PRACTICAL STATISTICS FOR PARTICLE PHYSICISTS

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LECTURES

1) $\mathcal{L}$ikelihood: Parameter determination and $\mathcal{L}$-ratio

   Chi-squared: Param determination & Goodness of Fit

2) Bayes & Frequentist Approaches

2) and 3) Searches for New Physics: Discovery and Limits

Possible 4) Learning to love the Covariance Matrix

Plus: Discussions

Problems

Working on statistical issues

Omitting introductory material

- Why spend time on understanding Statistics?
- Relation of Statistics to Probability Theory
- Random and systematic uncertainties
- Binomial distribution
- Poisson distribution
- Relationships among Binomial, Poisson & Gaussian
- Types of Statistical Procedures:

    Parameter determination

    Goodness of Fit

    Hypothesis Testing

    Decision Theory

$\mathcal{L}$ikelihoods

1) Brief Introduction
2) Do's & Dont's

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Topics

What it is

How it works: Resonance

Uncertainty estimates

Detailed example: Lifetime

Several Parameters

Extended maximum $\mathcal{L}$

Do's and Dont's with $\mathcal{L}$

DO'S AND DONT'S WITH $\mathcal{L}$

- NORMALISATION FOR LIKELIHOOD
- JUST QUOTE UPPER LIMIT
- $\Delta(\ln \mathcal{L}) = 0.5$ RULE ****
- $\mathcal{L}_{max}$ AND GOODNESS OF FIT ******
- $\int_{p_L}^{p_U} \mathcal{L}\, dp = 0.90$
- BAYESIAN SMEARING OF $\mathcal{L}$
- USE CORRECT $\mathcal{L}$ (PUNZI EFFECT)

Simple example: Angular distribution

Data = $\theta_1\ \theta_2\ \theta_3\ \ldots..\ \theta_n$

$y = N\,(1 + \beta \cos^2\theta)$ **{RULE 1: Write down pdf}**

$y_i = N\,(1 + \beta \cos^2\theta_i)$

= probability density of observing θ_i, given β

$\mathcal{L}(\beta) = \Pi\, y_i$

= probability density of observing the data set y_i, given β

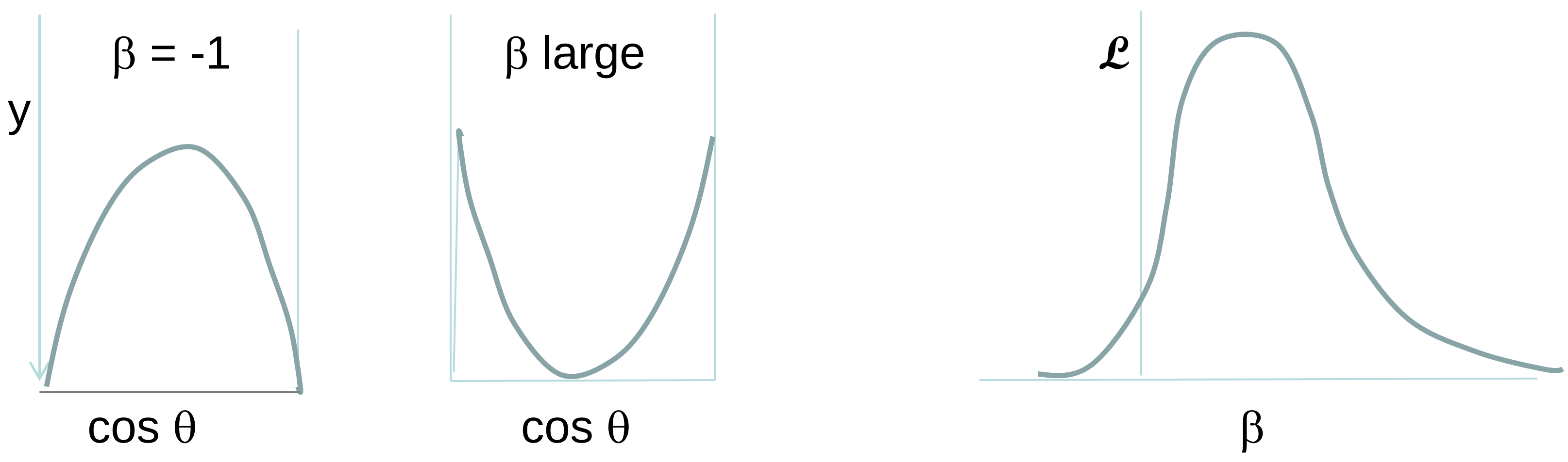
Best estimate of β is that which maximises $\mathcal{L}$

Values of β for which $\mathcal{L}$ is very small are ruled out

Uncertainty of estimate for β comes from width of $\mathcal{L}$ distribution

RULE 2: CRUCIAL to normalise y $N = 1/\{2(1 + \beta/3)\}$

(Information about parameter β comes from **shape** of exptl distribution of $\cos\theta$)



Conventional to consider

$$\ell = \ln(\mathcal{L}) = \Sigma \ln(y_i)$$

For large N, $\mathcal{L} \rightarrow$ Gaussian

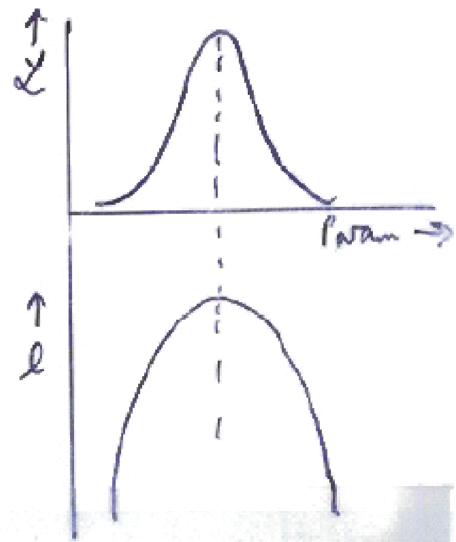
"Proof"

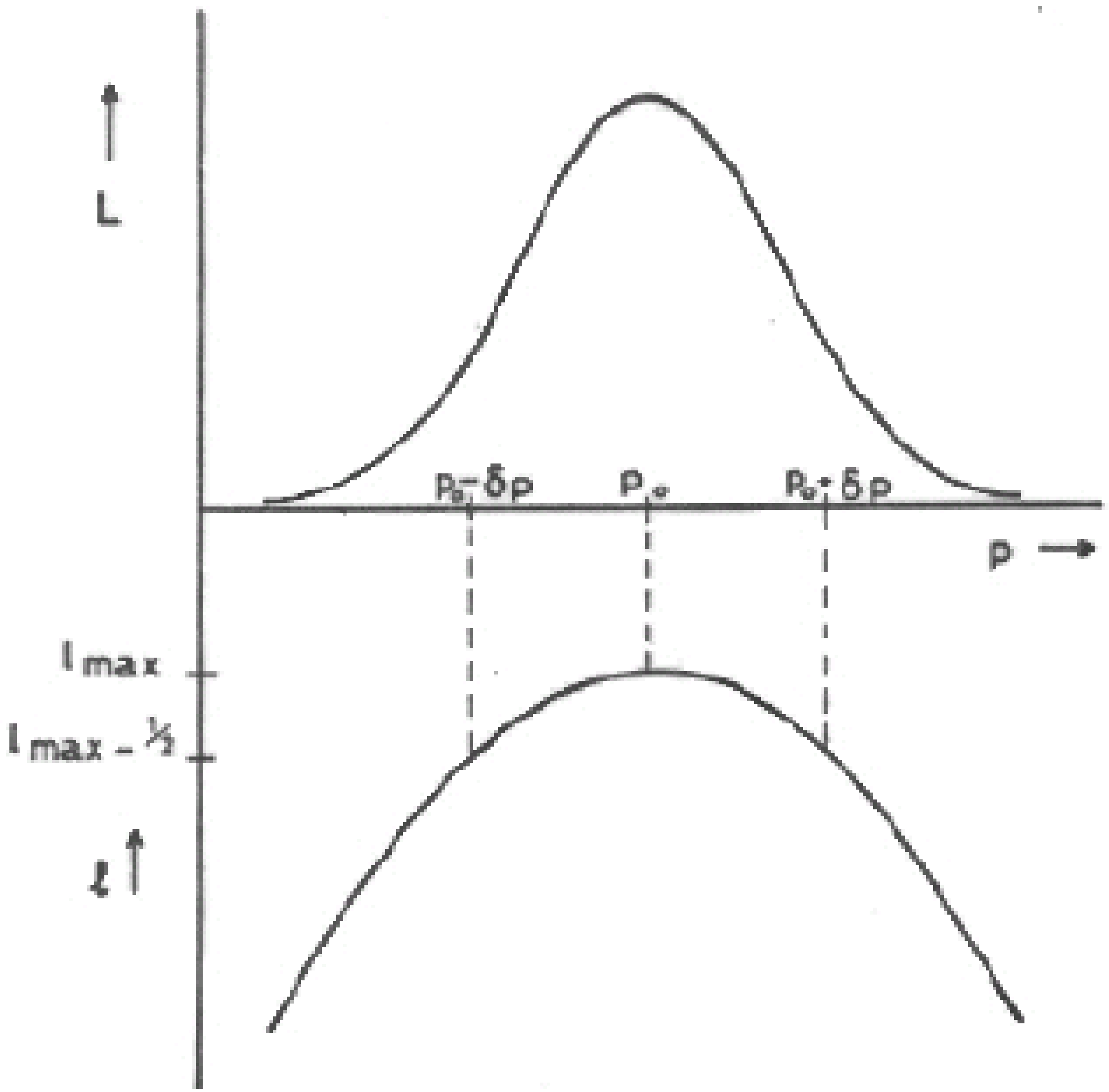
Taylor expand ℓ about its maximum

$$\ell = \ell_{max} + \frac{1}{2!}\ell''[\delta(b/a)]^2 + \ldots$$

$$= \ell_{max} - \frac{1}{2c}\delta^2 + \ldots \qquad c = -1/\ell''$$

$$\Rightarrow \mathcal{L} \sim \exp\left(-\frac{\delta^2}{2c}\right)$$





L
$p_o - \delta p$
p_o
$p_o + \delta p$
p
l max
l max − ½
ℓ

Maximum likelihood uncertainty

Range of likely values of param μ from width of $\mathcal{L}$ or ℓ dists.

