

# Detection: Overlapping Sources

David Jones

Harvard University Statistics Department

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Introduction

Model

Example

Simulation study

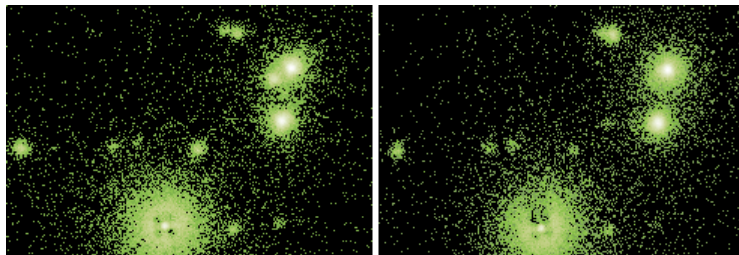
Chandra data

XMM data

Summary and discussion

# Introduction

- ▶ X-ray data: coordinates of photon detections, photon energy
- ▶ PSFs overlap for sources near each other
- ▶ Aim: inference for number of sources and their intensities, positions and spectral distributions
- ▶ Key points: (i) obtain posterior of number of sources, (ii) use spectral information



## Basic Model and Notation

$y_{ij}$  = spatial coordinates of photon  $j$  from source  $i$

$k$  = # sources (components)

$\mu_i$  = centre of source  $i$

$n_i$  = # photons detected from source  $i$

$$y_{ij} | \mu_i, n_i, k \sim \text{PSF centred at } \mu_i \quad j = 1, \dots, n_i, i = 0, \dots, k$$

$$(n_0, n_1, \dots, n_k) | w, k \sim \text{Mult}(n; (w_0, w_1, \dots, w_k))$$

$$(w_0, w_1, \dots, w_k) | k \sim \text{Dirichlet}(\lambda, \lambda, \dots, \lambda)$$

$$\mu_i | k \sim \text{Uniform over the image} \quad i = 1, 2, \dots, k$$

$$k \sim \text{Pois}(\theta)$$

- ▶ Component with label 0 is background and its "PSF" is uniform over the image (so its "centre" is irrelevant)
- ▶ Reasonably insensitive to  $\theta$ , the prior mean number of sources

## 3rd Dimension: Spectral Data

We can distinguish the background from the sources better if we jointly model spatial and spectral information:

$$\begin{aligned}e_{ij} | \alpha_i, \beta_i &\sim \text{Gamma}(\alpha_i, \beta_i) \text{ for } i = 1, \dots, k \text{ and } j = 1, \dots, n_i \\e_{0j} &\sim \text{Uniform to some maximum for } j = 1, \dots, n_0 \\ \alpha_i &\sim \text{Gamma}(a_\alpha, b_\alpha) \\ \beta_i &\sim \text{Gamma}(a_\beta, b_\beta)\end{aligned}$$

Using a (correctly) "informative" prior on  $\alpha_i$  and  $\beta_i$  versus a diffuse prior made very little difference to results.

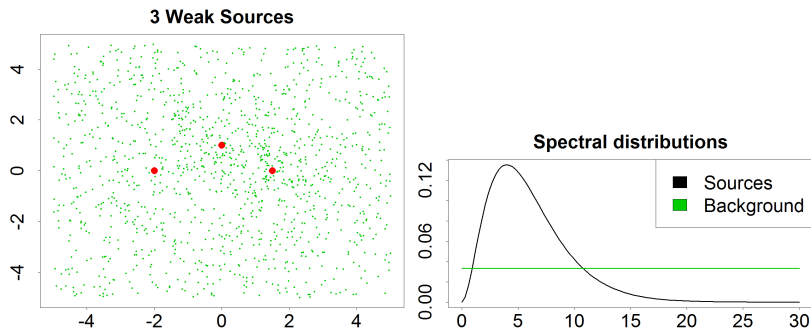
## Computation: RJMCMC

- ▶ Similar to Richardson & Green 1997
- ▶ Knowledge of the PSF makes things easier
- ▶ Insensitive to the prior on  $k$  e.g. posterior when  $k = 10$  and  $\theta = 3$ :

