# Biostatistics

**Other topics** 

Nuno Sepúlveda, 22.01.2025

### Syllabus

#### 1. General review

- a. What is Biostatistics?
- b. Population/Sample/Sample size
- c. Type of Data quantitative and qualitative variables
- d. Common probability distributions
- e. Work example Malaria in Tanzania

#### 2. Applications in Medicine

- a. Construction and analysis of diagnostic tools Binomial distribution, sensitivity, specificity, ROC curve, Rogal-Gladen estimator
- b. Estimation of treatment effects generalized linear models
- c. Survival analysis Kaplan-Meier curve, log-rank test, Cox's proportional hazards model

#### 3. Applications in Genetics, Genomics, and other 'omics data

- a. Genetic association studies Hardy-Weinberg test, homozygosity, minor allele frequencies, additive model, multiple testing correction
- b. Methylation association studies M versus beta values, estimation of biological age
- c. Gene expression studies based on RNA-seq experiments Tests based on Poisson and Negative-Binomial

#### 4. Other Topics

- a. Estimation of Species diversity Diversity indexes, Poisson mixture models
- b. Serological data analysis Gaussian (skew-normal) mixture models

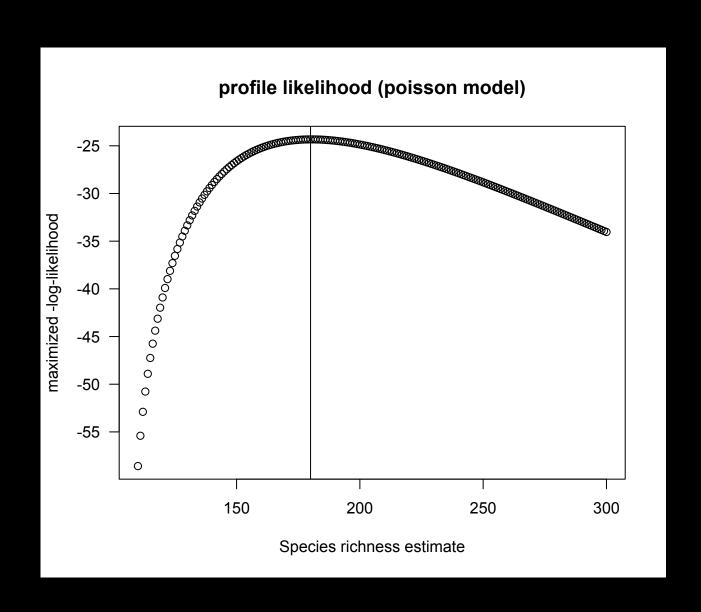
Abundance	Number of Species
0	D-k
1	m <sub>1</sub>
2	m <sub>2</sub>
3	m <sub>3</sub>
l	m <sub>l</sub>

Augmented Species-Abundance distribution

Second solution (profile likelihood)

$$f(\{m_i\} | D, \{\theta_i\}) = \frac{D!}{(D-k)! m_1! \cdots m_l!} \theta_0^{D-M} \prod_{i=1}^k \theta_i^{m_i}$$

- 1. Fix  $\hat{D}$ =k
- 2. Estimate the parameter of the Poisson distribution via maximum likelihood and calculate the respective maximized log-likelihood. (What is the MLE of  $\lambda$ ?
- 3. Do  $\hat{D} + 1$  in one unit and repeat previous step
- 4. Keep incrementing if the maximised log-likelihood is increasing
- 5. The estimate of D is the value immediately before when the maximized log-likelihood starts decreasing



# Exercise: Data\_lecture\_13\_TCR\_diversity.csv

Estimate the species richness D for the DP CD3low cells using the second solution.

