Multinomial + Cont. Joint

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CS109 Flow

Today

Discrete Joint Distributions: General Case

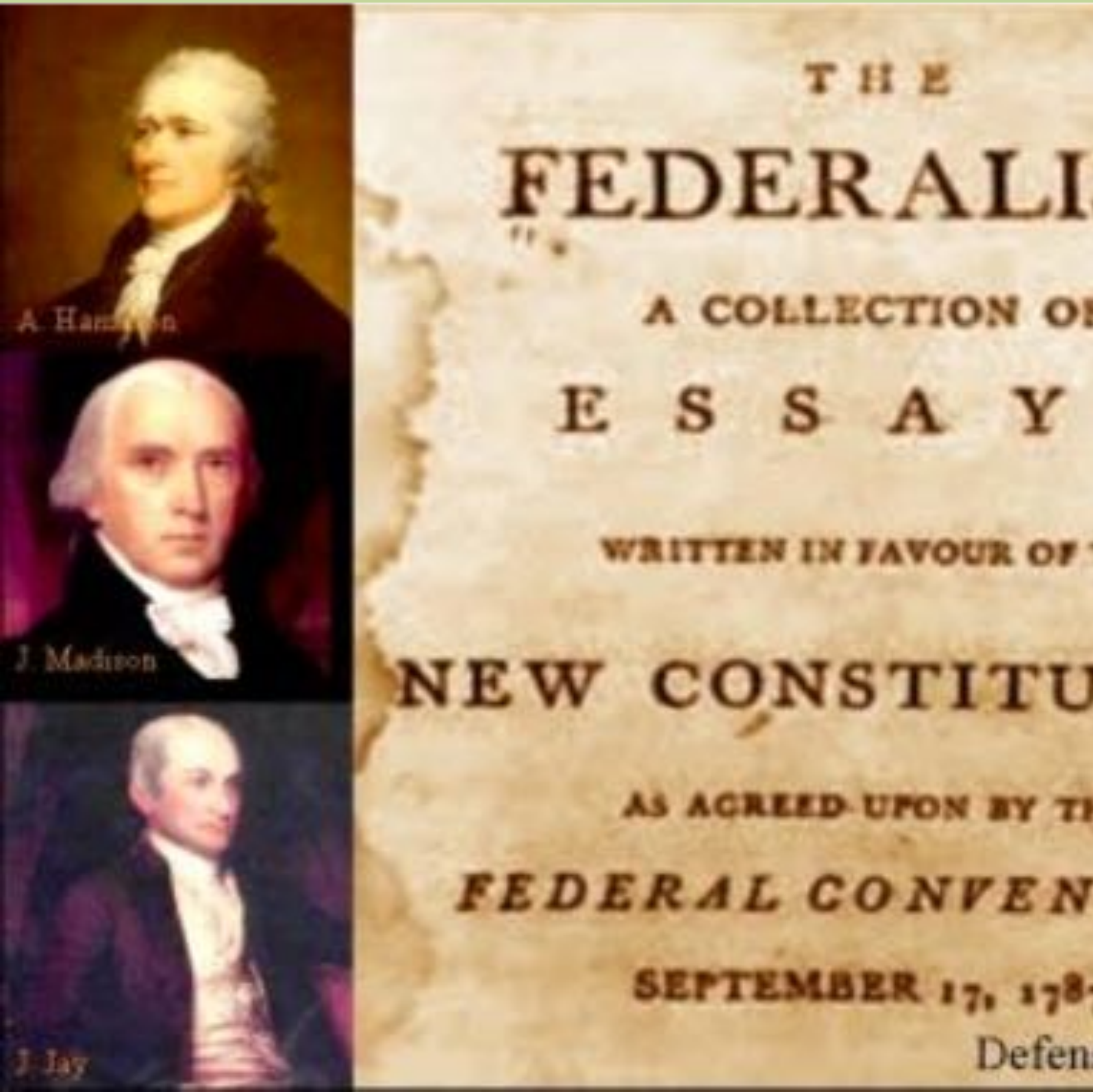
Multinomial: A parametric Discrete Joint

Cont. Joint Distributions: General Case

Learning Goals

1. Know how to use a multinomial
2. Be able to calculate large bayes problems using a computer
3. Use a Joint CDF

Motivating Examples

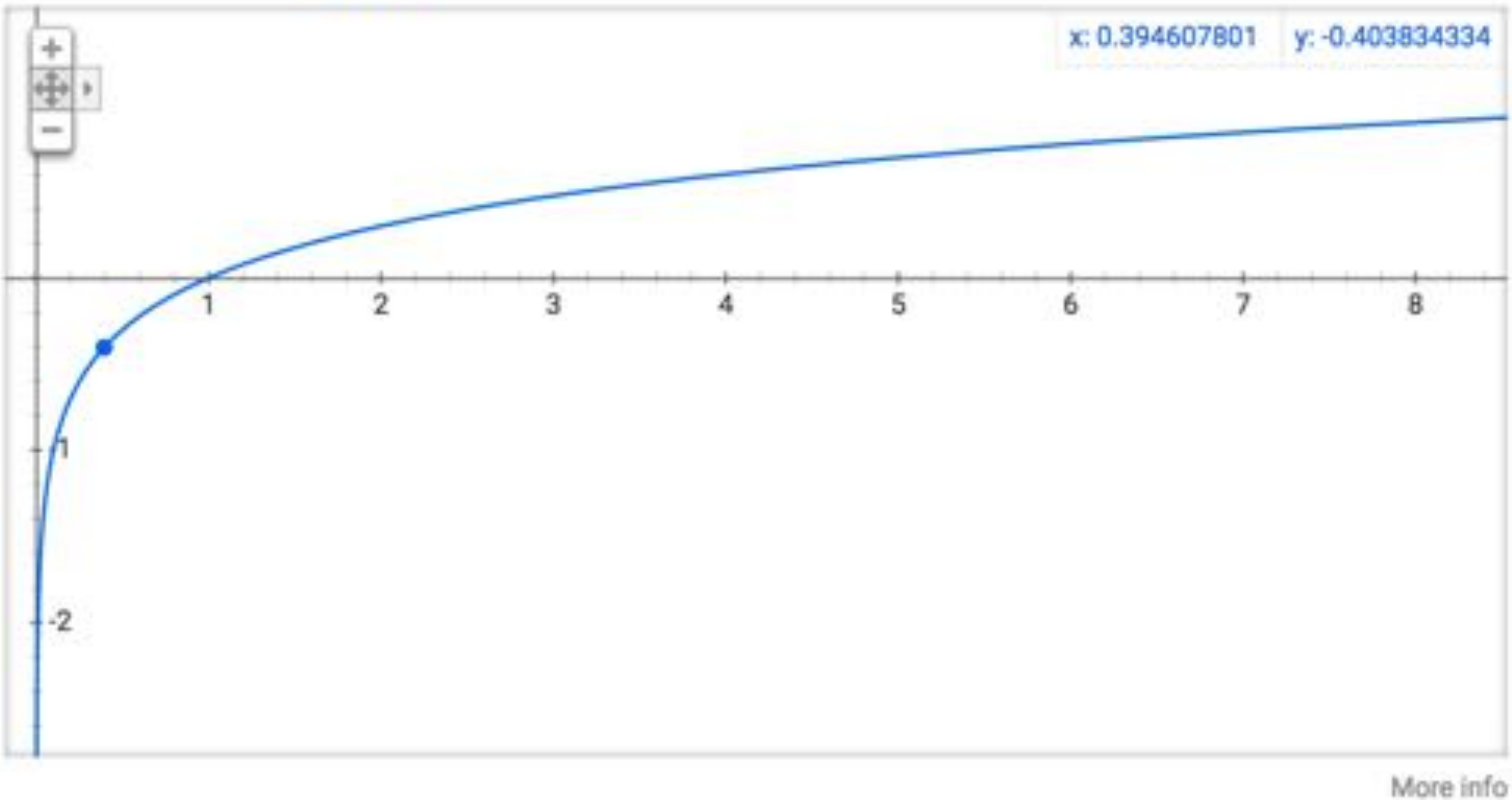


Recall logs

Log Review

$$e^y = x \qquad \log(x) = y$$

Graph for log(x)



Log Identities

$$\log(a \cdot b) = \log(a) + \log(b)$$

$$\log(a/b) = \log(a) - \log(b)$$

$$\log(a^n) = n \cdot \log(a)$$

Products become Sums!

$$\log(a \cdot b) = \log(a) + \log(b)$$

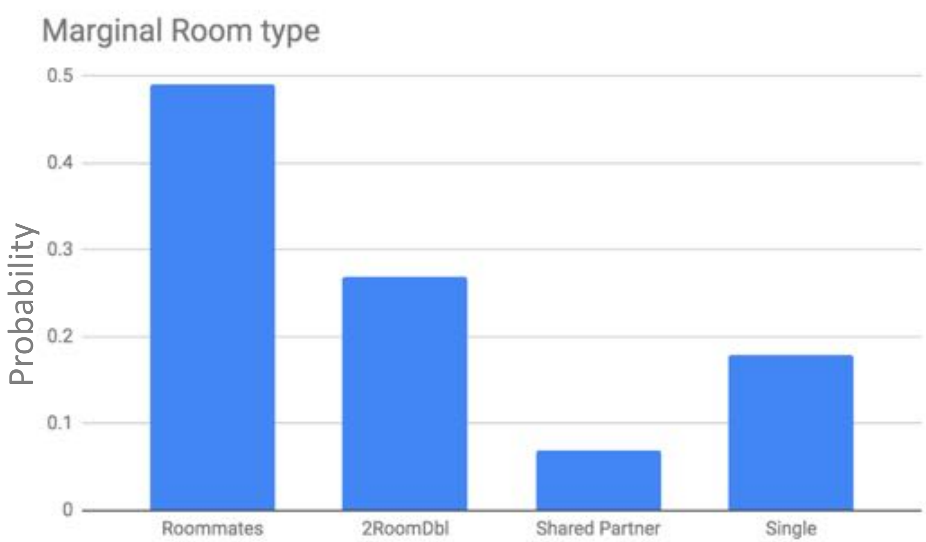
$$\log(\prod_i a_i) = \sum_i \log(a_i)$$

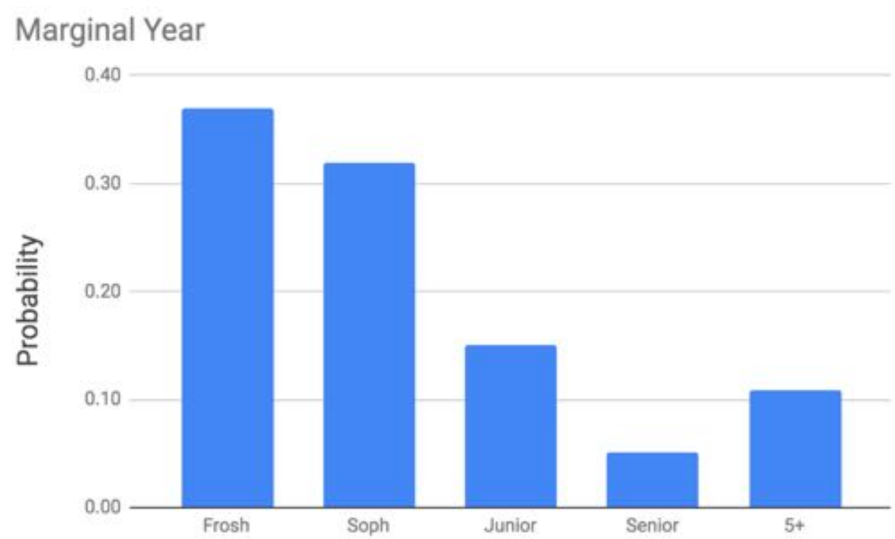
* Spoiler alert: This is important because the product of many small numbers gets hard for computers to represent.

