ROSAT and XMMSLEW2 counterparts using Nway--An accurate Bayesian algorithm to pair sources simultaneously between N catalogs.

Mara Salvato, J. Buchner, T. Budavari, T. Dwelly, A. Merloni, M. Brusa, A. Rau, S. Fotopoulou, K. Nandra

http://adsabs.harvard.edu/abs/2018MNRAS.473.4937S

https://github.com/JohannesBuchner/nway

Structure of the talk:

- Why multi-wavelength cross-matches are important ?
- Where is the problem, in particular for matches with X-ray ?
- The difficulties with the old solution ?
- New solution !
- Application and results
- Outlook to future applications

In Observational Astrophysics, Source Characterisation is the starting point

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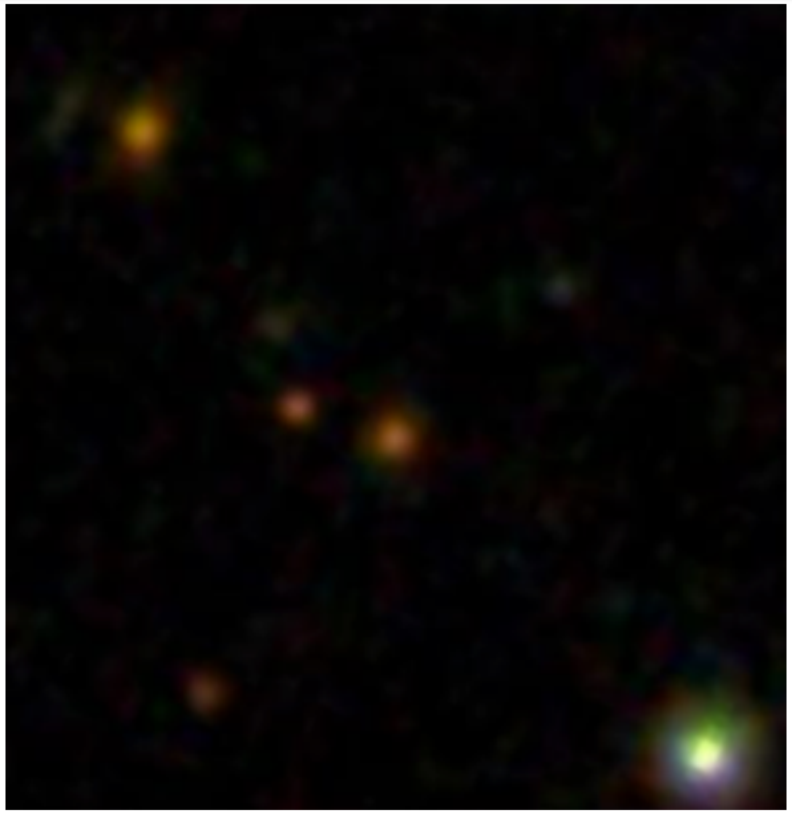

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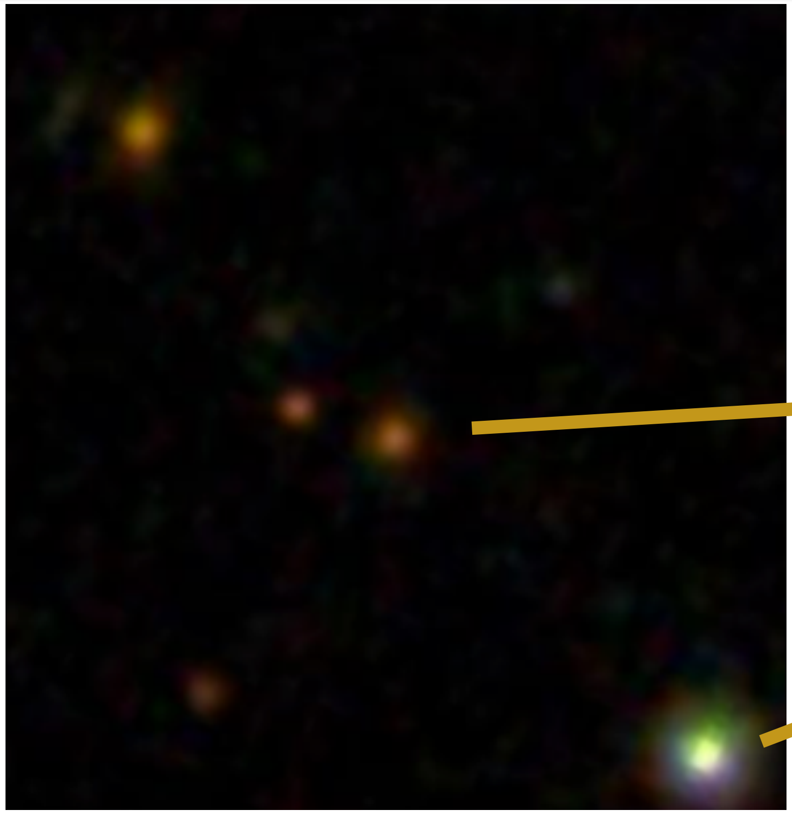

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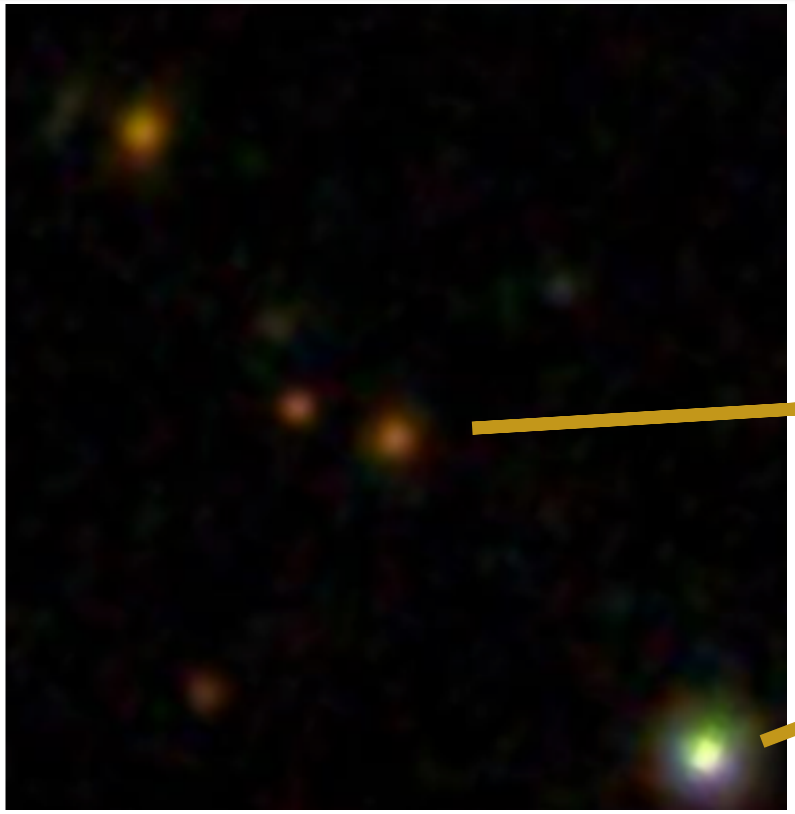
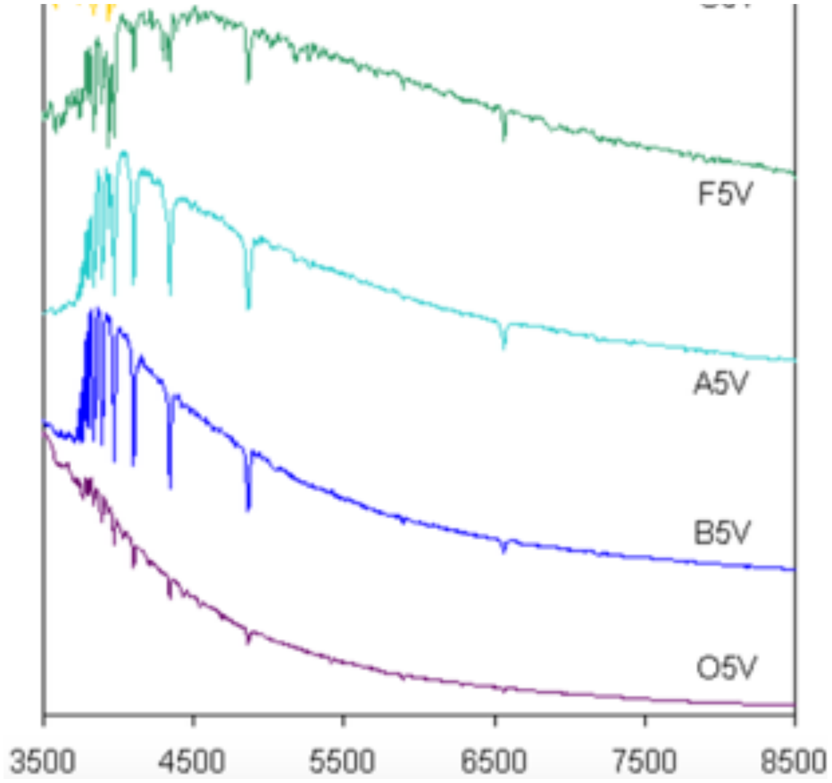
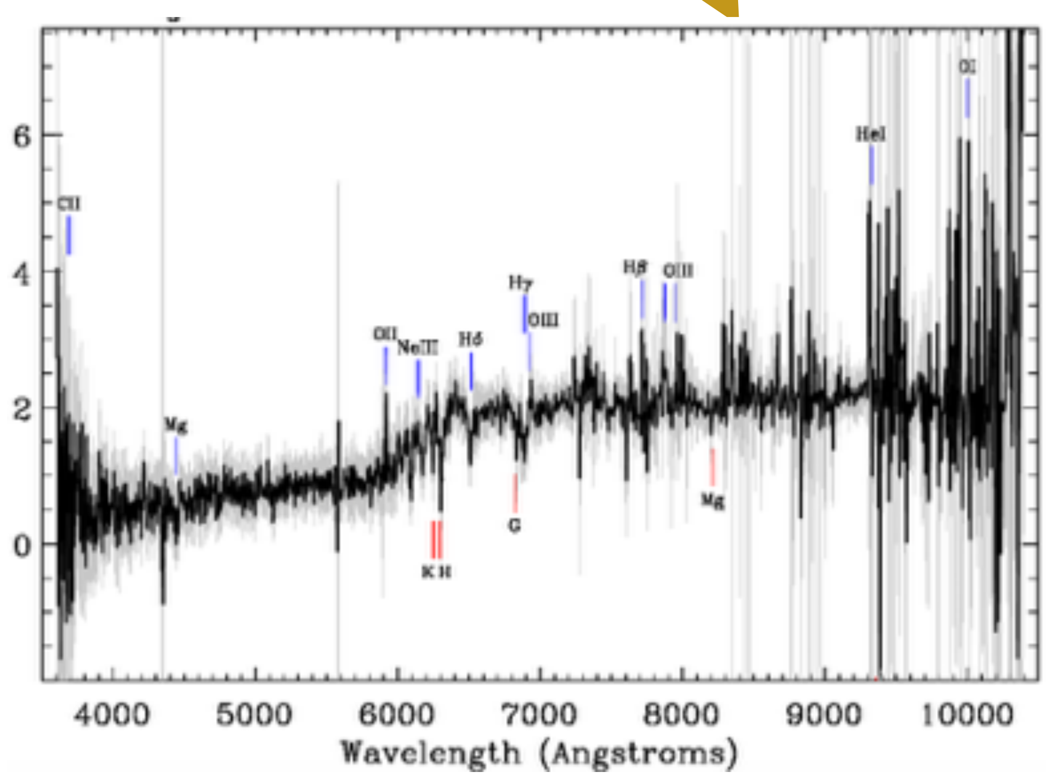
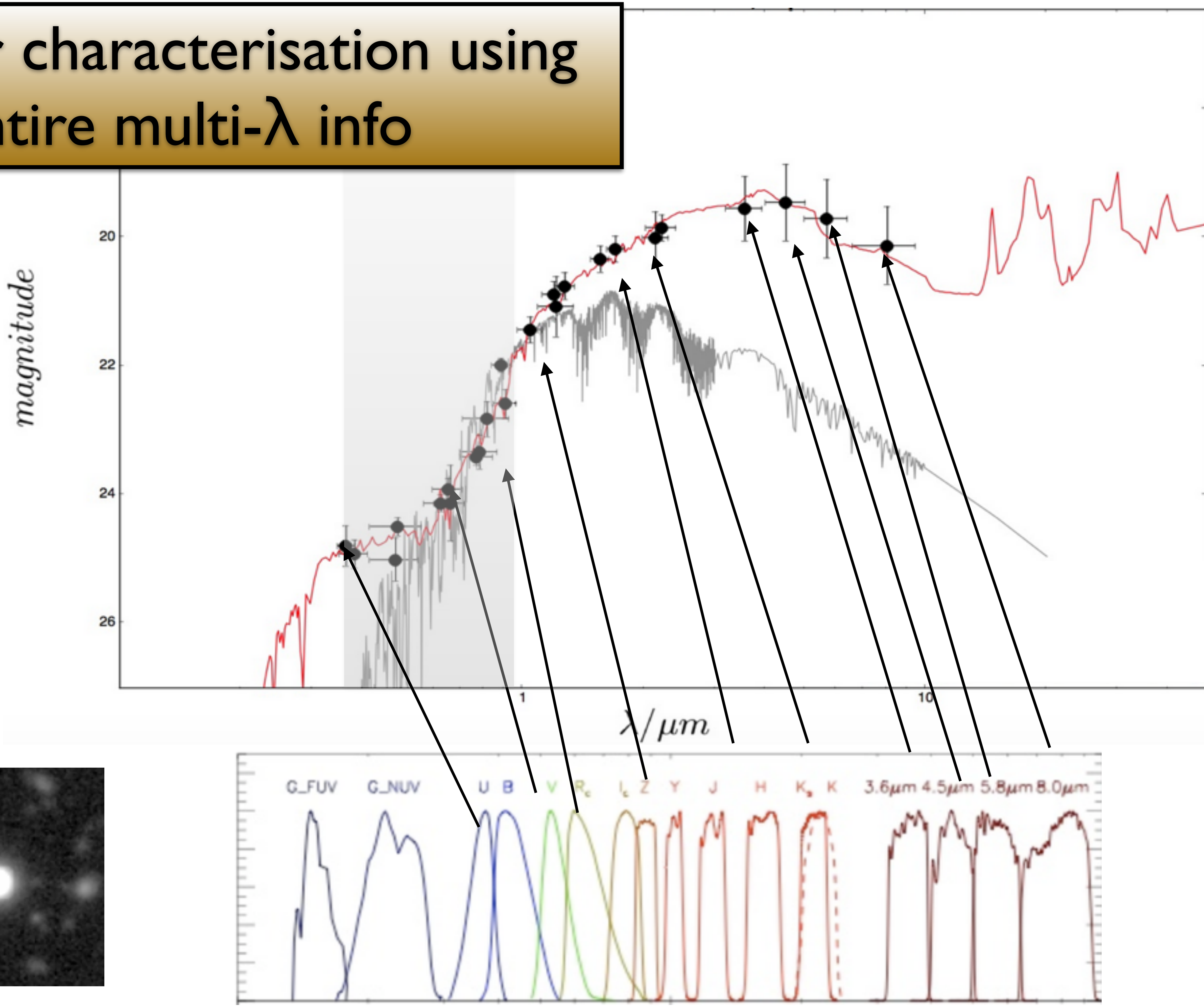
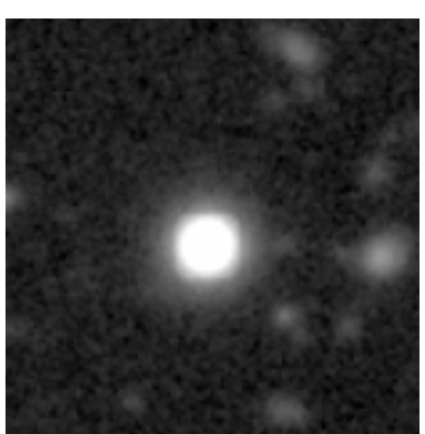






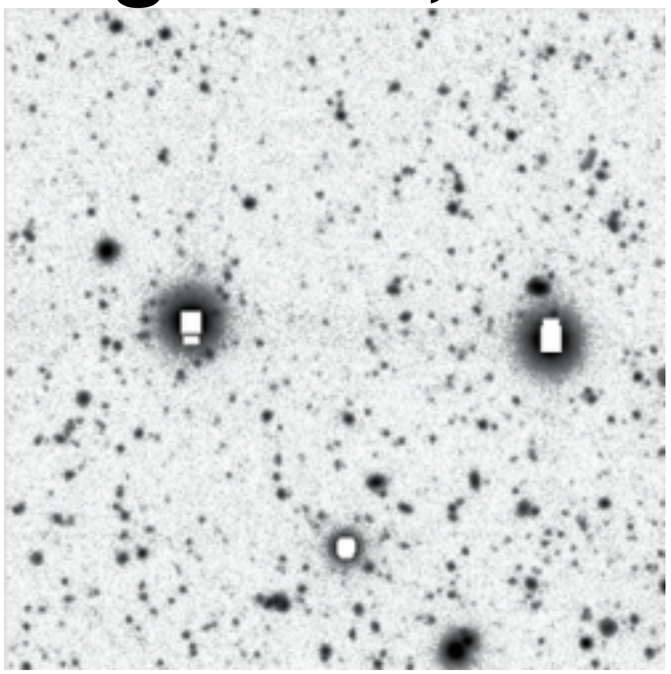
better characterisation using the entire multi-λ info



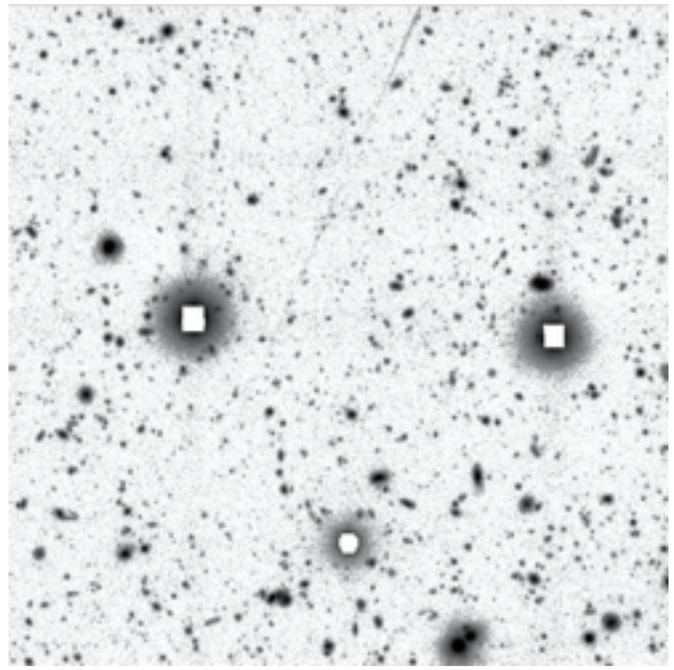


Pairing is easier at optical and near-infrared bands than between X-ray and other bands

g band, 3’



z band, 3’



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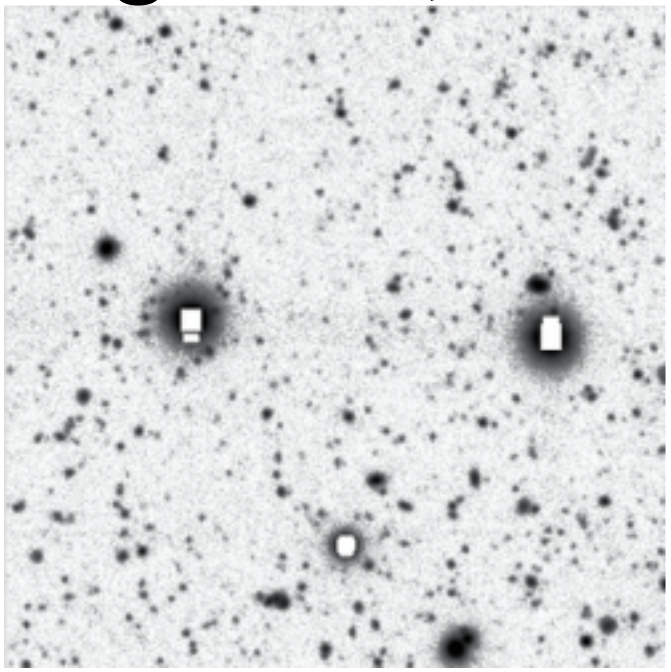

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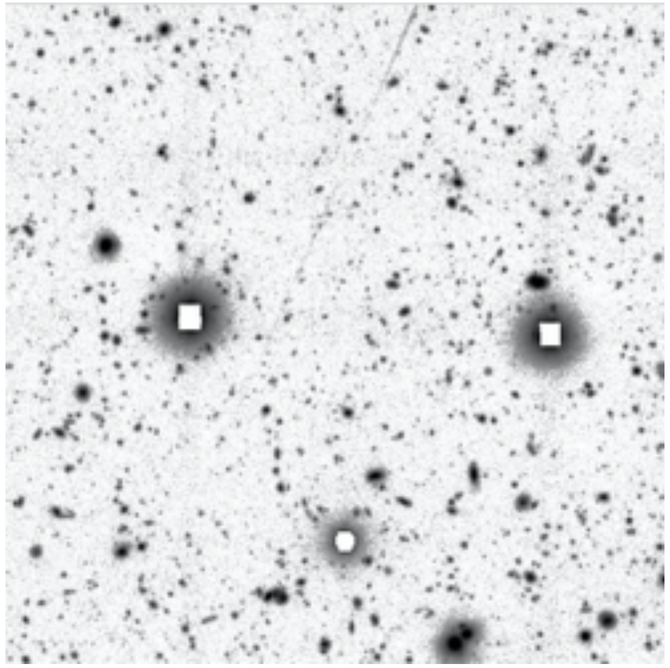
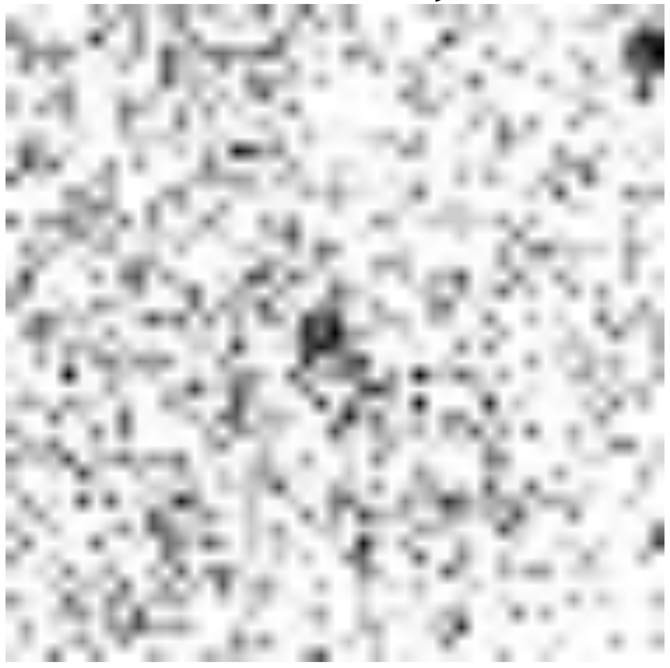


XMM, 3’



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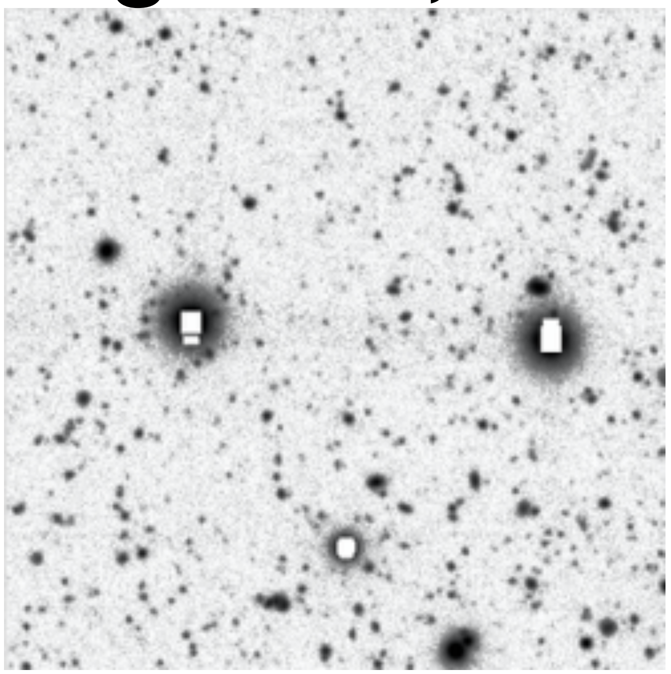

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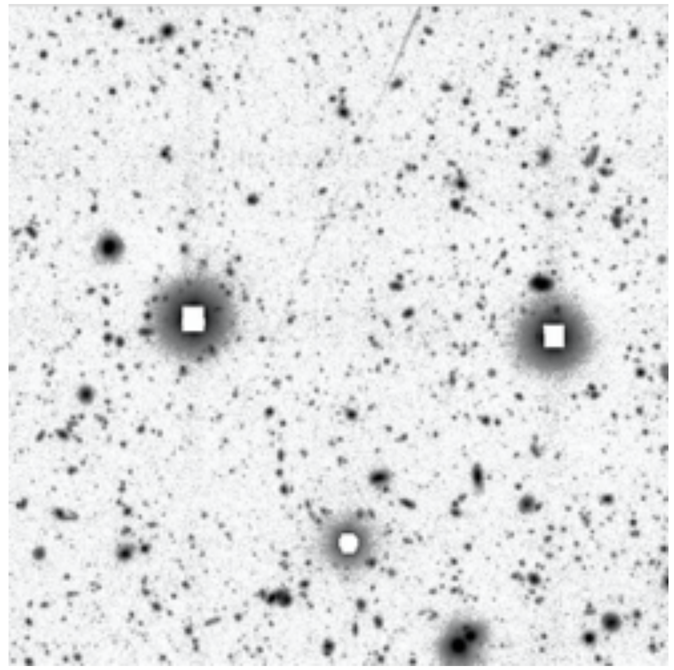

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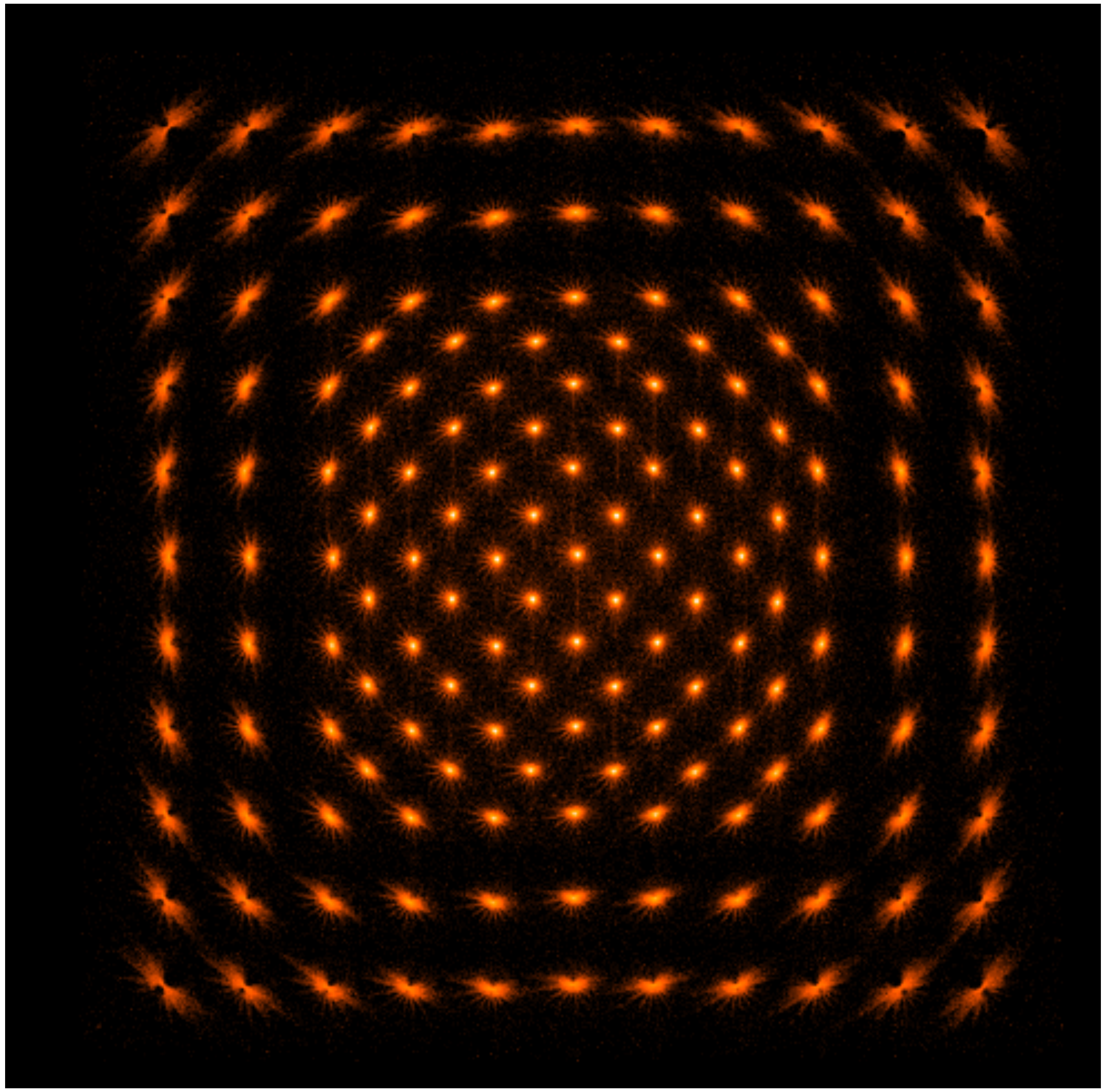

Huge difference in resolution between on/off-axis

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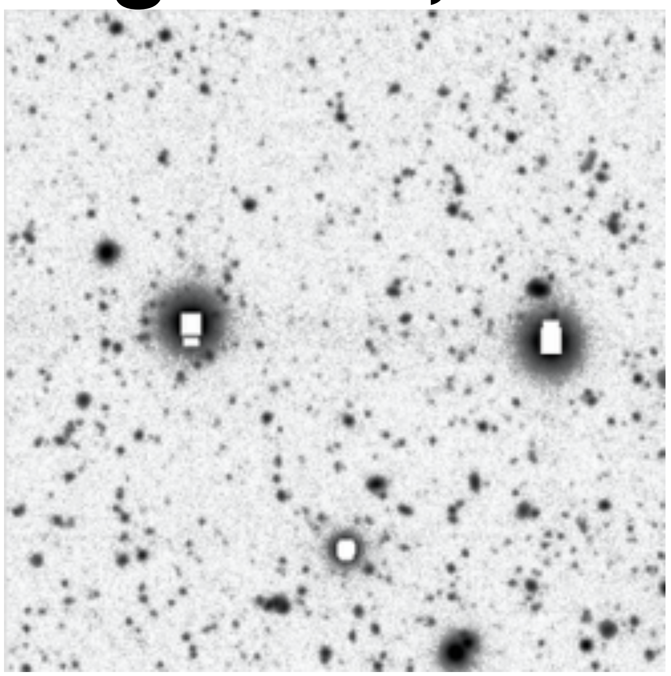

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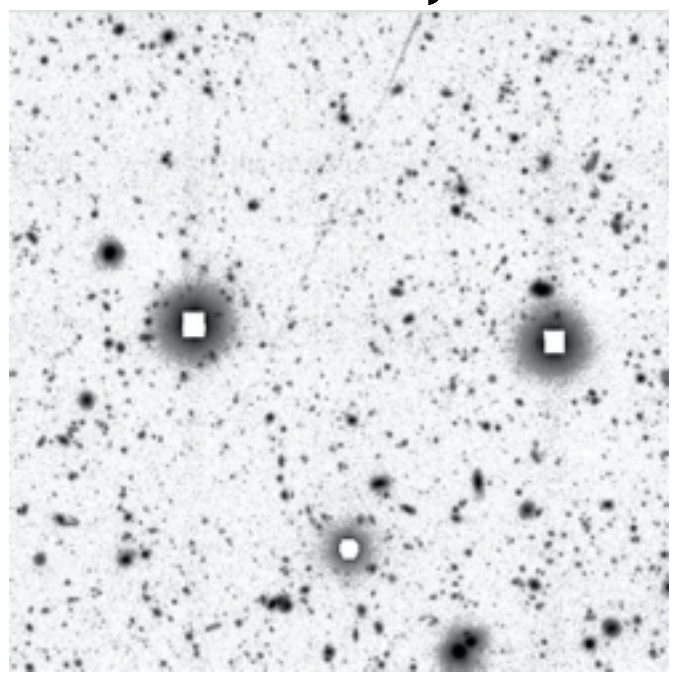
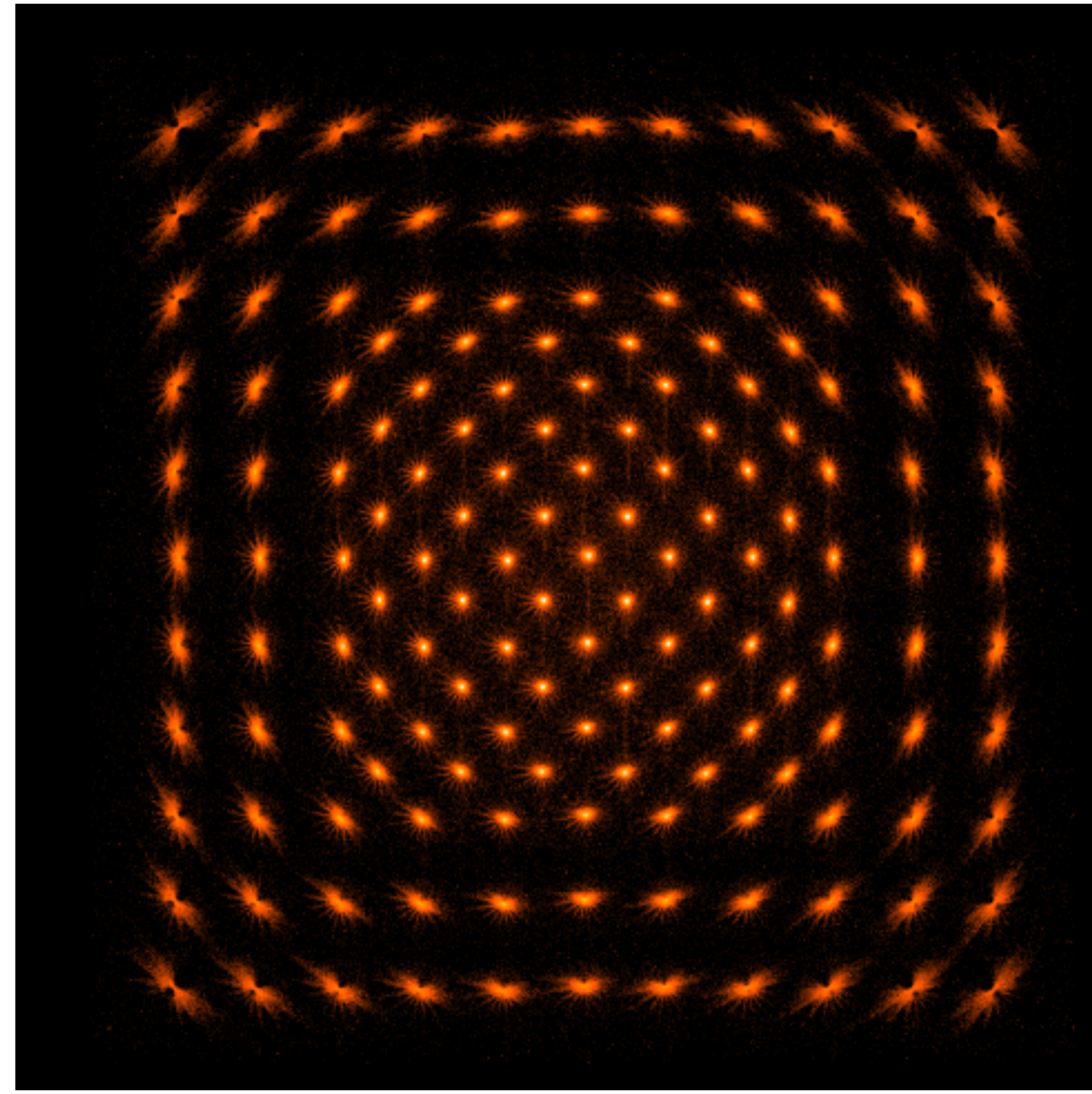


