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experimentelle physik 5
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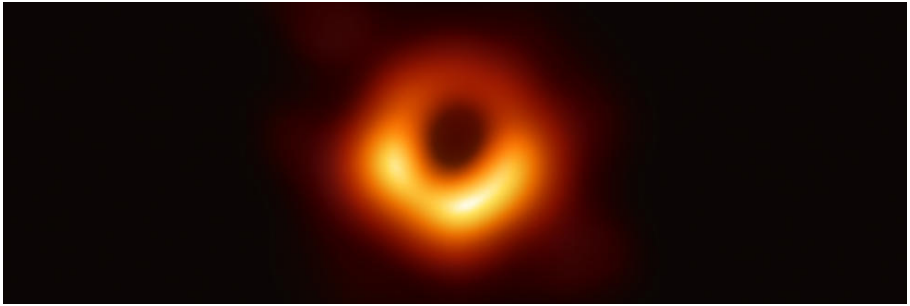
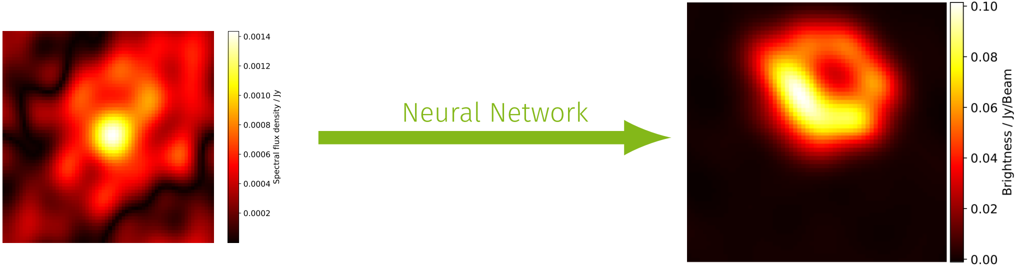


# A Neural Network Architecture For Radio Interferometric Imaging

Stefan Fröse

**22.10.2021**

# Goal


0.0014
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
Spectral flux density / Jy
Neural Network
0.10
0.08
0.06
0.04
0.02
0.00
Brightness / Jy/Beam

# What is Radio Astronomy?

# Radio Astronomy

- Ground-based telescopes
- Wavelength: mm to m
- **Problem:** Resolution is limited by Rayleigh criterion

$$\alpha = 1.22 \frac{\lambda}{D} = 1.22 \frac{1\,\text{mm}}{25\,\text{m}} \approx 10''$$

**Solution?**

Credit: NRAO/AUI/NSF

# Radio Interferometry

- Correlate multiple telescopes pairwise
- Resolution depends on baseline ($\alpha$ = 25 µ′′)
- Number of baselines $\frac{n^2-n}{2}$ (28@EHT)

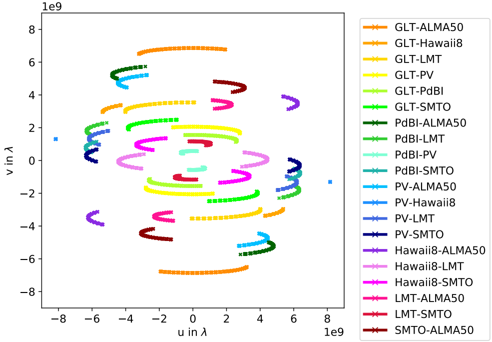
**But:**

- Telescopes measure Fourier transformed distribution

Credit: NRAO/AUI/NSF

# Radio Measurement

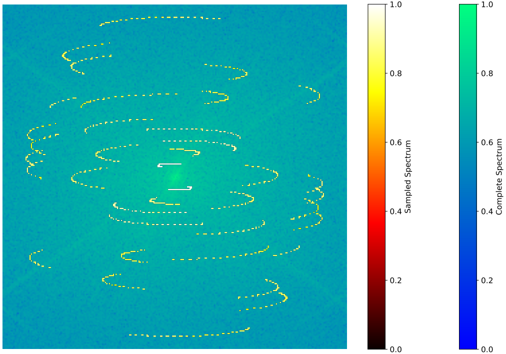
- Observe source **s**
- Baseline = projected distance
  ⇒ Array as it can be seen by **s**
- Baselines change due to earth rotation
- Every telescope pair samples <u>one</u> point from Fourier spectrum at time t



