

Review:

§ 3.5 Location and Scale Families

- Location families: $f(x - \mu) \leftarrow$ wherever x in pdf subtract μ .

$$\text{example: } N(\mu, 1) \quad f(x | \mu, \sigma=1) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}(x-\mu)^2\right) * I_{(-\infty, \infty)}^{(x)}$$

- Scale families: $\frac{1}{\sigma} f\left(\frac{x}{\sigma}\right) \leftarrow$ wherever x in pdf divided by σ .
+ extra $(\frac{1}{\sigma})$ out front.

$$\text{example: } N(0, \sigma^2) \quad f(x | \mu=0, \sigma^2) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma} \exp\left(-\frac{1}{2}\left(\frac{x}{\sigma}\right)^2\right) * I_{(-\infty, \infty)}^{(x)}$$

- Location-Scale families: $\frac{1}{\sigma} f\left(\frac{x-\mu}{\sigma}\right) \leftarrow$ x in pdf, μ subtract σ divide $\frac{1}{\sigma}$ out front.

$$\text{example: } N(\mu, \sigma^2) \quad f(x | \mu, \sigma^2) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma} \exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right) * I_{(-\infty, \infty)}^{(x)}$$

- Location, Scale, Location-Scale generated from a standard pdf

$$\text{example: } f(x | \mu=0, \sigma^2=1) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

\uparrow
 $\mu=0, \sigma=1$
 /
 location shift scale shift

Theorem 3.5.1 Let $f(x)$ be any pdf and let μ and $\sigma > 0$ be any given constants. Then the function

$$g(x | \mu, \sigma) = \frac{1}{\sigma} f\left(\frac{x-\mu}{\sigma}\right)$$

is a pdf.

ReviewLocation Family: $f(x-\mu)$

Definition 3.5.2 Let $f(x)$ be any pdf. Then the family of pdfs $f(x - \mu)$, indexed by the parameter μ , $-\infty < \mu < \infty$, is called the *location family with standard pdf* $f(x)$ and μ is called the *location parameter* for the family.

