Adaptive Smoothing

Why smoothing ?

Does not need much justification:

- Bring up low-significance features for further analysis
- Identify features of interest
- Create visually pleasing images

The simple solution

Smooth with a fixed kernel

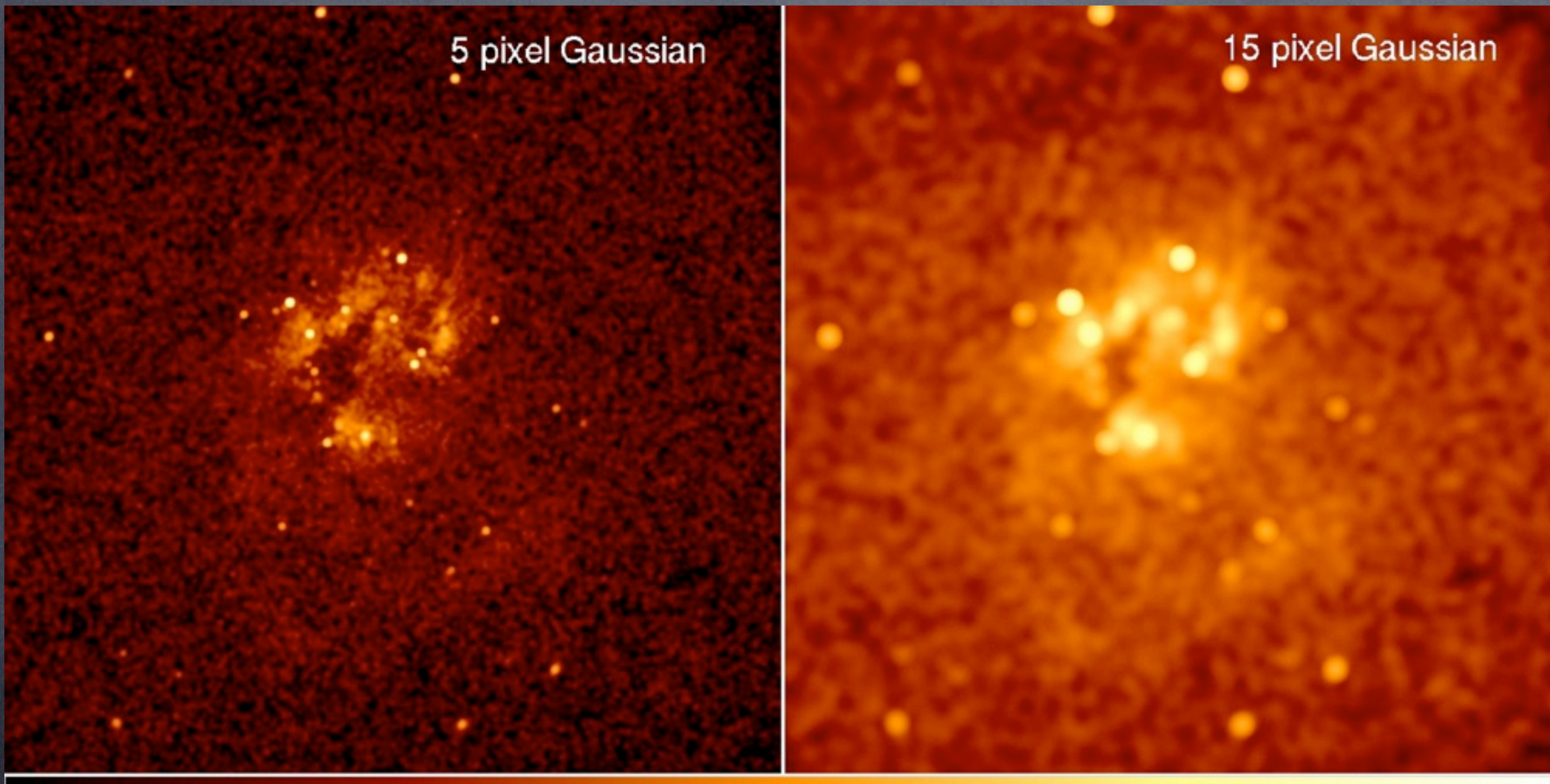
Advantages

- Simple
- Fast
- Can calculate loss of flux

Disadvantages

- Too simple
- It is nor flexible for sources of different intensity

A few examples



The next level up

Smooth with a variable (adaptive) kernel

Advantages

Adjustable to sources of different intensity

Can link to source significance and feature identification/detection

Visually pleasing

Disadvantages

Not statistically sound (esp. in Poisson regime)

