BUILDING FOUNDATION MODELS FOR BLACK HOLES

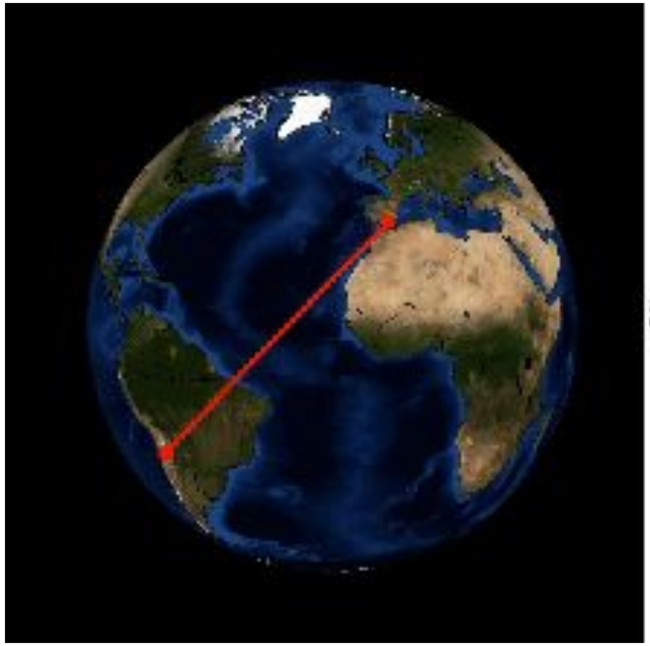
In collaboration with: Dr. S. Caron, Dr. J. Vos, Dr. J. Knollmuller, Prof. H. Falcke

Presentation by Renze Oosterhuis

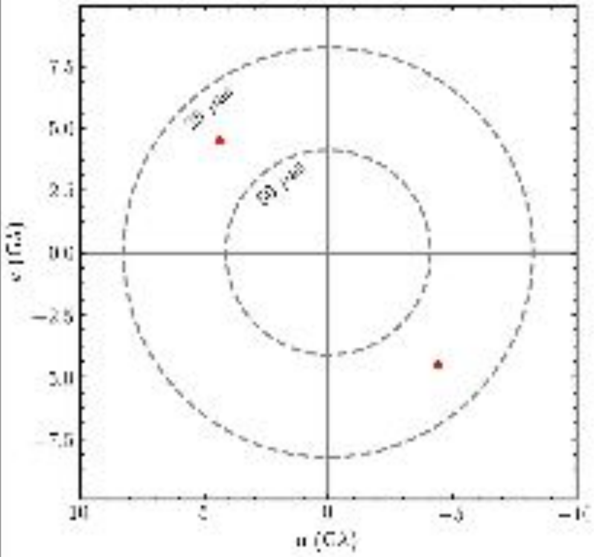
EUCAIFCon, Cagliari - June 19, 2025

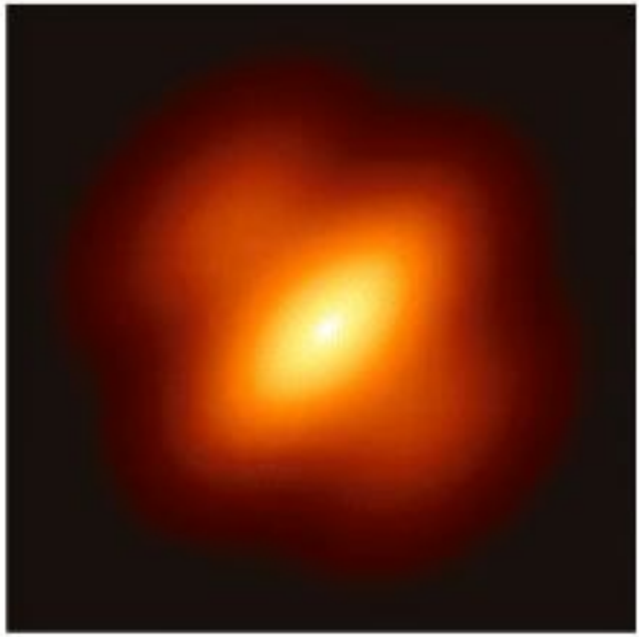
Event Horizon Telescope Collaboration (EHTC)

