



High Performance Computing in Astrophysics

and applications to Radio Interferometry

Authors:

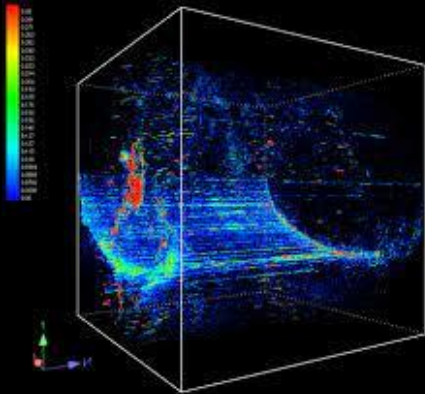
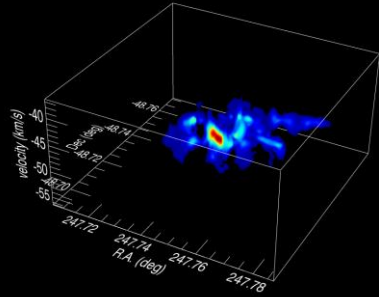
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BOLOGNA

0. Inferring models from Data

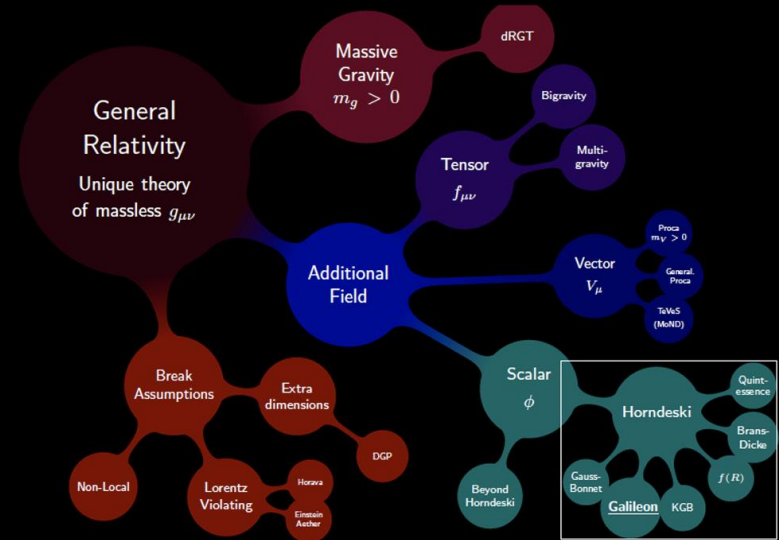
Data Cubes are pushing to the Big Data Regime



Resolution of Inverse Ill-posed problems



- Deconvolution
- Denoising
- Source Detection
- Source Characterisation
- Regression
- Classification



1. Inverse Problems

- Inferring causal factors from the observed reality

The generalised forward problem

$$V^{obs} = [A]T^m + n$$



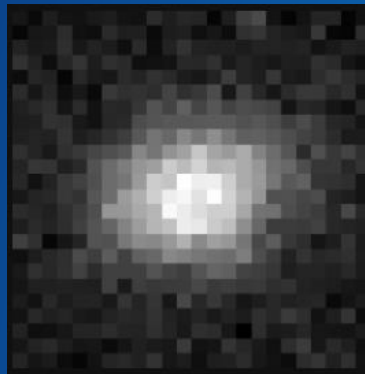
ALMASim

The generalised inverse problem

$$T^m = [A]^{-1}V^{obs} + n$$



DeepFocus



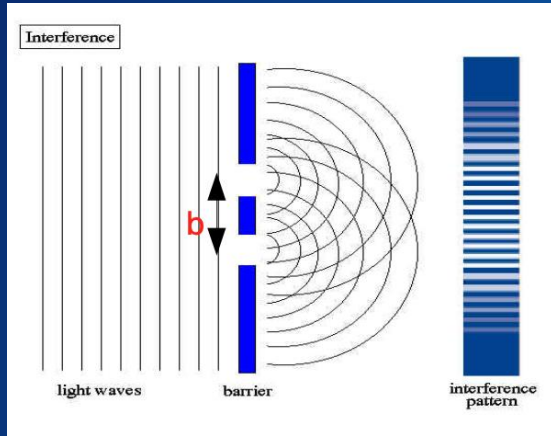
V_{obs}



T^m

2. Interferometers

- Inverse imaging devices



2D Fourier transform :

