

Generative Models for Discrete Data

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```
library(tidyverse)
library(BiocManager)
library(Biostrings)
library(BSgenome.Celegans.UCSC.ce2)
```

Goals for this chapter

- Learn how to obtain the probabilities of all possible outcomes from a given model and see how we can compare the theoretical frequencies with those observed in real data.
- Explore a complete example of how to use the Poisson distribution to analyse data on epitope detection.
- See how we can experiment with the most useful generative models for discrete data: Poisson, binomial, multinomial.
 - Poisson: Mostly used to calculate rates, for example, calculating the rate of cancer cell formation in an hour.
 - Binomial: can be used for testing a new drug that is being introduced to cure a disease, it either cures the disease (it's successful) or it doesn't cure the disease (it's a failure).
 - Multinomial: Used in genetics where a person may have 1 of many possible alleles, that occur with certain probabilities in a given population, at a gene locus.
- Use the R functions for computing probabilities and counting rare events. Generate random numbers from specified distributions.

Questions we will answer in this chapter

- Given a certain model, how can we obtain the probabilities for all possible outcomes?
- How do theoretical frequencies compare with those observed in real data?
- How can we use the Poisson distribution to analyse data on epitope detection?
- How can we apply the Multinomial distribution and Monte Carlo simulation to perform power tests?

Our first example

Let X be the number of mutations along a genome of HIV.

We are told that mutations occur at a rate of .00005 per nucleotide per replication cycle. Furthermore we assume that this genome contains 10000 nucleotides per cycle.

Thus, for one cycle, $X \sim \text{Poisson}(\lambda = .00005 * 10000 = 5)$

That's cool and all, but what does this tell us about our mutations?

Quite a lot actually! For example:

- We can expect that in the long run, each cycle will contain 5 mutations (aka the expected value of X)
- We can quantify the spread of the distribution of X in two ways
 - The standard deviation, which is equal to $\sqrt{5}$ in our example
 - The variance, which is equal to 5 in our example
 - Note that the standard deviation is just the square root of the variance.

Moreover, for any value(s) of X we can find the several probabilities:

- The probability of seeing exactly x mutations in a cycle
- The probability of seeing at least x mutations in a cycle
- The probability of seeing no more than x mutations in a cycle
- The probability of seeing between x_1 and x_2 mutations in a cycle ($x_1 < x_2$)

In general, a function $f : A \rightarrow [0, 1]$ that takes an integer as input (in the case of discrete data) and returns a probability as output is called a **probability mass function (PMF)**. In particular, we obtain the probability of the observable X being observed to have a value of x , denoted $P(X = x)$.

Given this, lets try some examples in R.

To obtain $P(X = x)$ where X follows a $\text{Poisson}(\lambda)$ distribution, we use the function called `dpois(x, lambda)`
For example, what is the probability that we observe exactly 5 mutations in our genome?

```
dpois(x = 5, lambda = 5)
```

```
## [1] 0.1754674
```

If we want to obtain the probability for multiple values, say 0 through 20, we can set the first parameter (x) to be a vector.

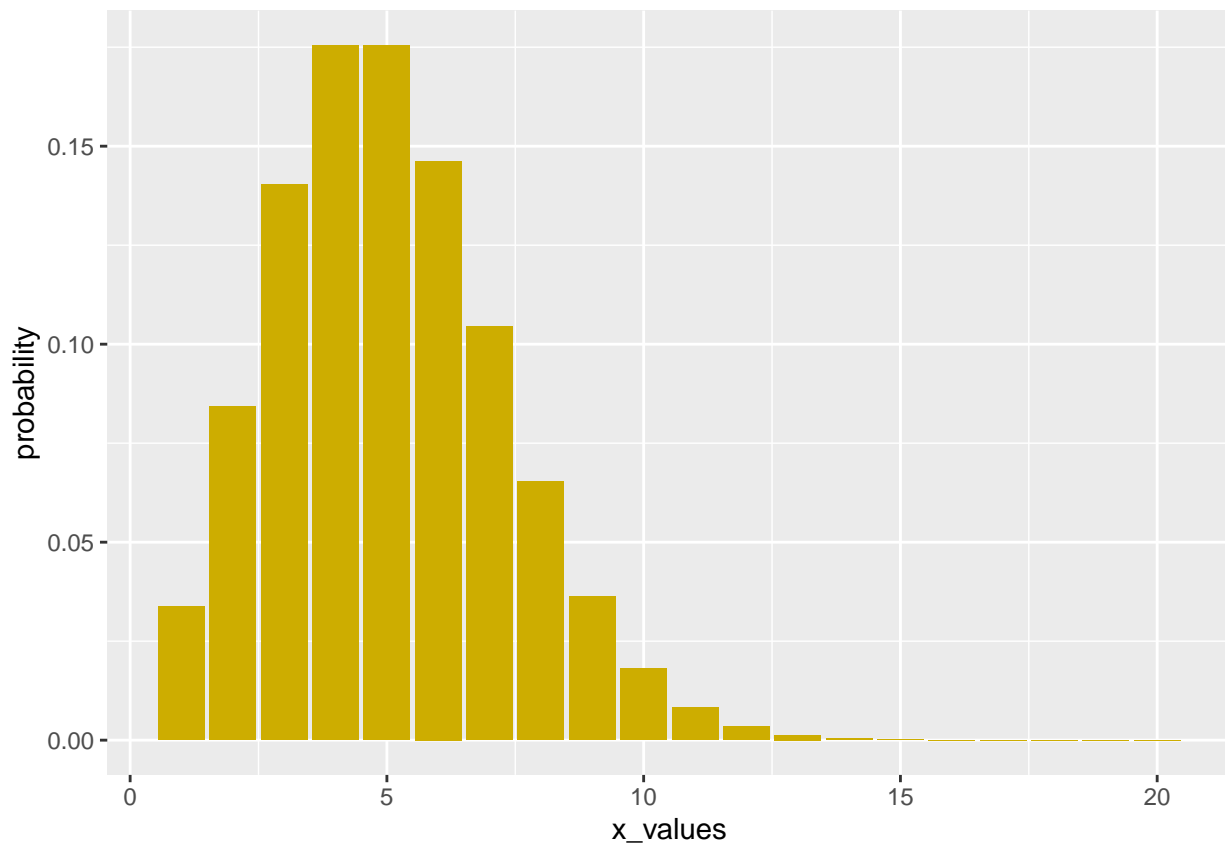
In R, we can use the colon (`:`) operator to generate a sequence of integers, i.e. `1:3 = (1,2,3)`.

```
dpois(x = 0:20, lambda = 5)
```

```
## [1] 6.737947e-03 3.368973e-02 8.422434e-02 1.403739e-01 1.754674e-01  
## [6] 1.754674e-01 1.462228e-01 1.044449e-01 6.527804e-02 3.626558e-02  
## [11] 1.813279e-02 8.242177e-03 3.434240e-03 1.320862e-03 4.717363e-04  
## [16] 1.572454e-04 4.913920e-05 1.445271e-05 4.014640e-06 1.056484e-06  
## [21] 2.641211e-07
```

We could use this to plot the pmf over certain values.