	Posterior of number of sources ( $k$ )						
	7	8	9	10	11	12	13
Mean	0.029	0.058	0.141	0.222	0.220	0.157	0.082
SD	0.018	0.019	0.022	0.029	0.027	0.021	0.014

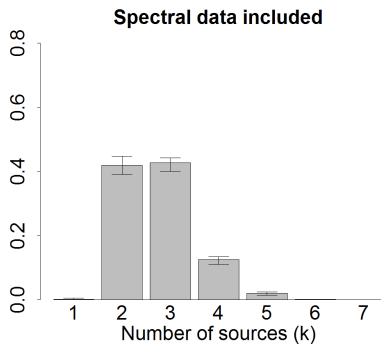
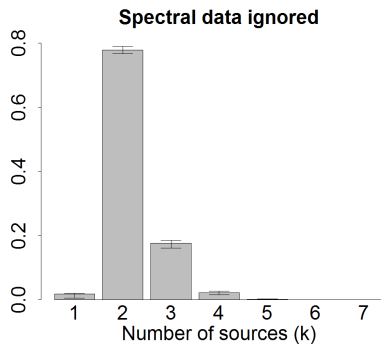
Used posterior probabilities given by 10 chains

## Example



- ▶ Region occupied by the three sources (2 SD) is about 28% of the area and contains about 41% of the observations
- ▶ Within this sources region around 48% is background
- ▶ Positions  $(-2, 0)$ ,  $(0, 1)$ ,  $(1.5, 0)$  with intensities 50, 100, 150 respectively

## Posterior of $k$



- ▶ Mean over 10 chains of the posterior probabilities (range indicated)
- ▶ When the spectral data is ignored we do not find the faintest source



## Parameter Inference

	$\mu_{11}$	$\mu_{12}$	$\mu_{21}$	$\mu_{22}$	$\mu_{31}$	$\mu_{32}$	$w_1$	$w_2$	$w_3$	$w_b$	$\alpha$	$\beta$
<b>Truth</b>	-2	0	0	1	1.5	0	0.038	0.077	0.115	0.769	3	0.5
<b>Spectral data ignored</b>												
Mean	-1.266	0.839	0.401	0.549	1.798	-0.054	0.049	0.067	0.086	0.798	NA	NA
SD	0.069	0.125	0.067	0.068	0.030	0.046	0.002	0.002	0.003	0.001	NA	NA
MSE	<b>0.543</b>	<b>0.718</b>	0.165	0.207	0.090	0.005					NA	NA
SD/Mean							0.050	0.027	0.032	0.001	NA	NA
<b>Spectral data included</b>												
Mean	-1.790	-0.101	-0.234	1.042	1.584	-0.044	0.040	0.077	0.115	0.768	2.827	0.459
SD	0.037	0.064	0.033	0.026	0.019	0.022	0.001	0.001	0.002	0.000	0.013	0.003
MSE	<b>0.045</b>	<b>0.014</b>	0.056	0.002	0.007	0.002					0.030	0.002
SD/Mean							0.036	0.018	0.014	0.000	0.004	0.006

- ▶ The effects are less pronounced when the sources are more easily distinguished from the background

## Allocation of Photons

Table: Allocation breakdown: (a) ignoring spectral data

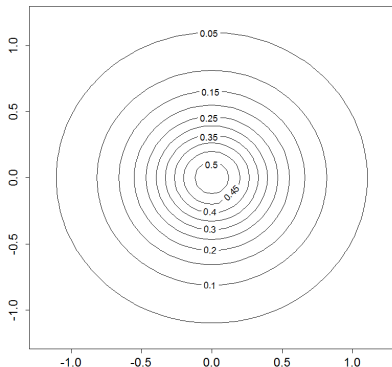
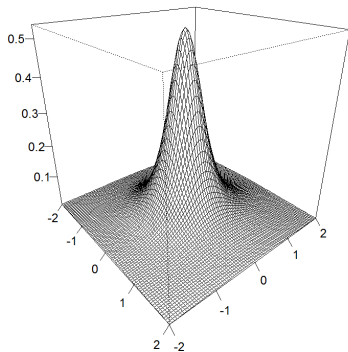
Source (intensity)	No. Photons	Allocation Breakdown			
		Background	Left	Middle	Right
Background (10/sq)	1015	0.876	0.035	0.040	0.049
Left (50)	38	0.798	0.121	0.067	0.014
Middle (100)	97	0.502	0.168	0.189	0.141
Right (150)	152	0.481	0.043	0.159	0.317

