

16: Continuous Joint Distributions

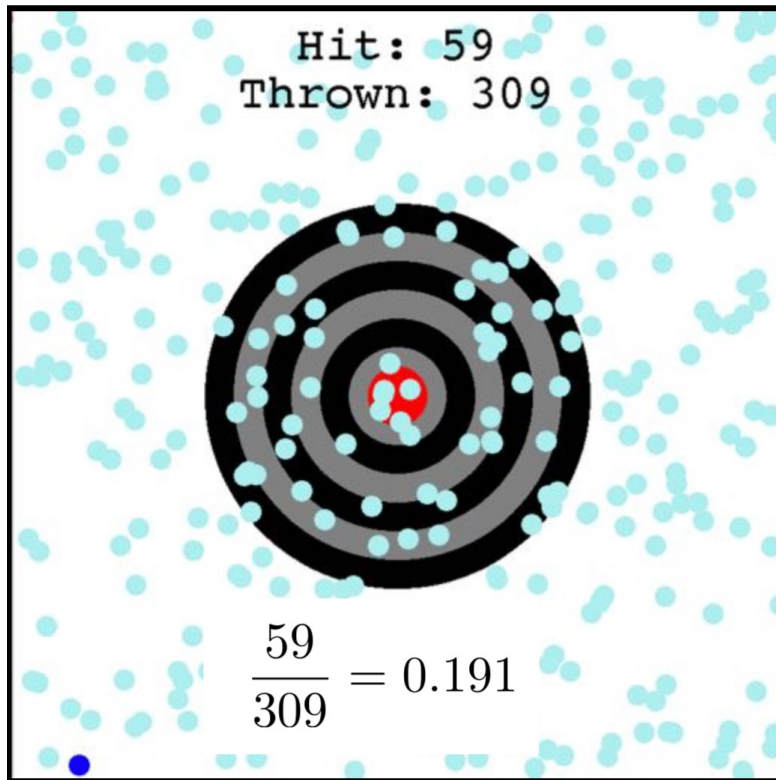
Jerry Cain

May 2, 2022



Continuous joint distributions

Remember target?



Good times...

CS109 logo with darts



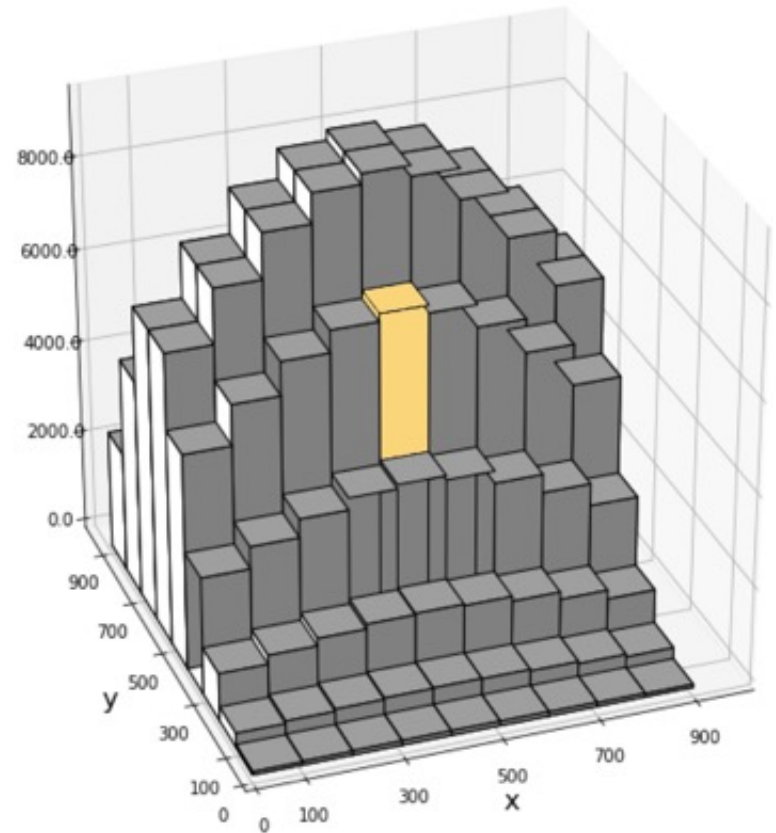
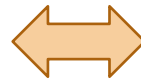
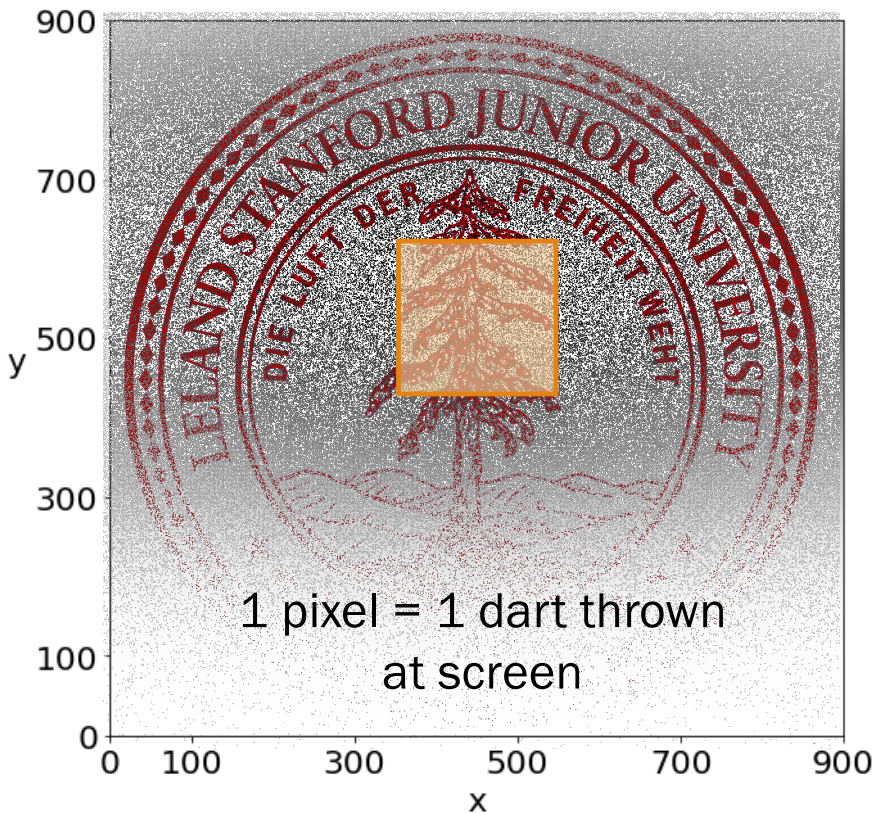
The CS109 logo was created by throwing 500,000 darts according to a joint distribution.

If we throw another dart according to the same distribution, what is $P(\text{dart hits within } r \text{ pixels of center})$?

Quick check: What is the probability that a dart hits at $(456.2344132343, 532.1865739012)$?

