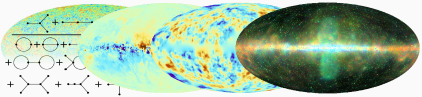


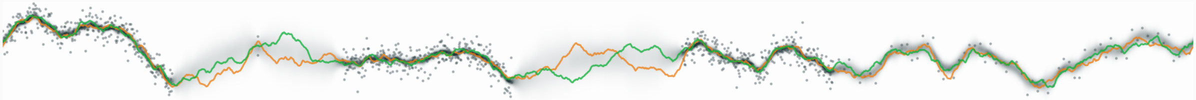
M87* in space, time and frequency

Dynamic VLBI imaging with information field theory

Philipp Arras, Philipp Frank, Jakob Knollmüller

June 28, 2021

Ludwig-Maximilians Universität LMU, Munich, Germany
Technical University TUM, Munich, Germany
Max-Planck Institute for Astrophysics, Garching, Germany



Acknowledgements

Our focus:

- Philipp Arras (TUM/MPA): radio imaging algorithms
- Jakob Knollmüller (TUM): approximate inference, machine learning
- Philipp Frank (LMU/MPA): statistical methods

Our co-authors:

- Philipp Haim (LMU/MPA): medical imaging
- Reimar Leike (LMU/MPA): galactic dust, machine learning
- Martin Reinecke (MPA): numerical algorithms
- Torsten Enßlin (MPA): head of *information field theory* group

LMU: Ludwig-Maximilians Universität München
TUM: Technical University Munich
MPA: Max-Planck Institute for Astrophysics, Garching

Organisational

- The talk is structured into three main parts:
    1. Overview and results (Philipp Arras)
    2. Prior and likelihood (Philipp Frank)
    3. Inference scheme and validation (Jakob Knollmüller)
- The presentation material (including the videos) is available at:

  `https://philipp-arras.de/2021cfa.html`
- Our paper [AFH+20] is available at:

  `https://arxiv.org/abs/2002.05218`
- The imaging code is available under GPL license (see link in paper).

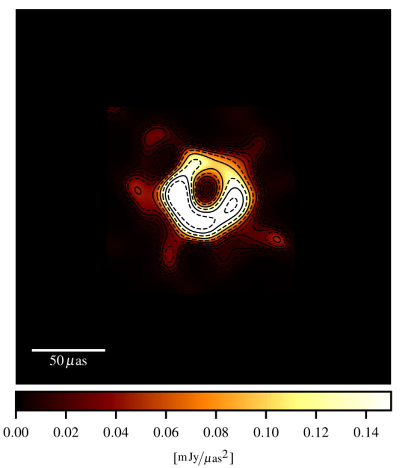
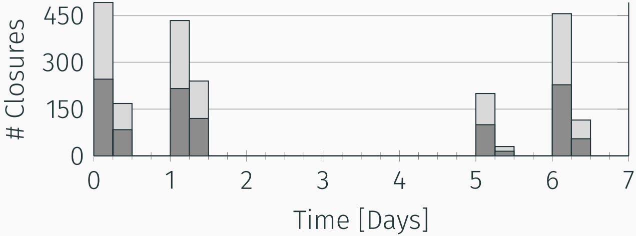


Figure 1: M87* on day 0 imaged with `ehtimaging` [AAA+19b]. Saturated color bar.

- Uncertainty quantification via multiple independent imaging teams
- Independent imaging for each observing day



Product Rule of Probabilities
aka Bayes' theorem

$$\mathcal{P}(s|d) = \frac{\mathcal{P}(d|s)\,\mathcal{P}(s)}{\mathcal{P}(d)}$$

$\mathcal{P}(A|B)$: conditional probability,
s: parameters, d: data.

(Some) assumptions

- The brightness is strictly positive.
- The source features correlation in spatial, temporal and frequency direction.

$\Longrightarrow$ Encoded in $\mathcal{P}(s)$.

Idea

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(Some) assumptions

- The brightness is strictly positive.
- The source features correlation in spatial, temporal and frequency direction.

$\implies$ Encoded in $\mathcal{P}(s)$.

In our case

- Correlation structure $\rightarrow$ full 4d-movie: sky brightness has shape (2, 28, 256, 256).
- The posterior $\mathcal{P}(s|d)$ is a ridiculously high-dimensional function:

$$\begin{cases} \mathbb{R}^{7.500.000} & \rightarrow \mathbb{R}^{\geq 0} \\ s & \mapsto \mathcal{P}(s|d) \end{cases}$$

- This function encodes our knowledge on M87* including uncertainties.

ehtimaging, [AAA+19b], day 6.

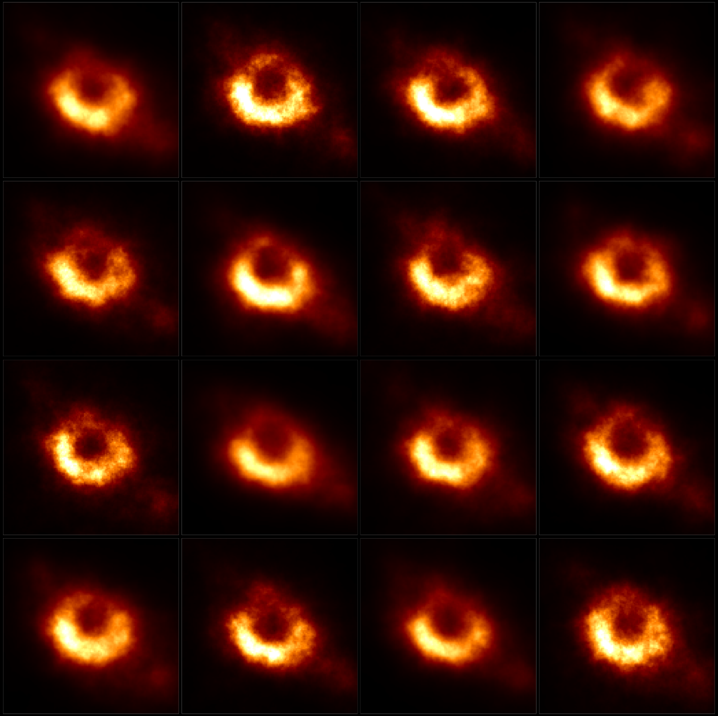
`ehtimaging`, [AAA+19b], day 5.

ehtimaging, [AAA+19b], day 1.

`ehtimaging`, [AAA+19b], day 0.

vlbi-resolve, [AFH+20], day 0.

`vlbi-resolve`, [AFH+20], posterior mean.



`vlbi-resolve`, [AFH+20], 16 posterior samples.

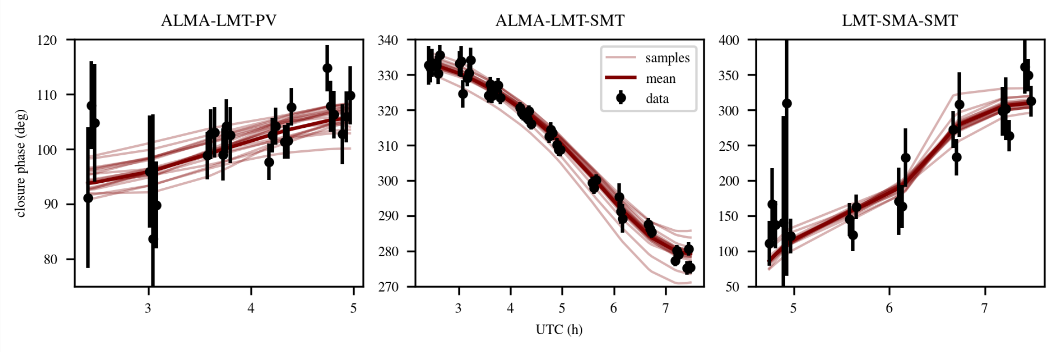


Figure 2: Three closure phases for triples of antennas as a function of time.

Ring fitting (see [AAA+19b, Table 7])

	d (μas)	w (μas)	η ($^\circ$)	A	f_C
eht-imaging [AAA+19b]					
April 5	39.3 ± 1.6	16.2 ± 2.0	148.3 ± 4.8	0.25 ± 0.02	0.08
April 6	39.6 ± 1.8	16.2 ± 1.7	151.1 ± 8.6	0.25 ± 0.02	0.06
April 10	40.7 ± 1.6	15.7 ± 2.0	171.2 ± 6.9	0.23 ± 0.03	0.04
April 11	41.0 ± 1.4	15.5 ± 1.8	168.0 ± 6.9	0.20 ± 0.02	0.04
Our method					
Uncertainty as per [AAA+19b, Table 7])					
April 5	44.4 ± 3.4	23.2 ± 5.2	164.9 ± 9.5	0.26 ± 0.04	0.365
April 6	44.4 ± 2.9	23.3 ± 5.4	161.7 ± 5.6	0.24 ± 0.04	0.374
April 10	44.8 ± 2.8	23.0 ± 5.0	176.7 ± 9.8	0.22 ± 0.03	0.374
April 11	44.6 ± 2.8	22.8 ± 4.8	180.1 ± 10.4	0.22 ± 0.03	0.372
Sample uncertainty					
April 5	44.1 ± 1.2	23.1 ± 2.4	163.9 ± 5.0	0.25 ± 0.03	0.377 ± 0.081
April 6	44.0 ± 1.2	22.9 ± 2.4	161.9 ± 6.0	0.24 ± 0.03	0.385 ± 0.085
April 10	44.6 ± 1.2	22.9 ± 2.5	176.2 ± 6.5	0.22 ± 0.03	0.383 ± 0.089
April 11	44.6 ± 1.2	23.0 ± 2.6	179.8 ± 6.2	0.22 ± 0.03	0.383 ± 0.090

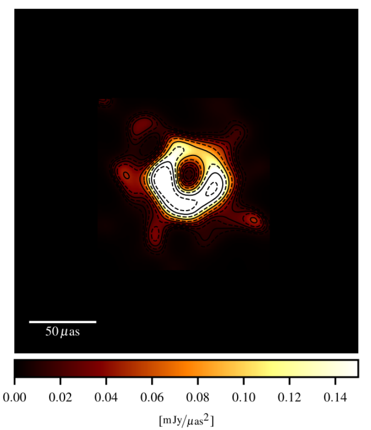


Figure 3: M87* on day 0 imaged with `ehtimaging` [AAA+19b]. Saturated color bar.

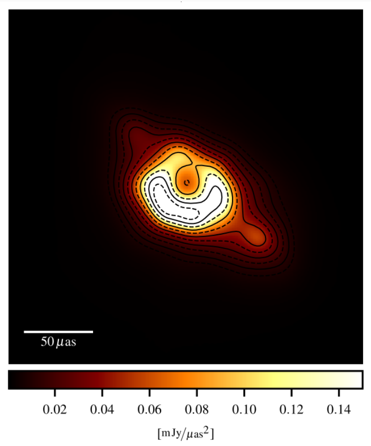


Figure 4: M87* on day 0 imaged with our algorithm [AFH+20]. Saturated color bar.