```
tibble(x_values = 1:20, probability = dpois(x = 1:20, lambda = 5)) %>%  
  ggplot(aes(x = x_values, y = probability)) +  
  geom_bar(stat = "identity", fill = "gold3")
```



Factors

In this section we will discuss factors and how they work in R.

With discrete data, we often associate labels with certain values. For example:

- Sex: Male, Female
- Pain Level: Low, Medium, High
- Blood Genotypes: AA, AB, AO, BB, BO, OO
- Binary outcomes: 0 = No, 1 = Yes

We use the function `factor()` to convert a vector to a factor vector.

```
pain_level <- c("low", "low", "medium", "high", "low", "medium", "high", "high") %>% factor()

pain_level

## [1] low    low    medium high    low    medium high    high
## Levels: high low medium
```

You'll notice that by default R sorts factors alphabetically, to fix this we set a parameter "levels" in side the call to `factor()`

```
pain_level <- c("low", "low", "medium", "high", "low", "medium", "high", "high") %>%
  factor(levels = c("low", "medium", "high"))

pain_level

## [1] low    low    medium high    low    medium high    high
## Levels: low medium high
```

Question

What if you want to create a factor that has some levels not yet in your data?

Solution

We would make the same call to `factor` and include the extra factors while setting "levels"

```
pain_level <- c("low", "low", "medium", "high", "low", "medium", "high", "high") %>%
  factor(levels = c("none", "low", "medium", "high"))

pain_level[1] <- "none"

pain_level

## [1] none    low    medium high    low    medium high    high
## Levels: none low medium high
```

Bernoulli Trials

Consider a binary event with two possible outcomes, say whether a new born baby is male or female. Further assume that each sex is equally likely and that 0 = male, and 1 = female.

If X represents the sex of a random new born, then we can say X follows a Bernoulli distribution with probability $p = .5$.

Note that a Bernoulli trial with probability p is equivalent to a binomial distribution with size n and probability p . We will talk more about the binomial distribution shortly.

Lets start by generating random samples from a Bernoulli trial with $p = .5$. To do this, we use the `rbinom()` function.

Say we wanted to simulated 20 births.

```
rbinom(n = 20, prob = .5, size = 1)
```

```
## [1] 1 1 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 1
```

Distributions in base R

At this point we've seen two ways to work with distributions in `r` (`dpois()` and `rbinom()`). `R` is actually very systematic about this and has a set of 4 functions for all the common distributions. Each function will start with one of (d, p, q, or r) and will end with an abbreviation of the name of the distribution (pois for Poisson, binom for binomial, norm for normal, etc...).

Here, I will state what each letter represents and how the functions work:

- d: probability distribution function, it gives $P(X = x)$ under a certain distribution.
- p: cumulative distribution function, it gives $P(X \leq x)$ under a certain distribution.
- q: quantile function, it gives the value of x for which the cumulative probability equals p under a certain distribution.
- r: random generation, it gives a random sample of size n under a certain distribution.

We will see more examples of theses functions throughout the class.

The Binomial Distribution

If we perform a Bernoulli trial n times and then ask how many of the trials ended in a success, we are sampling data from a **Binomial distribution**.

After some math, we can show that the PMF of the binomial distribution is: $\binom{n}{x} p^x q^{n-x}$, where:

- $p + q = 1$
- p is the probability of success, $q = (1 - p)$ is the probability of failure
- n is the total number of trials
- x is the random variable we are looking for

Say we are looking at mothers who are planning to have three children in the future. If X represents the number of boys that a individual mother has. Then we say X follows a binomial distribution with $n = 3$ and $p = .5$.

we can take a random sample of 10 mothers

Note that n in `rbinom()` refers to how many samples we want to take, whereas `size` refers to the size of each trial (usually denoted n when we refer to the binomial distribution).

```
rbinom(n = 10, prob = .5, size = 3)
```

```
## [1] 1 2 2 1 2 2 2 2 0 2
```

Whats the probability that a mother has two boys?

```
dbinom(x = 2, prob = .5, size = 3)
```

```
## [1] 0.375
```

The Poisson Distribution

We've seen examples of the Poisson distribution already.

However, if a binomial distribution has a small p and large n , we can use the Poisson distribution to approximate the Binomial distribution.

That is, $\text{Bin}(n, p) \approx \text{Pois}(\lambda = np)$ for small p and large n .

Math shows us that the PMF is: $\frac{e^{-\lambda} \lambda^x}{x!}$

One way of computing the Poisson distribution in R (say for $\lambda = 5$ and $x = 3$) is by using the PMF manually.

```
5^3 * exp(-5) / factorial(3)
```

```
## [1] 0.1403739
```

or we can use `dpois(q, lambda)`

```
dpois(3, 5)
```

```
## [1] 0.1403739
```

Order Statistics

For exercise 3 we need to know about rank statistics (ordered statistics). Given a random sample of size n , the order statistics are defined such that each random variable is ordered from smallest (minimum), to largest (maximum).

ie.) $x_{(1)} < x_{(2)} < \dots < x_{(n)}$

Complementary Events

We also need to know about the complementary event.

If we want to find $P(X \geq 1)$, we would have to compute $P(X = 1) + P(X = 2) + \dots + P(X = n)$.

This could take a long time if n is big. If $n = 100$, we would have to compute 100 terms.

However, since all the probabilities sum up to 1, we can compute the complementary event, which is $1 - P(X < 1)$.

Now we only need to compute one term, $P(X = 0)$.

Probability of the Maximum

If we want to calculate the probability of seeing a value as large as c when drawing from a sample of size n , what we are really asking is **what is the probability that the largest value in our sample is as large as c ?**

In other words, we wish to find $P(x_{(n)} \geq c)$. A little bit of math shows us:

$$\begin{aligned} &P(x_{(n)} \geq c) \\ &= 1 - P(x_{(n)} < (c - 1)) \\ &= 1 - P(x_{(1)} < (c - 1), x_{(2)} < (c - 1), \dots, x_{(n)} < (c - 1)) \\ &= 1 - P(x_{(1)} < (c - 1)) \times P(x_{(2)} < (c - 1)) \times \dots \times P(x_{(n)} < (c - 1)) \text{ [Since the } X'_i\text{'s are independent]} \\ &= 1 - P(x < (c - 1))^n \text{ [Since the } X'_i\text{'s are identically distributed]} \end{aligned}$$

we will come back to this formula in exercise 3 and 4, where we will design a function to calculate the probability of seeing a value as large as c , under the Poisson distribution.

The Multinomial Distribution

The multinomial distribution is an extension of the binomial distribution with more than two outcomes.

Math shows us that the PMF is: $\frac{n!}{x_1! \dots x_k!} p_1^{x_1} \dots p_k^{x_k}$

Let's look at an example.

If we are randomly choosing 8 people from an audience that contain 50% biologist, 30% statisticians, and 20% engineers, what is the probability of choosing exactly 4 biologist, 3 statisticians and 1 engineer?

we can use the `dmultinom()` function to solve this.