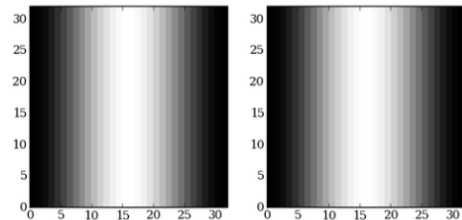
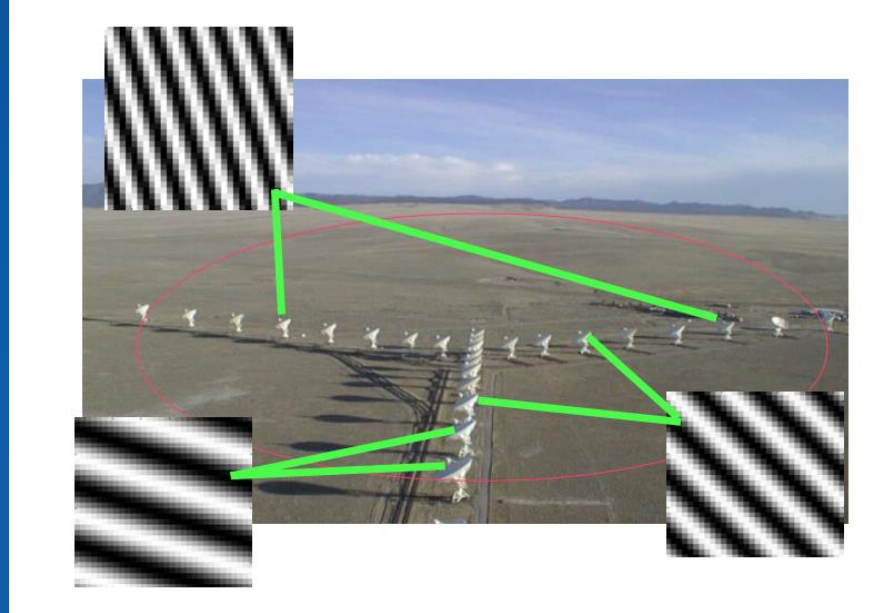


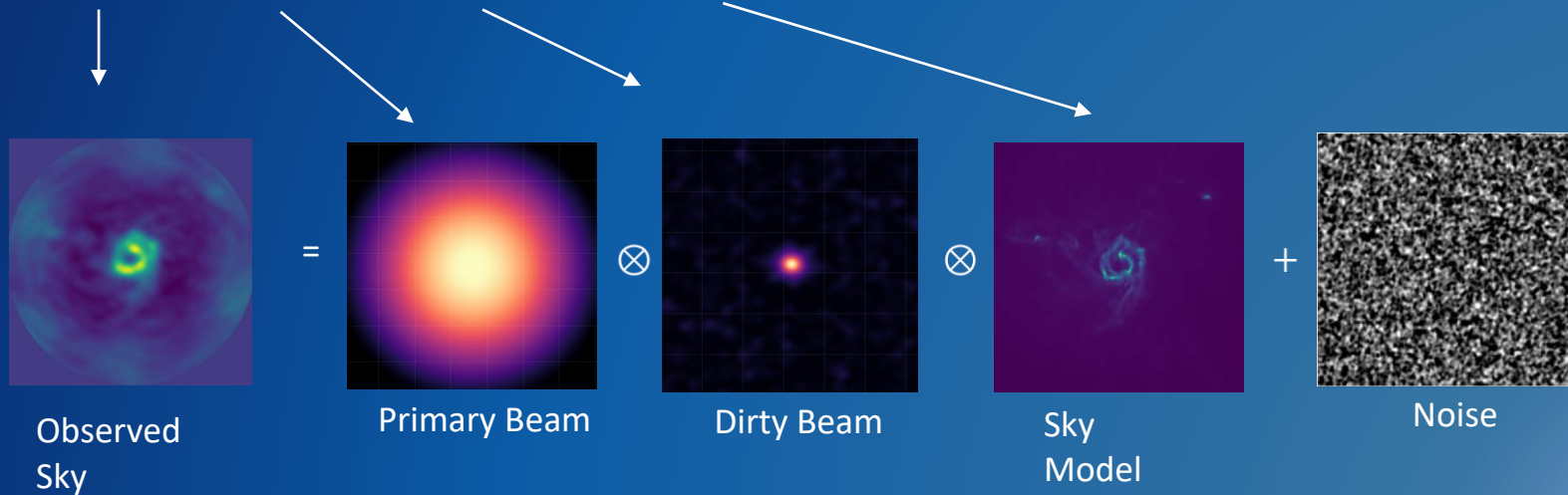
Image = sum of cosine 'fringes'.



4. The Interferometric Deconvolution Problem

The Radio Astronomer Equation (Van Cittert – Zernike Theorem)

$$D(l, m) = P(l, m) \otimes T(l, m) \otimes G(l, m) \approx \iint W(u, v) g(u, v) e^{2\pi i(ul+vm)} du dv$$