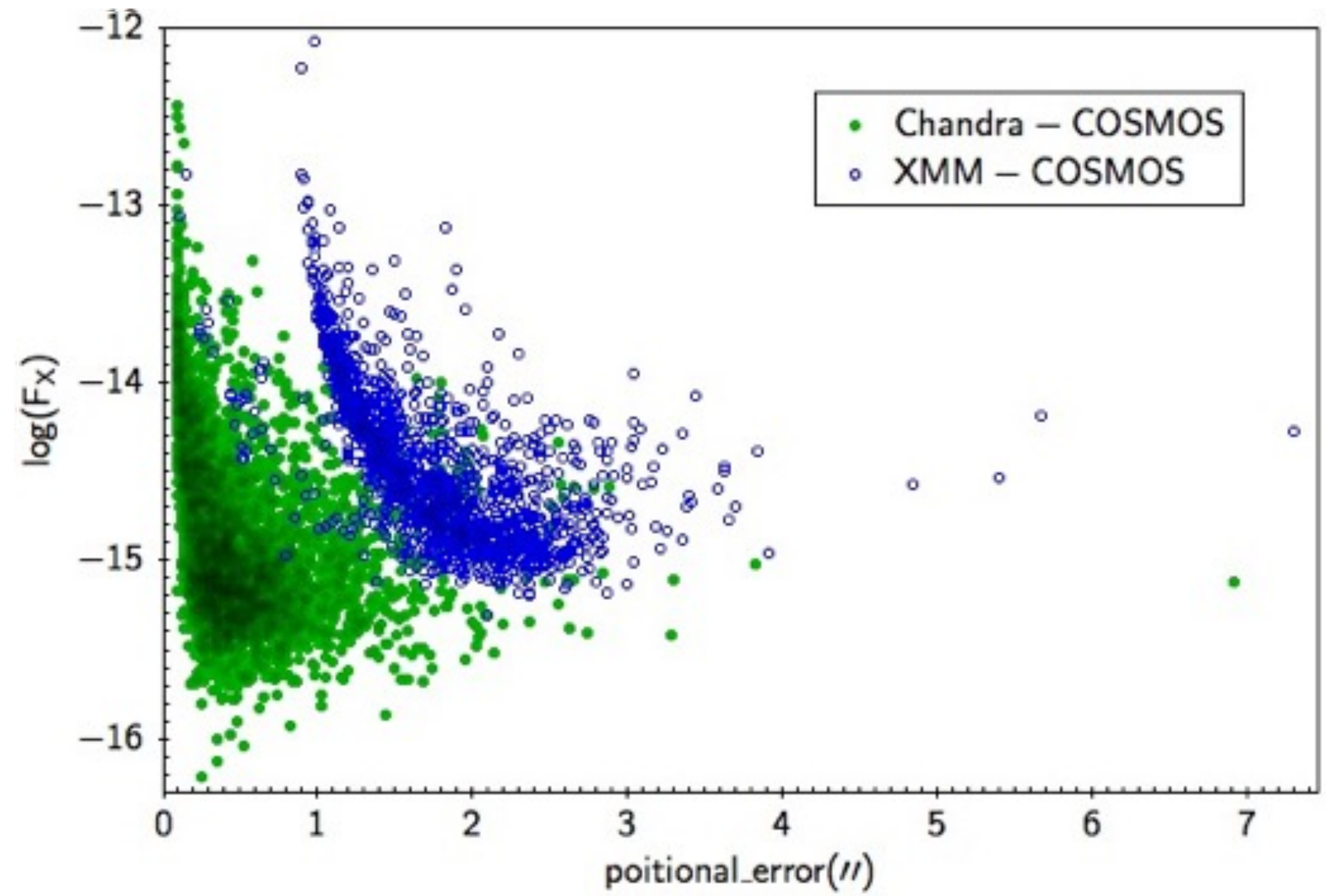
XMM, 3'



Huge difference in resolution between on/off-axis

+ few sources per pointing often not sufficient to provide a reliable astrometric solution

X-ray positional error is flux (and instrument) depending



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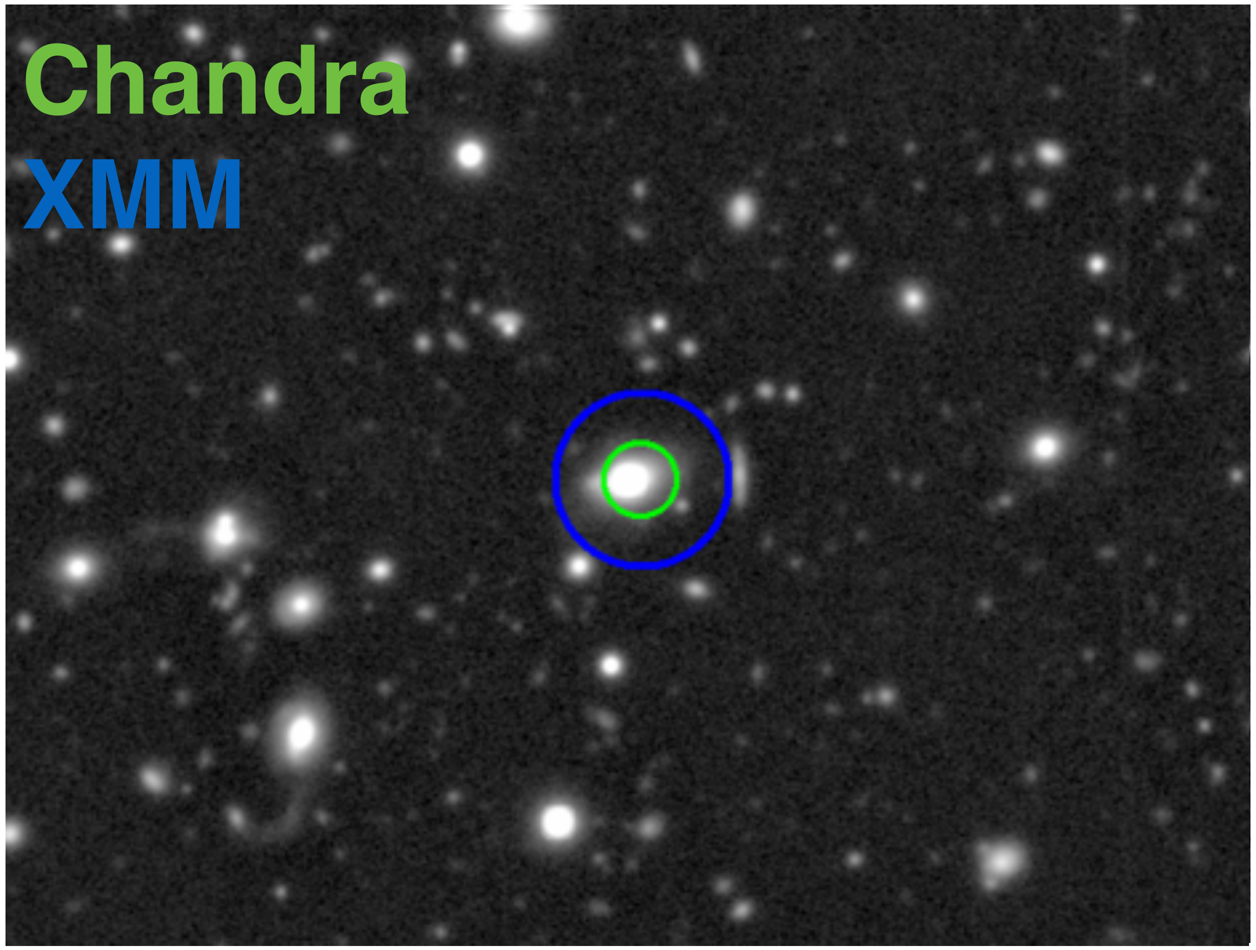

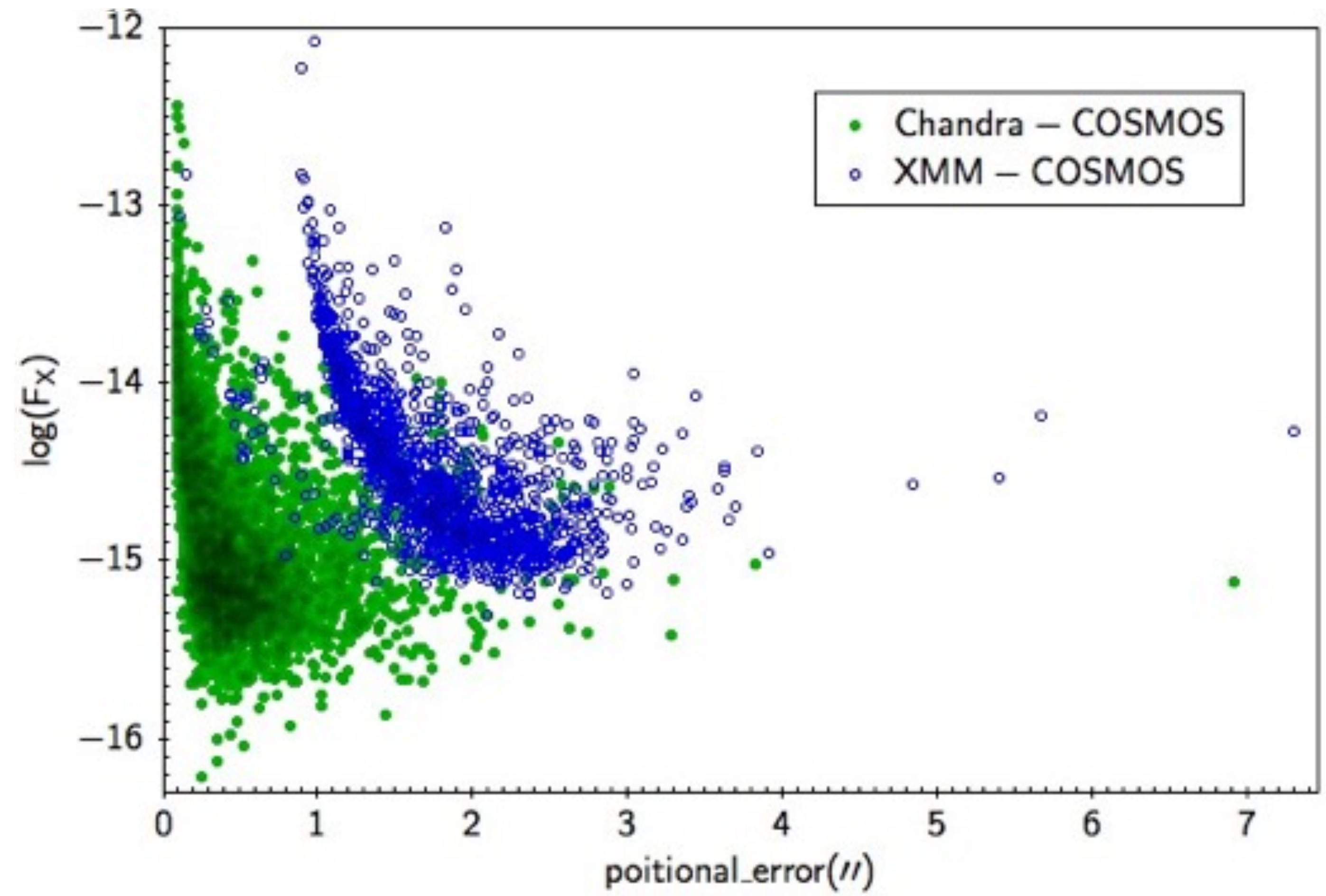

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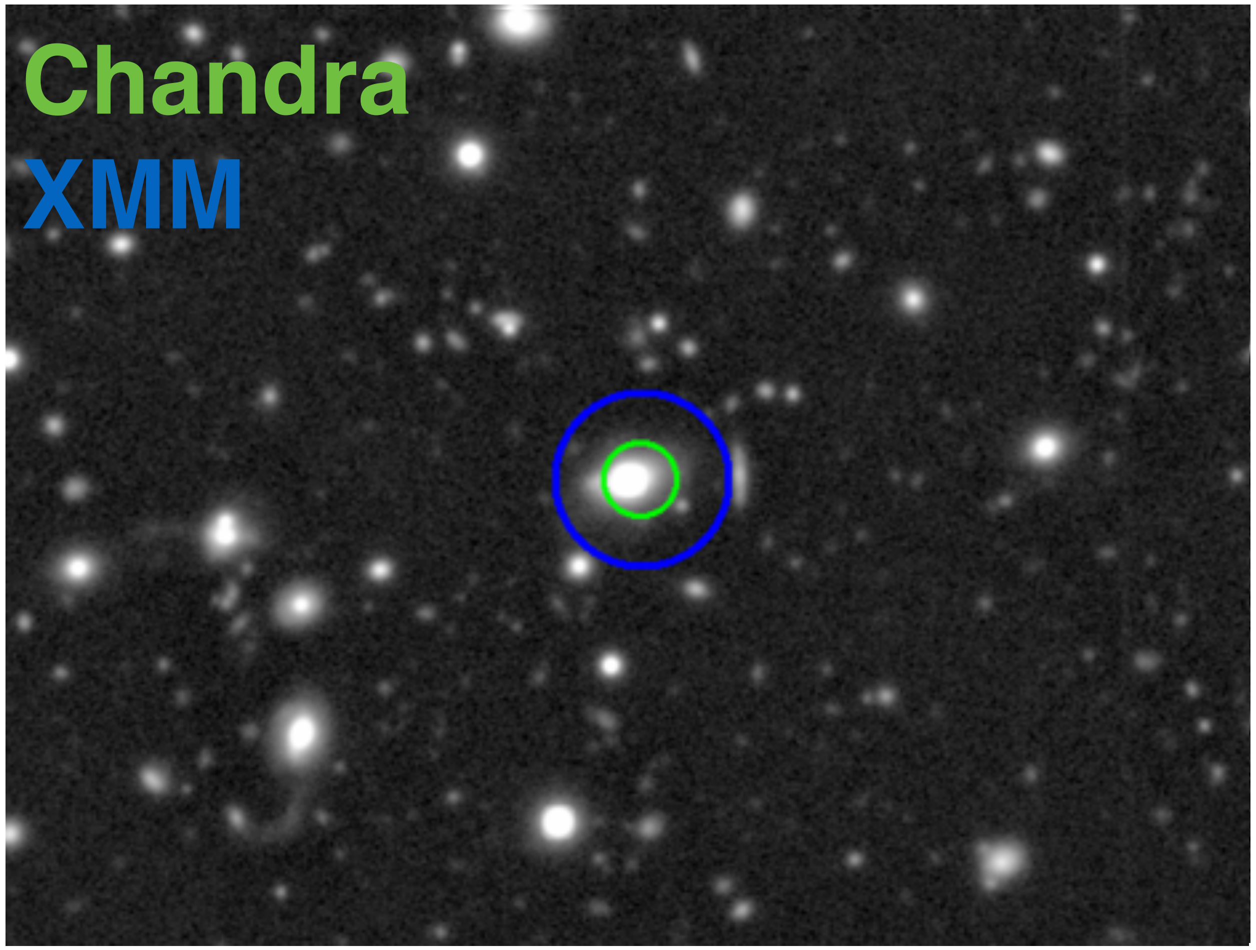

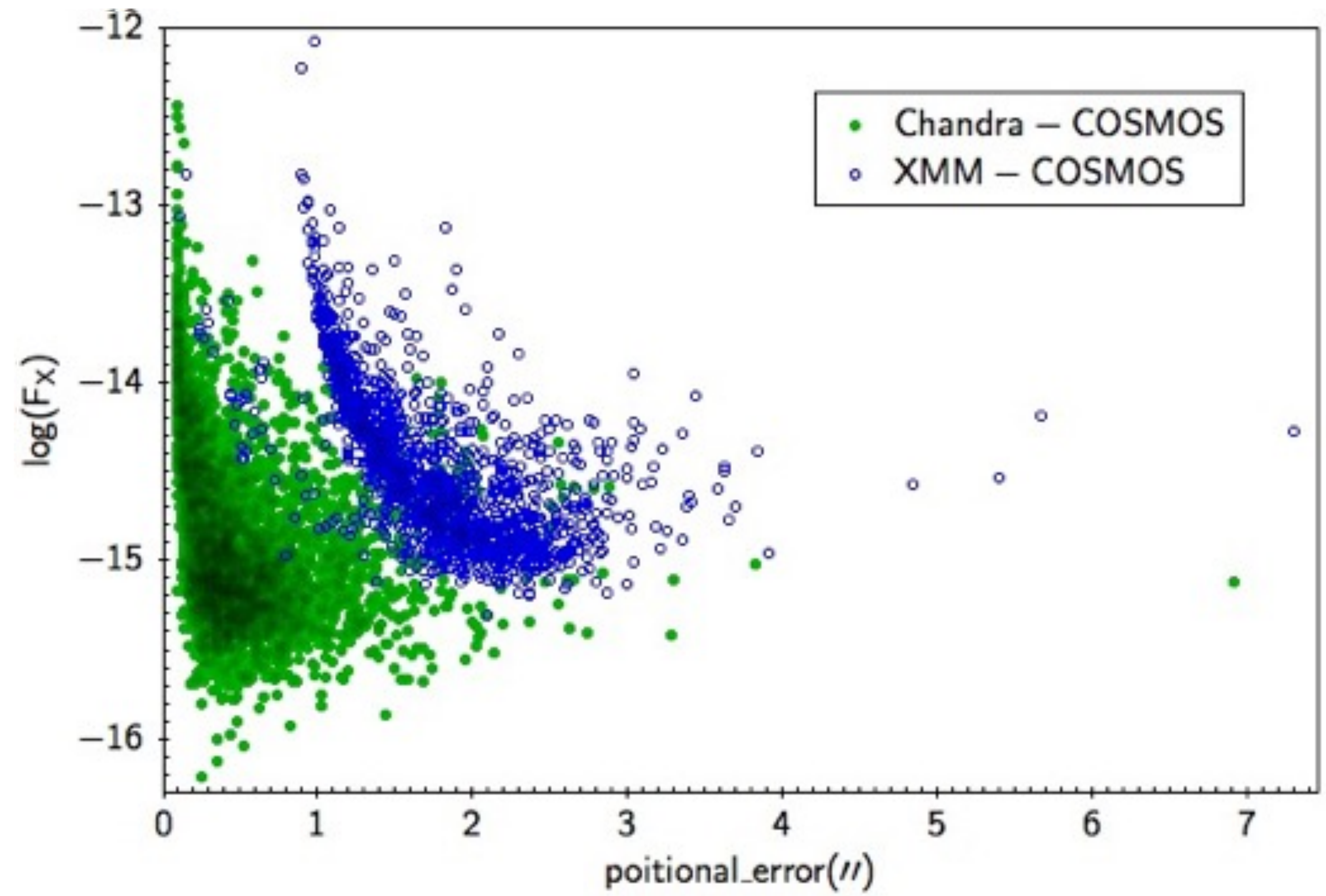

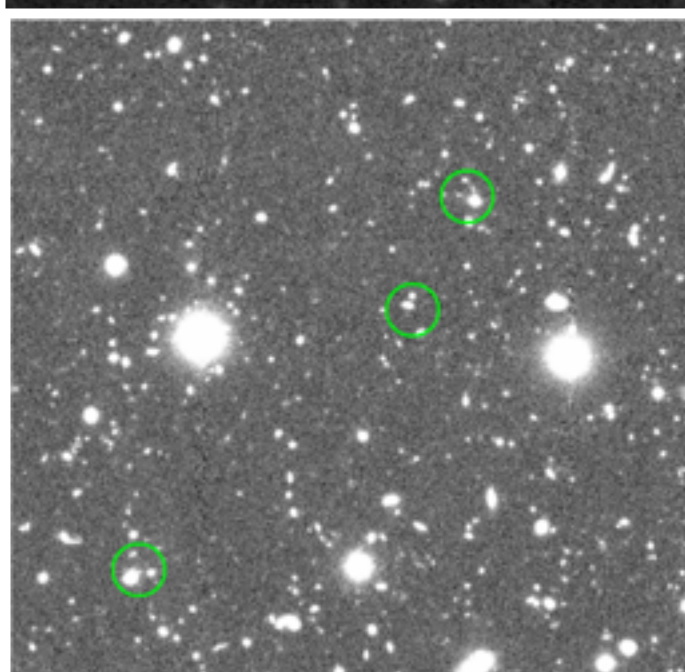

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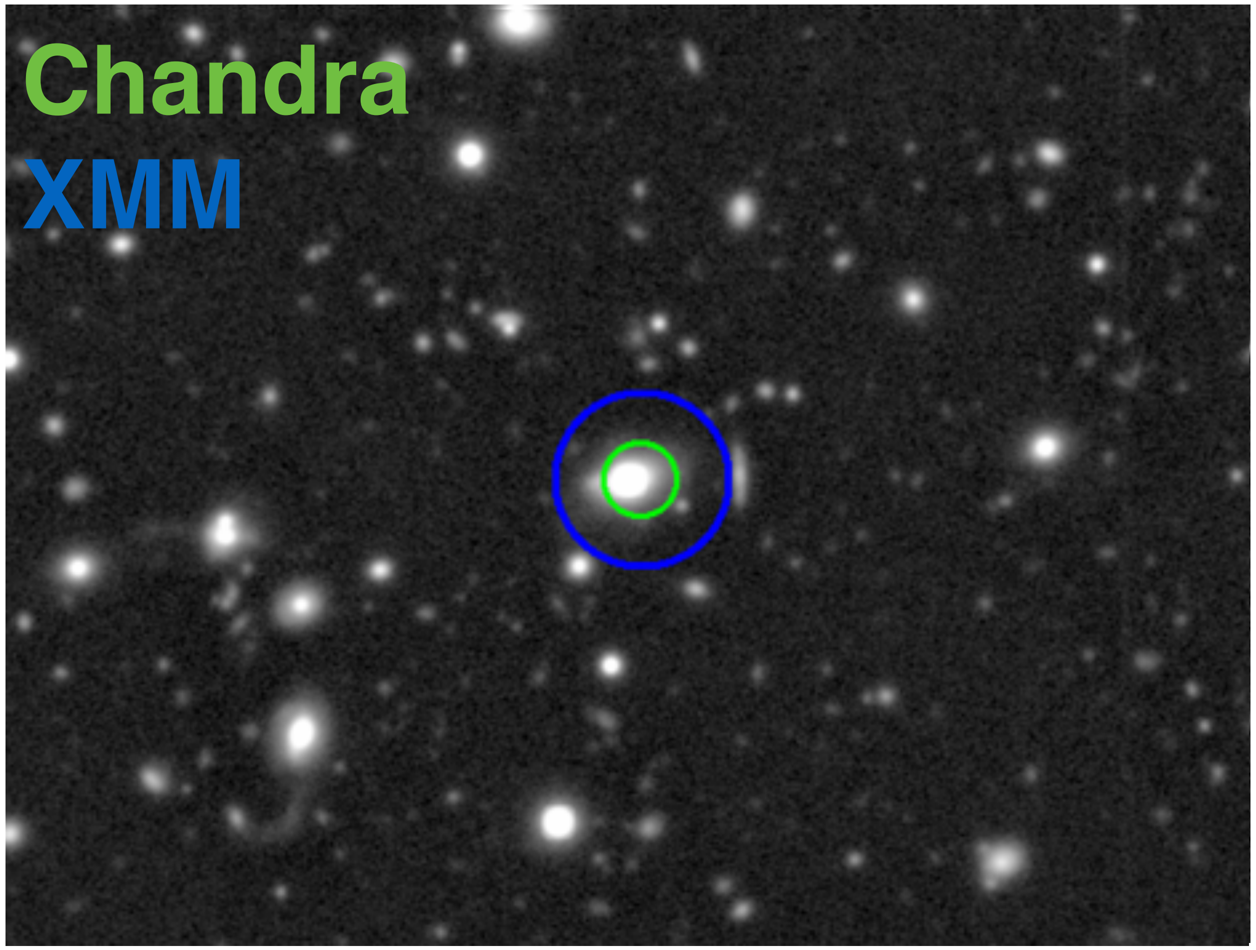
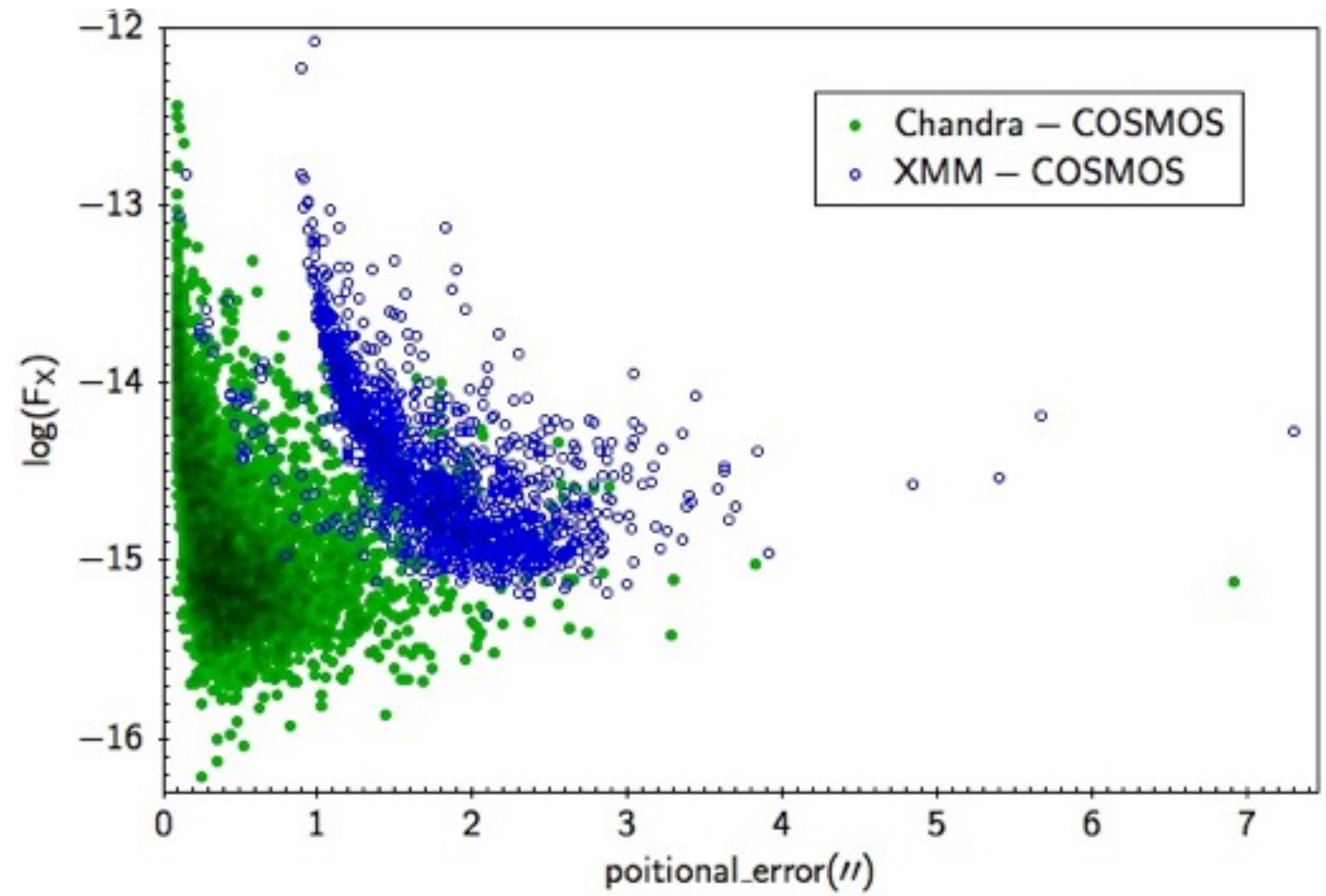
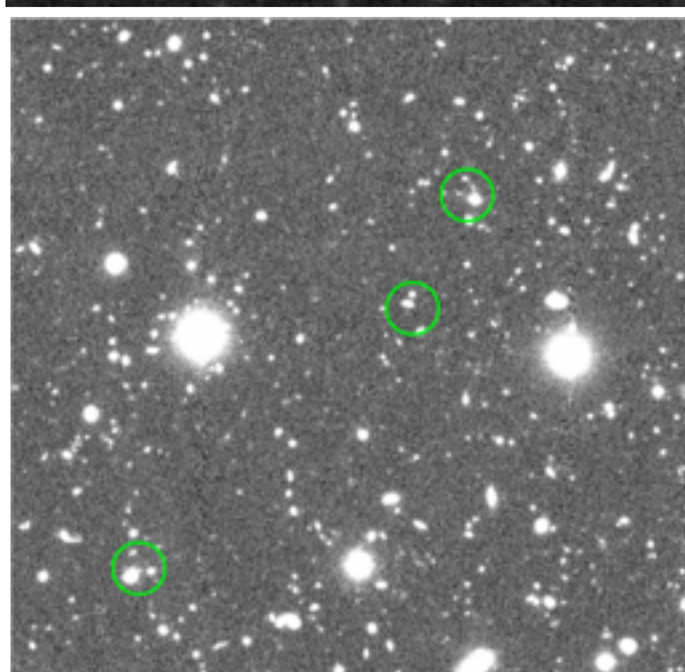
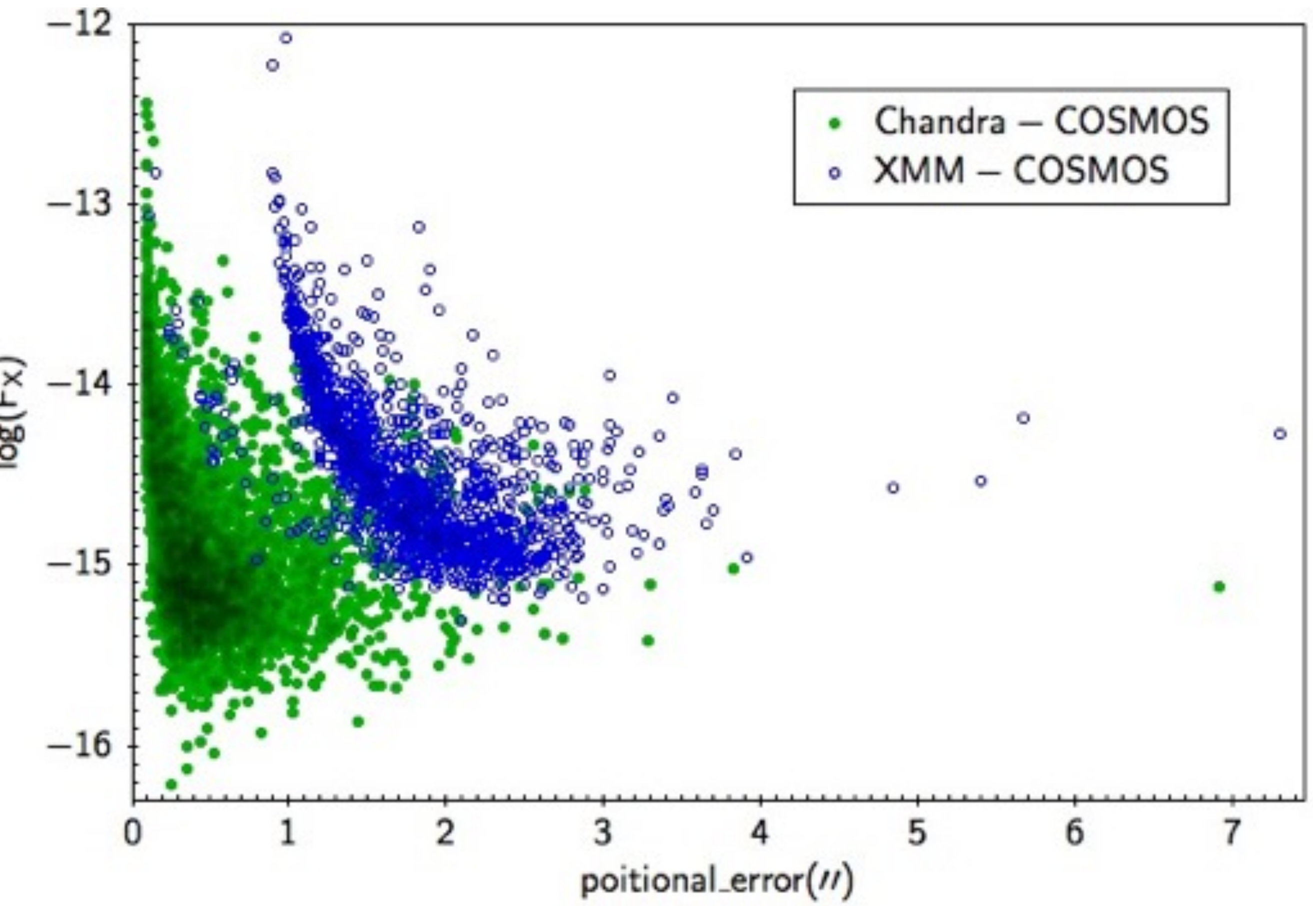






