Super-Resolution for Bright XMM-Newton Sources

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What is Super-Resolution (SR)?

Super-resolution example from Google Brain Team's SR3 (https://arxiv.org/pdf/2104.07636.pdf)

- Digital image processing technique to enhance the resolution of images beyond their original quality
- Approaches:
  - Classical techniques
  - Deep-learning based techniques
- Applications:
  - Medical imagery
  - Surveillance
  - Restoring pictures
  - Satellite images

How is Super-Resolution Useful for Us?

- Super-resolution **cannot**
  - provide unambiguous output images
  - provide outputs that can be used for analyses such as spectra

- However, it **can**
  - learn common noise and distortion patterns
  - provide a perceptual improvement in image clarity
  - increase the confidence about the presence of certain features (e.g. for deblending)

Super-Resolution can serve as a visual explorative tool and provide inspiration and more confidence for new proposals!

XMM-DeNoise and XMM-SuperRes

Deep Learning-Based Super-Resolution and De-Noising for XMM-Newton Images

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ABSTRACT

The field of artificial intelligence based image enhancement has been rapidly evolving over the last few years and is able to produce impressive results on non-astronomical images. In this work we present the first application of Machine Learning based super-resolution (SR) and de-noising (DN) to enhance X-ray images from the European Space Agency's *XMM-Newton* telescope. Using *XMM-Newton* images in band [0.5,2] keV from the European Photon Imaging Camera pn detector (EPIC-pn), we develop *XMM-SuperRes* and *XMM-DeNoise* — deep learning-based models that can generate enhanced SR and DN images from real observations. The models are trained on realistic *XMM-Newton* simulations such that *XMM-SuperRes* will output images with two times smaller point-spread function and with improved noise characteristics. The *XMM-DeNoise* model is trained to produce images with 2.5× the input exposure time from 20 to 50 ks. When tested on real images, DN improves the image quality by 8.2%, as quantified by the global peak-signal-to-noise ratio. These enhanced images allow identification of features that are otherwise hard or impossible to perceive in the original or in filtered/smoothed images with traditional methods. We demonstrate the feasibility of using our deep learning models to enhance *XMM-Newton* X-ray images to increase their scientific value in a way that could benefit the legacy of the *XMM-Newton* archive.

- Super-Resolution Neural Network effectively increasing exposure time and resolution of XMM-Newton images
- Trained on real XMM-Newton images and 30855 simulated images generated with the SIXTE X-Ray simulation software
- Convolutional neural network with Residual-in-Residual Dense Block (RRDB)

XMM-DeNoise and XMM-SuperRes

Metric	Input	Predicted (*XMM-SuperRes*)
L1	0.01096	0.006508
PSNR	33.525	38.034
Poisson	0.08285	0.04997
SSIM	0.8248	0.907
MS_SSIM	0.9499	0.9846
FSIM	0.8657	0.8688
HaarPsi	0.5312	0.697

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XMM-SuperRes: Network Architecture

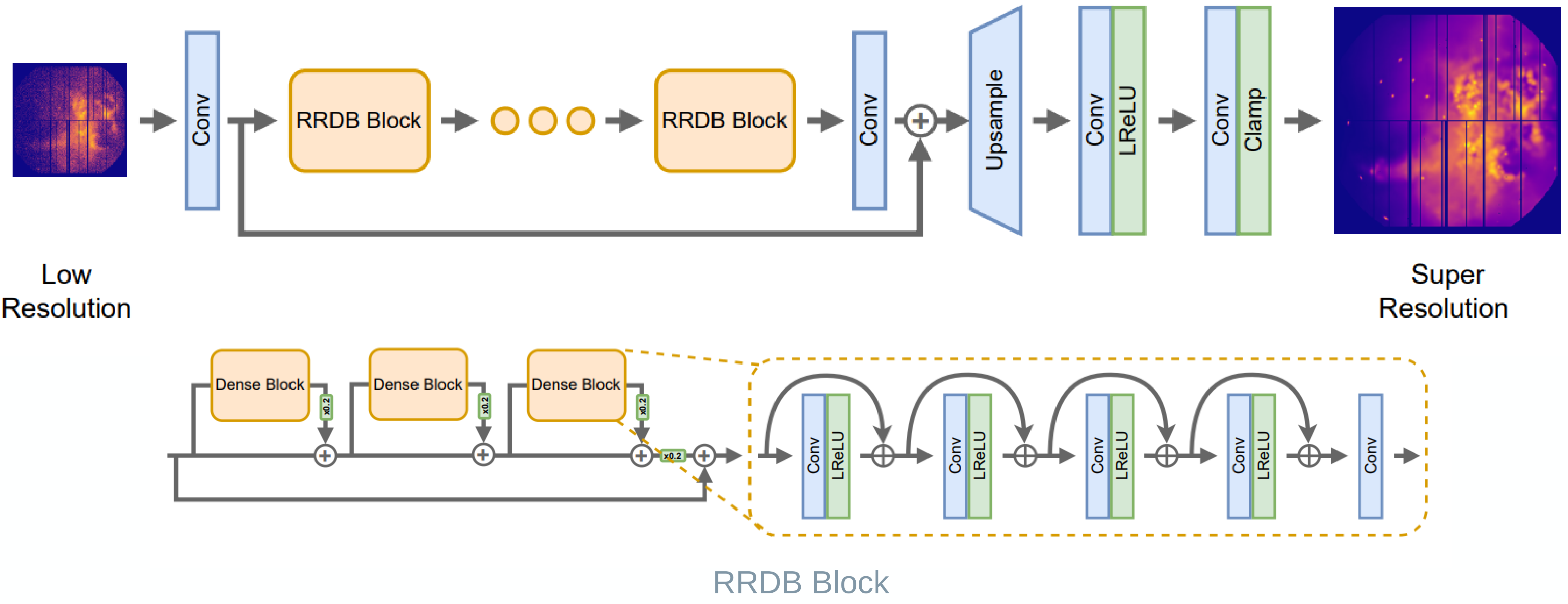
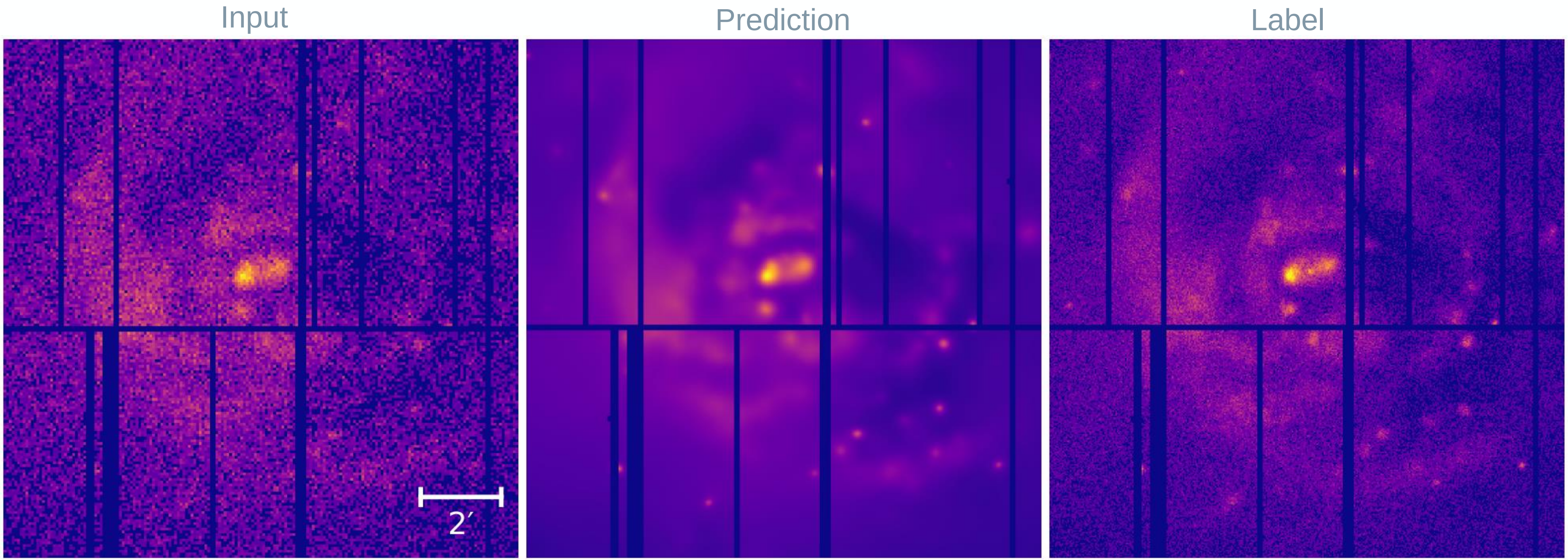


