

Introduction to modelbased clustering

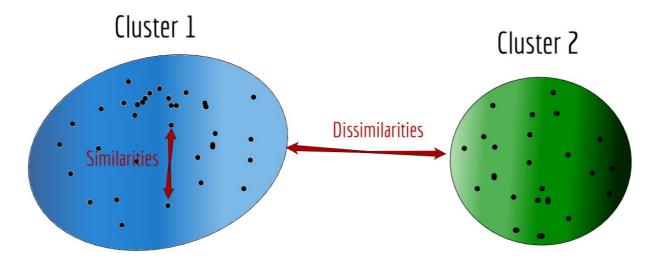
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What is clustering?

The procedure of partitioning a set of observations into a set of meaningful subclasses

→ Help to explore and understand the natural structure in a dataset





Applications of clustering

- Medicine
 - Ex. In medical imaging to distinguish between different types of tissue
- Business
 - Ex. To discover distinctive groups of customers to develop targeted marketing programs
- Social Sciences
 - Ex. To identify zones in a city by the type of committed crimes to manage law enforcement resources more effectively



Clustering methods

- Partitioning techniques
 - Find centers of clusters among the observations and each one is assigned to the cluster that has the closest center. Ex. Kmeans
- Hierarchical techniques
 - Connect the observations based on their similarity to form clusters. Ex.

Hierarchical clustering

- Model-base methods
 - Use probabilistic distributions to create the clusters. Ex. Mixture models



Gender dataset

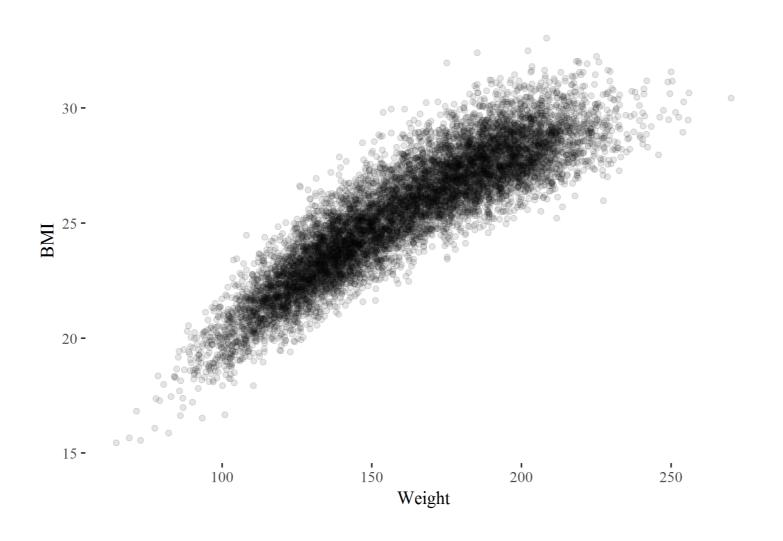
6 67.25302 152.2122 23.66049

```
gender <- read.csv("gender.csv")
head(gender)

Height Weight BMI
1 73.84702 241.8936 31.18576
2 68.78190 162.3105 24.12104
3 74.11011 212.7409 27.23291
4 71.73098 220.0425 30.06706
5 69.88180 206.3498 29.70803</pre>
```

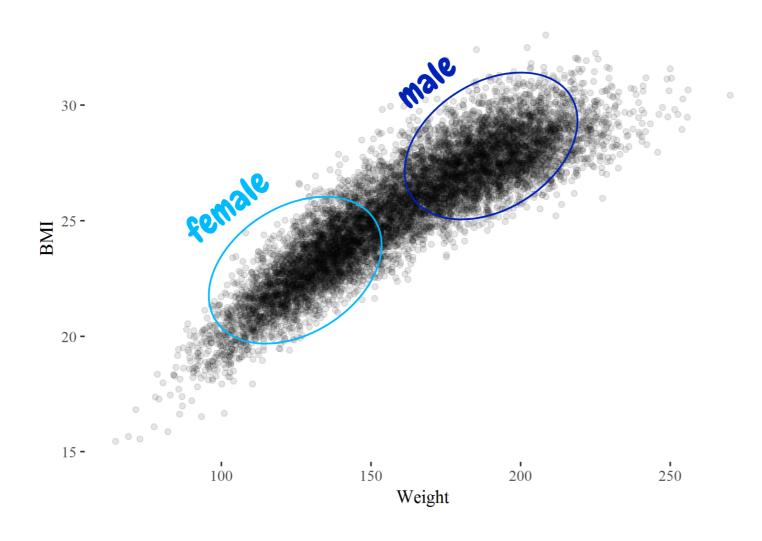
Gender dataset: Can you guess the gender?

```
library(ggplot2)
ggplot(gender, aes(x = Weight, y = BMI)) + geom_points()
```



