

*From Chandra to Lynx : 2017 Aug 8-10, Cambridge MA*

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# Lynx Data: Analysis Challenges

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**Vinay Kashyap (CHASC/CXC/CfA)**  
Pat Broos (Penn State), Peter  
Freeman (CMU), Andrew Ptak  
(GSFC), Aneta Siemiginowska  
(CfA), Alexey Vikhlinin (CfA),  
Andreas Zezas (Crete)

What do we want?



**MOAR ASTRONOMY**

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# More Astronomy

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The type of analysis you bring to bear on the data can have a significant impact on what inference is possible.

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# Example: Source Significance

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- ❖ Back in the '90s, the best measure of the reality of a source was  $S/N$ . Now, we compute the probability of observing a background fluctuation of the same size as the observed data.

- ❖ Switching from  $\frac{S}{N} = \frac{N_S - N_B/r_B}{\sqrt{N_S + N_B/r_B^2}}$

to

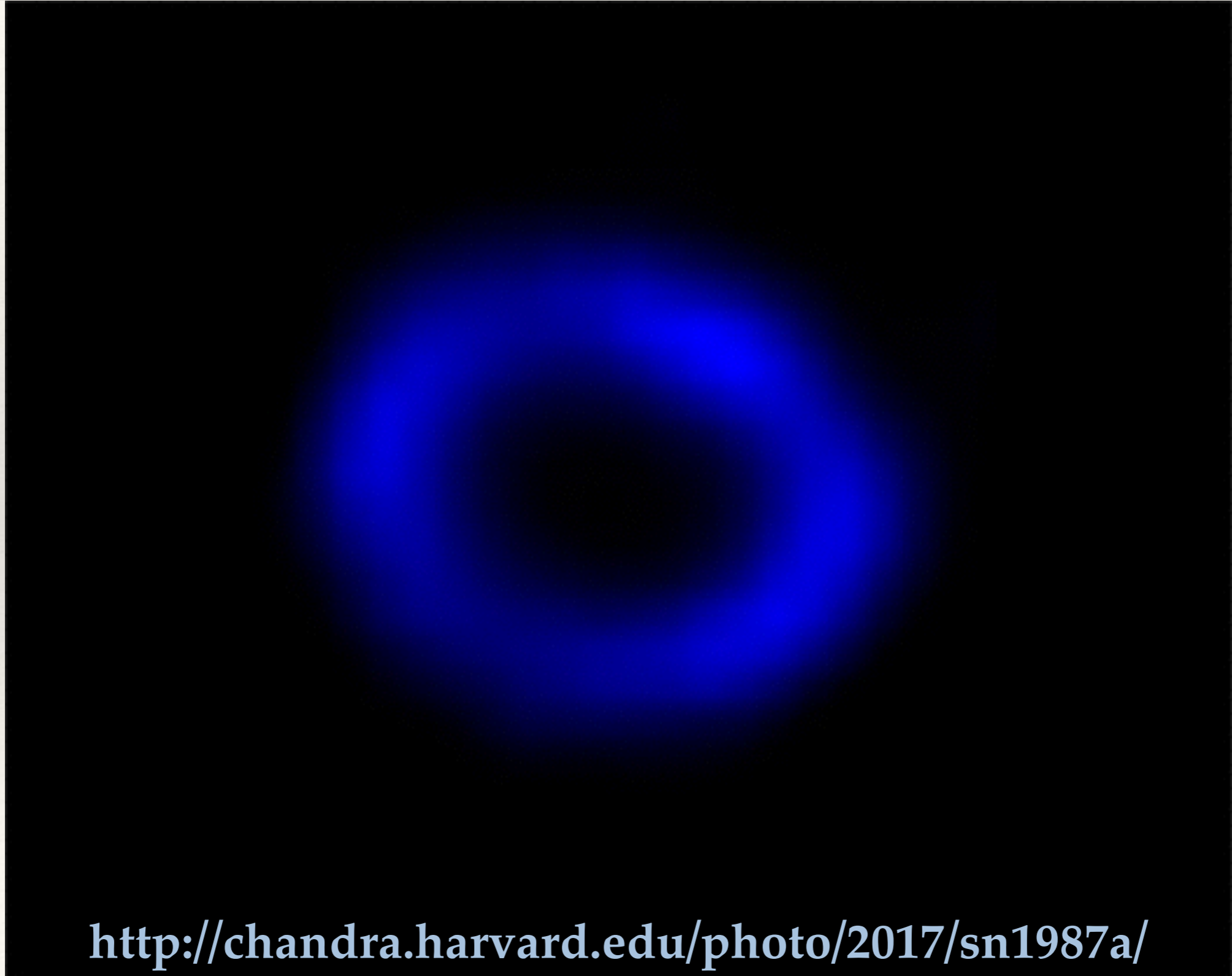
$$Pr(k \geq N_S) = \sum_{k \geq N_S} \frac{\left(\frac{N_B}{r_B}\right)^k e^{-\frac{N_B}{r_B}}}{\Gamma(k+1)}$$