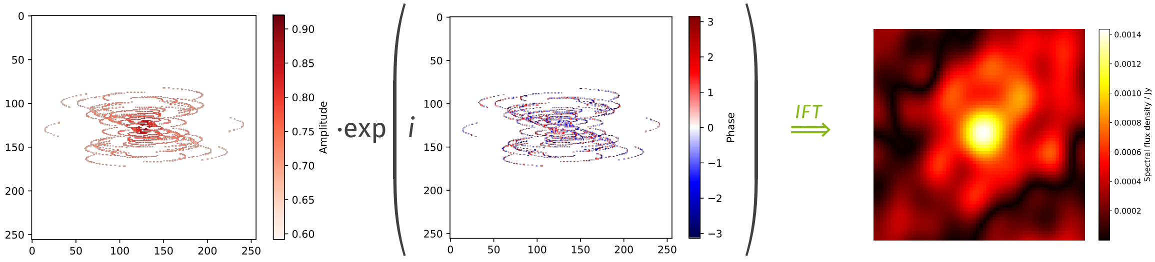
# Radio Measurement

- Sampled complex values $a + ib$
- Can be expressed as $A \exp(i\phi)$
- Amplitude image
- Phase image

$\Rightarrow$ **Inverse Fourier Transform**



# Radio Measurement



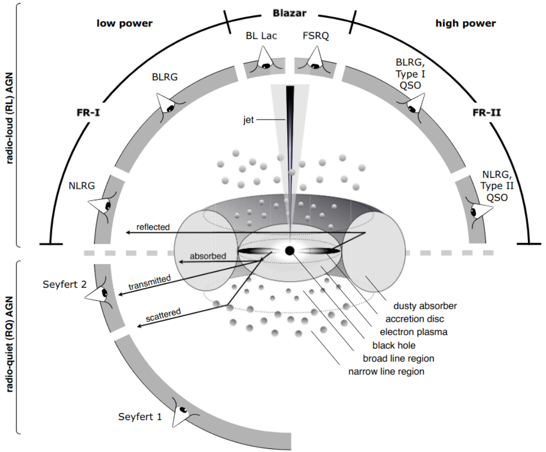

**⇒ Dirty Map**

# Sources to Reconstruct?

# Sources

- Active Galactic Nucleus (AGN)
- Found in central region of galaxy
- Black hole as central engine →**EHT**
- Radio-loud AGNs have a jet →**MOJAVE**

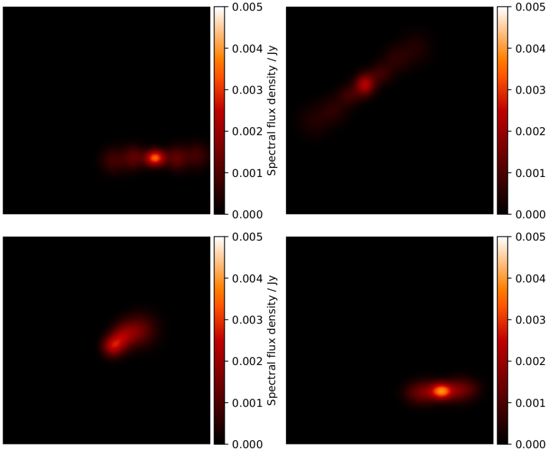
  ⇒**Simulate jets and black holes**




Volker Beckmann and Chris R. Shrader. Active Galactic Nuclei. Wiley-VCH,2012

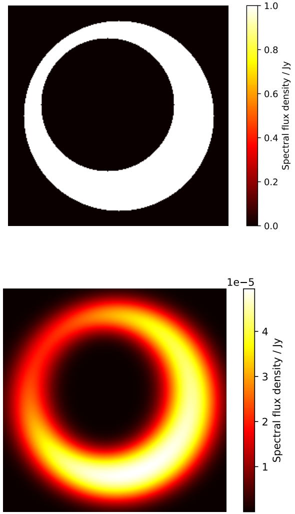
# Sources - Jet simulation

- **Motivation:** Kinematic jet analysis identifies components as Gaussians
- Generate random Gaussians along x-axis with small offsets
- $\mathbb{R}^3$ rotation and projection on xy-plane
- Normalize to 1 Jy



