

Working with Probabilities

NRES 746

Fall 2018

NOTE: for those wishing to follow along with the R-based demo in class, click [here](#) for the companion R-script for this lecture.

Note: some materials borrowed from White and Morgan's "STATISTICAL MODELS IN ECOLOGY USING R" course

In the last class, we reviewed basic programming in R, using basic structures like the iterative loop (e.g., "for()", "while()") and random sampling (e.g., using the 'sample()' function in R) to build our own analyses from first principles. We began the course this way because the ability to understand, use, and build algorithms is absolutely fundamental to modern data analysis.

Also fundamental to modern data analysis is an ability to work with probabilities. Again, many of you will find this a very basic review, but I really want to ensure that all of us are working with solid foundations before we venture into more advanced topics.

The central points:

- Most traditional statistics use mathematical assumptions (e.g., large sample size, Gaussian errors) to ensure that test statistics follow a particular distribution
- With more computational power, we are much less limited and can feasibly model alternative data generating processes involving a wide set of probability distributions.

Basic probability rules

Classic Urn Example

Consider an Urn filled with blue, red, and green spheres. To make the example more concrete, assume the following:

- red: 104
- blue: 55
- green: 30

```
#####  
# Classic Urn Example  
  
n_red <- 104  
n_blue <- 55  
n_green <- 30  
  
allSpheres <- c(n_red, n_blue, n_green)           # create vector of urn contents  
names(allSpheres) <- c("red", "blue", "green")    # make it a named vector, for convenience!
```

What is the probability of drawing a blue sphere?

```
P_blue <- allSpheres["blue"]/sum(allSpheres)      # probability of drawing a blue sphere  
P_blue
```

```
##      blue  
## 0.2910053
```

Let's generate a vector of probabilities for drawing each type of sphere...

```
Prob <- allSpheres/sum(allSpheres)    # probability of drawing each type of sphere
Prob
```

```
##      red      blue      green
## 0.5502646 0.2910053 0.1587302
```

What is the probability of drawing a blue **OR** a red sphere?

```
as.numeric( Prob["blue"] + Prob["red"] )    # probability of drawing a blue or red sphere
```

```
## [1] 0.8412698
```

What is the probability of drawing a blue **OR** a red sphere **OR** a green sphere?

```
as.numeric( Prob["blue"] + Prob["red"] + Prob["green"] )    # P(blue OR green)
```

```
## [1] 1
```

Q: What would it mean if this didn't sum to 1?

What is the probability of drawing a blue **AND THEN** a red sphere?

NOTE: in the next examples, assume that objects are replaced and that the urn is re-randomized before any subsequent draws! This is called “*sampling with replacement*”

```
#### Question: What is the probability of drawing a blue **AND THEN** a red sphere?
```

```
# [your command here]    # P(blue AND THEN red)
```

```
## [1] 0.1601299
```

What is the probability of drawing a blue and a red sphere in two consecutive draws (but in no particular order)?

```
as.numeric( (Prob["blue"] * Prob["red"]) + (Prob["red"] * Prob["blue"]) )    # P(blue then red OR red then blue)
```

```
## [1] 0.3202598
```

Less-classic urn example

Now consider an urn filled with blue & red objects of two different types: spheres & cubes. To make the example more concrete, assume the following:

- red sphere: 39
- blue sphere: 76
- red cube: 101
- blue cube: 25

```
#####
```

```
# Urn example #2
```

```
n_red_sphere <- 39    # contents of new urn
```

```
n_blue_sphere <- 76
```

```
n_red_cube <- 101
```

```
n_blue_cube <- 25
```

```

allSpheres <- c(n_red_sphere,n_blue_sphere)           # build up matrix from vectors
allCubes <- c(n_red_cube,n_blue_cube)
allTypes <- c(allSpheres,allCubes)
allTypes <- matrix(allTypes,nrow=2,ncol=2,byrow=T)     # matrix of urn contents
rownames(allTypes) <- c("sphere","cube")              # name rows and columns
colnames(allTypes) <- c("red","blue")
allTypes

```

```

##           red blue
## sphere   39   76
## cube    101   25

```

```

Prob_Shape <- apply(allTypes,1,sum)/sum(allTypes)      # marginal probabilities of shape
Prob_Shape

```

```

##      sphere      cube
## 0.4771784 0.5228216

```

```

Prob_Color <- apply(allTypes,2,sum)/sum(allTypes)     # marginal probabilities of color
Prob_Color

```

```

##           red      blue
## 0.5809129 0.4190871

```

What is the *marginal probability* of drawing a red object (and why do we call it a “marginal” probability?)

```

Prob_Color["red"]           # marginal probability of drawing a red object

```

```

##           red
## 0.5809129

```

What is the *joint probability* of drawing an object that is both blue AND a cube? $Prob(blue \cap cube)$

```

as.numeric( Prob_Color["blue"] * Prob_Shape["cube"])  # joint probability of drawing a blue object

```

```

## [1] 0.2191078

```

```

## NOTE: if the above answer is not correct, please correct it! And would I be asking this if it were correct?

```

Q: Is this correct? If not, why?

Q: Under what circumstances would this be correct?

What is the correct answer?

```

## [1] 0.1037344

```

What is the probability of drawing an object that is blue **OR** a cube? $Prob(blue \cup cube)$

```

as.numeric( Prob_Color["blue"] + Prob_Shape["cube"])  # probability of drawing something blue or a cube

```

```

## [1] 0.9419087

```

```

## NOTE: if the above answer is not correct, please correct it!

```

Q: Is this correct? If not, why? How would you compute the correct answer??