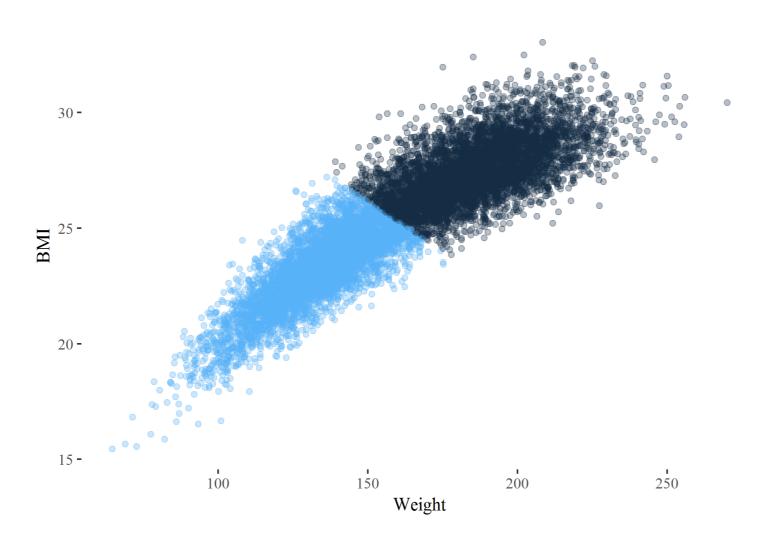


Gender dataset: Can you guess the gender?