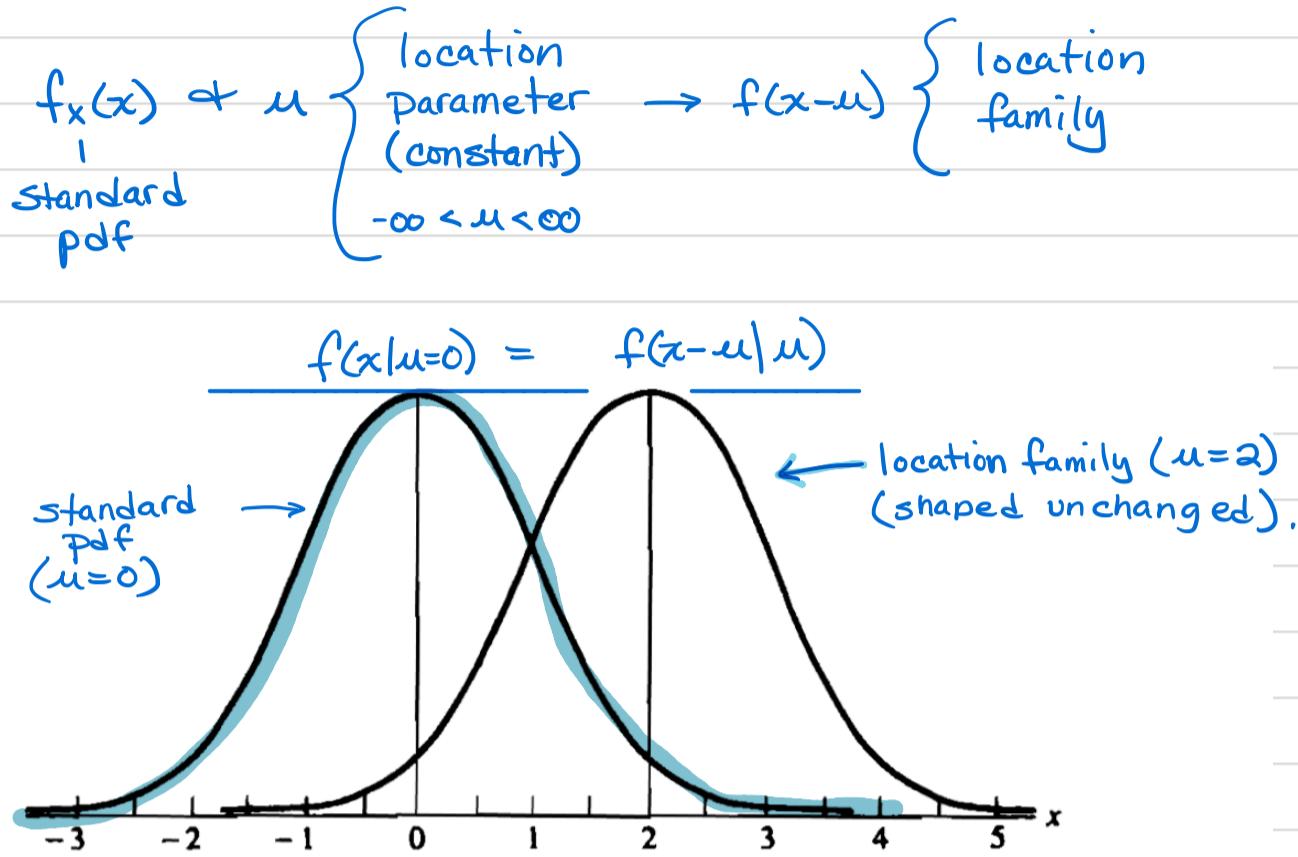


Figure 3.5.1. Two members of the same location family: means at 0 and 2
(same shape - shifted right by $\mu=2$)
 $f(x-\mu) = f(x)$

Scale family $\frac{1}{\sigma} f(\frac{x}{\sigma})$

Definition 3.5.4 Let $f(x)$ be any pdf. Then for any $\sigma > 0$, the family of pdfs $(1/\sigma)f(x/\sigma)$, indexed by the parameter σ , is called the *scale family with standard pdf* $f(x)$ and σ is called the *scale parameter* of the family.

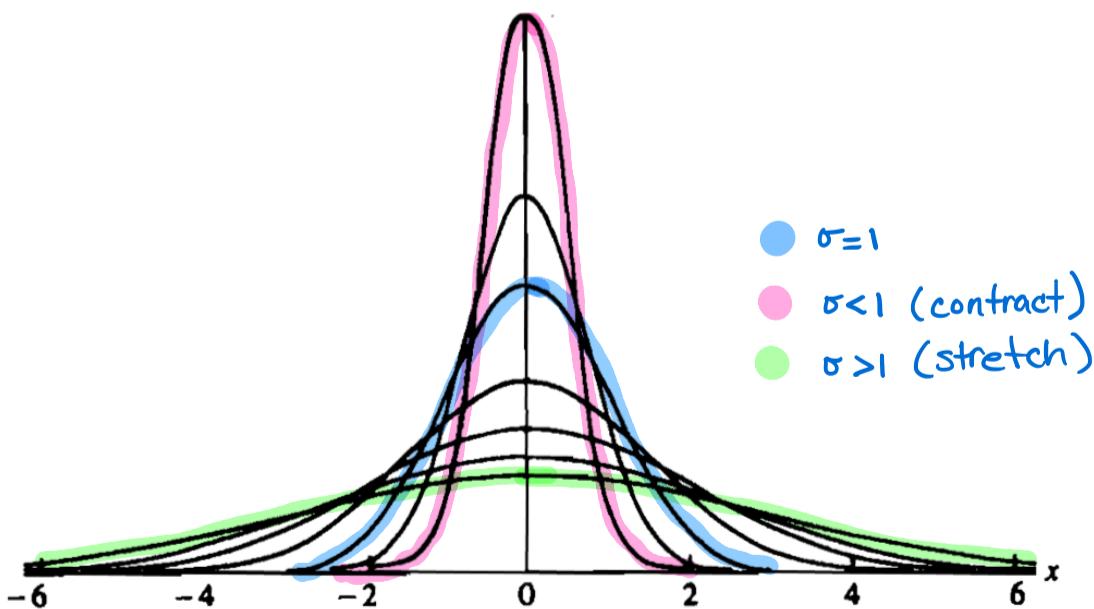


Figure 3.5.3. Members of the same scale family

Location-scale family

$$\frac{1}{\sigma} f\left(\frac{x-\mu}{\sigma}\right)$$

Definition 3.5.5 Let $f(x)$ be any pdf. Then for any μ , $-\infty < \mu < \infty$, and any $\sigma > 0$, the family of pdfs $(1/\sigma)f((x - \mu)/\sigma)$, indexed by the parameter (μ, σ) , is called the *location-scale family with standard pdf $f(x)$* ; μ is called the *location parameter* and σ is called the *scale parameter*.

Location-Scale cont.