# Sources - Black hole simulation

- **Motivation:** Doppler beaming and gravitational lensing leads to crescent-like BHs
  →**Geometric crescent model**
- Generate two circles
- Convolution of difference with asymmetric Gaussian
- Normalize to 1 Jy

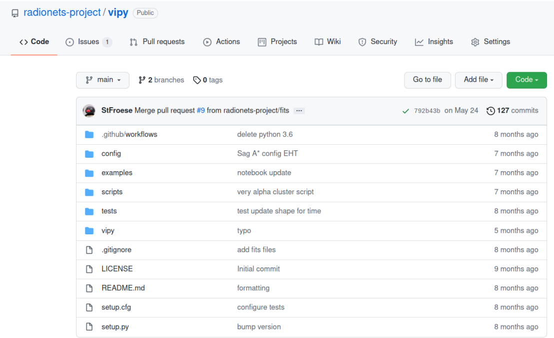


# vipy - A RIME simulation software

# vipy - A RIME simulation software

- Simulates measurement of custom sky distribution
- Based on Radio Interferometric Measurement Equation (**RIME**)
- Generates commonly used .fits file (AIPS memo 117)
- Available as open source software to the radio community

⇒ **Why do I need this?**



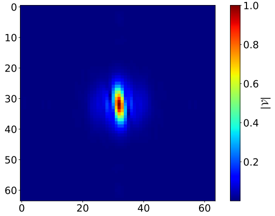
# Simple simulation

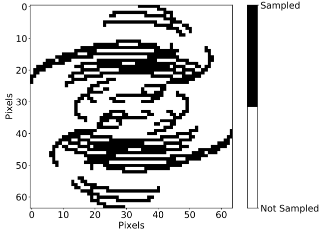
- Fourier transform of truth
- Generate mask based on sampled points in (u,v)-plot
- Apply mask to image

**But:**

- No telescope properties taken into account (Telescope Response, Antenna noise)
- No physical effects (Atmosphere, Polarization)

**⇒ Advanced Simulation with vipy**



# vipy - Simulation

$$V_{pq} = \iint_{lm} J_p(l,m)\, B(l,m)\, J_q^H(l,m)\, \mathrm{d}l\, \mathrm{d}m$$

- Radio Interferometer Measurement Equation **RIME**
- Visibility of telescope pair ***pq*** depends on Matrices $J_i$
- $J_i$ Jones matrices → describe different physical effects
- $J_i$ = **Baselineeffects** · **Polarization** · **Atmosphere** · **Noise** · **...**

**⇒ Choose Jones matrices & solve integral**

# Neural Network Architectures

# Problem Definition

- **Goal:** Fill missing information
- Missing pixels are maximal corrupted pixels

**Similar Problem:**

- Upscaling Low-Resolution to High-Resolution (HR) images
- First approach: Interpolation
- **Better:** Use Neural Network to predict HR images

⇒ **SRResNet**

bicubic

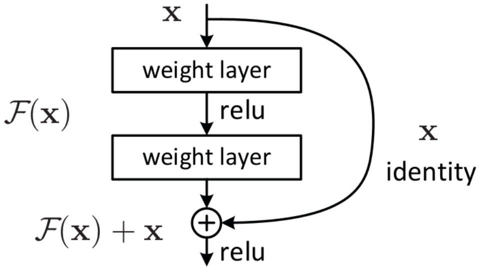
SRResNet

"Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network" C. Ledig et al., 2017 IEEE (CVPR), pp. 105-114