5. Data Cubes are changing the Game

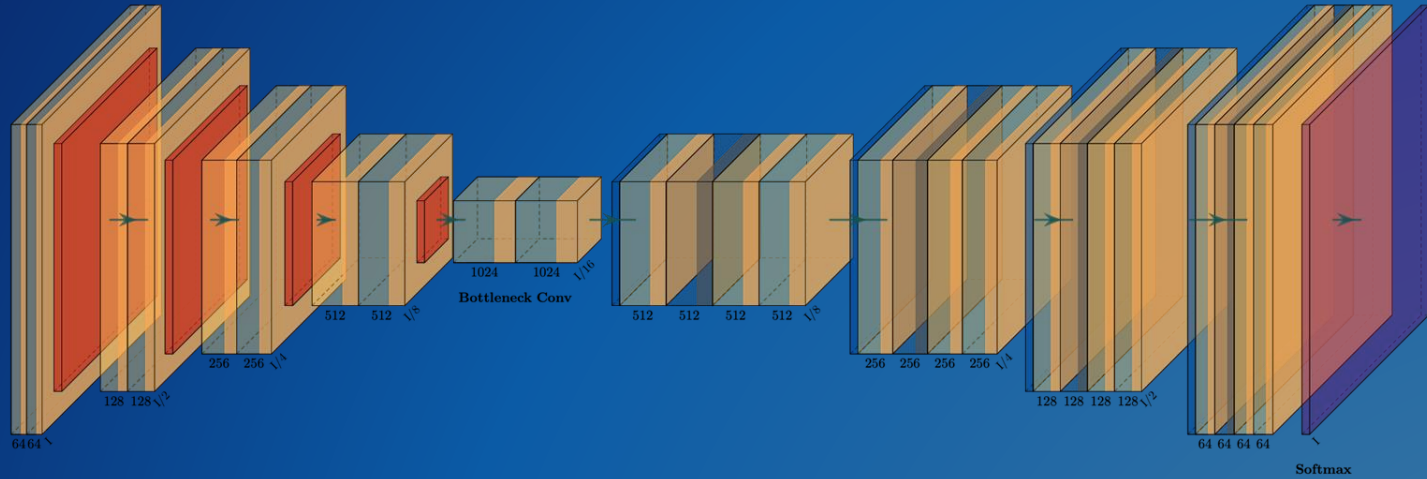
•SKA:

- weights ~ 1 TB
- 20 square degrees field of view, high sparsity;
- Expected to deliver 300 PB per antenna per year, with a total of ~ 8.5 Exabytes over the 15-year expected lifespan of the primary science program
- Online Processing required to cope with data volume and velocity

•ALMA:

- Weights ~ 1 GB
- Extended Sources
- Delivers 1 TB per day

6. Deep Learning for Inverse Problems



$$L(y, g(f(x)))$$

Encoder Network

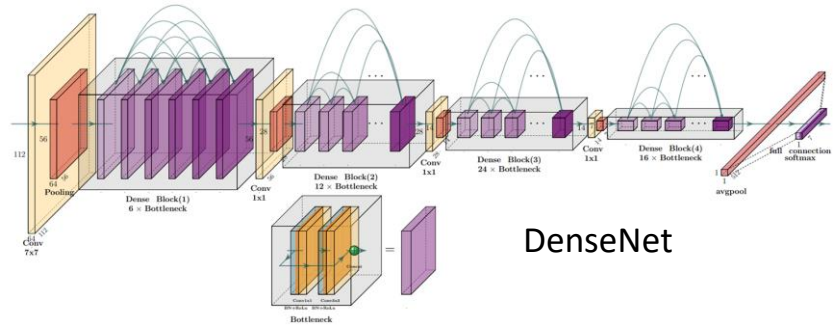
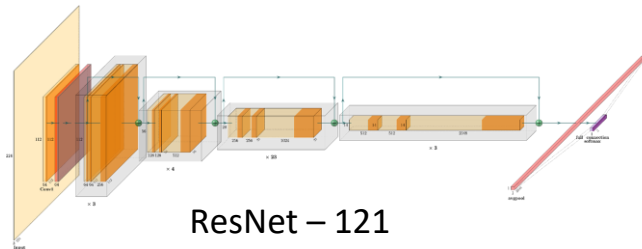
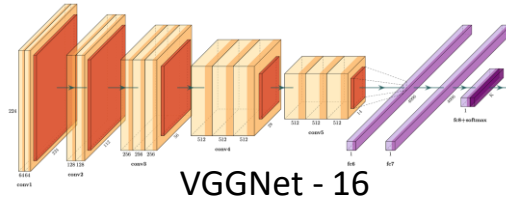
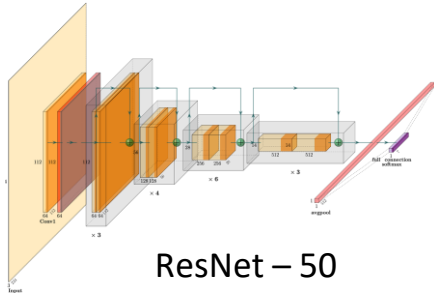
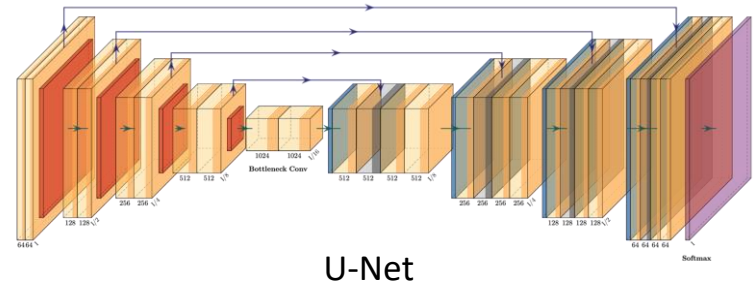
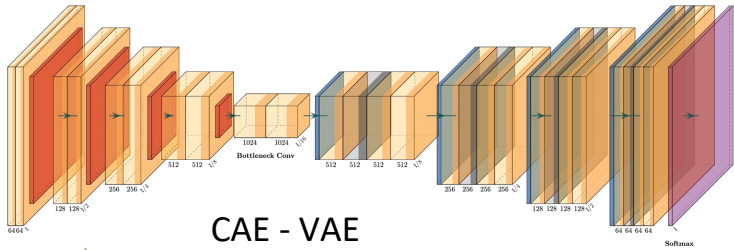
f