If $\mathcal{L}(\mu)$ is Gaussian, following definitions of σ are equivalent:

1) RMS of $\mathcal{L}(\mu)$

2) $1/\sqrt{(-d^2\ln\mathcal{L} / d\mu^2)}$ (Mnemonic)

3) $\ln(\mathcal{L}(\mu_0 \pm \sigma)) = \ln(\mathcal{L}(\mu_0)) - 1/2$

If $\mathcal{L}(\mu)$ is non-Gaussian, these are no longer the same

~~"Procedure 3) above still gives interval that contains the true value of parameter μ with 68% probability"~~

Uncertainties from 3) usually asymmetric, and asym uncertainties are messy. So choose param sensibly

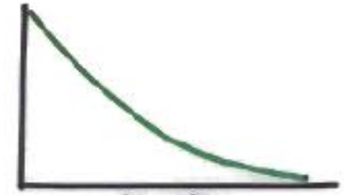
e.g 1/p rather than p; τ or λ

Lifetime Determination

Realistic analyses are more complicated than this

$$\frac{dn}{dt} = \frac{1}{\tau} e^{-t/\tau}$$

↑ NORMALISATION



Observe $t_1, t_2 \ldots\ldots t_N$

Use pdf to construct

$$\mathcal{L} = \prod \left(\frac{dn}{dt}\right)_i = \prod_i \frac{1}{\tau} e^{-t_i/\tau}$$

$$\therefore \ell = \sum_i \left(-t_i/\tau - \ln \tau\right)$$

$$\frac{\partial \ell}{\partial \tau} = \sum\left(+t_i/\tau^2 - \frac{1}{\tau}\right) = 0 = \frac{\sum t_i}{\tau^2} - \frac{N}{\tau}$$

$$\Rightarrow \tau = \sum t_i / N = \overline{t_i}$$

"Obvious"

$$\frac{\partial^2 \ell}{\partial \tau^2} = -\sum \frac{2t_i}{\tau^3} + \sum \frac{1}{\tau^2} = -2\frac{N}{\tau^2} + \frac{N}{\tau^2} = -\frac{N}{\tau^2}$$

$$\Rightarrow \sigma_\tau = 1\Big/\sqrt{-\frac{\partial^2 \ell}{\partial \tau^2}} = \tau/\sqrt{N}$$

N.B. 1) Usual $1/\sqrt{N}$ behaviour

2) $\sigma_\tau \propto \tau_{est}$

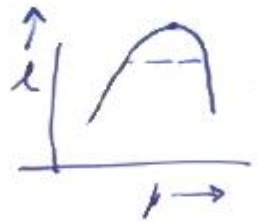
BEWARE FOR AVERAGING RESULTS

Several Parameters

1 param p

p from $\frac{\partial \ell}{\partial p} = 0$

$\sigma_p^2 = 1/\left(-\frac{\partial^2 \ell}{\partial p^2}\right)$



Many dimensions : $\ell(p_1, p_2, p_3 \ldots)$

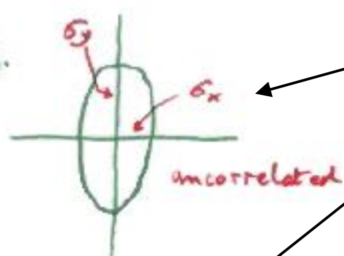
$p_1\ p_2\ p_3 \ldots$ from $\frac{\partial \ell}{\partial p_i} = 0$

For errors, define $H_{ij} = -\frac{\partial^2 \ell}{\partial p_i \partial p_j}$ = Inverse Error Matrix

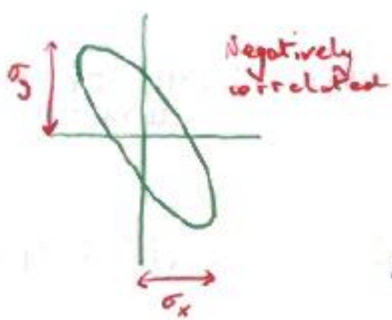
Error matrix $E_{ij} = (H^{-1})_{ij}$

Contours of ln$\mathcal{L}$

e.g.



or



N.B. ERROR NOT GIVEN BY $\ell = \ell_{max} - ½$ WHEN VARYING x FROM BEST VALUE WHILE KEEPING y.... CONSTANT

ERROR IS GIVEN BY $\ell = \ell_{max} - \frac{1}{2}$ WHEN VARYING x FROM BEST VALUE WHILE ......

PROFILE $\mathcal{L}$

$\mathcal{L}_{prof} = \mathcal{L}(\beta, \nu_{best}(\beta))$, where

β = param of interest

ν = nuisance param(s)

Uncertainty on β from decrease in $\ln(\mathcal{L}_{prof})$ by 0.5

a) Max Like

Prob for fixed N = Binomial

Prob of forwards → $= f^F (1-f)^B \dfrac{N!}{F!\,B!}$ ✡

Maximise $\ln P_a$ wrt f $\Rightarrow \hat{f} = F/N$

Error on $\hat{f}$: $1/\sigma^2 = -\dfrac{\partial^2 \ln P_a}{\partial f^2}$

$= \dfrac{N}{\hat{f}(1-\hat{f})}$ $f = \hat{f}$

$\Rightarrow$ Estimate of $\hat{F} = N\hat{f} = F \pm \sqrt{FB/N}$ ← Completely

. . . . . . $\hat{B} = N(1-\hat{f}) = B \pm \sqrt{FB/N}$ ← anti-corr

b) EML $P_b = P_a \times \dfrac{e^{-\nu}\,\nu^N}{N!}$ Poisson for overall rate (ν: expected overall rate)

Maximise $\ln P_b(\nu, f)$

$\Rightarrow \hat{\nu} = N \pm \sqrt{N}$

$\hat{f} = F/N \pm \sqrt{\dfrac{f(1-f)}{N}}$

} uncorrelated

For $\hat{F}$ & $\hat{B}$, either propagate errors for $\hat{F} = \hat{\nu}\hat{f}$ & $\hat{B} = \hat{\nu}(1-\hat{f})$

or rewrite eqn ✡ as product of 2 indep Poissons

$\hat{F} = F \pm \sqrt{F}$

$\hat{B} = B \pm \sqrt{B}$

DO'S AND DONT'S WITH $\mathcal{L}$

- COMBINING PROFILE $\mathcal{L}$s
- NORMALISATION FOR LIKELIHOOD
- JUST QUOTE UPPER LIMIT
- $\Delta(\ln \mathcal{L}) = 0.5$ RULE ******
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Danger of combining profile $\mathcal{L}$s

Experiments quote $\mathcal{L}$ikelihood, profiled over nuisance parameters, so that combinations can be performed.

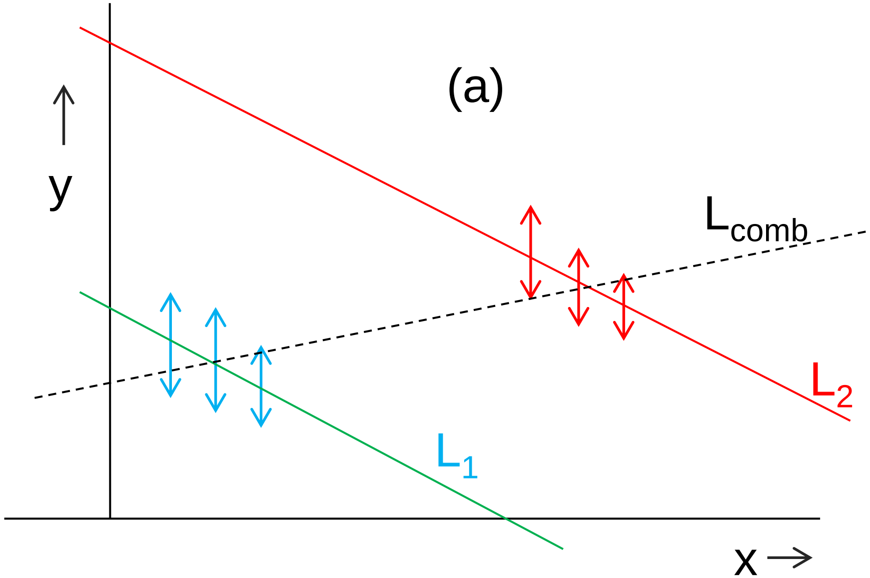
Very simple 'tracking' example:

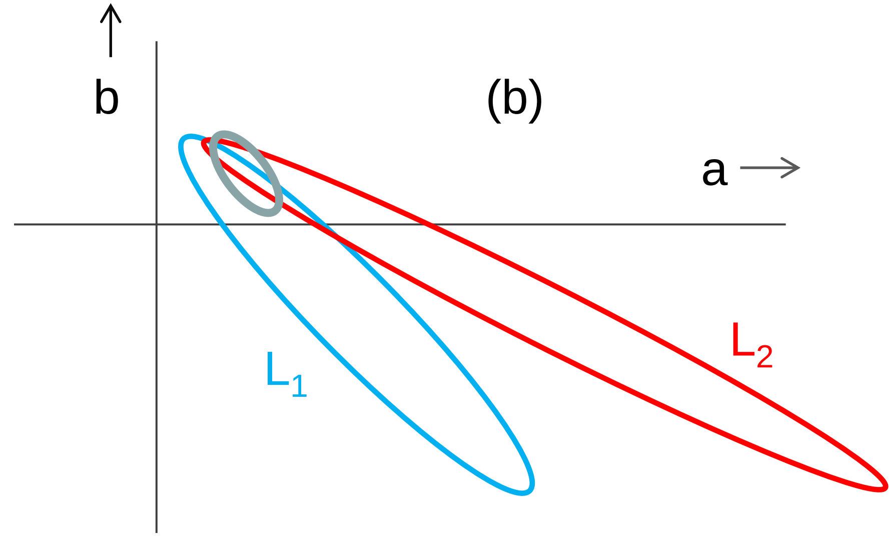
* No magnetic field

* 2-D fit of straight line y = a + bx

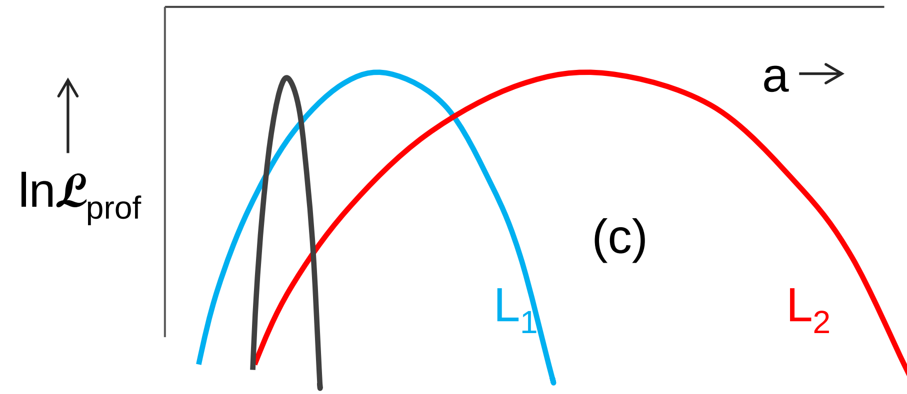
a = parameter of interest, b = nuisance param