CS109 logo with darts

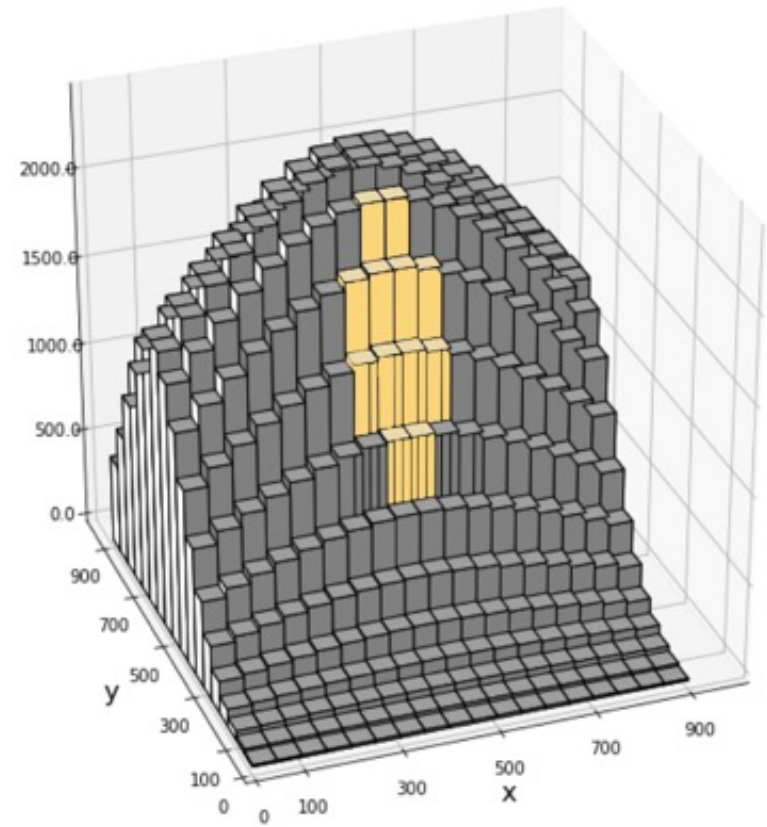
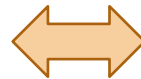
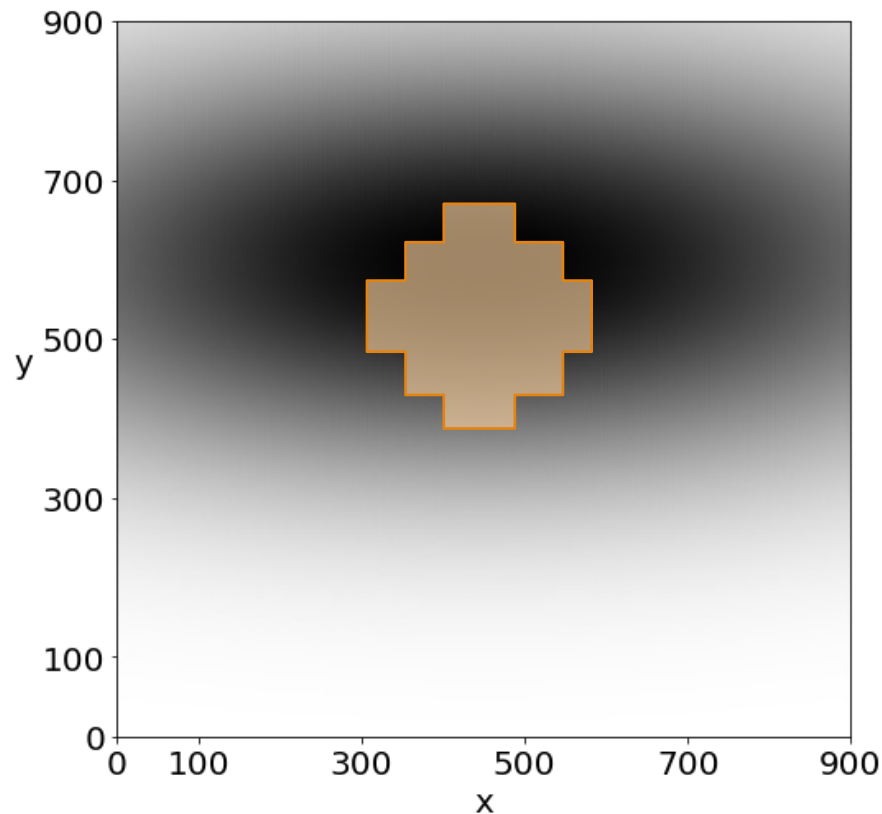
$P(\text{dart hits within } r \text{ pixels of center})?$



Possible dart counts (in 100x100 boxes)

CS109 logo with darts

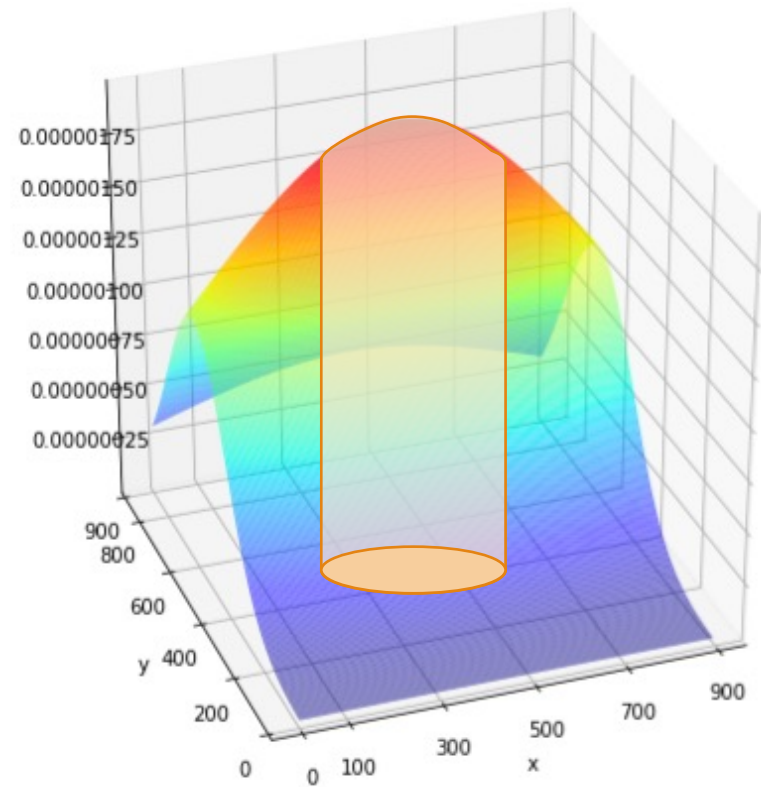
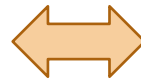
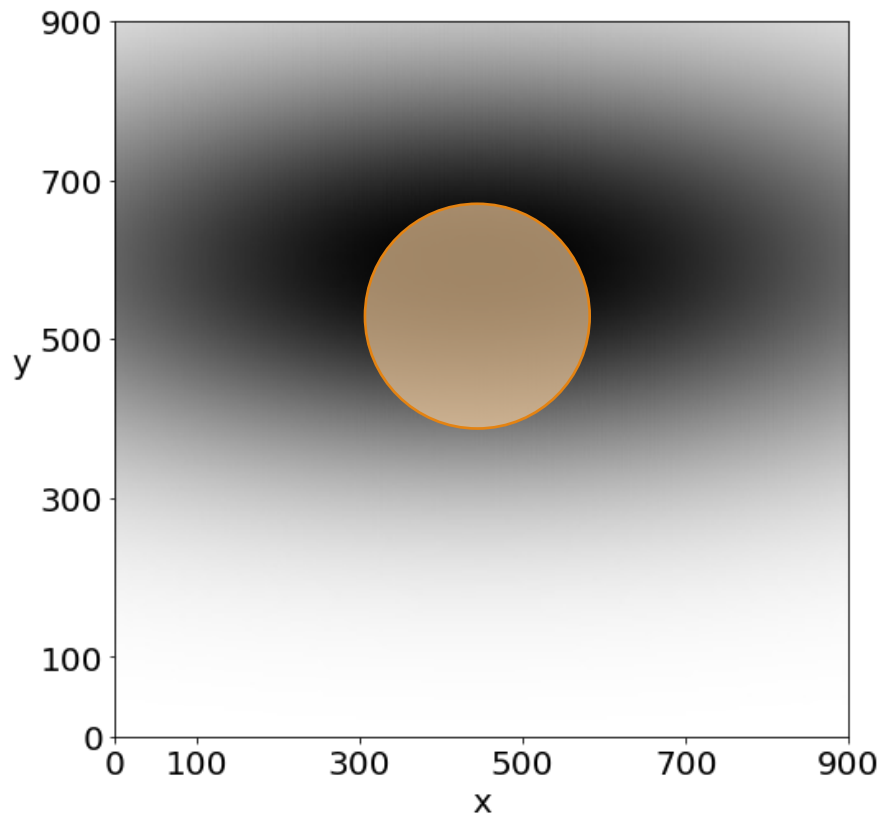
$P(\text{dart hits within } r \text{ pixels of center})?$



Possible dart counts (in 50x50 boxes)

CS109 logo with darts

$P(\text{dart hits within } r \text{ pixels of center})?$



Possible dart counts
(in infinitesimally small boxes) [iversity](#) 7

Continuous joint probability density functions

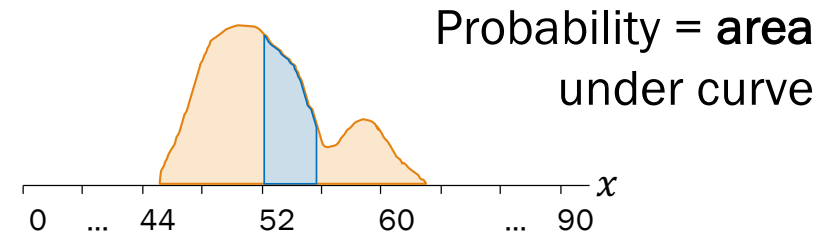
If two random variables X and Y are jointly continuous, then there exists a **joint probability density function** $f_{X,Y}$ defined over $-\infty < x, y < \infty$ such that:

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

From one continuous RV to jointly continuous RVs

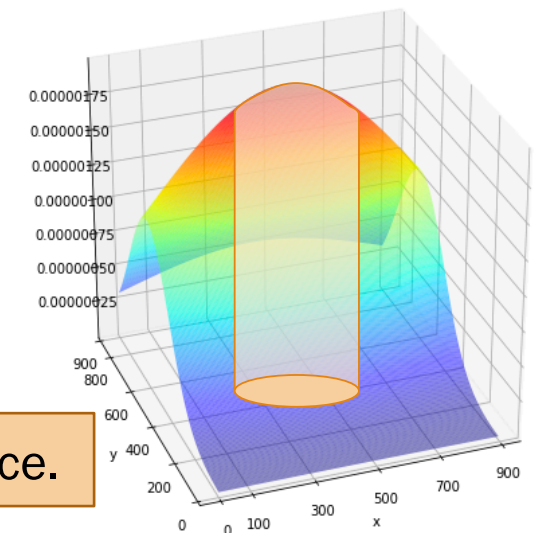
Single continuous RV X

- PDF f_X such that $\int_{-\infty}^{\infty} f_X(x) dx = 1$
- Integrate to get probabilities



Jointly continuous RVs X and Y

- PDF $f_{X,Y}$ such that $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy dx = 1$
- Double integrate to get probabilities



Probability for jointly continuous RVs is **volume** under a surface.

