

Statistical bias of fit parameters and bias reduction techniques

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- How to estimate statistical bias of fit parameters
- Which method, likelihood function or χ^2 , is better
- What's better: χ^2 with $\sigma = \sqrt{\mathcal{N}}$ or that with $\sigma = \sqrt{f}$
- Possible improvements of the χ^2 method
(bias reduction techniques)

likelihood function and functions $\chi^2_{\sigma_n=\sqrt{\mathcal{N}_n}}$ and $\chi^2_{\sigma_n=\sqrt{f}}$

Probability of experimental distribution to match theoretical model, given by function $f(\mathbf{x}, t)$, can be written as

$$\mathcal{P} = \prod_n \frac{[f(\mathbf{x}, t_n)]^{\mathcal{N}_n}}{\mathcal{N}_n!} \exp[-f(\mathbf{x}, t_n)] \approx \prod_n \frac{1}{\sqrt{2\pi\mathcal{N}_n}} \left(\frac{f(\mathbf{x}, t_n)}{\mathcal{N}_n} \right)^{\mathcal{N}_n} \exp[\mathcal{N}_n - f(\mathbf{x}, t_n)]$$

Here we use Poisson distribution of events (counts) in histogram channels and Stirling's formula for $\mathcal{N}_n!$ We use following definitions:

- n is n^{th} channel of a histogram
- \mathcal{N}_n is number of events in the n^{th} channel
- $N = \sum_n \mathcal{N}_n$ is total number of events in the histogram
- $f(\mathbf{x}, t) \equiv f$ is a fit function
- $\mathbf{x} \equiv \{x_i\}$ is a vector of fit parameters
- $f(\mathbf{x}, t_n)$ is a fit function value for the n^{th} channel of histogram

Introduce log-likelihood function $\mathcal{L} \equiv -\ln \mathcal{P}$:

$$\mathcal{L} = \sum_n \left(\frac{1}{2} \ln 2\pi + \frac{1}{2} \ln \mathcal{N}_n + \mathcal{N}_n \ln \frac{\mathcal{N}_n}{f} + f - \mathcal{N}_n \right) \Rightarrow \sum_n \left(\mathcal{N}_n \ln \frac{\mathcal{N}_n}{f} + f - \mathcal{N}_n \right)$$

Decompose $2\mathcal{L}$ into series on powers of small value $(f - \mathcal{N}_n)/\mathcal{N}_n$:

$$2\mathcal{L} = \sum_n \left(\frac{(f - \mathcal{N}_n)^2}{\mathcal{N}_n} - \frac{2}{3} \frac{(f - \mathcal{N}_n)^3}{\mathcal{N}_n^2} + \frac{1}{2} \frac{(f - \mathcal{N}_n)^4}{\mathcal{N}_n^3} - \dots \right)$$

Introduce function $\chi^2 = \sum_n \frac{(f(\mathbf{x}; t_n) - \mathcal{N}_n)^2}{\sigma_n^2}$, with 2 choices for σ_n :

$$\chi^2_{\sigma_n=\sqrt{\mathcal{N}_n}} = \sum_n \frac{(f - \mathcal{N}_n)^2}{\mathcal{N}_n}$$

$$\begin{aligned} \chi^2_{\sigma_n=\sqrt{f}} &= \sum_n \frac{(f - \mathcal{N}_n)^2}{f} = \sum_n \frac{(f - \mathcal{N}_n)^2}{\mathcal{N}_n + (f - \mathcal{N}_n)} = \\ &= \sum_n \left(\frac{(f - \mathcal{N}_n)^2}{\mathcal{N}_n} - \frac{(f - \mathcal{N}_n)^3}{\mathcal{N}_n^2} + \frac{(f - \mathcal{N}_n)^4}{\mathcal{N}_n^3} - \dots \right) \end{aligned}$$

