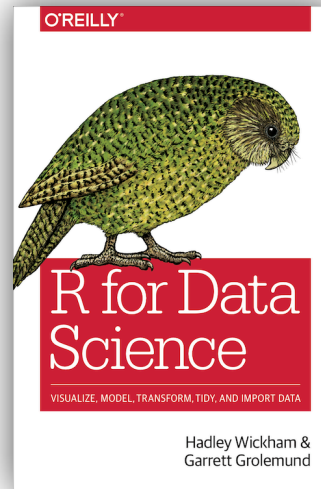
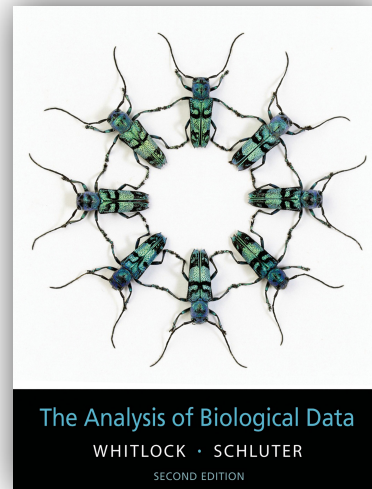


# Data Science in Bioinformatics

Palle Villesen & Thomas Bataillon

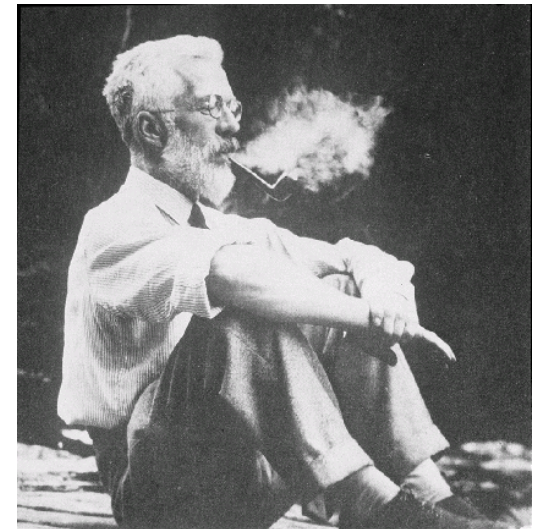


# Outline for week 13

- Tuesday: Chapter 20 Likelihood
  - Wasp example (R code)
  - Human trios (R markdown)
  - Important generalizations
- Thursday session is
  - Exercises on likelihood
  - Final assignment (prepare / post Qs)
- We need your feedback

# What is likelihood ? Why Bother?

- A general framework for **parameter estimation** and **hypothesis testing**
- An “old” idea (R.A. Fisher 1920s) that went a long way...
- Why likelihood is your “friend”
  - Think clearly about your data
  - Efficient way of extracting information from the data
  - Likelihood is often “hidden” behind tools you use...



# Likelihood in a nutshell

- Choose a **model  $M_\theta$**  for your data  **$D$**
- Write down the probability of your data  **$P(D)$**
- Figure out which parameter(s) value(s) of  $M_\theta$  **maximize  $P(D)$  (= make the data most likely)**
- Distrust your model !
- “Wash, rinse and repeat ...”

Which *model* behinds these data ?

=

Which probability *distributions* ?

- Height measurements of different individuals from a single population
- 
- Allele frequencies in a sample taken from a (large) population
  - Sex ratio in a progeny
  - Presence/ absence of a species in a locality

