Please Sign In for the CosmicAI Seminar

CosmicAI NSF SIMONS FOUNDATION

Credit: NRAO/AUI/NSF, S. Dagnello & W. Cotton; SARAO, DES

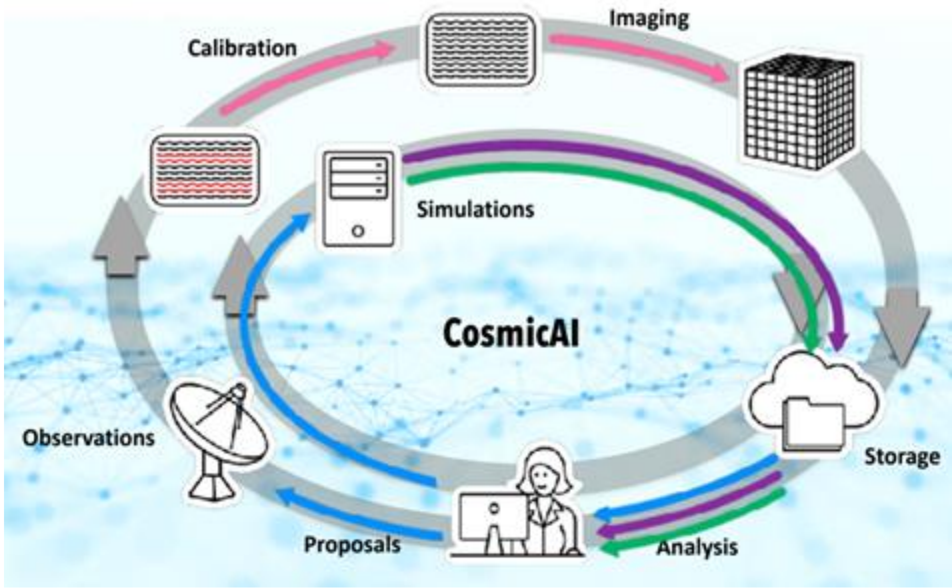
Imaging in Radio Interferometry

What do we measure, model, and make decisions about ?

Urvashi Rau, NRAO

Cosmic-AI seminar series

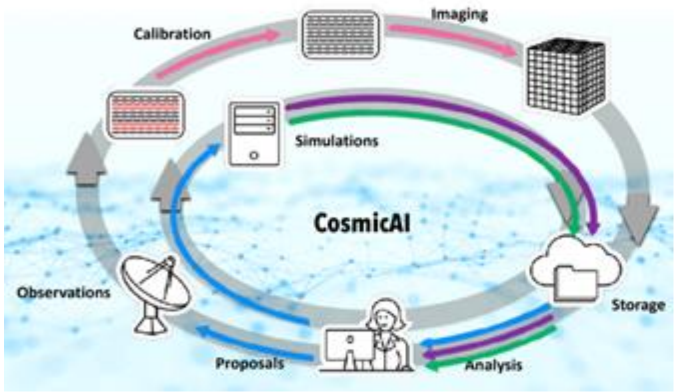
3 September 2025



Astronomy research cycle - Radio Interferometry

Processing

Observing



Interpretation

Astronomy research cycle - Radio Interferometry

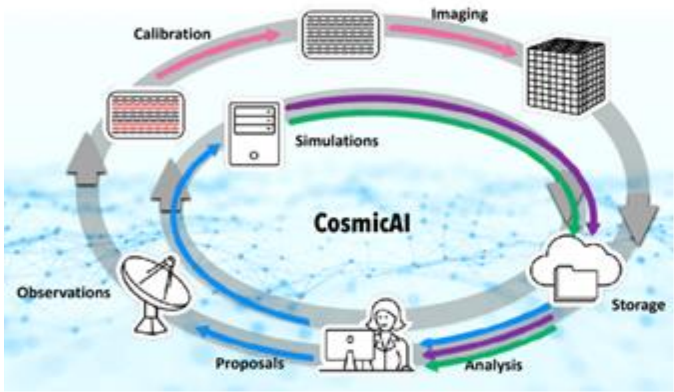
Observing

Telescope setup
and scheduling

Environment awareness
(weather, interference)

Predictive models
Adaptive observing

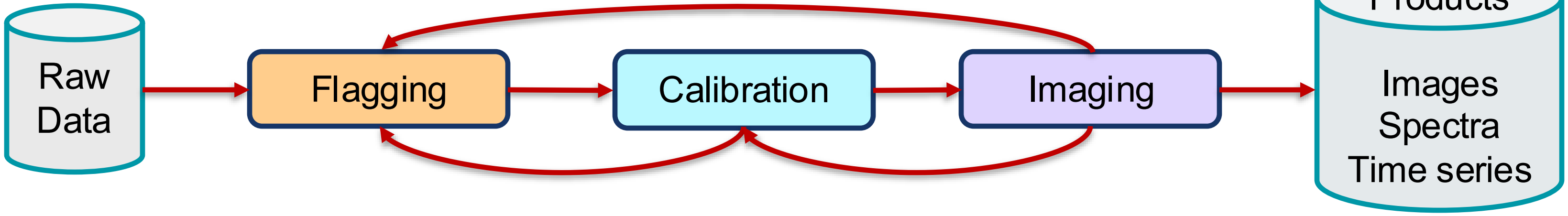
Processing



Interpretation

Astronomy research cycle - Radio Interferometry

Processing

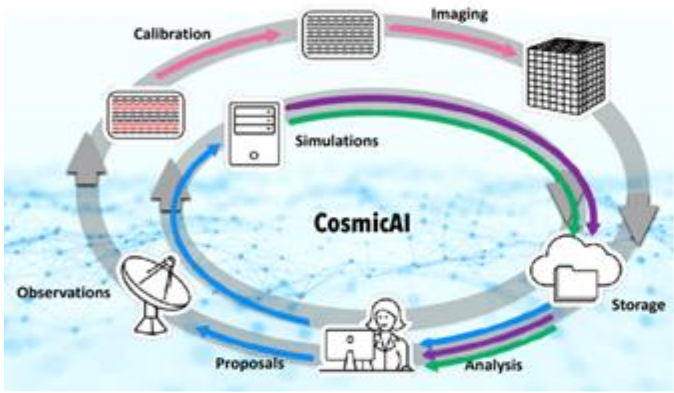


Observing

Telescope setup
and scheduling

Environment awareness
(weather, interference)

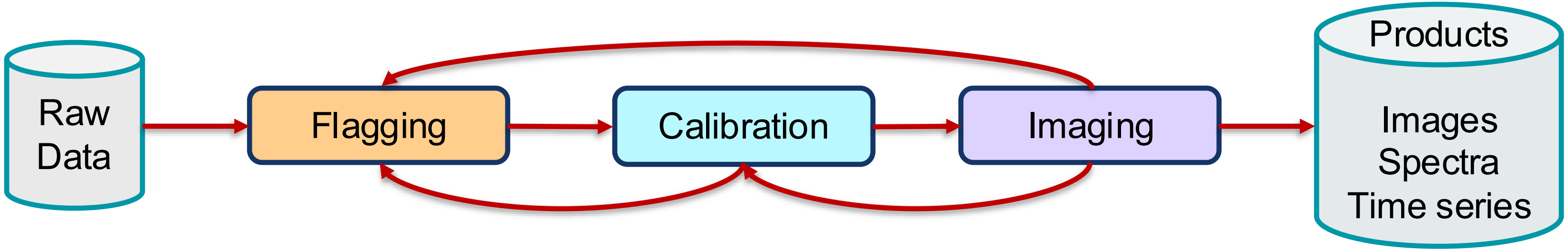
Predictive models
Adaptive observing



Interpretation

Astronomy research cycle - Radio Interferometry

Processing

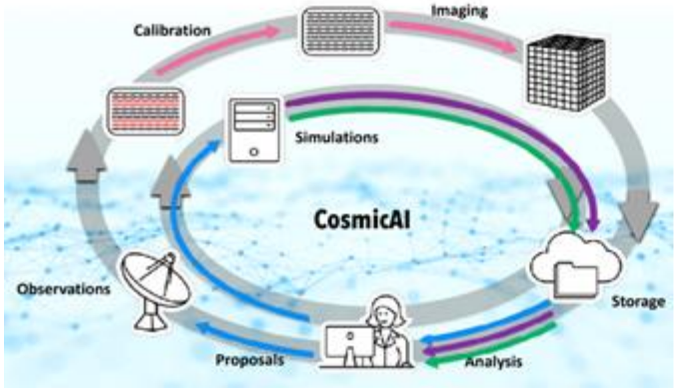


Observing

Telescope setup
and scheduling

Environment awareness
(weather, interference)

Predictive models
Adaptive observing



Interpretation

Feature identification,
classification

Astrophysical inference

- Mine vast databases
- Build and interpret models
- Interactive exploration

Astronomy research cycle - Radio Interferometry

Processing

Raw Data → Flagging → Calibration → Imaging → Products

Products

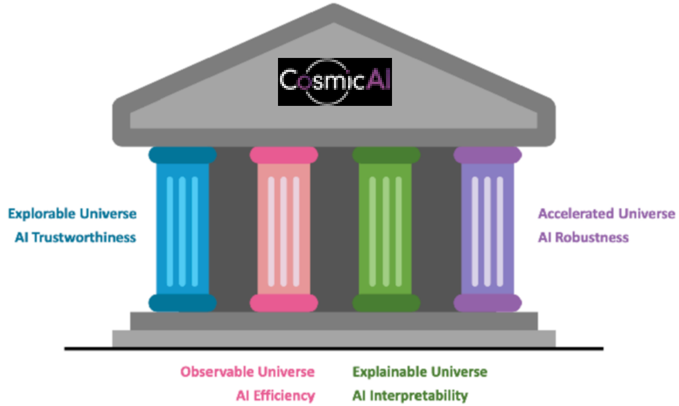
Images
Spectra
Time series

Observing

Telescope setup
and scheduling

Environment awareness
(weather, interference)

Predictive models
Adaptive observing



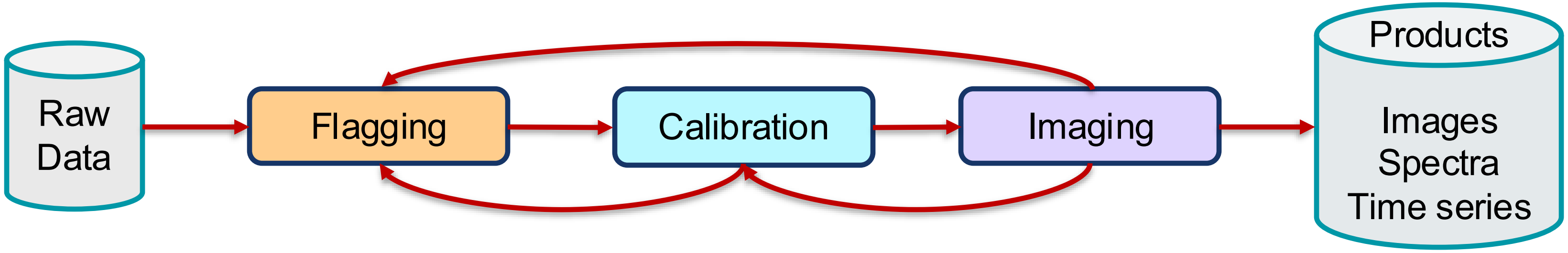
Interpretation

Feature identification,
classification

Astrophysical inference

- Mine vast databases
- Build and interpret models
- Interactive exploration

Processing : Turning raw data into image products



Data : What do we **measure** ?

Core Algorithms : What do we **model** and reconstruct ?

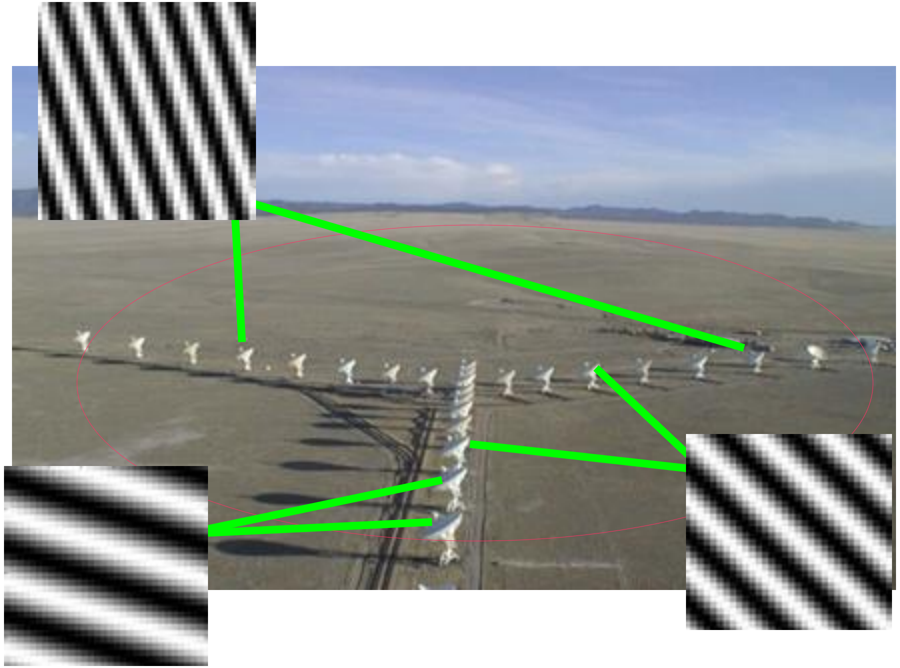
Pipelines : How do we **decide** the best sequence of algorithms to run ?

General themes : Data volumes, Signal sparsity (bases), Knowns vs unknowns,
Signal-to-noise ratio, Physics constraints, Sources of uncertainty

Principles of Radio Interferometric Imaging

An interferometer is an indirect imaging device

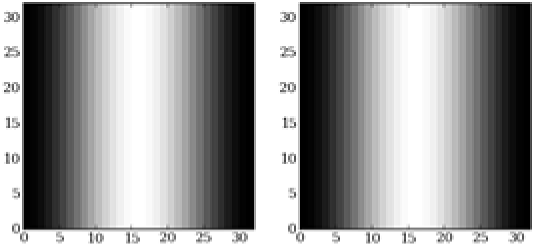
We sample the
spatial Fourier transform
of the
sky brightness

