

Rules of Probability

Bayesian Models for Ecologists

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Road map for today

- Rules of probability
- Factoring joint probabilities
- Directed acyclic graphs (a.k.a. Bayesian networks)

Random variables

The world can be divided into things that are observed and things that are unobserved.

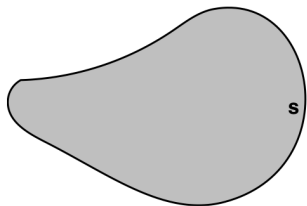
- 1 Bayesians treat all unobserved quantities as *random variables*.
- 2 The values of random variables are governed by chance.
- 3 Probability distributions quantify “governed by chance.”

All of Bayesian inference extends from three rules of probability

- 1 Conditional probability (and independence)
- 2 The law of total probability
- 3 The chain rule of probability

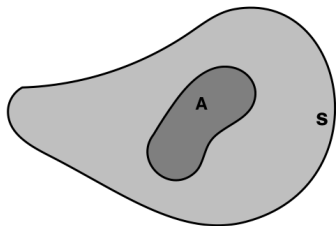
S = Sample space, a.k.a *support*

- The set of all possible values of a random variable.
- The sample space, S has a specific area.
- A specific value of a random variable within S is called an event or an outcome.

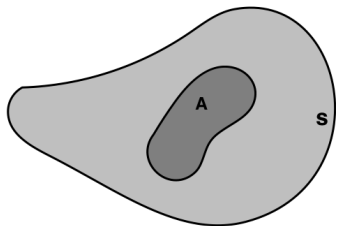


Events in S

- Can define an event, A .
- The area of event A is less than or equal to S .



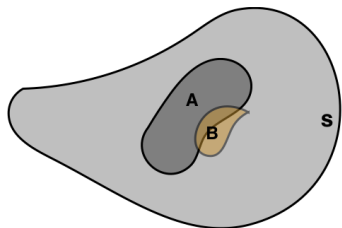
What is the probability of event A?



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

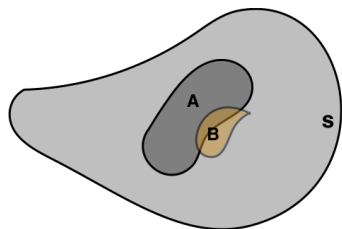
Conditional Probability

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



Conditional Probability

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

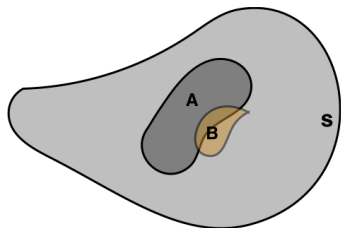


$\Pr(B|A)$ = probability of B conditional on knowing A has occurred

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

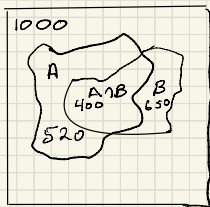
Conditional Probability

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



Example

A sample of 1000 voters



$$P(A) = P(\text{vote for Biden}) \\ = \frac{520}{1000} = .52$$

$$P(B) = P(\text{female}) \\ = \frac{650}{1000} = .65$$

$$P(A \cap B) = P(\text{female and vote for Biden}) \\ = \frac{400}{1000} = .40$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{.40}{.65} = .6$$

The knowledge that a voter was female changed the probability of a vote for Biden from .52 to .6

Independence

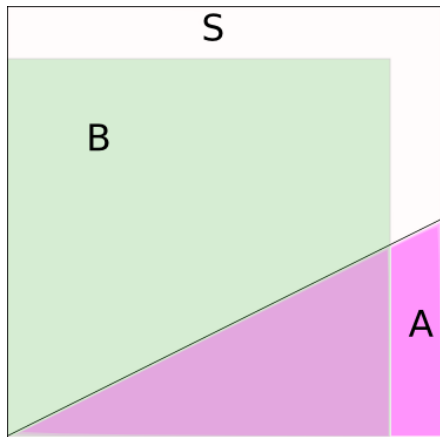
Event A and B are *independent* if the occurrence of event A does not tell us anything about event B .

Events are independent if and only if:

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

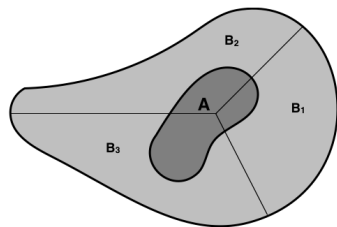
$$\Pr(B|A) = \Pr(B)$$

Independence



$$\Pr(A|B) = \frac{\text{area of } A \text{ and } B}{\text{area of } B} = \frac{\text{area of } A}{\text{area of } S}$$

The Law of Total Probability



$\Pr(A)$ is unknown, but can be calculated using the known probabilities of several events.

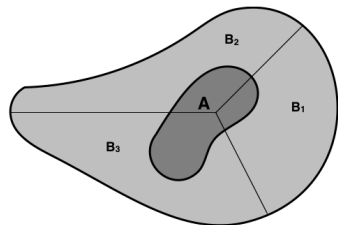
We can define a set of events $\{B_n : n = 1, 2, 3, \dots\}$, which taken together define the entire sample space, $\sum_n B_n = S$.

Rearranging the expression for conditional probability

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

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

What is the probability of event A?



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

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

Intuition about the chain rule of probability

$$\Pr(A|B) = \frac{\Pr(A, B)}{\Pr(B)}$$

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

We have *factored* $\Pr(A, B)$ into $\Pr(A|B)\Pr(B)$. How else could it be factored?

The Chain Rule of Probability

The chain rule of probability allows us to write joint distributions as a product of conditional distributions.

$$\Pr(z_1, z_2, \dots, z_n) = \Pr(z_n | z_{n-1}, \dots, z_1) \Pr(z_{n-1} | z_{n-2}, \dots, z_1), \dots, \Pr(z_3 | z_2, z_1) \Pr(z_2 | z_1) \Pr(z_1)$$

Notice the pattern here.

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

Example

$$\Pr(z_1, z_2, z_3, z_4, z_5) = \\ \Pr(z_5|z_4, z_3, z_2, z_1) \Pr(z_4|z_3, z_2, z_1) \Pr(z_3|z_2, z_1) \Pr(z_2|z_1) \Pr(z_1)$$

How else could this be written?

Factoring joint probabilities

Why is factoring useful?

- Factoring joint distributions is how we build Bayesian models.
- The rules of probability allow us to simplify complicated joint distributions, breaking them down into chunks.
- Chunks can be analyzed one at a time in MCMC.

Problem

Factor $[\sigma, \theta, \alpha, \gamma]$

Decisions on independence allow us to simplify factored expressions

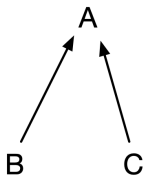
Factoring the joint distribution of A , B , and C :

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

Assuming B and C are independent we can simplify:

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

Consider the directed acyclic graph (DAG)



Represents $[A \mid B, C] [B] [C]$

This is *one* way to factor $[A, B, C]$.

- Directed acyclic graphs (aka Bayesian networks) specify how joint distributions are factored into conditional distributions using nodes to represent RV's and arrows to represent conditioning.
- 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.
- Nodes at heads of arrows are called “children”; at tails, “parents.”

Factoring joint probabilities using DAGs

Some board work.

Work on lab

Complete Probability Lab #1