Minimizing the expected reconstruction error is equivalent to maximizing the lower bound on mutual information $I(x, h)$. By imposing constraints on the *latent space*, it can be forced to capture relevant information in the data.

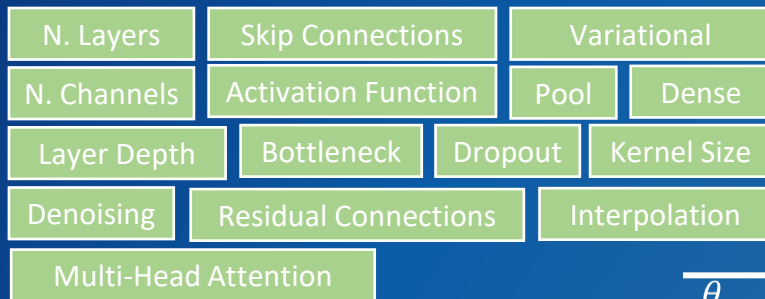
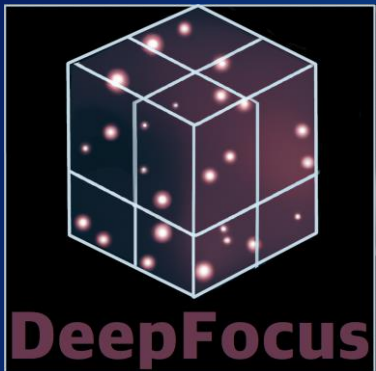
Decoder Network