Fluctuations of fit parameters versus fluctuations of \mathcal{N}_n

As a result of statistical fluctuations in individual histogram channels, optimization of $\mathcal{L} = \sum_n \left(\mathcal{N}_n \ln \frac{\mathcal{N}_n}{f} + f - \mathcal{N}_n \right)$ gives vector of “optimal” fit parameters \mathbf{x} , shifted with respect to the “true” value \mathbf{x}_o by some $\Delta\mathbf{x}$: $\mathbf{x} = \mathbf{x}_o + \Delta\mathbf{x}$. Elements of vector $\Delta\mathbf{x}$ can be found from the \mathcal{L} optimization requirement $\partial\mathcal{L}/\partial x_j = 0$:

$$\begin{aligned} 0 &= \frac{\partial\mathcal{L}}{\partial x_j} = \sum_n f'_j \left(-\frac{\mathcal{N}_n}{f} + 1 \right) = \sum_n f'_j \frac{f - \mathcal{N}_n}{f} \approx \sum_n f'_j \frac{f_o + (\sum_i f'_i \Delta x_i) - \mathcal{N}_n}{f_o} = \\ &= \sum_i \left(\sum_n \frac{f'_i f'_j}{f_o} \right) \Delta x_i - \left(\sum_n \frac{f'_j}{f_o} (\mathcal{N}_n - f_o) \right) = 0 \end{aligned}$$

and hence

$$\Delta x_i = \sum_j (\mathcal{A}^{-1})_{ij} \sum_n \frac{f'_j}{f_o} (\mathcal{N}_n - f_o), \quad \text{where} \quad \mathcal{A}_{ij} = \sum_n \frac{f'_i f'_j}{f_o}$$

Here we use:

- $f'_j \equiv \frac{\partial f}{\partial x_j}$ (notation)
- $f(\mathbf{x}) = f(\mathbf{x}_o + \Delta\mathbf{x}) \approx f_o + \sum_i f'_i \Delta x_i$, where $f_o \equiv f(\mathbf{x}_o, t)$
- $\langle \mathcal{N}_n - f_o \rangle = 0$
- $\langle (\mathcal{N}_n - f_o)^2 \rangle \equiv \sigma_n^2 = f_o$
- $\langle (\mathcal{N}_n - f_o)(\mathcal{N}_m - f_o) \rangle = 0$ for $n \neq m$

From that we have:

- $\langle \Delta x_i \rangle = 0$, since $\langle \mathcal{N}_n - f_o \rangle = 0$
- $\langle \Delta x_i (\mathcal{N}_m - f_o) \rangle = \sum_j (\mathcal{A}^{-1})_{ij} f'_j$

By $\langle \dots \rangle$ we denote average over ensemble of similar measurements (ensemble average)

Statistical bias of fit parameters for log-likelihood function fit

For \mathcal{L} minimization in the next-to-leading approximation we have:

$$0 = \frac{\partial \mathcal{L}}{\partial x_j} = \sum_n f'_j \frac{f - \mathcal{N}_n}{f} = \sum_n \frac{f'_j}{f} (f - \mathcal{N}_n) = \sum_n \frac{f'_j + \sum_i f''_{ji} \Delta x_i + \dots}{f_0 + \sum_i f'_i \Delta x_i + \dots} \times$$

$$\times \left(f_0 - \mathcal{N}_n + \sum_i f'_i \Delta x_i + \frac{1}{2} \sum_{ik} f''_{ik} \Delta x_i \Delta x_k + \dots \right)$$

We search for solution in form of successive approximations:

$\Delta x_i = \Delta x_i^0 + \Delta x_i^1 + \dots$ Then for Δx_i^1 we have equation:

$$\sum_n \frac{f'_i}{f_0} \left[\sum_p f'_p \Delta x_p^1 + \frac{1}{2} \sum_j \sum_k f''_{jk} \Delta x_j^0 \Delta x_k^0 + \left(-\frac{\sum_j f'_j \Delta x_j^0}{f_0} + \frac{\sum_j f''_{ij} \Delta x_j^0}{f'_i} \right) \left((f_0 - \mathcal{N}_n) + \sum_k f'_k \Delta x_k^0 \right) \right] = 0$$