* Track hits in 2 subdetectors, each of 3 planes

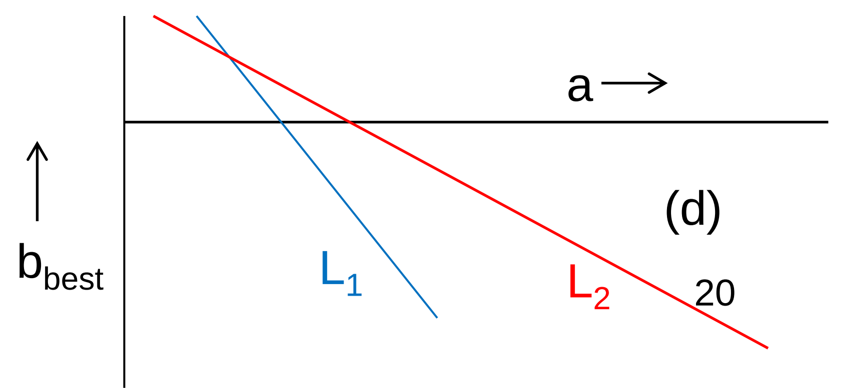




(a) Hits in 2 sub-detectors, each with 3 planes
(b) Covariance ellipses for separate fits L_1 and L_2, and combined L_{comb}
(c) $\ln\mathcal{L}_{prof}$ as function of a, for all 3 lines
(d) b_{best} as a function of a
N.B. b_{best} for L_1 and L_2 are the same



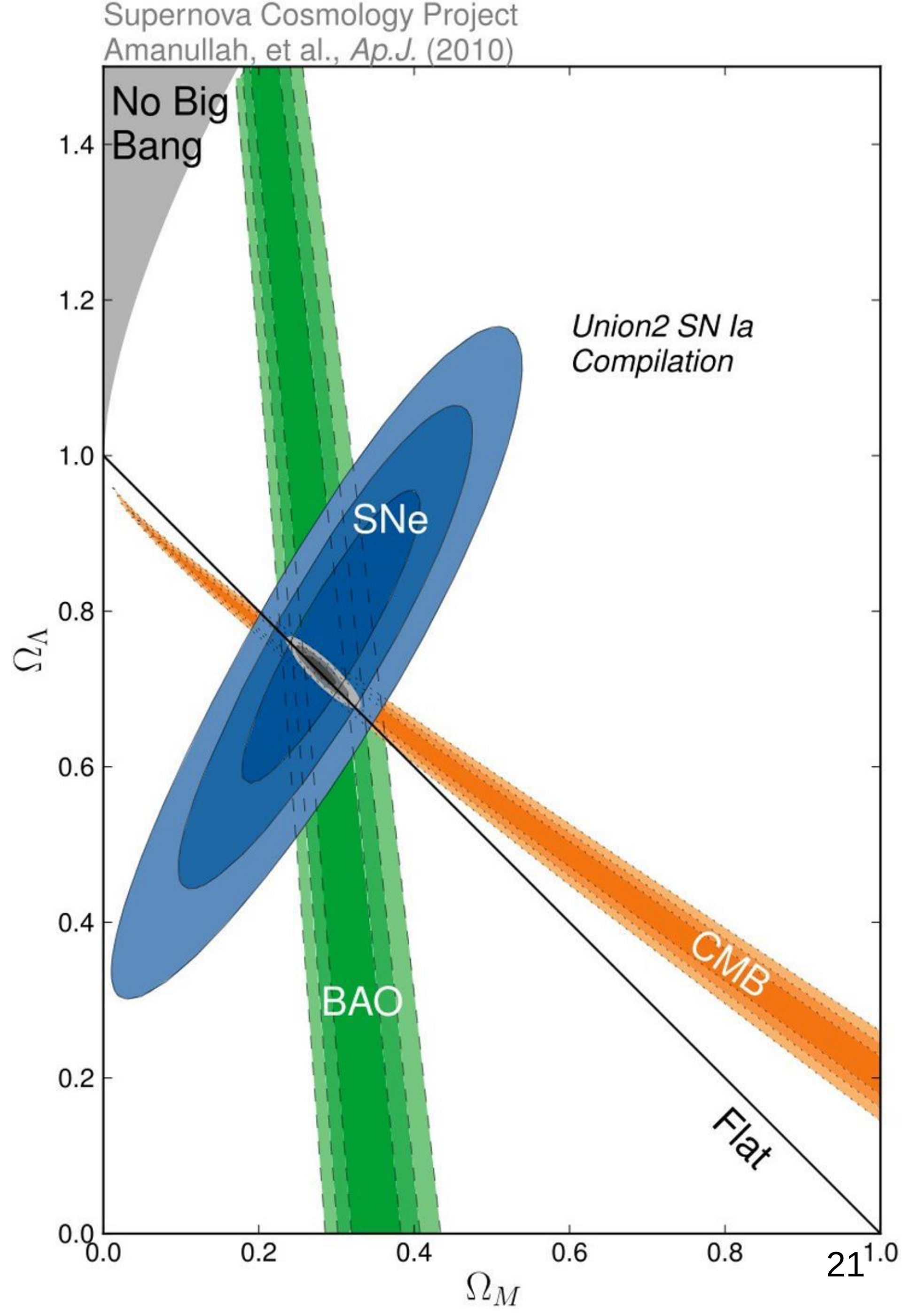
*** Combining $\mathcal{L}_{prof}$ for L_1 and L_2 loses a lot of information, and a_{best} wrong *****



COSMOLOGY EXAMPLE

Plot of dark energy fraction v dark matter fraction by various methods. Each determines dark energy fraction poorly, but combination is fine, because of different correlations.

Combining Profile Likelihoods would give very large uncertainty on dark energy fraction.



$\Delta \ln \mathcal{L} = -1/2$ rule

If $\mathcal{L}(\mu)$ is Gaussian, following definitions of σ are equivalent:

1) RMS of $\mathcal{L}(\mu)$

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3) $\ln(\mathcal{L}(\mu_0 \pm \sigma) = \ln(\mathcal{L}(\mu_0)) - 1/2$

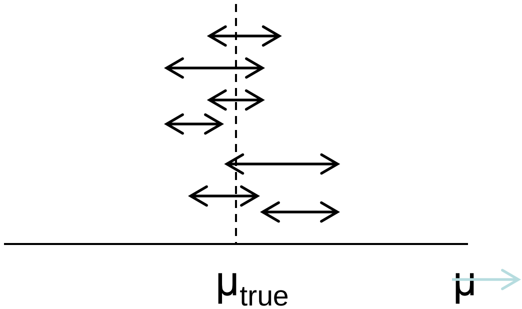
If $\mathcal{L}(\mu)$ is non-Gaussian, these are no longer the same

~~"Procedure 3) above still gives interval that contains the true value of parameter μ with 68% probability"~~

Heinrich: CDF note 6438 (see CDF Statistics Committee Web-page)

Barlow: Phystat05

Coverage



* What it is:

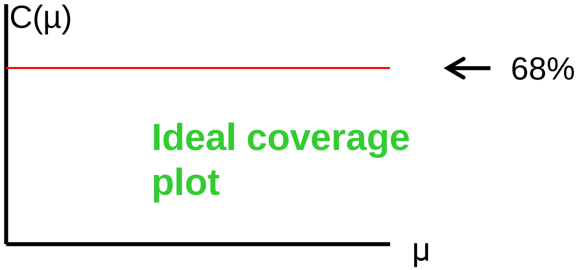
For given statistical method applied to many sets of data to extract confidence intervals for param μ, coverage C is fraction of ranges that contain true value of param.   Can vary with μ

* Does not apply to **your** data:

It is a property of the **statistical method** used

It is **NOT** a probability statement about whether μ_{true} lies in your confidence range for μ

* Coverage plot for Poisson counting expt



Observe n counts

Estimate μ_{best} from maximum of likelihood

$\mathcal{L}(\mu) = e^{-\mu}\mu^n/n!$ and range of μ from $\ln\{\mathcal{L}(\mu_{best})/\mathcal{L}(\mu)\} < 0.5$

For each μ_{true} calculate coverage $C(\mu_{true})$, and compare with nominal 68%

COVERAGE

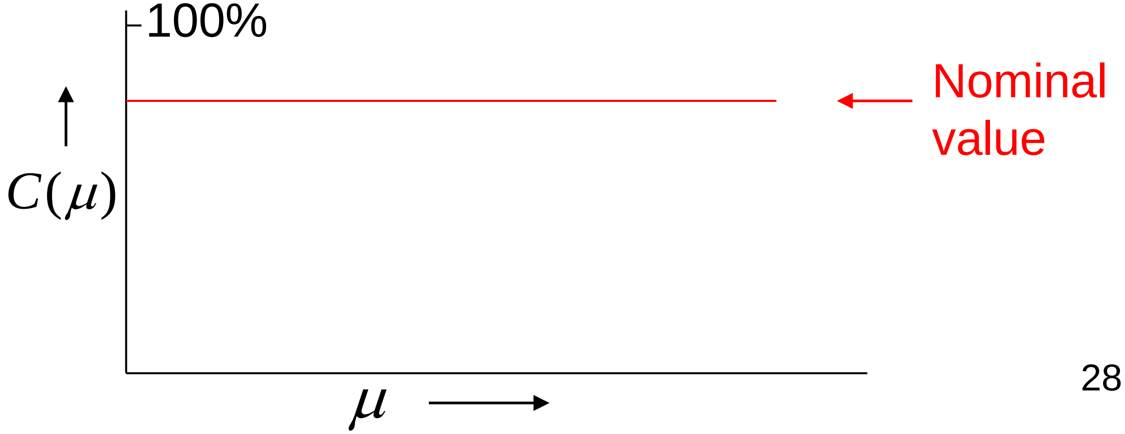
How often does quoted range for parameter include param's true value?