Inference model

Product Rule of Probabilities aka Bayes' theorem

$$\mathcal{P}(s|d,\mathcal{M}) = \frac{\mathcal{P}(d|s,\mathcal{M})\,\mathcal{P}(s|\mathcal{M})}{\mathcal{P}(d|\mathcal{M})}$$

Definitions: $s :=$ parameters, $d :=$ data, $\mathcal{M}$: model assumptions.

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Definitions: $s :=$ parameters, $d :=$ data, $\mathcal{M}$: model assumptions.

Generative prior model: $s(\xi) = F_M(\xi)$ with $P(\xi) = \mathcal{N}(\xi|0,\mathbb{1})$

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Prior

Sky brightness distribution

$s_{xt\nu}$ $\quad x \in \Omega \subset \mathbb{R}^2,\ t \in I \subset \mathbb{R},\ \nu \in V \subset \mathbb{R}^+$

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Positivity, exponential scaling $\quad s_{xt\nu} = e^{\tau_{xt\nu}}$

Sky brightness distribution

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Exploit correlations $\quad \left\langle \tau_{x,t,\nu}\ \tau_{x',t',\nu'} \right\rangle_{P(\tau)} = C(x, t, \nu, x', t', \nu')$

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- Independent correlations $\quad = C^{\Omega}(x,x')\ C^{I}(t,t')\ C^{V}(\nu,\nu')$

Sky brightness distribution

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Prior assumptions:

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\text{Positivity, exponential scaling} & s_{xt\nu} & = & e^{\tau_{xt\nu}} \\
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\bullet \text{ Independent correlations} & & = & C^{\Omega}(x,x')\ C^{I}(t,t')\ C^{V}(\nu,\nu') \\
\bullet \text{ Homogeneity and isotropy} & & = & C^{\Omega}\left(|x-x'|\right)\ C^{I}\left(|t-t'|\right)\ C^{V}\left(|\nu-\nu'|\right)
\end{array}
$$

Sky brightness distribution

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$\Rightarrow C^i$ fully determined by associated power spectrum $P^i(|k|) \quad \forall i \in \{\Omega, I, V\}$

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- Homogeneity and isotropy $\quad = C^\Omega(|x-x'|)\ C^I(|t-t'|)\ C^V(|\nu-\nu'|)$

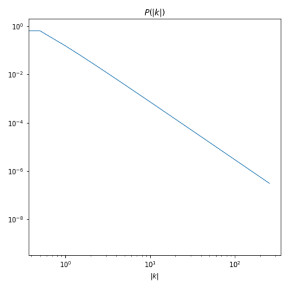
$\Rightarrow C^i$ fully determined by associated power spectrum $P^i(|k|) \quad \forall i \in \{\Omega, I, V\}$

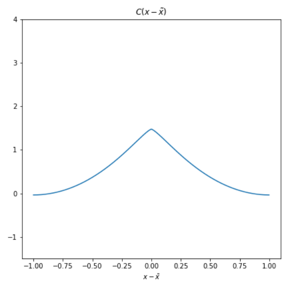
Uninformative $\quad \Rightarrow \quad P(\tau) = \mathcal{N}(\tau|0,C)$

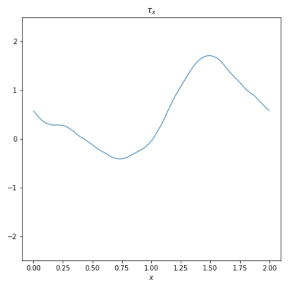
Prior - Correlations

$P^{(i)}(|k|) \qquad i \in \{\Omega, I, V\}$

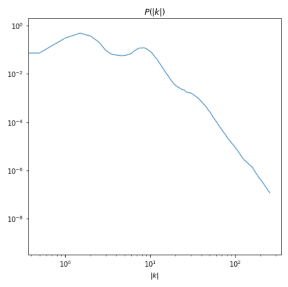
$$P^{(i)}(|k|) \propto |k|^{-\alpha} \quad i \in \{\Omega, I, V\}$$



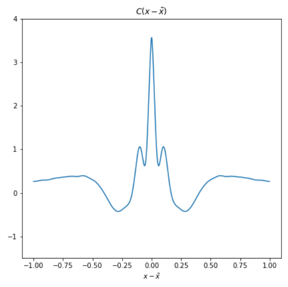




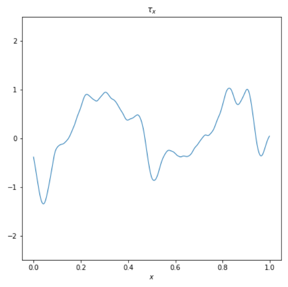
$P^{(i)}(|k|)$



P(|k|)
10⁰
10⁻²
10⁻⁴
10⁻⁶
10⁻⁸
10¹
10²
|k|



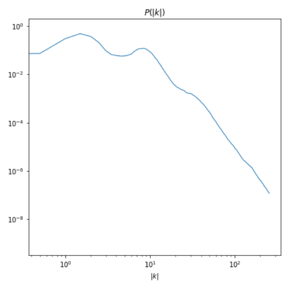
C(x − x̃)
4
3
2
1
0
−1
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
x − x̃

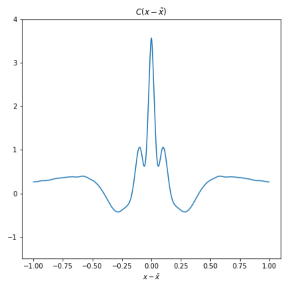


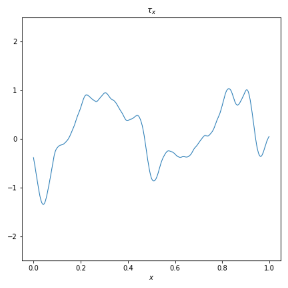
τx
2
1
0
−1
−2
0.0
0.2
0.4
0.6
0.8
1.0
x

$$P^{(i)}(|k|) = e^{q(l)} \qquad \text{with } l = \log(|k|)$$

$$\frac{\partial^2 q}{\partial l^2} = \sigma \xi_q \qquad P(\xi_q) = \mathcal{N}(\xi_q|0, \mathbb{1}) \quad \text{Integrated Wiener Process}$$







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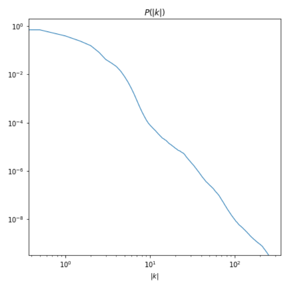

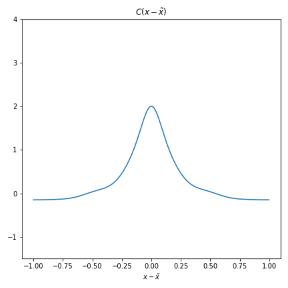

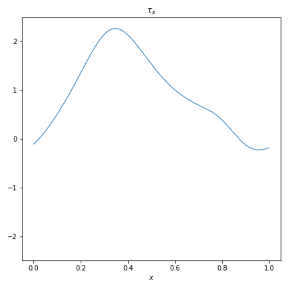

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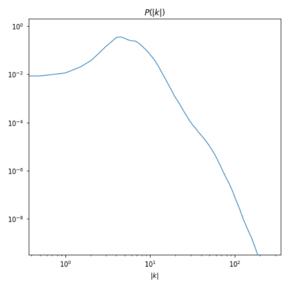

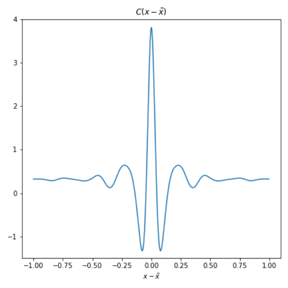

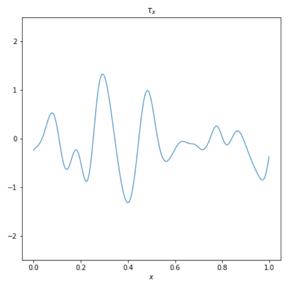

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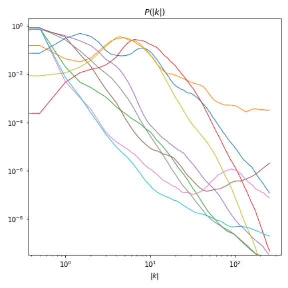

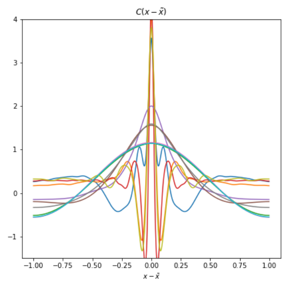

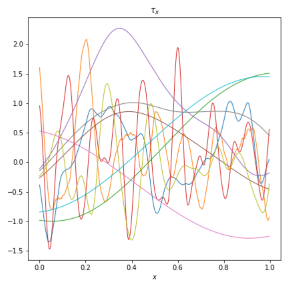

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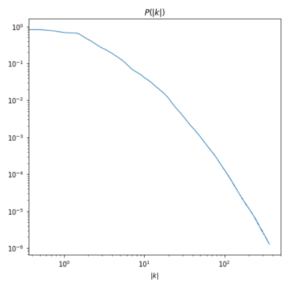
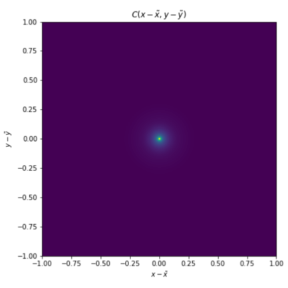
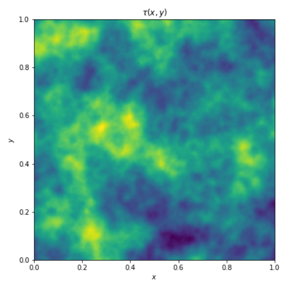
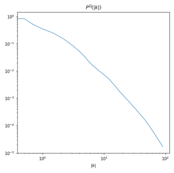
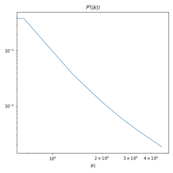