Where we left off

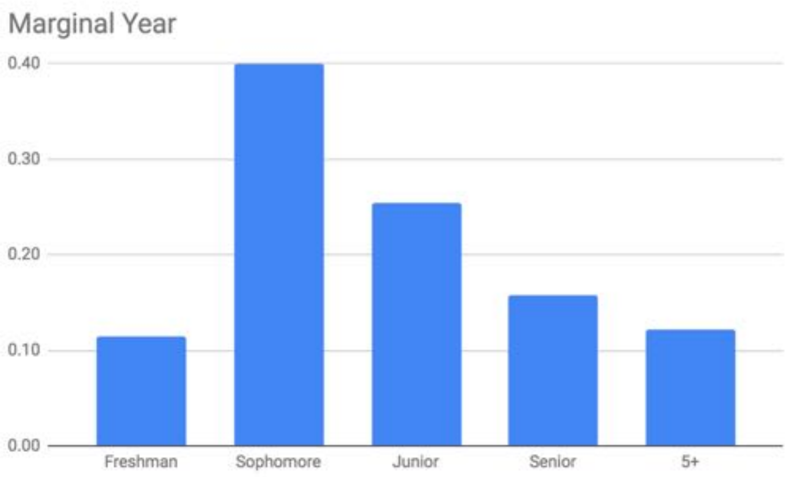
Joint Probability Table

	Roommates	2RoomDbl	Shared Partner	Single	
Frosh	0.30	0.07	0.00	0.00	0.37
Soph	0.12	0.18	0.00	0.03	0.32
Junior	0.04	0.01	0.00	0.10	0.15
Senior	0.01	0.02	0.02	0.01	0.05
5+	0.02	0.00	0.05	0.04	0.11
	0.49	0.27	0.07	0.18	1.00

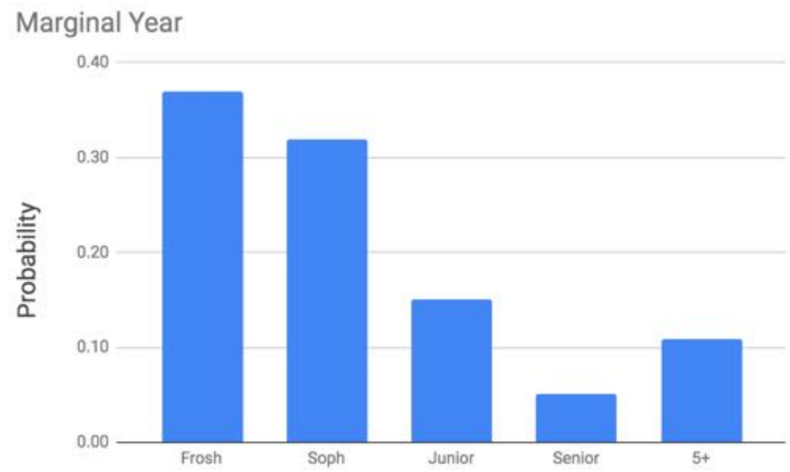




Change in Marginal Year



Fall quarter ‘18



Spr quarter ‘19

The Multinomial

- Multinomial distribution
  - n independent trials of experiment performed
  - Each trial results in one of m outcomes, with respective probabilities: $p_1, p_2, \ldots, p_m$ where $\sum_{i=1}^{m} p_i = 1$
  - X_i = number of trials with outcome i

$$P(X_1 = c_1, X_2 = c_2, \ldots, X_m = c_m) = \binom{n}{c_1, c_2, \ldots, c_m} p_1^{c_1} p_2^{c_2} \ldots p_m^{c_m}$$

Joint distribution

Multinomial # ways of ordering the successes

Probabilities of each ordering are equal and mutually exclusive

where $\sum_{i=1}^{m} c_i = n$ and $\binom{n}{c_1, c_2, \ldots, c_m} = \frac{n!}{c_1! c_2! \cdots c_m!}$

The Multinomial

- Multinomial distribution
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  - X_i = number of trials with outcome i

$$P(X_1 = c_1, X_2 = c_2, \ldots, X_m = c_m) = \binom{n}{c_1, c_2, \ldots, c_m} \prod_i p_i^{c_i}$$

Count of each word

Joint distribution

Multinomial # ways of ordering the successes

Probabilities of each word

where $\sum_{i=1}^{m} c_i = n$ and $\binom{n}{c_1, c_2, \ldots, c_m} = \dfrac{n!}{c_1! c_2! \cdots c_m!}$

Hello Die Rolls, My Old Friends

- 6-sided die is rolled 7 times
  - Roll results: 1 one, 1 two, 0 three, 2 four, 0 five, 3 six

$$P(X_1 = 1, X_2 = 1, X_3 = 0, X_4 = 2, X_5 = 0, X_6 = 3)$$

$$= \frac{7!}{1!1!0!2!0!3!}\left(\frac{1}{6}\right)^1\left(\frac{1}{6}\right)^1\left(\frac{1}{6}\right)^0\left(\frac{1}{6}\right)^2\left(\frac{1}{6}\right)^0\left(\frac{1}{6}\right)^3 = 420\left(\frac{1}{6}\right)^7$$

- This is generalization of Binomial distribution
  - Binomial: each trial had 2 possible outcomes
  - Multinomial: each trial has *m* possible outcomes

Probabilistic Text Analysis

According to the Global Language Monitor there are 988,968 words in the english language used on the internet.

Text is a Multinomial

Example document:
"Pay for Viagra with a credit-card. Viagra is great. So are credit-cards. Risk free Viagra. Click for free."
n = 18

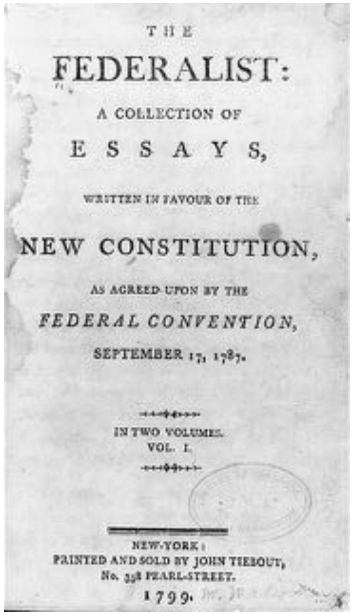
$$\underbrace{P\left(\begin{array}{l}\text{Viagra} = 2\\ \text{Free} = 2\\ \text{Risk} = 1\\ \text{Credit-card: } 2\\ \dots\\ \text{For} = 2\end{array}\middle|\,\text{spam}\right)}_{\text{Probability of seeing this document | spam}} = \overbrace{\frac{n!}{2!2!\dots2!}p^2_{\text{viagra}}p^2_{\text{free}}\cdots p^2_{\text{for}}}^{\text{It's a Multinomial!}}$$

The probability of a word in spam email being viagra

Who wrote the federalist papers?

Old and New Analysis

- Authorship of "Federalist Papers"
  - 85 essays advocating ratification of US constitution
  - Written under pseudonym "Publius"
    - Really, Alexander Hamilton, James Madison and John Jay
  - Who wrote which essays?
    - Analyzed probability of words in each essay versus word distributions from known writings of three authors


THE

FEDERALIST:

A COLLECTION OF

E S S A Y S,

WRITTEN IN FAVOUR OF THE

NEW CONSTITUTION,

AS AGREED UPON BY THE

FEDERAL CONVENTION,

SEPTEMBER 17, 1787.

IN TWO VOLUMES.

VOL. I.

NEW-YORK:

PRINTED AND SOLD BY JOHN TIEBOUT,

No. 358 PEARL-STREET.

1799.

Let’s write a program!

Text is a Multinomial

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"Pay for Viagra with a credit-card. Viagra is great. So are credit-cards. Risk free Viagra. Click for free."

n = 18

$$\underbrace{P\left(\begin{array}{l}\text{Viagra} = 2\\ \text{Free} = 2\\ \text{Risk} = 1\\ \text{Credit-card: } 2\\ \ldots\\ \text{For} = 2\end{array} \middle| \text{spam}\right)}_{\text{Probability of seeing this document | spam}} = \overbrace{\frac{n!}{2!2!\ldots2!} p_{\text{viagra}}^2 p_{\text{free}}^2 \ldots p_{\text{for}}^2}^{\text{It's a Multinomial!}}$$

The probability of a word in spam email being viagra woot

Continuous Random Variables

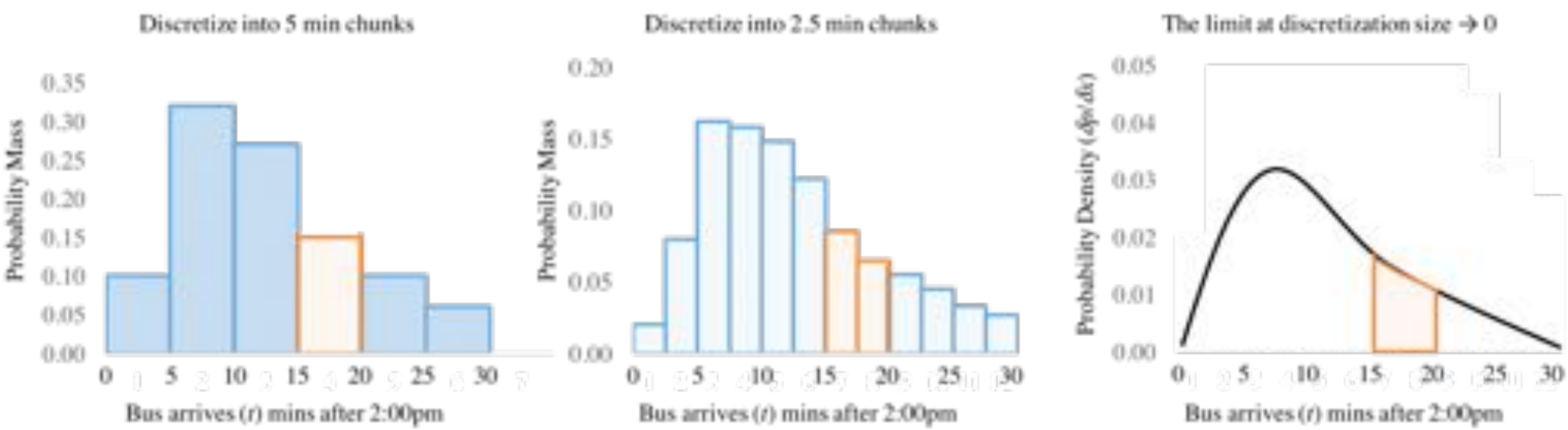
Joint Distributions

Continuous Joint Distribution

Riding the Marguerite

You are running to the bus stop. You don't know exactly when the bus arrives. You arrive at 2:20pm.

What is P(wait < 5 min)?



Joint Dart Distribution

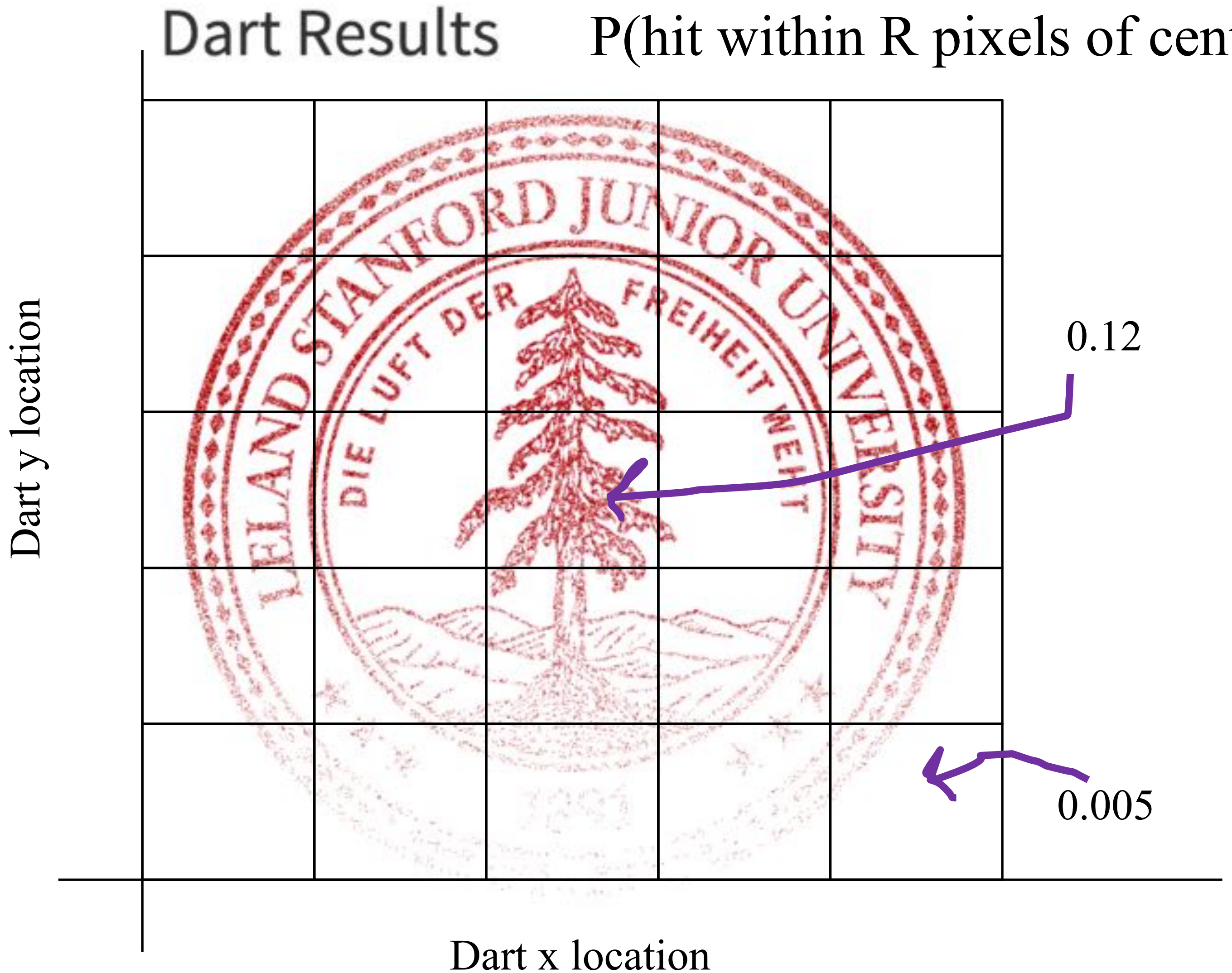
Dart Results

P(hit within R pixels of center)?