Q: What is the correct answer?

```

## [1] 0.7228009

```

What is the **conditional probability** of drawing a blue object, given that it is a cube? $Prob(blue|cube)$

This can be expressed as: $Prob(blue|cube) = Prob(blue, cube)/Prob(cube)$

```
allTypes["cube","blue"] / sum(allTypes["cube",]) # probability of drawing a blue object, given it is
```

```
## [1] 0.1984127
```

Now we can express the joint probability of drawing a blue cube in terms of conditional probabilities!

$$Prob(blue \cap cube) = Prob(cube|blue) * Prob(blue)$$

Does this now give us the correct answer?

```
as.numeric( allTypes["cube","blue"] / sum(allTypes[, "blue"]) * Prob_Color["blue"]) # probability of d
```

```
## [1] 0.1037344
```

What is an unconditional probability?

What is the unconditional probability of drawing a blue item, regardless of shape?

$$Prob(blue|cube) \cdot Prob(cube) + Prob(blue|notcube) \cdot Prob(notcube)$$

```
uncond_prob_blue <- (allTypes["cube","blue"] / sum(allTypes["cube",])) * Prob_Shape["cube"] +
  (allTypes["sphere","blue"] / sum(allTypes["sphere",])) * Prob_Shape["sphere"] # unc
```

```
as.numeric(uncond_prob_blue)
```

```
## [1] 0.4190871
```

Q: Can you interpret the above equation in words? Take a moment to try! How does this relate to the *marginal probability*?

Short exercise #2

What does it mean if the conditional probability of drawing a blue object (e.g., given it is a cube) is equal to the unconditional probability of drawing a blue item?

Bolker's medical example

Suppose the infection rate (prevalence) for a rare disease is one in a million:

```
#####
# Bolker medical example

Prob_Disease <- c(1,999999) # disease prevalence
Prob_Disease <- Prob_Disease/sum(Prob_Disease) # probability of disease
names(Prob_Disease) <- c("yes","no") # make it a named vector!
Prob_Disease

##      yes      no
## 0.000001 0.999999
```

Suppose there is a test that never gives a false negative (if you've got it you will test positive) but very rarely gives a false positive result (if you ain't got it, you might still test positive for the disease). Let's imagine a very low false positive rate of 1%.

Medical professionals (and patients!) often want to know the probability that a positive-testing patient actually has the disease. This quantity is known as the *Positive Predictive Value* or PPV. How can we compute this?

Stated another way, we want to know the *conditional probability* of having the disease, given a positive test result:

$$Prob(Disease|+test)$$

What do we have already?

First of all, we know the conditional probability of having a positive test result given the patient has the disease:

$$Prob(+test|Disease) = 1$$

Secondly, we know the conditional probability of having a positive test result given the patient doesn't have the disease

$$Prob(+test|noDisease) = 0.01$$

Third, we know the unconditional probability of having the disease

$$Prob(Disease) = 0.000001$$

Now, let's use basic probability rules to compute the PPV!

What is the unconditional probability of testing positive?

$$Prob(+test)$$

Well, we can either test positive and have the disease or we can test positive and not have the disease...

$$Prob(+test \cap Disease) + Prob(+test \cap noDisease)$$

Stated another way,

$$Prob(+test|Disease) * Prob(Disease) + Prob(+test|noDisease) * Prob(noDisease)$$

compute the unconditional probability of testing positive

```
as.numeric( 1*Prob_Disease["yes"] + 0.01*Prob_Disease["no"] )      # Prob(+test|Disease)*Prob(Disease) + Prob(+test|noDisease)*Prob(noDisease)
```

```
## [1] 0.01000099
```

This quantity can be interpreted as the probability of testing positive, regardless of whether or not you have the disease.

So now we have $Prob(+test|Disease)$, $Prob(Disease)$, and $Prob(+test)$. How can we use these components to compute $Prob(Disease|+test)$?

Q: What's the the *joint probability* of being infected and testing positive?

Q: What's the PPV??

Re-structure your PPV equation so that you consider the positive test result to be the "Data" and the positive disease status to be the "Hypothesis"

How does this simple rule of probability relate to Bayesian statistics??

As you can see, Bayes' theorem can be derived by simple probability rules.

Frequentism vs. Bayesianism (an aside)

What is Frequentism?

Under this paradigm, the true answers are hidden behind a veil of sampling variability. That is, if we had perfect knowledge (infinite sample size) we would know the answers we seek. Random sampling errors prevent this level of certainty. However, if we know the *frequency* with which random sampling yields anomalies of various magnitudes, then we can understand and control for the effects of sampling variability. For example, we can set an α level (false-positive rate that we can live with) and then make a "positive" conclusion about

a test only if random sampling variability could account for the observed effect size with a frequency at or below the pre-determined α level.

What is Bayesianism

In many ways, Bayesian analyses allow us to interpret uncertainty and probability in the way many of us intuitively want to – as degrees of belief about alternative hypotheses (e.g., possible model structures or parameter values). Given a set of plausible models for describing a system, Bayesian statistics can tell us the degree to which we can believe each model generated the observed data versus the other models in the candidate set. If we fit a regression model, Bayesian statistics can tell us the degree to which we can trust that the true regression parameter β_1 is above zero. That said, Bayesian analyses require specifying a *prior* probability on all fitted parameters and models. This can pose a philosophical problem: what if you don't have any prior knowledge? Furthermore, the interpretation of *probability* itself can get us in philosophical hot water; because Bayesian probabilities are best interpreted as “degree of belief” (scaled to sum to 1), your conclusions from the same data could be very different from mine... But maybe this is okay – at least these differences can be formalized in terms of different prior distributions!

Which paradigm is better?

The pragmatic analyst admits that they are both useful, and uses both methods freely!!

Question for pondering:

Likelihood is defined as: $Prob(data|model)$. Is the notion of a likelihood inherently Bayesian or Frequentist?

Let's make a deal!

This is a classic example for introducing Bayes rule...

The setup: you are in a game show, called *Let's Make a Deal!* There are three doors in front of you. One hides a fancy prize and the other two hide goats.

