

# How To Learn 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>

# Advice

- ▶ Keep in mind roles of probability and statistics
- ▶ Get your hands dirty!
- ▶ Don't be intimidated by mathematics
- ▶ Consume proofs judiciously
- ▶ Practice is crucial!
- ▶ Use computer simulations
- ▶ Don't miss the forest for the trees

## Running example

Learning how to jointly model **discrete and continuous** quantities

## Advice

*Keep in mind roles of probability and statistics*

# Probability vs statistics

## Probability

Defines mathematical objects and derives their properties

## Statistics

Provides methods to estimate these objects from data

## Example

Modeling precipitation and temperature

We represent precipitation as a discrete random variable  $\tilde{d}$  and temperature as a continuous random variable  $\tilde{c}$

# Probability

Provides formal definition of random variables and tools to manipulate them

Discrete variables: [Probability mass function](#) (pmf)

Continuous variables: [Probability density function](#) (pdf)

Discrete and continuous variables: [Conditional](#) pmfs / pdfs



# Statistics

Provides methods to estimate pmfs and pdfs from data:

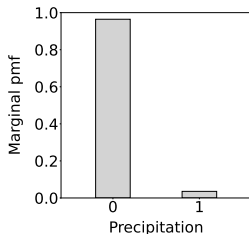
- ▶ **Nonparametric** estimation: Empirical probability, histogram, kernel density estimation
- ▶ **Parametric** estimation: Predefined distributions fit via maximum likelihood

## Advice

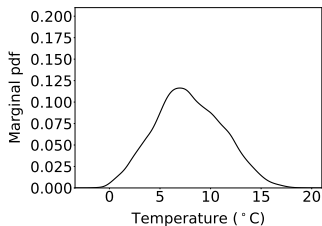
*Get your hands dirty!*

# Get some data and estimate!

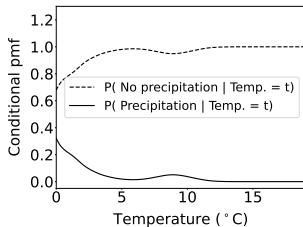
Pmf of precipitation



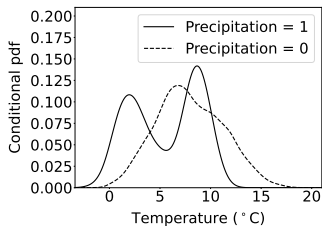
Pdf of temperature



Conditional pmf of precipitation



Conditional pdf of temperature



# Advice

*Don't be intimidated by mathematics*

Mathematical definitions have pragmatic motivations

Always ask yourself: *What do we actually estimate from data?*

# Random variables

Mathematically, functions from probability space to real numbers

## Pragmatic motivation:

Specifying random variables on same probability space enables us to model dependence between them

*What do we actually estimate from data?*

Probabilities and probability densities

## Conclusion:

We don't usually interpret random variables as functions, but as uncertain variables characterized by probabilities and densities

# Advice

*Consume proofs judiciously*

Proofs can feel overwhelming...

... but are valuable to gain understanding

Keep track of what each variable **means**

## Chain rule

For discrete  $\tilde{a}$  and  $\tilde{b}$

$$\begin{aligned} p_{\tilde{a}, \tilde{b}}(a, b) &= p_{\tilde{a}}(a) p_{\tilde{b} | \tilde{a}}(b | a) \\ &= p_{\tilde{b}}(b) p_{\tilde{a} | \tilde{b}}(a | b) \end{aligned}$$

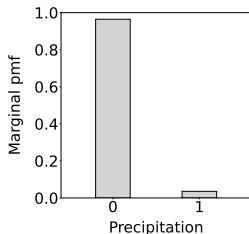
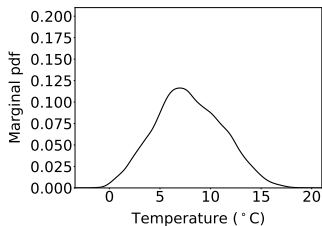
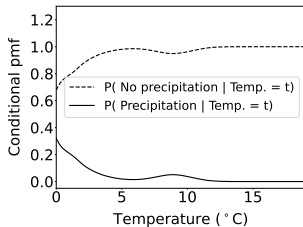
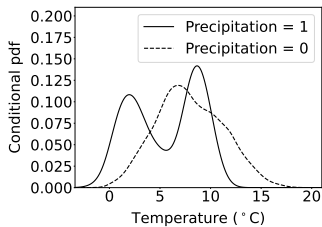
For continuous  $\tilde{a}$  and  $\tilde{b}$

$$\begin{aligned} f_{\tilde{a}, \tilde{b}}(a, b) &= f_{\tilde{a}}(a) f_{\tilde{b} | \tilde{a}}(b | a) \\ &= f_{\tilde{b}}(b) f_{\tilde{a} | \tilde{b}}(a | b) \end{aligned}$$