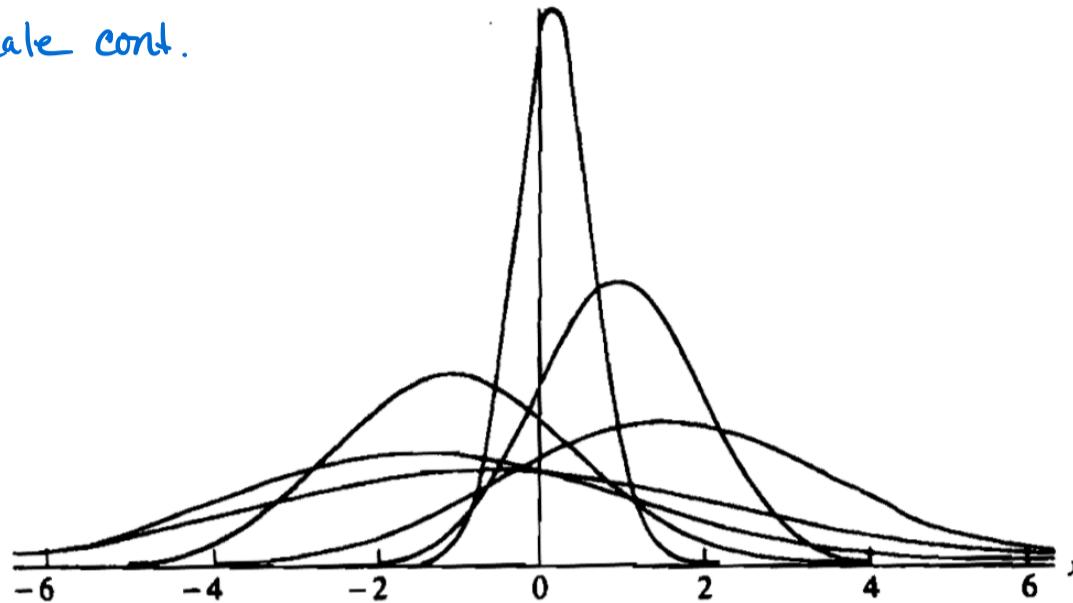


Figure 3.5.4. Members of the same location-scale family

Theorem 3.5.6 Let $f(\cdot)$ be any pdf. Let μ be any real number, and let σ be any positive real number. Then X is a random variable with pdf $(1/\sigma)f((x - \mu)/\sigma)$ if and only if there exists a random variable Z with pdf $f(z)$ and $X = \sigma Z + \mu$.

$$f_X(x) = \frac{1}{\sigma} f\left(\frac{(x-\mu)}{\sigma}\right) \stackrel{\text{iff}}{\Rightarrow} f(z) \text{ and } X = \sigma Z + \mu$$

Z standard dist'n : $\mu=0, \sigma=1$

Theorem 3.5.7 Let Z be a random variable with pdf $f(z)$. Suppose EZ and $\text{Var } Z$ exist. If X is a random variable with pdf $(1/\sigma)f((x - \mu)/\sigma)$, then

$$EX = \sigma EZ + \mu \quad \text{and} \quad \text{Var } X = \sigma^2 \text{Var } Z.$$

In particular, if $EZ = 0$ and $\text{Var } Z = 1$, then $EX = \mu$ and $\text{Var } X = \sigma^2$.

convenient
 Z standard pdf s.t. $E[Z] = 0$] works for Normal
 $\text{Var}[Z] = 1$] but not Double Exponential.

Review3.6 Inequalities and Identities

Theorem 3.6.1 (Chebychev's Inequality) Let X be a random variable and let $g(x)$ be a nonnegative function. Then, for any $r > 0$,

$$P(g(X) \geq r) \leq \frac{Eg(X)}{r}.$$

Example: Chebychev's (mean + variance)

$$\text{let } g(x) = \frac{(x-\mu)^2}{\sigma^2} \ (\geq 0) \text{ where } \begin{matrix} \mu = E[X] \\ \sigma^2 = \text{Var}[X] \end{matrix} \text{ let } r = t^2 (> 0)$$

$$P\left(\frac{(x-\mu)^2}{\sigma^2} \geq t^2\right) \leq \frac{1}{t^2} E\left[\left(\frac{(x-\mu)^2}{\sigma^2}\right)\right] = \frac{1}{t^2}$$

$$\rightarrow P(|x-\mu| \geq t\sigma) \leq \frac{1}{t^2}$$

$$\rightarrow P(|x-\mu| < t\sigma) \geq 1 - \frac{1}{t^2}$$

For dist'n with finite mean \rightarrow bound on $|x-\mu|$ in terms of σ .

$$t=2$$

$$P(|x-\mu| \geq 2\sigma) \leq \frac{1}{2^2} = .25$$

\rightarrow Probability random variable with 2σ of mean = .75
- No matter dist'n of X .