N.B. Coverage is a property of METHOD, not of a particular exptl result

Coverage can vary with μ

Study coverage of different methods of Poisson parameter μ, from observation of number of events n

Hope for:



COVERAGE

If true for all μ : "correct coverage"

P< α for some μ "undercoverage"
(this is serious !)

P> α for some μ "overcoverage"

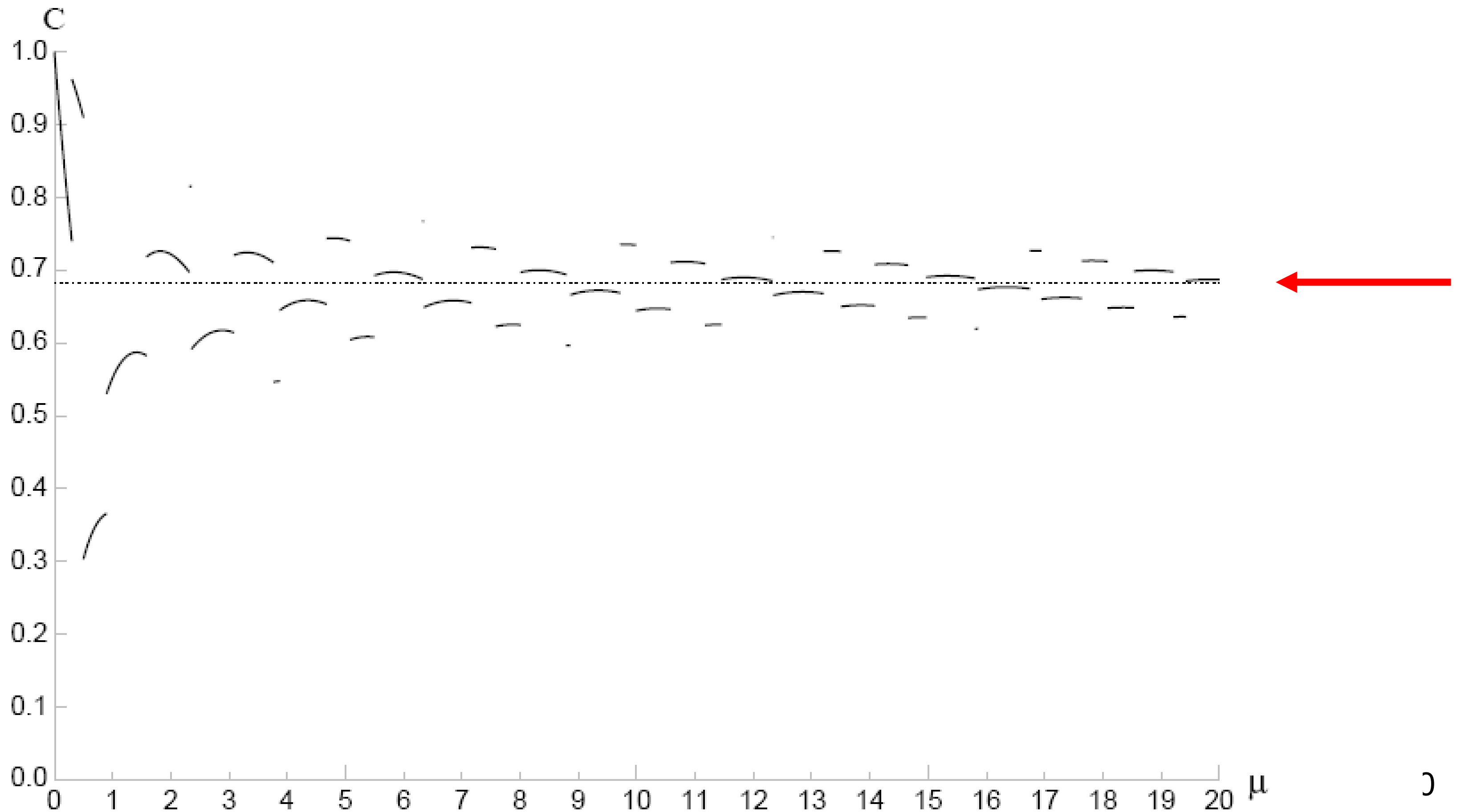
Conservative

Loss of rejection power

Coverage : $\mathcal{L}$ approach (Not Neyman construction)

$P(n,\mu) = e^{-\mu}\mu^n/n!$ (Joel Heinrich CDF note 6438)

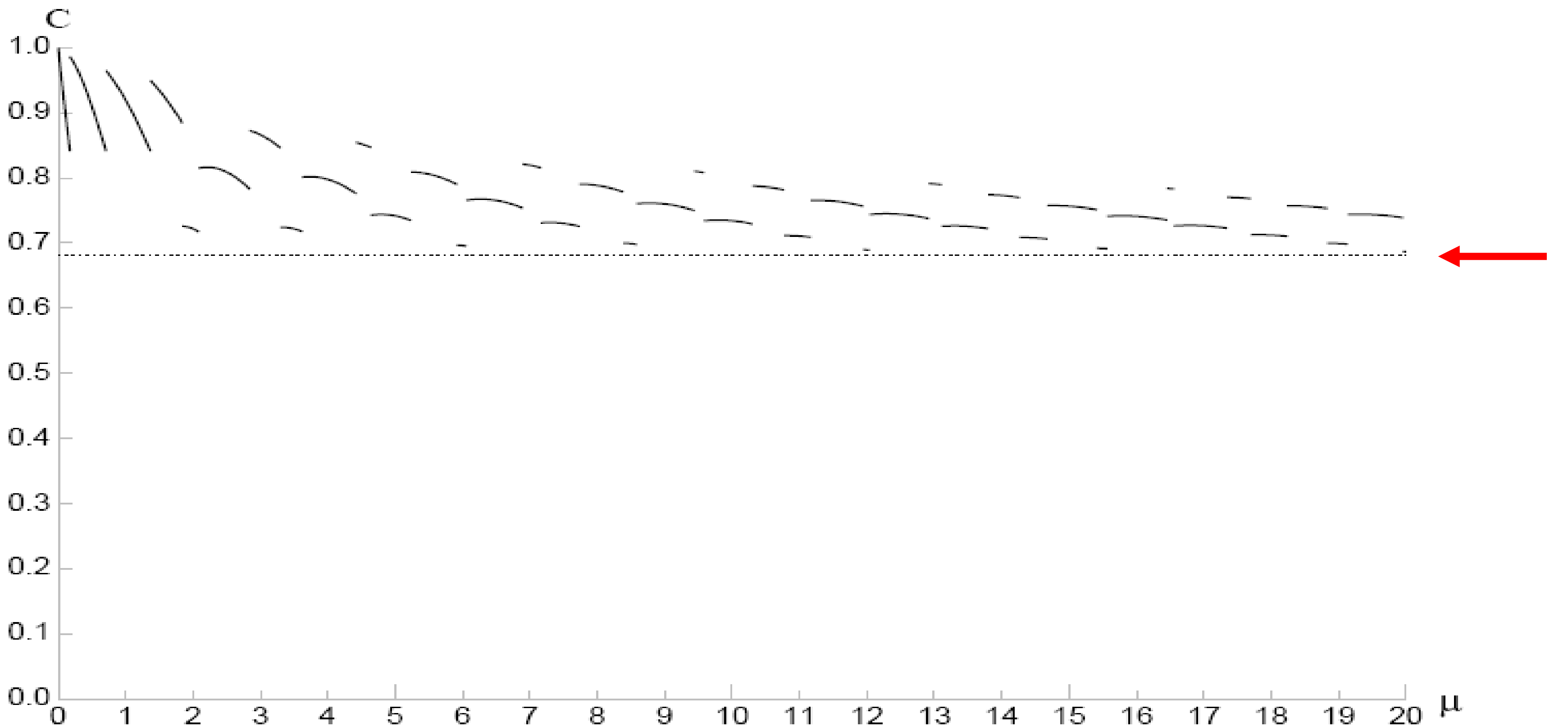
$-2 \ln\lambda < 1$ $\lambda = P(n,\mu)/P(n,\mu_{best})$ UNDERCOVERS



Coverage (C) vs μ: $-2\ln\lambda < 1$ ($C \to 0.6827$ as $\mu \to \infty$)