What is the probability that a dart hits at (456.234231234122355, 532.12344123456)?

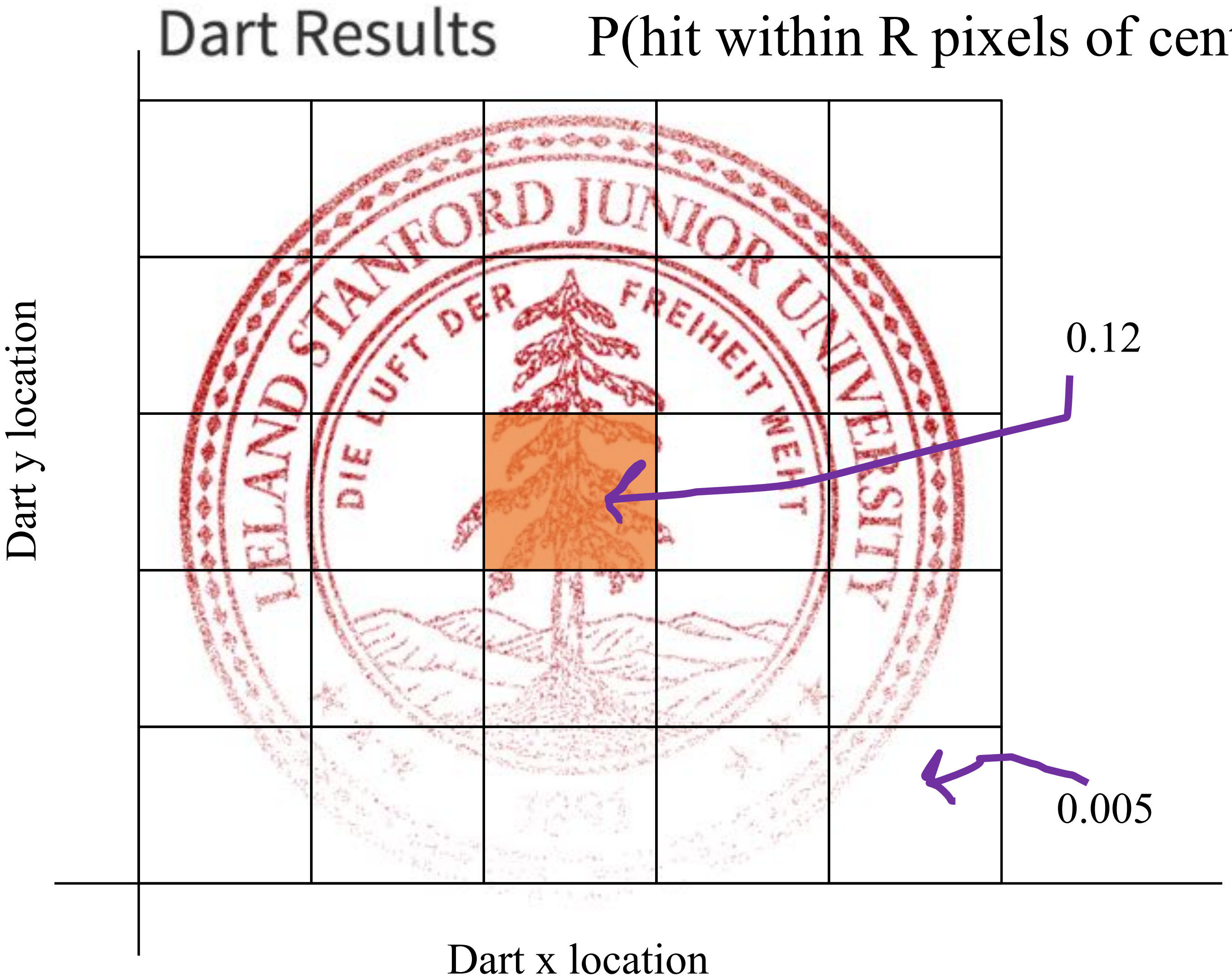
Joint Dart Distribution

P(hit within R pixels of center)?



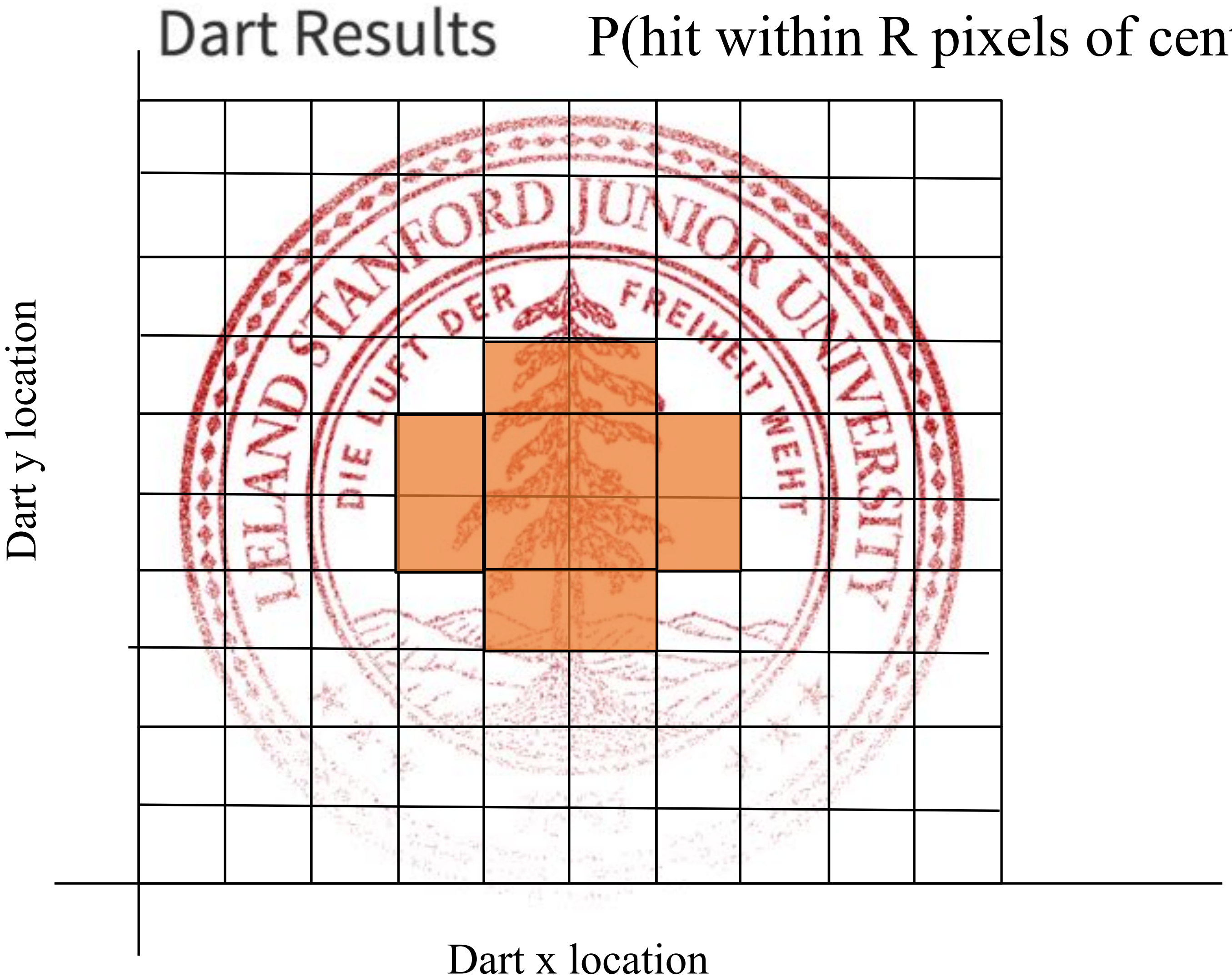
Joint Dart Distribution

P(hit within R pixels of center)?



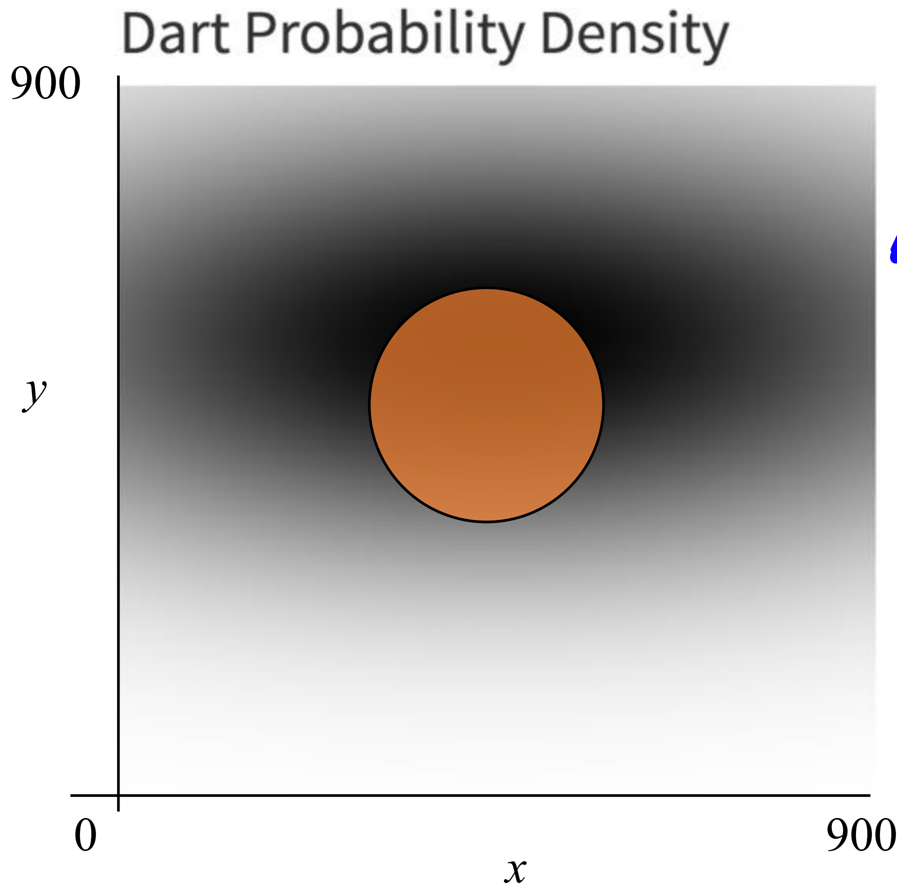
Joint Dart Distribution

P(hit within R pixels of center)?