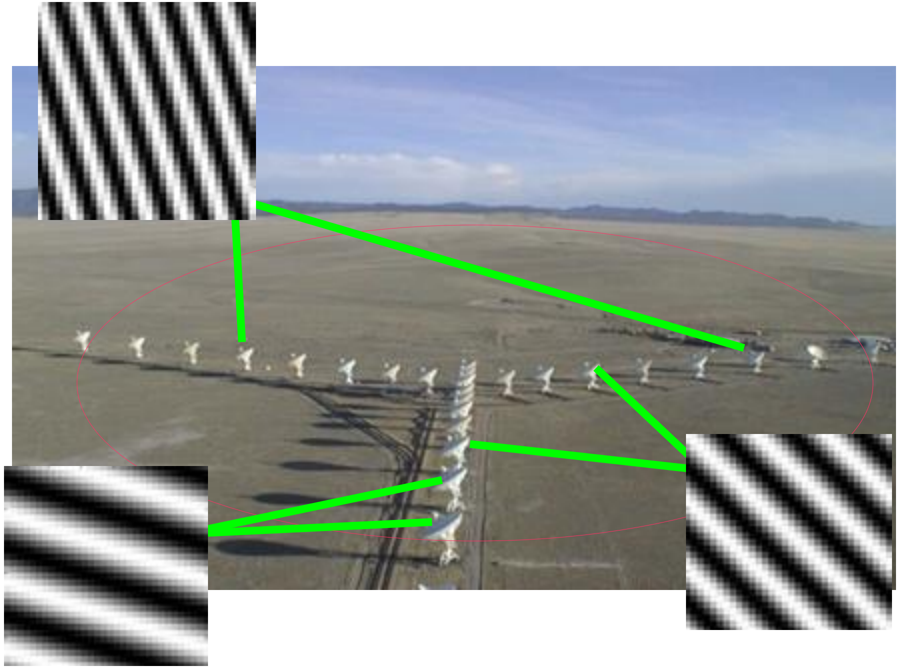


Principles of Radio Interferometric Imaging

An interferometer is an
indirect imaging device

We sample the
spatial Fourier transform
of the
sky brightness





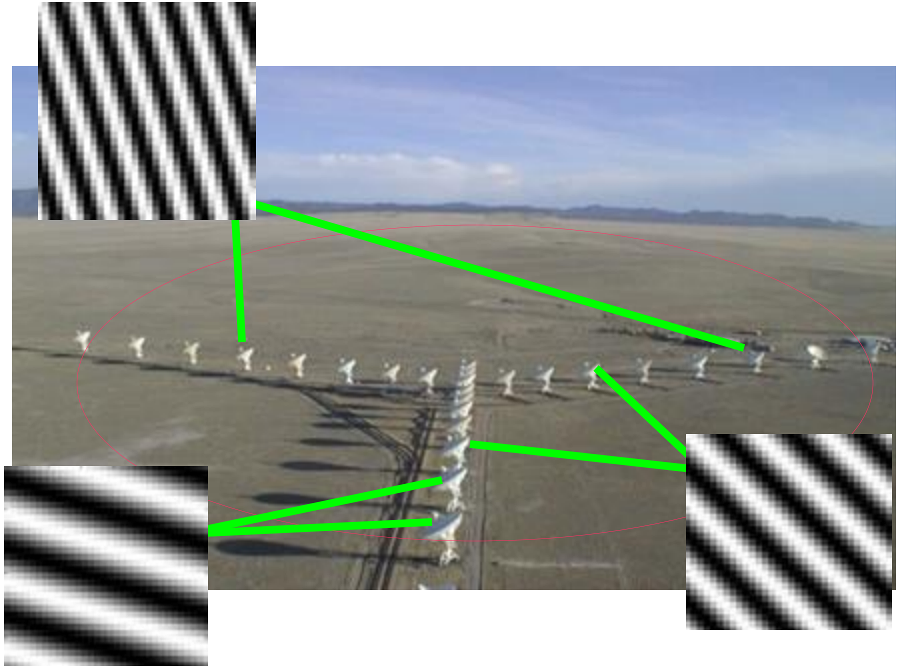
Principles of Radio Interferometric Imaging

Each measurement :

$$V^{obs}_{ij} = \langle E_i E_j^* \rangle_{\delta\tau,\delta\nu}$$

Parameters :

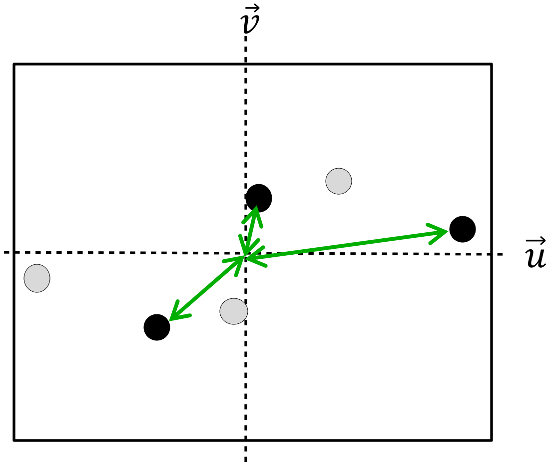
Amplitude, Phase,
Wavelength, Orientation

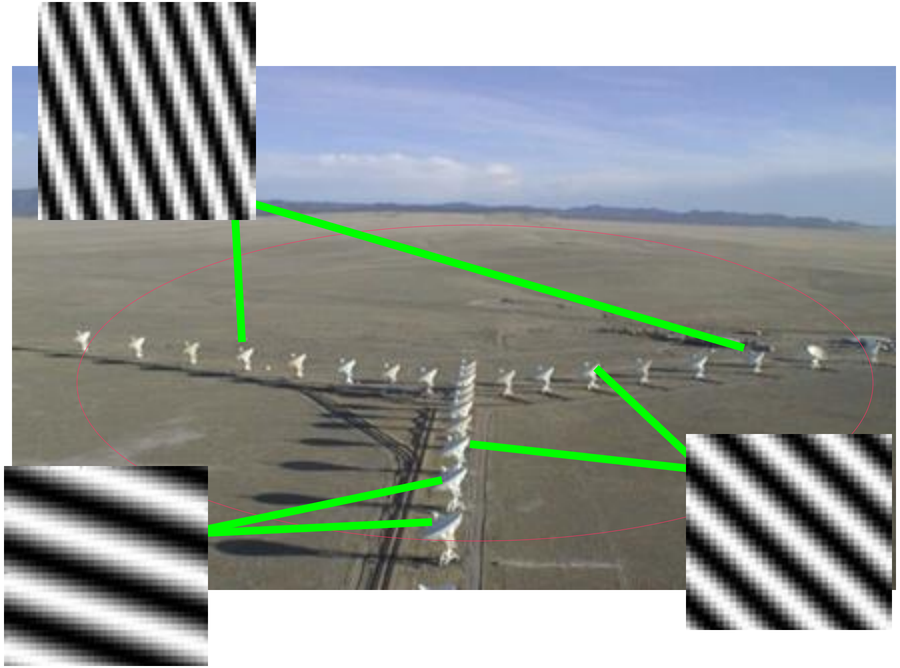


Principles of Radio Interferometric Imaging

Each measurement :

$$V^{obs}_{ij} = \langle E_i E_j^* \rangle_{\delta\tau,\delta\nu}$$





UV-space (or K-space) : 2D spatial frequency domain → iFFT → Image

Aperture Synthesis

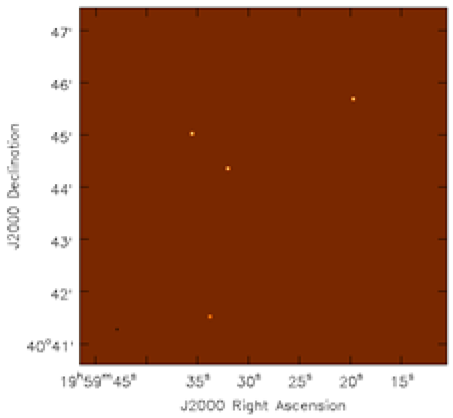
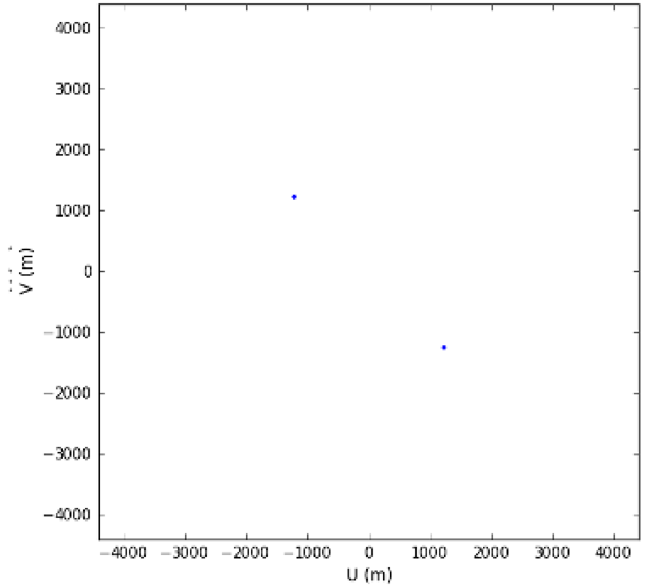


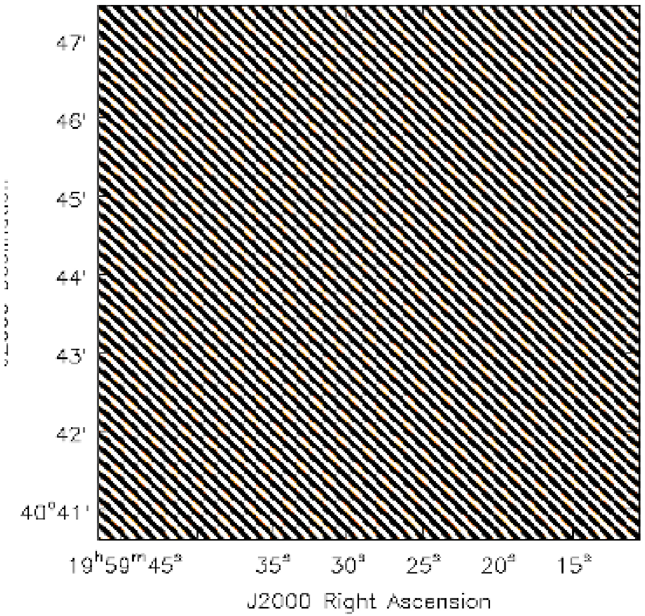
Image formed with

2 antennas

$S(u, v)$



$I^{obs}(l, m)$



Aperture Synthesis

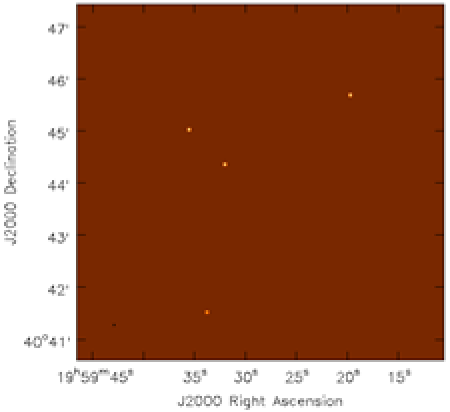
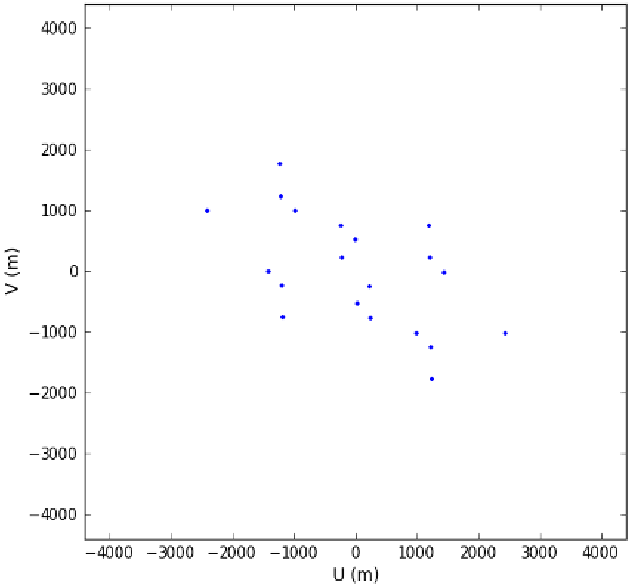


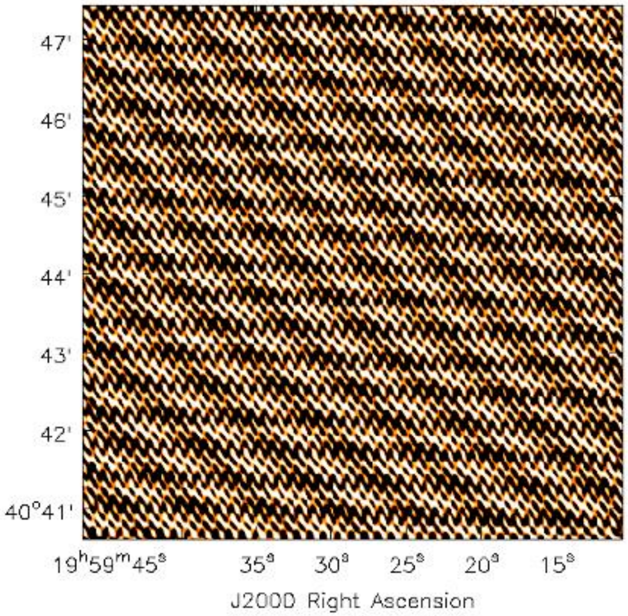
Image formed with

5 antennas

$S(u,v)$



$I^{obs}(l,m)$



Aperture Synthesis

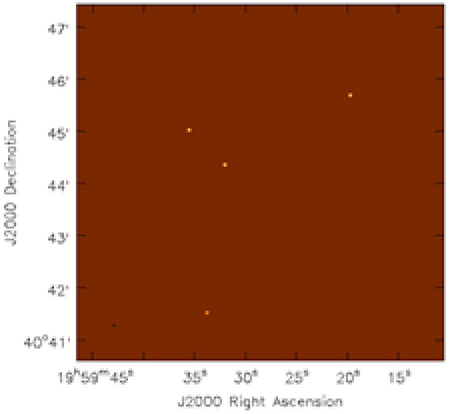
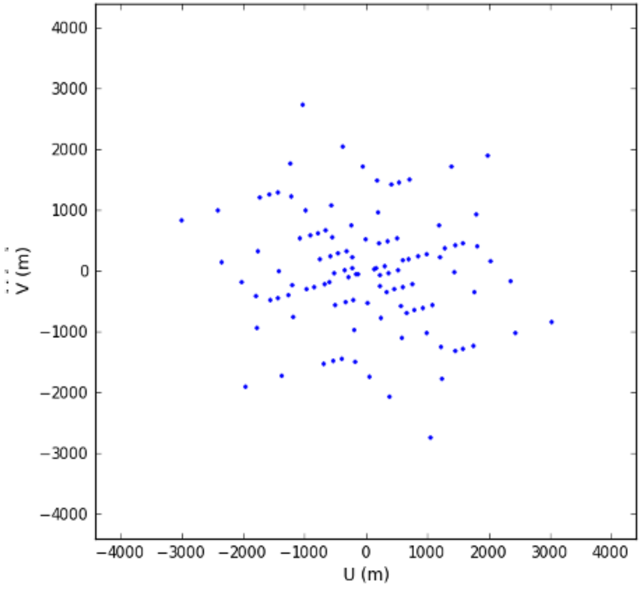


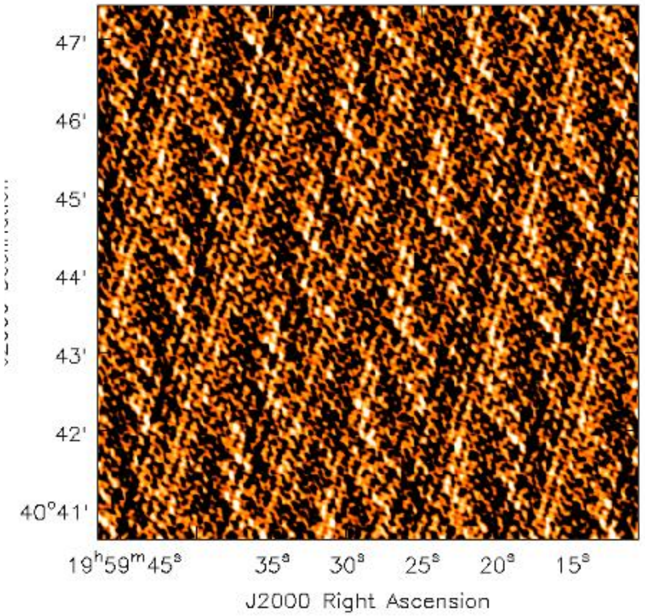
Image formed with

11 antennas

$S(u, v)$



$I^{obs}(l, m)$



Aperture Synthesis

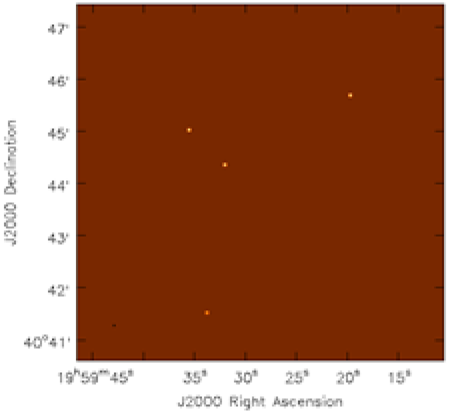
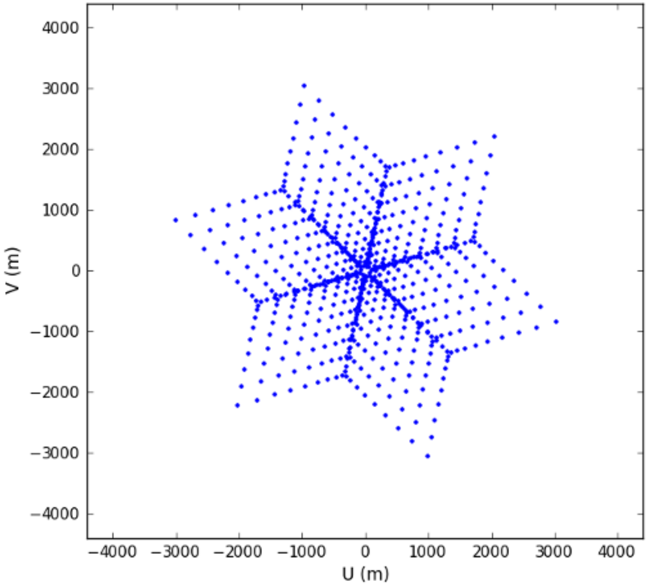


