

Consolidation of R programming skills

Distributions, functions, and variance

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Recap: Data types

CONTINUOUS

measured data, can have ∞ values within possible range.



I AM 3.1" TALL
I WEIGH 34.16 grams

DISCRETE

OBSERVATIONS CAN ONLY EXIST
AT LIMITED VALUES, OFTEN COUNTS.



I HAVE 8 LEGS
and
4 SPOTS!

NOMINAL

UNORDERED DESCRIPTIONS



ORDINAL

ORDERED DESCRIPTIONS



BINARY

ONLY 2 MUTUALLY EXCLUSIVE OUTCOMES





Part 1

Distributions and functions

Learn more about the tiny giraffes @ tinystats.github.io

Teacup giraffes



Imagine we've collected data
for two populations that live on
two different islands, like the
tiny giraffes

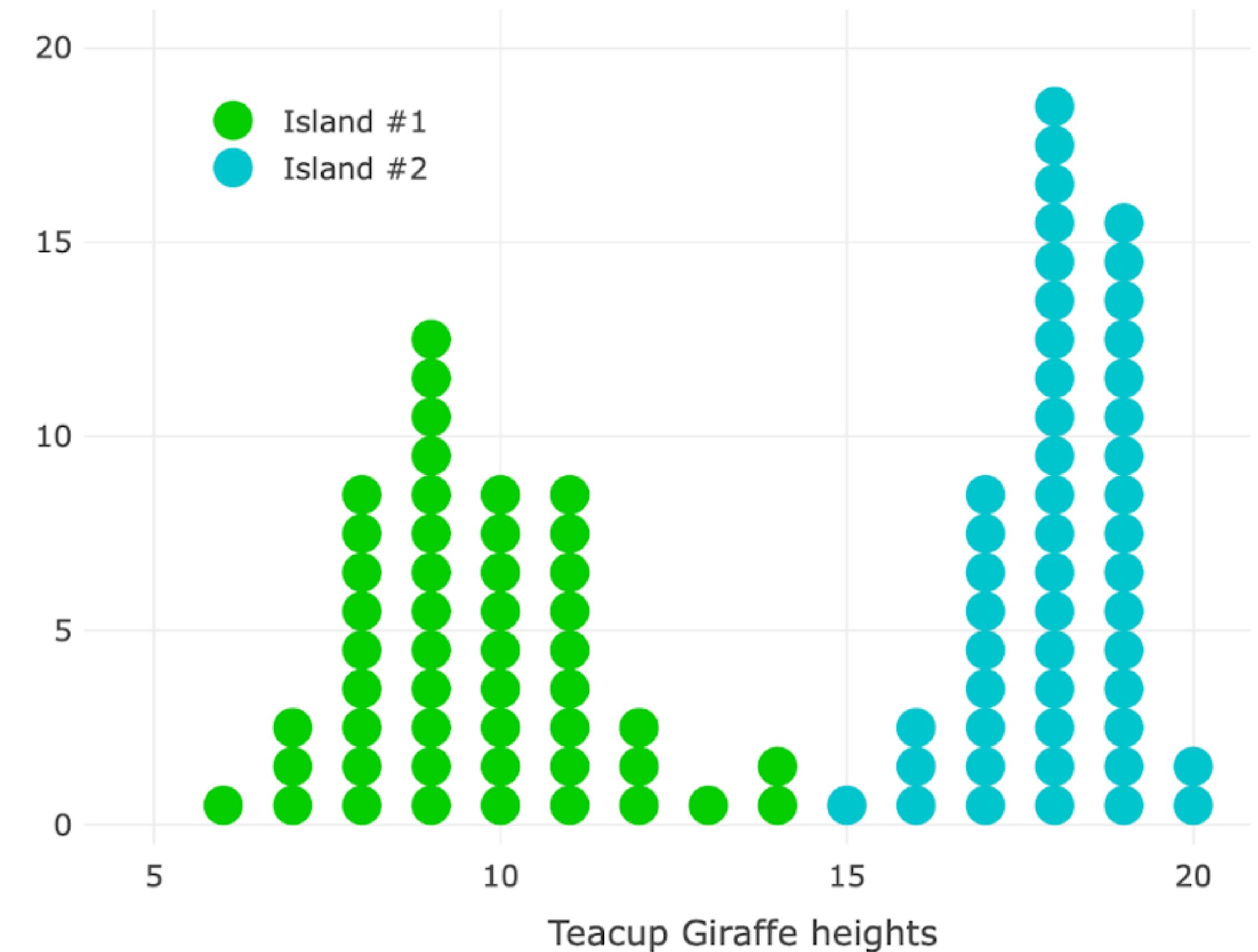


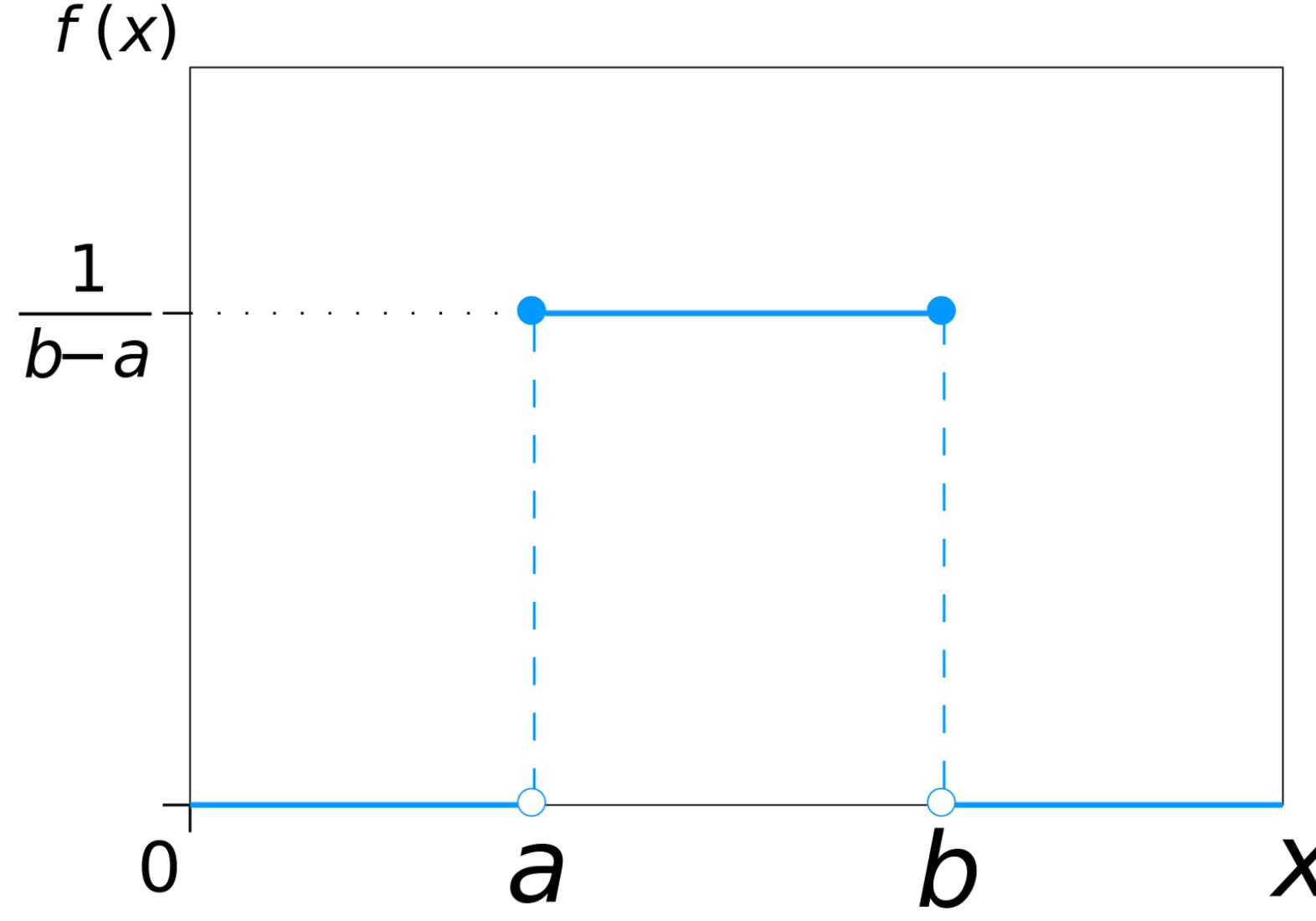
A distribution

Shows the range of values of your variable (e.g., height)

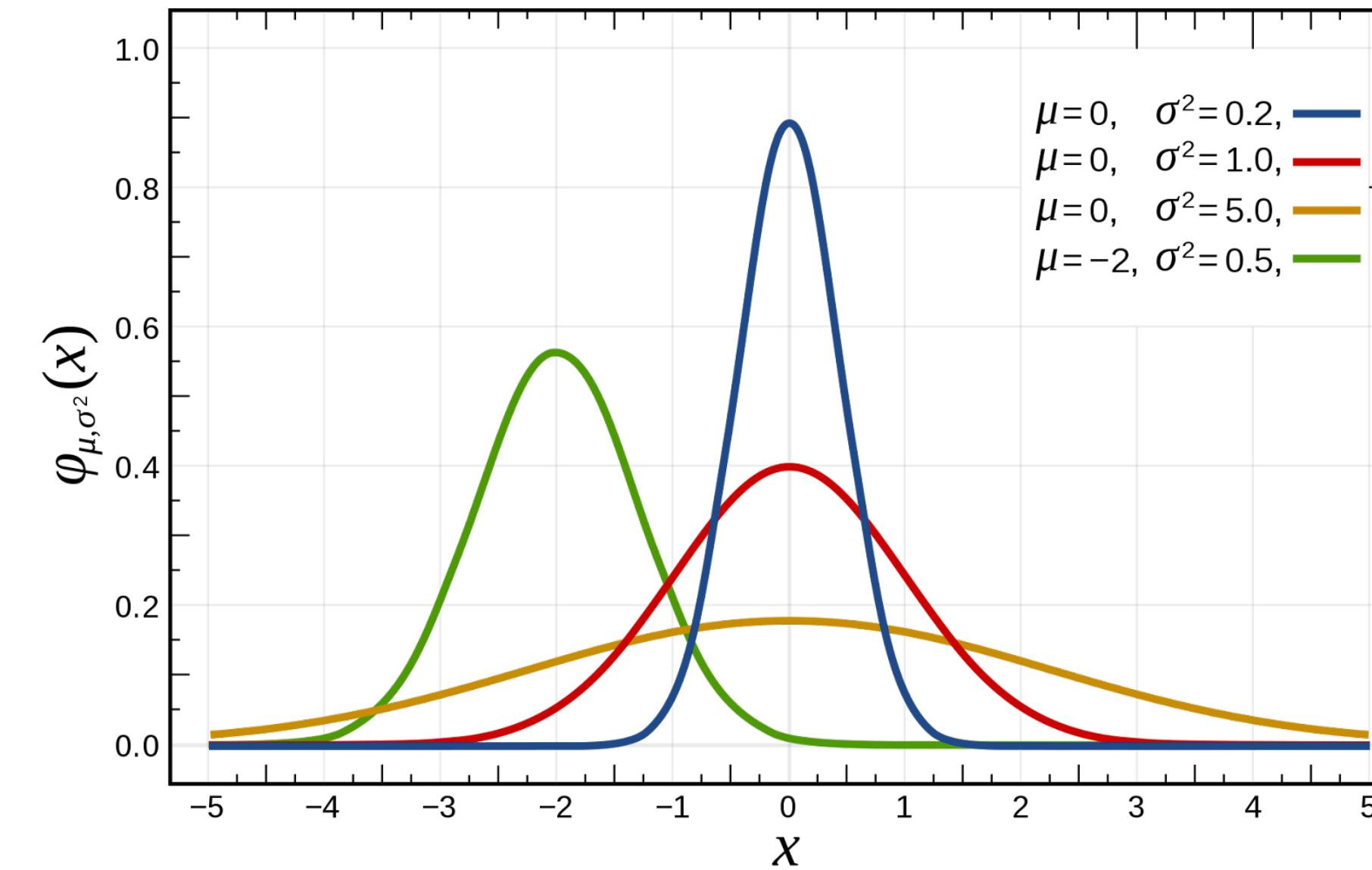
It captures: how often each value occurs

