Spectral fitting:

- Calibration uncertainties
- Randomization

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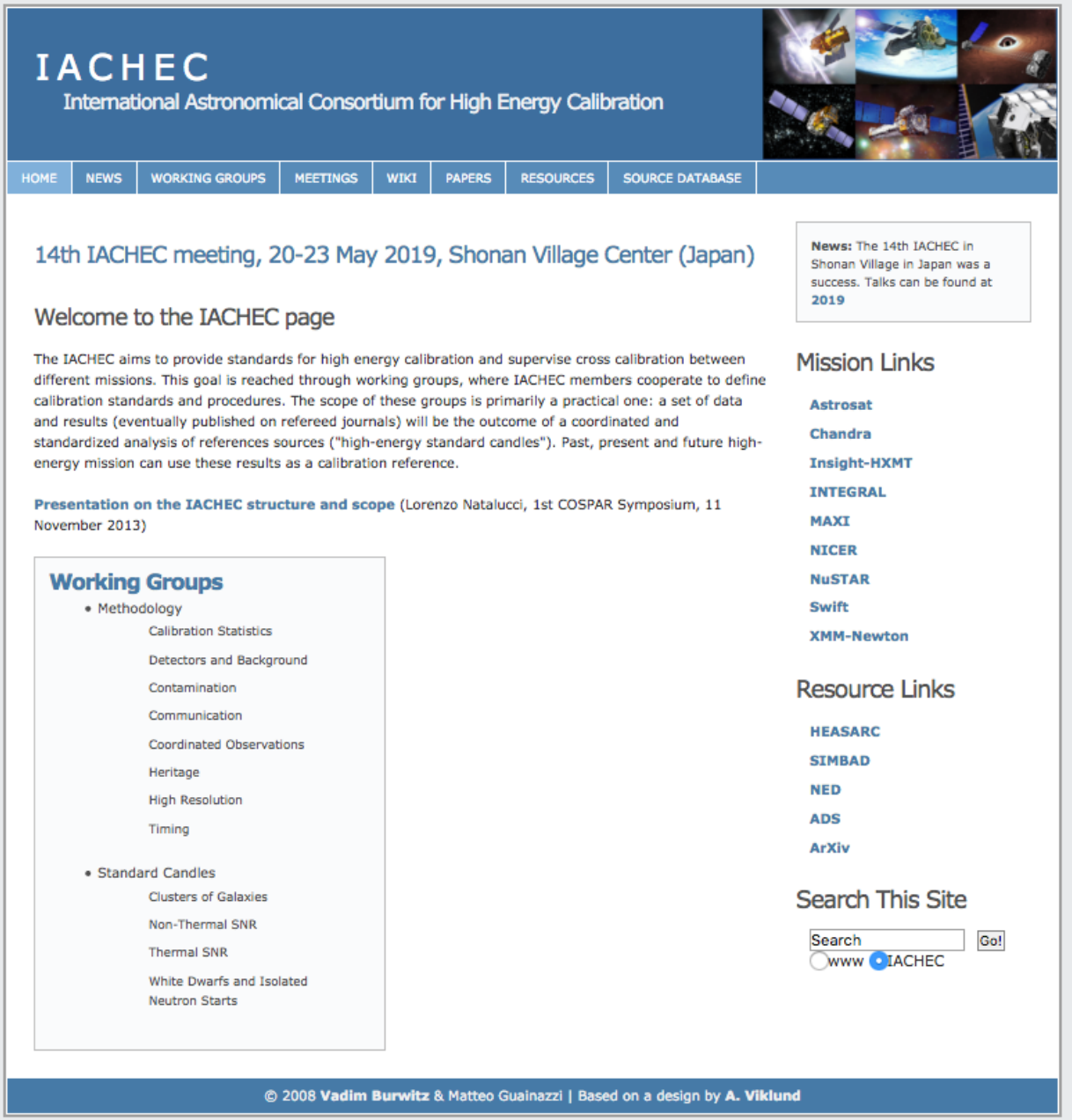
- Calibration uncertainties
- Randomization



IACHEC

International Astronomical Consortium for High Energy Calibration

HOME | NEWS | WORKING GROUPS | MEETINGS | WIKI | PAPERS | RESOURCES | SOURCE DATABASE

14th IACHEC meeting, 20-23 May 2019, Shonan Village Center (Japan)

Welcome to the IACHEC page

The IACHEC aims to provide standards for high energy calibration and supervise cross calibration between different missions. This goal is reached through working groups, where IACHEC members cooperate to define calibration standards and procedures. The scope of these groups is primarily a practical one: a set of data and results (eventually published on refereed journals) will be the outcome of a coordinated and standardized analysis of references sources ("high-energy standard candles"). Past, present and future high-energy mission can use these results as a calibration reference.

Presentation on the IACHEC structure and scope (Lorenzo Natalucci, 1st COSPAR Symposium, 11 November 2013)

Working Groups

- Methodology
  - Calibration Statistics
  - Detectors and Background
  - Contamination
  - Communication
  - Coordinated Observations
  - Heritage
  - High Resolution
  - Timing
- Standard Candles
  - Clusters of Galaxies
  - Non-Thermal SNR
  - Thermal SNR
  - White Dwarfs and Isolated Neutron Starts

News: The 14th IACHEC in Shonan Village in Japan was a success. Talks can be found at **2019**

Mission Links

Astrosat
Chandra
Insight-HXMT
INTEGRAL
MAXI
NICER
NuSTAR
Swift
XMM-Newton

Resource Links

HEASARC
SIMBAD
NED
ADS
ArXiv

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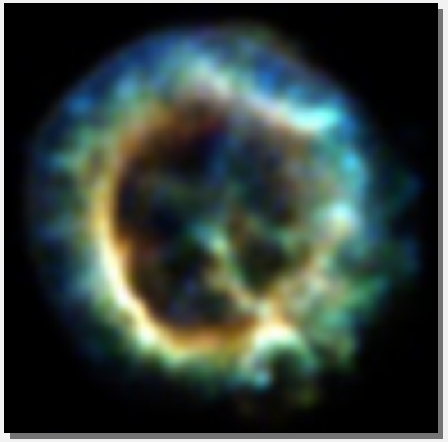
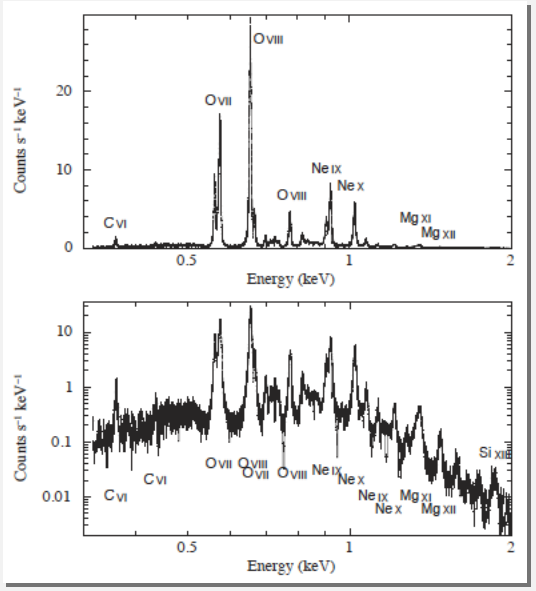
Plucinsky et al. 2017 (A&A 597)

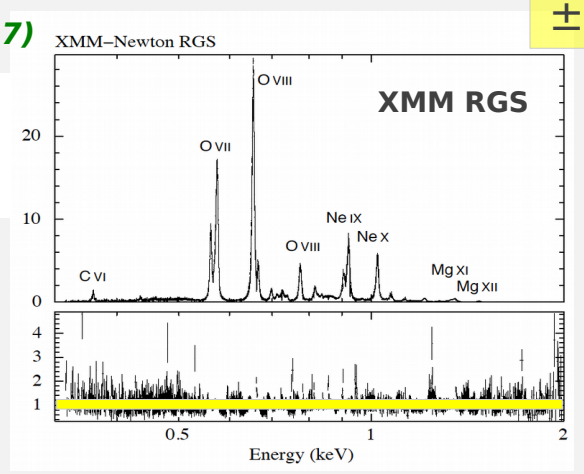
± 20%

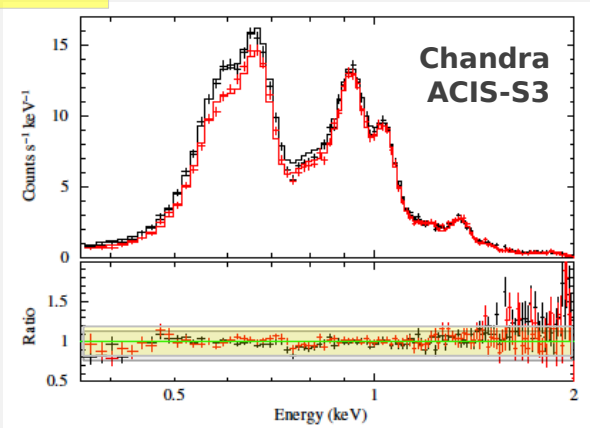
SNR 1E 0102.2-7219 as an X-ray calibration standard in the 0.5–1.0 keV bandpass and its application to the CCD instruments aboard *Chandra*, *Suzaku*, *Swift* and *XMM-Newton*

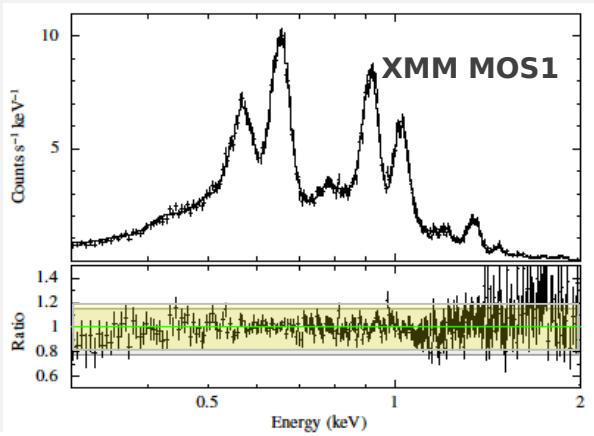
Paul P. Plucinsky[1], Andrew P. Beardmore[2], Adam Foster[1], Frank Haberl[3], Eric D. Miller[4], Andrew M. T. Pollock[5], and Steve Sembay[2]

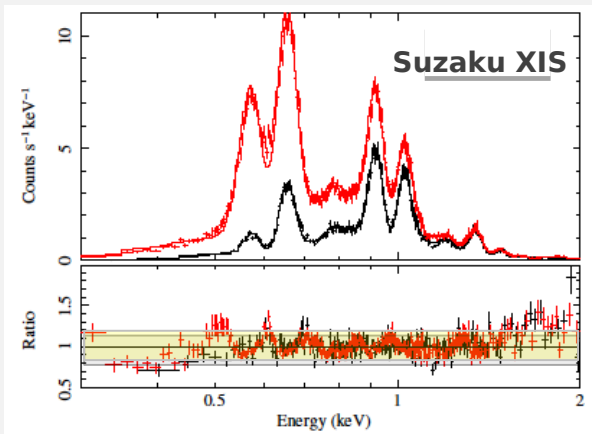


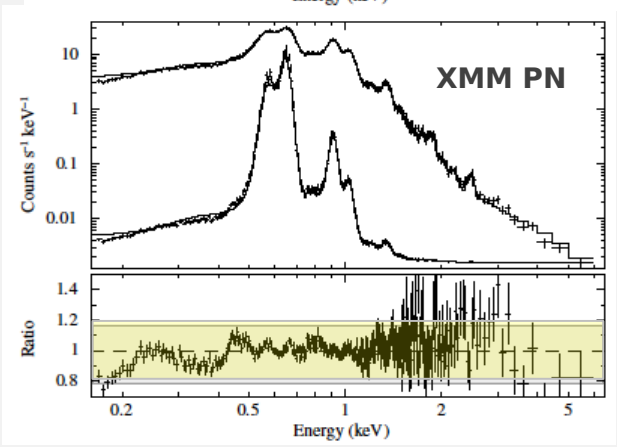


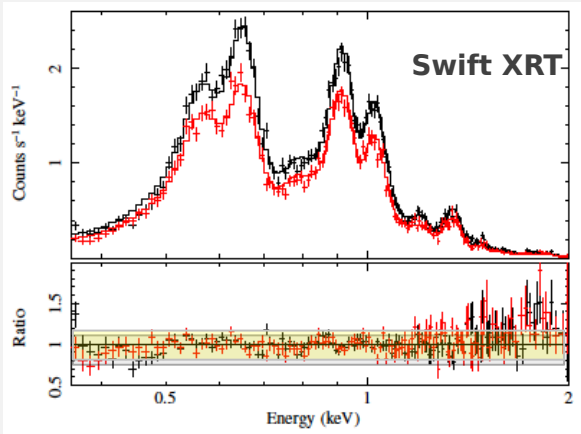






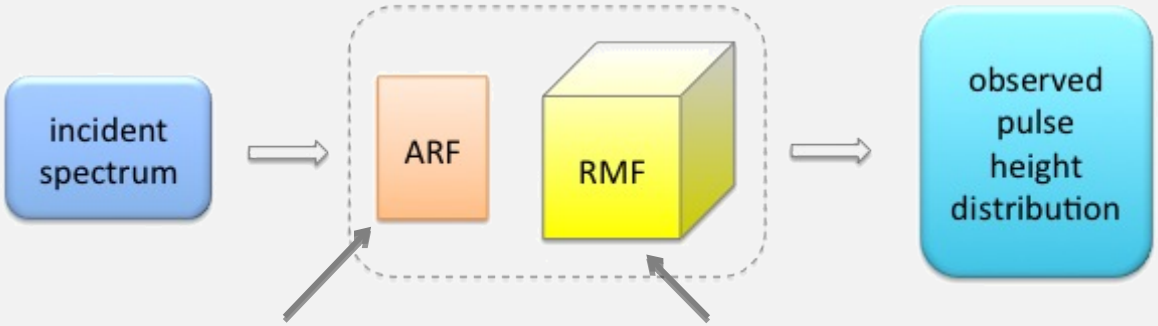






General properties of the ARF and RMF

ARF: „Ancillary Response File“, RMF: „Redistribution Matrix File“

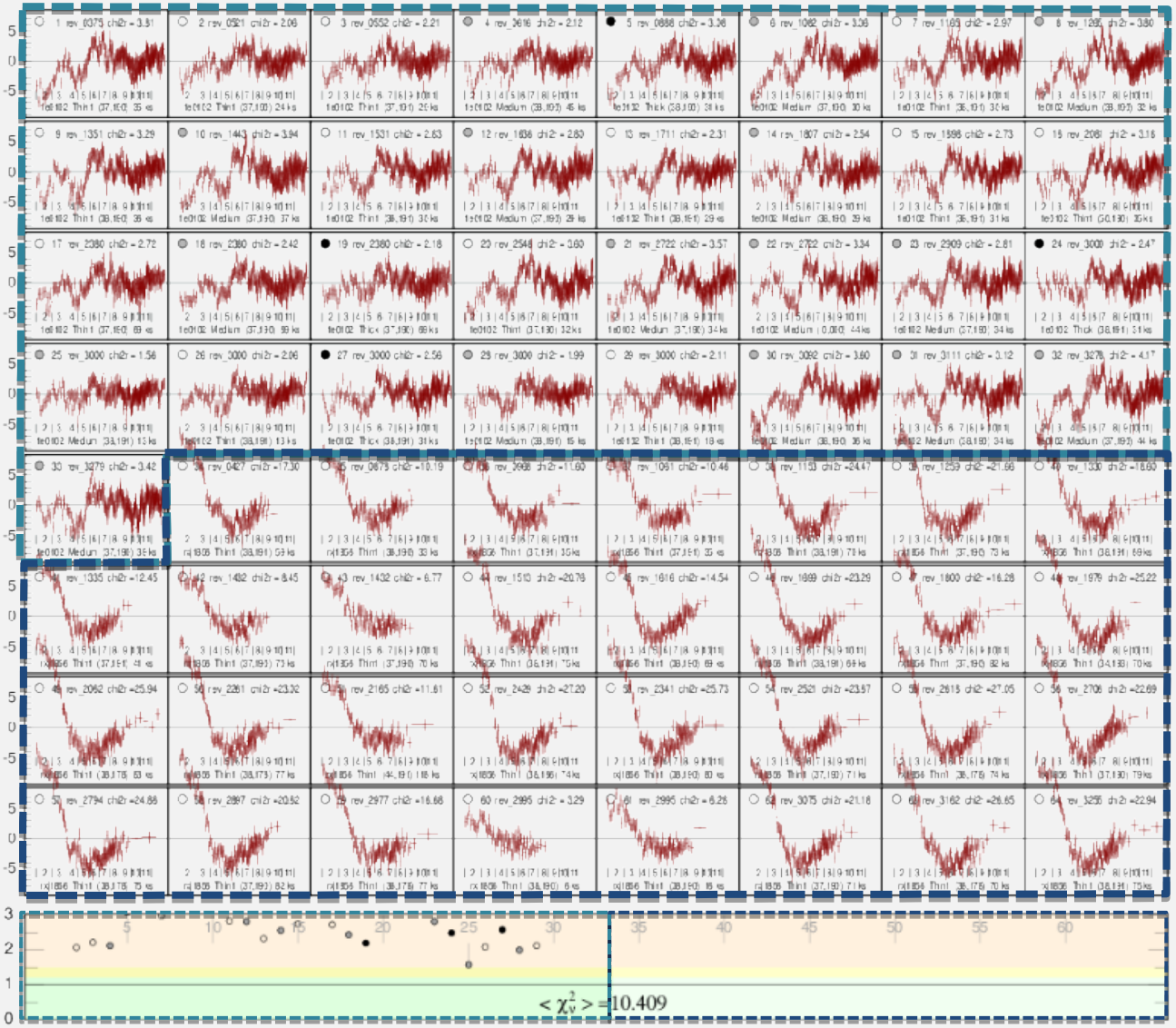


EPIC pn: 2067 vector elements 2067 x 4096 = 8 446 432 matrix elements

RMF @ EPIC pn: 4096 adu bins from 0.0 to 20.5 ‚keV‘ („EBOUNDS“)
2067 eV bins from 50 eV to 16 keV

