{0.5} \int_y^{1-y} 2e^{-x} e^{-y} dx dy \\ &= \int_0^{0.5} 2e^{-y} \int_y^{1-y} e^{-x} dx dy \\ &= \int_0^{0.5} 2e^{-y} \left[ e^{-y} - e^{-(1-y)} \right] dy \\ &= -e^{-1} + 1 - e^{-1} = 1 - 2e^{-1} \end{aligned}$$

# Ex 4.13 Find marginal PDFs of jointly Gaussian PDF

$$f_{X,Y}(x,y) = \frac{1}{2\pi\sqrt{1-\rho^2}} e^{-\frac{(x^2-2\rho xy+y^2)}{2(1-\rho^2)}}$$

$$f_X(x) = \frac{e^{-\frac{x^2}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}} \int_{-\infty}^{\infty} e^{-\frac{(-2\rho xy+y^2)}{2(1-\rho^2)}} dy$$

completing the square

$$= \frac{e^{-\frac{x^2(1-\rho^2)}{2(1-\rho^2)}}}{2\pi\sqrt{1-\rho^2}} \int_{-\infty}^{\infty} e^{-\frac{(\rho^2 x^2 - 2\rho xy + y^2)}{2(1-\rho^2)}} dy$$

$$= \frac{e^{-x^2/2}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \frac{1}{\sqrt{1-\rho^2} \sqrt{2\pi}} e^{-\frac{(y-\rho x)^2}{2(1-\rho^2)}} dy = \frac{e^{-x^2/2}}{\sqrt{2\pi}} = N(0,1)$$

it's a PDF

symmetry

$$f_Y(y) = f_X(x)$$



# Independence of two r.v.'s

---

discrete r.v.'s  $X$  and  $Y$  are independent

⇔ iff

joint PMF is product of marginal PMFs

$$\forall x_j, y_k$$

# Ex 4.15 another look at Ex 4.6 loaded dice

joint PMF in units of  $\frac{1}{42}$

$j \backslash k$	1	2	3	4	5	6		
1	2	1	1	1	1	1	}	
2	1	2	1	1	1	1		1
3	1	1	2	1	1	1		1
4	1	1	1	2	1	1		1
5	1	1	1	1	2	1		1
6	1	1	1	1	1	2		1
	}						1	
	1	1	1	1	1	1	/6	

marginals give no clue

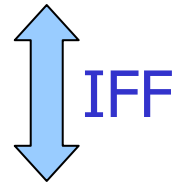
not independent

$$p_{X,Y}(x_j, y_k) \neq p_X(x_j) p_Y(y_k) \quad \forall x_j, y_k$$



# Independence of two r.v.'s in general

---



$$p_{X,Y}(x_j, y_k) = p_X(x_j) p_Y(y_k) \quad \forall x_j, y_k \quad \text{discrete}$$

$$F_{X,Y}(x, y) = F_X(x) F_Y(y) \quad \forall x, y$$

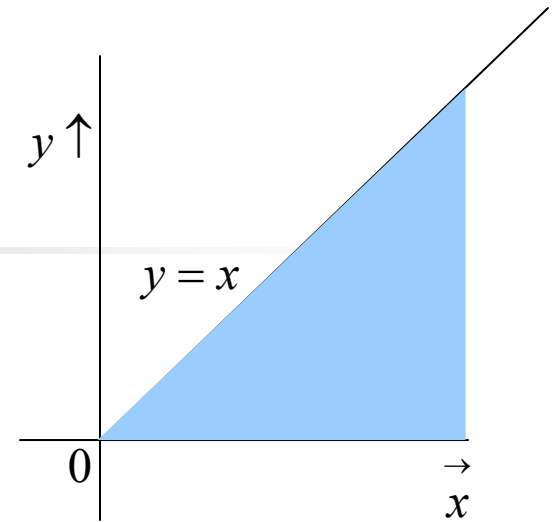
$$f_{X,Y}(x, y) = f_X(x) f_Y(y) \quad \forall x, y \quad \text{jointly continuous}$$



## Ex 4.17 back to Ex 4.11

joint

$$f_{X,Y}(x,y) = \begin{cases} 2e^{-x}e^{-y} & 0 \leq y \leq x < \infty \\ 0 & \text{o.w.} \end{cases}$$



$$f_X(x) = \int_0^x 2e^{-x}e^{-y} dy = 2e^{-x}(1 - e^{-x}) \quad 0 \leq x < \infty$$

marginal PDFs

$$f_Y(y) = \int_y^\infty 2e^{-x}e^{-y} dx = 2e^{-y}(e^{-y}) = 2e^{-2y} \quad 0 \leq y < \infty$$

product?  $2e^{-x}e^{-y} \neq 2e^{-x}(1 - e^{-x})2e^{-2y}$

**X and Y are not independent**



## Ex 4.18 back to Ex 4.13

$$\left. \begin{aligned} f_{X,Y}(x,y) &= \frac{1}{2\pi\sqrt{1-\rho^2}} e^{-\frac{(x^2-2\rho xy+y^2)}{2(1-\rho^2)}} \\ f_X(x) &= \frac{e^{-x^2/2}}{\sqrt{2\pi}} & f_Y(y) &= \frac{e^{-y^2/2}}{\sqrt{2\pi}} \\ f_X(x)f_Y(y) &= \frac{e^{-x^2/2}}{\sqrt{2\pi}} \frac{e^{-y^2/2}}{\sqrt{2\pi}} = \frac{e^{-\frac{(x^2+y^2)}{2}}}{2\pi} \end{aligned} \right\} \equiv \text{iff } \rho = 0$$