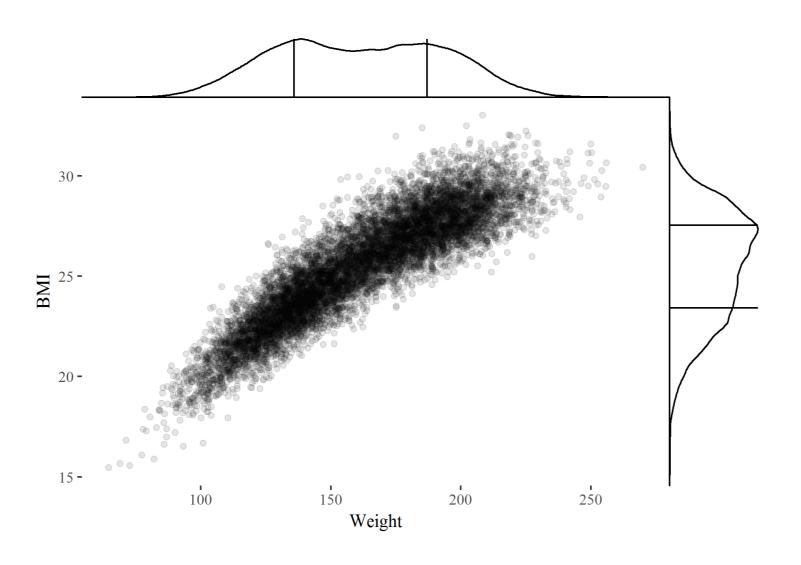


Under traditional cluster approaches



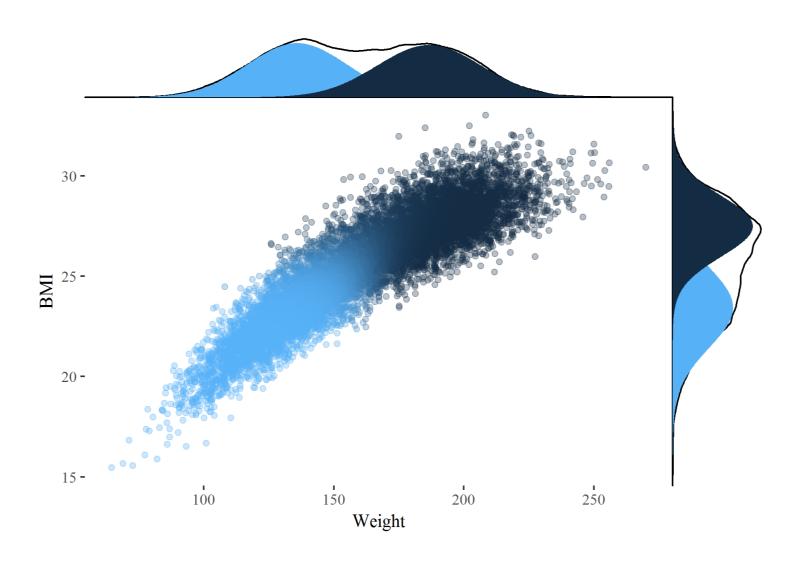


Model-based clustering

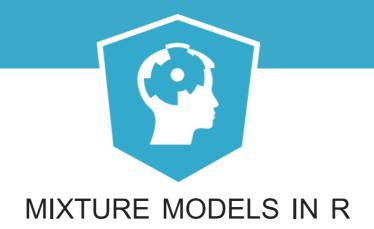




Model-based clustering

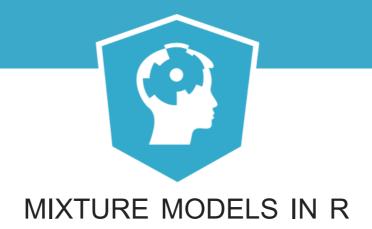






Let's practice!



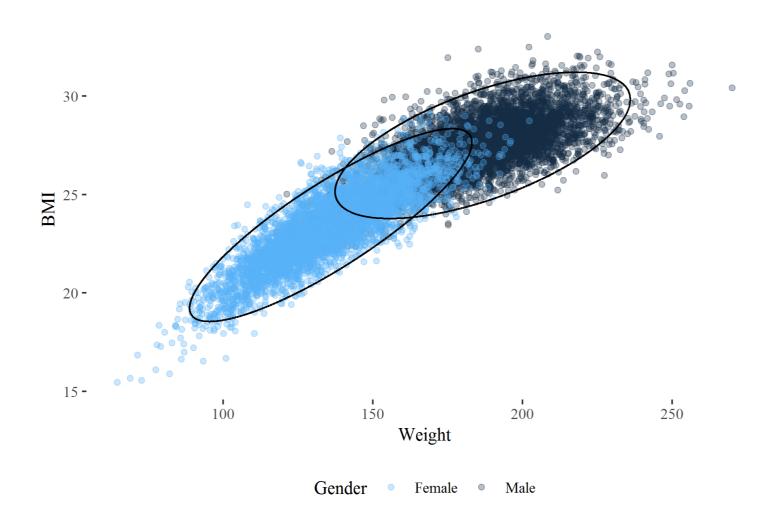


Gaussian distribution

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Mixture model to Gender dataset





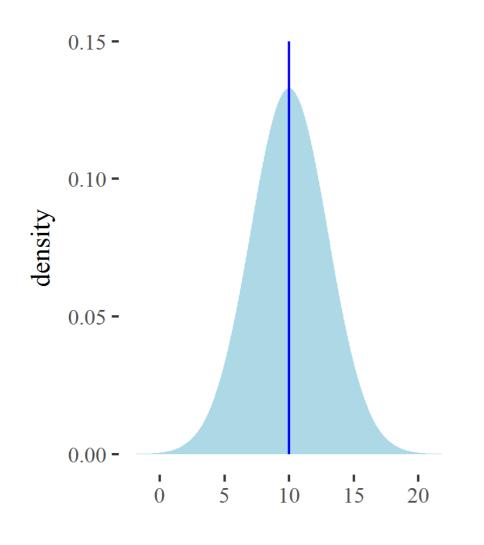
Packages for fitting Mixture Models

- mixtools
 - The Poisson distribution is not implemented.
- bayesmix
 - Bayesian inference is outside the scope of the course.
- EMCluster
 - Only Gaussian distributions.
- flexmix
 - Has all the distributions we need and gives you the flexibility to perform more complex models.

