

Time variable and spectral resolved Bayesian Imaging and the variable shadow of M87*

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Bayesian Inference

Given a Model M , what is the joint probability of an unknown signal s and the measured data d ?

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$$M = \{M_{lh}, M_{pr}\}$$

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$$M = \{M_{lh}, M_{pr}\}$$

Bayes Theorem

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

Bayes Theorem \Leftrightarrow Generative Models

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Transformation rule for probabilities

$$P(s) \, ds = P(\xi) \, d\xi$$

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$$P(s, d|M) \Leftrightarrow P(\xi, d|M) = P(d|s(\xi), M) \mathcal{G}(\xi, 1)$$

Modeling the sky brightness

$$s_{xt\nu} = e^{\tau_{xt\nu}} \quad \text{with} \quad x \in \Omega \subset \mathbb{R}^d, \quad t \in I \subset \mathbb{R}, \quad \nu \in V \subset \mathbb{R}^+$$

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Exploit correlations

$$\langle \tau_{x,t,\nu} \tau_{x',t',\nu'} \rangle = C(x, t, \nu, x', t', \nu')$$

Modeling the sky brightness

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Exploit correlations

$$\begin{aligned}\langle \tau_{x,t,\nu} \tau_{x',t',\nu'} \rangle &= C(x, t, \nu, x', t', \nu') \\ &= C(|x - x'|, |t - t'|, |\nu - \nu'|) \\ &= C^\Omega(|x - x'|) \ C^I(|t - t'|) \ C^V(|\nu - \nu'|)\end{aligned}$$

Modeling the sky brightness

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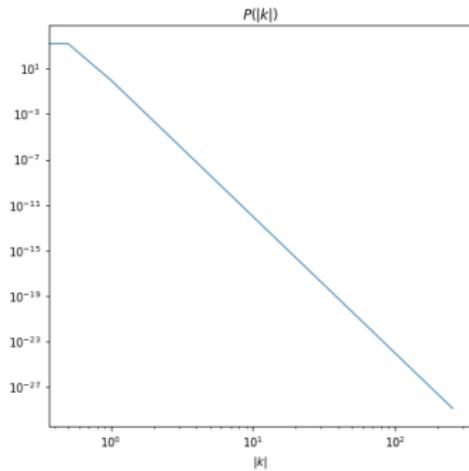
$$P(\tau|C) = \mathcal{G}(\tau, C) \quad \Leftrightarrow \quad \tau = \sqrt{C} \xi_\tau, \quad \xi_\tau \sim \mathcal{G}(\xi_\tau, 1)$$

Modeling the sky brightness

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

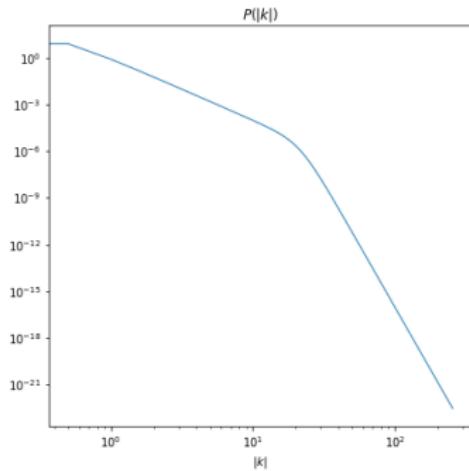
Modeling the sky brightness

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



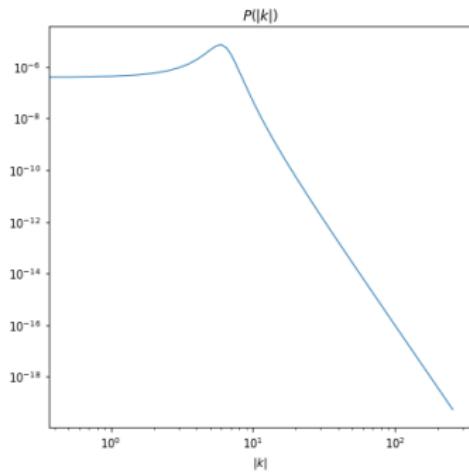
Modeling the sky brightness

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Modeling the sky brightness

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

Modeling the sky brightness

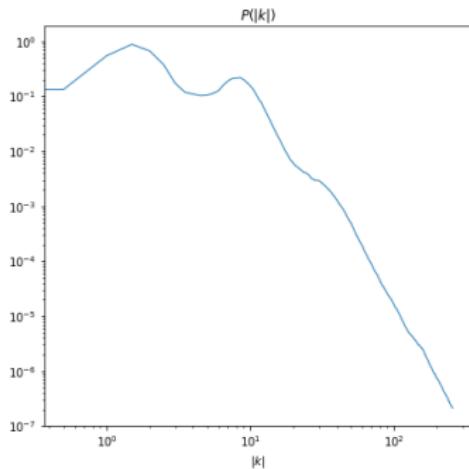
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$$\frac{\partial^2 q}{\partial l^2} = \sigma \xi_q \quad P(\xi_q) = \mathcal{G}(\xi_q, 1) \quad \text{Integrated Wiener Process}$$