You pick door 1. Before you see what's behind door 1, the host, Monty Hall, opens door 2 to reveal a goat. Now you can stay with 1 or switch to door 3. Should you switch? NOTE: no matter which door you choose at first, Monty will always open one of the other doors, and will never open the door with the prize (he knows where the prize is, after all). ALSO NOTE: you can't keep the goat even if you want it!

Given the new info, we now know that the prize isn't behind door 2. We want to know $Prob(door1|info)$ and $Prob(door3|info)$

As for the priors (knowledge about which door the prize is behind at the beginning of the game), let's assign a uniform distribution: $Prob(door1) = Prob(door2) = Prob(door3) = 1/3$

The data (*info*) is that Monty opened door 2 to reveal a goat.

What is the likelihood of the data (monty opened door 2) under the “stay” hypothesis (the hypothesis that the prize is behind door 1, which we originally chose), $Prob(info|door1)$?

What is the likelihood of the data (monty opened door 2) under the “switch” hypothesis (the hypothesis that the prize is behind door 3), $Prob(info|door3)$?

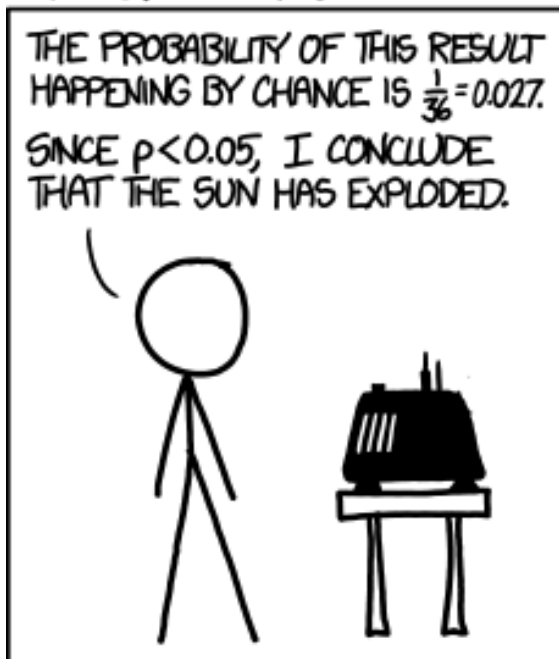
The last thing we need in order to compute the degree to which we can believe the “stay” hypothesis vs the “switch” hypothesis: we need to compute the denominator for Bayes theorem – in this case, $Prob(info)$. One way to get this unconditional probability is to use the conditional probabilities of the data under each model, multiply each by the unconditional model probabilities (priors), and sum up across all possible models:

$$Prob(info) = Prob(info|door1) \cdot Prob(door1) + Prob(info|door3) \cdot Prob(door3)$$

DID THE SUN JUST EXPLODE? (IT'S NIGHT, SO WE'RE NOT SURE.)



FREQUENTIST STATISTICIAN:



BAYESIAN STATISTICIAN:



Figure 1:
7

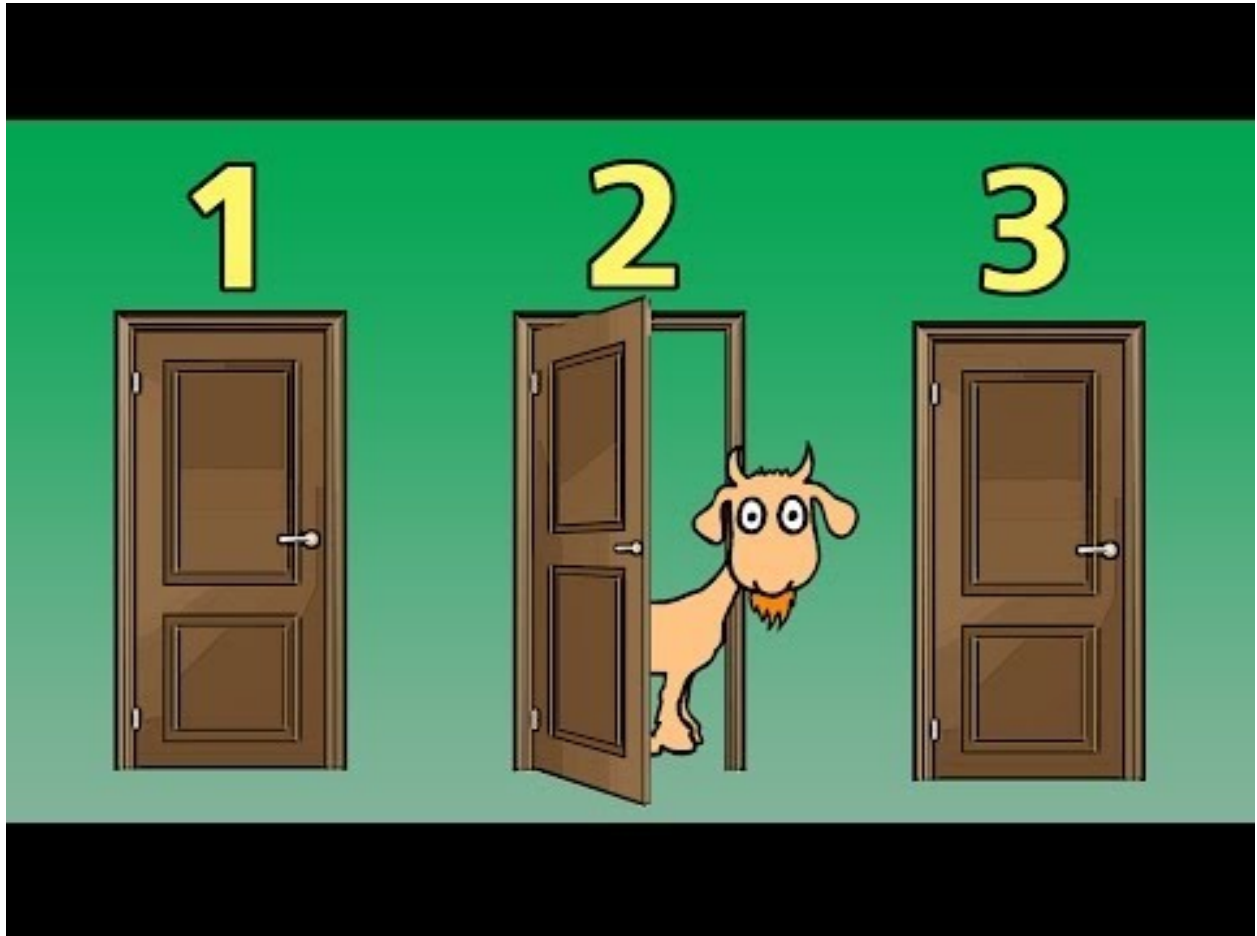


Figure 2: Monty Hall problem, setup

(either A (prize is behind door 1) is true *or* B (prize is behind door 3) is true and these possibilities are mutually exclusive).

So what's our degree of belief about the prize being behind door 1 ("staying")?

What's our degree of belief about door 3 ("switching")?

What should we do if we want to maximize our probability of winning the game??

Does this probability calculus convince you? Another way to convince yourself would be to simply simulate this result to convince ourselves that switching is the right move. Here is an R function for doing this:

```
##### Monty Hall simulation code (code by Corey Chivers 2012)
#####
# Simulation of the Monty Hall Problem
# Demonstrates that switching is always better
# than staying with your initial guess
#
# Corey Chivers, 2012
#####

monty<-function(strat='stay',N=1000,print_games=TRUE){
  doors<-1:3 #initialize the doors behind one of which is a good prize
  win<-0 #to keep track of number of wins

  for(i in 1:N){
    prize<-floor(runif(1,1,4)) #randomize which door has the good prize
    guess<-floor(runif(1,1,4)) #guess a door at random

    ## Reveal one of the doors you didn't pick which has a bum prize
    if(prize!=guess)
      reveal<-doors[-c(prize,guess)]
    else
      reveal<-sample(doors[-c(prize,guess)],1)

    ## Stay with your initial guess or switch
    if(strat=='switch')
      select<-doors[-c(reveal,guess)]
    if(strat=='stay')
      select<-guess
    if(strat=='random')
      select<-sample(doors[-reveal],1)

    ## Count up your wins
    if(select==prize){
      win<-win+1
      outcome<- 'Winner!'
    }else
      outcome<- 'Loser!'

    if(print_games)
      cat(paste('Guess: ',guess,
                '\nRevealed: ',reveal,
                '\nSelection: ',select,
                '\nPrize door: ',prize,
                '\n',outcome,'\n\n',sep=''))
  }
}
```

```

}
cat(paste('Using the ',strat,' strategy, your win percentage was ',win/N*100,'%\n',sep='')) #Print th
}

```

Now we can test out the different strategies.

```

#####
# run the monty hall code!

monty(strat="stay",print_games=FALSE)

```

```
## Using the stay strategy, your win percentage was 32.5%
```

And try a different strategy...

```

#####
# run the monty hall code!

monty(strat="switch",print_games=FALSE)

```

```
## Using the switch strategy, your win percentage was 66.8%
```

What if we had more prior information â€“ say, there was a strong smell of goat coming from door 1? The priors would be different ($Prob(1) > Prob(3)$). The likelihoods would remain exactly the same, but the posterior for door 1 would be greater than $1/3$. How strong would the odor have to be to convince you to stay rather than switch?

Thatâ€™s one benefit of the Bayesian approach â€“ you can integrate all the available information! Think about the XKCD comic above... Does it make sense that the Bayesian approach might have less of a tendency to produce “ridiculous” answers?