- Combine several telescopes into an ‘earth-sized’ VLBI array



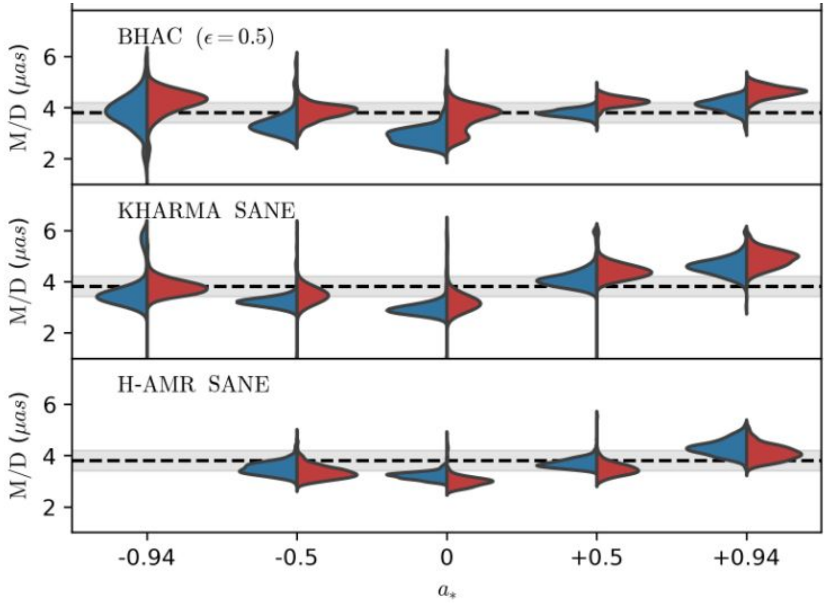
Credit: Lindy Blackburn

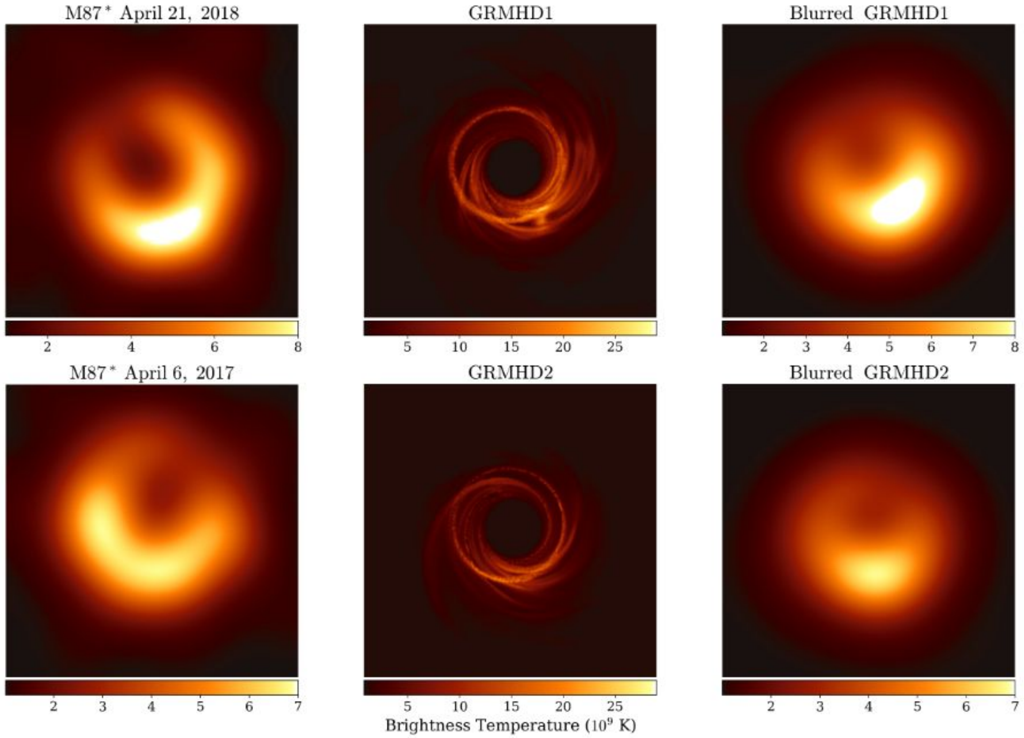