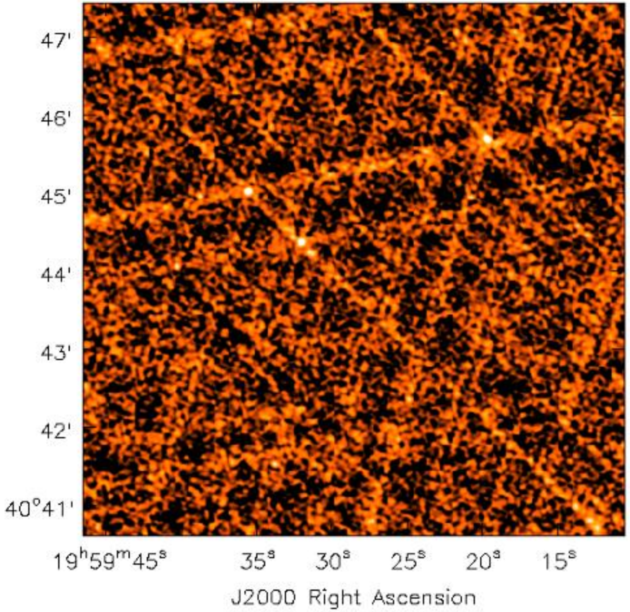
Image formed with

27 antennas

$S(u,v)$



$I^{obs}(l,m)$



Aperture Synthesis

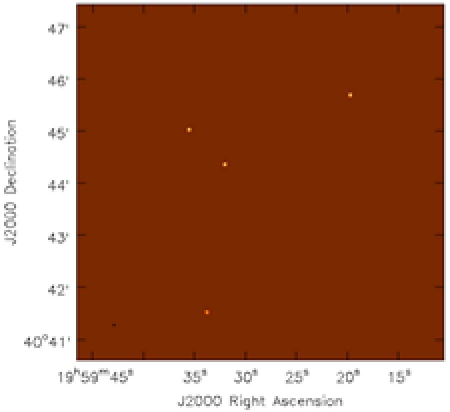
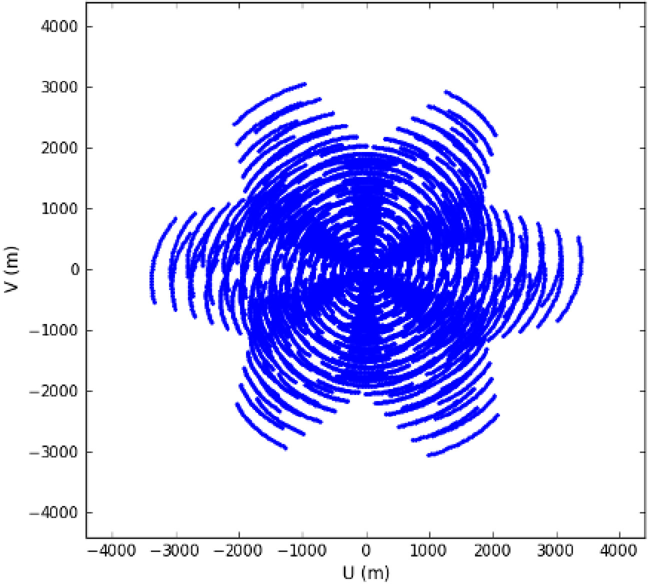


Image formed with

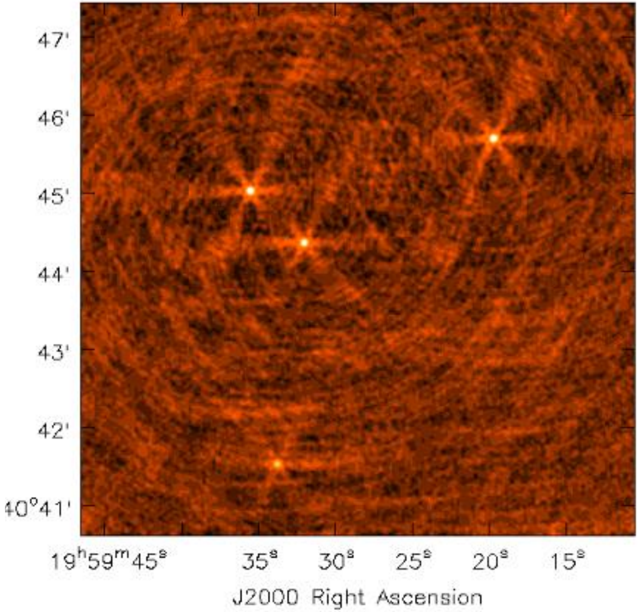
27 antennas

2 hours

$S(u,v)$



$I^{obs}(l,m)$



Aperture Synthesis

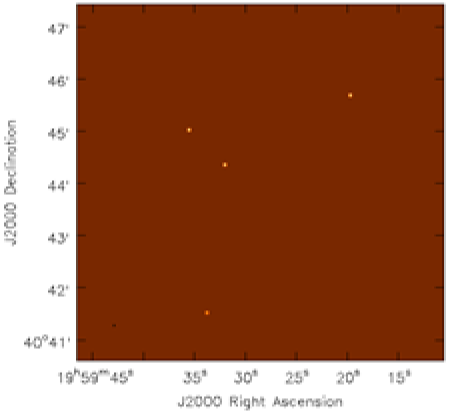
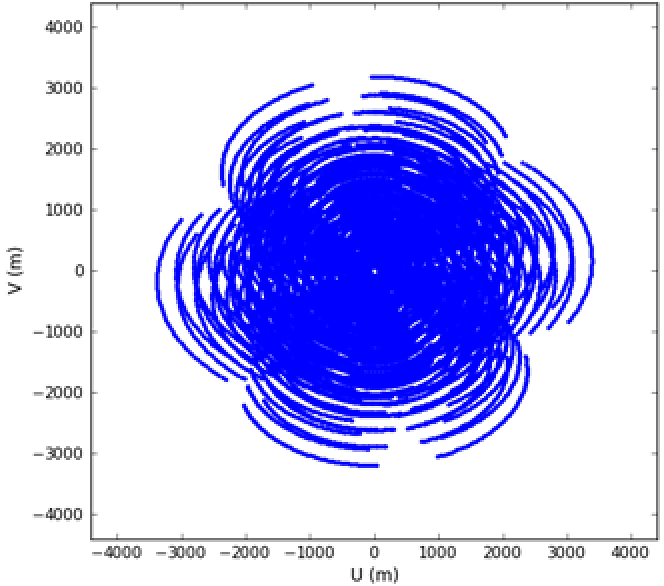


Image formed with

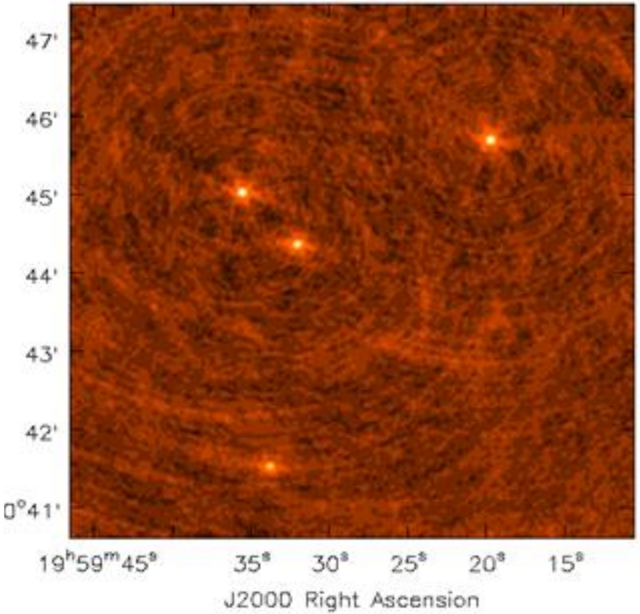
27 antennas

4 hours

$S(u,v)$

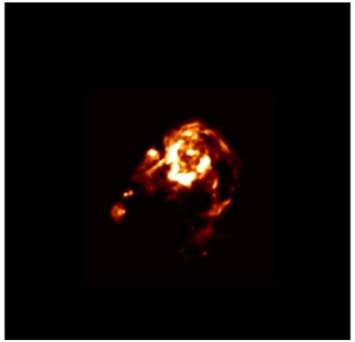


$I^{obs}(l,m)$

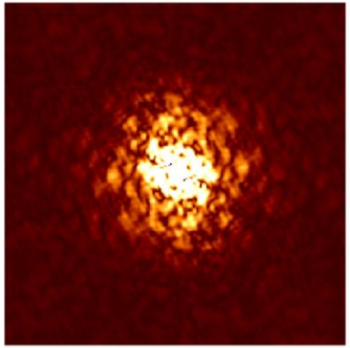


Measurement Eqns : $V^{obs} = [S]\,[F]\; I^{sky} + n$

Measurement Eqns : $V^{obs} = [S]\,[F]\,I^{sky} + n$



I^{sky}

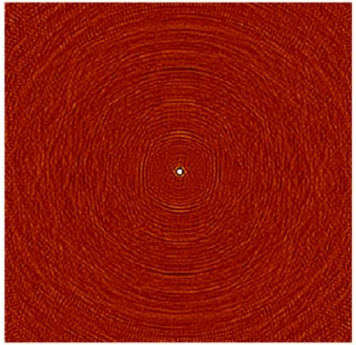


V^{obs} = [S] [F] I^{sky}

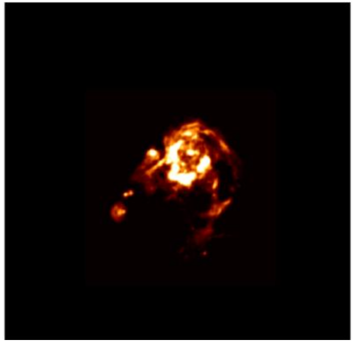
Image credits
Imaging-Deconv
Bhatnagar, 2006