Image from https://arxiv.org/pdf/2205.01152.pdf

XMM-SuperRes Example



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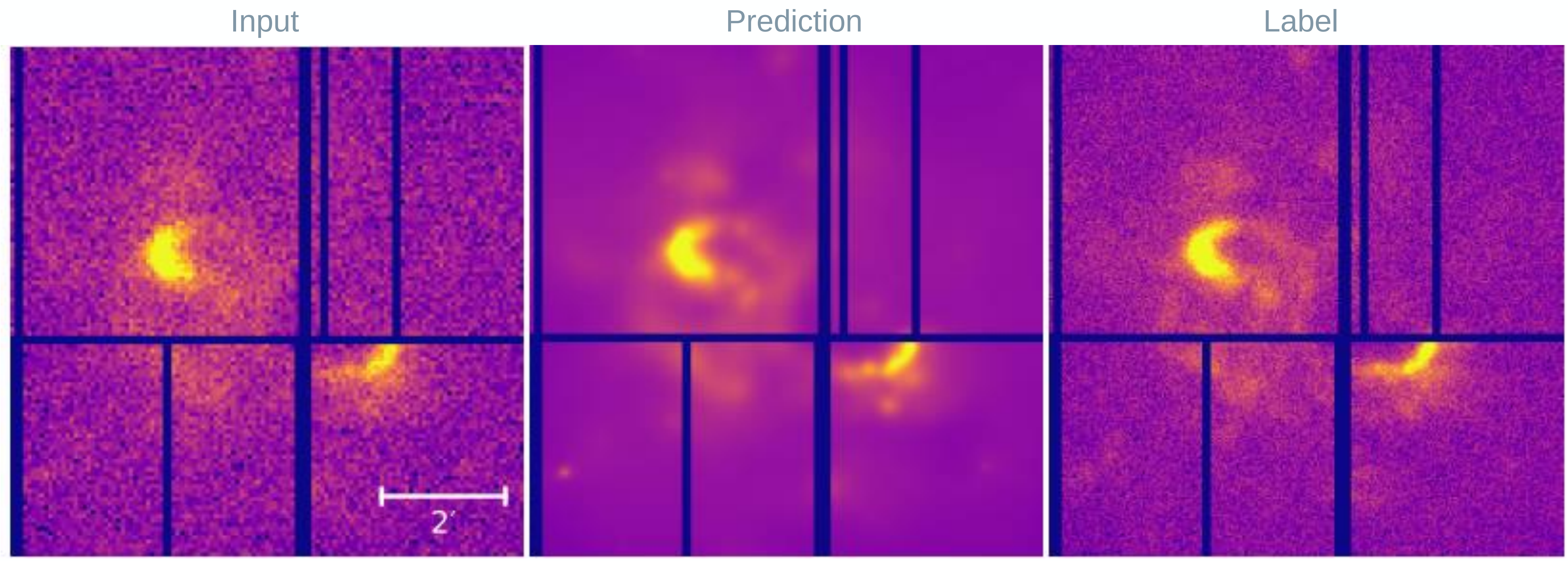
XMM-SuperRes Example



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XMM-SuperRes Challenges and Limitations