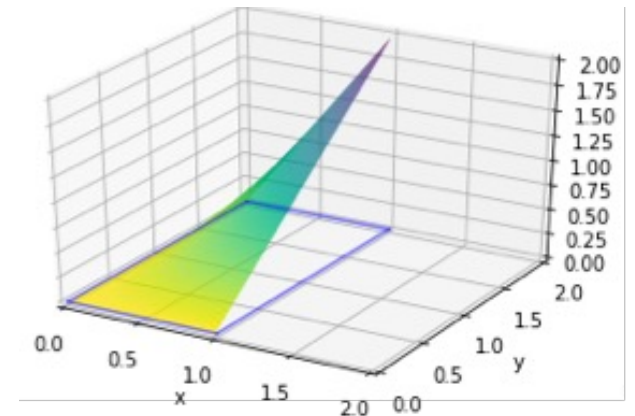
Double integrals without tears

Let X and Y be two continuous random variables.

- Support: $0 \leq X \leq 1$, $0 \leq Y \leq 2$.

Is $g(x, y) = xy$ a valid joint PDF over X and Y ?

Write down the definite double integral that must integrate to 1:



Double integrals without tears

Let X and Y be two continuous random variables.

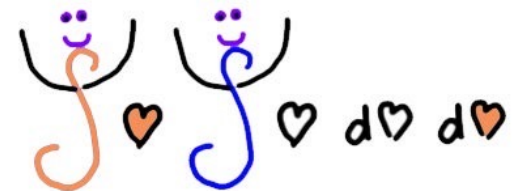
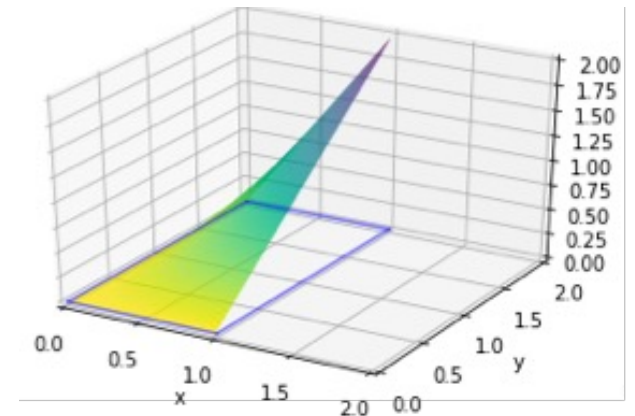
- Support: $0 \leq X \leq 1$, $0 \leq Y \leq 2$.

Is $g(x, y) = xy$ a valid joint PDF over X and Y ?

Write down the definite double integral that must integrate to 1:

$$\int_{y=0}^2 \int_{x=0}^1 xy \, dx \, dy = 1 \quad \text{or} \quad \int_{x=0}^1 \int_{y=0}^2 xy \, dy \, dx = 1$$

(used in next slide)



Double integrals without tears

Let X and Y be two continuous random variables.

- Support: $0 \leq X \leq 1$, $0 \leq Y \leq 2$.

Is $g(x, y) = xy$ a valid joint PDF over X and Y ?

0. Set up integral:

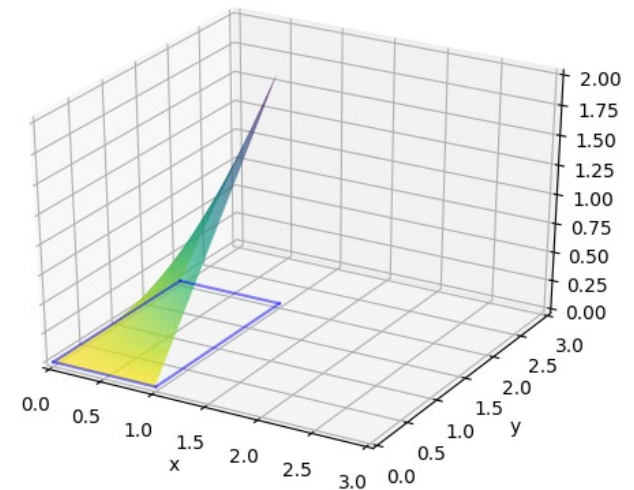
$$1 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) dx dy = \int_{y=0}^2 \int_{x=0}^1 xy dx dy$$

1. Evaluate inside integral by treating y as a constant:

$$\int_{y=0}^2 \left(\int_{x=0}^1 xy dx \right) dy = \int_{y=0}^2 y \left(\int_{x=0}^1 x dx \right) dy = \int_{y=0}^2 y \left[\frac{x^2}{2} \right]_0^1 dy = \int_{y=0}^2 y \frac{1}{2} dy$$

2. Evaluate remaining (single) integral:

$$\int_{y=0}^2 y \frac{1}{2} dy = \left[\frac{y^2}{4} \right]_{y=0}^2 = 1 - 0 = 1$$

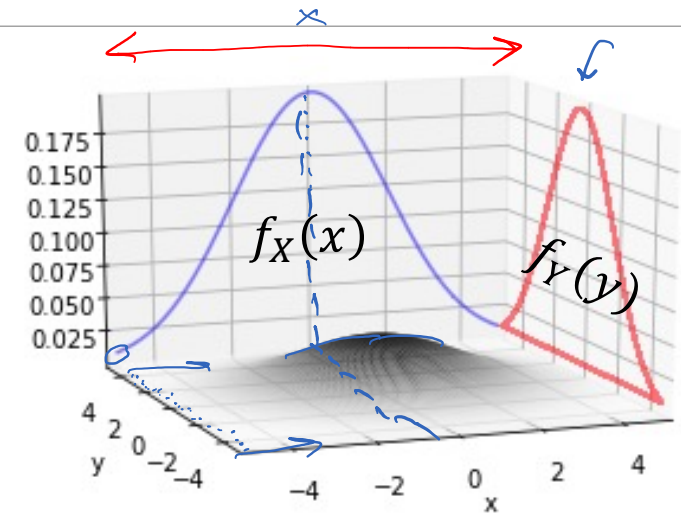


Yes, $g(x, y)$ is a valid joint PDF because it integrates to 1.

Marginal distributions

Suppose X and Y are continuous random variables with joint PDF:

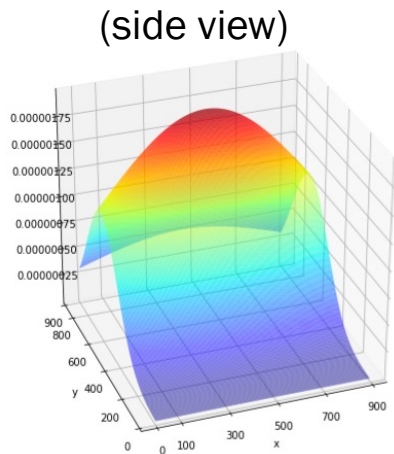
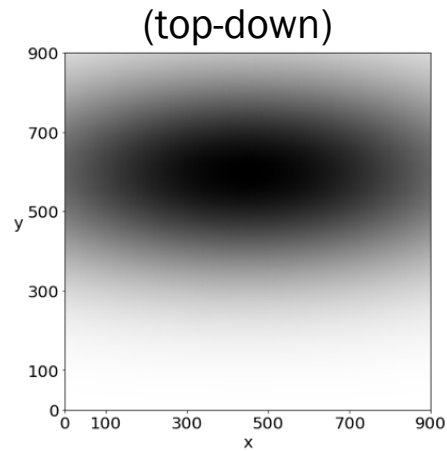
$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy dx = 1$$