Table: Allocation breakdown: (b) using spectral data

Source (intensity)	No. Photons	Allocation Breakdown			
		Background	Left	Middle	Right
Background (10/sq)	1015	0.894	0.024	0.038	0.045
Left (50)	38	0.531	0.278	0.165	0.026
Middle (100)	97	0.293	0.122	0.346	0.239
Right (150)	152	0.305	0.028	0.141	0.526

- ▶ Background is more easily distinguished from the sources when we include the spectral data

## Simulation Study: PSF (King 1962)



- ▶ King density has Cauchy tails
- ▶ Gaussian PSF leads to over-fitting in real data

## Simulation Study: Data Generation

- ▶ Bright source:

$$n_1 \sim \text{Pois}(1000)$$

- ▶ Dim source:

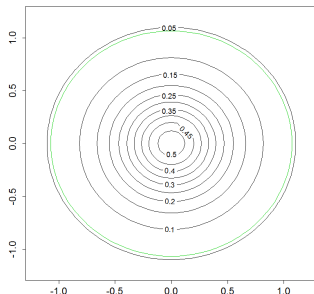
$$n_2 \sim \text{Pois}(1000/r)$$

where  $r = 1, 2, 10, 50$  gives the **relative intensity**

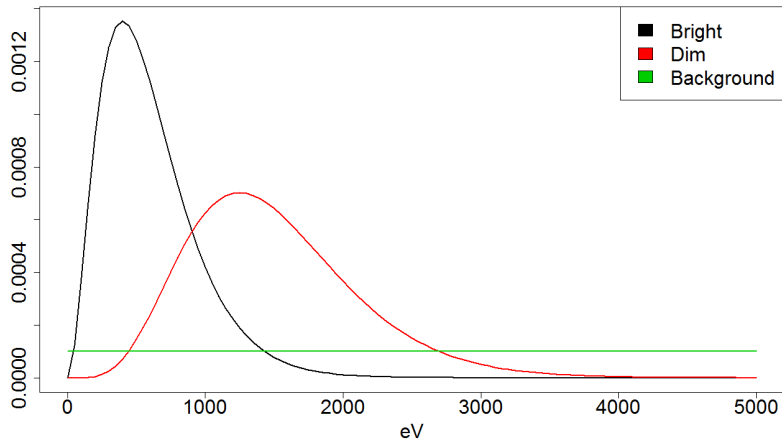
- ▶ Background per 'source region':

$$n_0 \sim \text{Pois}(bd1000/r)$$

where **relative background**  $b = 0.001, 0.01, 0.1, 1$ . Here  $d = 0.52$  is the proportion of photons from a source within the region defined by density greater than 10% of the maximum (essentially a circle with radius 1)