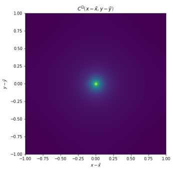


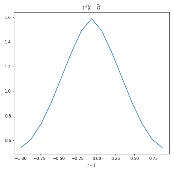


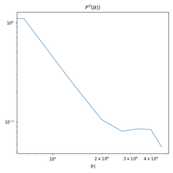
Prior - Correlations

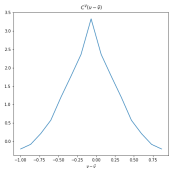




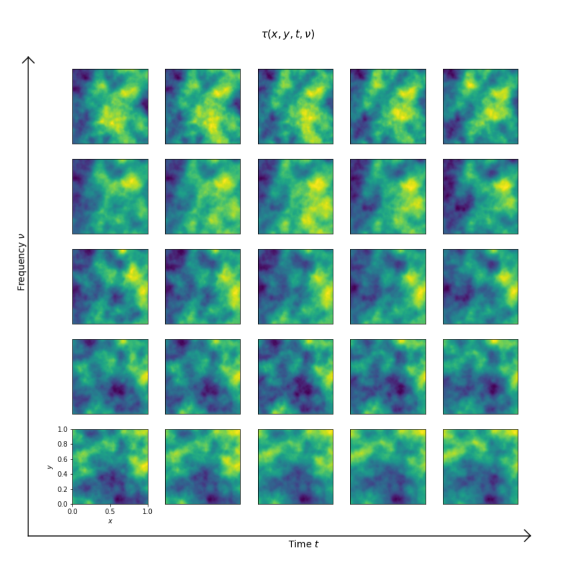








Prior



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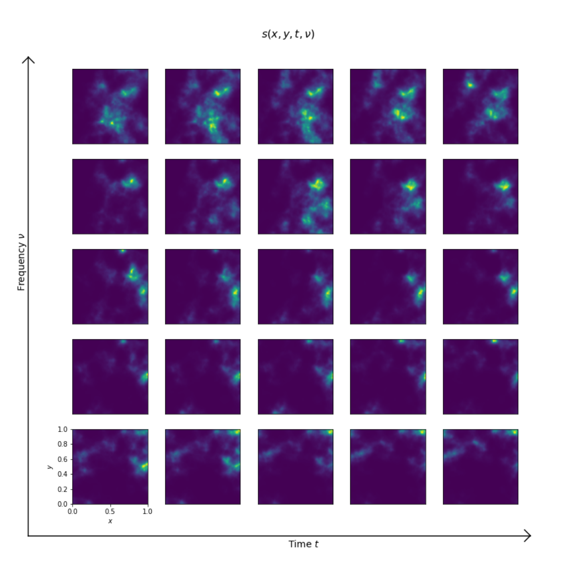

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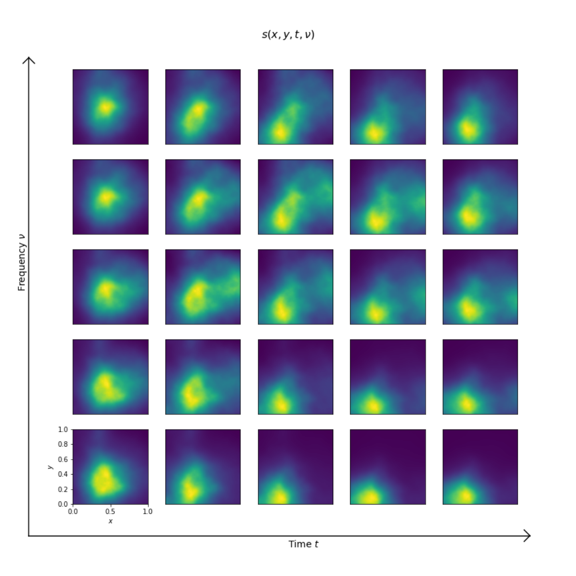

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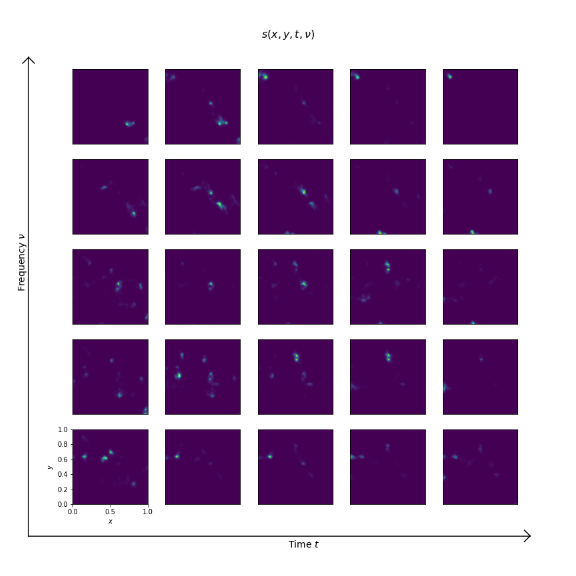

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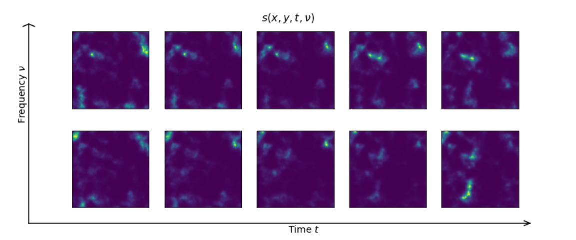
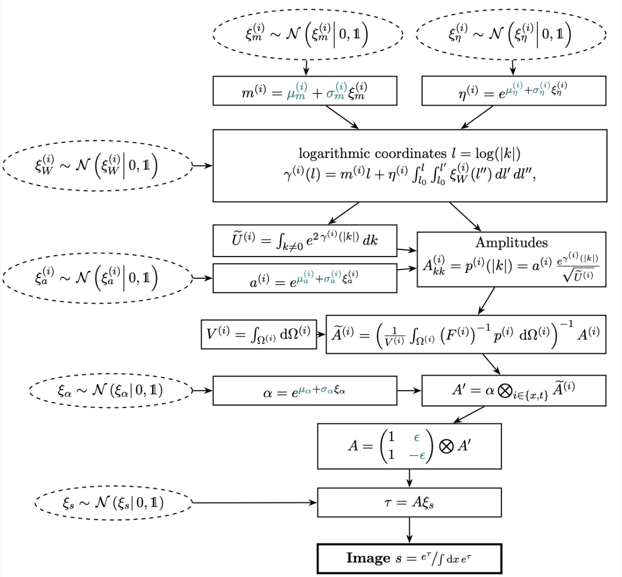
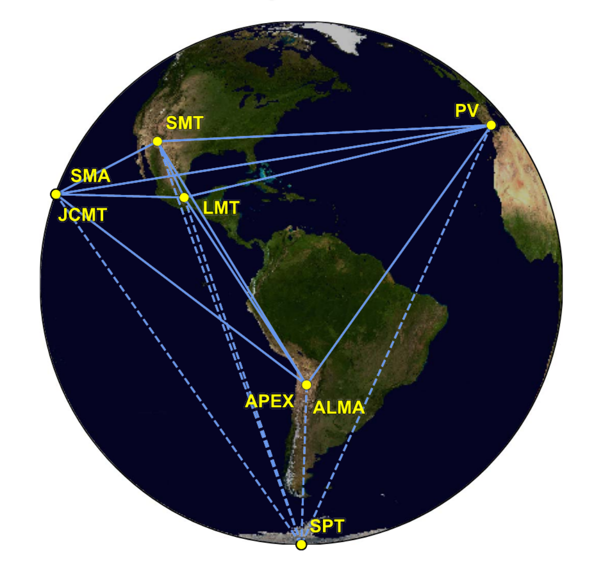


Prior

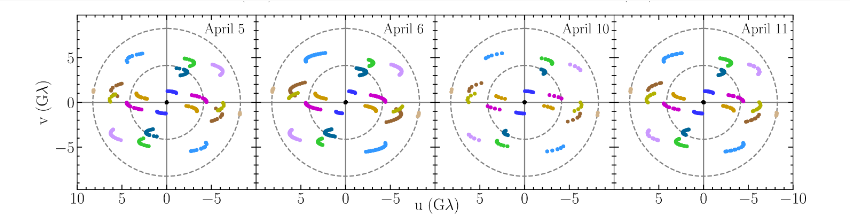


$\xi_m^{(i)} \sim \mathcal{N}\left(\xi_m^{(i)} \middle| 0, \mathbb{1}\right)$
$\xi_\eta^{(i)} \sim \mathcal{N}\left(\xi_\eta^{(i)} \middle| 0, \mathbb{1}\right)$
$m^{(i)} = \mu_m^{(i)} + \sigma_m^{(i)} \xi_m^{(i)}$
$\eta^{(i)} = e^{\mu_\eta^{(i)} + \sigma_\eta^{(i)} \xi_\eta^{(i)}}$
$\xi_W^{(i)} \sim \mathcal{N}\left(\xi_W^{(i)} \middle| 0, \mathbb{1}\right)$
logarithmic coordinates $l = \log(|k|)$
$\gamma^{(i)}(l) = m^{(i)} l + \eta^{(i)} \int_{l_0}^{l} \int_{l_0}^{l'} \xi_W^{(i)}(l'')\, dl'\, dl''$,
$\widetilde{U}^{(i)} = \int_{k \neq 0} e^{2\gamma^{(i)}(|k|)}\, dk$
Amplitudes
$A_{kk}^{(i)} = p^{(i)}(|k|) = a^{(i)} \frac{e^{\gamma^{(i)}(|k|)}}{\sqrt{\widetilde{U}^{(i)}}}$
$\xi_a^{(i)} \sim \mathcal{N}\left(\xi_a^{(i)} \middle| 0, \mathbb{1}\right)$
$a^{(i)} = e^{\mu_a^{(i)} + \sigma_a^{(i)} \xi_a^{(i)}}$
$V^{(i)} = \int_{\Omega^{(i)}} \mathrm{d}\Omega^{(i)}$
$\widetilde{A}^{(i)} = \left(\frac{1}{V^{(i)}} \int_{\Omega^{(i)}} \left(F^{(i)}\right)^{-1} p^{(i)}\, \mathrm{d}\Omega^{(i)}\right)^{-1} A^{(i)}$
$\xi_\alpha \sim \mathcal{N}\left(\xi_\alpha | 0, \mathbb{1}\right)$
$\alpha = e^{\mu_\alpha + \sigma_\alpha \xi_\alpha}$
$A' = \alpha \bigotimes_{i \in \{x,t\}} \widetilde{A}^{(i)}$
$A = \begin{pmatrix} 1 & \epsilon \\ 1 & -\epsilon \end{pmatrix} \otimes A'$
$\xi_s \sim \mathcal{N}\left(\xi_s | 0, \mathbb{1}\right)$
$\tau = A\xi_s$
Image $s = e^\tau / \int \mathrm{d}x\, e^\tau$

Likelihood



[AAA+19a]


April 5
April 6
April 10
April 11
v (Gλ)
u (Gλ)
5
0
−5
10
5
0
−5
5
0
−5
5
0
−5
5
0
−5
−10

[AAA+19b]

Likelihood

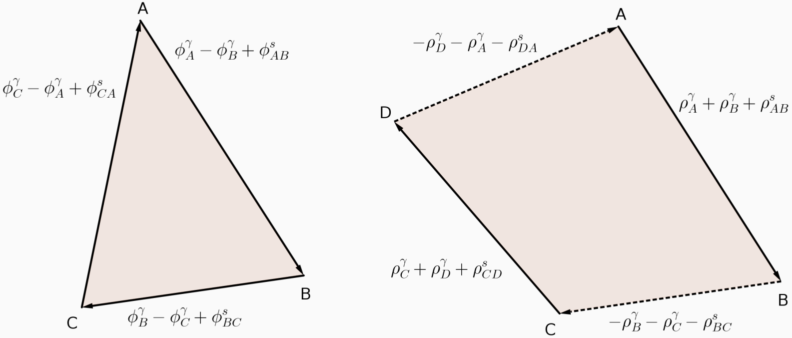
- Visibility data d and thermal noise level σ reported by [AAA$^+$19a]