EPIC pn RMF: 8.5 million matrix elements
EPIC pn ARFs: 3 x 2067 elements

Residuals obtained with xmmsas RMF



average reduced χ^2 = 10.409

spectral models:

1E 0102

IACHEC model

with **only 1 free parameter**: global normalization

+ gain fit (offset)

RX J1856

TBabs * bbodyrad

with **all parameters from Chandra** (no free parameter!)

nH == 7.25 10^{-19} cm^{-2}
kT == 62.4 eV
norm == 1.58 10^5

+ gain fit (offset)

Residuals obtained with parameterized RMF

average reduced χ^2 = 1.310

spectral models:

1E 0102

IACHEC model

with **only 1 free parameter**: global normalization

+ gain fit (offset)

RX J1856

TBabs * bbodyrad

with **all parameters from Chandra** (no free parameter!)

nH == 7.25 10^{-19} cm^{-2}
kT == 62.4 eV
norm == 1.58 10^5

+ gain fit (offset)

Spectral fitting:

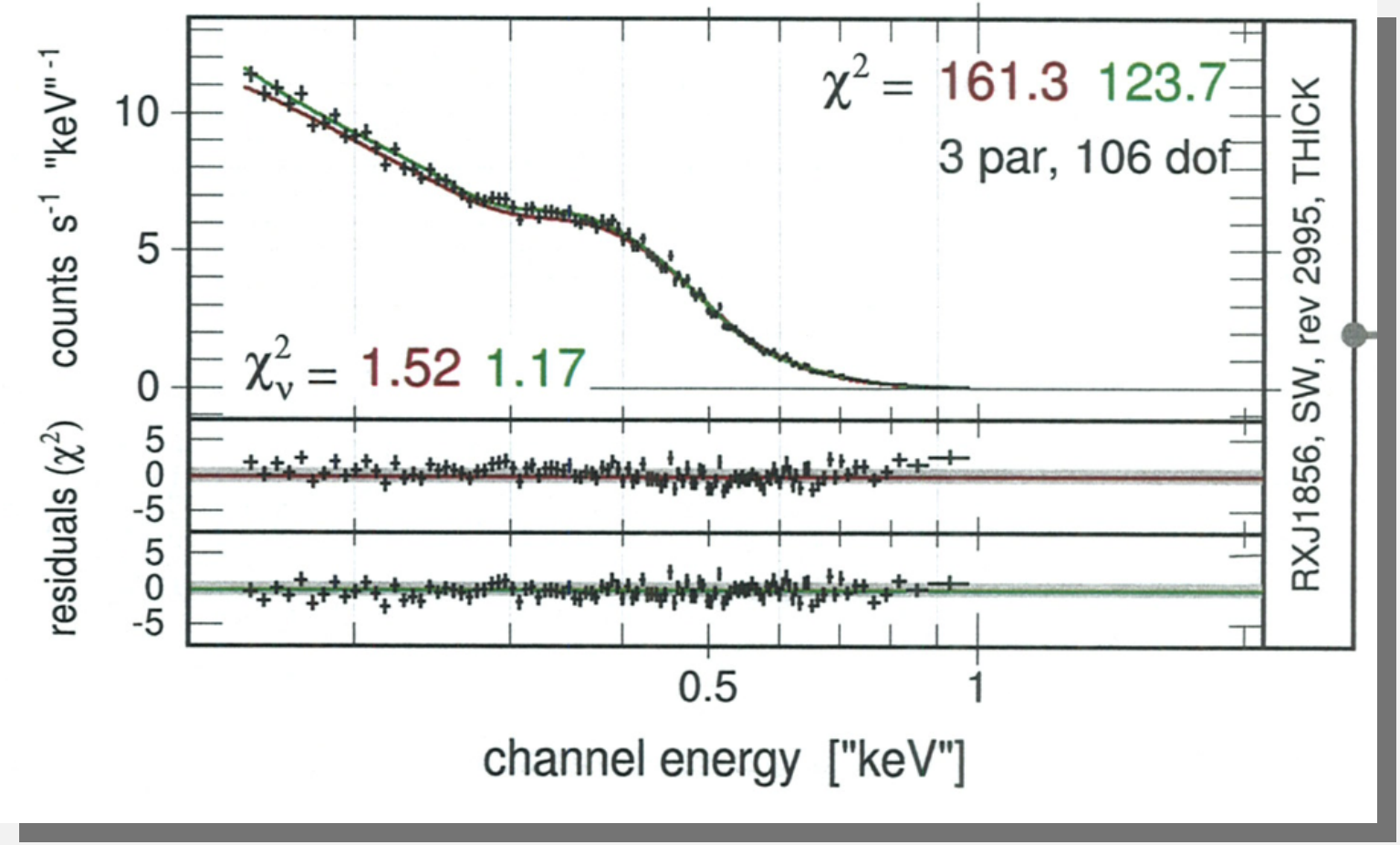
- Calibration uncertainties
- Randomization

Calibration uncertainties, especially in the RMF,
are generally not taken into account in spectral fits!

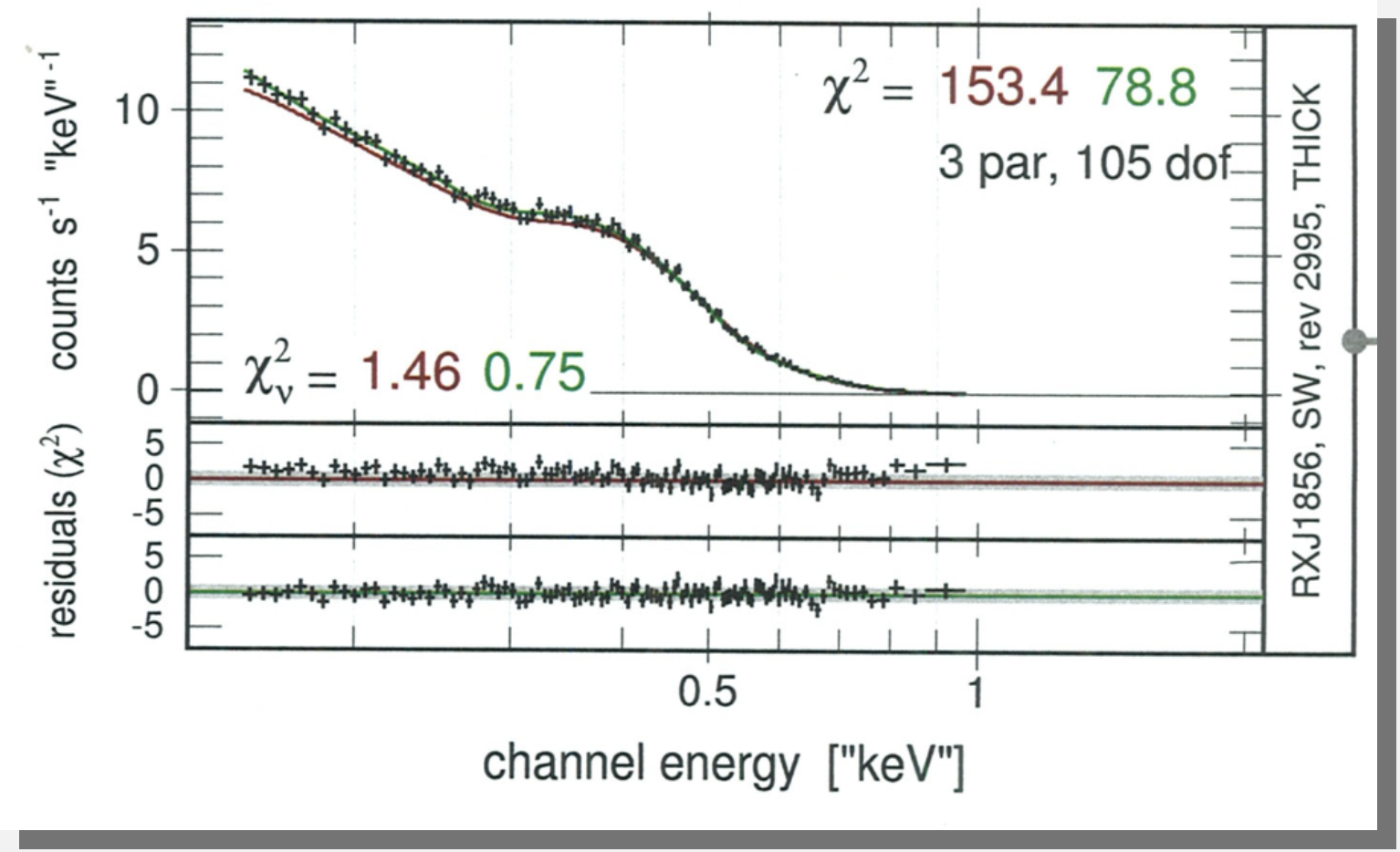
Spectral fitting:

- Calibration uncertainties
- Randomization

Fit to RXJ 1856 (rev 2995, SW, thick)

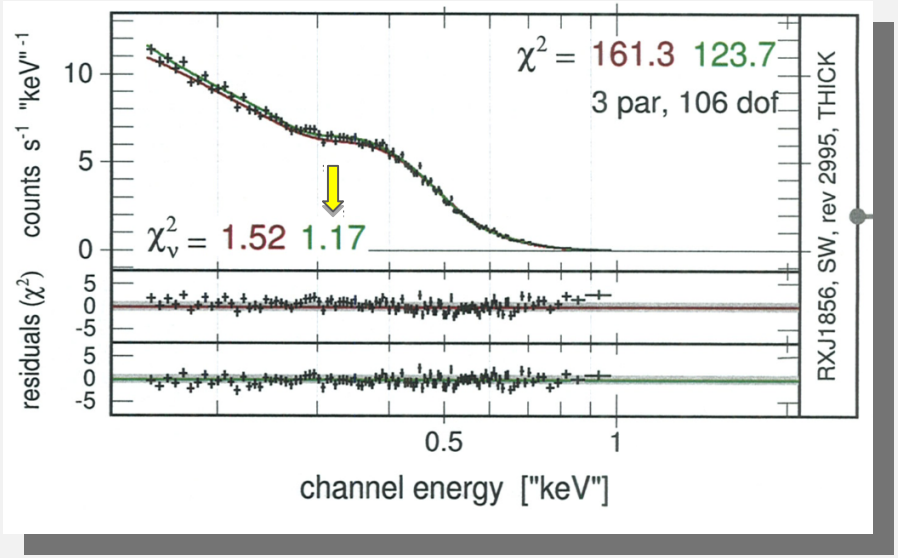


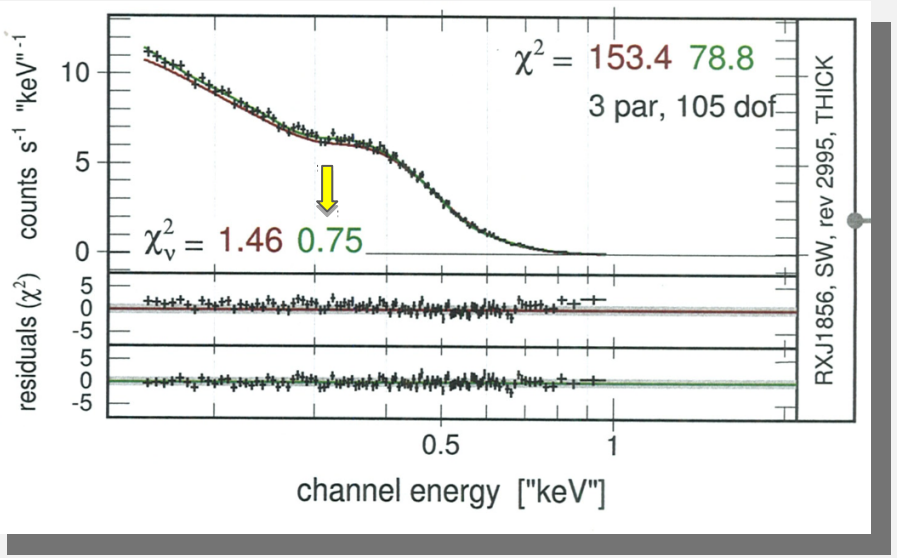
Fit to RXJ 1856 (rev 2995, SW, thick)



Fits to RXJ 1856 (rev 2995, SW, thick)

with the same RMFs and ARFs and the same spectral model, spectra produced in (almost) the same way with the same SAS version (20141104)





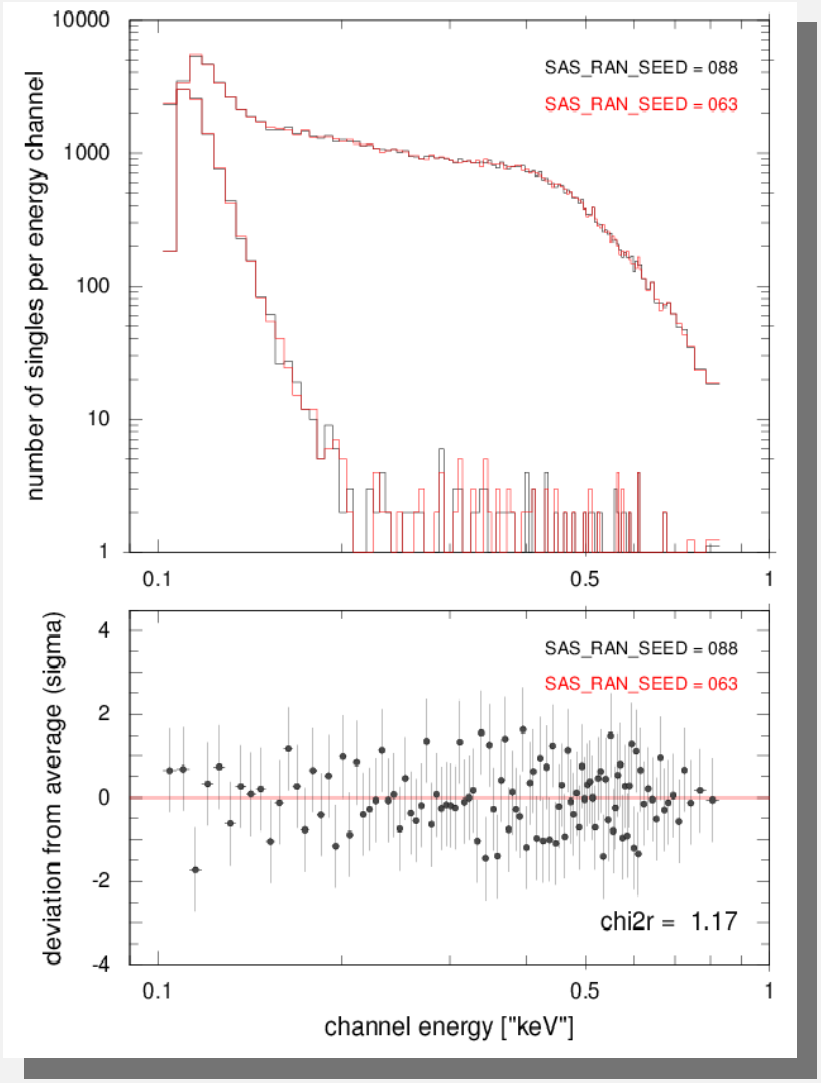
difference is probably caused by the randomization within the PHA channels

✉ numerical experiment: process the same data „identically“ 100 times ..