Parameter inference

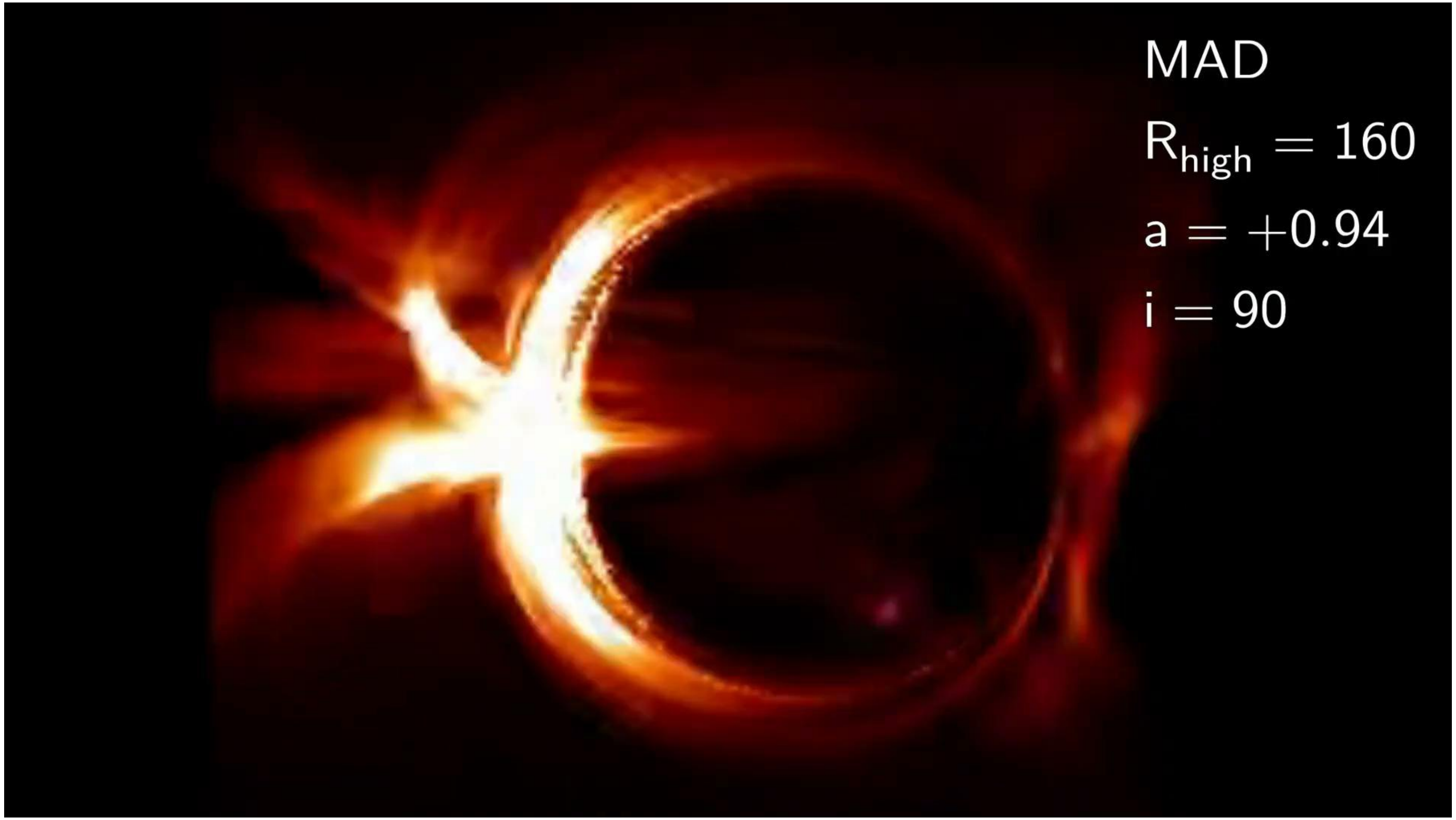
- Black holes are fully described by mass, spin, charge (no hair theorem)
- M ~ 10^9 Msun (inferred from shadow size)
- Spin ~ …