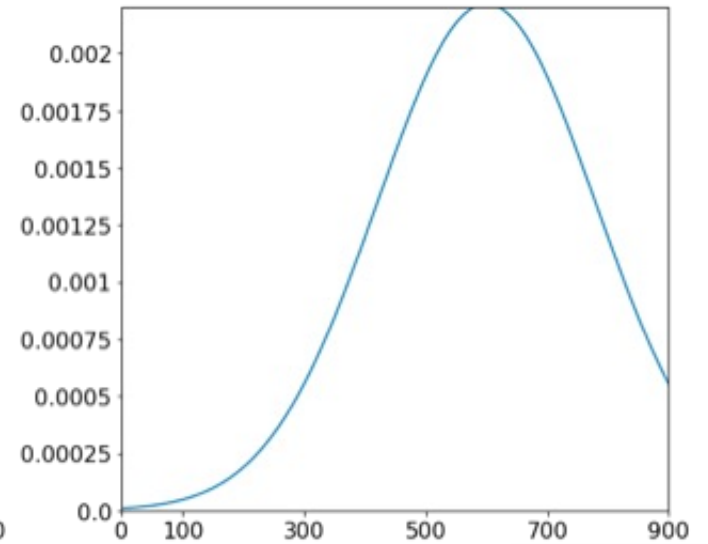
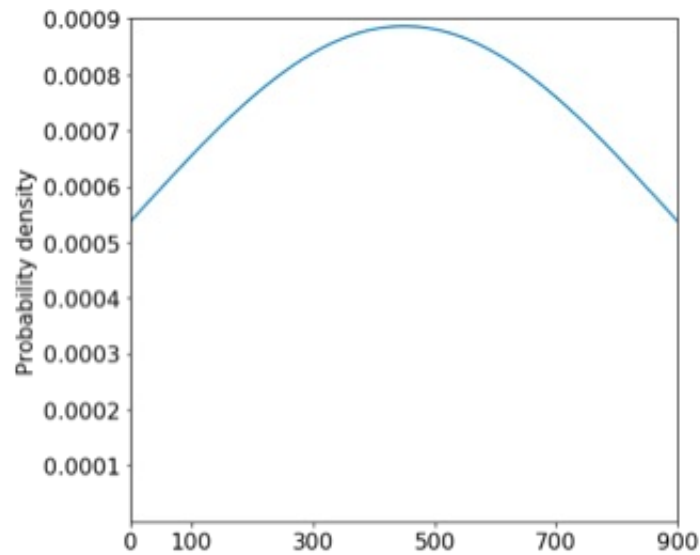
The marginal density functions (**marginal PDFs**) are therefore:

$$f_X(a) = \int_{-\infty}^{\infty} f_{X,Y}(a,y) dy \qquad f_Y(b) = \int_{-\infty}^{\infty} f_{X,Y}(x,b) dx$$

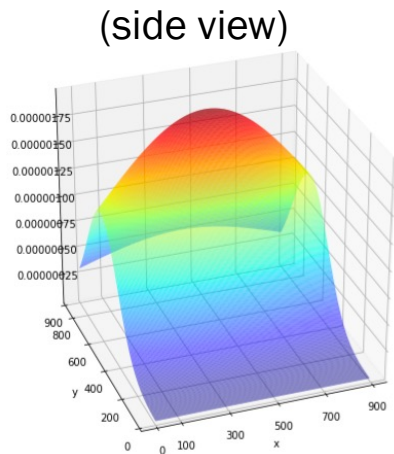
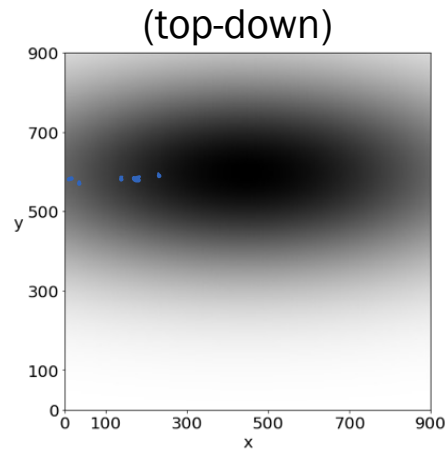
Back to darts!



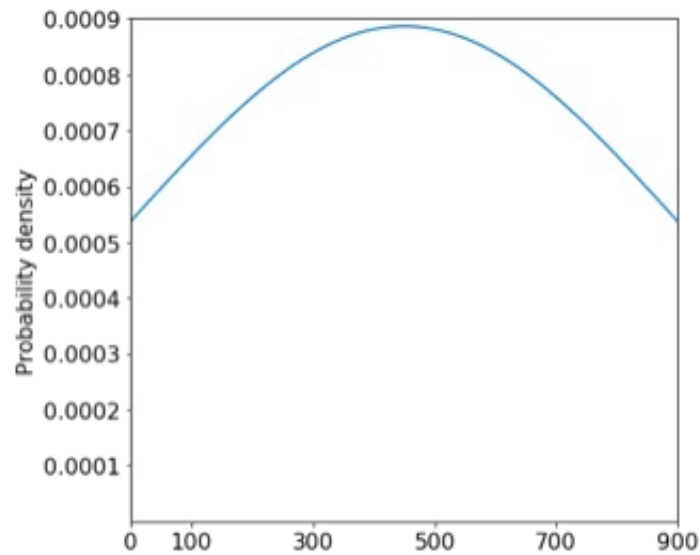
Match X and Y to their respective marginal PDFs:



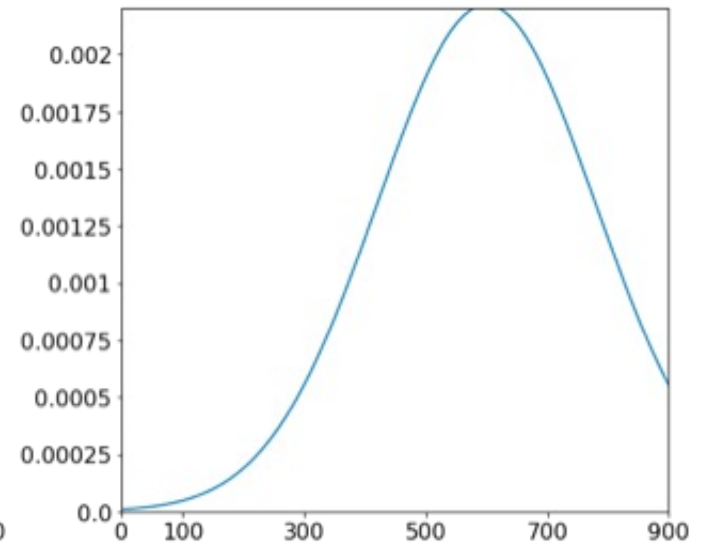
Back to darts!



Match X and Y to their respective marginal PDFs:



pixel x



pixel y



Joint CDFs

An observation: Connecting CDF to PDF

For a continuous random variable X with PDF f , the CDF (cumulative distribution function) is

$$F(a) = P(X \leq a) = \int_{-\infty}^a f(x) dx$$

The density f is therefore the derivative of the CDF, F :

$$f(a) = \frac{d}{da} F(a)$$

(Fundamental Theorem of Calculus)

Joint cumulative distribution function

For two random variables X and Y , there can be a **joint cumulative distribution function** $F_{X,Y}$:

$$F_{X,Y}(a, b) = \underbrace{P(X \leq a, Y \leq b)}$$

For discrete X and Y :

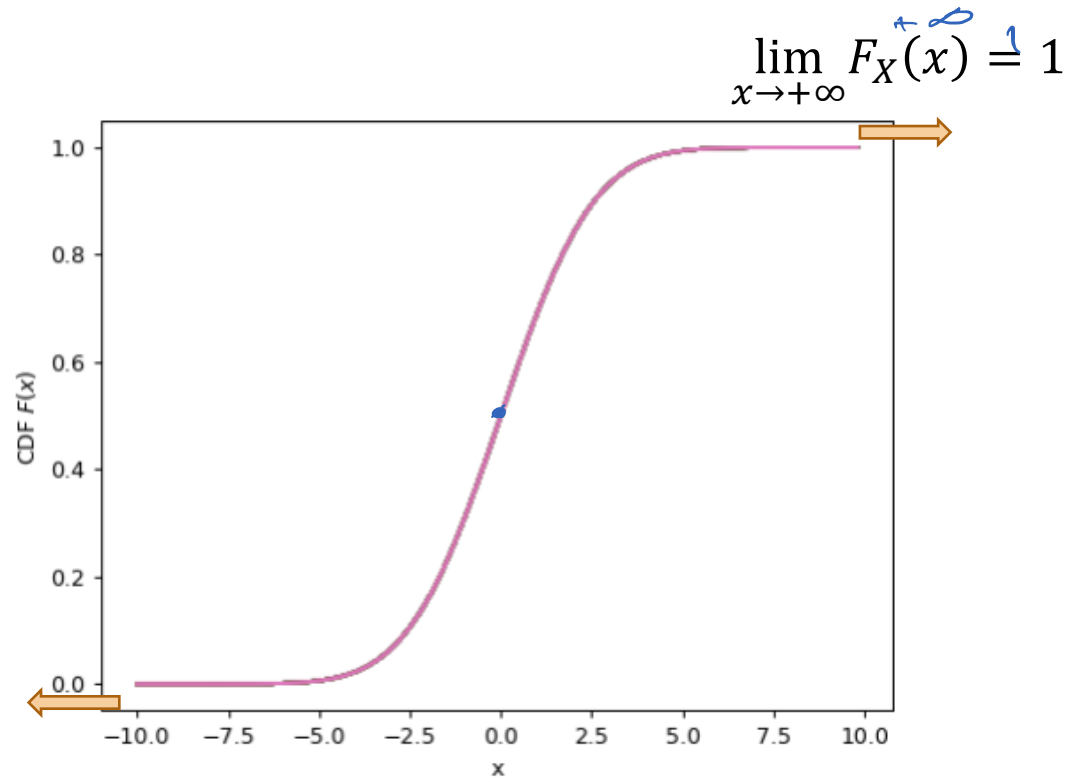
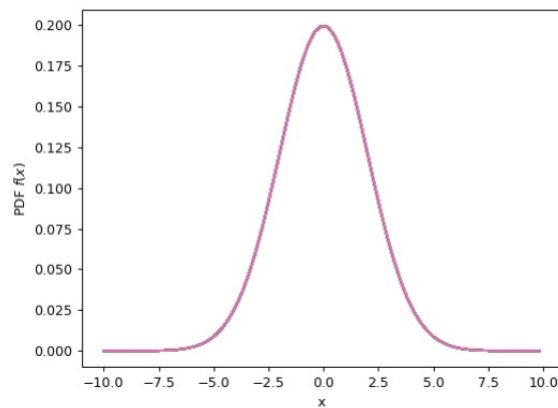
$$F_{X,Y}(a, b) = \sum_{x \leq a} \sum_{y \leq b} p_{X,Y}(x, y)$$