Modeling the sky brightness

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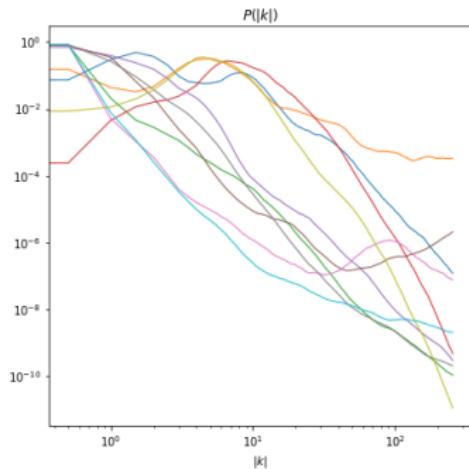
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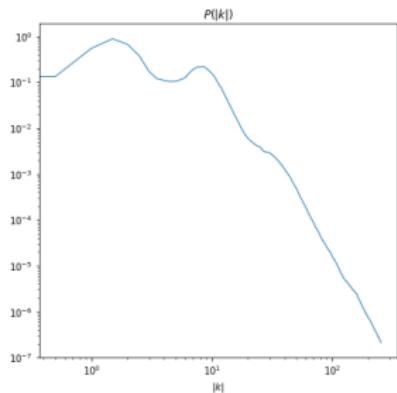
Modeling the sky brightness

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

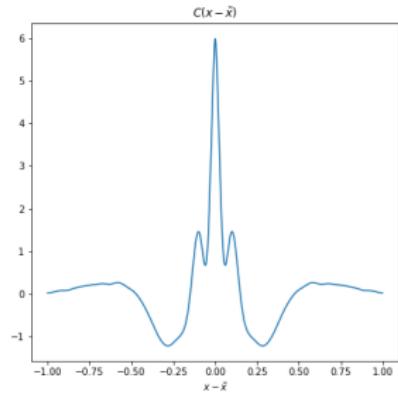
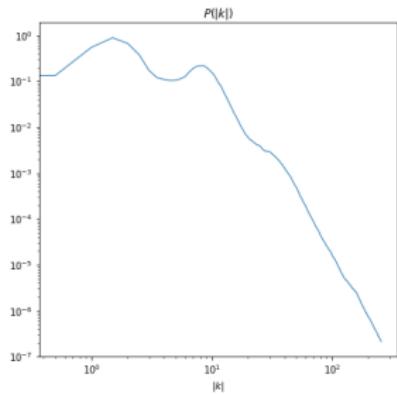
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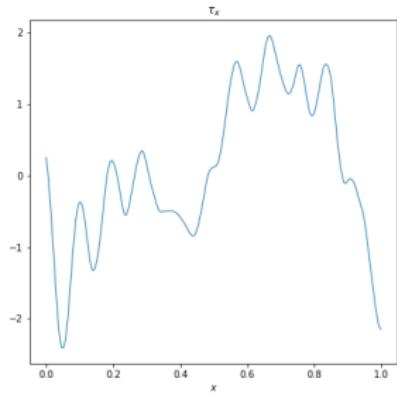
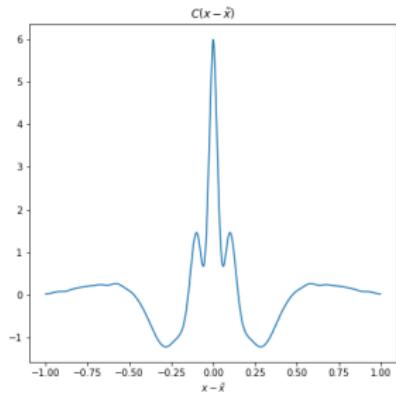
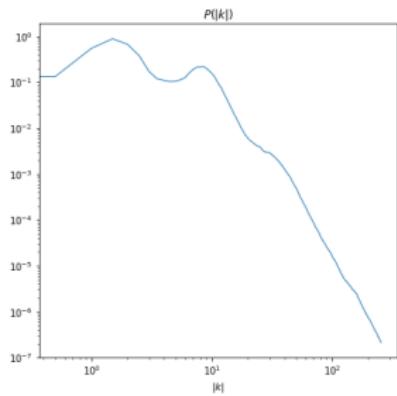
Modeling the sky brightness



