

# Joint Distribution of Discrete and Continuous Random Variables

Probability and Statistics for Data Science

Carlos Fernandez-Granda



These slides are based on the book [Probability and Statistics for Data Science](#) by Carlos Fernandez-Granda, available for purchase [here](#). A free preprint, videos, code, slides and solutions to exercises are available at <https://www.ps4ds.net>

# Goal

Manipulate discrete and continuous quantities in the **same** probabilistic model

# Notation

Deterministic variables:  $a$ ,  $b$ ,  $x$ ,  $y$

Random variables:  $\tilde{a}$ ,  $\tilde{b}$ ,  $\tilde{x}$ ,  $\tilde{y}$

# What is a random variable?

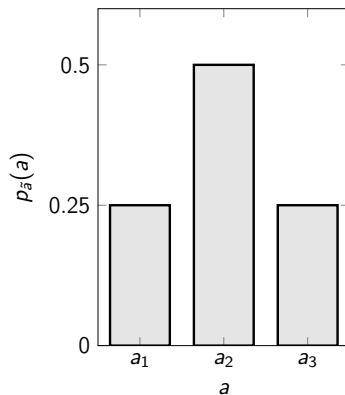
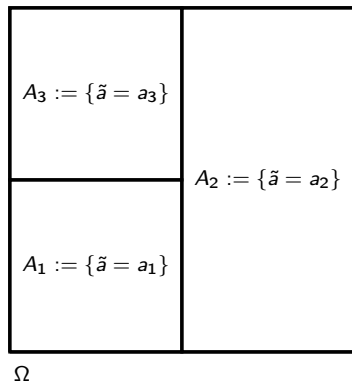
Data scientist:

*An uncertain variable described by probabilities estimated from data*

Mathematician:

*A function mapping outcomes in a probability space to real numbers*

# Discrete random variable

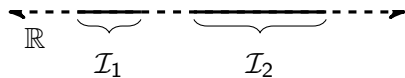
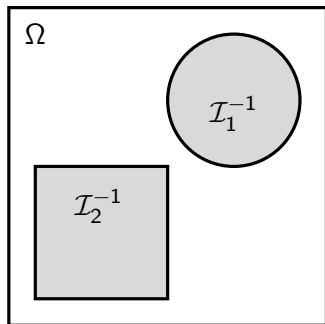


# Probability mass function

The probability mass function (pmf) of  $\tilde{a}$  is the probability that  $\tilde{a}$  equals each of its possible values  $a_1, a_2, \dots$ :

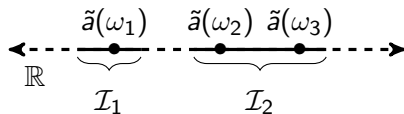
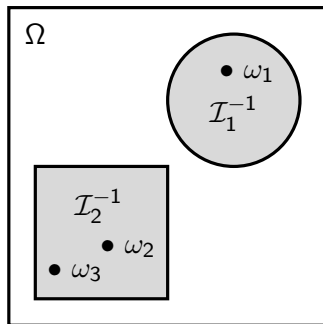
$$p_{\tilde{a}}(a_i) := \mathbf{P}(\{\omega \mid \tilde{a}(\omega) = a_i\})$$

# Continuous random variables





# Continuous random variables



## User interface

The cumulative distribution function (cdf) of a random variable  $\tilde{a}$  is

$$F_{\tilde{a}}(a) := \mathbb{P}(\tilde{a} \leq a)$$

Probability that  $\tilde{a}$  is less than or equal to  $a$ , for all  $a \in \mathbb{R}$

If  $F_{\tilde{a}}$  is differentiable, the probability density function (pdf) of  $\tilde{a}$  is

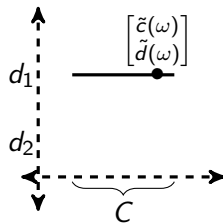
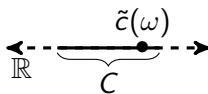
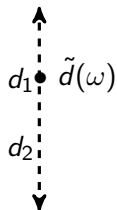
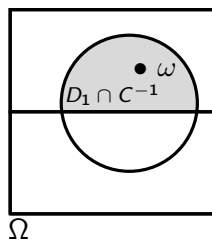
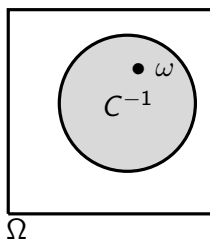
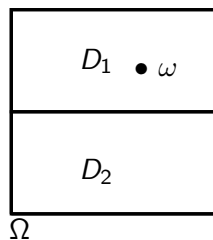
$$f_{\tilde{a}}(a) := \frac{dF_{\tilde{a}}(a)}{da}$$

# Discrete and continuous variables

How can we jointly model discrete and continuous quantities?