For continuous X and Y :

$$F_{X,Y}(a, b) = \int_{-\infty}^a \int_{-\infty}^b f_{X,Y}(x, y) dy dx$$
$$f_{X,Y}(a, b) = \underbrace{\frac{\partial^2}{\partial a \partial b} F_{X,Y}(a, b)}$$

Single variable CDF, graphically

Review

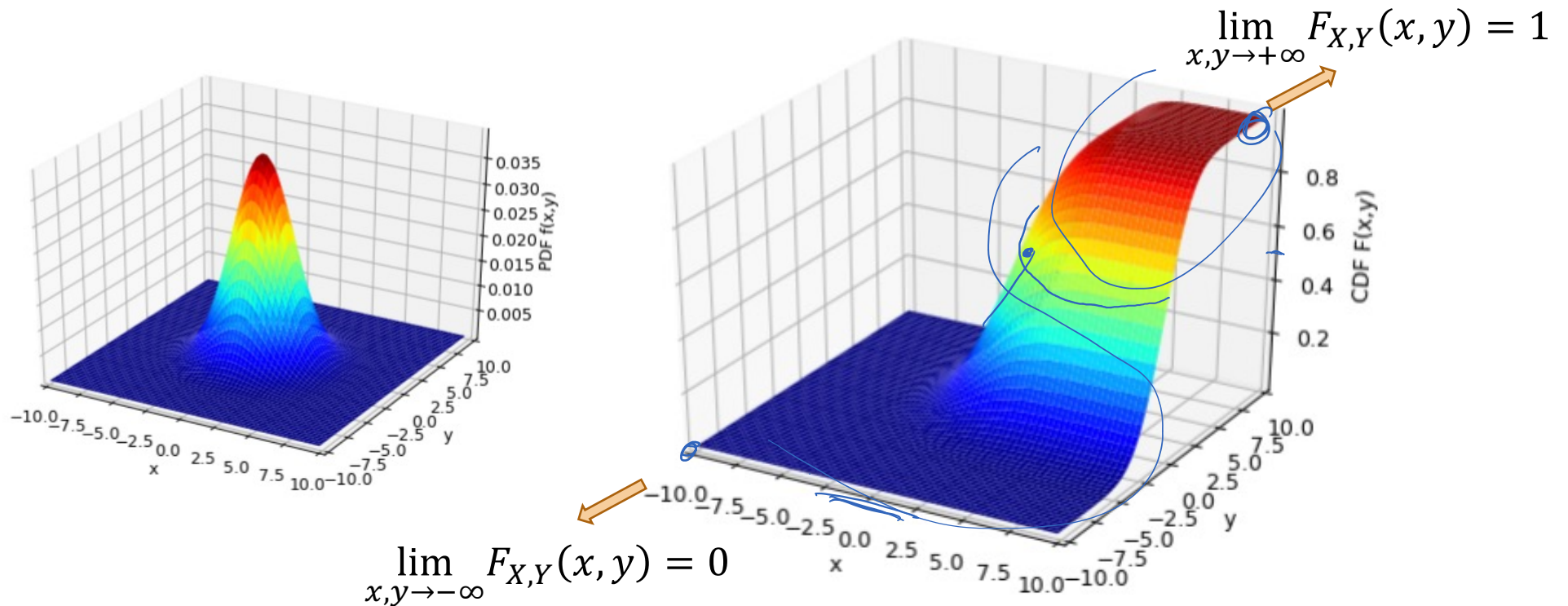


$$f_X(x)$$

$$\lim_{x \rightarrow -\infty} F_X(x) = 0$$

$$F_X(x) = P(X \leq x)$$

Joint CDF, graphically



$$f_{X,Y}(x,y)$$

$$F_{X,Y}(x,y) = P(X \leq x, Y \leq y)$$



Independent Continuous RVs

Independent continuous RVs

Two continuous random variables X and Y are **independent** if:

$$P(X \leq x, Y \leq y) = P(X \leq x)P(Y \leq y) \quad \forall x, y$$

Equivalently:

$$\begin{aligned} F_{X,Y}(x, y) &= F_X(x)F_Y(y) \\ f_{X,Y}(x, y) &= f_X(x)f_Y(y) \end{aligned} \quad \forall x, y$$

Proof of PDF:

$$\begin{aligned} f_{X,Y}(x, y) &= \frac{\partial^2}{\partial x \partial y} F_{X,Y}(x, y) = \frac{\partial^2}{\partial x \partial y} F_X(x)F_Y(y) \\ &= \frac{\partial}{\partial x} \frac{\partial}{\partial y} F_X(x)F_Y(y) = \frac{\partial}{\partial x} F_X(x) \frac{\partial}{\partial y} F_Y(y) \\ &= f_X(x)f_Y(y) \end{aligned}$$

Independent continuous RVs

Two continuous random variables X and Y are independent if:

$$P(X \leq x, Y \leq y) = P(X \leq x)P(Y \leq y)$$

Equivalently:


$$\begin{aligned} F_{X,Y}(x, y) &= F_X(x)F_Y(y) \\ f_{X,Y}(x, y) &= f_X(x)f_Y(y) \end{aligned}$$

More generally, X and Y are **independent** if joint density factors separately:

$$f_{X,Y}(x, y) = g(x)h(y), \text{ where } -\infty < \underbrace{x, y} < \infty$$

must be separable


Pop quiz! (just kidding)

$f_{X,Y}(x,y) = g(x)h(y)$,
where $-\infty < x, y < \infty$  independent
 X and Y

Are X and Y independent in the following cases?


1. $f_{X,Y}(x,y) = 6e^{-3x}e^{-2y}$
where $0 < x, y < \infty$

2. $f_{X,Y}(x,y) = 4xy$
where $0 < x, y < 1$

3. $f_{X,Y}(x,y) = 24xy$
where $0 < x + y < 1$




Pop quiz! (just kidding)

$f_{X,Y}(x,y) = g(x)h(y)$,
where $-\infty < x, y < \infty$  independent
 X and Y

Are X and Y independent in the following cases?

✓ 1. $f_{X,Y}(x,y) = 6e^{-3x}e^{-2y}$
where $0 < x, y < \infty$

Separable functions: $g(x) = 3e^{-3x}$ *is valid PDF*
 $h(y) = 2e^{-2y}$

✓ 2. $f_{X,Y}(x,y) = 4xy$
where $0 < x, y < 1$

Separable functions: $g(x) = 2x$
 $h(y) = 2y$

✗ 3. $f_{X,Y}(x,y) = 24xy$
where $0 < x + y < 1$

Cannot capture constraint on $x + y$
into factorization!

If you can factor densities over all of the support, you have independence.