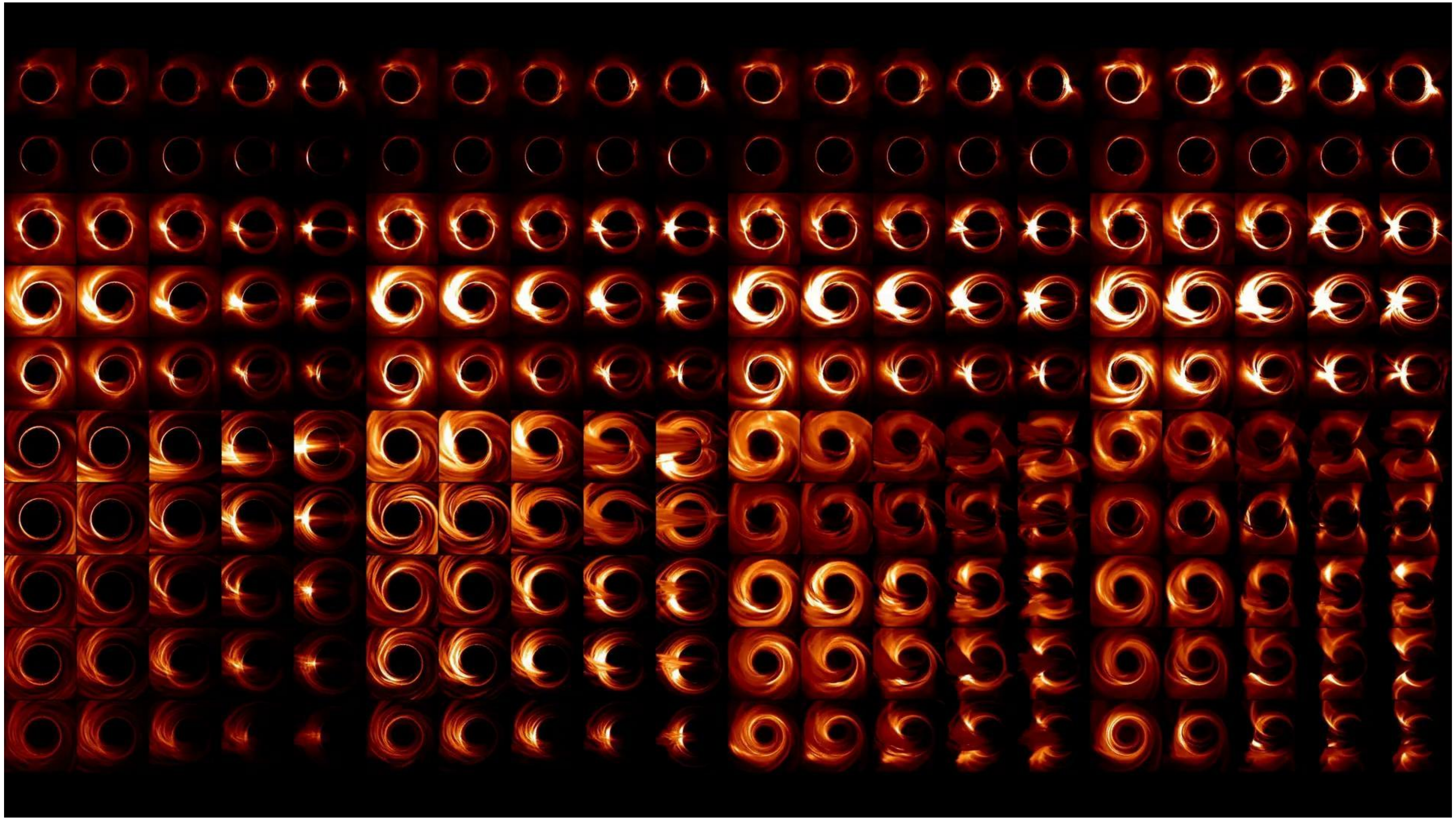
Credit: EHTC et al

Parameter inference from EHT data



Credit: EHTC et al

Parameter inference from EHT data



Credit: EHTC et al

Inference by simulations

- The full simulation library:
    - Different spins (a)
    - Plasma parameters
    - Accretion regimes
    - Simulation codes

- ML-based parameter inference networks have been published (vd Gucht+19, Janssen+25)

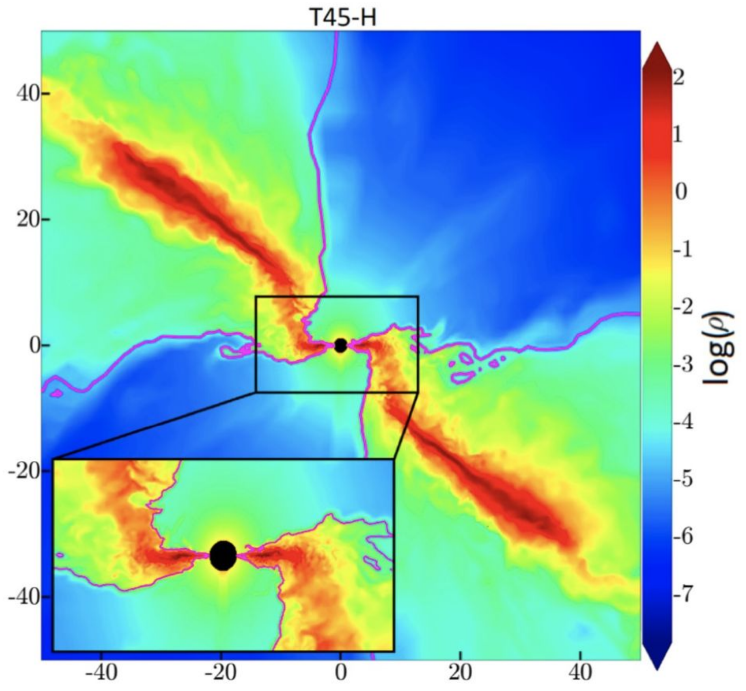
EHT: pass jet: pass	EHT: pass jet: fail	EHT: fail jet: pass	EHT: fail jet: fail

MAD thermal	$R_{\rm low}$	$R_{\rm high}$	$a_* = -0.94$	$a_* = -0.5$	$a_* = 0$	$a_* = 0.5$	$a_* = 0.94$
KHARMA	1	1					
H-AMR	1	1					
KHARMA	10	1					
KHARMA	1	10					
H-AMR	1	10					
KHARMA	10	10					
H-AMR	1	20					
KHARMA	1	40					
H-AMR	1	40					
BHAC	1	40					
BHAC	10	40					
KHARMA	10	40					
BHAC	1	80					
H-AMR	1	80					
BHAC	10	80					
BHAC	1	160					
KHARMA	1	160					
H-AMR	1	160					
KHARMA	10	160					
BHAC	10	160					
MAD nonthermal	**$R_{\rm low}$, ϵ**	**$R_{\rm high}$**	**$a_* = -0.94$**	**$a_* = -0.5$**	**$a_* = 0$**	**$a_* = 0.5$**	**$a_* = 0.94$**
BHAC	1, 0	40					
BHAC	1, 0	80					
BHAC	1, 0	160					
BHAC	1, 0.5	40					
BHAC	1, 0.5	80					
BHAC	1, 0.5	160					
SANE thermal	**$R_{\rm low}$**	**$R_{\rm high}$**	**$a_* = -0.94$**	**$a_* = -0.5$**	**$a_* = 0$**	**$a_* = 0.5$**	**$a_* = 0.94$**
KHARMA	1	1					
H-AMR	1	1					
KHARMA	10	1					
KHARMA	1	10					
H-AMR	1	10					
KHARMA	10	10					
H-AMR	1	20					
H-AMR	1	40					
KHARMA	1	40					
KHARMA	10	40					
H-AMR	1	80					
H-AMR	1	160					
KHARMA	1	160					
KHARMA	10	160					

Credit: EHTC et al

GENERAL RELATIVISTIC MAGNETO-HYDRO DYNAMICS (GRMHD)

- Essential in comparing observations to theory
- Evolve matter and magnetic fields in curved spacetime
- Only able to sparsely explore parameter ranges
- High computational costs (typically ~100K CPUh per simulation)
- Can we lift these ‘shortcomings’ using machine learning?