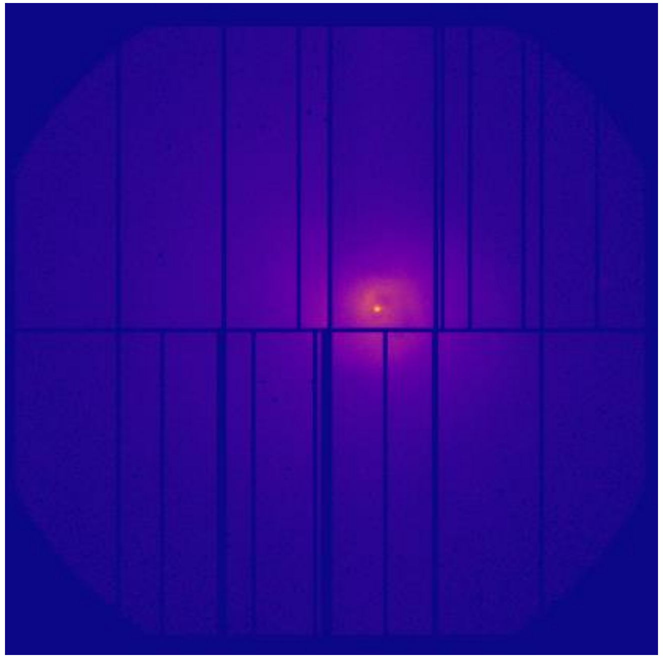
The current implementation of XMM-SuperRes shows two major limitations:

1. The currently employed clamping leads to a loss of information in very bright regions

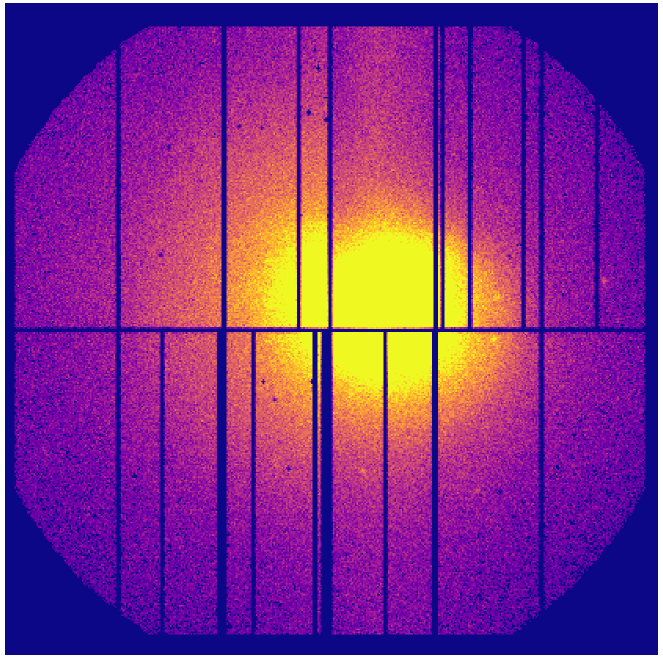
2. While a reduction in error has been shown, it is quite small and the ability to super-resolve has not been explicitly tested

XMM-SuperRes Clamping

- XMM-SuperRes employs clamping to avoid instability during training
- A constant value is used, defined based on the background noise
- **Due to the doubled resolution, the target clamping value is defined as a quarter of the input clamping value**
- However, using this constant value can lead to the loss of valuable information for bright sources