Joint Dart Distribution

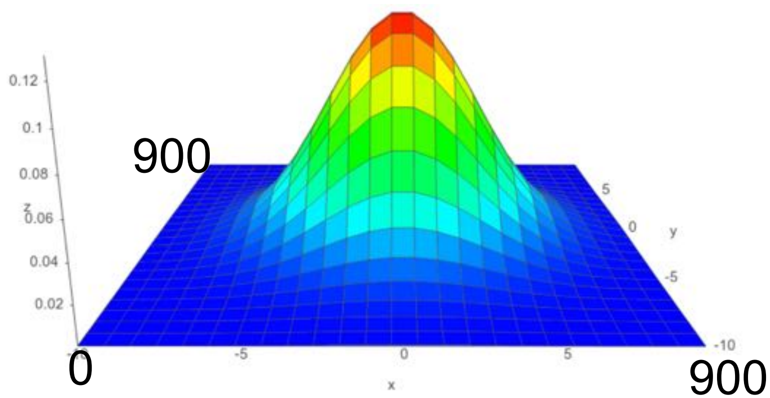
$$f(X = x, Y = y)$$

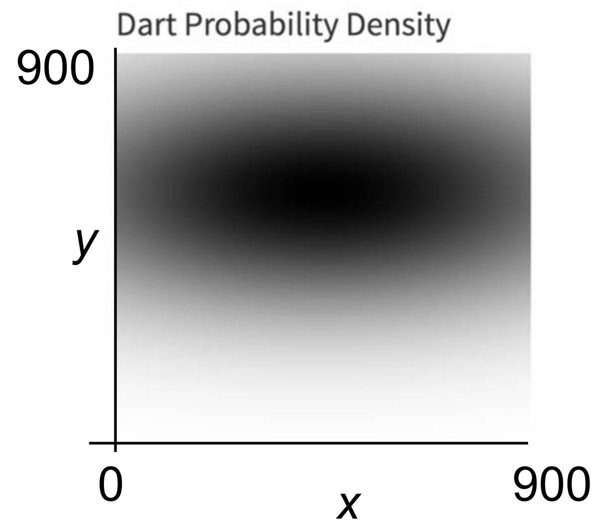


In the limit, as you break down continuous values into intestinally small buckets, you end up with multidimensional probability density

Joint Probability Density Funciton

A **joint probability density function** gives the relative likelihood of **more than one** continuous random variable **each** taking on a specific value.





$$P(a_1 < X < a_2, b_1 < Y < b_2) = \int_{x=a_1}^{a_2} \int_{y=b_1}^{b_2} f(X = x, Y = y)\ \partial y \partial x$$

Joint Probability Density Funciton

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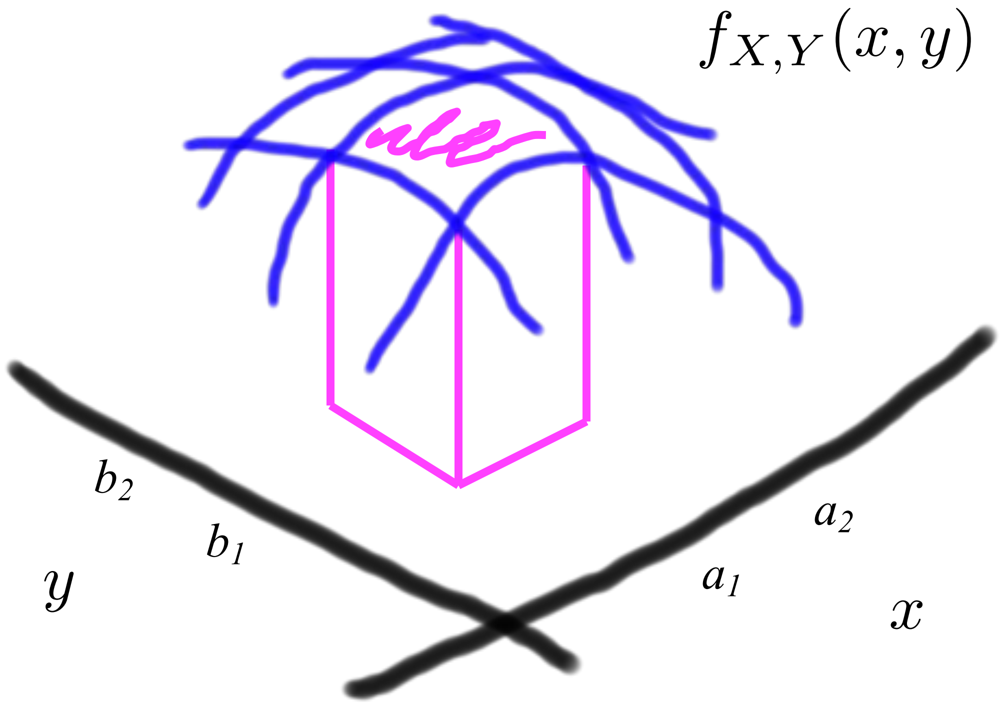
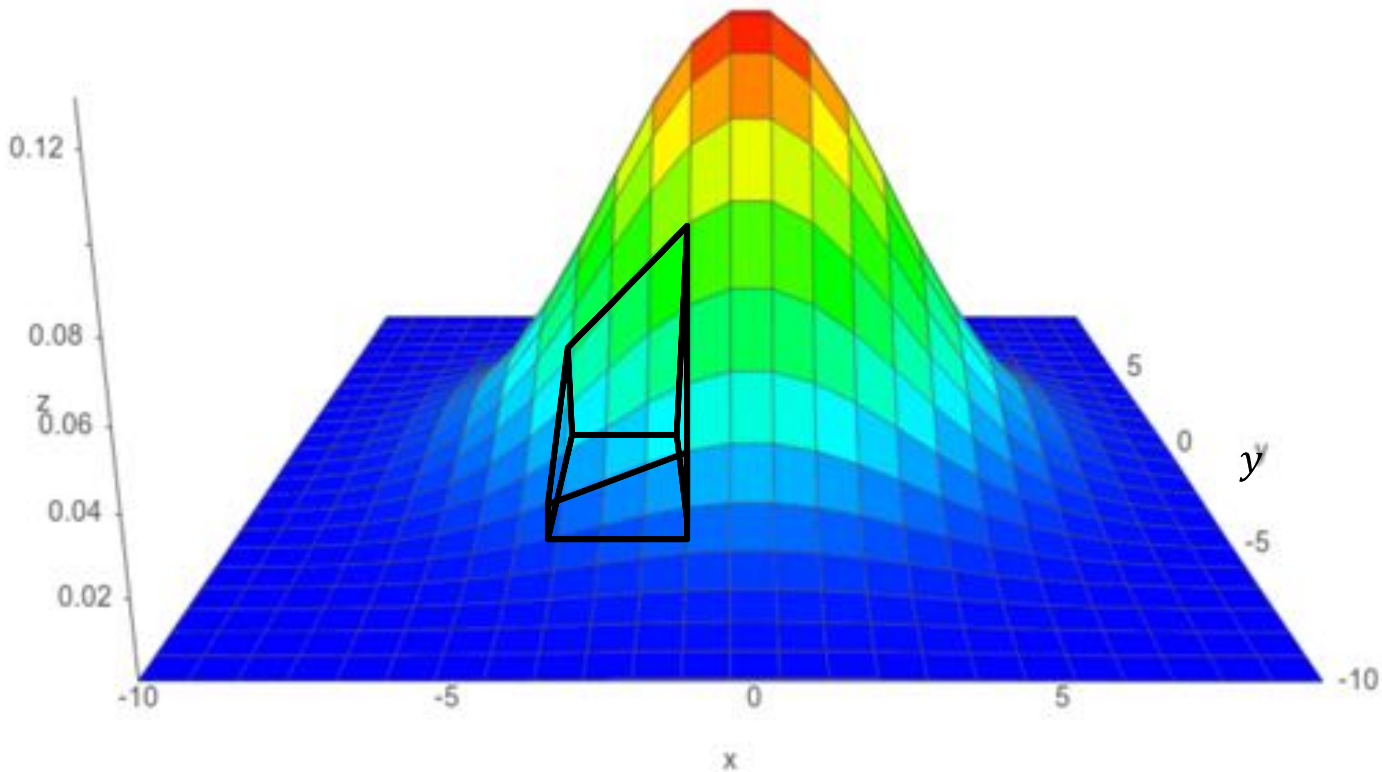


Joint Probability Density Function

$$P(a_1 < X < a_2, b_1 < Y < b_2) = \int_{x=a_1}^{a_2} \int_{y=b_1}^{b_2} f(X = x, Y = y)\ \partial y \partial x$$



plot by Academo

Multiple Integrals Without Tears

- Let X and Y be two continuous random variables
  - where $0 \le X \le 1$ and $0 \le Y \le 2$
- We want to integrate $g(x,y) = xy$ w.r.t. X and Y:
  - First, do "innermost" integral (treat y as a constant):

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

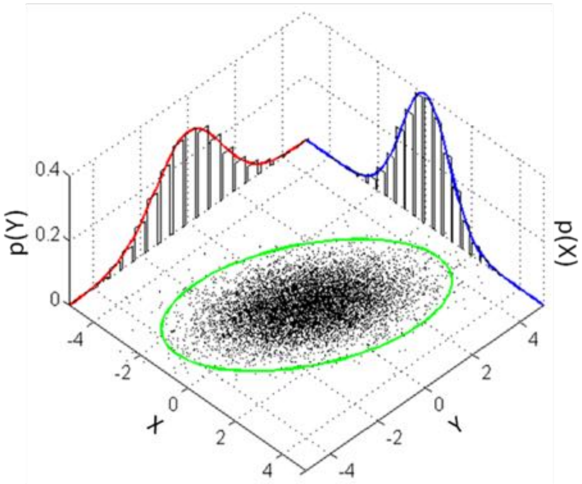
  - Then, evaluate remaining (single) integral:

$$\int_{y=0}^{2} y \frac{1}{2} dy = \left[\frac{y^2}{4} \right]_0^2 = 1 - 0 = 1$$

Marginalization

Marginal probabilities give the distribution of **a subset of the variables** (often, just one) of a joint distribution.

Sum/integrate over the variables you don't care about.



$$p_X(a) = \sum_y p_{X,Y}(a, y)$$

$$f_X(a) = \int_{-\infty}^{\infty} f_{X,Y}(a, y)\ dy$$

$$f_Y(b) = \int_{-\infty}^{\infty} f_{X,Y}(x, b)\ dx$$

Marginalization

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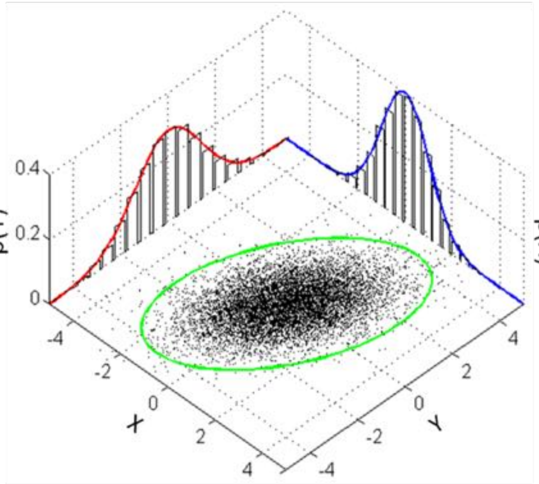

Sum/integrate over the variables you don't care about.

$$p_X(a) = \sum_y P(X = a, Y = y)$$

$$f_X(a) = \int_{-\infty}^{\infty} f_{X,Y}(a, y)\ dy$$

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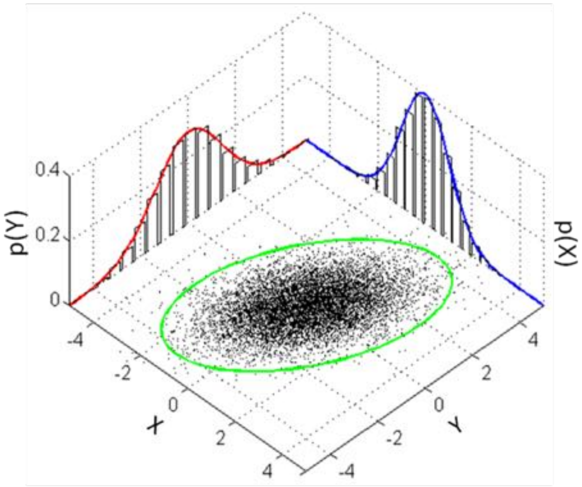

Sum/integrate over the variables you don't care about.

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$$f_X(a) = \int_{-\infty}^{\infty} f(X = a, Y = y)$$

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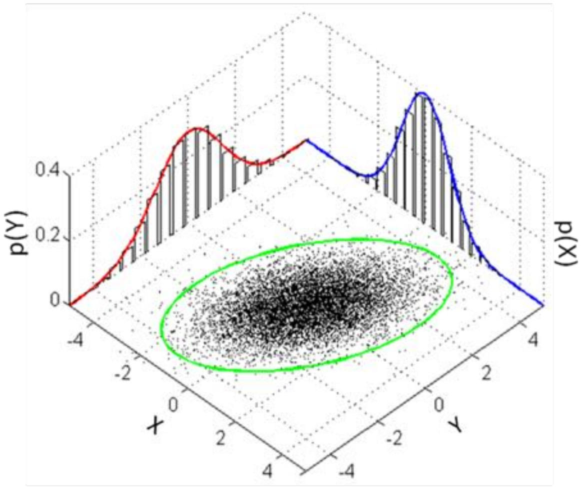
Marginalization



Marginal probabilities give the distribution of **a subset of the variables** (often, just one) of a joint distribution.