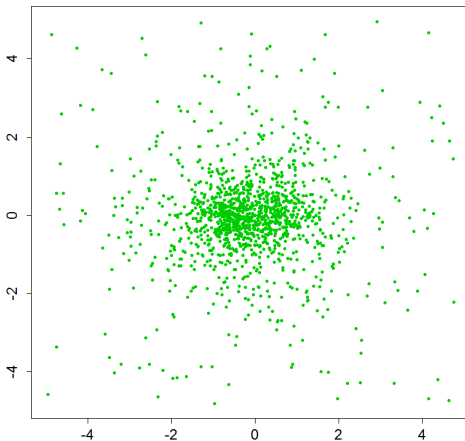


## Simulation Study: Data Generation



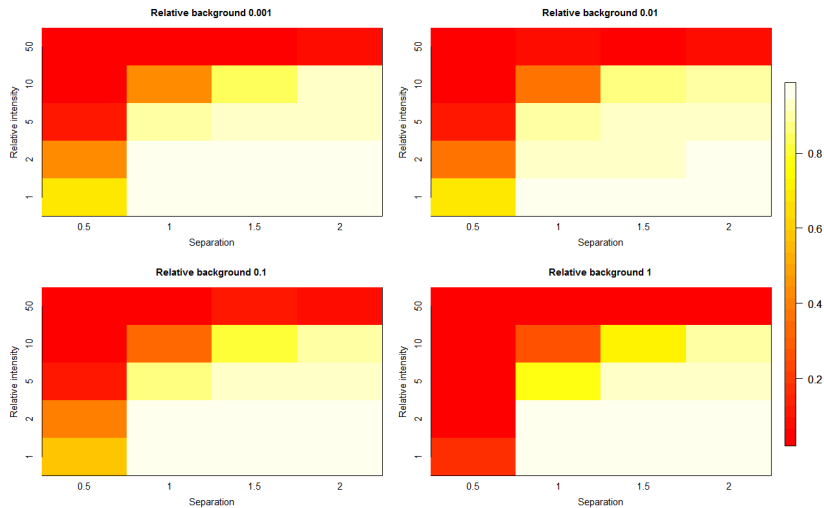
## Simulation Study: Example

Two sources: separation 1, relative intensity 1, background 0.01

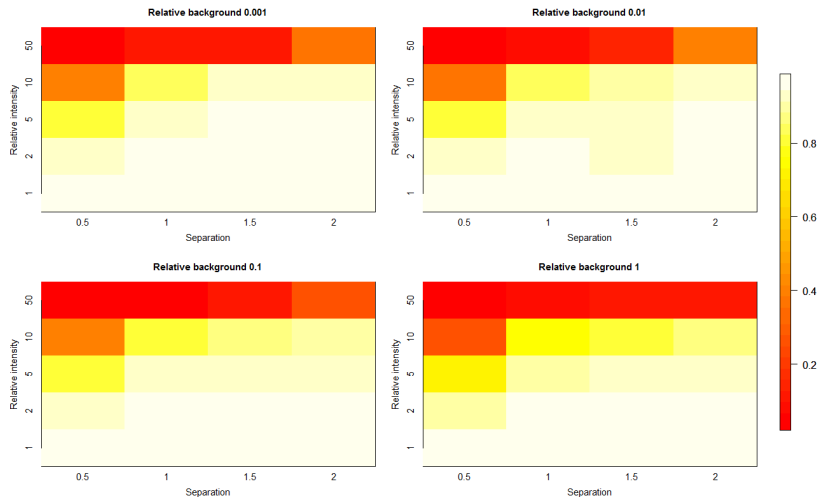


- ▶ 50 datasets simulated for each configuration
- ▶ Analysis with and without energy data
- ▶ Summarize posterior of  $k$  by posterior probability of two sources

# Posterior Probability at k=2: No Energy

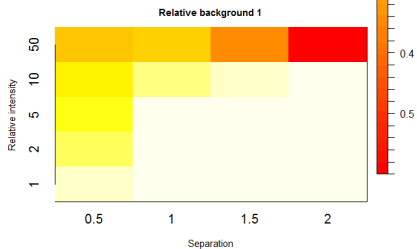
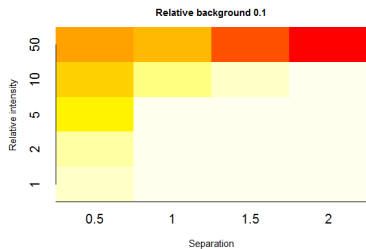
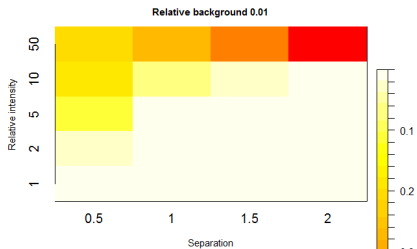
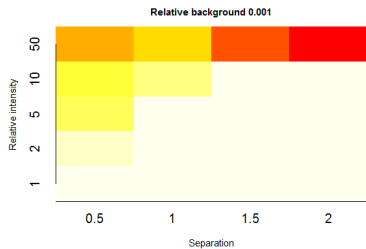