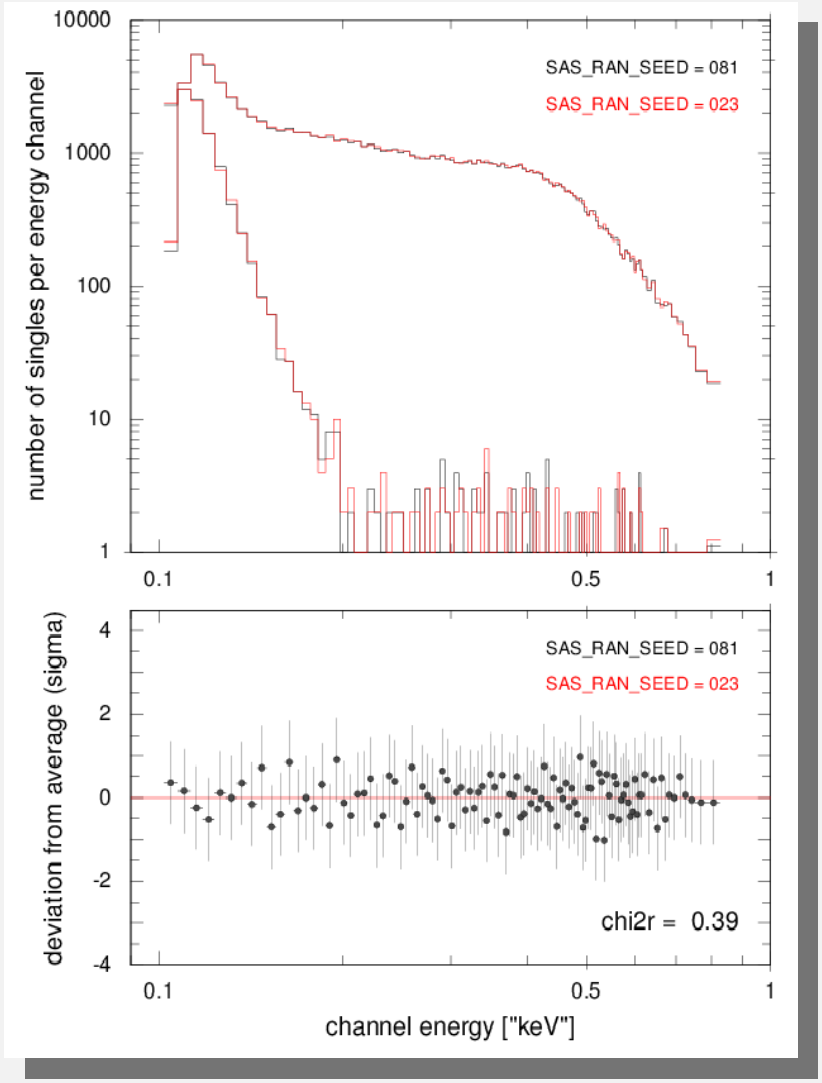
Pairwise comparison of PI spectra from repeated SAS processings (no spectral fit!)

RXJ 1856, SW, **thick** filter, rev 2995, statistical errors of both spectra considered

worst agreement



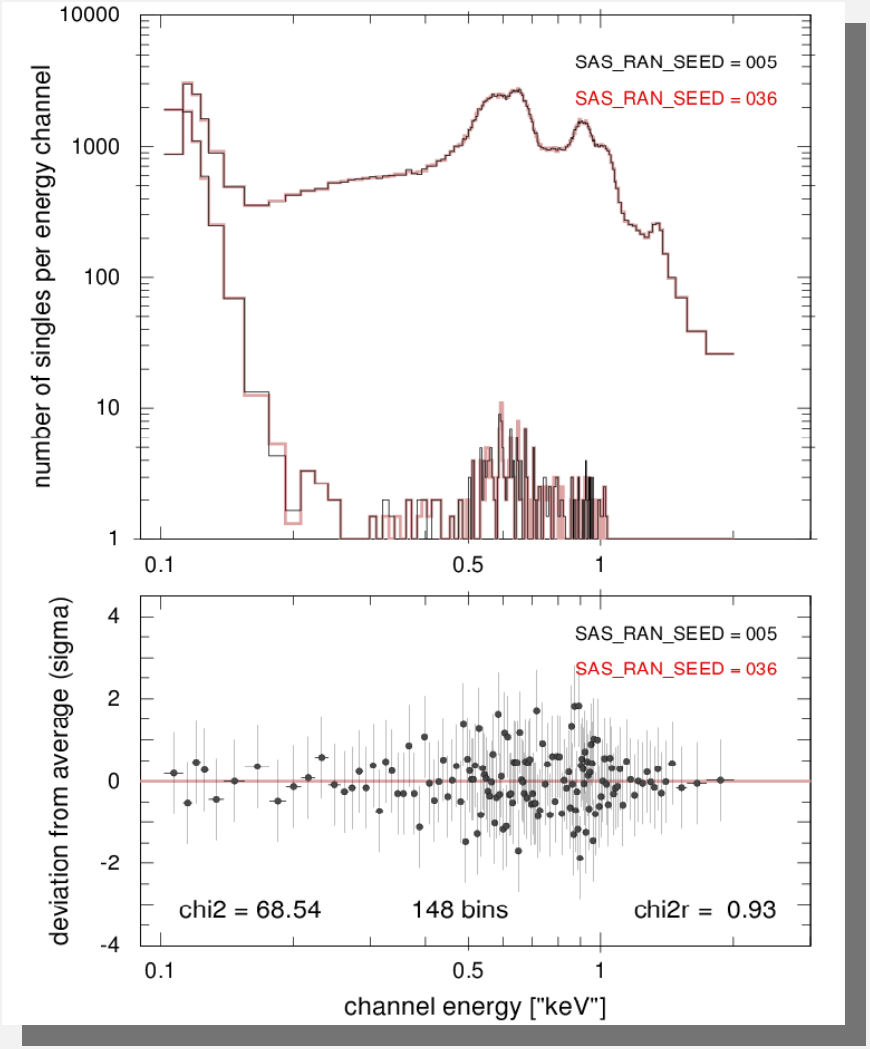
best agreement



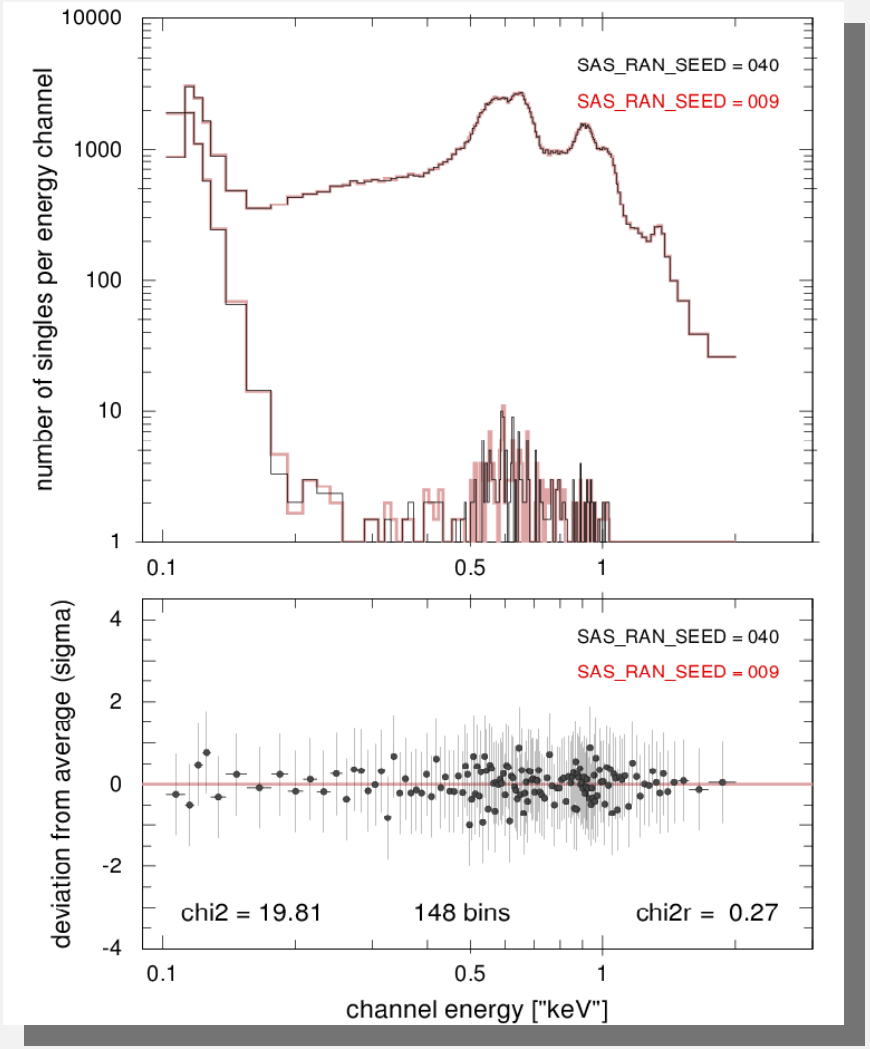
Pairwise comparison of PI spectra from repeated SAS processings (no spectral fit!)

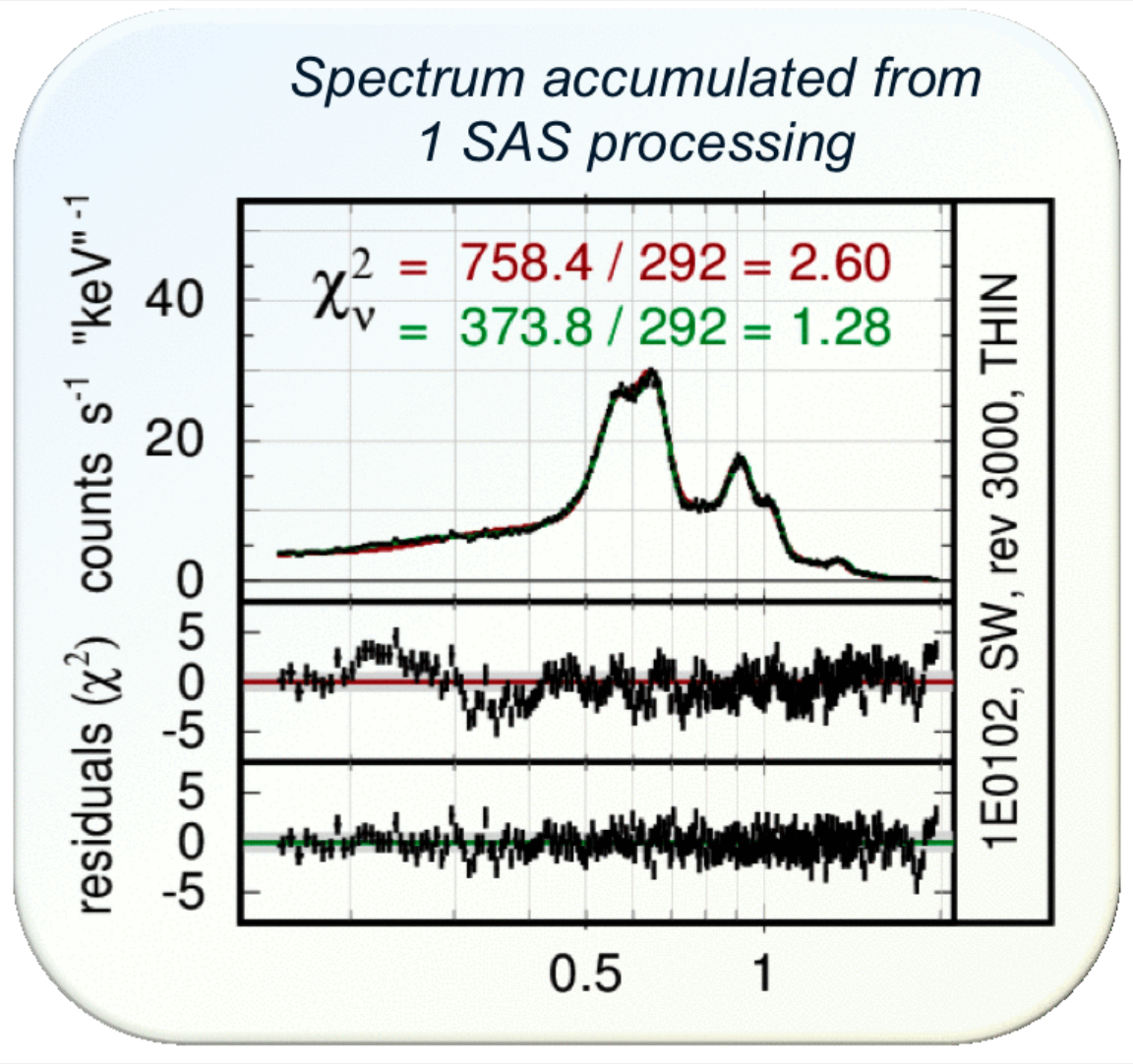
1E0102, SW, **medium** filter, rev 3000, statistical errors of both spectra considered

worst agreement



best agreement



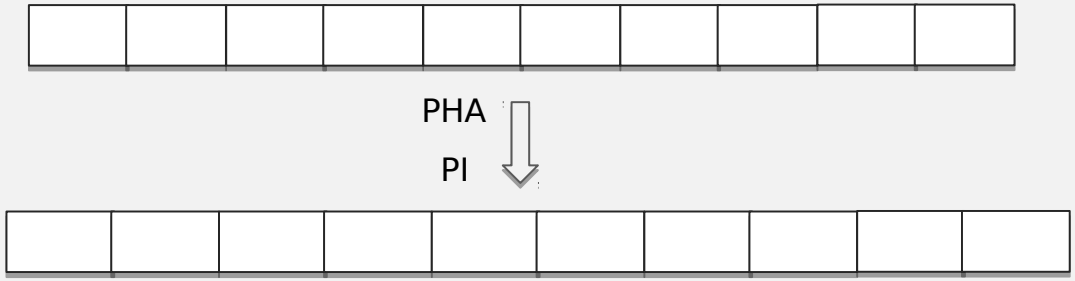

Spectrum accumulated from
1 SAS processing
χ^2_ν = 758.4 / 292 = 2.60
= 373.8 / 292 = 1.28
counts s^{-1} "keV"$^{-1}$
residuals (χ^2)
40
20
0
5
0
-5
5
0
-5
0.5
1
1E0102, SW, rev 3000, THIN

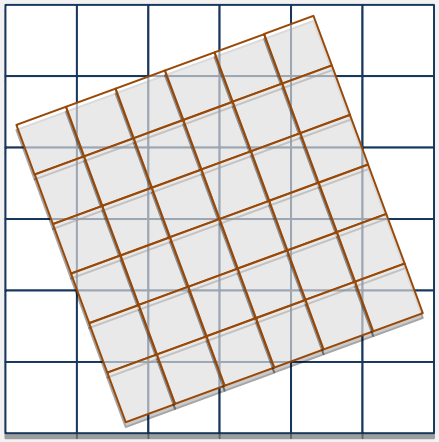
Reason for randomziation

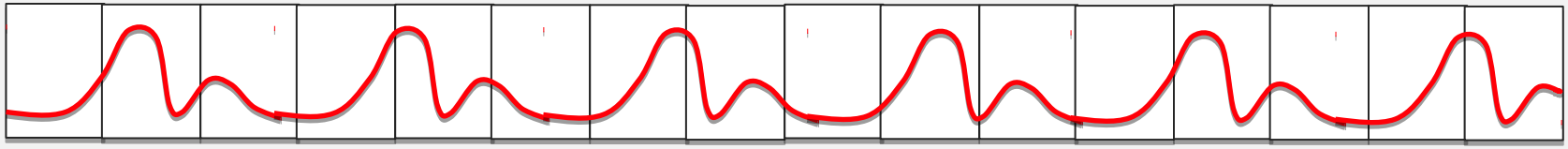
General problem: how to rebin binned data ?

urs frequently:

pectral rebinning: gain & CTI corrections
emporal rebinning: folding pulse profiles
patial rebinning: projection of pixels, image overlays