Neyman central intervals, NEVER undercover

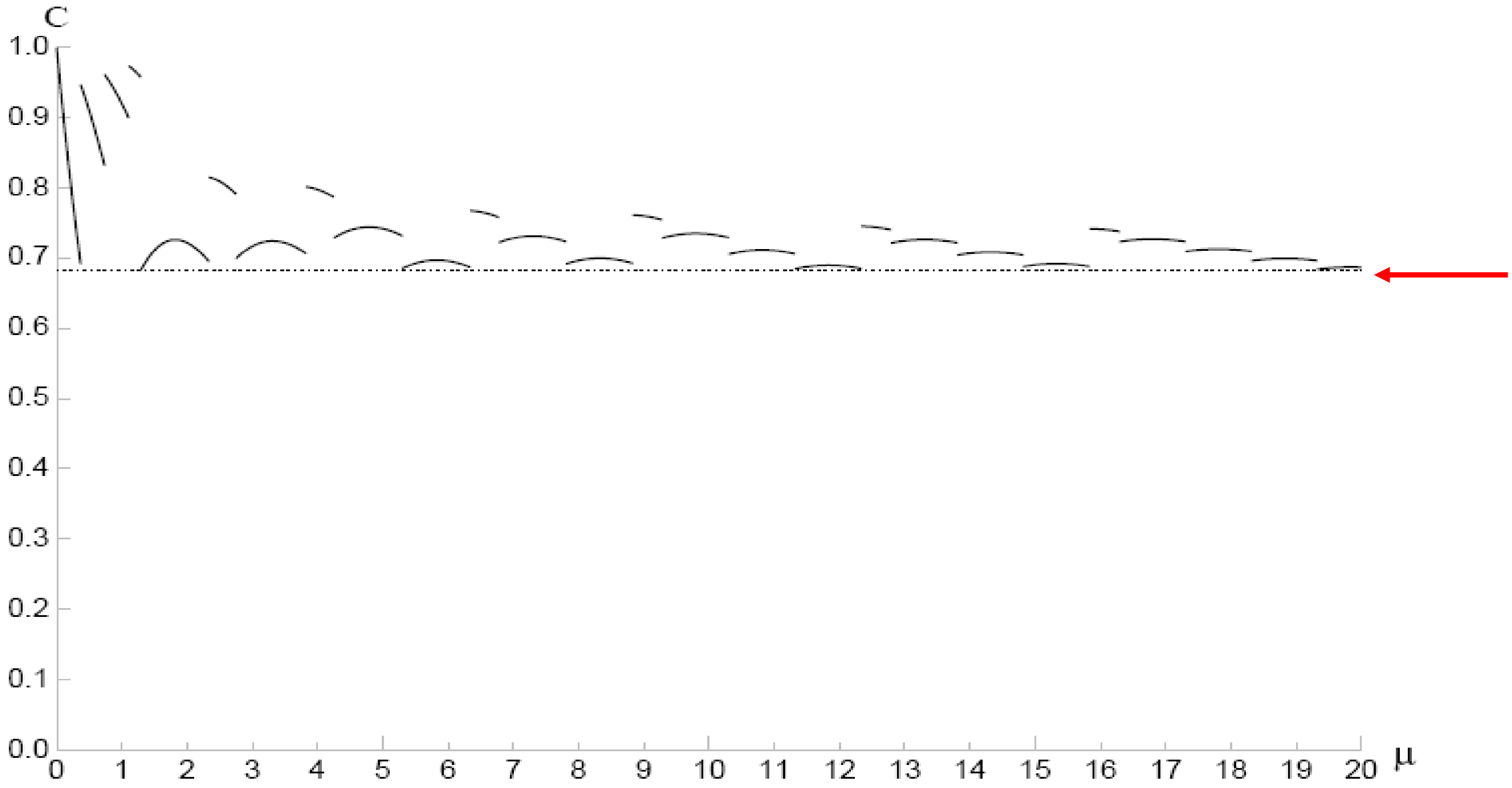
(Conservative at both ends)



Coverage (C) vs μ: Classical Central Intervals (C → 0.6827 as μ → ∞)

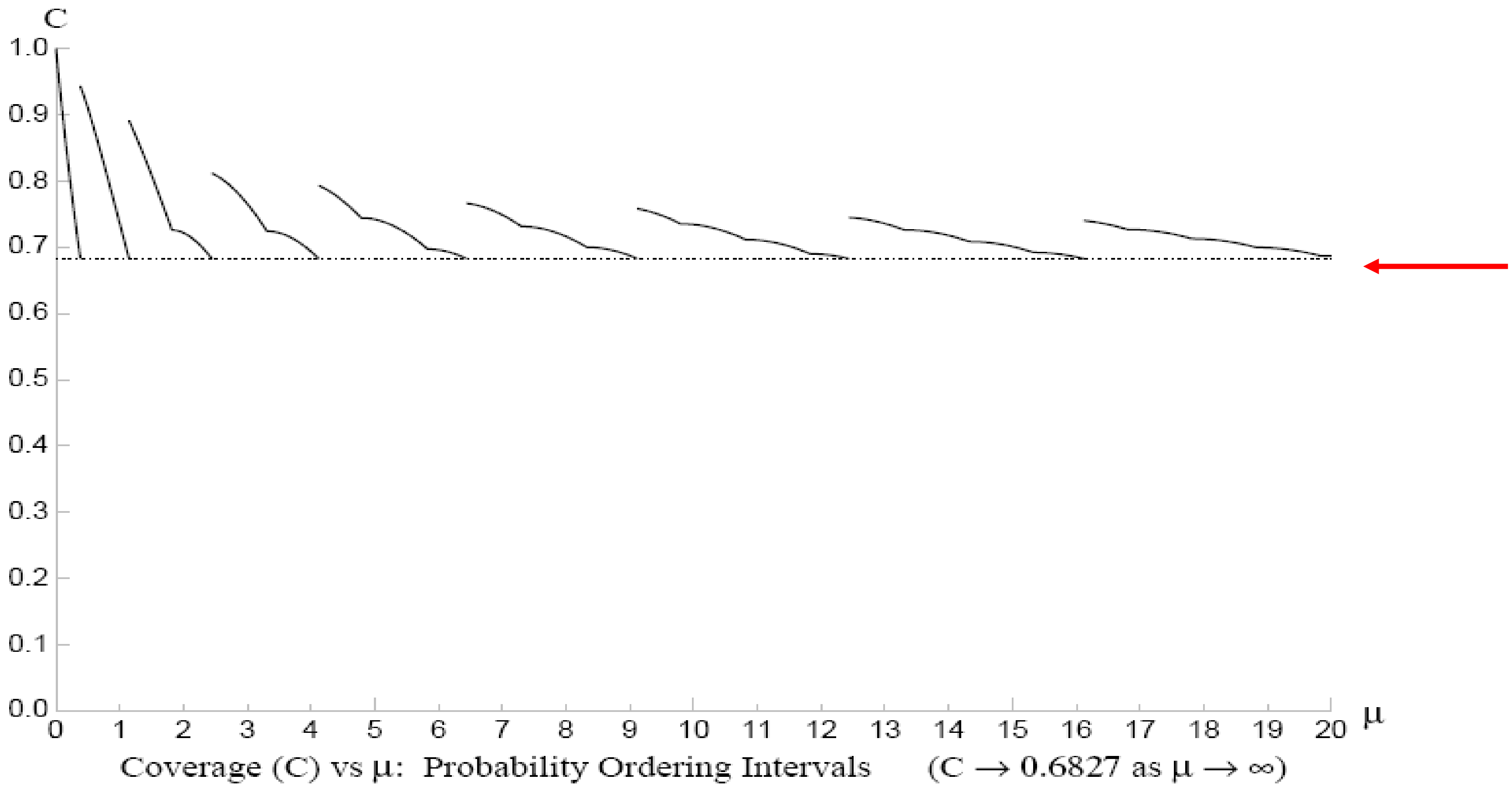
Feldman-Cousins Unified intervals

Neyman construction so NEVER undercovers



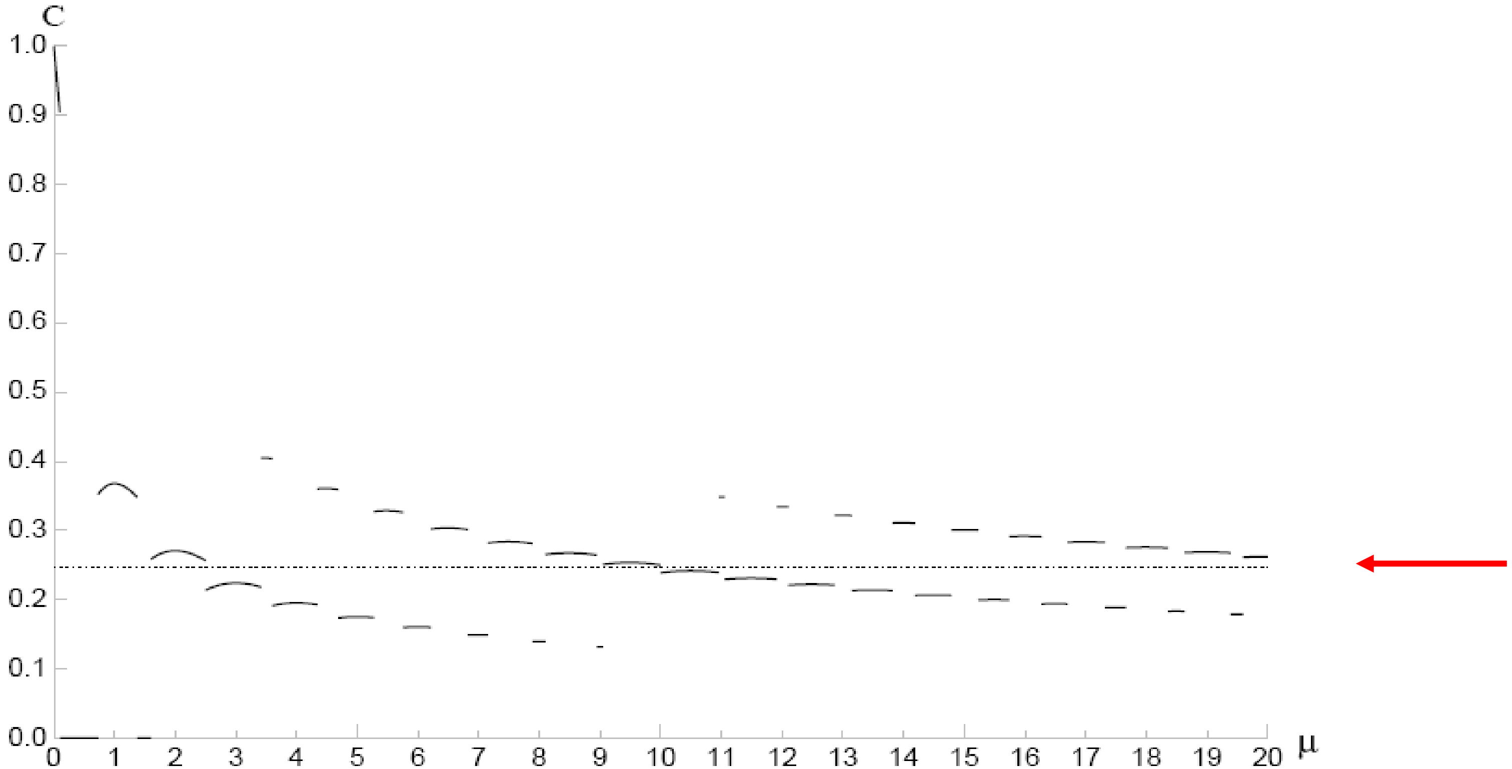
Coverage (C) vs μ: Unified Intervals ($C \to 0.6827$ as $\mu \to \infty$)

Probability ordering



$\chi^2 = (n-\mu)^2/\mu$ $\Delta\chi^2 = 0.1$ → 24.8% coverage?