+ The shape, centre, and amount of variability in the data

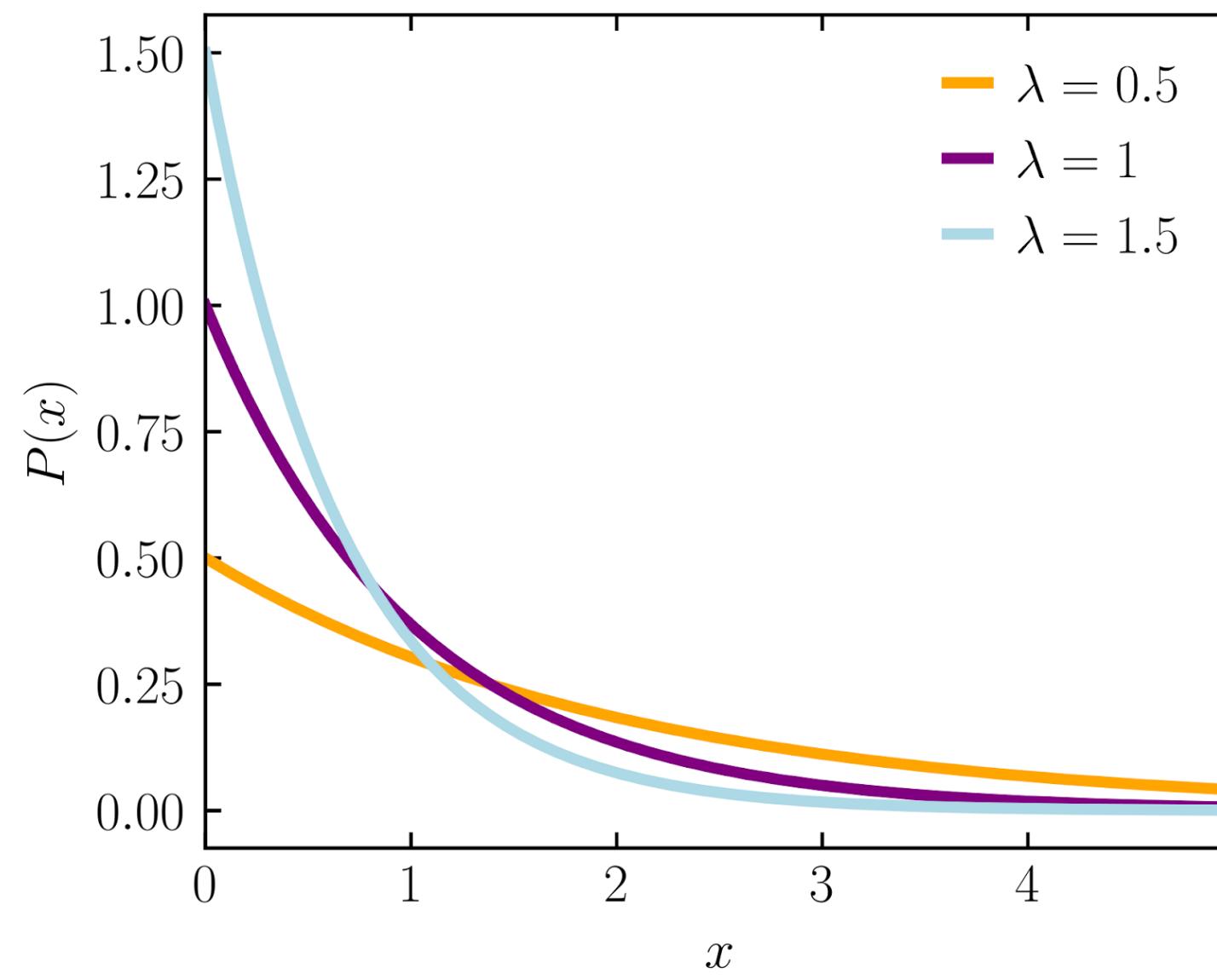




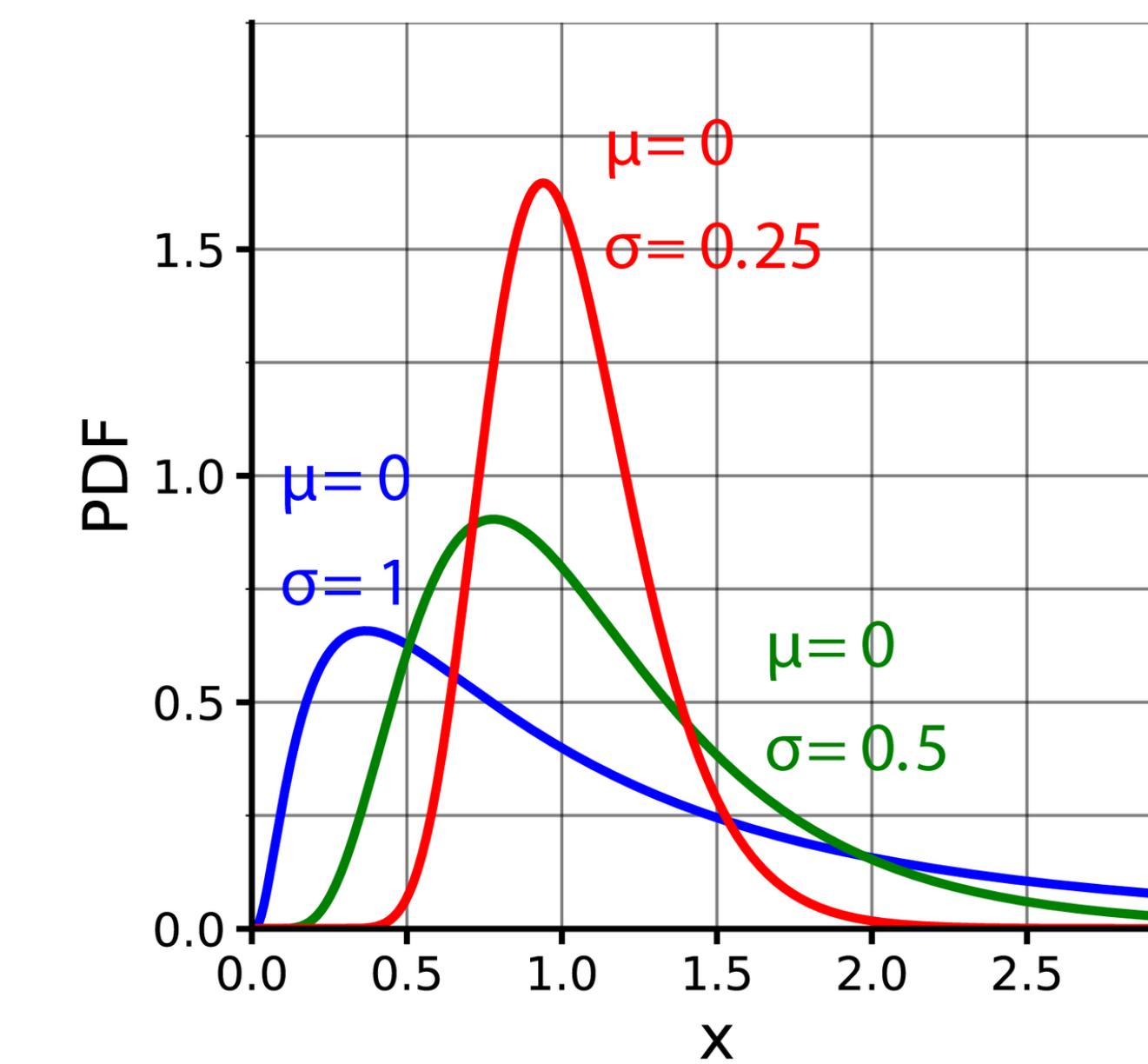
Uniform



Normal



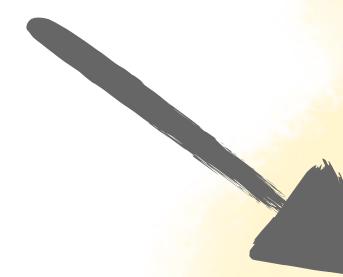
Exponential



Lognormal

CONTINUOUS

measured data, can have ∞ values within possible range.



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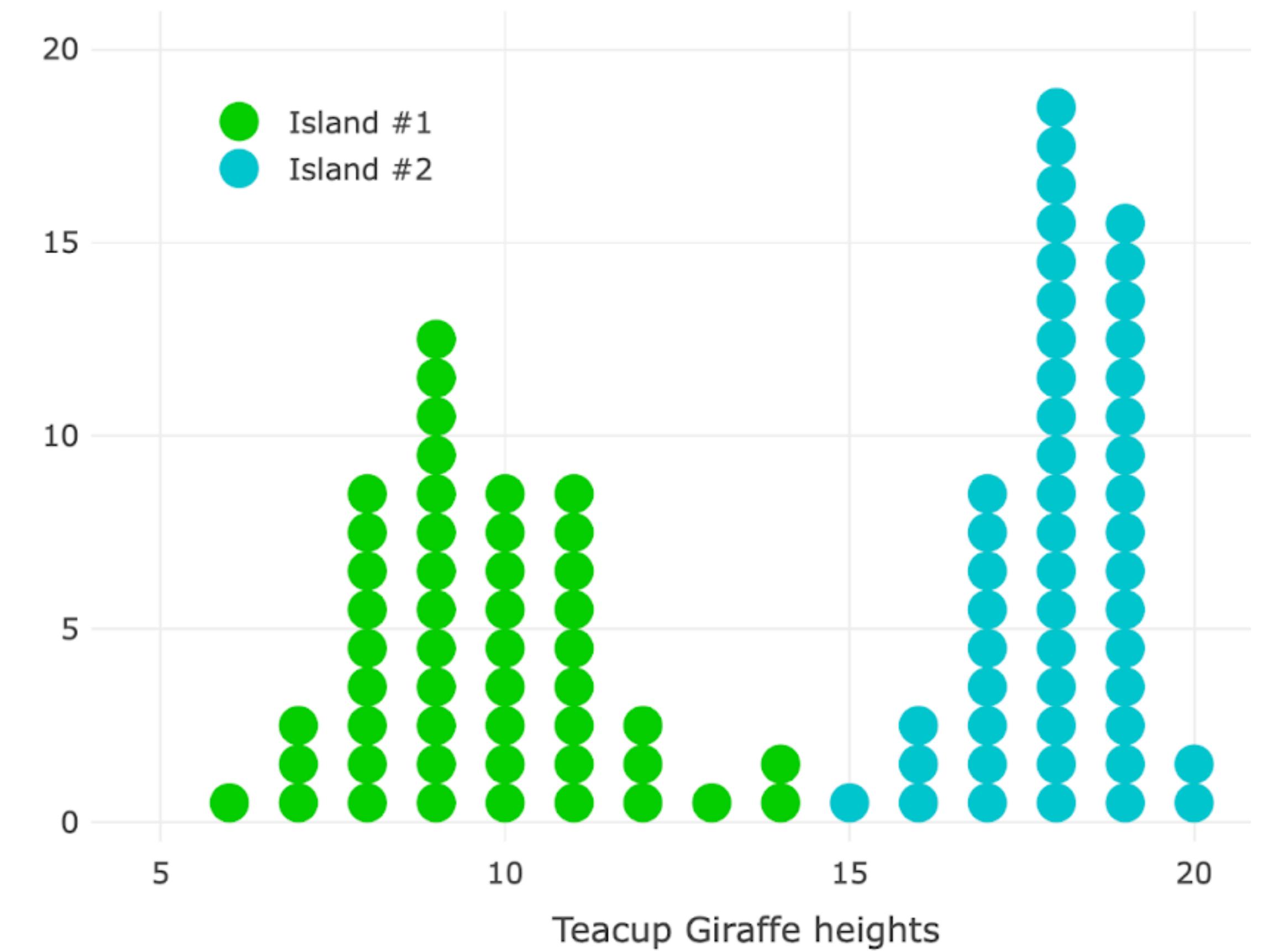
OBSERVATIONS CAN ONLY EXIST AT LIMITED VALUES, OFTEN COUNTS.



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@allison_horst

What distribution provides a good description of our giraffe data?



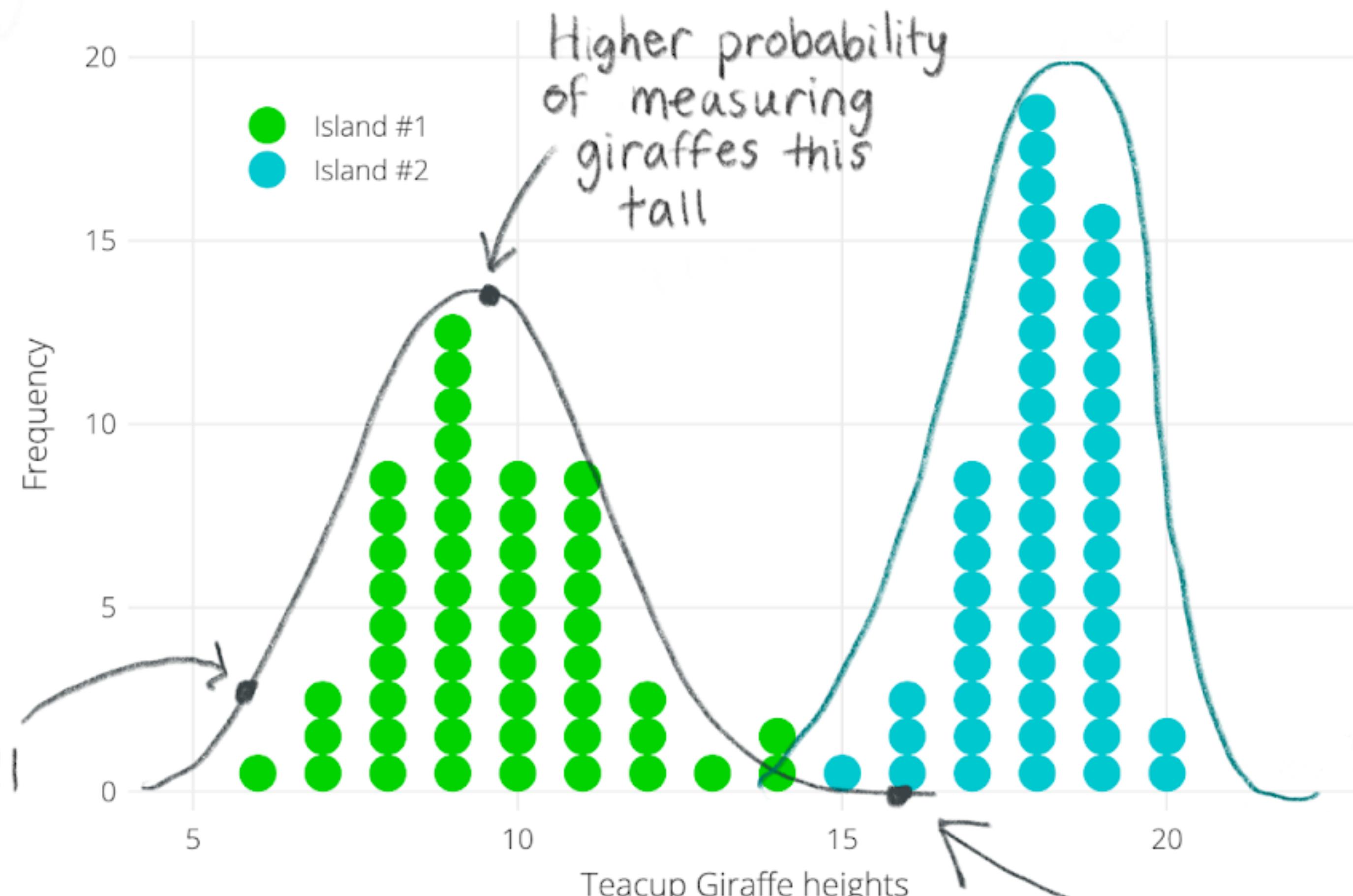
The normal distribution

Distributions of data can take on many shapes but there are some general shapes that occur frequently in nature.

The normal distribution is one of the most well-known. Also known as a **Gaussian distribution** or a **bell curve**.

Characteristics of the normal distribution:

- a single peak
- the mass of the distribution is at its centre
- **symmetry** about the centre line



A giraffe greater than 15 cm would be almost unheard of on island 1, but not on island 2.

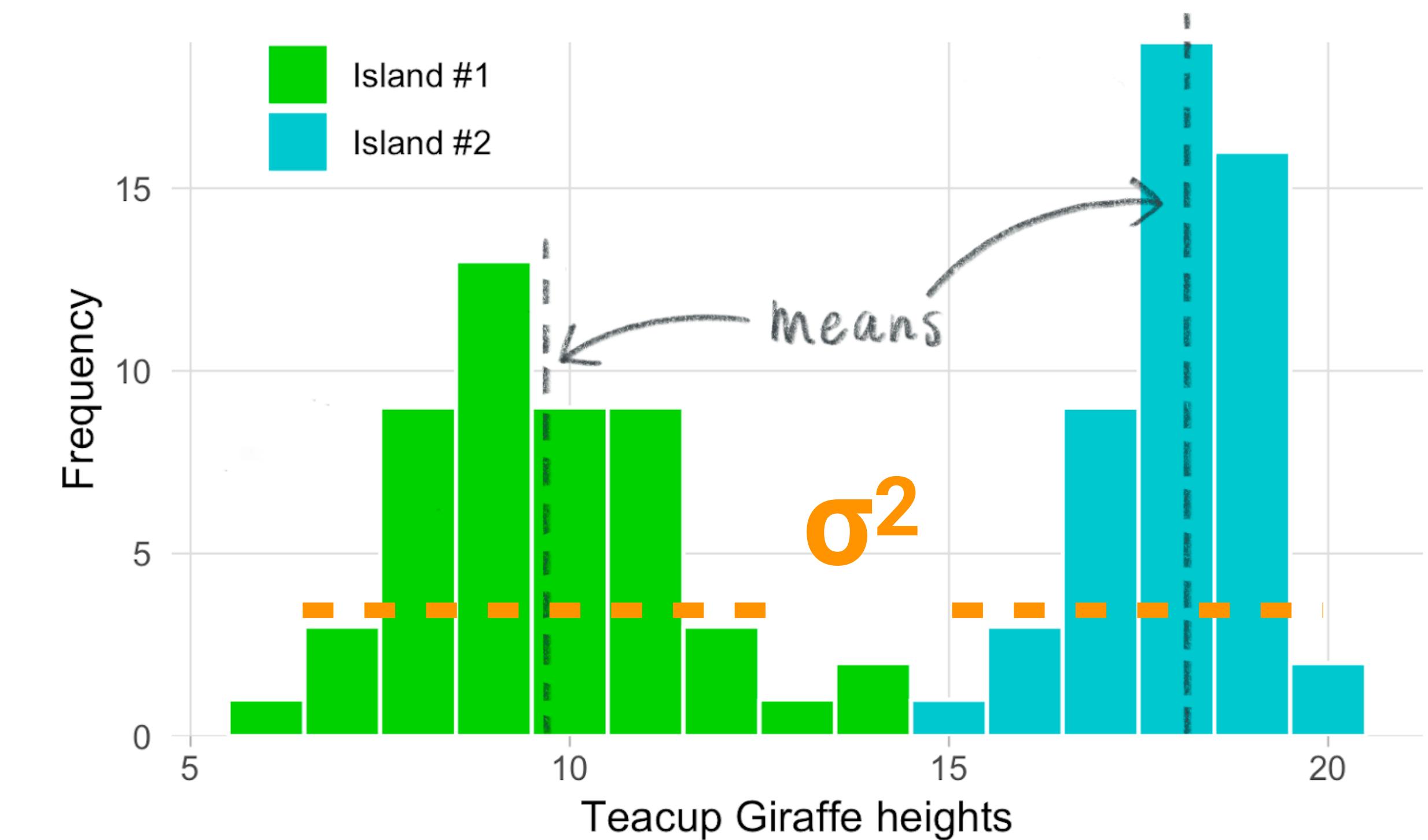
Encountering a giraffe this small would be rare