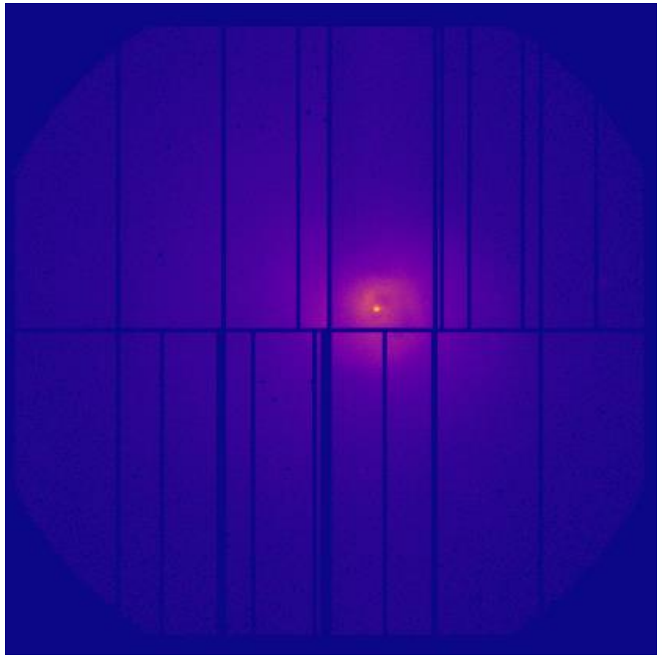
Unclamped input



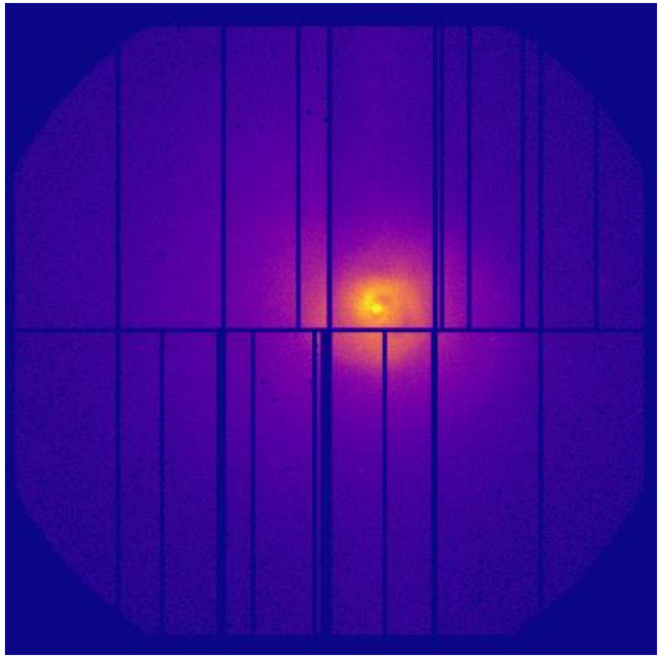
Clamped input

Quantile Clamping

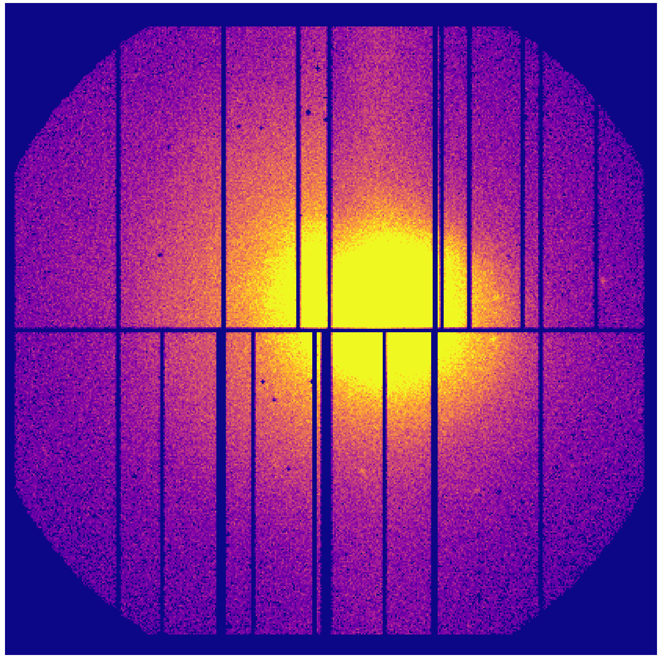
- Replaced constant clamping by adaptive quantile clamping
- Even when choosing a quantile of 0.9999 the training was still stable
- However, the accuracy dropped to 0.8823 (MS-SSIM)/ 23.1563 (PSNR)) (compared to 0.9846 (MS-SSIM)/ 38.034 (PSNR))
-