g

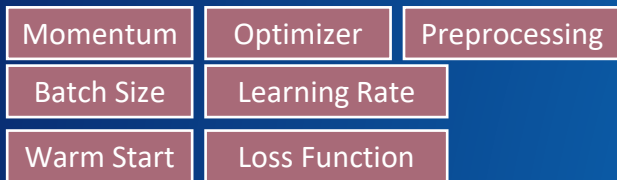
7. Deep Learning for Inverse Problems



8. Meta Learning

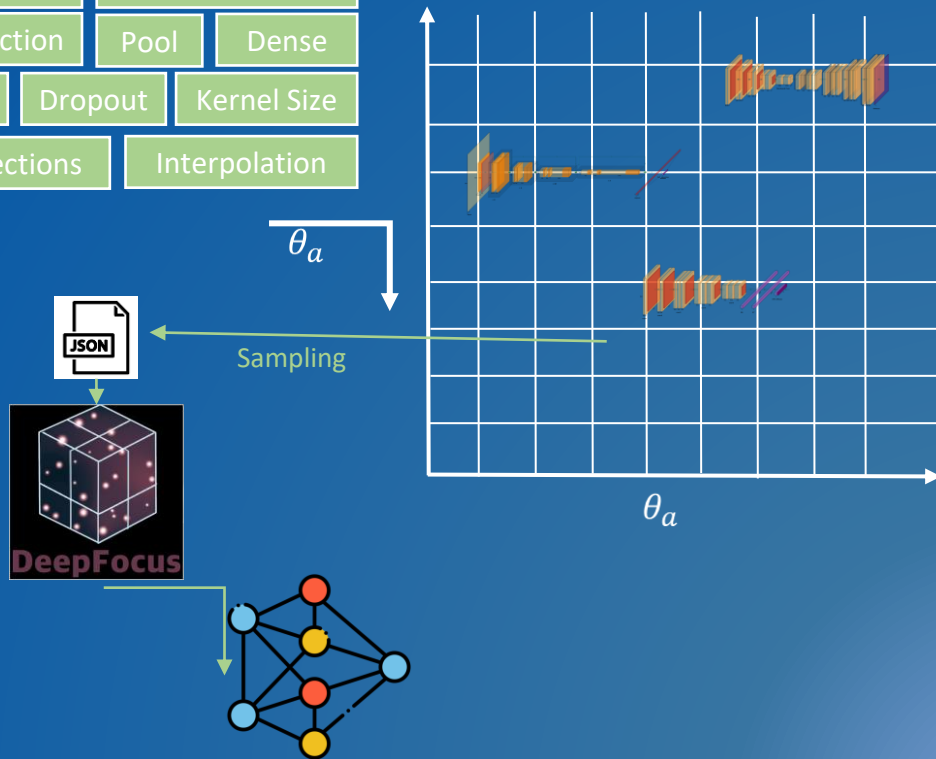


Classical Network Optimization

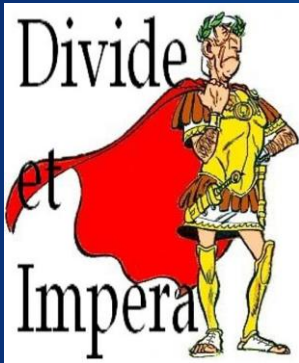
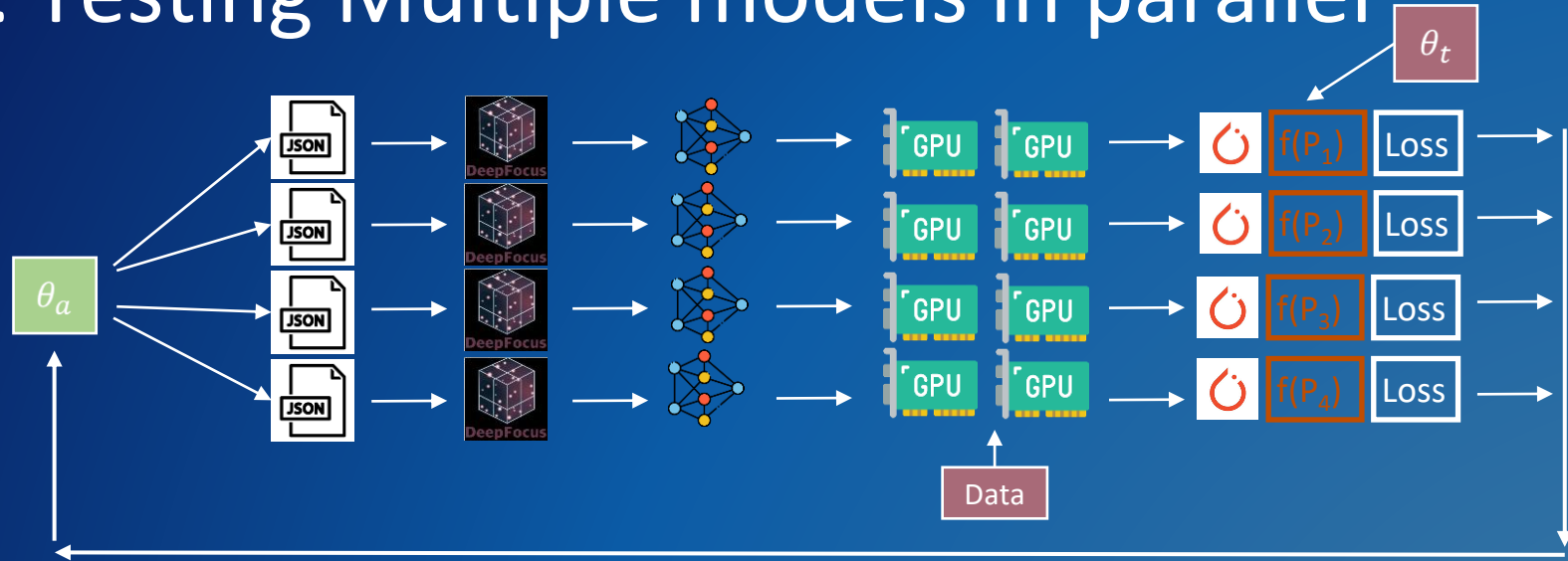


θ_t → Grid Search

$$x^* \in \theta_t : x^* = \underset{x \in \theta}{\operatorname{argmin}} f(x)$$



9. Testing Multiple models in parallel



- Multiple Parameter realizations are tested in parallel
- A subsample of the original problem is used to measure performance

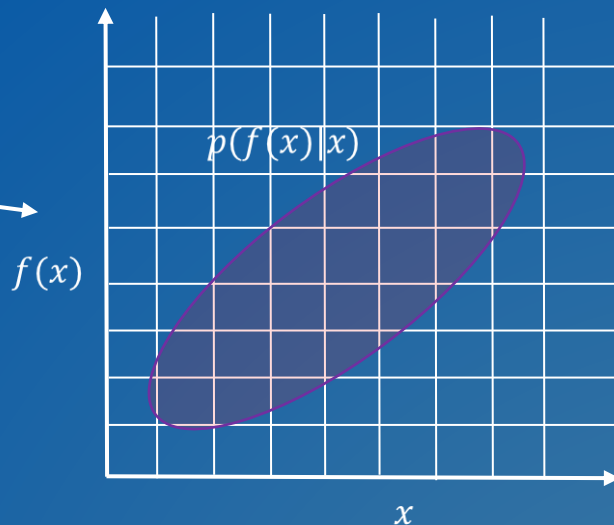
10. Bayesian Parameter Search

Surrogate Model

- probability model for $f(x)$
- For a value x , it gives the normal distribution for its prediction of f