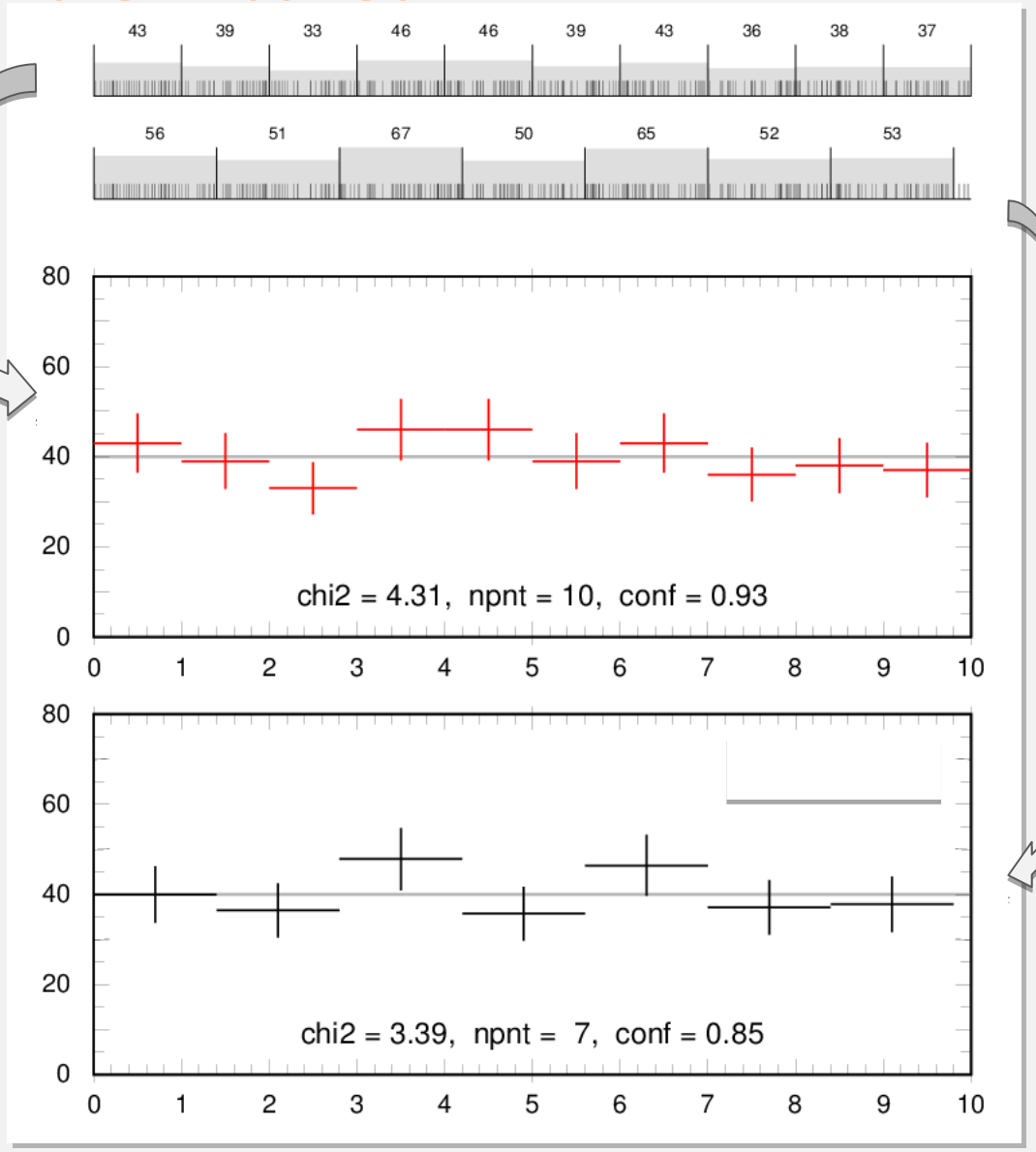


Simple example: 400 counts in 10 bins, uniformely distributed

„original“ bin size

binsize increased by factor 1.4

distributions resulting from binning unbinned data



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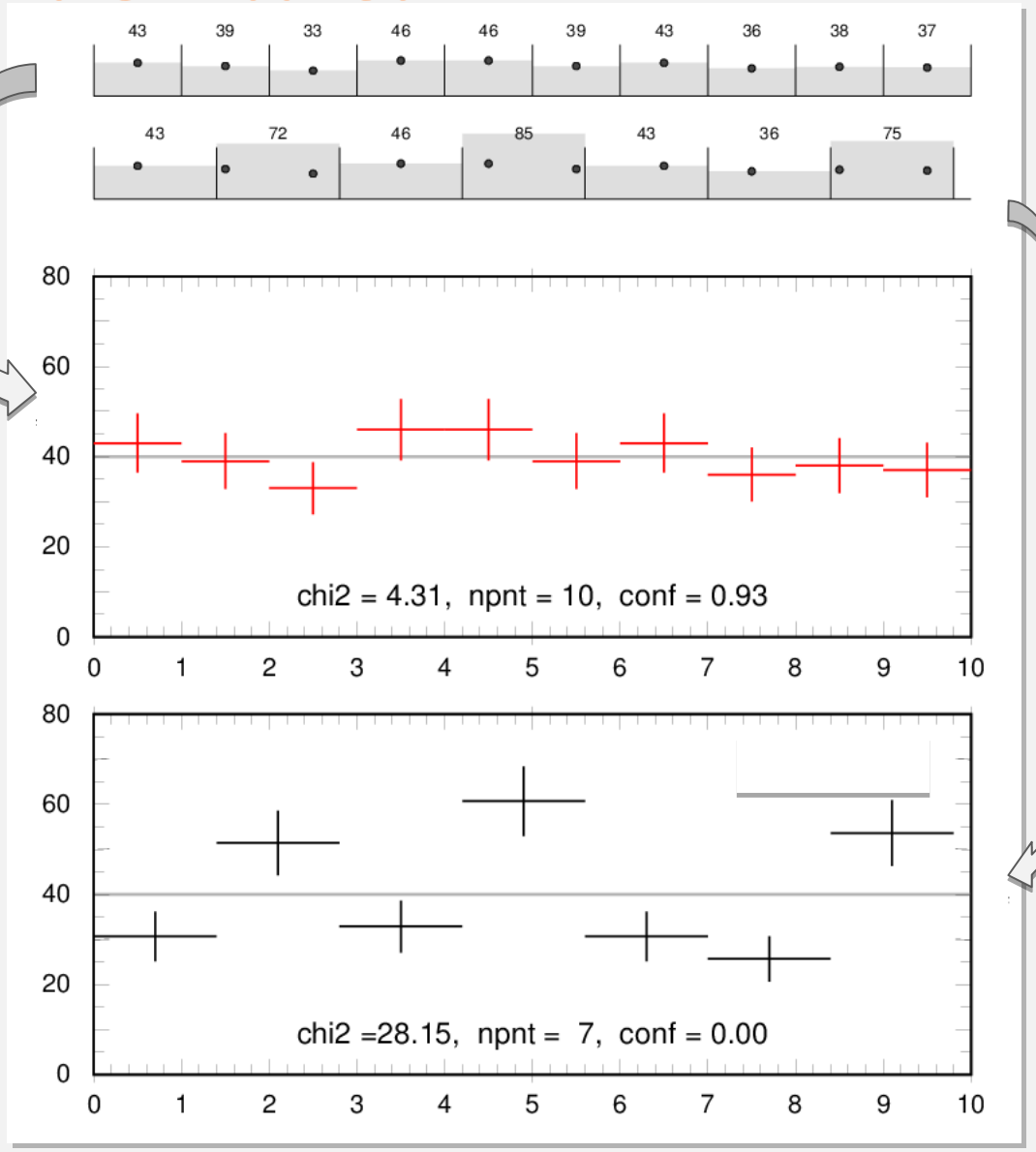


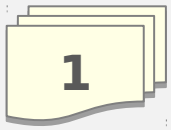
distributions resulting from binning binned data, using the bin centers

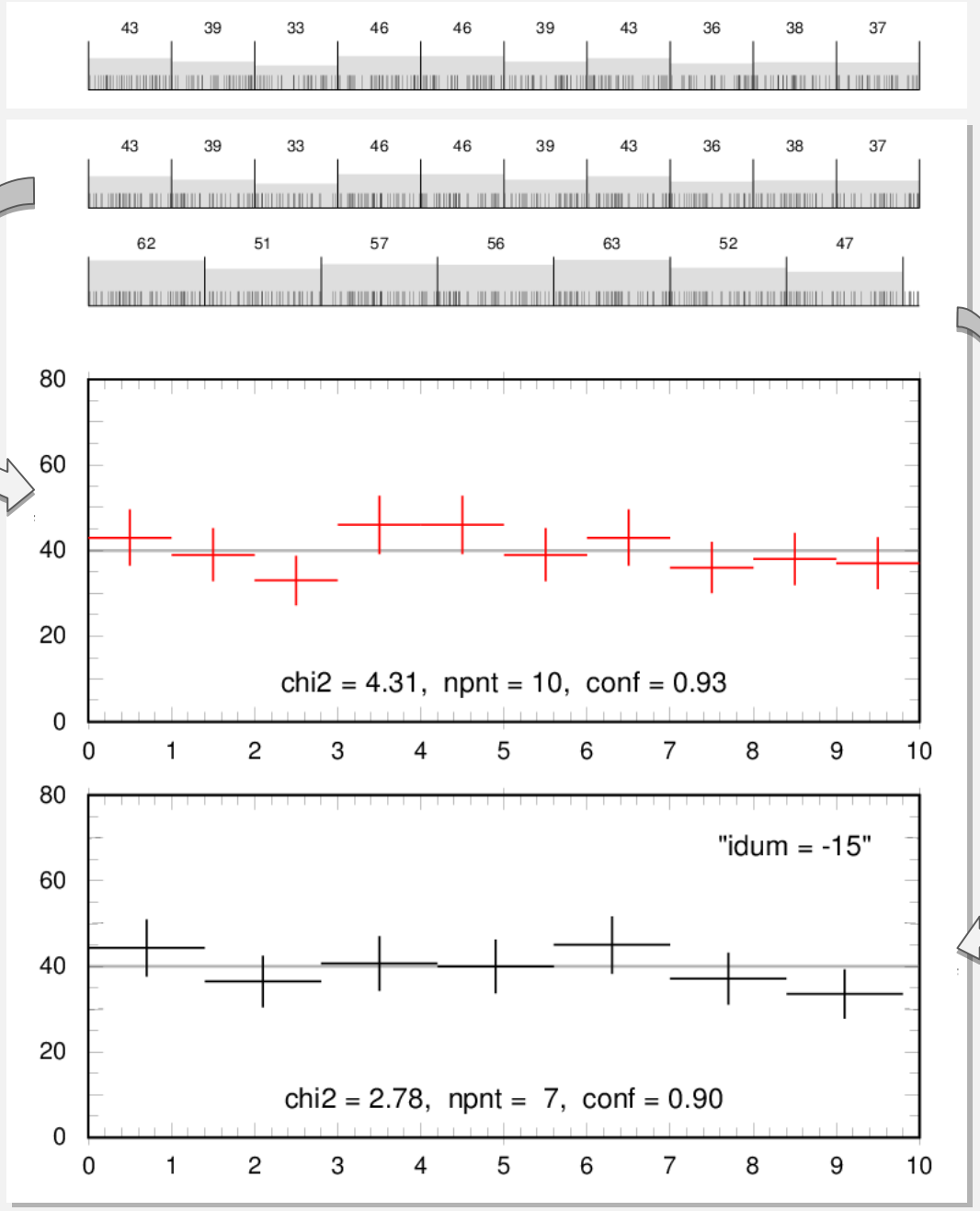
✉ beat pattern, wrong method

original distribution
(only available in binned form)

new randomization
according to information
in binned data

distributions
resulting from
binning
binned data,
using
randomization





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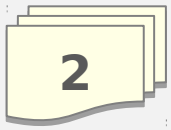

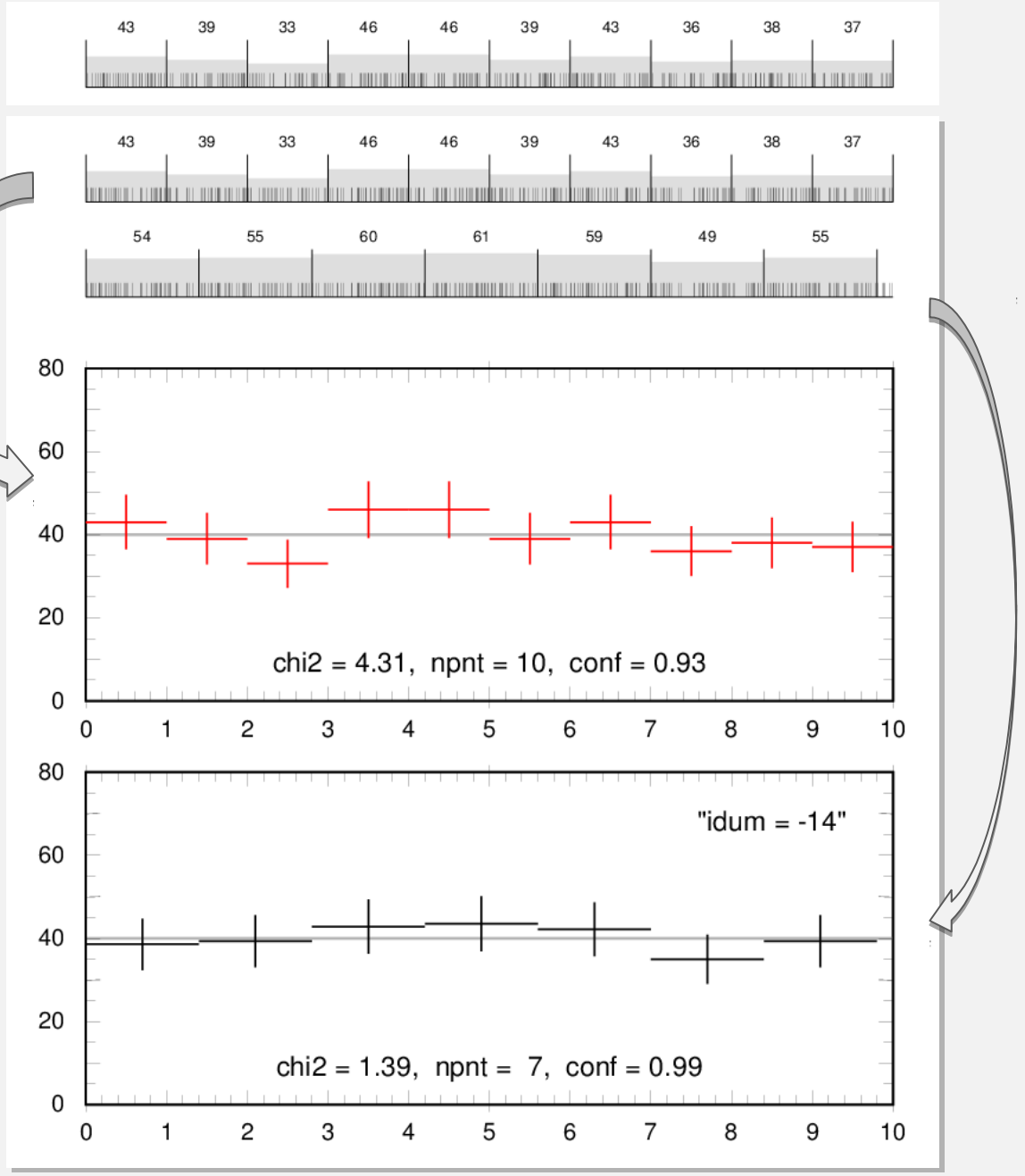

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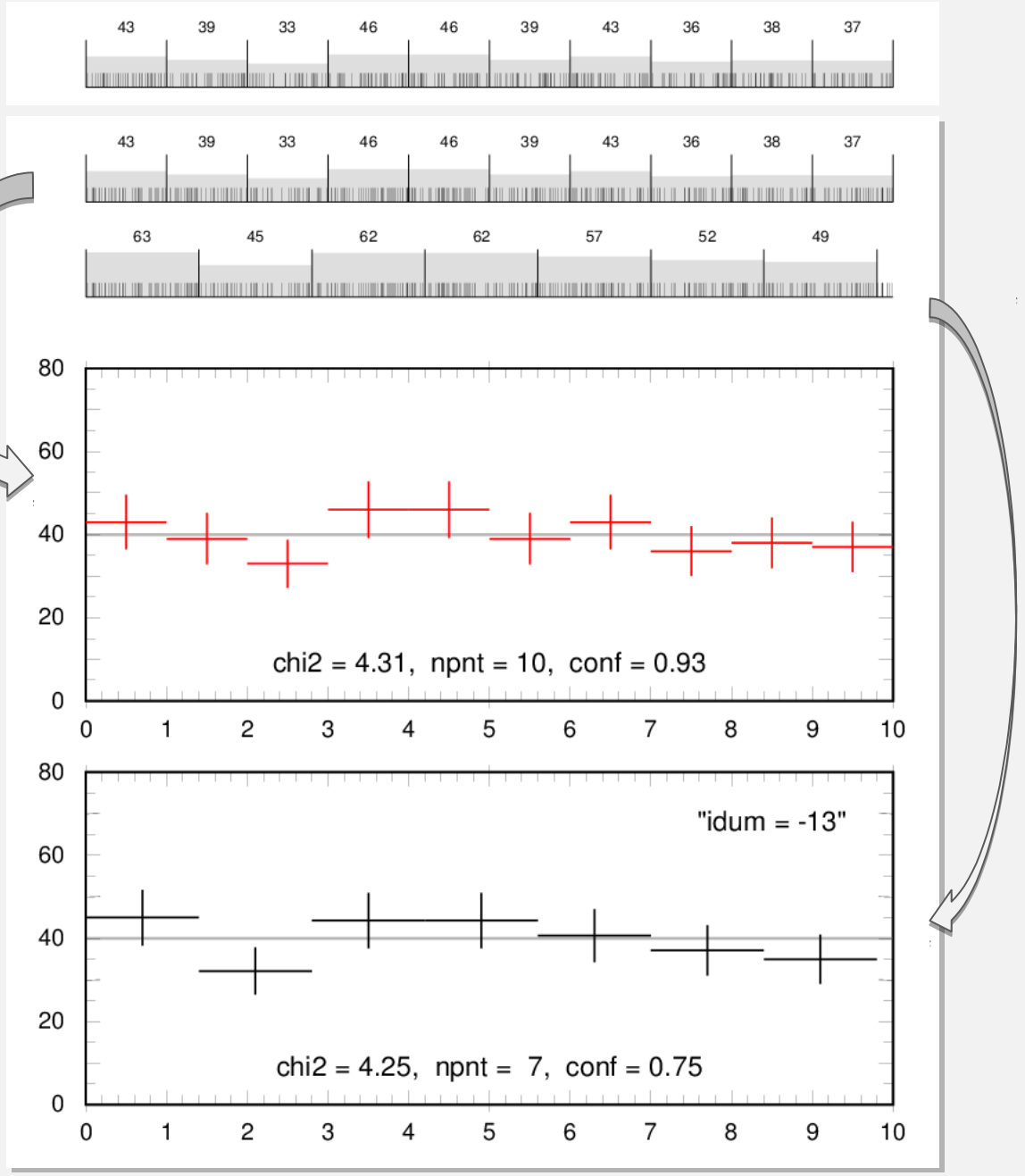