Inequality based on Standard Normal ($\mu=0, \sigma^2=1$)

Example (Normal dist'n):

integrating over $x > t$,
so $\frac{x}{t} > 1$

$$P(z \geq t) = \frac{1}{\sqrt{2\pi}} \int_t^\infty e^{-x^2/2} dx \leq \frac{1}{\sqrt{2\pi}} \int_t^\infty \frac{x}{t} e^{-x^2/2} dx$$

$$= \frac{1}{\sqrt{2\pi}} \frac{e^{-t^2/2}}{t}$$

$$P(|z| \geq t) \leq 2 \left(\frac{1}{\sqrt{2\pi}} \frac{e^{-t^2/2}}{t} \right) = \frac{\sqrt{2}}{\sqrt{\pi}} \frac{e^{-t^2/2}}{t}$$

$$P(|z| \geq 2) \leq \sqrt{\frac{2}{\pi}} \frac{e^{-2^2/2}}{2} = \frac{1}{\sqrt{2\pi}} e^{-2} \approx .054 .$$

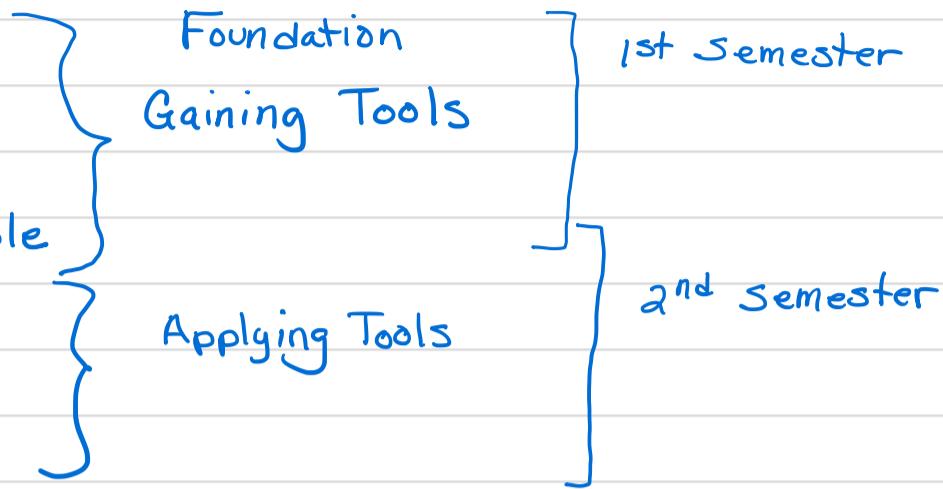
Prob R.V. with 2σ of mean $\approx (1 - .054) = .946$

Chapter 4

Course Overview

C&B Chapters:

- 1: Probability Theory
- 2: Transformations / Expectations
- 3: Common Families of Distributions
- 4: Multiple Random Variables
- 5: Properties of a Random Sample
- 6: Principles of Data Reduction
- 7: Point Estimation
- 8: Hypothesis Testing
- 9: Interval Estimation
- 10: Asymptotic Evaluations



Chapter 4 (Multiple Random Variables) Outline

- Joint and Marginal Dist'ns
- Conditional Dist'ns and independence
- Bivariate transformation
- Hierarchical Models + Mixture dist'n
- Covariance & Correlation
- Multivariate Dist'ns
- Inequalities
 - + Numerical
 - + Functional

$$\int_y f_{x,y}(x,y) = f_x(x)$$

$$f_{x|y}(x|y) = f_{xy}(x,y)/f_y(y)$$

$$u = g(x,y) \quad v = h(x,y)$$

$$E[X] = E[E[X|Y]]$$

$$\rho_{xy} = \text{Cov}(x,y)/(s_x s_y)$$

$$f_{x_1, x_2, \dots, x_n}(x_1, x_2, \dots, x_n)$$

$$|E[XY]| \leq E[|XY|] \leq (E[|X|^2])^{1/2} (E[|Y|^2])^{1/2}$$

$$\text{Convex } g(x) \rightarrow E[g(x)] \geq g(E[X]).$$

§ 4.1 Joint and Marginal Dist'ns

- Univariate models \rightarrow Probs involving 1 R.V. (X)
- Bivariate models \rightarrow " " 2 R.V.s (X, Y)
- Multivariate models \rightarrow " " n R.V.s (X_1, \dots, X_n)

Biostatisticians work with datasets...

- Collect an outcome on many subjects
- Collect many variables on many subjects...