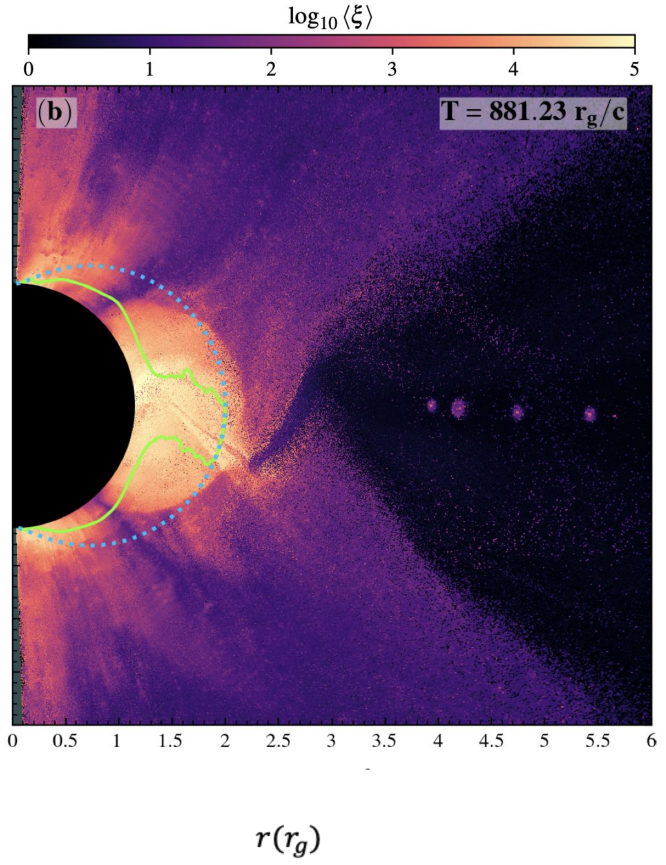


Credit: Y. Mizuno (2022)

A unifying black hole foundation model

The holy grail: unify all black hole physics into one **foundation model**

- **Reduce computational costs by orders of magnitude:**
  - Run simulations for longer / with higher precision
- **Interpolate between simulation pipelines:**
  - Interpolate between different (spin-) parameters of black holes
  - Combine large-scale jet MHD with small-scale GRMHD
  - Maneuver between grid-/particle-based simulations?
- **Perform faster and better parameter interference of EHT data**



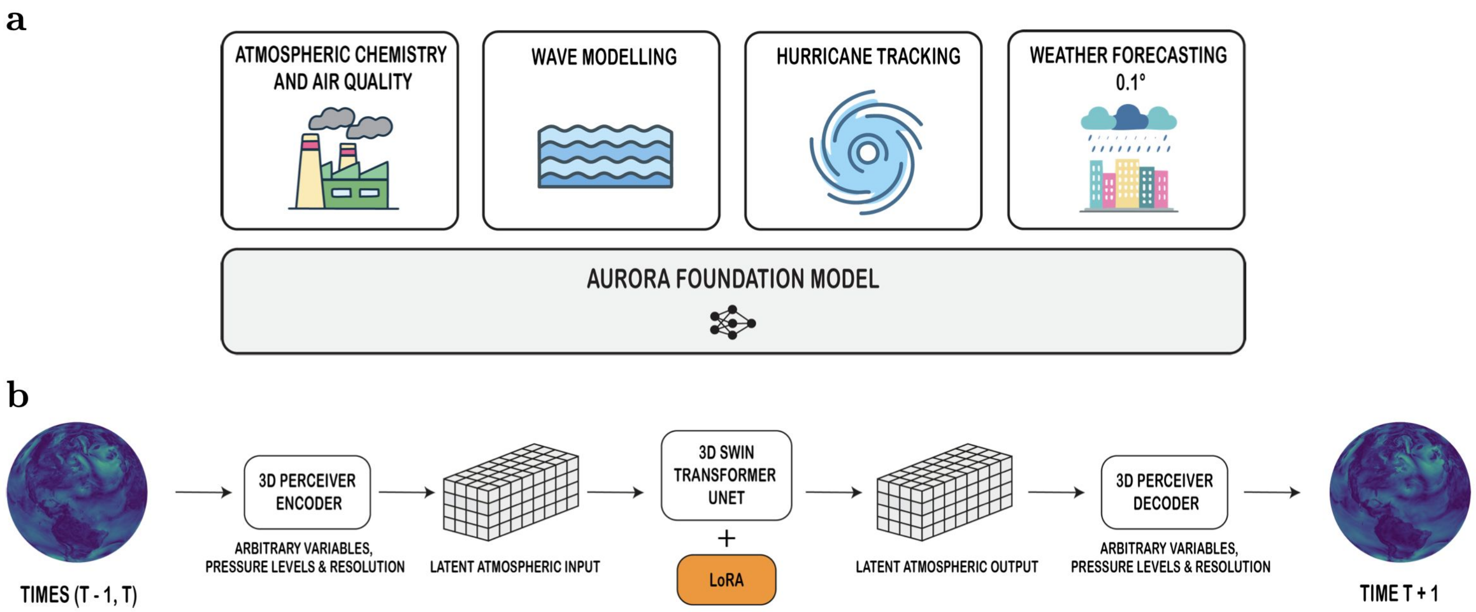
Credit: Vos et al. (2024)