Number of sources depends on depth of images

The problem: ROSAT positional uncertainties are even larger



Salvato+ 2018,
Dwelly+2017

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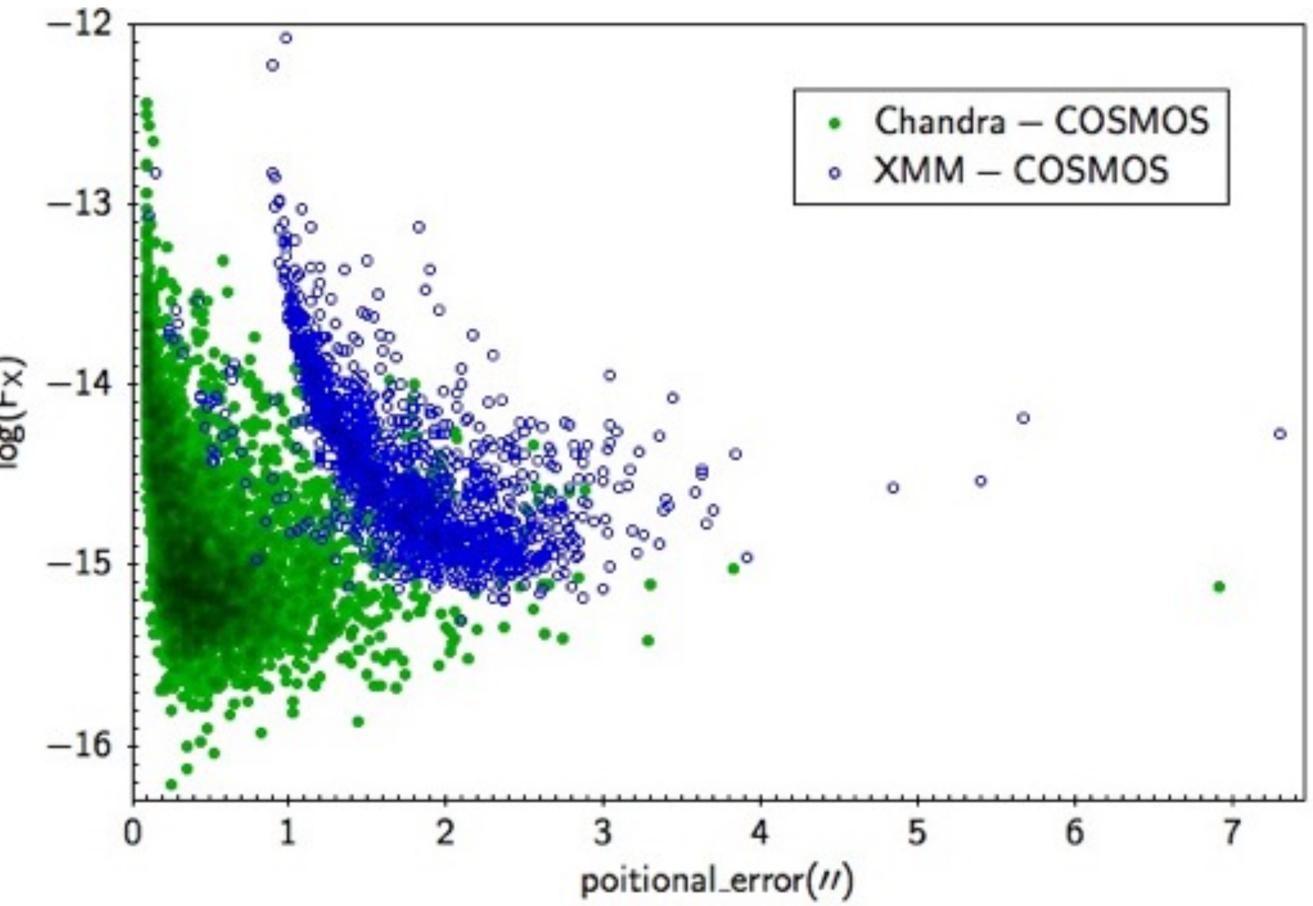

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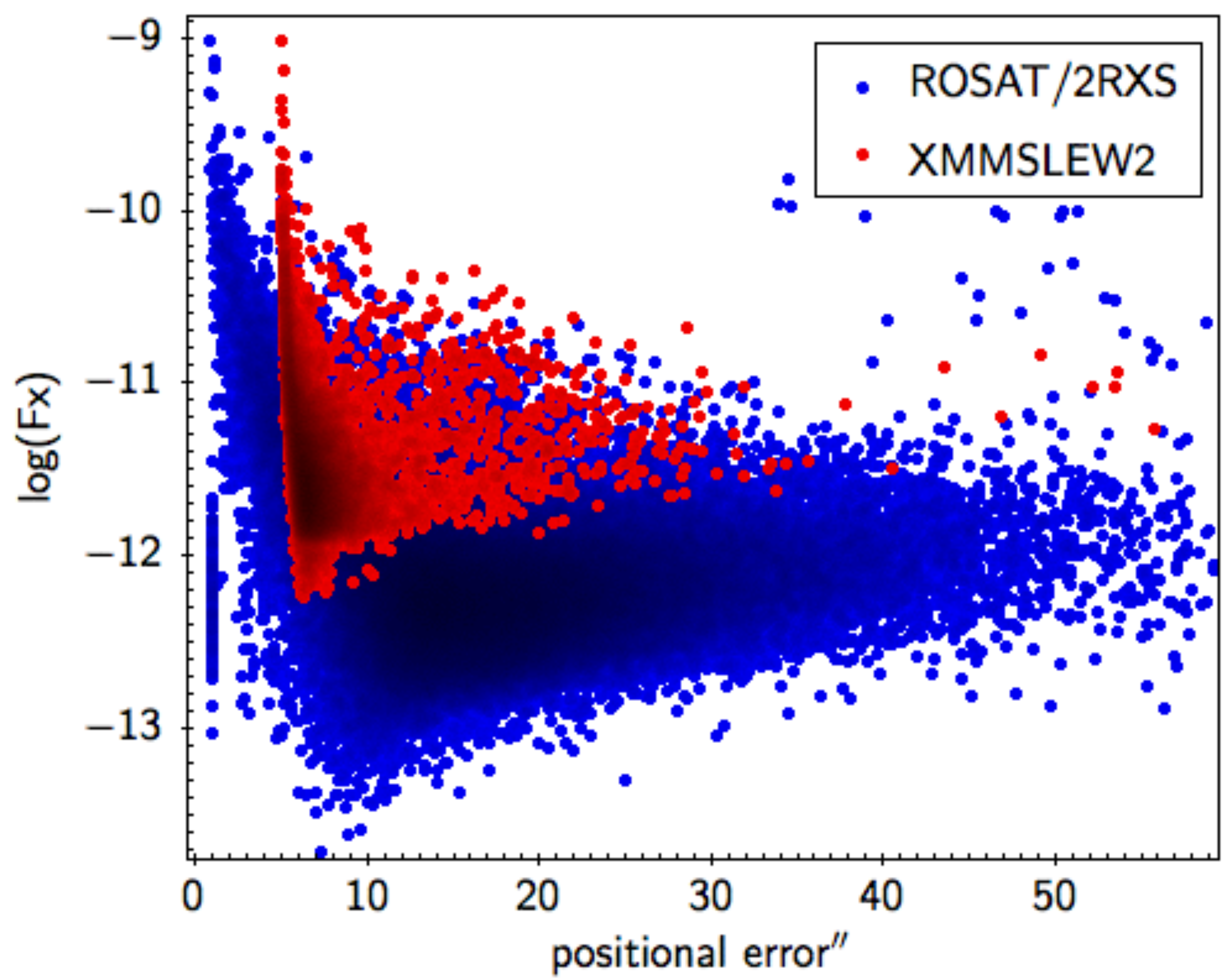

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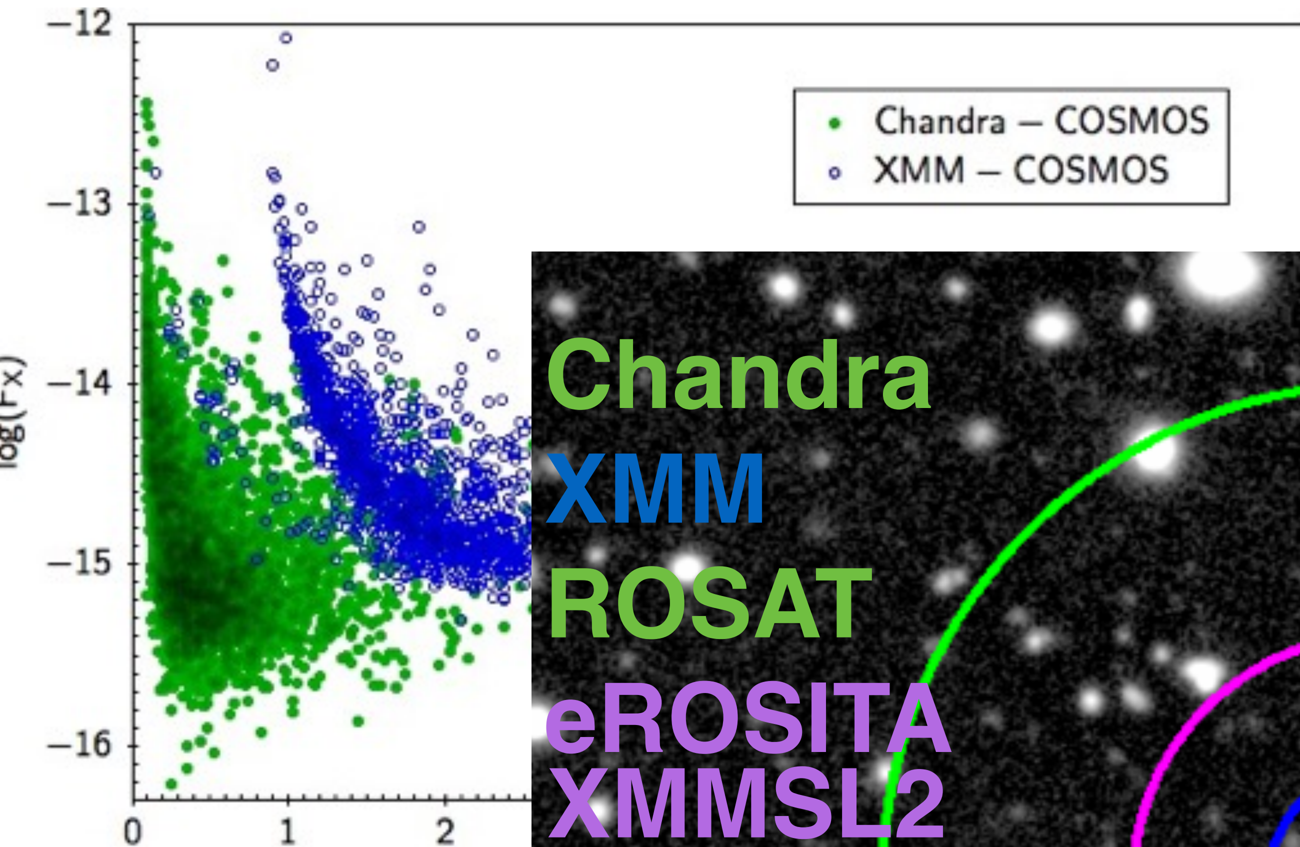

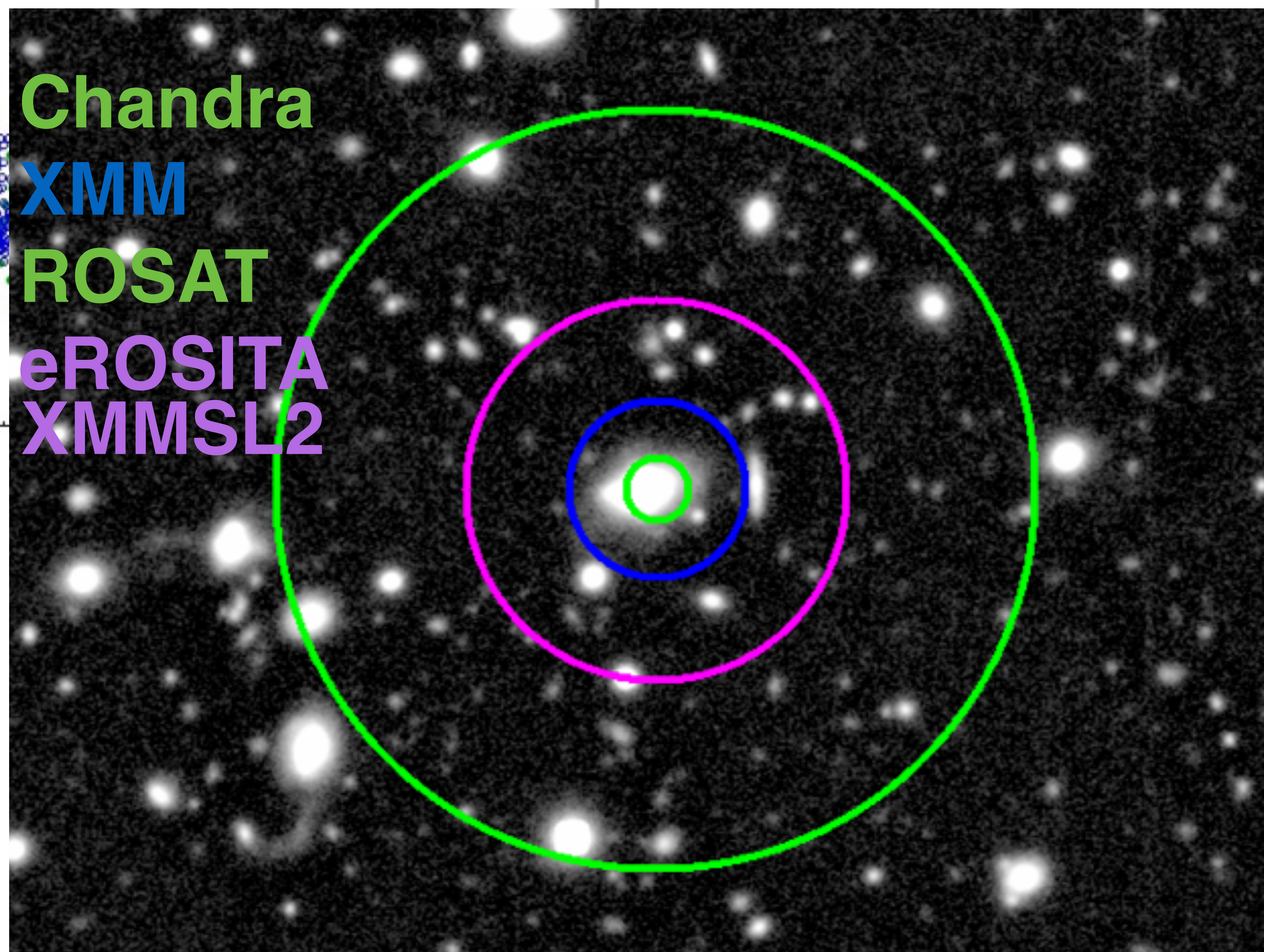

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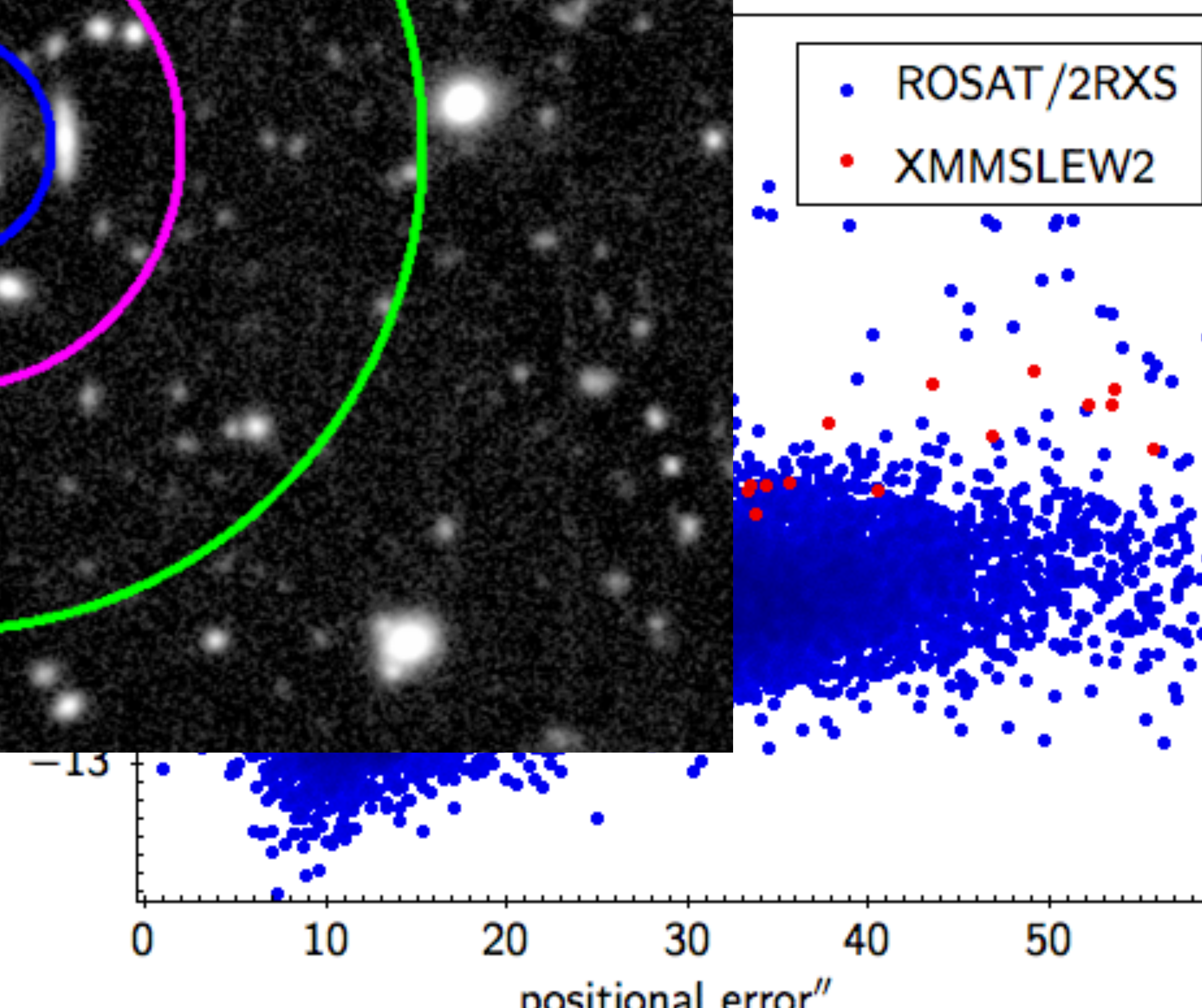
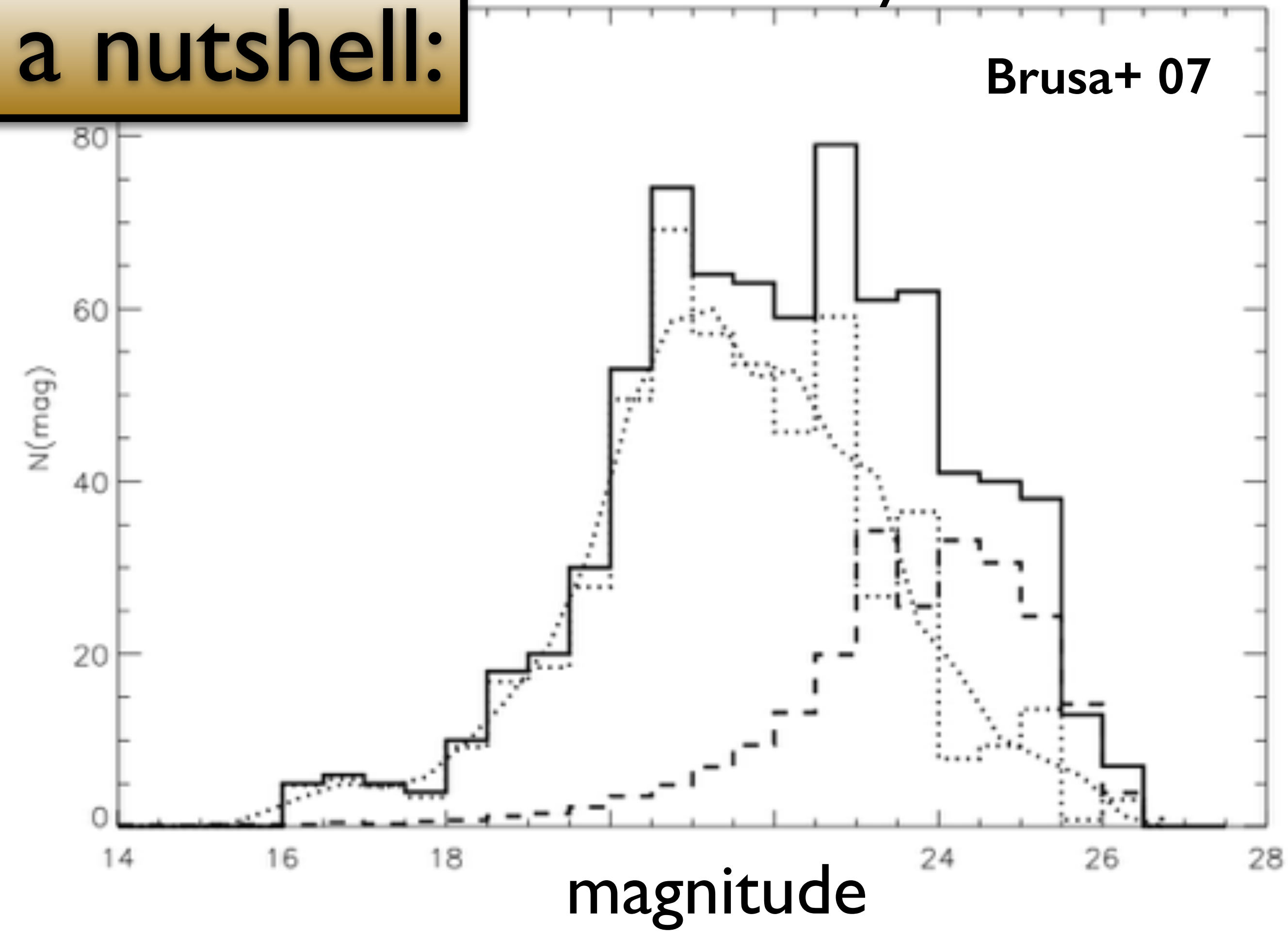


Maximum Likelihood (ML) in a nutshell:

Naylor+13 for a review



Sutherland&Saunders 92

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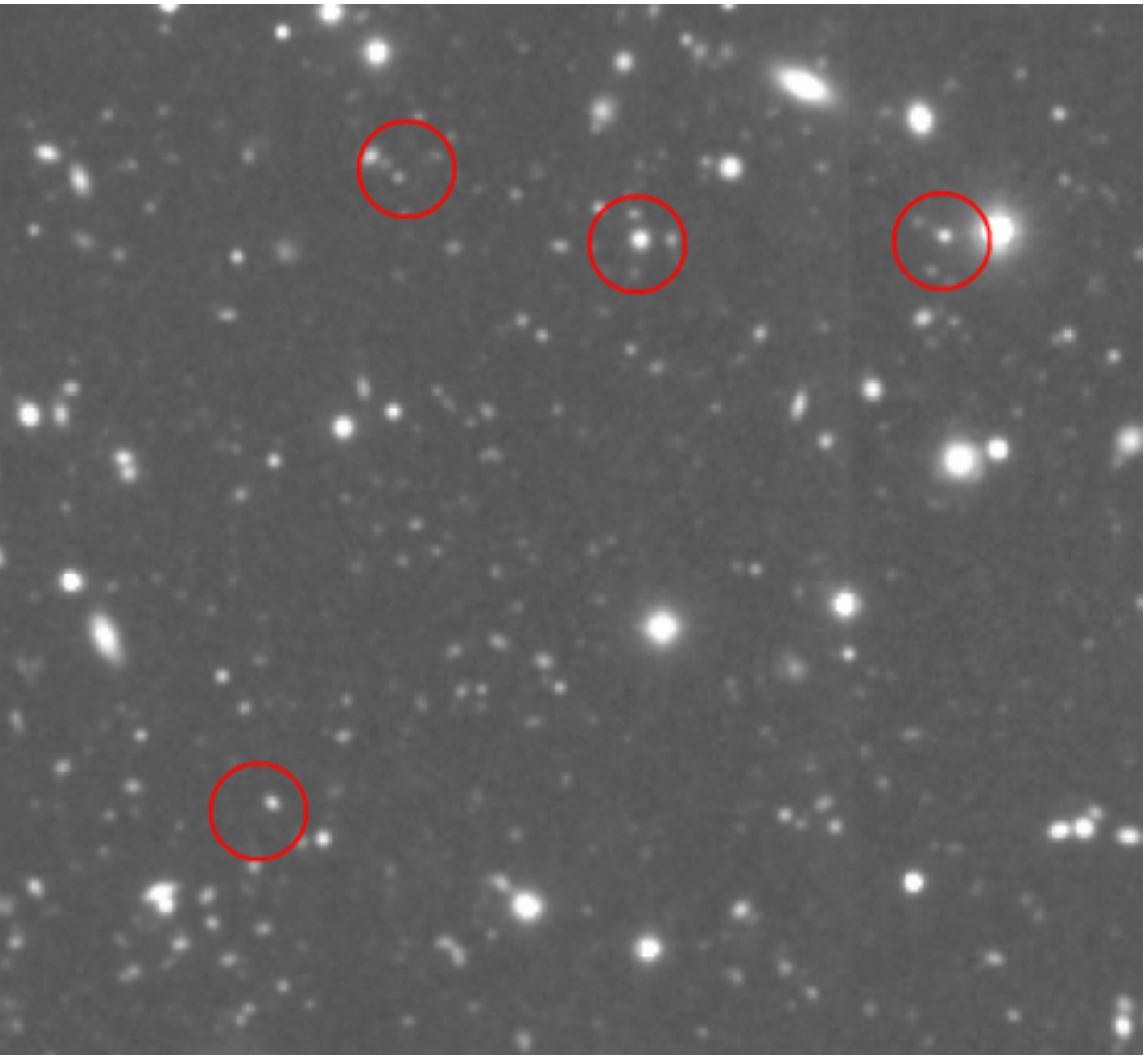

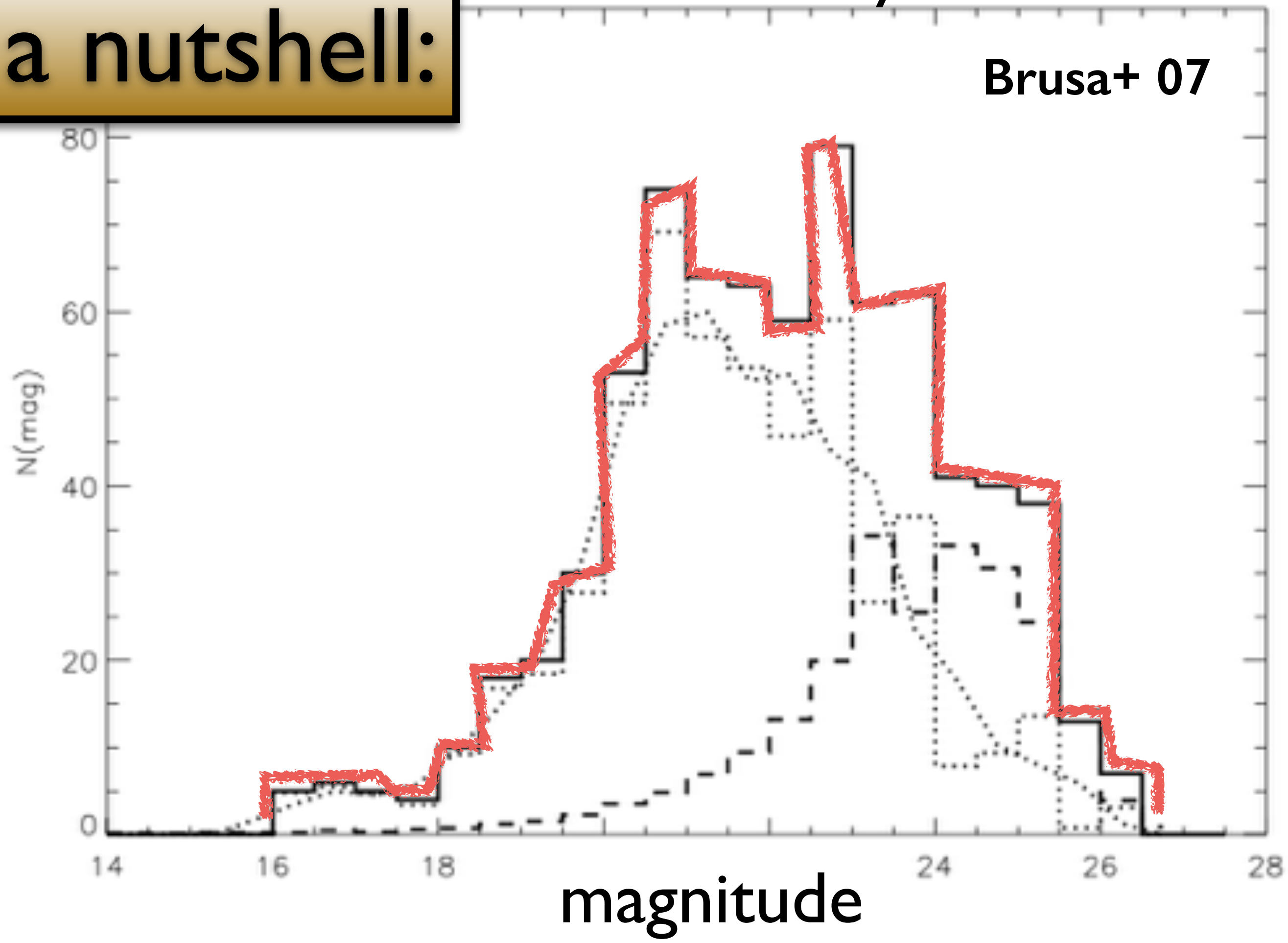

Sutherland&Saunders 92

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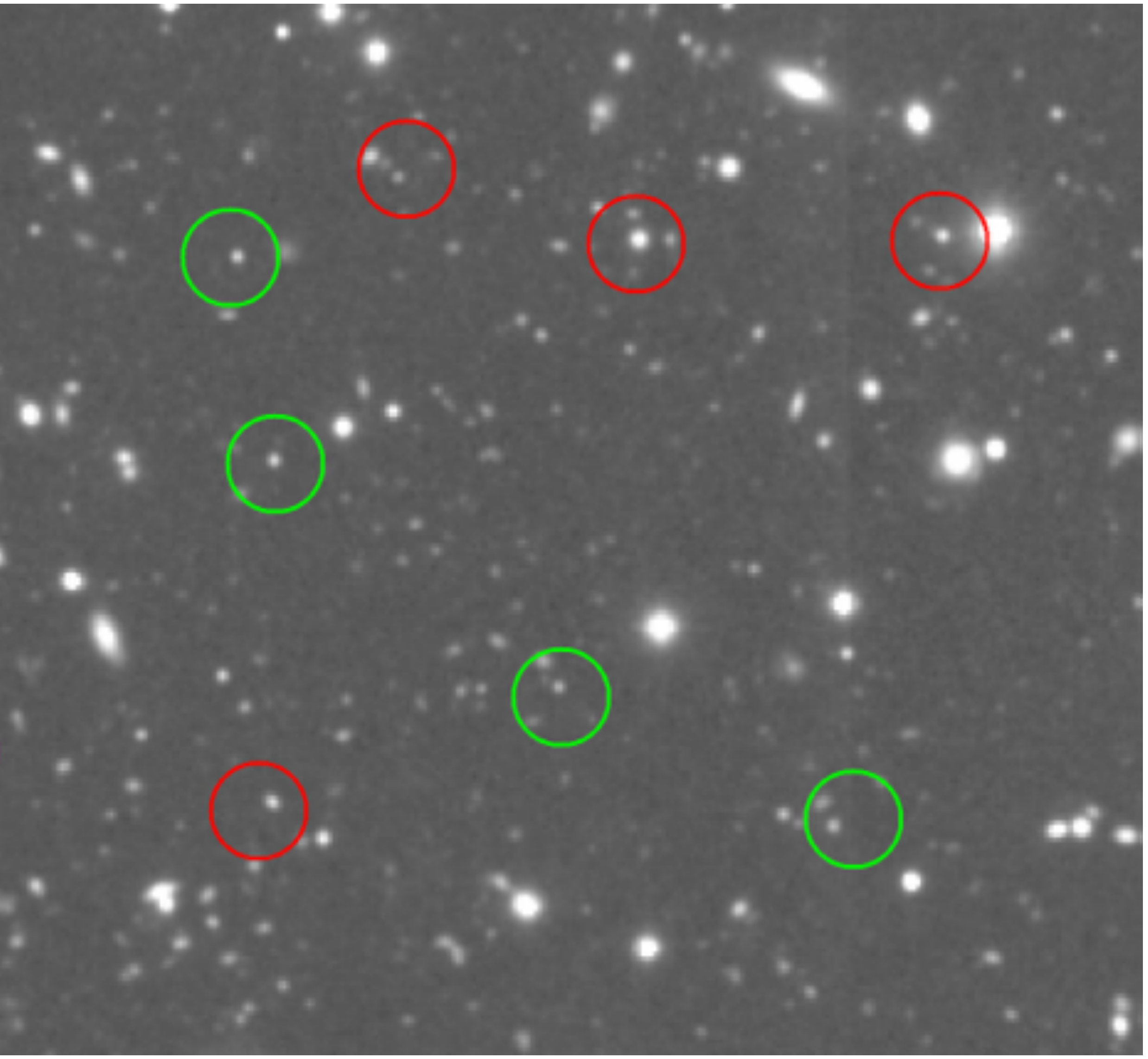