meant you went from needing 10 counts for a detection to needing 3

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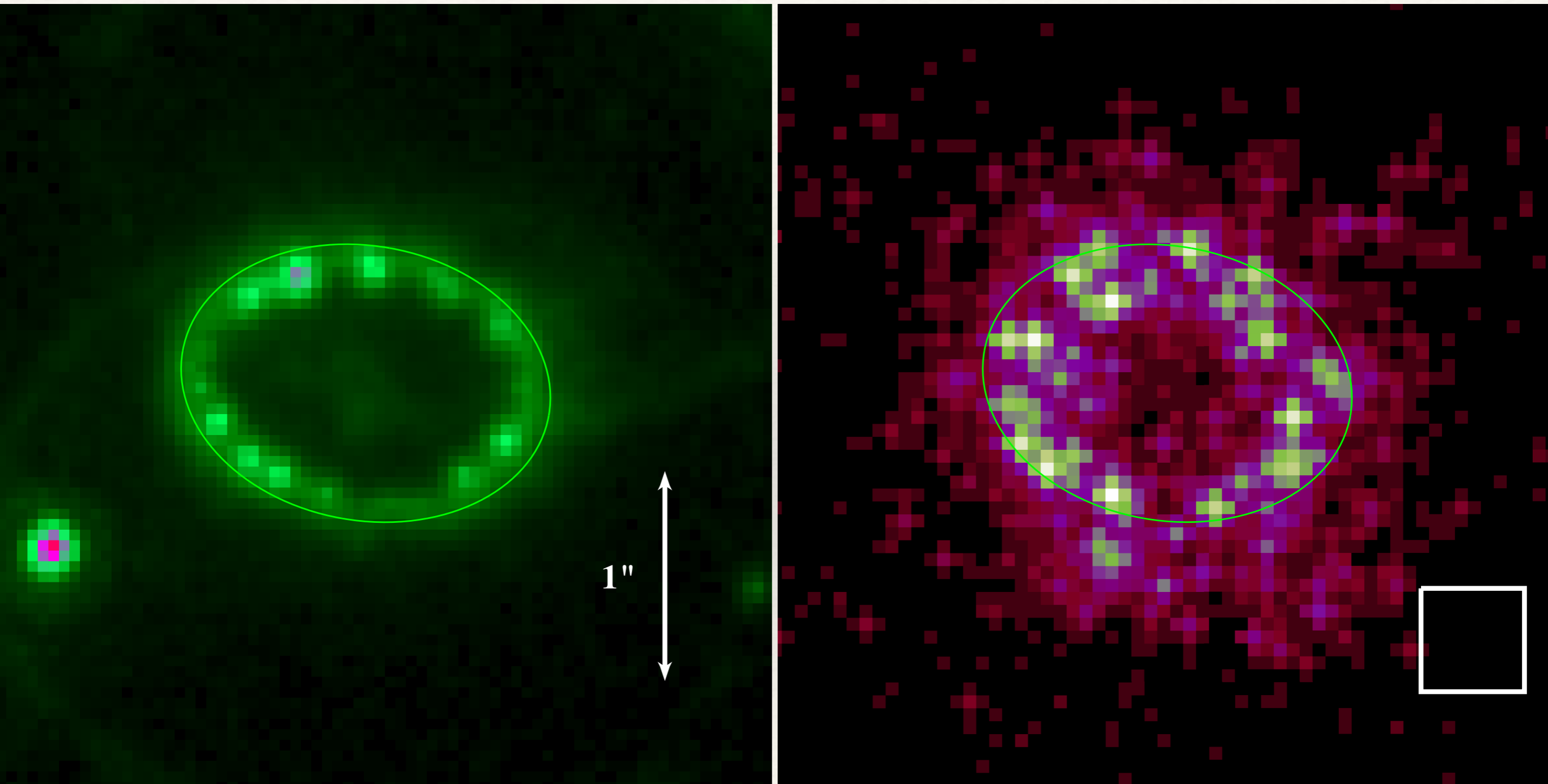
# Example: SN 1987A

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<http://chandra.harvard.edu/photo/2017/sn1987a/>

# Example: SN 1987A



Contemporaneous *HST* (left) and *Chandra* (right) from 2001-dec

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# The lesson from AXAF

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AXAF deliberately and explicitly invested in analysis technology.

The AXAF Beta Sites at Chicago and Hawaii produced `wavdetect`<sup>1</sup>, and `vtpdetect`<sup>2</sup>, and helped to plan the toolset for CIAO.

and from whence the statistical foundations of Sherpa were acquired

*Chandra* supported the collaboration between high-energy astrophysicists and statisticians via CHASC<sup>3</sup>,

which has given us `pyBLoCXS`<sup>4</sup>, the MCMC tool in Sherpa, also used to handle calibration uncertainty<sup>5,6</sup>, hardness ratio<sup>7</sup> and aperture photometry<sup>8</sup> tools in CIAO and CSC, and LIRA<sup>9,10,11</sup>, among others.

<sup>1</sup>Freeman et al. 2002, <sup>2</sup>Ebeling & Wiedenman 1993, <sup>3</sup>Siemiginowska et al. 1997, <sup>4</sup>van Dyk et al. 2001, <sup>5</sup>Lee et al. 2011, <sup>6</sup>Xu et al. 2014, <sup>7</sup>Park et al. 2006, <sup>8</sup>Primini & Kashyap 2014, <sup>9</sup>Esch et al. 2004, <sup>10</sup>Connors & van Dyk 2007, <sup>11</sup>McKeough et al. 2016

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# A Laundry List

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## **A. Calibration issues**

Analysis algorithms are often constrained by what is made possible by spacecraft design and what can be calibrated

## **B. New algorithms**

Many new algorithms are currently being developed with *Chandra* data in mind, could make *Lynx* data more valuable

## **C. Advances in Statistics**

New techniques are being developed by Statisticians, and will allow for better inferences to be drawn



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(A)

