

# How to assess MH statistical significance in future projects

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# 1 The usual deal

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# 2 Frequentist methods

**1** The usual deal

**2** Frequentist methods

**3** Bayesian methods

- 1 The usual deal
- 2 Frequentist methods
- 3 Bayesian methods
- 4 Summary and conclusions

# 1 The usual deal

## 2 Frequentist methods

## 3 Bayesian methods

## 4 Summary and conclusions

# Parameter estimation sensitivity

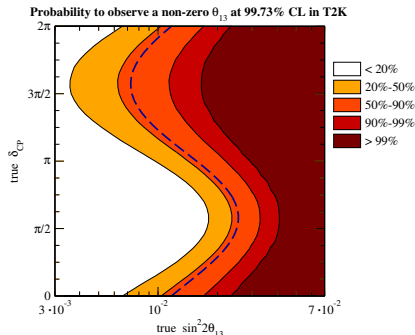
- Define the test statistic “ $\Delta\chi^2$ ”

$$\Delta\chi^2(\theta) = -2 \log \left[ \frac{\mathcal{L}(\theta|d)}{\sup_{\theta'} \mathcal{L}(\theta'|d)} \right]$$

- Assume it is  $\chi^2$  distributed with  $n$  degrees of freedom
- Use the data set without statistical fluctuations (Asimov data)
- Quote result

# The interpretation

- $\Delta\chi^2$  is asymptotically  $\chi^2$  (Wilk's theorem)
- The Asimov data is representative
- Works for *nested hypotheses*
- Some additional requirements



Schwetz, Phys.Lett. B648 (2007) 54



# Not a nested hypothesis

- Mass ordering is not nested
- Wilk's theorem not applicable
- Some different choices of test statistic

$$\Delta\chi^2 = \chi_{\text{NO}}^2 - \min \chi^2$$

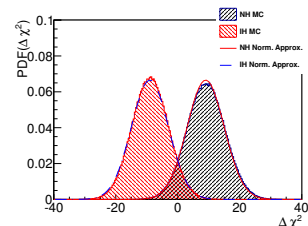
$$T = \chi_{\text{IO}}^2 - \chi_{\text{NO}}^2$$

$$T' = \chi^2(\theta) - \min \chi^2$$

- All have different distributions
- We concentrate on  $T$

$$T \simeq \mathcal{N}(T_0, 2\sqrt{T_0})$$

$T_0$  = value for Asimov data



Qian, et al., Phys.Rev. D86 (2012) 113011

1 The usual deal

**2 Frequentist methods**

3 Bayesian methods

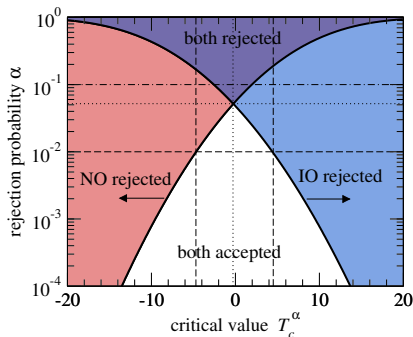
4 Summary and conclusions

# Back to basics

- Hypothesis testing
- Test hypothesis  $H_0$ , alternative hypothesis  $H_1$
- Critical region defined by  $T_c$
- Reject  $H_0$  if  $T < T_c$
- Test significance:  $1 - \alpha = 1 - P(T < T_c | H_0)$
- Test power:  $1 - \beta = P(T < T_c | H_1)$
- *Both*  $\alpha$  and  $\beta$  are relevant

# Testing both orderings

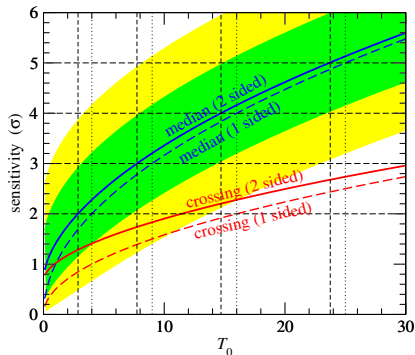
- Depending on the significance it may be possible to:
  - Reject exactly one hypothesis
  - Reject both hypotheses
  - Not reject any hypothesis
- It is natural, the true hypotheses *should* be rejected with probability  $\alpha$