# Conditional probability

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- Many r.v.'s are not independent, such as when measuring one variable to learn about another one, or when sampling slowly relative to the rate of change of a signal.
- We're then interested in the probability of an event related to  $Y$ , given the knowledge of  $X=x$  (a measurement)
- We'll see that  $E[Y|X=x]$  is of significance also

# Conditional probability

$$P[Y \in A | X = x] = \frac{P[Y \in A, X = x]}{P[X = x]}$$

$X$  discrete

$$F_Y(y | x_k) = \frac{P[Y \leq y, X = x_k]}{P[X = x_k]} \text{ for } P[X = x_k] > 0$$

if derivative exists

$$f_Y(y | x_k) = \frac{d}{dy} F_Y(y | x_k)$$

independence

$$F_Y(y | x) = F_Y(y)$$

$$f_Y(y | x) = f_Y(y)$$

$$P[Y \in A | X = x_k] = \int_{y \in A} f_Y(y | x_k) dy$$

# Conditional probability

$$P[Y \in A | X = x] = \frac{P[Y \in A, X = x]}{P[X = x]}$$

$X$  and  $Y$  discrete

$$p_Y(y_j | x_k) = P[Y = y_j | X = x_k] = \frac{P[X = x_k, Y = y_j]}{P[X = x_k]}$$

$\delta$  functions  
 $\sim$  PMF weights

$$= \begin{cases} \frac{p_{X,Y}(x_k, y_j)}{p_X(x_k)} & \text{for } P[X = x_k] = p_X(x_k) > 0 \\ 0 & \text{for } P[X = x_k] = p_X(x_k) = 0 \end{cases}$$

in general

$$P[Y \in A | X = x_k] = \sum_{y_j \in A} p_Y(y_j | x_k) = \sum_{y_j \in A} p_Y(y_j)$$

if also independent



## Ex 4.20 back to Ex 4.14

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- $X$  is the input and  $Y$  the output of a communication channel.  $P[Y < 0 | X = +1]$ ?

$$f_Y(y|1) \sim U[-1, 3] \implies P[Y < 0 | X = +1] = \int_{-1}^0 \frac{1}{4} dy = \frac{1}{4}$$

integrate over event



# Conditional CDF of $Y$ given $X=x$

$$F_Y(y | x) \triangleq \lim_{h \rightarrow 0} F_Y(y | x < X \leq x + h)$$

$$= \frac{P[Y \leq y, x < X \leq x + h]}{P[x < X \leq x + h]} = \frac{\int_{-\infty}^y \int_x^{x+h} f_{X,Y}(x', y') dx' dy'}{\int_x^{x+h} f_X(x') dx'}$$

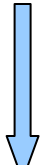
$$\simeq \frac{h \int_{-\infty}^y f_{X,Y}(x, y') dy'}{h f_X(x)} = \frac{\int_{-\infty}^y f_{X,Y}(x, y') dy'}{f_X(x)}$$

$$= \int_{-\infty}^y f_Y(y') dy' = F_Y(y) \quad \text{if independent}$$



# Conditional PDF of $Y$ given $X=x$


$$F_Y(y|x) = \frac{\int_{-\infty}^y f_{X,Y}(x, y') dy'}{f_X(x)}$$


$$f_Y(y|x) = \frac{d}{dy} F_Y(y|x) = \frac{f_{X,Y}(x, y)}{f_X(x)}$$

almost Bayes' rule

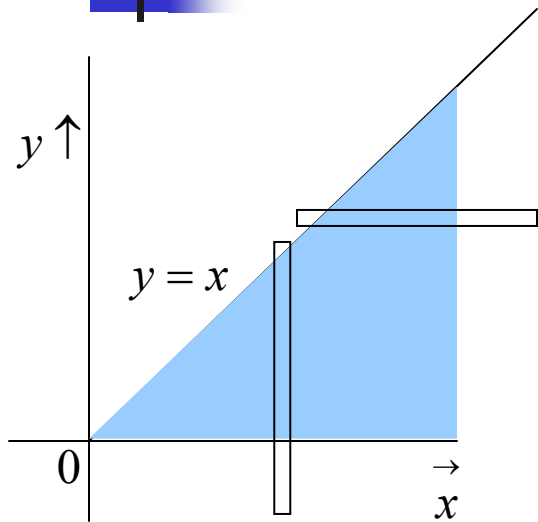
$$f_Y(y|x) dy = \frac{f_{X,Y}(x, y) dx dy}{f_X(x) dx}$$

if independent


$$f_Y(y|x) = f_Y(y)$$



## Ex 4.21 back to Ex 4.11



$$f_{X,Y}(x,y) = \begin{cases} ce^{-x}e^{-y} & 0 \leq y \leq x < \infty \\ 0 & \text{o.w.} \end{cases}$$

$$f_X(x) = 2e^{-x}(1 - e^{-x}) \quad 0 \leq x < \infty$$

$$f_Y(y) = 2e^{-2y} \quad 0 \leq y < \infty$$

$$f_X(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)} = \frac{2e^{-x}e^{-y}}{2e^{-2y}} = e^{-(x-y)}; y \leq x < \infty$$

$$f_Y(y|x) = \frac{f_{X,Y}(x,y)}{f_X(x)} = \frac{2e^{-x}e^{-y}}{2e^{-x}(1 - e^{-x})} = \frac{e^{-y}}{1 - e^{-x}}; 0 \leq y < x$$