Likelihood

- Visibility data d and thermal noise level σ reported by [AAA+19a]
- Direct imaging using visibilities is challenging for VLBI

- Visibility data d and thermal noise level σ reported by [AAA+19a]
- Direct imaging using visibilities is challenging for VLBI

$\Rightarrow$ Imaging using closure quantities (phases ϕ^d and logarithmic amplitudes ρ^d)



$$\phi^d_{clos} = M\phi^d \qquad \rho^d_{clos} = L\rho^d$$

$$\mathcal{P}\left(\phi^d_{clos}|s\right) \approx \mathcal{N}\left(e^{i\phi^d_{clos}}|e^{i\phi^s_{clos}}, MNM^\dagger\right) \quad \text{with} \quad N = \text{diag}\left(\frac{\sigma^2}{|d|^2}\right)$$

$$\mathcal{P}\left(\rho^d_{clos}|s\right) \approx \mathcal{N}\left(\rho^d_{clos}|\rho^s_{clos}, LNL^\dagger\right)$$

$$\mathcal{P}\left(\phi^d_{clos}|s\right) \approx \mathcal{N}\left(e^{i\phi^d_{clos}}|e^{i\phi^s_{clos}}, MNM^\dagger\right) \quad \text{with} \quad N = \text{diag}\left(\frac{\sigma^2}{|d|^2}\right)$$

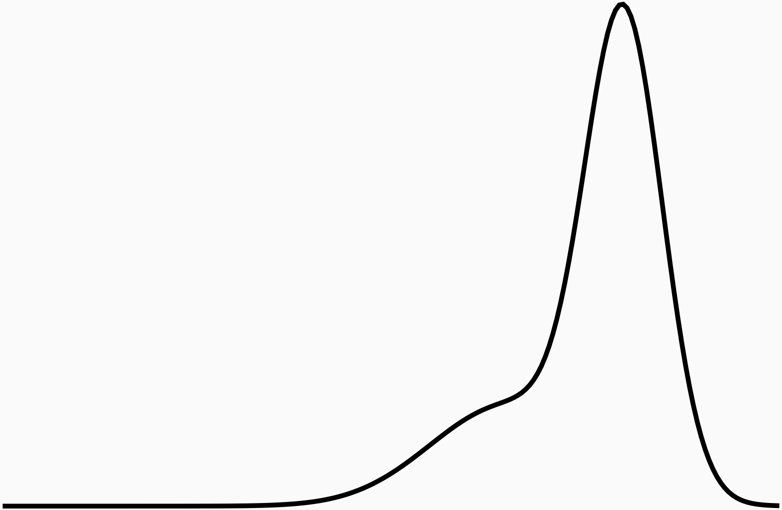
$$\mathcal{P}\left(\rho^d_{clos}|s\right) \approx \mathcal{N}\left(\rho^d_{clos}|\rho^s_{clos}, LNL^\dagger\right)$$

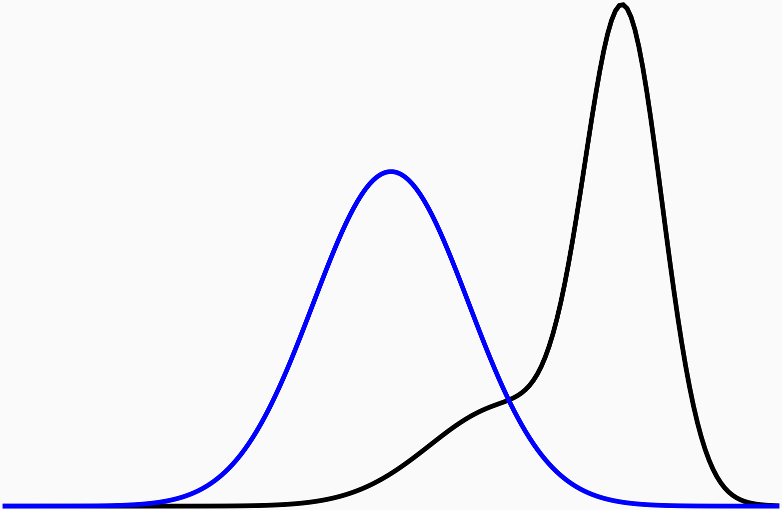
Posterior distribution

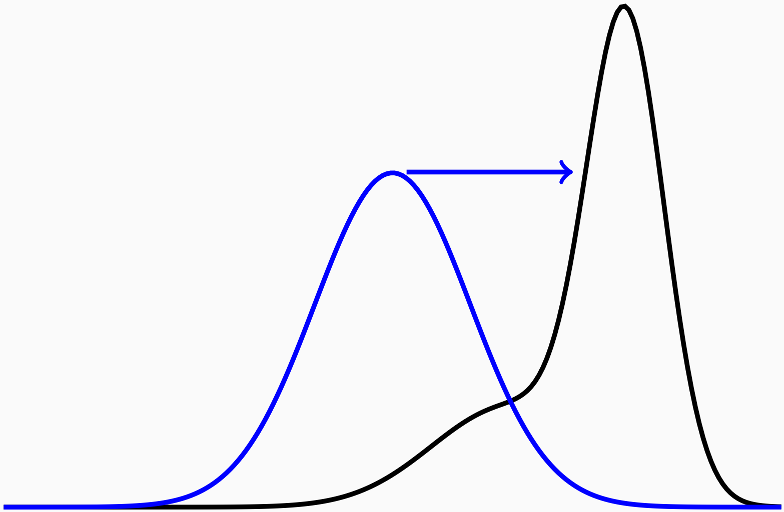
$$\mathcal{P}\left(\xi|\phi^d_{clos}, \rho^d_{clos}\right) \propto \mathcal{P}\left(\phi^d_{clos}|s(\xi)\right)\mathcal{P}\left(\rho^d_{clos}|s(\xi)\right)\ \mathcal{N}(\xi|0, \mathbb{1})$$

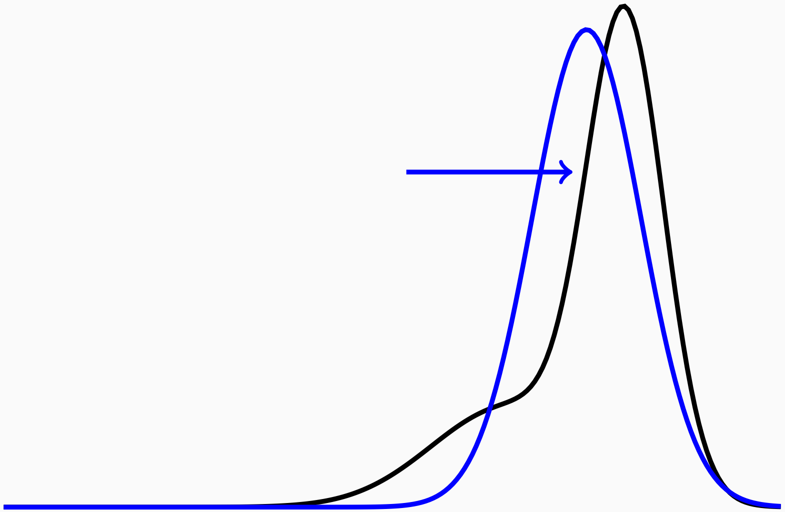
with generative prior $s(\xi) = F_M(\xi)$

Metric Gaussian Variational Inference









Kullback-Leibler Divergence

$$\mathcal{D}_{\mathrm{KL}}(\mathcal{Q}_\eta(\xi)||\mathcal{P}(\xi|d)) = \int d\xi \; \mathcal{Q}_\eta(\xi) \ln \frac{\mathcal{Q}_\eta(\xi)}{\mathcal{P}(\xi|d)}$$

$$\mathcal{Q}_\eta(\xi) = \mathcal{N}(\xi|\bar{\xi}, \Xi)$$

$$\mathcal{Q}_\eta(\xi) = \mathcal{N}(\xi|\bar{\xi},\Xi)$$

$$\Xi = \begin{pmatrix} \ddots & \ddots & \ddots & \ddots \\ \ddots & \ddots & \ddots & \ddots \\ \ddots & \ddots & \ddots & \ddots \\ \ddots & \ddots & \ddots & \ddots \end{pmatrix}$$

full-covariance

$$\mathcal{Q}_\eta(\xi) = \mathcal{N}(\xi|\bar{\xi},\Xi)$$

$$\Xi = \begin{pmatrix} \ddots & & & \\ & \ddots & & \\ & & \ddots & \\ & & & \ddots \end{pmatrix}$$

mean-field

$$\mathcal{Q}_\eta(\xi) = \mathcal{N}(\xi|\bar{\xi},\Xi)$$

$$\Xi(\xi) = \left(J(\xi)^\dagger I_d(\theta) J(\xi) + \mathbb{1}\right)^{-1}$$

inverse Fisher metric

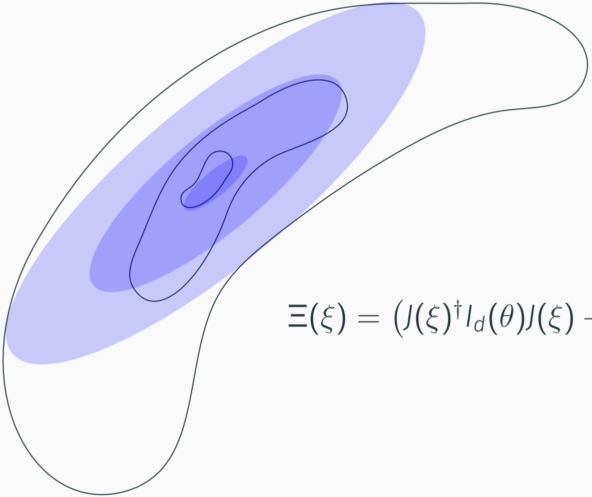
$$\mathcal{Q}_\eta(\xi) = \mathcal{N}(\xi|\bar{\xi},\Xi)$$

$$\Xi(\xi) = \left(J(\xi)^\dagger I_d(\theta) J(\xi) + \mathbb{1}\right)^{-1}$$

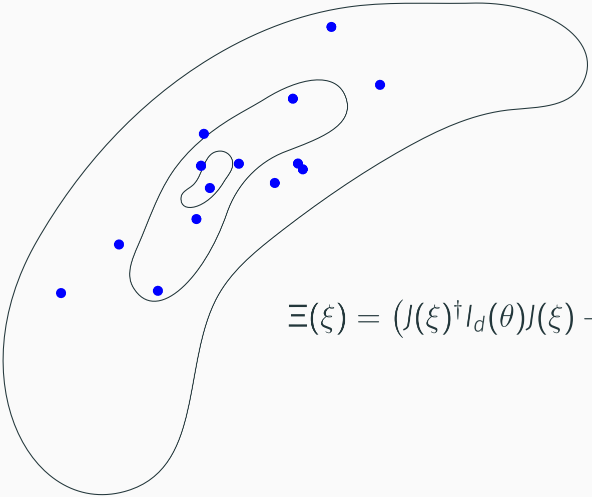
inverse Fisher metric

$$J(\xi) = \frac{\partial\theta(\xi)}{\partial\xi} \qquad I_d(\theta) = \left\langle \frac{\partial\mathcal{H}(d|\theta)}{\partial\theta}\frac{\partial\mathcal{H}(d|\theta)}{\partial\theta^\dagger}\right\rangle_{\mathcal{P}(d|\theta)}$$