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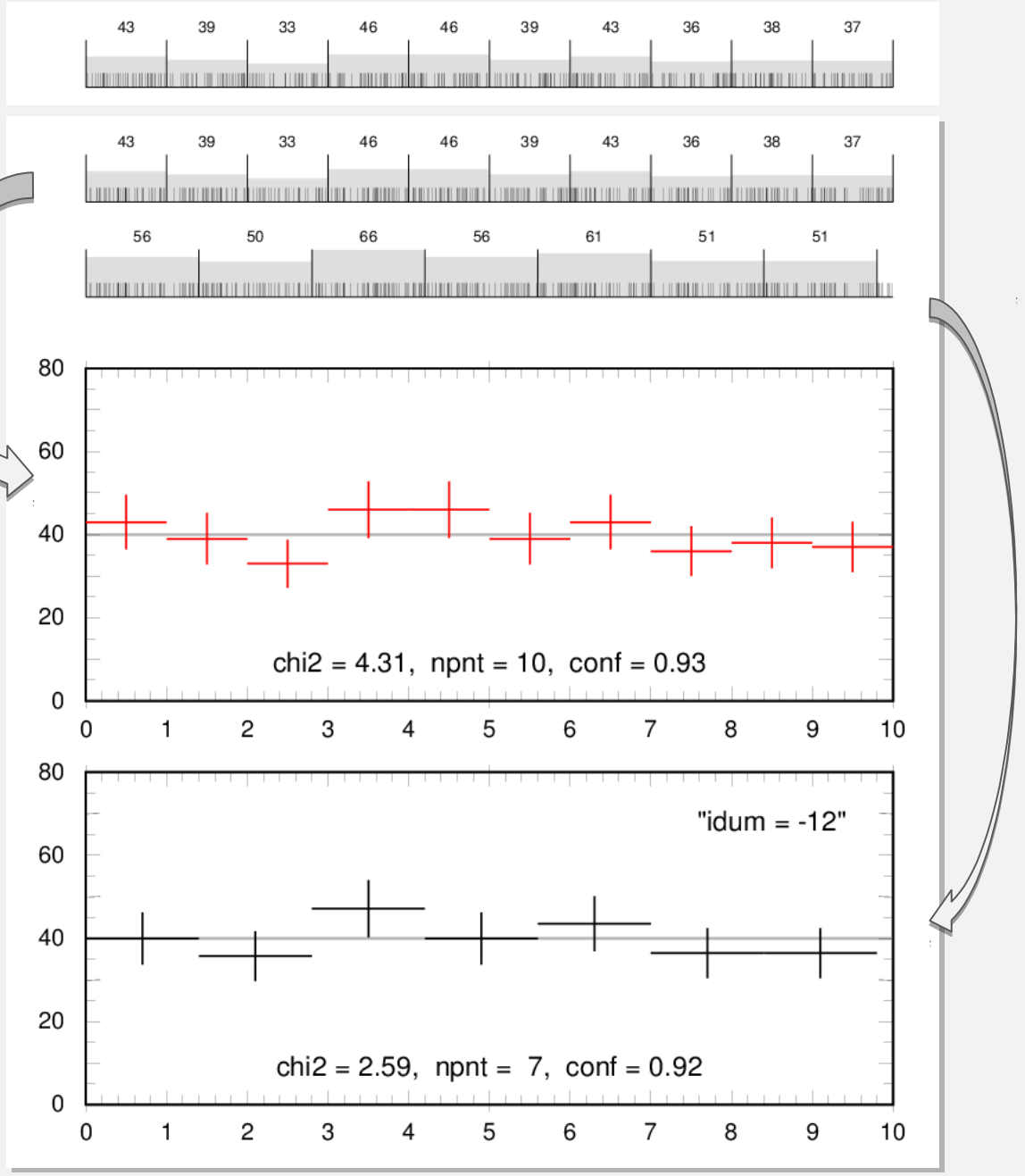

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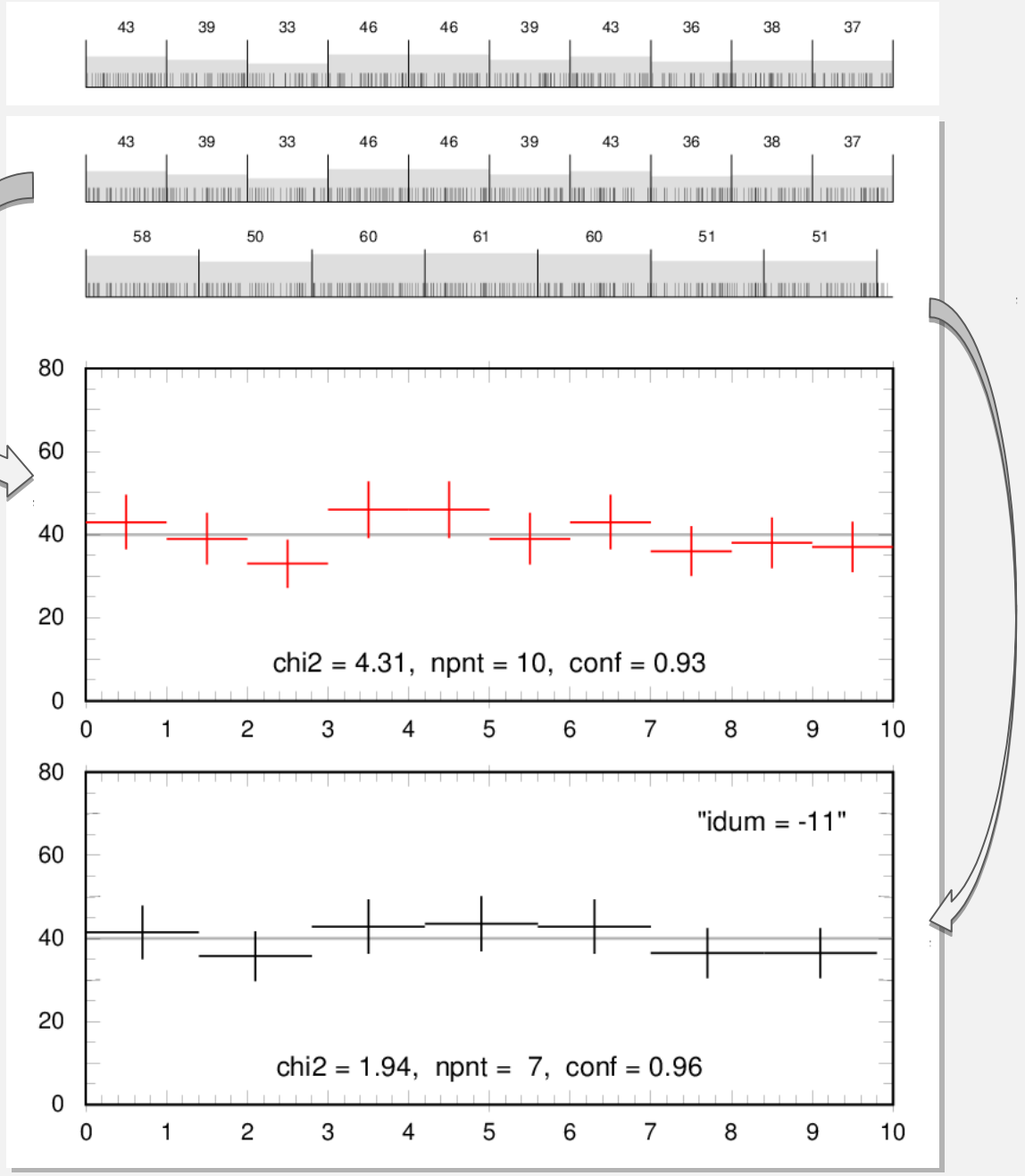

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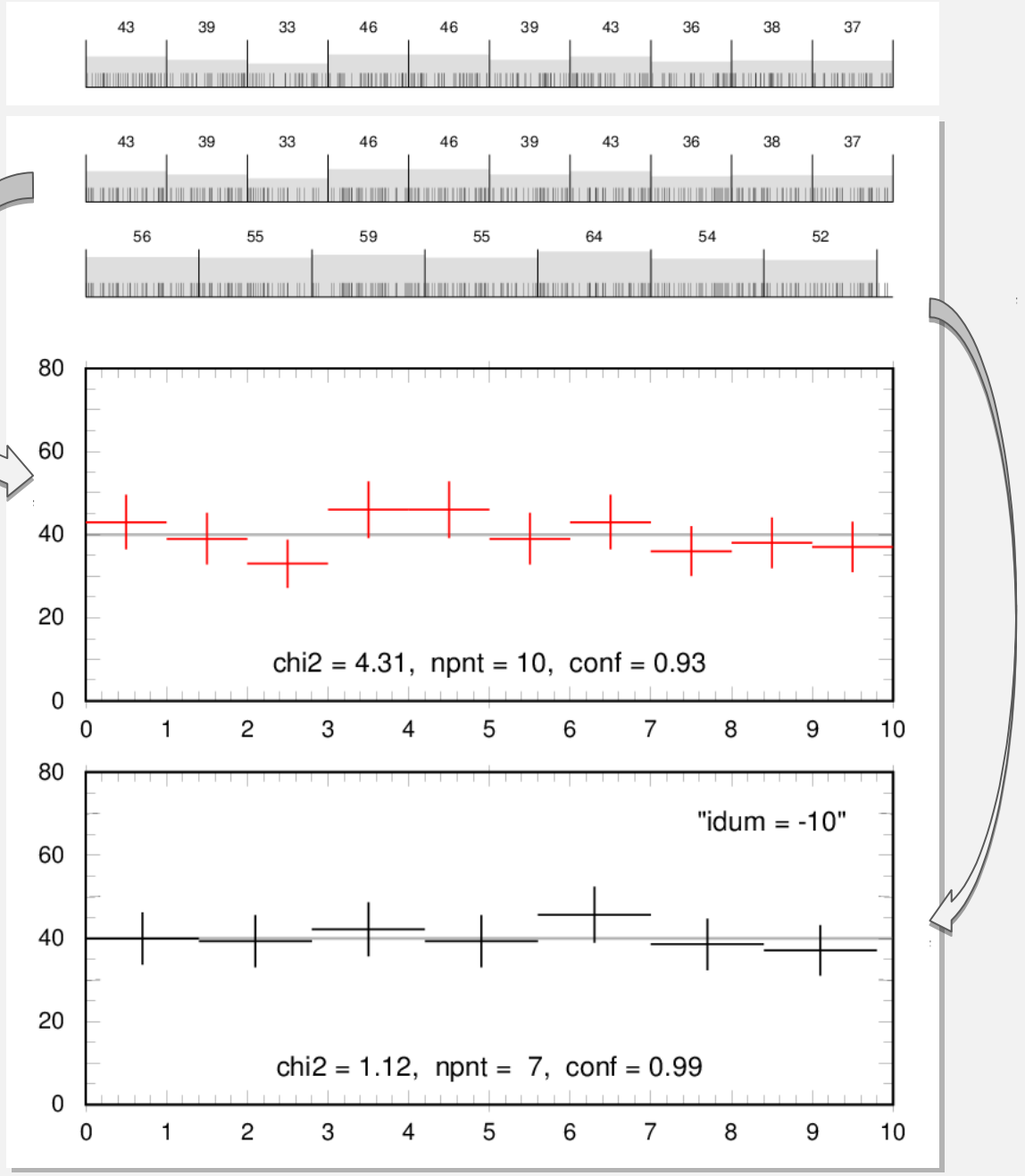
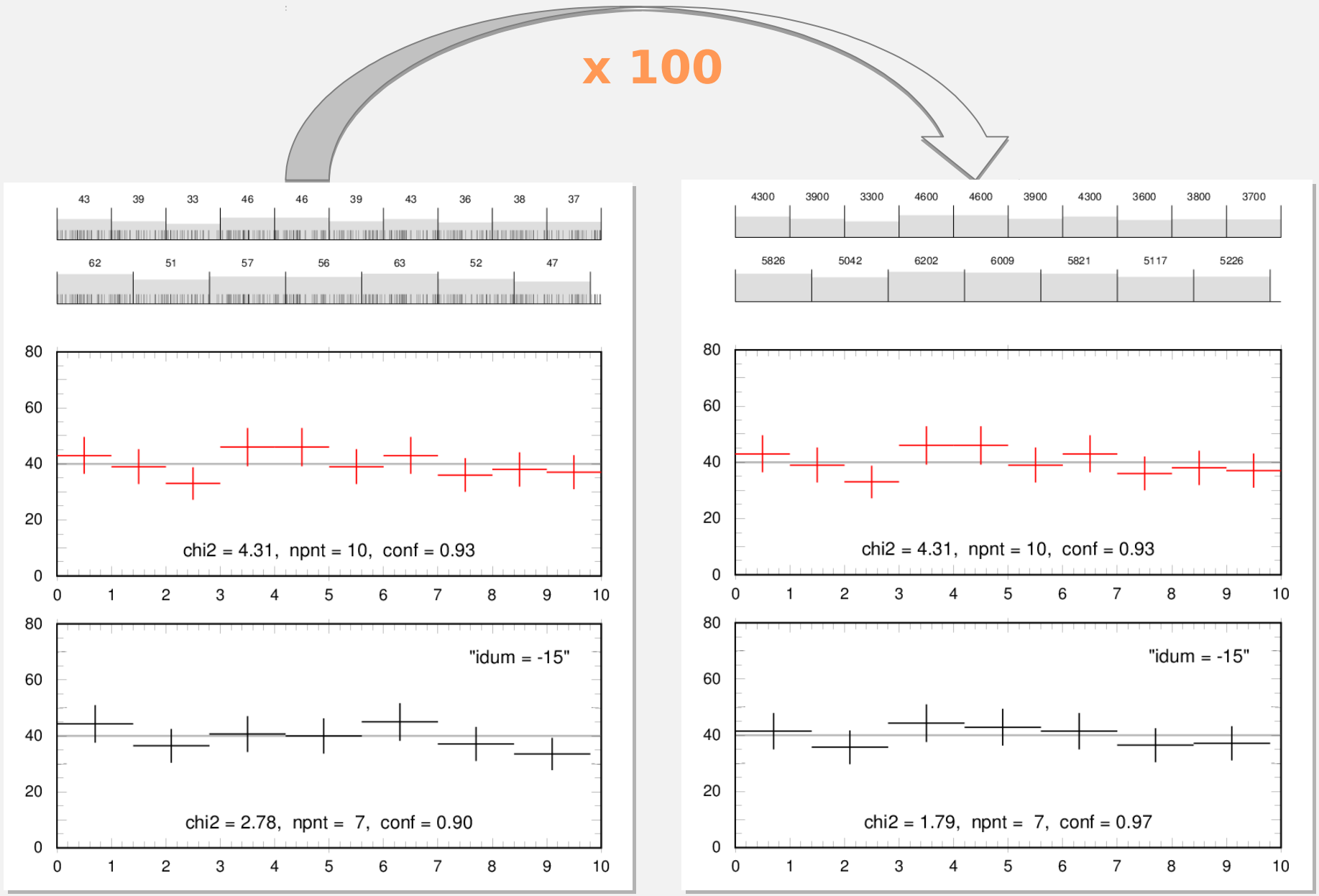
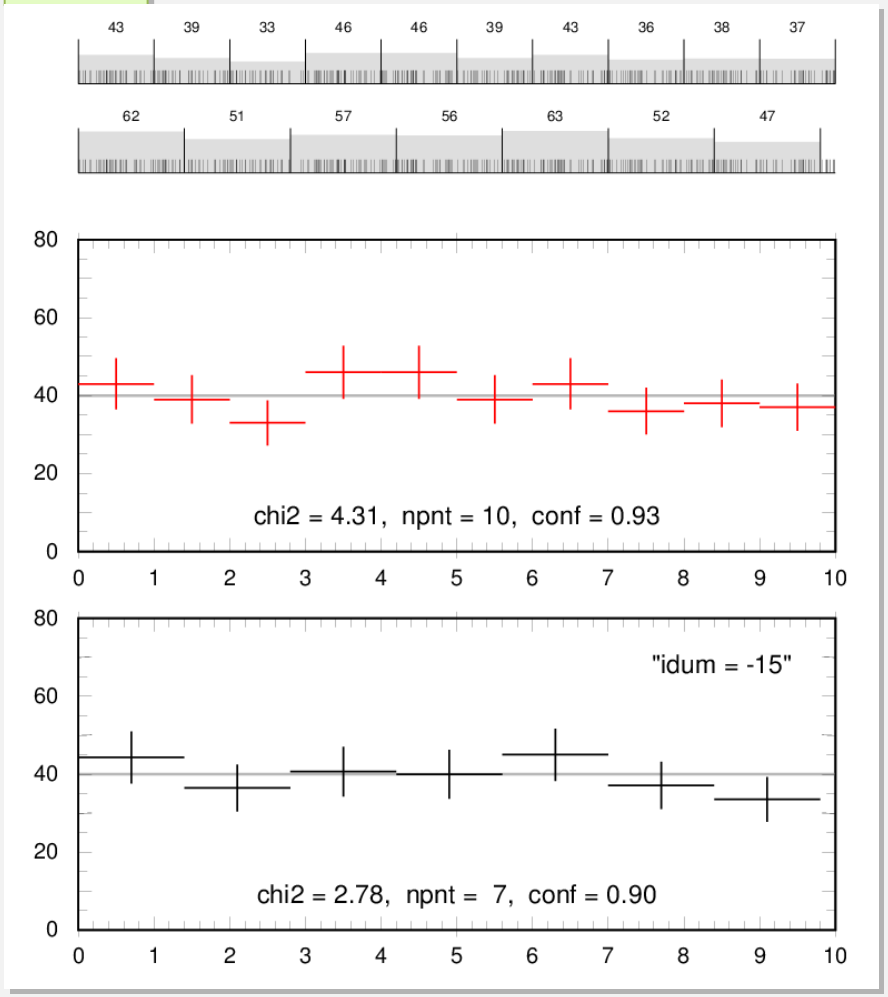


