KATY MCKEOUGH

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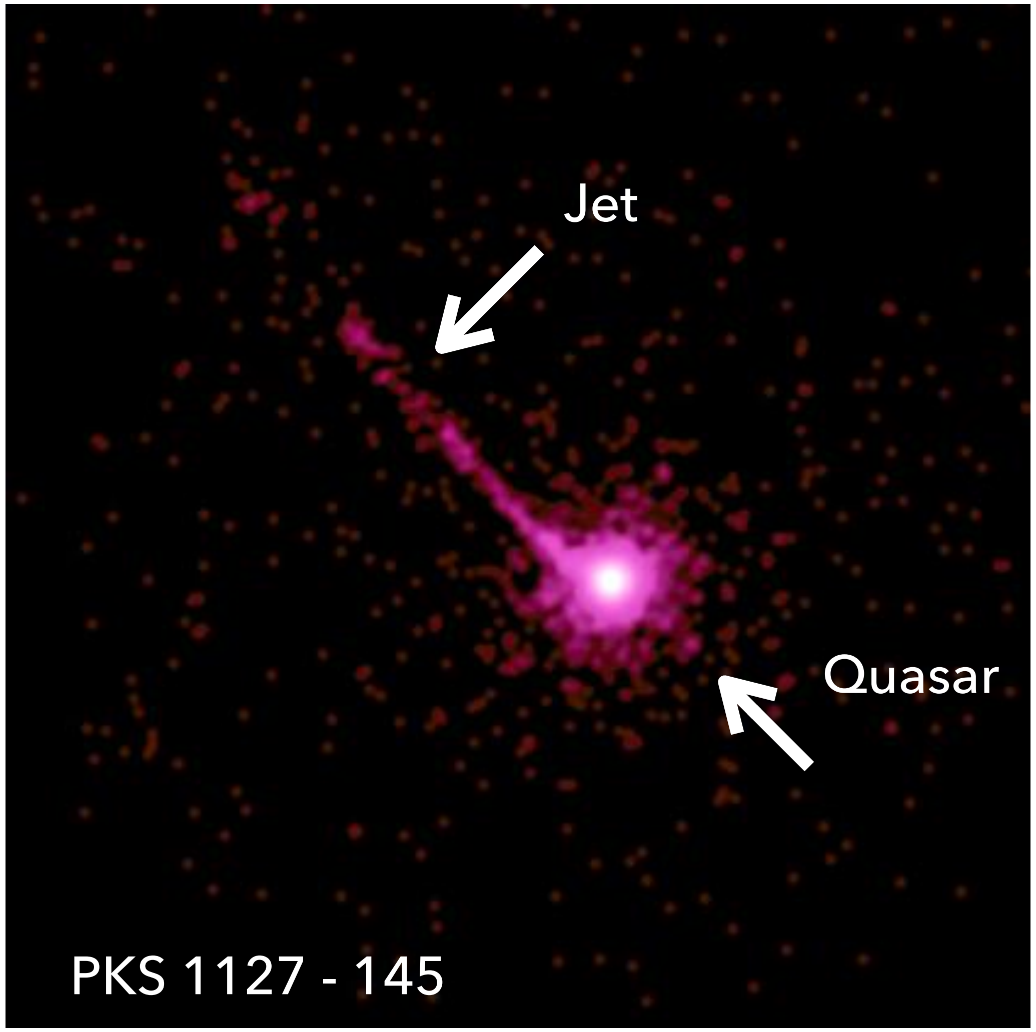
DEFINING REGIONS THAT CONTAIN COMPLEX ASTRONOMICAL STRUCTURES

SCIENTIFIC MOTIVATION

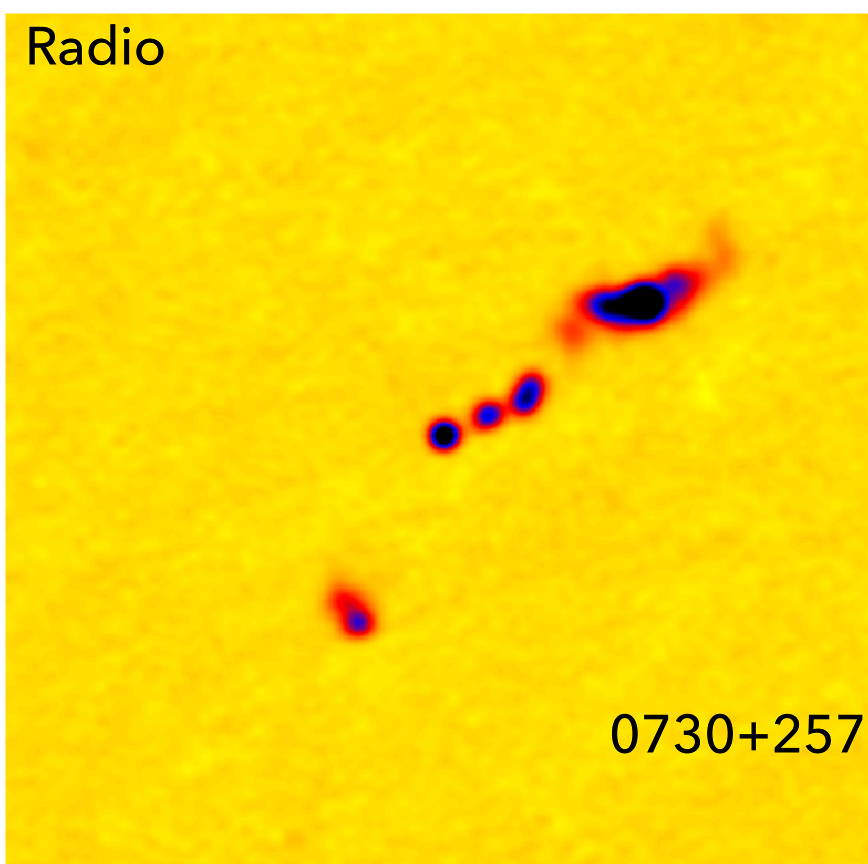
- We are interested in defining an outline around extragalactic jets coming from quasars at high redshift (z>2.1) in X-ray images
- Defining this boundary is important for accurate luminosity and flux calculations.
- Detecting jets is difficult because they are diffuse sources (no edges, or center) and dim compared to the quasar.
- Images of high redshift jets are of low resolution and few X-ray photons

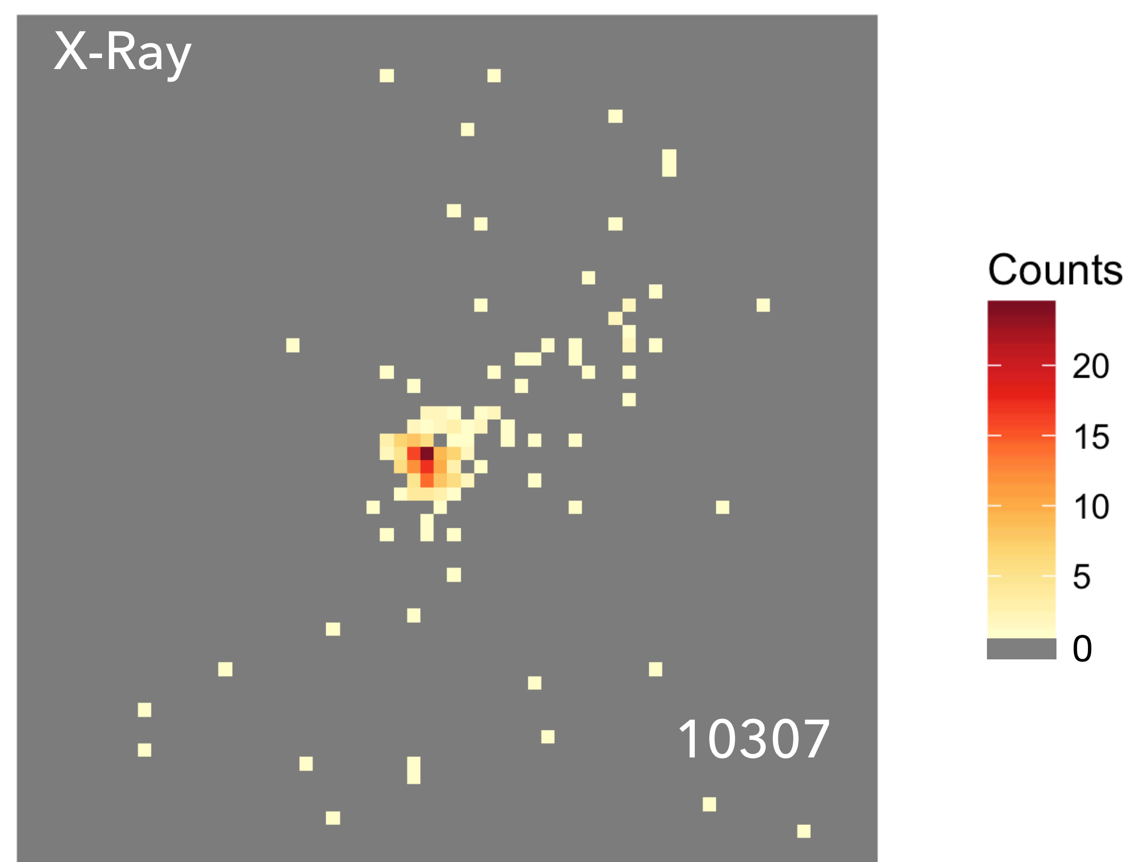


NASA/CXC/A.Siemiginowska(CfA)/
J.Bechtold(U.Arizona)