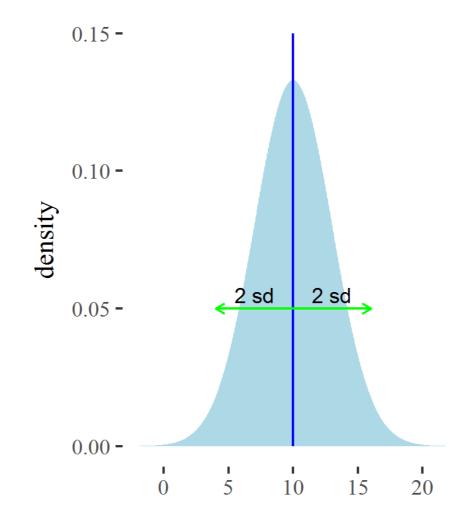


Properties of Gaussian distribution

Mean



Standard deviation



Sample from a Gaussian distribution

To generate samples from a Gaussian distribution:

```
• rnorm(n, mean, sd)
```

Example: Generate 100 values from a Gaussian distribution with a mean of 10 and a standard deviation of 5

```
> population_sample <- rnorm(n = 100, mean = 10, sd = 5)
> head(population_sample)

[1] 6.248874 9.564190 16.006521 9.139647 10.114969 16.423538
```

Estimation of the Mean

- Don't know the mean and the standard deviation, only know the observations
 - Need to be estimated from the observations
- To estimate the mean, we can calculate the sample mean

```
> mean_estimate <- mean(population_sample)
```

[1] 10.35759

Estimation of the Standard Deviation (sd)

• To estimate the sd, we perform the following procedure

$$value_i
ightarrow (.-mean_estimate)
ightarrow (.)^2
ightarrow mean(.)
ightarrow \sqrt(.)$$

```
> population_sample %>%
+    subtract(mean_estimate) %>%
+    raise_to_power(2) %>%
+    mean() %>%
+    sqrt()
[1] 5.318641
```