FOUNDATION MODELS

- Machine learning models pretrained on vast datasets, later finetuned on more specific tasks
- Applicable to wide usage of cases
  - Large-Language models, text-to-image models, MusicGen
- Fairly low computational costs to evaluate once trained

APPLYING FOUNDATION MODELS TO PHYSICAL SYSTEMS

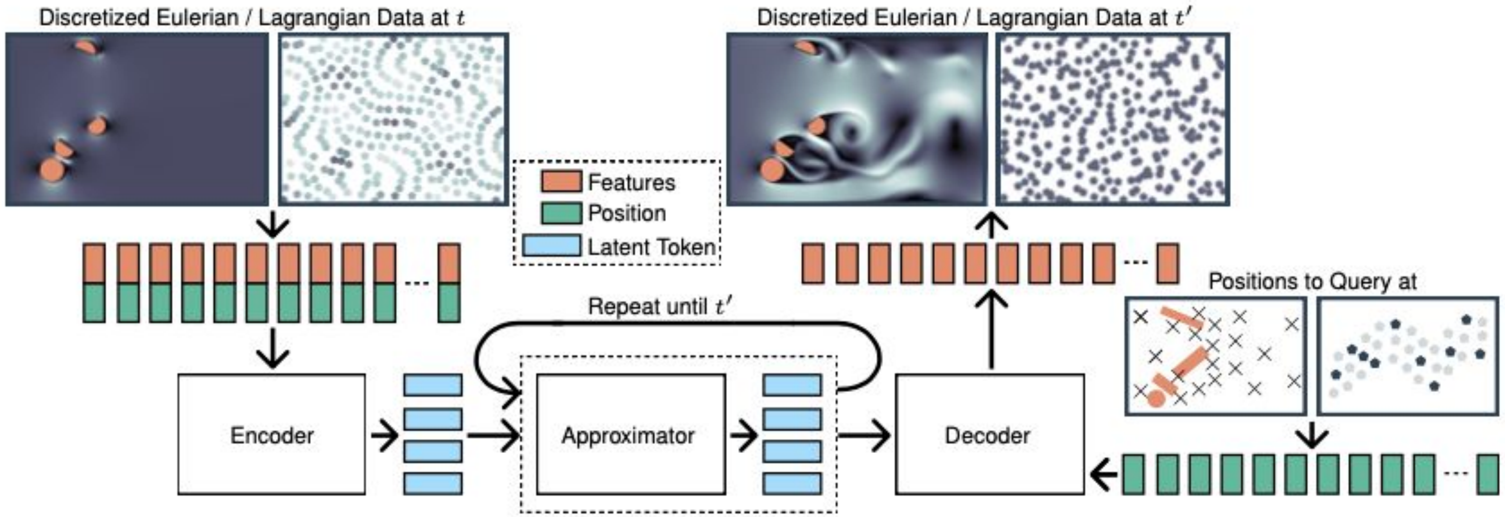
- Aurora: A foundation model for the earth system
- Very similar in data size and structure to GRMHD
- Immense computational speedup (× ~5000)
- Pretrained on low resolution (0.25°) data, later finetuned on high resolution (0.1°) data



Credit: Bodnar et al. (2024)

UNIVERSAL PHYSICS TRANSFORMERS (UPTS)

- Using one universal (machine-) learning paradigm for different spatio-temporal problems
- Does not rely on grid/particle based structures
- High efficiency due to reduced latent space modelling and leveraging scalability of transformers