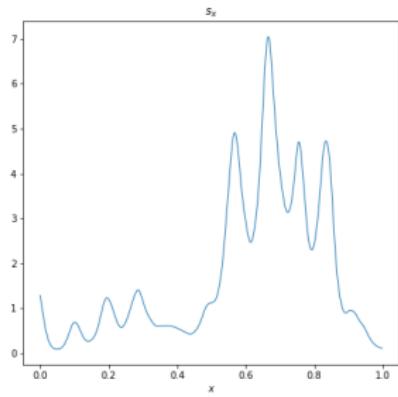
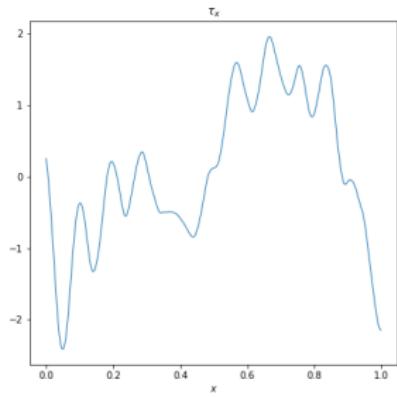
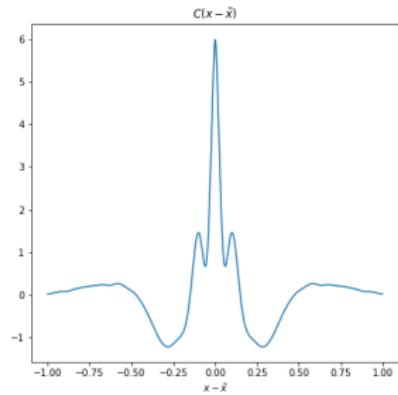
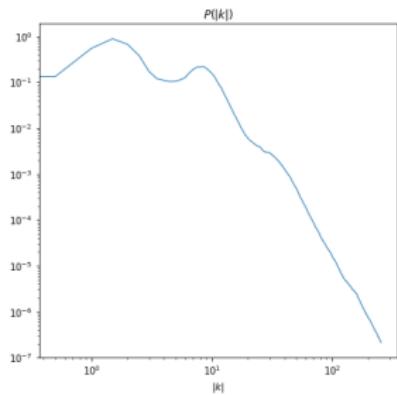
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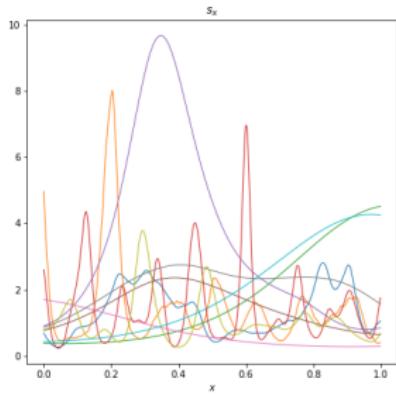
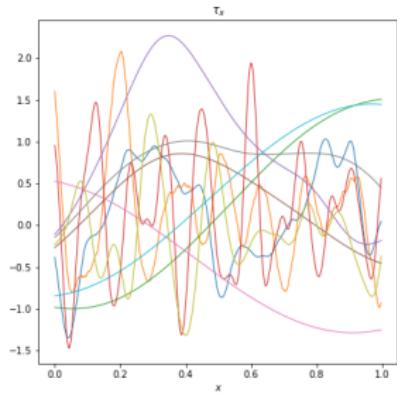
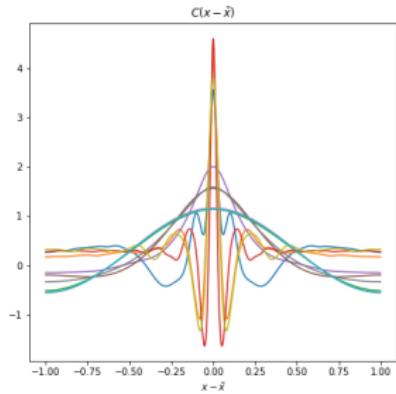
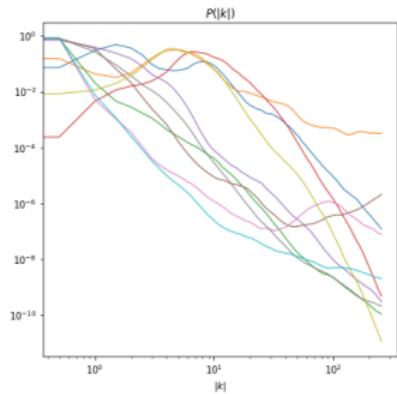
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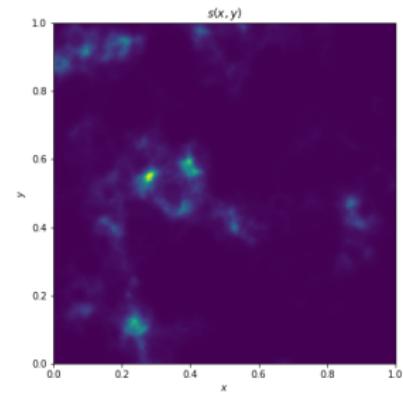
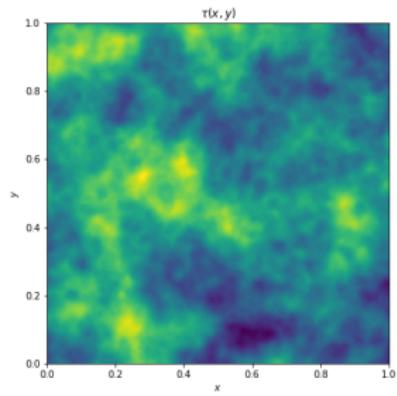
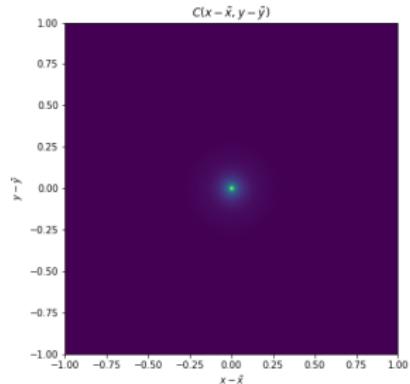
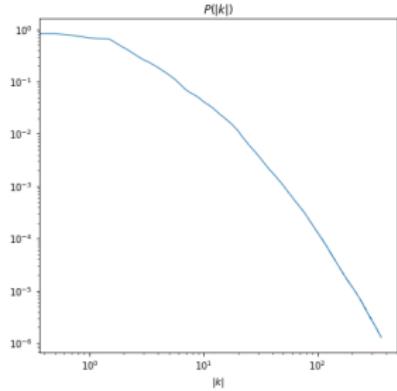
Modeling the sky brightness