Recall

Definition 1.4.1 A random variable is a function from a sample space S into the real numbers.

univariate: $X(s) \in \mathbb{R}'$ or $X \in \mathbb{R}'$

Definition 4.1.1 An n -dimensional random vector is a function from a sample space S into \mathbb{R}^n , n -dimensional Euclidean space.

bivariate: $(X(s), Y(s)) \in \mathbb{R}^2$ or $(X, Y) \in \mathbb{R}^2$

multivariate $(X_1(s), X_2(s), \dots, X_n(s)) \in \mathbb{R}^n$
or $(X_1, X_2, \dots, X_n) \in \mathbb{R}^n$

"Classic" Example:

Roll 2 fair 6-sided dice (36 possible outcomes, all equally likely)

$S =$	<table border="1"> <tbody> <tr><td>1,1</td><td>1,2</td><td>1,3</td><td>1,4</td><td>1,5</td><td>1,6</td></tr> <tr><td>2,1</td><td>2,2</td><td>2,3</td><td>2,4</td><td>2,5</td><td>2,6</td></tr> <tr><td>3,1</td><td>3,2</td><td>3,3</td><td>3,4</td><td>3,5</td><td>3,6</td></tr> <tr><td>4,1</td><td>4,2</td><td>4,3</td><td>4,4</td><td>4,5</td><td>4,6</td></tr> <tr><td>5,1</td><td>5,2</td><td>5,3</td><td>5,4</td><td>5,5</td><td>5,6</td></tr> <tr><td>6,1</td><td>6,2</td><td>6,3</td><td>6,4</td><td>6,5</td><td>6,6</td></tr> </tbody> </table>	1,1	1,2	1,3	1,4	1,5	1,6	2,1	2,2	2,3	2,4	2,5	2,6	3,1	3,2	3,3	3,4	3,5	3,6	4,1	4,2	4,3	4,4	4,5	4,6	5,1	5,2	5,3	5,4	5,5	5,6	6,1	6,2	6,3	6,4	6,5	6,6
1,1	1,2	1,3	1,4	1,5	1,6																																
2,1	2,2	2,3	2,4	2,5	2,6																																
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5,1	5,2	5,3	5,4	5,5	5,6																																
6,1	6,2	6,3	6,4	6,5	6,6																																

$X = \text{sum of dice}$

$X = (2, 3, \dots, 12)$

$Y = |\text{difference of 2 dice}|$

$Y = (0, 1, \dots, 5)$

example: Roll (3,3) $X = 6 + Y = 0$ $\Pr(\text{Roll } (3,3)) = 1/36$
(4,1) $X = 5$ $Y = 3$ $\Pr(\text{Roll } (4,1)) = 1/36$
(5,2) $X = 7$ $Y = 3$ $\Pr(\text{Roll } (5,2)) = 1/36$

$$\text{What is } \Pr(X=6 + Y=0) ? = \Pr(\text{Roll } (3,3)) = 1/36$$

$$\Pr(X=5 + Y=3) ? = \Pr((4,1) \text{ or } (1,4)) = 2/36 = 1/18$$

$$\Pr(X=7 + Y=3) ? = \Pr((5,2) \text{ or } (2,5)) = 2/36 = 1/18$$

$$\Pr(X=7 + Y=0) ? = \Pr(\emptyset) = 0$$

$$\Pr(X=7 + Y \leq 4) ? = \Pr((4,3) \text{ or } (3,4) \text{ or } (5,2) \text{ or } (2,5)) = \frac{4}{36} = \frac{1}{9}$$

In dice example : Are X and Y independent ?

Notation $P(X=x \text{ and } Y=y) = P(X=x, Y=y)$

Clearly (X, Y) is a discrete random vector - (has a countable (finite) number of values.)

joint pmf of X and Y : $f(x, y) = f_{XY}(x, y) = P(X=x, Y=y)$

		x										
		2	3	4	5	6	7	8	9	10	11	12
y	0	$\frac{1}{36}$				$\frac{1}{36}$	$\frac{1}{36}$					$\frac{1}{36}$
	1		$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$		$\frac{1}{18}$	$\frac{1}{18}$		$\frac{1}{18}$
	2			$\frac{1}{18}$		$\frac{1}{18}$						
	3				$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$		$\frac{1}{18}$
	4					$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$			
	5						$\frac{1}{18}$					

Table 4.1.1. Values of the joint pmf $f(x, y)$

all possible values of (X, Y) .

For other (x, y)
 $P(X=x, Y=y)=0$

(i.e. $P(X=7, Y=0)=0$)

match earlier results using S.