# PSF

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- ❖ *Lynx*'s PSF will have more degrees of freedom (more shells, mirror adjustability) than *Chandra*'s and will need a correspondingly greater effort to characterize and use
- ❖ Need high-fidelity models of the mirrors and the detectors, and tools to deal with variations in energy and across the FOV
- ❖ Photometry via PSF-fitting in the Poisson regime is still not bread-and-butter as in optical/IR
- ❖ Pileup could be a big problem because of high EA — mitigation via hardware (higher frame rates, oversampling) or software (modeling the pileup process, bootstrapping from the wings)

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(A)

# Pointings

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- ❖ *Chandra* has shown the value of mosaic observations. Analysis tools to deal with such re-aligned datasets are still kludgy
- ❖ Need to consider strategies to handle absolute alignments of multiple observations
- ❖ Need tools for source confusion analysis

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(A)

# RMF

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- ❖ Need to consider strategies to ameliorate and correct for long-term CTI and contamination
- ❖ Fitting global models to high-resolution calorimeter data is fraught with peril — we have had a taste with Chandra and XMM grating data, but Lynx data will push the boundaries in counts, resolution, and number
  - ❖ fitting algorithms must learn to guard against model misspecification<sup>1</sup>, become more intelligent at discounting  $\delta\chi$  where systematics are known to be large, find better ways to simultaneously fit spectra of different resolutions
- ❖ Improvements to atomic line databases (e.g., AtomDB, Chianti) must continue, and new algorithms are needed to propagate the highly non-linear error structure into analysis and inference

<sup>1</sup> *All models are wrong, but some are useful.* — George Box (British Statistician)

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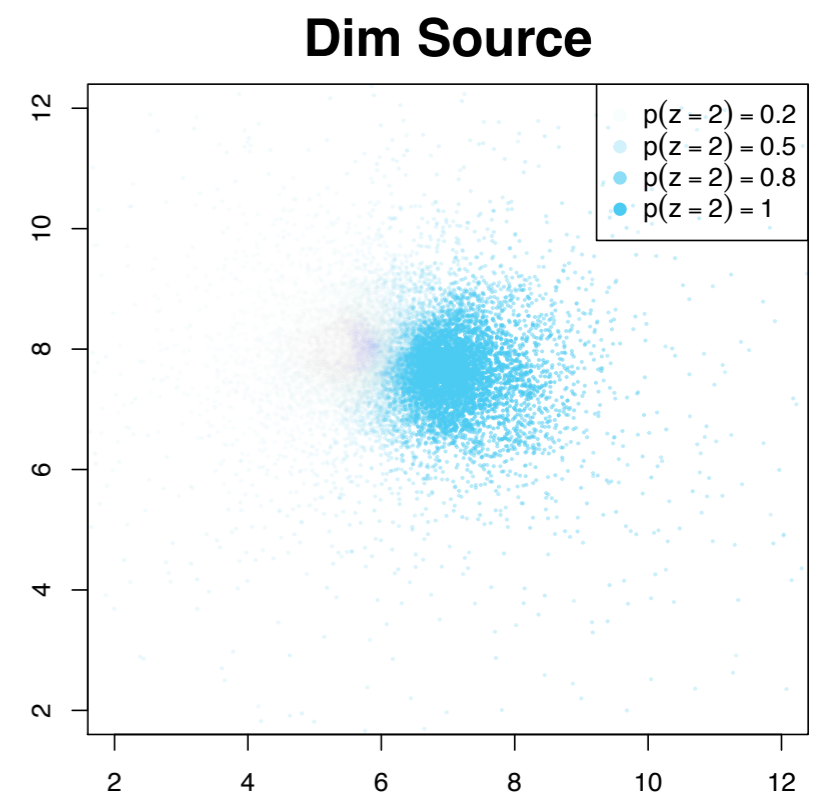
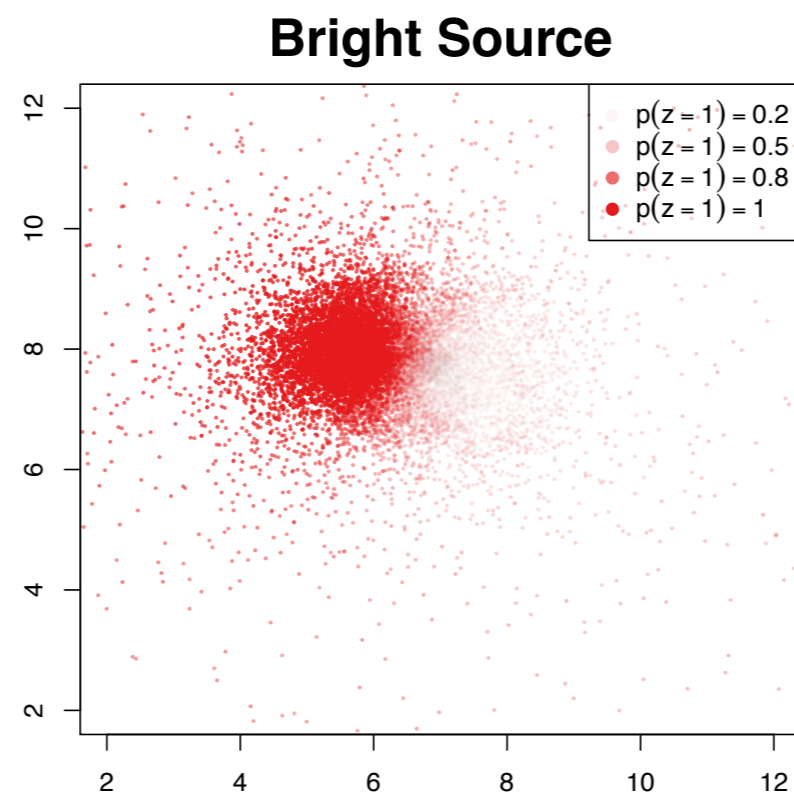
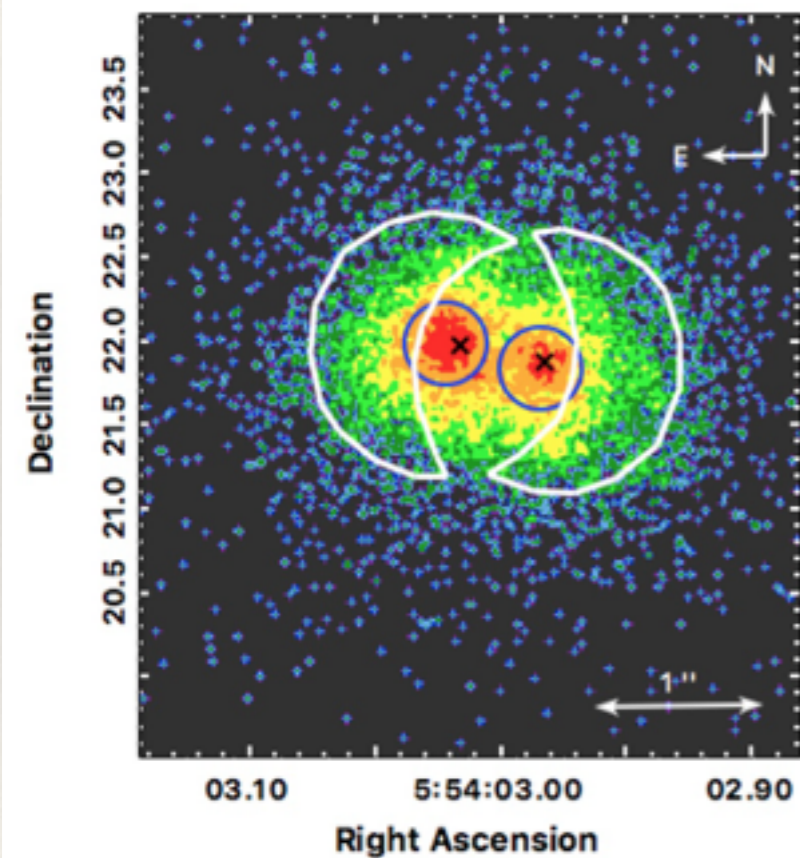
# (B) Disambiguate Overlaps