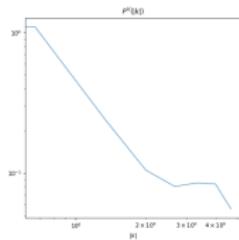
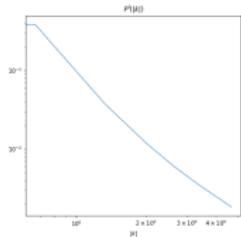
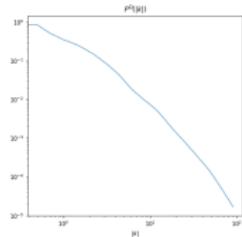
Modeling the sky brightness



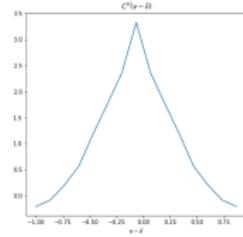
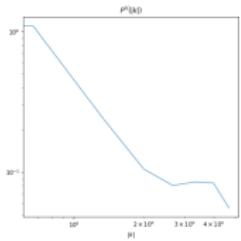
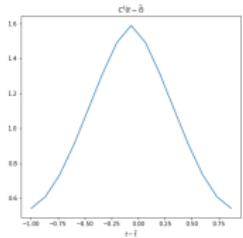
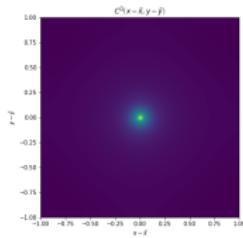
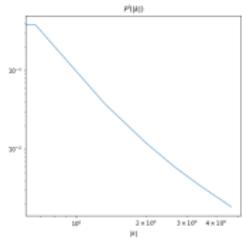
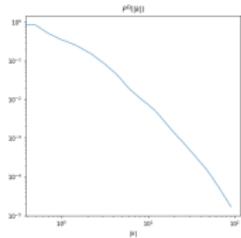
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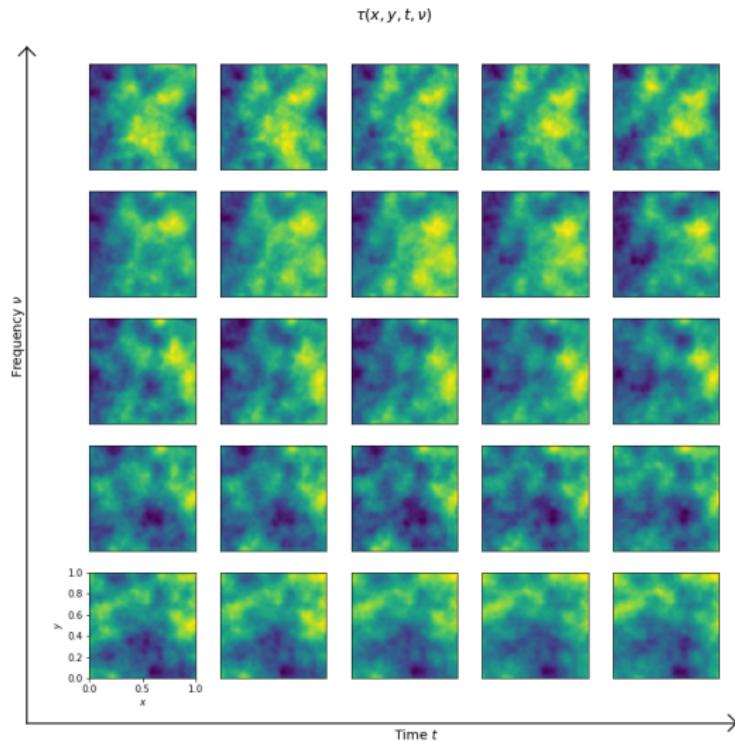
Modeling the sky brightness