We represent them as random variables in the same probability space

# Discrete and continuous variables



# User interface

Joint pmf? ✗

Joint pdf? ✗

Joint cdf? ✓ but ☹

How about marginal pmf and conditional cdf/pdf?

## Pmf + conditional cdf / pdf

Discrete random variable  $\tilde{d}$  and continuous random variable  $\tilde{c}$

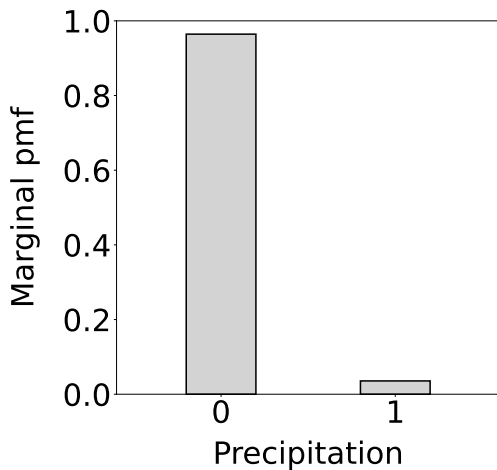
$$\begin{aligned} \mathbb{P}(\tilde{d} = d, \tilde{c} \leq c) &= \mathbb{P}(\tilde{d} = d) \mathbb{P}(\tilde{c} \leq c | \tilde{d} = d) \\ &= p_{\tilde{d}}(d) F_{\tilde{c}|\tilde{d}}(c | d) \end{aligned}$$

$$\begin{aligned} f_{\tilde{c}|\tilde{d}}(c | d) &:= \lim_{\epsilon \rightarrow 0} \frac{\mathbb{P}(c - \epsilon < \tilde{c} \leq c | \tilde{d} = d)}{\epsilon} \\ &= \lim_{\epsilon \rightarrow 0} \frac{F_{\tilde{c}|\tilde{d}}(c | d) - F_{\tilde{c}|\tilde{d}}(c - \epsilon | d)}{\epsilon} \\ &= \frac{dF_{\tilde{c}|\tilde{d}}(c | d)}{dc} \end{aligned}$$

# Mauna Loa

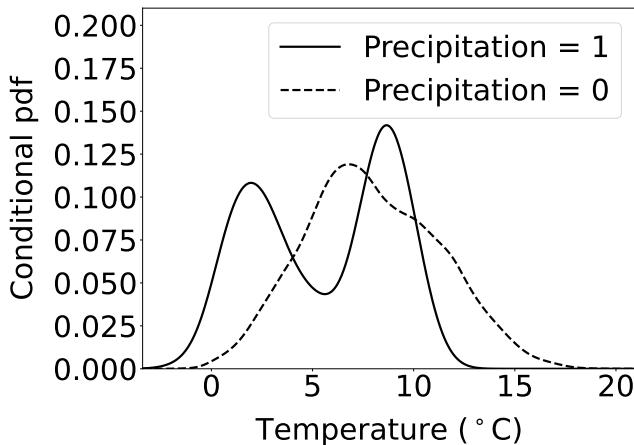
Temperature ( $\tilde{c}$ ) and precipitation ( $\tilde{d}$ )

## Marginal pmf of precipitation





## Conditional pdf of temperature given precipitation



## Marginal distribution of $\tilde{c}$

We know  $p_{\tilde{d}}$  and  $f_{\tilde{c}|\tilde{d}}(\cdot | d)$  for all  $d$

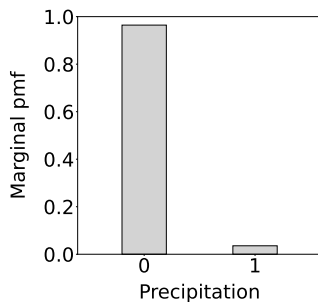
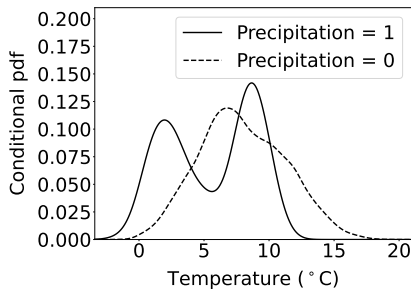
Marginal distribution of  $\tilde{c}$ ?

$$\begin{aligned} F_{\tilde{c}}(c) &= P(\tilde{c} \leq c) \\ &= \sum_{d \in D} P(\tilde{d} = d) P(\tilde{c} \leq c | d) \\ &= \sum_{d \in D} p_{\tilde{d}}(d) F_{\tilde{c}|\tilde{d}}(c | d) \end{aligned}$$

$$f_{\tilde{c}}(c) = \sum_{d \in D} p_{\tilde{d}}(d) f_{\tilde{c}|\tilde{d}}(c | d)$$