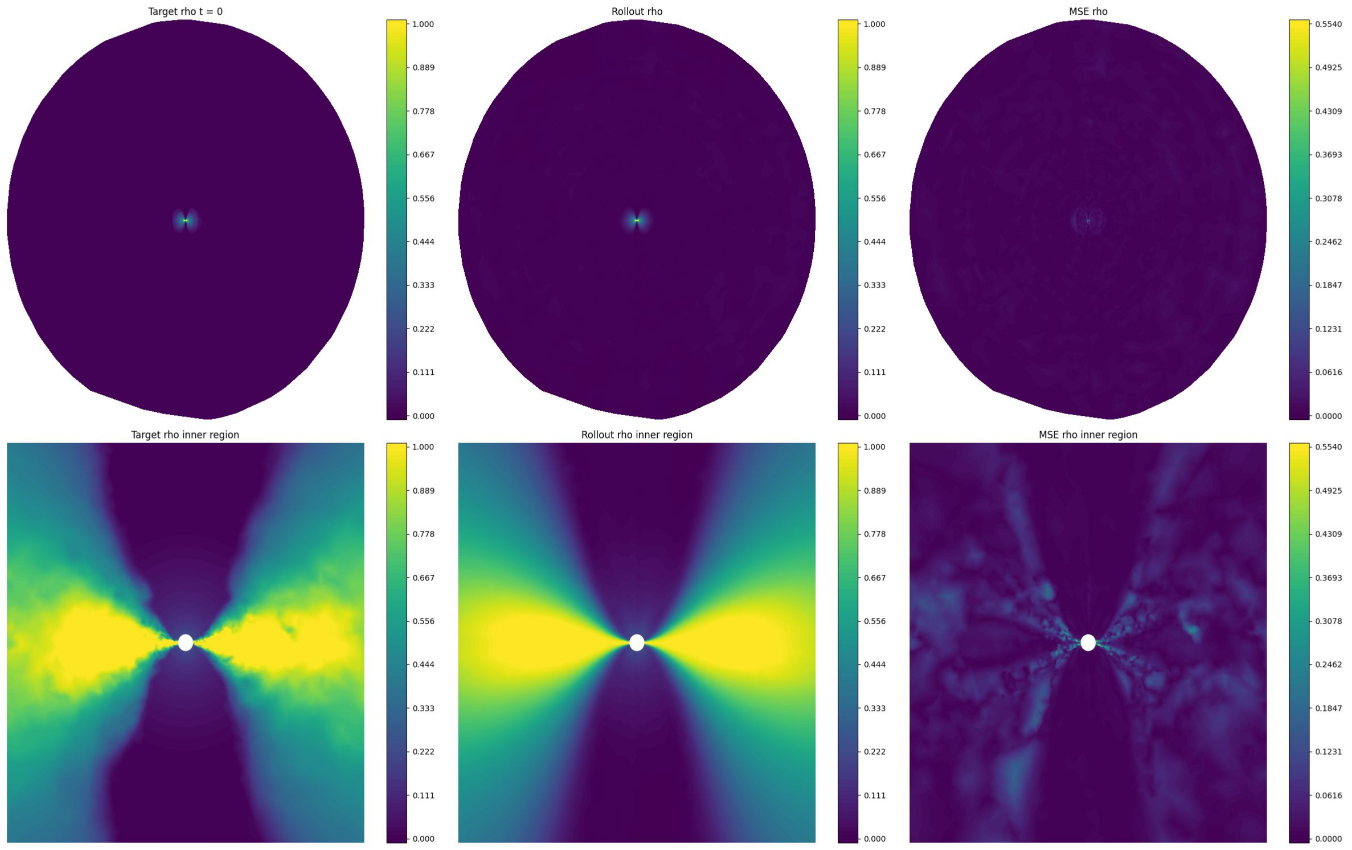


Credit: Alkin et al. (2024)

Results

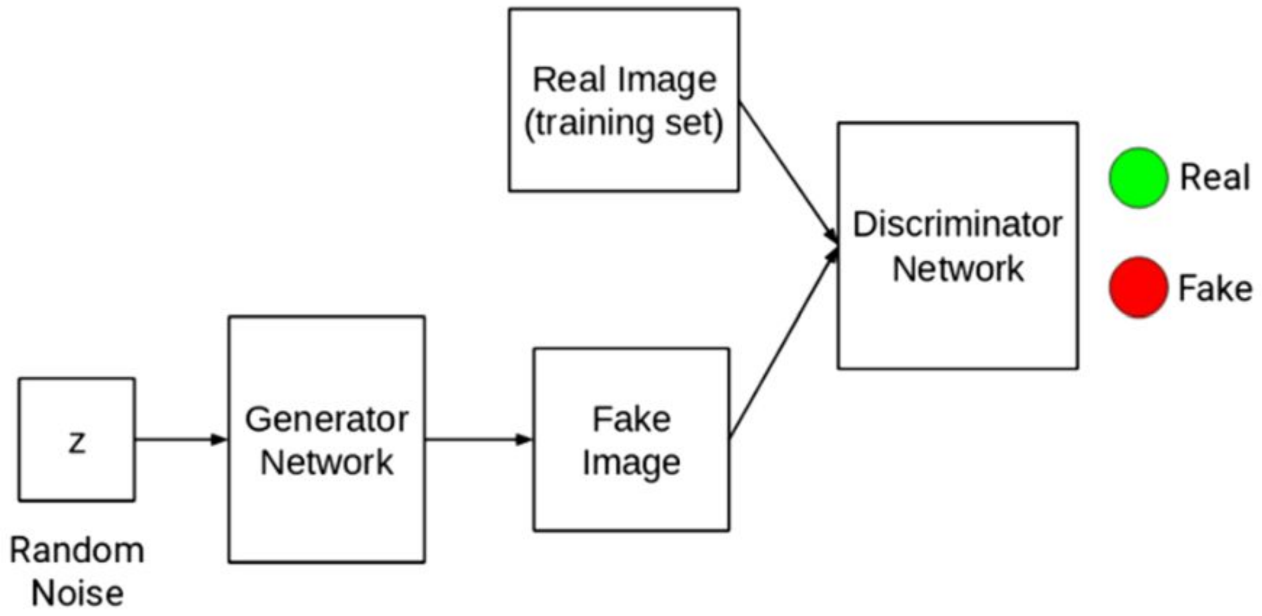
- UPT adapted to train on 2d/3d GRMHD datasets, with an arbitrary number of parameters
- We can simulate global dynamics, except for small turbulences
- Bottlenecks:
  - Training data
  - Error metric
  - Architecture

Simulation | Model | Training loss



Stochastic approach: GANs

- Use a binary classifier to distinguish between real/fake images
- Use the classifier output in the loss function of the generator