# Residual Learning

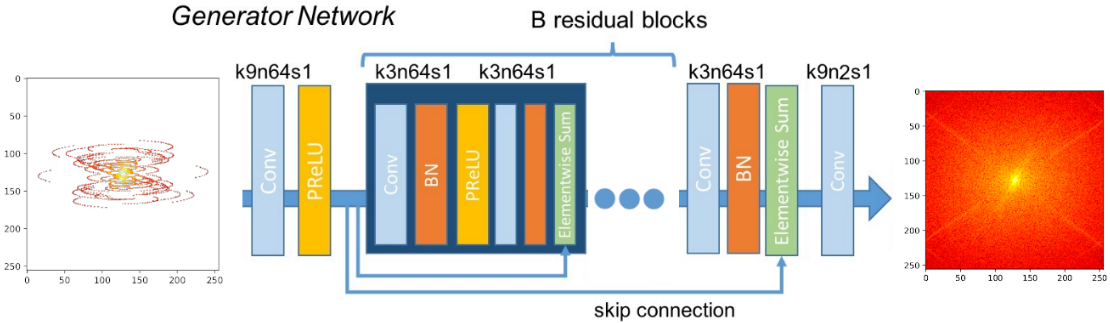
- Input *x*, Output *y*
- Use of skip connections
- Gives residual approach
- NN has to learn underlying mapping function

$$F(x) = y - x$$




"Deep Residual Learning for Image Recognition", K. He et al., 2016 IEEE (CVPR), pp. 770-778

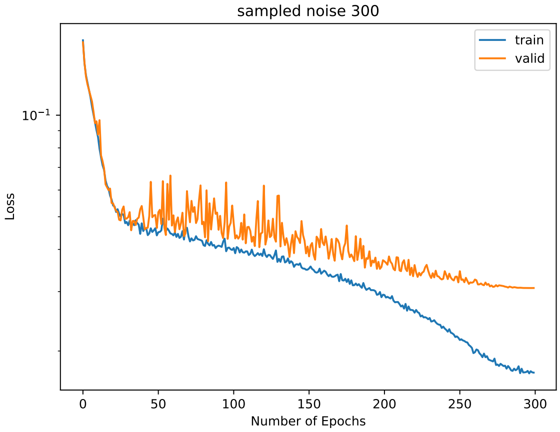
# SRResNet




"Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network" C. Ledig et al., 2017 IEEE (CVPR), pp. 105-114