Probability distributions

Discrete vs. continuous

In *discrete distributions*, each outcome has a specific probability (like the probability of flipping a coin 10 times and getting 4 heads). For example, let’s consider the Poisson distribution

```

#####
# Probability distributions

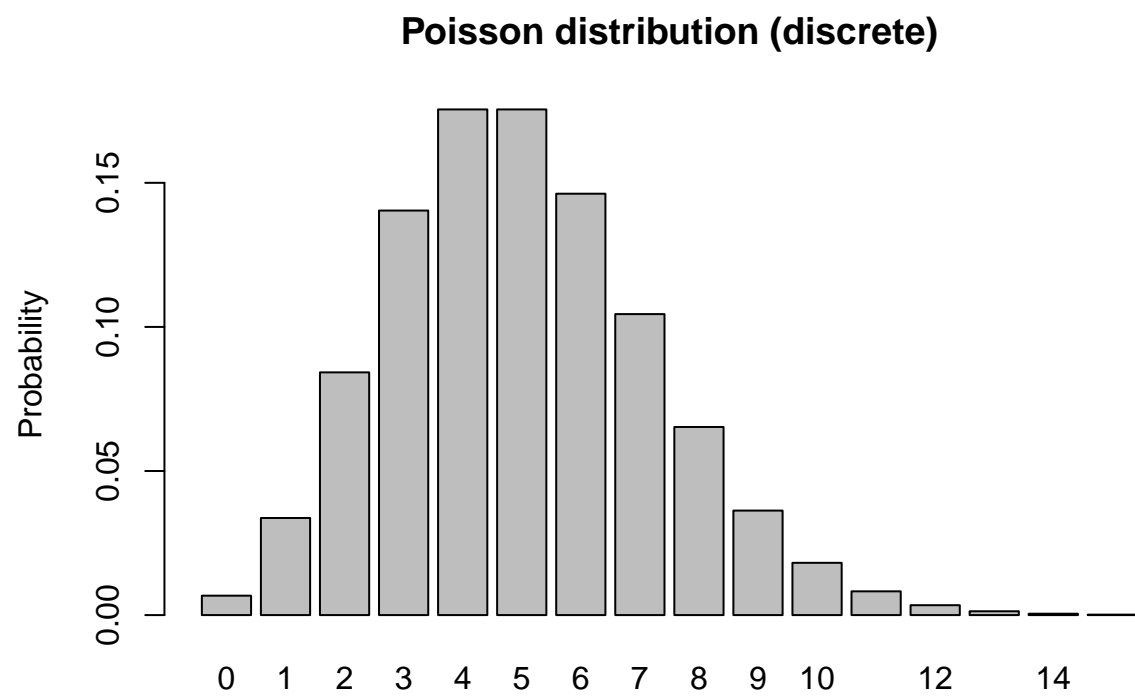
mean <- 5
rpois(10,mean)    # the random numbers have no decimal component

## [1] 4 5 4 4 3 4 1 6 5 2

# plot a discrete distribution!
xvals <- seq(0,15,1)
probs <- dpois(xvals,lambda=mean)
names(probs) <- xvals

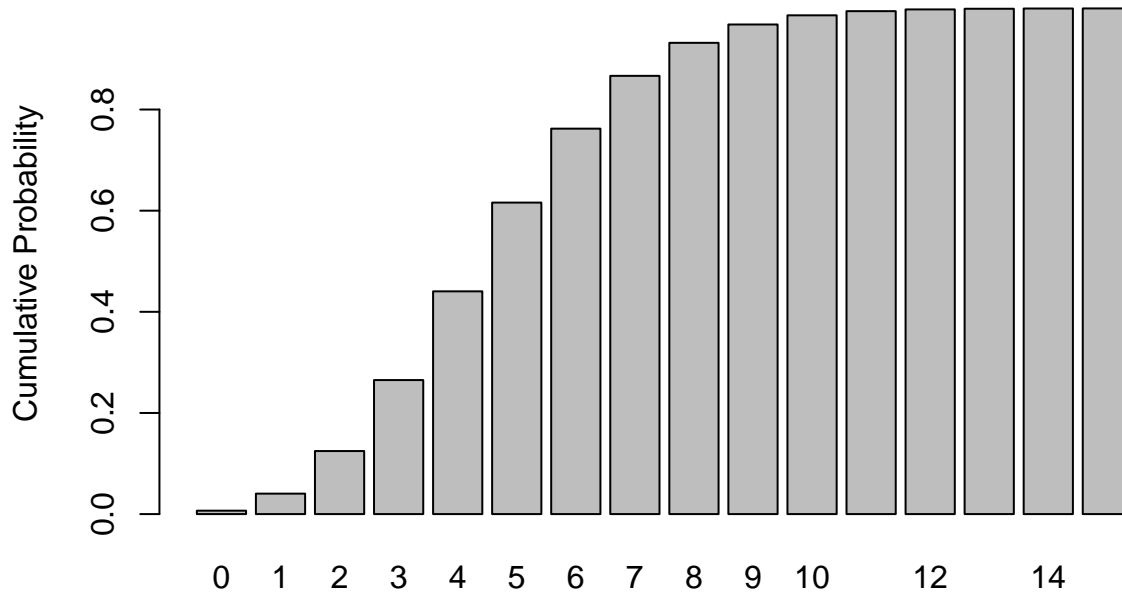
barplot(probs,ylab="Probability",main="Poisson distribution (discrete)")

```



```
barplot(cumsum(probs),ylab="Cumulative Probability",main="Poisson distribution (discrete)") # cumulat
```

Poisson distribution (discrete)



```
sum(probs)    # just to make sure it sums to 1! Does it???
```

```
## [1] 0.999931
```

In *continuous distributions*, the height of the curve corresponds to *probability density*, $f(x)$, not probability $Prob(x)$. This is because the probability of getting exactly one value in a continuous distribution is effectively zero. This arises from the problem of precision. The sum of the probability distribution must be 1 (there is only 100% of probability to go around). In a continuous distribution, there are an infinite number of possible values of x . So any individual probability is always divided by infinity, which makes it zero. Therefore we have to talk about probability density, unless we want to specify a particular range of values $\hat{=}$ we canâ€™t calculate $Prob(x = 5)$, but we can calculate $Prob(4 < x < 6)$ or $Prob(x > 5)$. Let's consider the beta distribution:

```
#####
```

```
# continuous distributions
```

```
shape1 = 0.5
```