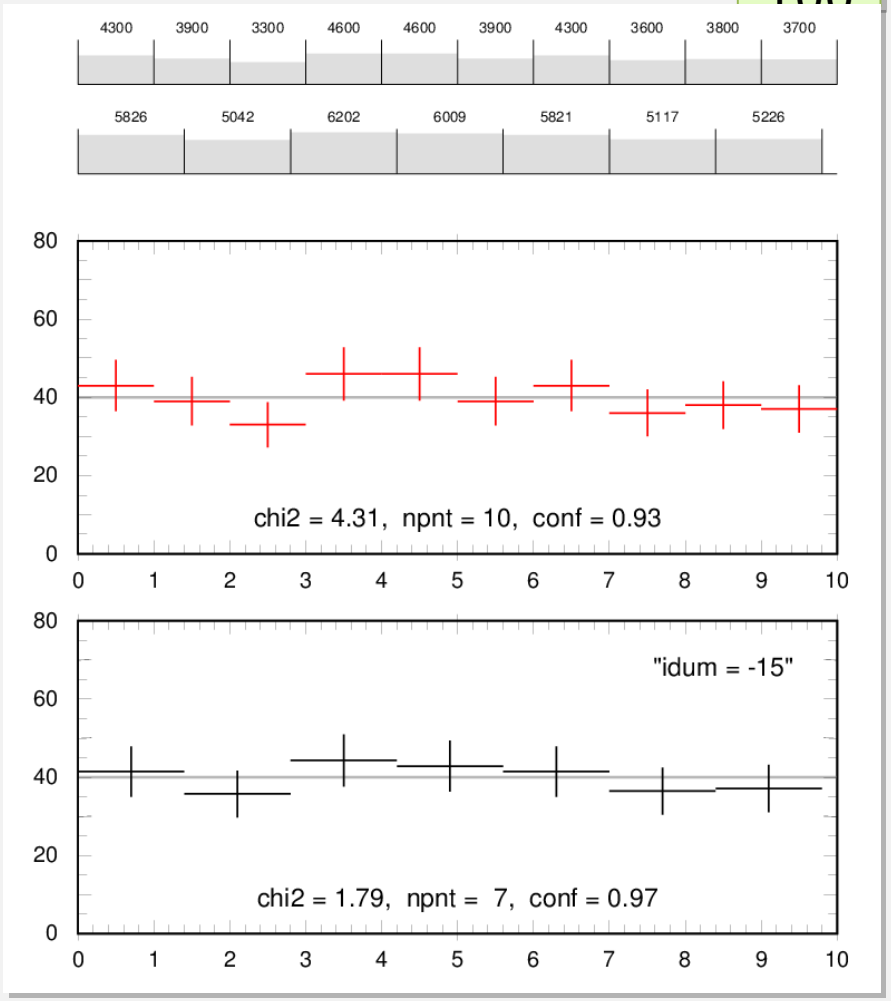

x 100
43 39 33 46 46 39 43 36 38 37
62 51 57 56 63 52 47
chi2 = 4.31, npnt = 10, conf = 0.93
"idum = -15"
chi2 = 2.78, npnt = 7, conf = 0.90
4300 3900 3300 4600 4600 3900 4300 3600 3800 3700
5826 5042 6202 6009 5821 5117 5226
chi2 = 4.31, npnt = 10, conf = 0.93
"idum = -15"
chi2 = 1.79, npnt = 7, conf = 0.97

Refined method: multiply the number of counts per original bin with a constant factor (e.g. 100), perform the randomization, and divide the resulting counts by that factor

x 1

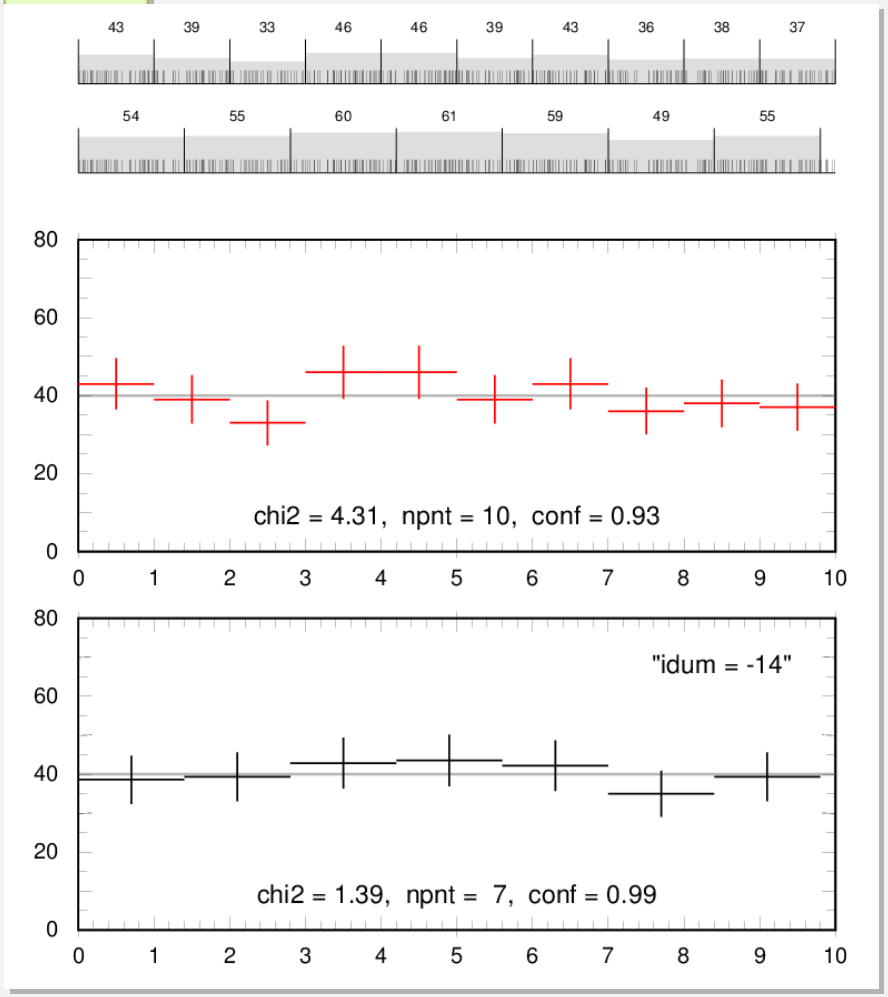


x 100

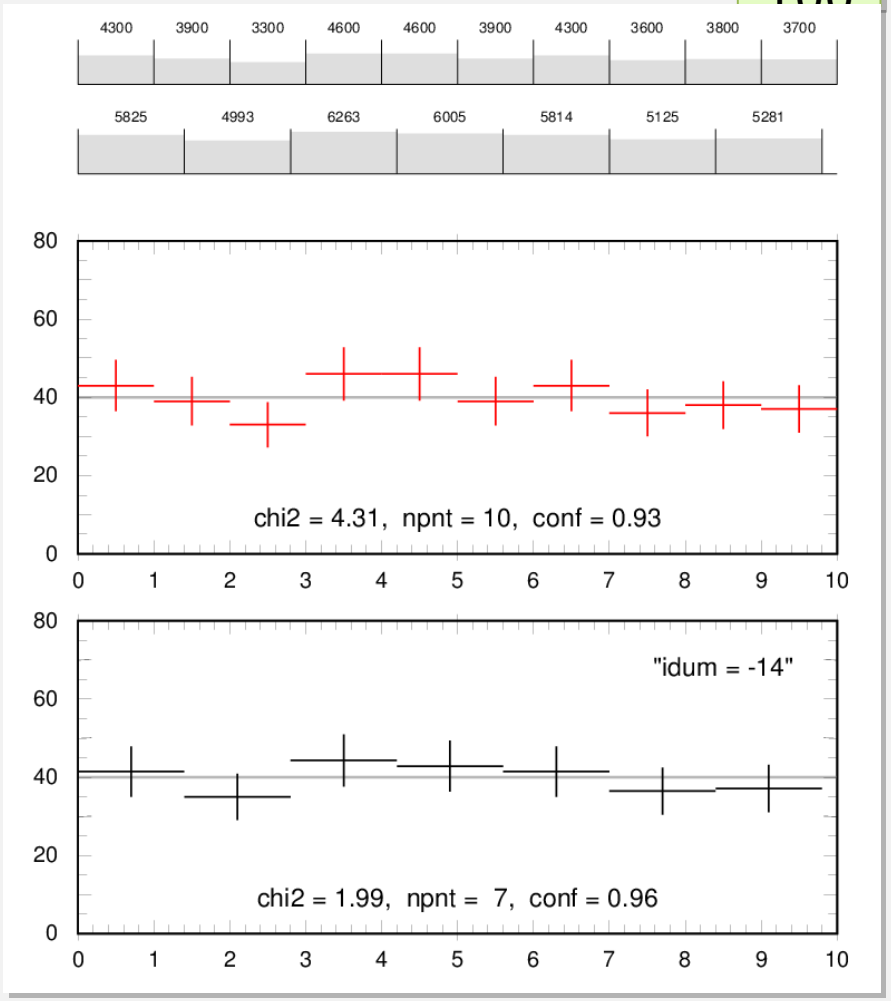


Refined method: multiply the number of counts per original bin with a constant factor (e.g. 100), perform the randomization, and divide the resulting counts by that factor

x 1



x 100



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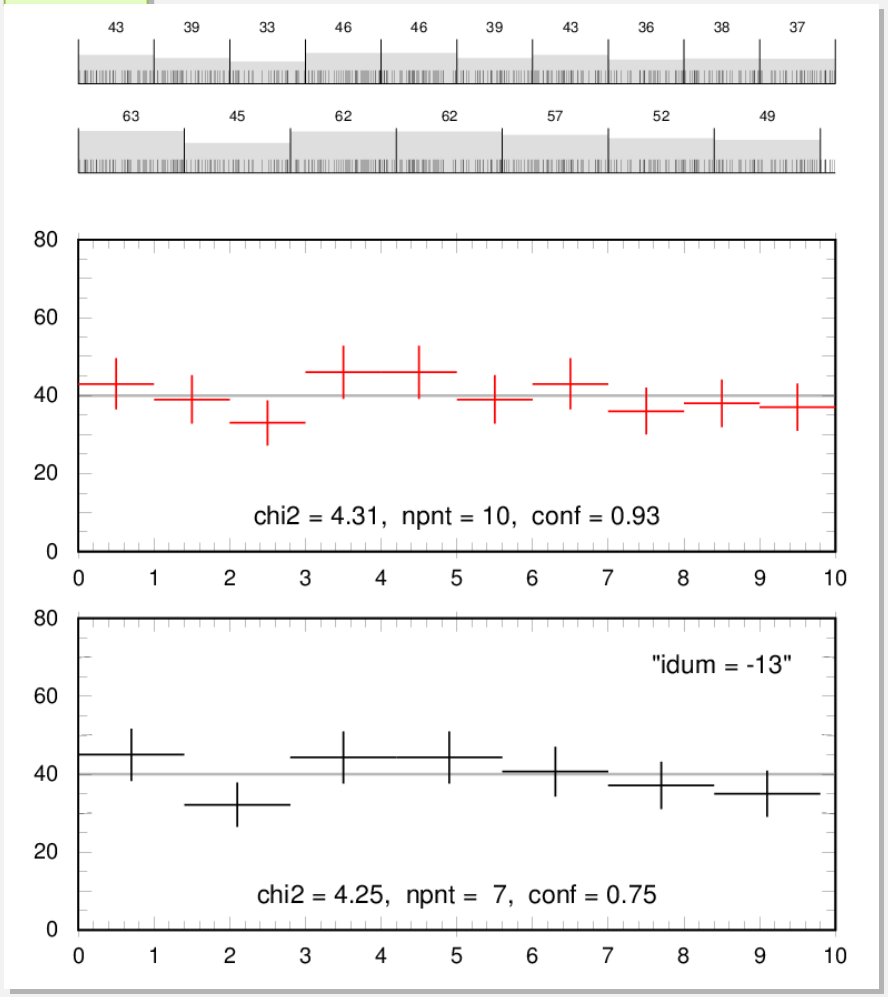
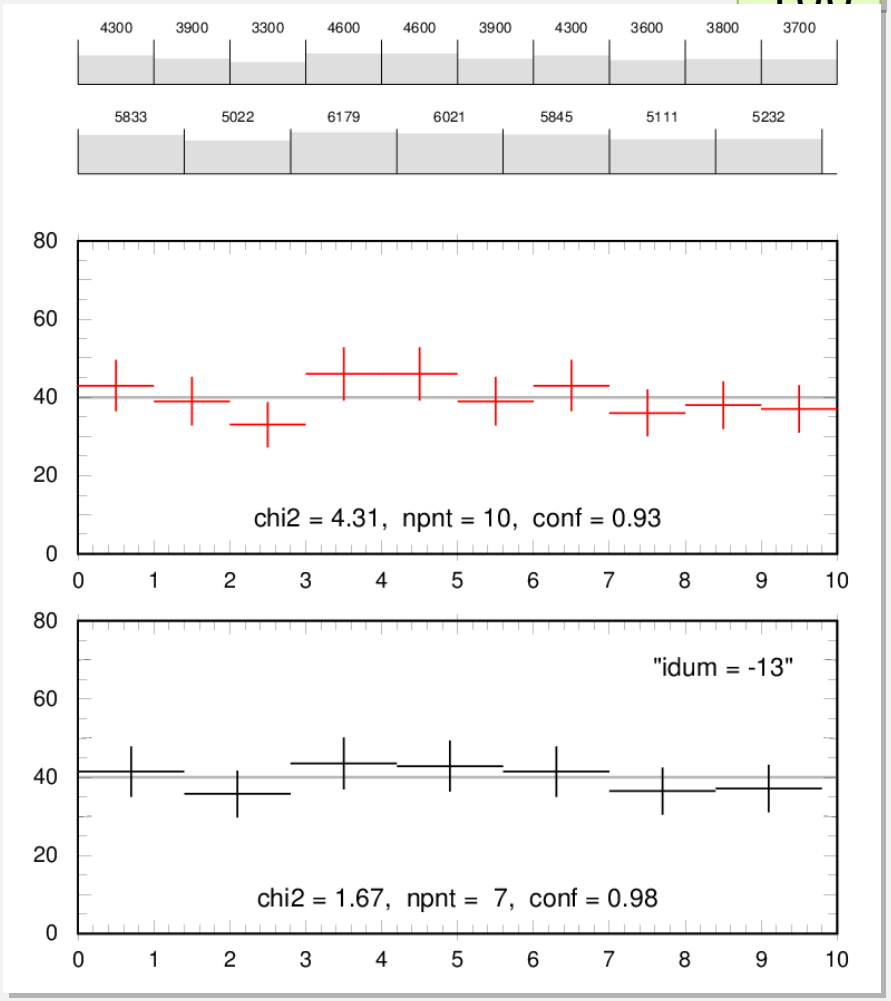
x 1