Higher probability of measuring giraffes this tall

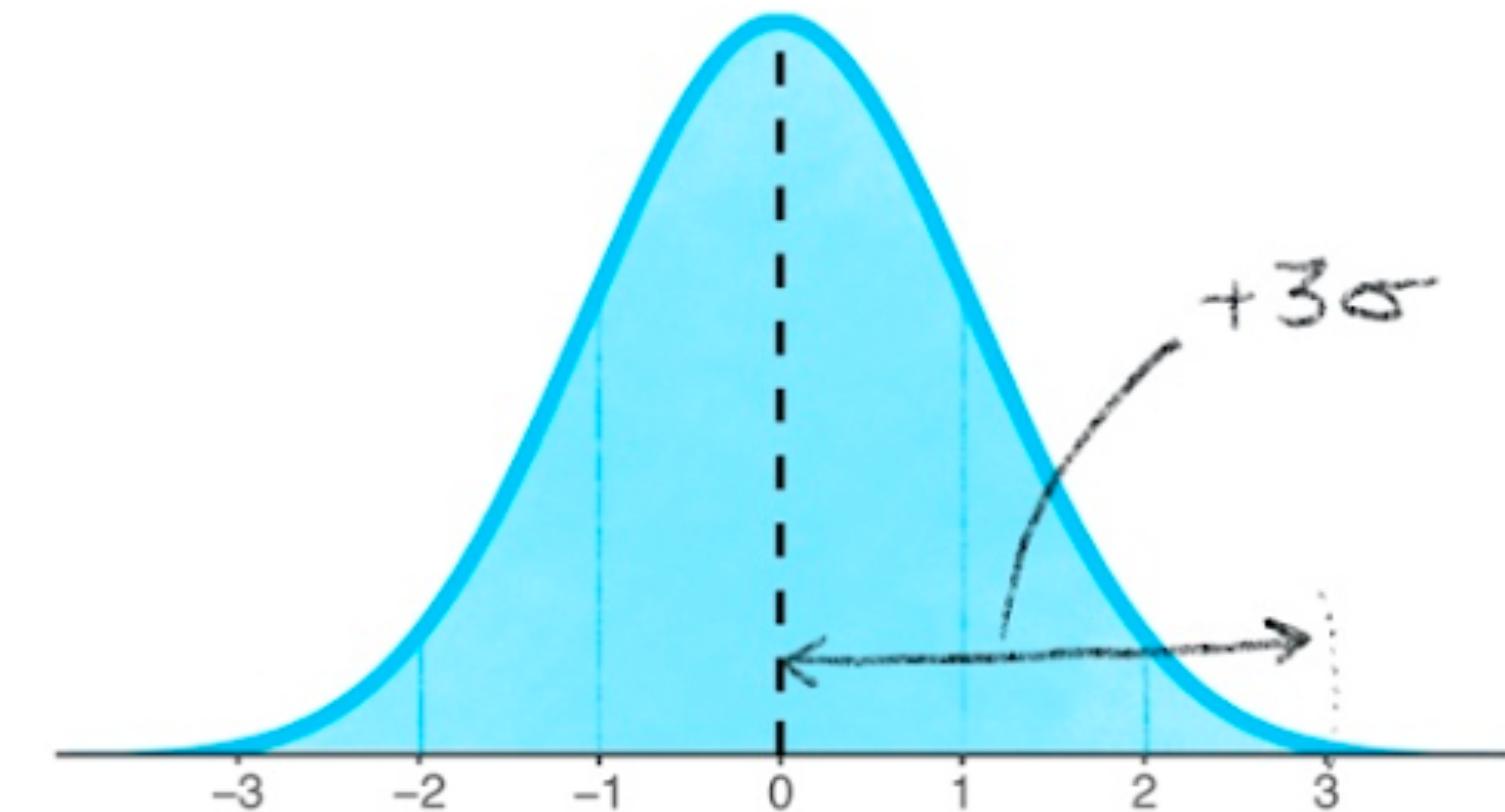
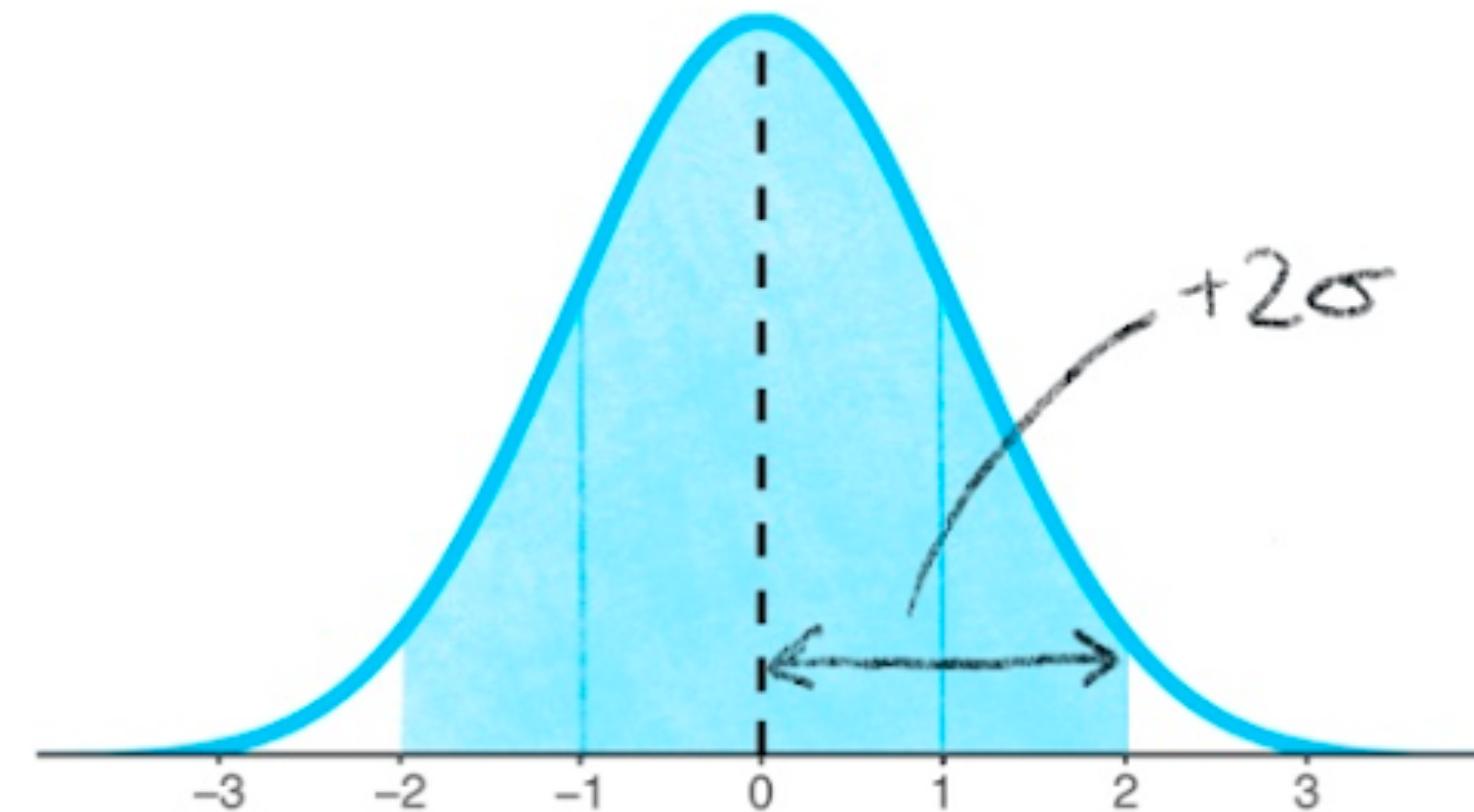
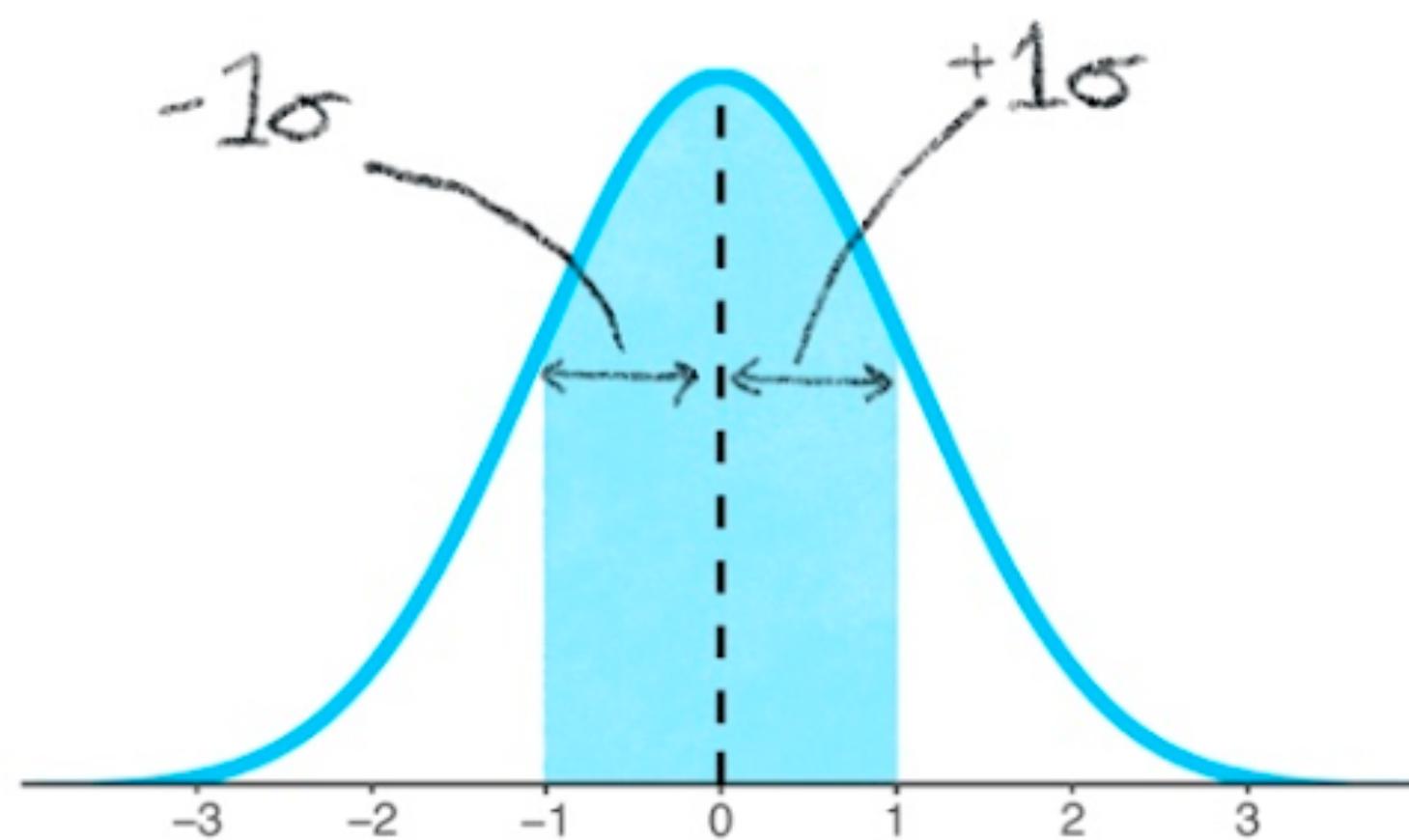
Parameters of the normal distribution

μ - the mean or expectation

σ - the standard deviation
or σ^2 - the variance



The standard deviation measures the spread of the data



Continuous distributions in R

Are associated with 4 standard functions, beginning d, p, q, and r:

`dnorm(x, mean = 0, sd = 1)` - probability density function

`pnorm(q, mean = 0, sd = 1)` - cumulative distribution function (% of values < than q)

`qnorm(p, mean = 0, sd = 1)` - quantile function (inverse of cumulative distribution)

`rnorm(n, mean = 0, sd = 1)` - generates random numbers

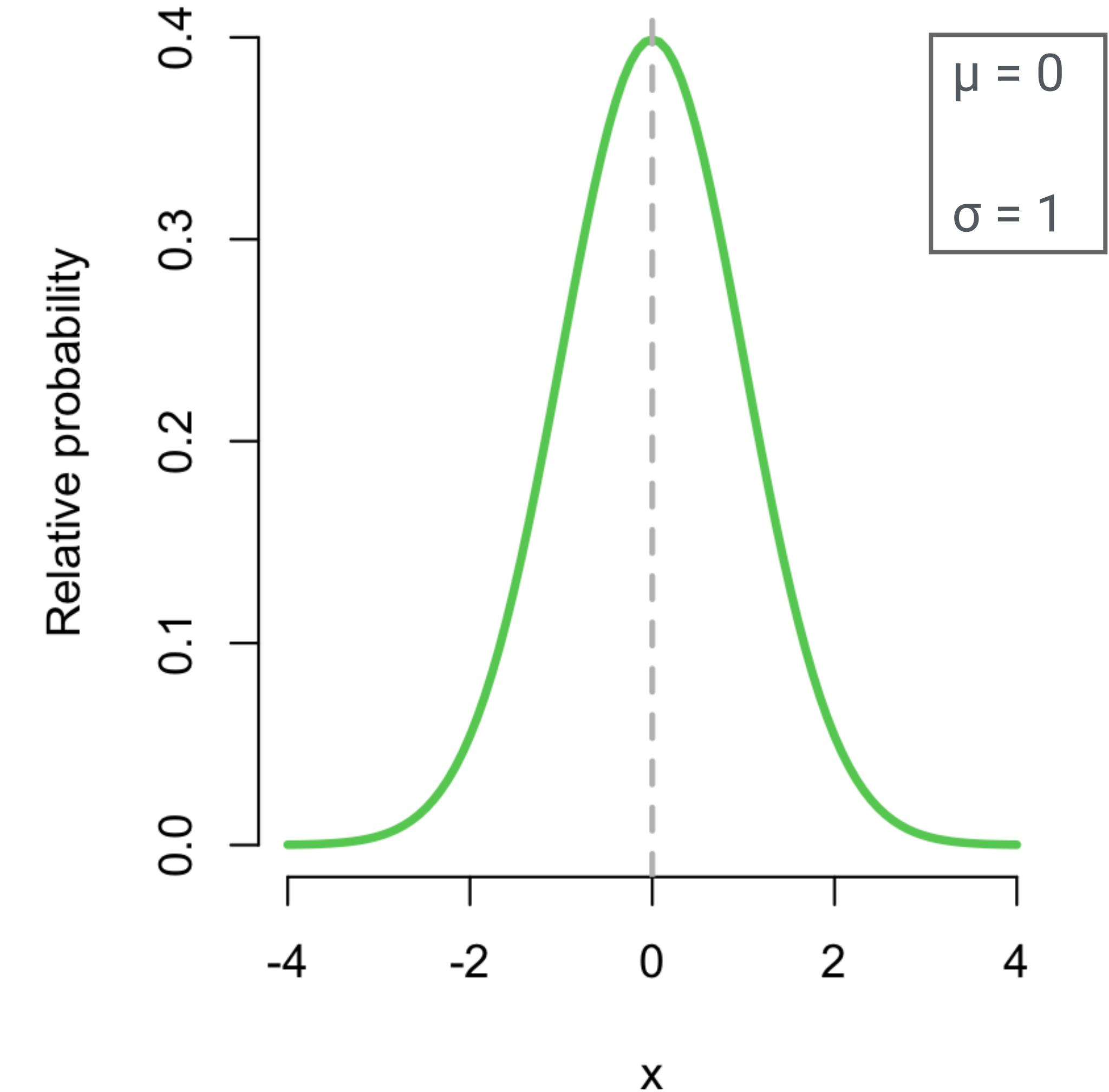
Let's see these in action!

dnorm() - probability density function

Describes the probability of a value at any point along the x-axis*

This function can be used to draw the distribution

The dashed line shows the mean

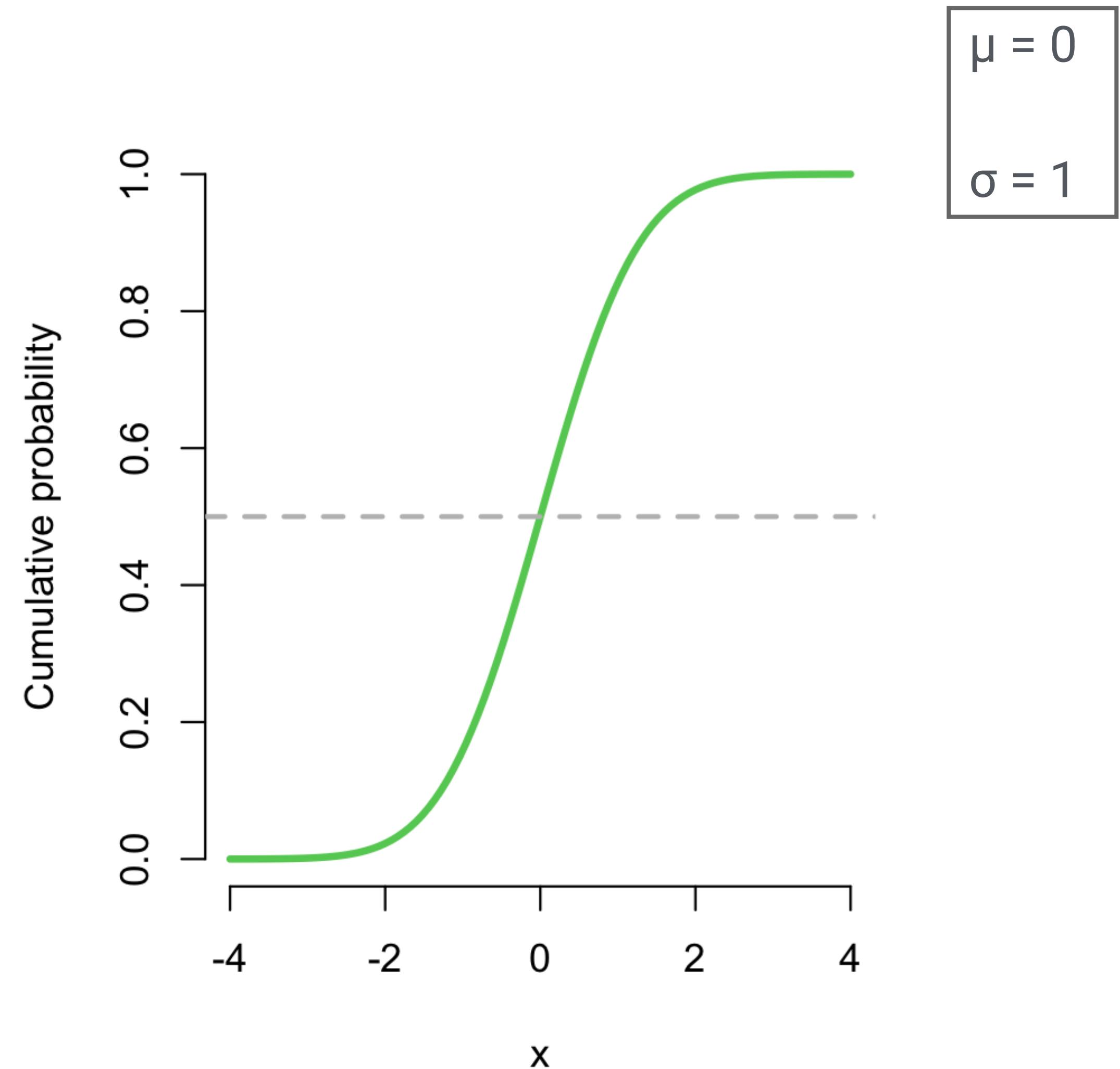


*Actually the probability of being a precise value can very small, so it's sometimes more useful to think of the probability of being within a range, e.g. the probability of being between 1 and 2

pnorm() - cumulative distribution function

The probability that a value will be less than or equal to x

The dashed line shows the cumulative probability is = 0.5 at 0, (the distribution mean), i.e., 50% of values ≤ 0



qnorm() - quantile function

It gives you the value of x at a given quantile, i.e., at a given cumulative probability