Measurement Eqns : $V^{obs} = [S]\,[F]\, I^{sky} + n$

$=$

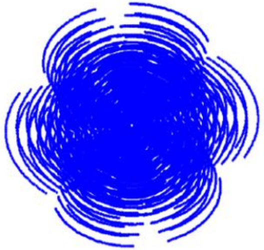


$*$

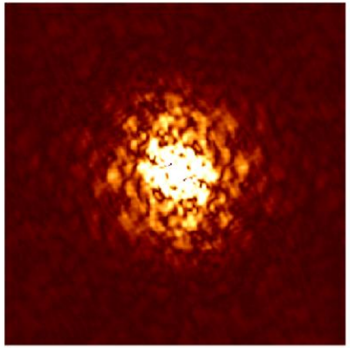


I^{sky}

$=$



$\cdot$



$V^{obs} = [S] \quad [F]\, I^{sky}$

Image credits
Imaging-Deconv
Bhatnagar, 2006

Measurement Eqns : $V^{obs} = [S]\,[F]\ I^{sky} + n$

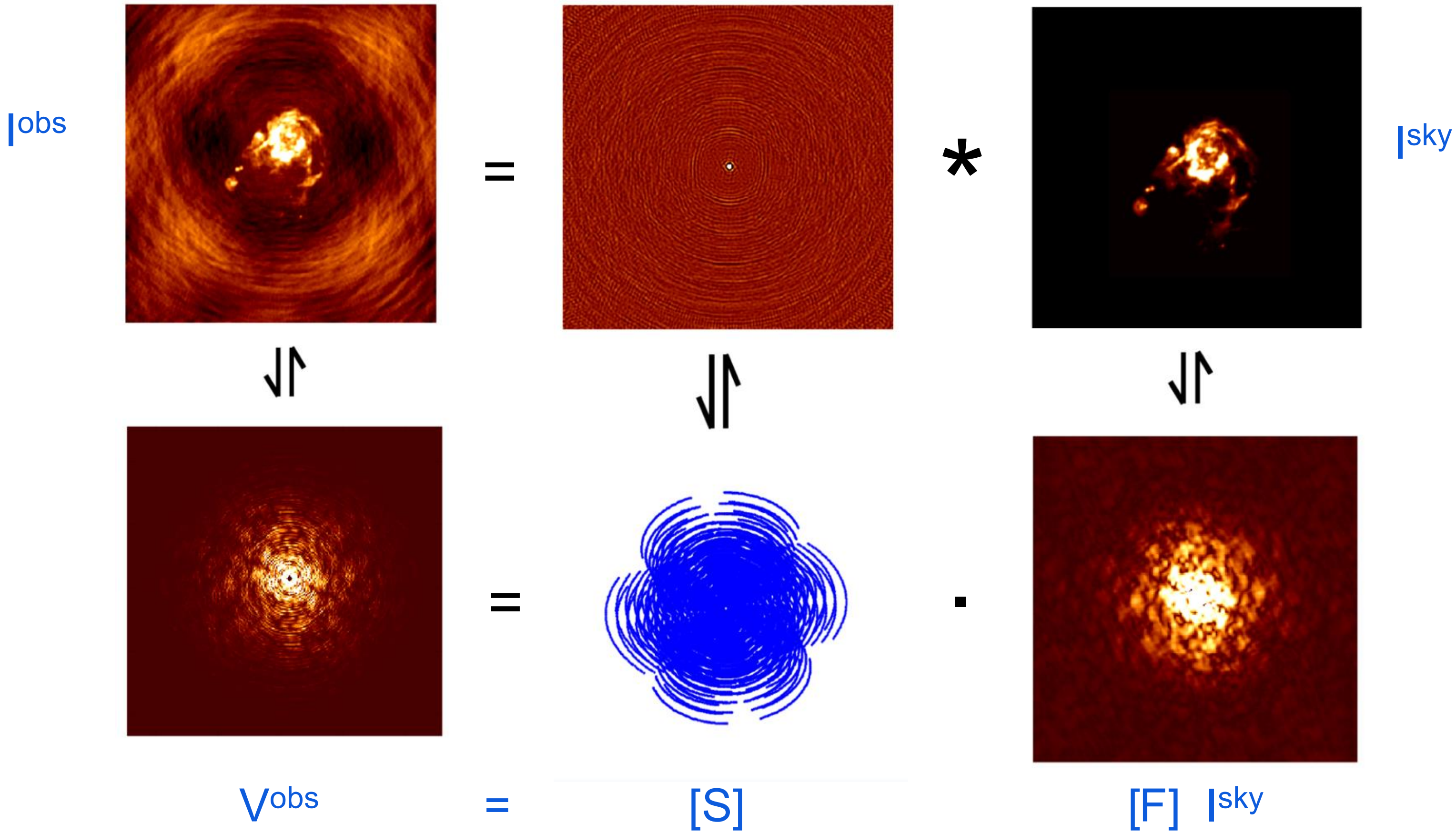


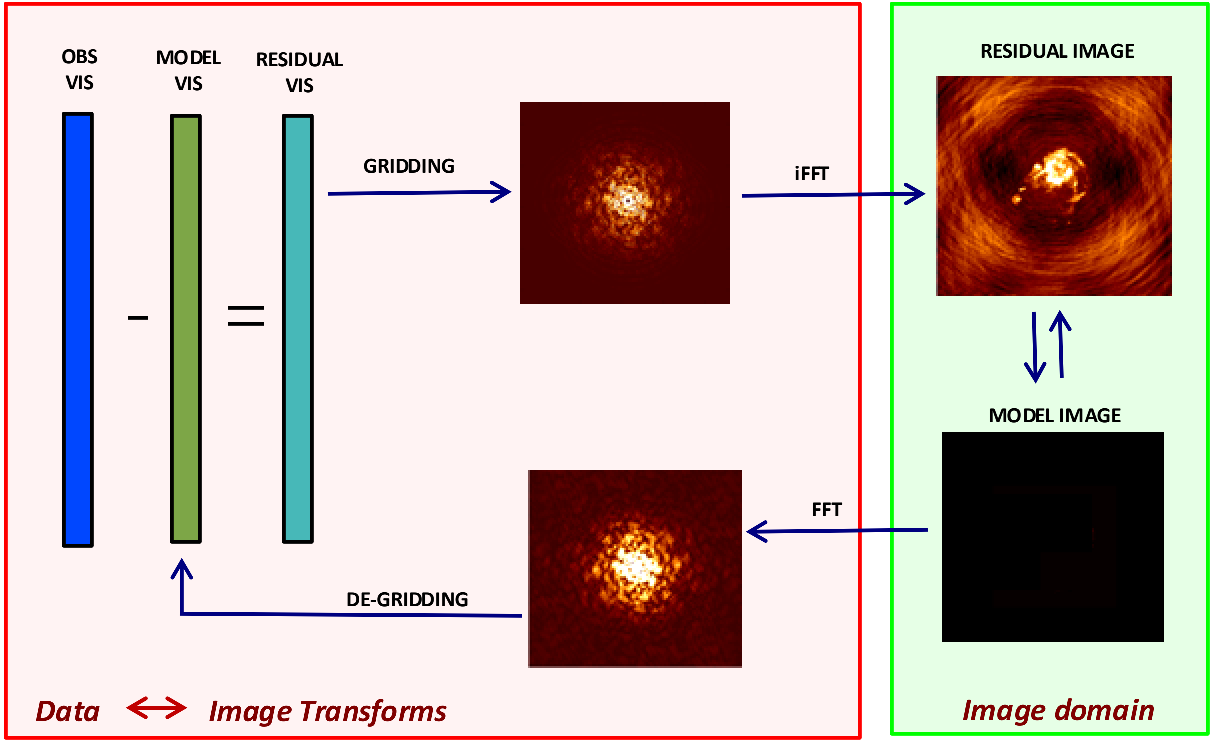
Image credits
[Imaging-Deconv](#)
Bhatnagar, 2006

Image Reconstruction : $V^{obs} = [S]\,[F]\, I^{sky} + n$

$$\min \{ \| V^{obs} - [S]\,[F]\, I^{model} \|_2^2 + \lambda R(I^{model}) \}$$

Image Reconstruction : $V^{obs} = [S]\,[F]\,I^{sky} + n$

$$\min \{ \; || V^{obs} - [S]\,[F]\,I^{model} ||_2^2 + \lambda R(I^{model}) \}$$



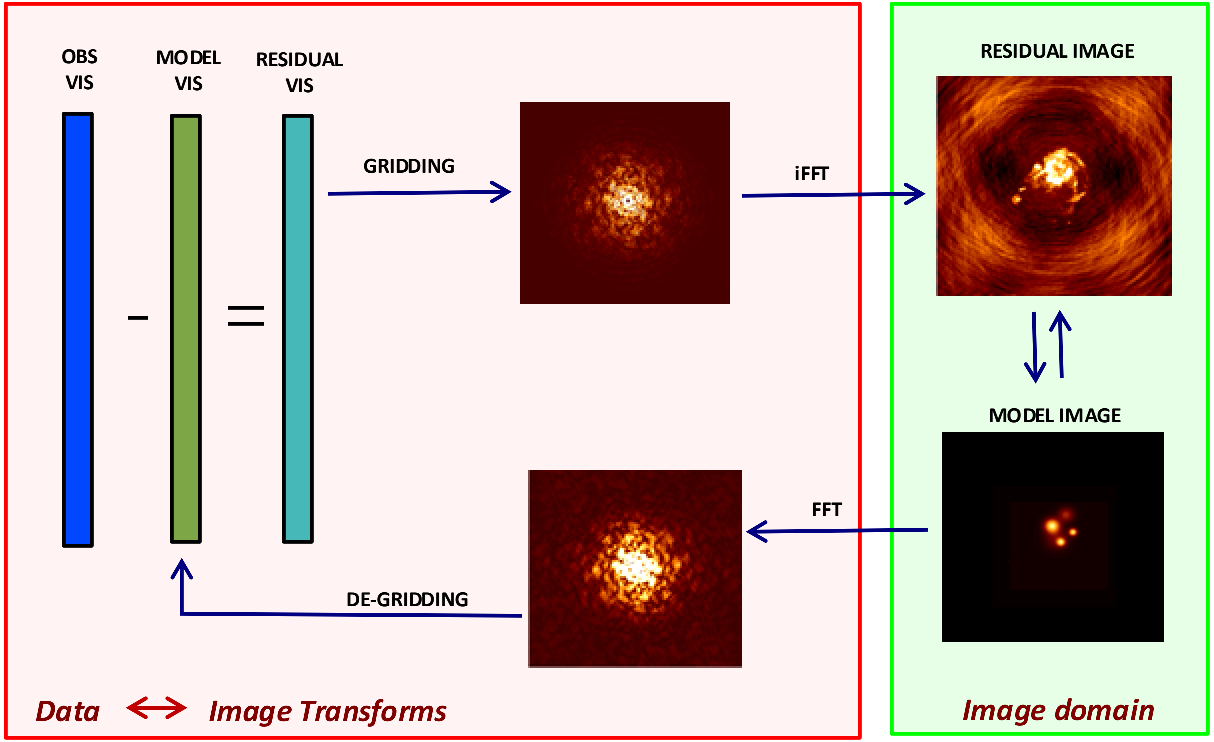
Algorithm Ingredients

- Sky Model basis
- Priors & Regularizers
- Optimization Strategy
- Instrumental Corrections

Ref : [CASA algorithms/software]

Image Reconstruction : $V^{obs} = [S]\,[F]\,I^{sky} + n$

$$\min\{\ \| V^{obs} - [S]\,[F]\,I^{model} \|_2^2 + \lambda R(I^{model})\ \}$$



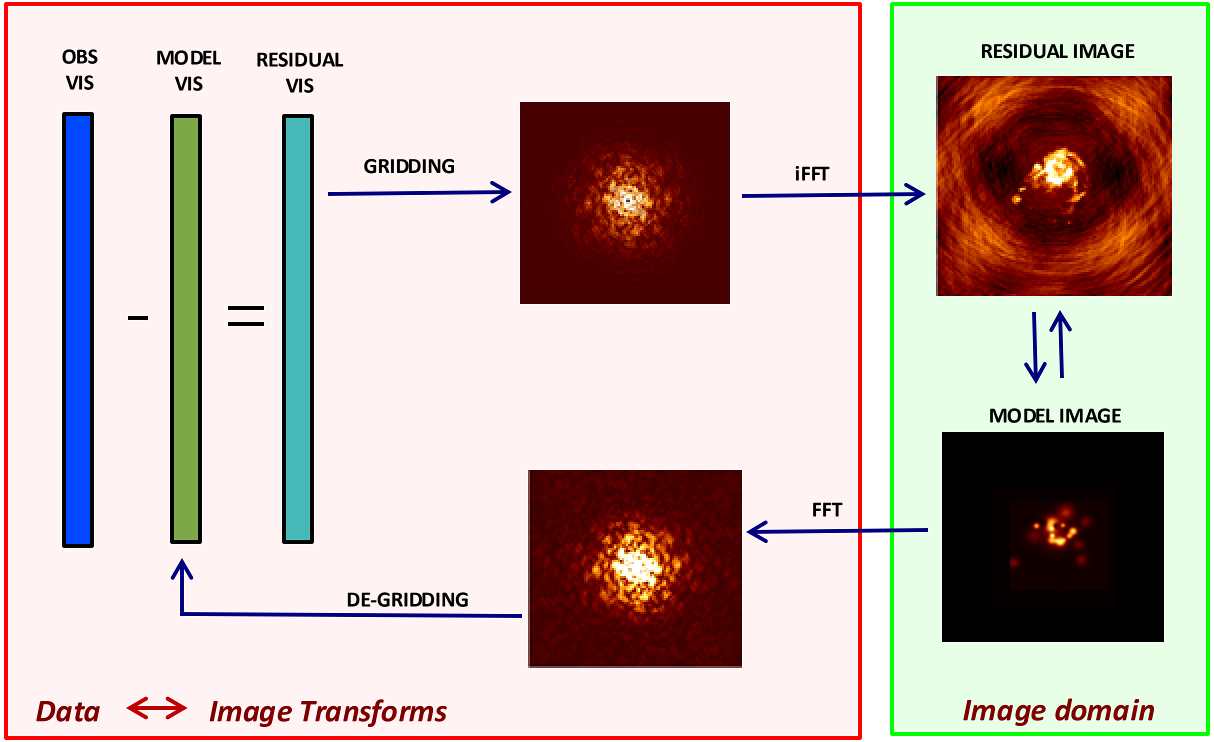
Algorithm Ingredients

- Sky Model basis
- Priors & Regularizers
- Optimization Strategy
- Instrumental Corrections

Ref : CASA algorithms/software

Image Reconstruction : $V^{obs} = [S]\,[F]\, I^{sky} + n$

$$\min \{ \; || V^{obs} - [S]\,[F]\, I^{model} ||_2^2 + \lambda R(I^{model}) \}$$



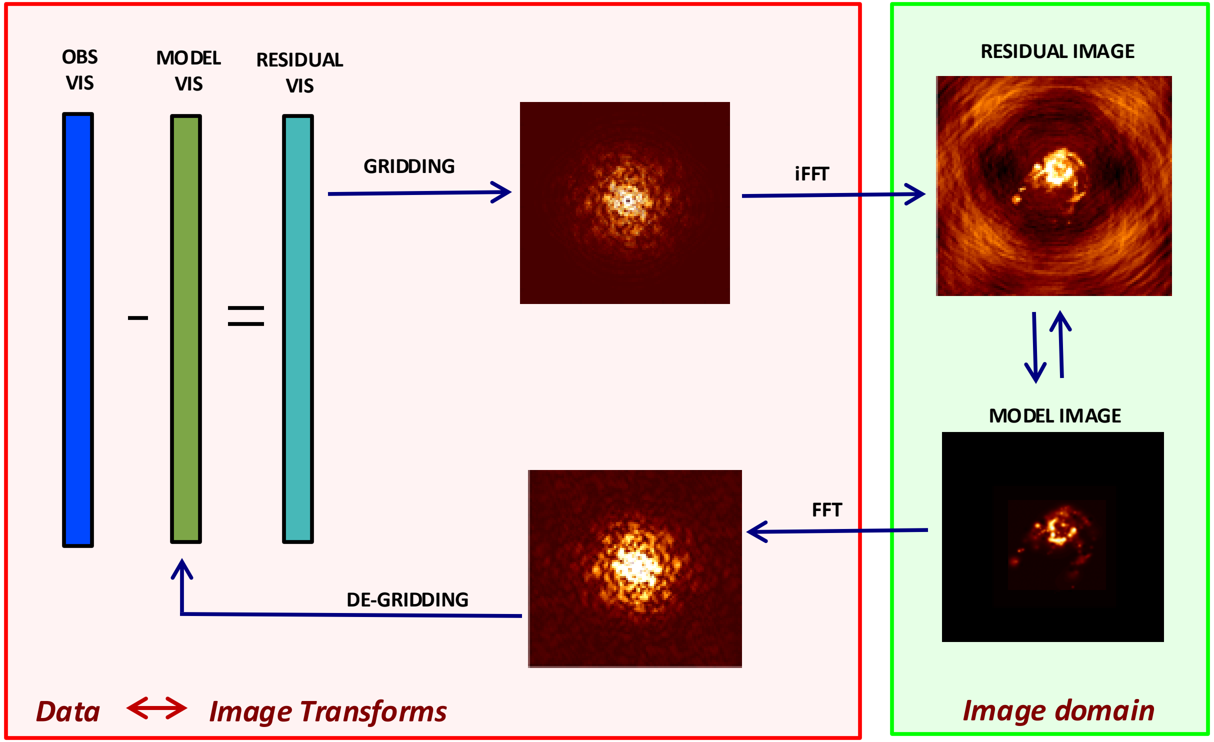
Algorithm Ingredients

- Sky Model basis
- Priors & Regularizers
- Optimization Strategy
- Instrumental Corrections

Ref : CASA algorithms/software

Image Reconstruction : $V^{obs} = [S]\,[F]\, I^{sky} + n$

$$\min \{ \; || V^{obs} - [S]\,[F]\, I^{model} ||_2^2 + \lambda R(I^{model}) \}$$



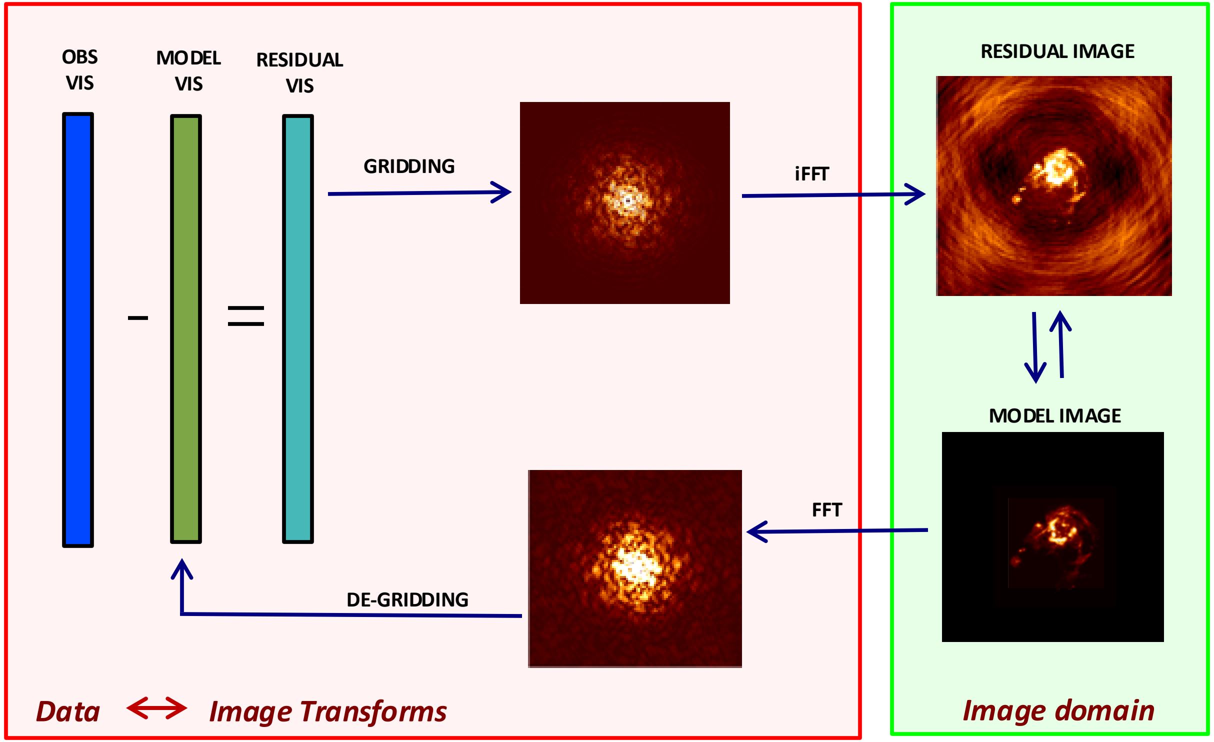
Algorithm Ingredients

- Sky Model basis
- Priors & Regularizers
- Optimization Strategy
- Instrumental Corrections

Ref : [CASA algorithms/software]

Image Reconstruction : $V^{obs} = [S]\,[F]\,I^{sky} + n$

$$\min \{ \; || V^{obs} - [S]\,[F]\,I^{model} ||_2^2 + \lambda R(I^{model}) \}$$



Ref : CASA algorithms/software

Algorithm Ingredients

- Sky Model basis
- Priors & Regularizers
- Optimization Strategy
- Instrumental Corrections

ML / AI ?