Does not preserve flux

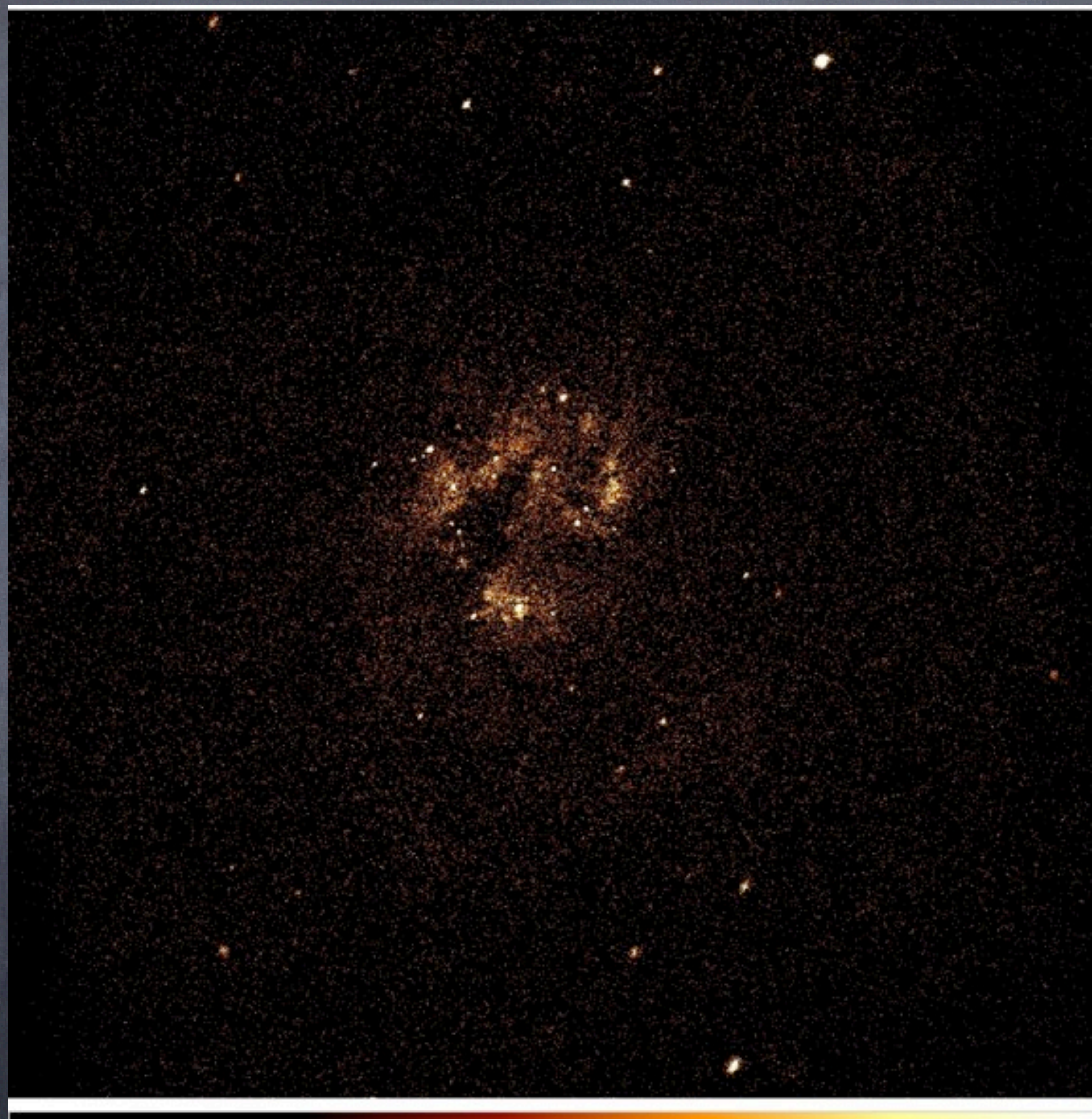
Interpretation of images not clear

Slow

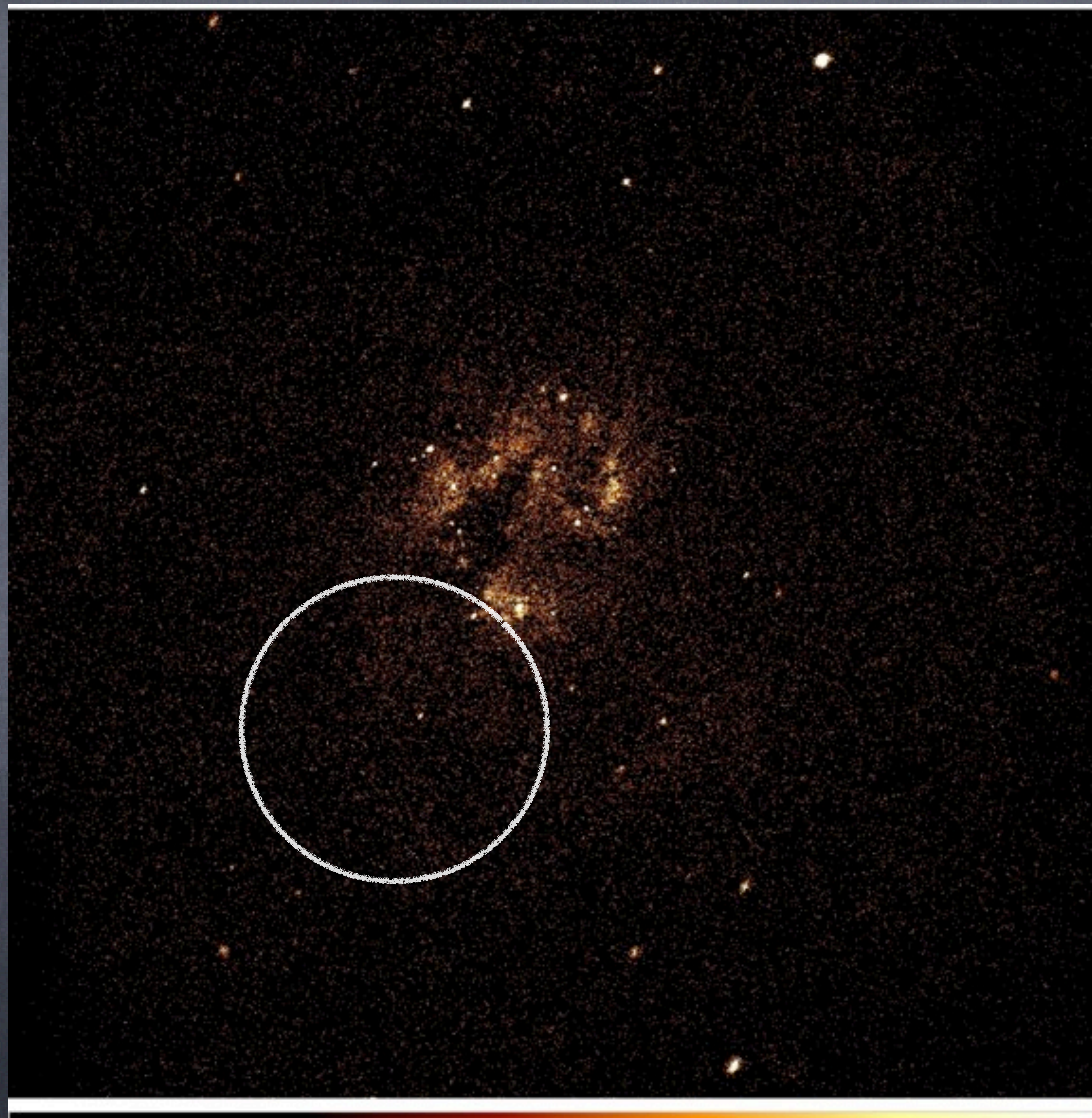
Adaptive smoothing flow-chart

- Set S/N threshold and smallest kernel size
- Identify brightest pixels
- Measure local background
- Smooth with smallest kernel
- Go to next brightest pixels (ignore smoothed pixels)
- Increase kernel size (area) until desired S/N is reached
- Repeat until all pixels are smoothed