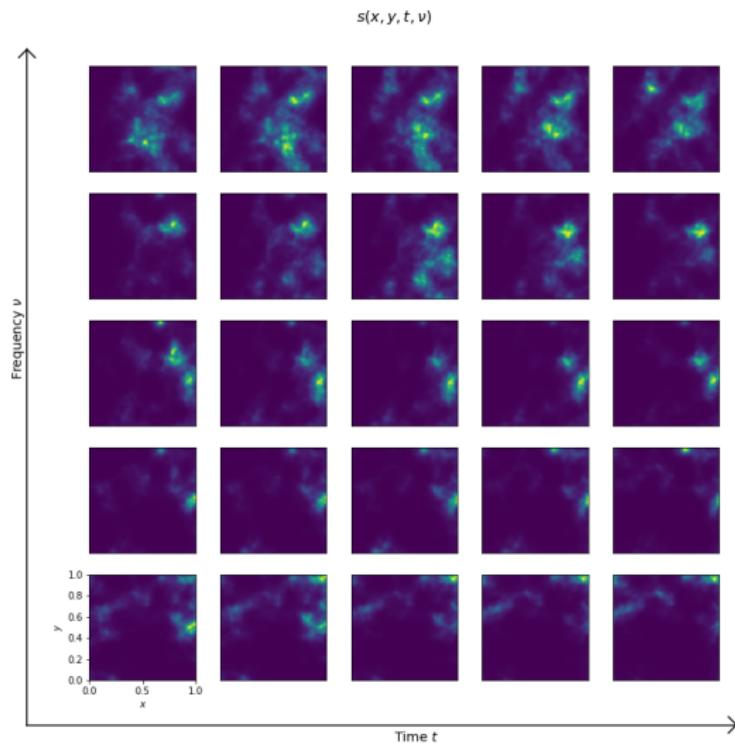
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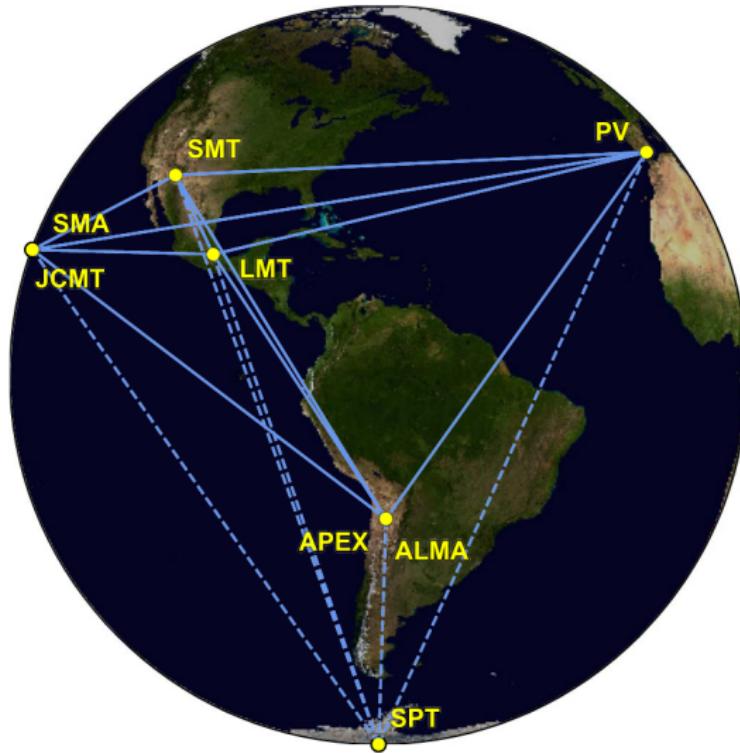
Modeling the sky brightness



Time Variable Imaging of M87*

- ▶ Data provided by the Event Horizon Telescope (EHT)
- ▶ Extremely sparse measurements (~ 4100 Visibilities in total)
- ▶ Significant temporal variability on observational scales
- ▶ Averaged down to two frequency bands at 227 and 229 Ghz

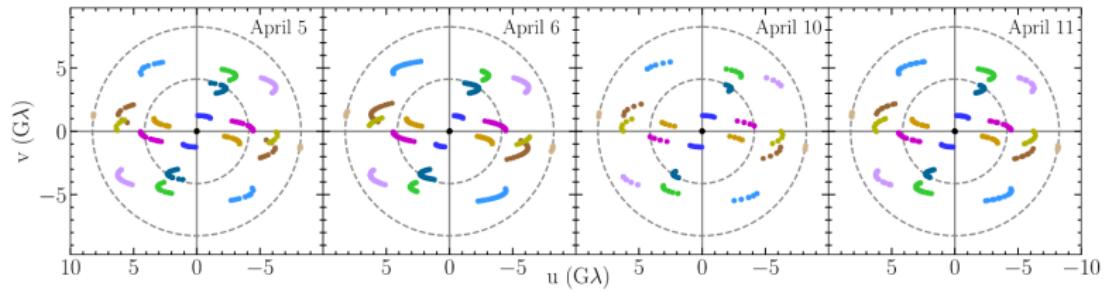
The Event Horizon Telescope (EHT)



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¹Event Horizon Telescope Collaboration et al., "First M87 Event Horizon Telescope Results. I. The Shadow of the Supermassive Black Hole".

The Event Horizon Telescope (EHT)



Likelihood

$$(Rs)_{AB} = \int e^{-2\pi i(u_{AB}x + v_{AB}y)} s_{x,y} dx = e^{\rho_{AB}^s + i\phi_{AB}^s}$$

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$$d_{AB} = \gamma_A \gamma_B^* (Rs)_{AB} + n_{AB} \quad \text{with} \quad n_{AB} \sim \mathcal{G}(n_{AB}, \sigma^2)$$

