A short discussion about statistical methods

Shi Xiaodong, Peng Haiping State Key Laboratory of Particle Detection and Electronics University of Science and Technology of China

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Outline

- Introduction
- Bayes Method
- Frequentist Method
- Wald approximation for profile likelihood ratio

Introduction

In particle physics experiments, results' statistical significance can be quantified by p-value or its equivalent Gaussian significance. When the significance is not strong, the upper limit is expected to describe the sensitivity.

There are two basic statistic method: Bayes and Frequentist.

Bayes Method

Bayes' theorem (alternatively Bayes' law or Bayes' rule) describes the probability of an event, based on **prior** knowledge of conditions that might be related to the event.

Bayes' law:
$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{\sum_{j} P(B|A_j)P(A_j)}$$

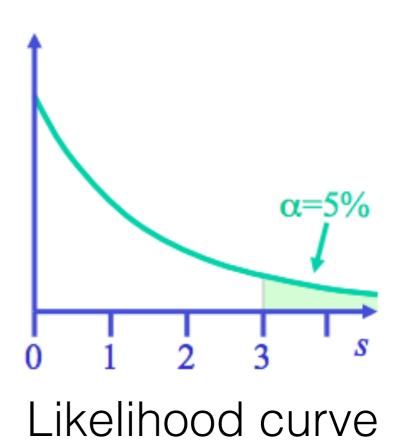
$$f(\theta|x) = \frac{f(x|\theta)f(\theta)}{p(x)} = \frac{f(x|\theta)f(\theta)}{\int f(x|\theta)f(\theta)d\theta}$$

Bayes Method

 To get the upper limit. One needs to assume varying signal strengths, then get the likelihood values by fitting, then integrate the likelihood curve to make the formula equals to (1-alpha).

$$\int_0^{s^{\text{up}}} P(s|n) ds = \frac{\int_0^{s^{\text{up}}} L(n;s)\pi(s) ds}{\int_0^{\infty} L(n;s)\pi(s) ds}$$

A uniform prior, $\pi(s) = 1$



 Frequentist inference is a type of statistical inference that draws conclusions from sample data by emphasizing the **frequency** or proportion of the data. An alternative name is frequentist statistics.

—Wikipedia

$$P(A) = Limit_{N \to \infty} \frac{N_A}{N}$$

Do experiment with infinite times.

Hypothesis Testing (Frequentist Technique)

Null hypothesis H₀: hypothesis which you try to falsify / reject

Always just bkg.

Test statistic t: any function of your data which is used

to quantify (dis-)agreement with H₀

(one can not verify / approve hypothesis)

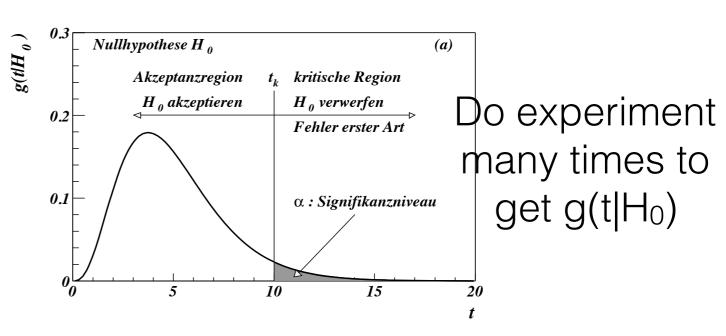
g(t|H0): probability density function PDF for test statistics

under null hypothesis H₀

Critical region: range of test statistic for which H₀ is rejected

a: significance (level)
size of test
error of 1st kind.
probability to reject H₀,
if H₀ is true

$$\alpha = \int_{t_k}^{\infty} g(t|H_0)dt.$$



• p-value: probability to observe at least n_{obs} events if the null hypothesis H_0 (s=0) is true

Hypothesis Testing

In principle: infinity many possibilities to choose critical region for given α (especially for one sided tests you need an alternative hypothesis to decide what you call inconsistent with null hypothesis)

Alternative hypothesis H_1 : hypothesis which you would like to approve

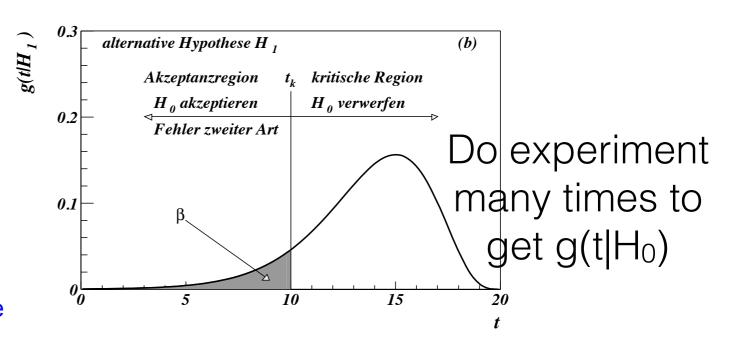
 $g(t|H_1)$: probability density function for test statistics under alternative hypothesis H_1

Include bkg & signal.

$$\beta = \int_{-\infty}^{t_k} g(t|H_1)dt.$$

β: error of 2nd kind M=1-β: power

β prob. to reject H₁, if H₁ is true 1-β prob to "accept" H₁, if H₁ is true



How to do experiment many times?