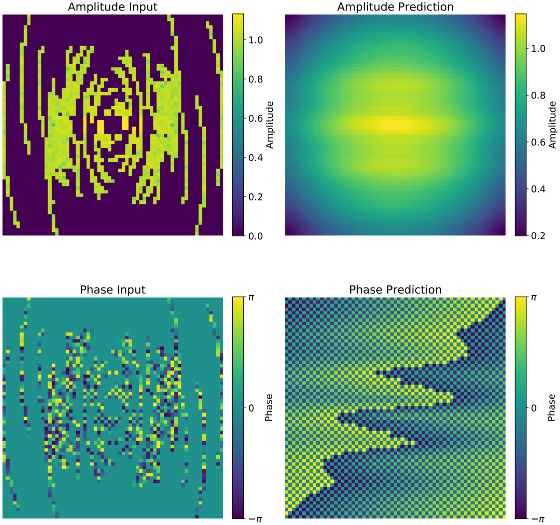
# SRResNet Training

- 50000 jet images (older simulation)
- 63 × 63 pixel
- L1 loss
- 300 epochs



# SRResNet Results

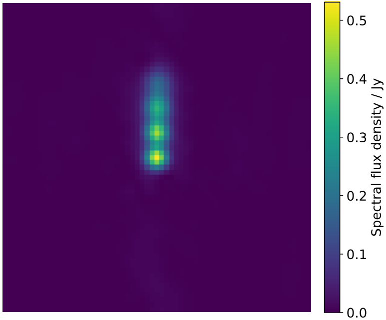
Input

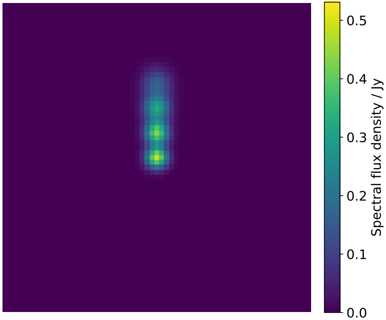



Prediction

# SRResNet Results

Predic-
tion




Truth

## ⇒ Alternative: Clean dirty map

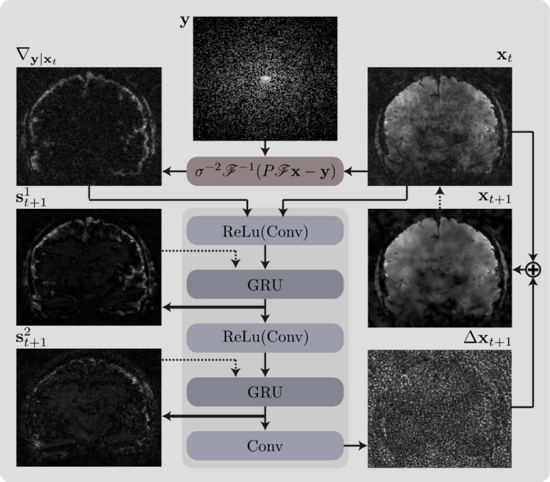
# RIM

- Recurrent Inference Machine (RIM) from MRI
- Solve inverse problems

$$I_{\text{Dirty}}(l, m) = F(S(u, v)V(u, v)) + n$$

- Iteratively clean dirty map

$$x_{t+1} = x_t + \Delta x_{t+1} \quad (1)$$




K. Lønning et al. "Recurrent inference machines for accelerated MRI reconstruction." In: 2018.

# RIM Training

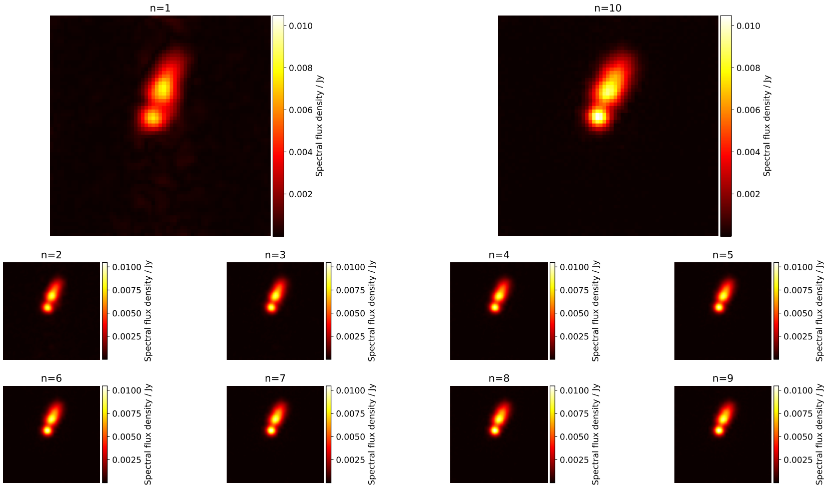
**jetRIM:**

- 2400 images of jet simulations
- $63 \times 63$ px
- 10 inference iterations
- 300 epochs
- L1 loss

**bhRIM:**

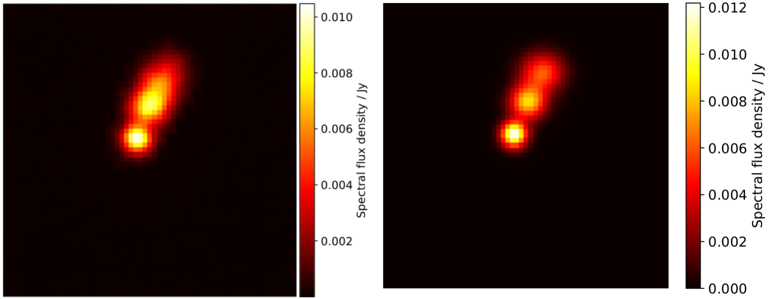
- 5000 images of black hole simulations
- $64 \times 64$ px
- 10 inference iterations
- 300 epochs
- L1 loss