MB, Coloma, Huber, Schwetz, arXiv:1311.1822

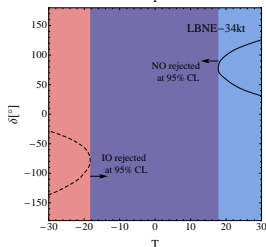
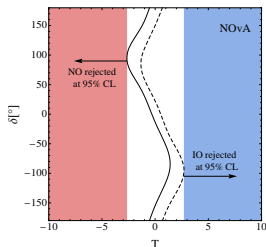
# Simple hypotheses

- Hypotheses are not parameter dependent
- Nyman-Pearson lemma applies
- Straight forward
- Applicable to reactor experiments



MB, Coloma, Huber, Schwetz, arXiv:1311.1822

# Composite hypotheses



- Hypotheses that have parameter dependence
- To reject = Rejecting all parameter sets
- Distribution of  $T$  is parameter dependent

$$T_c = \min_{\theta} T_c(\theta)$$

- Extensive Monte Carlo simulations
- Approximation (must check validity)

$$T(\theta) = \mathcal{N}(T_0(\theta), 2\sqrt{T_0(\theta)})$$

MB, Coloma, Huber, Schwetz,  
arXiv:1311.1822

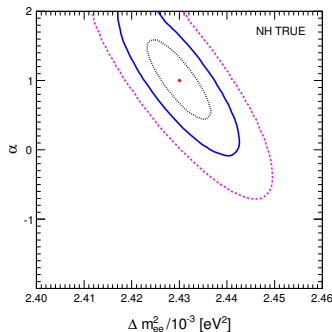
# Interpolating parameters

- Introduce an interpolating continuous parameter  $\alpha$  such that

$$P(\alpha = \pm 1, \theta) = P(\theta, \text{NO/IO})$$

see, e.g., Capozzi, Lisi, Marrone, arXiv:1309.1638

- Wilk's theorem now applies
- Put bounds on  $\alpha$
- If  $\alpha = 1$  ( $-1$ ) is allowed, NO (IO) is allowed
- Personal comment:  $\alpha = 0$  is not special, it being allowed a priori does not affect the rejection of NO/IO

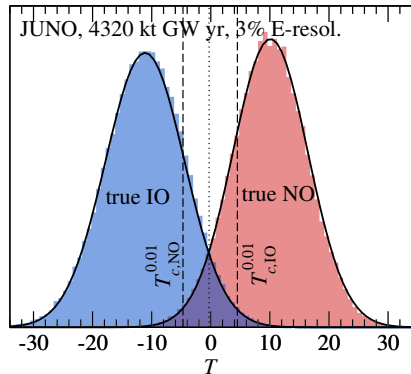


Capozzi, Lisi, Marrone, arXiv:1309.1638

# Reactor experiments

- Distribution of  $T$  essentially parameter independent
- Simple hypotheses
- Gaussian limit well satisfied
- Median sensitivity  $n\sigma$ :

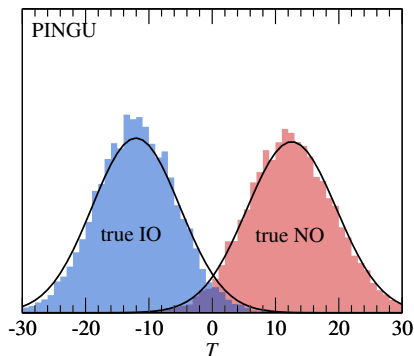
$$n \simeq \sqrt{2} \operatorname{erfc}^{-1} \left[ \frac{1}{2} \operatorname{erfc} \left( \sqrt{\frac{T_0}{2}} \right) \right]$$



MB, Coloma, Huber, Schwetz, arXiv:1311.1822



# Atmospheric experiments



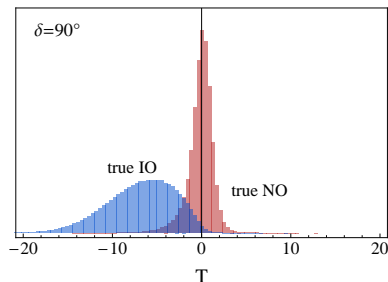
MB, Coloma, Huber, Schwetz, arXiv:1311.1822

- Distribution of  $T$  mainly depends on  $\theta_{23}$
- Gaussianity is still well satisfied for each  $\theta_{23}$
- Analytic as function of  $T_0(\theta_{23})$
- Boils down to evaluating the Asimov data:  $T_0$

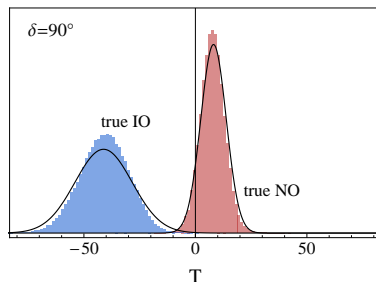
# Accelerator experiments - distributions