Inverse of pnorm()

Shown right: the 10th, 25th, 50th, 75th, 90th percentiles

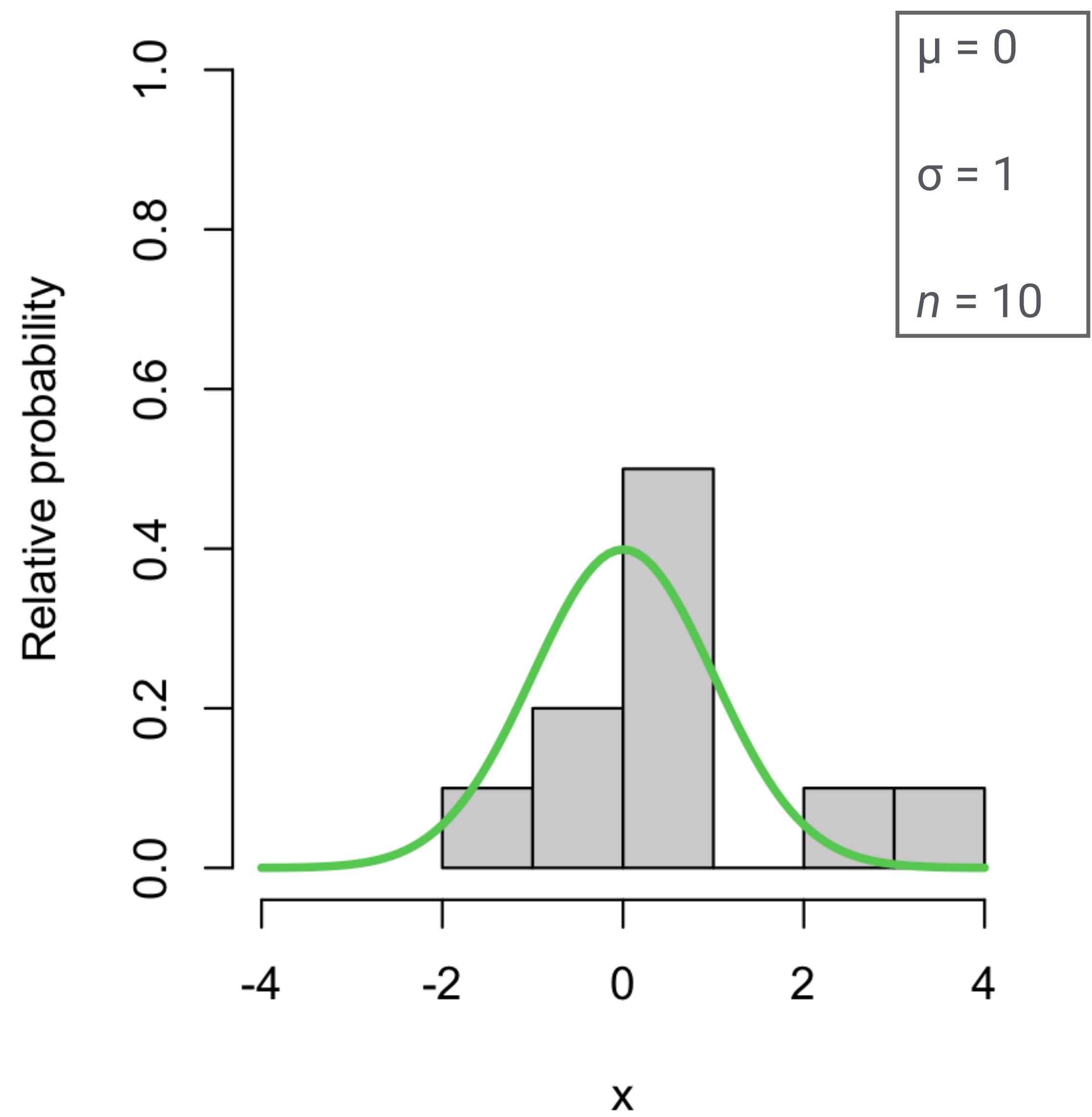
```
> qnorm(0.1, mean = 0, sd = 1)
[1] -1.281552
> qnorm(0.25, mean = 0, sd = 1)
[1] -0.6744898
> qnorm(0.5, mean = 0, sd = 1)
[1] 0
> qnorm(0.75, mean = 0, sd = 1)
[1] 0.6744898
> qnorm(0.90, mean = 0, sd = 1)
[1] 1.281552
```

`rnorm()` - generates
pseudo random numbers

There are lots of reasons we might want to generate random numbers

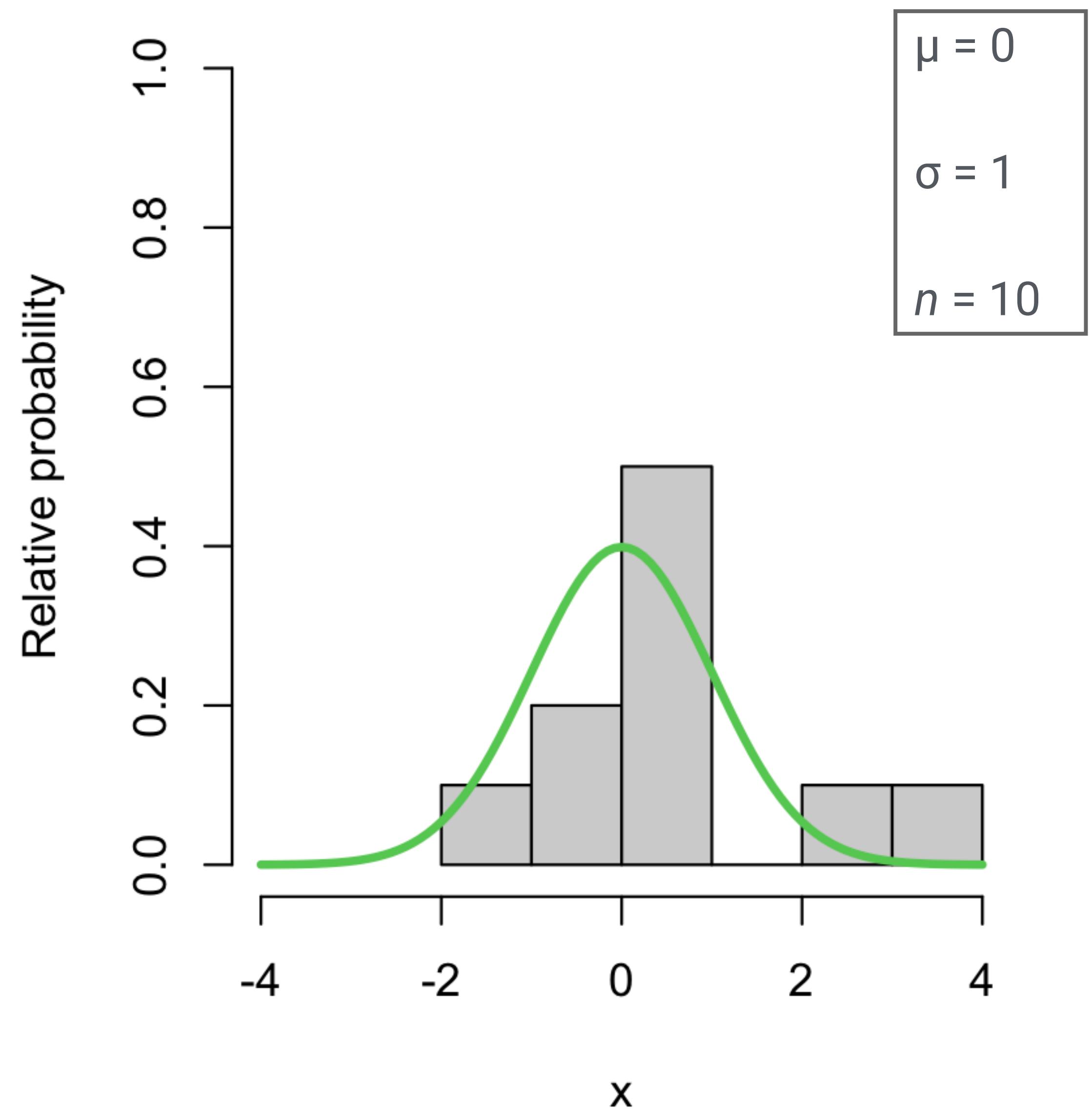
This plot shows random draws (n) from a normal distribution as a histogram

Why is it pseudo random?

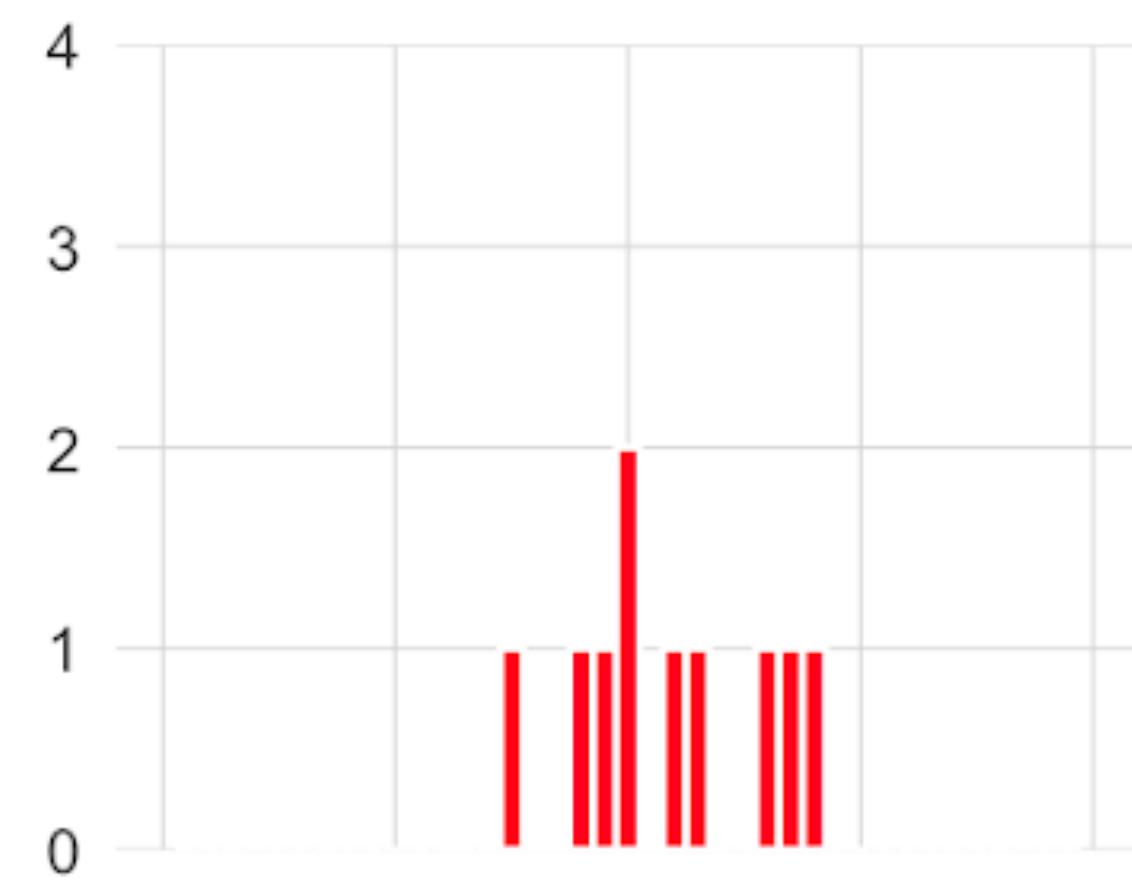


What do you predict will happen if we increase the number of random draws?

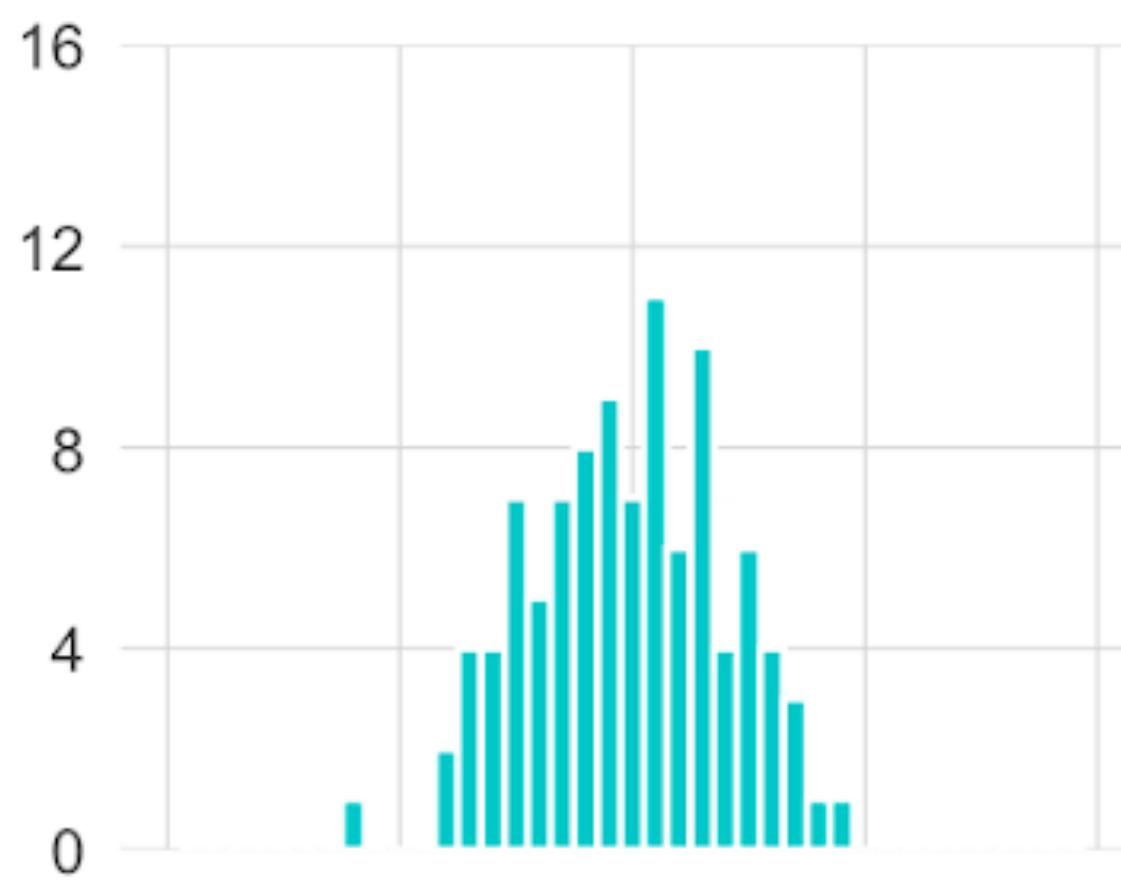
e.g., $n = 100$, $n = 1000$ etc.



