

# Likelihood and Log Likelihood

Andy Grogan-Kaylor

2024-09-18

## Table of contents

<b>1</b>	<b>Background</b>	<b>1</b>
<b>2</b>	<b>An Empirical Example</b>	<b>2</b>
<b>3</b>	<b>Maximum Likelihood Estimation</b>	<b>2</b>
<b>4</b>	<b>Log-Likelihood</b>	<b>2</b>
<b>5</b>	<b>Visualizing the Likelihood and Log-Likelihood</b>	<b>4</b>
<b>6</b>	<b>Conclusion</b>	<b>4</b>

## 1 Background

The likelihood is the probability that a given set of parameters would give rise to a given data set.

Formally, the likelihood is a product of probabilities.

$$\mathcal{L}(\beta) = \prod p(\beta|x, y) \tag{1}$$

## Line With Slope Most Likely To Produce Data

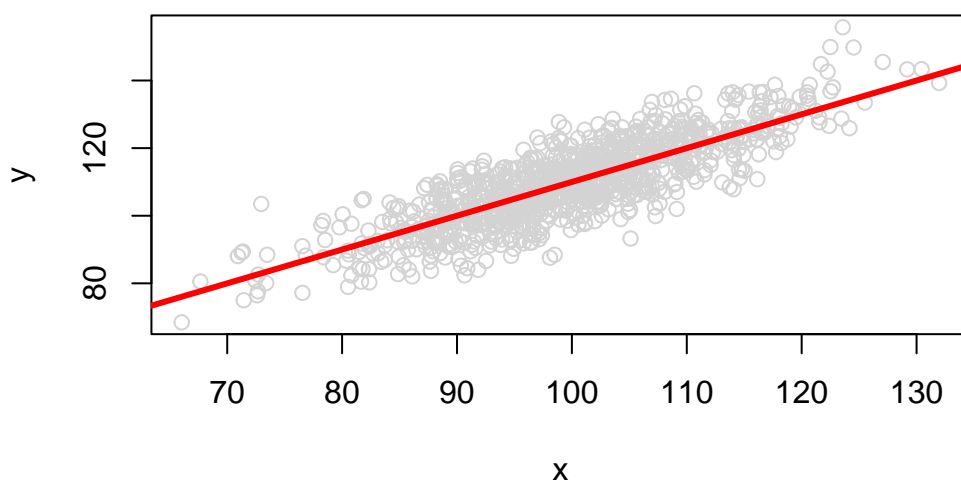


Figure 1: An Empirical Example

## 2 An Empirical Example

## 3 Maximum Likelihood Estimation

Maximum Likelihood Estimation is essentially the process of finding the *combination* of parameters (e.g.  $\beta$ ) which maximizes the likelihood of producing the data.

## 4 Log-Likelihood

Because probabilities are by definition  $< 1$ , the likelihood  $\mathcal{L}$  tends to be a very small number. For a variety of reasons, it is often easier to work with the logarithm of the likelihood:  $\ln \mathcal{L}$ .

## Joint Likelihood of Two Parameters

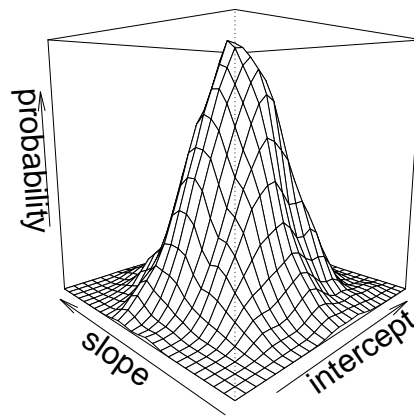


Figure 2: Joint Likelihood of Two Parameters

## Simulated Likelihood and Log-Likelihood

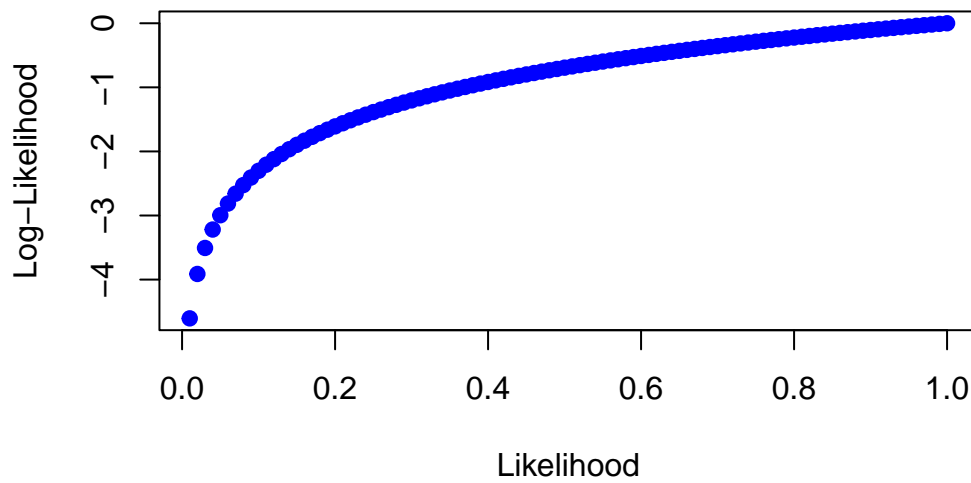


Figure 3: Likelihood and Log-Likelihood

## 5 Visualizing the Likelihood and Log-Likelihood

## 6 Conclusion

Higher values of the *log-likelihood*, closer to 0, represent models with a better fit.