- Not always Gaussian!
- Typical for low-sensitivity experiments
- Need to perform Monte Carlo studies for accuracy
- Rejection power *depends on the true parameters*

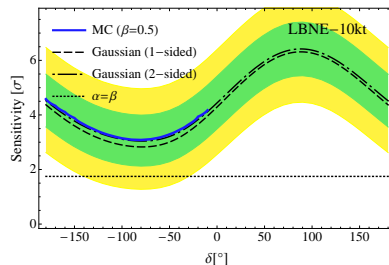
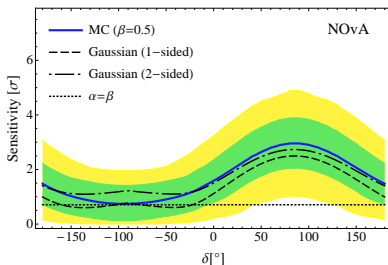
NO $\nu$ A



LBNE

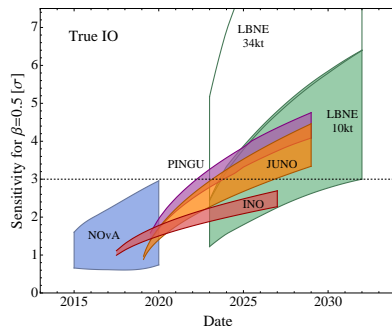
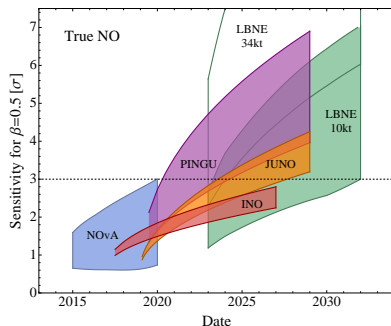


# Accelerator experiments - results



MB, Coloma, Huber, Schwetz, arXiv:1311.1822

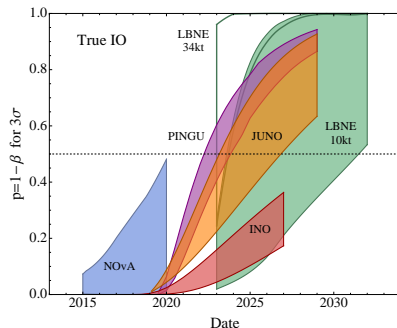
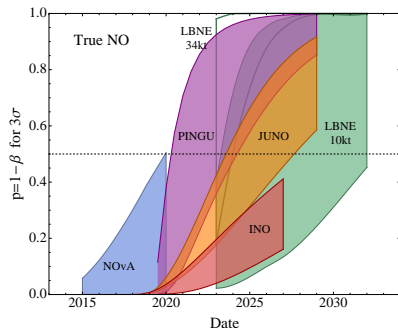
# Comparison of experiments - specific $\beta$



MB, Coloma, Huber, Schwetz, arXiv:1311.1822

**Note:** Bands have different meanings!

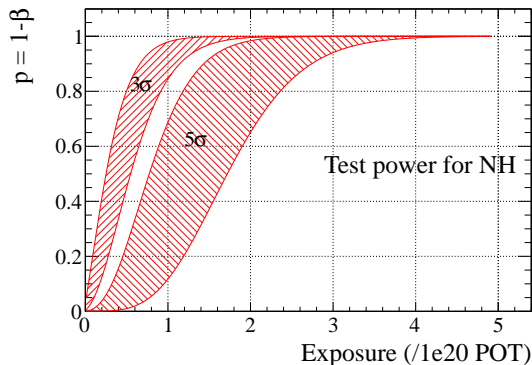
# Comparison of experiments - specific $\alpha$



MB, Coloma, Huber, Schwetz, arXiv:1311.1822

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# LBNO predictions



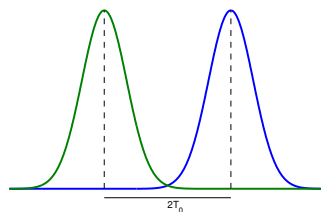
LBNO collaboration, arXiv:1312.6520

# At the end of the day

For the simple hypotheses:

- Two Gaussians,  
 $H_{\pm} : \mathcal{N}(\pm T_0, 2\sqrt{T_0})$
- For  $H_+$ , *typical* (median) result is  $+T_0$
- $+T_0$  is  $T_0 - (-T_0) = 2T_0$  away from the expected  $H_-$  result
- $2T_0 / (2\sqrt{T_0}) = \sqrt{T_0}$