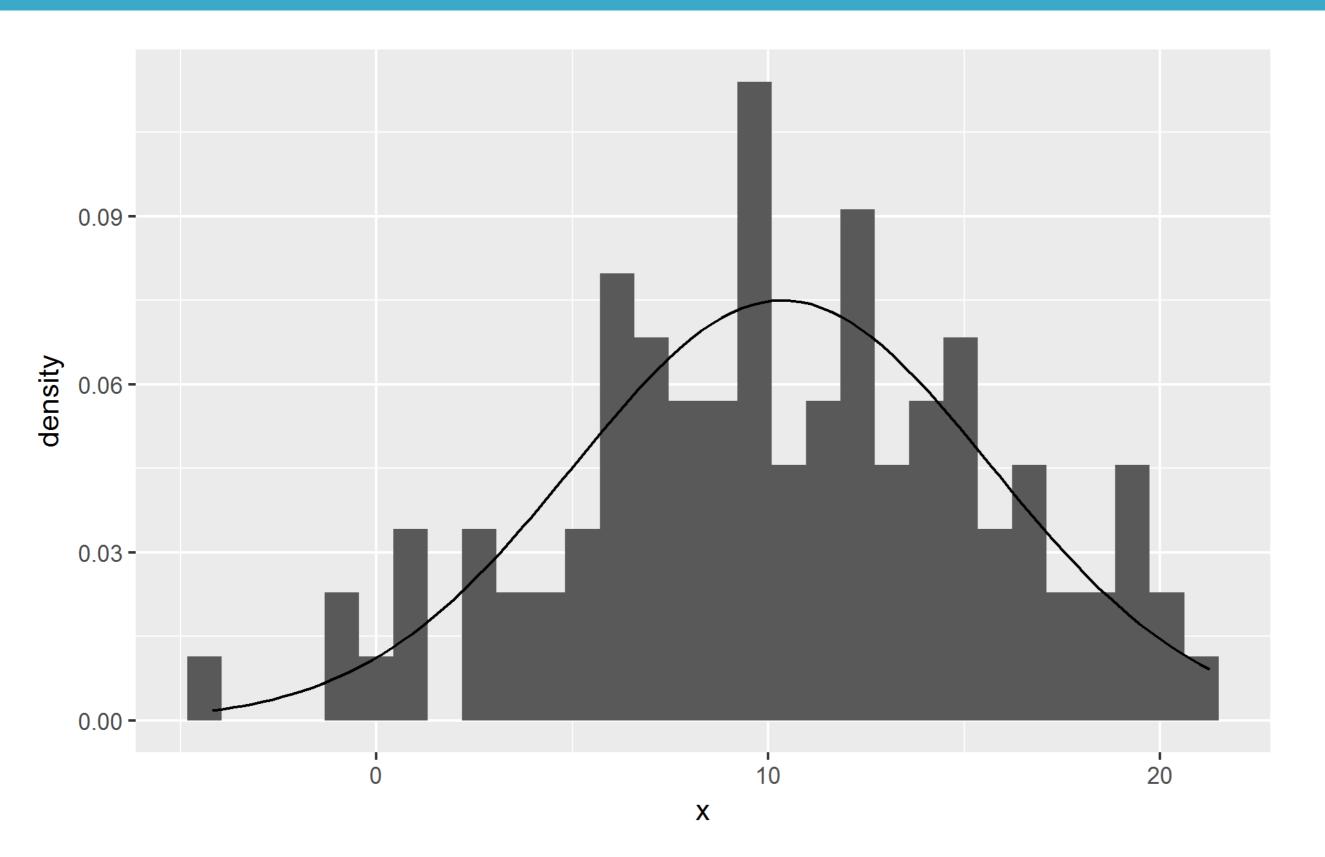
• Using the sd function

```
> standard_deviation_estimate <- sd(population_sample)
> standard_deviation_estimate
```

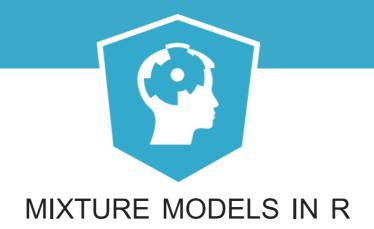
```
[1] 5.345435
```



Visualizing the sample with estimated Gaussian distribution

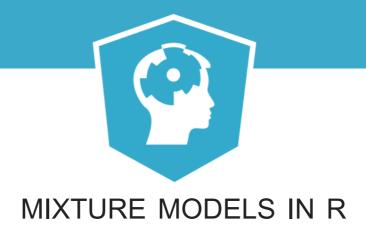






Let's practice!





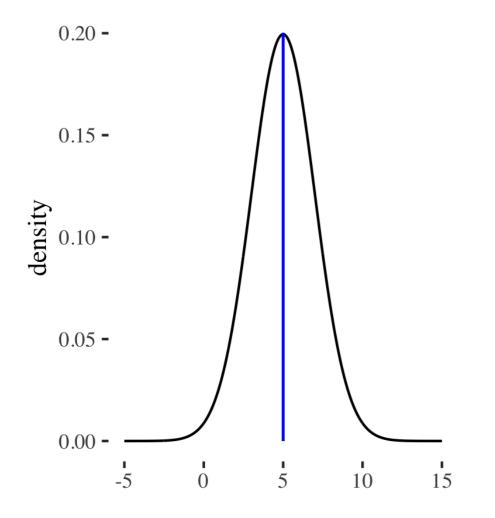
Gaussian mixture models (GMM)

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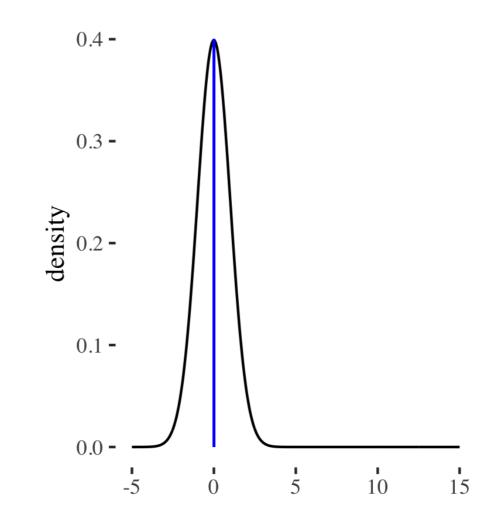