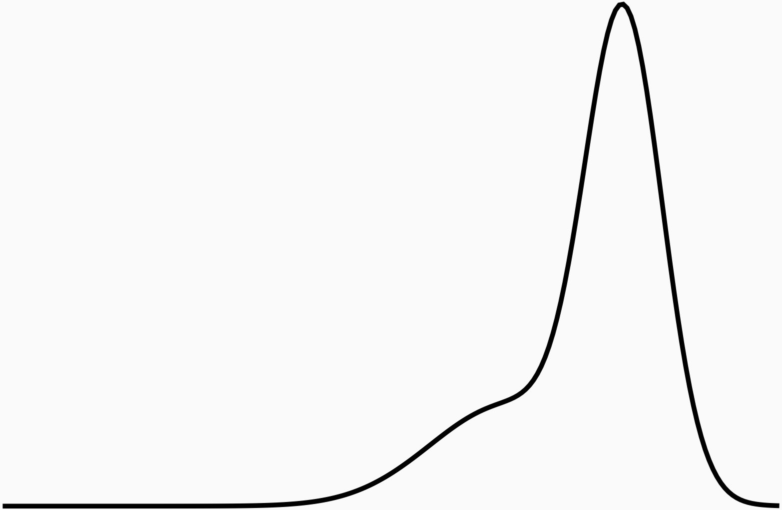
Metric Gaussian Variational Inference

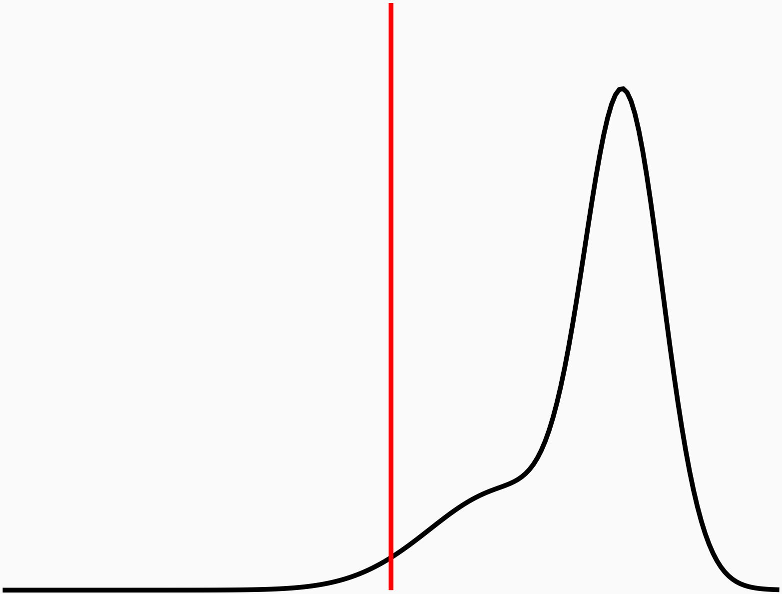


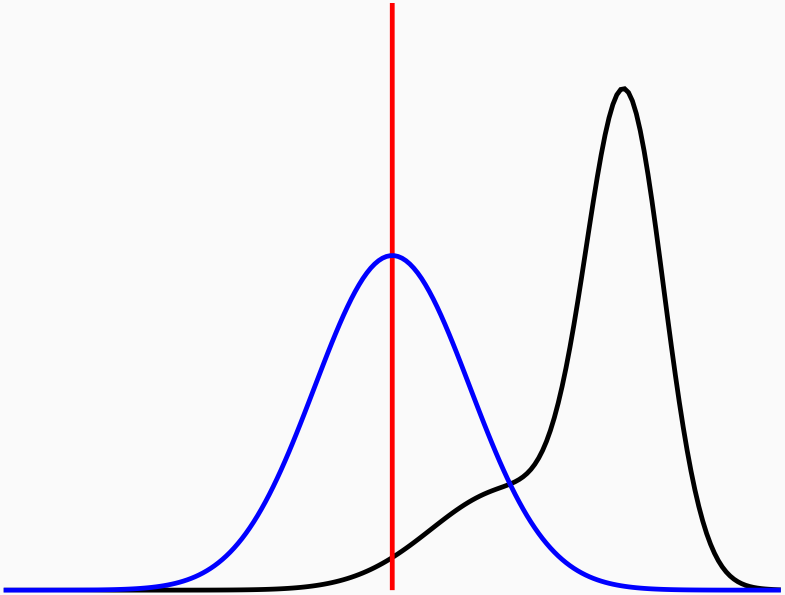
$$\Xi(\xi) = \left(J(\xi)^\dagger I_d(\theta) J(\xi) + \mathbb{1}\right)^{-1}$$