# Posterior Probability at k=2: Energy

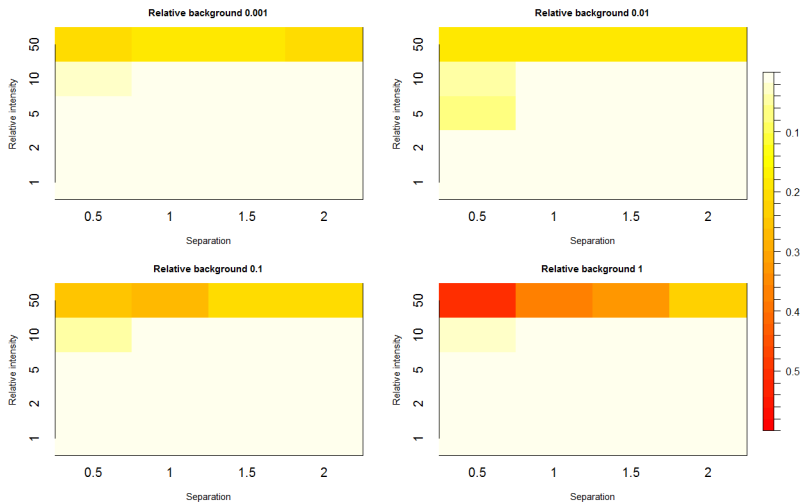




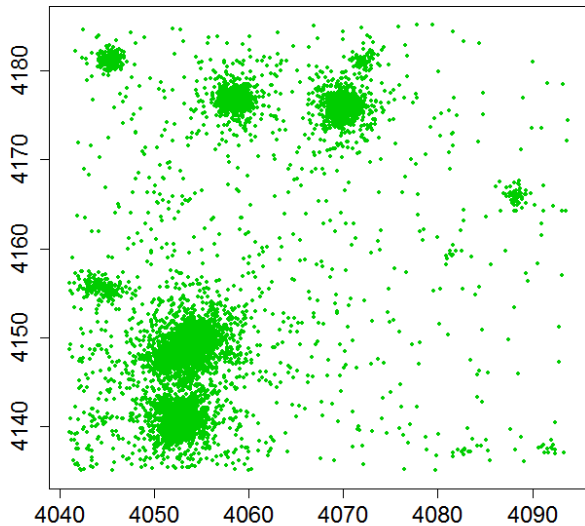
## Average MSE of Positions: No Energy



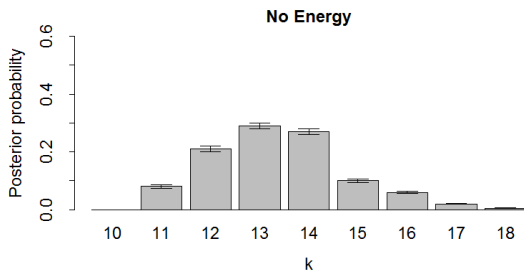
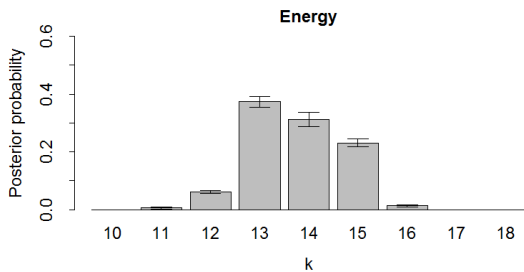
# Average MSE of Positions: Energy