Unclamped



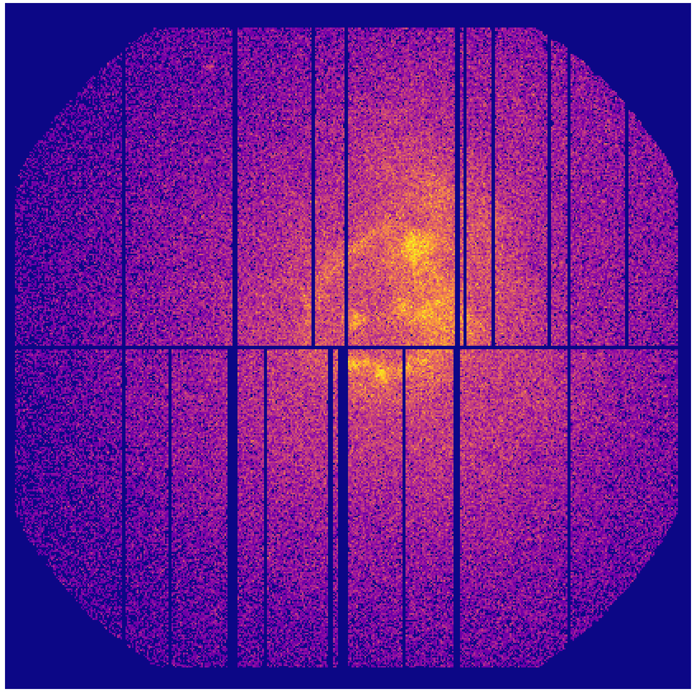
0.9999 quantile clamping



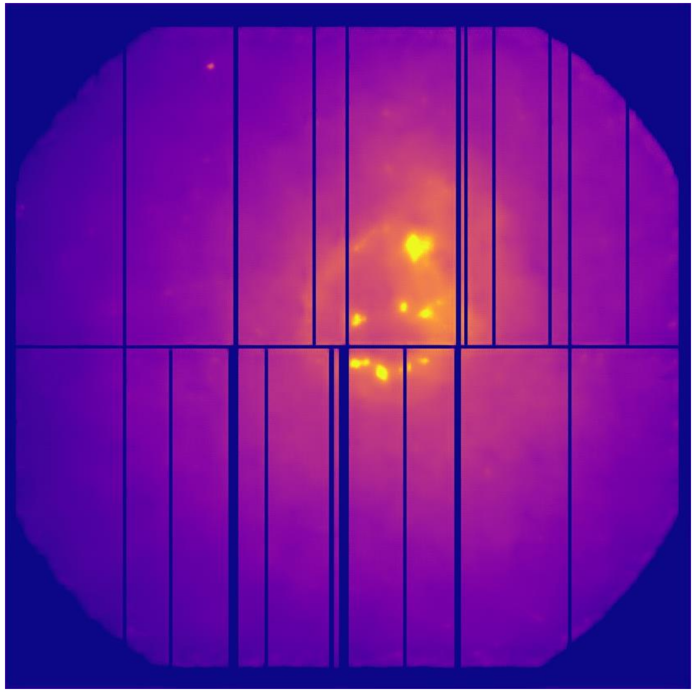
Constant clamping

Quantile Clamping Results

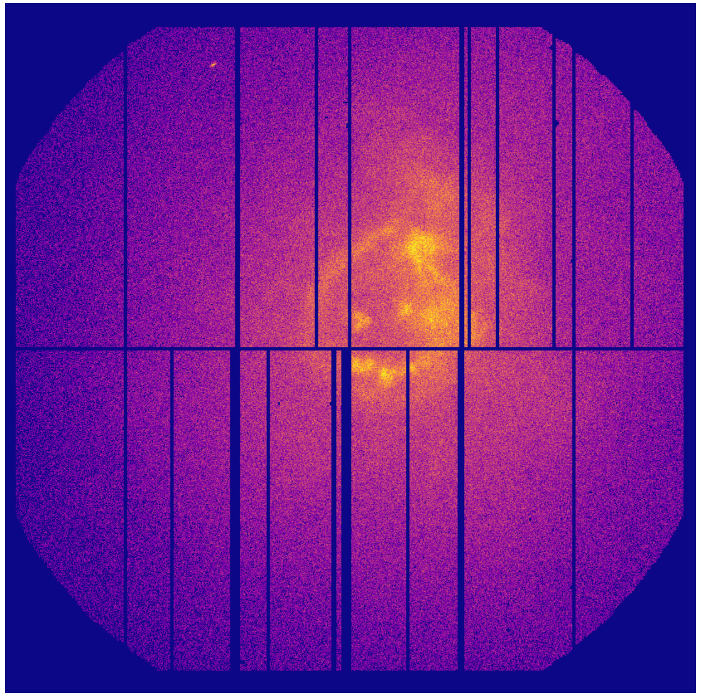
Input



Prediction



Label



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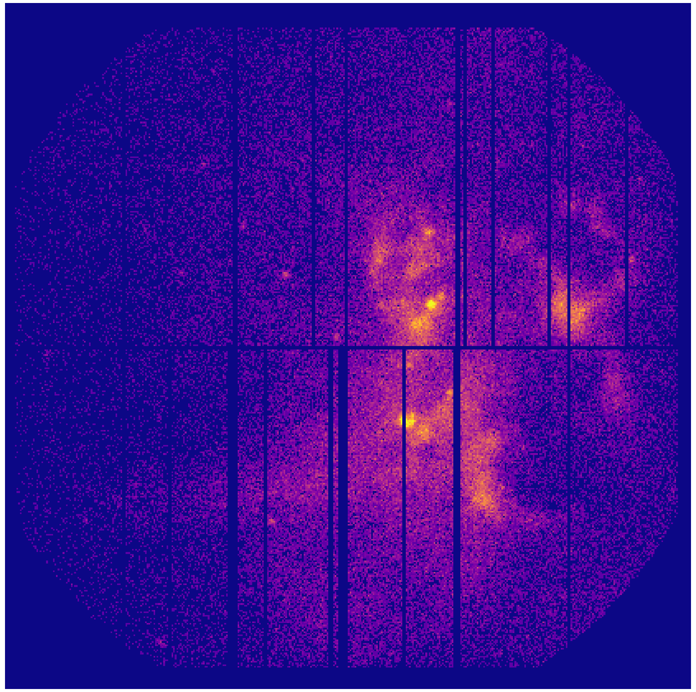
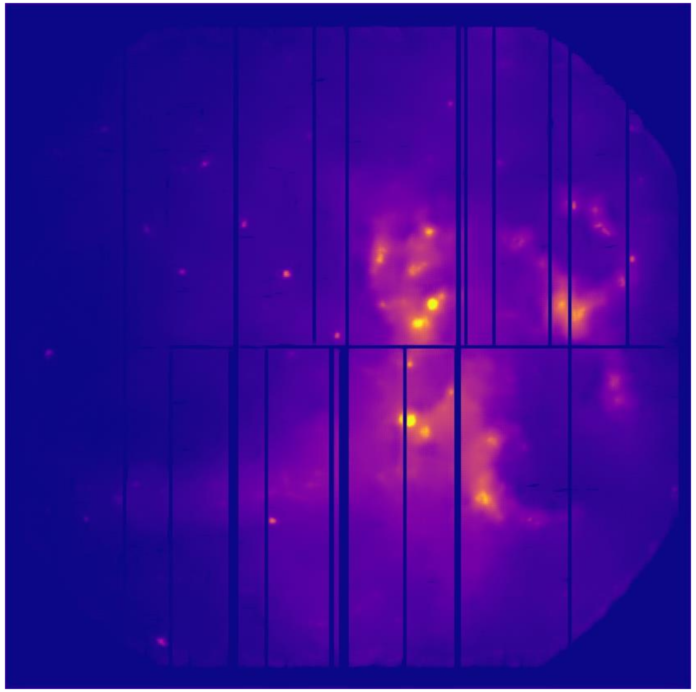
Quantile Clamping Results