```
dmultinom(c(4, 3, 1), prob = c(0.5, 0.3, 0.2))
```

```
## [1] 0.0945
```

The multinomial also has many uses in genetics where a person may have 1 of many possible alleles, that occur with certain probabilities in a given population, at a gene locus.

Monte Carlo Simulation

Monte Carlo is a method to solve problems with the use of randomness. There are three main problems that can be addressed with Monte Carlo: optimization, numerical integration, and generating draws from a probability distribution.

We've seen one example of Monte Carlo so far when we were doing epitope detection.

Now we will switch gears and look at how Monte Carlo can be used to simulate power for a hypothesis test.

In statistics, power is the probability that we reject our null hypothesis given that the null hypothesis is false.

Since we most often wish to reject the null hypothesis, we can view power as the **true positive rate**.

Lets say that we wish to test the null hypothesis (H_0) that DNA data we've collected comes from a fair process. That is:

$H_0 : P_A = .25, P_C = .25, P_G = .25, P_T = .25$ v.s. H_a : At least one P_i differs from the rest.

Before we define the test, lets first take 20 random samples from a multinomial distribution with $n = 20$ and $P_A = \dots = P_G = .25$.

```
set.seed(20190919)
rmultinom(10, prob = rep(.25,4), size = 20)
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]
## [1,]    8    3    4    2    3    8    5    2    3     1
## [2,]    3    2    2    5    2    6    5    8    4     7
## [3,]    6   10    9    6   11    3    4    5    7     4
## [4,]    3    5    5    7    4    3    6    5    6     8
```

We can see that even with 20 samples, there is quite a lot of variability in the placements of the boxes.

Spoiler alert! The test we are about to simulate is called the chi-squared test for goodness of fit. Although we can do this test without any simulation (one of the focus points in chapter 2), it still a good idea to get experience with Monte Carlo simulation, as it might be the only option for certain situations.

The test statistic is defined to be:

$$\chi^2 = \sum_{i=1}^n \frac{(E[x_i] - x_i)^2}{E[x_i]}$$

That is, for each individual observed x , we take the squared difference of its expected value and the observed value, then divide by the expected value. We will show the step by step process of generating this statistic directly from the above sampling.

First, let's store this matrix (this is what `rmultinom()` gives us as output) into an object.

```
set.seed(1234)
dna_data <- rmultinom(10, prob = rep(.25,4), size = 20)
dna_data
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]
## [1,]    3    6    1    5    4    7    3    4    3     8
## [2,]    6    7    5    6    8    3    4    3    7     6
## [3,]    6    4    8    5    3    4    6    3    5     1
## [4,]    5    3    6    4    5    6    7   10    5     5
```


Now we will want the expected values for each x_i , since we have the probabilities, $E[X_i] = p_i * n$

Note: we can multiply a vector by a constant and R will do that multiplication for each element in the vector.

```
exp_x <- rep(.25,4) * 20
exp_x
```

```
## [1] 5 5 5 5
```

We can continue to perform these operations on the entire matrix, R handles this for us in a elegant way.

If we subtract a vector from a matrix, R will recycle the values in the vector until the last element in the matrix is reached. This works perfectly for us if the number of elements in the vector matches the number of rows in the matrix.

```
dna_data <- dna_data - exp_x
dna_data
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]
## [1,]  -2    1  -4    0  -1    2  -2  -1  -2    3
## [2,]   1    2   0    1   3   -2  -1  -2    2    1
## [3,]   1  -1    3    0  -2   -1    1  -2    0   -4
## [4,]   0  -2    1   -1   0    1    2    5    0    0
```

We can perform other operation on the matrix, R will sill do this element wise. Note that squaring a matrix usually means something different. In our context, however, this is exactly what we need.

```
dna_data <- dna_data^2
dna_data
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]
## [1,]    4    1   16    0    1    4    4    1    4    9
## [2,]    1    4    0    1    9    4    1    4    4    1
## [3,]    1    1    9    0    4    1    1    4    0   16
## [4,]    0    4    1    1    0    1    4   25    0    0
```

Now we just need to divide by $E[X_i]$

```
dna_data <- dna_data / exp_x
dna_data
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]
## [1,]  0.8  0.2  3.2  0.0  0.2  0.8  0.8  0.2  0.8  1.8
## [2,]  0.2  0.8  0.0  0.2  1.8  0.8  0.2  0.8  0.8  0.2
## [3,]  0.2  0.2  1.8  0.0  0.8  0.2  0.2  0.8  0.0  3.2
## [4,]  0.0  0.8  0.2  0.2  0.0  0.2  0.8  5.0  0.0  0.0
```

In fact, to make things easier, lets make a function that combines all the above steps.

```
generate_stat_test <- function(matrix, exp_value){
  return((matrix-exp_value)^2 / exp_value)
}
```

Now we can generate much larger samples.