What is $P(X=6 + Y=0)$? $= P(\text{Roll } (3,3)) = \frac{1}{36}$

$P(X=5 + Y=3)$? $= P((4,1) \text{ or } (1,4)) = \frac{2}{36} = \frac{1}{18}$

$P(X=7 + Y=3)$? $= P((5,2) \text{ or } (2,5)) = \frac{2}{36} = \frac{1}{18}$

$P(X=7 + Y=0)$? $= P(\emptyset) = 0$

$P(X=7 + Y \leq 4)$? $= P((4,3) \text{ or } (3,4) \text{ or } (5,2) \text{ or } (2,5)) = \frac{4}{36} = \frac{1}{9}$

Joint pmf:

Definition 4.1.3 Let (X, Y) be a discrete bivariate random vector. Then the function $f(x, y)$ from \mathbb{R}^2 into \mathbb{R} defined by $f(x, y) = P(X = x, Y = y)$ is called the *joint probability mass function* or *joint pmf* of (X, Y) . If it is necessary to stress the fact that f is the joint pmf of the vector (X, Y) rather than some other vector, the notation $f_{X,Y}(x, y)$ will be used.

Joint pmf used to compute $P((x,y) \in A)$

$$P((x,y) \in A) = \sum_{(x,y) \in A} f(x,y)$$

$$\underline{P(x=7, y \leq 4) = P((x,y) \in A) = f(7,1) + f(7,3) = \frac{1}{18} + \frac{1}{18} = \frac{1}{9}}$$

Joint pmf used to compute $E[g(x,y)]$

$$E[g(x,y)] = \sum_{(x,y) \in \mathbb{R}^2} g(x,y) f(x,y)$$

Dice Example: Let $g(x,y) = x * y$ Find $E[x * y]$

$$(2)(0)\frac{1}{36} + (4)(0)\frac{1}{36} + \dots + (8)(4)\frac{1}{18} + (7)(5)\frac{1}{18} = (13)\left(\frac{11}{18}\right)$$

Properties of Thm 2.2.5 still apply:

Theorem 2.2.5 Let X be a random variable and let a, b , and c be constants. Then for any functions $g_1(x)$ and $g_2(x)$ whose expectations exist,

- a. $E(ag_1(X) + bg_2(X) + c) = aEg_1(X) + bEg_2(X) + c$.
- b. If $g_1(x) \geq 0$ for all x , then $Eg_1(X) \geq 0$.
- c. If $g_1(x) \geq g_2(x)$ for all x , then $Eg_1(X) \geq Eg_2(X)$.
- d. If $a \leq g_1(x) \leq b$ for all x , then $a \leq Eg_1(X) \leq b$.

$$\text{i.e. } E[a g_1(x,y) + b g_2(x,y) + c] = a E[g_1(x,y)] + b E[g_2(x,y)] + c \dots$$

$$\text{Also, since pmf: } \sum_{(x,y) \in \mathbb{R}^2} f(x,y) = P((x,y) \in \mathbb{R}^2) = 1$$

$$\text{Dice example (Table 4.1.1)} \quad 15 * \left(\frac{1}{18}\right) + 6 * \frac{1}{36} = \frac{30 + 6}{36} = 1$$

Dice Question: What is $P(Y=0)$

Based on Rolling die = $\Pr(\text{doubles}) =$

$$P((1,1) \cap (2,2) \cap \dots \cap (6,6)) = \frac{6}{36} = \frac{1}{6}$$

$$\text{Based on joint pmf} = P((2,0) \cap (4,0) \cap \dots \cap (12,0)) = 6 * \left(\frac{1}{36}\right) = \frac{1}{6}$$

$$\begin{aligned} (\text{Table 4.1.1}) \quad &= f_{x,y}(2,0) + f_{x,y}(4,0) + f_{x,y}(6,0) \\ &+ f_{x,y}(8,0) + f_{x,y}(10,0) + f_{x,y}(12,0) = \frac{1}{6} \end{aligned}$$

- Usually simpler to work with joint pdf.

May be interested in only dist'n of X or y ($f_X(x)$ or $f_Y(y)$)
 'marginal' of x 'marginal' of y

Theorem 4.1.6 Let (X, Y) be a discrete bivariate random vector with joint pmf $f_{X,Y}(x, y)$. Then the marginal pmfs of X and Y , $f_X(x) = P(X = x)$ and $f_Y(y) = P(Y = y)$, are given by

$$f_X(x) = \sum_{y \in \mathbb{R}} f_{X,Y}(x, y) \quad \text{and} \quad f_Y(y) = \sum_{x \in \mathbb{R}} f_{X,Y}(x, y).$$

Example dice marginals:

		x												$f_Y(y)$
		2	3	4	5	6	7	8	9	10	11	12		
		0	$\frac{1}{36}$	$\frac{4}{18}$										
		1		$\frac{1}{18}$	$\frac{5}{18}$									
y		2			$\frac{1}{18}$	$\frac{4}{18}$								
		3				$\frac{1}{18}$	$\frac{3}{18}$							
		4					$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{2}{18}$	
		5						$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	$\frac{1}{18}$	
		$f_X(x)$:												1