Sum/integrate over the variables you don't care about.

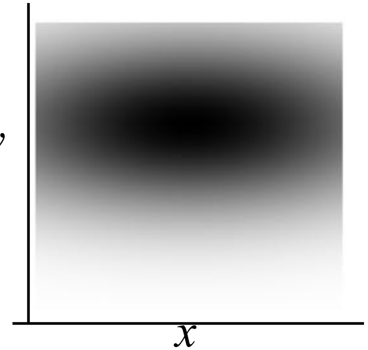
$$P(X=a) = \sum_y P(X=a, Y=y)$$

$$f(X=a) = \int_{-\infty}^{\infty} f(X=a, Y=y)$$

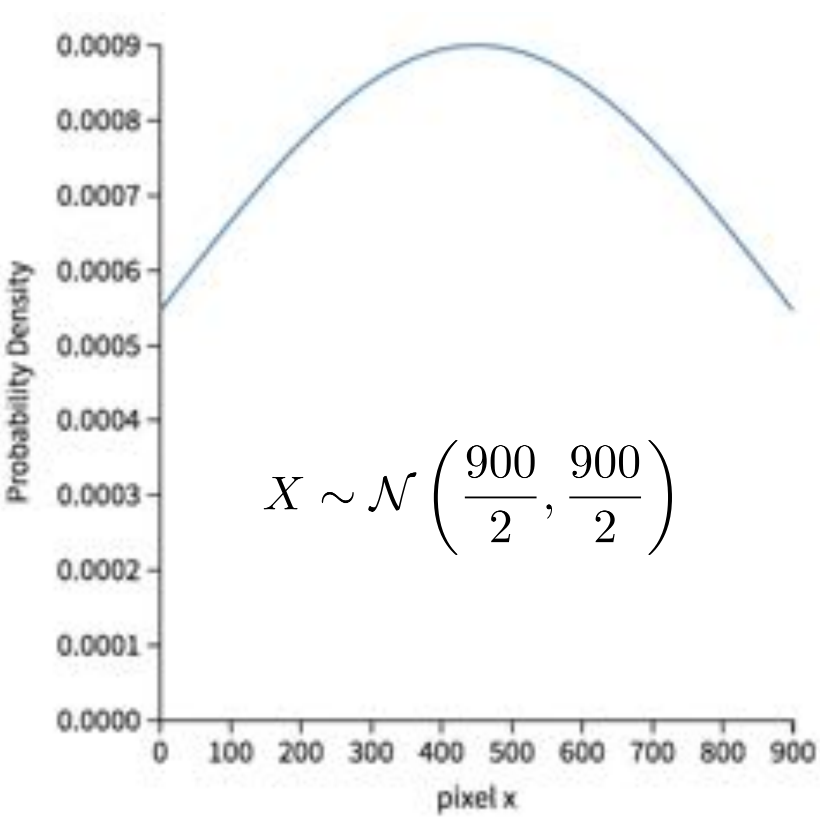
$$f_Y(b) = \int_{-\infty}^{\infty} f_{X,Y}(x,b)\; dx$$

Darts!

Dart PDF

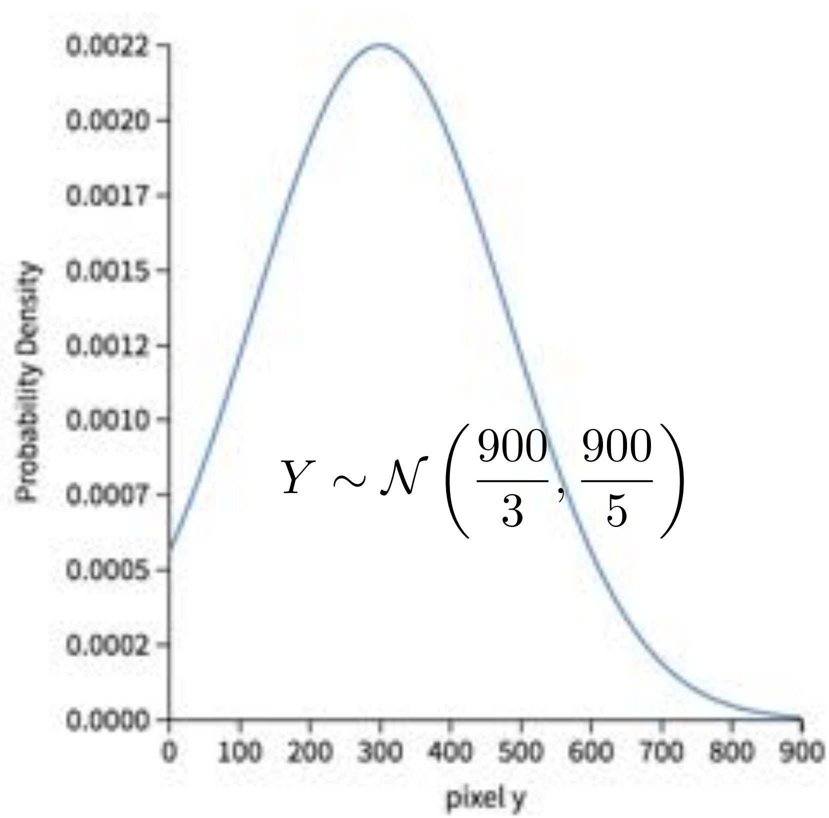


X-Pixel Marginal



$$X \sim \mathcal{N}\left(\frac{900}{2}, \frac{900}{2}\right)$$

Y-Pixel Marginal



$$Y \sim \mathcal{N}\left(\frac{900}{3}, \frac{900}{5}\right)$$

Joint Cumulative Density Function

Cumulative Density Function (CDF):

$$F_{X,Y}(a,b) = P(X < a, Y < b)$$

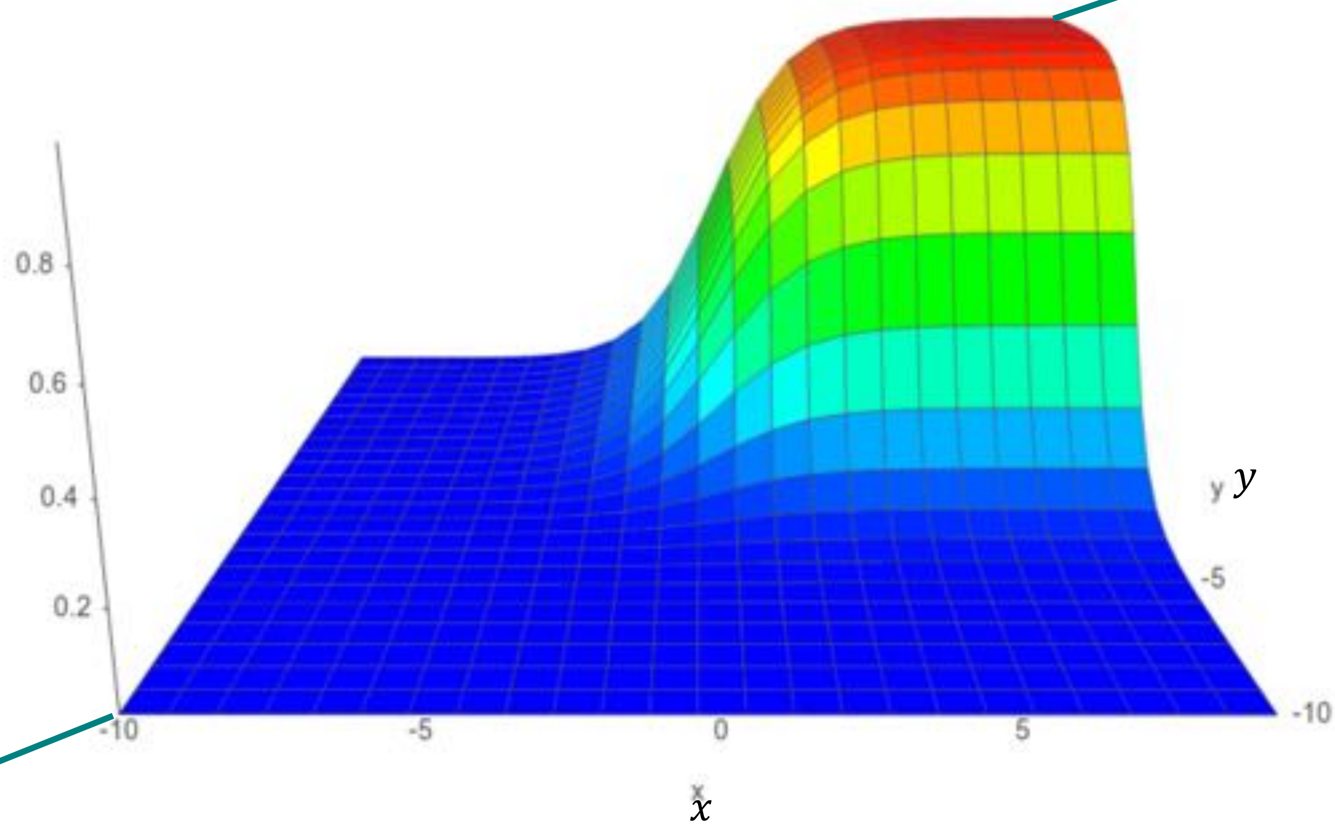
$$F_{X,Y}(a,b) = \int_{-\infty}^{a} \int_{-\infty}^{b} f_{X,Y}(x,y)\, dy\, dx$$

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

Joint CDF

$$F_{X,Y}(a,b) = P(X < a, Y < b)$$

to 1 as
x → +∞,
y → +∞

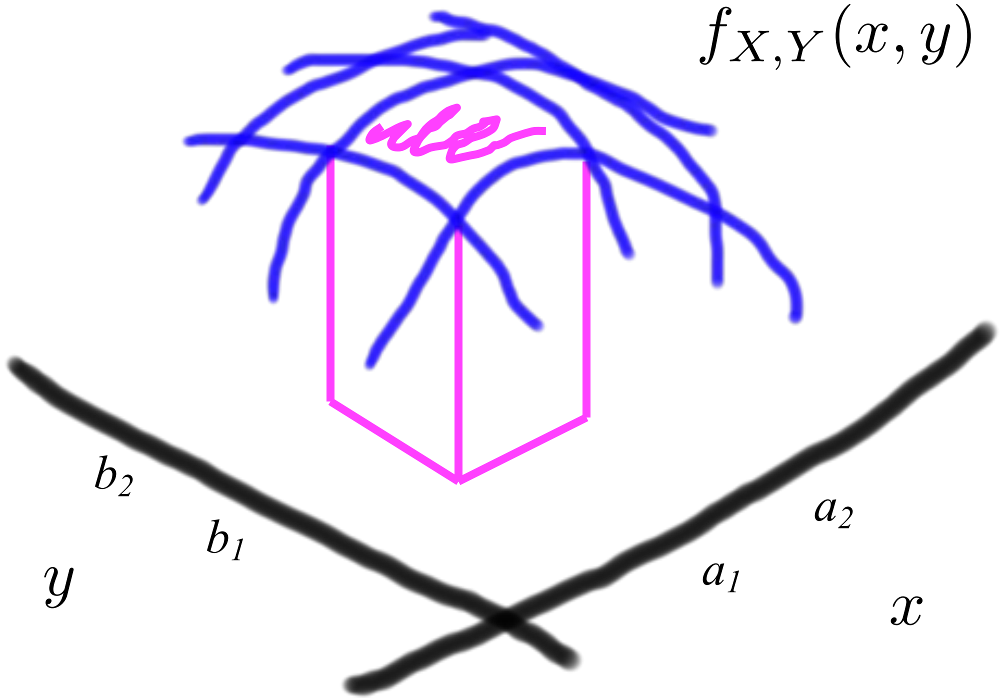


to 0 as
x → -∞,
y → -∞

plot by [Academo]