	Thymus			Lymph	nodes
i	DP CD3low	SP CD4 <sup>+</sup>	SP CD8 <sup>+</sup>	LN CD4 <sup>+</sup>	LN CD8 <sup>+</sup>
1	79	33	16	34	17
2	17	6	3	8	8
3	6	2	3	2	1
4	5	2	5	1	2
5	1	0	3	0	1
6	1	0	1	0	0
7	1	0	1	0	0
8		0	1	1	0
10		1	0	1	0
11		0	1	0	0
16		1		0	0
20		0		1	0
21		0			1
28		1			0
52					1

Abundance	Number of Species
0	D-k
1	m <sub>1</sub>
2	m <sub>2</sub>
3	m <sub>3</sub>
I	m <sub>l</sub>

Calculation of a 95% confidence interval using the profile likelihood

Use the critical value of the Wilks's ratio test

$$H_0: D = D_0 \text{ versus } H_1: D \neq D_0$$

$$\Lambda = -2(\log L_{D_0} - \log L_{\hat{D}}) | H_0 \rightsquigarrow \chi^2_{(1)}$$
 critical value  $= q_{95\%,\chi^2_{(1)}}$ 

Augmented Species-Abundance distribution

accept 
$$H_0$$
 if  $\Lambda < q_{95\%,\chi^2_{(1)}}$ 

Abundance	Number of Species
0	D-k
1	m <sub>1</sub>
2	m <sub>2</sub>
3	m <sub>3</sub>
l	m <sub>l</sub>

Augmented Species-Abundance distribution

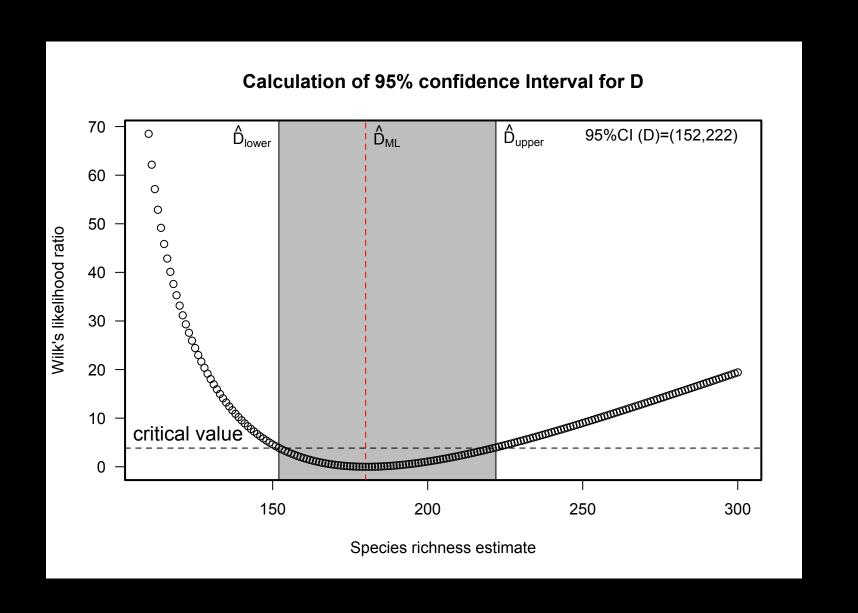
Calculation of a 95% confidence interval using the profile likelihood

Use the critical value of the Wilks's ratio test

$$q_{95\%,\chi_{(1)}^2} = -2(\log L_{D_0} - \log L_{\hat{D}})$$

$$(\hat{D}_{lower};\hat{D}_{upper})$$

 $\hat{D}_{lower}$  and  $\hat{D}_{upper}$  are the solutions of the above question



Abundance	Number of Species
1	$m_1$
2	m <sub>2</sub>
3	m <sub>3</sub>
1	m <sub>l</sub>
>	0

Pearson's goodness of fit test to check whether the model fits the data well

Use only the observed data

$$f(\{m_i\} | k, \{\theta_i\}) = \frac{k!}{m_1! \cdots m_l!} \prod_{i=1}^k \left(\frac{\theta_i}{1 - \theta_0}\right)^{m_i}$$

$$\hat{\theta}_i = \frac{e^{-\hat{\lambda}} \, \hat{\lambda}^i}{i!}$$

Augmented Species-Abundance distribution

# Exercise: Data\_lecture\_13\_TCR\_diversity.csv

Calculate the confidence interval for the species richness D for the DP CD3low cells using the profile likelihood plot. Check whether the Poisson model fits the data well using the Pearson's goodness of fit test.

