

# Likelihood

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*Statistical Modeling in R*

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# Outline

## Likelihood

*relative probability, support, combine data sources*

## Estimation

*MLE, log likelihood, confidence interval*

## Normal distribution

*$N(\mu, \sigma)$ ,  $dnorm$*

## Profile likelihood

*procedure, uncertainty*

## Likelihood concepts

### Relative probability

$$P(A_1) = 0.5 \quad P(A_2) = 0.3 \quad P(A_3) = 0.2$$

$$L(A_1) = 500 \quad L(A_2) = 300 \quad L(A_3) = 200$$

$$L(A_1) = 0.005 \quad L(A_2) = 0.003 \quad L(A_3) = 0.002$$

## Likelihood concepts

Expresses how well the data **support** some parameter value  
or hypothesis

$$L(\theta | \text{data})$$

Like *RSS* but even more useful:

not only point estimate, but also **uncertainty**

## Likelihood concepts

We can fit a model to many types of data at once and **combine** the likelihood components with simple multiplication

$$L = L_1 \times L_2 \times \dots$$

Unified framework, for simple or complex models

## Likelihood concepts

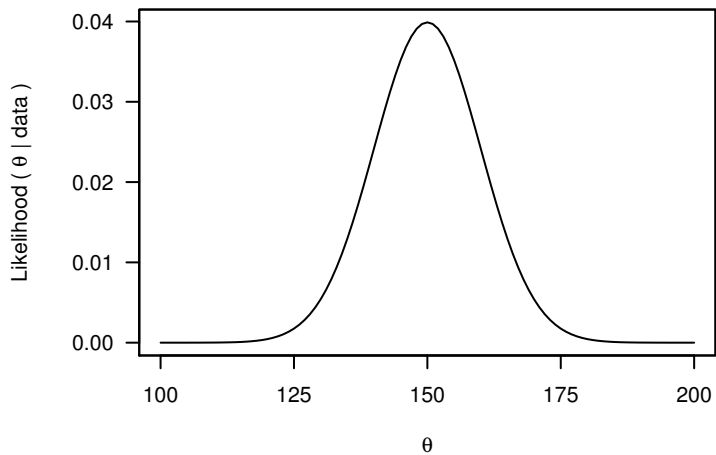
Choose between models with different number of parameters