```
set.seed(1234)
dna_data <- rmultinom(1000, prob = rep(.25,4), size = 20)
dna_data_matrix_H0 <- generate_stat_test(dna_data, exp_x)
dna_data_matrix_H0[1:4,1:20]
```

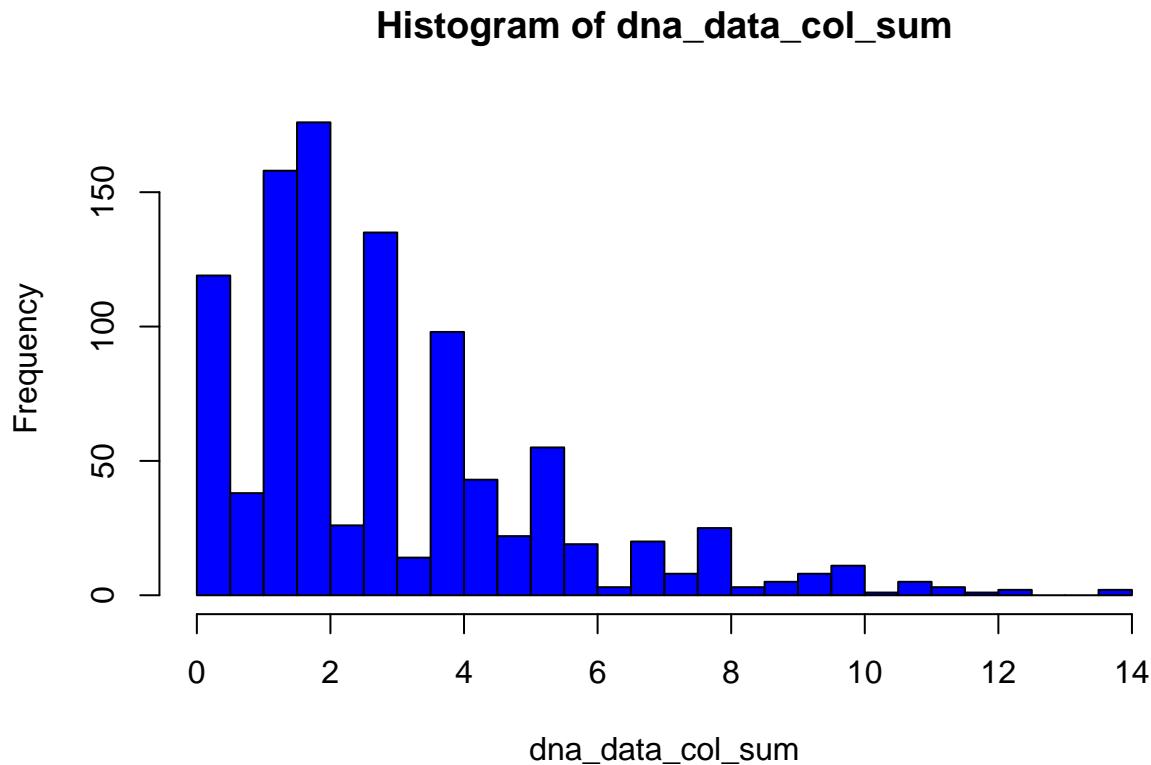
```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## [1,]  0.8  0.2  3.2  0.0  0.2  0.8  0.8  0.2  0.8   1.8  0.0  0.0  0.8
## [2,]  0.2  0.8  0.0  0.2  1.8  0.8  0.2  0.8  0.8   0.2  0.2  0.8  0.2
## [3,]  0.2  0.2  1.8  0.0  0.8  0.2  0.2  0.8  0.0   3.2  0.0  0.8  7.2
## [4,]  0.0  0.8  0.2  0.2  0.0  0.2  0.8  5.0  0.0   0.0  0.2  0.0  1.8
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20]
## [1,]   0.8   0.2   0.0   0.2   0.2   0.8   0.2
## [2,]   0.0   0.2   0.2   0.8   0.2   0.2   0.8
## [3,]   0.0   0.2   0.2   1.8   0.0   0.0   0.8
## [4,]   0.8   0.2   0.0   0.8   0.0   0.2   0.2
```

To proceed with the simulation, we will need to find the overall variability for each DNA sample. Lucky base R has a function to do this called `colSums()`.

```
dna_data_col_sum <- colSums(dna_data_matrix_H0)
```

This is also useful if we want to plot the distribution of `x`.

```
hist(dna_data_col_sum, breaks = 25, col = "blue")
```



In particular, we would like to obtain the 95th percentile for the overall variability of all DNA samples.

```
percent_95th <- quantile(dna_data_col_sum, .95)
```

This means that 5% of DNA samples vary by a value of 7.6. We will use this number to detect if a individual DNA sample comes from a different (not fair) process.

To do this, lets first generate DNA data again, but this time we will change the probabilities so that the process is no longer fair. That is, this new DNA will follow a multinomial distribution with $P_A = .375$, $P_C = .25$, $P_G = .25$, $P_T = .125$ and $n = 20$. We will take 1000 samples.

```
set.seed(1234)
dna_data_nf <- rmultinom(1000, prob = c(.375, .25, .25, .125), size = 20)
dna_data_nf[1:4,1:20]
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## [1,]    5    8    3    8    6   10    6    6    6   10    7    7    6
## [2,]    7    7    5    6    8    3    4    4    7    5    4    4    4
## [3,]    5    3    7    4    5    5    7    9    5    5    7    5    3
## [4,]    3    2    5    2    1    2    3    1    2    0    2    4    7
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20]
## [1,]     9     6     7     6     6     5     9
## [2,]     5     6     6     7     7     6     3
## [3,]     4     6     5     6     5     6     4
## [4,]     2     2     2     1     2     3     4
```

```
dna_data_matrix_H0_nf <- generate_stat_test(dna_data_nf, exp_x)
dna_data_matrix_H0_nf[1:4,1:20]
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## [1,] 0.0  1.8  0.8  1.8  0.2  5.0  0.2  0.2  0.2      5  0.8  0.8  0.2
## [2,] 0.8  0.8  0.0  0.2  1.8  0.8  0.2  0.2  0.8      0  0.2  0.2  0.2
## [3,] 0.0  0.8  0.8  0.2  0.0  0.0  0.8  3.2  0.0      0  0.8  0.0  0.8
## [4,] 0.8  1.8  0.0  1.8  3.2  1.8  0.8  3.2  1.8      5  1.8  0.2  0.8
##      [,14] [,15] [,16] [,17] [,18] [,19] [,20]
## [1,]  3.2   0.2   0.8   0.2   0.2   0.0   3.2
## [2,]  0.0   0.2   0.2   0.8   0.8   0.2   0.8
## [3,]  0.2   0.2   0.0   0.2   0.0   0.2   0.2
## [4,]  1.8   1.8   1.8   3.2   1.8   0.8   0.2
```

```
dna_data_col_sum_nf <- colSums(dna_data_matrix_H0_nf)
dna_data_col_sum_nf[1:20]
```

```
## [1]  1.6  5.2  1.6  4.0  5.2  7.6  2.0  6.8  2.8 10.0  3.6  1.2  2.0  5.2
## [15]  2.4  2.8  4.4  2.8  1.2  4.4
```

Since we know this new DNA data does, in fact, not come from a fair process, we can calculate the power of our test by taking the total number of DNA samples that vary by more than 7.6 (ie, we would have rejected that test), and divide by the total number of tests we performed (1000 in this case).

```
power <- mean(dna_data_col_sum_nf > percent_95th)
power
```

```
## [1] 0.186
```

Thus, our power is only 20% when use 20 samples per test. This brings us to an interesting question.

What is the minimum sample size (per test) required to guarantee a power of 80%?

Solution:

A good approach is to perform the simulation many time for various values of n, and then plot the relationship between the sample size and power.

First, let's define a function that will generate power.

```
get_power <- function(data, probs, crit_v) {
  data_matrix_H0 <- generate_stat_test(data, (1/nrow(data)) * colSums(data[])[1])
  data_col_sum <- colSums(data_matrix_H0)
  power <- mean(data_col_sum > crit_v)
  return(power)
}
```

The first thing we will need to do is generate 100 matrices, each containing 1000 DNA samples with sizes varying from 1 to 100.

To do this we will use a purrr function called map. A typical call to map is as follows:

map(.x, .f, ...) where:

- `.x` is a vector that contains the parameter you wish to vary per call.
- `.f` is a function that you want to use on the above vector.
- ... are any other (constant) parameters in the above function.