Acquisition Function

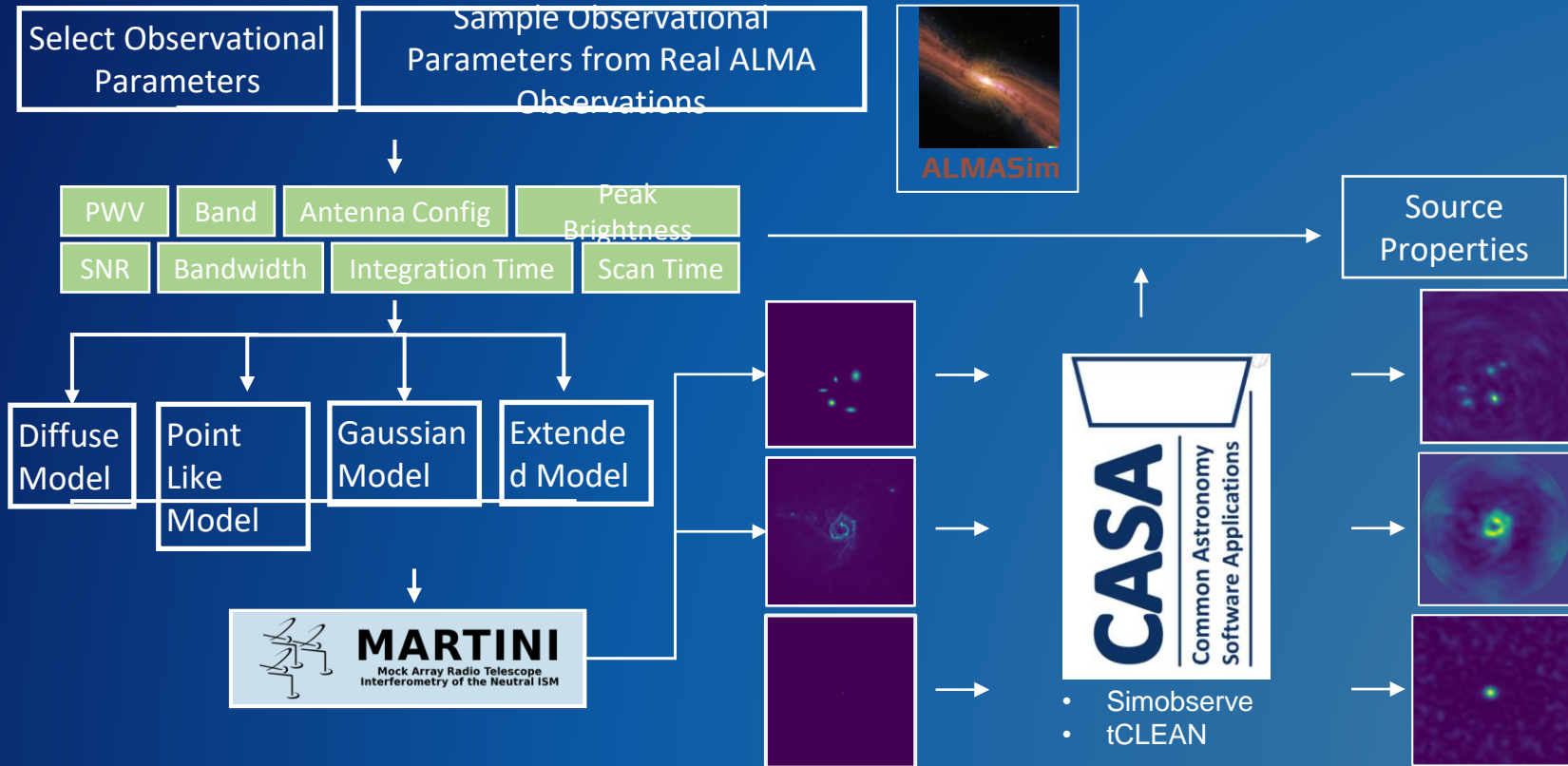
- where to search next ?
- probability model for $f(x)$
- It tell us how advantageous is to evaluate the objective function f at x



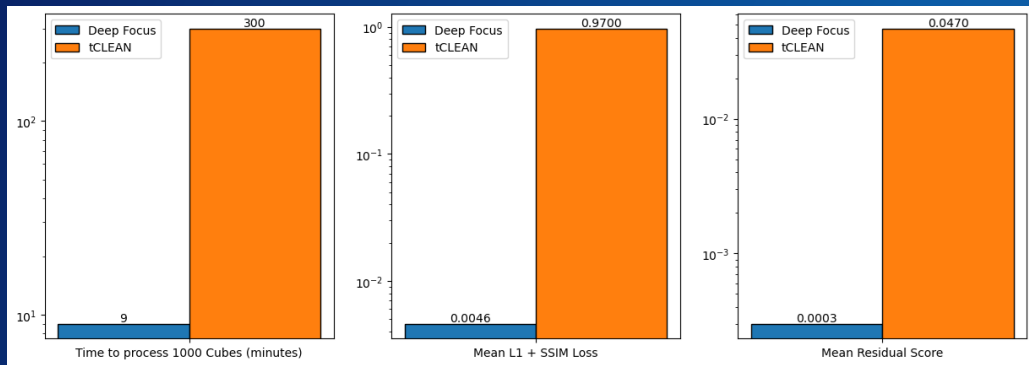
Assumption: the time spent selecting the hyperparameters is inconsequential with respect to the time it takes to evaluate the objective function.