$$2 \log \frac{L_1}{L_0} \sim \chi^2_{\Delta df}$$

$$\text{AIC} = -2 \log L + 2k$$

$$\text{BIC} = -2 \log L + \log(n)k$$

## Maximum likelihood estimation



## Log likelihood

Log transformation makes things easier

$$L(\theta|\text{data}) = p(\text{data}|\theta)$$

$$p(y_1, \dots, y_n|\theta)$$

$$p(y_1|\theta) \times \dots \times p(y_n|\theta)$$

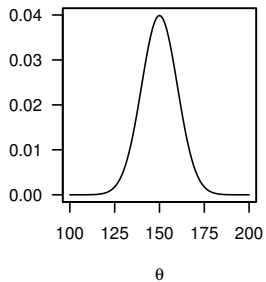
$$\prod p(y_i|\theta)$$

$$\log L(\theta|\text{data}) = \sum \log p(y_i|\theta)$$

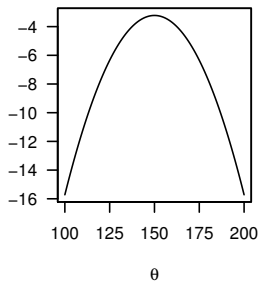


# Log likelihood

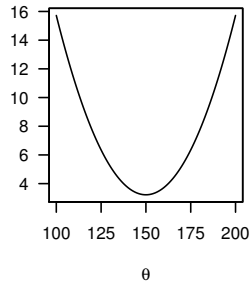
**L**



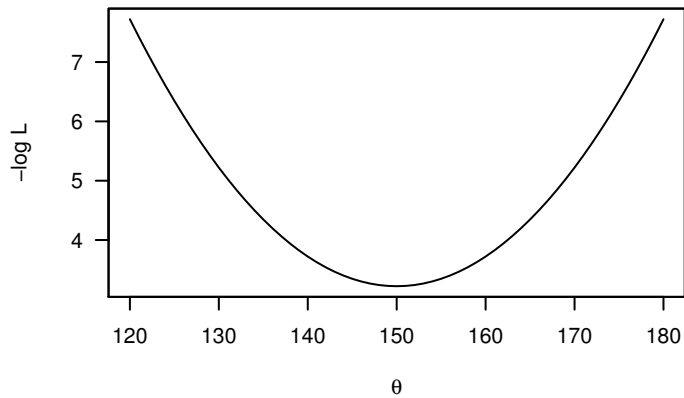
**log L**



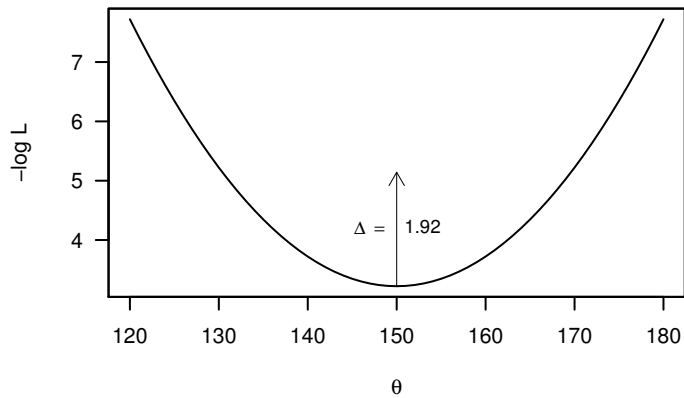
**$-\log L$**



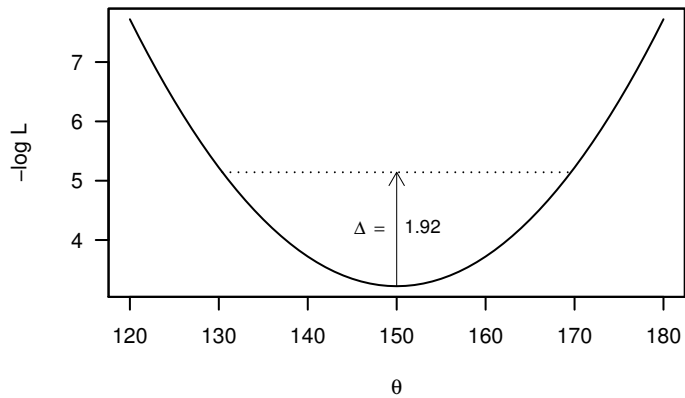
## Confidence interval



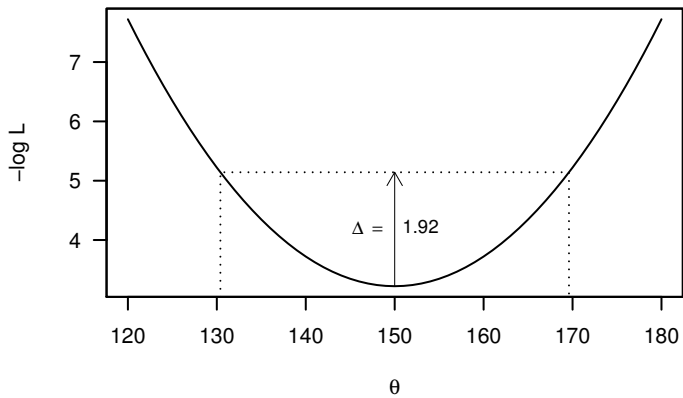
## Confidence interval



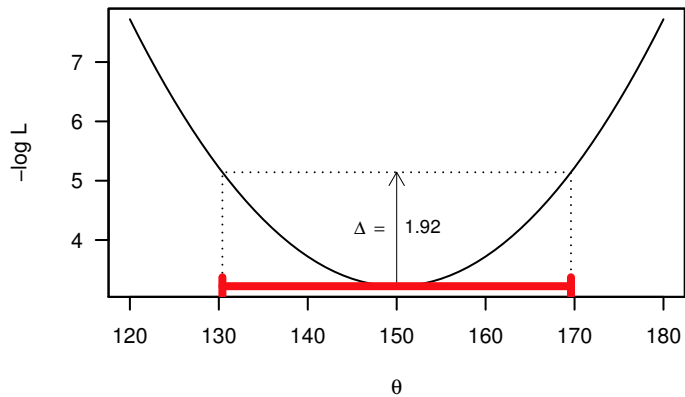
## Confidence interval



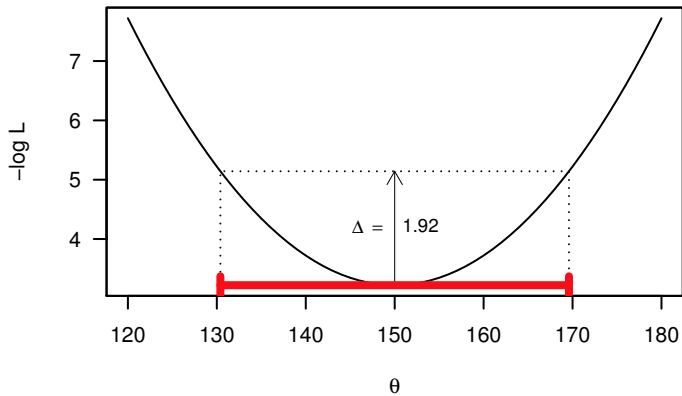
## Confidence interval



## Confidence interval



## Confidence interval



$0.5\chi^2_{df=1} = 1.92$  for 95% confidence interval