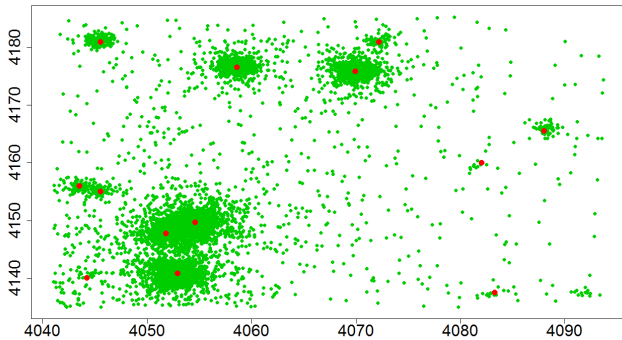
## Chandra Data

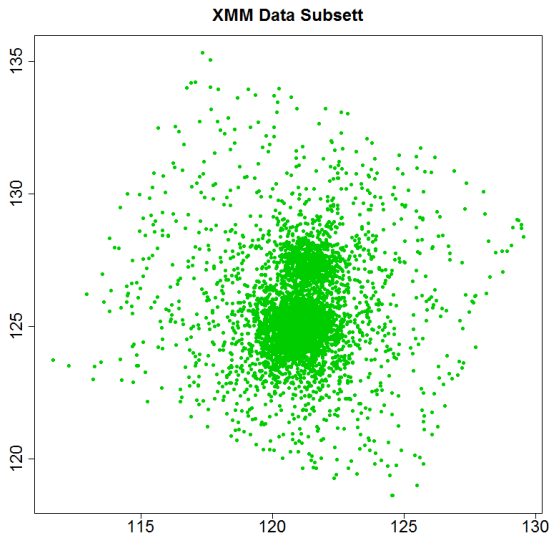


# Chandra $k$ Results



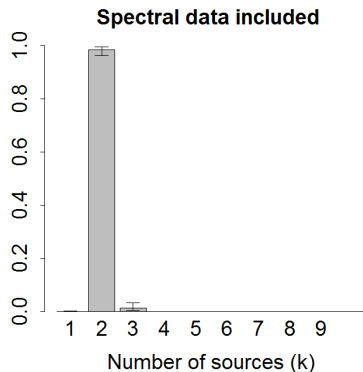
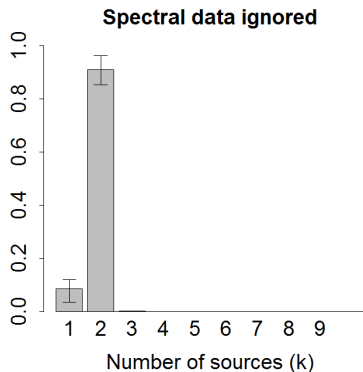
# Locations





- ▶ Additional question: how do the spectral distributions of the sources compare?

## k posterior



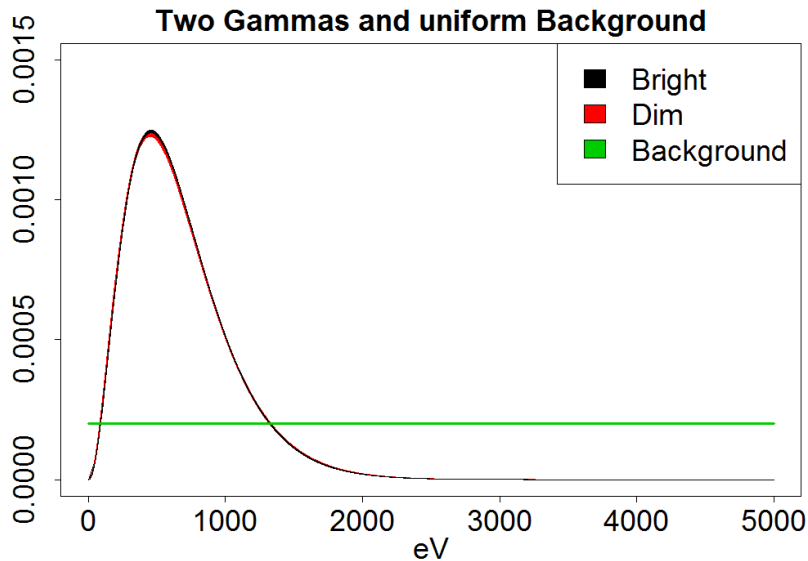
- ▶ Mean over 10 chains of the posterior probabilities (range indicated)
- ▶ Spectral information focuses posterior on 2 sources