# jetRIM


n=1
0.010
0.008
0.006
0.004
0.002
Spectral flux density / Jy
n=10
n=2
n=3
n=4
n=5
n=6
n=7
n=8
n=9
0.0100
0.0075
0.0050
0.0025

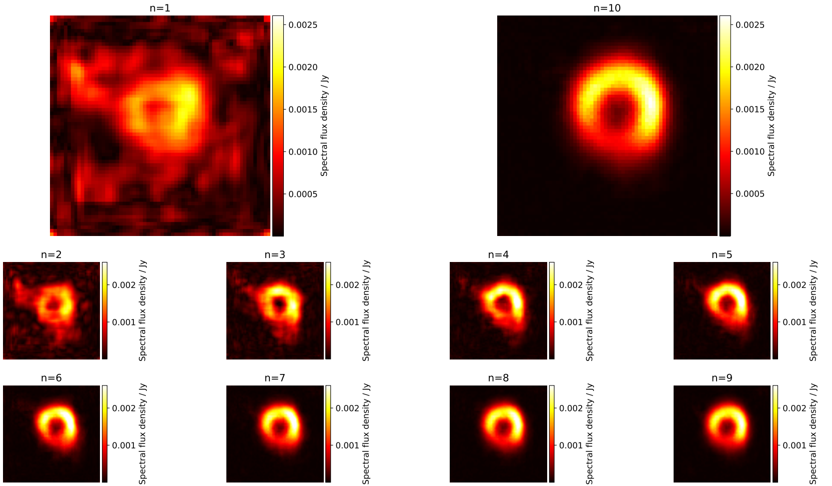
# jetRIM Results

**Predic-
tion**



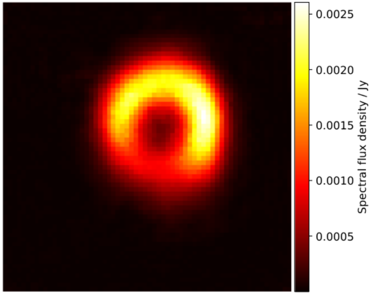

**Truth**

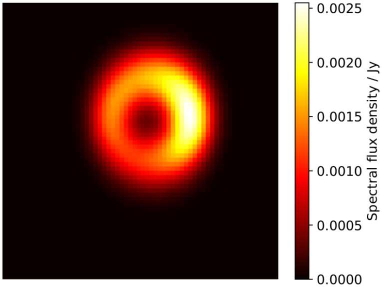
# jetRIM


n=1
0.0025
0.0020
0.0015
0.0010
0.0005
Spectral flux density / Jy
n=10
0.0025
0.0020
0.0015
0.0010
0.0005
Spectral flux density / Jy
n=2
0.002
0.001
Spectral flux density / Jy
n=3
0.002
0.001
Spectral flux density / Jy
n=4
0.002
0.001
Spectral flux density / Jy
n=5
0.002
0.001
Spectral flux density / Jy
n=6
0.002
0.001
Spectral flux density / Jy
n=7
0.002
0.001
Spectral flux density / Jy
n=8
0.002
0.001
Spectral flux density / Jy
n=9
0.002
0.001
Spectral flux density / Jy