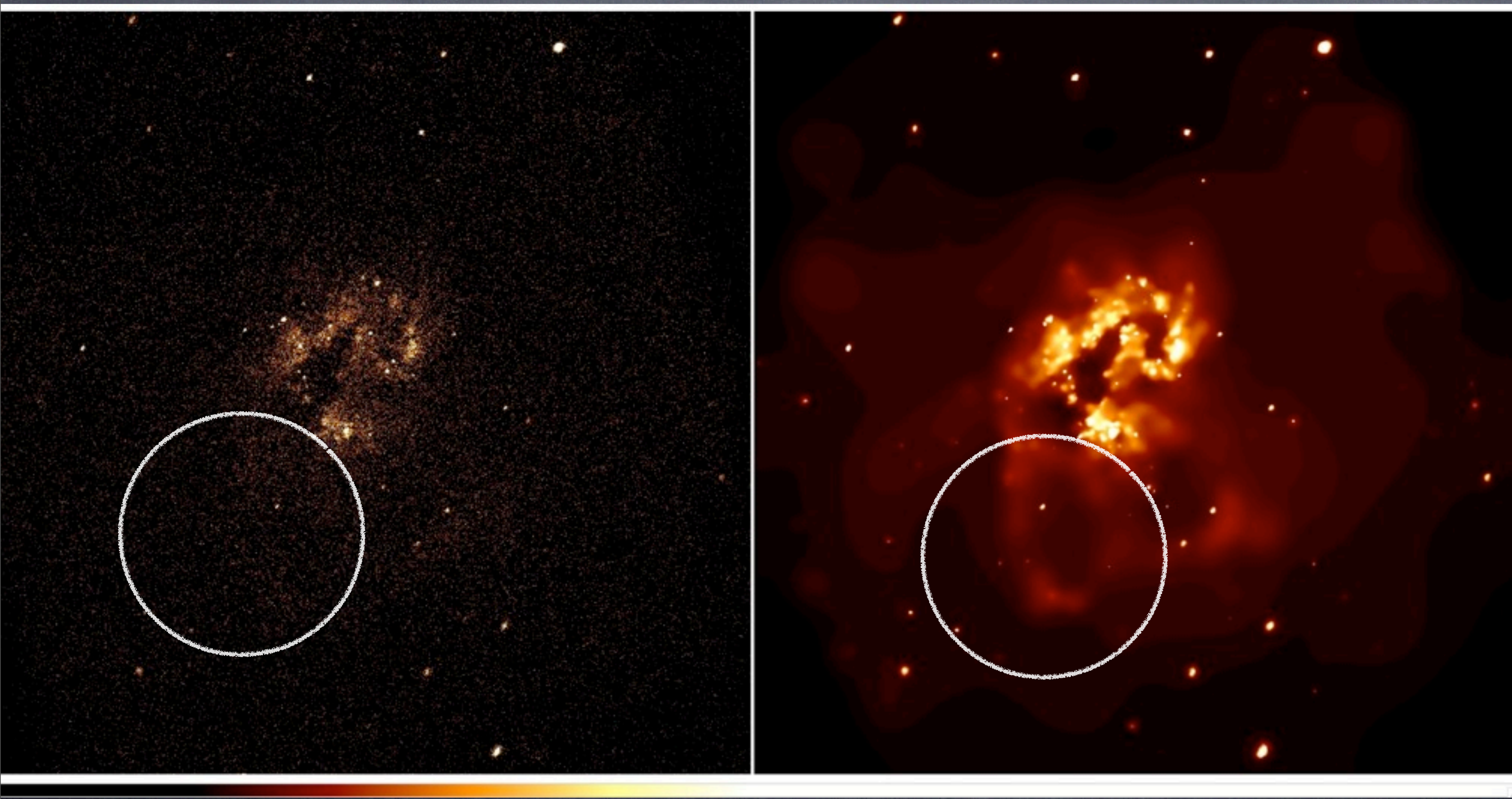
A few examples



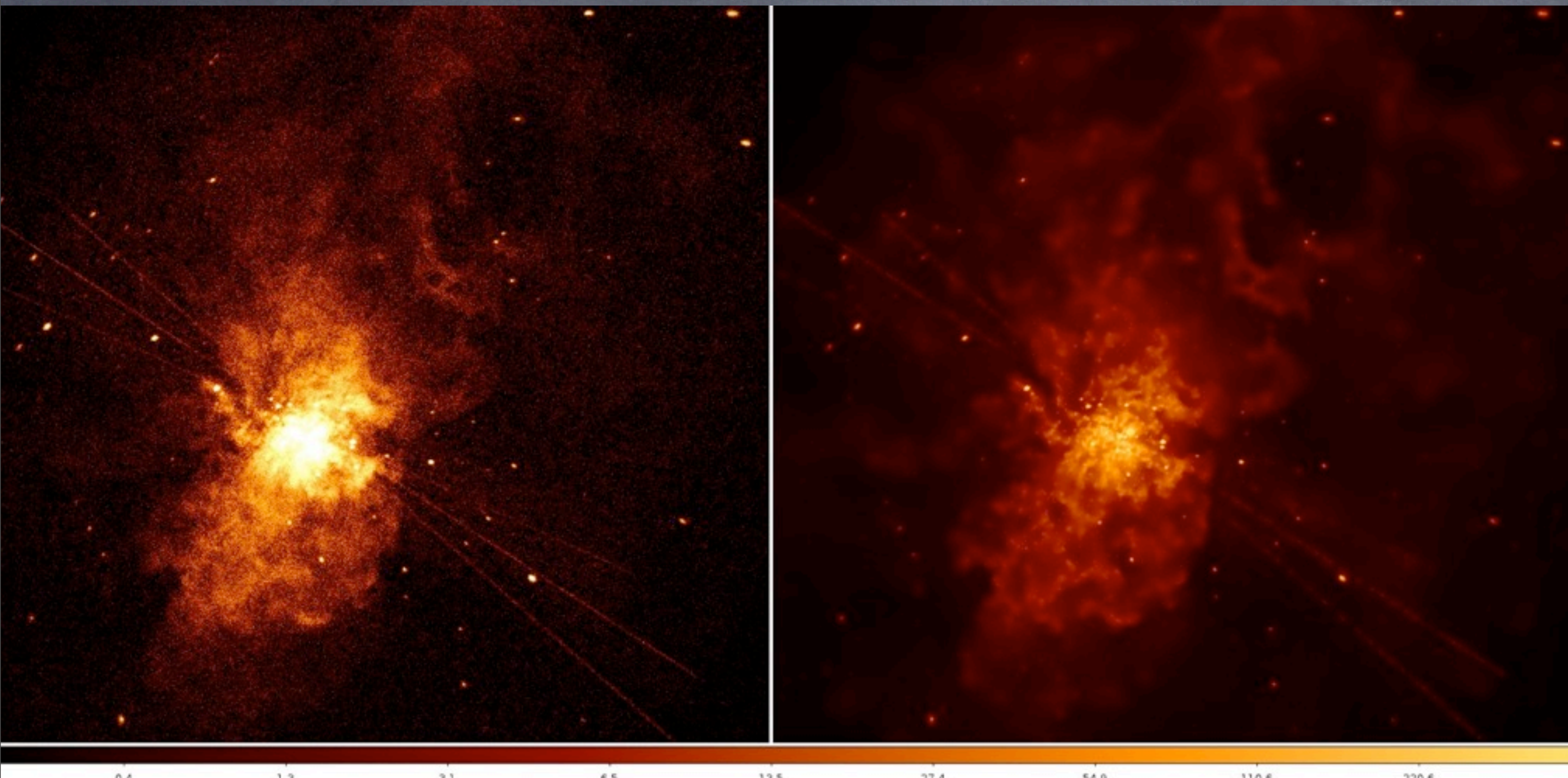
A few examples



A few examples



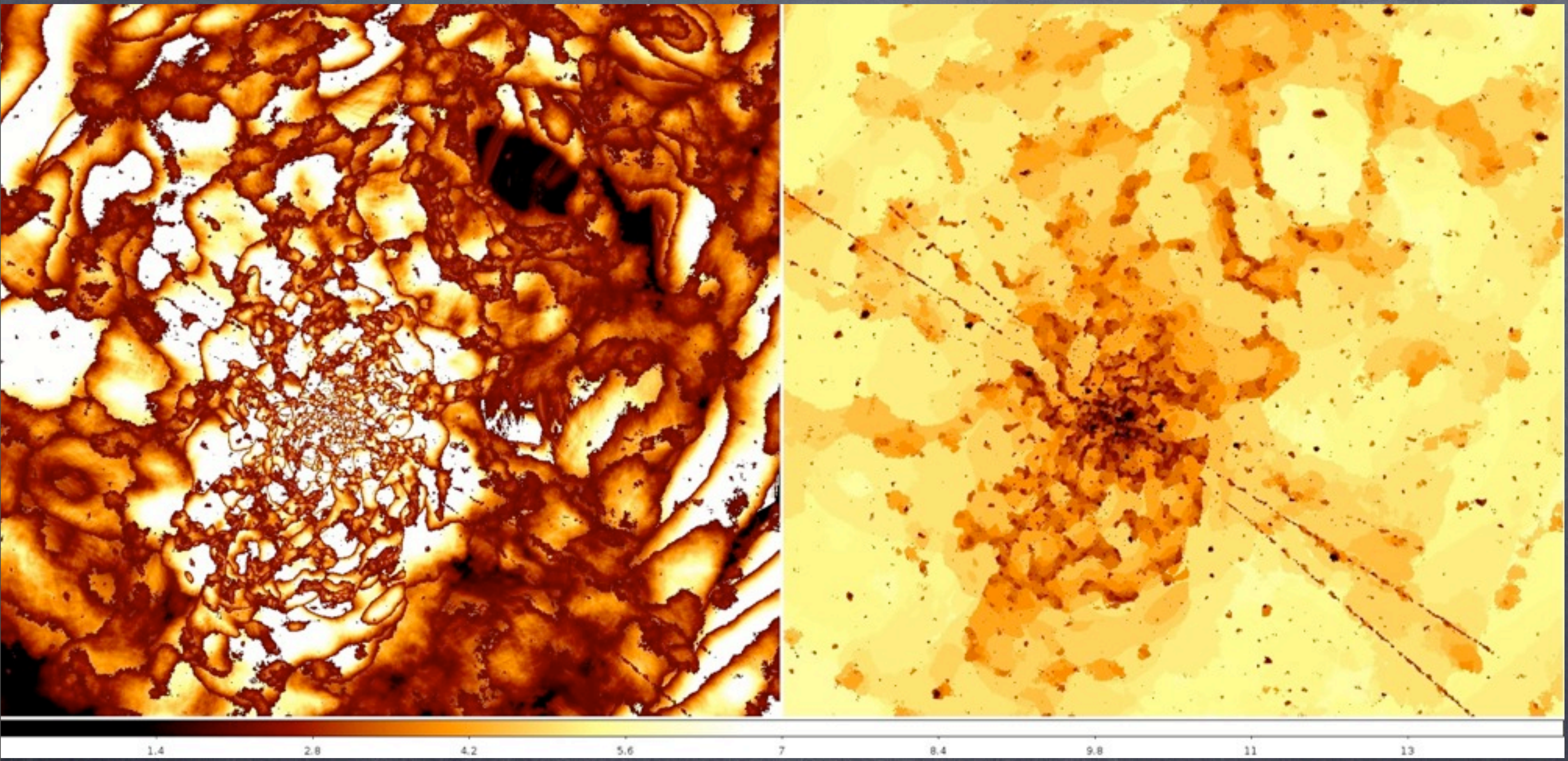
A few examples



Before

After