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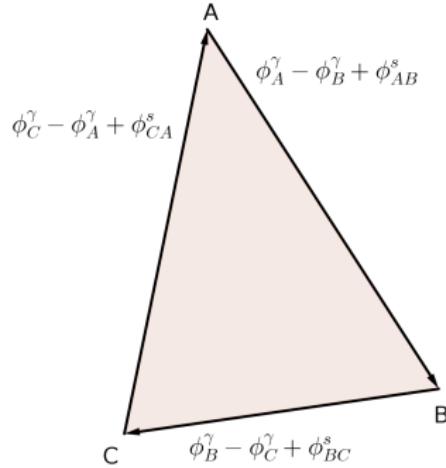
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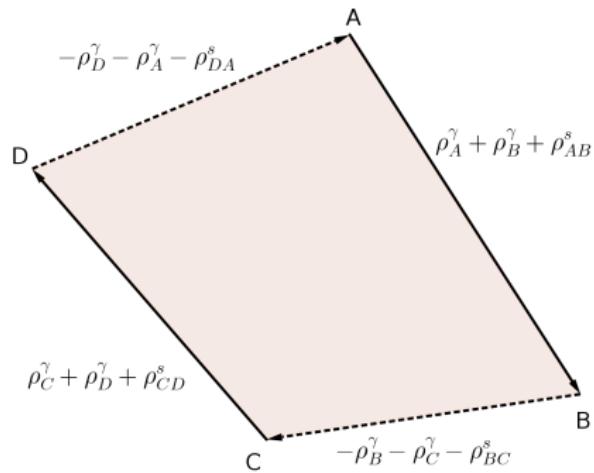
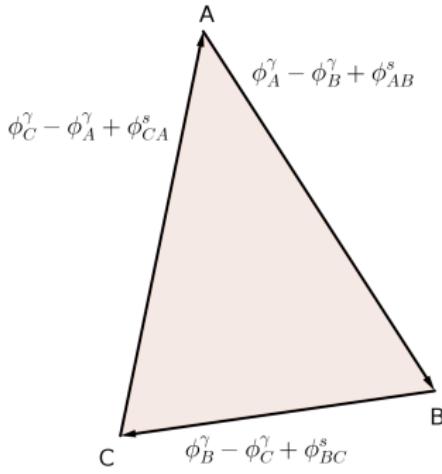
$$\phi_{AB}^d \approx \phi_A^\gamma - \phi_B^\gamma + \phi_{AB}^s + n_{AB}^\phi \quad \text{with} \quad n_{AB}^\phi \sim \mathcal{G}\left(n_{AB}^\phi, \frac{\sigma^2}{|d|^2}\right)$$

$$\rho_{AB}^d \approx \rho_A^\gamma + \rho_B^\gamma + \rho_{AB}^s + n_{AB}^\rho \quad \text{with} \quad n_{AB}^\rho \sim \mathcal{G}\left(n_{AB}^\rho, \frac{\sigma^2}{|d|^2}\right)$$

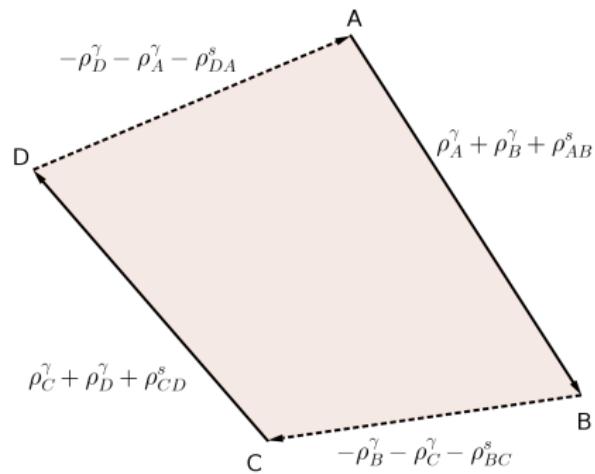
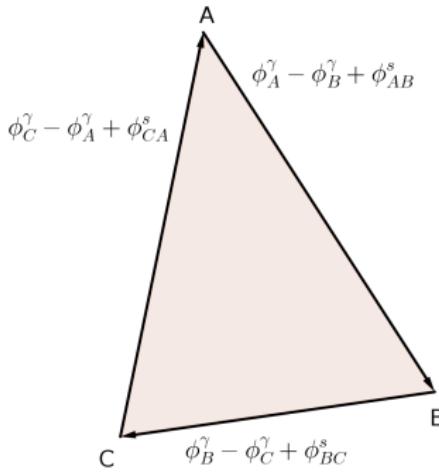
Likelihood



Likelihood



Likelihood



$$\phi_{clos}^d = P\phi^d$$

$$\rho_{clos}^d = L\rho^d$$

Likelihood

$$P\left(\phi_{clos}^d | s\right) \approx \mathcal{G}\left(e^{i\phi_{clos}^d} - e^{i\phi_{clos}^s}, PNP^\dagger\right)$$

$$P\left(\rho_{clos}^d | s\right) \approx \mathcal{G}\left(\rho_{clos}^d - \rho_{clos}^s, LNL^\dagger\right) \quad \text{with} \quad N = \text{diag}\left(\frac{\sigma^2}{|d|^2}\right)$$

Likelihood

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$$s(\xi) = F_M(\xi)$$

$$P\left(\xi | \phi_{clos}^d, \rho_{clos}^d\right) \propto P\left(\phi_{clos}^d | s(\xi)\right) P\left(\rho_{clos}^d | s(\xi)\right) \mathcal{G}(\xi, \mathbb{1})$$