	Thymus			Lymph	nodes
i	DP CD3low	SP CD4 <sup>+</sup>	SP CD8 <sup>+</sup>	LN CD4 <sup>+</sup>	LN CD8 <sup>+</sup>
1	79	33	16	34	17
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16		1		0	0
20		0		1	0
21		0			1
28		1			0
52					1

# Poisson-Gamma mixture model for estimating diversity richness

Abundance	Number of Species
0	D-k
1	m <sub>1</sub>
2	m <sub>2</sub>
3	m <sub>3</sub>
••••	
_	m <sub>l</sub>

Modelling  $\theta_i$ 

$$\theta_i = P[X = i \mid \lambda]$$

$$X \mid \lambda \rightsquigarrow \mathsf{Poisson}(\lambda)$$

$$X \mid \lambda \rightsquigarrow \mathsf{Poisson}(\lambda)$$
  $\lambda \mid \alpha, \beta \rightsquigarrow \mathsf{Gamma}(\alpha, \beta)$ 

$$P[X = x] = \int_0^\infty P[X = x \,|\, \lambda] P[\lambda] d\lambda = \int_0^\infty \frac{e^{\lambda} \lambda^x}{x!} \times \frac{\beta^{\alpha} \lambda^{\alpha - 1} e^{\beta \lambda}}{\Gamma(\alpha)} d\lambda$$

$$= \frac{\Gamma(i+\alpha)}{\Gamma(i+1)\Gamma(\alpha)} \left(\frac{\beta}{\beta+1}\right)^{\alpha} \left(\frac{1}{\beta+1}\right)^{i}$$

**Augmented Species-Abundance** distribution

**Negative Binomial** 

Abundance	Number of Species
0	D-k
1	m <sub>1</sub>
2	m <sub>2</sub>
3	m <sub>3</sub>
••••	
_	m <sub>l</sub>

First solution (truncated Negative Binomial)

$$k \mid D, \theta_0 \Rightarrow \text{Binomial}(D, 1 - \theta_0)$$

$$f(\lbrace m_i \rbrace | k, \lbrace \theta_i \rbrace) = \frac{k!}{m_1! \cdots m_l!} \prod_{i=1}^k \left( \frac{\theta_i}{1 - \theta_0} \right)^{m_i}$$

- 1. Estimate a Poisson truncated at zero using raw data only
- 2. Estimate D from the binomial using  $\hat{D} = \frac{k}{1 \hat{\theta}_0}$

$$\hat{\theta}_0 = e^{-\hat{\lambda}}$$

Abundance	Number of Species
0	D-k
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l	m <sub>l</sub>

Augmented Species-Abundance distribution

Second solution (profile likelihood)

$$f(\{m_i\} | D, \{\theta_i\}) = \frac{D!}{(D-k)!m_1!\cdots m_l!} \theta_0^{D-M} \prod_{i=1}^k \theta_i^{m_i}$$

- 1. Fix  $\hat{D}$ =k
- 2. Estimate the parameters of the Negative distribution via maximum likelihood and calculate the respective maximized log-likelihood. (What is the MLE of  $\lambda$ ?
- 3. Do  $\hat{D}+1$  in one unit and repeat previous step
- 4. Keep incrementing if the maximised log-likelihood is increasing
- 5. The estimate of D is the value immediately before when the maximized log-likelihood starts decreasing

# Exercise: Data\_lecture\_13\_TCR\_diversity.csv

Estimate the species richness D for the DP CD3low cells using the Negative Binomial distribution. Estimate via the second solution.

	Thymus			Lymph	nodes
i	DP CD3low	SP CD4 <sup>+</sup>	SP CD8 <sup>+</sup>	LN CD4 <sup>+</sup>	LN CD8 <sup>+</sup>
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### Serology



INFECTED

after infection.