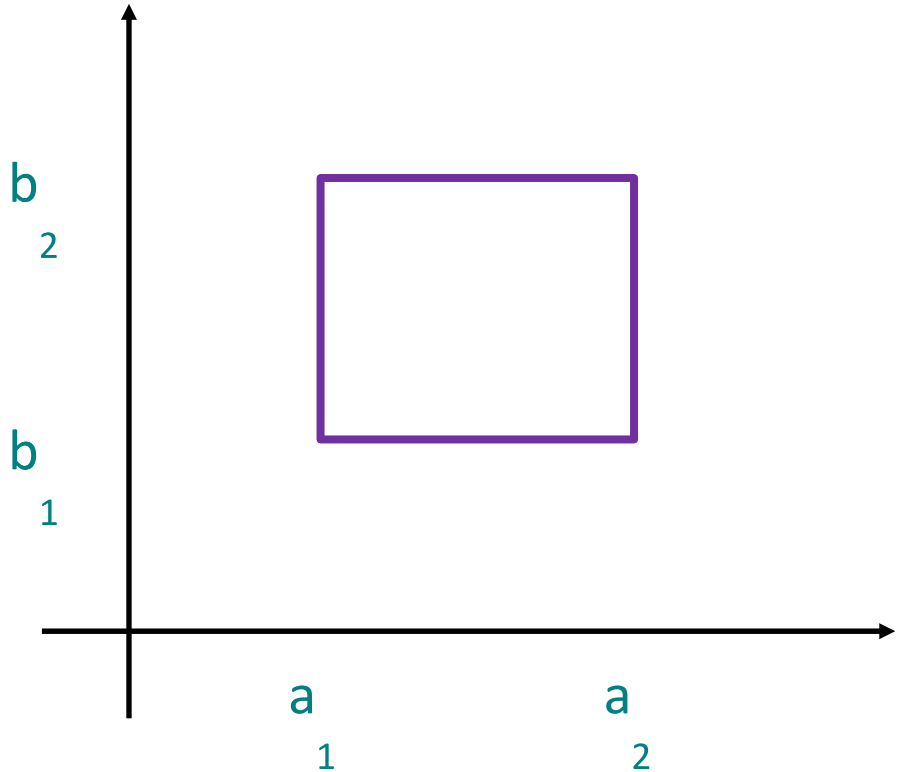
Jointly Continuous

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



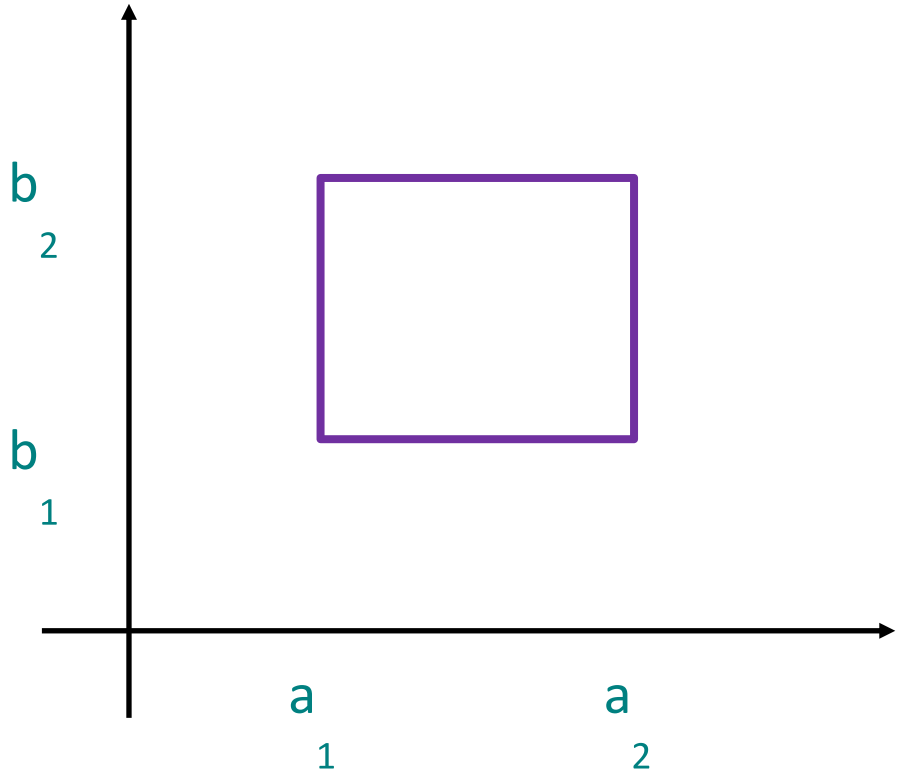
Probabilities from Joint CDF

$$P(a_1 < X \le a_{2,} b_1 < Y \le b_2)$$



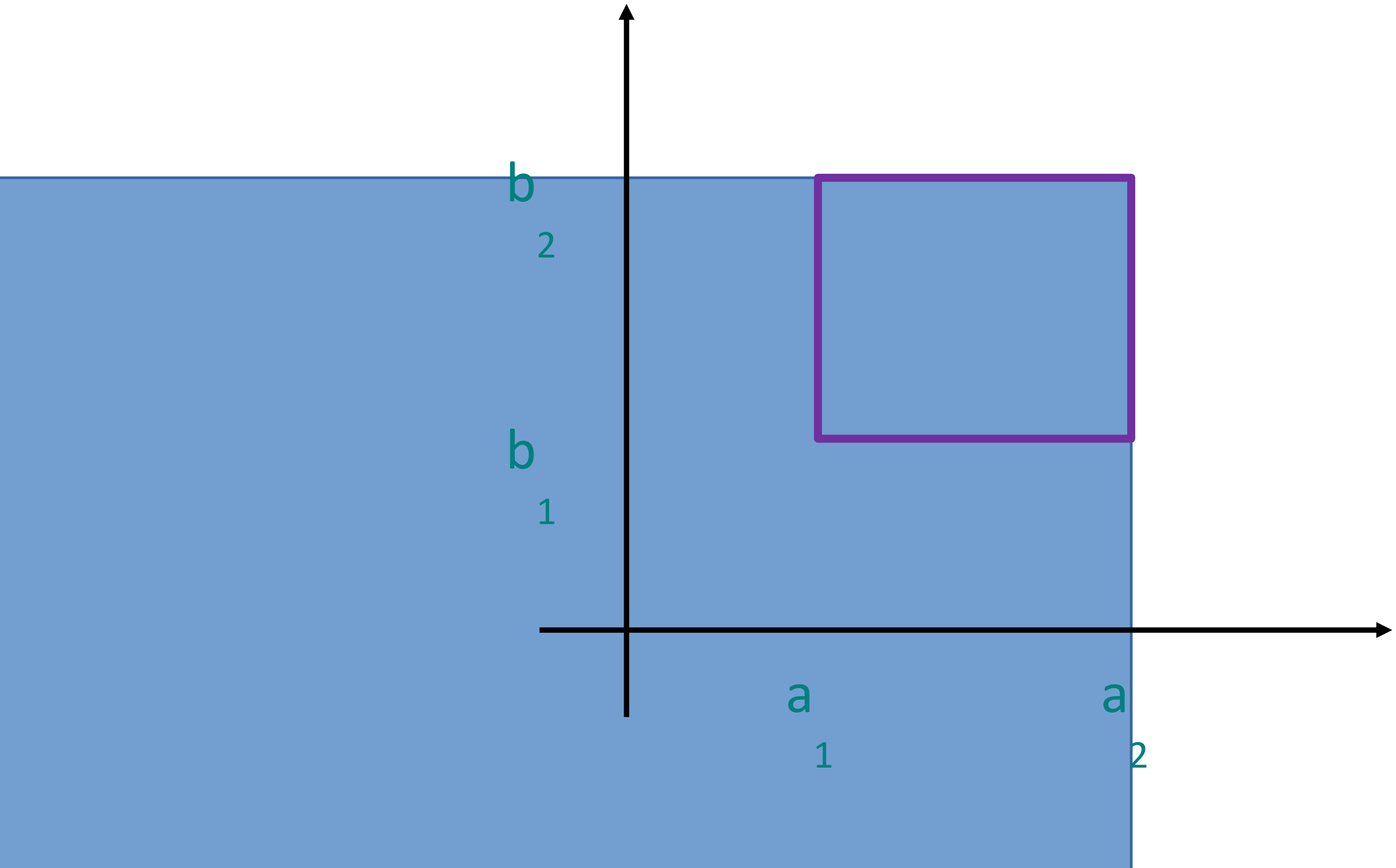
Probabilities from Joint CDF

$$P\left(a_1 < X \leq a_{2,} b_1 < Y \leq b_2\right) = F_{X,Y}\left(a_{2,} b_2\right)$$