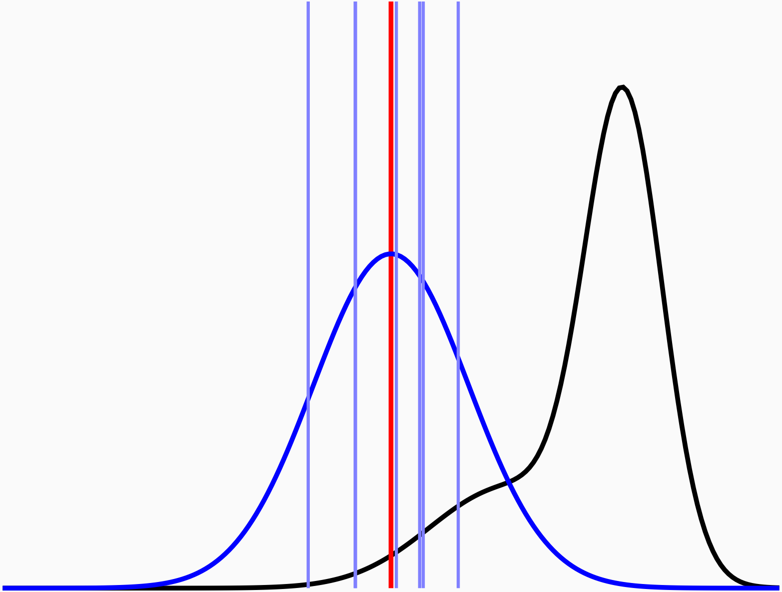


$$\Xi(\xi) = \left(J(\xi)^\dagger I_d(\theta) J(\xi) + \mathbb{1}\right)^{-1}$$

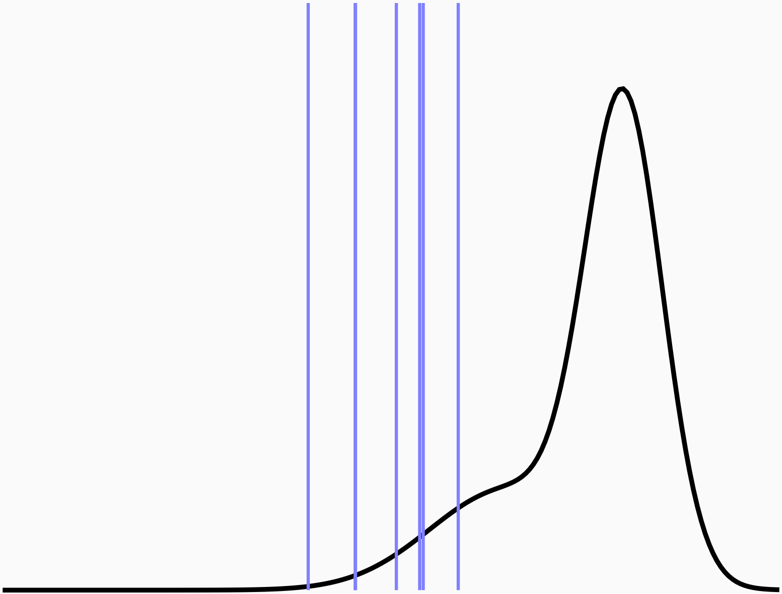


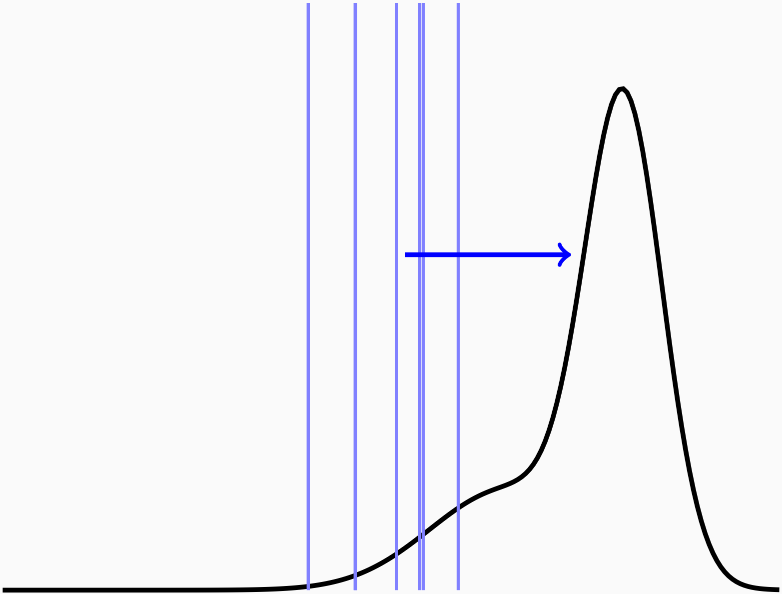


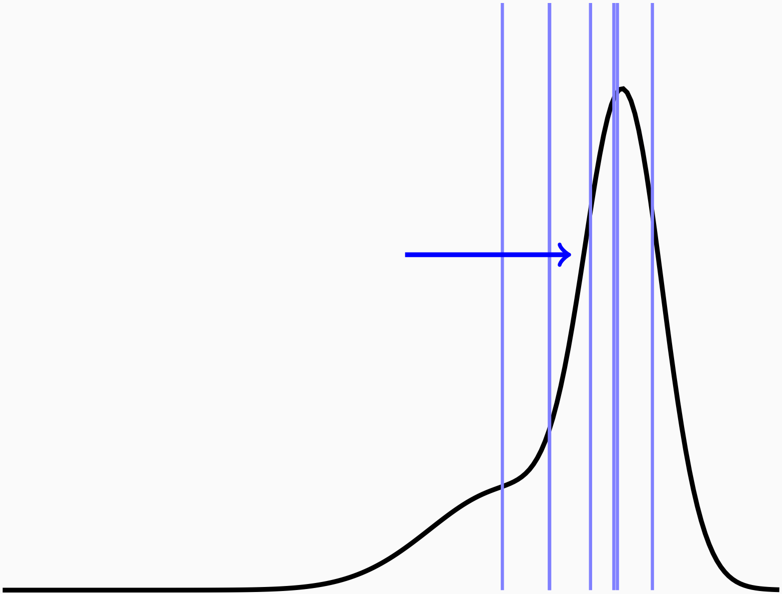


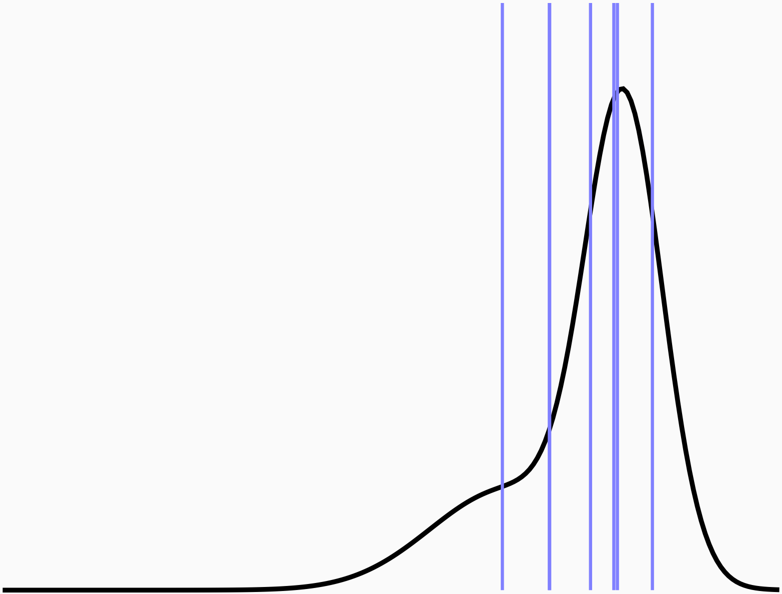


Metric Gaussian Variational Inference

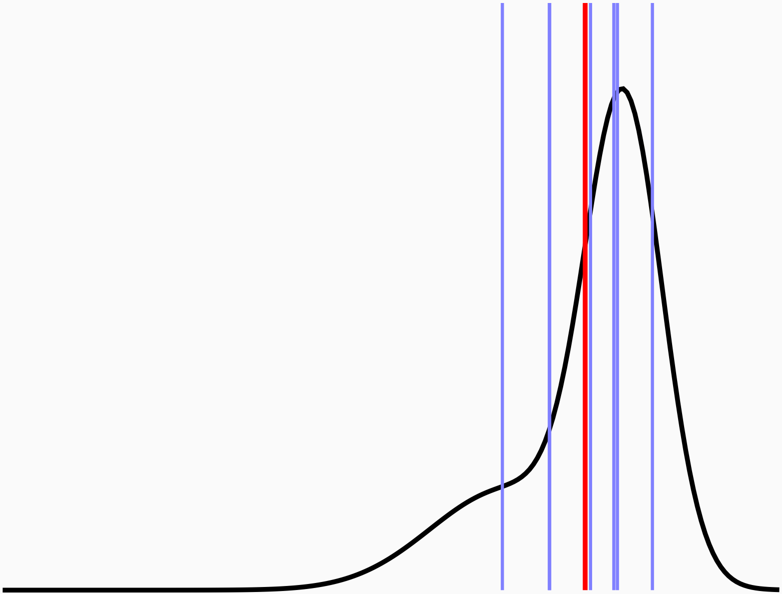


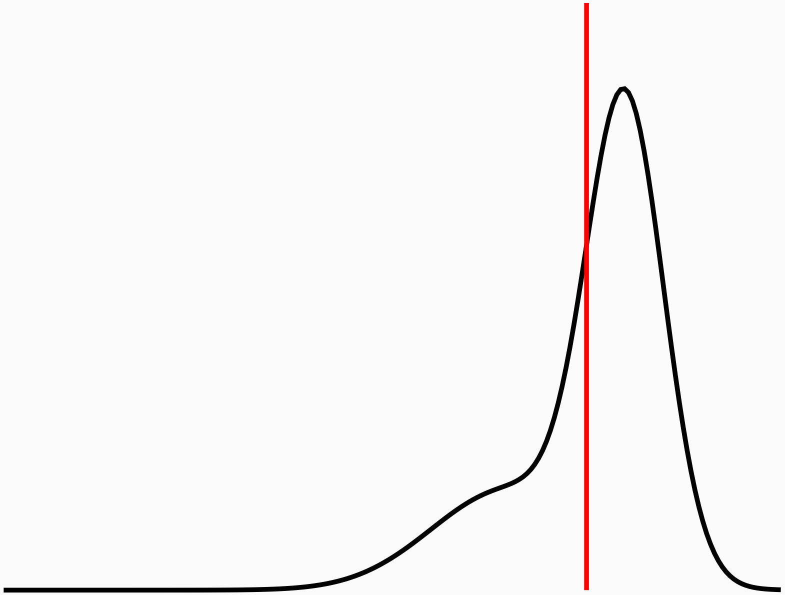


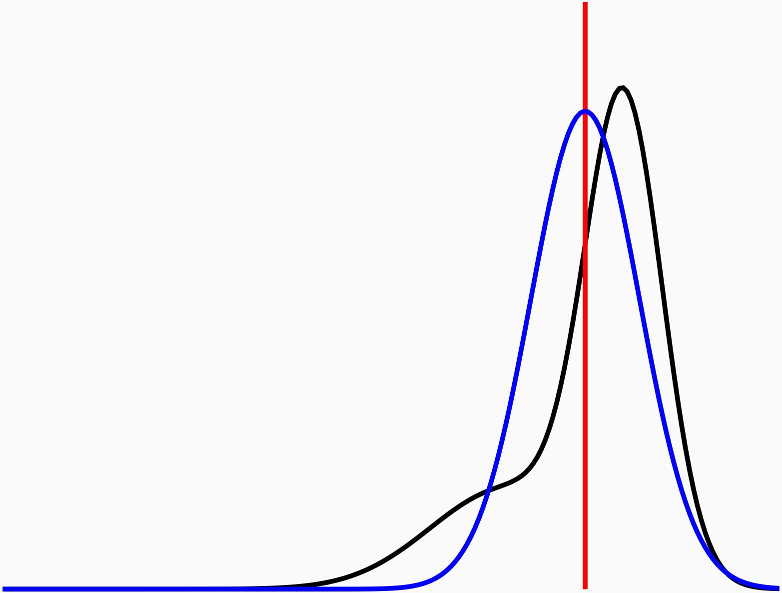


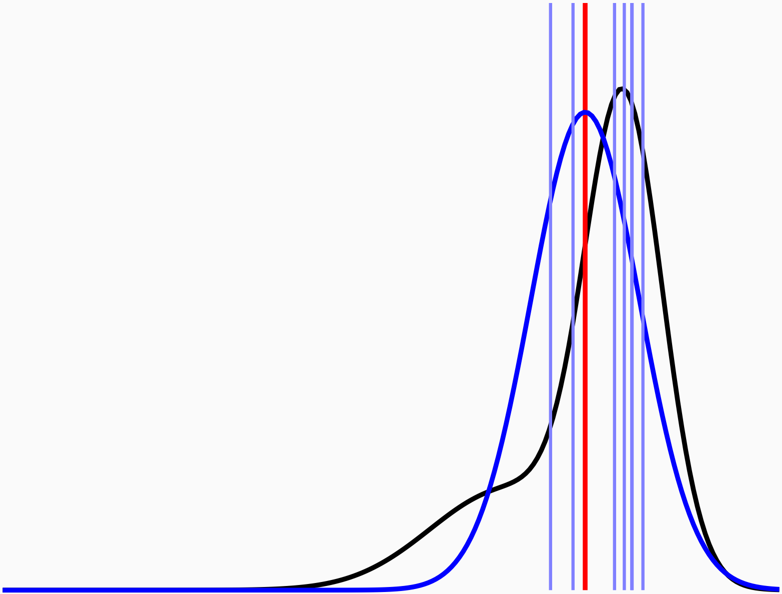


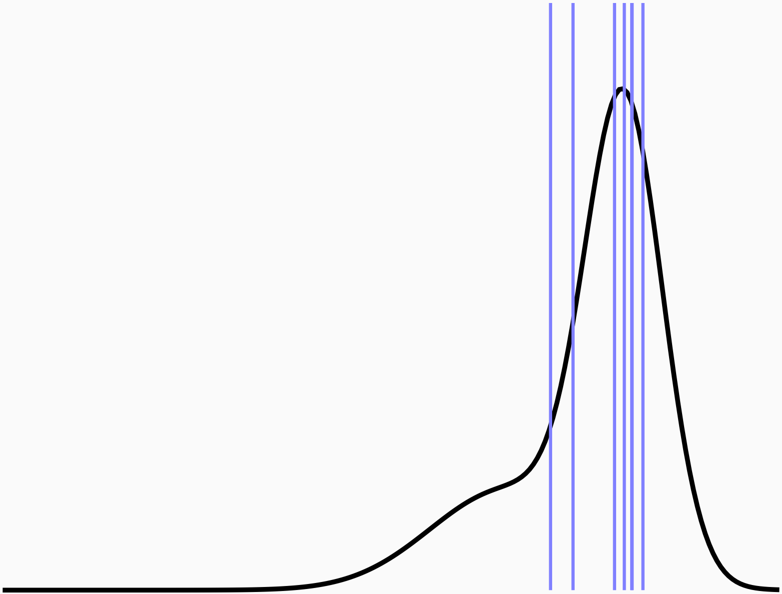
Metric Gaussian Variational Inference





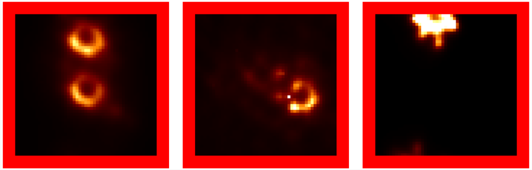






Practical Challenges for VLBI

- Nonlinear optimization
- Stochastic loss function
- No absolute source position or brightness
- Multi-modality
  - Multiple source copies
  - “Source Teleportation”



Inference Heuristic

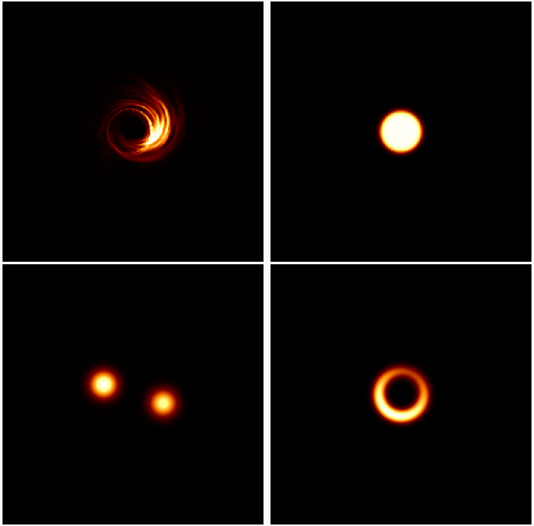
- Initially fit model to Gaussian shape
- Start with data of the first two days
- Alternate between phase and amplitude likelihood
- Reduce stochasticity of loss towards the end