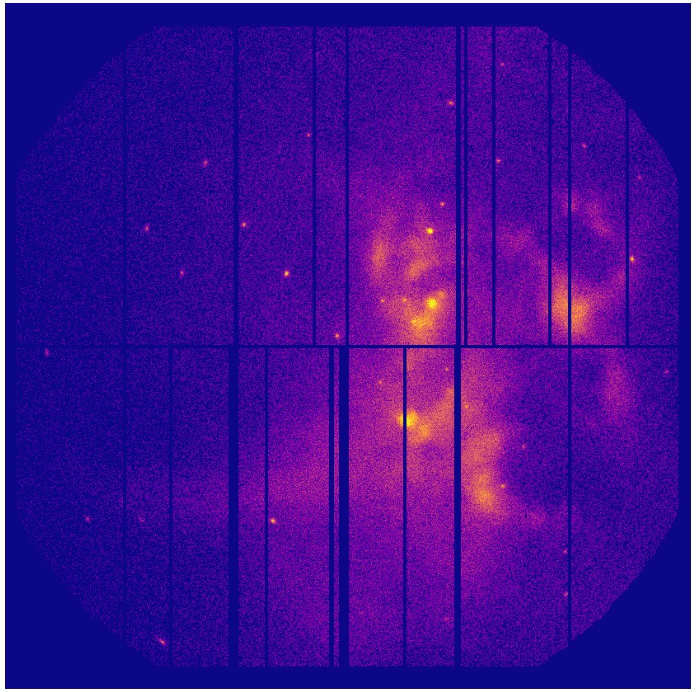
Input



Prediction



Label



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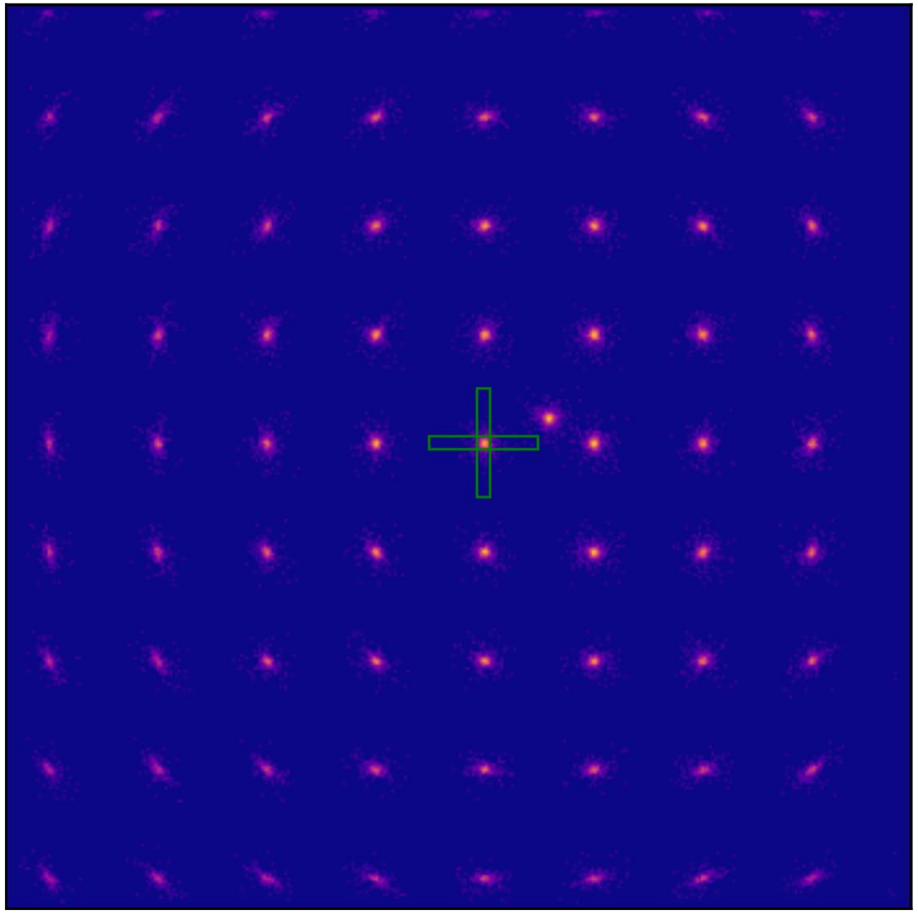
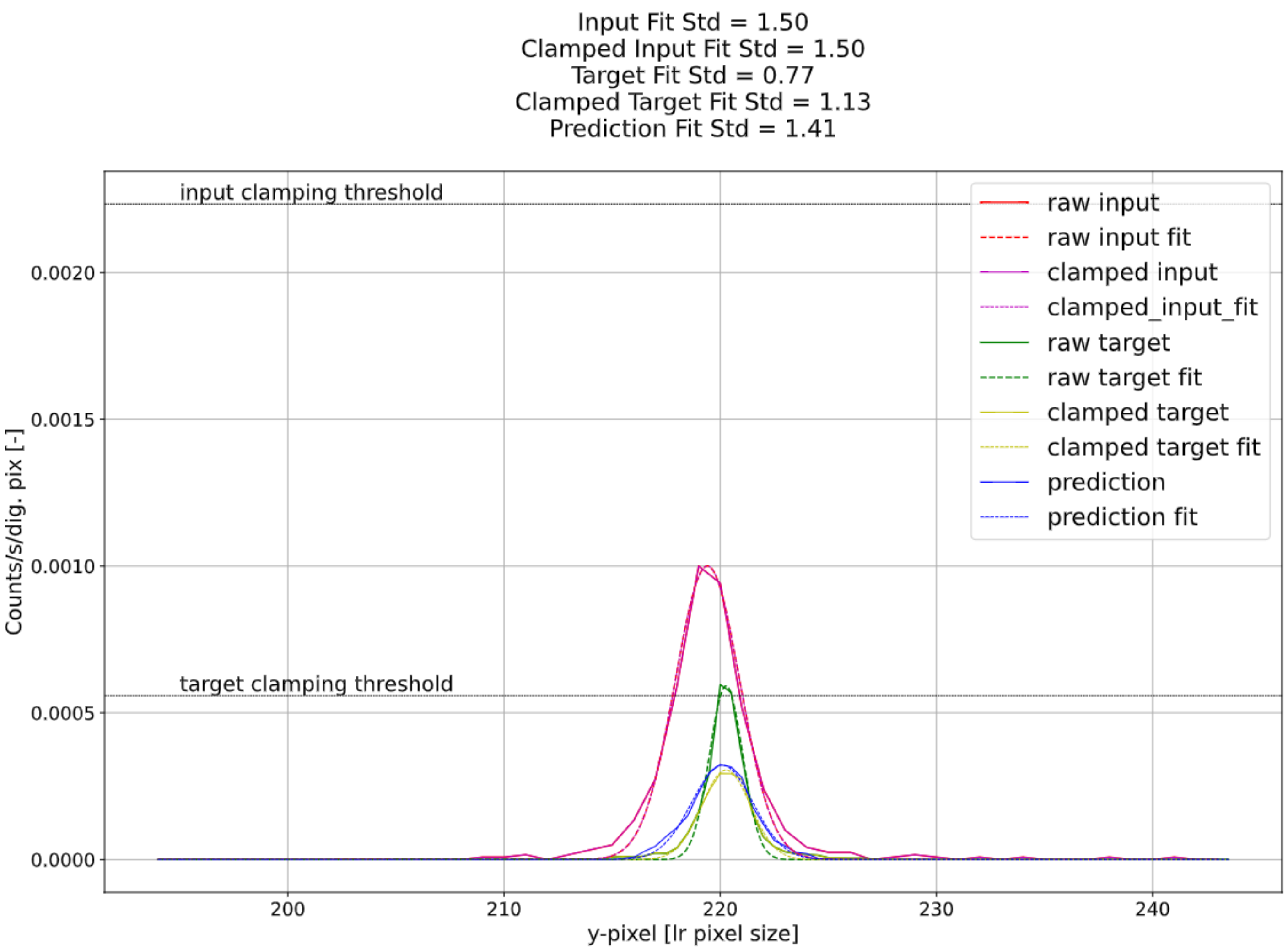
Testing the Point Spread Function (PSF)