Super-resolution / denoising
-- Train for a range of PSFs

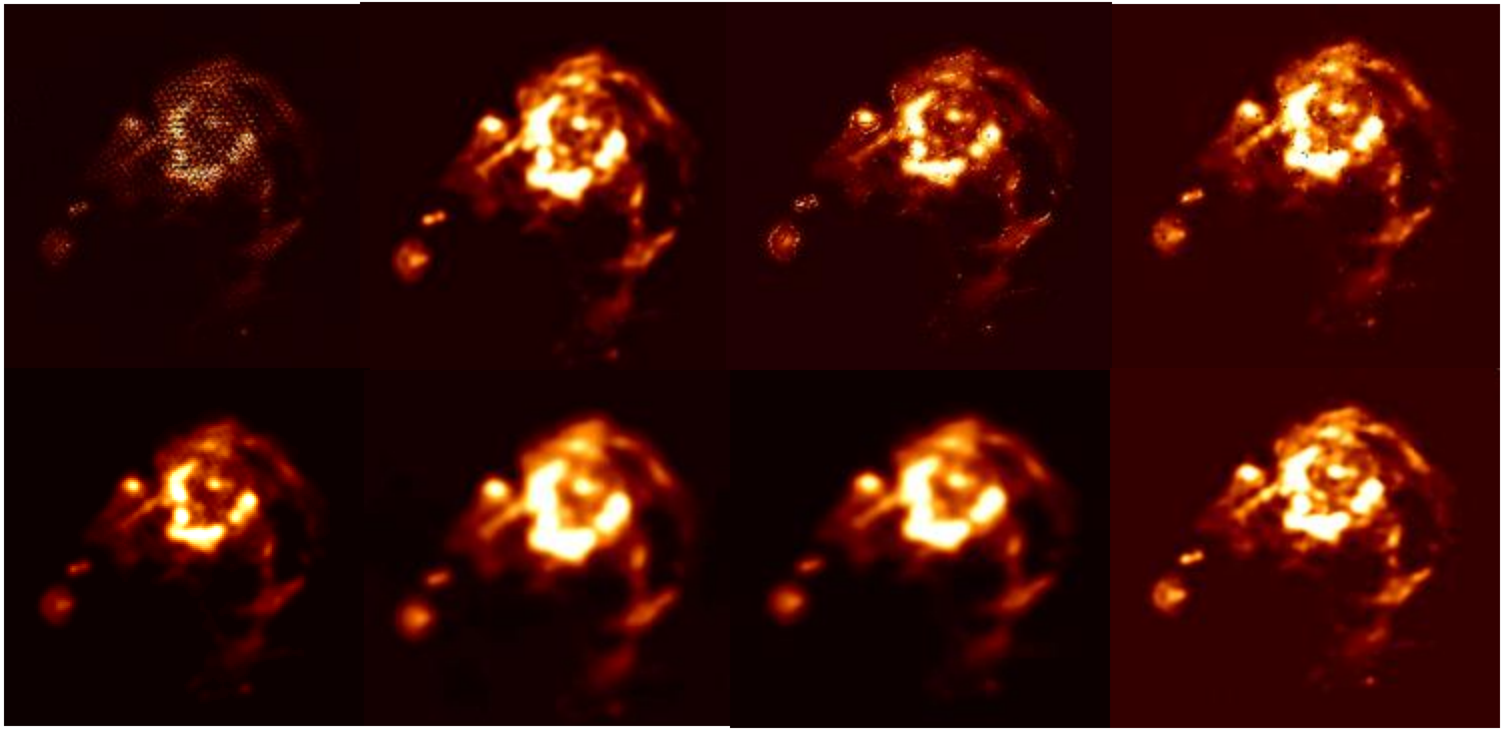
Learn a basis (latent space)

Image Reconstruction : $V^{obs} = [S]\,[F]\,I^{sky} + n$

CLEAN | Max-Ent | Multi-Scale | Adaptive-Scale

I^m

I^{out}



(Hogbom 1974, Clark 1980, Schwab & Cotton 1983) | (Cornwell & Evans, 1985) | (Cornwell, 2008) | (Bhatnagar & Cornwell 2004)

\+ many, many more algorithms…

Uncertainty quantification is important

Image credits
Imaging-Deconv
Bhatnagar, 2006

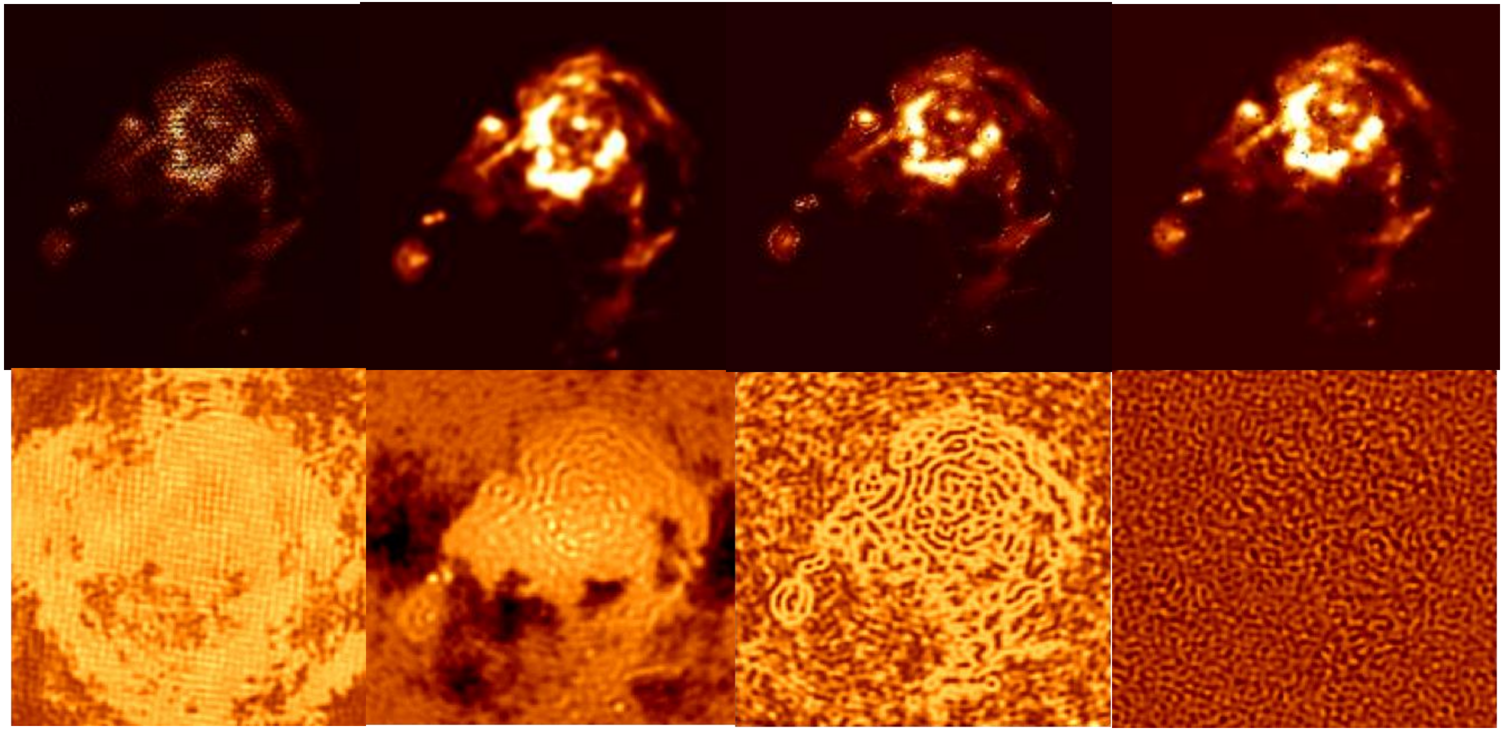
Image Reconstruction : $V^{obs} = [S]\,[F]\,I^{sky} + n$

CLEAN | Max-Ent | Multi-Scale | Adaptive-Scale

+ many, many more algorithms…

I^m

I^{res}



(Hogbom 1974, Clark 1980, Schwab & Cotton 1983)

(Cornwell & Evans, 1985)

(Cornwell, 2008)

(Bhatnagar & Cornwell 2004)

Uncertainty quantification is important

Standardized vs Optimal ?

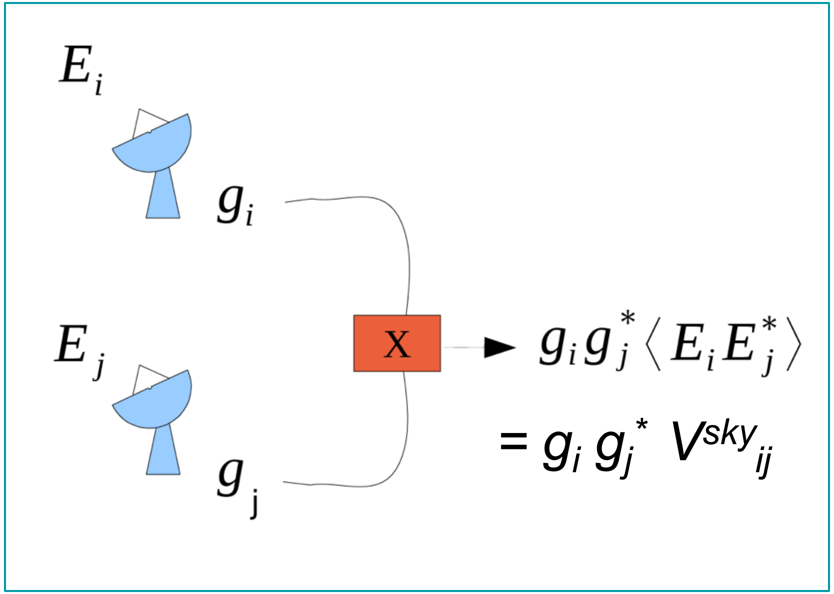
Image credits
Imaging-Deconv
Bhatnagar, 2006

Measurement Eqns : $V^{obs} = [S]\,[F]\,I^{sky} + n$

Measurement Eqns : $V^{obs}_{ij} = g_i\, g_j^* \; [S_{ij}]\; [F] \; I^{sky} + n_{ij}$

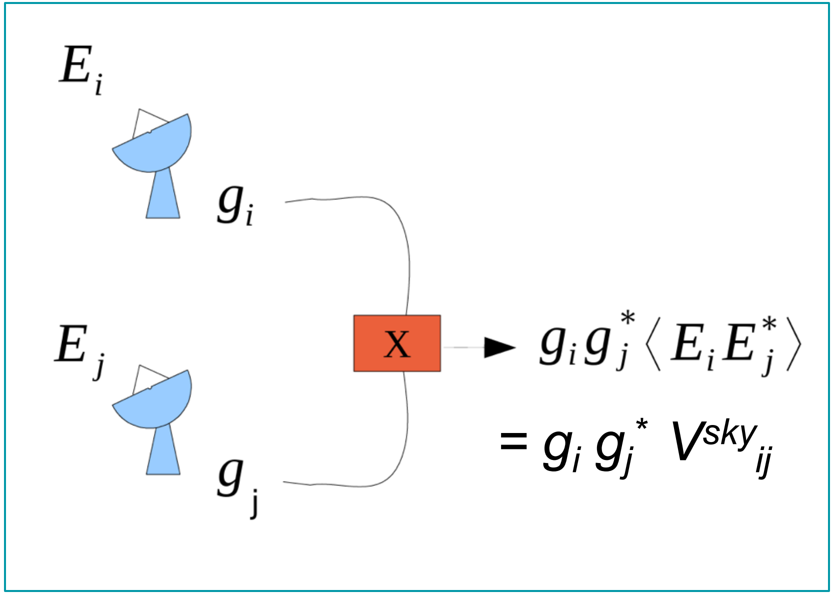
Measurement Eqns : $V^{obs}_{ij} = g_i\, g_j^* \; [S_{ij}]\, [F]\; I^{sky} + n_{ij}$

Front-end electronics and signal path introduce a complex gain per antenna.



Measurement Eqns : $V^{obs}_{ij} = g_i\, g_j^*\ [S_{ij}]\,[F]\ I^{sky} + n_{ij}$

Front-end electronics and signal path introduce a complex gain per antenna.



To remove this instrumental effect :

(1) Observe a known calibrator source before/after the target scans

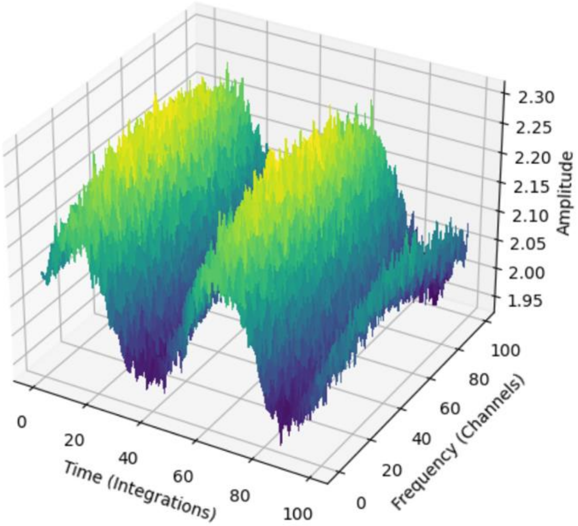
(2) Derive a model of g_i for all i (NLLS)

(3) Interpolate (generate from the model) $g_i\, g_j^*$ for the target time range

(4) Divide the target data by $g_i\, g_j^*$

Measurement Eqns : $V^{obs}_{ij} = g_i\, g_j^* \; [S_{ij}]\,[F]\; I^{sky} \quad + \quad n_{ij}$

Accurate gain solutions depend on data SNR, gain variation, sky structure



$g_i\,(t, f)\; g_j^*\,(t, f) \;\; V^{sky}_{ij}\,(t, f)$

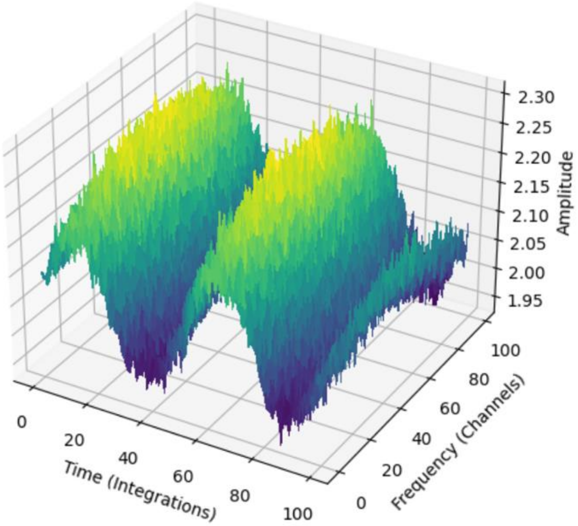
Choices to make :

- Is SNR sufficient ?
  - Average across time or freq ?
- Is the sky model good enough ?

Fig from B.Kirk

Measurement Eqns : $V^{obs}_{ij} = g_i \, g_j^* \; [S_{ij}] \, [F] \; I^{sky} \; + \; n_{ij}$

Accurate gain solutions depend on data SNR, gain variation, sky structure



$$g_i\,(t, f)\; g_j^*\,(t, f) \;\; V^{sky}_{ij}\,(t, f)$$

Fig from B.Kirk

Choices to make :

- Is SNR sufficient ?
  - Average across time or freq ?
- Is the sky model good enough ?