Iteration	Data Set	Tempering	Optimizer	Sample Pairs
$i = 0$	$i \geq 0$ first two days	$i \geq 0$ full likelihood	$i \geq 0$ V-LBFGS $4 * (4 + i//4)$ iterations	$i \geq 0$ $N = 10 * (1 + i//8)$
		$i \geq 10$ alternating		
	$i \geq 30$ all days			
		$i \geq 50$ full likelihood	$i \geq 50$ Natural Gradient 20 iterations	
$i = 59$				

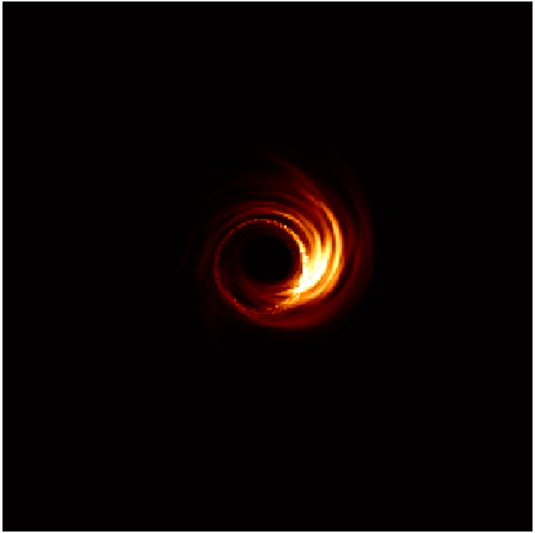
Validation

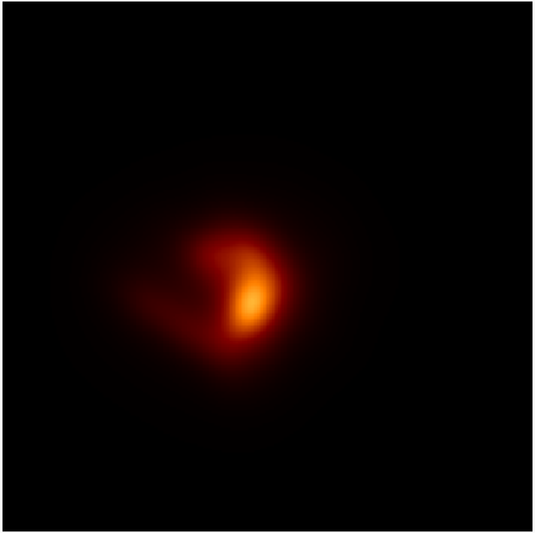
Strategy

- Synthetic source
- Generate data according to EHT observation
- Reconstruct
- Compare to truth

