Statistical Challenges in Modeling High Resolution X-ray Spectra

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Challenges

- Global fitting
- Line detection and fitting low counts lines
- Massive model misspecification
- Building complex models

Lack of Pretty Pictures?



Global Fitting

- Poisson data
- Poisson Likelihood in modeling the data
 - Cash/Cstat/Wstat
 - Bias in chi-gehrels 1+sqrt(di+0.75)
- Background?
- Group data ?
- High S/N Fit individual lines
- Large number of parameters
 - MCMC methods (Markov-Chain Monte Carlo)
 - Bayesian methodology

Ungrouped for Fitting



Line detection

- Critical for plasma diagnostics
 - Densities from line ratios, e.g. He-like OVI and NeIX
 - Temperature diagnostics
- Measurements of line intensities:
 - Accounting for background, continuum, instrumental line spread, effective area calibration, contamination from other lines, line profile fitting.
- Issues
 - Binning the data
 - Uncertainties
 - Line significance

Binning

- Loss of resolution
 - blending of lines
 - line disappearing
 - wrong line properties etc.
- Loss of information
 - binned lines can contribute to the continuum
 - wrong normalization and source flux

Continuum vs. Lines



Detecting Lines in Poisson Data

Computational challenges Multimodal likelihood Bayesian methods



Profile posterior distribution

Uncertainties

Based on MCMC samples





Blended Lines



Uncertainties via MCMC?

Significance of the Line - Simulations



Park et al 2008 Protassov et al 2002

Model Misspecification

- Atomic data bases have offsets between theoretical and true line locations
- Blending of individual lines
- Problems with pseudo-continuum
- Variable abundances across the line-of-sight
- Multi-temperature plasmas require DEM analyses subject to high frequency instabilities, requiring ad hoc regularization

Building Complex Models: Decision Process

• First look at the residuals, use some simple tests:

- 1. symmetry of distribution
- 2. Cumulative sums
- 3. Model the residuals and then move this model to the primary model
- Look at the parameters posterior pdf if you have them
- If you do MCMC, always double check the convergence
 - Multiple starting points
 - Lots of iterations



Look at Residuals



Giustini et al 2015



Scott et al 2014





Building Complex Models: Decision Process

- Selecting a model number of parameters vs. model simplicity:
 - Ockham's razor selecting a simpler model
 - AIC/BIC/DIC/MDL criteria as a guide
 - Bayes Factors calculation of integrals, depending on prior
- Classical tests require that a simpler model must be nested inside a complex model
 - mixture models
 - KDE (kernel density estimates)

Classical Model Selections

- χ^2 goodness of fit test
- F-test
- Likelihood Ratio Tests
- AIC Akaike Information Criterion

Given ML for a set of models. The model with the largest value provides the best description of the data. Need to incorporate number of model parameters. The model with the lowest AIC value is the best model.

$$AIC = -2\ln[L(M)] + 2k + \frac{2k(k+1)}{N-k-1}$$
finite sample correction

K - number of model parameters

N - number of data points

$$\chi^2$$
 - assuming Normality



Kelly et al 2014, ApJ 788,33

Mixture Models: Example



AstroML package

Summary

- Global fitting
- Line detection and fitting low counts lines
- Massive model misspecification
- Building complex models
- Statistical methods exist and can be applied
- Need good statistics software tools.

Bayesian Model Selection

- Odds Ratio $O_{21} = \frac{p(M_2|D,I)}{p(M_1|D,I)} \qquad \qquad \mathsf{M}_2,\mathsf{M}_1 \mathsf{models}_1$
- Bayes Factors $B_{21} = rac{p(D|M_2, I)}{p(D|M_1, I)}$
- BIC Bayesian Information Criterion $BIC = -2\ln[L(M)] + k\ln N$
- DIC Deviance Information Criterion

 $DIC = -2\ln p(\mathbf{y}|\theta) + 2\mathbf{p}_{DIC}$



Model Summaries: Posterior Distributions



Buchner et al. 2014

Calibrate the test statistics

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STATISTICS, HANDLE WITH CARE: DETECTING MULTIPLE MODEL COMPONENTS WITH THE LIKELIHOOD RATIO TEST

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FIG. 1.—Null distribution of the LRT test statistic. The histograms illustrate the simulated null distribution of the LRT statistic in three scenarios and should be compared with nominal χ^2 distributions, which are also plotted. As detailed in § 3.2, the histograms corresponds to (*a*) testing for a narrow emission line with fixed location, (*b*) testing for a wide emission line with fitted location, and (*c*) testing for an absorption line. The vertical lines show the nominal cutoff for a test with a 5% false positive rate; note that the actual false positive rates vary greatly at 2.6%, 1.5%, and 31.5%. The label on the *y*-axis stands for the probability density function.]

Multi-line model of NeIX region in HEG spectrum of Capella





Ness et al 2003