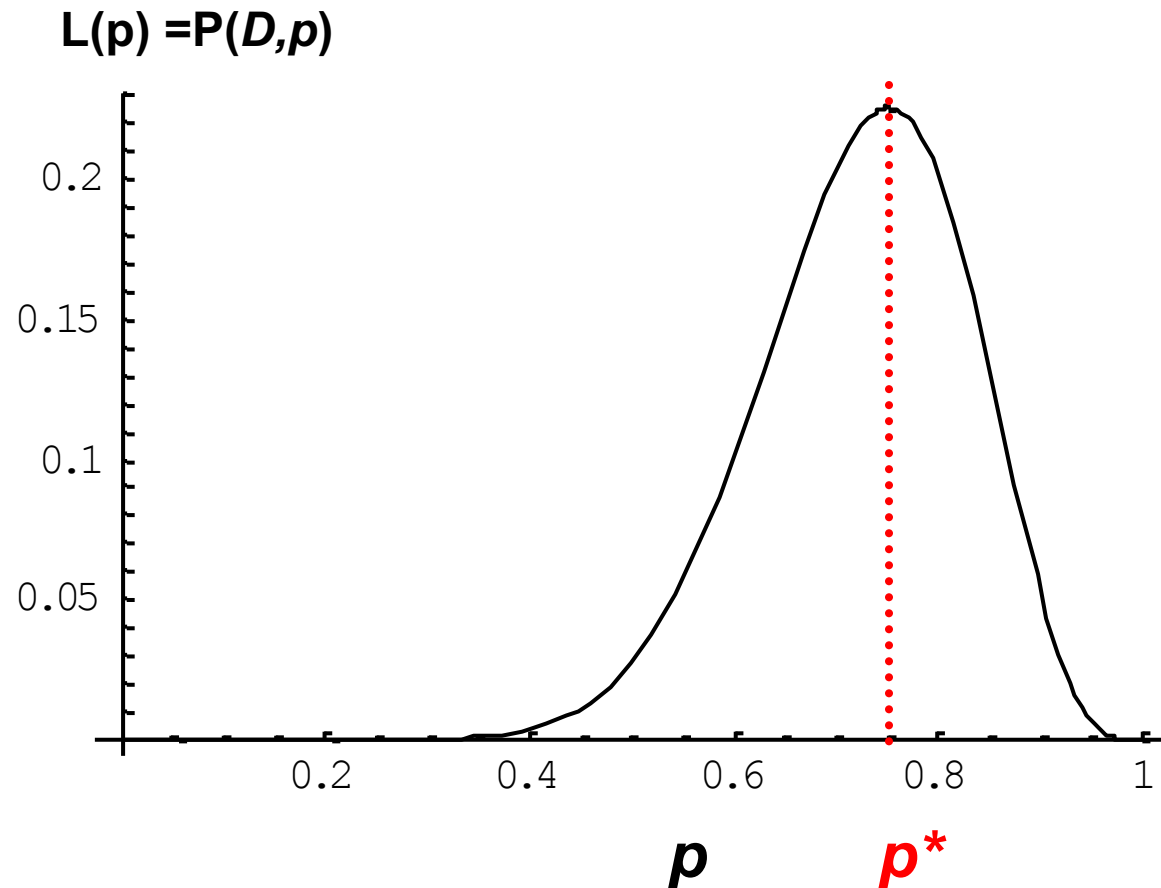
# The Binomial distribution

- “Thought Experiment”:
  - $n$  independent trials with probability of success  $p$  for each trial
  - $X$  is a **random variable**
  - Formally  $X \sim B(n,p)$
- What do we know about  $X$  ?
  - $E(X) = n p$     $V(X) = n p (1-p)$
  - $P(X=i) = \frac{n!}{i!(n-i)!} p^i (1-p)^{n-i}$
  - if  $n$  is large (  $np$  CONSTANT ) ,  $X$  becomes Poisson or even “normal”

# The Likelihood principle

- $L=P(D;\theta)$  is a function of data  $D$  and parameters  $\theta$
  - Likelihood principle:
    - The Data  $D$  is fixed
    - Choose the parameter(s) value(s)  $\theta^*$  that make the data  $D$  most likely
- > Maximize  $L$  (THAT's IT !)
- The **invariance principle**: if  $\alpha$  is a parameter and  $\beta=f(\alpha)$ , with  $f$  continuous and monotonic, then
$$ML_{\beta}=f(ML_{\alpha})$$