**Absolutely True
for Deep Learning
Models**

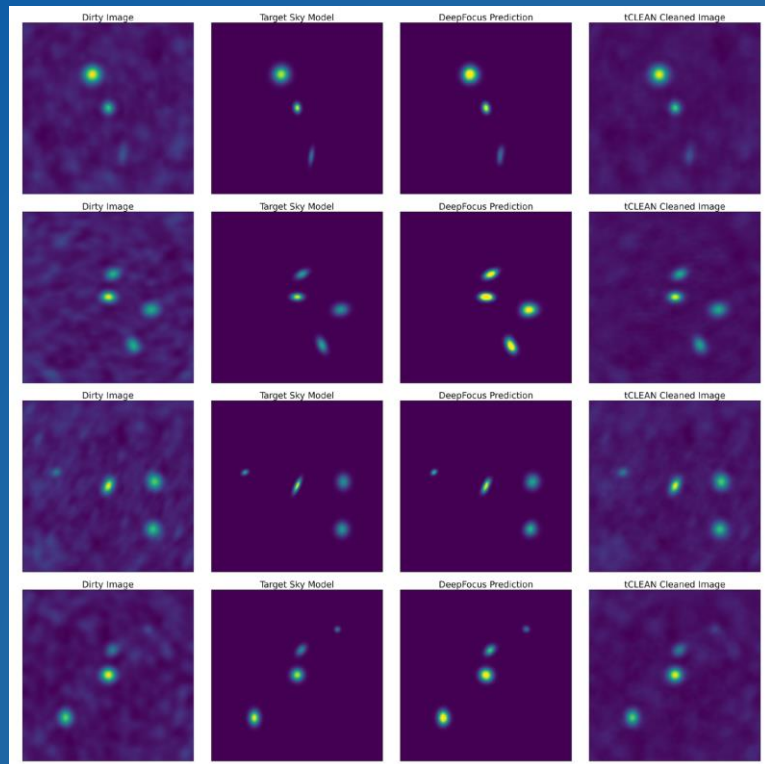
11. Building a Training Set with ALMASim



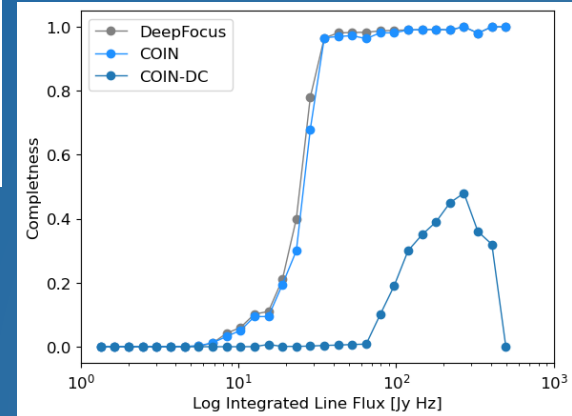
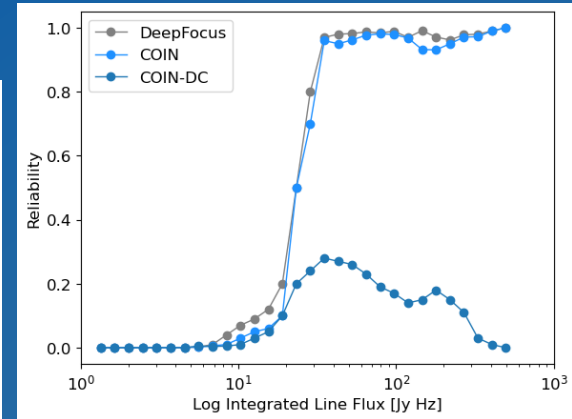
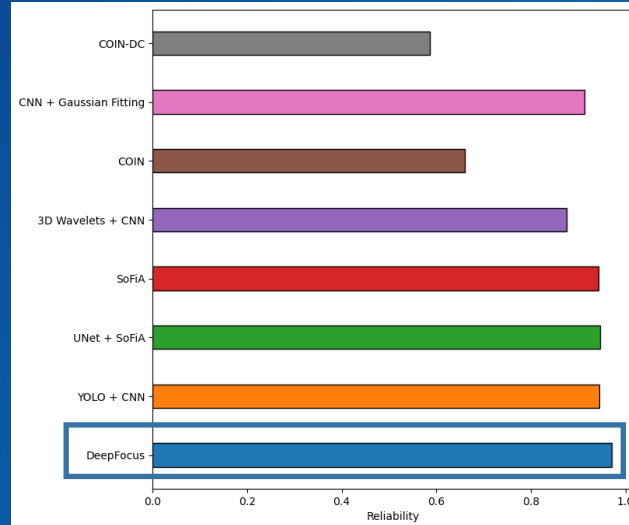
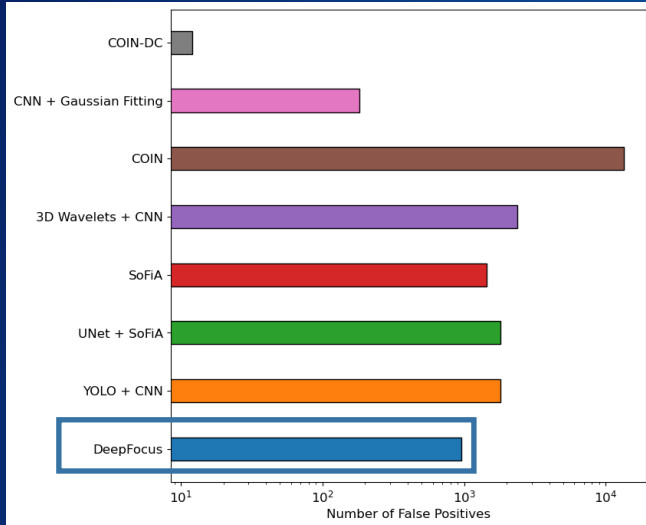
13. Deep Focus – Comparison with tCLEAN in solving the Deconvolution Problem