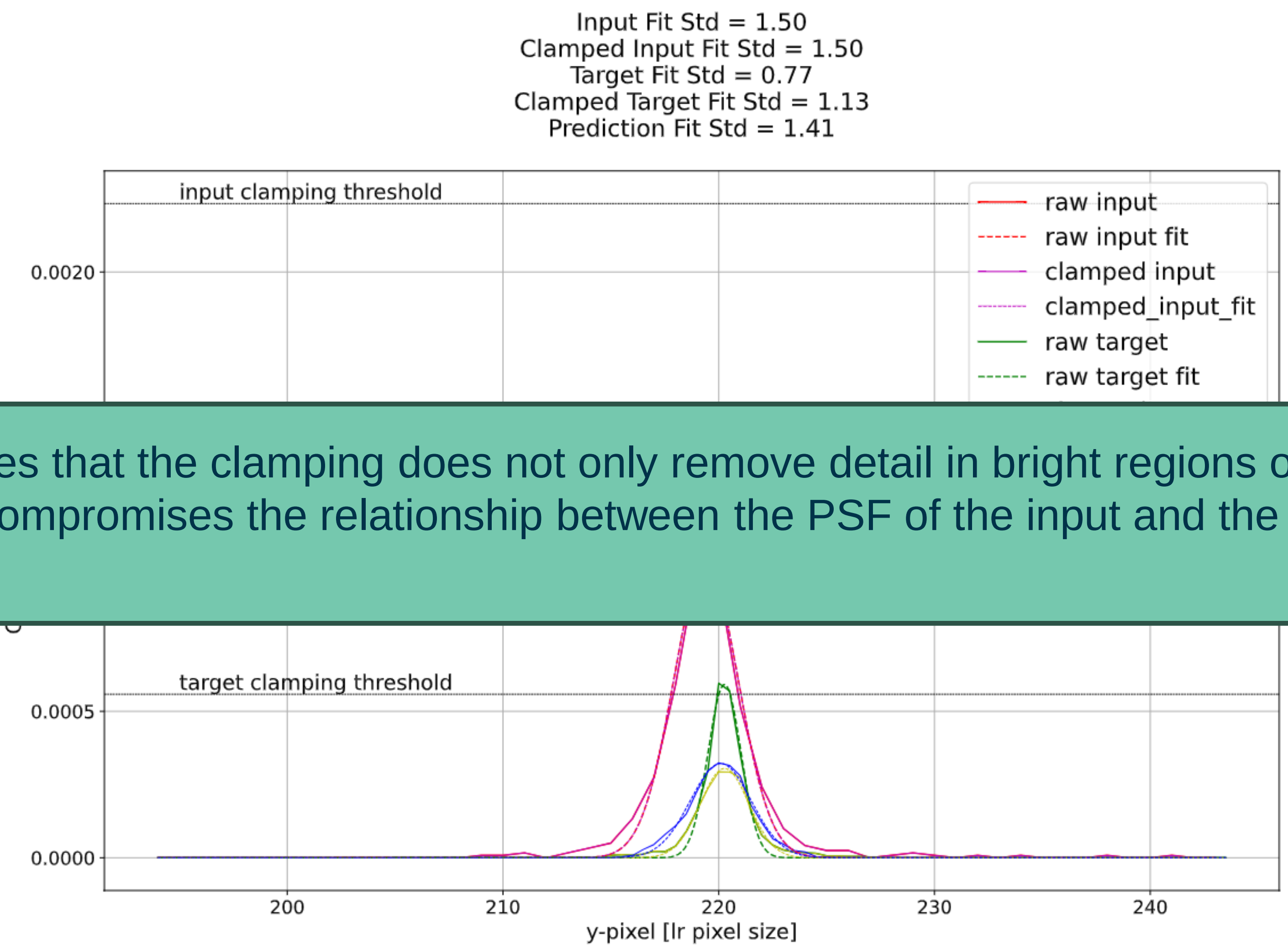
- The width of the point spread function is proportional to the resolution of the image
- Used simulated grid of point sources as input to XMM-SuperRes
- Summed up the counts within a small window of both the input and output
- Fit Gaussians to the results to see if the width decreases