For discrete  $\tilde{d}$  and continuous  $\tilde{c}$  ?

$$p_{\tilde{d}}(d) f_{\tilde{c} | \tilde{d}}(c | d) = f_{\tilde{c}}(c) p_{\tilde{d} | \tilde{c}}(d | c) \quad ?$$

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

 $p_{\tilde{d}}(d)$ 

 $f_{\tilde{c}}$ 

 $p_{\tilde{d}|\tilde{c}}(d|c)$ 

 $f_{\tilde{c}|\tilde{d}}(c|d)$ 




# Proof

$$\begin{aligned} & p_{\tilde{d}}(d) f_{\tilde{c}|\tilde{d}}(c|d) \\ &= P(\tilde{d} = d) \lim_{\epsilon \rightarrow 0} \frac{P(c - \epsilon < \tilde{c} \leq c | \tilde{d} = d)}{\epsilon} \\ &= \lim_{\epsilon \rightarrow 0} \frac{P(\tilde{d} = d) P(c - \epsilon < \tilde{c} \leq c | \tilde{d} = d)}{\epsilon} \\ &= \lim_{\epsilon \rightarrow 0} \frac{P(\tilde{d} = d, c - \epsilon < \tilde{c} \leq c)}{\epsilon} \\ &= \lim_{\epsilon \rightarrow 0} \frac{P(c - \epsilon < \tilde{c} \leq c)}{\epsilon} P(\tilde{d} = d | c - \epsilon < \tilde{c} \leq c) \\ &= f_{\tilde{c}}(c) p_{\tilde{d}|\tilde{c}}(d|c) \end{aligned}$$

## Advice

*Practice is crucial!*

## Exercise

A magician hands you a coin.

You don't know what the probability of heads is, so you model it as a uniform random variable between 0 and 1.

You toss the coin and it lands on heads.

Assuming tosses are conditionally independent given the probability of heads, what is the conditional probability that it lands on heads if you toss it again?

# How to solve an exercise

- ▶ Formulate question mathematically
- ▶ Determine what information is available
- ▶ Use **step-by-step** reasoning
- ▶ Try it out **on your own**, then check references,  
*then* look at the solution

## Coin tosses

A magician hands you a coin. You don't know what the probability of heads is, so you model it as a uniform random variable between 0 and 1. You toss the coin and it lands on heads. Assuming tosses are conditionally independent given the probability of heads, what is the conditional probability that it lands on heads if you toss it again?



# Advice

*Use computer simulations*

# Monte Carlo method

**Main idea:** Simulate and compute empirical probabilities

To approximate the conditional probability of an event  $B$  **conditioned on  $A$** , we

1. Generate  $n$  simulated outcomes:  $s_1, s_2, \dots, s_n$
2. Compute fraction of outcomes in  $A$  that are **also in  $B$**

$$P_{\text{MC}}(B | A) := \frac{\sum_{i=1}^n 1_{s_i \in A \cap B}}{\sum_{i=1}^n 1_{s_i \in A}}$$



# Conditional probability?

```
1 n = 1000000
2 n_head_1 = 0
3 n_head_2_head_1 = 0
4
5 for ind in range(n):
```

Generate parameter representing probability of heads

```
1     theta = rng.uniform(0,1)
```

Generate first coin flip

```
1     c_1 = rng.binomial(1,theta)
```

If first coin flip is heads, generate second coin flip

```
1         if c_1 == 1:
2             n_head_1 += 1
3             c_2 = rng.binomial(1,theta)
4             if c_2 == 1:
5                 n_head_2_head_1 += 1
```

## Monte Carlo estimate

1

$$p_{\text{head}_2 \text{head}_1} = n_{\text{head}_2 \text{head}_1} / n_{\text{head}_1}$$

Conditional probability: 0.666290

## Advice

*Don't miss the forest for the trees*

To model discrete and continuous quantities, we

- ▶ Represent them as random variables
- ▶ Estimate associated probabilities / densities from data via statistical methods
- ▶ Manipulate them using properties of probability

## Advice

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- ▶ Practice is crucial!
- ▶ Use computer simulations
- ▶ Don't miss the forest for the trees
- ▶ Be patient!