One way is:

Sample the number observed with Poisson function many times. For one time, get one t value. After sample enough times(do experiment), one can get g(t|H0). Then one can get p-value. If the result is a distribution, split into several bins then sample in every bin.

In order to get upper limit, one can get a p_{μ} -value for each $H_{\mu}(\mu \text{ is POI}, \text{ parameter of interest})$. Then 90% CLupper limit on μ is highest value for p_{μ} -value is not less than 0.1.

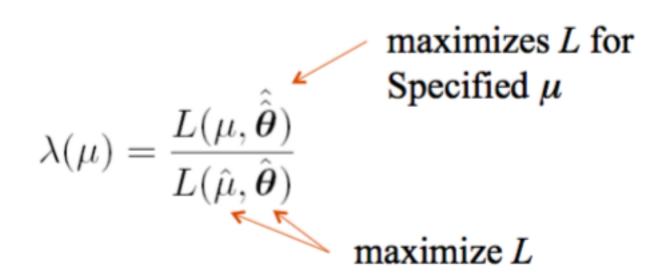
One technology problem:

In order to get p.d.f. of test statistic(t), one need to sample for many times, calculate t for many times. To get the upper limit, one need much more cpu time.

One solution: use asymptotic formulae for special t.

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Base on the profile likelihood ratio:



the parameter μ determines the strength of the signal process use $\boldsymbol{\theta} = (\boldsymbol{\theta}_s, \boldsymbol{\theta}_b, b_{\text{tot}})$ to denote all of the nuisance parameters.

We can use $t_{\mu} = -2 \ln \lambda(\mu)$ as test statistic.

Use approximation due to Wald (1943)

$$-2\ln\lambda(\mu) = \frac{(\mu-\hat{\mu})^2}{\sigma^2} + \mathcal{O}(1/\sqrt{N})$$

$$\hat{\mu} \sim \text{Gaussian}(\mu',\sigma)$$
 sample size

μ' H₀

If we can neglect the $O(1/\sqrt{N})$ term, $-2\ln\lambda(\mu)$ follows a noncentral chi-square distribution for one degree of freedom with noncentrality parameter

$$\Lambda = \frac{(\mu - \mu')^2}{\sigma^2}$$

$$f(t_{\mu};\Lambda) = \frac{1}{2\sqrt{t_{\mu}}} \frac{1}{\sqrt{2\pi}} \left[\exp\left(-\frac{1}{2} \left(\sqrt{t_{\mu}} + \sqrt{\Lambda}\right)^2\right) + \exp\left(-\frac{1}{2} \left(\sqrt{t_{\mu}} - \sqrt{\Lambda}\right)^2\right) \right]$$

The Asimov data set To estimate sigma, consider special data set where all statistical fluctuations suppressed and parameters are replaced by their expectation values. $\hat{\mu} = \mu' \quad \hat{\theta} = \theta$

$$\lambda_{\rm A}(\mu) = \frac{L_{\rm A}(\mu,\hat{\pmb{\theta}})}{L_{\rm A}(\hat{\mu},\hat{\pmb{\theta}})} = \frac{L_{\rm A}(\mu,\hat{\pmb{\theta}})}{L_{A}(\mu',\hat{\pmb{\theta}})} \quad \text{Asimov value of } \\ -2 \ln \lambda(\mu) \text{ gives now }$$

$$-2\ln\lambda_{\rm A}(\mu) = \frac{(\mu-\mu')^2}{\sigma^2} = \Lambda \qquad \text{centrality param. \varLambda,} \\ \text{or equivalently, σ.}$$

Asimov value of $-2\ln\lambda(\mu)$ gives noncentrality param. Λ , or equivalently, σ .

Then by using Asimov set, one can get p.d.f. of t, then the calculation is much easier.

About error band

$$\hat{\mu} \sim \text{Gaussian}(\mu', \sigma)$$

It is convenient to calculate error bands for the median significance corresponding to the $\pm N\sigma$ variation of $\hat{\mu}$. As $\hat{\mu}$ is Gaussian distributed, these error bands on the significance are simply the quantiles that map onto the variation of $\hat{\mu}$ of $\pm N\sigma$ about μ' .

About the package used in one group of Atlas.

Input:

- data distribution; bkg distribution; signal distribution.(all in histogram form)
- Systematic error.
- Control region if need.