Testing the Point Spread Function

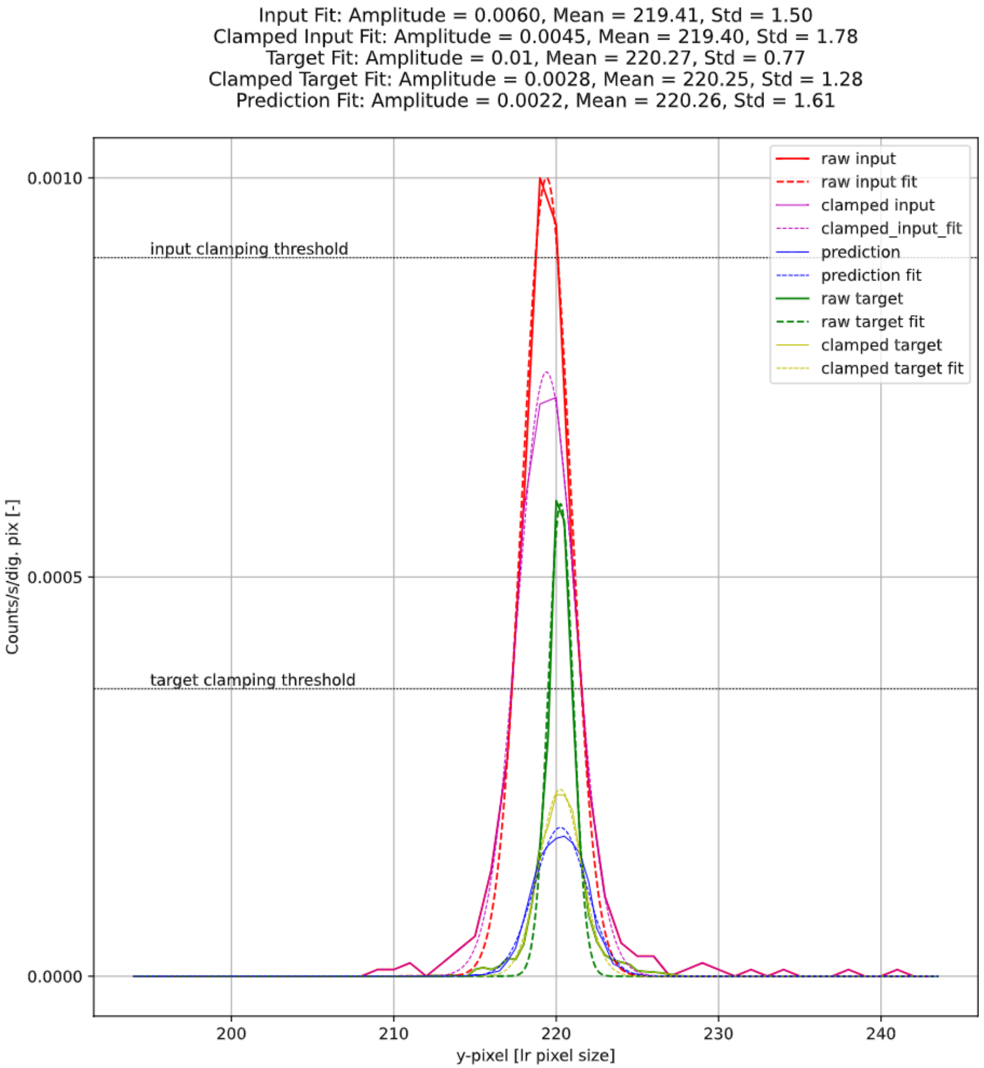


Testing the Point Spread Function

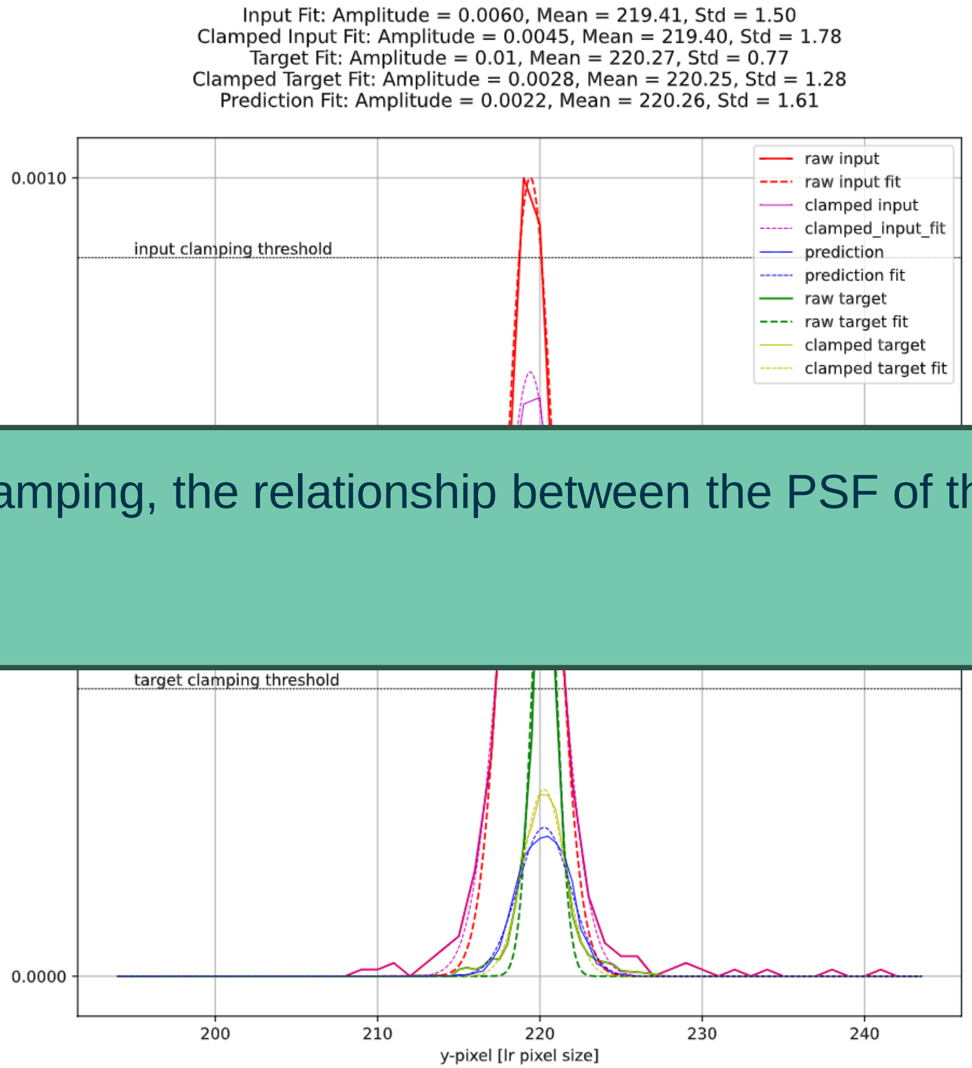


This implies that the clamping does not only remove detail in bright regions of the image, but also compromises the relationship between the PSF of the input and the target!

Testing the PSF with Quantile Clamping



Testing the PSF with Quantile Clamping



Even with quantile clamping, the relationship between the PSF of the input and target is compromised!

Conclusion

- Super-Resolution can serve as a visual explorative tool and provide inspiration and more confidence for new proposals
- It already provides output images with perceived increase in resolution and decrease in noise
- Using quantile clamping overcomes the issue of lost detail in bright regions
- However, both constant and quantile clamping compromise the relationship between the input and target PSF
- The high dynamic range of X-ray images makes the application of super-resolution tricky, and the clamping needs to be chosen with care!

- Outlook:
    - Look into ways to adjust the network such that no clamping is required
    - Adjust occurrence of bright sources within the dataset
    - Possibly apply the approach to large parts of the catalogue