```
size <- c(1:200)
dna_data_n_1_to_200 <- map(size, rmultinom, n = 1000, prob = c(.375, .25, .25, .125))

# The first matrix where each DNA sample has size 1.
dna_data_n_1_to_200[[1]][,1:10]
```

```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]
## [1,]    1    0    0    1    0    0    1    0    0    0
## [2,]    0    0    0    0    1    1    0    0    1    0
## [3,]    0    1    1    0    0    0    0    1    0    1
## [4,]    0    0    0    0    0    0    0    0    0    0
```

```
# The last matrix where each DNA sample has size 200.
dna_data_n_1_to_200[[200]][,1:10]
```

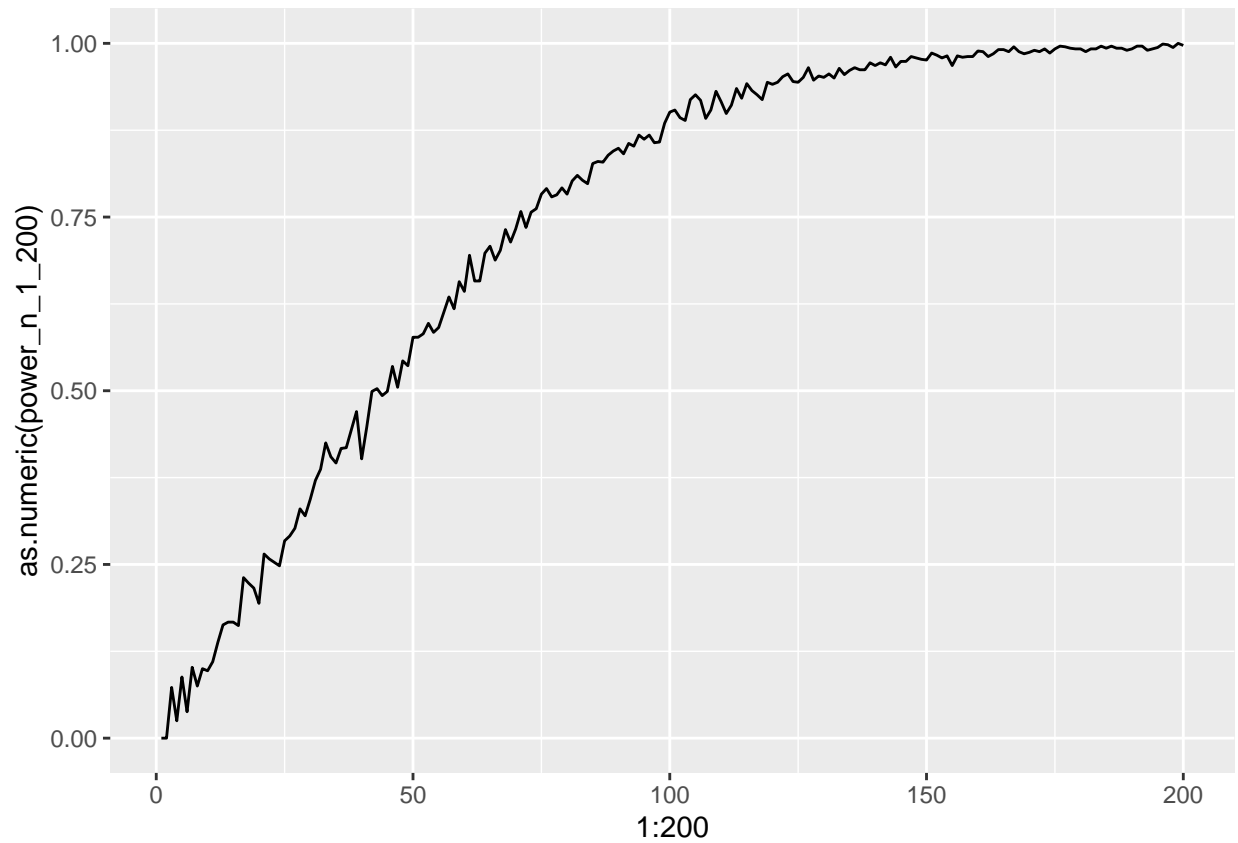
```
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]
## [1,]   89   74   83   72   77   72   75   78   66   74
## [2,]   38   52   43   62   42   55   57   47   55   48
## [3,]   46   55   51   45   49   52   44   47   51   51
## [4,]   27   19   23   21   32   21   24   28   28   27
```

We will use `map` again, this time on the list of matrices using our `get_power` function.

```
data = dna_data_n_1_to_200
power_n_1_200 = map(data, get_power, probs = rep(.25,4), crit_v = percent_95th)
```

We can plot the relationship

```
qplot(x=1:200, y=as.numeric(power_n_1_200), geom="line")
```



And finally find the answer we were looking for!

```
detect_index(as.numeric(power_n_1_200), ~ .x >= .8)
```

```
## [1] 81
```

So, if we want our test to have a power equal to 80% we must have a minimum sample size of 81.

Exercises

1.1

Task:

Other than Poisson, Binomial, and Multinomial, find two discrete distribution that have base R functions associated to them.

Solution:

Geometric Distribution:

Given a probability p , how many failures will it take to see the first success?

```
# A random sample of size 5 from a geometric distribution with p=.25  
rgeom(5, .25)
```

```
## [1] 2 1 2 5 2
```

```
# What is the probability that we will see 4 failures before the first success?  
dgeom(4, .25)
```

```
## [1] 0.07910156
```

```
# What is the probability that we will see no more than 3 failures before the first success?  
pgeom(3, .25)
```

```
## [1] 0.6835938
```

Hypergeometric Distribution:

Given a population of size N where K of the N objects are “success states.” How many success state objects will I obtain from drawing a sample of size n without replacement?

```
# A random sample of size 5 from a hyper geometric distribution with a population of N=25, K=5 success  
# given a sample of n=10  
rhyper(5, 5, 20, 10)
```

```
## [1] 3 1 2 2 2
```

```
# What is the probability that we will see 5 success state objects?  
dhyper(5, 5, 20, 10)
```

```
## [1] 0.004743083
```

```
# What is the probability that we will see at least 1 success state object?  
phyper(0, 5, 20, 10, lower.tail = F)
```

```
## [1] 0.9434783
```

1.2

Task:

Given that X follows a Binomial distribution with $n = 10$ and $p = .3$ what is $P(X \leq 2)$?

Try this two ways, the first using only `dbinom()`, and the other with a different function.

Solution:

$X = 2$ for a `Binom(10, 0.3)` here:

- $x = 2$
- $n = 10$
- $p = 0.3$
- $q = 0.7$

`dbinom(x, n, p)`

```
dbinom( 2, 10, 0.3 )
```

```
## [1] 0.2334744
```

$X \leq 2$ for a `Binom(10, 0.3)`
here:

- $x = 0, 1, 2$
- n, p and q remain the same

```
dbinom( 0, 10, 0.3 ) + dbinom( 1, 10, 0.3 ) + dbinom( 2, 10, 0.3 )
```

```
## [1] 0.3827828
```

or we can say $x = 0:2$ and plug it into `dbinom(x, n, p)`

```
sum(dbinom( 0:2, 10, 0.3 ))
```

```
## [1] 0.3827828
```

We can check with another function `pbinom(x, n, p)`

```
pbinom( 2, 10, 0.3 )
```

```
## [1] 0.3827828
```


1.3

Task:

Write a function to compute the probability of having a maximum as big as m when looking across n Poisson variables with rate lambda

Solution:

```
poisson_max_function = function(n, m, lambda) {  
  prob = 1 - ppois( m-1, lambda )^n  
  return(prob)  
}
```

1.4

Task:

Rewrite the functions in 1.3 to have default values for its arguments.

Solution:

We write the function to have default values for its arguments so that when you do not have any parameters it will assume you want the default parameters. In this case, Poisson_max_function would give us an error. After this exercise, Poisson_max_function will give us an output.