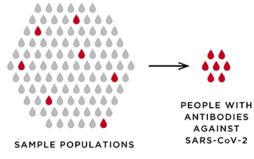
**Serology**, or **antibody**, testing checks a sample of a person's blood to look for antibodies against SARS-CoV-2, the virus that causes COVID-19. Antibodies usually become detectable in the blood **1-3 weeks** after someone is infected.

may not develop antibodies. It is currently unknown how long antibodies are detectable



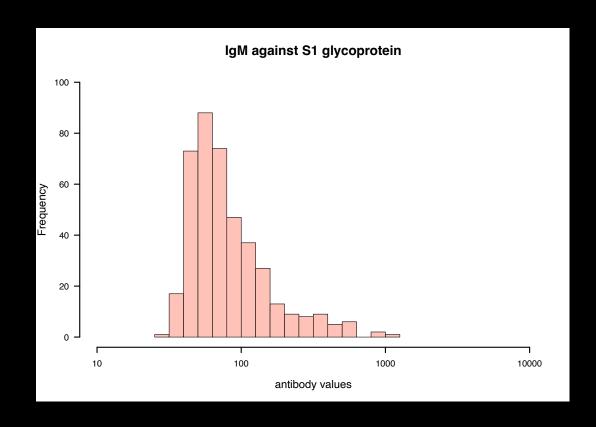
### Sero-epidemiological surveys

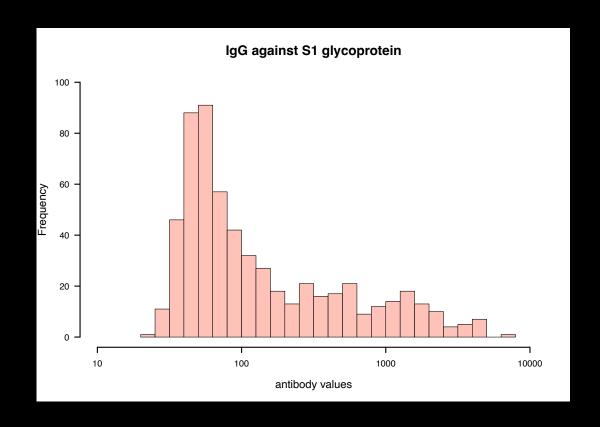
#### Seroprevalence



The percentage of individuals in a population who have antibodies to an infectious agent is called **seroprevalence.** 

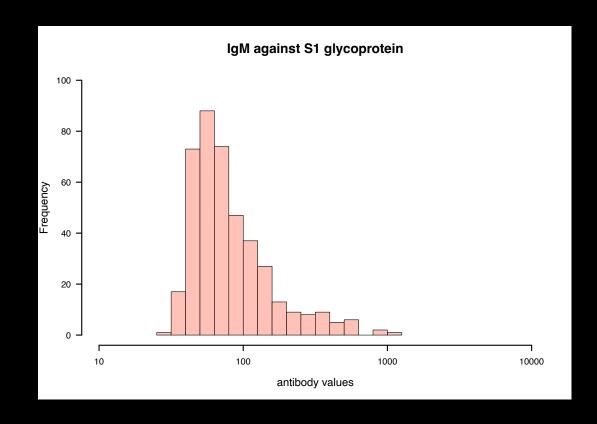
### Antibody data are intrinsically quantitative

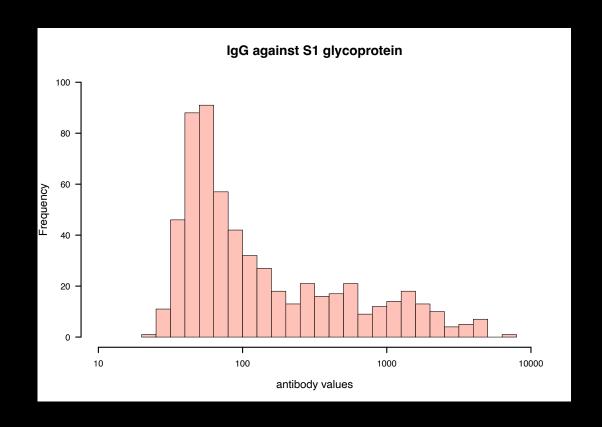




Rosado et al (2020). Serological signatures of SARS-CoV-2 infection: Implications for antibody-based diagnostics. medRxiv 2020.05.07.20093963.