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- ❖ The goal is to sift the photons that belong to overlapping sources into separate piles probabilistically and carry out spectral and timing analyses on them
  - ❖ Use both spatial and rudimentary gross spectral information — Jones et al. 2015, ApJ 808, 137
  - ❖ Use spatial, gross spectral, *and* temporal information — Campos et al., in development
  - ❖ Use spatial and temporal information, and astrophysical spectral modeling information, hooked into Sherpa — Campos et al., contemplated

# (B) Disambiguate Overlaps

HBC 515 Aa+Ab weak-lined T-Tauri binary (Principe et al. 2016)



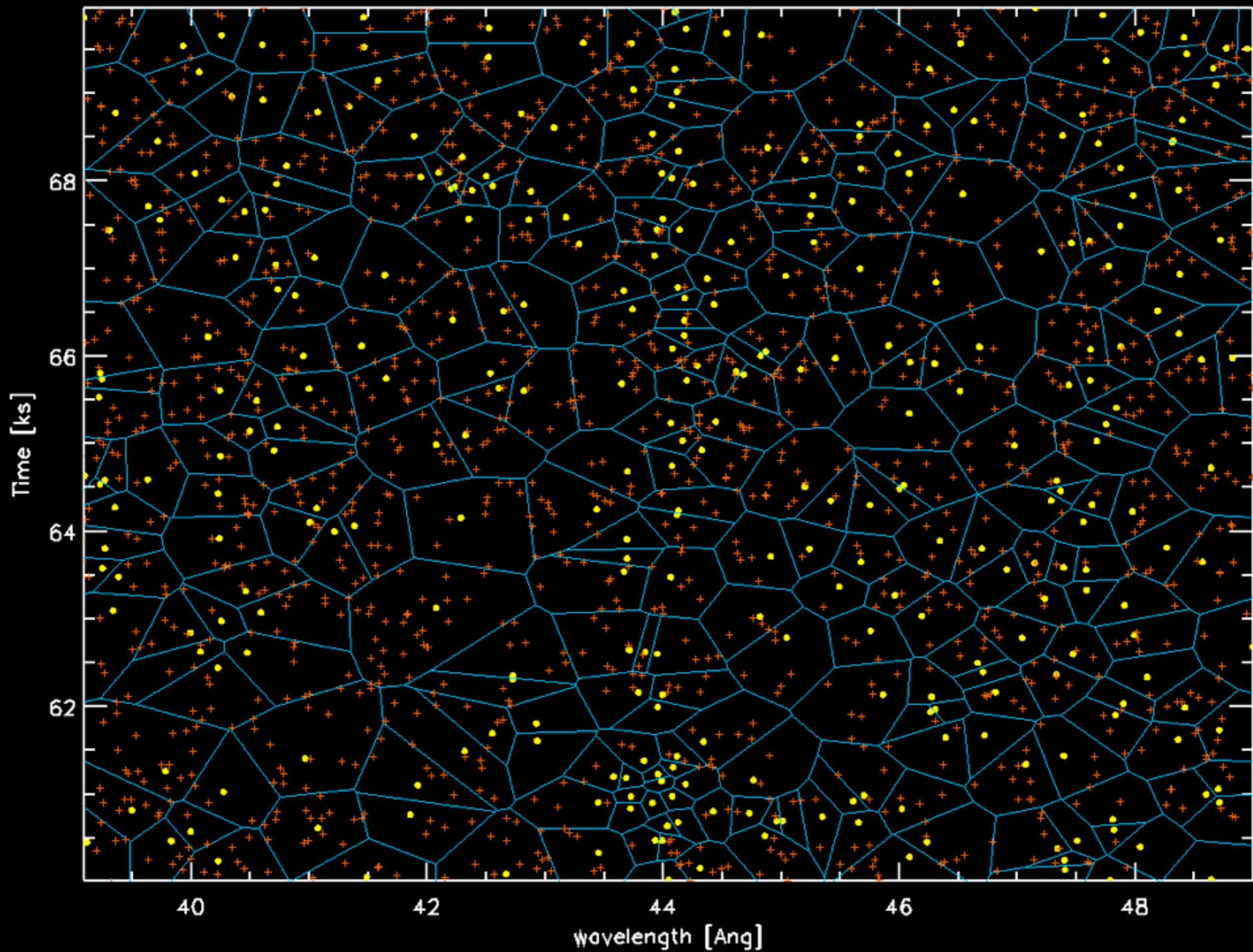
E-BASCS probability assignments based on spectral and temporal disambiguation