ML/AI ?

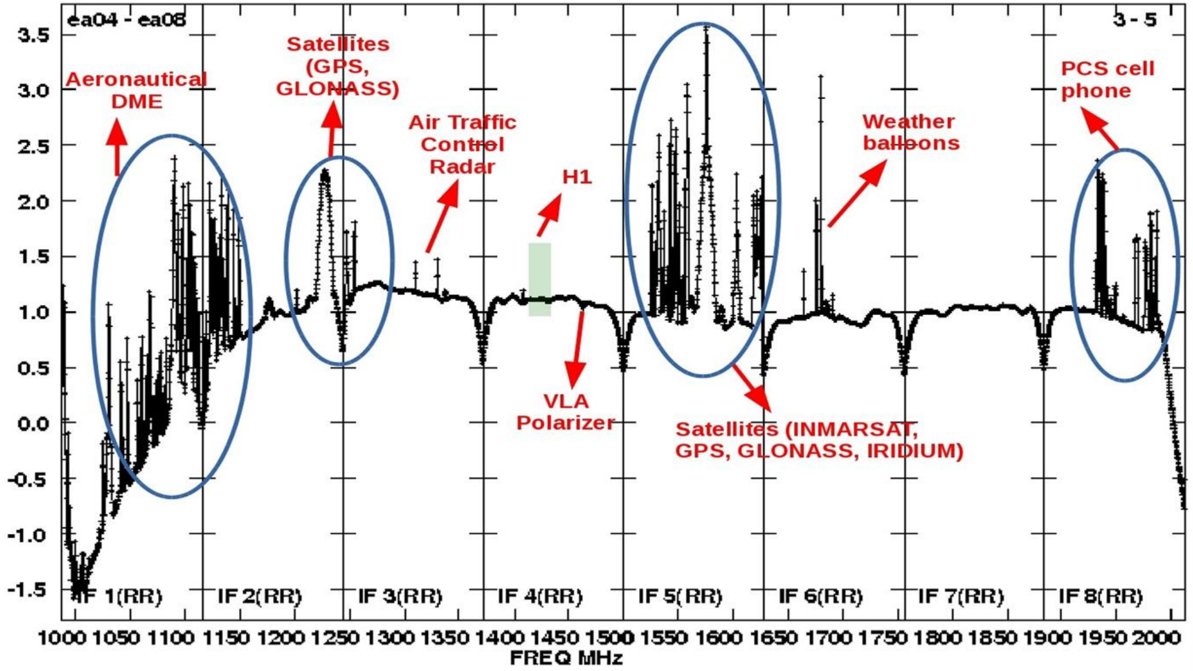
- Adaptive data-dependent choices
- Predictive ? Tel monitoring / weather ?

Measurement Eqns : $V^{obs}_{ij} = g_i\, g_j^* \; [S_{ij}]\, [F]\; I^{sky} + n_{ij}$

Measurement Eqns : $V^{obs}_{ij} = g_i\, g_j^{*}\; [S_{ij}]\, [F]\; I^{sky} + n_{ij} + N^{rfi}_{ij}$

Measurement Eqns : $V^{obs}_{ij} = g_i\, g_j^* \; [S_{ij}]\, [F]\; I^{sky} + n_{ij} + N^{rfi}_{ij}$

Some data are contaminated by unwanted signals. Need to find and remove.



Radio Frequency Interference

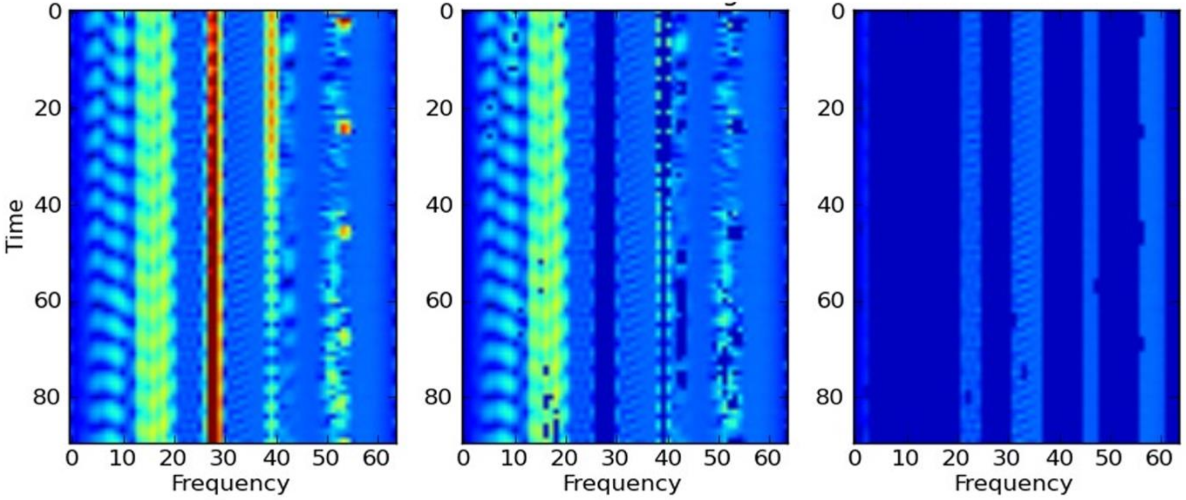
- Cell phones, Aircraft comm, Satellite comm, radar, etc.

Instrumental Effects

- Antenna tracking delays, glitches in signal processing, antenna dropouts, shadowing...

Measurement Eqns : $V^{obs}_{ij} = g_i\, g_j^* \; [S_{ij}]\, [F]\; I^{sky} + n_{ij} + N^{rfi}_{ij}$

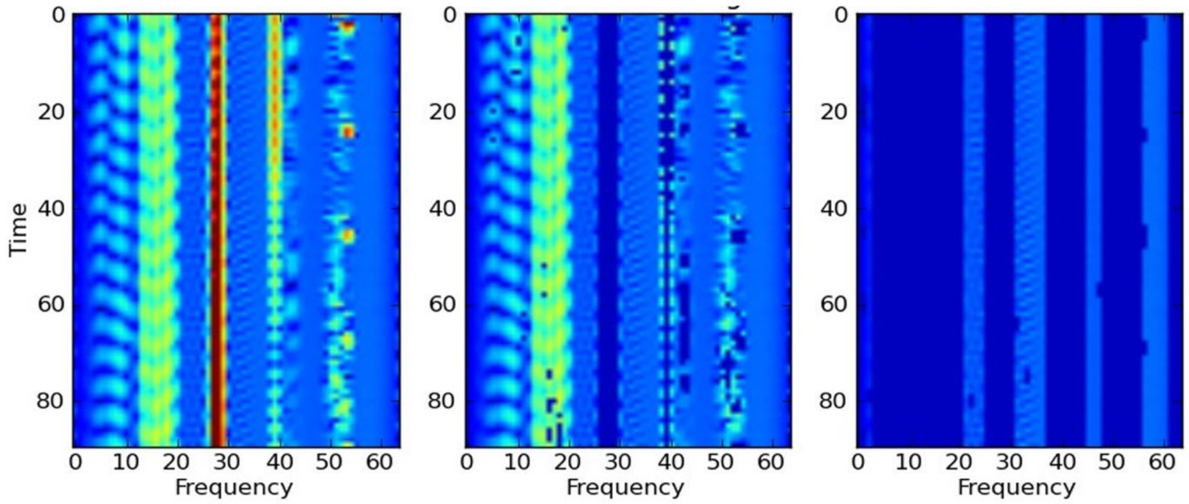
Algorithms : Outlier detectors + Masking : Manual, Automated (with tuning knobs)



- Model based flagging
  (derive model from data)
- Statistical flagging
- Use a-priori RFI info
- Model & subtract ?

Measurement Eqns : $V^{obs}_{ij} = g_i \, g_j^* \; [S_{ij}] \; [F] \; I^{sky} + n_{ij} + N^{rfi}_{ij}$

Algorithms : Outlier detectors + Masking : Manual, Automated (with tuning knobs)



- Model based flagging
  (derive model from data)

- Statistical flagging

- Use a-priori RFI info

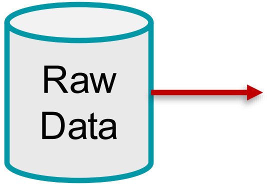
- Model & subtract ?

ML / AI ?

Model RFI signatures (mask/subtract), Pattern recognition, Prediction from past behavior….

Processing : Turning raw data into image products

$$V^{obs}_{ij} = g_i \, g_j^* \; [S_{ij}] \, [F] \; I^{sky} \quad + \quad n_{ij} \quad + \quad N^{rfi}_{ij}$$

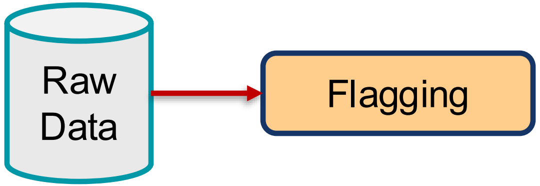


Data = Lists of complex numbers + metadata

N_ant (N_ant – 1) / 2 x N_chan x N_time x N_pol

Processing : Turning raw data into image products

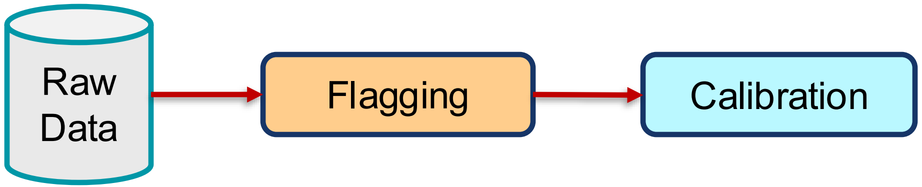
$$V^{obs}_{ij} = g_i \, g_j^* \; [S_{ij}] \, [F] \; I^{sky} \; + \; n_{ij} \; + \; \cancel{N^{rfi}_{ij}}$$



Step 1 : Identify and remove contaminated data

Processing : Turning raw data into image products

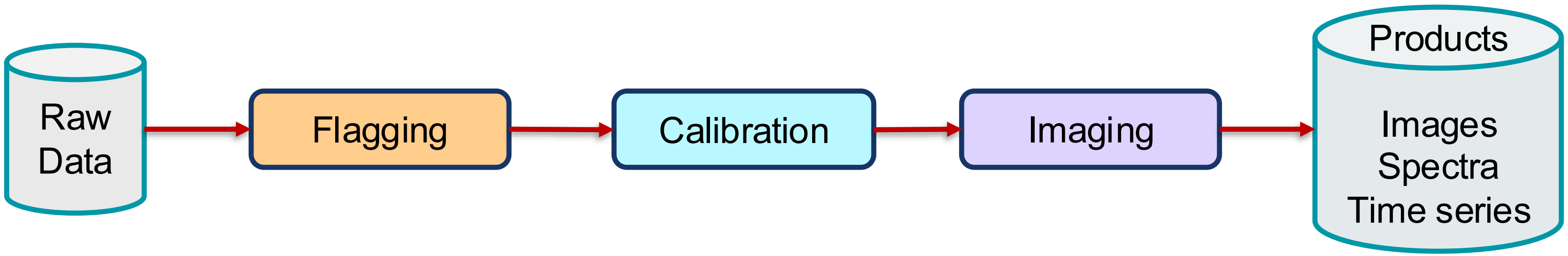
$$V^{obs}_{ij} = \cancel{g_i g_j^*} \; [S_{ij}] \; [F] \; I^{sky} + n_{ij} + \cancel{N^{rfi}_{ij}}$$



Step 2 : Model and correct for instrumental effects

Processing : Turning raw data into image products

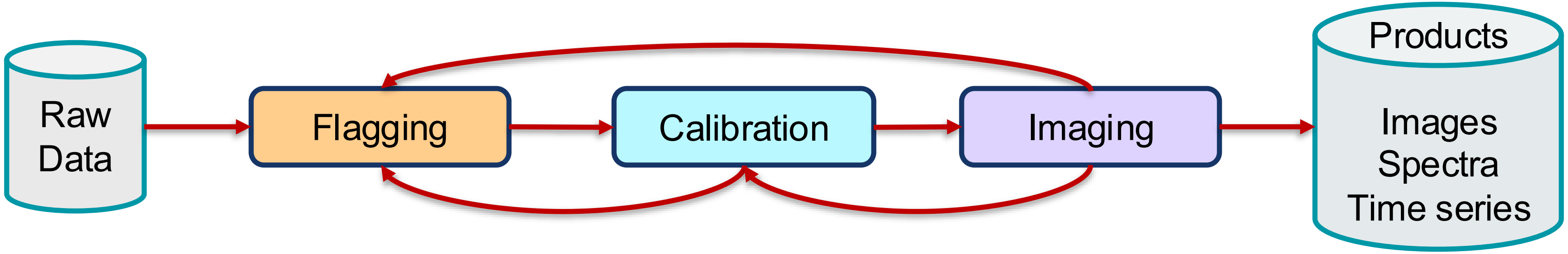
$$V^{obs}_{ij} = \cancel{g_i g_j^*} \; \cancel{[S_{ij}]} [F] \; I^{sky} + \cancel{n_{ij}} + \cancel{N^{rfi}_{ij}}$$



Step 3 : Reconstruct the image. Derive spectra and time series. Archive.

Processing : Turning raw data into image products

$$V^{obs}_{ij} = \cancel{g_i\, g_j^*}\ \cancel{[S_{ij}]}\ [F]\ \ I^{sky} + \cancel{n_{ij}} + \cancel{N^{rfi}_{ij}}$$



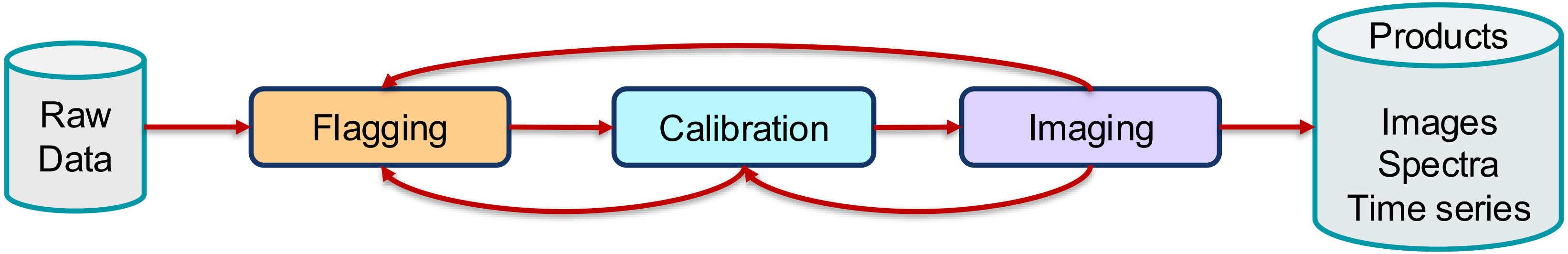
When RFI is weak, SNR is low or the sky brightness is complicated

=> Need many steps (and repetitions) to navigate the error surface…

Algorithm Architecture (Bhatnagar et al 2025)

Processing : Turning raw data into image products

$$V^{obs}_{ij} = g_i\, g_j^{*}\ [S_{ij}]\ [F]\ [M_{ij}]\ I^{sky} \quad + \quad n_{ij} \quad + \quad N^{rfi}_{ij}$$