OBSERVATIONAL DATA

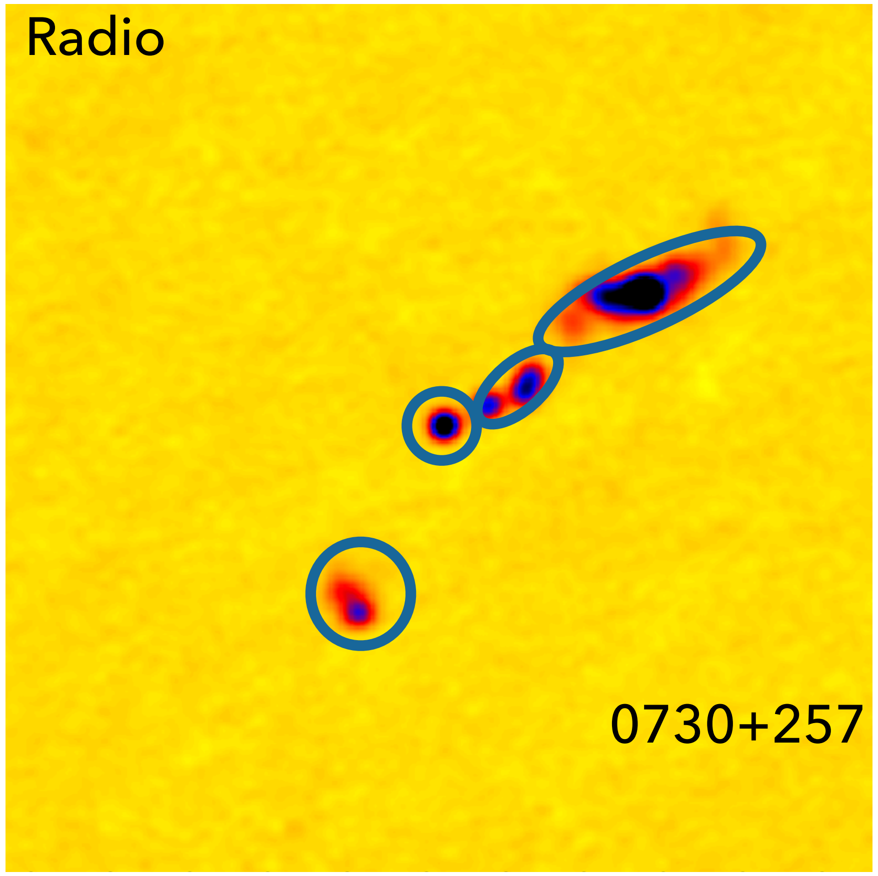
- Chandra X-ray Observatory - ACIS
- 64 x 64 or 128 x 128 pixel image centered on quasar
- High to intermediate redshift (2.10 < z< 4.72)

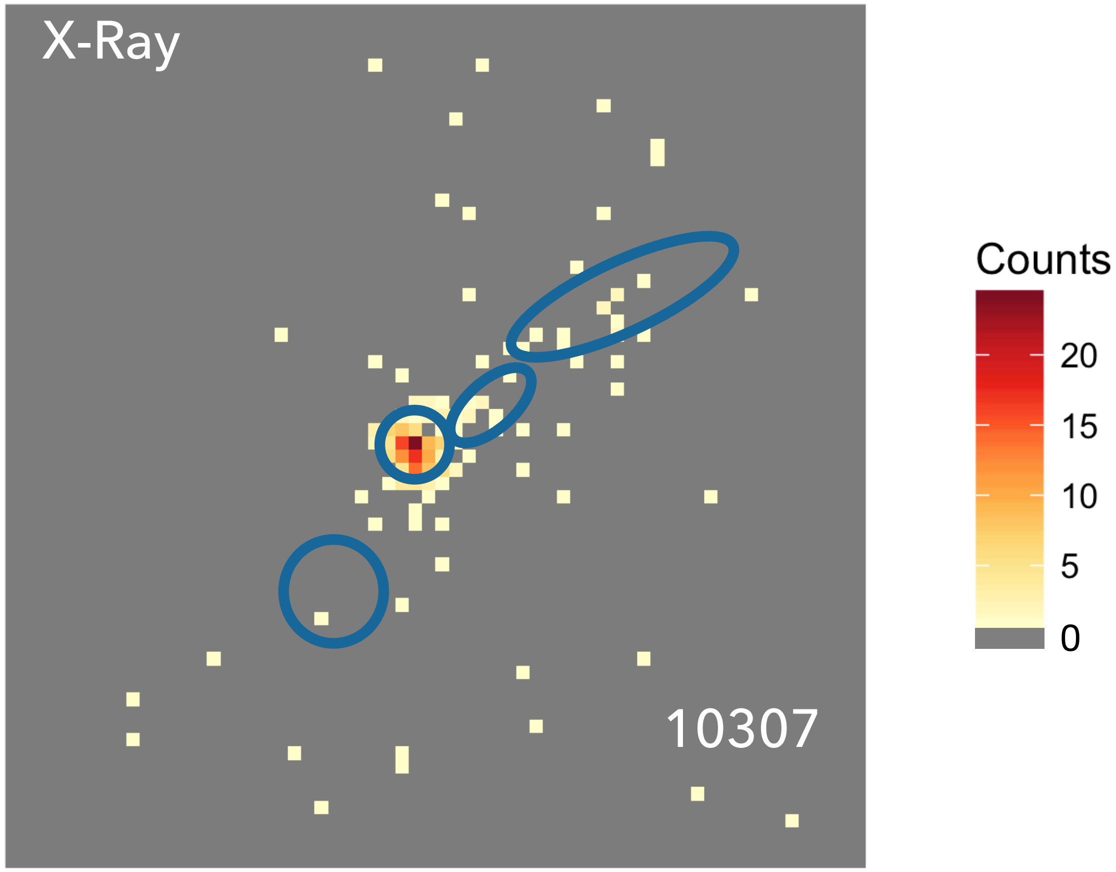




REGION OF INTEREST

- **Region of Interest (ROI)** - region containing the jet or a partition of the jet (e.g. node or lobe)
- Previous work tests whether or not a jet exists in a predefined ROI (McKeough et al. 2016, Stein et al. 2015)