which has solution: $\Delta x_p^1 = \sum_i (\mathcal{A}^{-1})_{pi} \times$

$$\times \left[-\sum_j \sum_n \frac{f'_i f'_j}{f_0^2} (\mathcal{N}_n - f_0) \Delta x_j^0 + \sum_{jkn} \frac{f'_i f'_j f'_k}{f_0^2} \Delta x_j^0 \Delta x_k^0 + \sum_j \sum_n \frac{f''_{ij}}{f_0} (\mathcal{N}_n - f_0) \Delta x_j^0 - \sum_{jkn} \frac{f''_{ij} f'_k}{f_0} \Delta x_j^0 \Delta x_k^0 - \frac{1}{2} \sum_{jkn} \frac{f'_i f''_{jk}}{f_0} \Delta x_j^0 \Delta x_k^0 \right]$$

$$\langle \Delta x_p^1 \rangle = -\frac{1}{2} \sum_{ijk} (\mathcal{A}^{-1})_{pi} (\mathcal{A}^{-1})_{jk} \sum_n \frac{f'_i f''_{jk}}{f_0} \neq 0$$

For a single parameter fit:

$$\mathcal{L} : \langle \Delta x^1 \rangle = -\frac{1}{2} \sigma^4 \sum_n \frac{f' f''}{f_0}$$

$$\text{For } \chi^2_{\sigma_n = \sqrt{\mathcal{N}_n}} : \langle \Delta x^1 \rangle = -\frac{1}{2} \sigma^4 \sum_n \frac{f' f''}{f_0} - \sigma^2 \sum_n \frac{f'}{f_0} + \sigma^4 \sum_n \frac{f'^3}{f_0^2}$$

$$\text{For } \chi^2_{\sigma_n = \sqrt{f}} : \langle \Delta x^1 \rangle = -\frac{1}{2} \sigma^4 \sum_n \frac{f' f''}{f_0} + \frac{1}{2} \sigma^2 \sum_n \frac{f'}{f_0} - \frac{1}{2} \sigma^4 \sum_n \frac{f'^3}{f_0^2}$$

Estimates of bias of fit parameters for the fit function $G(t) = N_0 e^{-t/\tau}(1 + A \cos(\omega t + \phi))$

For analytical evaluations and numerical estimates we replace sums by integrals: $\sum_n(\dots) \approx \frac{1}{b} \int(\dots) dt = \frac{N}{\int f dt} \int(\dots) dt$ where b is bin width and $N = \sum_n N_n \approx \sum_n f(\mathbf{x}, t_n) \approx \frac{1}{b} \int f dt$ is total number of events in the histogram.

$$\begin{aligned} \langle \Delta\omega \rangle_1 &\approx \frac{1}{2} \left(\frac{\sqrt{2}}{\tau A \sqrt{N}} \right)^4 \times \frac{N}{\int_{-\tau}^{\infty} N_0 e^{-t/\tau} [1 + A \cos(\omega t + \phi)] dt} \times \\ &\times \int_{-\tau}^{t_{\max}} \frac{N_0 e^{-t/\tau} A t \sin(\omega t + \phi) \times N_0 e^{-t/\tau} A t^2 \cos(\omega t + \phi)}{N_0 e^{-t/\tau} [1 + A \cos(\omega t + \phi)]} dt \approx \\ &\approx \frac{2}{\tau^4 A^2 N} \times \frac{1}{e\tau} \times \frac{1}{2\omega} \left[-e^{-t/\tau} t^3 \cos 2(\omega t + \phi) \right] \Big|_{-\tau}^{t_{\max}} \sim \frac{1}{\omega \tau^2 A^2 N} \end{aligned}$$