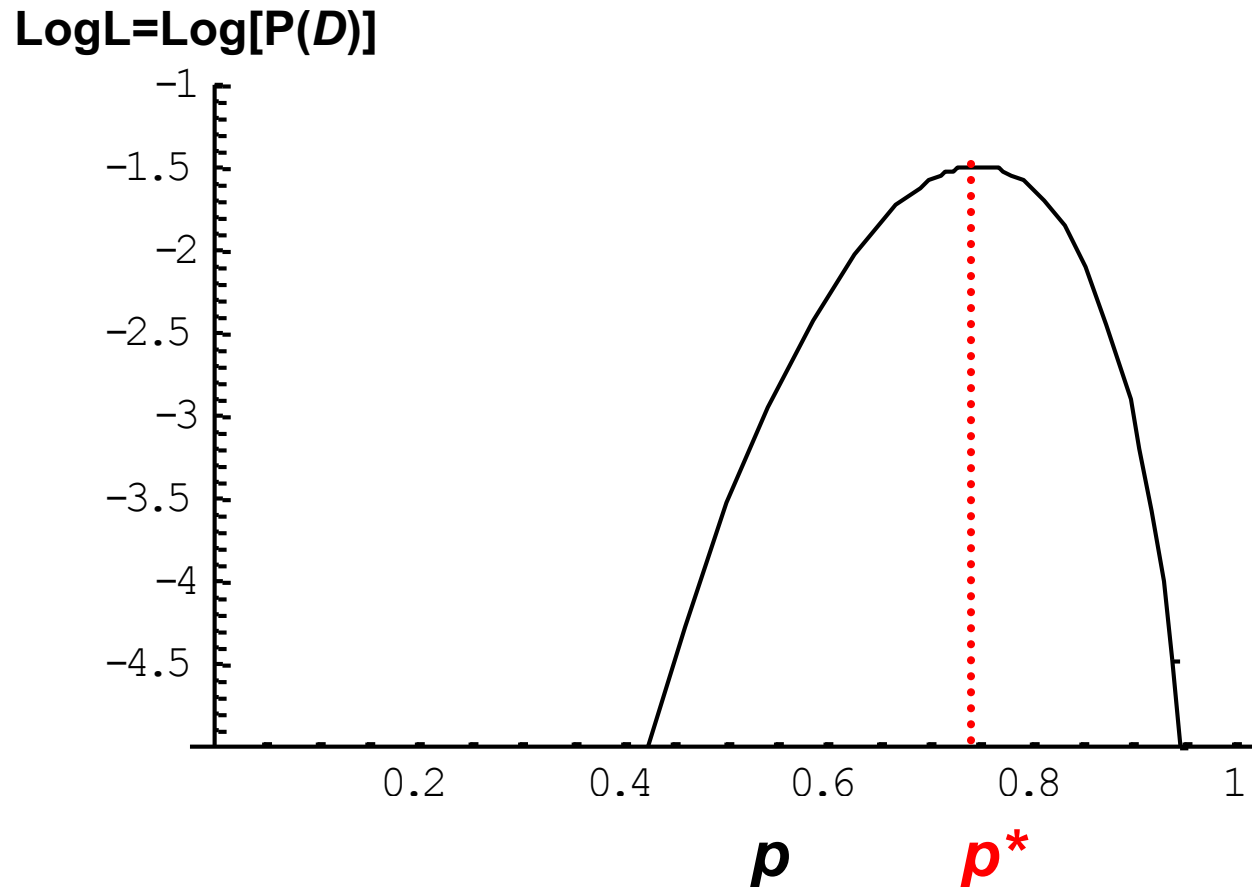
# Visualizing the likelihood function



NB:  $L$  is a **continuous** function defined for  $p$  in  $[0,1]$



# Visualizing the (natural) log Likelihood function

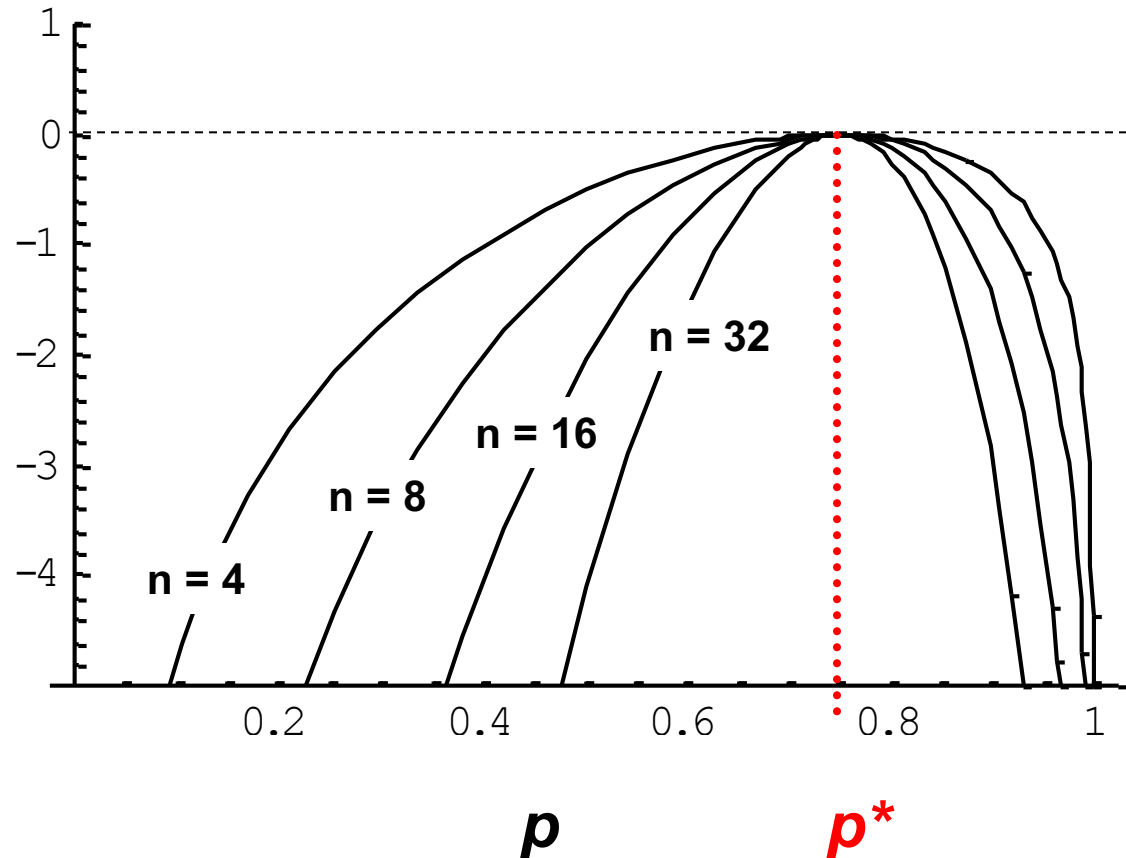


# Maximizing the likelihood

- Binomial example (continued)
- Finding the maximum of a function
  1. set the derivative to zero,
  2. check for a maximum.
- Generalization MLEs for several variables...