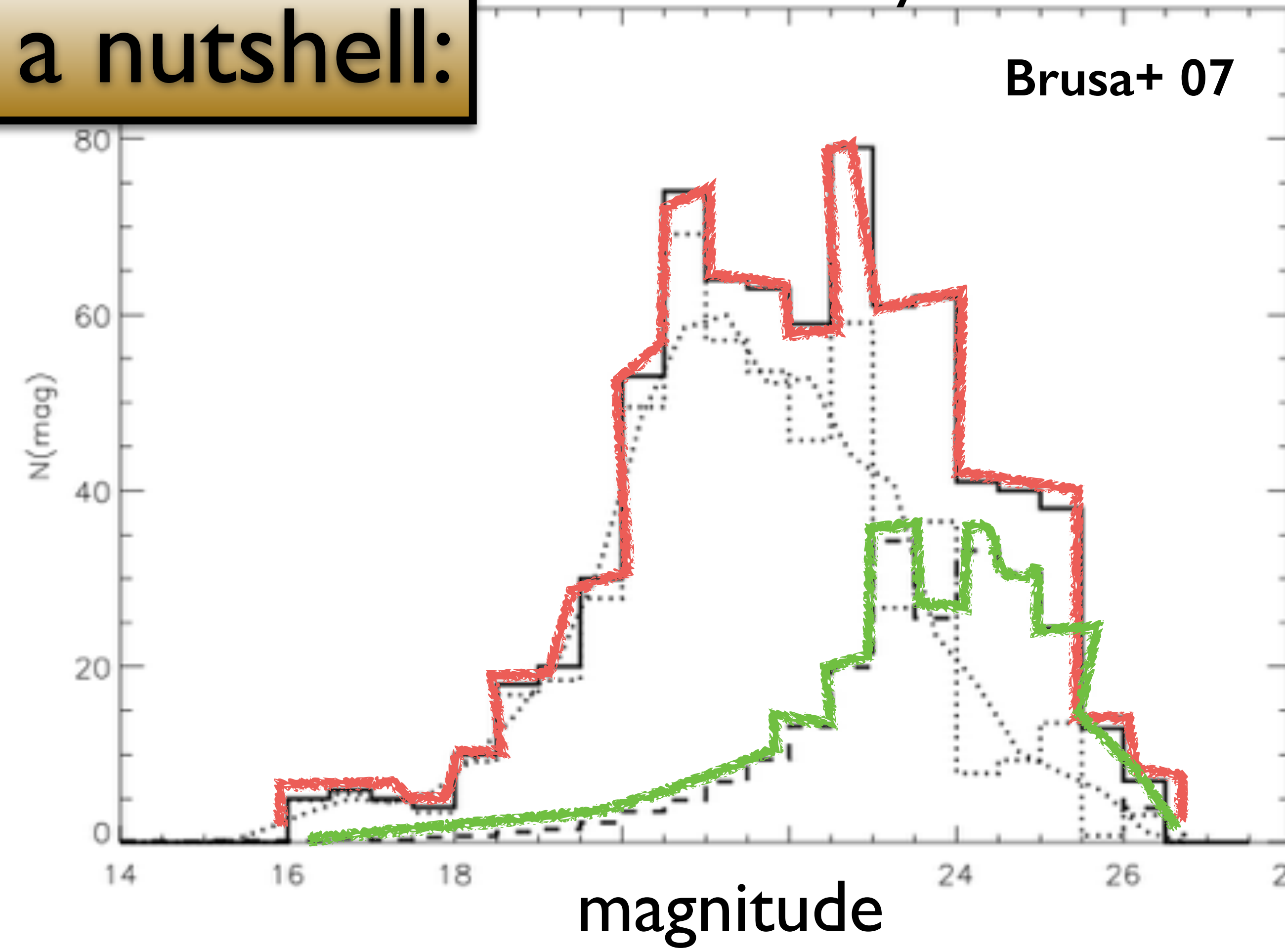

Sutherland&Saunders 92

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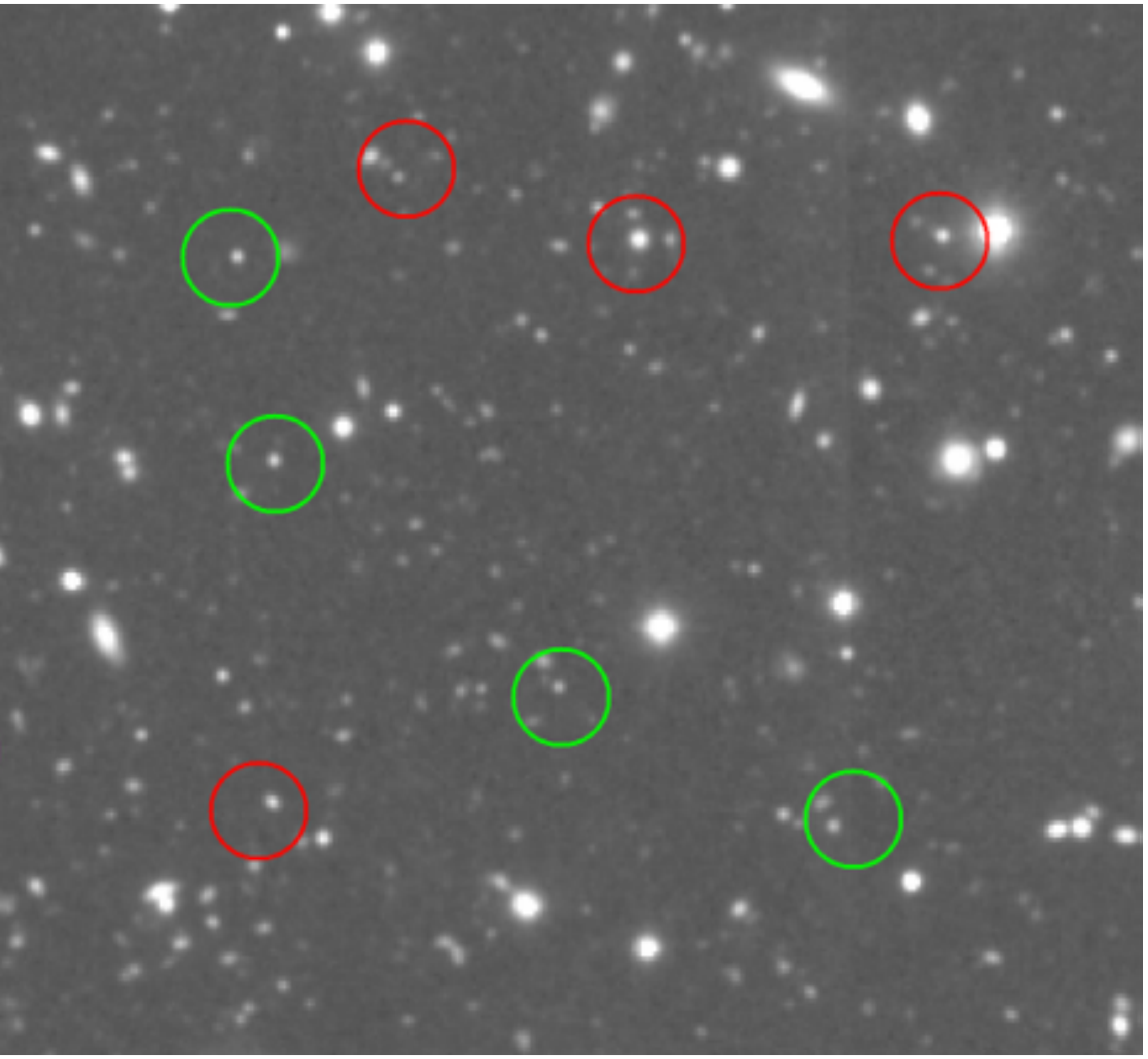

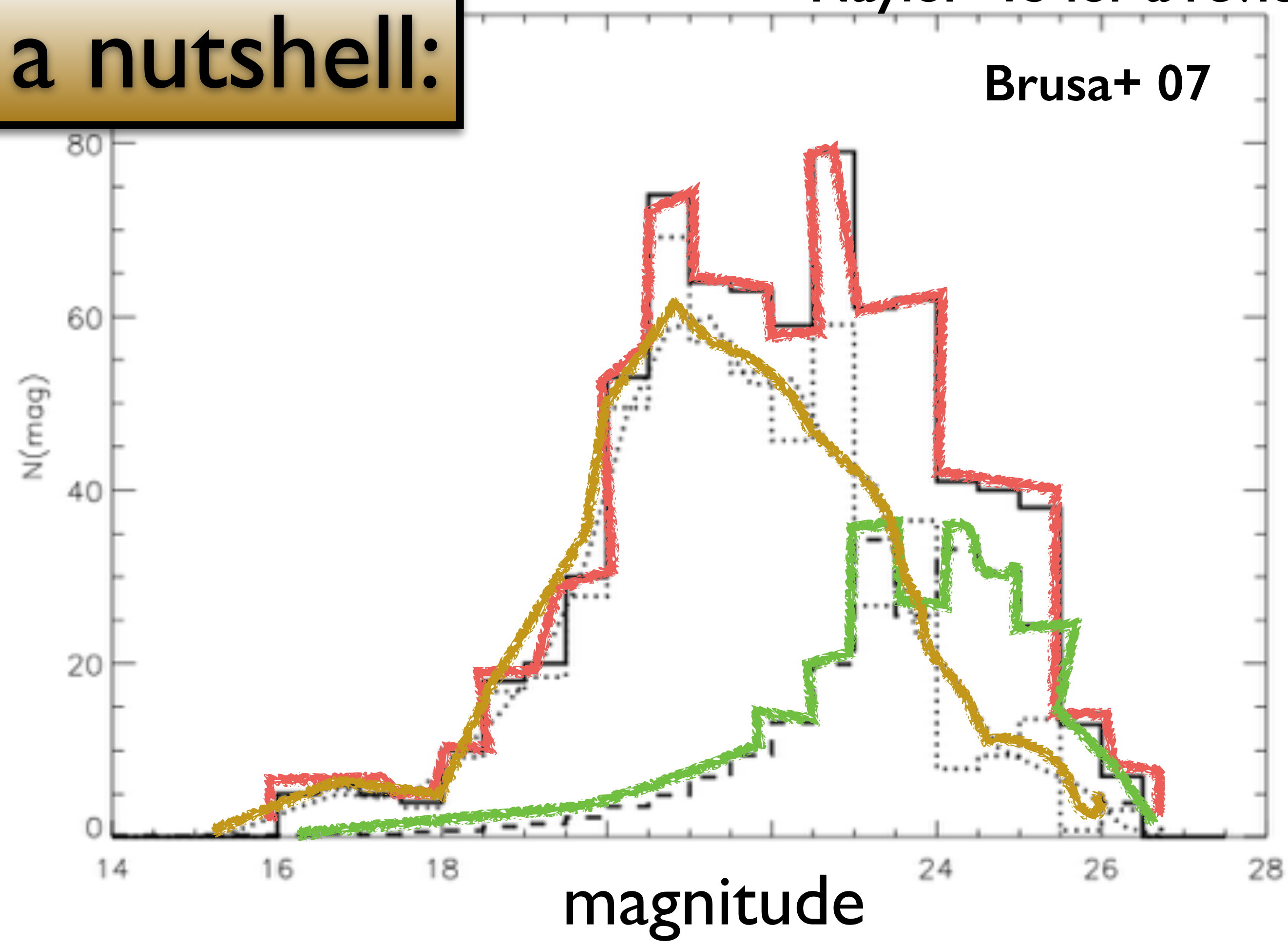

Sutherland&Saunders 92

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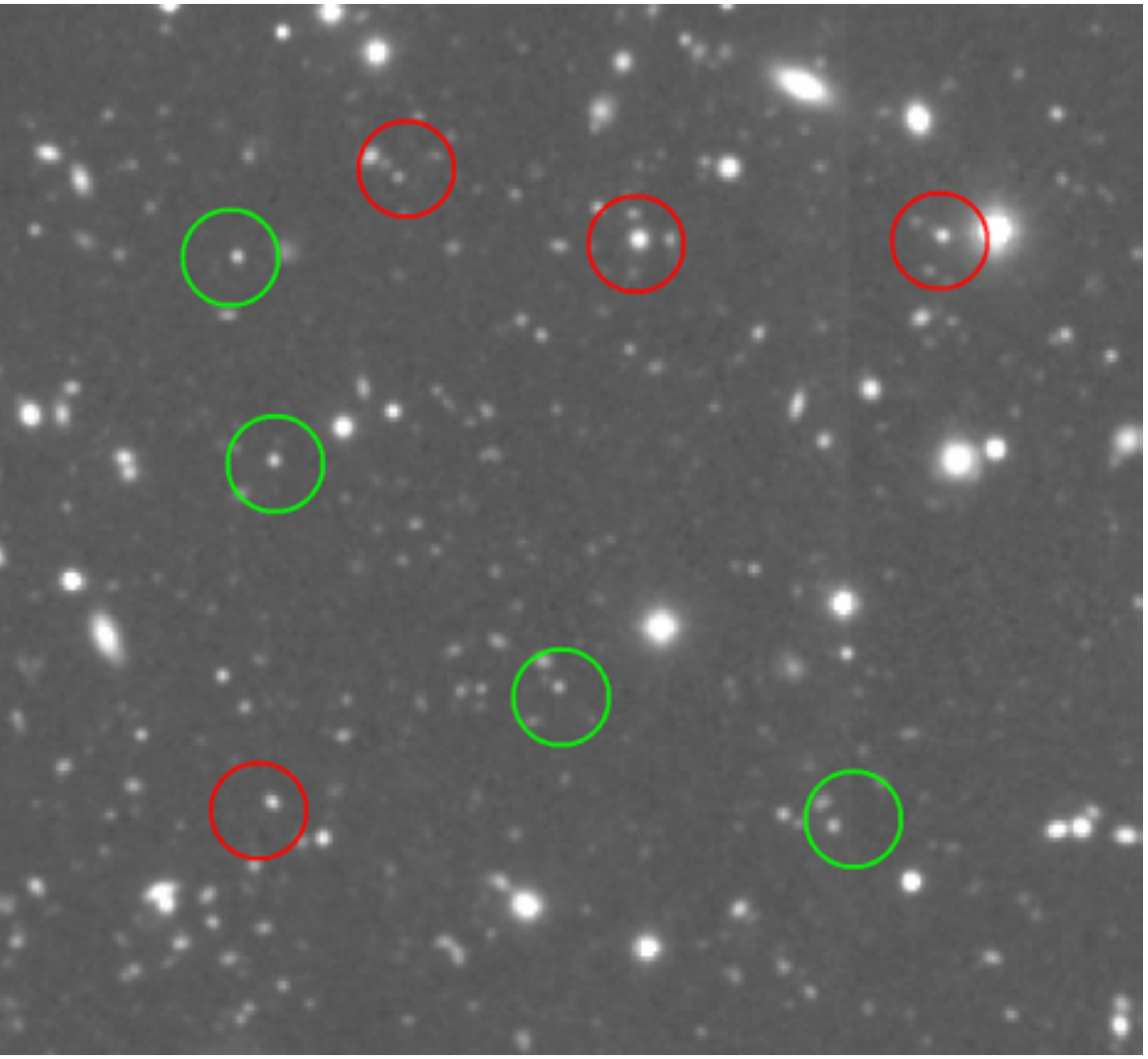

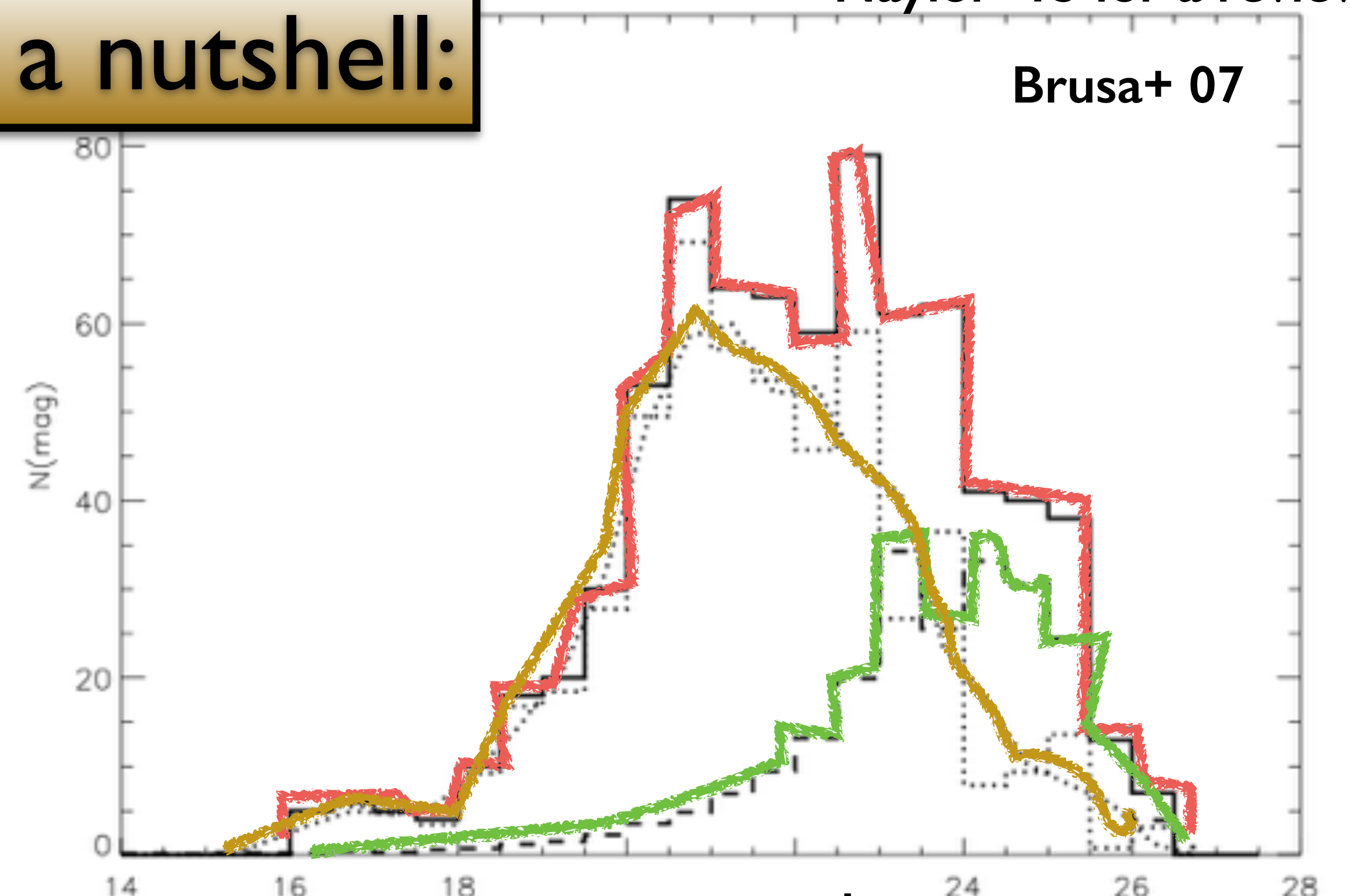

magnitude

LR=q(m) f(r)/n(m)

$$R_j = \frac{(LR)_j}{\Sigma_i (LR)_i + (1 - Q)}$$

<u>**Sutherland&Saunders 92**</u>

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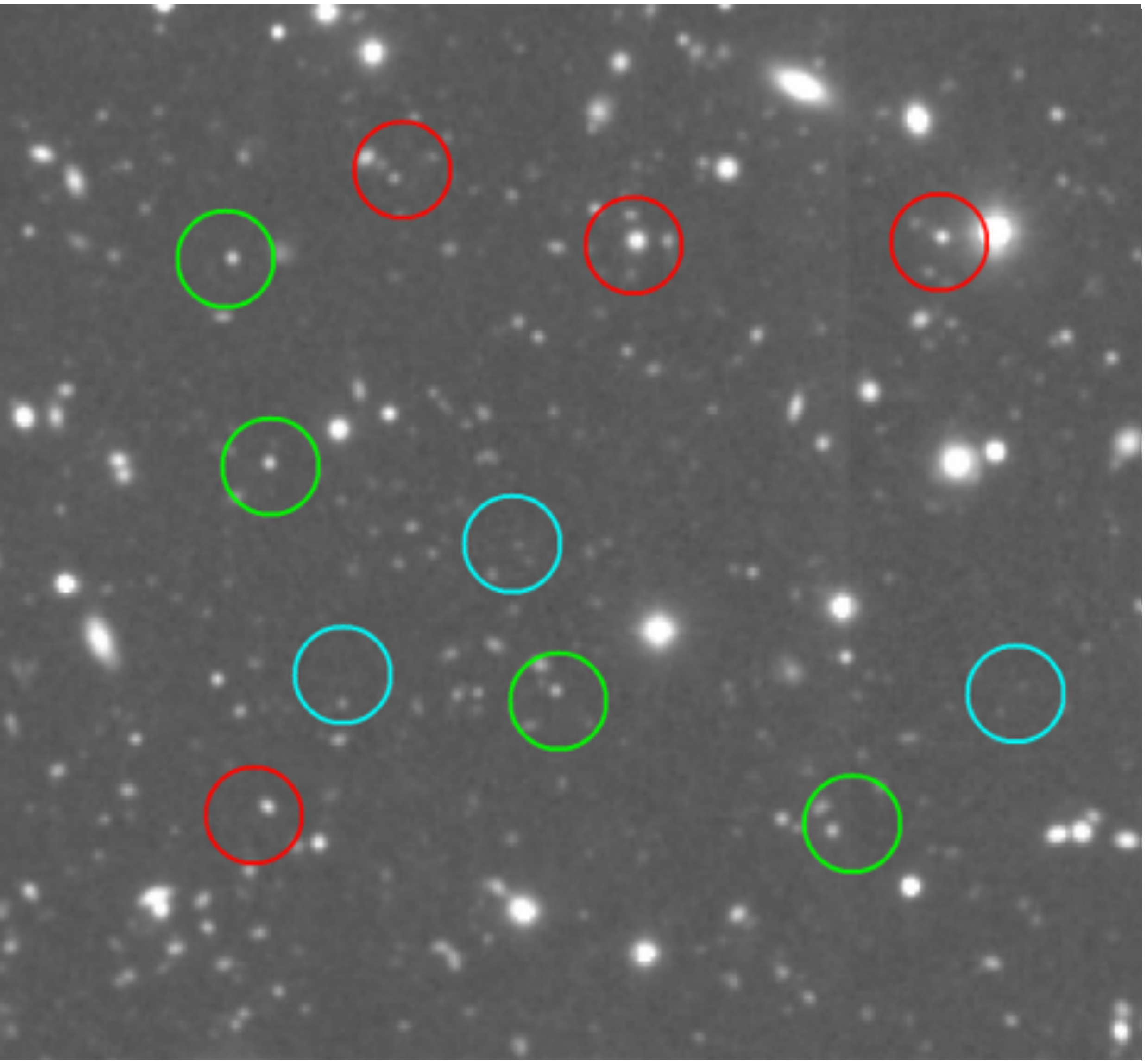

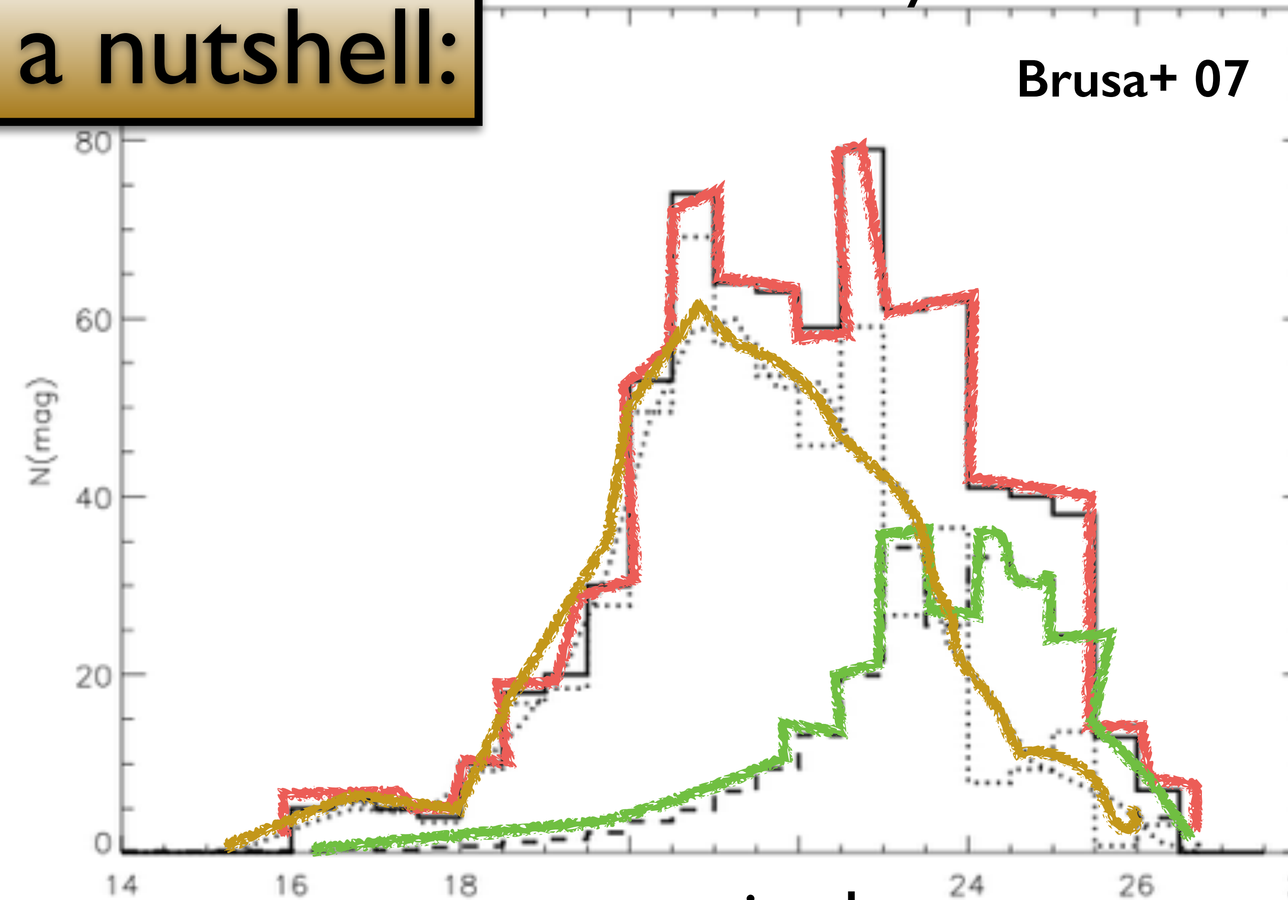

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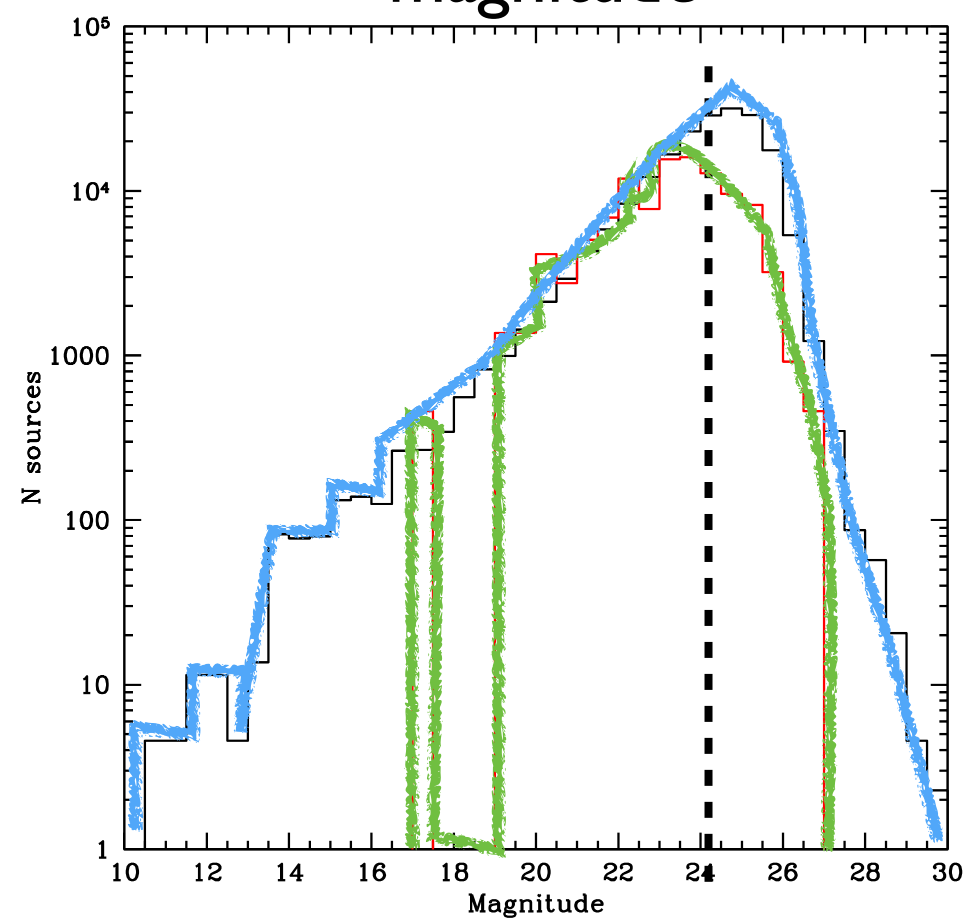

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Sutherland&Saunders 92

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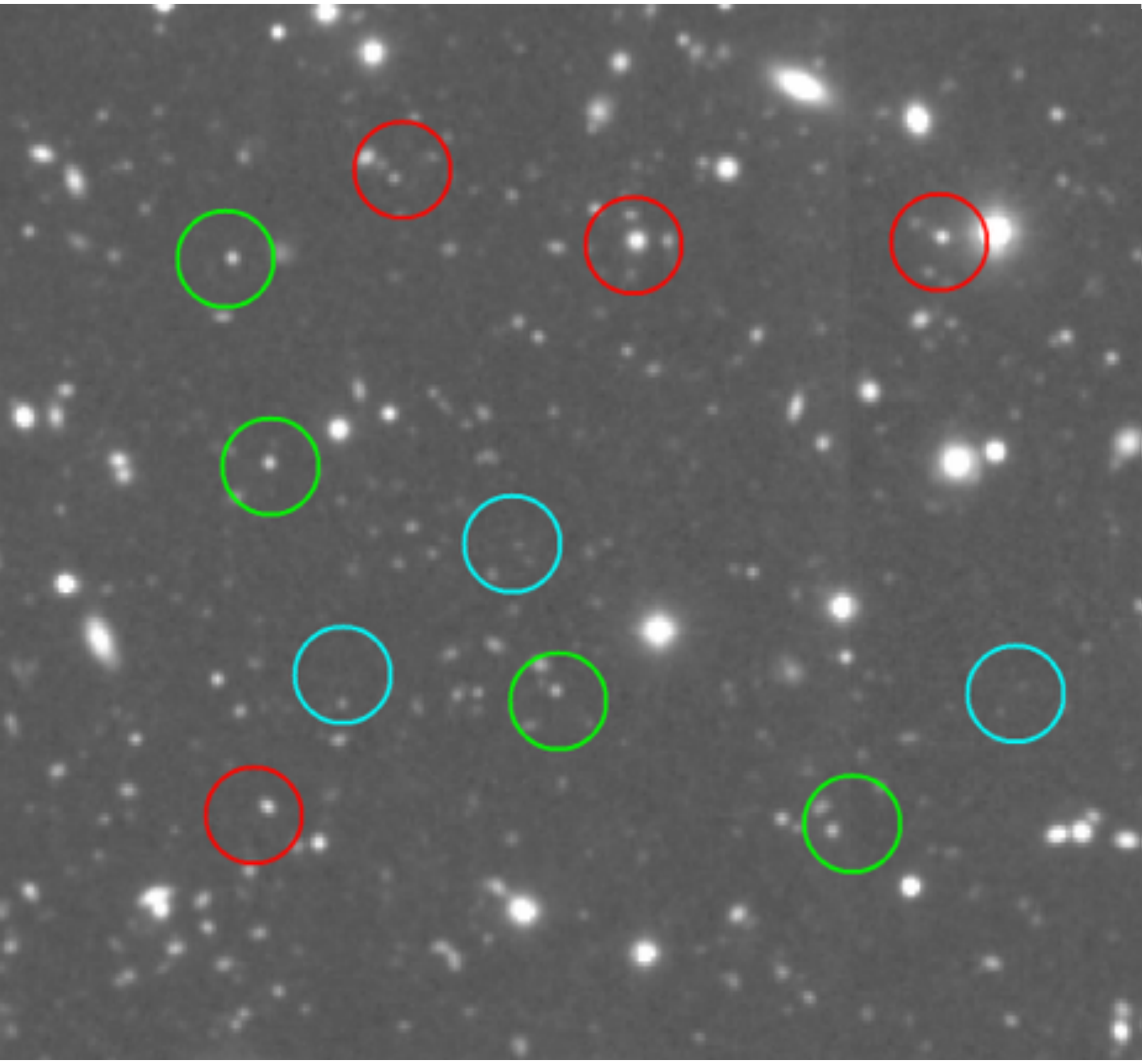