```
poisson_max_function = function(n = 100, m = 1, lambda = 5 ) {  
  prob = 1 - ppois( m-1, lambda )^n  
  return(prob)  
}
```

```
poisson_max_function()
```

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

1.5

Task:

Using the epitope example, what is the probability of having a maximum of 9 or larger in 100 trials? Find the answer by using simulation.

How many simulations would you need to run to prove that the probability is smaller than .000001

Solution:

Writing functions is always a good idea when we want to repeat a task.

```
# Real answer  
poisson_max_function(100, 9, .5)
```

```
## [1] 3.43549e-07
```

```

# Simulation

# Simulates one instance of a Poisson dist. sampled n times and checks if any of the samples are > max.
pois_has_max = function(n, max, lamda) {
  result_vector = rpois(n, lamda)
  return(max(result_vector >= max))
}
# repeat the simulation 10000 times
a = replicate(1e5, pois_has_max(100, 9, .5))
# obtain the probability
mean(a)

```

```
## [1] 0
```

We would need $\frac{1}{.000001} = 1,000,000$ simulations

1.6

Task:

Using the dXXXX() functions create various plots, list five continuous distributions.

Solution:

The key here is that we can feed the distribution functions a vector and it will give us the probabilities for each value. Also seq is a nice way to generate sequences.

```

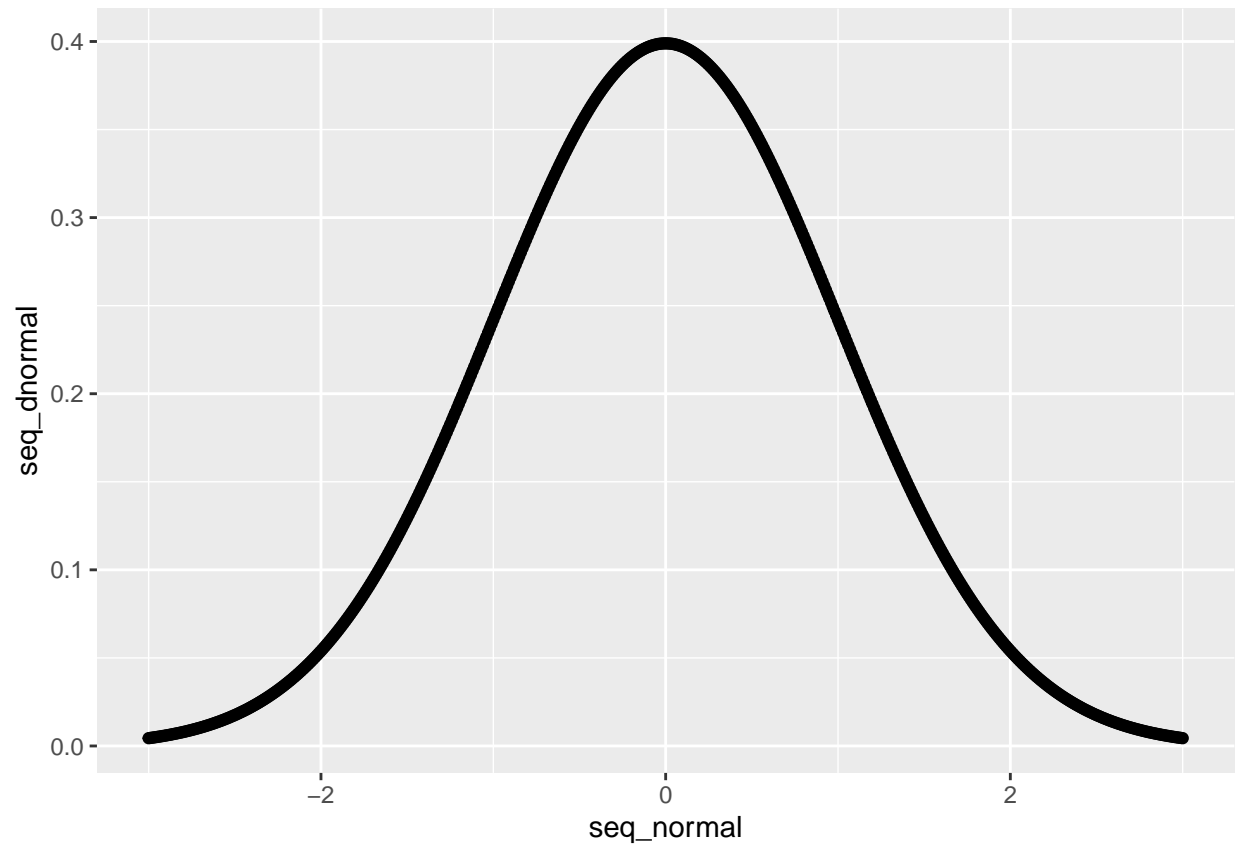
# Standard normal

seq_normal = seq(-3, 3, .01)