$$\begin{aligned} \langle \Delta\omega \rangle_2 &\approx \frac{1}{2} \left(\frac{\sqrt{2}}{\tau A \sqrt{N}} \right)^2 \frac{1}{b} \int_{-\tau}^{t_{\max}} \frac{N_0 e^{-t/\tau} A t \sin(\omega t + \phi)}{N_0 e^{-t/\tau} [1 + A \cos(\omega t + \phi)]} dt \approx \\ &\approx \frac{1}{\omega^2 \tau^2 A N b} \left[-\omega t \cos(\omega t + \phi) \right] \Big|_{-\tau}^{t_{\max}} \sim \frac{t_{\max} + \tau}{\omega \tau^2 A N b} = \frac{N_{ch}}{\omega \tau^2 A N} \end{aligned}$$

$$\begin{aligned} \langle \Delta\omega \rangle_3 &\approx \frac{1}{2} \left(\frac{\sqrt{2}}{\tau A \sqrt{N}} \right)^4 \times \frac{N}{\int_{-\tau}^{\infty} N_0 e^{-t/\tau} [1 + A \cos(\omega t + \phi)] dt} \times \\ &\times \int_{-\tau}^{t_{\max}} \frac{\left(N_0 e^{-t/\tau} A t \sin(\omega t + \phi) \right)^3}{\left(N_0 e^{-t/\tau} [1 + A \cos(\omega t + \phi)] \right)^2} dt \approx \\ &\approx \frac{2}{\tau^4 A N} \times \frac{1}{e\tau} \times \frac{3}{4\omega} \left[-e^{-t/\tau} t^3 \cos(\omega t + \phi) \right] \Big|_{-\tau}^{t_{\max}} \sim \frac{3}{2\omega \tau^2 A N} \end{aligned}$$

where $(t_{\max} + \tau)/b = N_{ch} \sim 3600$ is the typical number of histogram channels

Possible improvement of χ^2 fit

It's straight forward to verify that some linear combination of **results** of $\chi^2_{\sigma_n=\sqrt{\mathcal{N}_n}}$ and $\chi^2_{\sigma_n=\sqrt{f}}$ fits, namely:

$$x_{comb} \equiv \frac{1}{3}(x)_{\sigma_n=\sqrt{\mathcal{N}_n}} + \frac{2}{3}(x)_{\sigma_n=\sqrt{f}}$$

has same bias as the log-likelihood function fit.

Note that similar combination of **functions** $\chi^2_{\sigma_n=\sqrt{\mathcal{N}_n}}$ and $\chi^2_{\sigma_n=\sqrt{f}}$ gives :

$$\frac{1}{3}\chi^2_{\sigma_n=\sqrt{\mathcal{N}_n}} + \frac{2}{3}\chi^2_{\sigma_n=\sqrt{f}} = \sum_n \left[\frac{(f - \mathcal{N}_n)^2}{\mathcal{N}_n} - \frac{2}{3} \frac{(f - \mathcal{N}_n)^3}{\mathcal{N}_n^2} + \frac{2}{3} \frac{(f - \mathcal{N}_n)^4}{\mathcal{N}_n^3} - \dots \right]$$

which coincides with decomposition of $2\mathcal{L}$ in two lowest terms. That gives a hint for possible improvement of χ^2 fit : one should use a function which coincides with decomposition of $2\mathcal{L}$ in two (or more) lowest terms.

Examples:

$$\chi^2_{corr} = \sum_n \left[\frac{(f - \mathcal{N}_n)^2}{\mathcal{N}_n} - \frac{2}{3} \frac{(f - \mathcal{N}_n)^3}{\mathcal{N}_n^2} \right]$$