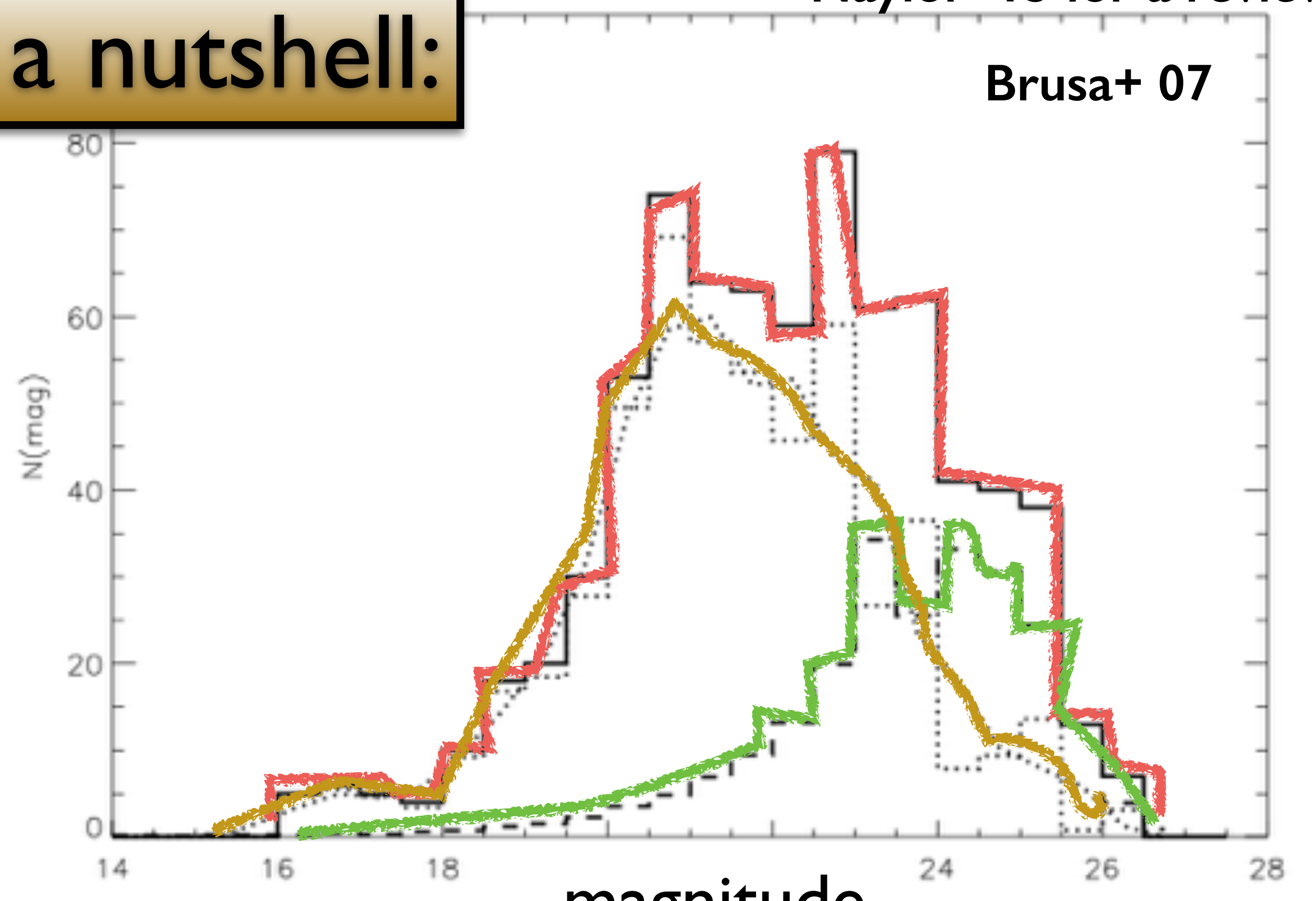

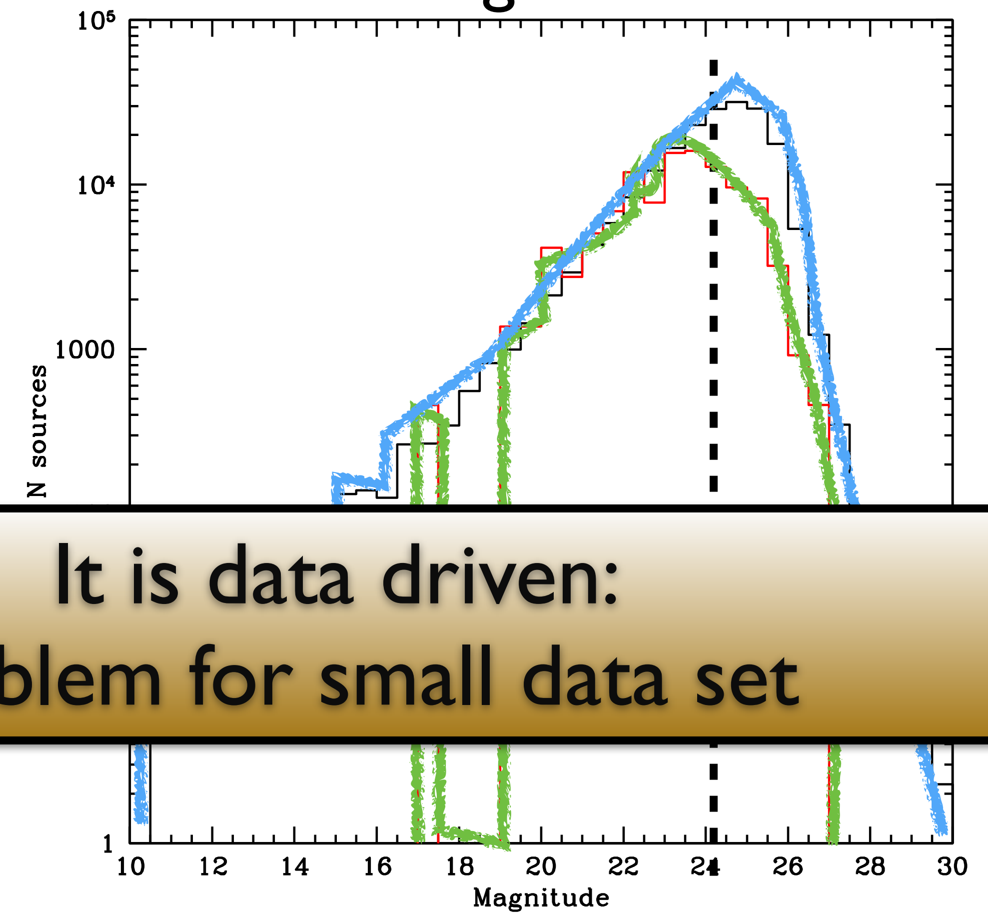

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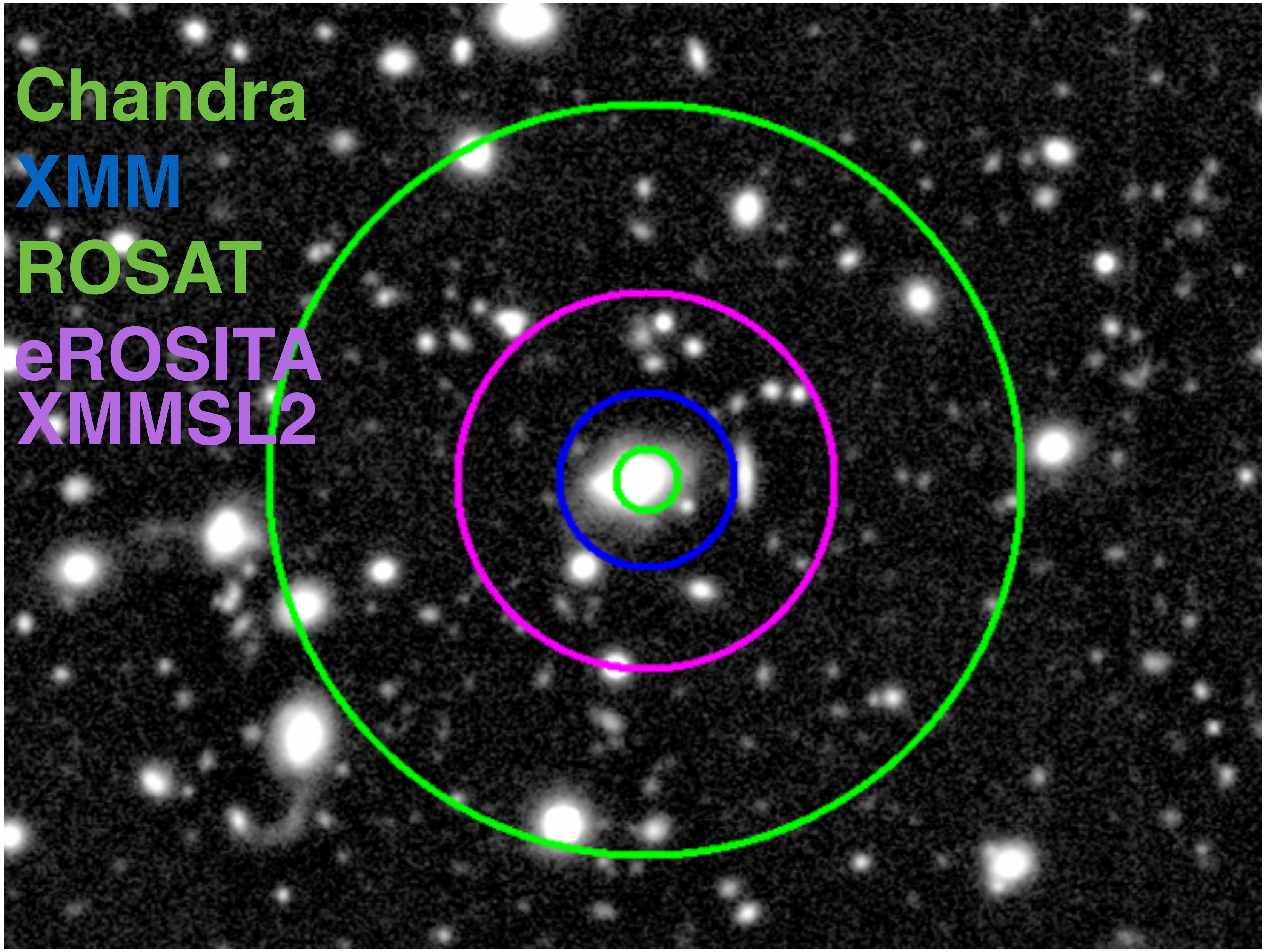
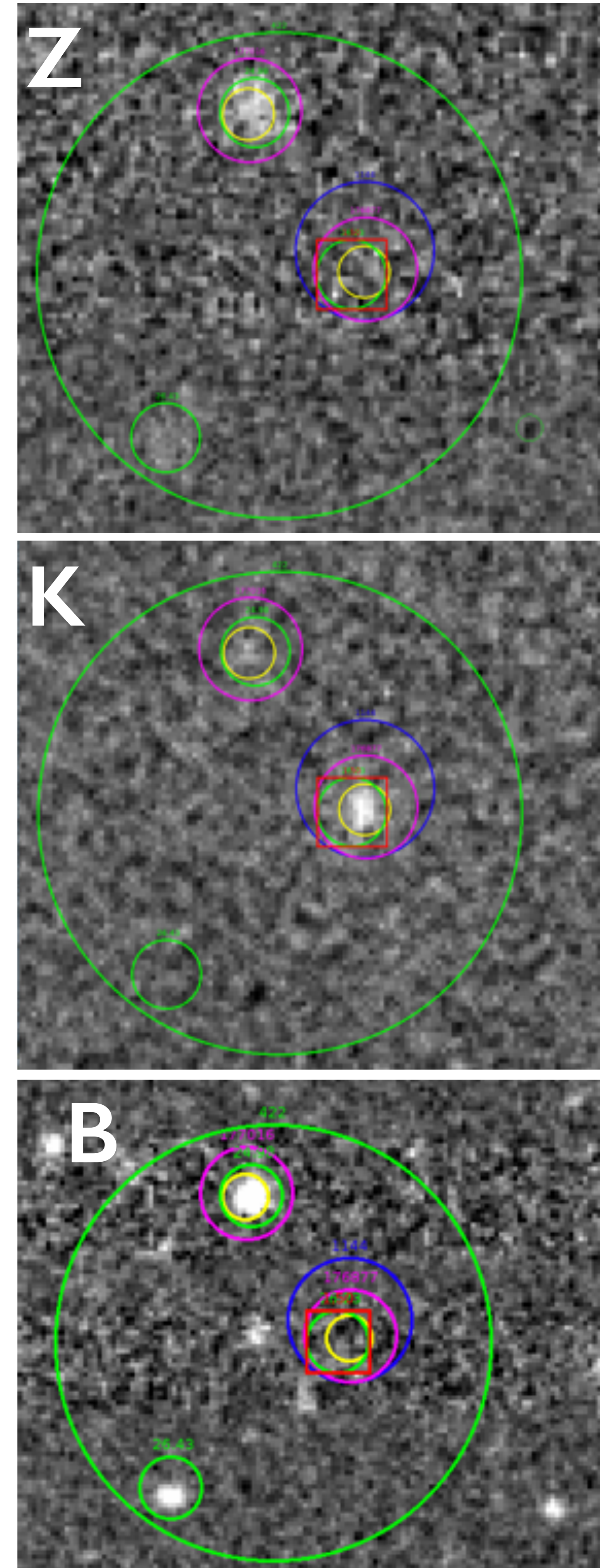
$$R_j = \frac{(LR)_j}{\Sigma_i (LR)_i + (1 - Q)}$$

It is data driven:
problem for small data set

Sutherland&Saunders 92

X-ray counterparts identification





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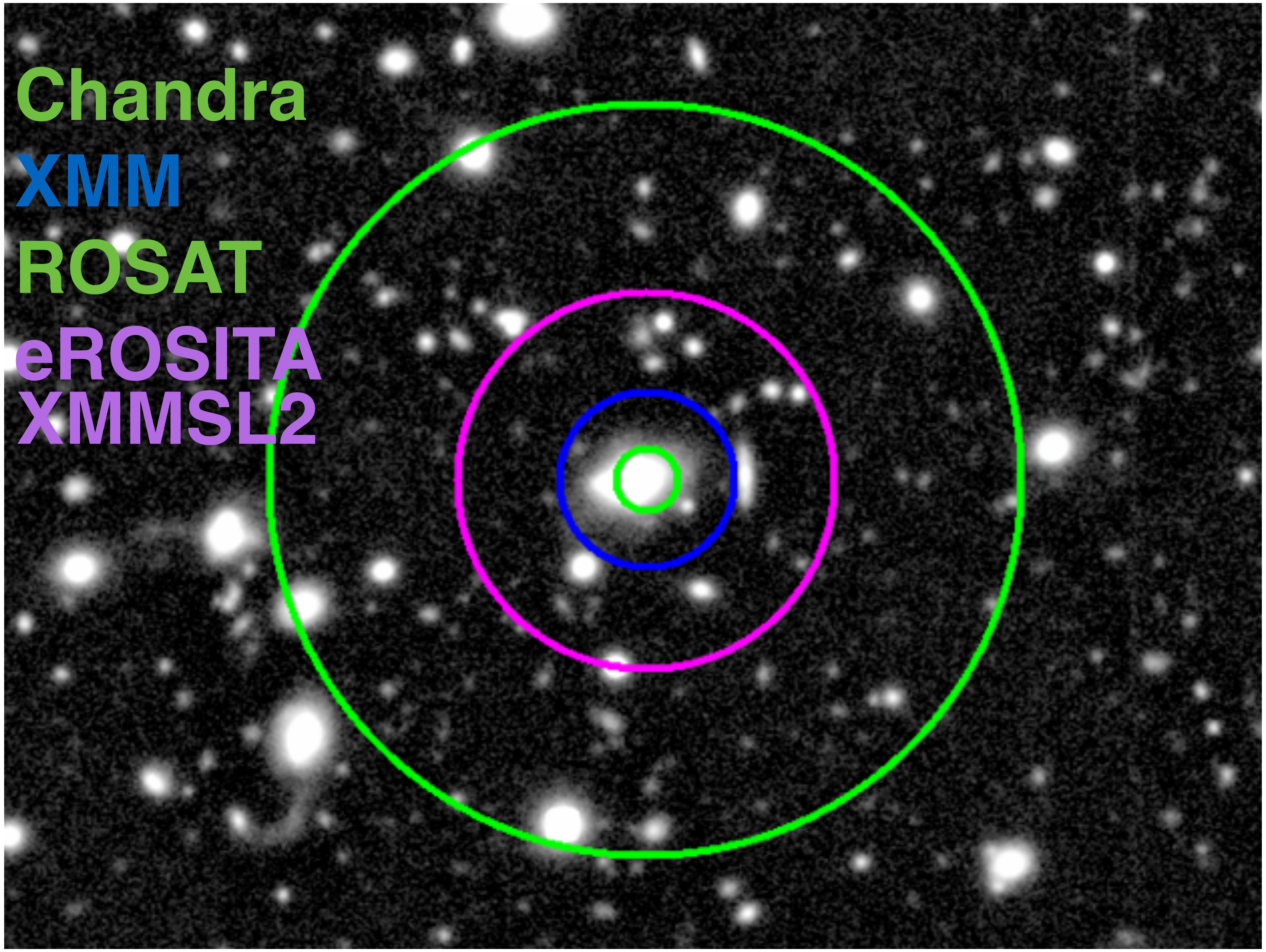
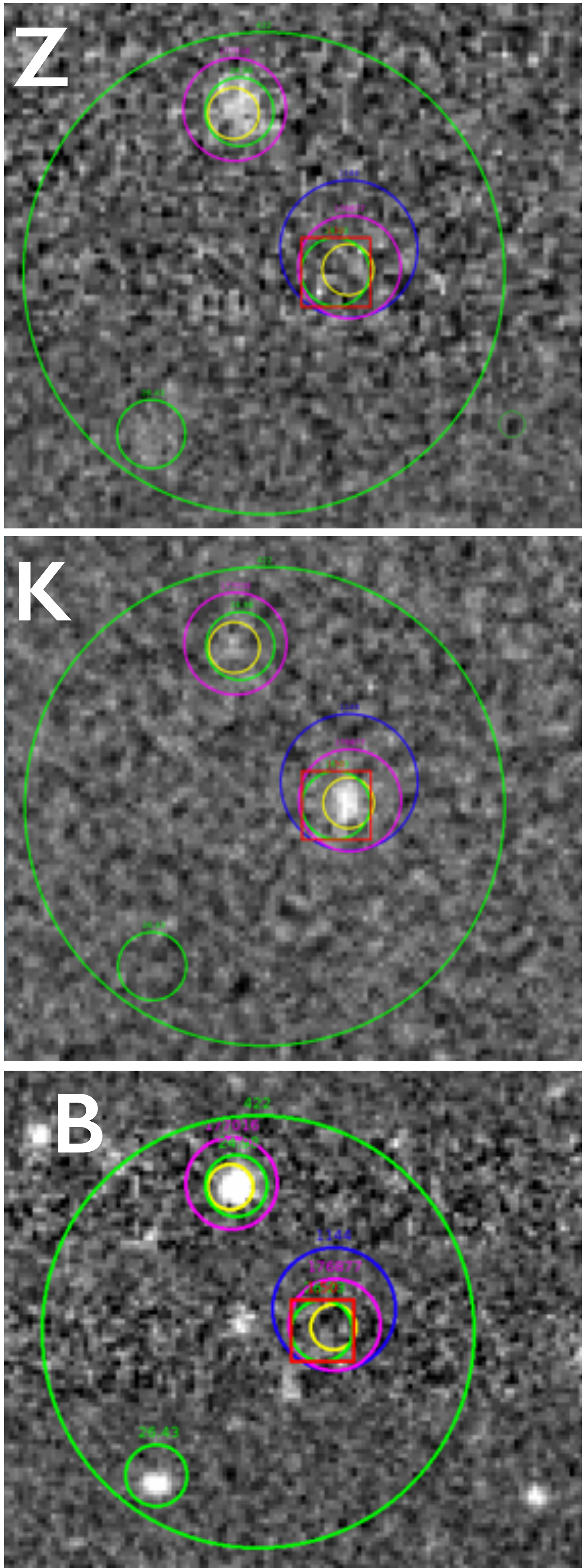
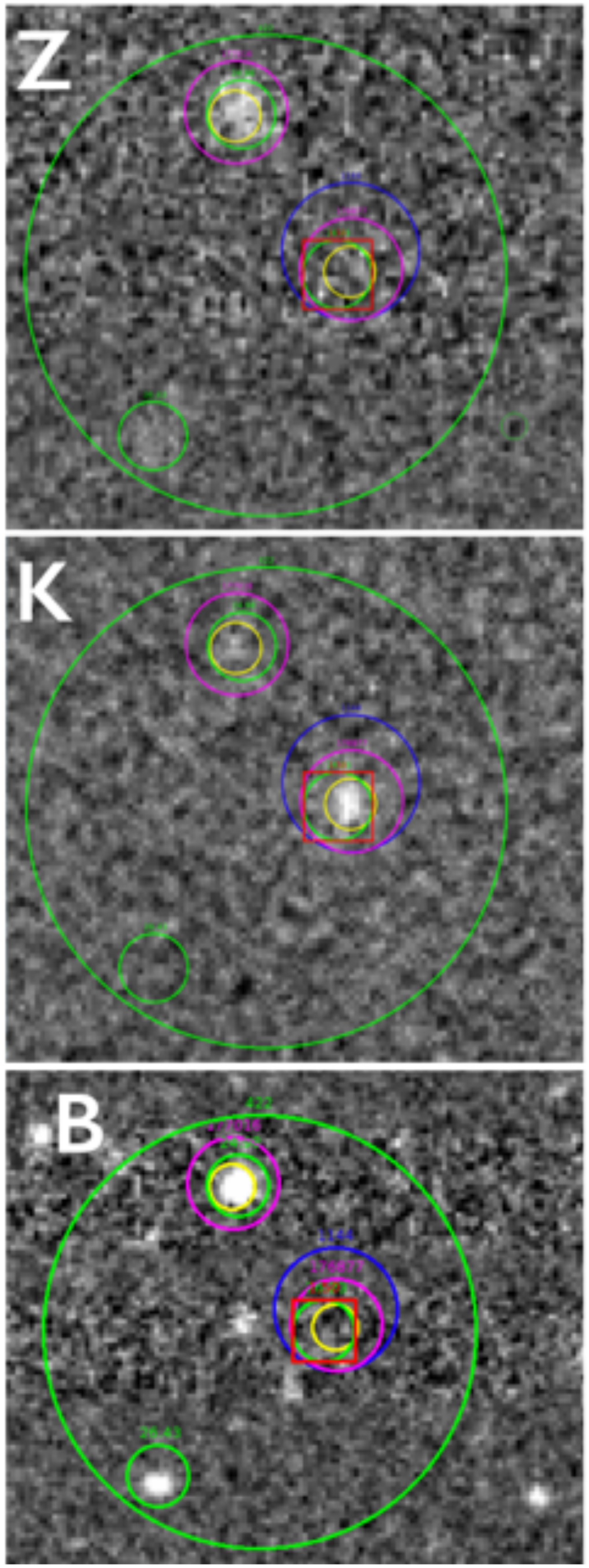
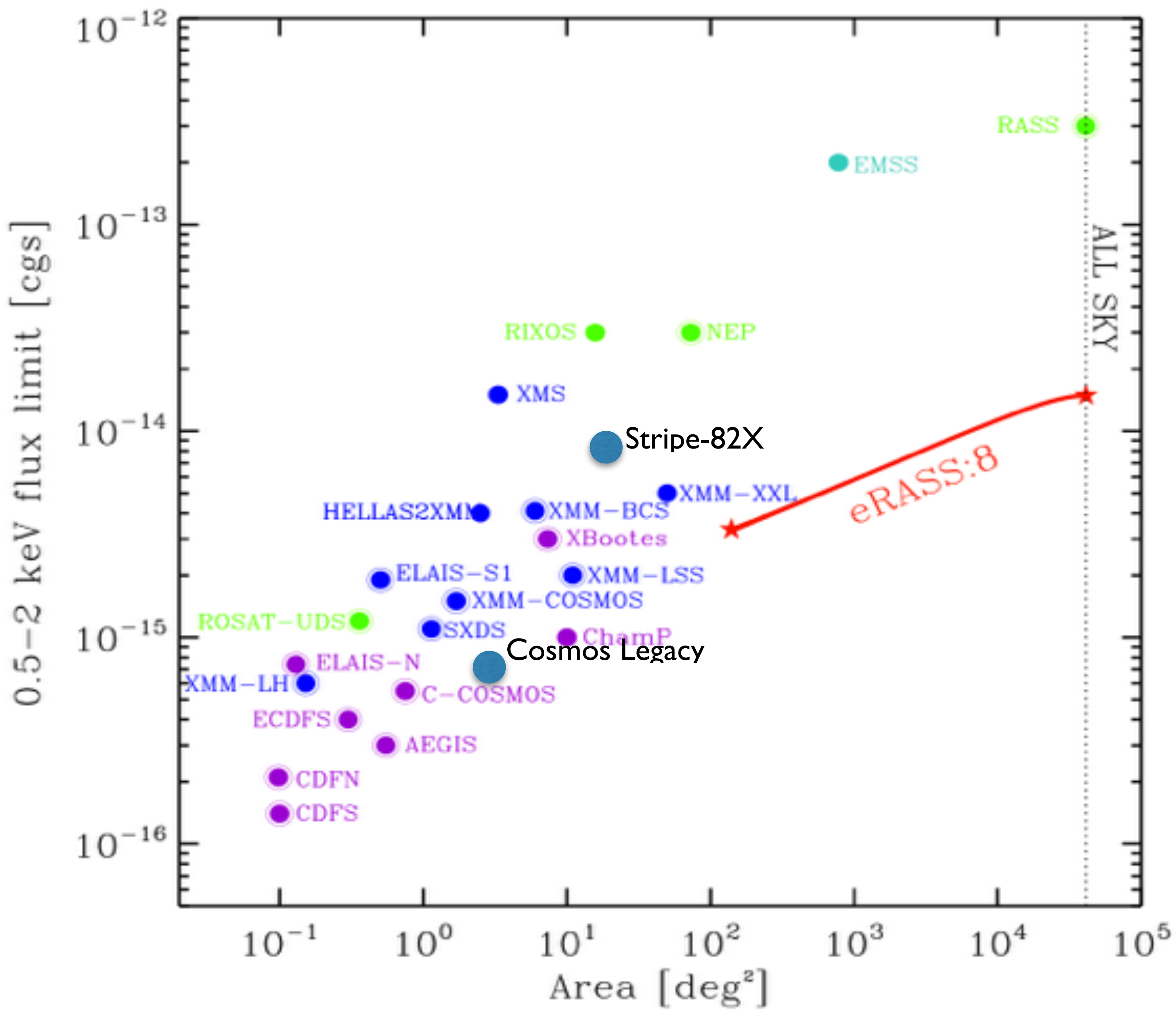




Because of variety of SEDs and large redshift range, one band only, even if deep, is not sufficient

Use ALL what we know, simultaneously



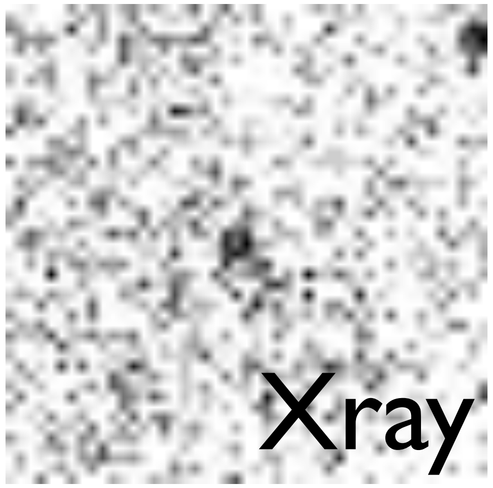


NWAY (NOT in a nutshell...)