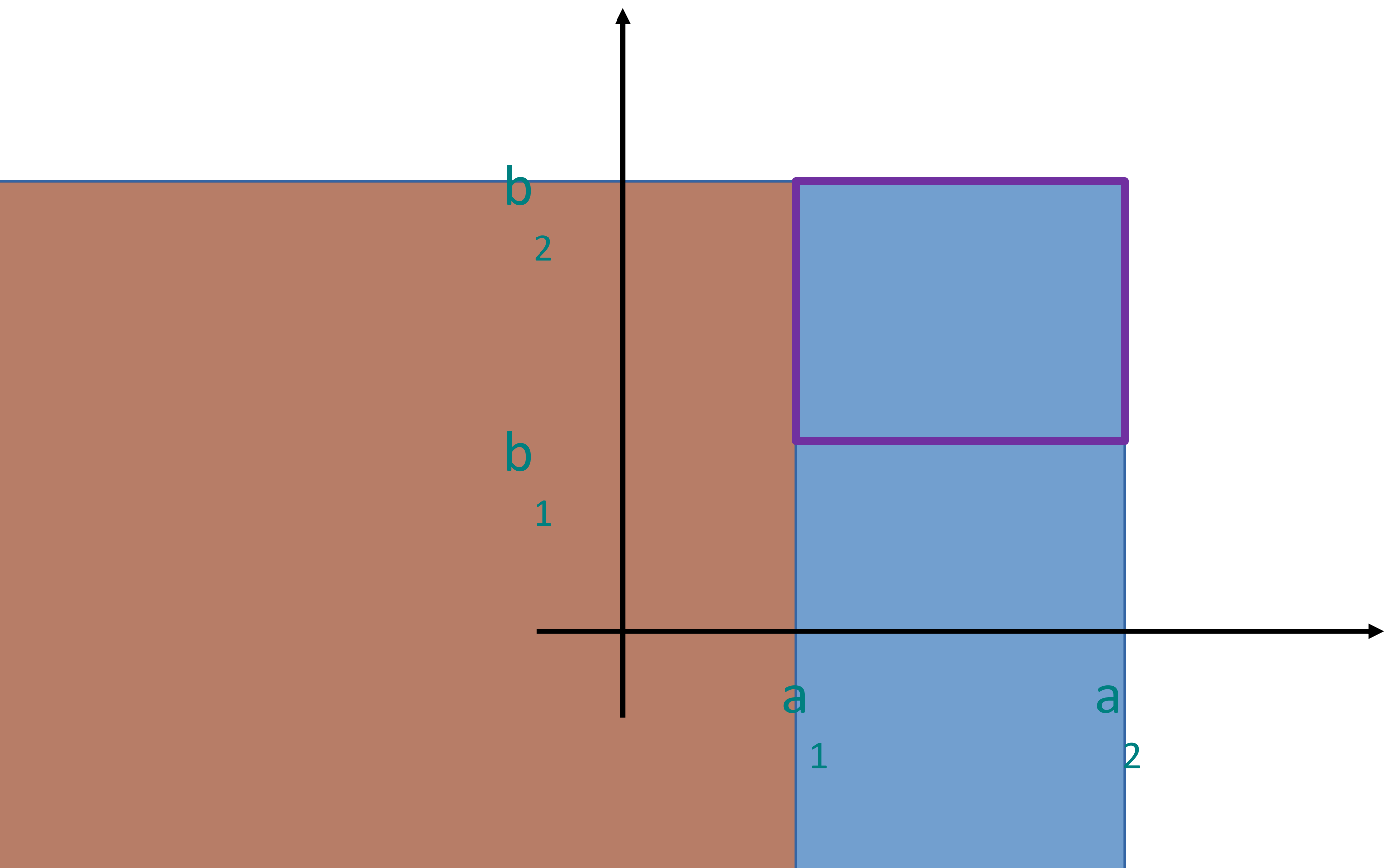
Probabilities from Joint CDF

$$P(a_1 < X \leq a_2, b_1 < Y \leq b_2) = F_{X,Y}(a_2, b_2)$$



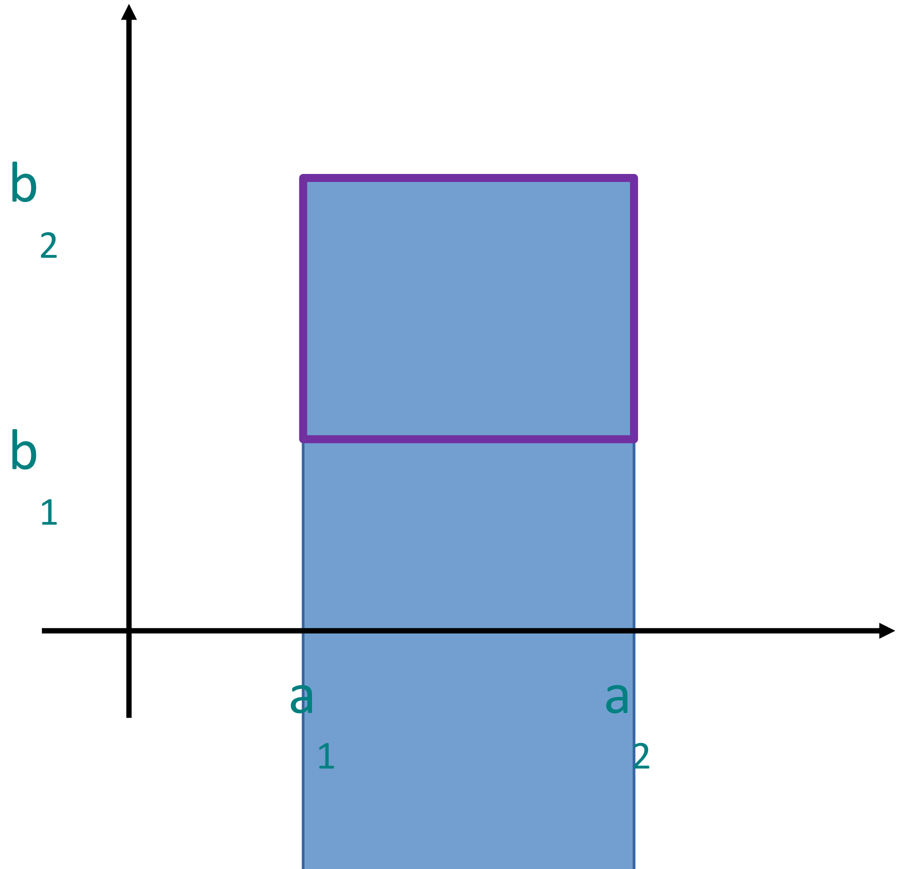
Probabilities from Joint CDF

$$P(a_1 < X \leq a_{2,} b_1 < Y \leq b_2) = F_{X,Y}(a_{2,} b_2)$$
$$-F_{X,Y}(a_{1,} b_2)$$



Probabilities from Joint CDF

$$P(a_1 < X \le a_2, b_1 < Y \le b_2) = F_{X,Y}(a_2, b_2)$$
$$-F_{X,Y}(a_1, b_2)$$



Probabilities from Joint CDF

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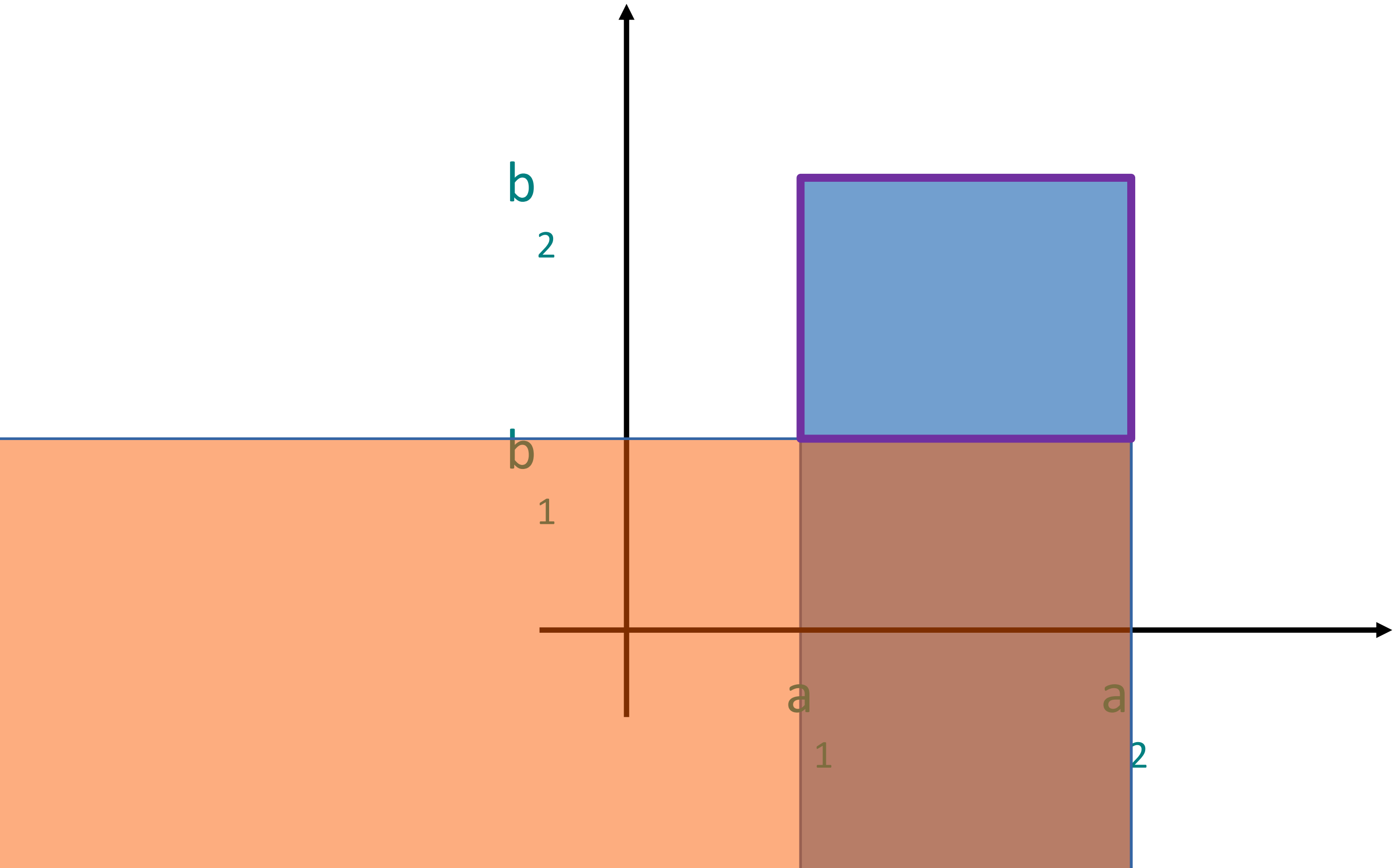

Probabilities from Joint CDF

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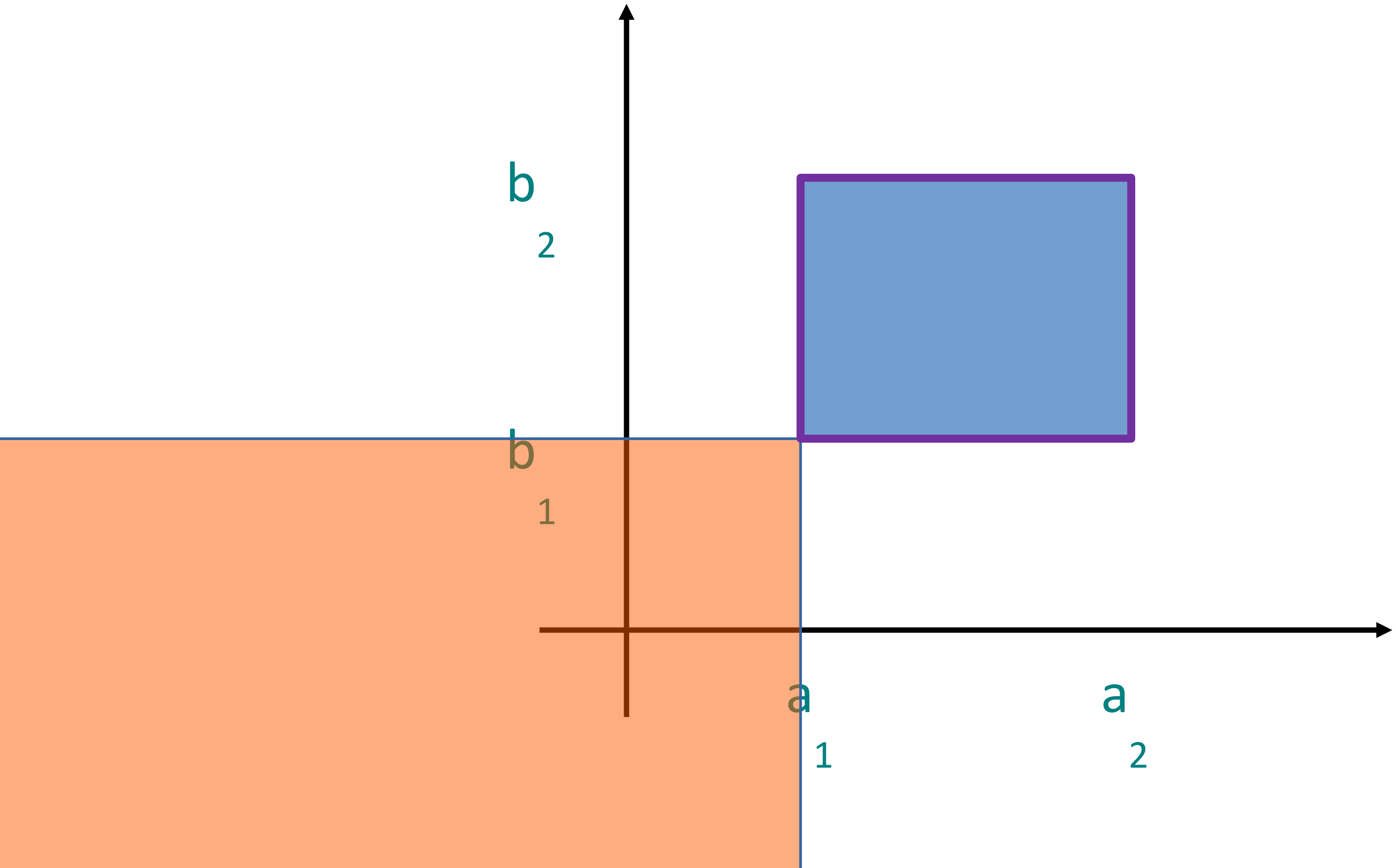

Probabilities from Joint CDF

$$P(a_1 < X \le a_2, b_1 < Y \le b_2) = F_{X,Y}(a_2, b_2)$$
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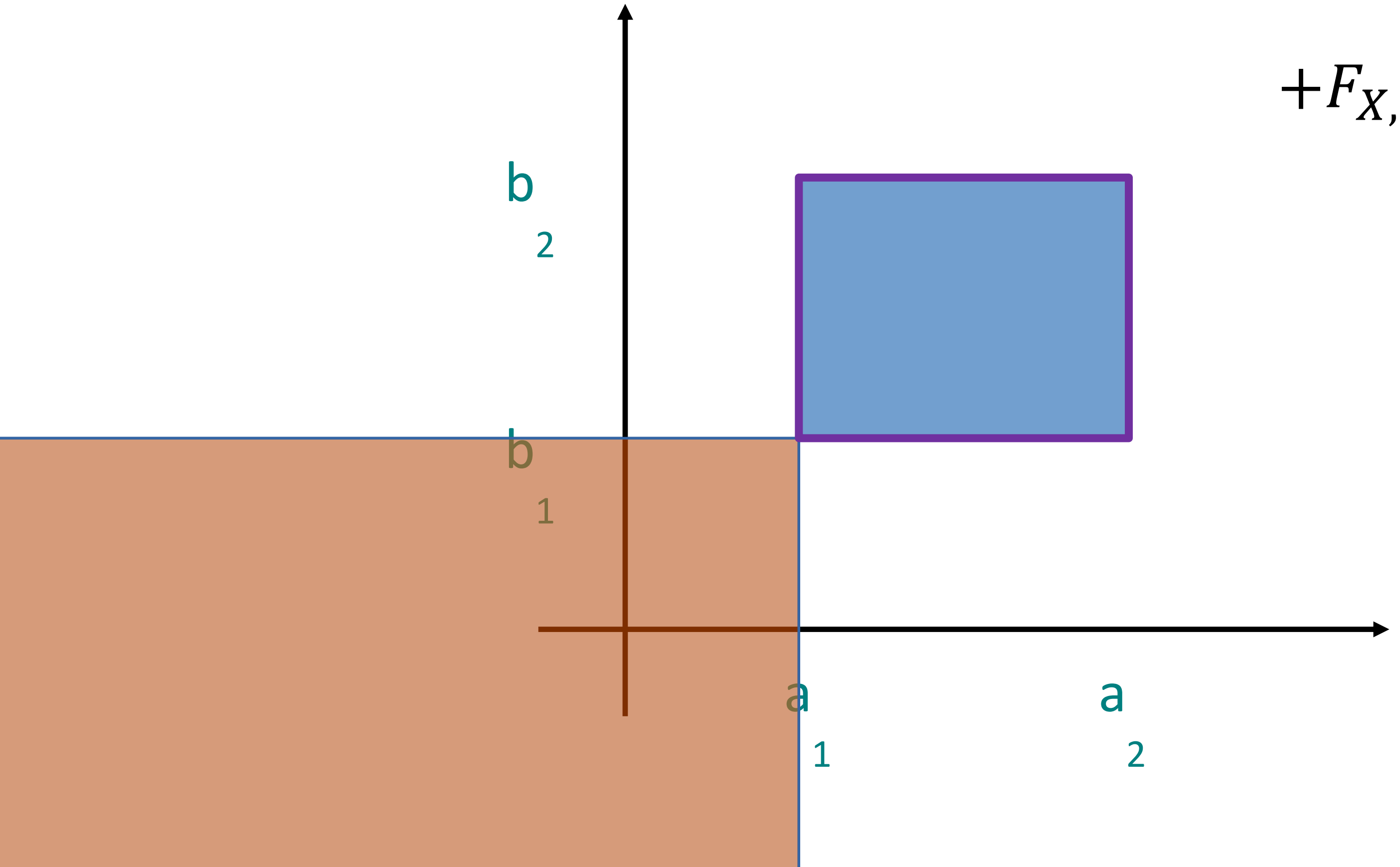