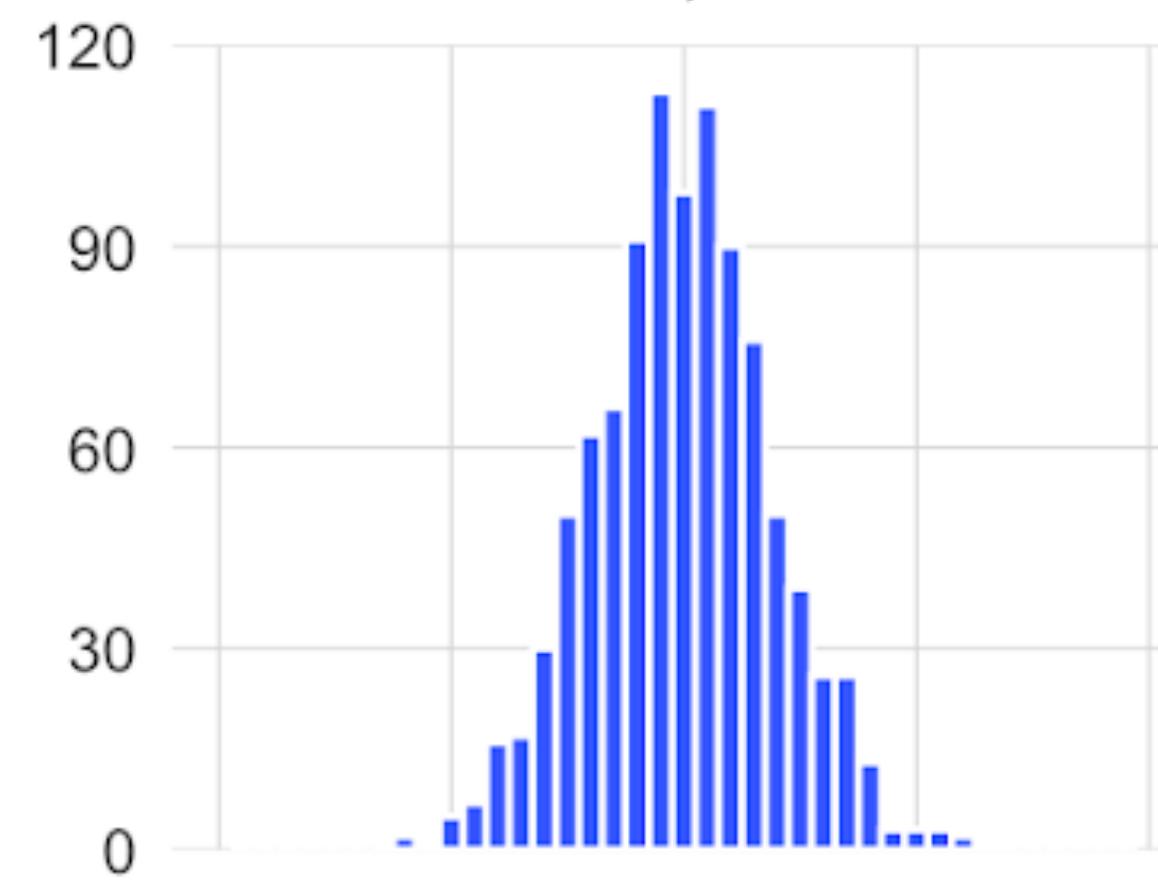
$N=10$



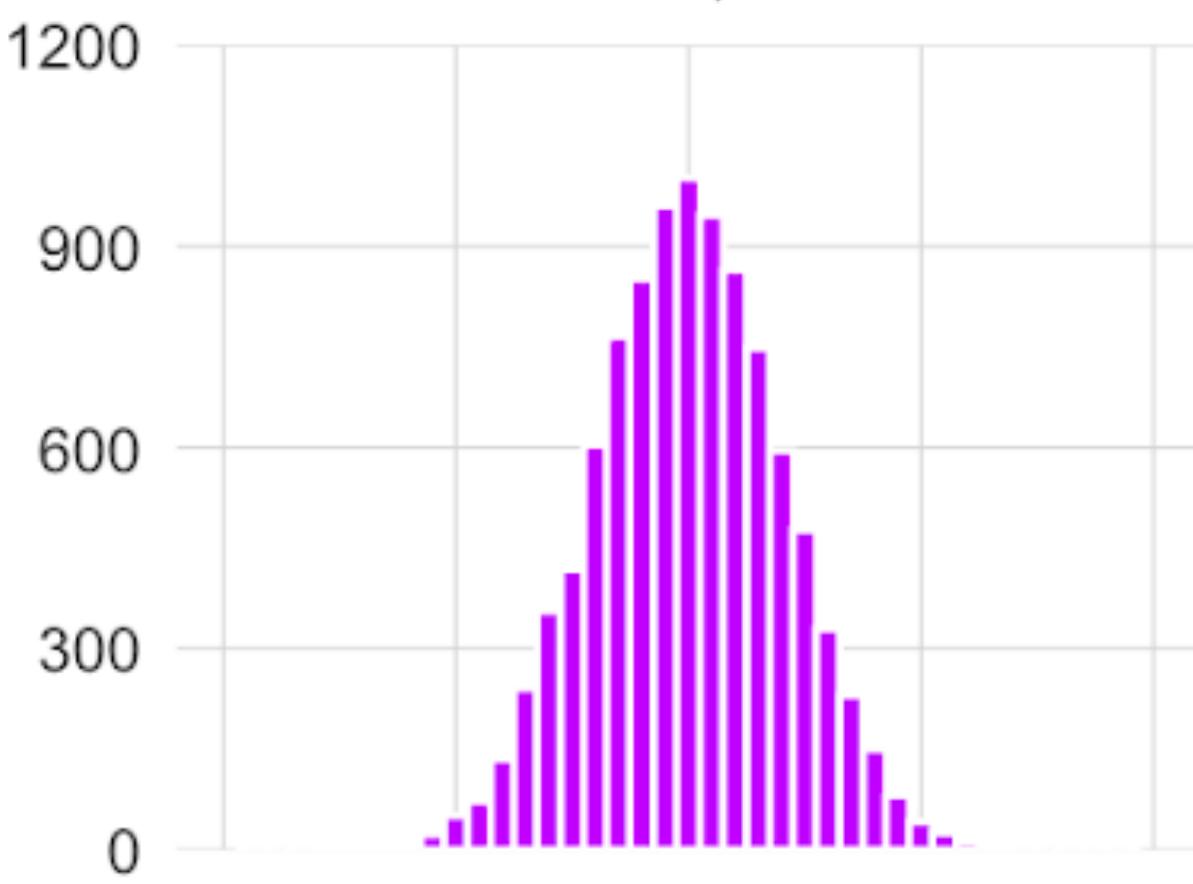
$N=100$



$N=1,000$



$N=10,000$

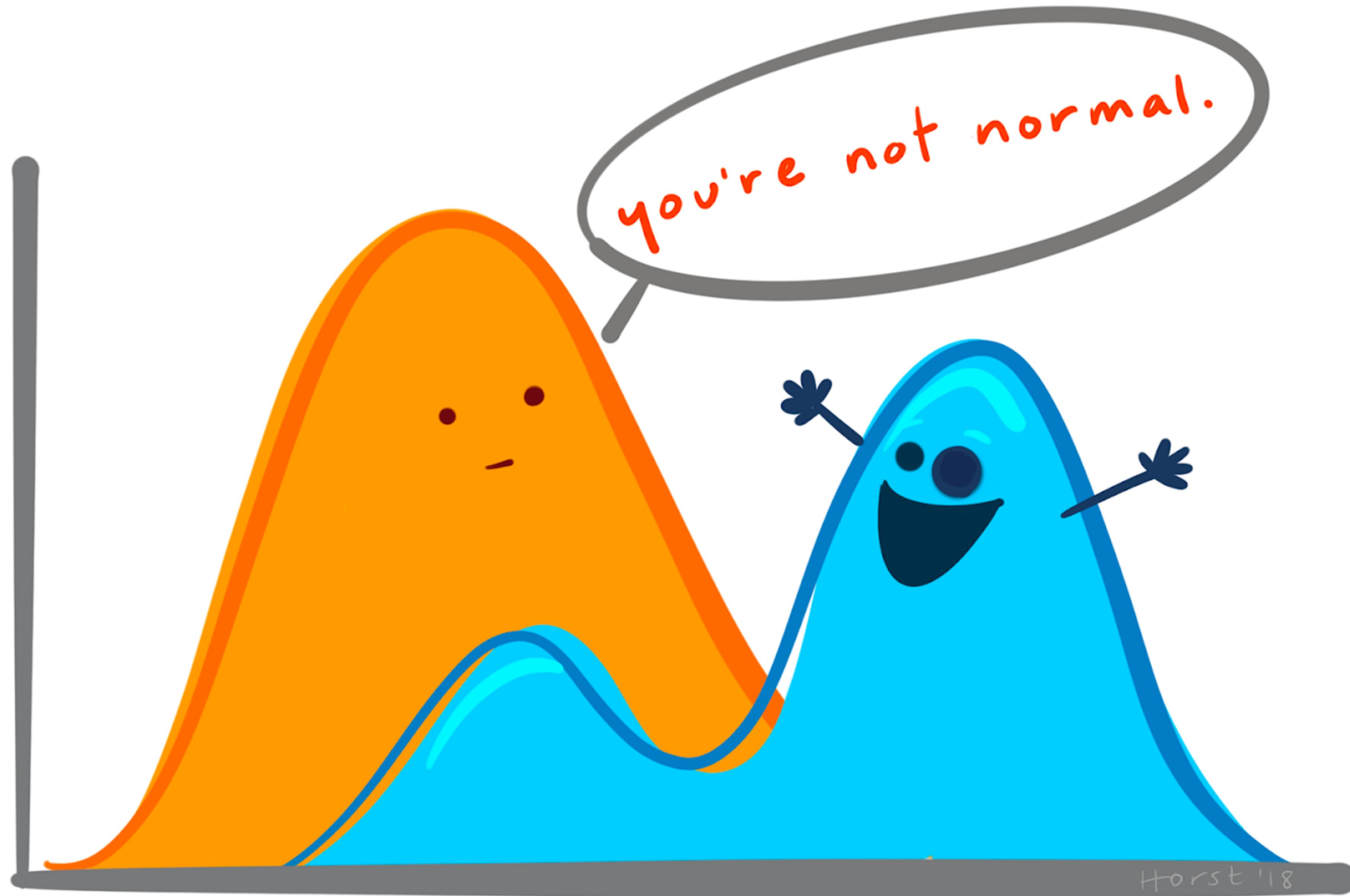


Exercise

Explore the properties and
plot an alternative
distribution to the normal

Hint: [Plot the normal distribution](#)

Hint: see earlier
examples! (link to [slide](#))





Part 2

Standard deviation and variance

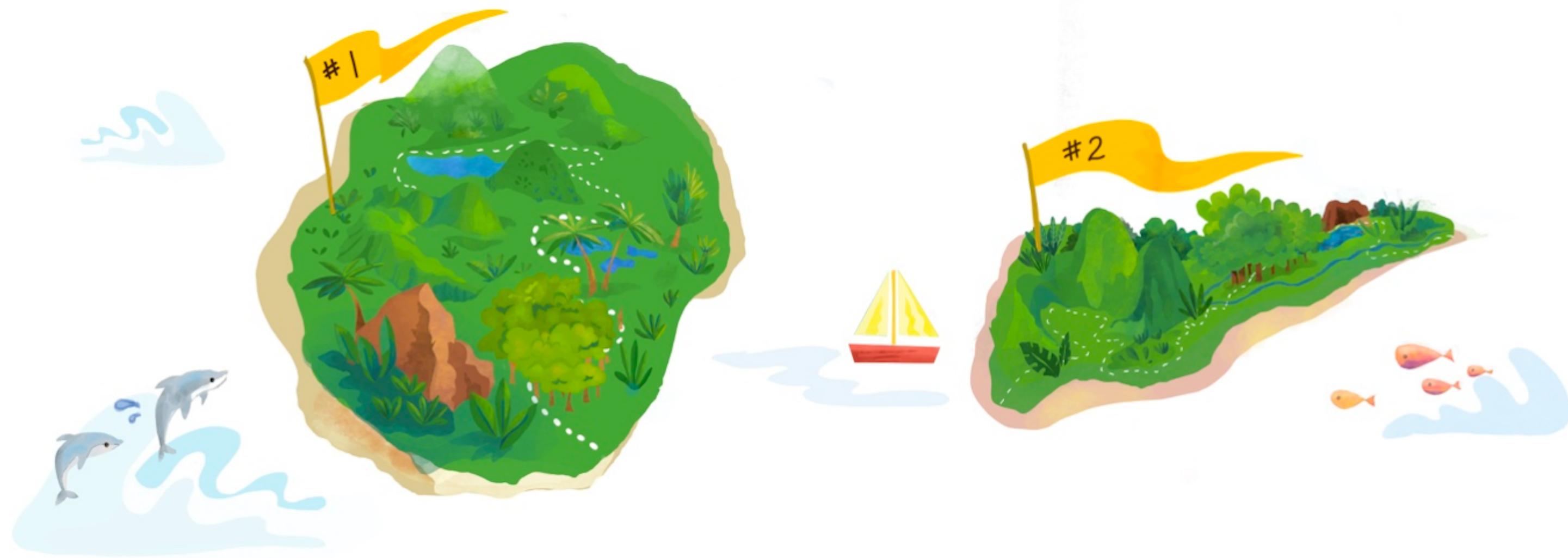
Learn more about the tiny giraffes @ tinystats.github.io

Teacup giraffes

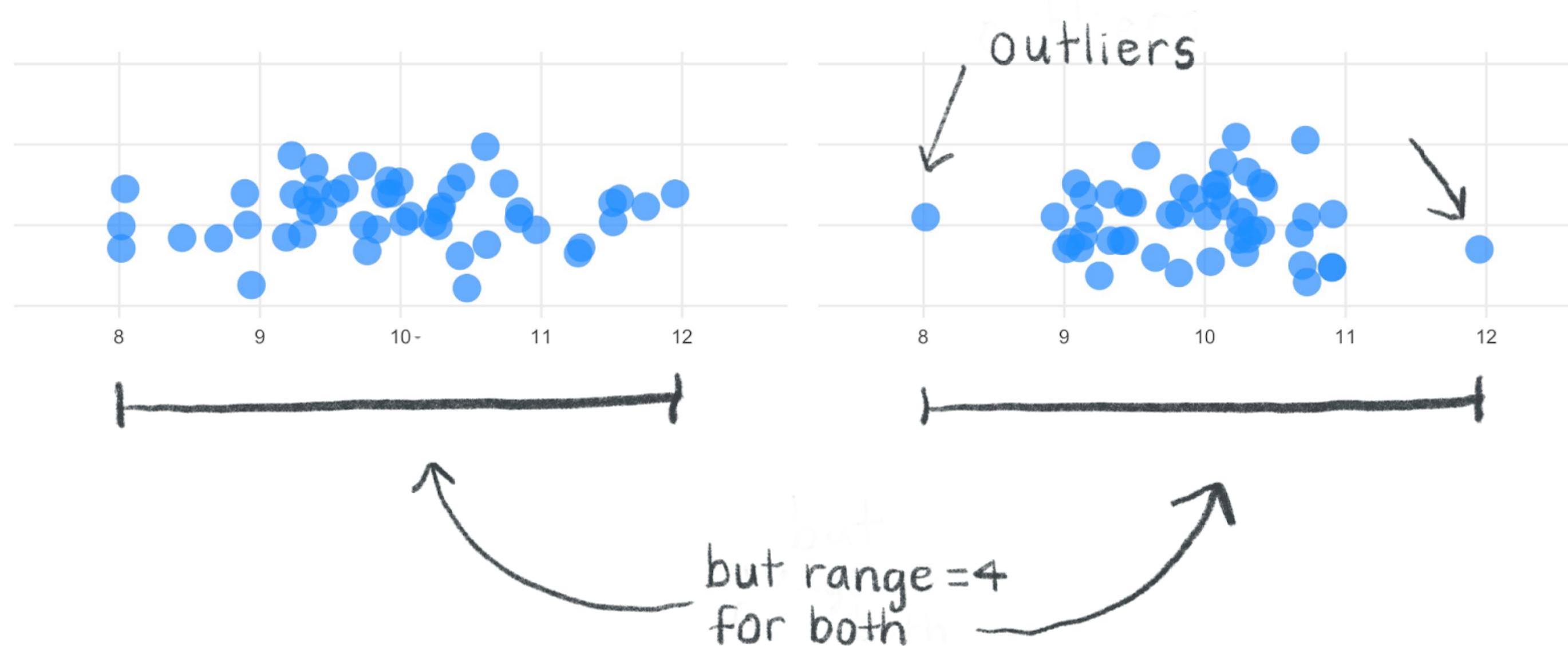
Reminder



Imagine we've collected data
for two populations that live on
two different islands, like the
tiny giraffes