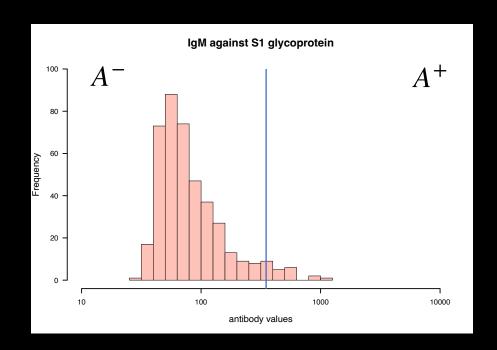
### Who are the seropositive individuals?

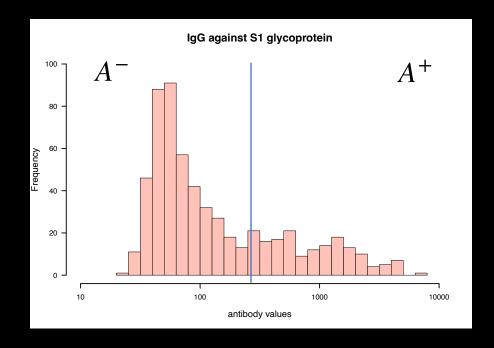


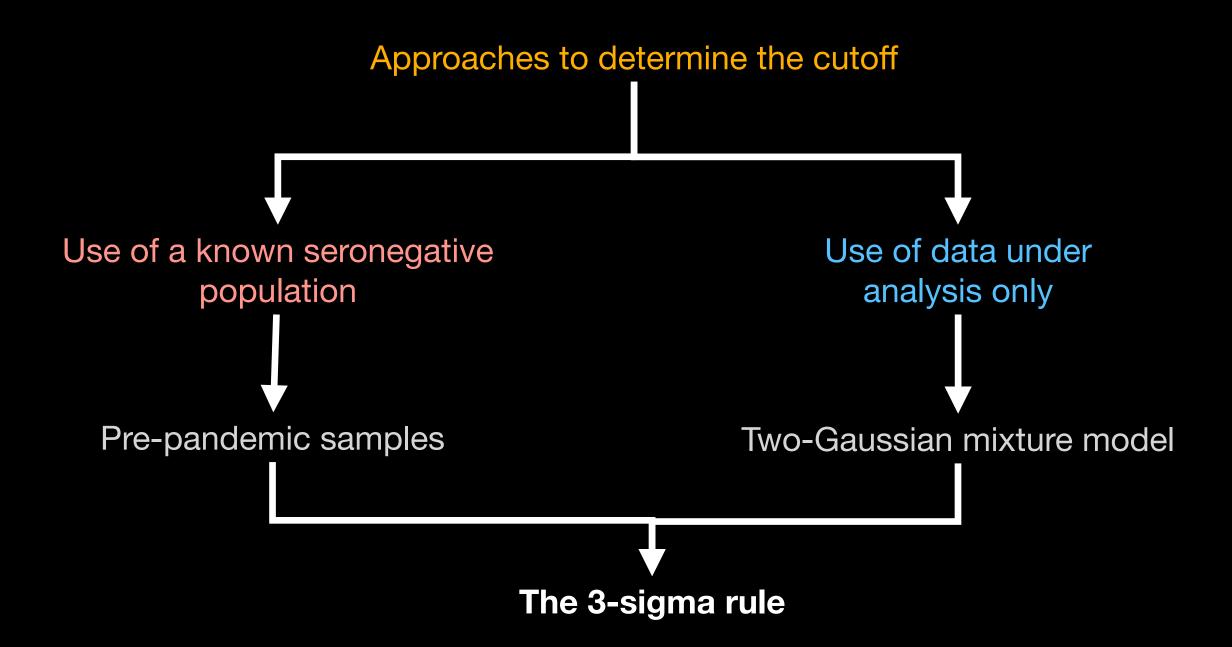


Rosado et al (2020). Serological signatures of SARS-CoV-2 infection: Implications for antibody-based diagnostics. medRxiv 2020.05.07.20093963.