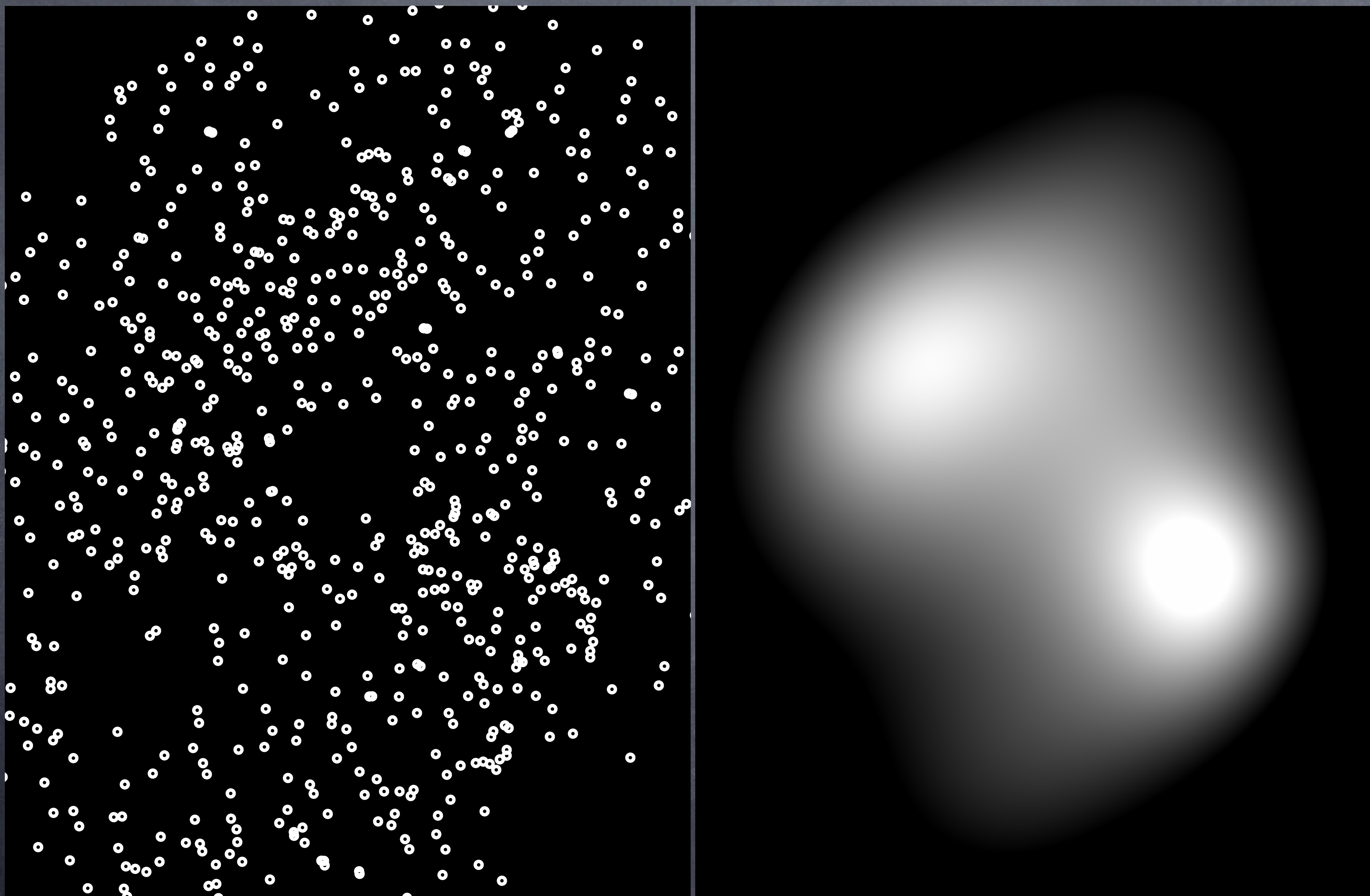
A few examples



Significance

Scales

And non-standard applications...



Complications

- Background (often variable)
- Low number of counts (Poisson regime)
- Need to preserve flux
- Uncertainties ?

What we need

A smoothing method that:

- is statistically correct in the Poisson regime
- it can deal with (non-uniform) background
- it can be used for the identification of features above a given S/N
- it is fast
- it produces visually "nice" results (if possible)

Several methods developed for the “smoothing” of 1D data.

Need : extension to 2D space
Application to Poisson regime