Flipping and sampling

Heads



Tails





Flipping the coin



Sampling and simulate the mixture

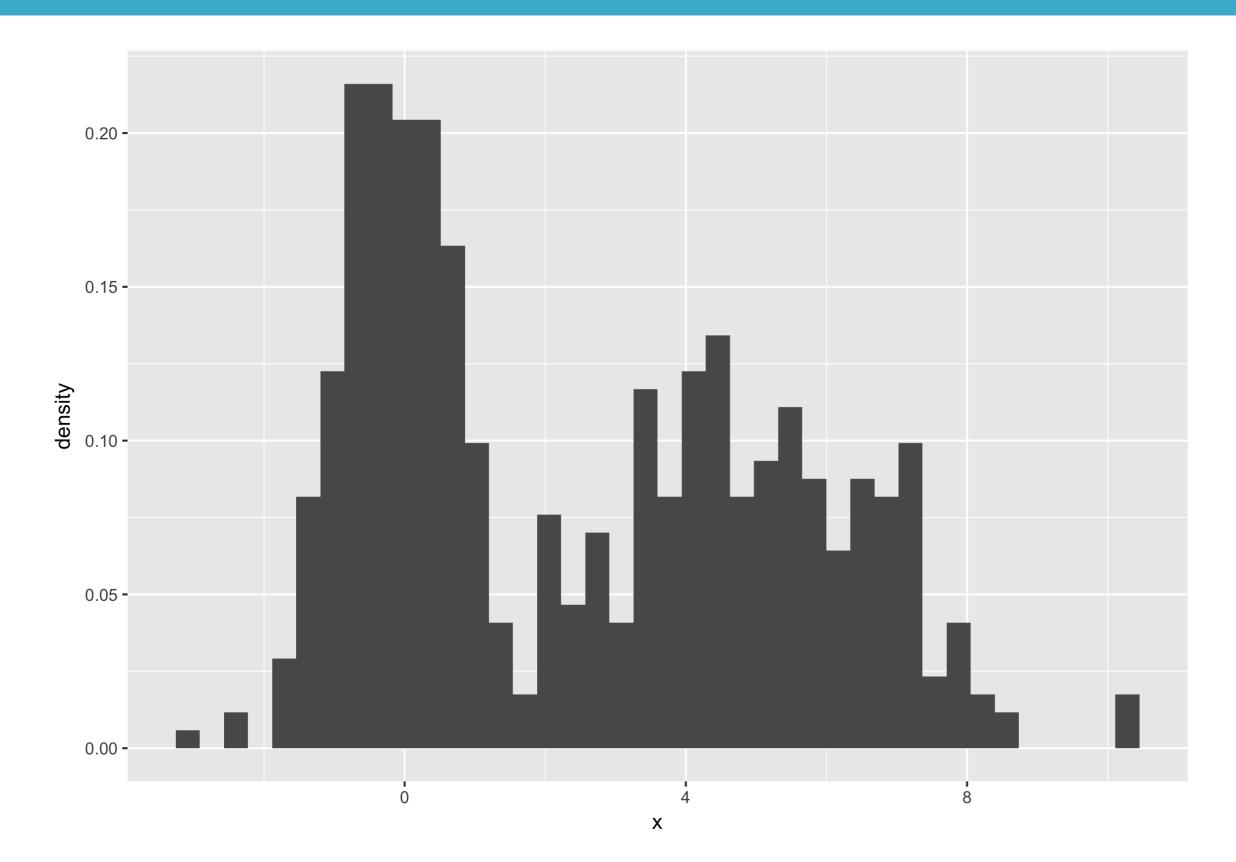
```
> # Gaussian 1 "heads"
> gauss_1 <- rnorm(n = number_of_obs, mean = 5, sd = 2)
> # Gaussian 2 "tails"
> gauss_2 <- rnorm(n = number_of_obs)

> # Simulate the mixture
> mixture_simulation <- ifelse(coin, gauss_1, gauss_2)
> head(cbind(coin, gauss_1, gauss_2, mixture_simulation))
```

```
coin gauss 1 gauss 2 mixture simulation
       0 \ 7.3787\overline{12} \ -0.45595\overline{9}6
                                      -0.4559596
[1,]
       1 6.102770 3.3595880
                                     6.1027696
[2,]
      0 5.707269 -0.0731496
                               -0.0731496
[4,]
                               3.5920586
      1 3.592059 -1.2407104
[5,]
      0 5.236851 -0.5110058
                                     -0.5110058
[6,]
       0 4.152619 -0.5124031
                                      -0.5124031
```