starting from the basics,
adding informations, step by step

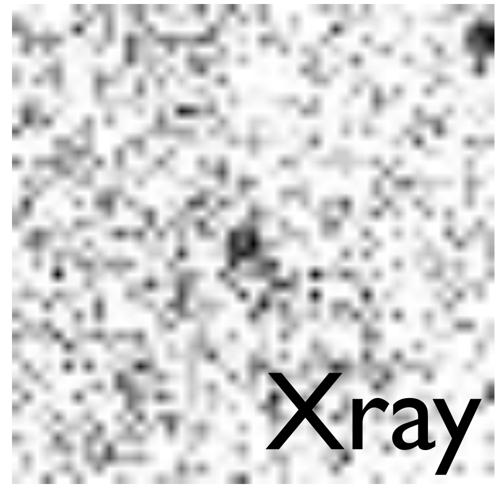
Inputs

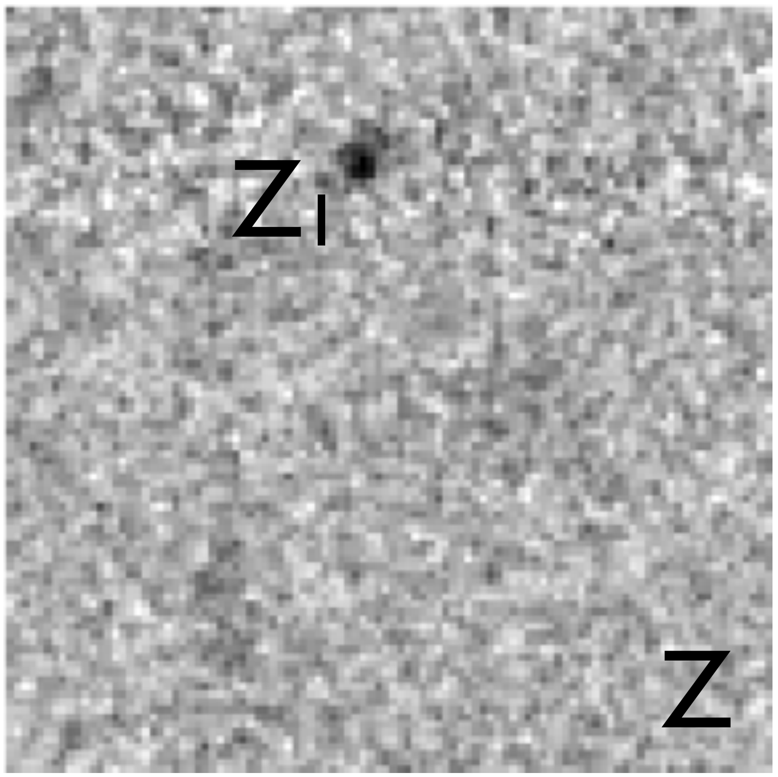
X_I RA_I Dec_I σ_I

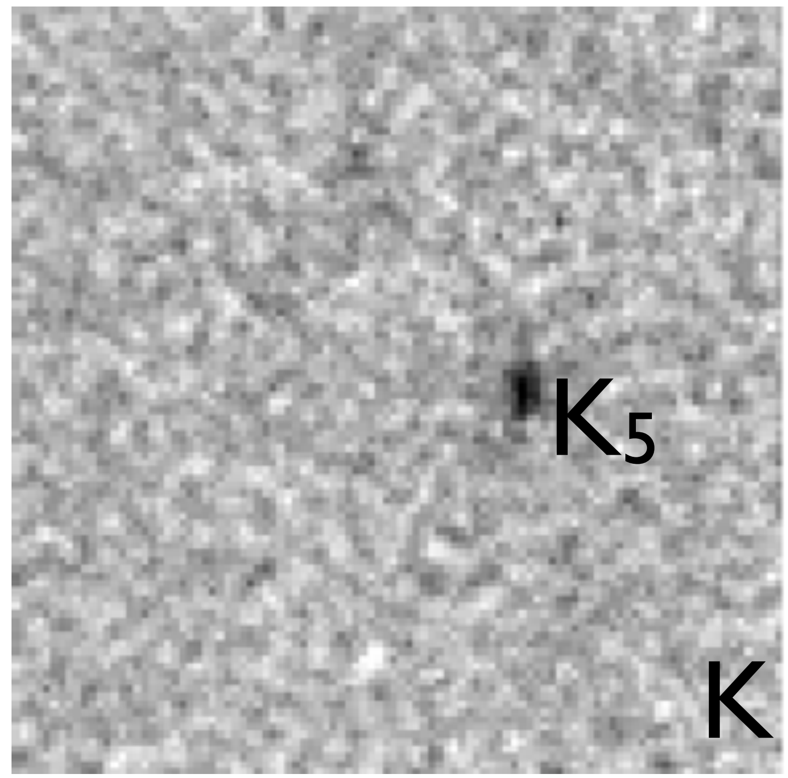


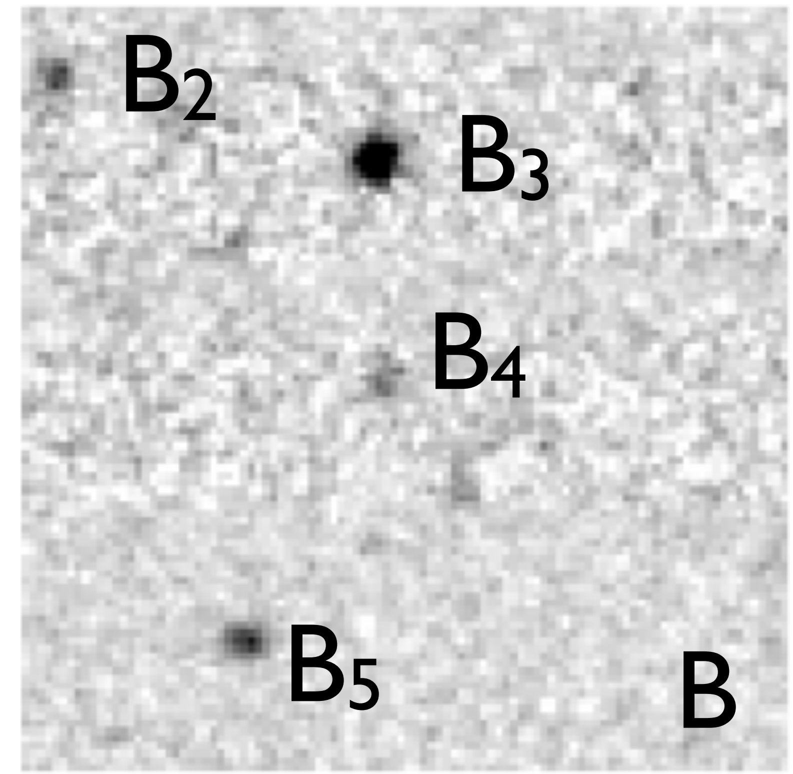
Inputs

X_1 RA_1 Dec_1 σ_1









Z_1 RA_{z1} Dec_{z1} σ_{z1} mag_{z1}

K_5 RA_{k5} Dec_{k5} σ_{k5} mag_{k5}

B_2 RA_{B2} Dec_{B2} σ_{B2} mag_{B2}

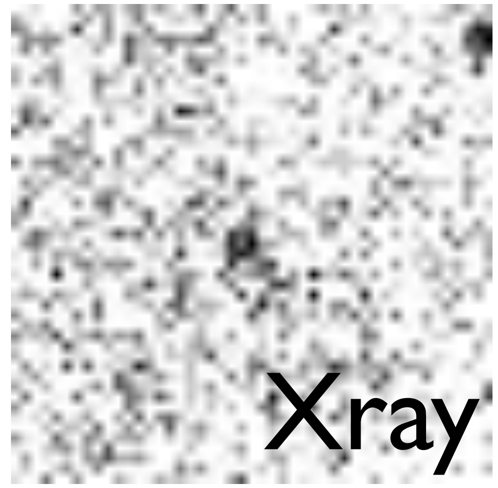
B_3 RA_{B3} Dec_{B3} σ_{B3} mag_{B3}

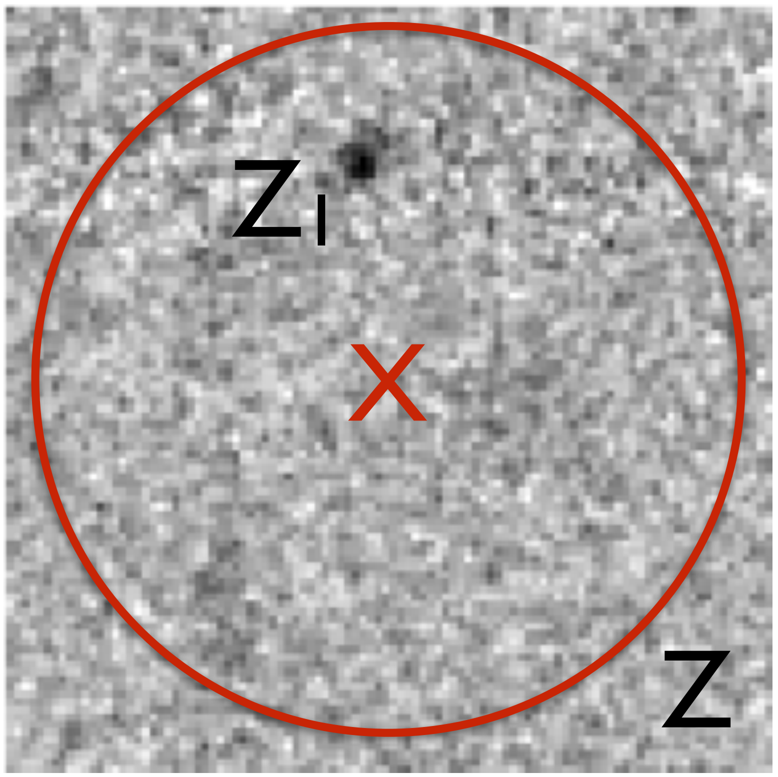
B_4 RA_{B4} Dec_{B4} σ_{B4} mag_{B4}

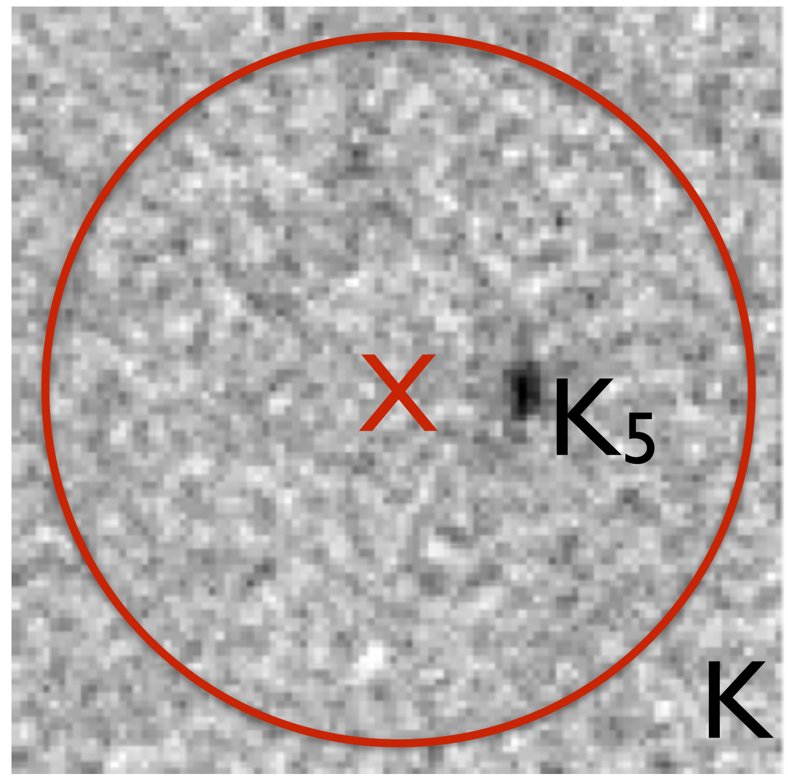
B_5 RA_{B5} Dec_{B5} σ_{B5} mag_{B5}

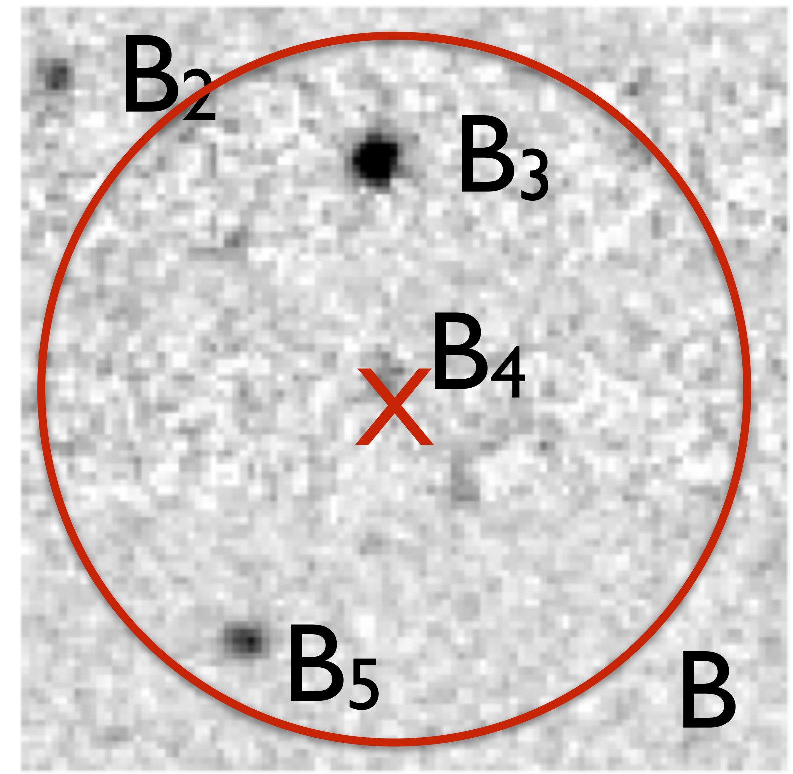
Inputs

X_1 RA_1 Dec_1 σ_1









Z_1 RA_{z1} Dec_{z1} σ_{z1} mag_{z1}

K_5 RA_{k5} Dec_{k5} σ_{k5} mag_{k5}

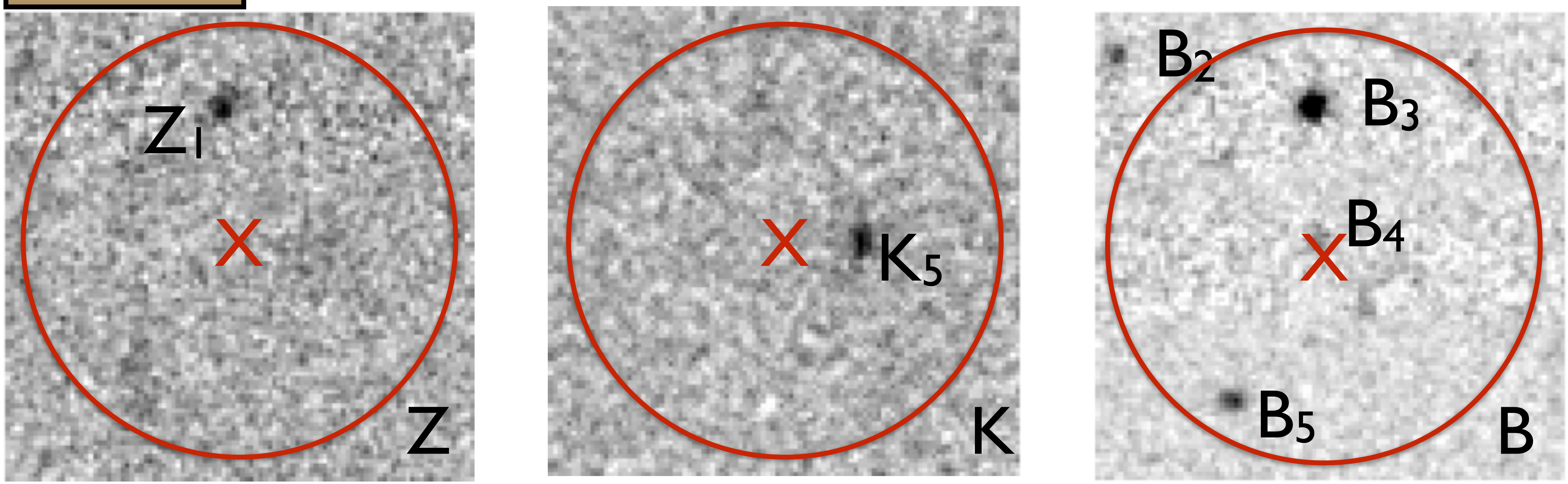
B_2 RA_{B2} Dec_{B2} σ_{B2} mag_{B2}

B_3 RA_{B3} Dec_{B3} σ_{B3} mag_{B3}

B_4 RA_{B4} Dec_{B4} σ_{B4} mag_{B4}

B_5 RA_{B5} Dec_{B5} σ_{B5} mag_{B5}

output



X cat. entry	Z cat. entry	K cat. entry	B cat. entry	P (X has a ctp)	P (this is the correct ctp)
1	1	—	3	0.8	0.4
1	—	5	—	0.8	0.9
1	—	—	4	0.8	0.1
1	—	—	5	0.8	0.2
2	...	...	...	...	...
2	...	...	...	...	...

(i) Matching of N catalogues simultaneously.

(ii) Computation of all combinatorially possible matches

catalogues X, Z, K, B with N_x, N_z, N_k, N_B sources and density $\nu_i = N_i/\Omega_i$

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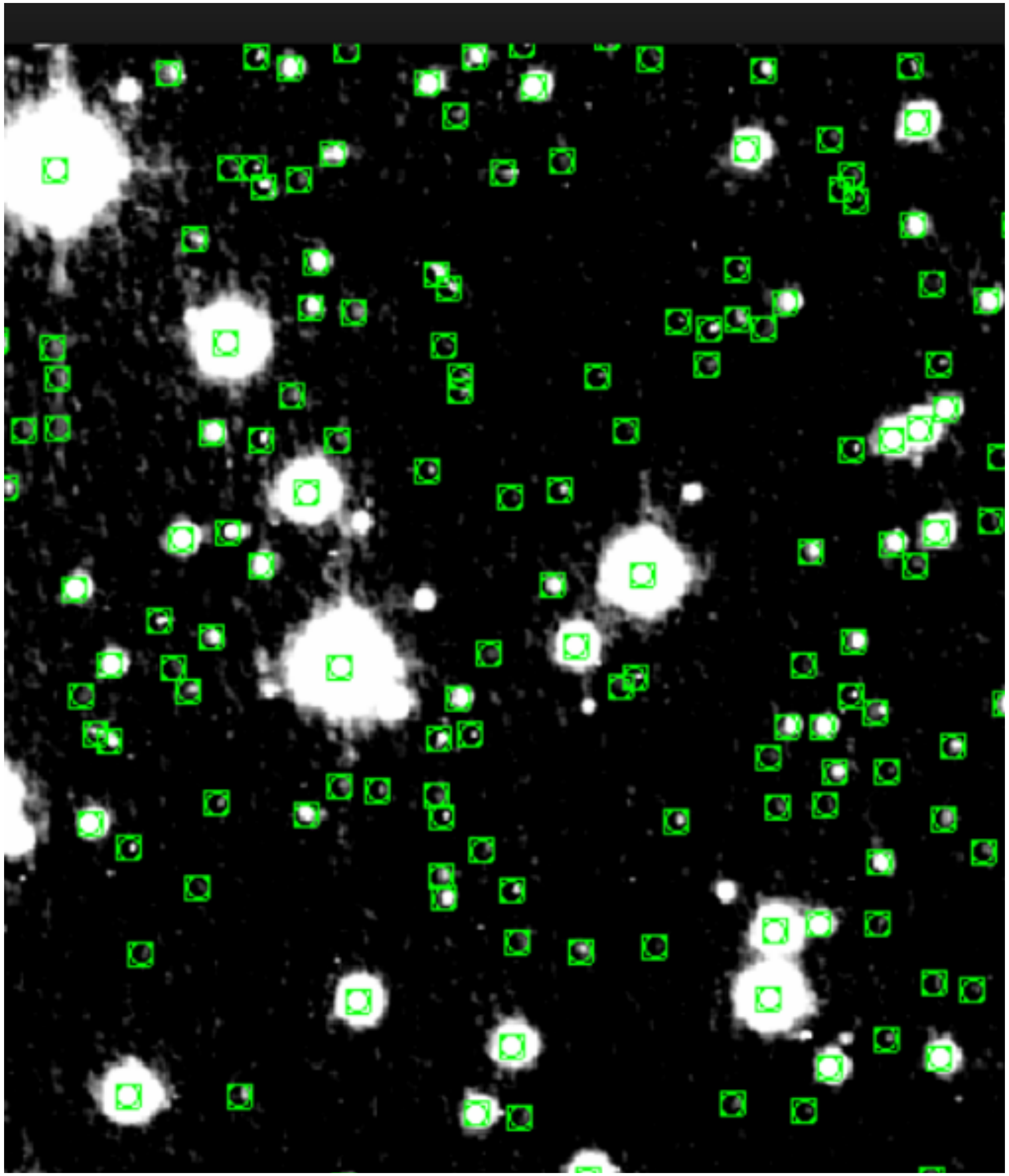
If each catalogue covers the same area with some respective, homogeneous source density, **the probability of one X-ray source to be associated with k (physically unrelated) objects** is provide by combinatorial analysis:

prior P of an association

$$P(H) = N_1 / \prod_{i=1}^{k} N_i = 1 / \prod_{i=2}^{k} N_i = 1 / \prod_{i=2}^{k} \nu_i \Omega_i . \qquad \text{(B1)}$$

Reality: sources are missing from the catalogs



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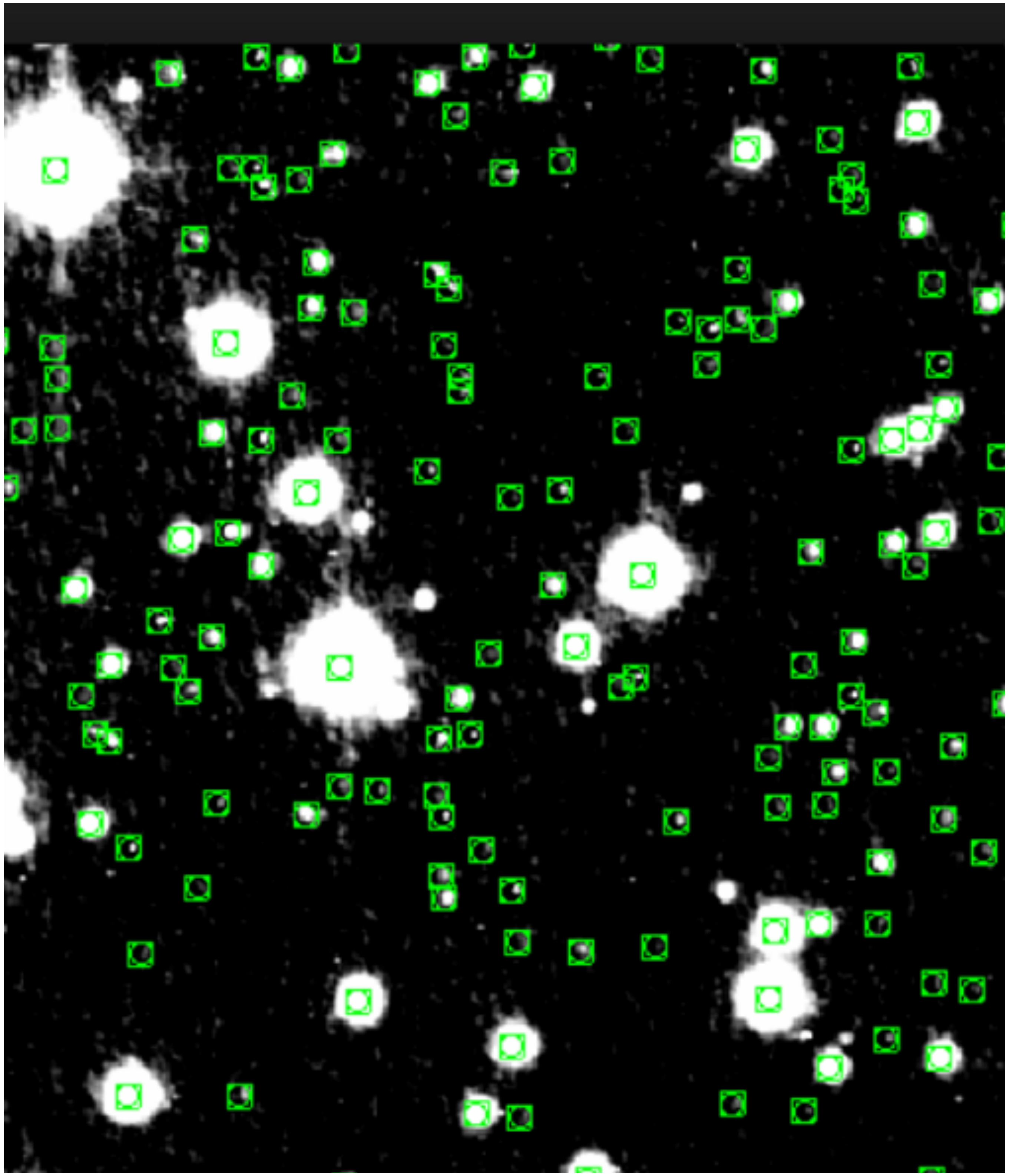
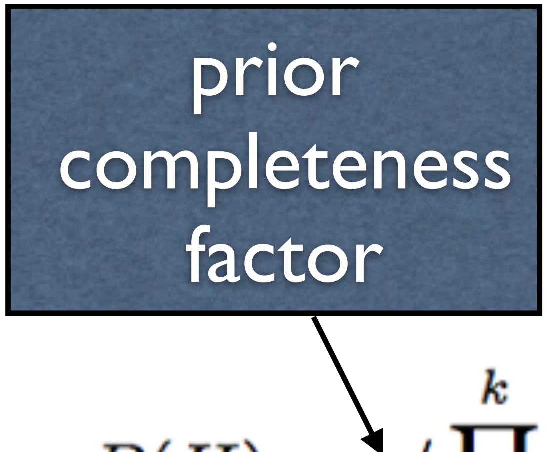
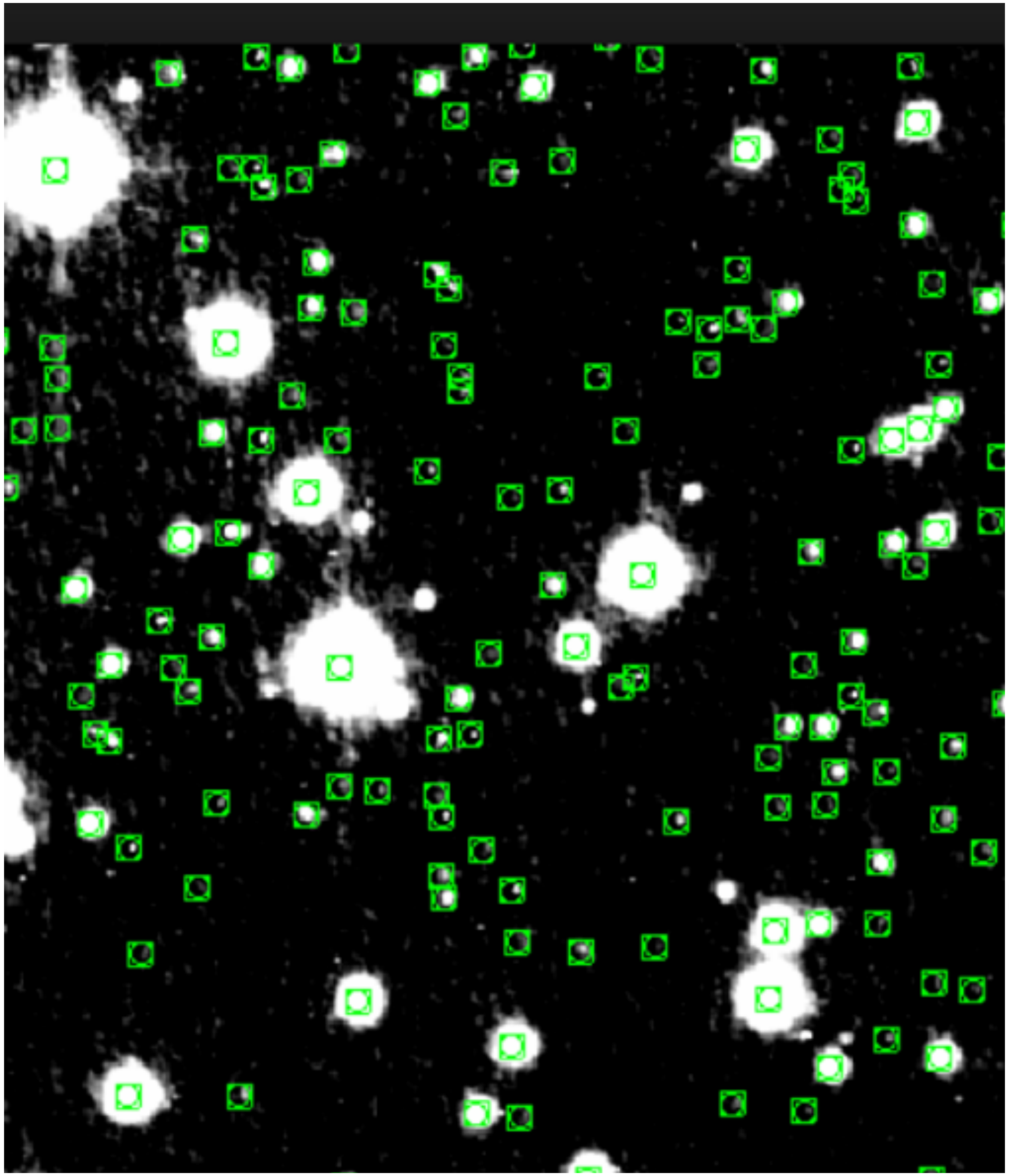




$$P(H) = c / \prod_{i=2}^{k} \nu_i \Omega_1 .$$

Reality: sources are missing from the catalogs



prior completeness factor

$$P(H) = c / \prod_{i=2}^{k} \nu_i \Omega_1 .$$

"c" gained by experience with associations done with high resolution instruments (e.g.Chandra) and deep ancillary data

(iii) Computation of the probability of each possible match, using distances, errors and number densities.

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Budavari&Szalai 2008

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For a source X_1 in catalogue X and a source Z_1 in a catalog Z

$$P(D|X_1\ ass.\ Z_1) = \frac{2}{(\sigma^2_{X_1} + \sigma^2_{Z_1})} \exp[-\frac{Dist^2_{X_1 Z_1}}{2(\sigma^2_{X_1} + \sigma^2_{z_1})}]$$

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For a source X_1 in catalogue X and a source Z_1 in a catalog Z and K_1 in catalog K

$$P(D|X_1\ ass.\ Z_1\ ass. K_1) == \frac{4\exp\left\{-\frac{\sigma^2_{K_1} Dist^2_{X_1 Z_1} + \sigma^2_{X_1} Dist^2_{Z_1 K_1} + \sigma^2_{Z_1} Dist^2_{K_1 X_1}}{2(\sigma^2_{X_1}\sigma^2_{Z_1} + \sigma^2_{Z_1}\sigma^2_{K_1} + \sigma^2_{K_1}\sigma^2_{X_1})}\right\}}{\sigma^2_{X_1}\sigma^2_{Z_1} + \sigma^2_{Z_1}\sigma^2_{K_1} + \sigma^2_{K_1}\sigma^2_{X_1}}$$

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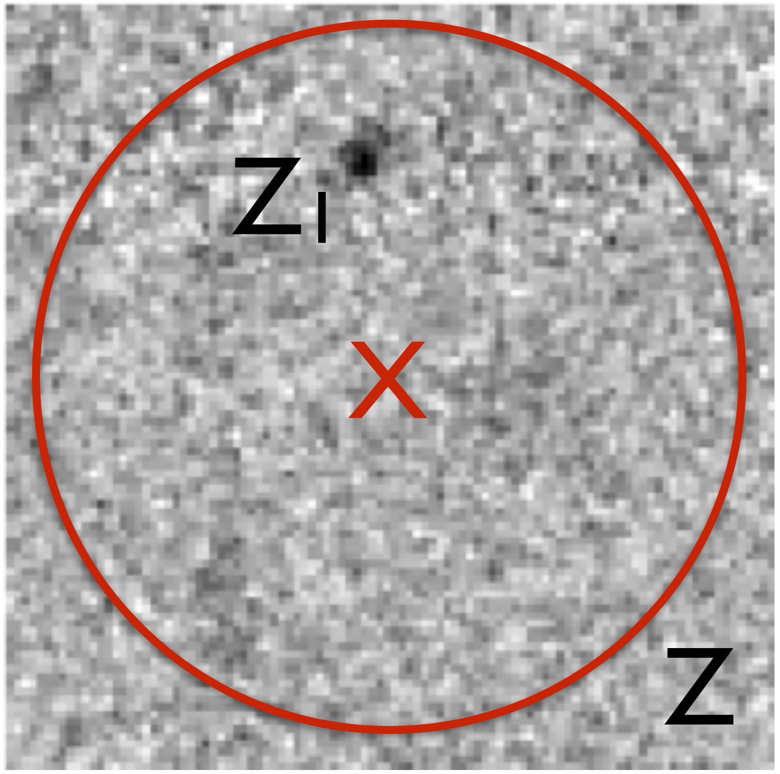
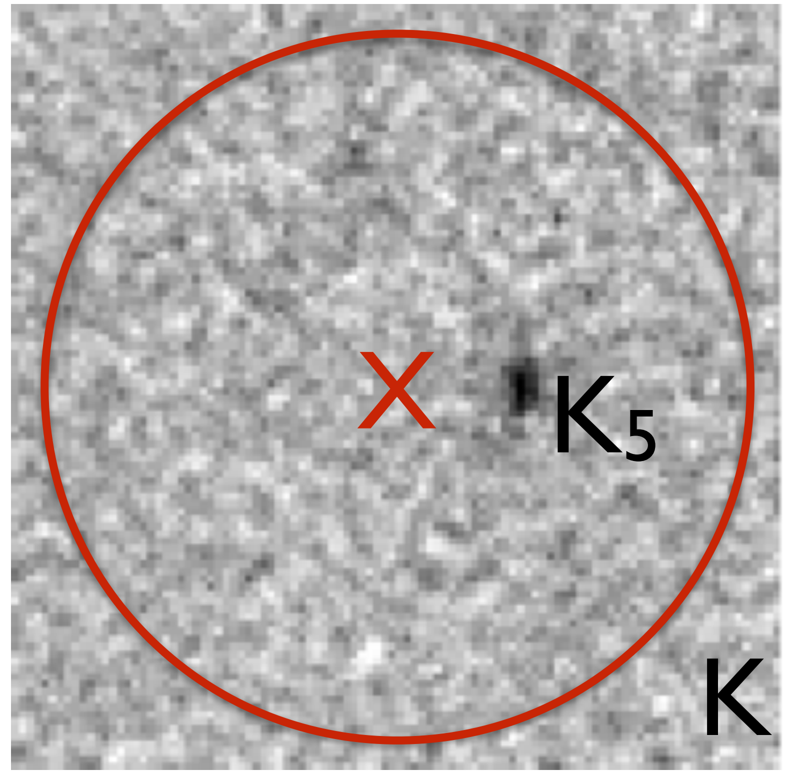
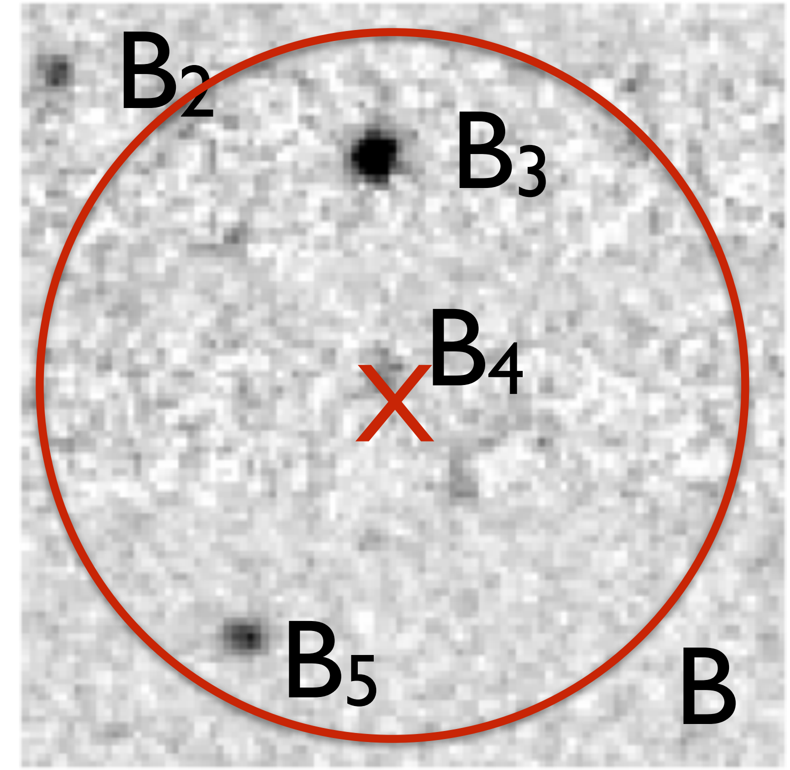
Compact form

$$P(D|H) = 2^{k-1} \frac{\prod \sigma_i^{-2}}{\sum \sigma_i^{-2}} \exp\left\{-\frac{\sum_{i<j} Dist^2_{ij}\sigma_j^{-2}\sigma_i^{-2}}{2\sum \sigma_i^{-2}}\right\}$$