More pop quiz! (still kidding)

X and Y have the following joint PDF:

$$f_{X,Y}(x, y) = 3e^{-3x}$$

where $0 < x < \infty, 1 < y < 2$

1. Are X and Y independent?
2. What is the marginal PDF of X ? Of Y ?
3. What is $E[X + Y]$?



More pop quiz! (still kidding)

X and Y have the following joint PDF:

$$f_{X,Y}(x,y) = 3e^{-3x}$$

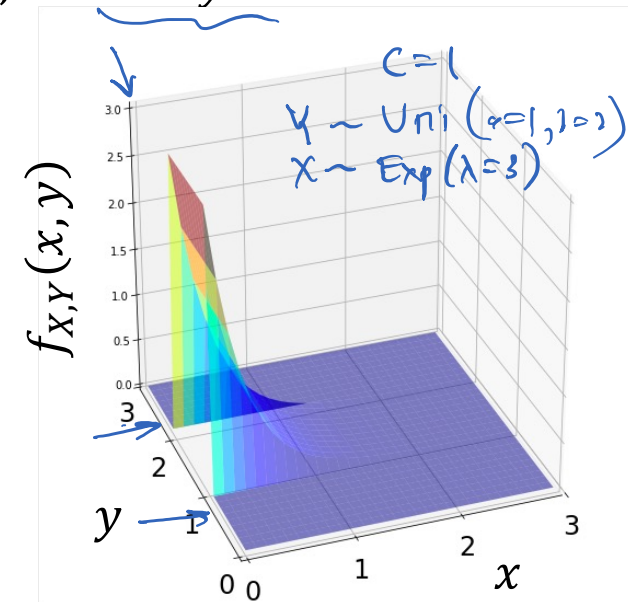
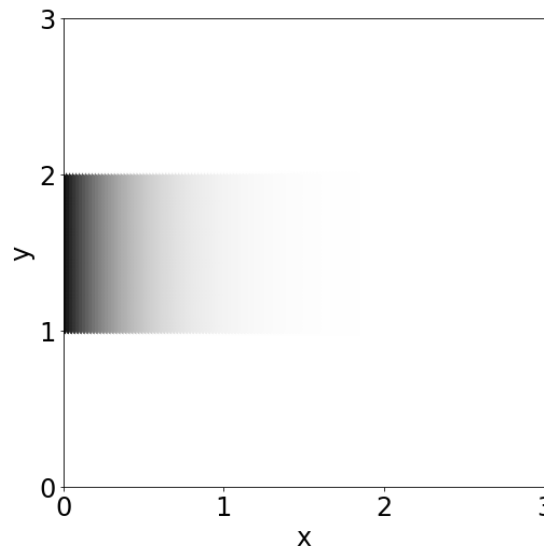
where $0 < x < \infty, 1 < y < 2$

1. Are X and Y independent?

$$g(x) = 3Ce^{-3x}, 0 < x < \infty \quad C \text{ is a constant}$$
$$h(y) = 1/C, 1 < y < 2$$

2. What is the marginal PDF of X ? Of Y ?

3. What is $E[X + Y]$?



More pop quiz! (still kidding)

X and Y have the following joint PDF:

$$f_{X,Y}(x,y) = 3e^{-3x}$$

where $0 < x < \infty, 1 < y < 2$

1. Are X and Y independent?

$$g(x) = 3Ce^{-3x}, 0 < x < \infty$$
$$h(y) = 1/C, 1 < y < 2$$

$C=1$
 C is a constant

2. What is the marginal PDF of X ? Of Y ?

$$g(x) = 3e^{-3x}$$
$$h(y) = 1$$

$X \sim \text{Exp}(\lambda=3)$
 $Y \sim \text{Uni}(a=1, b=2)$

3. What is $E[X + Y]$?

Approach 1: LOTUS

$$E[X+Y] = \int_0^{\infty} \int_1^2 (x+y) dy dx$$

Approach 2:

$$E[X+Y] = \underbrace{E[X]}_{1/3} + \underbrace{E[Y]}_{3/2} = 11/6$$



Bivariate Normal Distribution

Bivariate Normal Distribution

X_1 and X_2 follow a bivariate normal distribution if their joint PDF f is

$$f(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}\left(\frac{(x_1-\mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1-\mu_1)(x_2-\mu_2)}{\sigma_1\sigma_2} + \frac{(x_2-\mu_2)^2}{\sigma_2^2}\right)}$$

Can show that $X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2)$, $X_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$ (Ross chapter 6, example 5d)

Often written as:

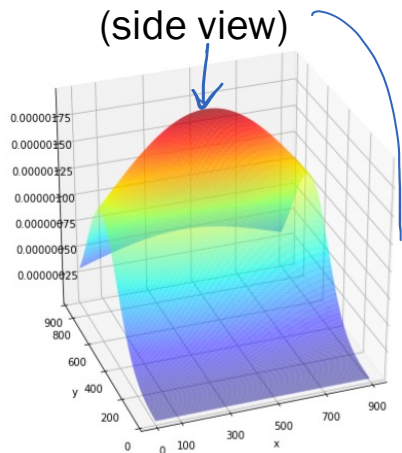
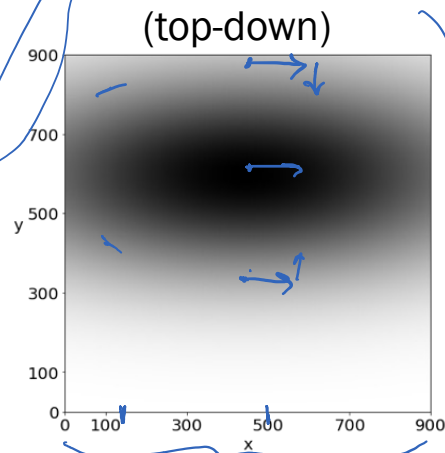
$$\mathbf{X} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

- Vector $\mathbf{X} = (X_1, X_2)$
- Mean vector $\boldsymbol{\mu} = (\mu_1, \mu_2)$, Covariance matrix: $\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}$

Recall correlation: $\rho = \frac{\text{Cov}(X_1, X_2)}{\sigma_1\sigma_2}$

We will focus on understanding the shape of a bivariate Normal RV.

Back to darts



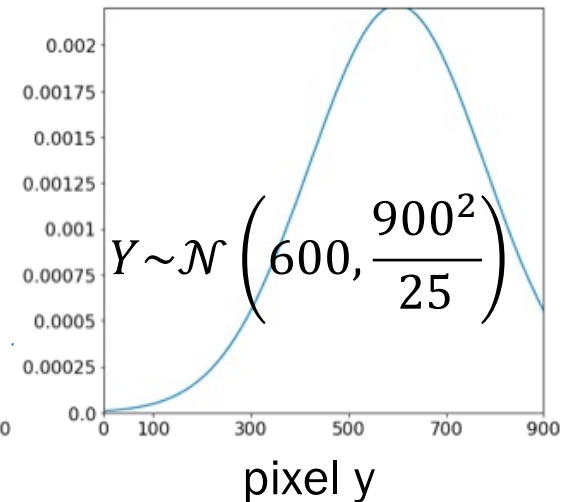
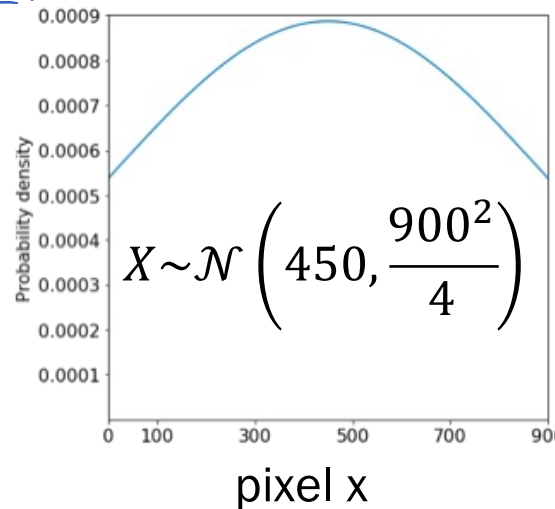
These darts were actually thrown according to a bivariate normal distribution:

$$(X, Y) \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

$$\boldsymbol{\mu} = (450, 600)$$

$$\boldsymbol{\Sigma} = \begin{bmatrix} 900^2/4 & 0 \\ 0 & 900^2/25 \end{bmatrix}$$

Marginal PDFs:



A diagonal covariance matrix

$$f(x, y) = g(x)h(y)$$

Let $\mathbf{X} = (X_1, X_2)$ follow a bivariate normal distribution $\mathbf{X} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, where

$$\boldsymbol{\mu} = (\mu_1, \mu_2),$$

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix}$$

Are X_1 and X_2 independent?

$$f(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}\left(\frac{(x_1-\mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1-\mu_1)(x_2-\mu_2)}{\sigma_1\sigma_2} + \frac{(x_2-\mu_2)^2}{\sigma_2^2}\right)}$$

$$\begin{aligned} &= \frac{1}{2\pi\sigma_1\sigma_2} e^{-\frac{1}{2}\left(\frac{(x_1-\mu_1)^2}{\sigma_1^2} + \frac{(x_2-\mu_2)^2}{\sigma_2^2}\right)} \quad (\text{Note covariance: } \rho\sigma_1\sigma_2 = 0) \\ &= \underbrace{\frac{1}{\sigma_1\sqrt{2\pi}} e^{-(x_1-\mu_1)^2/2\sigma_1^2}}_{f(x_1)} \underbrace{\frac{1}{\sigma_2\sqrt{2\pi}} e^{-(x_2-\mu_2)^2/2\sigma_2^2}}_{g(x_2)} \end{aligned}$$