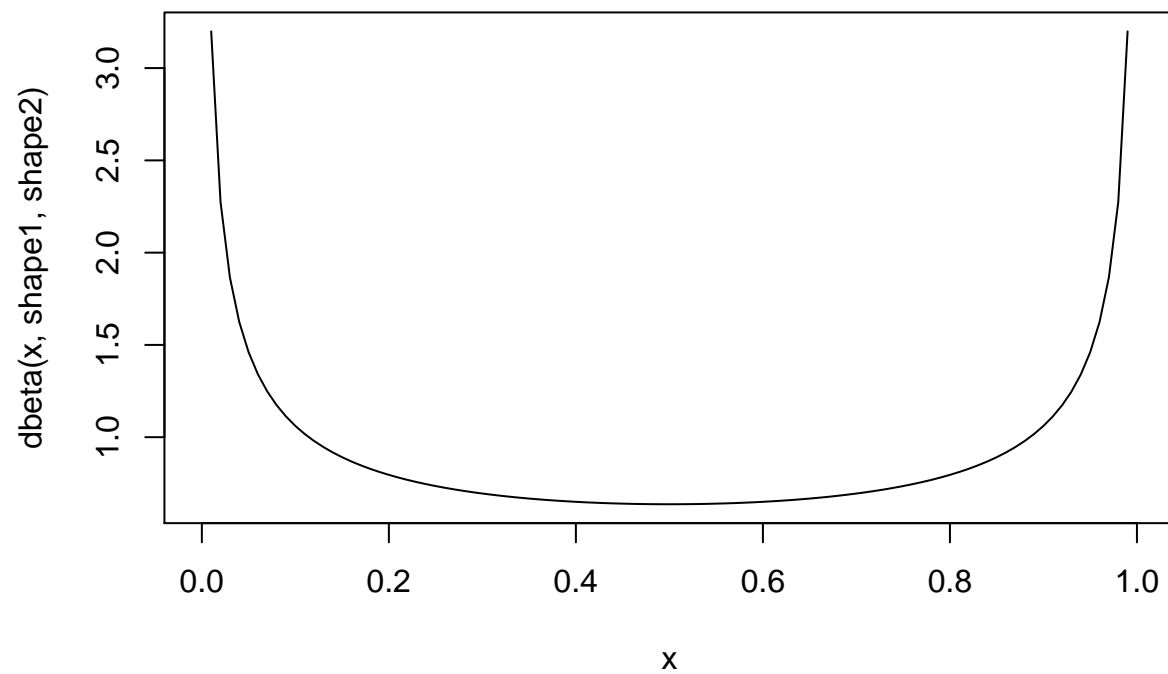
```
shape2 = 0.5
```

```
rbeta(10,shape1,shape2)
```

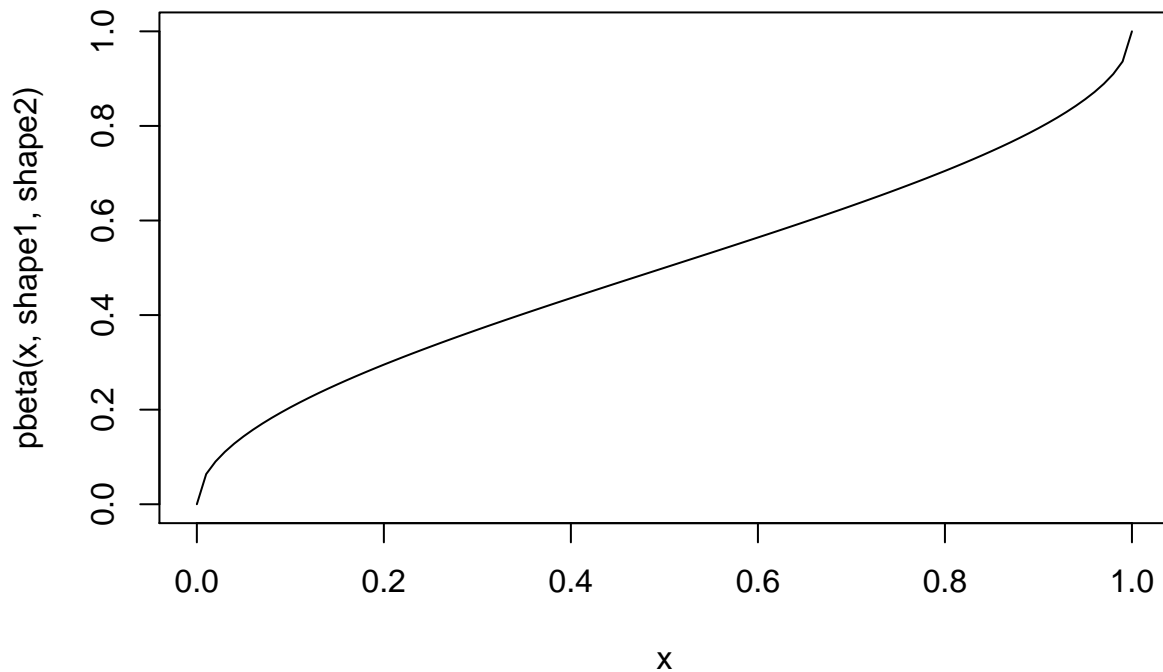
```
## [1] 0.99995578 0.04469571 0.99925977 0.07176016 0.24555179 0.94973634
```

```
## [7] 0.24560718 0.09514785 0.89112679 0.16341661
```

```
curve(dbeta(x,shape1,shape2))    # probability density
```



```
curve(pbeta(x, shape1, shape2)) # cumulative distribution
```



```
integrate(f=dbeta,lower=0,upper=1,shape1=shape1,shape2=shape2) # just to make sure it integrates to 1
## 1 with absolute error < 3e-06
```

Some other probability distribution terms:

Moments are descriptions of the distribution. For a bounded probability distribution, the collection of all the moments (of all orders, from 0 to ∞) uniquely determines the distribution.

- The zeroth central moment ($\int (x - \mu)^0 \text{Prob}(x) \partial x$) is the total probability (i.e. one),
- The first central moment ($\int (x - \mu)^1 \text{Prob}(x) \partial x$) is the mean.
- The second central moment ($\int (x - \mu)^2 \text{Prob}(x) \partial x$) is the variance.
- The third central moment ($\int ((x - \mu) / \sigma)^3 \text{Prob}(x) \partial x$) is the skewness.

Parameters are the values in the probability distribution function, describing the exact shape and location of the distribution. *Parametric statistics* require assuming certain things about distributions & parameters, while *nonparametric stats* do not require these assumptions.