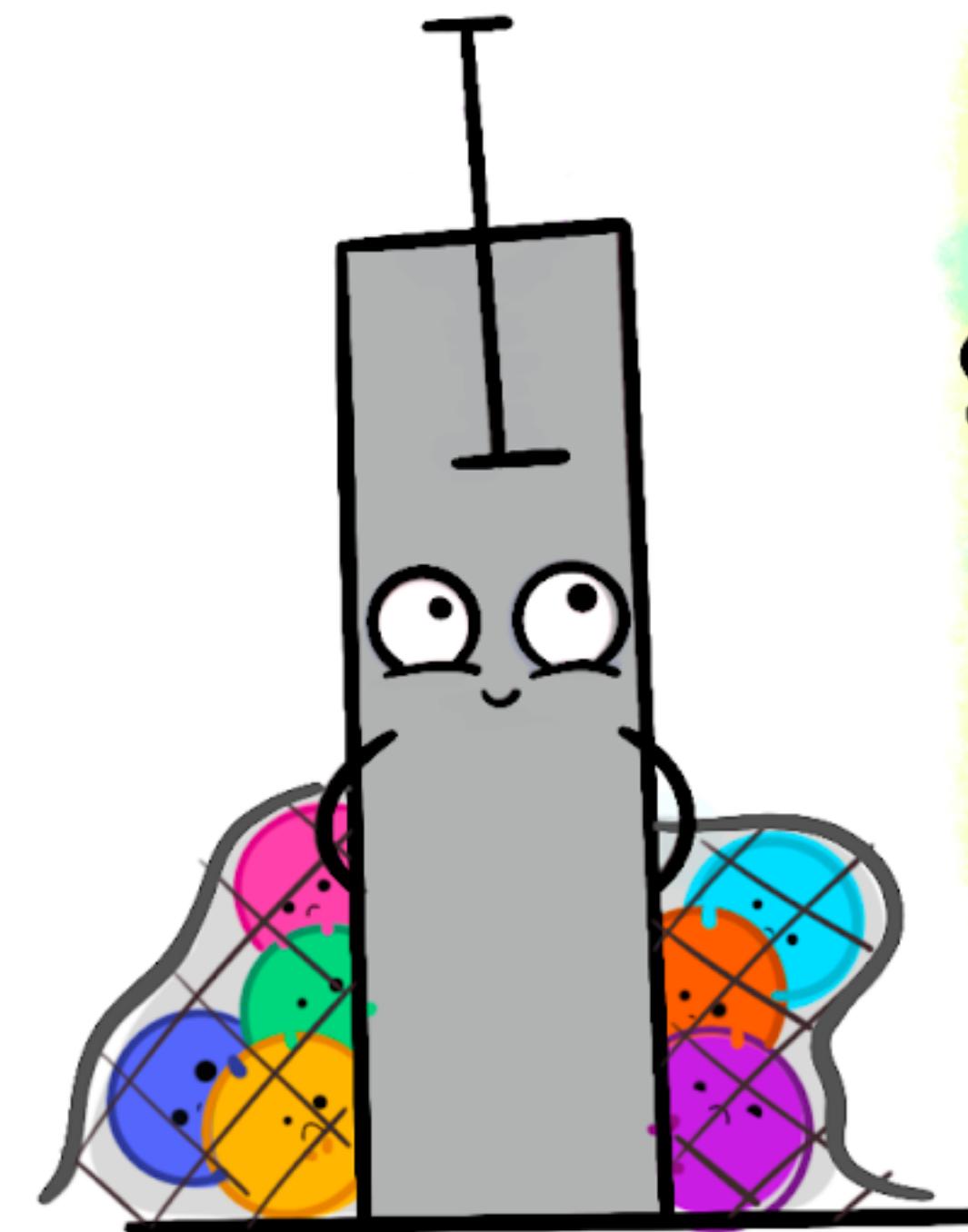


Spread of the data: the range

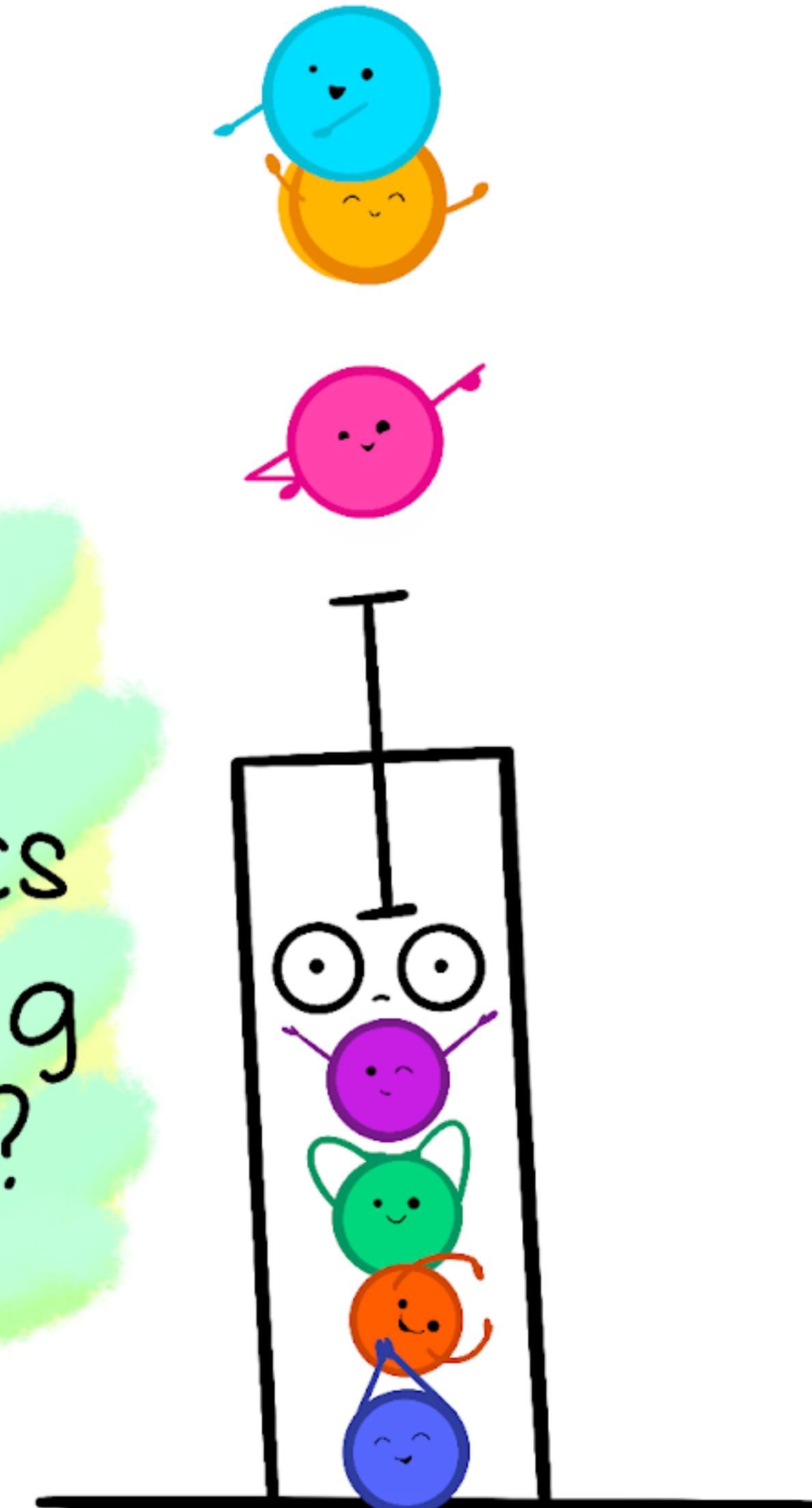


The first step of any analysis
is often to **visualise the data**

If we want to avoid undue
influence of the outliers, the
range is not good measure



are your
summary statistics
hiding something
interesting?

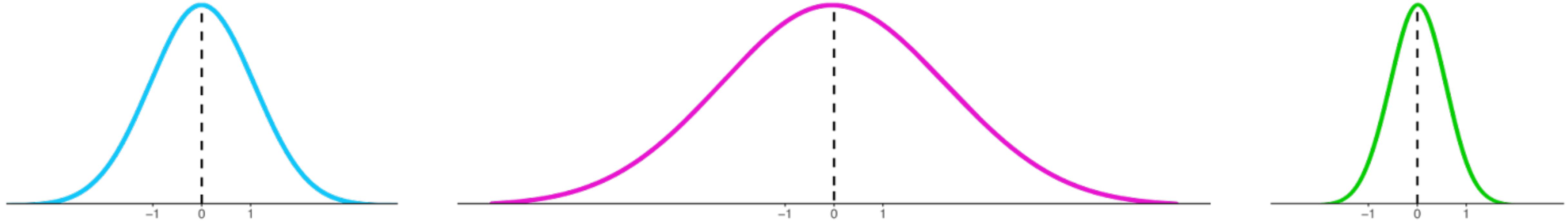


@allison_horst

Spread of the data: the standard deviation

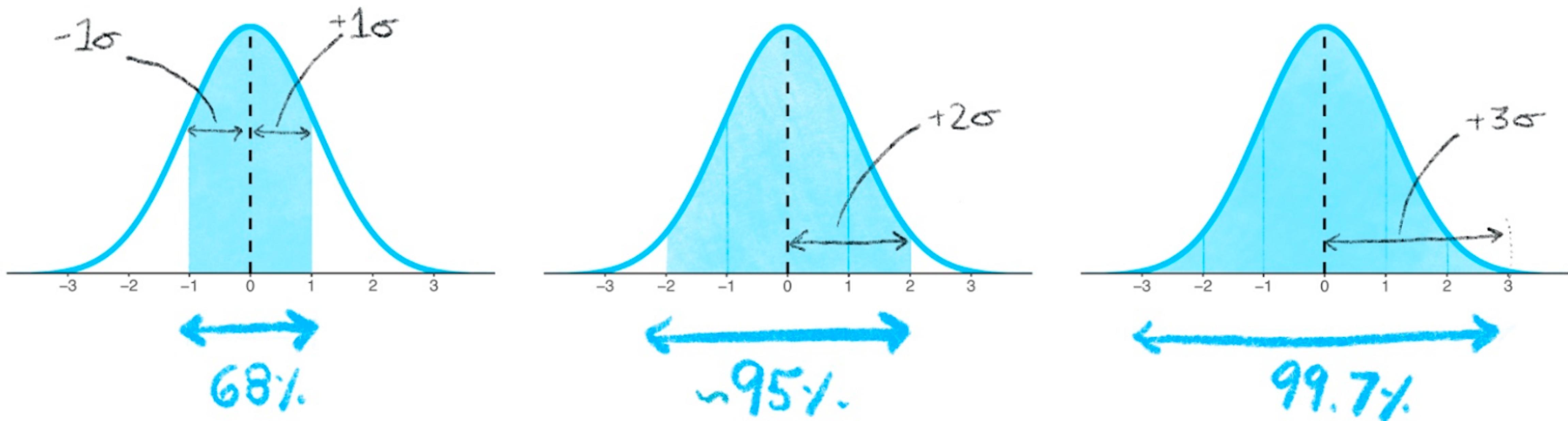
The **standard deviation (σ)** and **variance (σ^2)** account for outliers

It is a measure of how many your data **scatter around the mean**



To grasp the mechanics of common statistical tests, it is useful to have a good understanding of the s.d.

Standard deviation

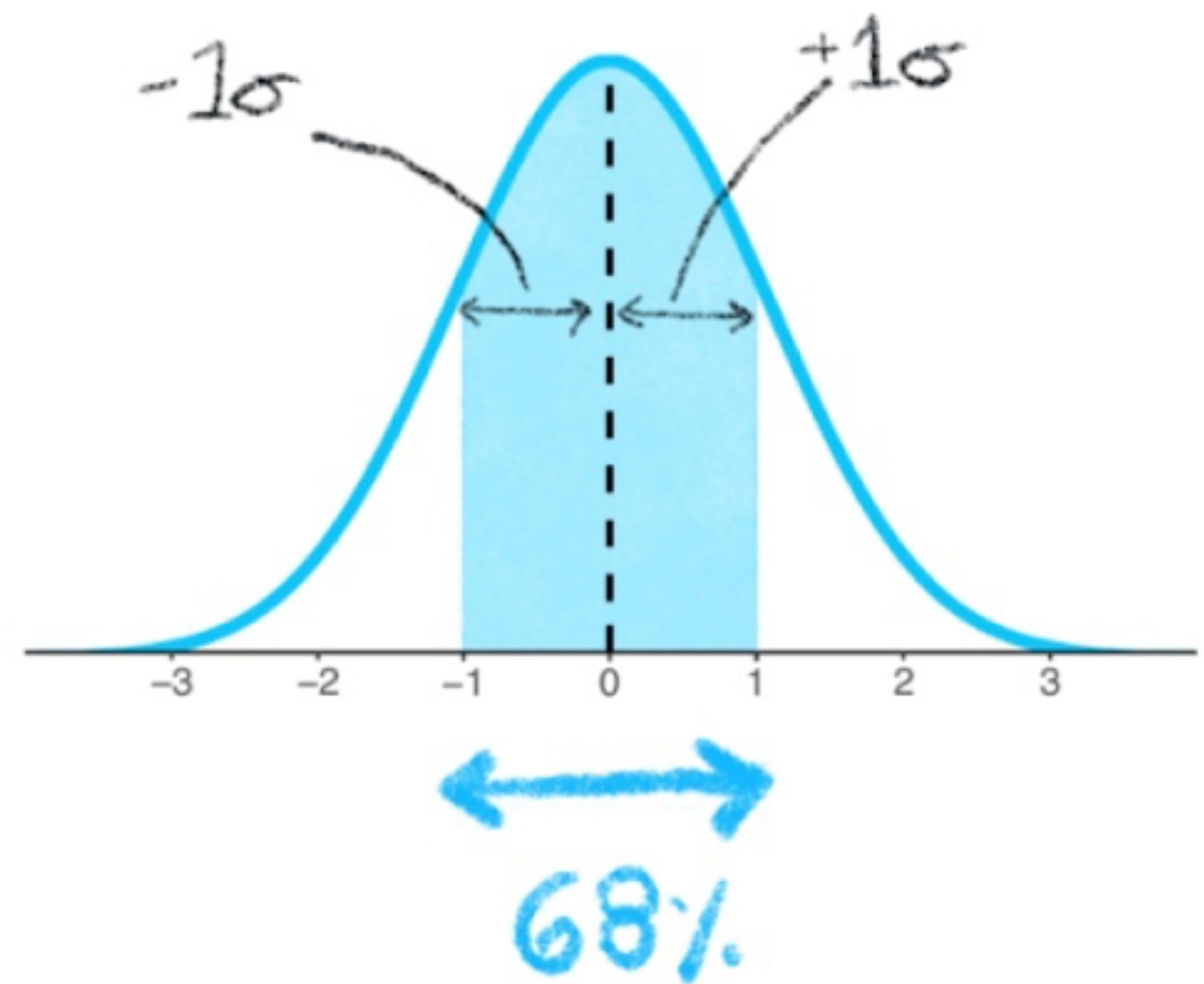


The 68–95–99.7 rule - a property of the normal distribution

Standard deviation

A measure of the amount of **variation or dispersion** in a set of normally distributed values

How do we calculate this?

