

# A GitBook template

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# Chapter 1

## Introduction

This is a template GitBook based on *A GitBook Example for Teaching and bookdown: Authoring Books and Technical Documents with R Markdown*.

This is how we would reference a book (Xie, 2015) or Xie (2015).

This is how we would reference articles Gu, Mulder, & Hoijsink (2018) or (Hoijsink, Klugkist, & Boelen, 2008).



## Chapter 2

# Monte Carlo Simulations

```
library(tidyverse)
```

### 2.1 The Confidence Interval

In this exercise I will try to repeat the example given by Gerko Vink

The main idea of this exercise is to illustrate the nature of the *Confidence Interval* as described by Neyman (1934)

We set a seed to make our results reproducible:

```
set.seed(6465)
```

- The first step is to take 100 samples (in this case of size 800) from a *normal distributuon* with  $\mu = 0$  and  $\sigma = 1$ :

```
samples <-plyr::rply(100, rnorm(800, 0, 1))
```

- Secondly, we need to calculate for the mean of each sample: the absolute bias; standard error lower bound of the 95% confidence interval and upper bound of the 95% confidence interval.

We can construct a function that does this:

Table 2.1: Here is a table of the samples

| Mean       | Bias      | Std.Err   | Lower      | Upper      | Covered |
|------------|-----------|-----------|------------|------------|---------|
| -0.0945589 | 0.0945589 | 0.0353553 | -0.1639592 | -0.0251585 | 0       |
| 0.0740058  | 0.0740058 | 0.0353553 | 0.0046055  | 0.1434062  | 0       |

```
samp_function <- function(x) {
  m <- mean(x)
  n <- length(x)
  se <- 1/sqrt(n)
  bias <- abs(-0 - m)
  df <- n - 1
  interval <- qt(.975, df) * se
  return(c(m, bias, se, m - interval, m + interval))
}

format <- c("Mean" = 0, "Bias" = 0, "Std.Err" = 0, "Lower" = 0, "Upper" = 0)
```

Now we use the constructed function `samp_function` on all 100 samples contained in the object `samples`. And we also add a new column to the results that indicates which CI of the respective samples does contain  $\mu$ .

```
results <- samples %>%
  vapply(., samp_function, format) %>%
  t %>%
  as_tibble %>%
  mutate(Covered = ifelse(Lower < 0 & Upper > 0, 1, 0))
```

We can also add a table with the sample statistics of the samples whose CI's do not contain  $\mu$ .

```
results %>%
  filter(Covered == 0) %>%
  kableExtra::kable(caption = "Here is a table of the samples" )
```

And finally we can also make a nice plot illustrating everything that we did so far.

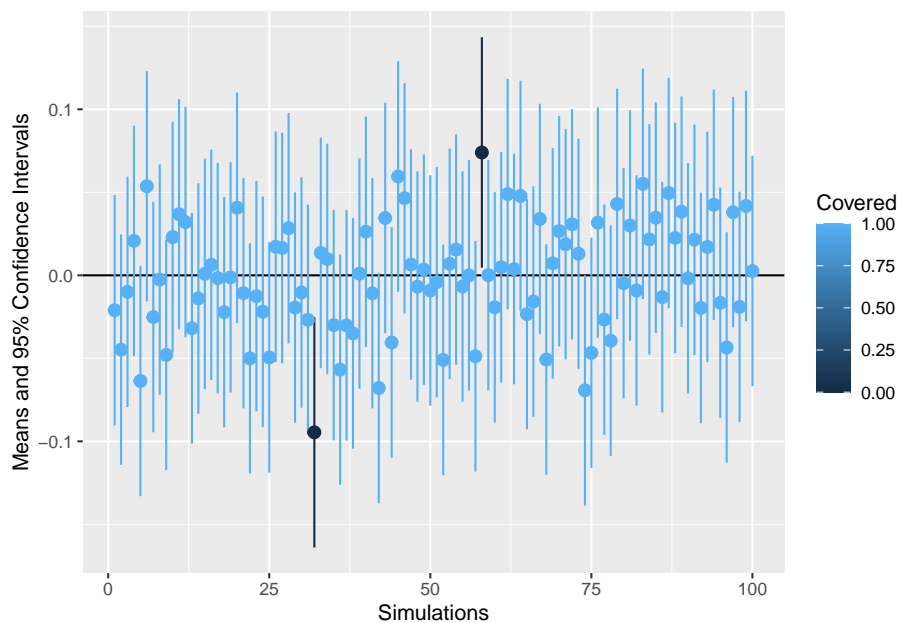
```
lims <- aes(ymax = results$Upper, ymin = results$Lower)
ggplot(results, aes(y=Mean, x=1:100, colour = Covered)) +
  geom_hline(aes(yintercept = 0)) +
```



```
geom_pointrange(lims) +
xlab("Simulations") +
ylab("Means and 95% Confidence Intervals")
```

```
## Warning: Use of `results$Upper` is discouraged. Use `Upper` instead.
```

```
## Warning: Use of `results$Lower` is discouraged. Use `Lower` instead.
```