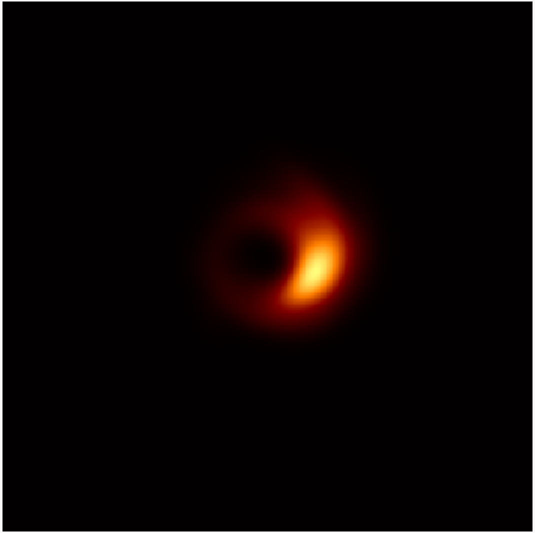


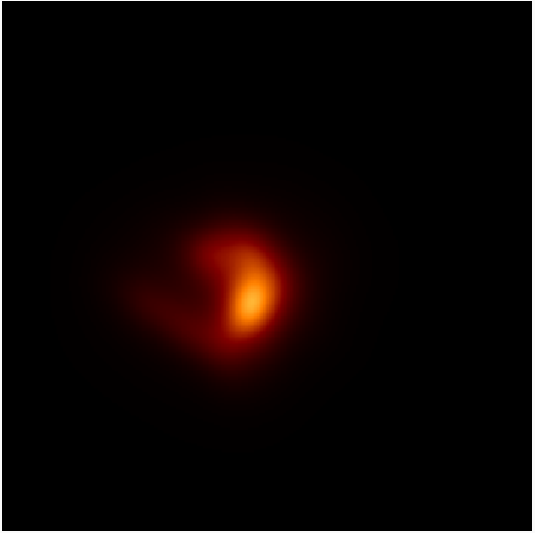
Static Source: Simulation

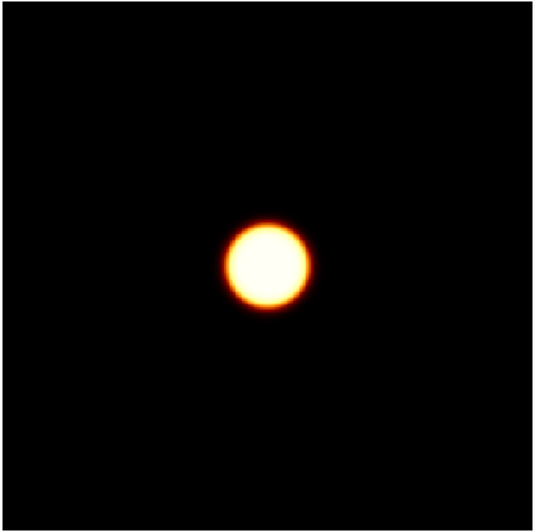


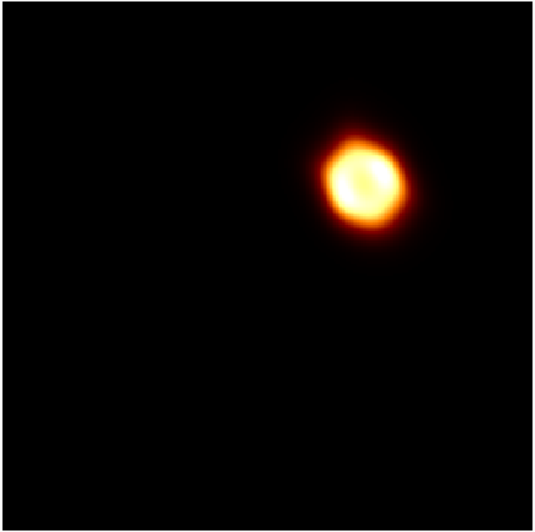


Static Source: Simulation

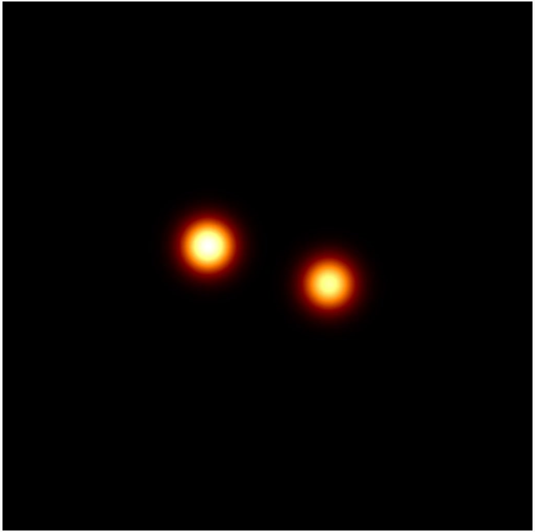


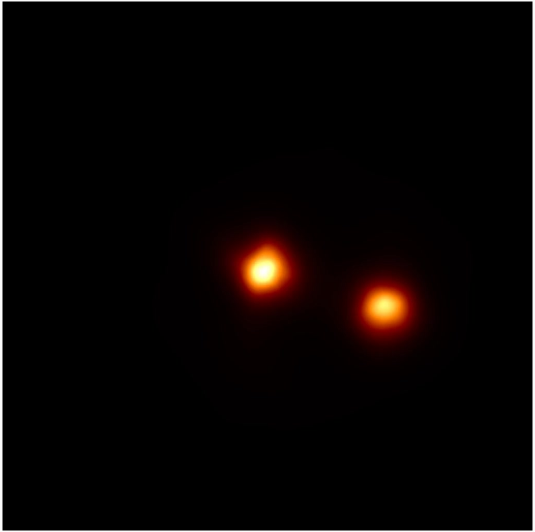




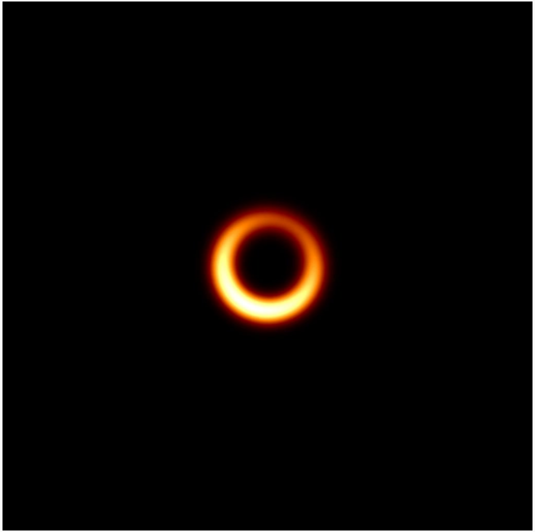


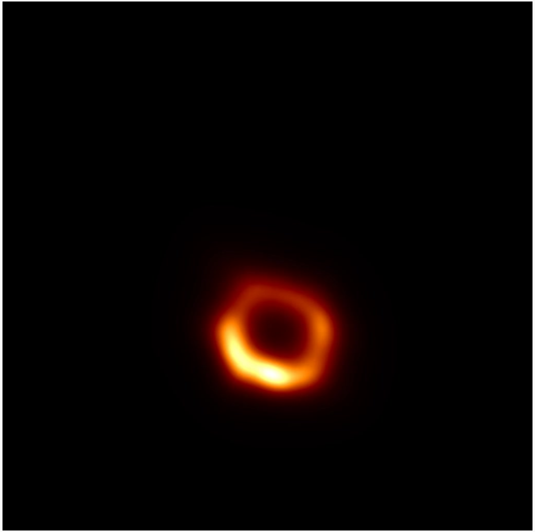
Dynamic Source: Gaussian Shapes





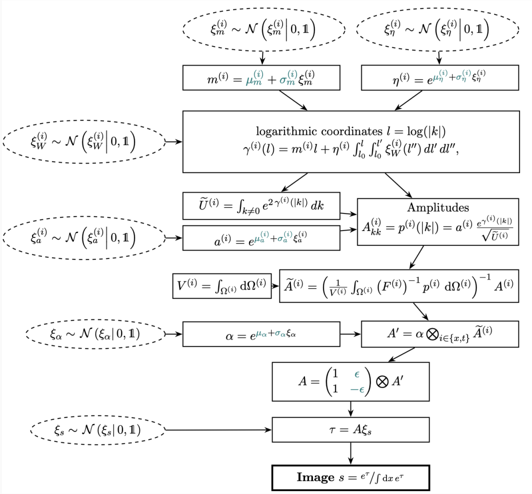
Dynamic Source: Crescent

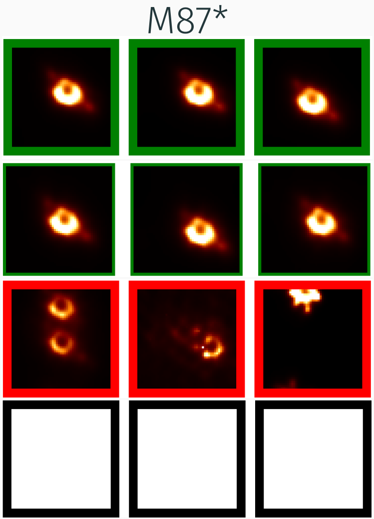


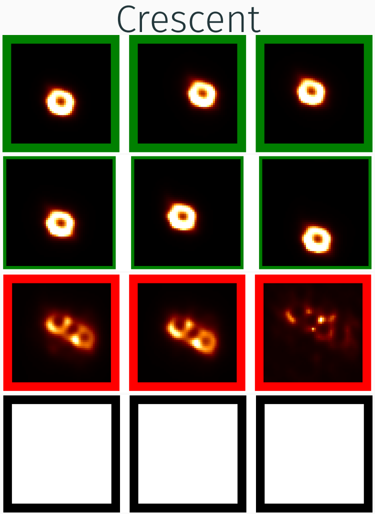


Hyperparameter Validation

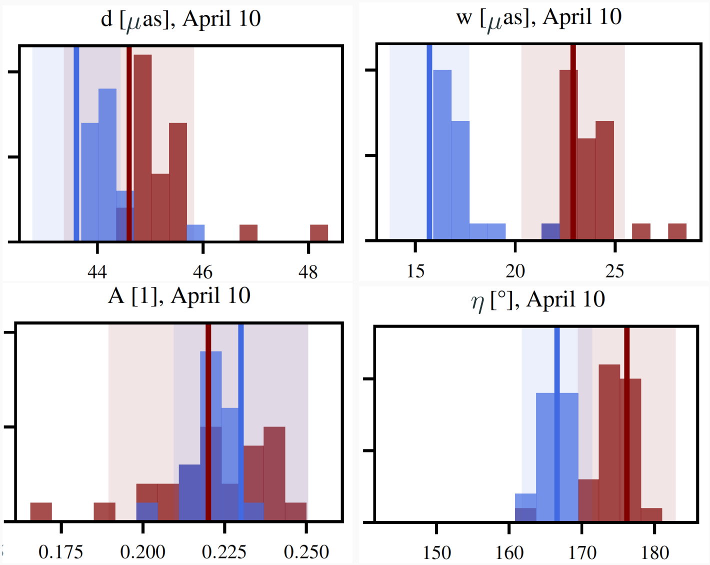
- In total 15 hyperparameters
- Specifying mean and variance
- Draw mean hyperparameters within a uniform 3σ interval
- Perform 100 reconstructions




M87*


Crescent

Ring Parameters



- Reconstruction works on various sources
- We recover dynamics
- Results are widely insensitive to hyperparameters
- Room for improvement in the inference heuristic

Conclusion

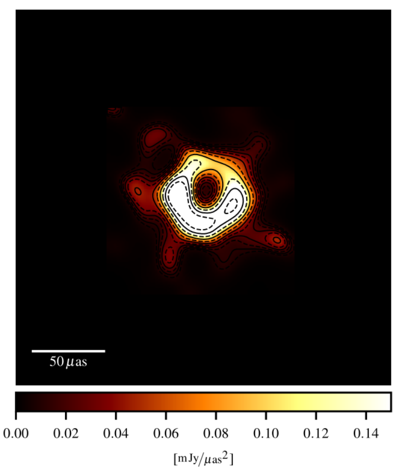


Figure 5: M87* on day 0 imaged with `ehtimaging` [AAA+19b]. Saturated color bar.

Differences to [AAA+19b]

- Uncertainty quantification via multiple independent imaging teams
- Independent imaging for each observing day

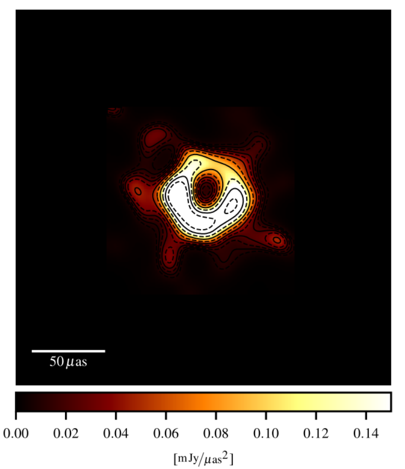


Figure 5: M87* on day 0 imaged with `ehtimaging` [AAA+19b]. Saturated color bar.

Differences to [AAA+19b]

- Intrinsic uncertainty quantification
- Independent imaging for each observing day

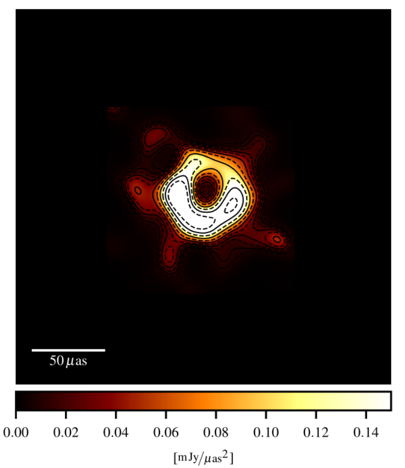


Figure 5: M87* on day 0 imaged with `ehtimaging` [AAA+19b]. Saturated color bar.

Differences to [AAA+19b]

- Intrinsic uncertainty quantification
- Temporal correlations $\rightarrow$ full 4d-movie

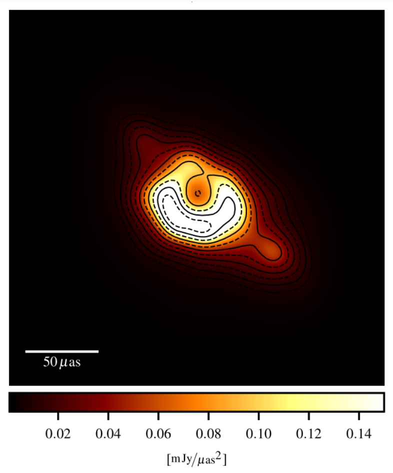


Figure 5: M87* on day 0 imaged with `vlbi-resolve` [AFH+20]. Saturated color bar.

Differences to [AAA+19b]

- Intrinsic uncertainty quantification
- Temporal correlations → full 4d-movie

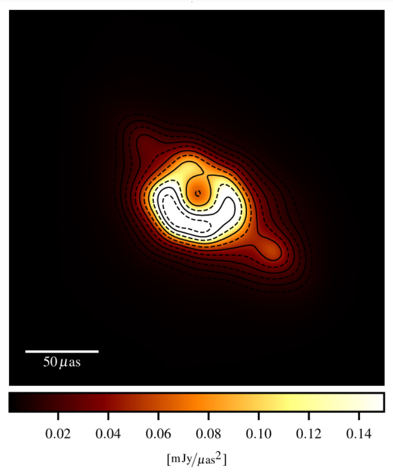


Figure 5: M87* on day 0 imaged with `vlbi-resolve` [AFH+20]. Saturated color bar.

Differences to [AAA+19b]

- Intrinsic uncertainty quantification
- Temporal correlations $\rightarrow$ full 4d-movie

Some aspects

- Four-dimensional (time, frequency, space) resonstruction of M87*
- Correlation kernel is non-parametrically learned from the data
- Bayesian treatment despite huge problem size (10^7 dofs)

Questions? Discussion!

References

- Kazunori Akiyama, Antxon Alberdi, Walter Alef, Keiichi Asada, Rebecca Azulay, Anne-Kathrin Baczko, David Ball, Mislav Baloković, John Barrett, Dan Bintley, et al.
  First M87 Event Horizon Telescope Results. I. The Shadow of the Supermassive Black Hole.
  The Astrophysical Journal Letters, 875(1):L1, April 2019.
- Kazunori Akiyama, Antxon Alberdi, Walter Alef, Keiichi Asada, Rebecca Azulay, Anne-Kathrin Baczko, David Ball, Mislav Baloković, John Barrett, Dan Bintley, et al.
  First M87 Event Horizon Telescope Results. IV. Imaging the Central Supermassive Black Hole.
  The Astrophysical Journal Letters, 875(1):L4, April 2019.
- Philipp Arras, Philipp Frank, Philipp Haim, Jakob Knollmüller, Reimar Leike, Martin Reinecke, and Torsten Enßlin.
  M87* in space, time, and frequency.
  arXiv e-prints, page arXiv:2002.05218, February 2020.

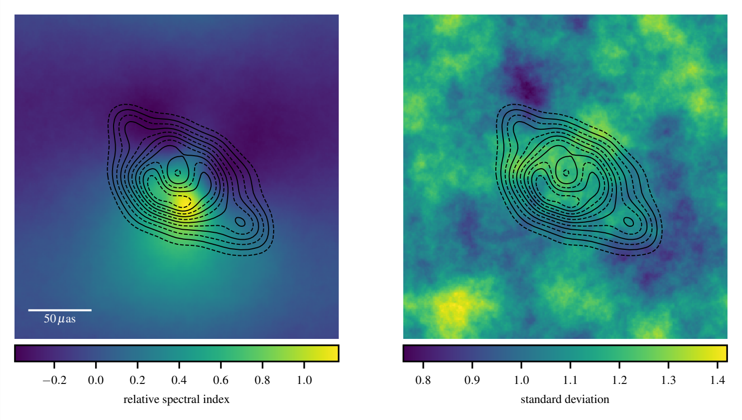


Figure 6: The relative spectral index and the pixel-wise uncertainty, as calculated from the 227–229 GHz channels.

Reduced χ^2

	April 5	April 6	April 10	April 11
Simulation	1.2, 1.0	1.3, 1.2	1.4, 1.3	1.1, 1.1
Disk	1.6, 1.2	1.4, 1.3	1.5, 1.4	1.3, 1.2
Double Sources	1.2, 1.1	1.2, 1.1	1.3, 1.3	1.4, 1.1
Crescent	1.2, 1.0	1.3, 0.9	1.0, 0.9	1.4, 1.1
M87*	1.1, 0.9	1.1, 0.8	1.1, 0.9	1.1, 0.9

Table 1: The χ^2 of the reconstruction for closure (phase, amplitude).