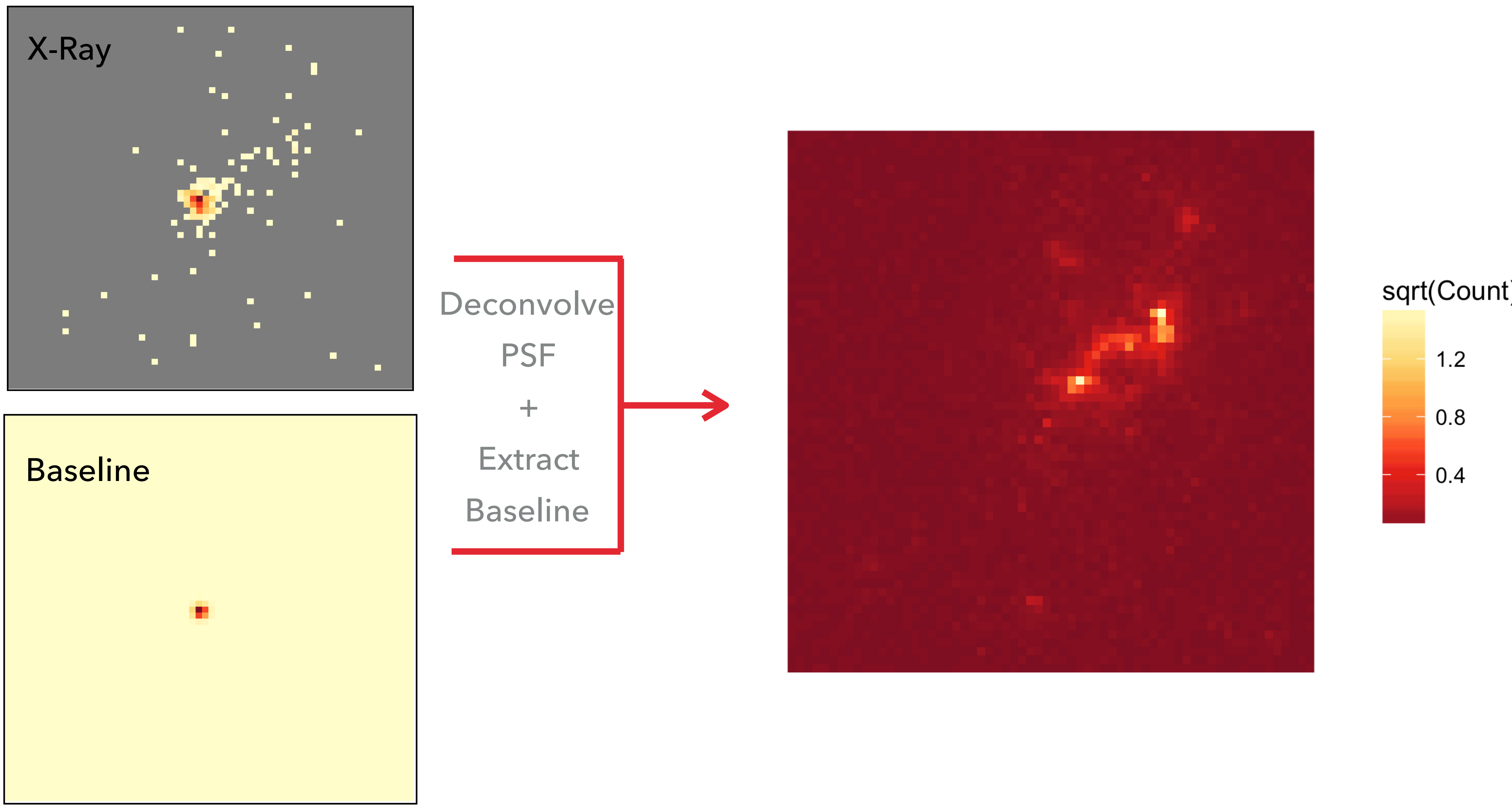




GOAL

Define a probabilistic ROI around a diffuse source as a post-processing step to LIRA.

LOW COUNT IMAGE RECONSTRUCTION AND ANALYSIS (LIRA)



LIKELIHOOD

$$\sqrt{\tilde{\lambda}_{ij}}|Z, \tau_{\pm}, \sigma^2_{\pm} \sim \text{Normal}(\tau_-, \sigma^2_-)\mathbb{I}_{z_{ij}=-1} + \text{Normal}(\tau_+, \sigma^2_+)\mathbb{I}_{z_{ij}=+1}$$

- We are given observation Y from which we draw the LIRA output: $\tilde{\lambda}|Y$
- We want to assign each pixel to either the background (-1) or the ROI (+1): $z_{ij} = \{-1, +1\}$
- Each pixel assignment will have its own average intensity: τ_-, τ_+
- We suspect the variance of the source will be greater than the background: σ^2_-, σ^2_+

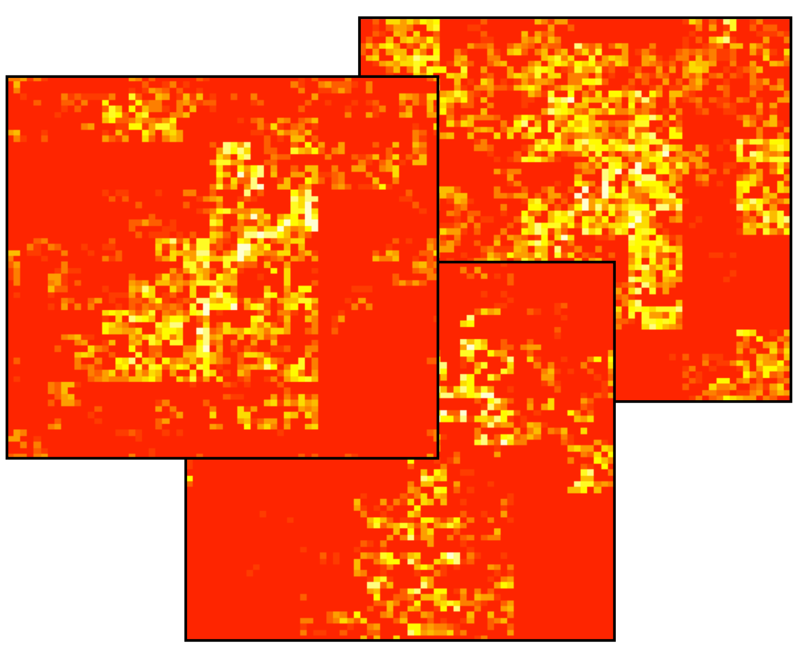
2D ISING PRIOR

$$p(z|\beta) = \frac{\exp(\beta \sum_{ij,i'j' \in |ij-i'j'|=1} z_{ij} z_{i'j'})}{\tilde{Z}(\beta)}$$

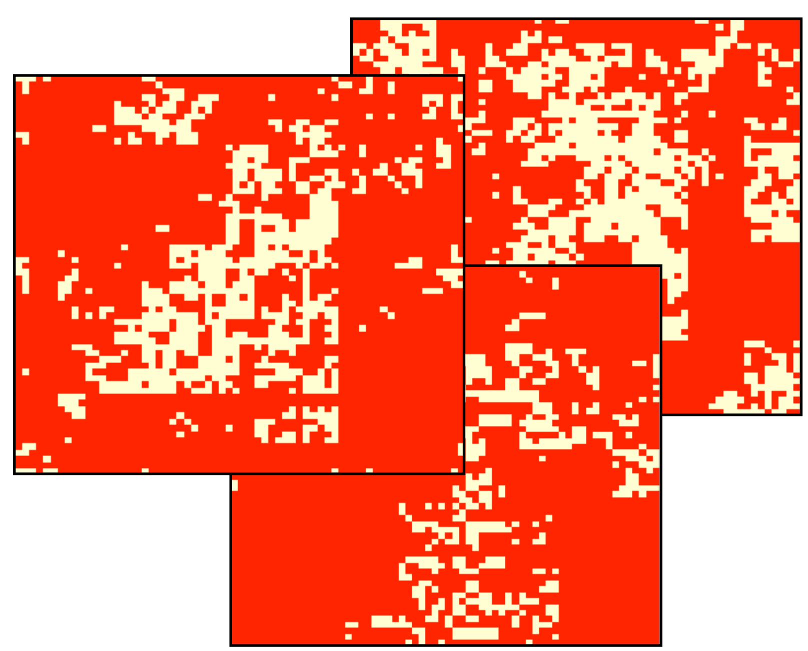
- Inverse temperature: β
  - Higher β induces more correlation between pixels
- Partition function: $\tilde{Z}(\beta)$
  - Estimated via Beale (1996) assuming periodic structure
- Commonly used in modeling ferromagnetism.
- Induces spatial correlation; adjacent pixels will tend to have the same assignment.

ISING-LIRA ITERATIONS

1. Get many posterior draws from LIRA
2. Apply Ising step to each LIRA draw
3. Average across LIRA-Ising iterations to get probability map.