Probabilities from Joint CDF

$$P(a_1 < X \le a_2, b_1 < Y \le b_2) = F_{X,Y}(a_2, b_2)$$
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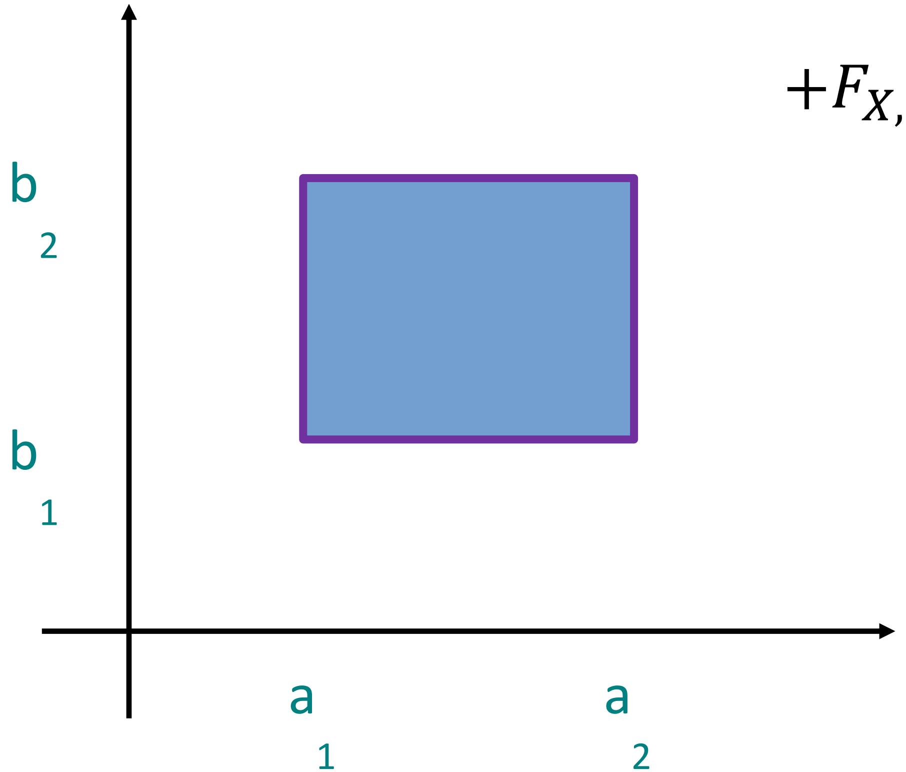
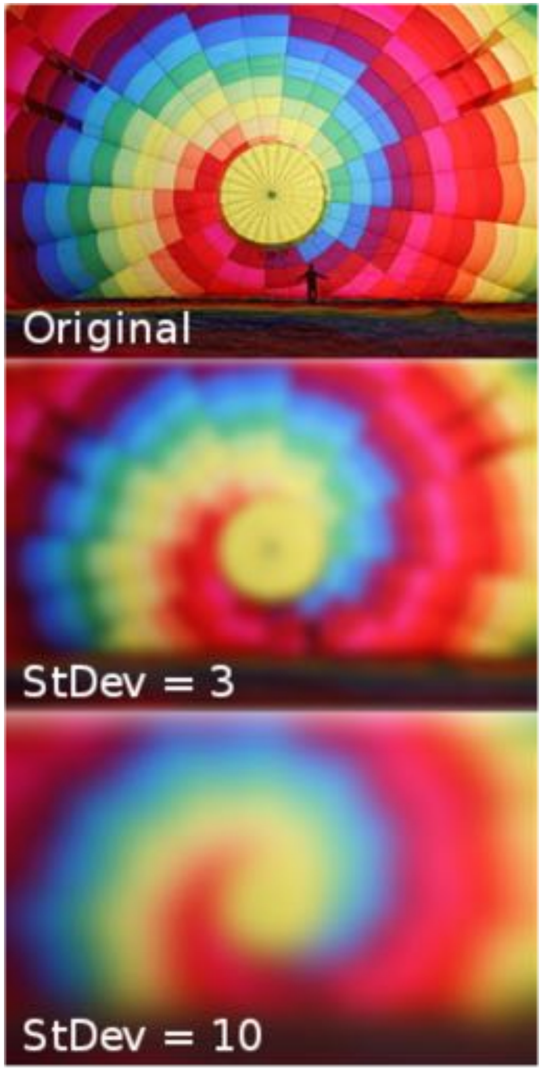


Probability for Instagram!

Gaussian Blur



In image processing, a Gaussian blur is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise.

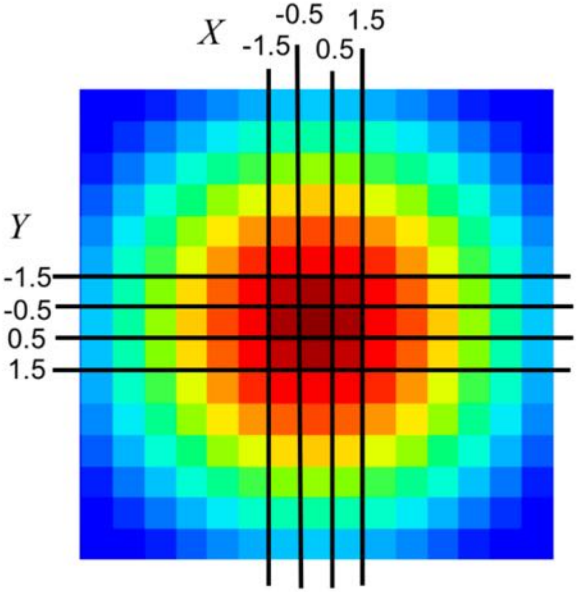
Gaussian blurring with StDev = 3, is based on a joint probability distribution:

Joint PDF

$$f_{X,Y}(x,y) = \frac{1}{2\pi \cdot 3^2} e^{-\frac{x^2+y^2}{2\cdot 3^2}}$$

Joint CDF

$$F_{X,Y}(x,y) = \Phi\left(\frac{x}{3}\right) \cdot \Phi\left(\frac{y}{3}\right)$$



Used to generate this weight matrix

Gaussian Blur

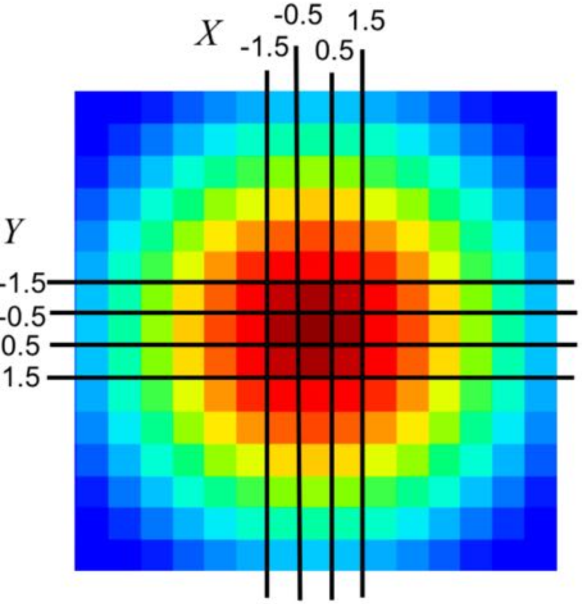
Joint PDF

$$f_{X,Y}(x,y) = \frac{1}{2\pi \cdot 3^2} e^{-\frac{x^2+y^2}{2\cdot 3^2}}$$

Joint CDF

$$F_{X,Y}(x,y) = \Phi\left(\frac{x}{3}\right) \cdot \Phi\left(\frac{y}{3}\right)$$

Weight Matrix



Each pixel is given a weight equal to the probability that X and Y are both within the pixel bounds. The center pixel covers the area where

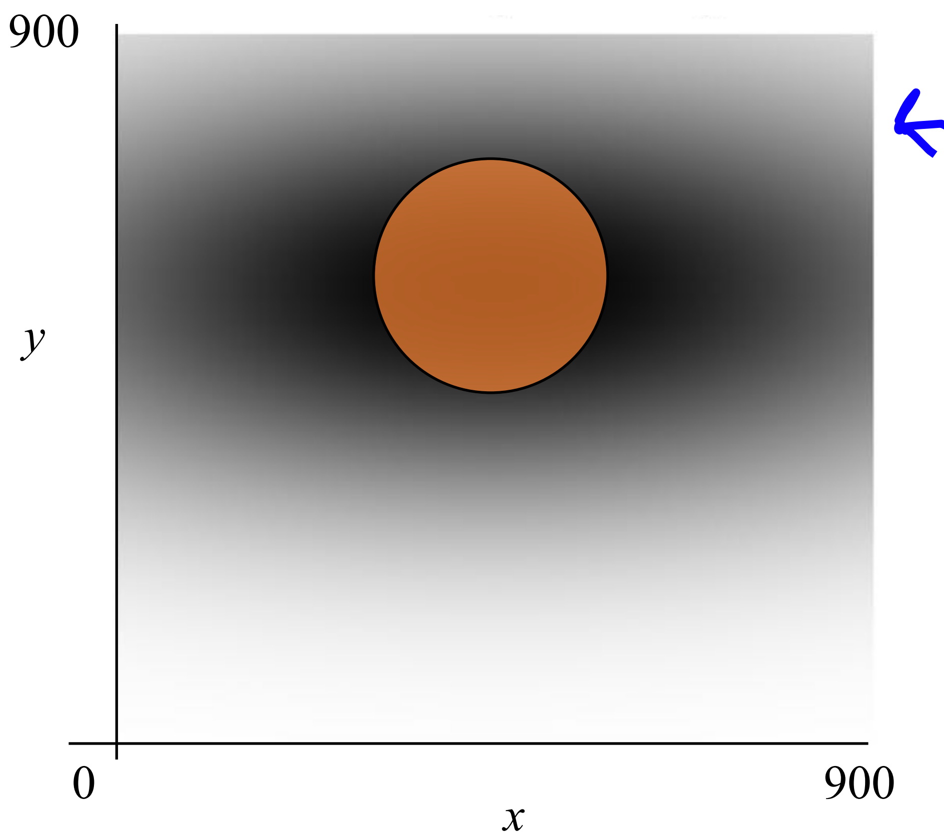
-0.5 ≤ x ≤ 0.5 and -0.5 ≤ y ≤ 0.5

What is the weight of the center pixel?

$$
\begin{aligned}
&P(-0.5 < X < 0.5, -0.5 < Y < 0.5) \\
=&P(X < 0.5, Y < 0.5) - P(X < 0.5, Y < -0.5) \\
&- P(X < -0.5, Y < 0.5) + P(X < -0.5, Y < -0.5) \\
=&\phi\left(\frac{0.5}{3}\right) \cdot \phi\left(\frac{0.5}{3}\right) - 2\phi\left(\frac{0.5}{3}\right) \cdot \phi\left(\frac{-0.5}{3}\right) \\
&+ \phi\left(\frac{-0.5}{3}\right) \cdot \phi\left(\frac{-0.5}{3}\right) \\
=&0.5662^2 - 2 \cdot 0.5662 \cdot 0.4338 + 0.4338^2 = 0.206
\end{aligned}
$$

How do you integrate under a circle?

$$f(X = x, Y = y)$$



Have a great weekend!