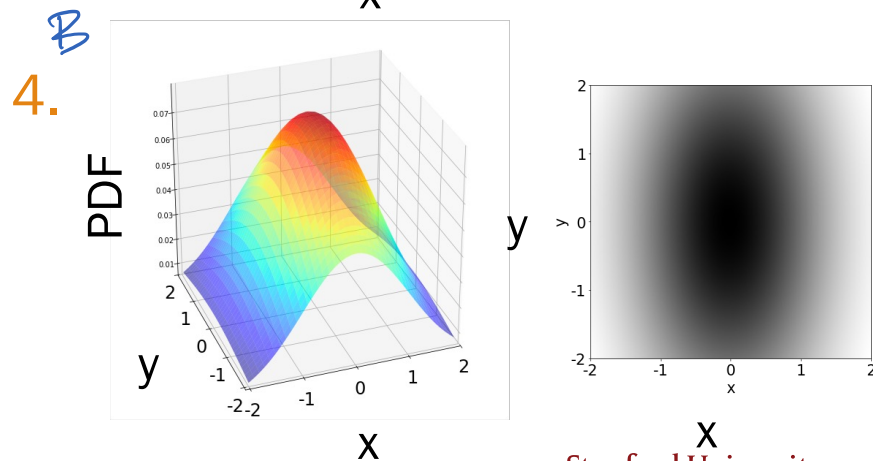
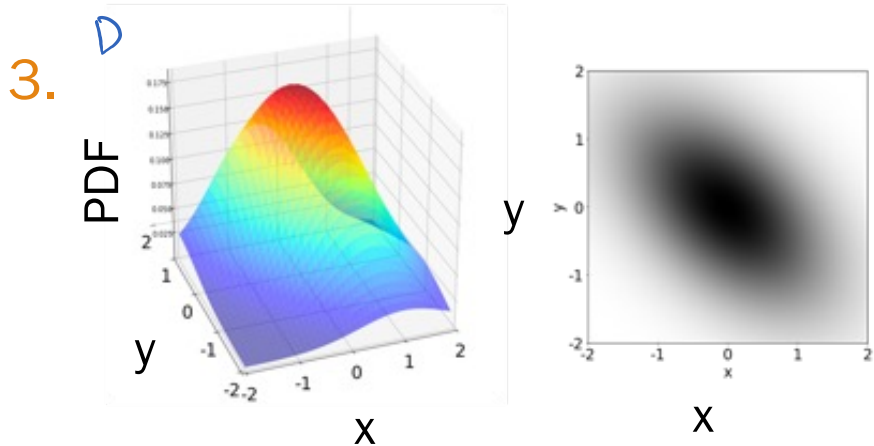
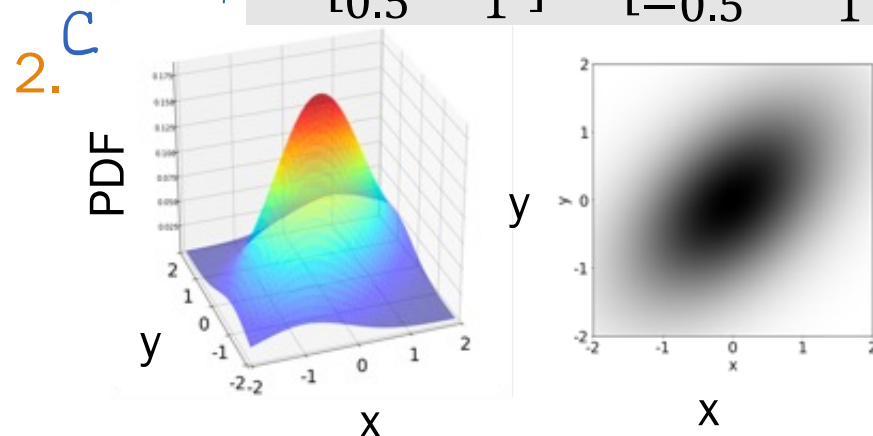
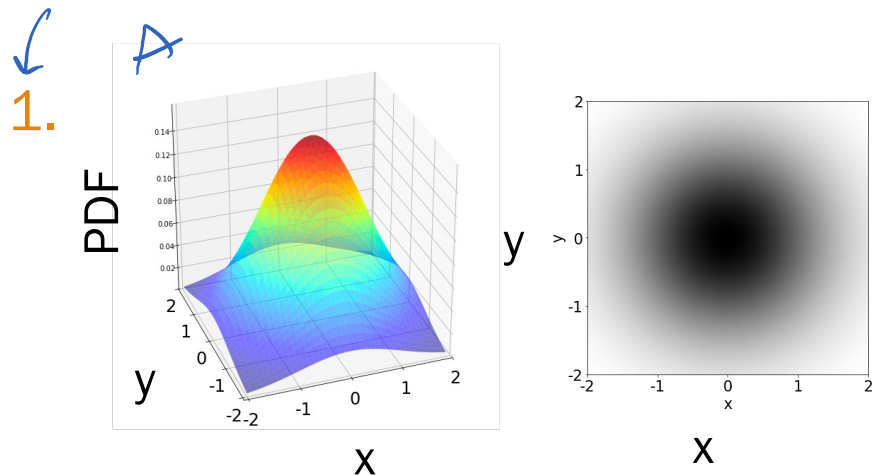
X_1 and X_2 are independent with marginal distributions $X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2)$, $X_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$



(X, Y) Matching (all have $\mu = (0, 0)$)



- A. $\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ B. $\begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$
 C. $\begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$ D. $\begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix}$



(X, Y) Matching (all have $\mu = (0, 0)$)

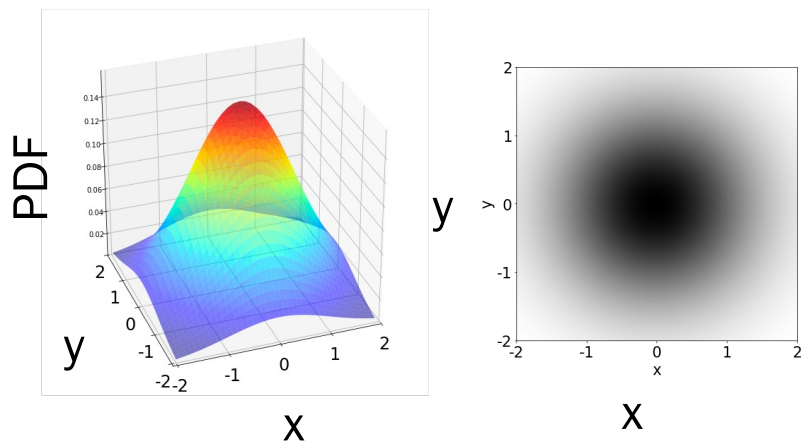
A. $\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

B. $\begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix}$

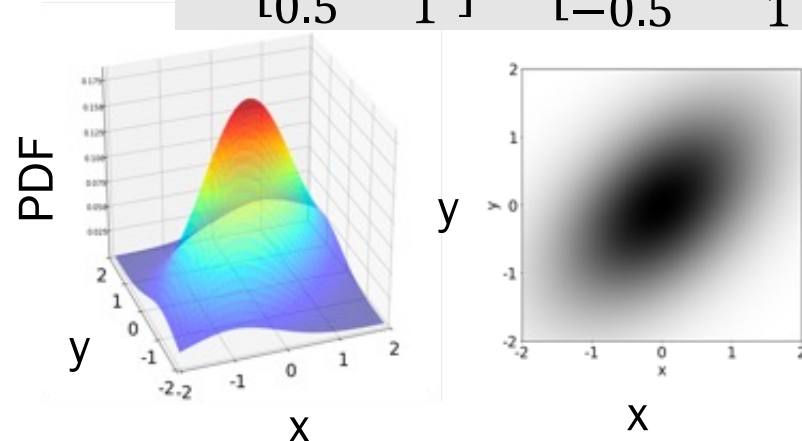
C. $\begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$

D. $\begin{bmatrix} 1 & -0.5 \\ -0.5 & 1 \end{bmatrix}$

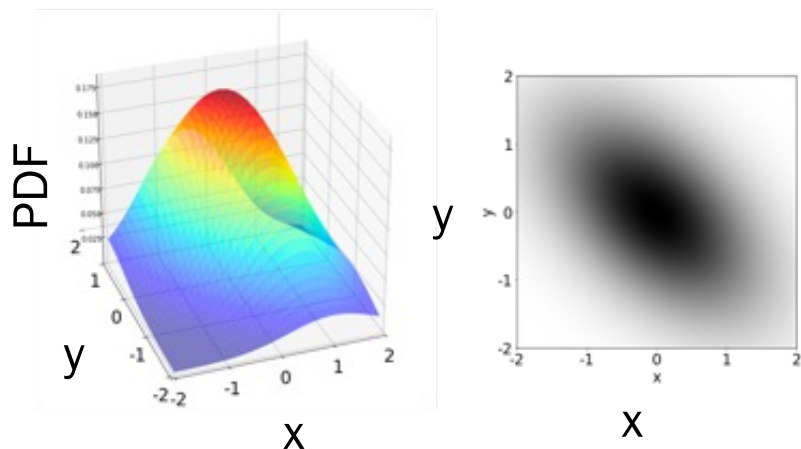
1.