In this case only two out of 100 CI's do not include the true population mean.

## 2.2 The Central Limit Theorem

Here we will also try to illustrate the Central Limit Theorem, in it's most basic form, with a very simple example.

First we draw 1000 samples (again of size 800), from , say, a *Poisson* distribution, of course we could've drawn them from a uniform or an exponential as well.

```
samples_2 <- samples <-plyr::rply(1000, rpois(800, 2))
```

Now we calculate the mean for each sample:

```
means <- samples_2 %>%  
  lapply(., mean) %>%  
  as.data.frame() %>%  
  t()
```

And now we plot a histogram of the resulting means:

```
hist(t(means))
```

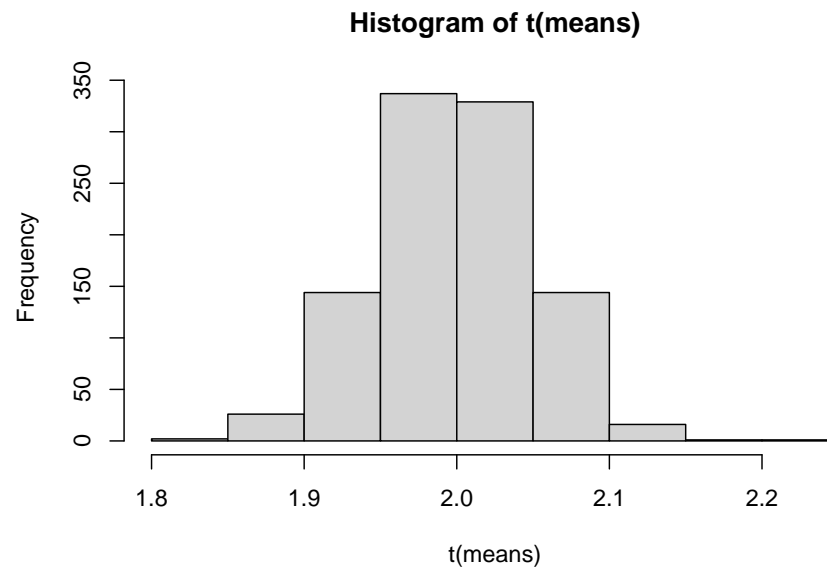


Figure 2.1: Histogram of the sampling distribution of the mean

## Chapter 3

# Equations

### 3.1 Bayes' theorem

$$p(\theta|D) = \frac{p(D|\theta)p(\theta)}{p(D)} \quad (3.1)$$

### 3.2 Normal PDF

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right) \quad (3.2)$$

This is how we refer to equations: -see equation (3.2)



# References

- Gu, X., Mulder, J., & Hoijtink, H. (2018). Approximated adjusted fractional bayes factors: A general method for testing informative hypotheses. *British Journal of Mathematical and Statistical Psychology*, *71*, 229–261.
- Hoijtink, H., Klugkist, I., & Boelen, P. A. (2008). *Bayesian evaluation of informative hypotheses*. Springer.
- Xie, Y. (2015). *Dynamic documents with R and knitr* (2nd ed.). Boca Raton, Florida: Chapman; Hall/CRC.



# Appendix A