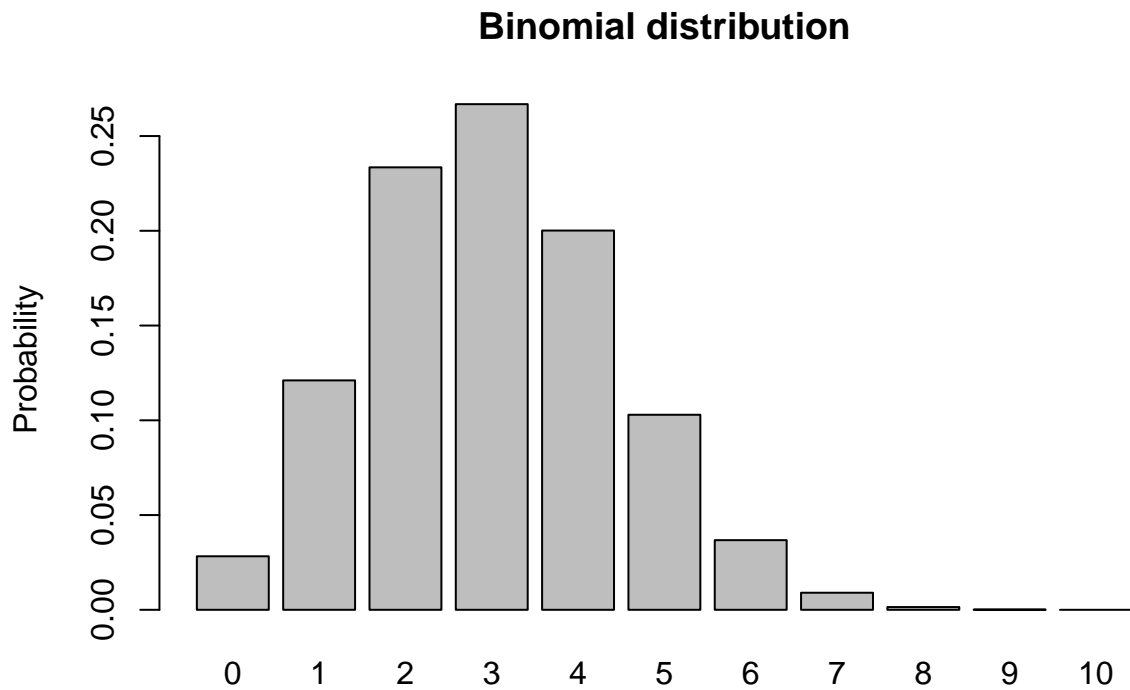
Some probability distributions

The Bolker book goes through the main distributions we will be using in this course. Pay particular attention to the type of *process* described by each distribution. The key to using these correctly is to figure out which statistical process best matches the ecological process you're studying, then use that distribution. e.g., am I counting independent, random events occurring in a fixed window of time or space (like sampling

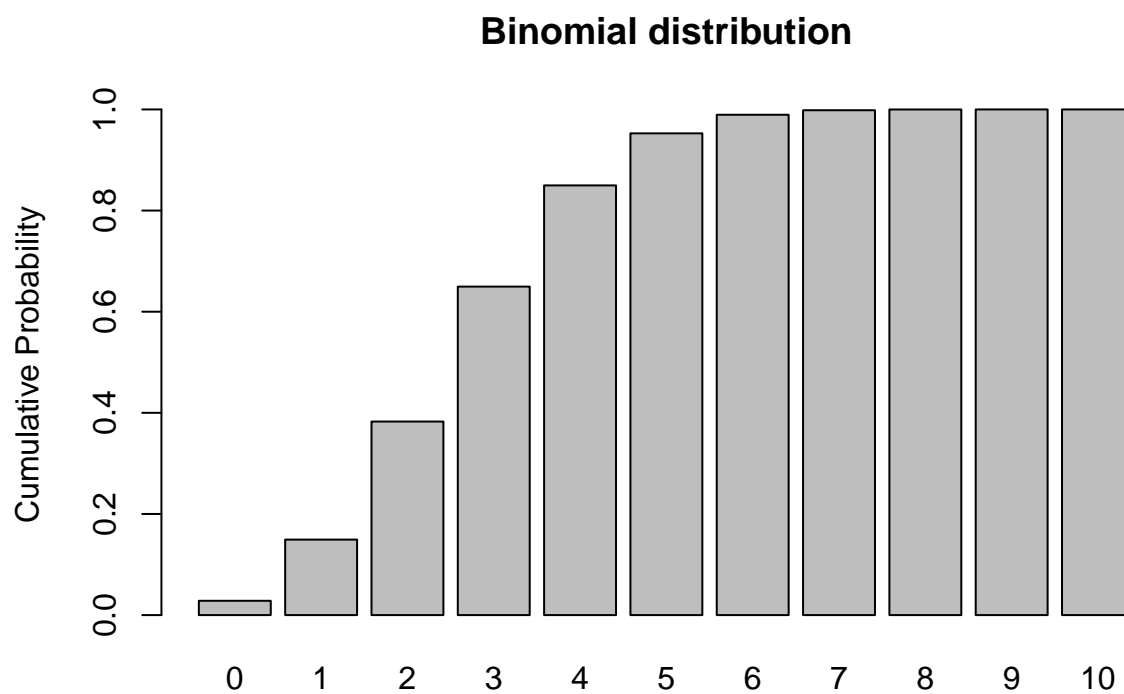
barnacles in quadrats on an intertidal bench)? Then the distribution of their occurrence probably follows a Poisson distribution.