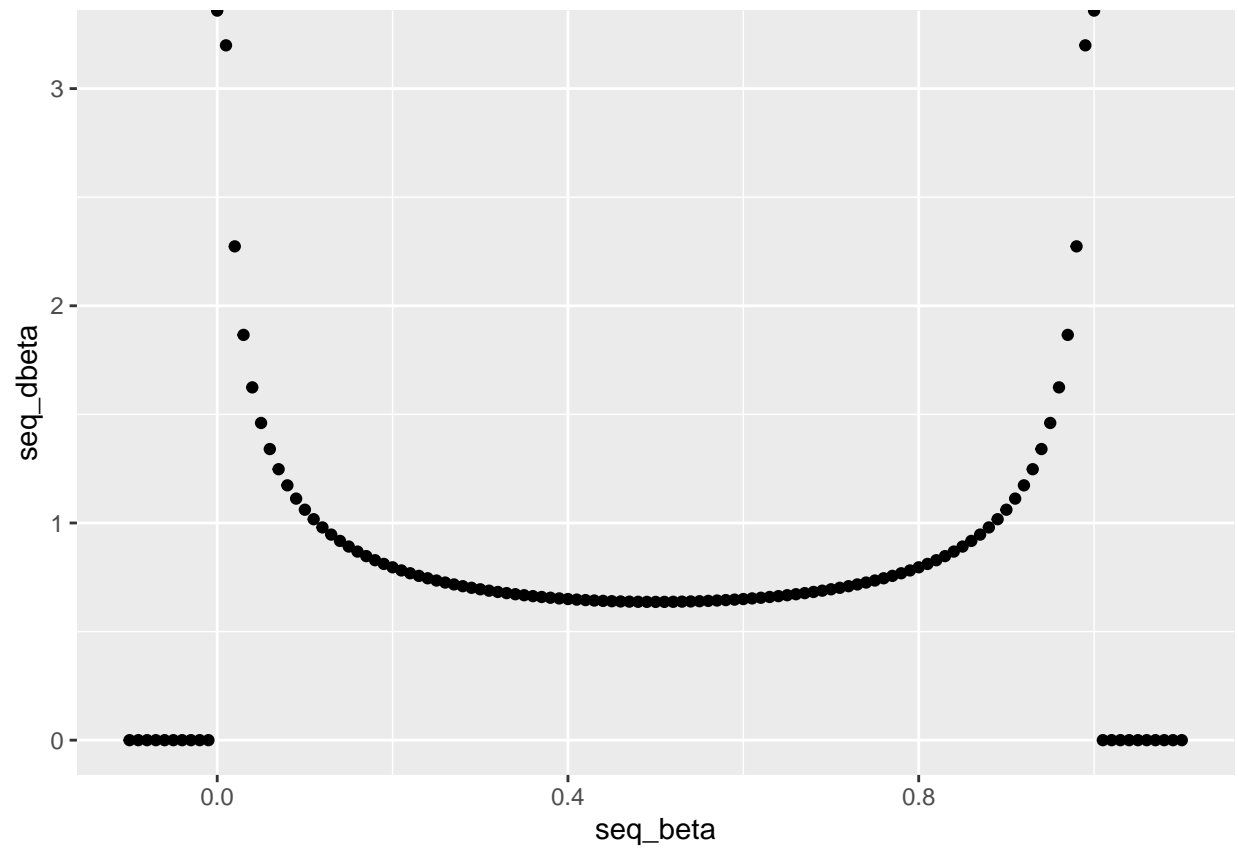
seq_dnormal = dnorm(seq_normal, 0, 1)

qplot(x = seq_normal, y = seq_dnormal)