Approximate Inference

$$D = (\phi_{\text{clos}}^d, \rho_{\text{clos}}^d)$$

$$KL(Q(\xi), P(\xi|D)) = - \int Q(\xi) \log \left(\frac{P(\xi|D)}{Q(\xi)} \right) d\xi$$

$$Q(\xi) = \mathcal{G}(\xi - m, \mathcal{M}_m^{-1})$$

$$\mathcal{M}_m = - \left\langle \frac{\partial^2 \log(P(D|\xi))}{\partial \xi \partial \xi} \right\rangle_{P(D|\xi)} \Bigg|_{\xi=m} + 1$$

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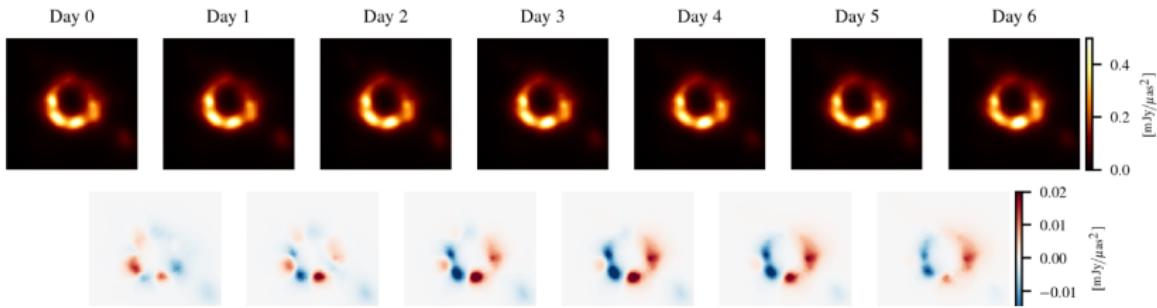
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Set of N approximate posterior samples $\{\xi_i\}_i$

$$\langle s \rangle_{P(s|D)} = \langle s(\xi) \rangle_{P(\xi|D)} \approx \frac{1}{N} \sum_{i=1}^N s(\xi_i)$$

