Systematic errors in calibration are important, and must be dealt with, either by working to eliminate them, or by providing people with means to deal with them: these are the two main goals of this WG.
Schedule

- Mar 1, WG meeting, 9:00am-10:45am IST
  - Intro to WG and pyBLoCXS, Vinay Kashyap
  - RMF parameterization, Konrad Dennerl
  - Intro to Cal Concordance, Herman Marshall
  - Updates to XSPEC, Keith Arnaud [skype]
  - Status of Cal Concordance Project, Yang Chen/Xufei Wang/Xiao-Li Meng [skype]
  - Discussion

- Mar 2, Improving Cross-Calibration Status, 9:45am-12:45pm IST
  - Monte Carlo constraints on instrument calibration, Jeremy Drake
  - NuSTAR and PyBlocks, Kristin Madsen [skype]
  - Panel Discussion: what next?
Calibration has Uncertainties

• The fundamental equation of observational astronomy

\[ C(i,j,k_1,k_2,t_f,\Delta t;\theta) = \int dt \int dxdy \int dE \cdot f(x,y,E,t;\theta) \]

\[ R(t,t_f) \text{ PSF}(x,y,E;t) \text{ RMF}(E,k;x,y,t) \text{ ARF}(E;x,y,t) \]

• Calibration analysis inverts the usual analysis method

• Given ARF, RMF, PSF, evaluate expected model spectrum to compare with observed counts

• Given known model spectrum, compare with observed counts to evaluate ARF, RMF, PSF
Calibration has Uncertainties

- How to find the uncertainties?

- Once known, how to account for them?

- And then how to minimize them?
Calibration has Uncertainties

- How to find and tabulate the uncertainties?
  - MCCal
- Once known, how to account for them?
  - pyBLoCXS
- And then how to minimize them?
  - Concordance
pyBLoCXS

Vinay Kashyap (CXC/CfA)

MCMC scheme to incorporate defined calibration uncertainty into analysis

Simulated = Nominal + Bias + randomized components + residuals
fitting to simulated data

\[
f(\varepsilon; \theta) = \theta_3 \ e^{-\theta_1} \ e^{-\theta_2} \ \sigma(\varepsilon)
\]
fitting to simulated data

\[ f(\varepsilon; \theta) = \theta_3 \varepsilon^{-\theta_1} e^{-\theta_2} \sigma(\varepsilon) \]

\[ p(\theta|D,A_0) \]

— Jin Xu and Shandong Min
fitting to simulated data

\[ f(\varepsilon; \theta) = \theta_3 \varepsilon^{-\theta_1} e^{-\theta_2 \sigma(\varepsilon)} \]

\[
p(\theta|D,A_0)
\]

\[
p(\theta|D,A_i)
\]
fitting to simulated data

\[ f(\varepsilon; \theta) = \theta_3 \varepsilon^{-\theta_1} e^{-\theta_2} \sigma(\varepsilon) \]

\[
p(\theta|D, A_0) \quad p(A) \ p(\theta|D, A) \quad p(\theta|D, A_i)
\]
fitting to simulated data

\[ f(\varepsilon; \theta) = \theta_3 \varepsilon^{\theta_1} e^{\theta_2} \sigma(\varepsilon) \]

\[ p(\theta|D,A_0) \quad p(A) \ p(\theta|D,A) \quad p(A,\theta|D) \]

\[ p(\theta|D,A_i) \]
fitting to simulated data

\[ f(\varepsilon; \theta) = \theta_3 \varepsilon^{-\theta_1} e^{-\theta_2} \sigma(\varepsilon) \]

- Jin Xu and Shandong Min
pyBLoCXS resources


• Sherpa (PragBayes): http://cxc.harvard.edu/sherpa/ahelp/pyblocxs.html

• github (FullBayes): https://github.com/astrostat/pyblocxs

• tutorial from IACHEC 2014: http://hea-www.harvard.edu/AstroStat/Demo/pyBLoCXS/IACHEC2014/