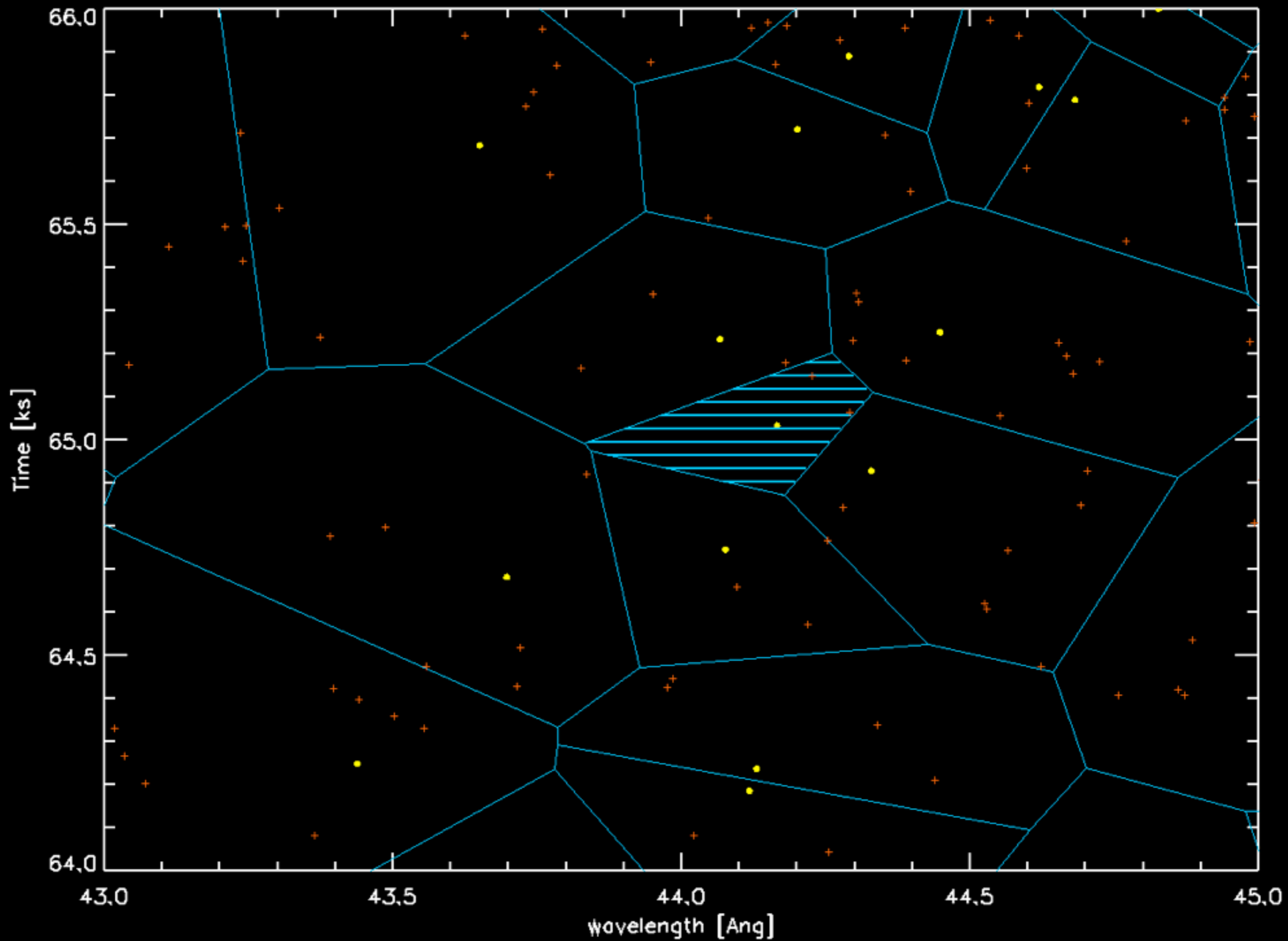
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# (B) Non-parametric Fluxes

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- ❖ `eff2evt`: convert measured photon energies to flux using detector QE and telescope EA
- ❖ Works fine when there are a lot of photons, but blows up when EA is small or events are sparse, and does not provide error bars
- ❖ New technique that accounts for possible range over which event can appear, and draws information from likely spectral model if available is in development