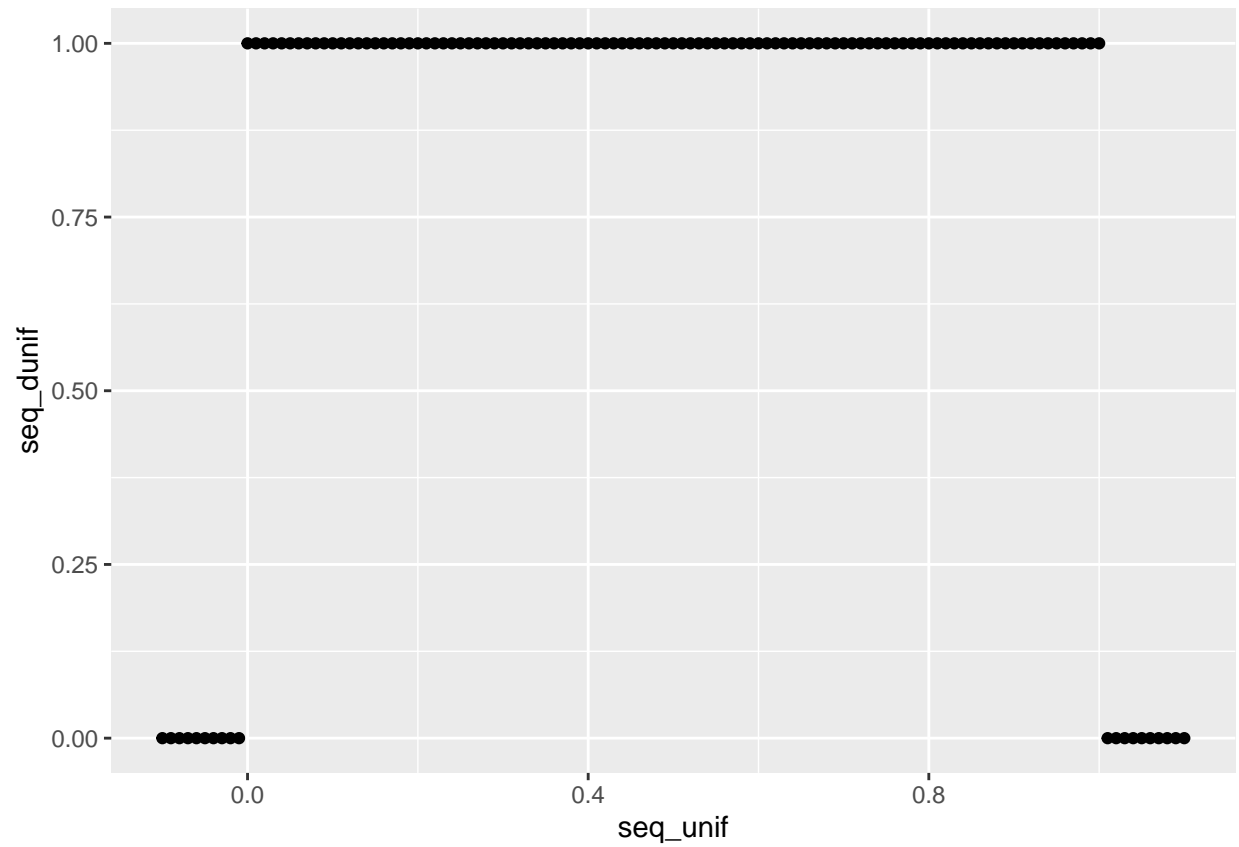
```



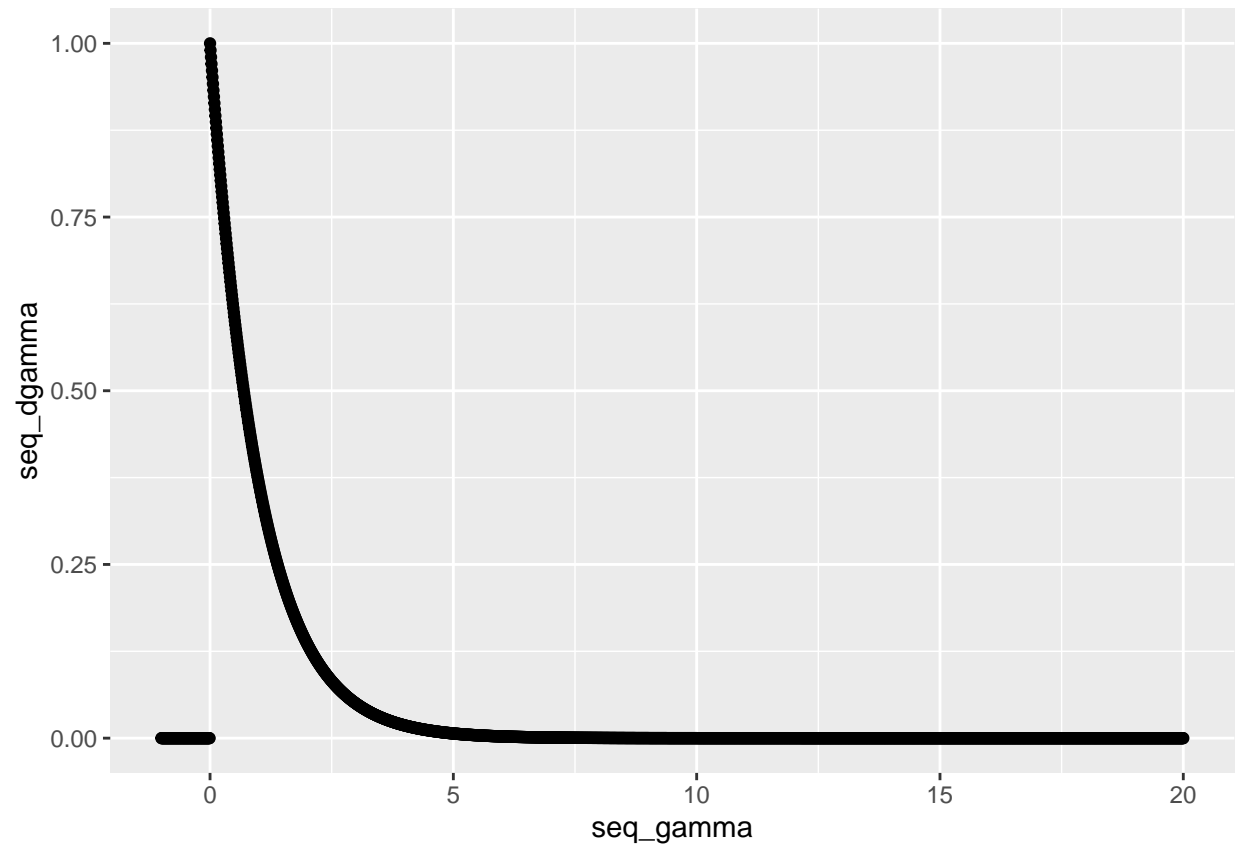
```
# Beta(.5,.5)
seq_beta = seq(-.1, 1.1, .01)
seq_dbeta = dbeta(seq_beta, .5, .5)
qplot(x = seq_beta, y = seq_dbeta)
```



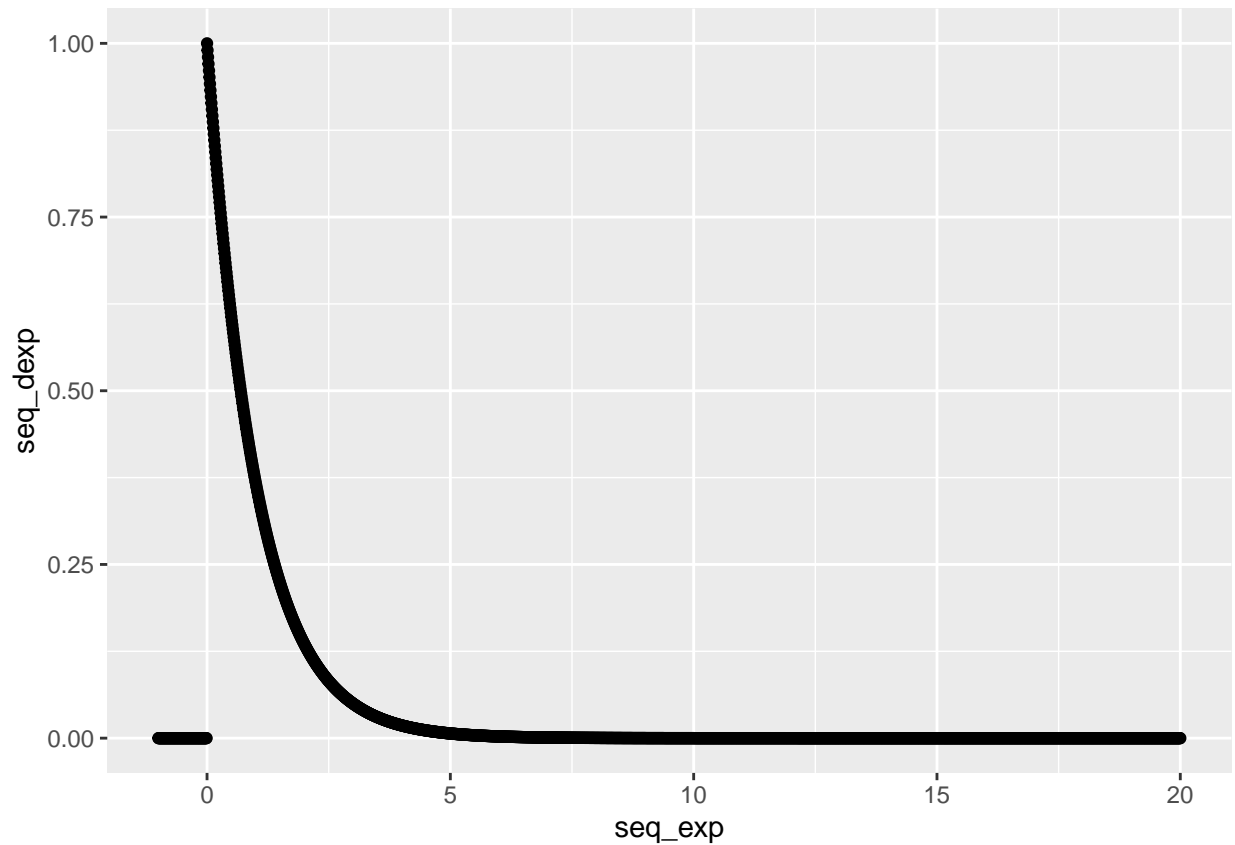
```
# Uniform (0,1)
seq_unif = seq(-.1, 1.1, .01)
seq_dunif = dunif(seq_unif, 0, 1)
qplot(x = seq_unif, y = seq_dunif)
```



```
# Gamma(1,1)
seq_gamma = seq(-1, 20, .01)
seq_dgamma = dgamma(seq_gamma, 1, 1)
qplot(x = seq_gamma, y = seq_dgamma)
```



```
# Exponential(1)  
seq_exp = seq(-1, 20, .01)  
seq_dexp = dexp(seq_exp, 1)  
qplot(x = seq_exp, y = seq_dexp)
```



1.7

Task:

Generate 100 instances of a $\text{Poisson}(3)$ random variable.

What is the mean? What is the variance?

Solution:

Note that the mean of a $\text{pois}(3)$ is 3, and the variance is also 3.

```
poisson_rv = rpois(100,3)
mean(poisson_rv)
```

```
## [1] 3.1
```

```
var(poisson_rv)
```

```
## [1] 2.414141
```

1.8

Task:

a.) Explore the nucleotide frequencies of chromosome M by using a dedicated function in the Biostrings package from Bioconductor.

b.) Test if the C. elegans data is consistent with the uniform model (all nucleotide frequencies are the same) via simulation.

Solution:

Work in progress, might do it live in class!

```
cel = BSgenome.Celegans.UCSC.ce2
```

```
dna_seq = cel$chrM
```