1



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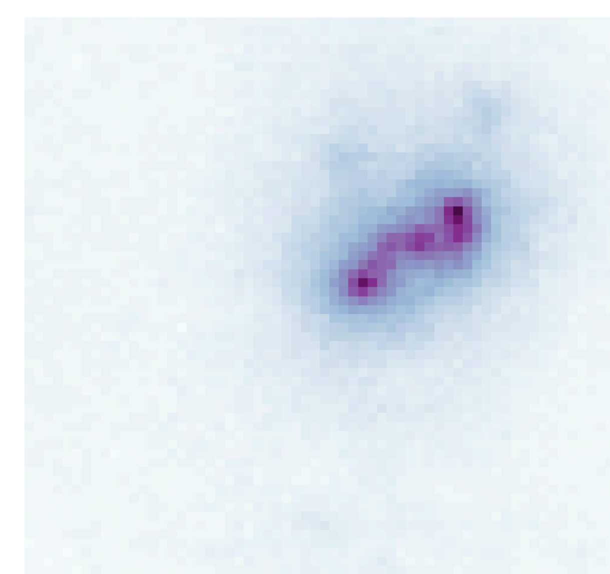
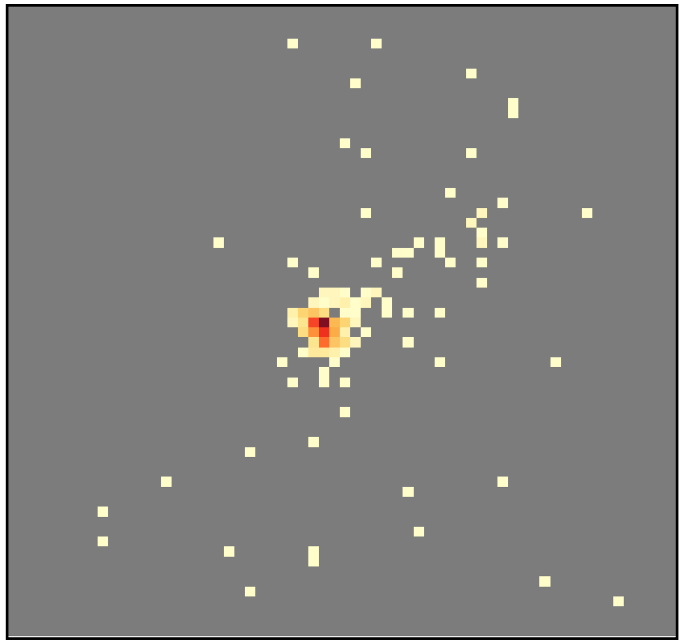
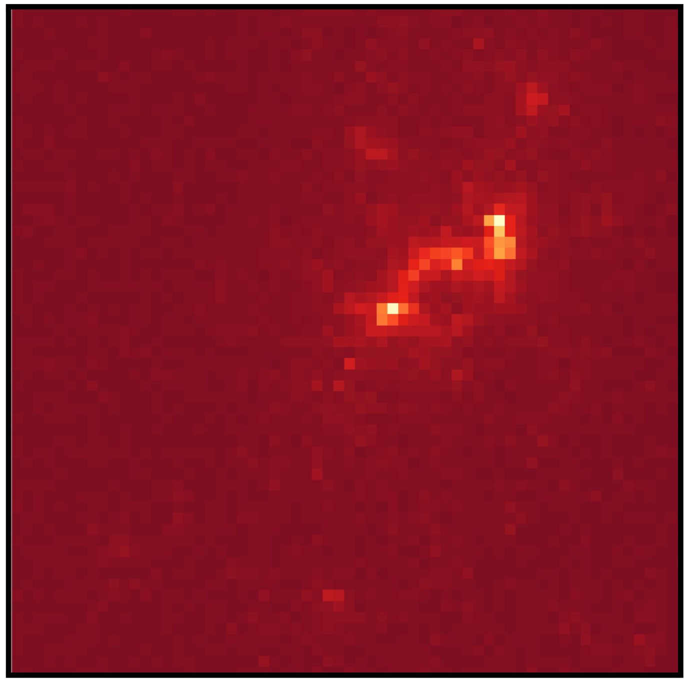


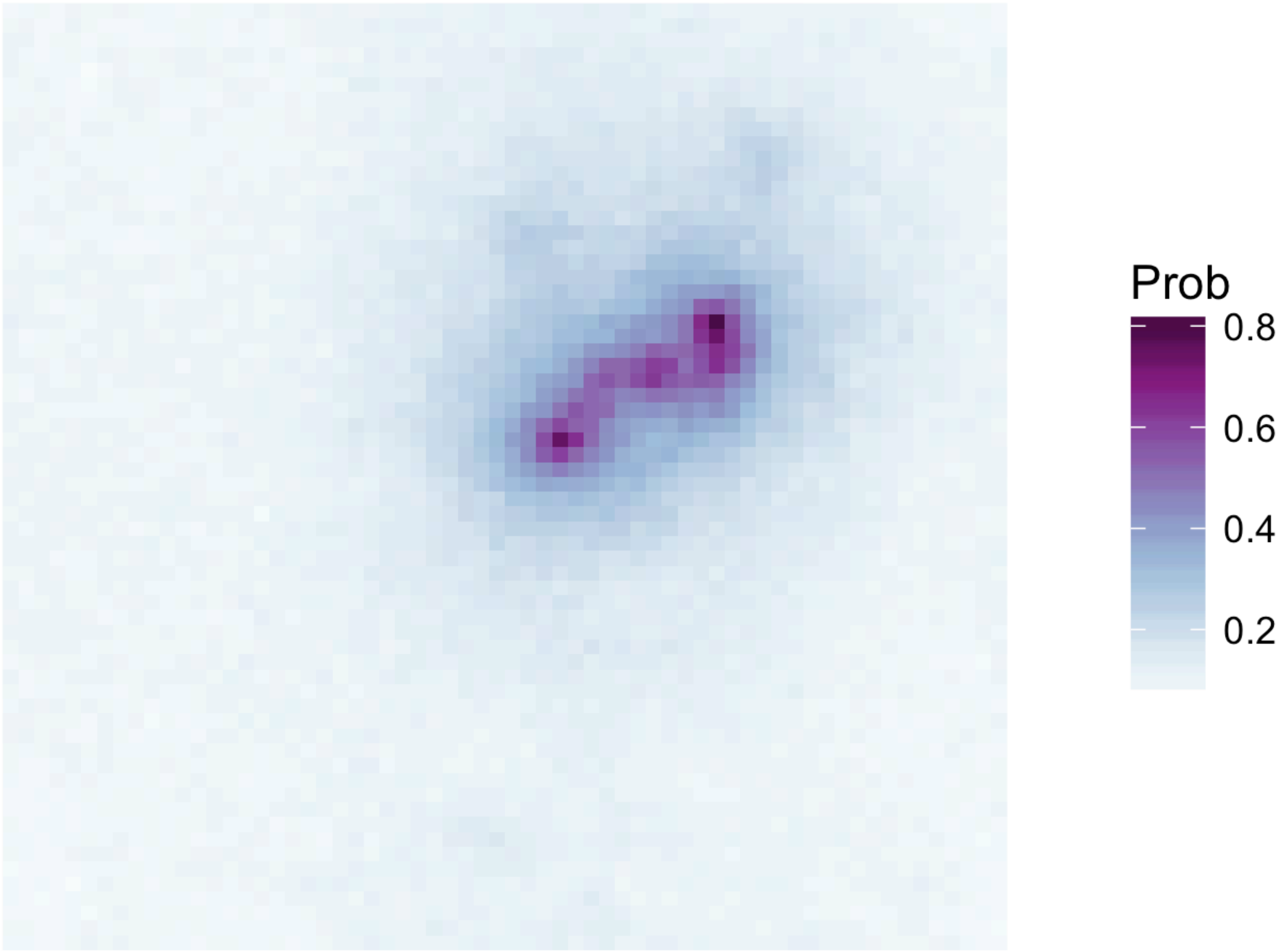
3

PROBABILITY MAP

- Probability each pixel is a member of the ROI:







LOCATION PROBABILITY

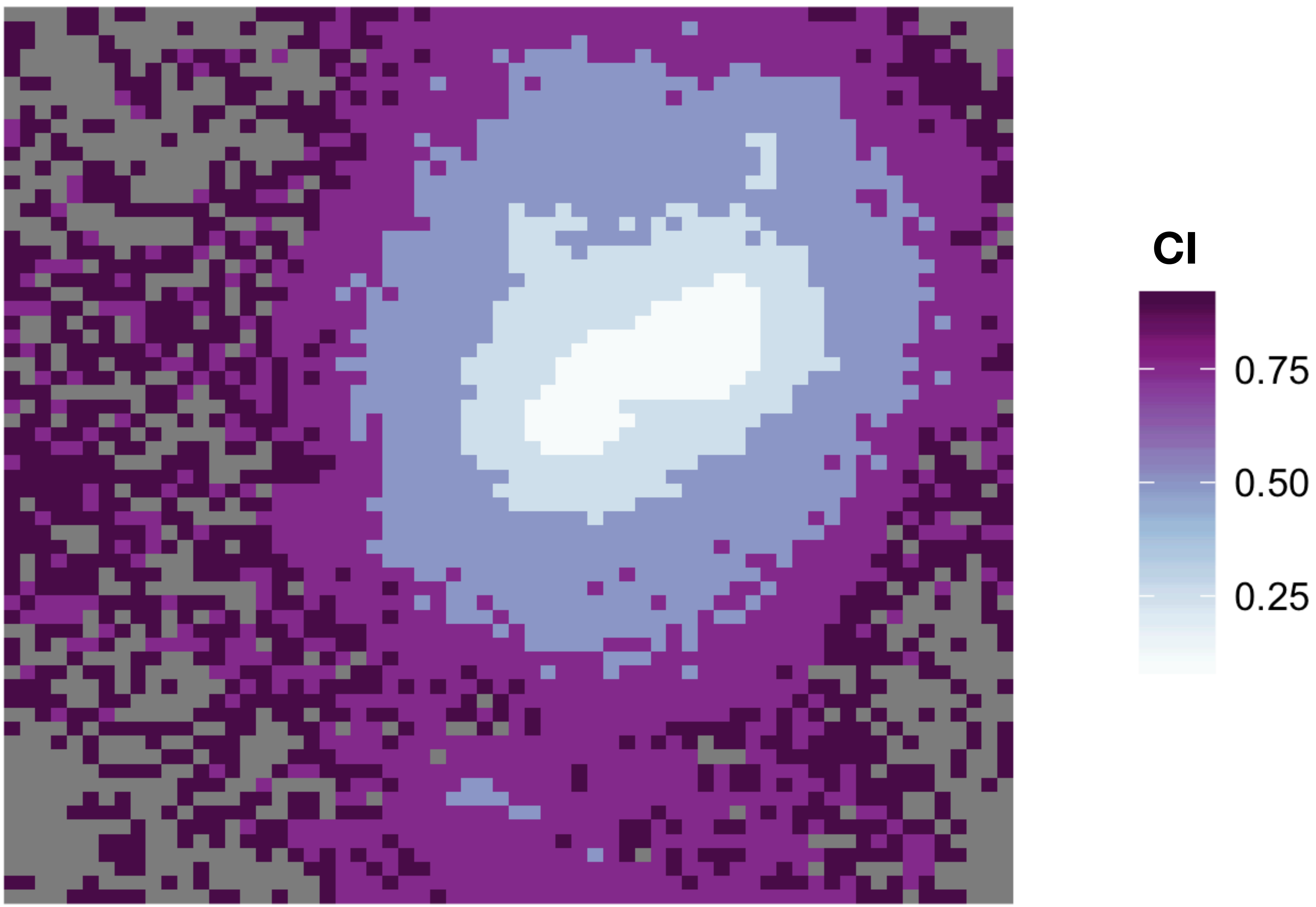
- Think about location as a random variable

$$P(z_{ij} = 1|-) \quad \rightarrow \quad P(z = 1|l = (i,j), -)$$

- Transform to probability ROI is in location *(i,j)*

$$P(l = (i,j)|z = 1) \quad = \quad \frac{P(z = 1|l = (i,j))}{\sum_{ij} P(z = 1|l = (i,j))}$$

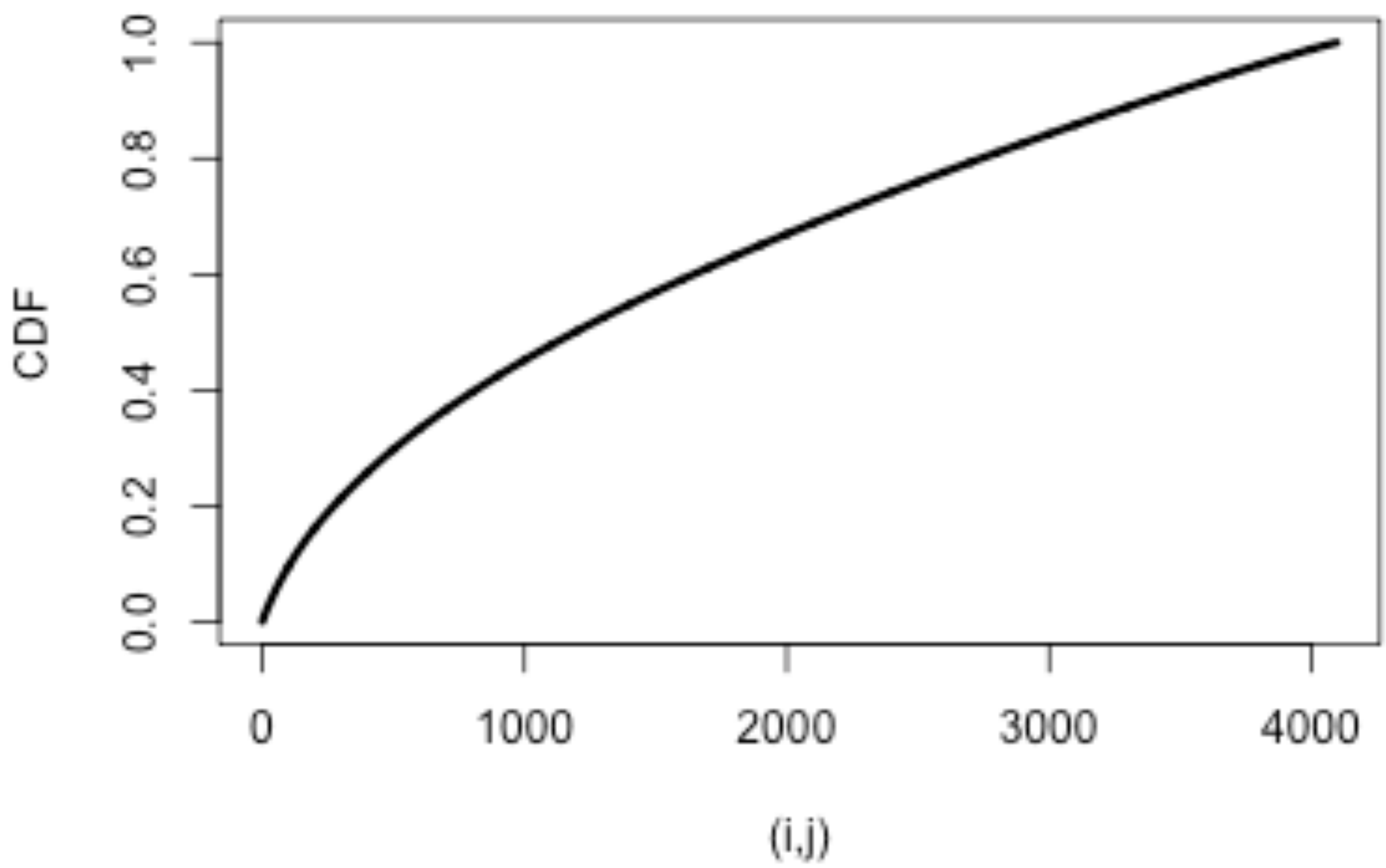
LOCATION PROBABILITY - CREDIBLE INTERVALS