See also: Vitelis, Read, 1311.4076



# How to interpret the median sensitivity

- It is *representative* for how well the experiment will do
- 50 % probability of not reaching it
- 50 % probability of *doing better*
- *Not* 50 % probability of “being wrong”
- Not the only relevant quantity, distribution matters (do Brazilian bands!)
- Personal preference: Quote the power  $1 - \beta$  for a target sensitivity



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# Bayesian basics

- Assign a degree of belief in each hypothesis  $P(H)$
- Update the degree of belief depending on observations
- Bayes' theorem

$$P(A, B) = P(A; B)P(B) = P(B; A)P(A)$$

$$P(A; B) = \frac{P(B; A)P(A)}{P(B)}$$

- Take  $A =$  hypothesis  $H$ ,  $B =$  data  $d$

$$P(H; d) = \frac{\mathcal{L}_H(d)P(H)}{P(d)}$$

# Bayesian hypothesis testing

- Study the relative degrees of belief in two hypotheses

$$\frac{P(H_1; d)}{P(H_2; d)} = \frac{\mathcal{L}_{H_1}(d) P(H_1)}{\mathcal{L}_{H_2}(d) P(H_2)}$$

- Strength of the evidence for  $H_1$ :

$$\kappa = 2 \log \left[ \frac{P(H_1; d)}{P(H_2; d)} \right]$$

- Kass-Raftery scale:

Strength of evidence for H	$\kappa$	Posterior odds	Degree of belief
Barely worth mentioning	0 to 2	ca 1 to 3	< 73.11%
Positive	2 to 6	ca 3 to 20	> 73.11%
Strong	6 to 10	ca 20 to 150	> 95.26%
Very strong	> 10	$\gtrsim$ 150	> 99.33%

# What can be said about the future?

- Can compute probability of obtaining evidence at least strength  $\kappa_0$  for the true ordering

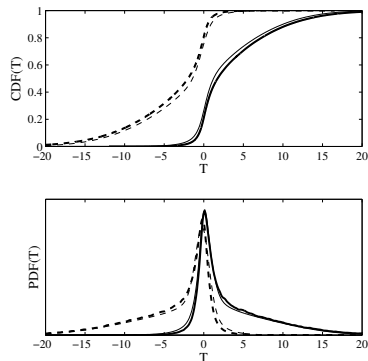
$$P(\kappa_0) = P(\kappa > \kappa_0; H_1)P(H_1) + P(\kappa < -\kappa_0; H_2)P(H_2)$$

- Typical choice  $P(H_1) = P(H_2) = 0.5$
- Takes into account information on oscillation parameters

$$\mathcal{L}_H(d) = \int \mathcal{L}_{H(\theta)}(d)\pi(\theta)d\theta$$

- Compactifies all of the available information to one number
- Easy to simulate through Monte Carlo methods
- Prior dependent

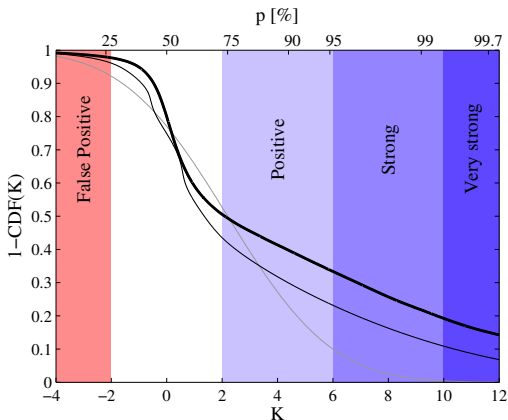
# Example: $\text{NO}\nu\text{A}$



MB, arXiv:1311.3183

- $\text{NO}\nu\text{A}$  experiment
- GLoBES implementation
- Only  $\delta$  and  $\Delta m_{31}^2$  varying
- Flat and 10 % Gaussian priors, respectively

# Example: $\text{NO}\nu\text{A}$ , results



MB, arXiv:1311.3183

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# Summary and conclusions

- Wilk's theorem is not applicable, the test statistic is not  $\chi^2$  distributed
- Regardless,  $\sqrt{T_0}$  is still a good approximation of the (median) sensitivity
- Frequentist methods are perfectly applicable
- Bayesian methods equally applicable, matter of preference
- Important not to mix the concepts and be aware of the proper interpretation