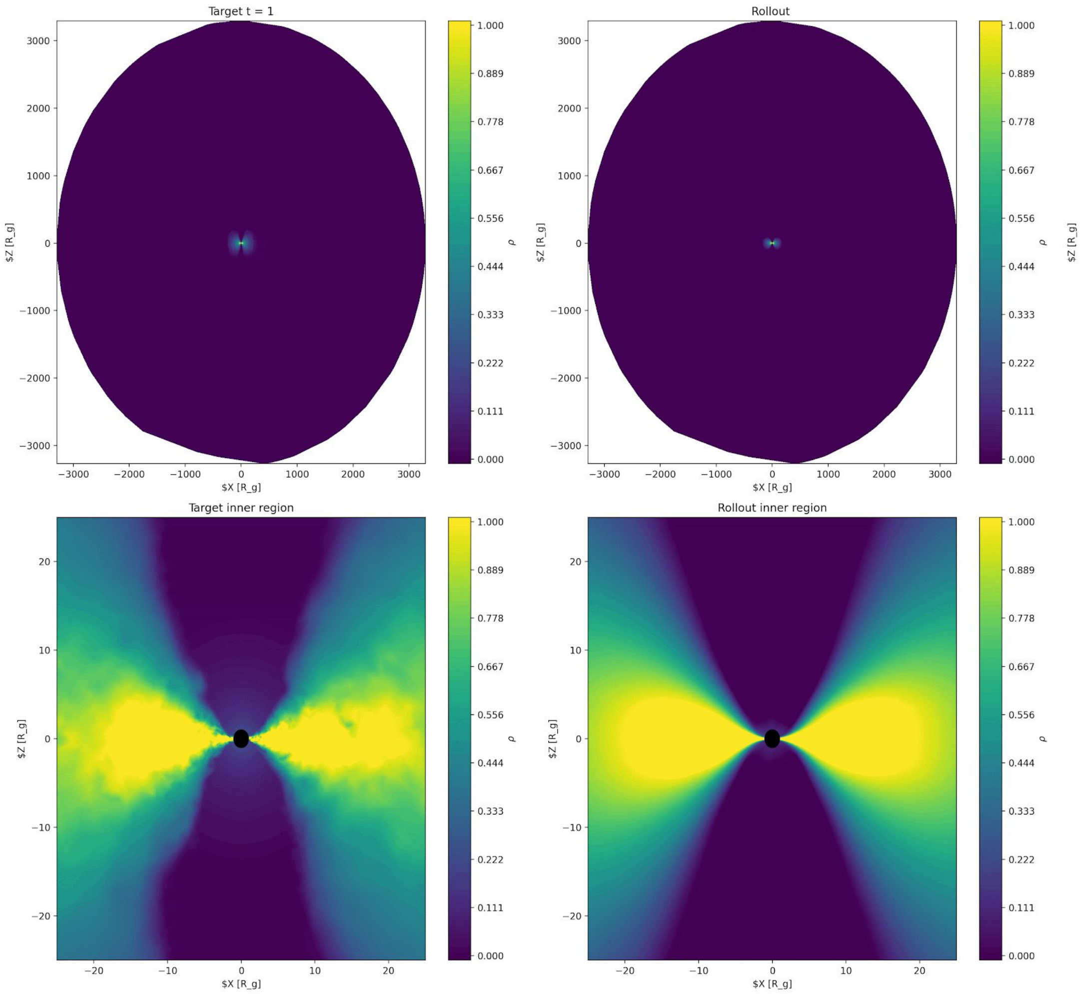
Credit: Sharma (2025)

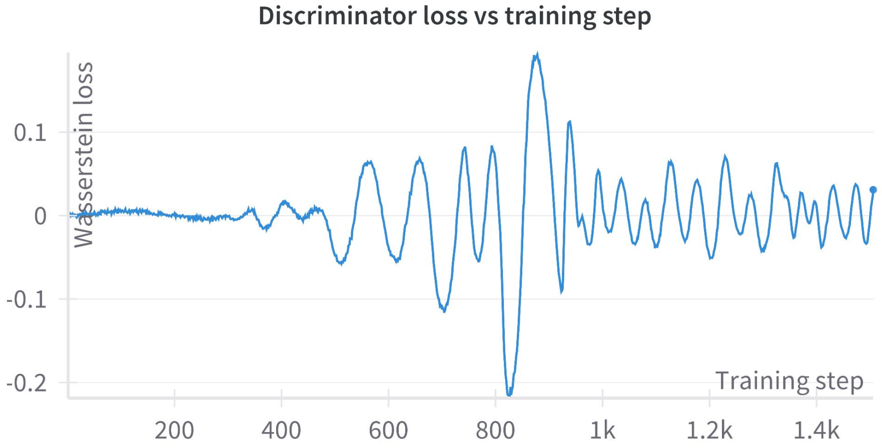
Results for GANs

- More dynamical behavior
- Generator can easily 'fool' the discriminator

Simulation

Model





Conclusions and further steps

- We are able to model large scale GRMHD dynamics with UPTs
- However, modelling small turbulences is not possible with the limited resources we have
- Different ML architectures are necessary to model turbulence in GRMHD:
  - GANs
  - Discrete tokenization
  - (Tensorized) FNOs
  - …

Thank you for your attention!