Binomial

```
#####  
# Binomial  
  
size <- 10  
prob <- 0.3  
rbinom(10,size,prob)  
  
## [1] 3 3 1 2 5 4 1 4 3 2  
  
xvals <- seq(0,size,1)  
probs <- dbinom(xvals,size,prob)  
names(probs) <- xvals  
  
barplot(probs,ylab="Probability",main="Binomial distribution")
```



```
barplot(cumsum(probs),ylab="Cumulative Probability",main="Binomial distribution") # cumulative distri
```



```
sum(probs)    # just to make sure it sums to 1! Does it???
```

```
## [1] 1
```

Normal

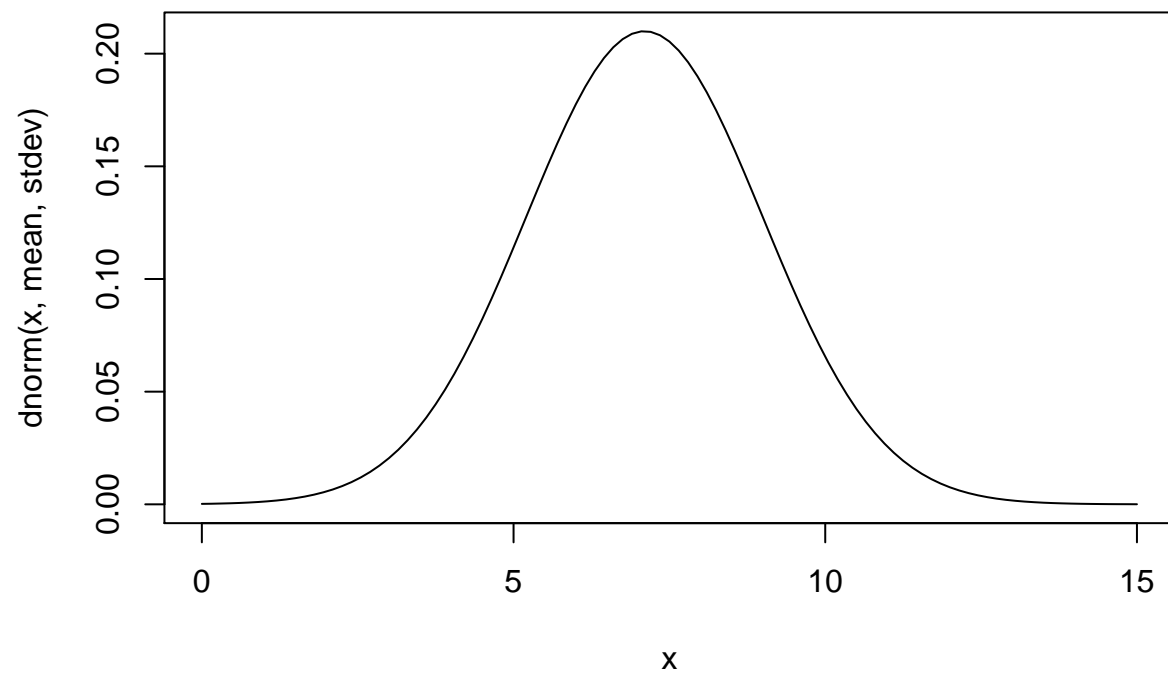
```
#####  
# Gaussian
```

```
mean = 7.1  
stdev = 1.9
```

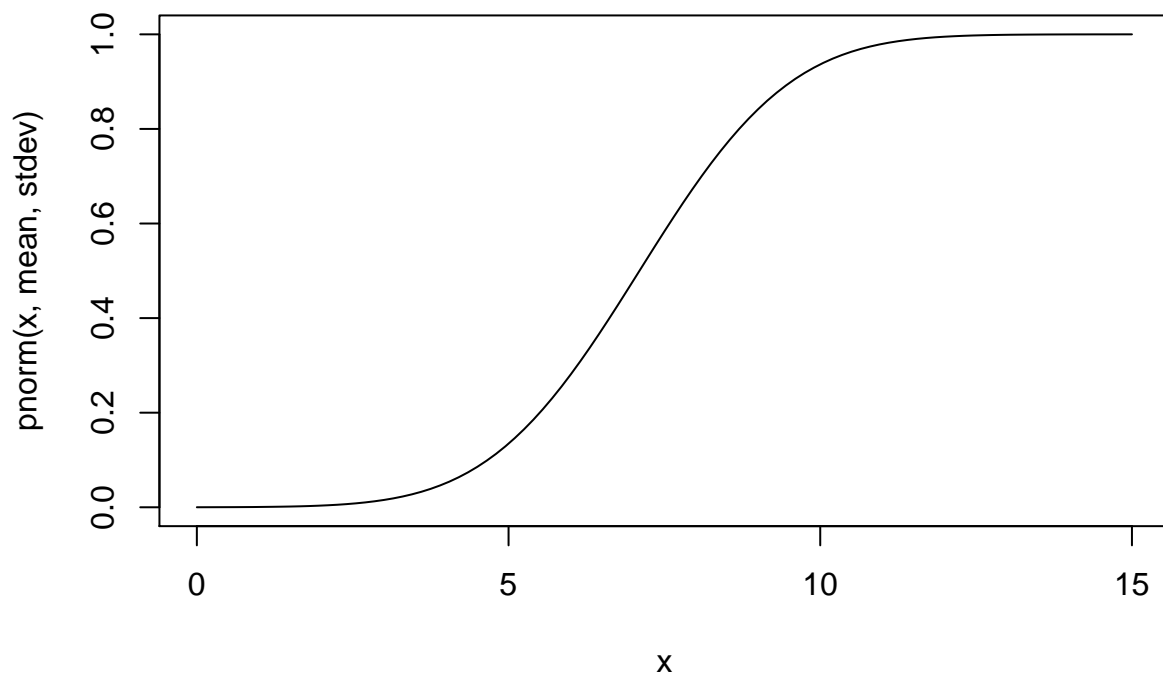
```
rnorm(10,mean,stdev)
```

```
## [1] 3.981139 8.953969 7.169246 7.457227 5.730110 7.082168 4.793121  
## [8] 6.039288 7.860525 5.079271
```

```
curve(dnorm(x,mean,stdev),0,15)    # probability density
```

```
curve(pnorm(x,mean,stdev),0,15)  # cumulative distribution
```



```
integrate(f=dnorm,lower=-Inf,upper=Inf,mean=mean,sd=stdev)    # just to make sure it integrates to 1!!  
  
## 1 with absolute error < 1.1e-05
```

Exercise:

Visualize the following distributions as above: Gamma, Exponential, Lognormal, Negative Binomial.