NOT Neyman : Coverage = 0% → 100%



Coverage (C) vs μ: $\chi^2 < 0.1$ (C → 0.2482 as μ → ∞)

Unbinned $\mathcal{L}_{max}$ and Goodness of Fit?

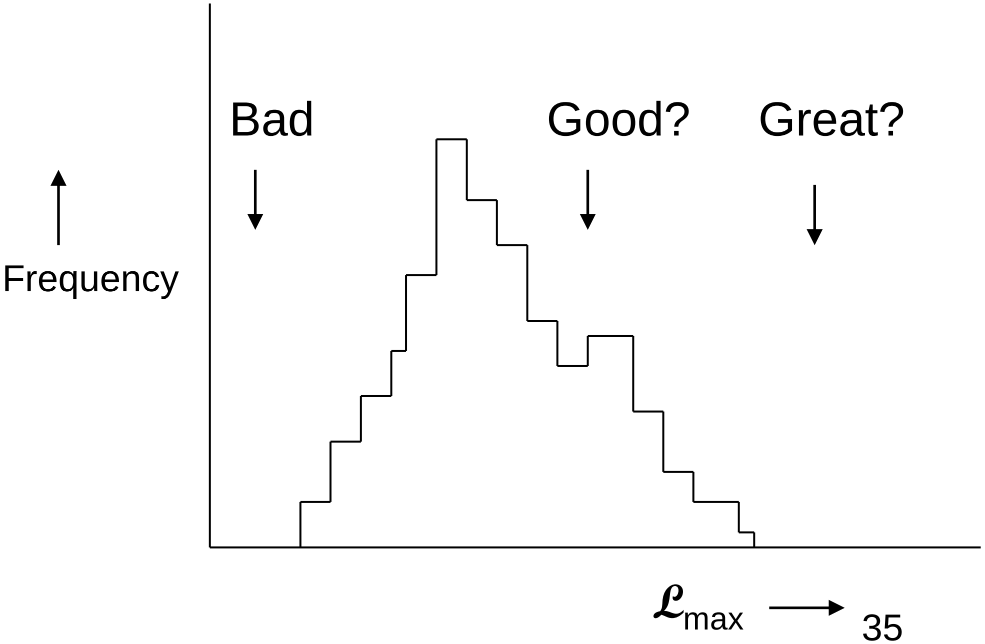
Find params by maximising $\mathcal{L}$

So larger $\mathcal{L}$ better than smaller $\mathcal{L}$

So $\mathcal{L}_{max}$ gives Goodness of Fit??

Monte Carlo distribution

of unbinned $\mathcal{L}_{max}$



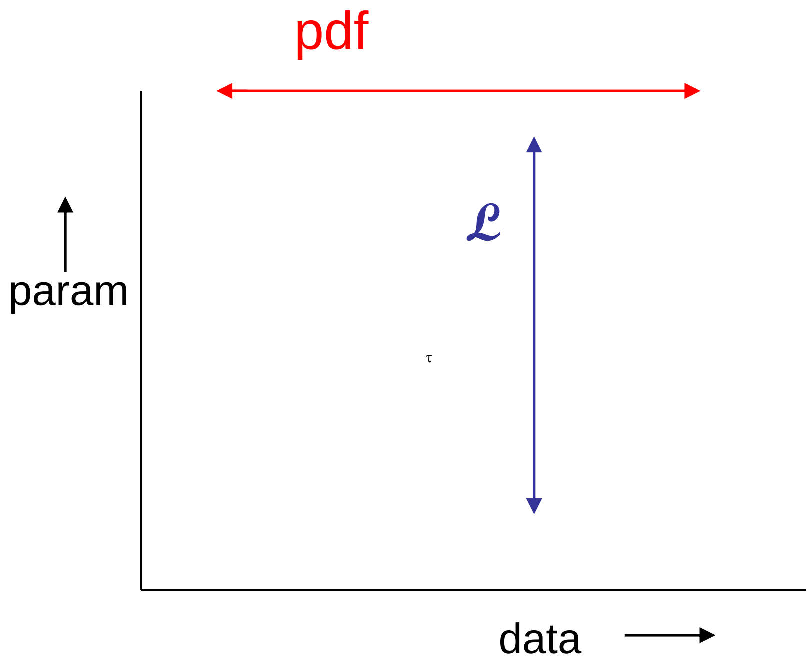
Not necessarily:

ℒ(data,params)

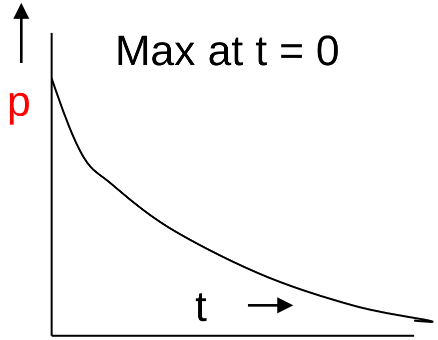
fixed vary

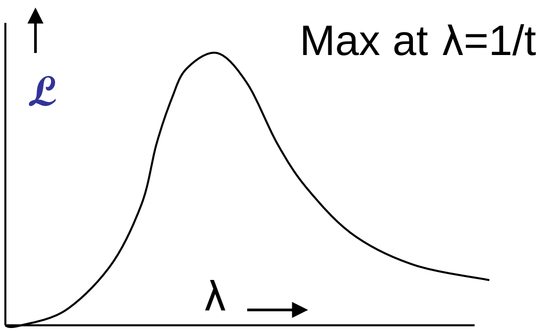
Contrast pdf(data,params)

vary fixed



e.g. p(λ) = λ exp(-λt)





Example 1

Fit exponential to times t_1, t_2 , t_3 ……. [Joel Heinrich, CDF 5639]

$\mathcal{L} = \prod \lambda \exp(-\lambda t_i)$

$\ln\mathcal{L}_{max} = -N(1 + \ln t_{av})$ (Follows from slide 12}

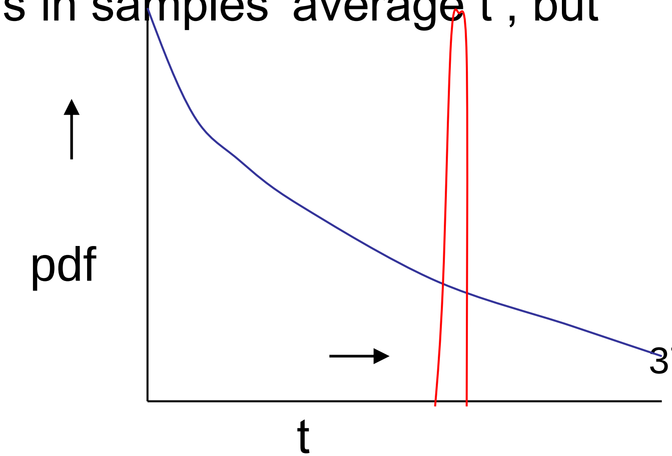
i.e. Depends only on AVERAGE t, but is

INDEPENDENT OF DISTRIBUTION OF t (except for……..)

(Average t is a 'sufficient statistic')

Variation of $\mathcal{L}_{max}$ in Monte Carlo is due to variations in samples' average t , but

NOT TO BETTER OR WORSE FIT

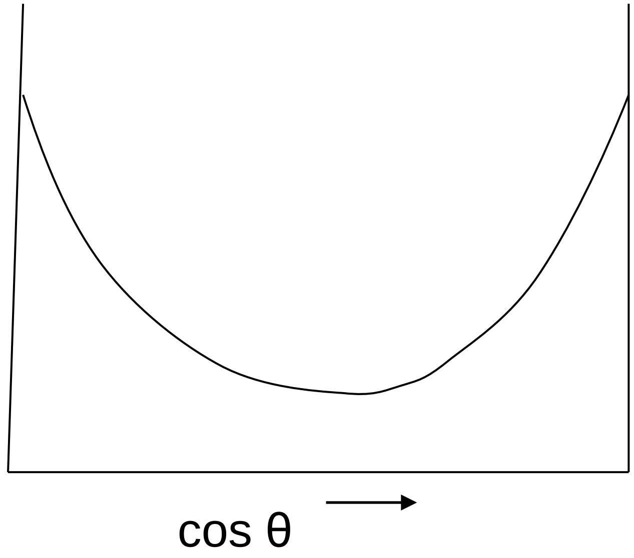


Same average t ⇨ same $\mathcal{L}_{max}$

Example 2

$$\frac{dN}{d\cos\theta} = \frac{1+\alpha\cos^2\theta}{1+\alpha/3}$$

$$\mathcal{L} = \prod_i \frac{1+\alpha\cos^2\vartheta_i}{1+\alpha/3}$$



pdf (and likelihood) depends only on $\cos^2\theta_i$

Insensitive to sign of $\cos\theta_i$

So data can be in very bad agreement with expected distribution

e.g. all data with $\cos\theta < 0$

and $\mathcal{L}_{max}$ does not know about it.

Example of general principle

$\mathcal{L}_{max}$ and Goodness of Fit?

Conclusion:

$\mathcal{L}$ has sensible properties with respect to parameters

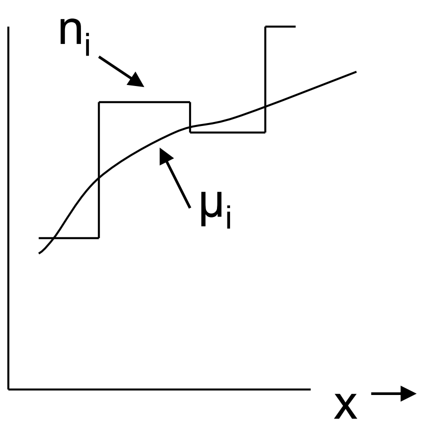
NOT with respect to data

$\mathcal{L}_{max}$ within Monte Carlo peak is NECESSARY

not SUFFICIENT

('Necessary' doesn't mean that you have to do it!)