Could combine different channels or even different experiments(just no correlation case). The Likelihood is based on poisson function.

$$\mathcal{L}(\mu, \vec{\theta}) = \left\{ \prod_{k=e\mu,\mu e}^{N_{\text{category}}} \prod_{j=0}^{N_{\text{bins}}} P(N_{ijk} | \mu s_{ijk} + \sum_{m}^{N_{\text{bkg}}} b_{ijkm}) \right\} \times \prod_{i=1}^{N_{\theta}} N(\tilde{\theta} | \theta)$$

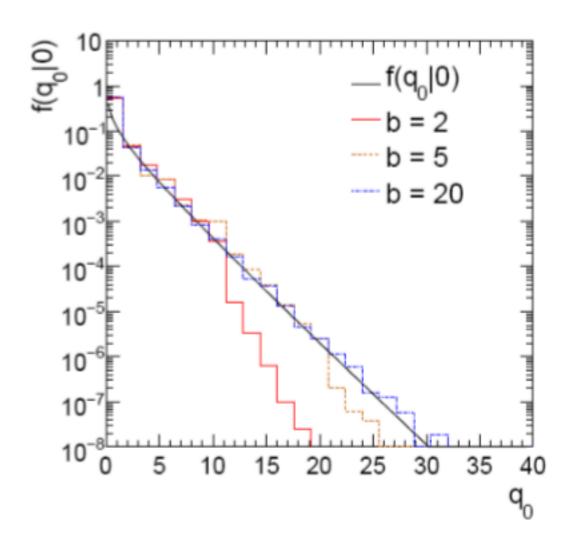
Monte Carlo test of asymptotic formula

$$n \sim \text{Poisson}(\mu s + b)$$

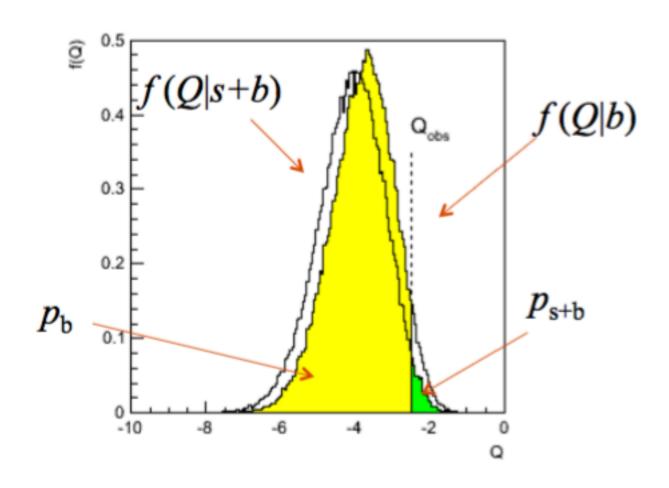
$$m \sim \text{Poisson}(\tau b)$$

Here take $\tau = 1$.

Asymptotic formula is good approximation to 5σ level ($q_0 = 25$) already for $b \sim 20$.



One more issue



Sometimes these two distributions are close to each other.

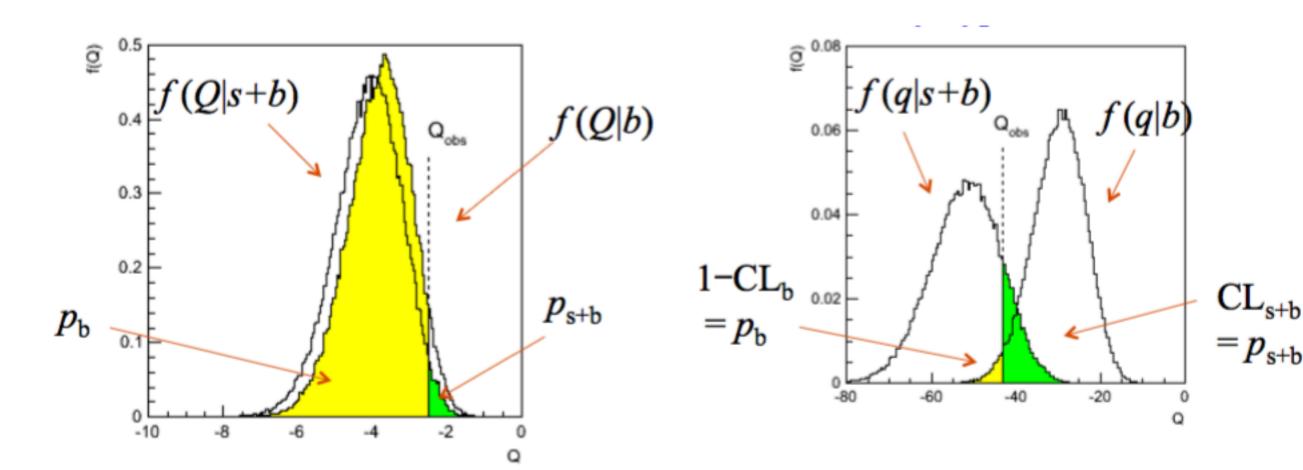
Even if p_{s+b} is little, we should not regard a model as excluded.

solution

In the CLs method the p-value is reduced according to the

recipe

 $p_{\mu} \to \frac{p_{\mu}}{1 - p_{\rm b}}$



Summary

Brief discussion about Bayes and Frequentist method on upper limit.

Introduction about Wald approximation for Frequentist method. Debate your preferred statistical technique in a statistics forum, not a physics result publication!

We should debate and choose statistic method. Comparing their results may be meaningless.

Back-up