### How to determine the cut-off?







# Approaches to determine the cutoff Use of data under Use of a known seronegative population analysis only Pre-pandemic samples Two-Gaussian mixture model The 3-sigma rule

### The 3-sigma rule

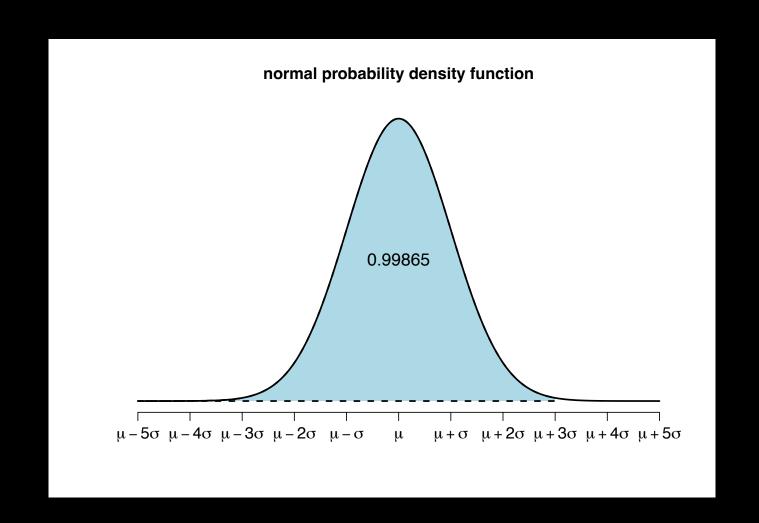
$$\mu_{A^{-}} = E\left[X \mid A^{-}\right]$$

$$\sigma_{A^{-}} = \sqrt{Var\left[X|A^{-}\right]}$$

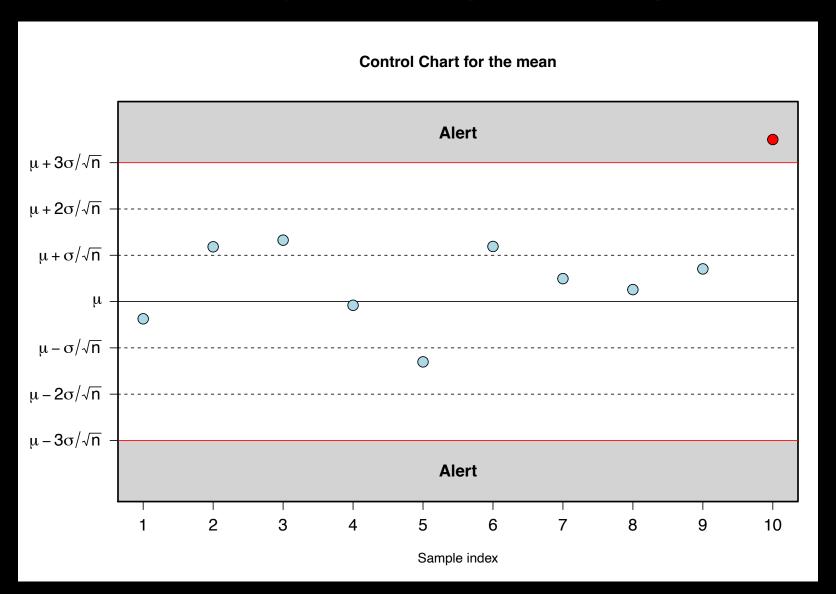
Seronegative, if  $X_i \leq \mu_{A^-} + 3\sigma_{A^-}$ 