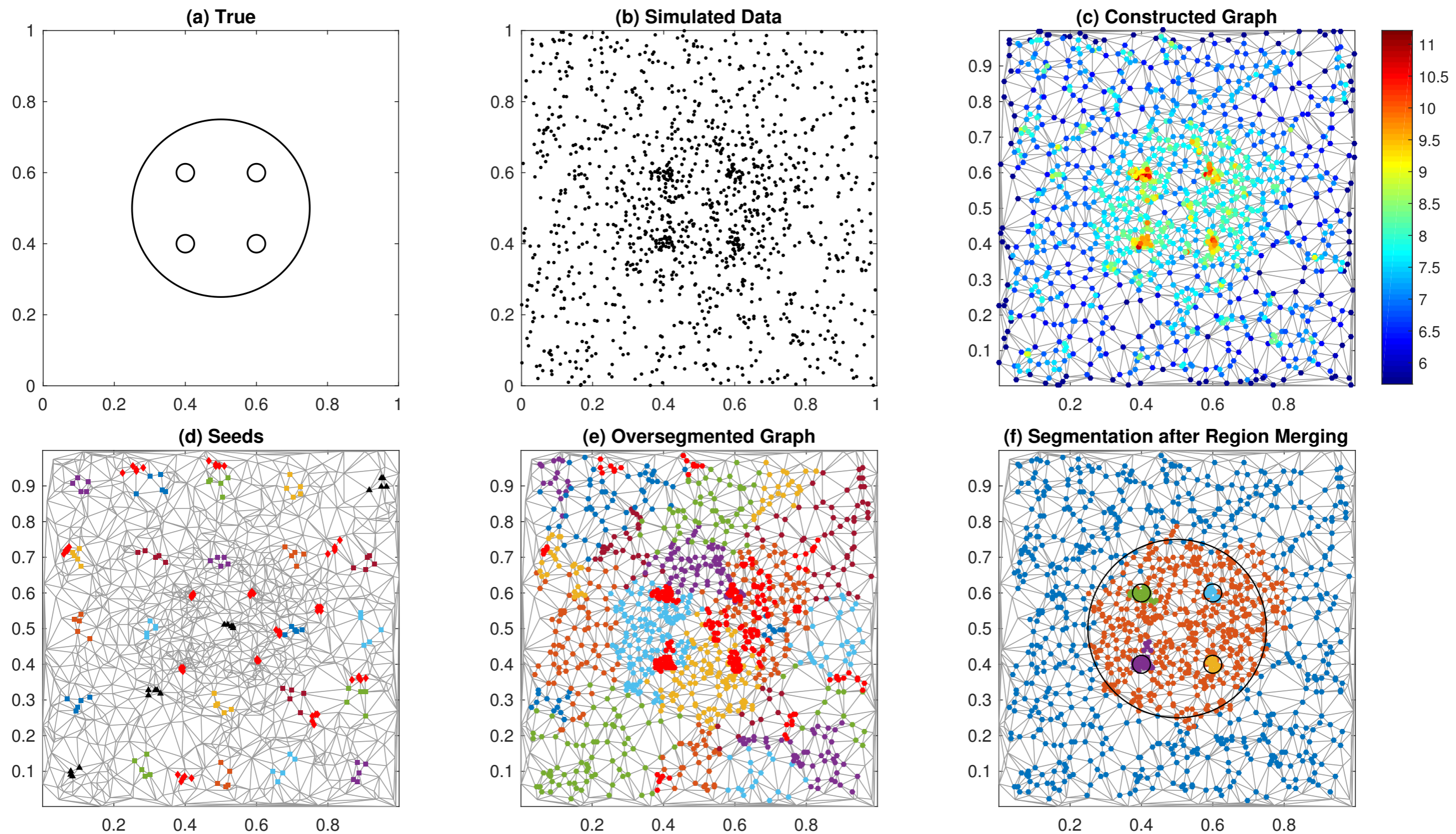
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# (B) Adaptive Segmentation

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- ❖ csmooth: adaptively smooth image by enforcing a S/N
- ❖ Highly successful for displaying Chandra data, but difficult to do science with
- ❖ What if we could segment the events list based on some criterion for local similarity?
- ❖ Graphed oversegmented seeded region growing, with subsequent merging using likelihood ratio type tests — Minjie Fan et al. 2017, in preparation