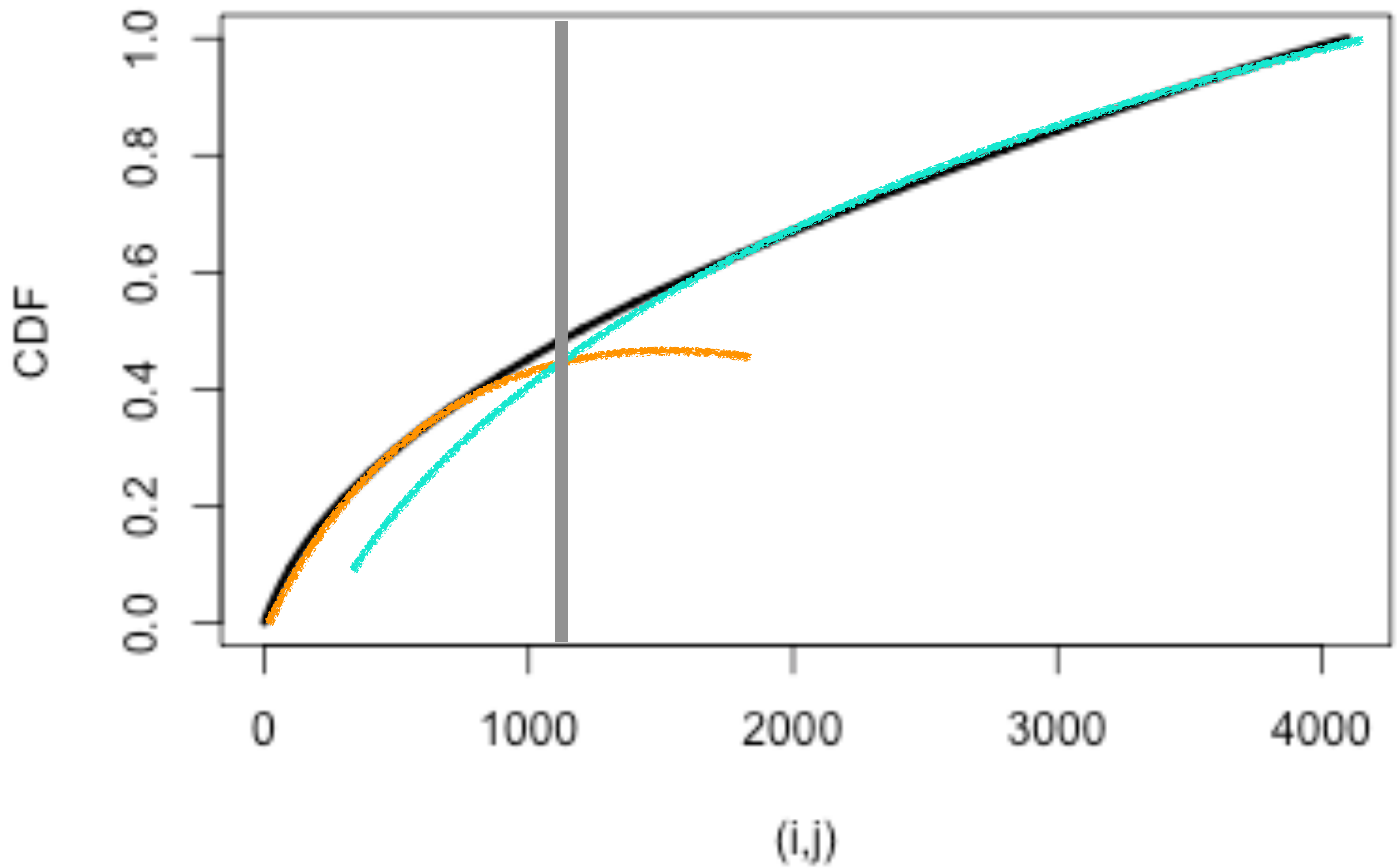
DROPPING POINT

- **Dropping Point** - The point where the ROI becomes indistinguishable from the background
- Can be defined as a change point in the ordered CDF of the location