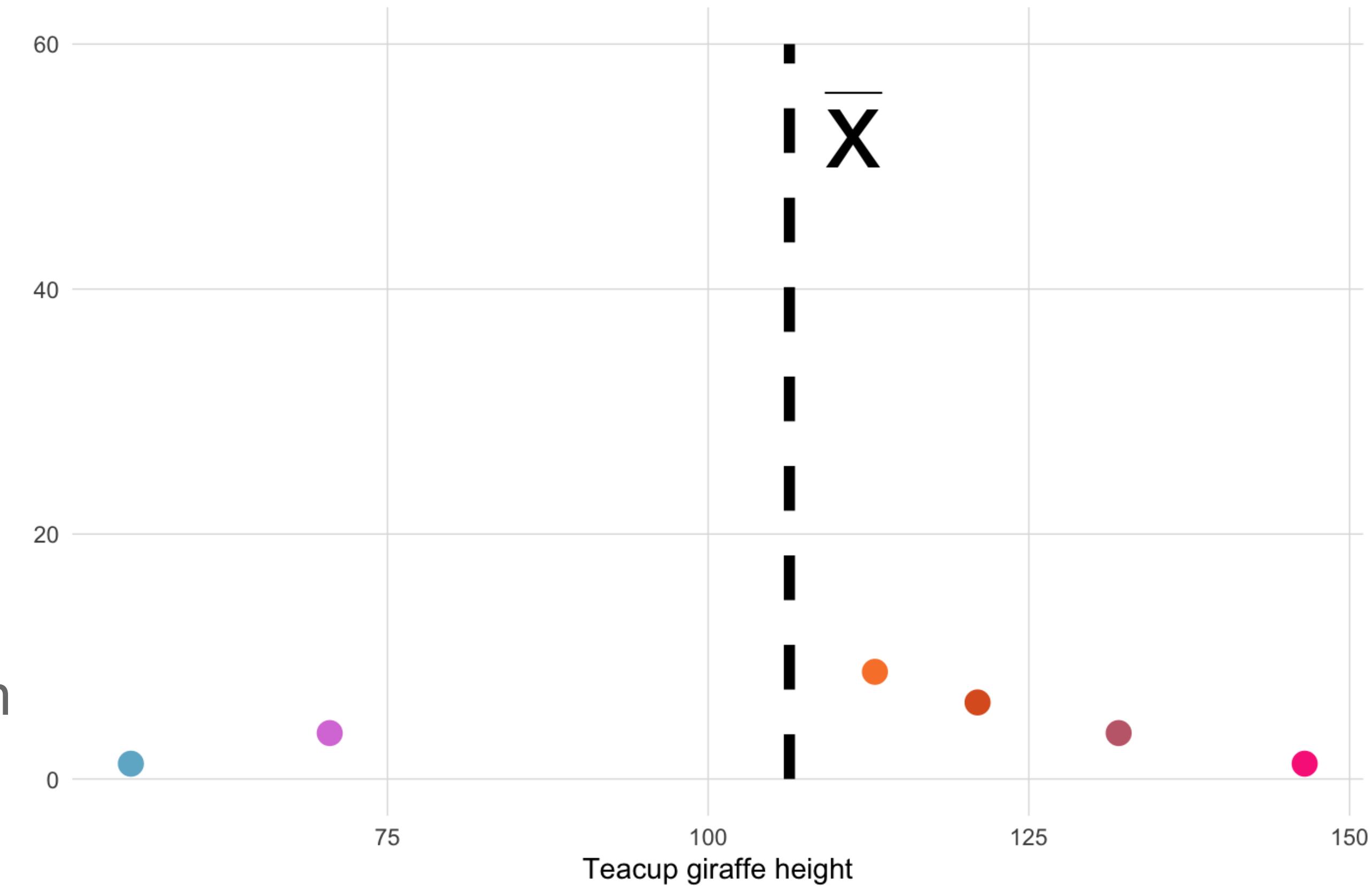


Calculating the variance and standard deviation

1. Calculate the **sample mean** (\bar{x})

2. **Square the deviations** from the mean (this ensures the values are all positive)

→ How much do our data points deviate from the mean on average?



See [Variance and Standard Deviation](#)

Calculating the variance

$$\sum_{i=1}^N (x_i - \mu)^2$$

3. Calculate the sum of squared deviations



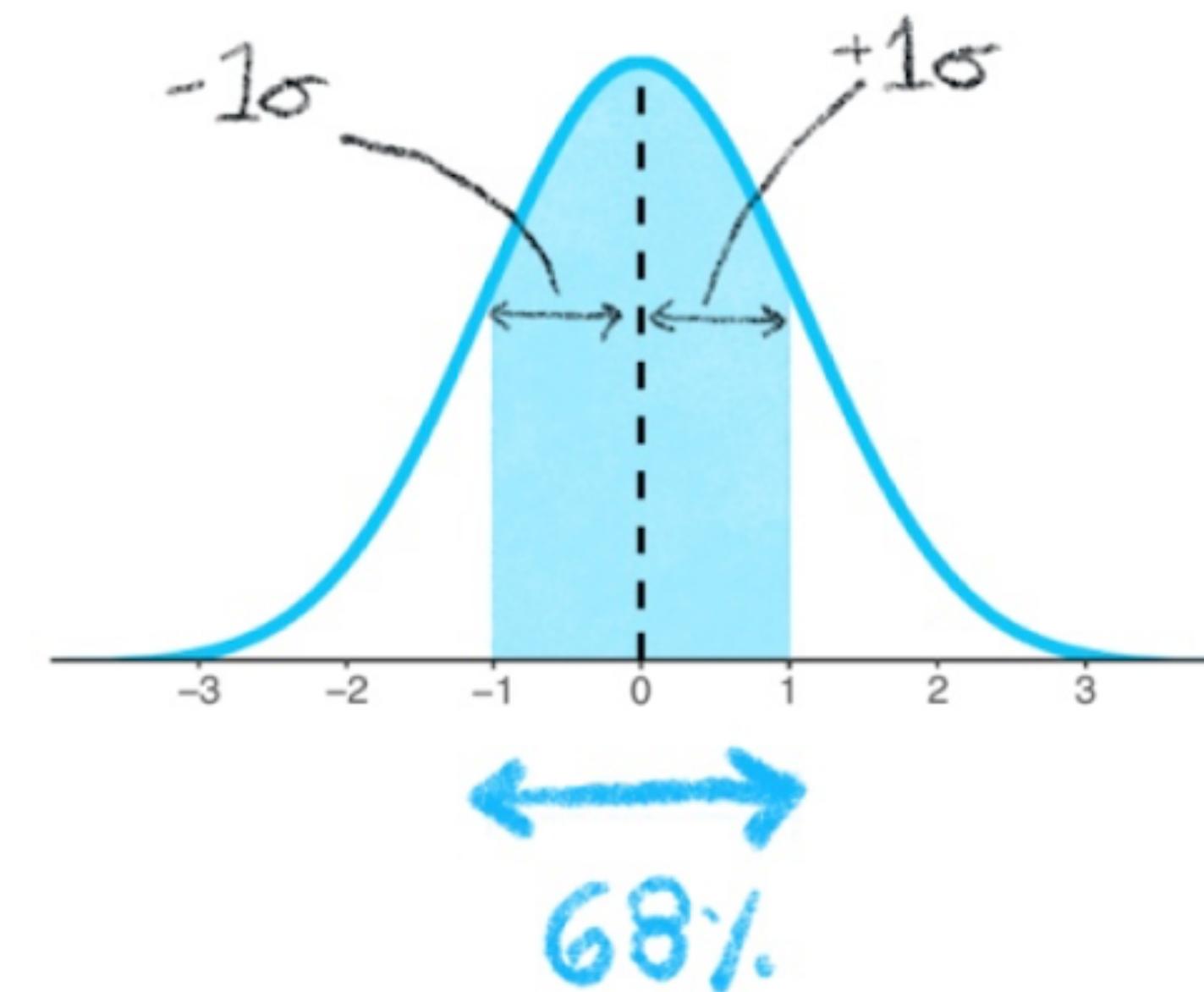
4. Calculate the average squared differences from the mean (i.e., the average of step 3)

$$\sigma^2 = \frac{\sum_{i=1}^N (x_i - \mu)^2}{N}$$

Calculating the standard deviation

$$\sigma = \sqrt{\frac{\sum_{i=1}^N (x_i - \mu)^2}{N}}$$

5. Variance is not easily interpretable → so we “unsquare” the variance to return to the data’s original units (e.g., cm, ml, etc.)



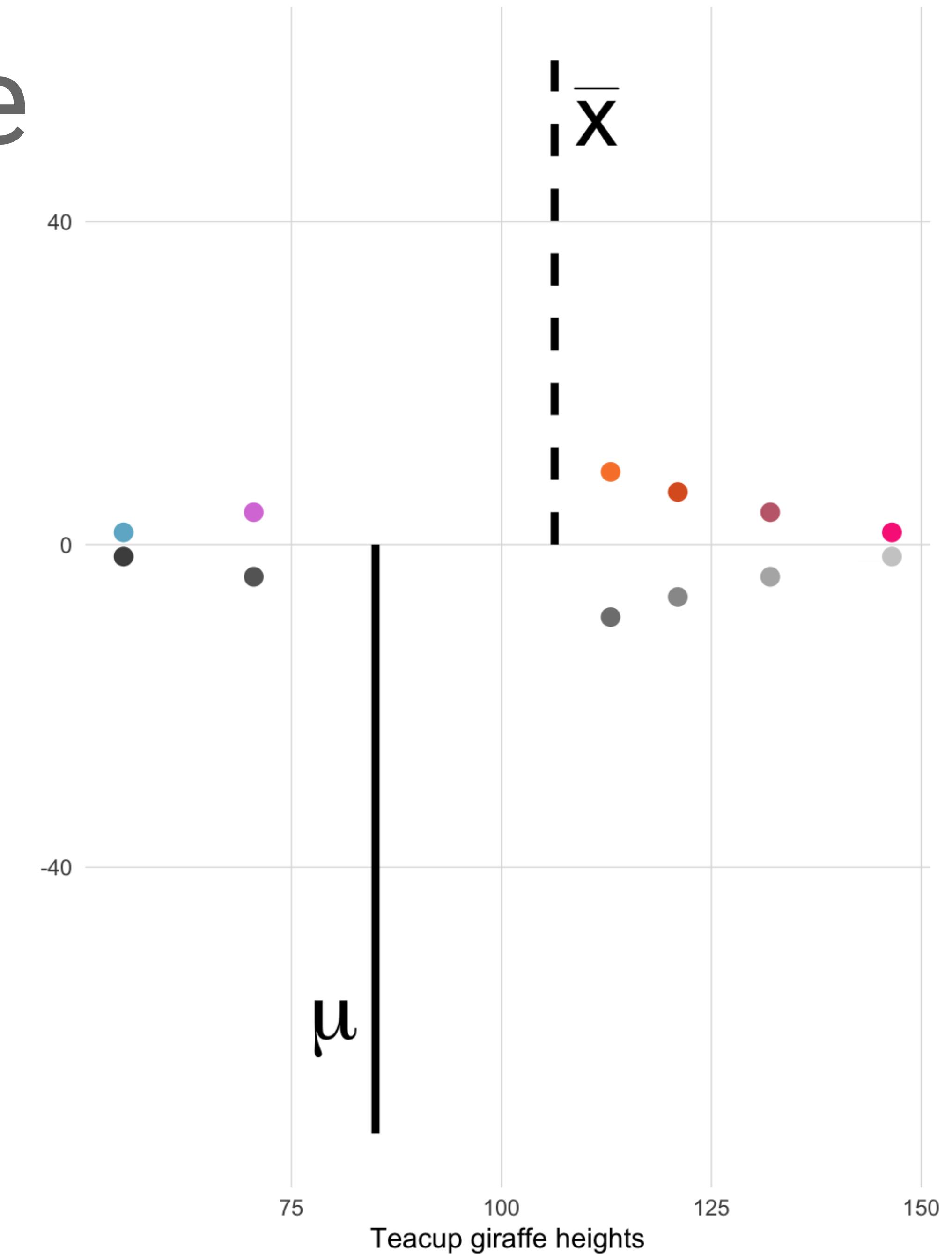
Population vs. sample

however

We only have the sample mean as our centre point

The true population mean μ is unknowable

The smaller the sample, the less likely the sample mean x will be close to the true mean μ



Population vs. sample

$$\text{---} + \text{---} + \text{---} + \text{---} + \text{---} + \text{---} = \text{---}$$

The top row shows a horizontal sequence of six squares: blue, pink, purple, light red, orange, and a small orange square. Below them is a plus sign followed by an equals sign. To the right of the equals sign is a stack of three squares: a pink square at the bottom, a blue square in the middle, and a small orange square on top of the blue one. Below this stack is another plus sign and an equals sign. To the right of the second equals sign is a large red square.

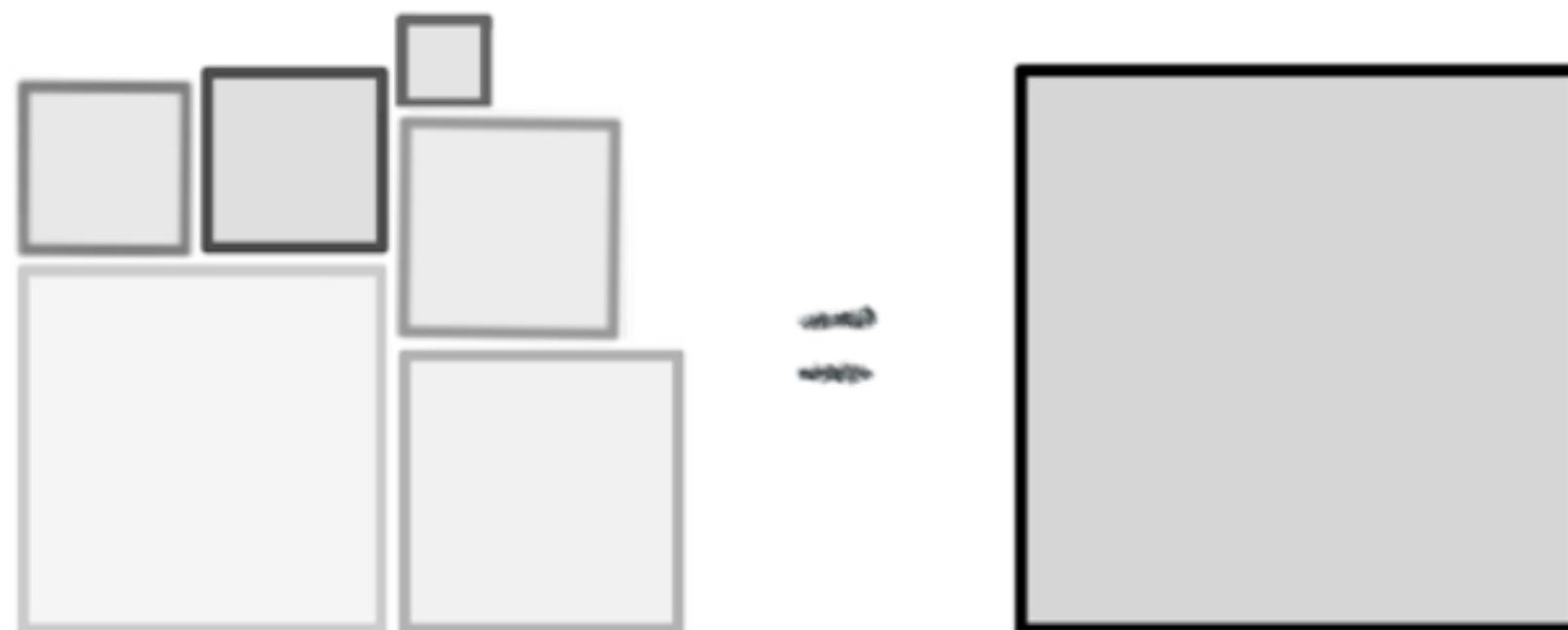
$$\text{---} + \text{---} + \text{---} + \text{---} + \text{---} + \text{---} = \text{---}$$

The bottom row shows a horizontal sequence of six gray squares. Below them is a plus sign followed by an equals sign. To the right of the equals sign is a stack of four gray squares: the first two are larger and overlapping, while the last two are smaller and positioned below the first two. Below this stack is another plus sign and an equals sign. To the right of the second equals sign is a large gray square.

Population vs. sample

The sum of squares from μ will
always be greater than the sum of
squares from x

By definition, the location of x
minimises the total distance of all
the observations to the centre



Solution: $n - 1$

→ If we divide by $n - 1$, we ensure the overall variance and standard deviation is a little larger, correcting for this bias (4.)