RESULTS 1







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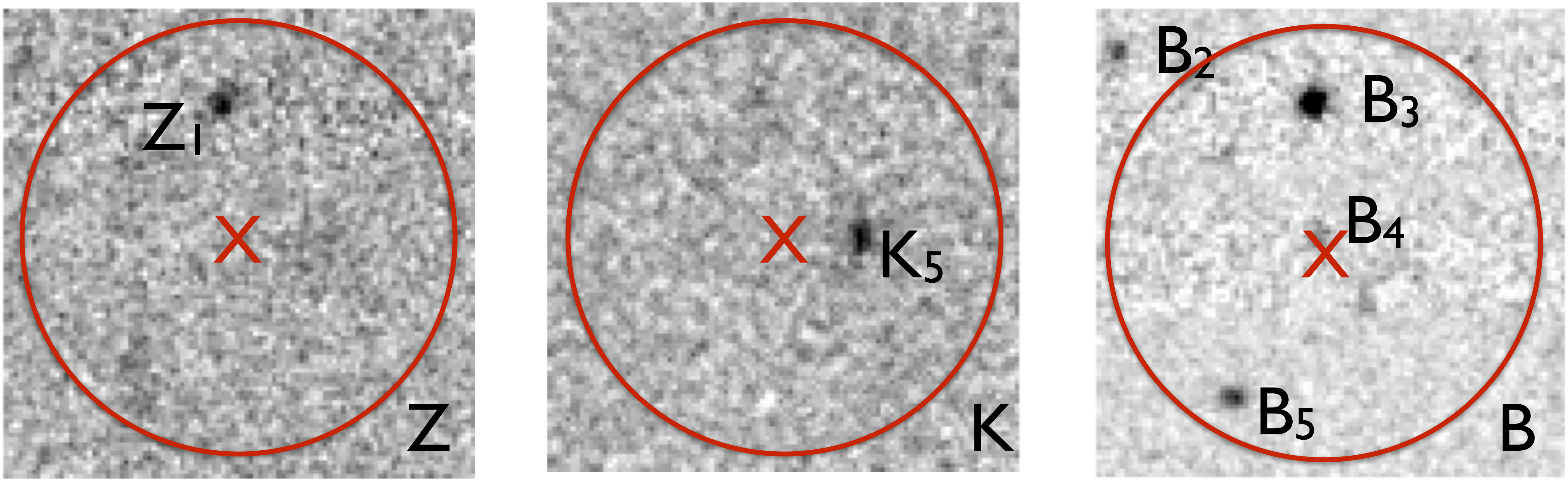
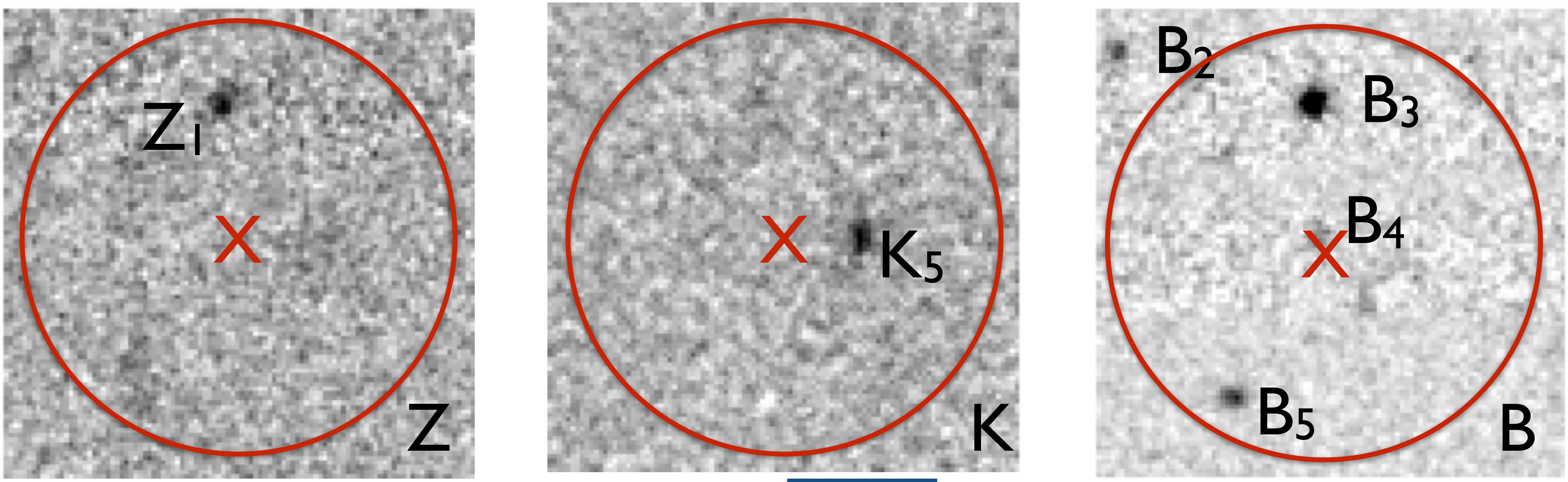


$$P(H|D) \propto P(H) \times P(D|H).$$

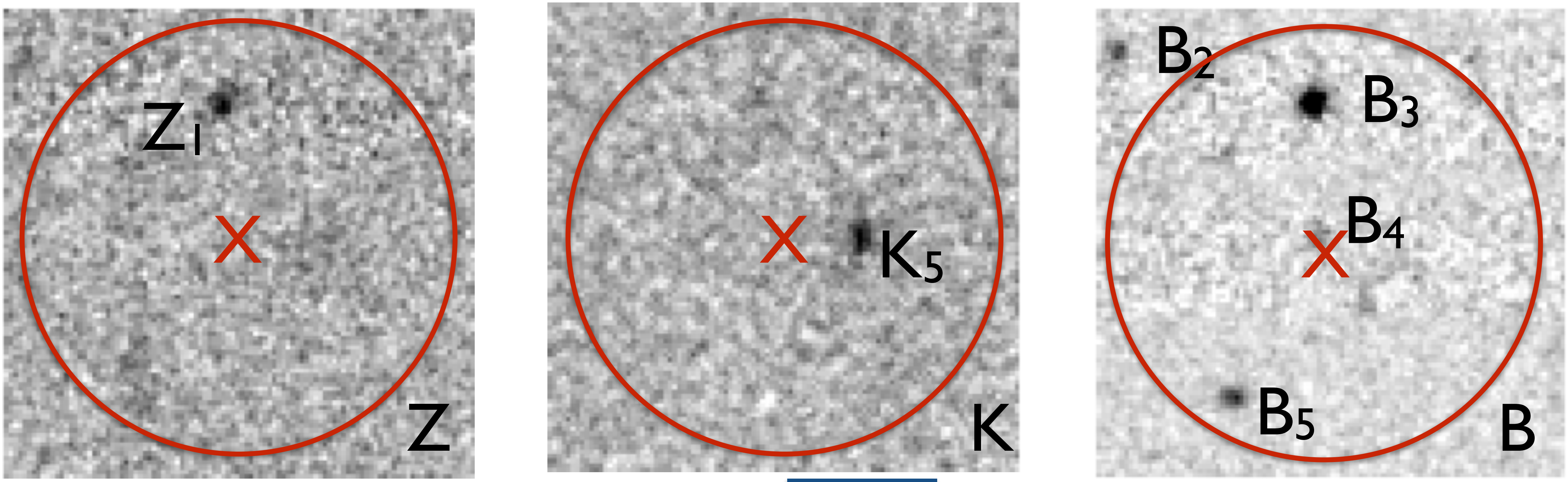
RESULTS I



prior

posterior prob. $P(H|D) \propto P(H) \times P(D|H)$. likelihood

RESULTS I



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$$p\_any = 1 - (P(H_0|D)/\sum_i P(H_i|D))$$

$$P(H_0|D) \propto P(H_0)P(D|H_0) = c \times 1$$

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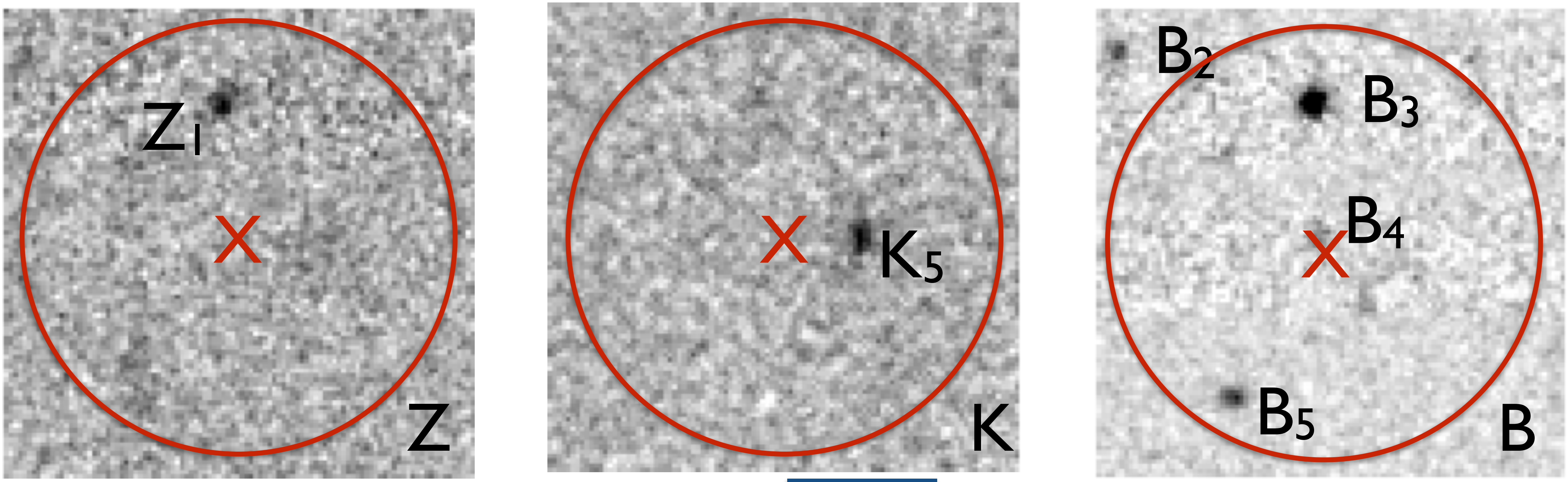

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The relative posterior probability for an association, **p_i**

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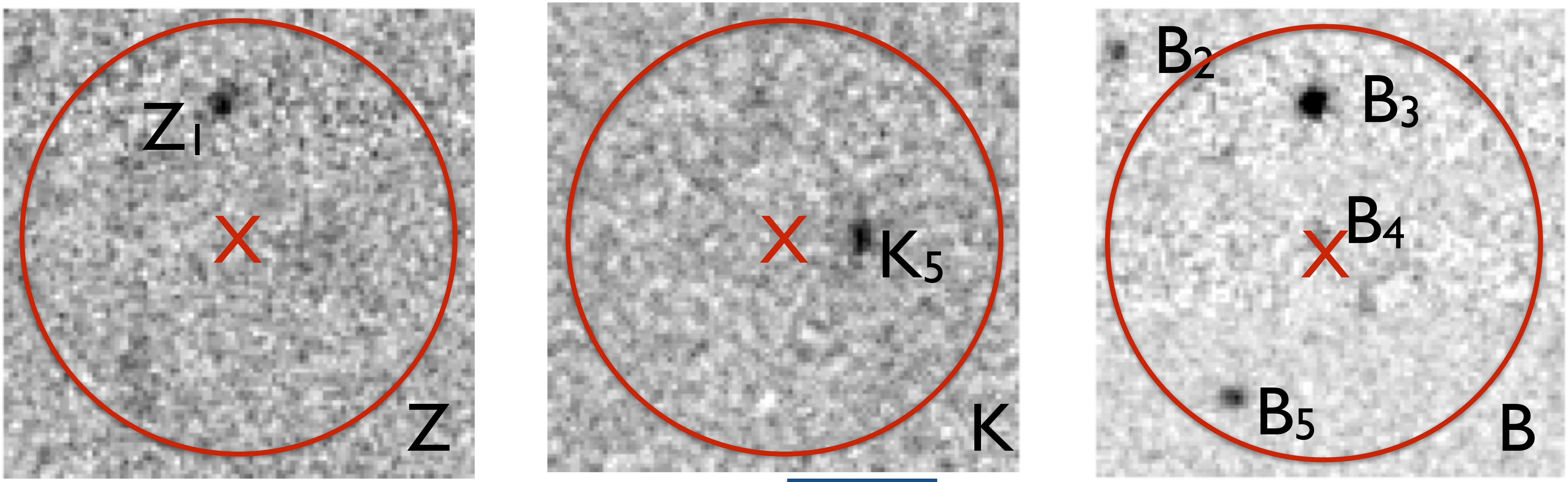
RESULTS I

See also Pineau et al 2017



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(vi) Refining the match probabilities by incorporating magnitude distribution, colors, magnitude&colors or other information about the sources of interest …

ML
(Sutherland&Saunders 92)

$$LR = \frac{q(m)}{n(m)} \times f(r)$$

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$$\begin{aligned} P(D|H) &= P(D_\phi|H) \times P(D_m|H) && \text{(B11)} \\ &= P(D_\phi|H) \times \frac{\bar{q}(m)}{\bar{n}(m)}, && \text{(B12)} \end{aligned}$$

probability that a correct ctp to a X-ray source or a generic field source has magnitude m, respectively.

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probability that a correct ctp to a X-ray source or a generic field source has magnitude m, respectively.

for many catalogs:

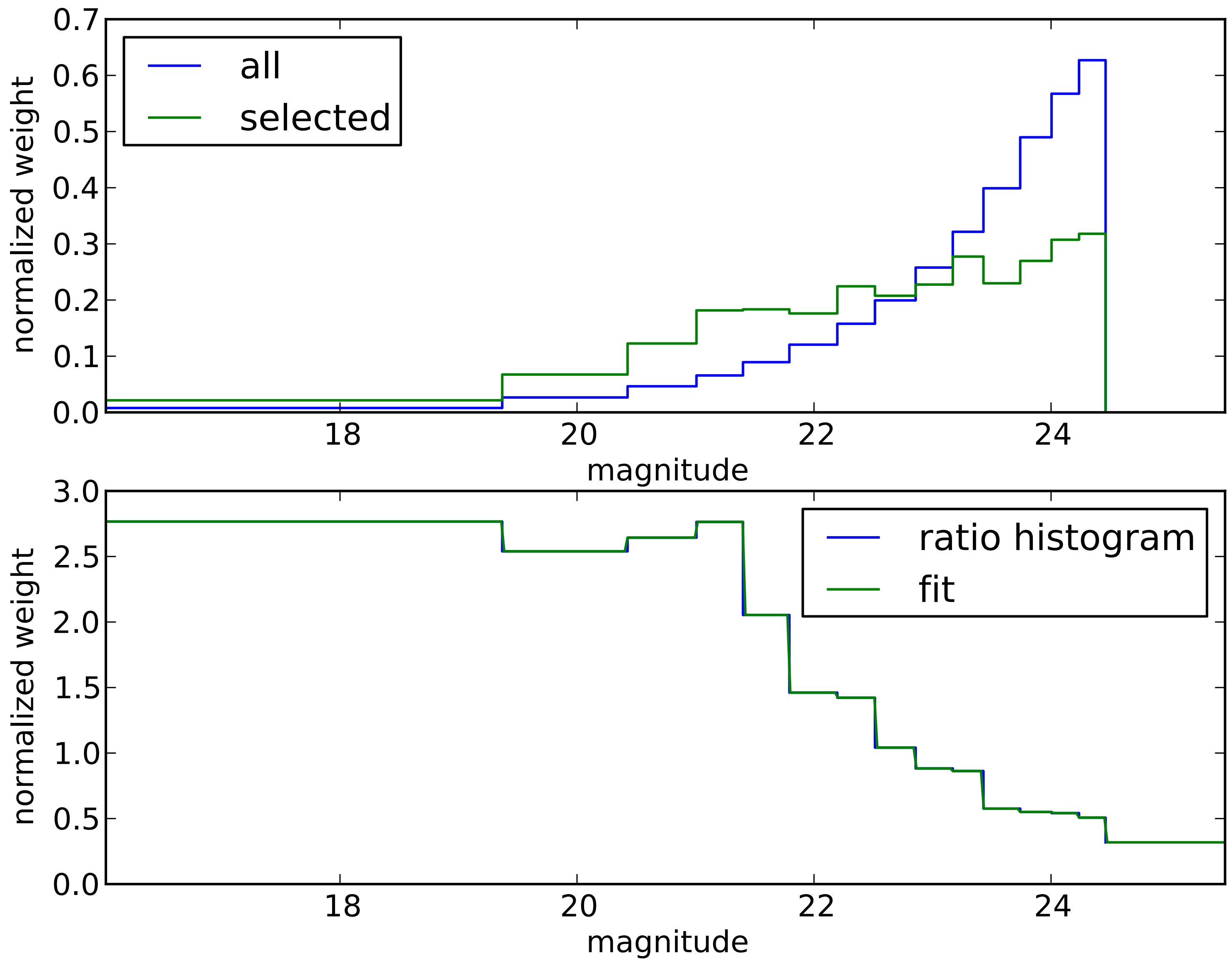
$$P(D_m|H) = \prod \frac{\int_m \bar{q}(m)\, p(m|D_m)\, dm}{\int_m \bar{n}(m)\, p(m|D_m)\, dm} \quad \text{(B13)}$$

Gaussian error distribution with mean m and standard deviation σ_m

(vii) ...either with an external information or internal calibration

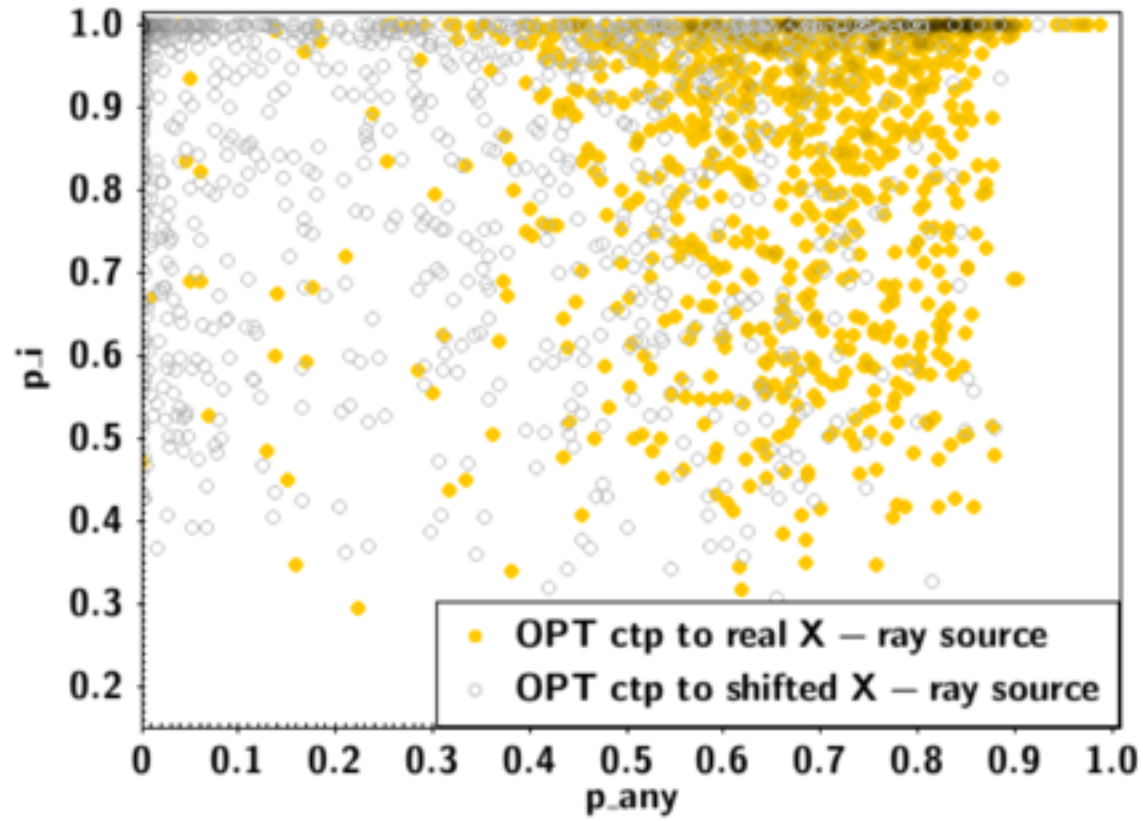
internal calibration

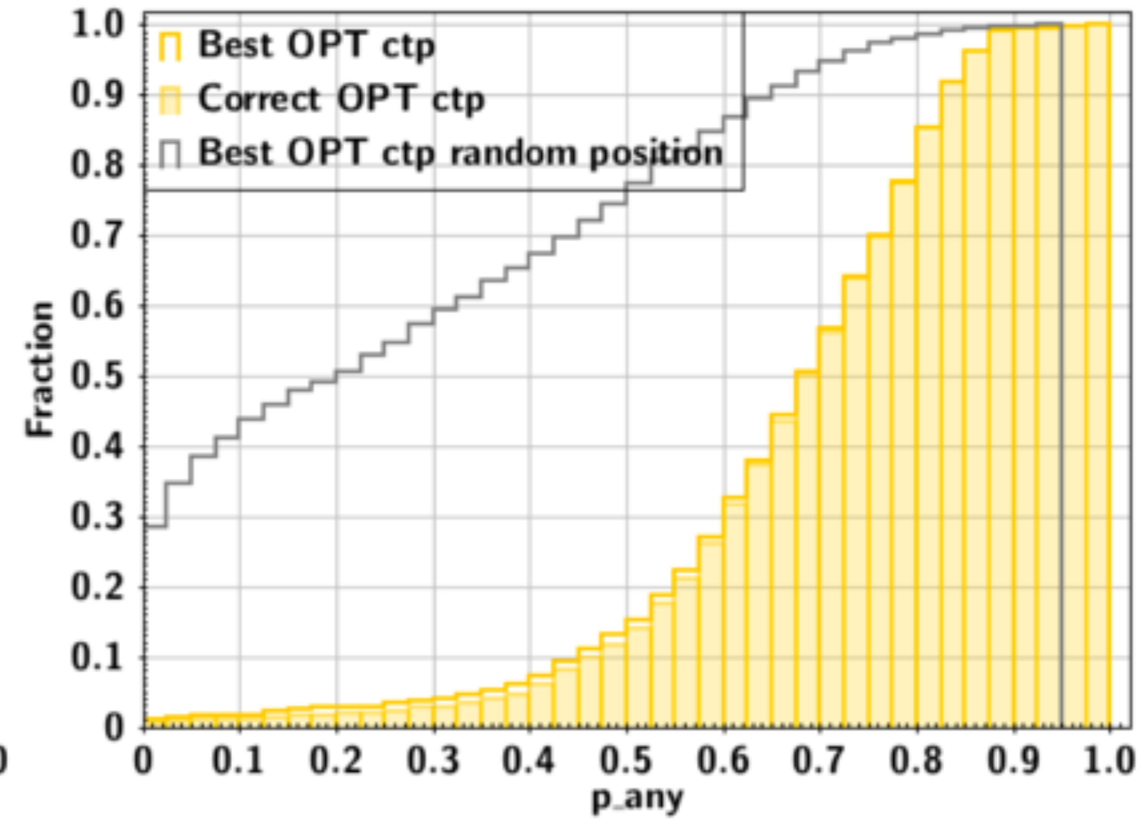
using the sources with
p_any_Φ>0.9 and
p_any_Φ<0.1
for creating
the likelihood



Example of result from internal calibration: XMM-COSMOS

X+OPT





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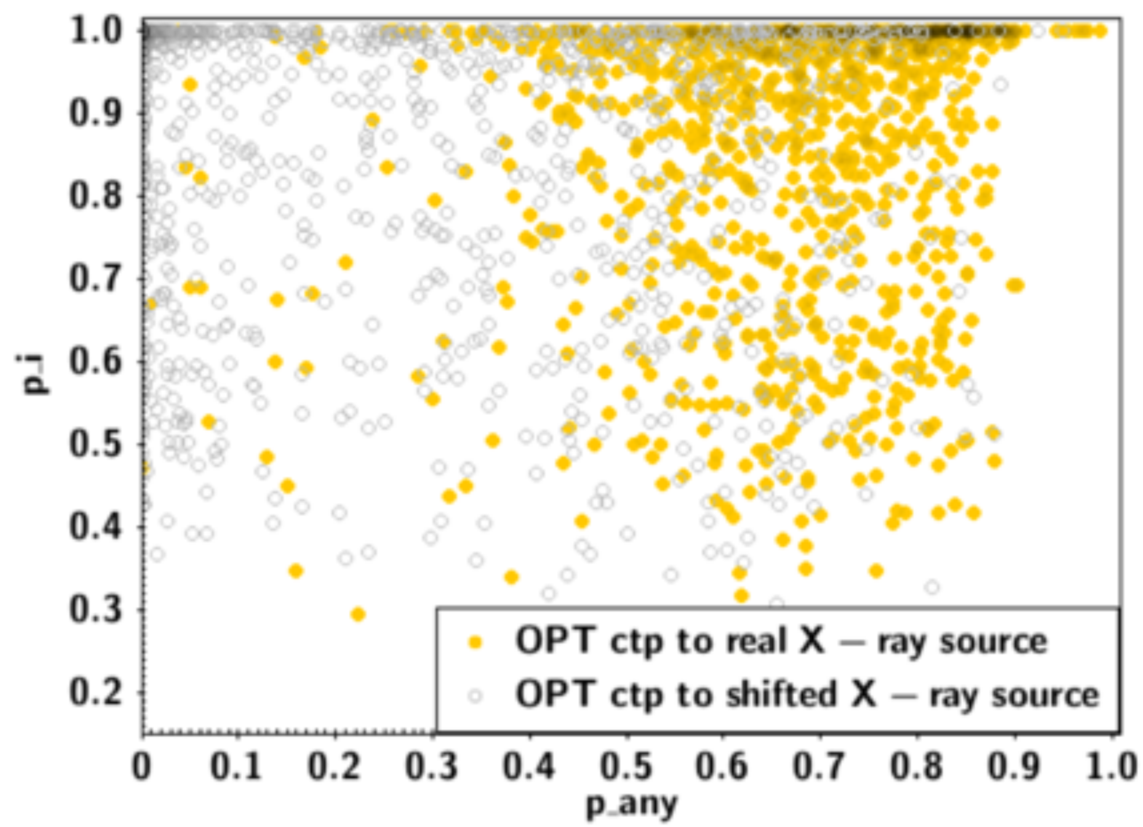
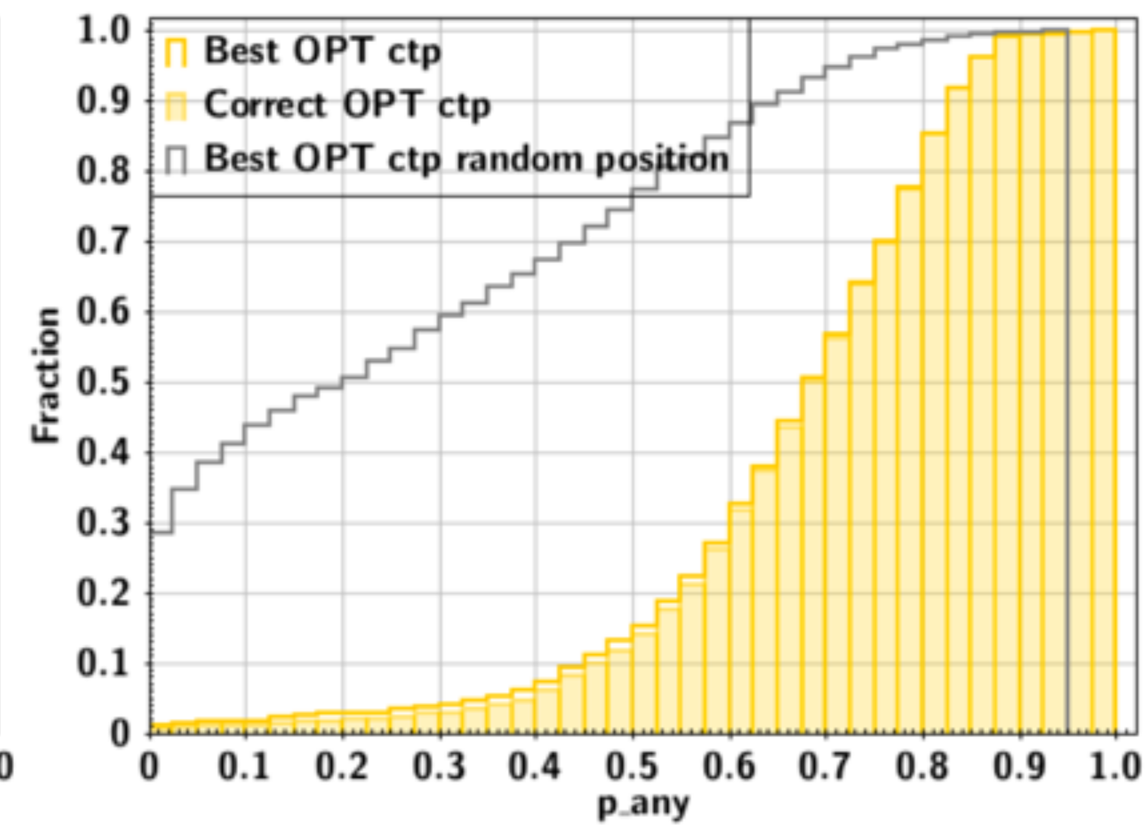
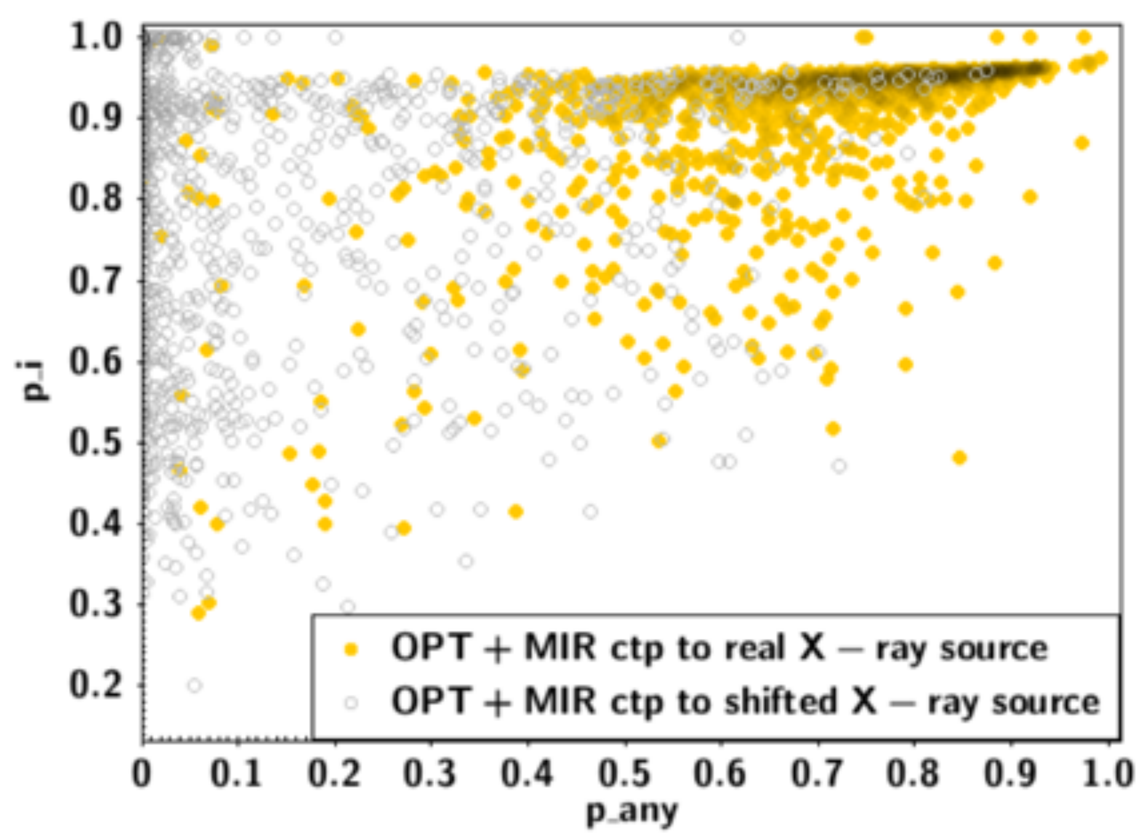
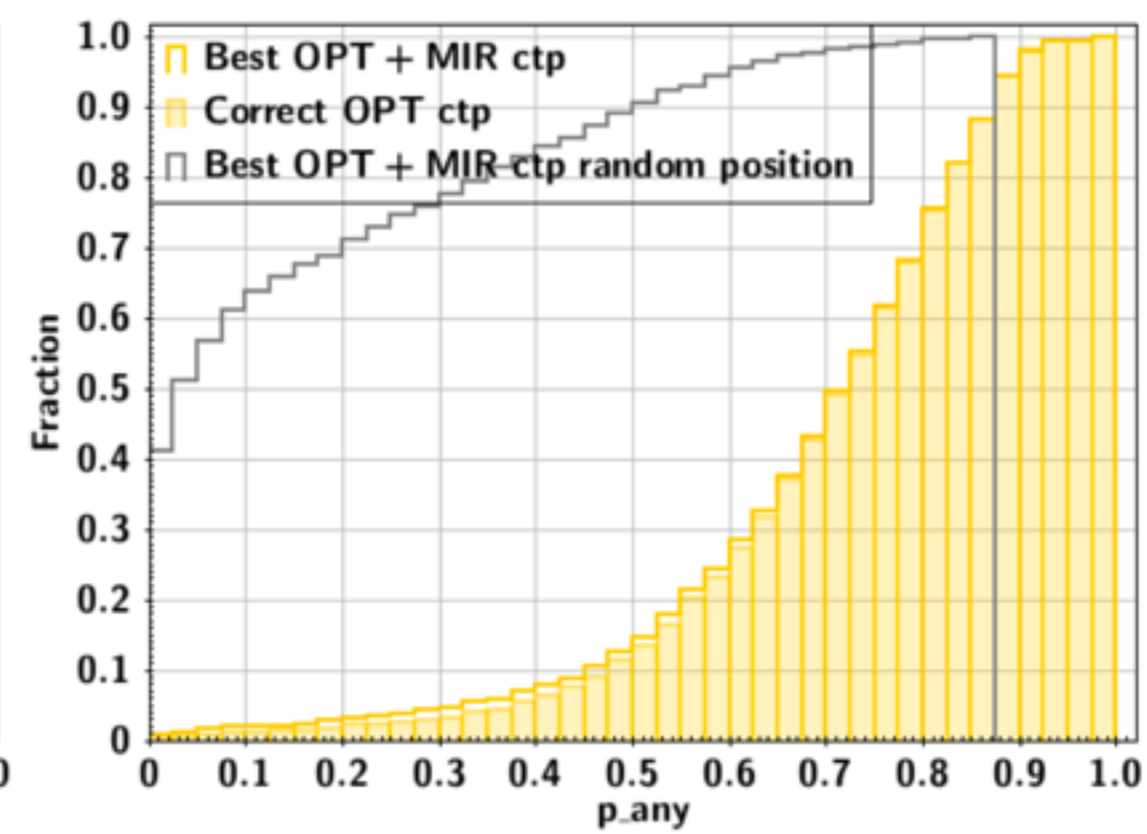