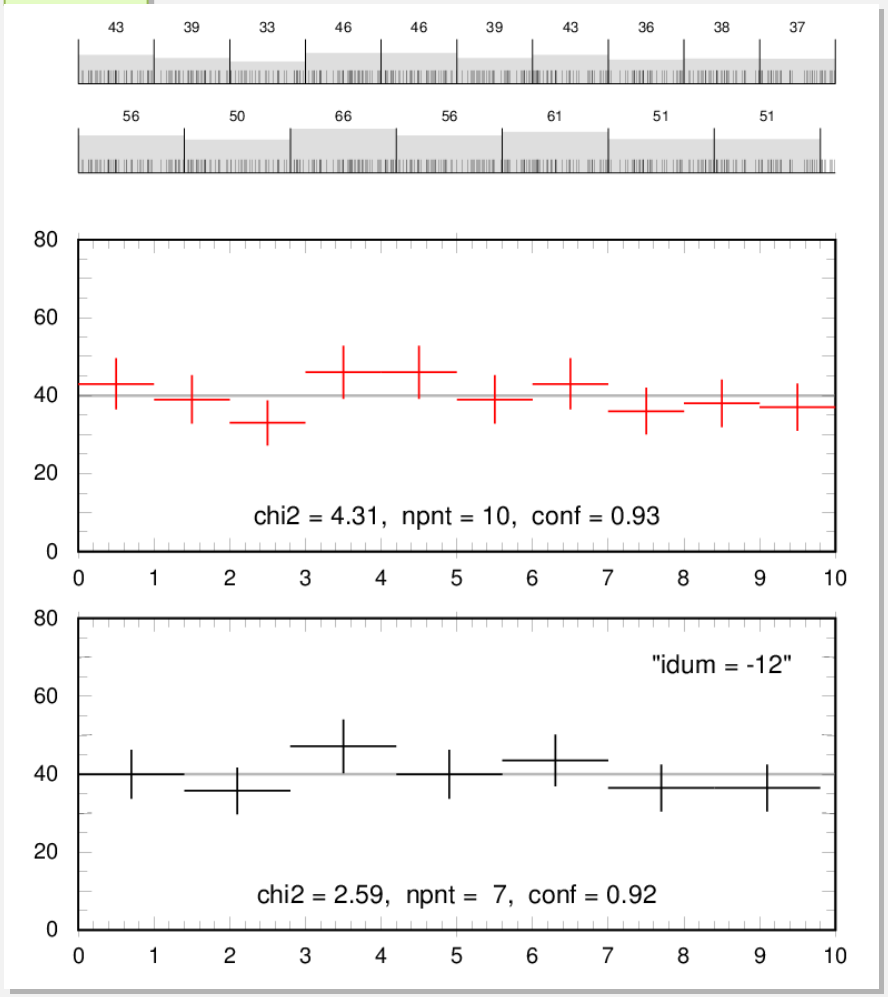


x 100

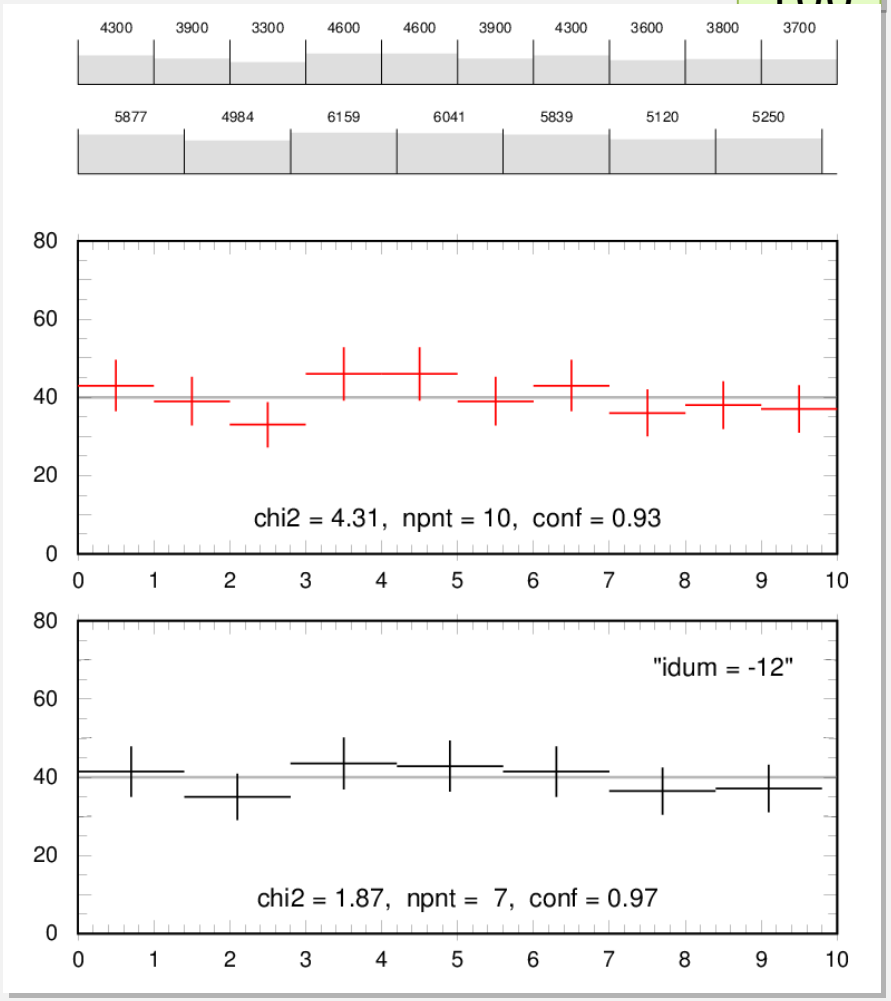


Refined method: multiply the number of counts per original bin with a constant factor (e.g. 100), perform the randomization, and divide the resulting counts by that factor

x 1

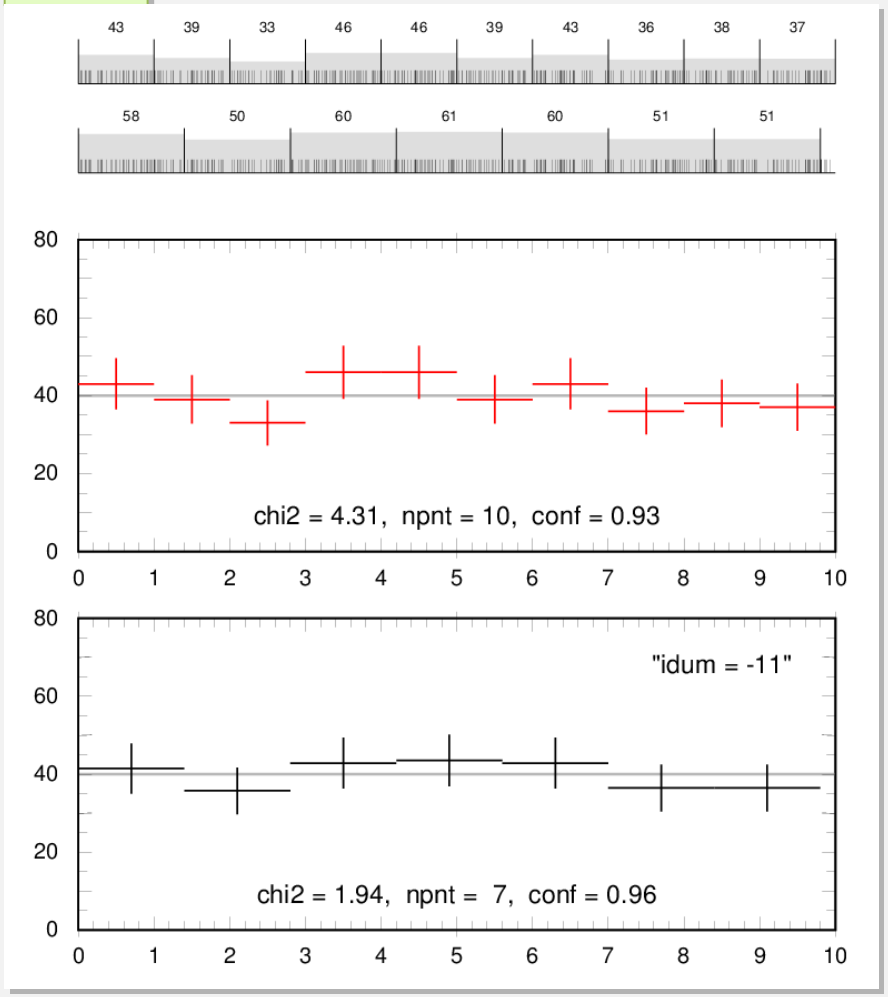


x 100

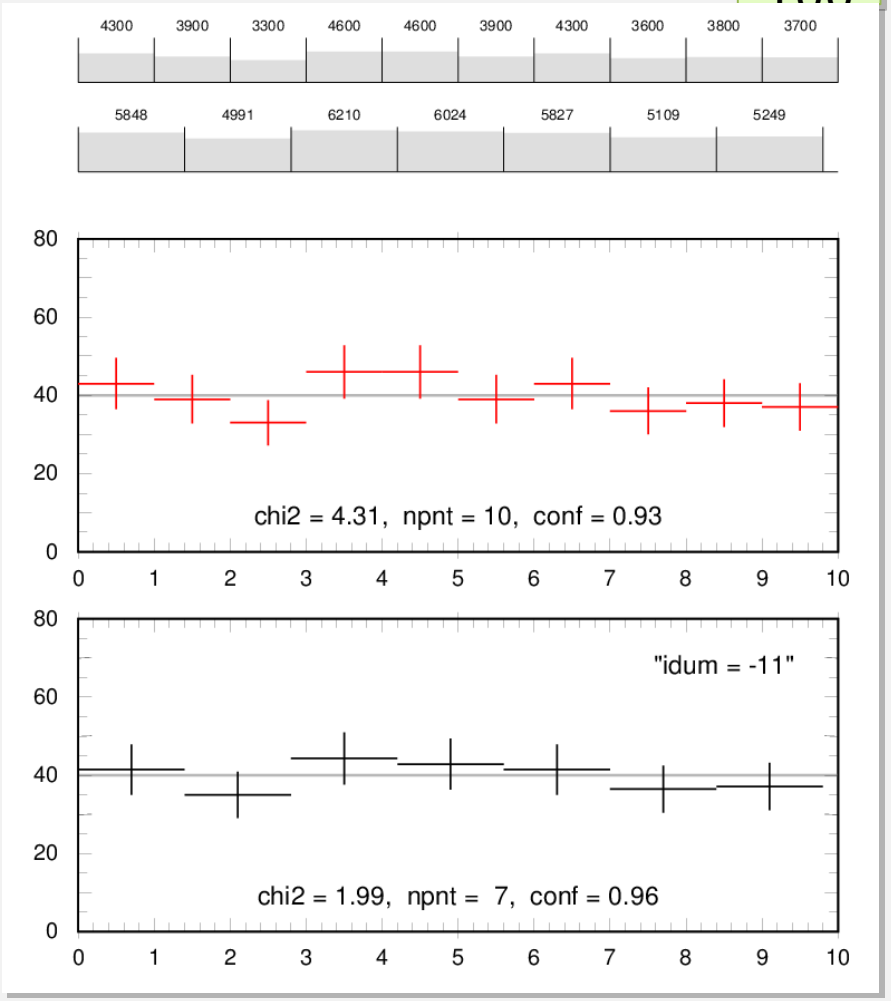


Refined method: multiply the number of counts per original bin with a constant factor (e.g. 100), perform the randomization, and divide the resulting counts by that factor

x 1

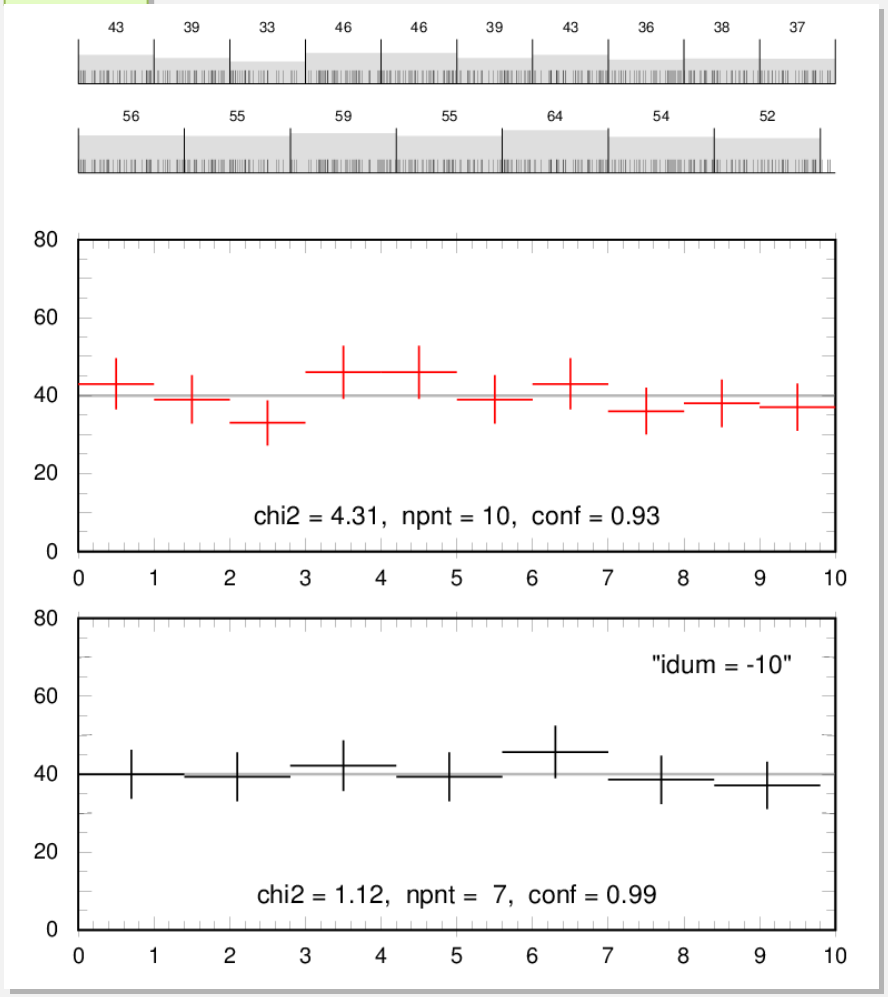


x 100

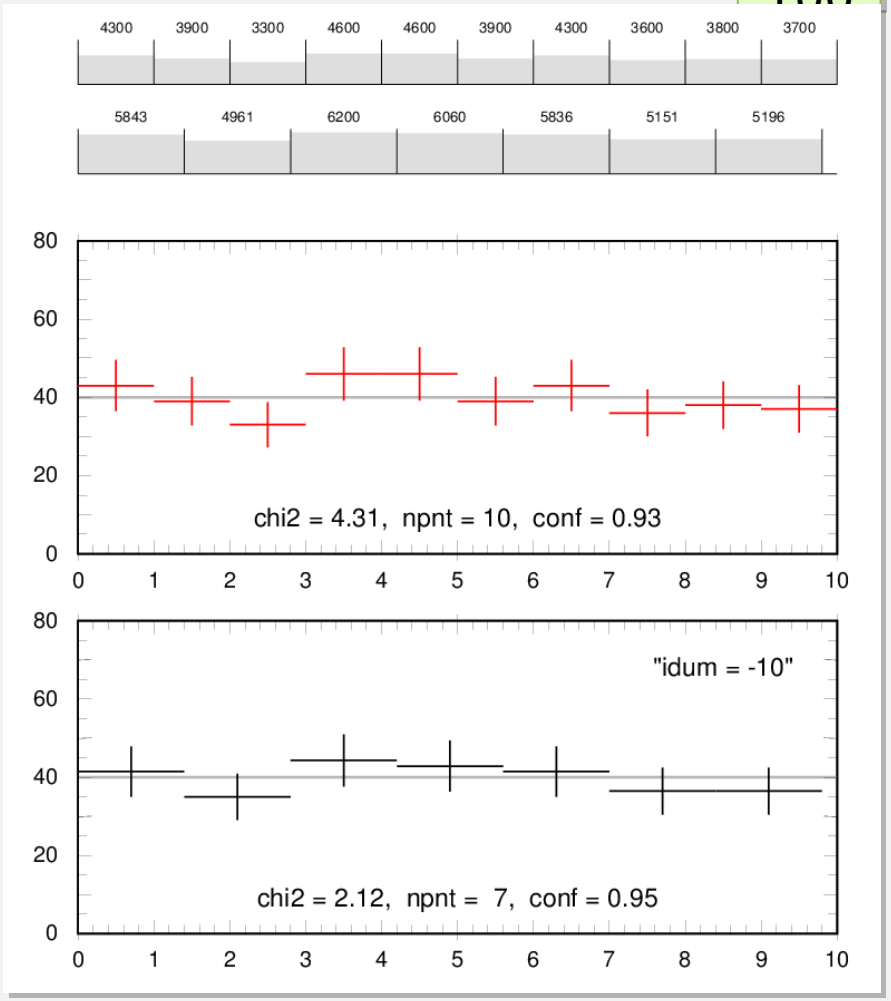


Refined method: multiply the number of counts per original bin with a constant factor (e.g. 100), perform the randomization, and divide the resulting counts by that factor

x 1



x 100



Running the XMM SAS
100 times
is neither efficient nor elegant

Is there a better way ?