- The cube average size is 0.65 GBs
- Benchmarks have been performed using the following hardware:
 - 2 Intel Xeon E5-2680 (8 Cores each) -> 16 Cores
 - 1 NVIDIA Tesla V100 GPU
 - 1 TB of DDR5 RAM

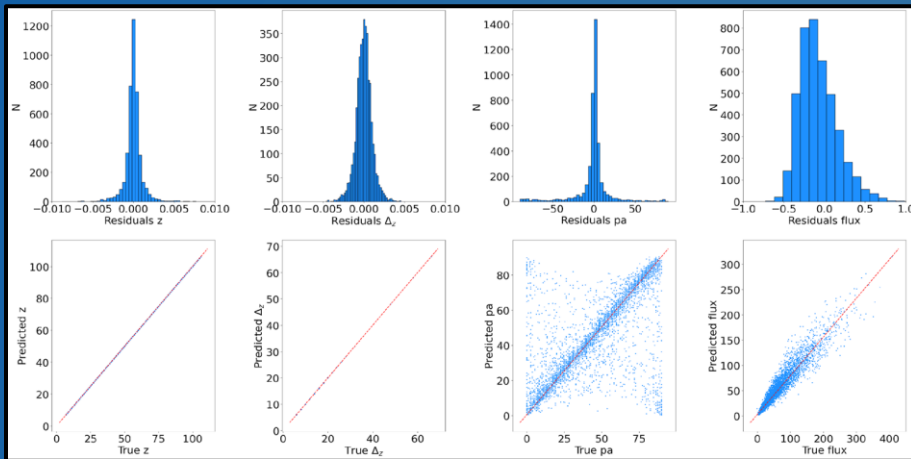
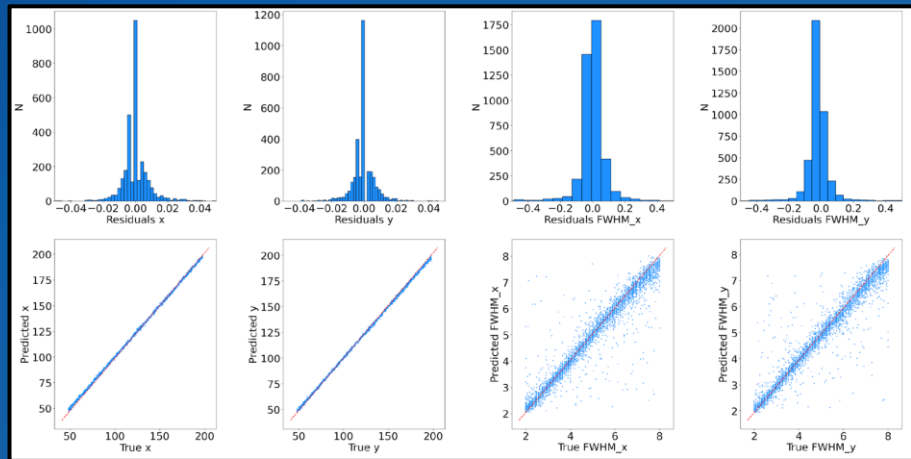


14. Deep Focus – Comparison with other DL models on Source Finding Task



15. Deep Focus – Characterizing Sources around Calibrators

Algorithm	Completeness	Reliability
DF	96.7%	99.6%
Sofia 2	22.2%	20.1%
BlobCat	60.9%	53.0%
CAE	78.1%	82.0%



Grazie per l'attenzione



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