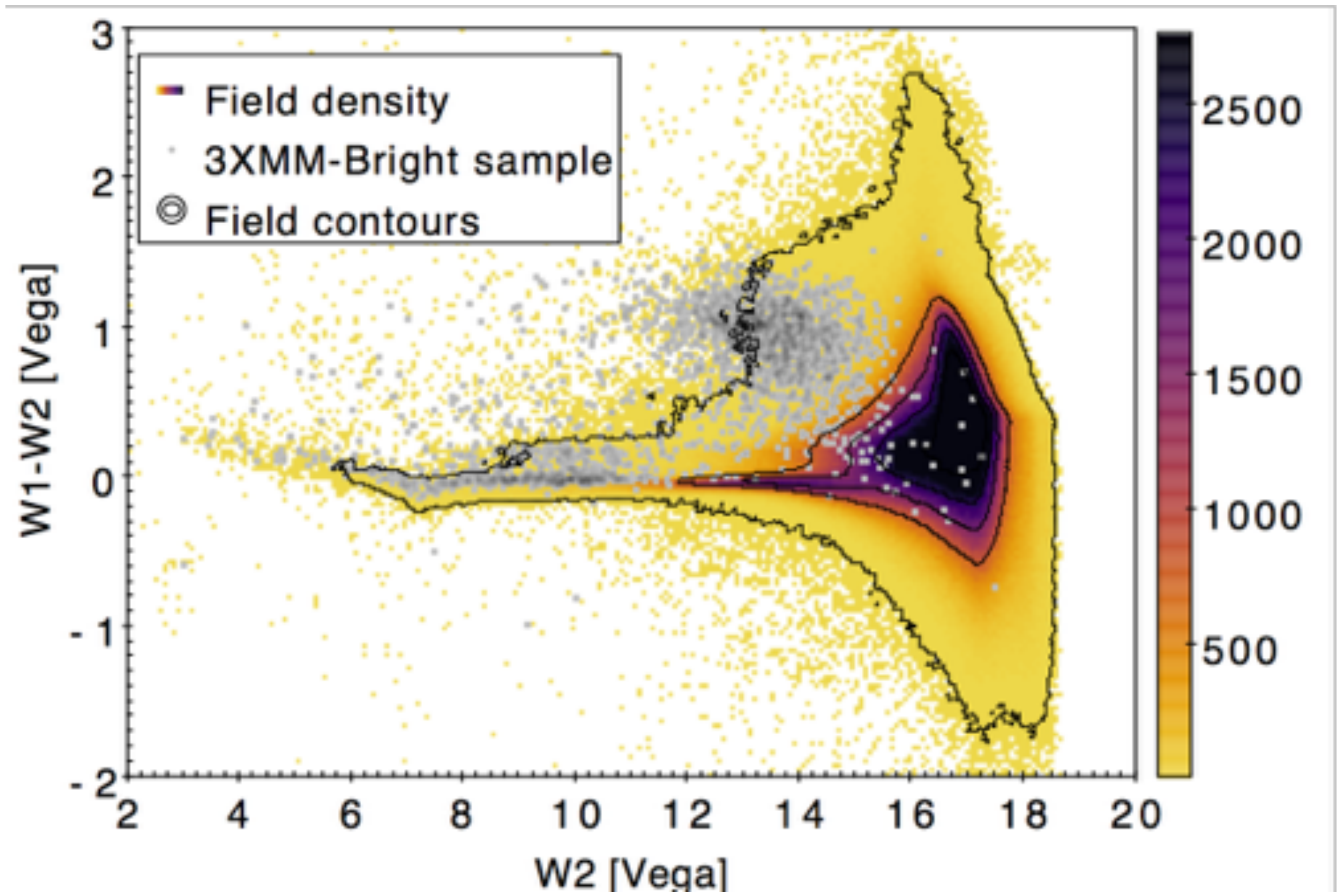


X+
OPT+
MIR

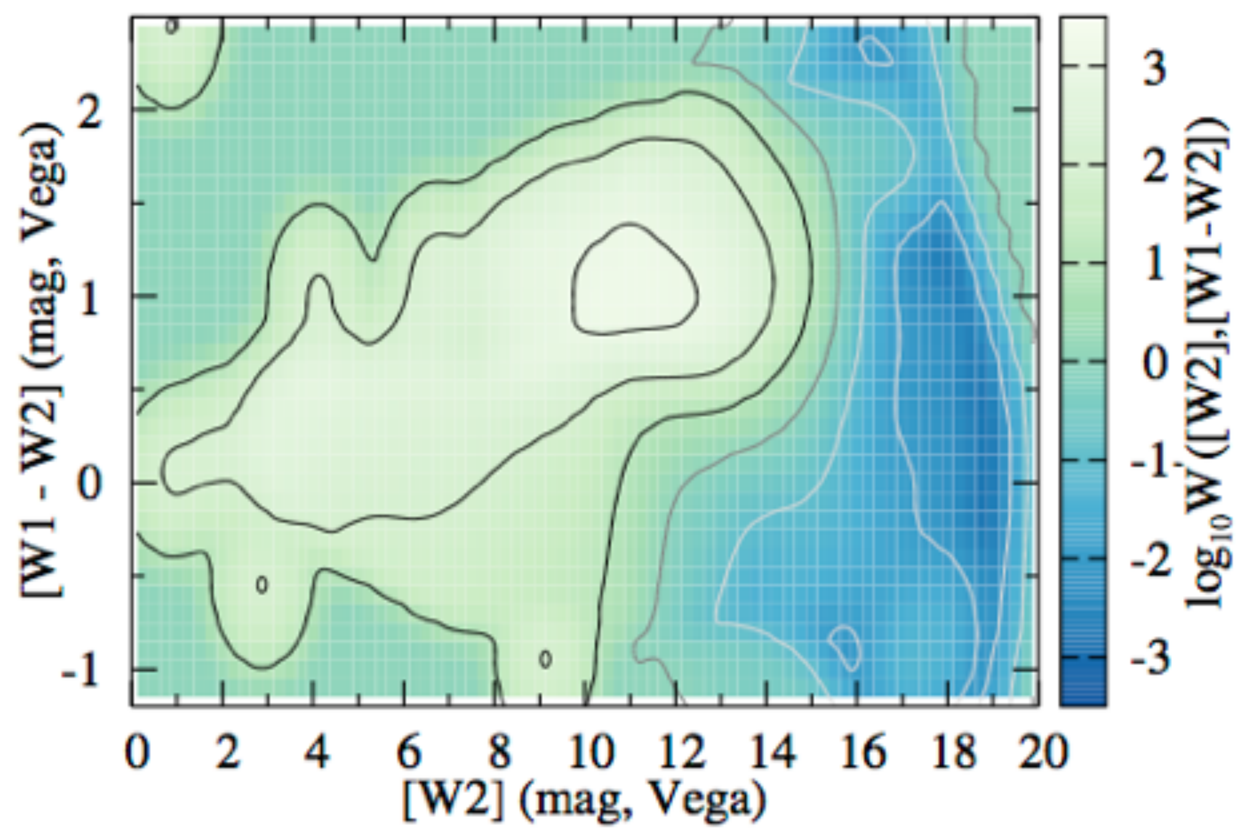




Actual application to ROSAT and XMMSLEW2



the data used for the prior



The actual likelihood

Counterparts comparison

Table 1. XMMSL2 vs 2RXS AllWISE association for sources in common

XMMSL2-2RXS Sep. arcsec	Mean Sep. arcsec	Sources in common N	Identical Best AllWISE ctp. %
≤5	3.2	1145	98.5
≤10	6.1	3559	98.5
≤30	12.4	8202	95.7
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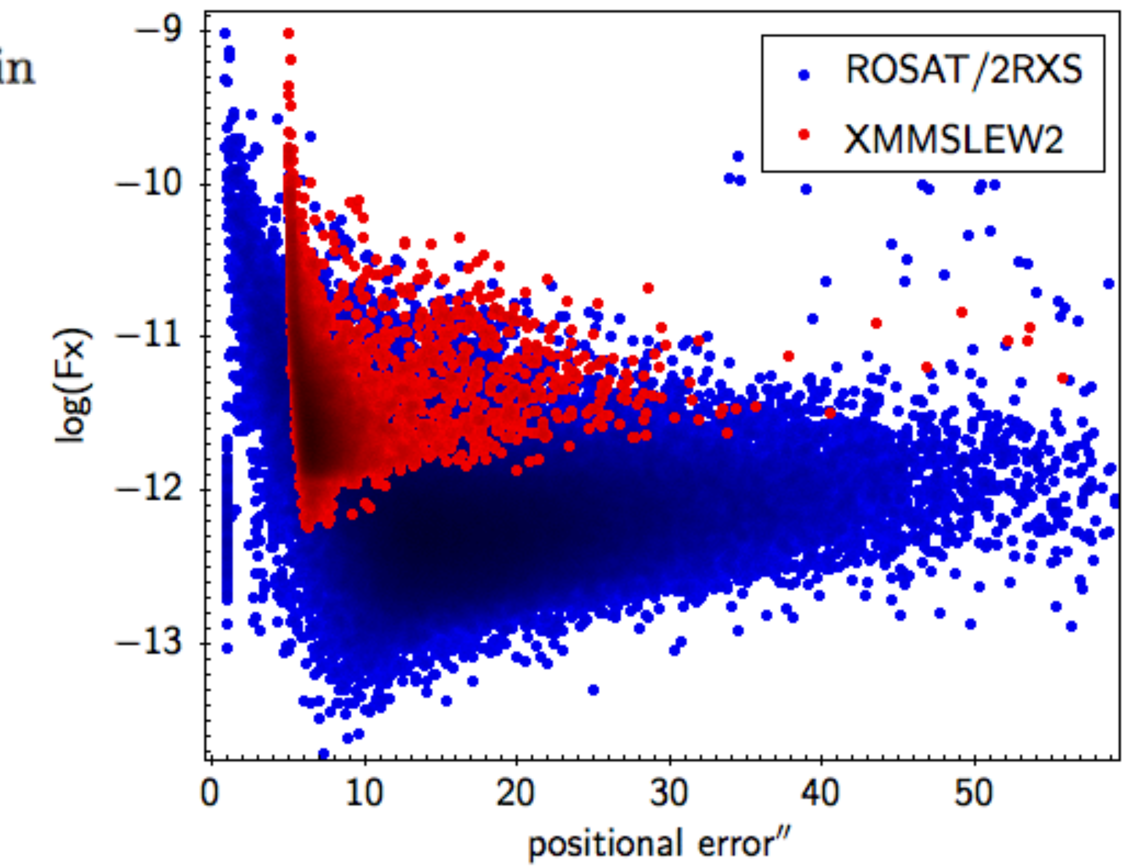

what p_any tells us :

1) is the X-ray source real?

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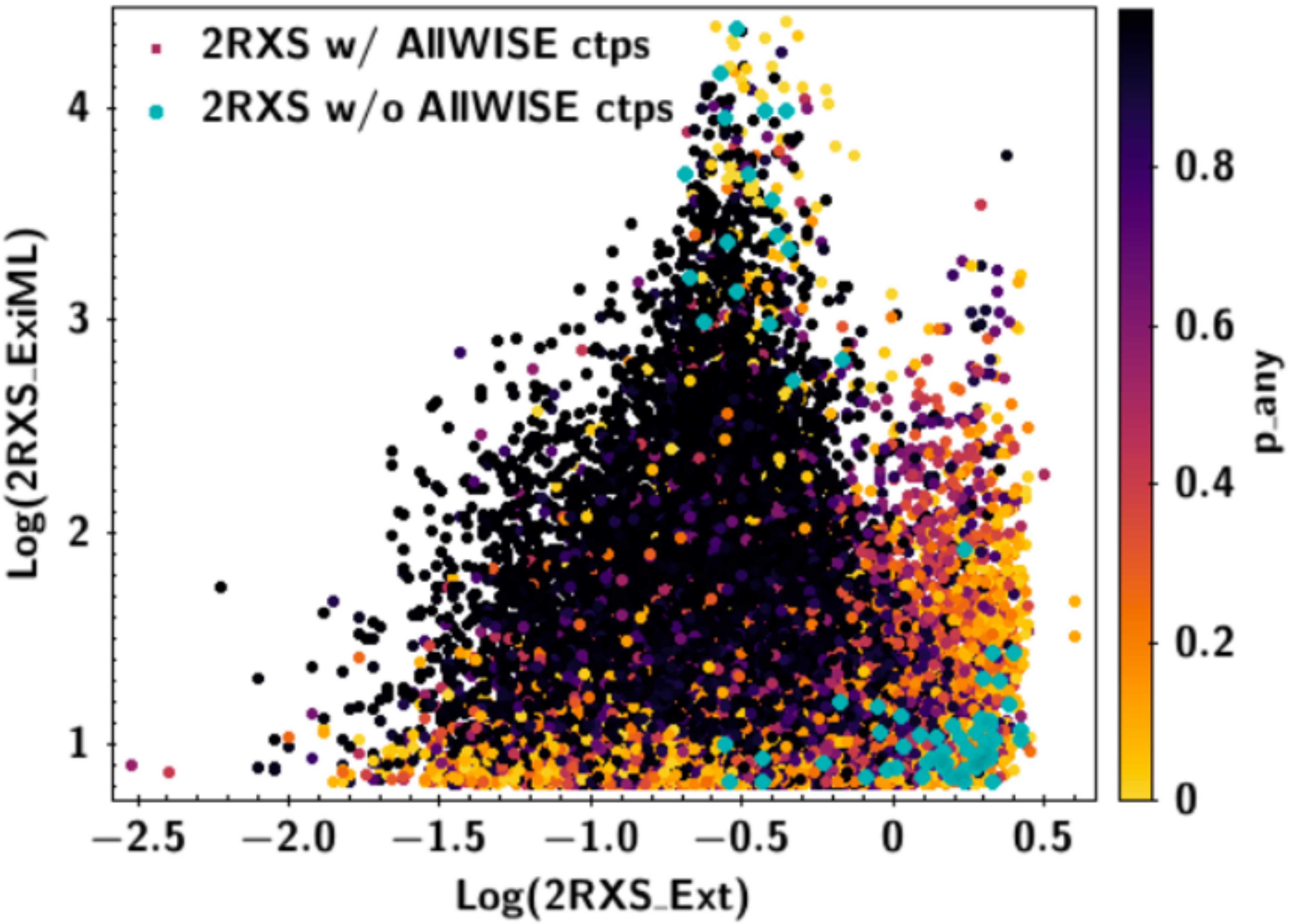
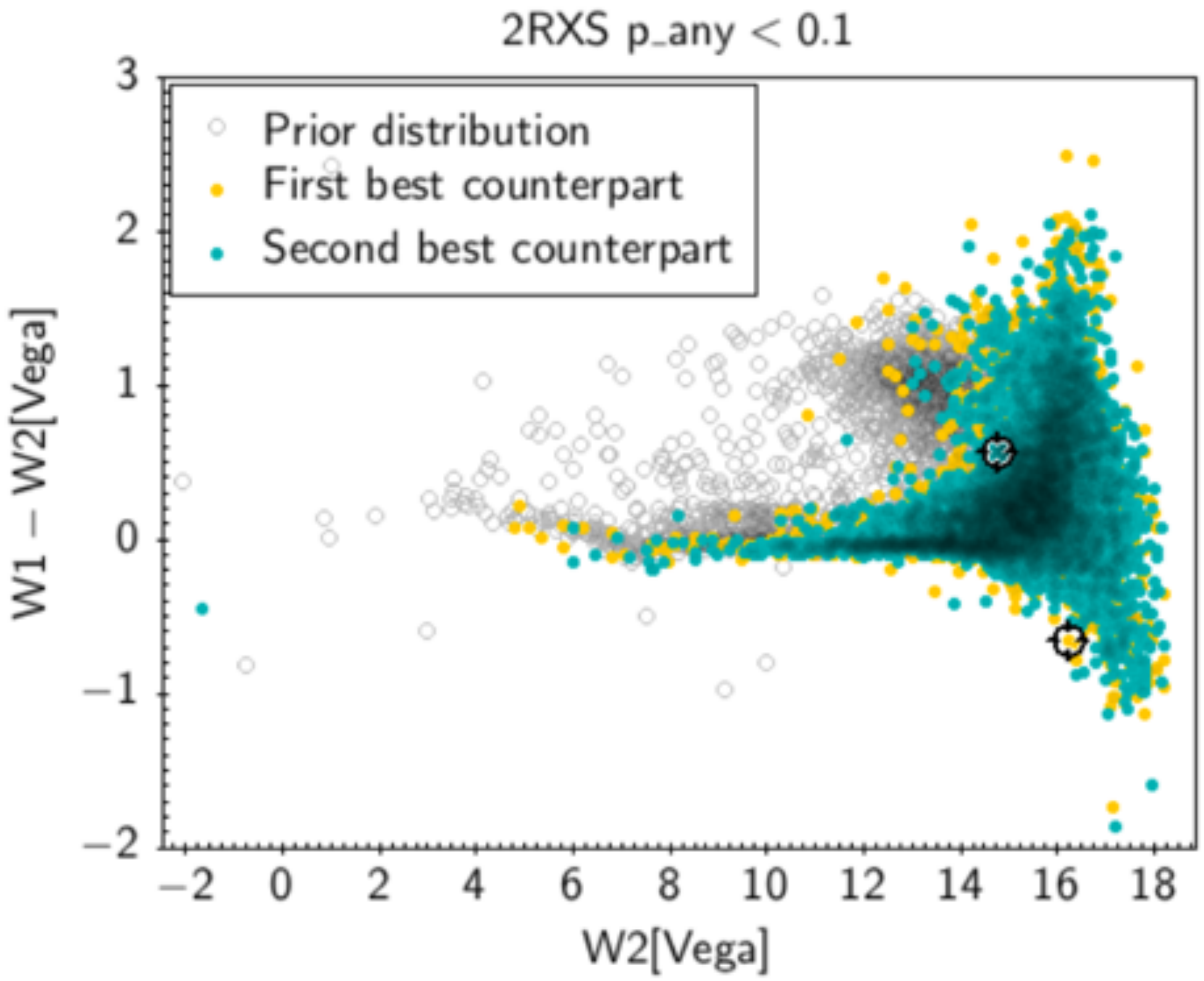
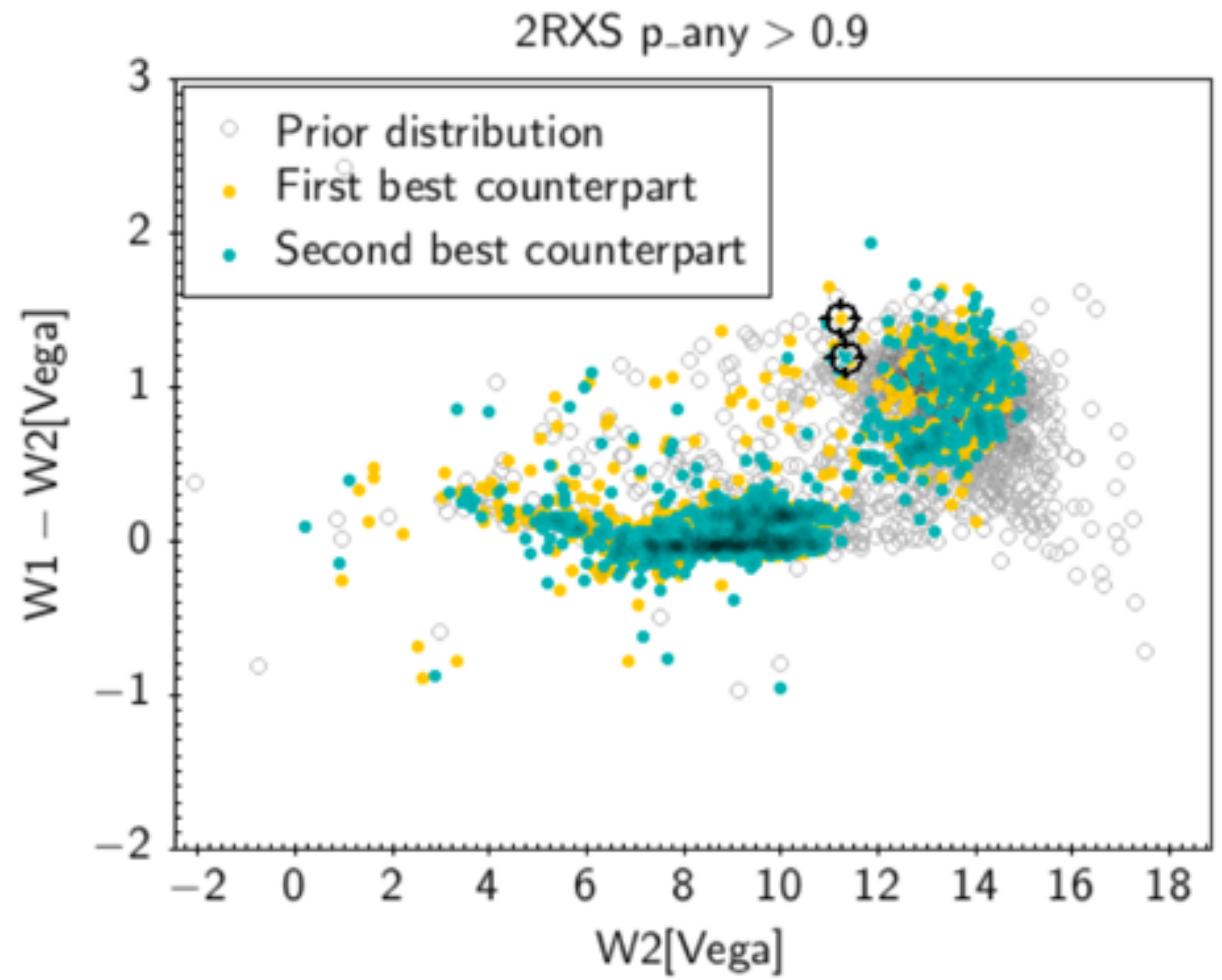
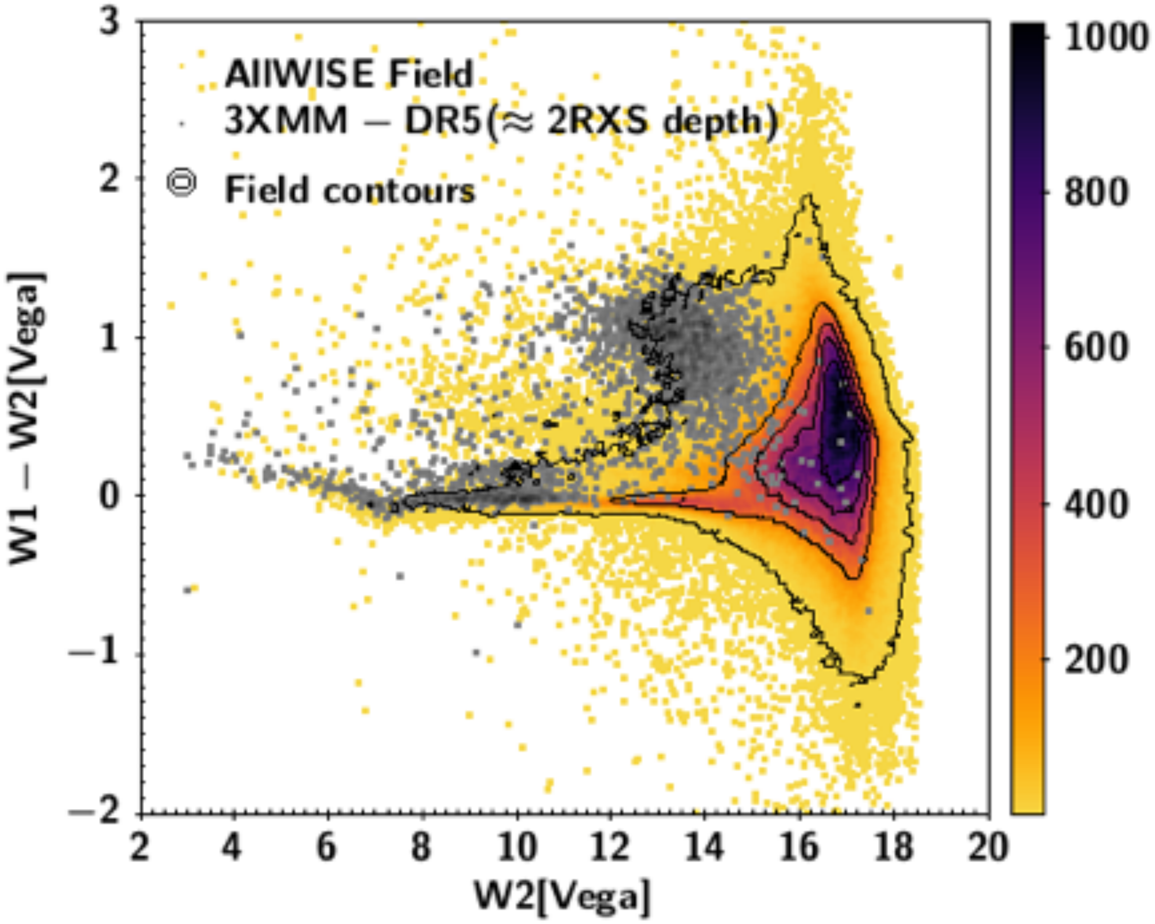


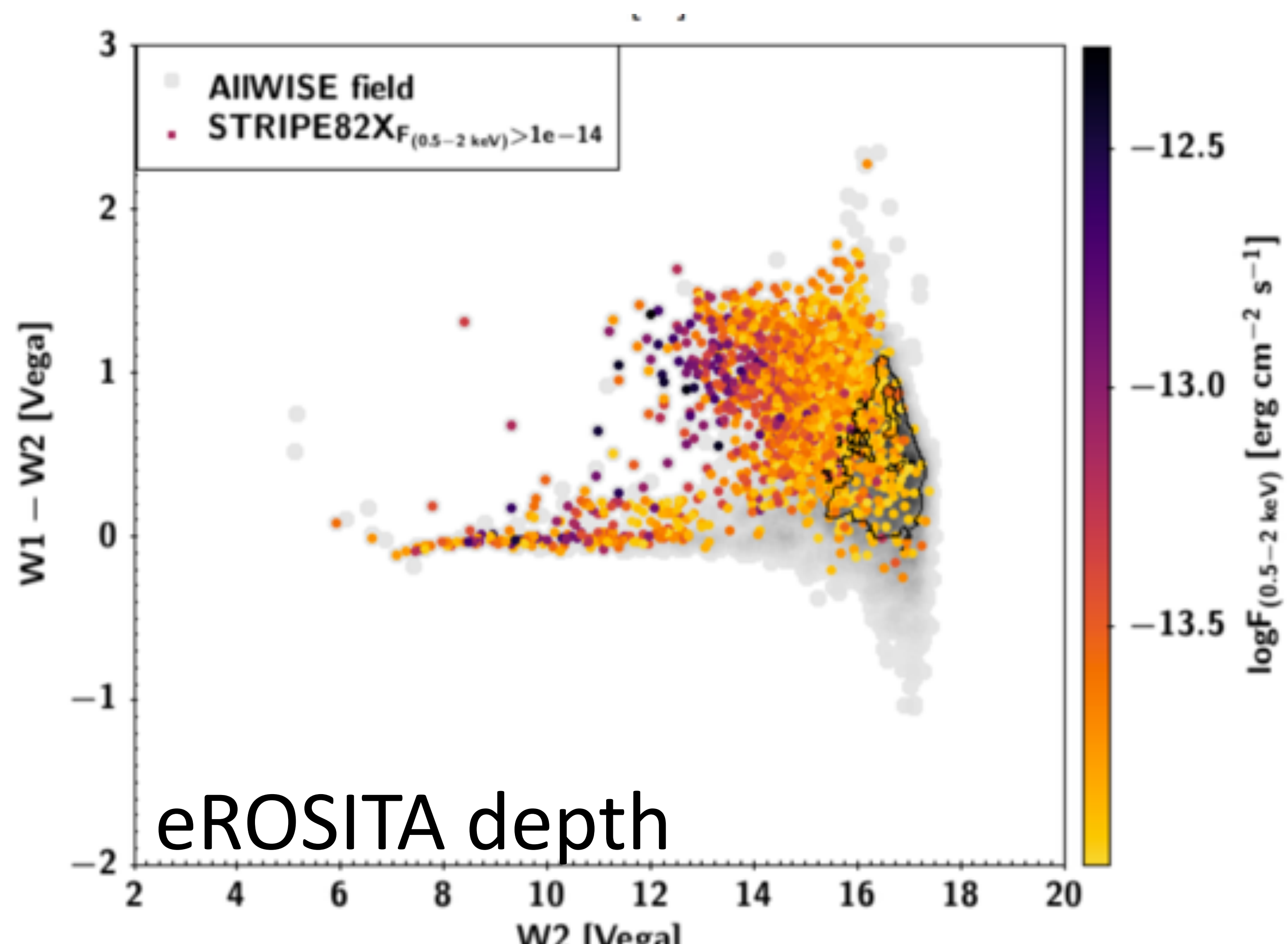
what p_any tells us :
1) is there a deblending issue?



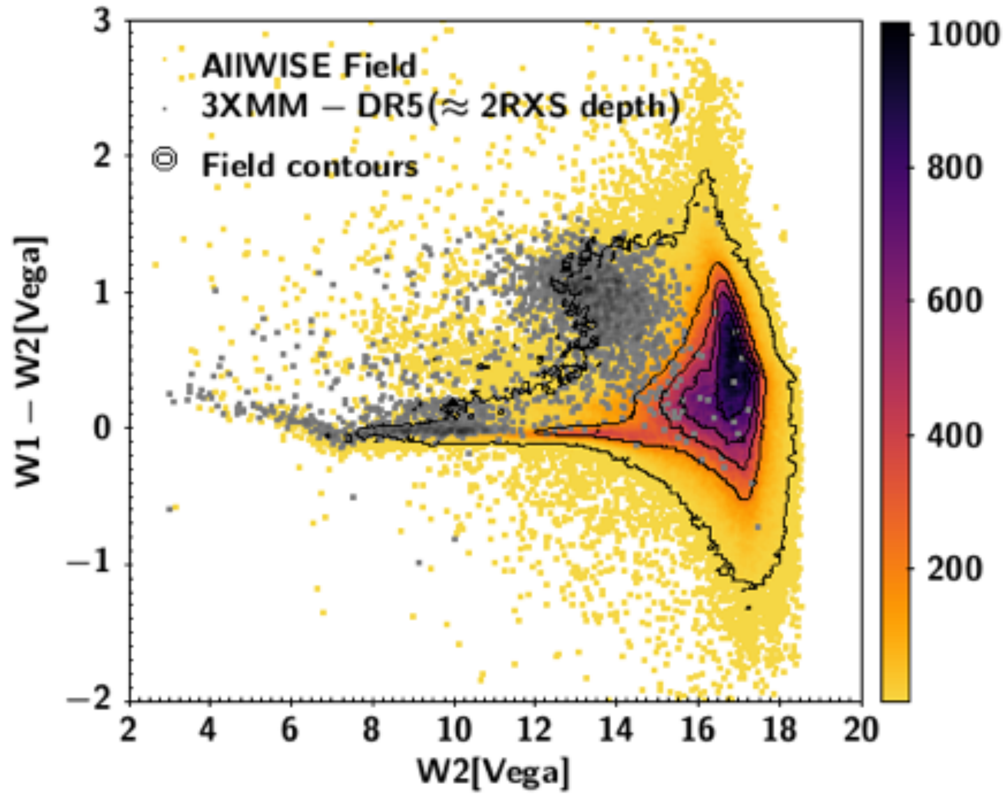


Prior must be proper

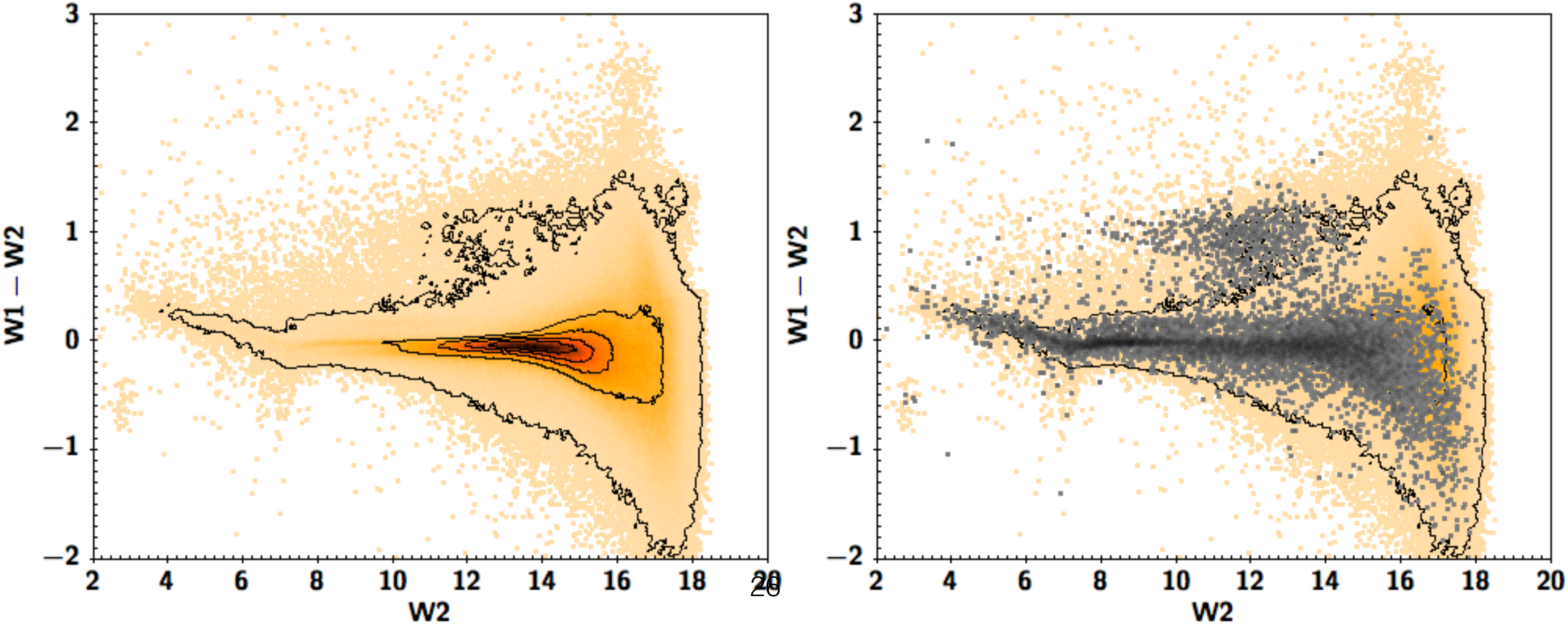




Prior must be proper!



ROSAT in the galactic plane



Summary

- NWAY provides the mean to use as much as you already know for finding the right ctp of X-ray/radio/mid-infrared/etc sources

- Choose carefull your prior: it will effect your results

- Know well your imput catalog of sources

- For each of the sources within a certain radius we provide the probability to be the right ctp. It is up to the user to decide the threshold (compromise of purity and completeness).

- https://github.com/JohannesBuchner/nway
  Nway is released together with a manual, data for training and examples of applications.