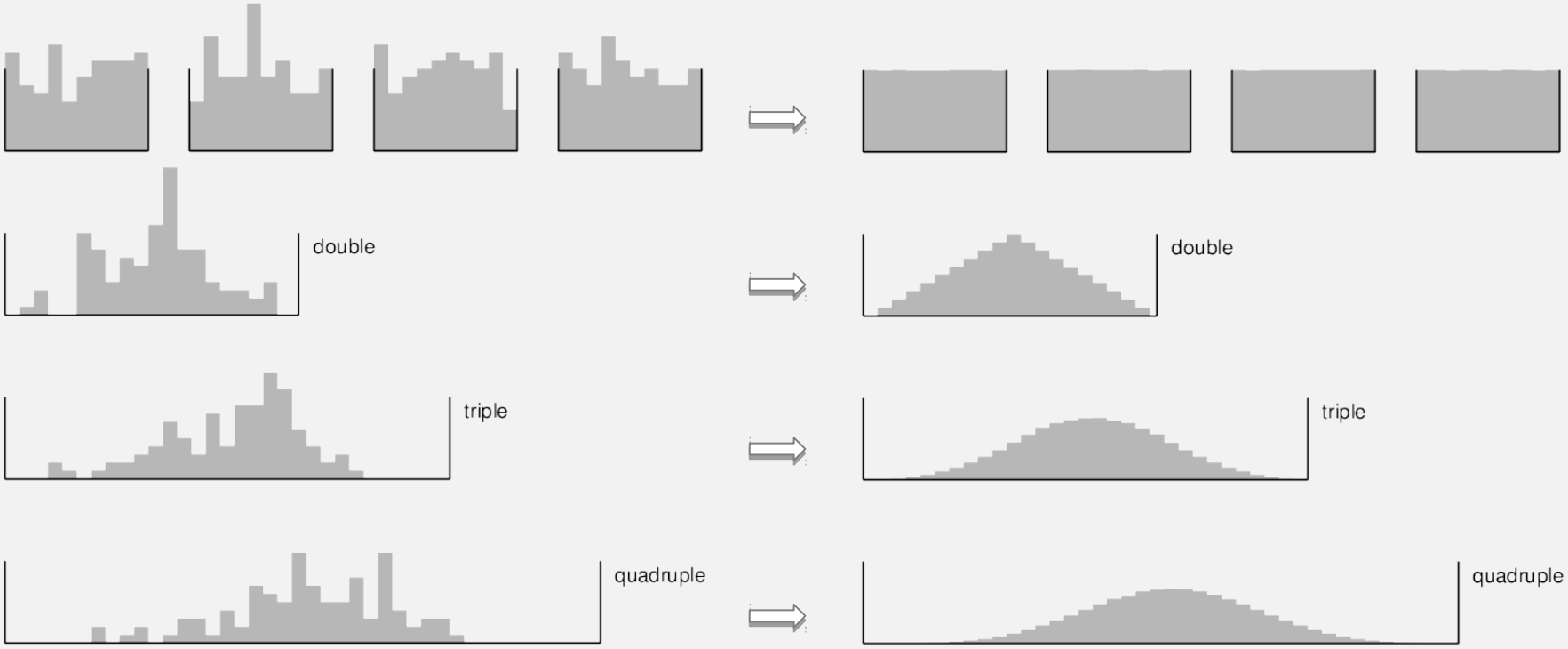
Probably yes ..

A novel way of processing X-ray data ?

From randomization to probability distributions ..

100 random values per PHA channel
10 sub-bins within each PHA channel

1 000 000 random values per PHA channel
10 sub-bins within each PHA channel

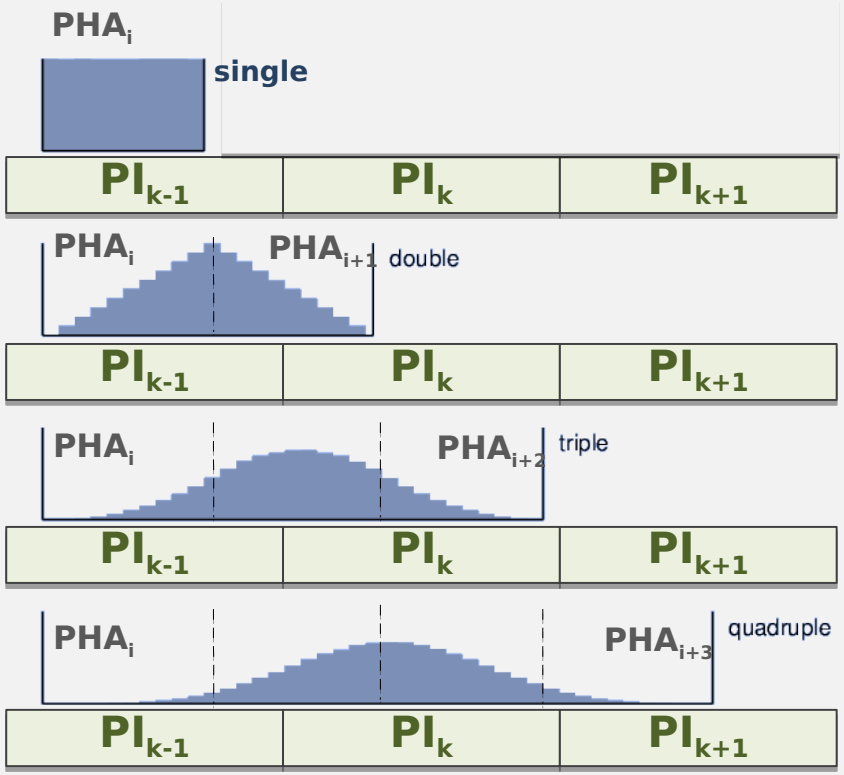


A novel way of processing X-ray data ?

From randomization to probability distributions ..

.. and from PHA channels to PI channels ..

.. for all valid patterns



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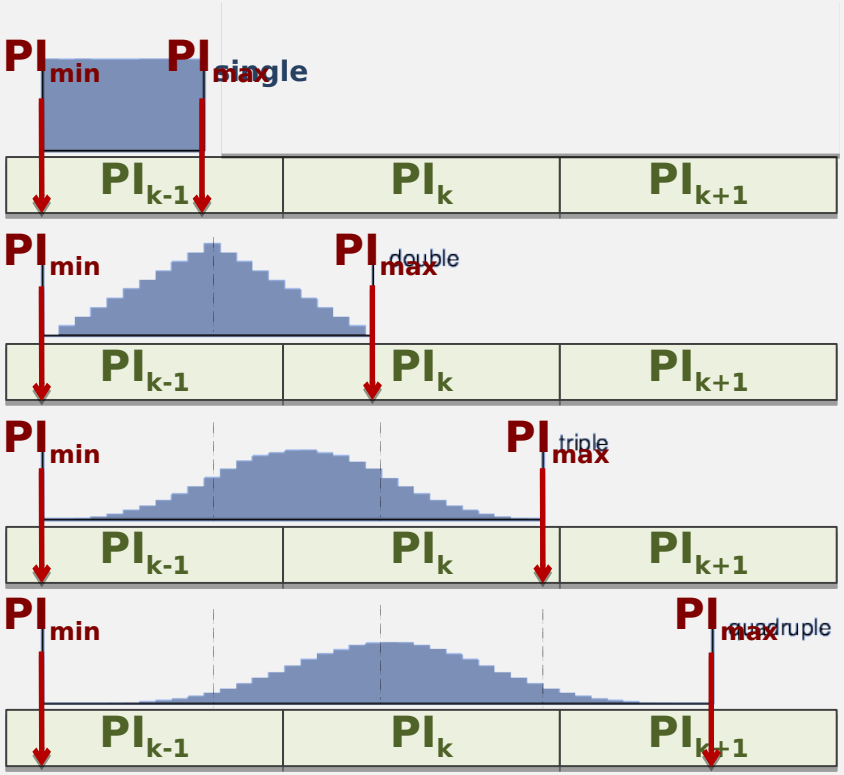
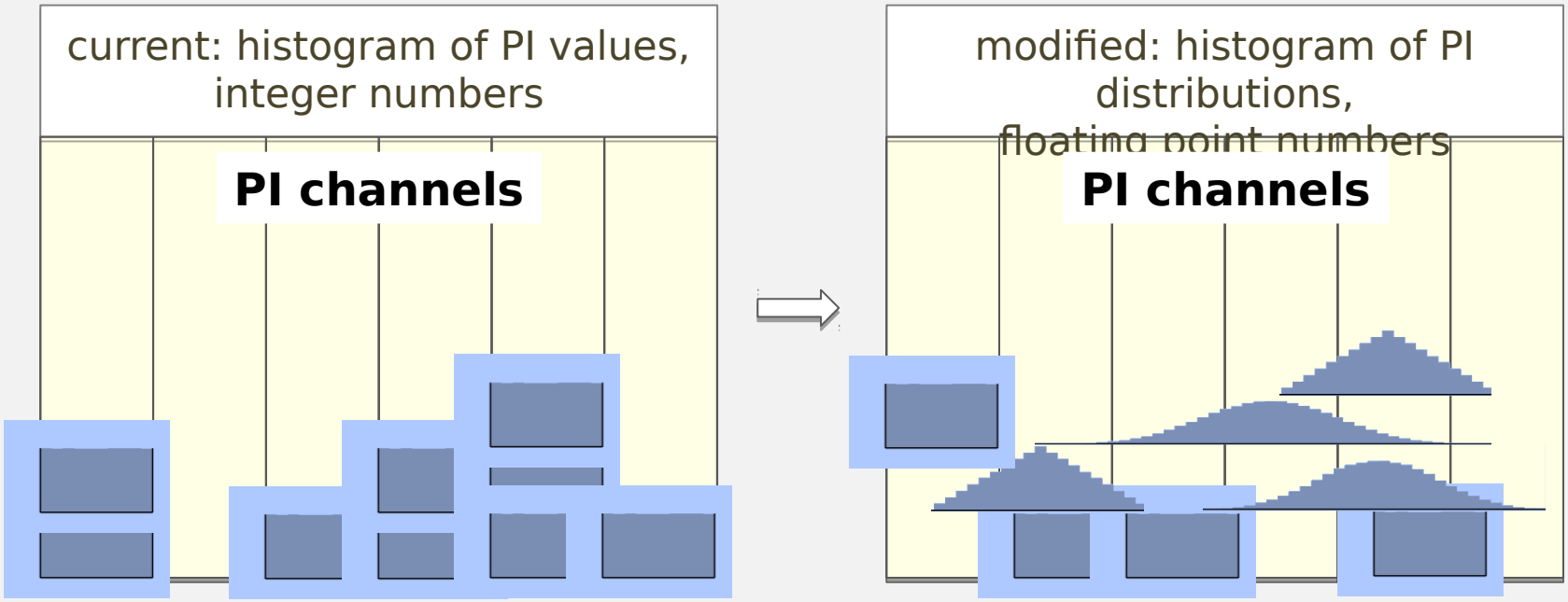
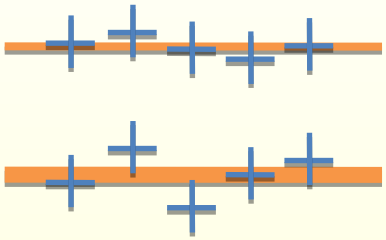


A novel way of accumulating an X-ray spectrum



Immediate benefits of propagating probability distributions

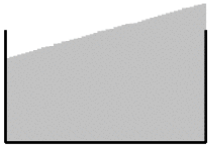
less jitter ✉ „better“ fits
✉ reduced uncertainties in spectral parameters



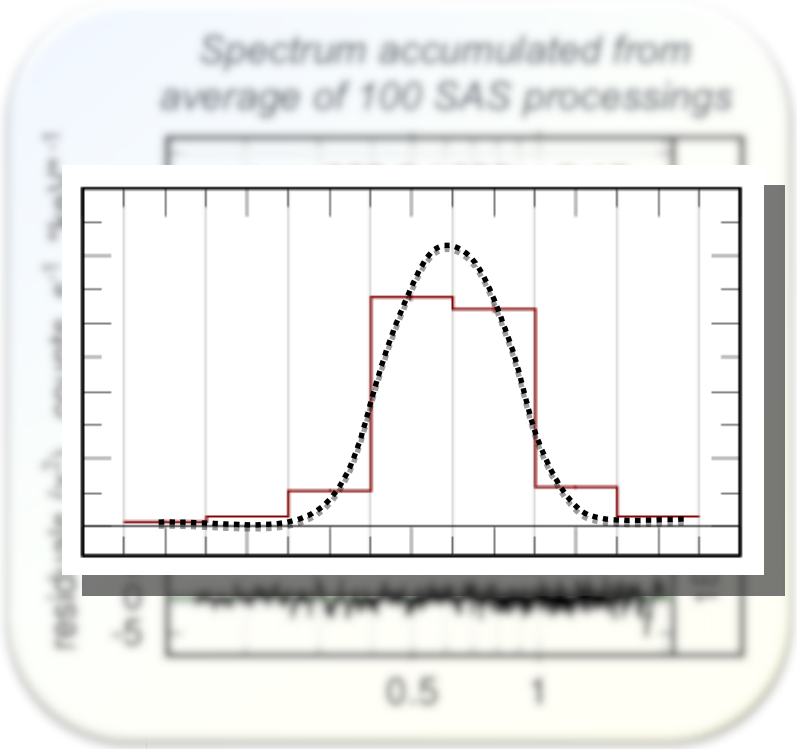
$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2}$$

no randomization necessary ✉ full reproducibility of results

Additional benefit: possibility of taking spectral gradients into account

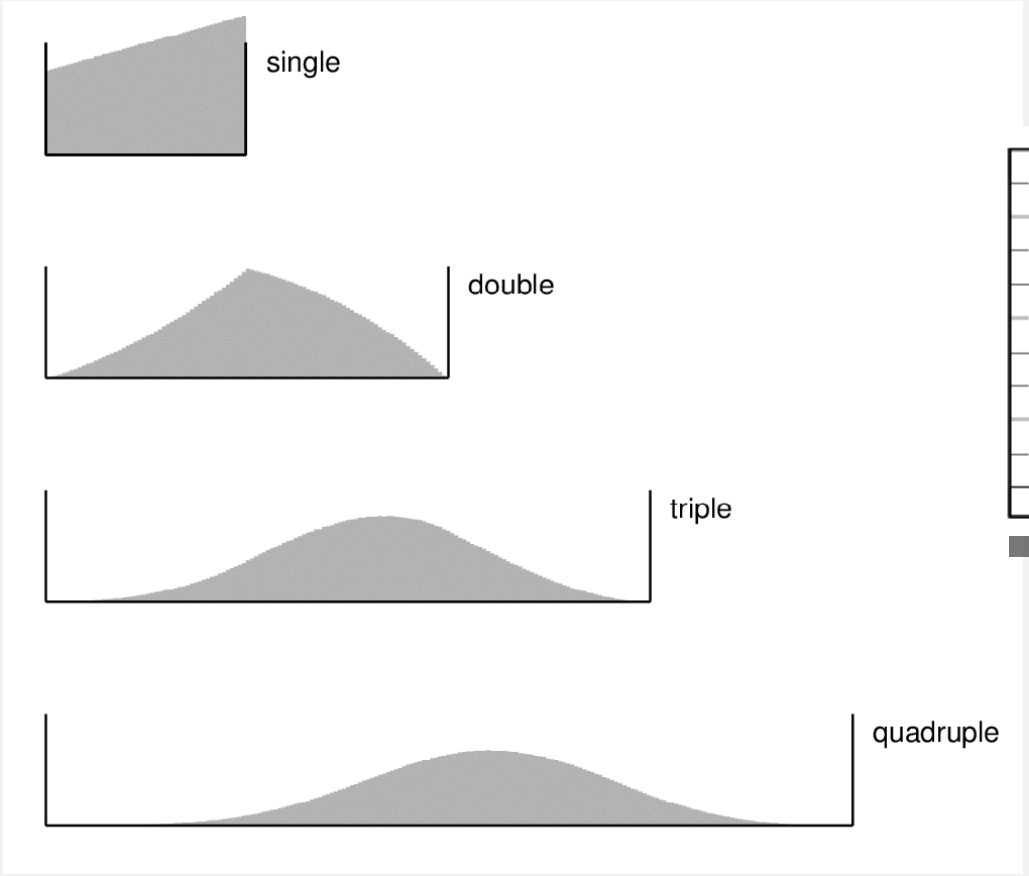


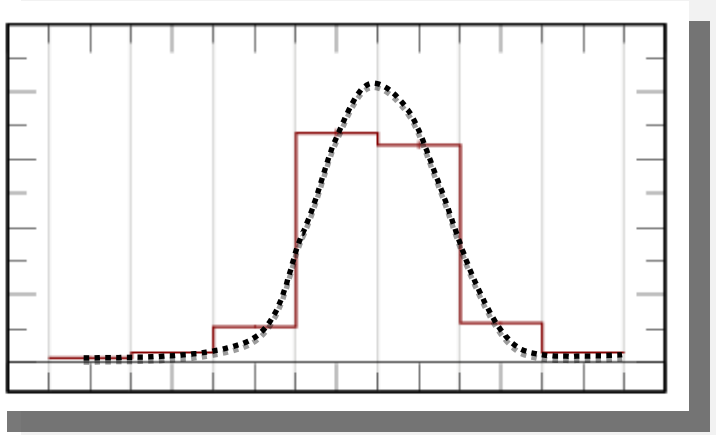
single



- ✓ **distortions of the probability distributions can be considered when a spectrum is accumulated**
- ✓ **this might even improve the spectral resolution**

Additional benefit: possibility of taking spectral gradients into account





- ✓ **distortions of the probability distributions can be considered when a spectrum is accumulated**
- ✓ **this might even improve the spectral resolution**

Randomization appears as an approximation to propagating probability distributions

Drawbacks of the randomization method:

- unnecessarily large jitter in the data
- unnecessarily large χ^2 values
- complications in reproducing the results
- in extreme cases the scientific interpretation may depend on the random number generator

All these drawbacks can be avoided by the method of propagating probability distributions

additional possible benefits:

- ✓ better determination of spectral parameters
- ✓ spectral gradients can be taken into account

Products would be consistent with existing
spectral fitting packages and could be made
fully backwards compatible

.. perhaps worth a try ?

Spectral fitting:

- Calibration uncertainties
- Randomization

Randomization appears as an approximation to propagating probability distributions and may have a non negligible effect on spectral fits!