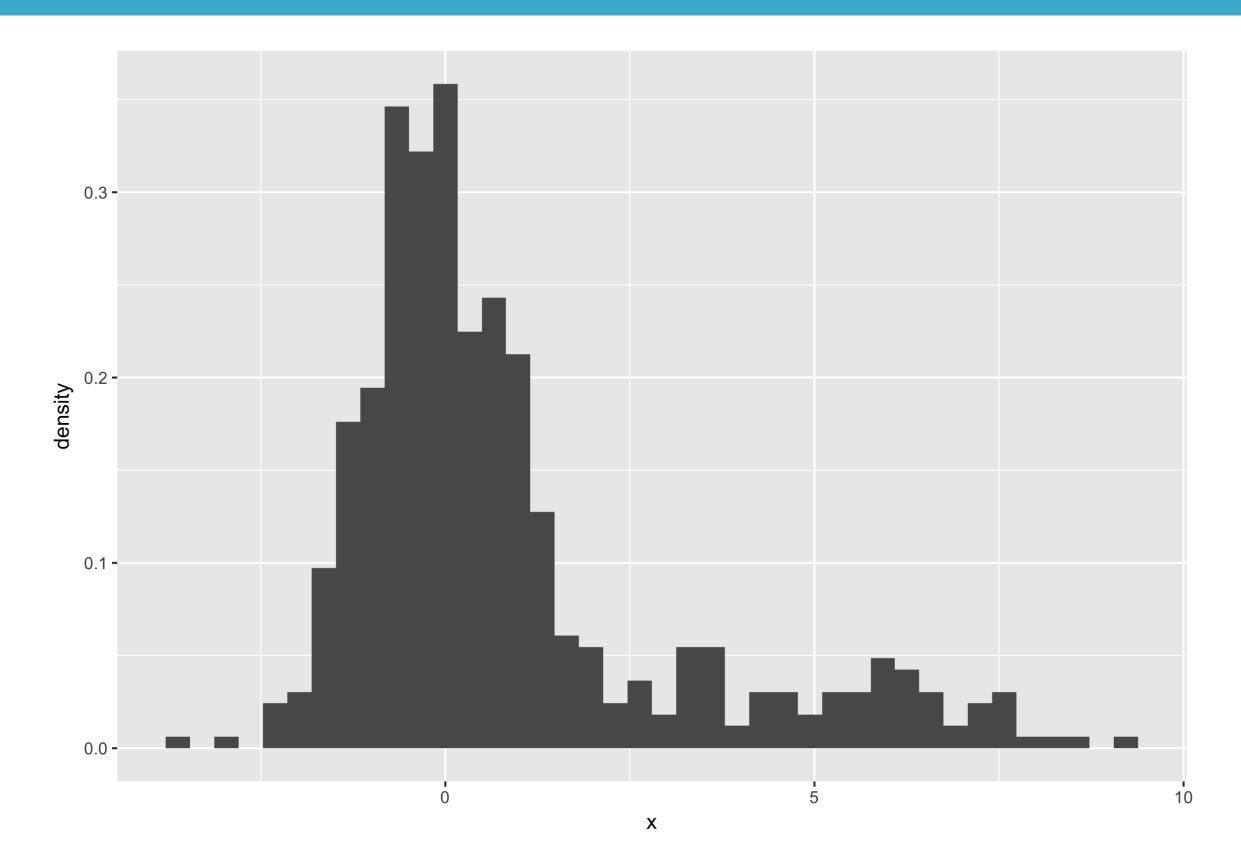


Plot the mixture



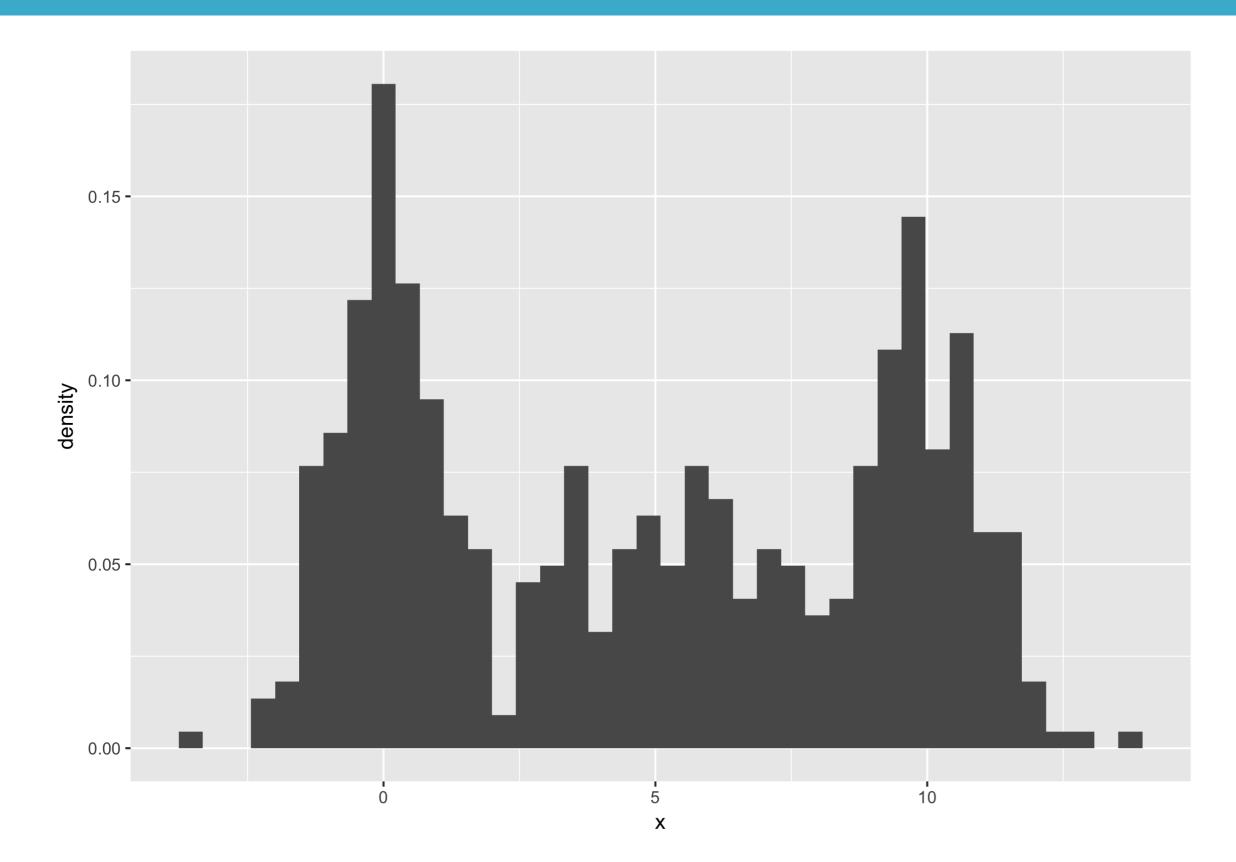


Changing the proportions

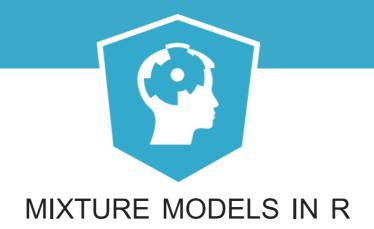




Mixture of three distributions







Let's practice!