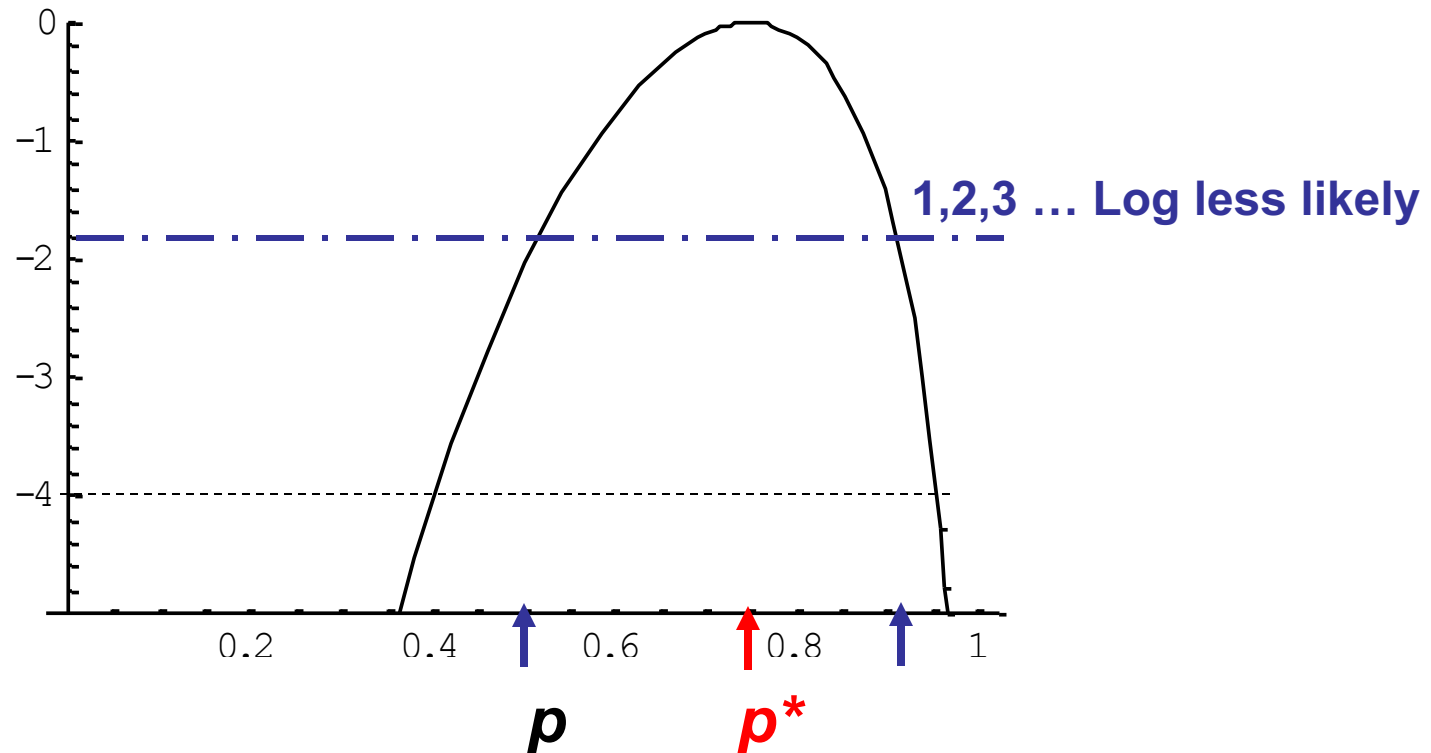
The curvature of Likelihood function reflects the amount of info in your data