Table 4.1.1. Values of the joint pmf $f(x, y)$

$$f_Y(0) = f_{X,Y}(2,0) + f_{X,Y}(4,0) + f_{X,Y}(6,0) + f_{X,Y}(8,0) + f_{X,Y}(10,0) + f_{X,Y}(12,0) = \frac{1}{6}$$

$$f_Y(1) = f_{X,Y}(3,1) + f_{X,Y}(5,1) + f_{X,Y}(7,1) + f_{X,Y}(9,1) + f_{X,Y}(11,1) = \frac{5}{18}$$

$$f_Y(2) = f_{X,Y}(4,2) + f_{X,Y}(6,2) + f_{X,Y}(8,2) + f_{X,Y}(10,2) = \frac{4}{18} = \frac{2}{9}$$

$$f_Y(3) = f_{X,Y}(5,3) + f_{X,Y}(7,3) + f_{X,Y}(9,3) = \frac{3}{18} = \frac{1}{6}$$

$$f_Y(4) = f_{X,Y}(6,4) + f_{X,Y}(8,4) = \frac{2}{18} = \frac{1}{9}$$

$$f_Y(5) = f_{X,Y}(7,5) = \frac{1}{18}$$

$$\sum_{y=0}^5 f_Y(y) = \frac{1}{6} + \frac{5}{18} + \frac{2}{9} + \frac{1}{6} + \frac{1}{9} + \frac{1}{18} = \frac{3+5+4+3+2+1}{18} = \frac{18}{18} = 1$$

Sample Space $\rightarrow f_{xy}(x,y) \rightarrow f_x(x), f_y(y)$

~~$f_{xy}(x,y)$~~

Rolling fair dice $\rightarrow f_x(x,y) \rightarrow f_x(x), f_x(y)$

~~$f_x(x,y)$~~ ~~$f_x(y)$~~

Example: Assume Joint pmf for some bivariate vector (X, Y) .

$$\begin{aligned} f(0,0) &= f(0,1) = \frac{1}{6} \\ f(1,0) &= f(1,1) = \frac{1}{3} \\ f(x,y) &= 0 \text{ else} \end{aligned} \quad \begin{aligned} f(x,y) &> 0 \\ \sum_{(x,y) \in \mathbb{R}^2} f(x,y) &= 1 \end{aligned} \quad \left. \begin{aligned} &f(x,y) > 0 \\ &\sum_{(x,y) \in \mathbb{R}^2} f(x,y) = 1 \end{aligned} \right\} \text{pmf}$$

Can Compute Prob's such as:

$$P(X=Y) = f(0,0) + f(1,1) = \frac{1}{6} + \frac{1}{3} = \frac{1}{2}$$

$$P(X>Y) = f(1,0) = \frac{1}{3}$$

$$P(Y \geq X) = f(0,0) + f(0,1) + f(1,1) = \frac{1}{6} + \frac{1}{6} + \frac{1}{3} = \frac{2}{3}$$

⋮

Given $f(x,y)$:

Don't need original sample space that defined $f(x,y)$;

X & Y (or $X(s)$ & $Y(s)$) to compute these probs.

In fact many sample spaces & functions that could lead to this $f_{xy}(x,y)$.

- * Such as: $S = 36$ outcomes from rolling 2 six-sided dice
- $X=0$ 1st die ≤ 2 $Y=0$ 2nd die odd number
- $X=1$ 1st die > 2 $Y=1$ 2nd die even number
- (details homework.)

- * Could also do with 2 3-sided dice. ... other
- ⋮

Different Joint Dist'n's: $f(0,0) = f(0,1) = \frac{1}{6}$
 $f(1,0) = f(1,1) = \frac{1}{3}$
 $f(x,y) = 0$ else

$$\begin{aligned} f(0,0) &= \frac{1}{12} & f(1,0) &= \frac{5}{12} \\ f(0,1) &= f(1,1) = \frac{3}{12} \\ f(x,y) &= 0 \text{ else} \end{aligned}$$

Same
 Marginal Dist'n's

$$\begin{aligned} f_X(0) &= \frac{1}{6} + \frac{1}{6} = \frac{1}{3} \\ f_X(1) &= \frac{1}{3} + \frac{1}{3} = \frac{2}{3} \\ f_Y(0) &= \frac{1}{6} + \frac{1}{3} = \frac{1}{2} \\ f_Y(1) &= \frac{1}{6} + \frac{1}{3} = \frac{1}{2} \end{aligned}$$

$$\begin{aligned} f_X(0) &= \frac{1}{12} + \frac{5}{12} = \frac{4}{12} = \frac{1}{3} \\ f_X(1) &= \frac{5}{12} + \frac{3}{12} = \frac{8}{12} = \frac{2}{3} \\ f_Y(0) &= \frac{1}{12} + \frac{5}{12} = \frac{1}{2} \\ f_Y(1) &= \frac{3}{12} + \frac{3}{12} = \frac{1}{2} \end{aligned}$$