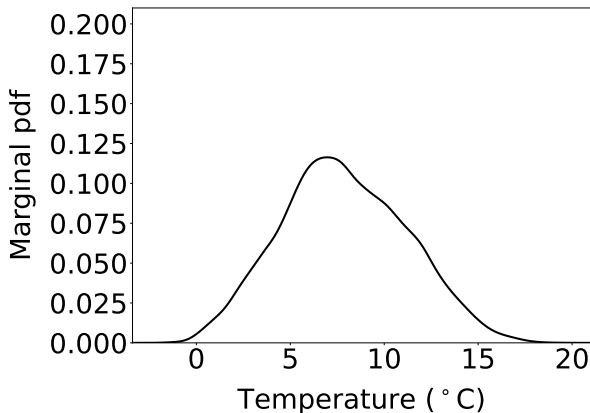
# Mauna Loa

Temperature ( $\tilde{c}$ ) and precipitation ( $d$ )



## Mauna Loa

$$f_{\tilde{c}}(c) = p_{\tilde{d}}(0) f_{\tilde{c}|\tilde{d}}(c|0) + p_{\tilde{d}}(1) f_{\tilde{c}|\tilde{d}}(c|1)$$

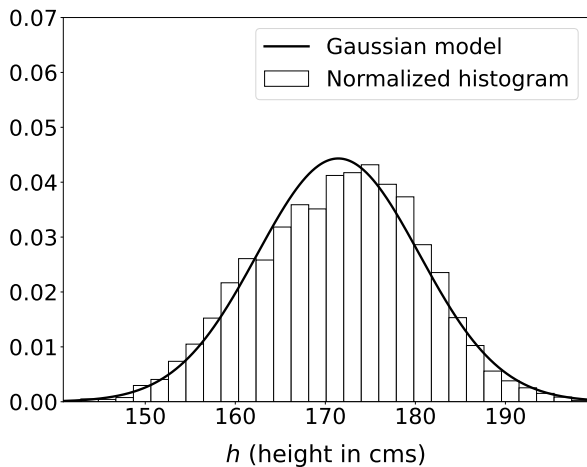


# Height data

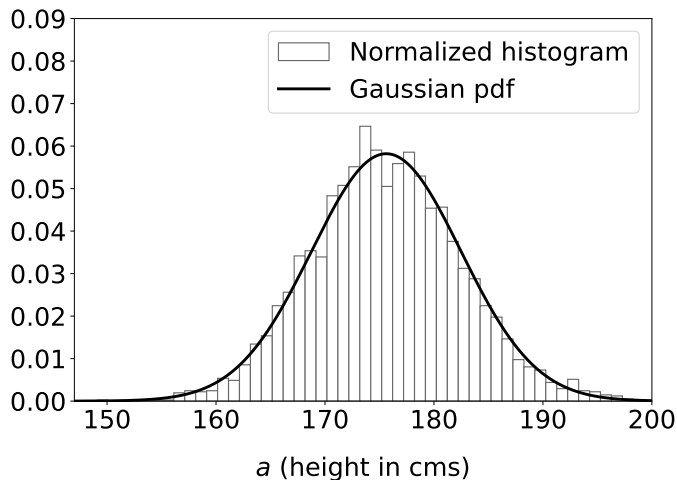
4,082 men and 1,986 women in the United States army

**Goal:** Design parametric model

## Gaussian model



## Just the men



# Gaussian mixture model

Height: Continuous random variable  $\tilde{h}$

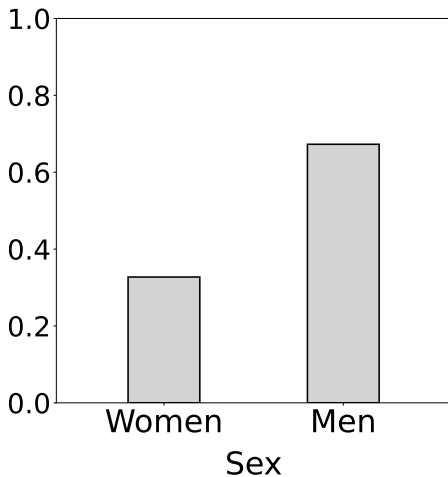
Sex: Discrete random variable  $\tilde{s}$

Conditional distribution of  $\tilde{h}$  given  $\tilde{s}$  is Gaussian



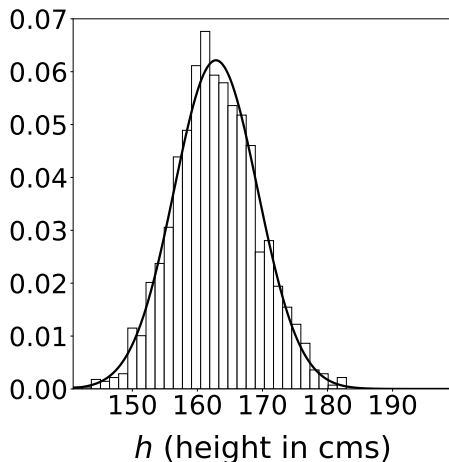
## Distribution of $\tilde{s}$ ?