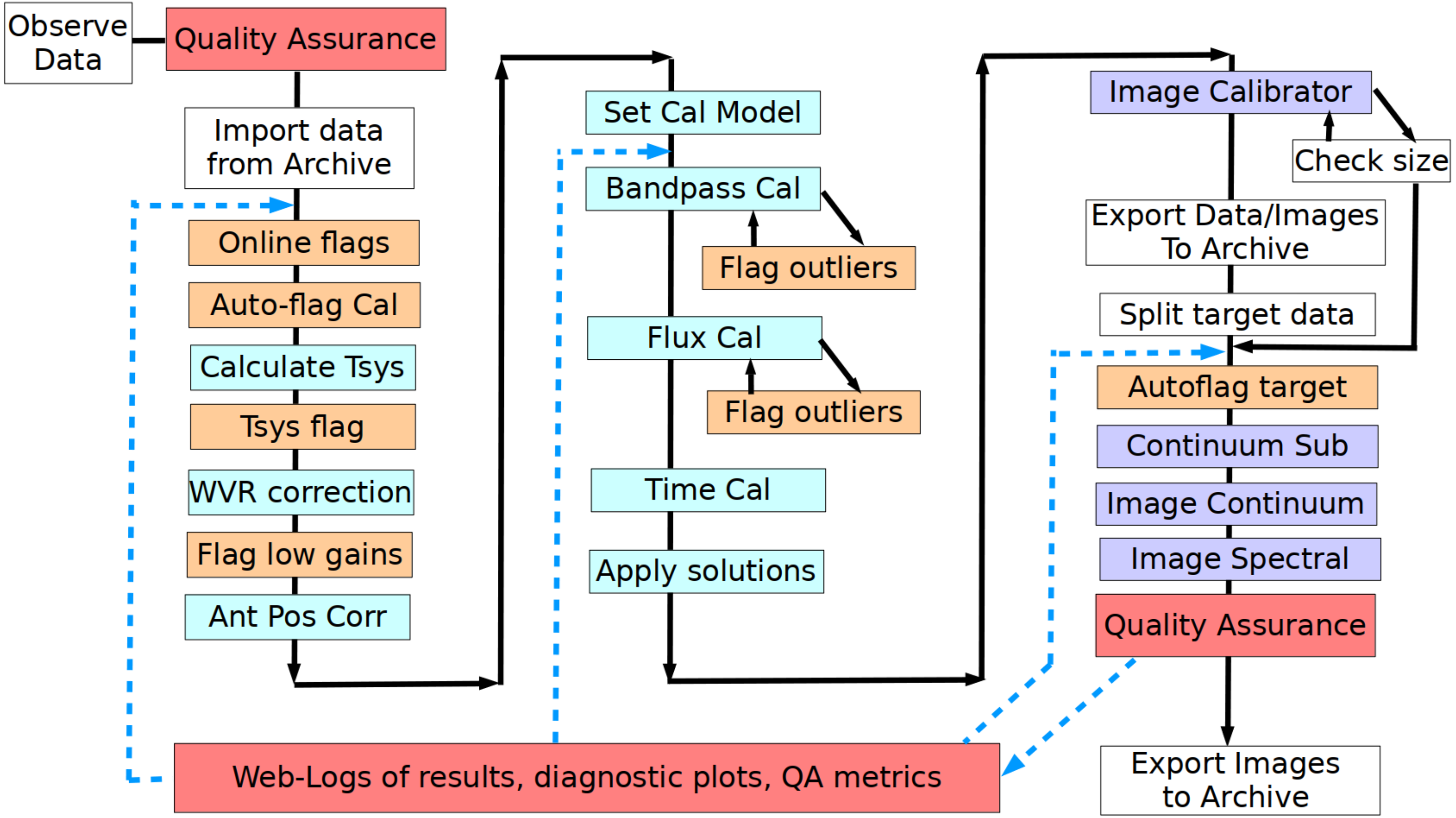


High-dynamic-range $[M_{ij}]$ → More Instrumental effects + 2D approximations break

=> More algorithm choices to make when navigating the error surface…..

Algorithm Architecture (Bhatnagar et al 2025)

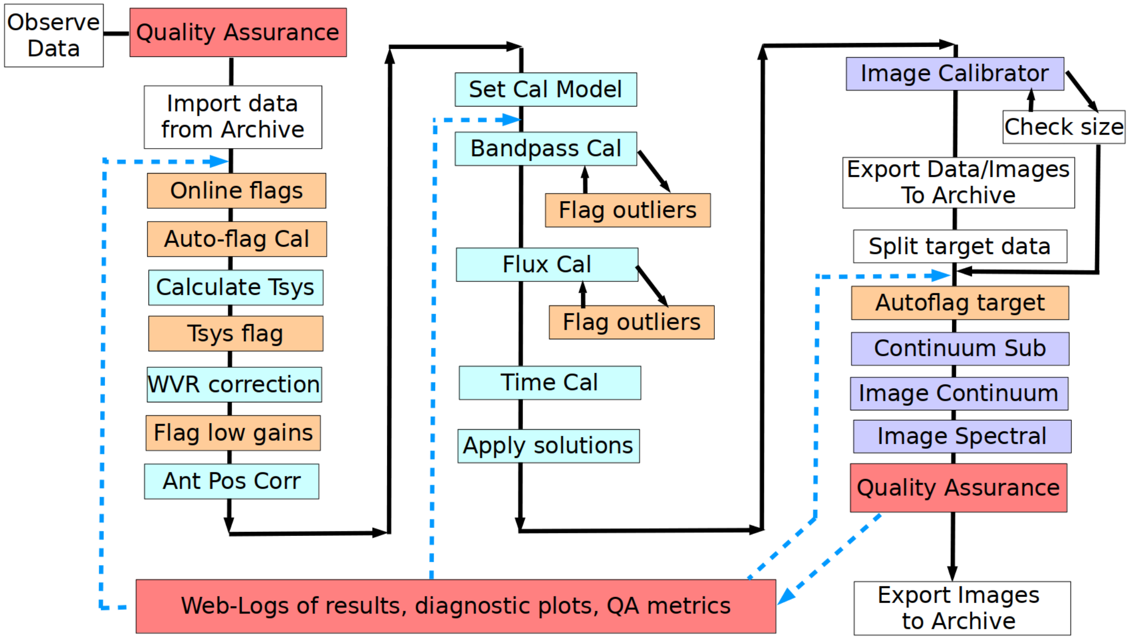
Data Analysis Pipelines



A simplified depiction of the ALMA Pipeline

Current pipeline heuristics : Hunter et al 2023

Data Analysis Pipelines



Team of Scientists

Define & update
the pipeline model

→ Flowchart of steps

Team of Data Analysts

Monitor QA logs
Intervene as needed

Data Analysis Pipelines

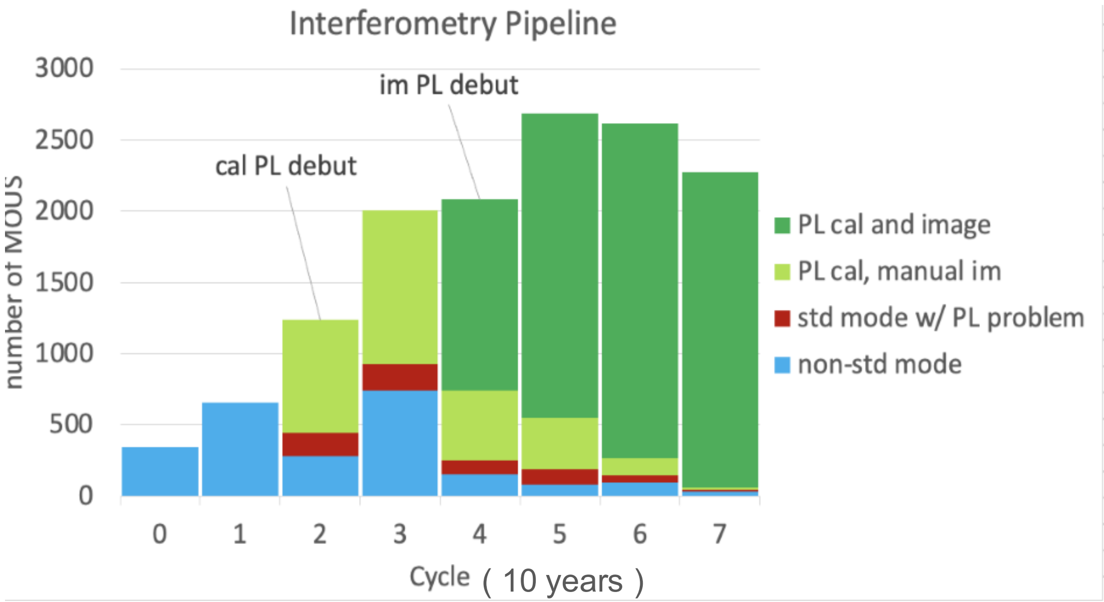


Fig credit : R.Indebetouw

For the chosen metrics :

The (model) accuracy and completeness has improved steadily over 10 years.

Improvements continue…

Archived product metrics :

-- Standardized ?
-- Optimal ?

Goal : both…

Feature Identification and Extraction

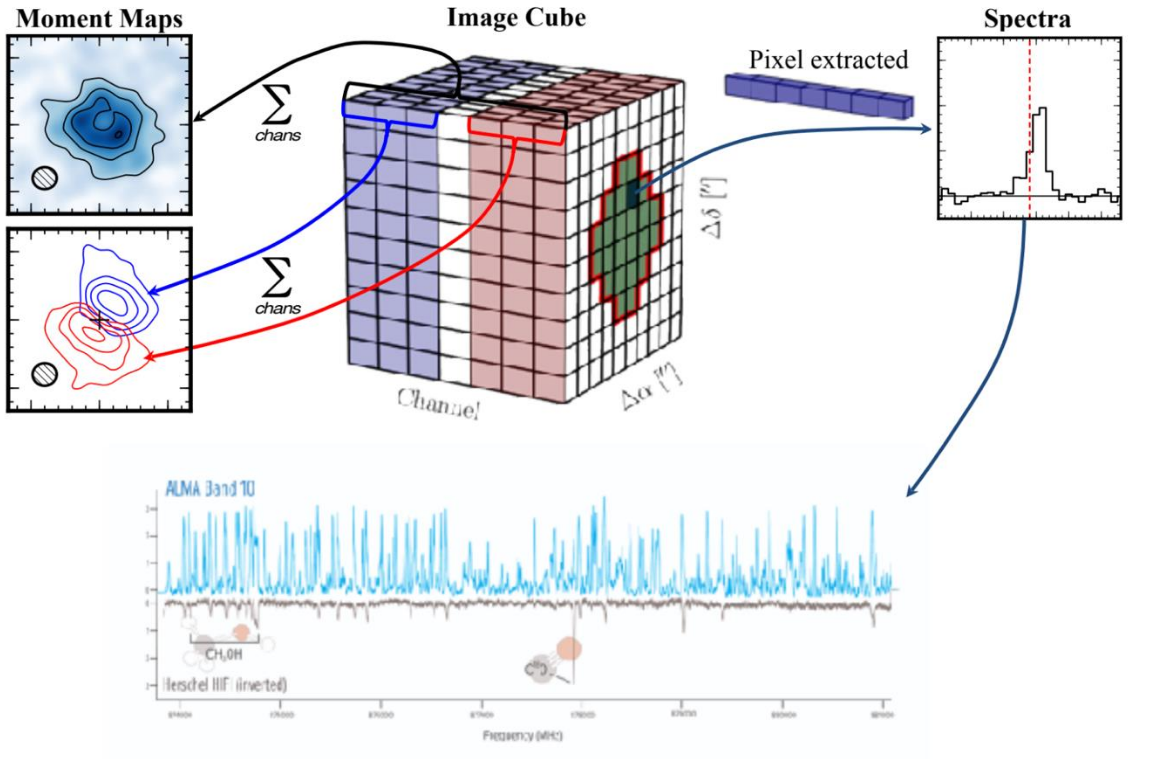


Image Products

Astrophysics is done via many derived quantities

- Source counts / ids
- Spectra (pixel, integrated)
- Moments
- Time series
- Find/group/classify structures and shapes

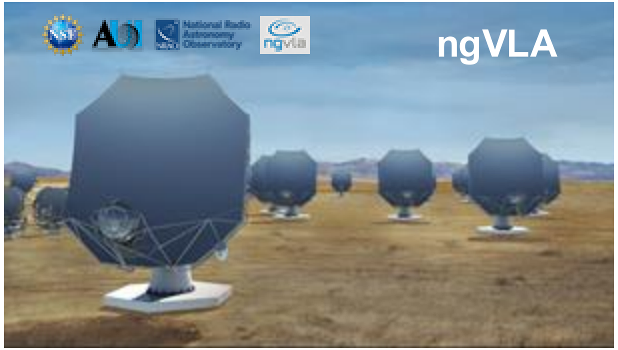
Need to understand uncertainties and error bars from data processing choices…

Figure copied from CosmicAI town hall slides (Oct 2024)

Large Data Volumes

2K dishes, 1M dipoles (50 MHz - 30 GHz).

66 dishes (35 GHz - 950 GHz).



263 dishes (1 GHz - 100 GHz).

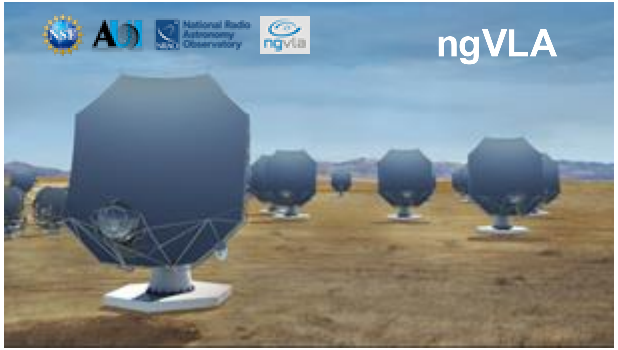
Large Data Volumes

More Observed Data

- Reduce Image Noise
- Better Resolution

2K dishes, 1M dipoles (50 MHz - 30 GHz).

66 dishes (35 GHz - 950 GHz).



263 dishes (1 GHz - 100 GHz).

Large Data Volumes

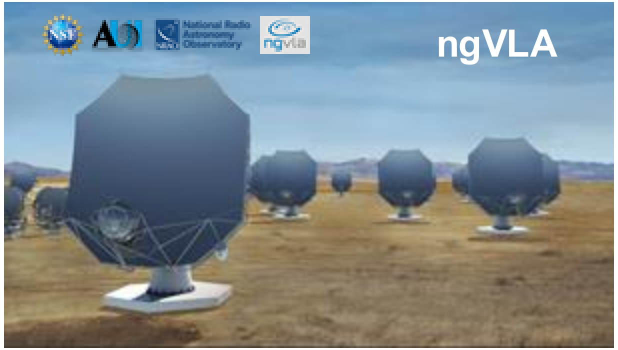
More Observed Data

- Reduce Image Noise
- Better Resolution

Compute Cost Increases

2K dishes, 1M dipoles (50 MHz - 30 GHz).

66 dishes (35 GHz - 950 GHz).



263 dishes (1 GHz - 100 GHz).

Large Data Volumes

More Observed Data

- Reduce Image Noise
- Better Resolution

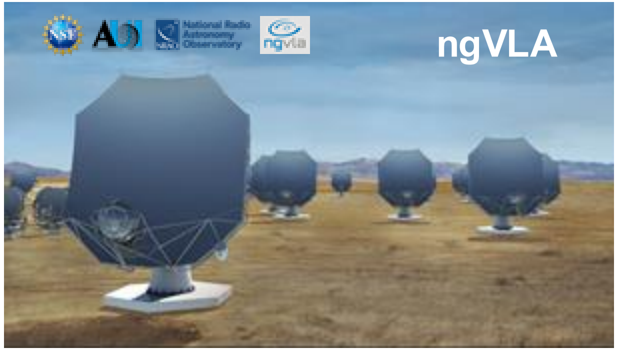
Instrumental effects more easily seen

- Need more complex algorithms
- More analysis steps / choices

Compute Cost Increases

2K dishes, 1M dipoles (50 MHz - 30 GHz).

66 dishes (35 GHz - 950 GHz).



263 dishes (1 GHz - 100 GHz).