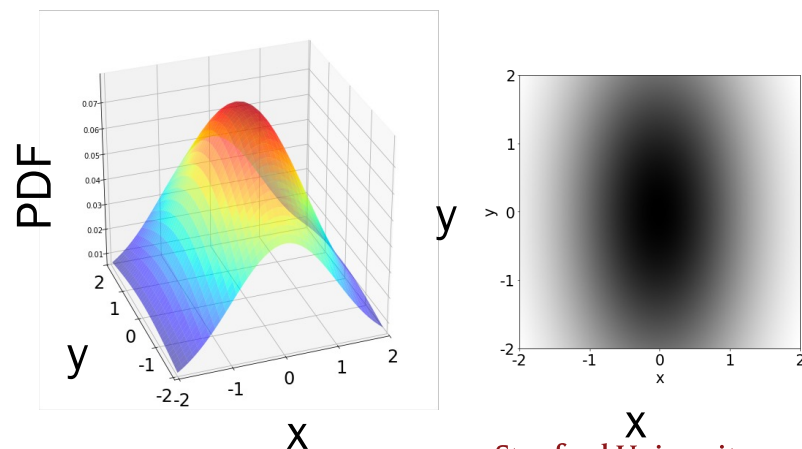
2.



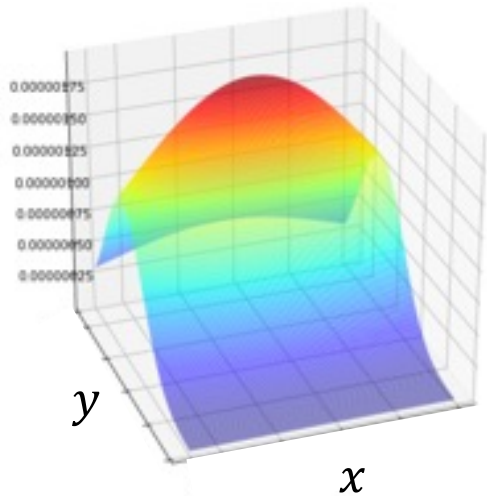
3.



4.



Why are joint PDFs useful?



- How 2 continuous RVs vary with each other
- How continuous RV is distributed given evidence (next time)
- How a continuous RV can be decomposed into 2 RVs (or vice versa)

$$P(X < Y), \\ \text{Cov}(X, Y), \rho(X, Y)$$

Given $Y = y$, the distribution of X

Distribution of $Z = X + Y$
(which is a 1-D RV!)

Independence
2-D support
Joint PDF
Joint CDF
Marginal PDF
(next time) Conditional PDF

Virus infections

Suppose you are working with the WHO to plan a response to the initial conditions of a virus. There are two exposed groups:

- G1: 200 people, each independently infected with $p_1 = 0.1$
- G2: 100 people, each independently infected with $p_2 = 0.4$

What is $P(\text{people infected} \geq 55)$? An approximation is okay.

1. Define RVs & state goal

Let $A = \#$ infected in G1.

$$A \sim \text{Bin}(200, 0.1)$$

$B = \#$ infected in G2.

$$B \sim \text{Bin}(100, 0.4)$$

Want: $P(A + B \geq 55)$

Strategy:

- A. Sum of indep. Binomials
- B. (approximate) Sum of indep. Poissons
- C. (approximate) Sum of indep. Normals
- D. None/other

Virus infections

Suppose you are working with the WHO to plan a response to the initial conditions of a virus. There are two exposed groups:

- G1: 200 people, each independently infected with $p_1 = 0.1$
- G2: 100 people, each independently infected with $p_2 = 0.4$

What is $P(\text{people infected} \geq 55)$? An approximation is okay.

1. Define RVs & state goal

Let $A = \#$ infected in G1.

$$A \sim \text{Bin}(200, 0.1)$$

$B = \#$ infected in G2.

$$B \sim \text{Bin}(100, 0.4)$$

Want: $P(A + B \geq 55)$

Strategy:

A. Sum of indep. Binomials

B. (approximate) Sum of indep. Poissons

C. (approximate) Sum of indep. Normals

D. None/other

Virus infections

Suppose you are working with the WHO to plan a response to the initial conditions of a virus. There are two exposed groups:

- G1: 200 people, each independently infected with $p_1 = 0.1$
- G2: 100 people, each independently infected with $p_2 = 0.4$

What is $P(\text{people infected} \geq 55)$?

$$X \sim N(20, 18) \\ Y \sim N(40, 24)$$

$$X + Y \sim \overset{N}{??} (\overset{60}{}, \overset{42}{})$$

1. Define RVs
& state goal

Let $A = \#$ infected in G1.
 $A \sim \text{Bin}(200, 0.1)$
 $B = \#$ infected in G2.
 $B \sim \text{Bin}(100, 0.4)$

2. Approximate as sum of Normals

$$A \approx X \sim \mathcal{N}(\underline{20}, \overline{18}) \quad B \approx Y \sim \mathcal{N}(\underline{40}, \overline{24})$$

$$P(A + B \geq 55) \approx P(X + Y \geq 54.5) \quad \text{continuity correction}$$

3. Solve

Want: $P(A + B \geq 55)$

Virus infections

Suppose you are working with the WHO to plan a response to the initial conditions of a virus. There are two exposed groups:

- G1: 200 people, each independently infected with $p_1 = 0.1$
- G2: 100 people, each independently infected with $p_2 = 0.4$

What is $P(\text{people infected} \geq 55)$?

1. Define RVs
& state goal

Let $A = \#$ infected in G1.
 $A \sim \text{Bin}(200, 0.1)$
 $B = \#$ infected in G2.
 $B \sim \text{Bin}(100, 0.4)$

Want: $P(A + B \geq 55)$

2. Approximate as sum of Normals

$$A \approx X \sim \mathcal{N}(20, 18) \quad B \approx Y \sim \mathcal{N}(40, 24)$$

$$P(A + B \geq 55) \approx P(X + Y \geq 54.5) \quad \text{continuity correction}$$

3. Solve

$$\text{Let } W = X + Y \sim \mathcal{N}(20 + 40 = 60, 18 + 24 = 42)$$

$$P(W \geq 54.5) = 1 - \Phi\left(\frac{54.5 - 60}{\sqrt{42}}\right) \approx 1 - \Phi(-0.85) \\ \approx 0.8023$$

Linear transforms vs. independence



Let $X \sim \mathcal{N}(\mu, \sigma^2)$ and $Y = \overset{2X}{X} + X$. What is the distribution of Y ?

- Are both approaches valid?



Independent RVs approach

Let $X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2)$, $X_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$
be independent.
Then $Y = X_1 + X_2 \sim \mathcal{N}(\underbrace{\mu_1 + \mu_2}, \underbrace{\sigma_1^2 + \sigma_2^2})$

Linear transform approach

Let $X \sim \mathcal{N}(\mu, \sigma^2)$.
If $Y = aX + b$,
then $Y \sim \mathcal{N}(a\mu + b, a^2\sigma^2)$.



Linear transforms vs. independence



Let $X \sim \mathcal{N}(\mu, \sigma^2)$ and $Y = X + X$. What is the distribution of Y ?

- Are both approaches valid?

Independent RVs approach 

Let $X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2), X_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$
be independent.
Then $Y = X_1 + X_2 \sim \mathcal{N}(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$

$$Y = X + X$$

$$X + X \sim \mathcal{N}(\mu + \mu, \sigma^2 + \sigma^2)?$$

$$Y \sim \mathcal{N}(2\mu, 2\sigma^2)?$$

X is NOT
independent
of X !

Linear transform approach 

Let $X \sim \mathcal{N}(\mu, \sigma^2)$.
If $Y = aX + b$,
then $Y \sim \mathcal{N}(a\mu + b, a^2\sigma^2)$.

$$Y = 2X$$

$$Y \sim \mathcal{N}(2\mu, 4\sigma^2)$$

For independent $X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2), X_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$,
 $aX_1 + bX_2 + c \sim \mathcal{N}(a\mu_1 + b\mu_2 + c, a^2\sigma_1^2 + b^2\sigma_2^2)$