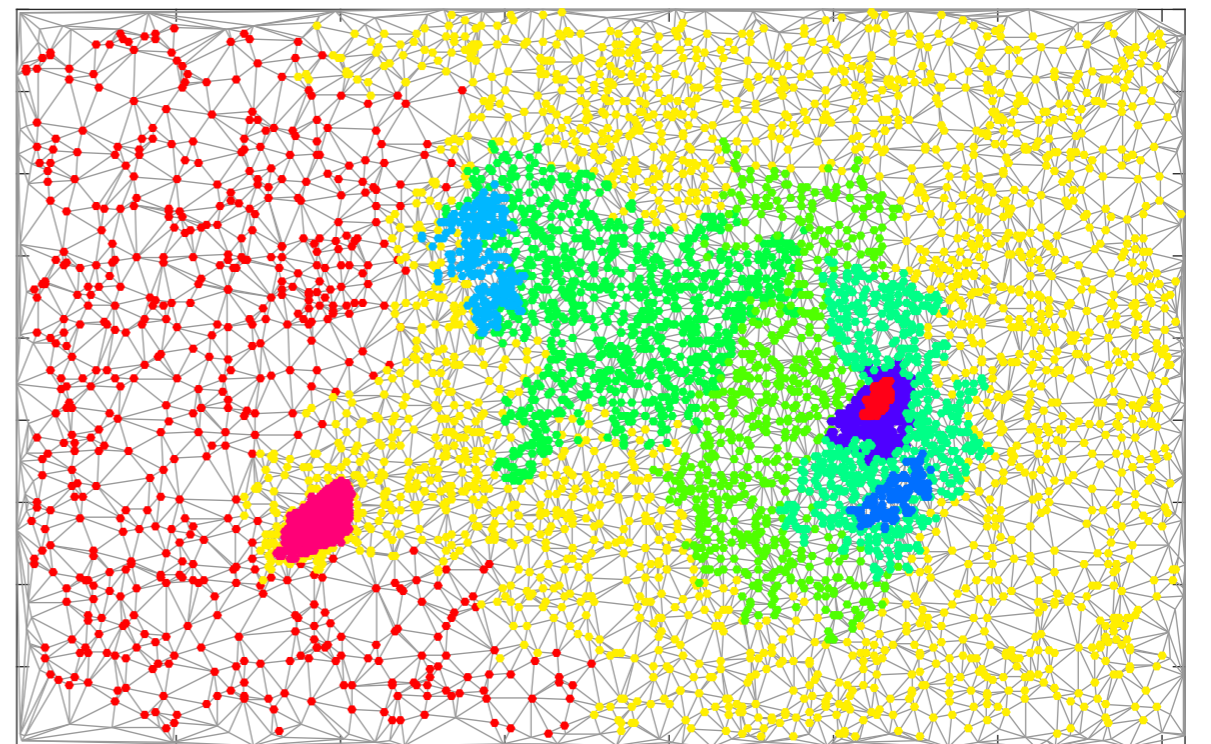
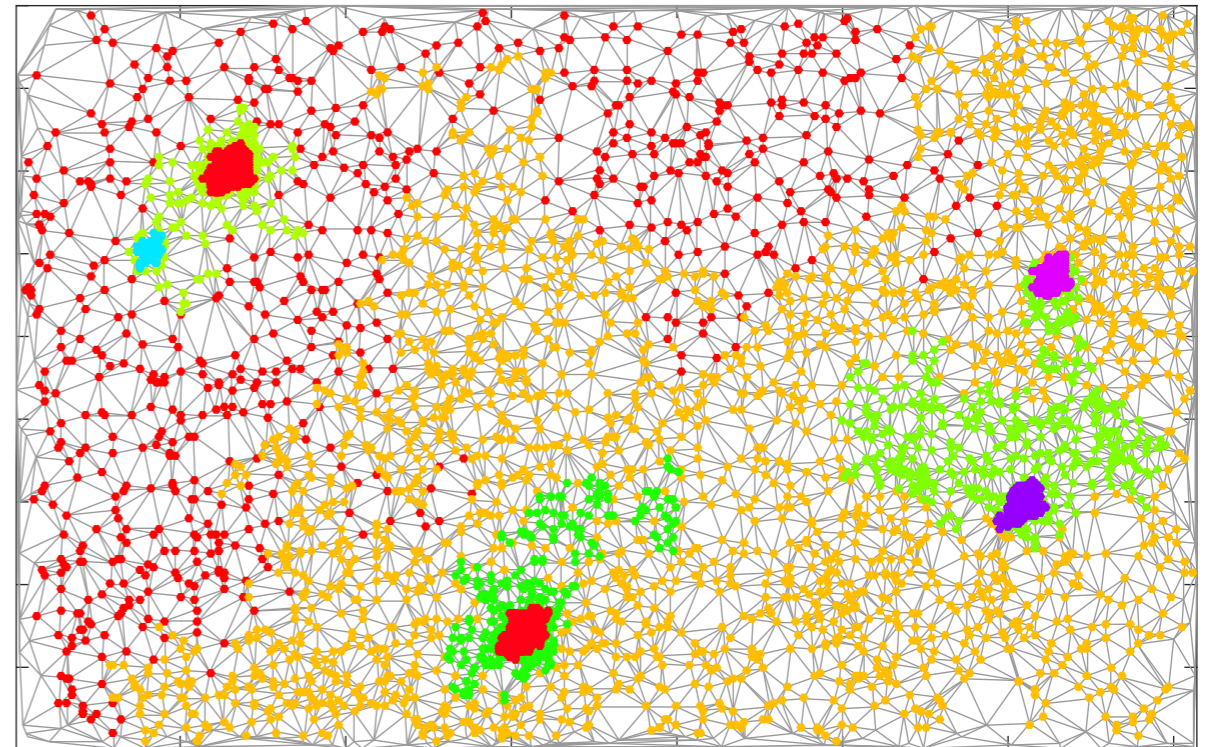
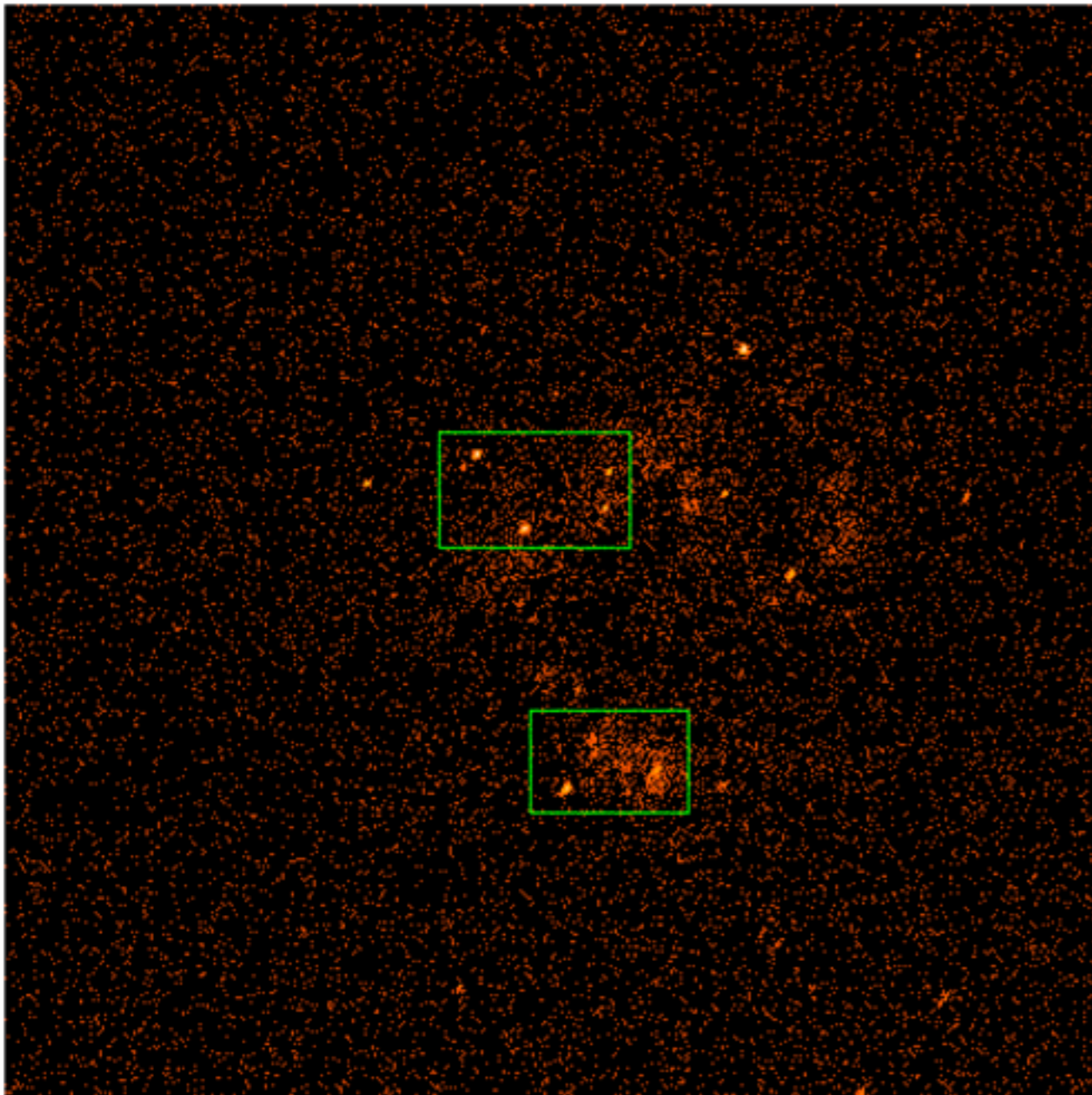
# Seeded Region Growing in Poisson Regime