Seropositive, otherwise

### The link to the Normal distribution



## **Quality control (Shewhart)**



### In practice (known seronegative population)

$$\mu_{A^-} o ar{X}_{A^-}$$

$$\sigma_{A^-} o S_{A^-}$$

Seronegative, if  $x_i \leq \bar{X}_{A^-} + 3s_{A^-}$ 

Seropositive, otherwise

### Theoretical property of the 3-sigma

Cantelli-Chebyshev inequality

$$P\left[X \ge \mu + \lambda\right] \le \frac{\sigma^2}{\sigma^2 + \lambda^2}, \text{ if } \lambda > 0$$

$$\mu = E[X]$$
  $\sigma^2 = Var[X] < \infty$ 

Application to  $\lambda = 3\sigma$ 

$$P\left[X \ge \mu_{A^{-}} + 3\sigma_{A^{-}}\right] \le \frac{1}{10} \equiv 0.1$$



$$P\left[X < \mu_{A^-} + 3\sigma_{A^-}\right] > 0.9$$

### Exercise: data\_lecture\_14\_SARS\_COV2\_serology.csv

Articles

Multiplex assays for the identification of serological signatures of SARS-CoV-2 infection: an antibody-based diagnostic and machine learning study



Jason Rosado, Stéphane Pelleau, Charlotte Cockram, Sarah Hélène Merkling, Narimane Nekkab, Caroline Demeret, Annalisa Meola, Solen Kerneis, Benjamin Terrier, Samira Fafi-Kremer, Jerome de Seze, Timothée Bruel, François Dejardin, Stéphane Petres, Rhea Longley, Arnaud Fontanet, Marija Backovic, Ivo Mueller, Michael T White



Apply the 3s-rule to pre-pandemic samples (status=negative) to calculate the cut-off for seropositivity of the anti-Spike-protein antibodies (Spike\_IPP\_IgG\_MFI).

Calculate the proportion of these samples are above the threshold and check if this proportion agrees with the Cantelli-Chebyshev inequality.

Is the Normal distribution a reasonable distribution for the samples of SARS-CoV2-infected individual?

Apply this cutoff to calculate seroprevalence in SARS-CoV2-infected individual (status=positive).

# Approaches to determine the cutoff Use of data under Use of a known seronegative population analysis only Two-Gaussian mixture model Pre-pandemic samples The 3-sigma rule

### Gaussian mixture models

$$f_X(x) = \sum_{i=1}^k \pi_i f_{N(\mu_i, \sigma_i)}(x) \qquad \text{where } \sum_{i=1}^k \pi_i = 1$$

The most common model  $\rightarrow k = 2$ 

$$f_X(x) = (1 - \pi) f_{N(\mu_{S^-}, \sigma_{S^-})}(x) + \pi f_{N(\mu_{S^+}, \sigma_{S^+})}(x)$$

Definition of  $S^- \Rightarrow \mu_{S^-} < \mu_{S^-}$ 

### Estimation of the model

#### EM (Expectation-Maximization) Algorithm

- 1. Start with initial estimates for the parameters
- 2.E-Step calculate the probability of each individual belonging to a given subpopulation according to estimates at 1.
- 3.M-Step re-estimate the parameters using these probabilities and repeat the E-step with these new estimates
- 4. Stop with the increment in the log-likelihood is below a given tolerance error.

Package mixtools

### Estimation of the model

EM (Expectation-Maximization) Algorithm

- 1. Start with initial estimates for the parameters
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- 3.M-Step re-estimate the parameters using these probabilities and repeat the E-step with these new estimates
- 4. Stop with the increment in the log-likelihood is below a given tolerance error.

Calculate the cutoff for seropositivity according to  $\hat{\mu}_{S^-}$  and  $\hat{\sigma}_{S^-}$ 

Package mixtools

### Exercise: data\_lecture\_14\_SARS\_COV2\_serology.csv



Use the normalmixEM from the mixtools package to estimate a two-Gaussian mixture model to the data of anti-Spike-protein antibodies (Spike\_IPP\_IgG\_MFI) from the SARS-CoV2-infected individual (status=positive).

Apply the 3s-rule to calculate the respective cut-off for seropositivity of the anti-Spike-protein antibodies (Spike\_IPP\_IgG\_MFI).

Apply this cutoff to estimate the seroprevalence in these individuals.