Continuous Random Vectors

Definition 4.1.10 A function $f(x, y)$ from \mathbb{R}^2 into \mathbb{R} is called a *joint probability density function* or *joint pdf* of the continuous bivariate random vector (X, Y) if, for every $A \subset \mathbb{R}^2$,

$$P((X, Y) \in A) = \int_A \int f(x, y) dx dy.$$

double integrals,
integrate over
all $(x, y) \in A$.

$$E[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f(x, y) dx dy$$

$$f_x(x) = \int_{-\infty}^{\infty} f(x, y) dy$$

$$f_y(y) = \int_{-\infty}^{\infty} f(x, y) dx$$

Function satisfying $f(x, y) \geq 0 \quad \forall (x, y) \in \mathbb{R}^2$

$$\text{and } \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dx dy = 1.$$

is joint pdf of continuous random vector (X, Y) .

Example: Calculating joint probabilities - I

$$f(x, y) = 6xy^2 I_{(0,1)}^{(x)} I_{(0,1)}^{(y)}$$

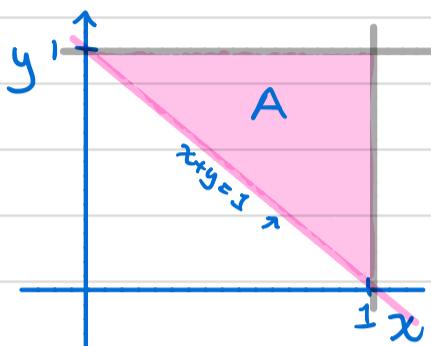
- Check pdf; Clearly $f(x, y) \geq 0$ for $0 < x < 1$ & $0 < y < 1$

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dx dy = \int_0^1 \int_0^1 6xy^2 dx dy = \int_0^1 3x^2 y^2 \Big|_0^1 dy$$

$$= \int_0^1 3y^2 dy = y^3 \Big|_0^1 = 1,$$

Example cont. $f(x,y) = 6xy^2 I_{(0,1)}^{(x)} I_{(0,1)}^{(y)}$

Calculate: $P(X+Y \geq 1)$ let $A = \{(x,y) : x+y \geq 1\}$
 $= P((x,y) \in A)$



$$\begin{aligned} A &= \{(x,y) : x+y \geq 1, 0 < x < 1, 0 < y < 1\} \\ &= \{(x,y) : x \geq 1-y, 0 < x < 1, 0 < y < 1\} \\ &= \{(x,y) : 1-y \leq x < 1, 0 < y < 1\} \end{aligned}$$

$$\begin{aligned} P(X+Y \geq 1) &= \int_A \int f(x,y) dx dy = \int_0^1 \int_{1-y}^1 6xy^2 dx dy = \int_0^1 [3x^2 y^2]_{1-y}^1 dy \\ &= \int_0^1 [3y^2 [1^2 - (1-y)^2]] dy = \int_0^1 [3y^2 [1 - (1-2y+y^2)]] dy = \int_0^1 [6y^3 - 3y^4] dy \\ &= \left[\frac{6y^4}{4} - \frac{3y^5}{5} \right]_0^1 = \left[\frac{3}{2}y^4 - \frac{3}{5}y^5 \right]_0^1 = \left[-\frac{3y^4(2y-5)}{10} \right]_0^1 = \left[-\frac{3(2-5)}{10} \right] = \frac{9}{10} \end{aligned}$$

Calculate $f_x(x)$ $f_x(x) = \int_y f(x,y) dy = \int_0^1 6xy^2 dy$
 $= 2xy^3 \Big|_0^1 = 2x \quad 0 < x < 1$

$$f_x(x) = 2x I_{(0,1)}^{(x)}$$

Check $f_x(x)$ is a pdf

$$f_x(x) \geq 0 \text{ for } 0 < x < 1$$

$$\int_0^1 2x dx = x^2 \Big|_0^1 = 1$$

Calculate $P(\frac{1}{2} < X < \frac{3}{4}) = \int_{1/2}^{3/4} 2x dx = x^2 \Big|_{1/2}^{3/4}$
 $= \frac{9}{16} - \frac{1}{4} = \frac{9}{16} - \frac{4}{16} = \frac{5}{16}$