Binned data and Goodness of Fit using $\mathcal{L}$-ratio



$$\mathcal{L} = \prod_i p_{ni}(\mu_i)$$

$$\mathcal{L}_{best} = \prod_i p_{ni}(\mu_{i,best})$$

$$= \prod_i p_{ni}(n_i)$$

$$\ln[\mathcal{L}\text{-ratio}] = \ln[\mathcal{L}/\mathcal{L}_{best}]$$

$$\xrightarrow[\text{large } \mu_i]{} -0.5\chi^2 \qquad \text{i.e. Goodness of Fit}$$

$\mathcal{L}_{best}$ is independent of parameters of fit,

and so same parameter values from $\mathcal{L}$ or $\mathcal{L}$-ratio

Baker and Cousins, NIM A221 (1984) 437

For comparing 2 hypotheses

e.g. Does data favour 'Just SM' or 'SM + New Physics'.

(Much more later in Lecture 2)

If hypotheses are "simple", then Neyman-Peason lemma says that $\mathcal{L}$-ratio is "best" for separating them.

"simple" = no free parameters

"best" = minimum contamination for fixed efficiency.

Even when hypotheses are not simple, $\mathcal{L}$-ratio may still be useful.

$\mathcal{L}$ and pdf

Example 1: Poisson

pdf = Probability density function for observing n, given μ

$$P(n;\mu) = e^{-\mu} \mu^n/n!$$

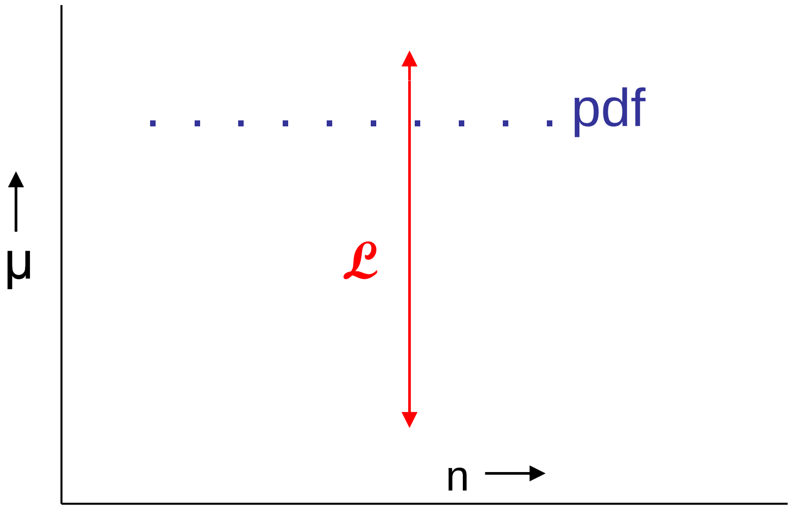
From this, construct $\mathcal{L}$ as

$$\mathcal{L}(\mu;n) = e^{-\mu} \mu^n/n!$$

i.e. use same function of μ and n, but

for pdf, μ is fixed, but

for $\mathcal{L}$, n is fixed



N.B. $P(n;\mu)$ exists only at integer non-negative n

$\mathcal{L}(\mu;n)$ exists only as continuous function of non-negative μ

Example 2 Lifetime distribution

pdf $p(t;\lambda) = \lambda e^{-\lambda t}$

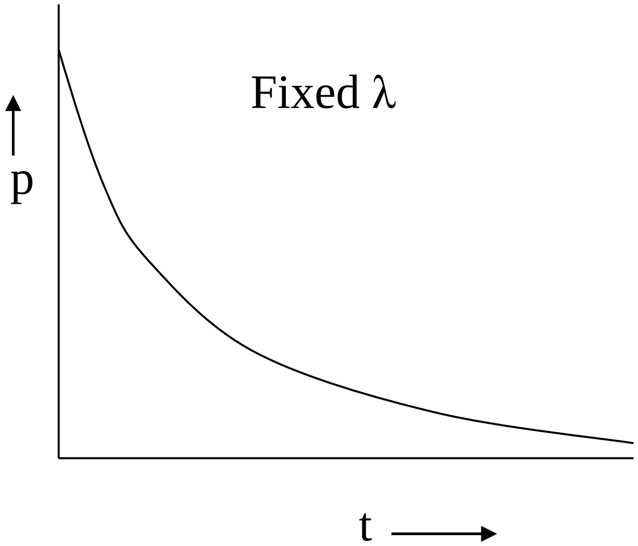
So $\mathcal{L}(\lambda;t) = \lambda e^{-\lambda t}$ (single observed t)

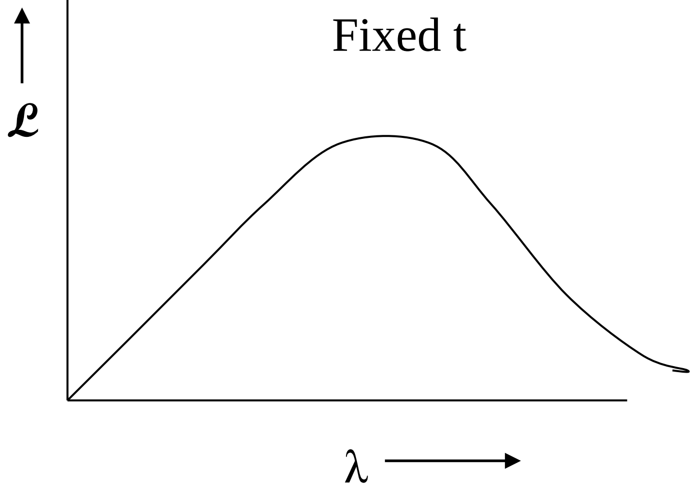
Here both t and λ are continuous

pdf maximises at $t = 0$

$\mathcal{L}$ maximises at $\lambda = t$

N.B. Functional form of $p(t)$ and $\mathcal{L}(\lambda)$ are different





Example 3: Gaussian

$$\text{pdf}(x;\mu) = \exp\{-(x-\mu)^2/2\sigma^2\} /(\sigma\sqrt{2\pi})$$

$$\mathcal{L}(\mu;x) \quad = \exp\{-(x-\mu)^2/2\sigma^2\} /(\sigma\sqrt{2\pi})$$

N.B. In this case, same functional form for pdf and $\mathcal{L}$

So if you consider just Gaussians, can be confused between pdf and $\mathcal{L}$

So examples 1 and 2 are useful

Transformation properties of pdf and $\mathcal{L}$

Lifetime example: dn/dt = λ e $^{-\lambda t}$

Change observable from t to y = √t

$$\frac{dn}{dy} = \frac{dn}{dt}\frac{dt}{dy} = 2y\lambda e^{-\lambda y^2}$$

So (a) pdf changes, BUT

(b) $$\int_{t_0}^{\infty} \frac{dn}{dt} dt = \int_{\sqrt{t_0}}^{\infty} \frac{dn}{dy} dy$$

i.e. corresponding integrals of pdf are INVARIANT

Now for $\mathcal{L}$ikelihood

When parameter changes from λ to $\tau = 1/\lambda$

(a') $\mathcal{L}$ does not change

dn/dt = $(1/\tau) \exp\{-t/\tau\}$

and so $\mathcal{L}(\tau;t) = \mathcal{L}(\lambda=1/\tau;t)$

because identical numbers occur in evaluations of the two $\mathcal{L}$'s

BUT

(b') $$\int_0^{\lambda_0} L(\lambda;t)\, d\lambda \neq \int_{\tau_0}^{\infty} L(\tau;t)\, d\tau$$

So it is NOT meaningful to integrate $\mathcal{L}$

(However,………)

	pdf(t;λ)	$\mathcal{L}$(λ;t)
Value of function	Changes when observable is transformed	INVARIANT wrt transformation of parameter
Integral of function	INVARIANT wrt transformation of observable	Changes when param is transformed
Conclusion	Max prob density not very sensible	Integrating $\mathcal{L}$ not very sensible

CONCLUSION:

$$\int_{p_l}^{p_u} L\,dp = \alpha$$ NOT recognised statistical procedure

[Metric dependent:

τ range agrees with τ_{pred}

λ range inconsistent with $1/\tau_{pred}$]

BUT

1) Could regard as "black box"

2) Make respectable by $\mathcal{L}$ ⇨ Bayes' posterior

Posterior(λ) ~ $\mathcal{L}$(λ)* Prior(λ) [and Prior(λ) can be constant]

6) BAYESIAN SMEARING OF $\mathcal{L}$

"USE $\ln \mathcal{L}$ FOR p + σ_p

SMEAR IT TO INCORPORATE

SYSTEMATIC UNCERTAINTIES"

SCENARIO:

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

PARAM OF INTEREST (s)

EFFIC/ACCEPTANCE/$\int \mathcal{L}$ (ϵ)

BACKGROUND (b)

UNCERTAINTIES MEASURED IN 'SUBSIDIARY' EXPT

$$P(s, \epsilon | n) = \frac{P(n | s, \epsilon)\, \pi(s, \epsilon)}{\iint \cdots \cdots \, ds\, d\epsilon}$$

($P(n | s, \epsilon)$ = $\mathcal{L}$)

$$P(s | n) = \int P(s, \epsilon | n)\, d\epsilon$$

$$= \frac{\int \mathcal{L}\, \pi(s)\, \pi(\epsilon)\, d\epsilon}{\iint \cdots \cdots \, ds\, d\epsilon}$$

e.g. $\pi(s)$ = truncated const. $\pi(\epsilon) \sim e^{-\frac{1}{2}\left(\frac{\epsilon - \epsilon_0}{\sigma}\right)^2}$ [BEWARE]

i.e. SMEAR $\mathcal{L}$ (not $\ln \mathcal{L}$) by "prior" for ϵ

Getting $\mathcal{L}$ wrong: Punzi effect

Giovanni Punzi @ PHYSTAT2003

"Comments on $\mathcal{L}$ fits with variable resolution"