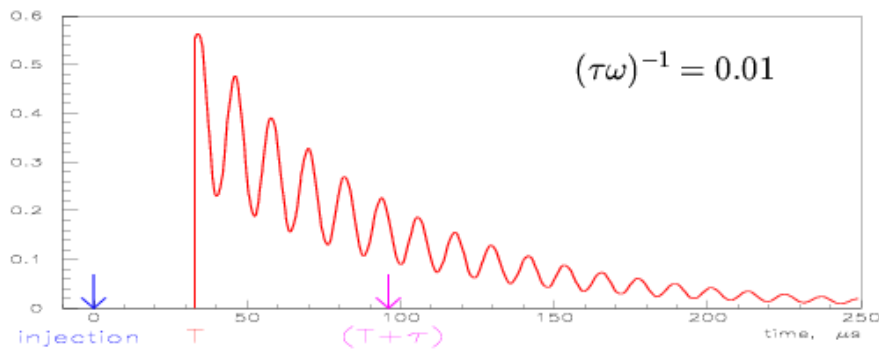
$$\chi^2_{\sigma_n^2 = \mathcal{N}_n^{1/3} \times f^{2/3}} = \sum_n \left[\frac{(f - \mathcal{N}_n)^2}{\mathcal{N}_n} - \frac{2}{3} \frac{(f - \mathcal{N}_n)^3}{\mathcal{N}_n^2} + \frac{5}{6} \frac{(f - \mathcal{N}_n)^4}{\mathcal{N}_n^3} - \dots \right]$$

Direct calculations show that indeed χ^2_{corr} and $\chi^2_{\sigma_n^2 = \mathcal{N}_n^{1/3} \times f^{2/3}}$ fits have same bias as the log-likelihood function fit.

Bias of ω for muon g-2 experiment at BNL

Time distribution of high energy electrons ($E > E_{thr}$) from muon decays:

$$G(t) = N_o e^{-t/\tau} [1 + A \cos(\omega t + \phi)]$$



$$\sigma_{N_o} = \frac{N_o}{\sqrt{N}} \sqrt{(T/\tau + 1)^2 + 1} \quad \sigma_\tau = \frac{\tau}{\sqrt{N}} \quad \sigma_A = \frac{\sqrt{2}}{\sqrt{N}} \quad \sigma_\omega = \frac{\sqrt{2}}{\tau A \sqrt{N}} \quad \sigma_\phi = \frac{\sqrt{2}}{A \sqrt{N}} \sqrt{(T/\tau + 1)^2 + 1}$$

For $b = 0.15 \mu\text{s}$, $A = 0.4$ and $N = 10^6$ decay electrons:

$$\frac{\sigma_\omega}{\omega} = \frac{\sqrt{2}}{\tau \omega A \sqrt{N}} = 38 \text{ ppm}$$

$$\left\langle \frac{\Delta\omega}{\omega} \right\rangle_2 = \frac{1}{\omega} \frac{\sigma_\omega^2}{2} \sum_n \frac{1}{G} \frac{\partial G}{\partial \omega} \approx \frac{1}{2\omega} \left(\frac{\sqrt{2}}{\tau A \sqrt{N}} \right)^2 \frac{1}{b} \int_{-\tau}^{T_{max}} \frac{N_o e^{-t/\tau} A t \sin(\omega t + \phi)}{N_o e^{-t/\tau} [1 + A \cos(\omega t + \phi)]} dt \approx 1 \text{ ppm}$$

$$\left\langle \frac{\Delta\omega}{\omega} \right\rangle_1 = \frac{1}{\omega} \frac{\sigma_\omega^4}{2} \sum_n \frac{1}{G} \frac{\partial G}{\partial \omega} \frac{\partial^2 G}{\partial \omega^2} \approx \frac{1}{2\omega} \left(\frac{\sqrt{2}}{\tau A \sqrt{N}} \right)^4 \times \frac{N}{\int_{-\tau}^{\infty} N_o e^{-t/\tau} [1 + A \cos(\omega t + \phi)] dt} \times \int_{-\tau}^{\infty} \frac{N_o e^{-t/\tau} A t \sin(\omega t + \phi) \times N_o e^{-t/\tau} A t^2 \cos(\omega t + \phi)}{N_o e^{-t/\tau} [1 + A \cos(\omega t + \phi)]} dt \approx 0.4 \text{ ppb}$$

Suppose we have $N = 10^9$ events and want to

- split them into 1000 parts, $N = 10^6$ in each;
- fit these 1000 parts separately;
- find ω as weighted average

then we'll have ~ 1 ppm bias, which is now comparable with statistical error $38 \text{ ppm} \times \sqrt{10^6/10^9} = 1.2 \text{ ppm}$.