Fan, Lee et al.

[from Andreas Zezas]

# Seeded Region Growing in Poisson Regime



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# (B) Multi-band Deconvolution

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- ❖ Deconvolution and / or reconstruction is currently limited to images. To derive spectral information requires making images in different bands and independently analyzing them
- ❖ Not optimal, because fewer counts in each image means larger errors, and independent analyses imply loss of connecting information
- ❖ Work is in progress to upgrade LIRA to simultaneously reconstruct images in multiple passbands

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# (B) Robust Fitting

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- ❖ There is a big problem with simultaneously fitting multiple datasets using a likelihood-based ( $\chi^2$ , cstat) statistic, if the sizes of the datasets differ significantly.
- ❖ You can't easily fit a high-resolution grating spectrum together with a low-resolution CCD spectrum, or an SED to spectroscopic and photometric data, or a small point source in the wing of a bright source
- ❖ Work is in progress to develop suitable weighting functions to loosen the tyranny of the bins

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(B)

cstat gof

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- ❖ A long standing problem with fitting spectra in the Poisson regime has been the lack of a measure of the goodness of fit when using cstat.
- ❖ A new parameterization of goodness of fit using the mean and stddev of expected cstat has been derived recently by Kaastra 2017, arXiv:1707.09202
- ❖ This is an encouraging breakthrough, but more work is needed!

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(C)

# New Stats

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- ❖ We have got a lot of mileage out of  $\chi^2$  and Maximum Likelihood and MaxEnt and wavelets
- ❖ Markov Chain Monte Carlo is becoming widely used
- ❖ What could be next?

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(C)

# New Stats

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- ❖ **Hierarchical Bayes**

- ❖ ability to build complex models for inference and classification and account for large amount of interrelationships among model parameters and instrument behavior

- ❖ **Gaussian Processes**

- ❖ Continuous stochastic process that can be used to make extrapolations and distinguishing multiple trends from known or trained data

- ❖ **Fiducial Inference**

- ❖ Compute probabilities and confidence bounds without having to set up prior probability distributions

- ❖ **Deep learning**

- ❖ Applying multi-level, cascading non-linear transformations (aka artificial neural networks) to extract relevant features from a dataset (aka Machine Learning)



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# The $\Omega$ Group

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- ❖ An informal  $\omega$ G, just send one of us an email to “join”. We will also be recruiting real statisticians to consult with.
  - ❖ Pat Broos
  - ❖ Peter Freeman
  - ❖ Vinay Kashyap
  - ❖ Andrew Ptak
  - ❖ Aneta Siemiginowska
  - ❖ Alexey Vikhlinin
  - ❖ Andreas Zezas