## Normal distribution

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$p(y_i|\theta) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(y_i-\mu_i)^2}{2\sigma^2}}$$

$$L(\theta|y) = \prod \left( \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(y_i-\mu_i)^2}{2\sigma^2}} \right)$$

$$-\log L = [0.5n \log(2\pi)] + n \log \sigma + \frac{\sum (y_i - \mu_i)^2}{2\sigma^2}$$

$$= [0.5n \log(2\pi)] + n \log \sigma + \frac{RSS}{2\sigma^2}$$

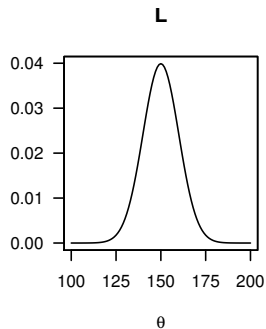


## dnorm in R

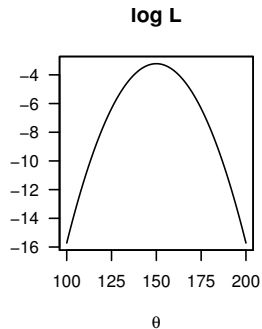
```
L <- prod(dnorm(y, mu, sigma))
```

```
neglogL <- -sum(dnorm(y, mu, sigma, log=TRUE))
```

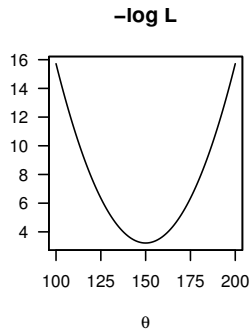
## dnorm in R



```
dnorm(theta,  
m=150, s=10)
```



```
dnorm(theta,  
m=150, s=10, log=TRUE)
```



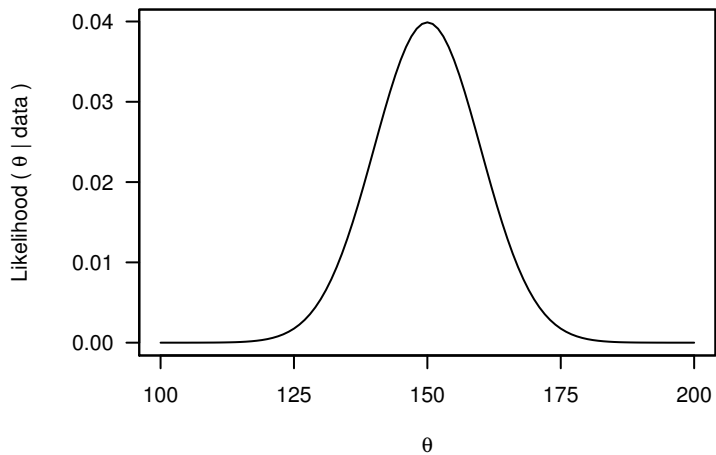
```
-dnorm(theta,  
m=150, s=10, log=TRUE)
```

## Profile likelihood

1. Fix  $\theta$  (a parameter of interest) at some value
2. Minimize  $-\log L$  by estimating all other parameters
3. Save this value of  $-\log L$

Repeat over a range of  $\theta$  values

## Profile likelihood



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