$\text{Log}[L(p)] - \text{Log}[L(p^*)]$



# Visualizing the log Likelihood function rescaled

$\text{Log}[L(p)] - \text{Log}[L(p^*)]$

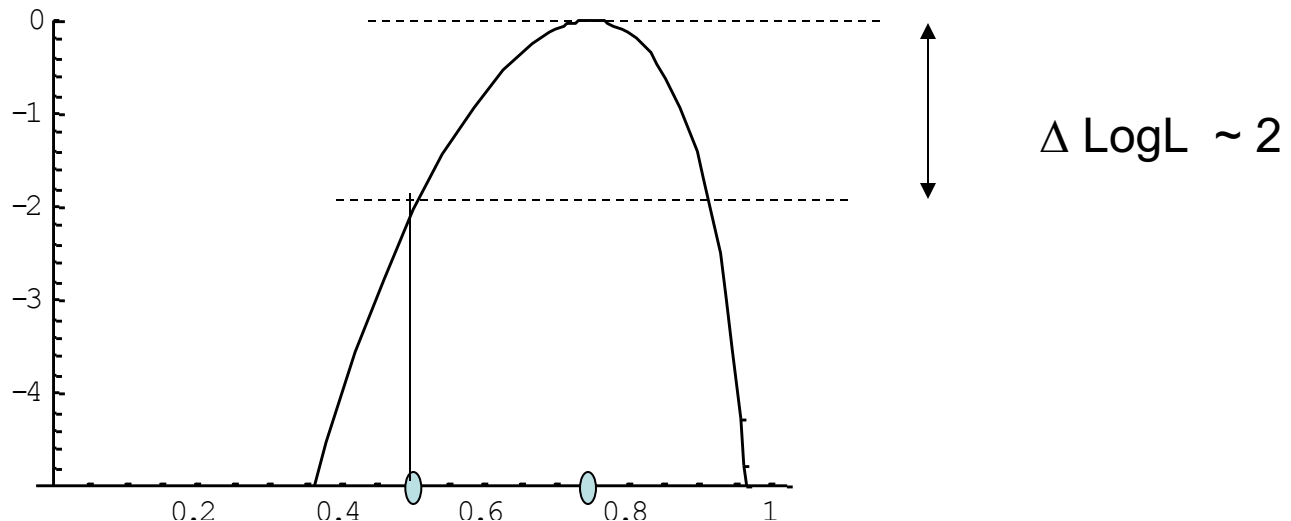


# The likelihood profile (graph)

- Intuition: curvature says something about the precision on ML estimates
- General results
  - **Asymptotic** normality of MLE
  - **Asymptotic** unbiased of MLE
  - Known sampling variance ...
  - Approximate 95% Confidence intervals:  
Find the region of parameter values that yield up to  $\sim 2$  log drop in likelihood ...

# Hypothesis testing in a likelihood framework

- Binomial example ...continued  
Q: How to test against the Fisherian  $\frac{1}{2}$  sex ratio?  
A: compare maximum likelihood with likelihood under the "model"  $p=1/2$ .



# The likelihood ratio test (LRT)

- Idea : comparing the fit of competing (**nested**) model to the data via their likelihood
- LRT statistic
  - 2 competing models  $M_a$  and  $M_b$  with  $M_b$  nested in  $M_a$
  - $G = 2[\text{LogL}(M_a) - \text{LogL}(M_b)]$
- What is the “null” distribution of  $\Lambda$  ?

If  $M_a$  is correct  $G \sim \chi^2_n$

$n$  is the difference in the number of free parameters fitted in  $M_a$  and  $M_b$

# Comparing non nested models

- Akaike's Information Criteria (AIC)
- Collection of Models
  - $M_1$        $n_1$  free parameters
  - $M_2$        $n_2$  free parameters
  - ...
- Compute AIC for each **fitted** model:  
$$AIC_i = -2 \log[L(M_i)] + 2 n_i$$
- Choose model with **lowest AIC**
- Perspective: robust estimation with **model averaging** ...



# Some good reads...

- **Lynch, M. and B. Walsh, *Genetics and Analysis of Quantitative Traits*. 1998, Sunderland: Sinauer Associates, Inc.**

Appendix 4 of this book is a good introduction to likelihood that reviews most of the general results that I find useful when analyzing real data. A bunch of worked simple examples. Connection between LT and the so called G test for goodness of fit

- **Burnham, Kenneth P., Anderson, David R. 2nd ed. 2002 *Model Selection and Multi-Model Inference A Practical Information-Theoretic Approach* Springer Verlag ISBN: 0-387-95364-7**

Good introduction to AIC and model selection/averaging

- **Likelihood AWF 1992 Edwards J. Hopkins U Press 2<sup>nd</sup> edition**

Old fashioned especially in the style and notations but this book was for me the only gateway to the more technical likelihood literature. A must if you enjoy the British academic style !