Large Data Volumes

More Observed Data

- Reduce Image Noise
- Better Resolution

Instrumental effects more easily seen

- Need more complex algorithms
- More analysis steps / choices

Compute Cost Increases

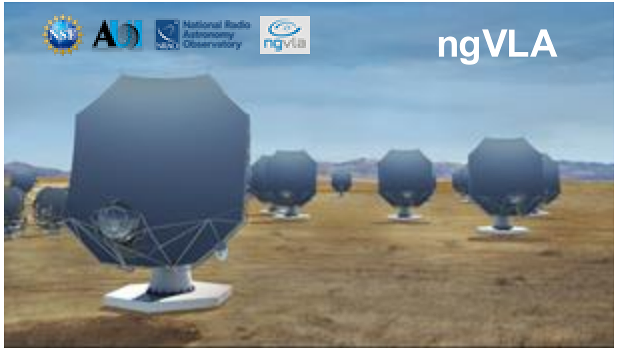
=> Need High-throughput and High-performance computing

Manual intervention is harder

=> Need More Automation

2K dishes, 1M dipoles (50 MHz - 30 GHz).

66 dishes (35 GHz - 950 GHz).



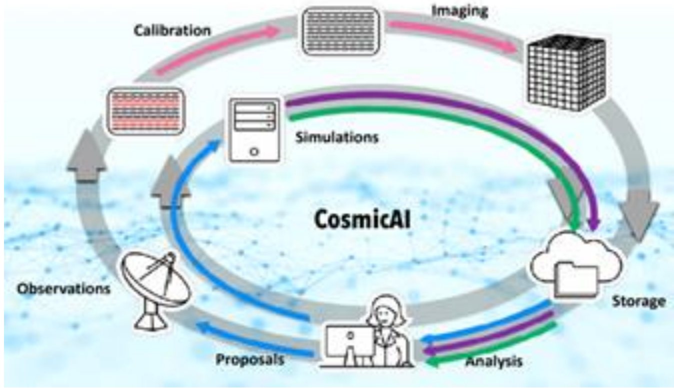
263 dishes (1 GHz - 100 GHz).

Examples of ML/AI application (an illustrative list, not exhaustive)

Processing

Observing

Interpretation



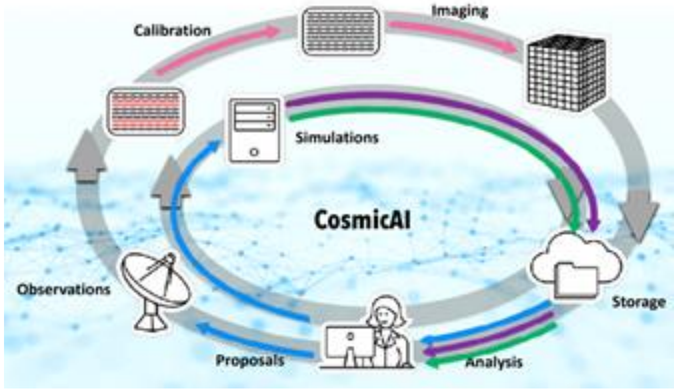
Examples of ML/AI application (an illustrative list, not exhaustive)

Processing

Core Algorithms

POLISH : Train for DSA PSFs
AIRI : Plug'n'play DNN deconvolver
DEEP-FOCUS : AutoEnc with meta learner
RFI identification : Pattern recognition
DIReCT : Using closure quantities

Observing



Interpretation

Examples of ML/AI application (an illustrative list, not exhaustive)

Processing

Core Algorithms

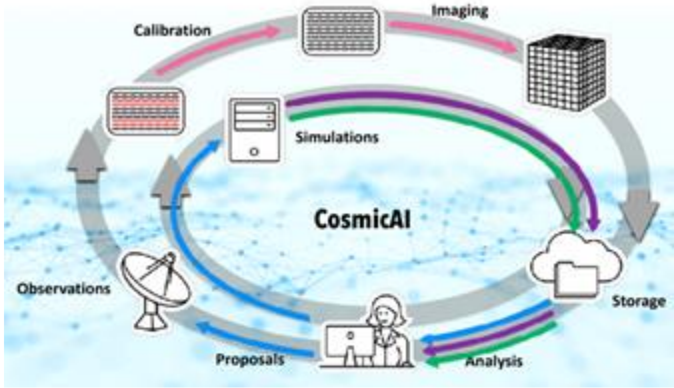
POLISH : Train for DSA PSFs
AIRI : Plug'n'play DNN deconvolver
DEEP-FOCUS : AutoEnc with meta learner
RFI identification : Pattern recognition
DIReCT : Using closure quantities

Pipelines

Anomaly Detection – CosmicAI project, VLASS pipeline
Auto-tune 'solint' , a pipeline parameter, using RL

AlphaCal – A Flag/Cal/Im pipeline model using reinforcement learning

Observing



Interpretation

Examples of ML/AI application (an illustrative list, not exhaustive)

Processing

Core Algorithms

POLISH : Train for DSA PSFs
AIRI : Plug'n'play DNN deconvolver
DEEP-FOCUS : AutoEnc with meta learner
RFI identification : Pattern recognition
DIReCT : Using closure quantities

Pipelines

Anomaly Detection – CosmicAI project, VLASS pipeline
Auto-tune 'solint' , a pipeline parameter, using RL

AlphaCal – A Flag/Cal/Im pipeline model using reinforcement learning

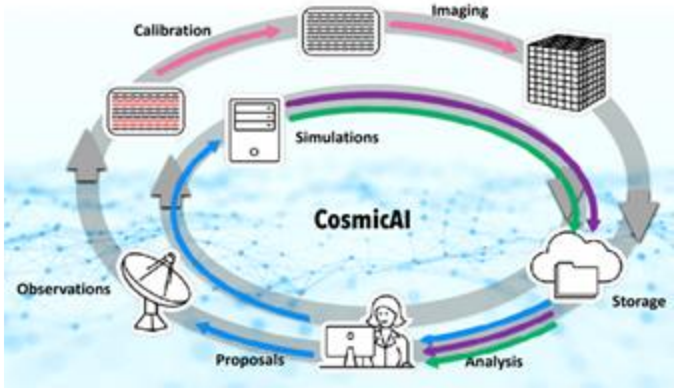
Observing

SAURON – ASKAP scheduler (no ML yet)

Servimon – Predictive maintenance

ALeRCE – Alerts mgmt

Tel Scheduling with RL



Interpretation

Examples of ML/AI application (an illustrative list, not exhaustive)

Processing

Core Algorithms

POLISH : Train for DSA PSFs
AIRI : Plug'n'play DNN deconvolver
DEEP-FOCUS : AutoEnc with meta learner
RFI identification : Pattern recognition
DIReCT : Using closure quantities

Pipelines

Anomaly Detection – CosmicAI project, VLASS pipeline
Auto-tune 'solint' , a pipeline parameter, using RL

AlphaCal – A Flag/Cal/Im pipeline model using reinforcement learning

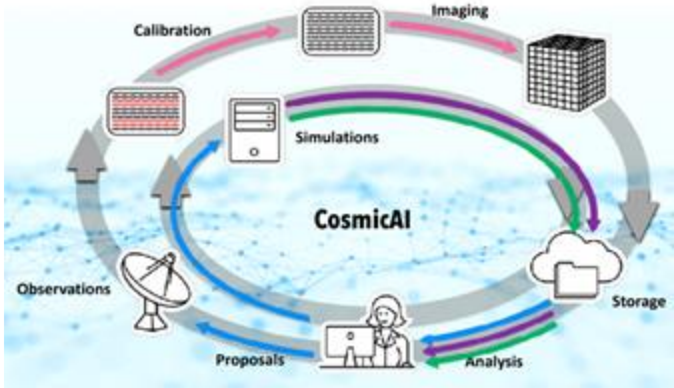
Observing

SAURON – ASKAP scheduler (no ML yet)

Servimon – Predictive maintenance

ALeRCE – Alerts mgmt

Tel Scheduling with RL



Interpretation

A very large body of work …

Highlighting 3 recent tools :

Polymathic Multimodal Universe
(FM for Astro : No radio data yet)

OneAstronomy : LLM + databases
(specCLIP, FALCO)

EMUSE : LLM + image archive

ML / AI in other indirect imaging domains ?

We have V = [S] [F] I

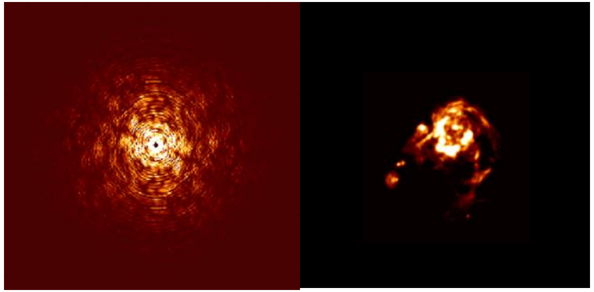
Others ?

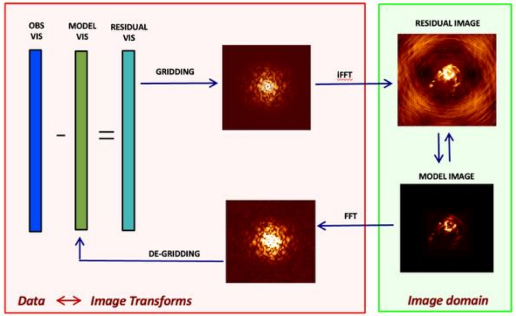
- Medical imaging (e.g. MRI)
- Synthetic Aperture Radar imaging

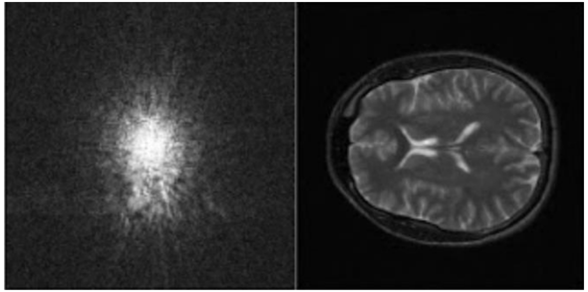
Much larger algorithm R&D communities than radio astronomy !

➔ Can we learn from their ML / AI exploration ?

Similar signal reconstruction problems…







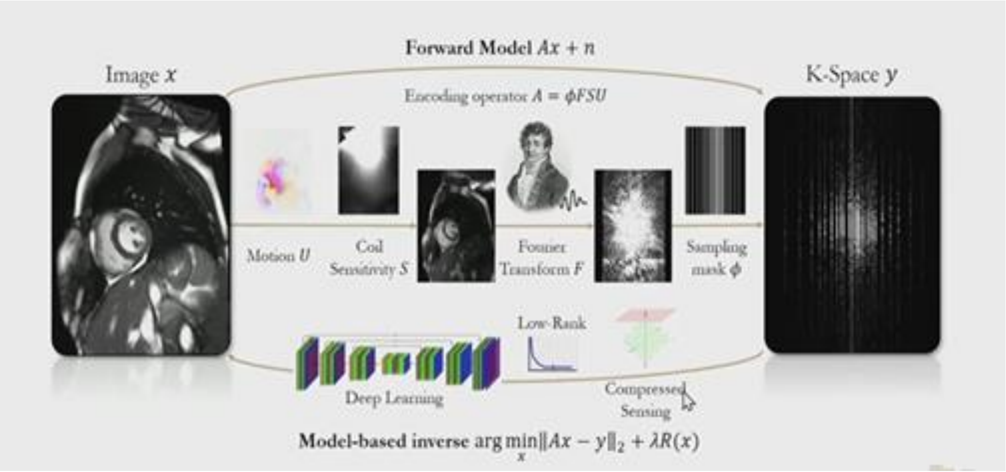


Fig from ISMRM 2024 review talk (T.Kustner) - Classic and AI Methods for Image Recon

What can we learn from medical imaging ?

Image Reconstruction

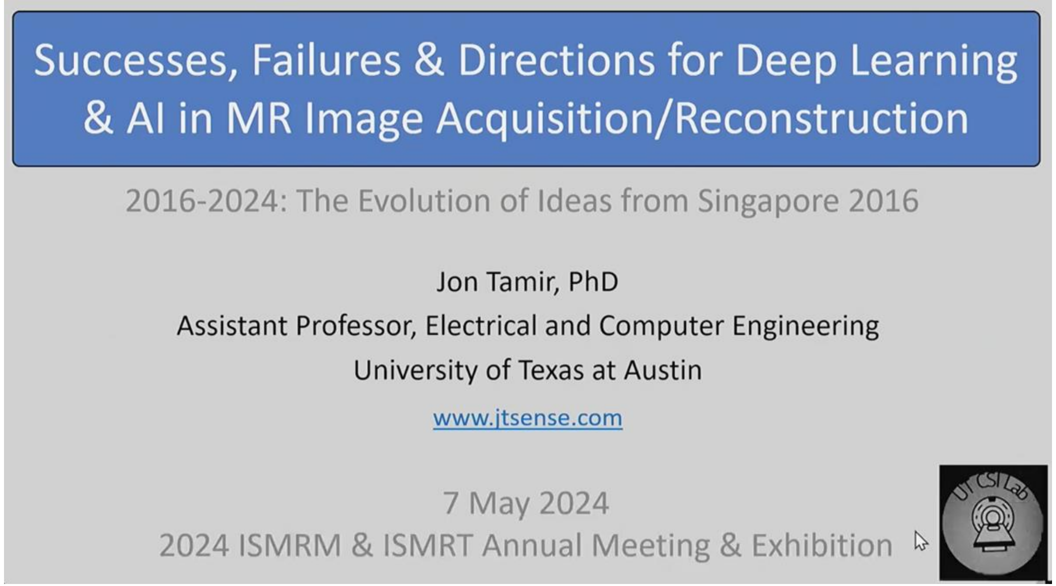
Classic Methods,

Plug-n-play / Unrolled,

Generative Modeling

→ Where are they useful ?

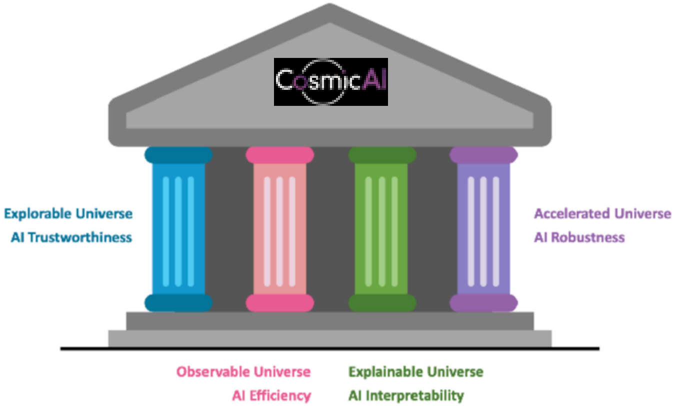
→ Where do they tend to fail ?



Analysis and Interpretation

Ref : Bridging gaps with computer vision – AI in biomedical imaging and astronomy (2025)

Summary – Observable Universe with AI



Summary – Observable Universe with AI

Processing

Raw Data

Solve : $V^{obs}_{ij} = g_i \, g_j^* \; [S_{ij}] \, [F] \; I^{sky} + n_{ij} + N^{rfi}_{ij}$

Model the sky, the instrument and the environment …

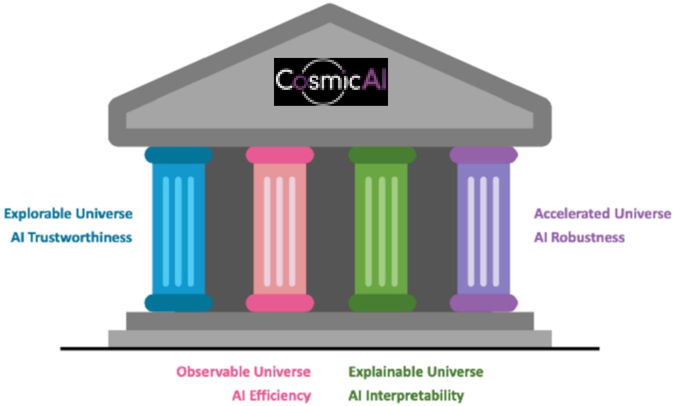
Products

Images
Spectra
Time series

Observing

Customize observations for science goals and signal characteristics

Awareness of observing environment



Interpretation

Understanding reconstruction uncertainty and model biases

Astrophysics modeling and inference closer to the data