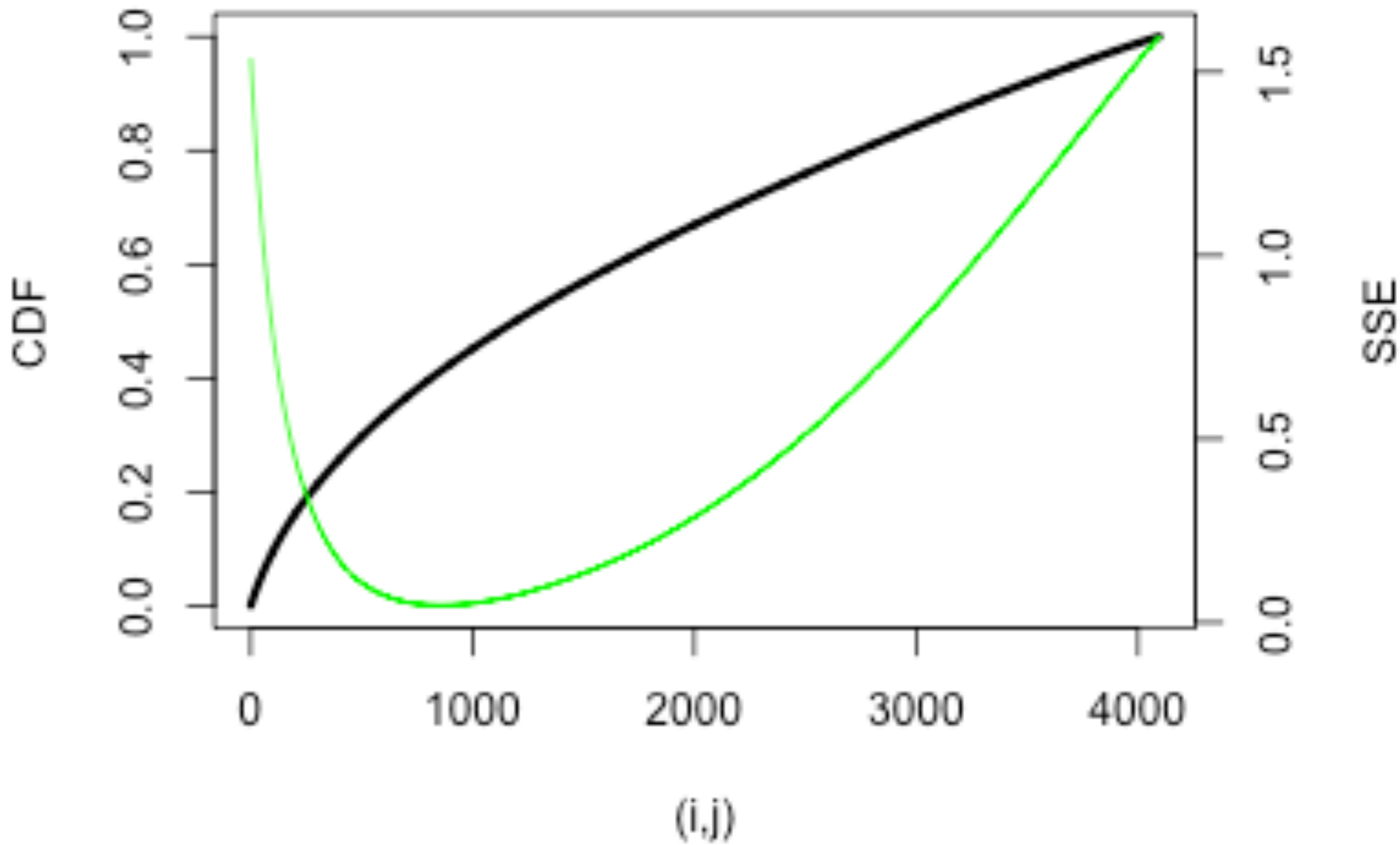
ORDERED LOCATION CDF



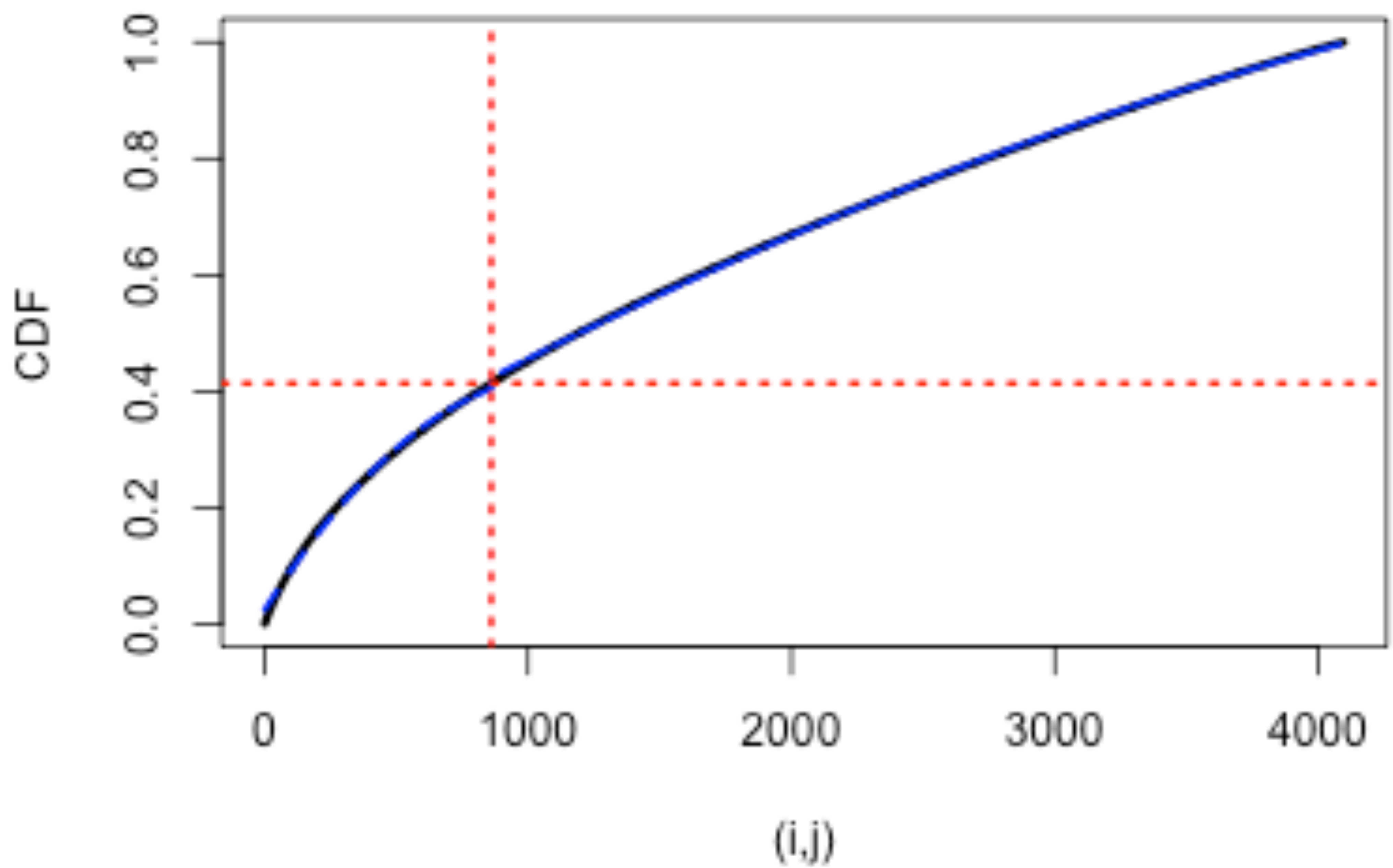
FINDING DROPPING POINT



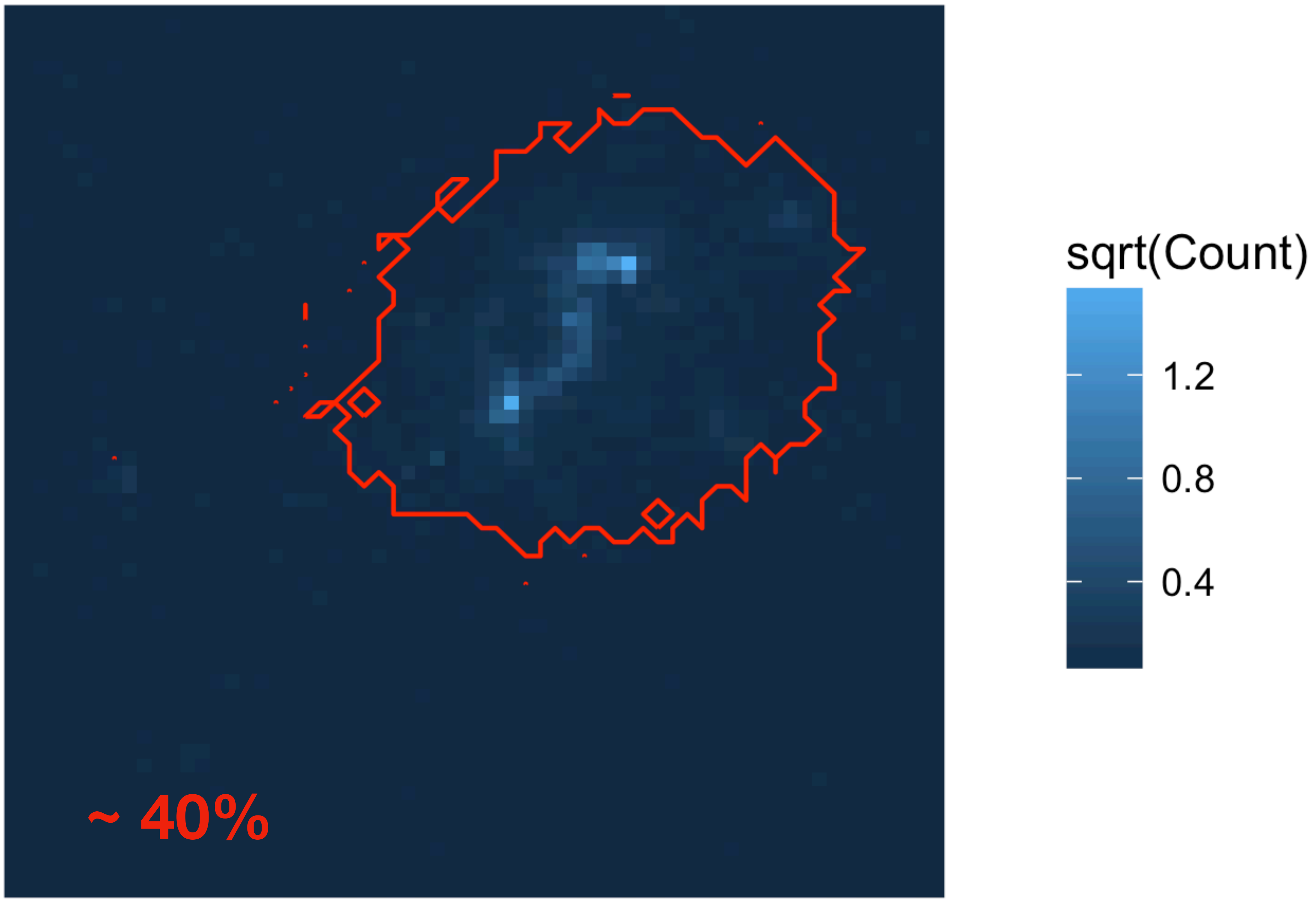
FINDING DROPPING POINT



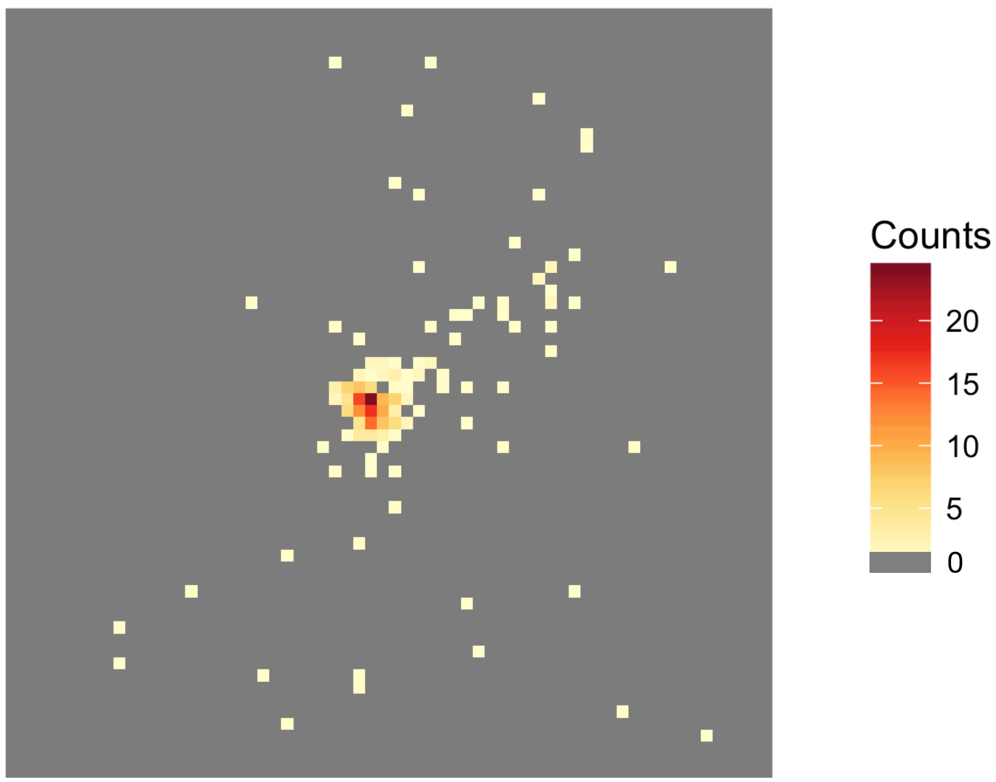
DROPPING POINT

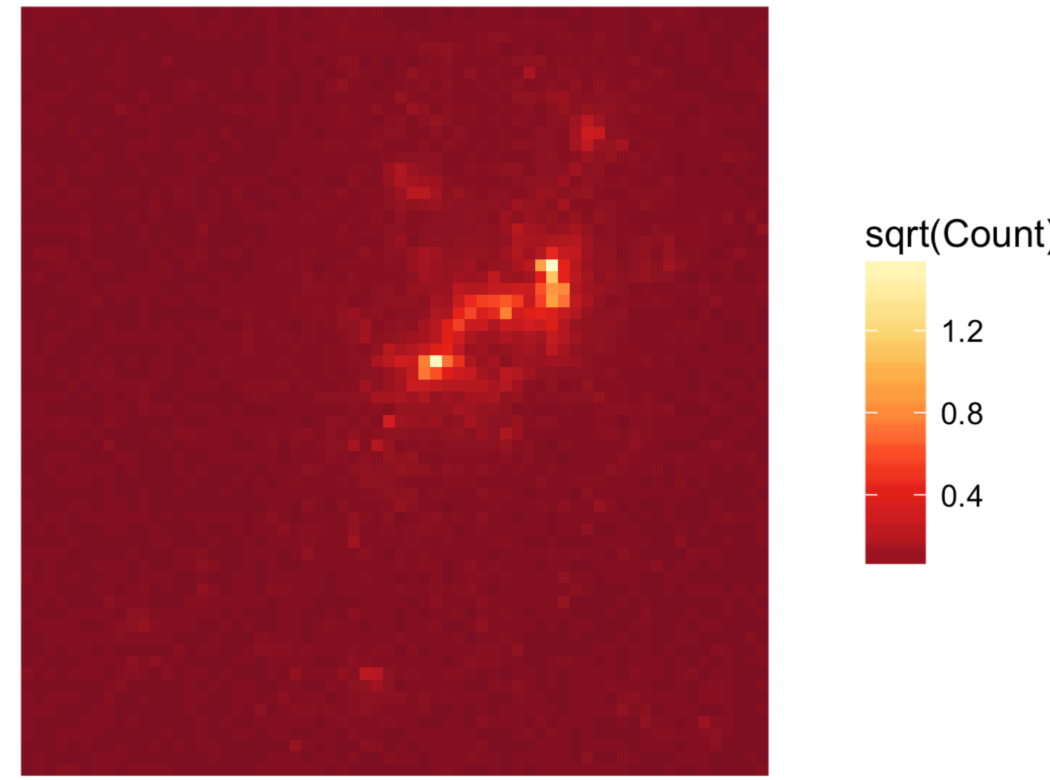


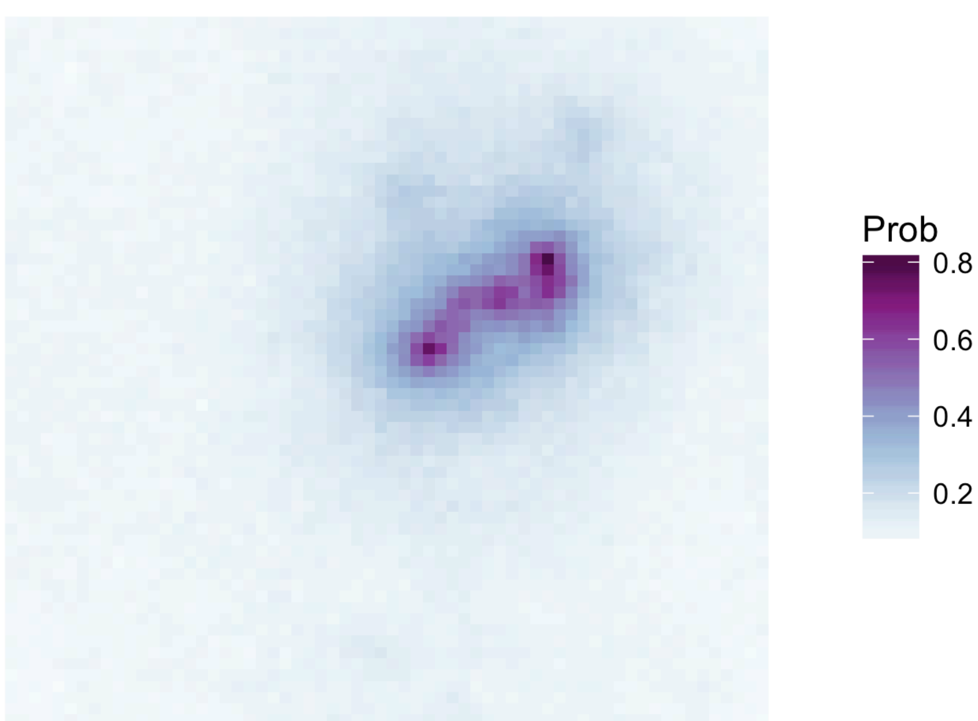
DROPPING POINT – BOUNDARY ESTIMATE

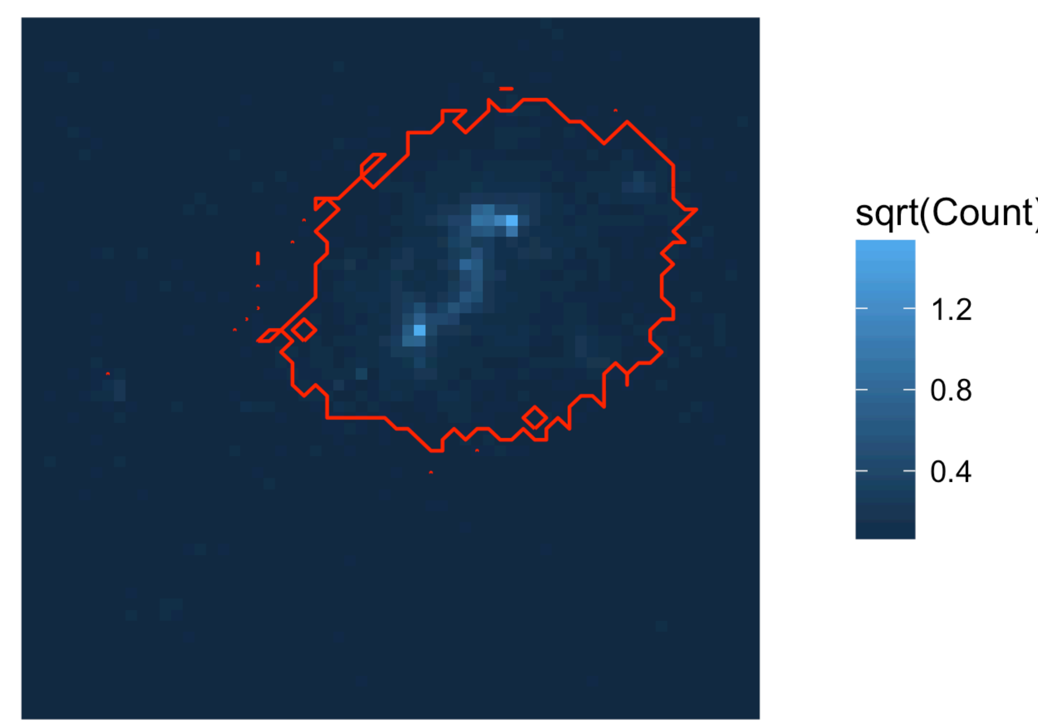


RESULTS


Counts
20
15
10
5
0


sqrt(Count)
1.2
0.8
0.4


Prob
0.8
0.6
0.4
0.2


sqrt(Count)
1.2
0.8
0.4

Joint Model

$$P_{\mathcal{J}}(\tilde{\lambda}, z|Y) \propto f(Y|\tilde{\lambda}, z)\pi_{\mathcal{J}}(\tilde{\lambda}, z)$$

Multi-Step Process

$$\begin{aligned} P_{\mathcal{S}}(\tilde{\lambda}, z|Y) &= P_{\mathcal{S}_1}(\tilde{\lambda}|Y)P_{\mathcal{S}_2}(z|\tilde{\lambda}) \\ &\propto f(Y|\tilde{\lambda})\pi_{\mathcal{S}_1}(\tilde{\lambda})\frac{P_{\mathcal{S}_2}(\tilde{\lambda}|z)\pi_{\mathcal{S}_2}(z)}{P_{\mathcal{S}_2}(\tilde{\lambda})} \end{aligned}$$

REFERENCES

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