## Parameter Inference

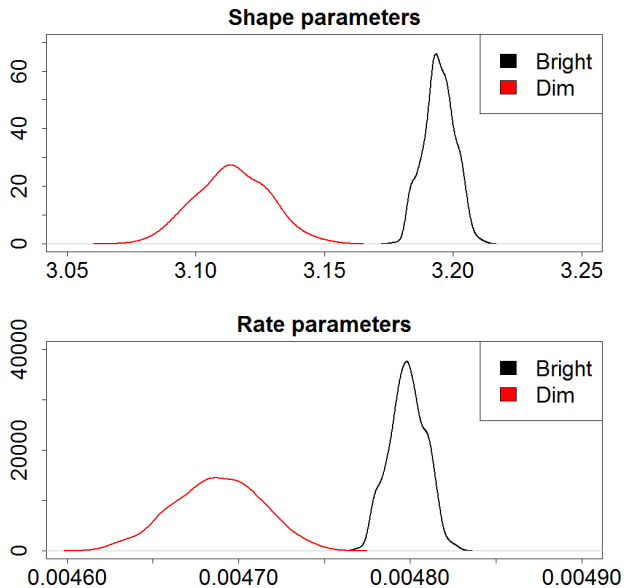
Table: Parameter estimation for FK Aqr and FL Aqr (using spectral data)

	$\mu_{11}$	$\mu_{12}$	$\mu_{21}$	$\mu_{22}$	$w_1$	$w_2$	$w_b$	$\alpha$	$\beta$
Mean	120.988	124.891	121.366	127.376	0.808	0.182	0.009	3.182	0.005
SD	0.001	0.002	0.016	0.027	0.001	0.001	0.000	0.000	0.000
SD/Mean	0.000	0.000	0.000	0.000	0.001	0.005	0.011	0.000	0.000






## Posteriors of source spectral parameters

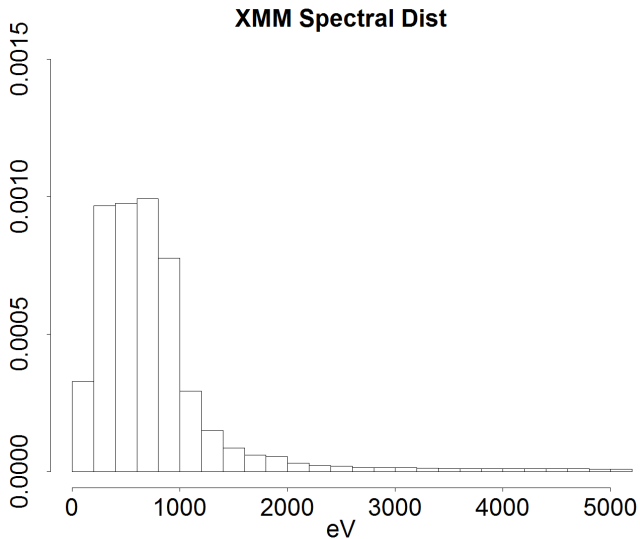


## Summary

- ▶ Coherent method for dealing with overlapping sources that uses spectral as well as spatial information
- ▶ Flexibility to include other phenomenon
- ▶ How to combine Chandra datasets?
- ▶ Other models/computation possible
- ▶ Approximation to full method could be desirable

-  S. Richardson, P. J. Green *On Bayesian analysis of mixtures with an unknown number of components* (with discussion), *J. R. Statist. Soc. B*, 59, 731792, 1997; corrigendum, 60 (1998), 661.
-  I. King, *The structure of star clusters. I. An empirical density law*, *The Astronomical Journal*, 67 (1962), 471.
-  C. M. Bishop, N. M. Nasrabadi, *Pattern recognition and machine learning*, Vol. 1. New York: springer, 2006.
-  A. P. Dempster, N. M. Laird, D. B. Rubin. *Maximum likelihood from incomplete data via the EM algorithm*, *Journal of the Royal Statistical Society, Series B (Methodological)* (1977): 1-38.
-  S. P. Brooks, A. Gelman, *General Methods for Monitoring Convergence of Iterative Simulations*, *Journal of Computational and Graphical Statistics*, Vol. 7, No. 4. (Dec., 1998), pp. 434-455.

## XMM data spectral distribution



## Four models