1,986 women and 4,082 men



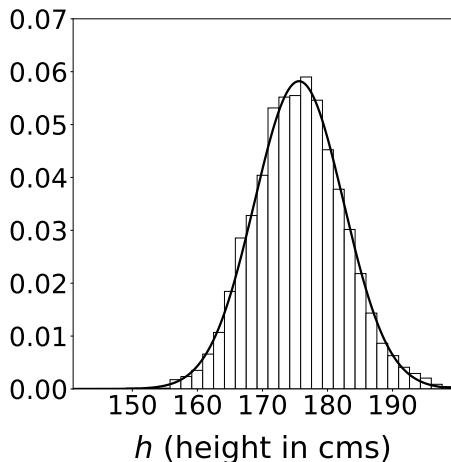
## Conditional distribution of $\tilde{h}$ given $\tilde{s} = \text{woman}$ ?

Gaussian with  $\mu_{\text{women}} = 163$  cm and  $\sigma_{\text{women}} = 6.4$  cm



## Conditional distribution of $\tilde{h}$ given $\tilde{s} = \text{man}$ ?

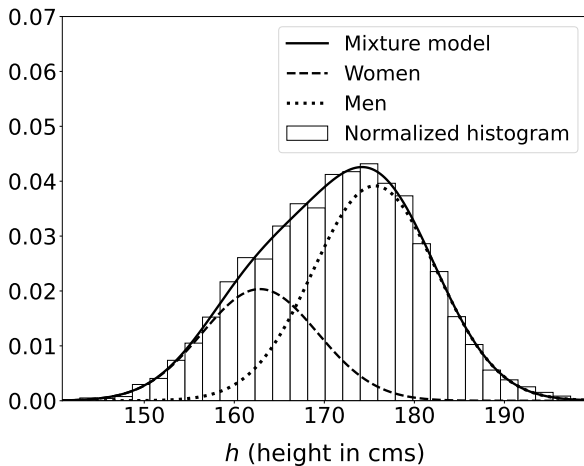
Gaussian with  $\mu_{\text{men}} = 176$  cm and  $\sigma_{\text{men}} = 6.9$  cm



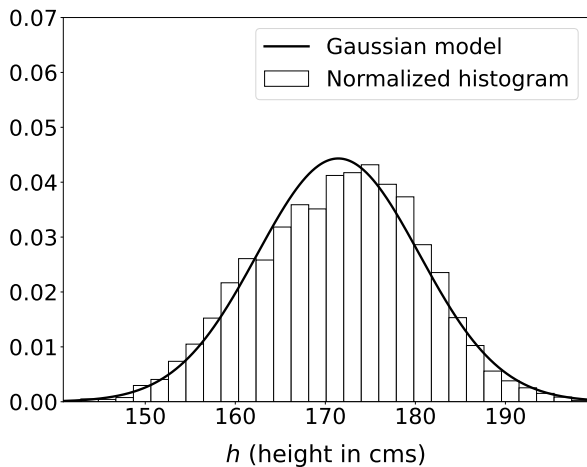
Marginal distribution of  $\tilde{h}$ ?

$$\begin{aligned} f_{\tilde{h}}(h) &= \sum_{s=0}^1 p_{\tilde{s}}(s) f_{\tilde{h}|\tilde{s}}(h|s) \\ &= \frac{\pi_{\text{women}}}{\sqrt{2\pi}\sigma_{\text{women}}} \exp\left(-\frac{1}{2}\left(\frac{h - \mu_{\text{women}}}{\sigma_{\text{women}}}\right)^2\right) \\ &\quad + \frac{\pi_{\text{men}}}{\sqrt{2\pi}\sigma_{\text{men}}} \exp\left(-\frac{1}{2}\left(\frac{h - \mu_{\text{men}}}{\sigma_{\text{men}}}\right)^2\right) \end{aligned}$$

# Gaussian mixture model



## Gaussian model



# What have we learned?

How to jointly model discrete and continuous variables

Gaussian mixture models