This means if we calculate the sum of squares (and thus, the variance and standard deviation) using the sample mean, our estimate will (most likely) be biased downwards

$$\sigma^2 = \frac{\sum_{i=1}^N (x_i - \mu)^2}{N}$$

$$s^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n - 1}$$

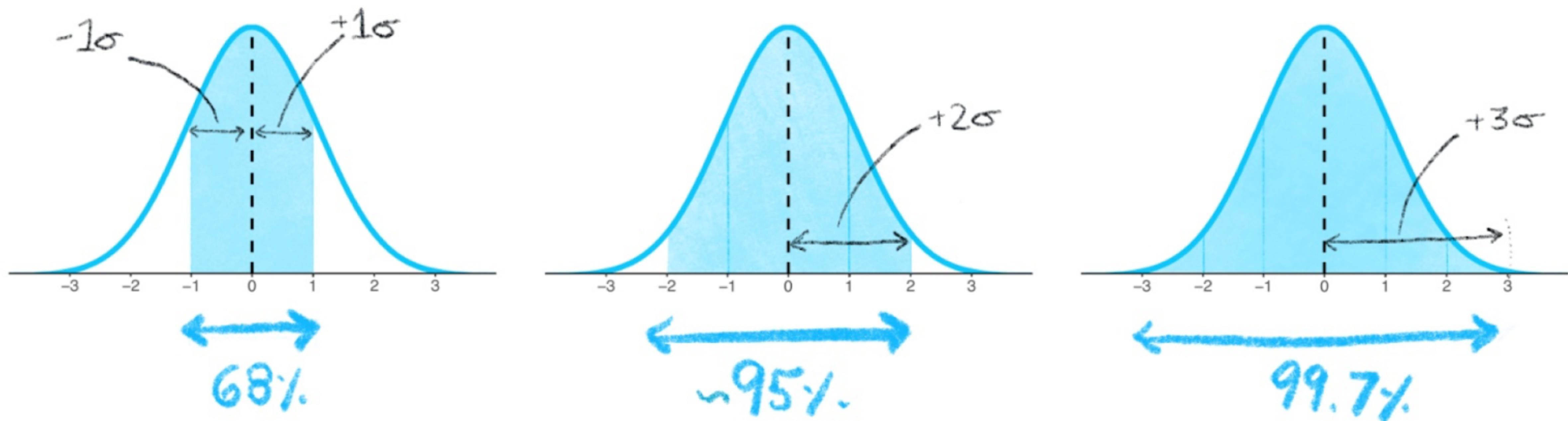
$$\sigma = \sqrt{\frac{\sum_{i=1}^N (x_i - \mu)^2}{N}}$$

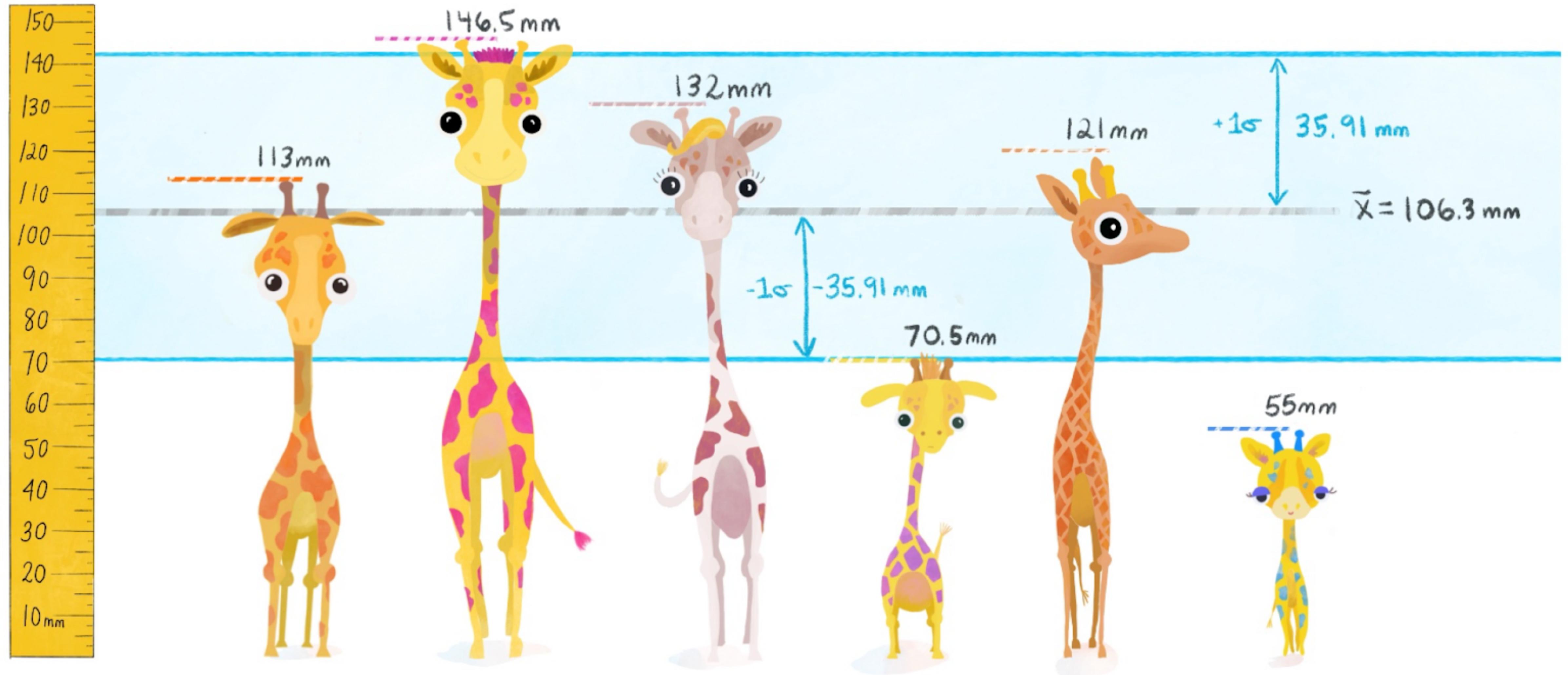
$$s = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n - 1}}$$

Summary of steps used to calculate the standard deviation

- 1. Calculate the sample mean**
- 2. Square the deviations from the mean**
- 3. Calculate the sum of squares**
- 4. Calculate average squared differences (apply the $n-1$ correction)**
- 5. Unsquare to get the standard deviation**

Interpreting the standard deviation





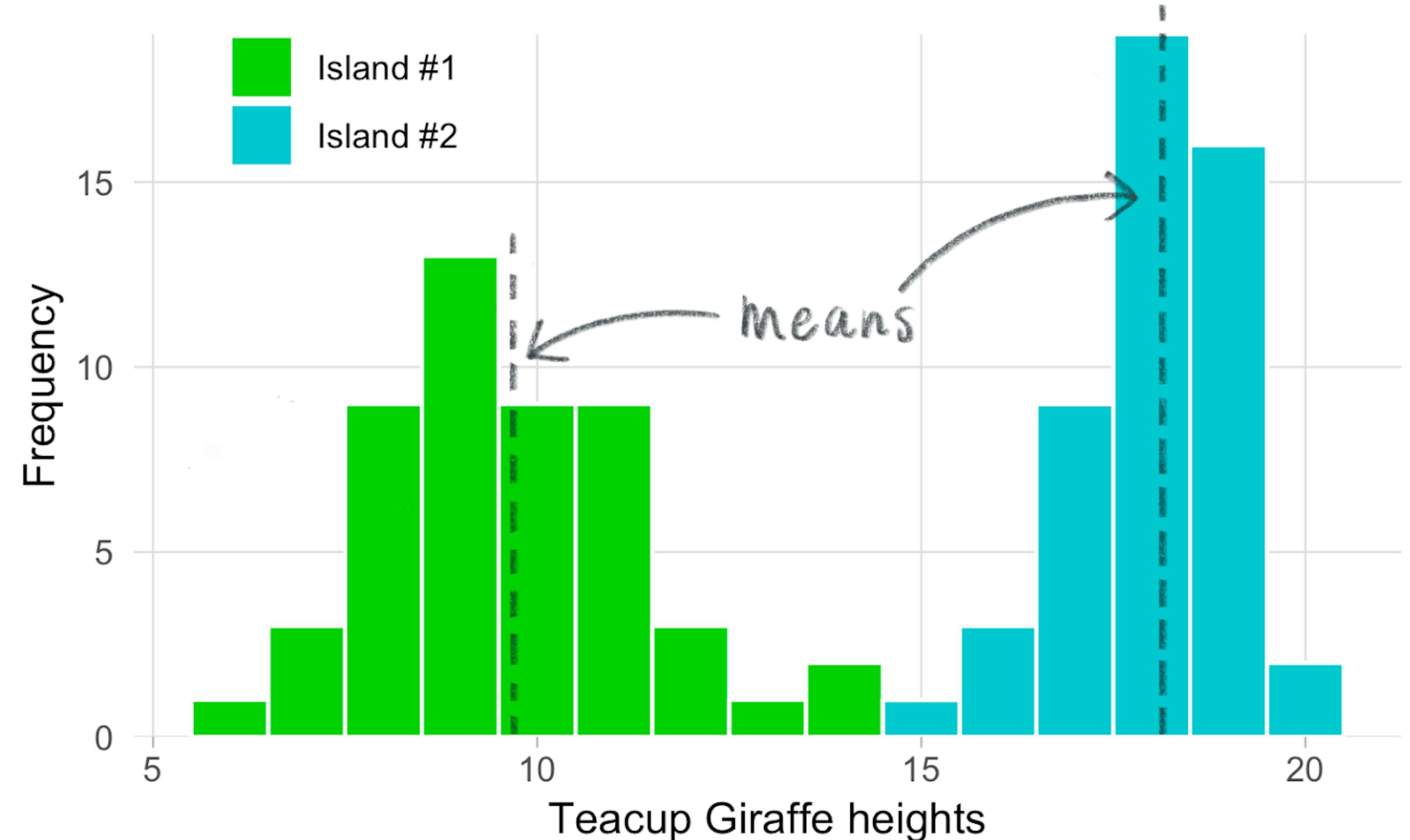
Functions in R

demo

```
my_function <- function(){  
  print("hello world")  
}
```

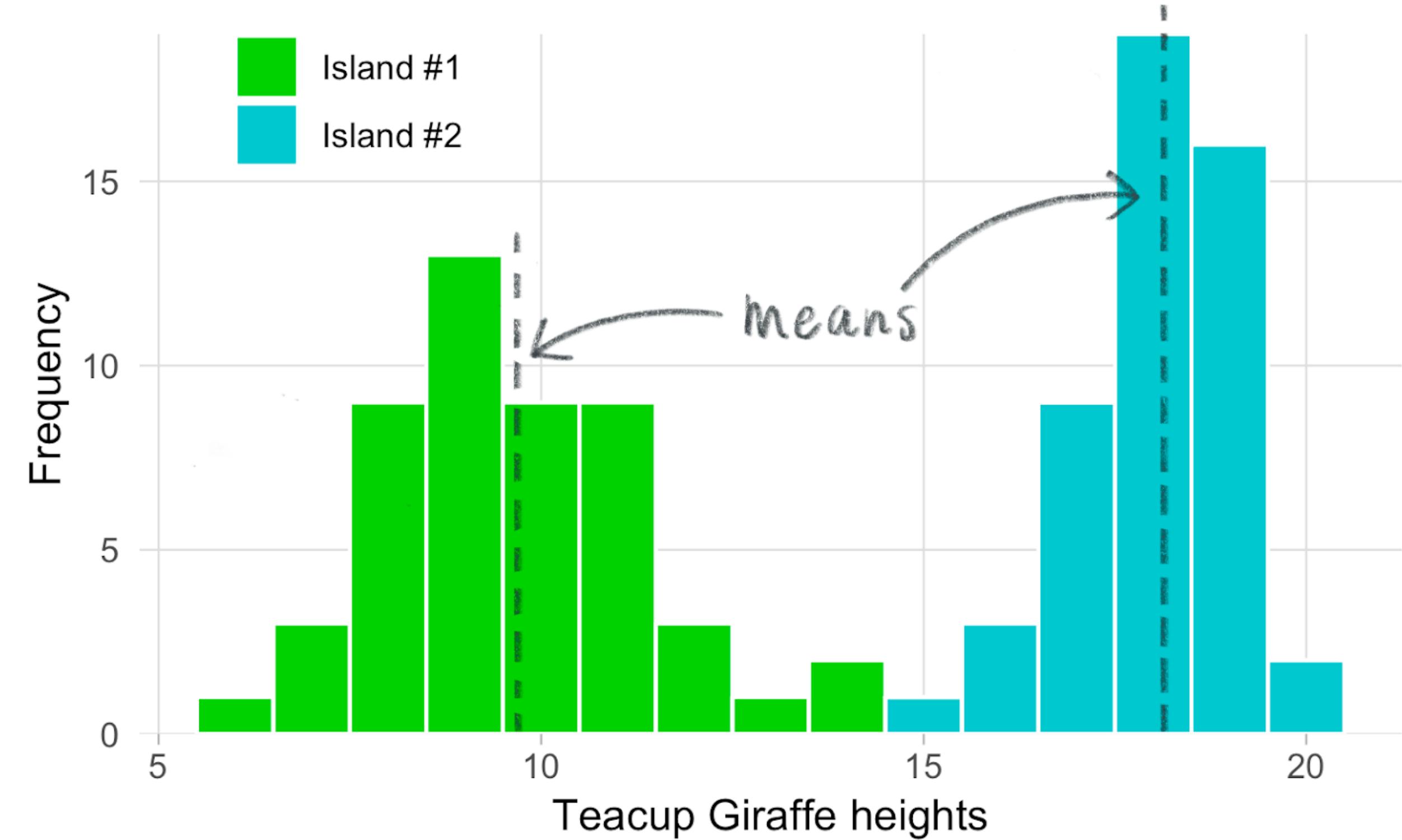
Exercise

Write a function
that calculates the
mean for a vector



Exercise

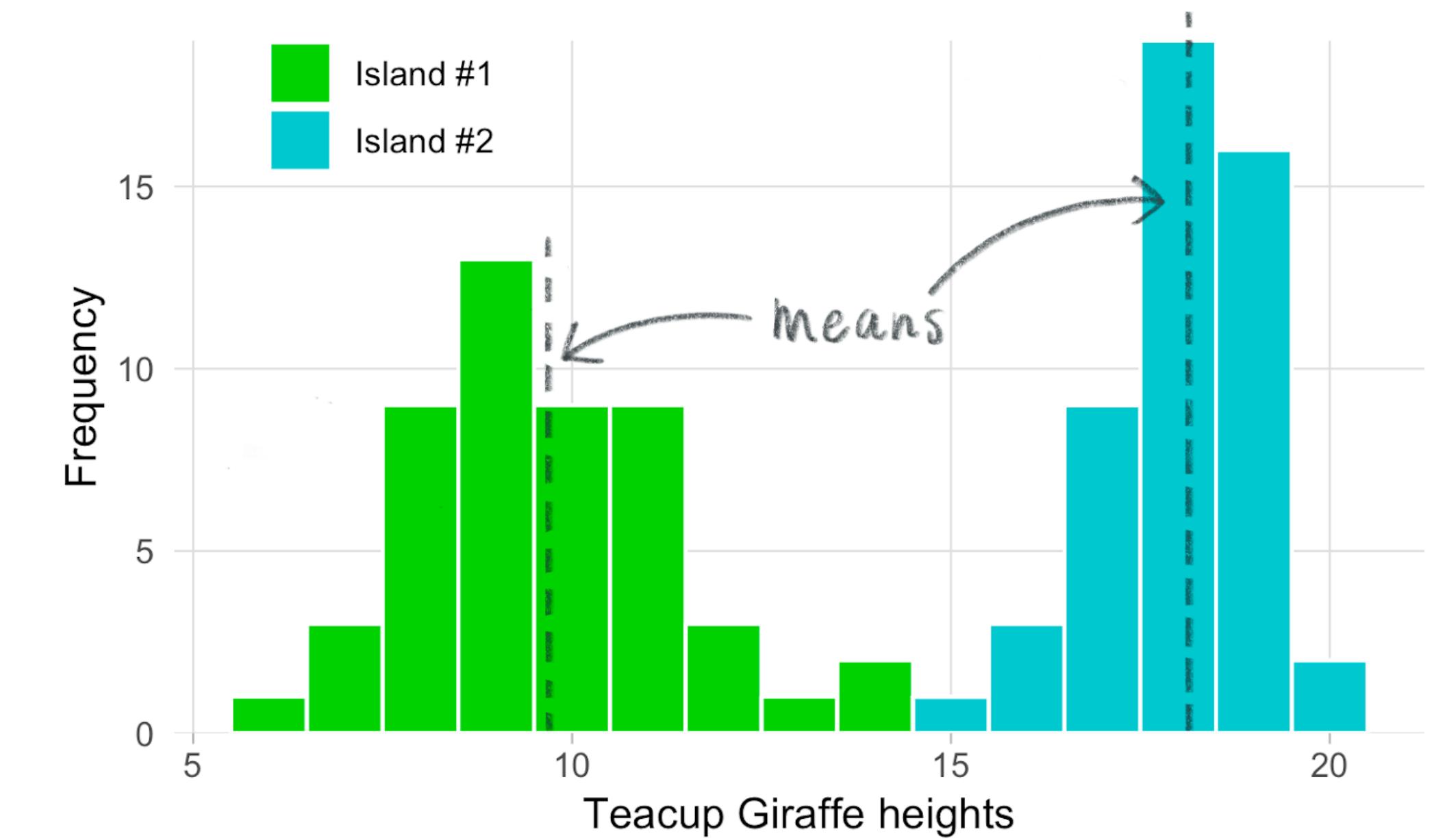
Write a **function** that
calculates the **standard**
deviation for a **vector**



Homework

Can you write a function that calculates mode or median?

Next, we'll talk more about the standard deviation / variance



Resources

Tools for exploring the normal distribution

[Compare two normal distributions](#)

[Plot the normal distribution](#)

Learn more about s.d. and variance

[Variance and Standard Deviation: Why divide by n-1?](#) Zed Statistics

[Standard deviation \(simply explained\)](#) DATAtab