

# Rules of Probability

## Bayesian Modeling for Socio-Environmental Data

Chris Che-Castaldo, Mary B. Collins, N. Thompson Hobbs

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# Road map

- Rules of probability
  - ▶ Conditional probability
  - ▶ Chain rule
  - ▶ Independence
  - ▶ The law of total probability
- Factoring joint probabilities

# Why do we need to know this stuff?

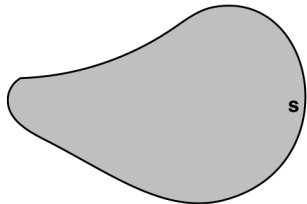
- ① **Conditional probability** foundational for all the inferences that we make.
- ② **The law of total probability** is the denominator of Bayes' Theorem.
- ③ **Factoring** joint distributions is how we deal with complexity, reducing high dimensional problems (the chain rule allows us to do this).
- ④ **Independence** allows us to simplify fully factored joint distributions.

## Random variables

- are quantities governed by chance.
- have a specific value called an *events* or *outcomes*.
- are summarized by probability distributions.
- *Bayesians treat every unobserved quantity as a random variable.*

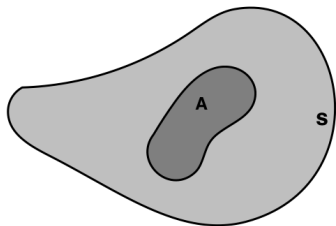
# $S$ =Sample Space

- The set of all possible events or outcomes of an experiment or survey.
- The sample space,  $S$  has a specific area.

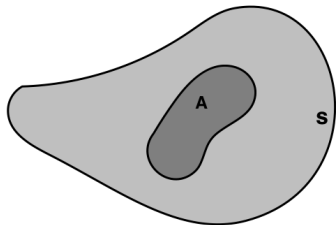


# Events in $S$

- Can define an event,  $A$ .
- The area of event  $A$  is less than  $S$ .



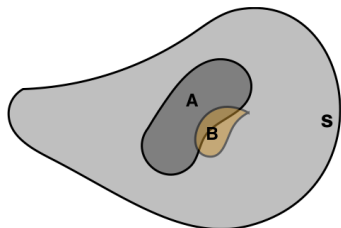
What is the probability of event A?



$$\Pr(A) = \frac{\text{Area of } A}{\text{Area of } S}$$

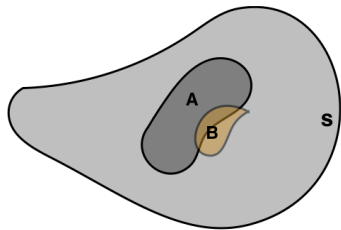
# Conditional Probability

*Conditional probability*: the probability of an event given that *we know* another event has occurred.



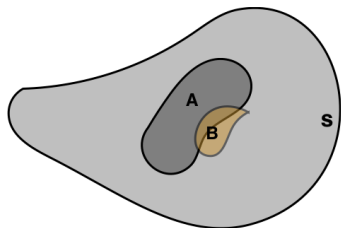


What is the probability of event  $B$ , given that event  $A$  has occurred?



$\Pr(B|A)$  = probability of  $B$  conditional on knowing  $A$  has occurred

What is the probability of event  $B$ , given that event  $A$  has occurred?



$$Pr(B|A) = \frac{\text{Joint Probability}}{\text{Probability of A}} = \frac{Pr(A,B)}{Pr(A)}$$

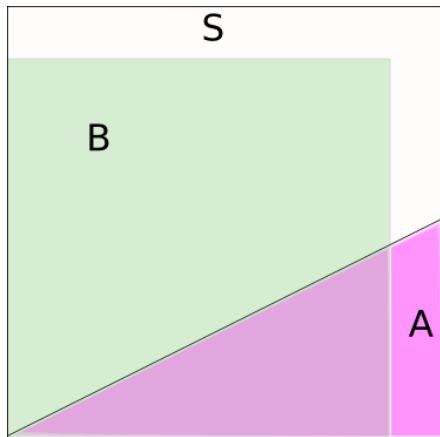
If the occurrence of event  $A$  does not tell us anything about event  $B$ ?

*In this case, events  $A$  and  $B$  are said to be **independent***

Events are independent if and only if. . .

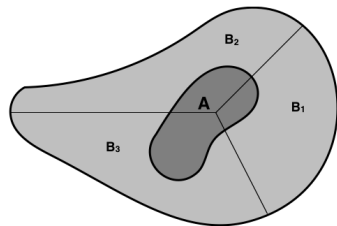
$$\Pr(A|B) = \Pr(A)$$

Assuming independence, the joint probability of event A and event B



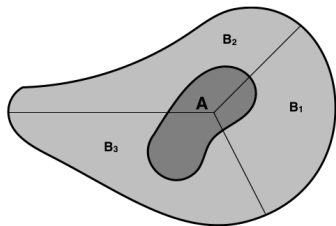
$$\Pr(A, B) = \Pr(A)\Pr(B)$$

# The Law of Total Probability



We can define a set of events  $\{B_n : n = 1, 2, 3, \dots\}$ , which taken together define the entire sample space,  $\sum_n B_n = S$ .

What is the probability of event A?



$$\Pr(A) = \sum_n \Pr(A|B_n) \Pr(B_n) \text{ (discrete case)}$$

$$\Pr(A) = \int \Pr(A|B) \Pr(B) dB \text{ (continuous case)}$$

# The Chain Rule of Probability

The chain rule of probability allows us to calculate any number of joint distributions using only conditional probabilities.

$$\Pr(z_1, z_2, \dots, z_n) = \Pr(z_n | z_{n-1}, \dots, z_1) \dots \Pr(z_3 | z_2, z_1) \Pr(z_2 | z_1) \Pr(z_1)$$

Notice the pattern here.

- $z$ 's can be scalars or vectors.
- Sequence of conditioning doesn't matter.
- When we build models, we choose a sequence that makes sense.



## Chain rule of probability board work and independence

# Factoring joint probabilities

Why is factoring useful?

- The rules of probability allow us to simplify complicated joint distributions, breaking them down into chunks.
- Chunks can be analyzed one at a time.
- Provide a usable graphical and mathematical foundation, *critical* for the model specification step.

Consider a Bayesian Network (represented by a directed acyclic graph or DAG)



- Bayesian networks specify how joint distributions are factored into conditional distributions using nodes to represent RV's and arrows to represent dependencies.
- Nodes at the heads of arrows *must* be on the left hand side of the conditioning symbols;
- Nodes at the tails of arrows are on the right hand side of the conditioning symbols.
- Any node at the tail of an arrow without an arrow leading into it must be expressed unconditionally.

## Factoring with DAGs at the board

# Work on lab

Complete parts I-VI