Separate two close signals, when resolution σ varies event by event, and is different for 2 signals

e.g. 1) Signal 1 $1+\cos^2\theta$

Signal 2 Isotropic

and different parts of detector give different σ

2) M (or τ)

Different numbers of tracks → different σ_M (or σ_τ)

Events characterised by x_i and σ_i

A events centred on x = 0

B events centred on x = 1

$\mathcal{L}(f)_{wrong} = \Pi\ [f * G(x_i,0,\sigma_i) + (1-f) * G(x_i,1,\sigma_i)]$

$\mathcal{L}(f)_{right} = \Pi\ [f*p(x_i,\sigma_i;A) + (1-f) * p(x_i,\sigma_i;B)]$

$$p(S,T) = p(S|T) * p(T)$$

$$p(x_i,\sigma_i|A) = p(x_i|\sigma_i,A) * p(\sigma_i|A)$$

$$= G(x_i,0,\sigma_i) * p(\sigma_i|A)$$

So

$\mathcal{L}(f)_{right} = \Pi[f * G(x_i,0,\sigma_i) * p(\sigma_i|A) + (1-f) * G(x_i,1,\sigma_i) * p(\sigma_i|B)]$

If $p(\sigma|A) = p(\sigma|B)$, $\mathcal{L}_{right} = \mathcal{L}_{wrong}$

but NOT otherwise

Punzi's Monte Carlo for

A : $G(x,0,\sigma_A)$

B : $G(x,1,\sigma_B)$

$f_A = 1/3$

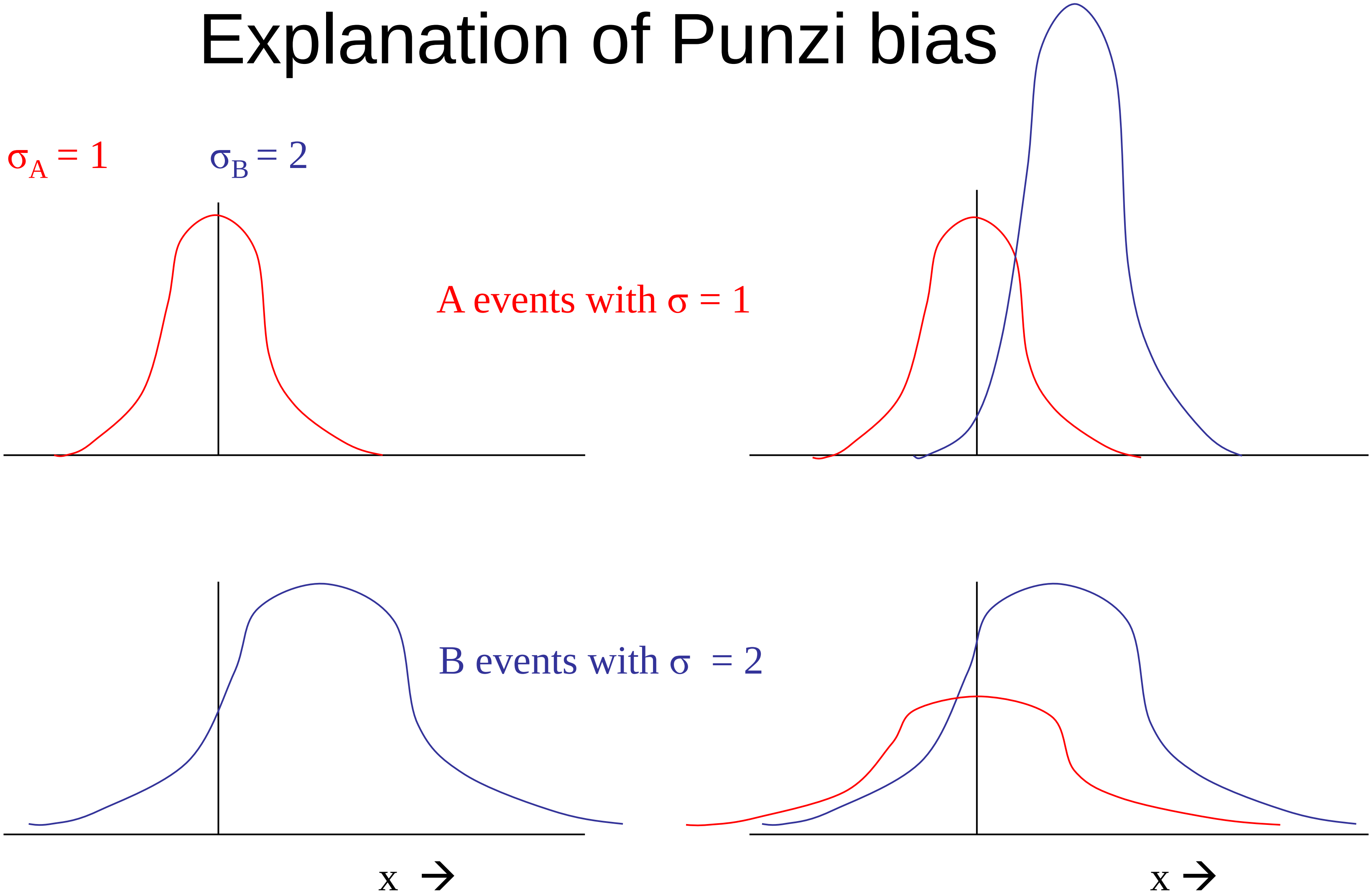
		$\mathcal{L}_{wrong}$		$\mathcal{L}_{right}$	
σ_A	σ_B	f_A	σ_f	f_A	σ_f
1·0	1·0	0·336(3)	0·08	Same	
1·0	1·1	0·374(4)	0·08	0· 333(0)	0
1·0	2·0	0·645(6)	0·12	0·333(0)	0
1 → 2	1.5 →3	0·514(7)	0·14	0·335(2)	0·03
1.0	1 → 2	0.482(9)	0.09	0.333(0)	0

1) $\mathcal{L}_{wrong}$ OK for $p(\sigma_A) = p(\sigma_B)$, but otherwise BIASSED

2) $\mathcal{L}_{right}$ unbiassed, but $\mathcal{L}_{wrong}$ biassed (enormously)!

3) $\mathcal{L}_{right}$ gives smaller σ_f than $\mathcal{L}_{wrong}$

Explanation of Punzi bias



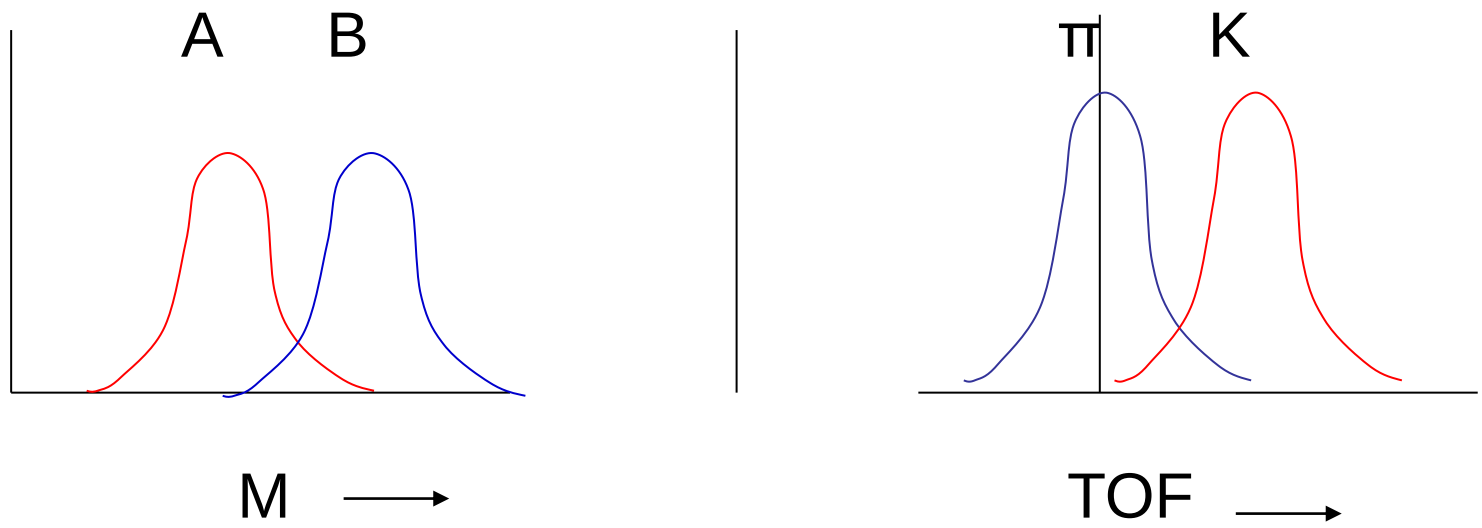
ACTUAL DISTRIBUTION FITTING FUNCTION

[N_A/N_B variable, but same for A and B events]

Fit gives upward bias for N_A/N_B because (i) that is much better for A events; and

(ii) it does not hurt too much for B events

Another scenario for Punzi problem: PID



Originally:

Positions of peaks = constant

K-peak → π-peak at large momentum

σ_i variable, $(\sigma_i)_A \neq (\sigma_i)_B$

$\sigma_i \sim$ constant, $p_K \neq p_\pi$

COMMON FEATURE: Separation/Error ≠ Constant

Where else??

MORAL: Beware of event-by-event variables whose pdf's do not appear in $\mathcal{L}$

Avoiding Punzi Bias

BASIC RULE:
Write pdf for ALL observables, in terms of parameters

- Include p(σ|A) and p(σ|B) in fit
  (But then, for example, particle identification may be determined more by momentum distribution than by PID)

OR

- Fit each range of σ_i separately, and add $(N_A)_i \rightarrow (N_A)_{total}$, and similarly for B

Incorrect method using $\mathcal{L}_{wrong}$ uses weighted average of $(f_A)_j$, assumed to be independent of j

Talk by Catastini at PHYSTAT05

Conclusions

How it works, and how to estimate uncertainties

$\Delta(\ln \mathcal{L}) = 0.5$ rule and coverage

Several Parameters

Likelihood does not guarantee coverage

Unbinned $\mathcal{L}_{max}$ and Goodness of Fit

Use correct $\mathcal{L}$ (Punzi effect)