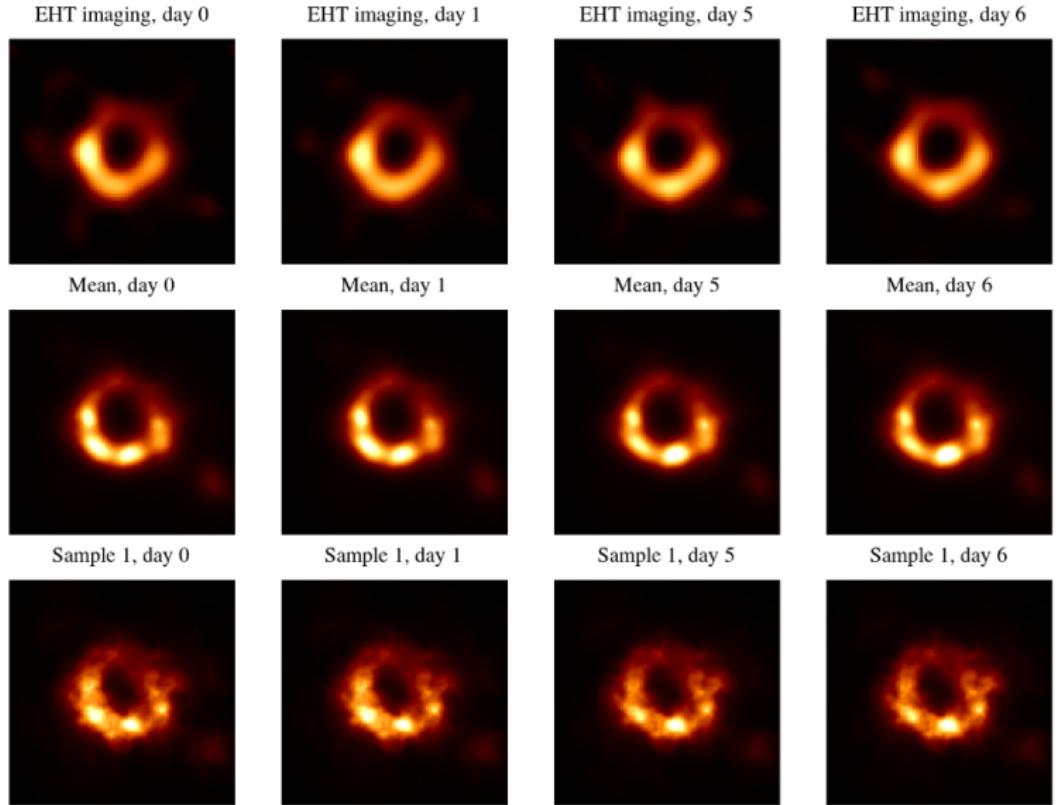
Results

Results

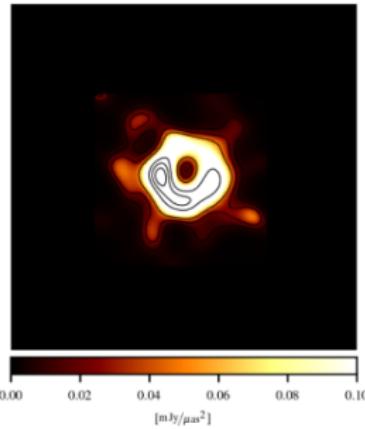
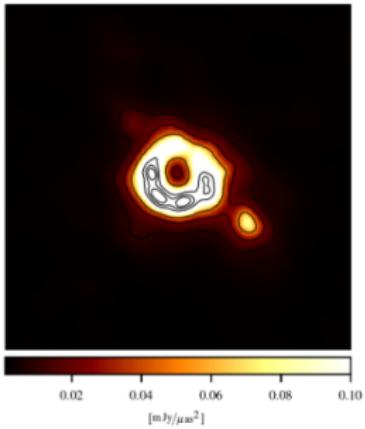
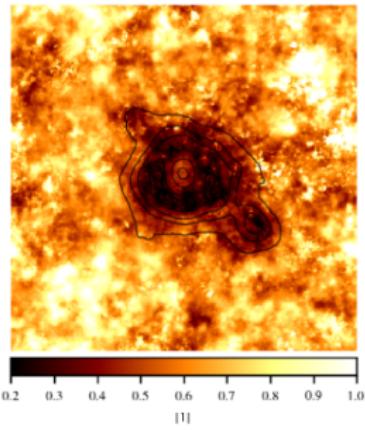
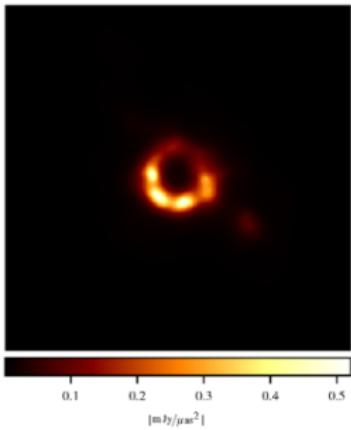


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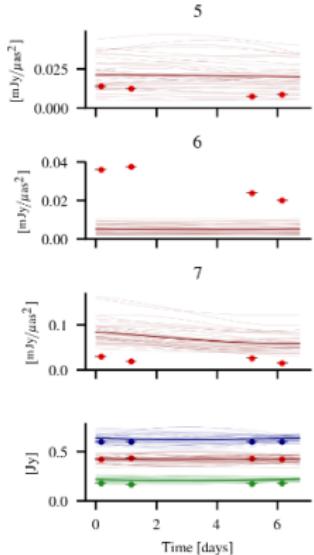
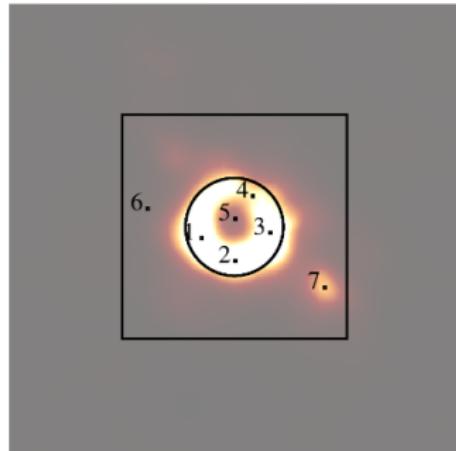
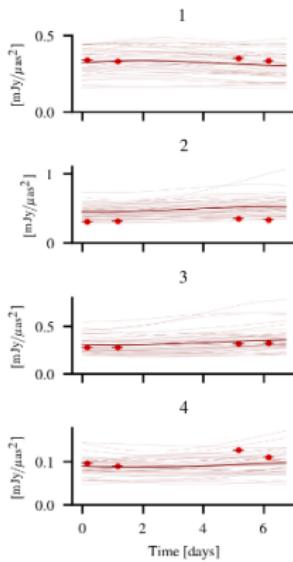
Results



Results



Results



5

Results

Day	d (μ as)	w (μ as)	η ($^{\circ}$)	A	f_C
EHT-IMAGING					
0	39.3 ± 1.6	16.2 ± 2.0	148.3 ± 4.8	0.25 ± 0.02	8×10^{-1}
1	39.6 ± 1.8	16.2 ± 1.7	151.1 ± 8.6	0.25 ± 0.02	6×10^{-2}
5	40.7 ± 1.6	15.7 ± 2.0	171.2 ± 6.9	0.23 ± 0.03	4×10^{-2}
6	41.0 ± 1.4	15.5 ± 1.8	168.0 ± 6.9	0.20 ± 0.02	4×10^{-2}
OUR METHOD (SAMPLE UNCERTAINTY)					
0	40.2 ± 1.1	13.4 ± 2.4	158.3 ± 4.5	0.28 ± 0.02	1×10^{-4}
1	40.3 ± 1.1	13.3 ± 2.5	157.1 ± 4.1	0.29 ± 0.02	1×10^{-4}
5	40.8 ± 1.2	13.3 ± 2.4	172.8 ± 4.4	0.27 ± 0.03	1×10^{-4}
6	41.0 ± 1.1	13.3 ± 2.5	176.6 ± 4.7	0.27 ± 0.03	1×10^{-4}

Data products

EHT observation data: <https://doi.org/10.25739/g85n-f134>

Posterior samples⁶: <https://doi.org/10.5281/zenodo.3664583>

IFT Imaging Pipeline: https://gitlab.mpcdf.mpg.de/ift/vlbi_resolve

⁶Arras et al., “The variable shadow of M87*”.