# jetRIM Results

Predic-
tion



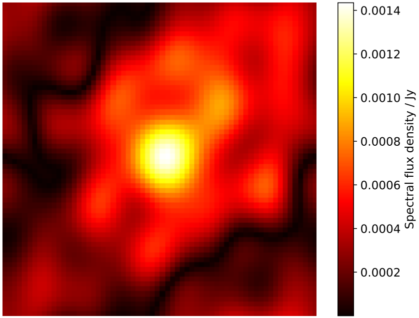




Truth

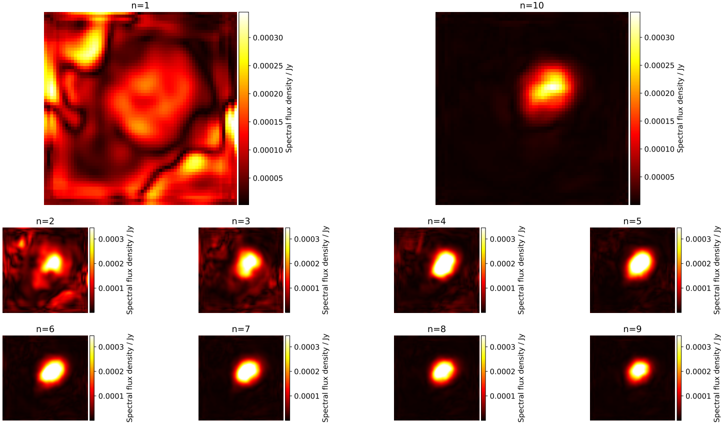
# M87 Black Hole

# M87 - Dirty Map

- EHT observation from 05.04.2017
- Self-calibration using DIFMAP
- Unknown total flux →RIM activations don't get triggered



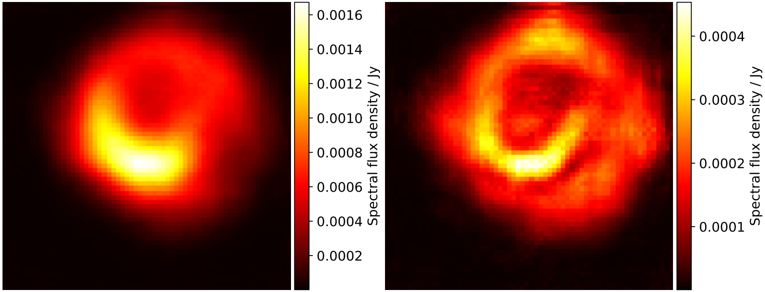
# bhRIM - M87




⇒ **Multiply dirty map with scaling factor** $\alpha = 1 - 20$

# bhRIM - M87

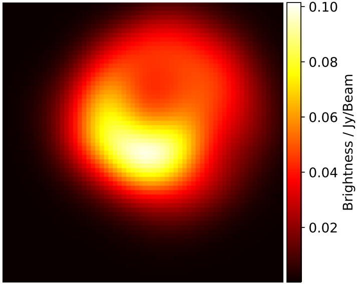
**Mean**

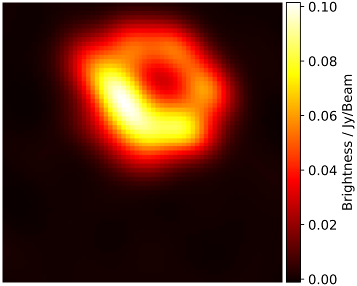



**Standard Deviation**

# bhRIM - M87

**Predic-
tion RIM**



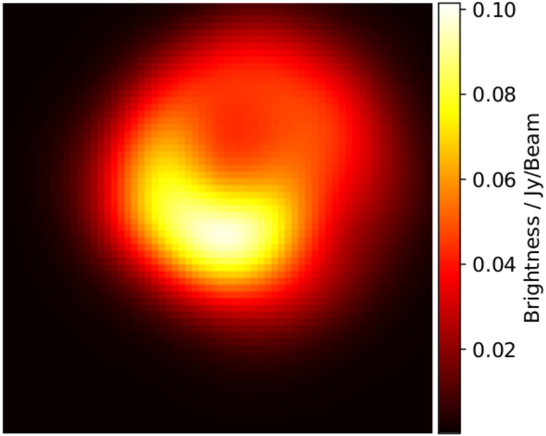

**Results
EHT**

## ⇒ Further Investigation

# Outlook

# Outlook

- Enhancement of the vipy software
  →Implementation of different Jones matrices
- Improvement of the RIM architecture (e.g. parallel convolutions)
- More versatile and larger training dataset
- Investigation of SKA sized images



# Thank you!