Modelling galaxy kinematics with self-supervised, physics-aware, Bayesian neural networks

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CARDIFF UNIVERSITY
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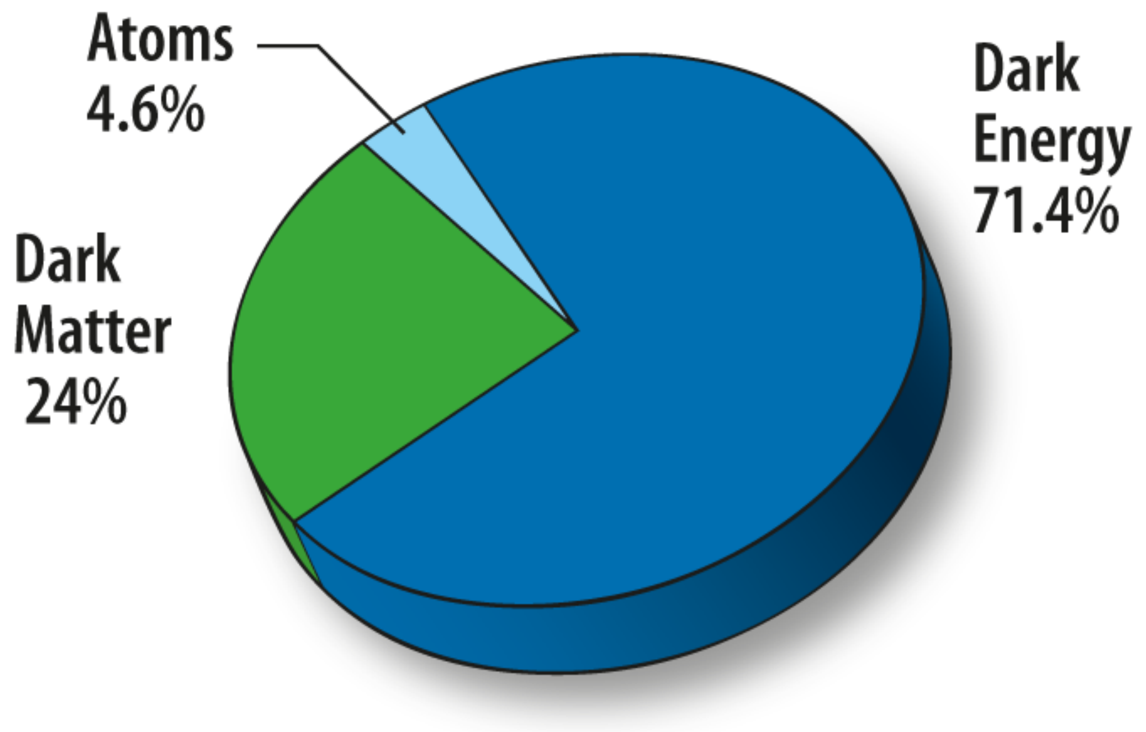
Dynamical probes of galaxy evolution with machine learning

- Our best current model of the universe suggests ~95% of its constituents are “dark”
- i.e. we still don’t understand them!



→ AI and machine learning have a lot of offer in our hunt to understand these dark components.

→ Here I will touch on ways ML is helping us probe DM and Baryons

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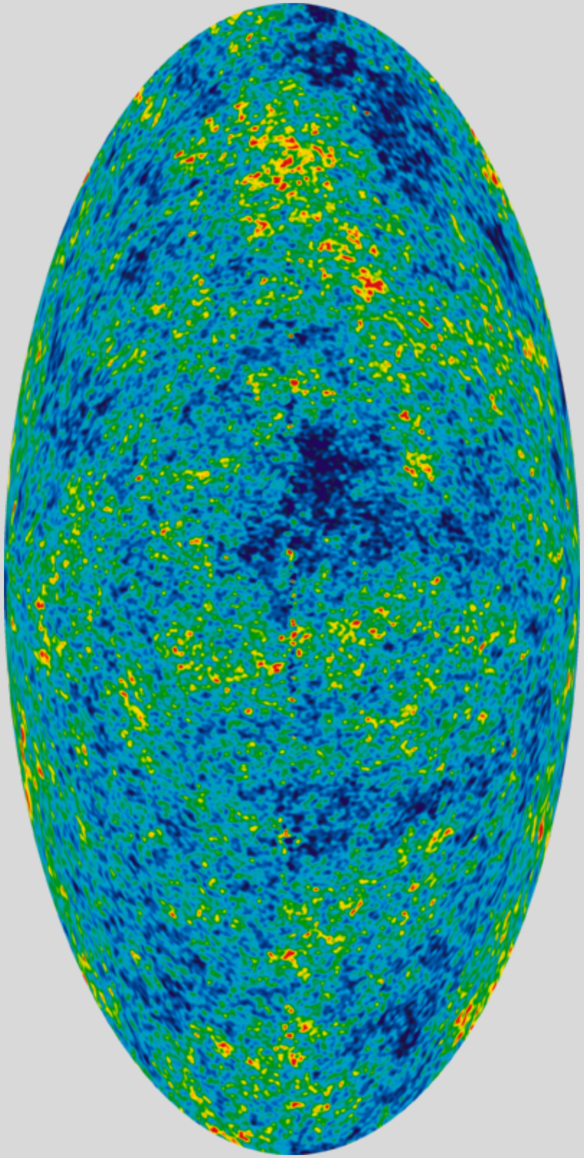
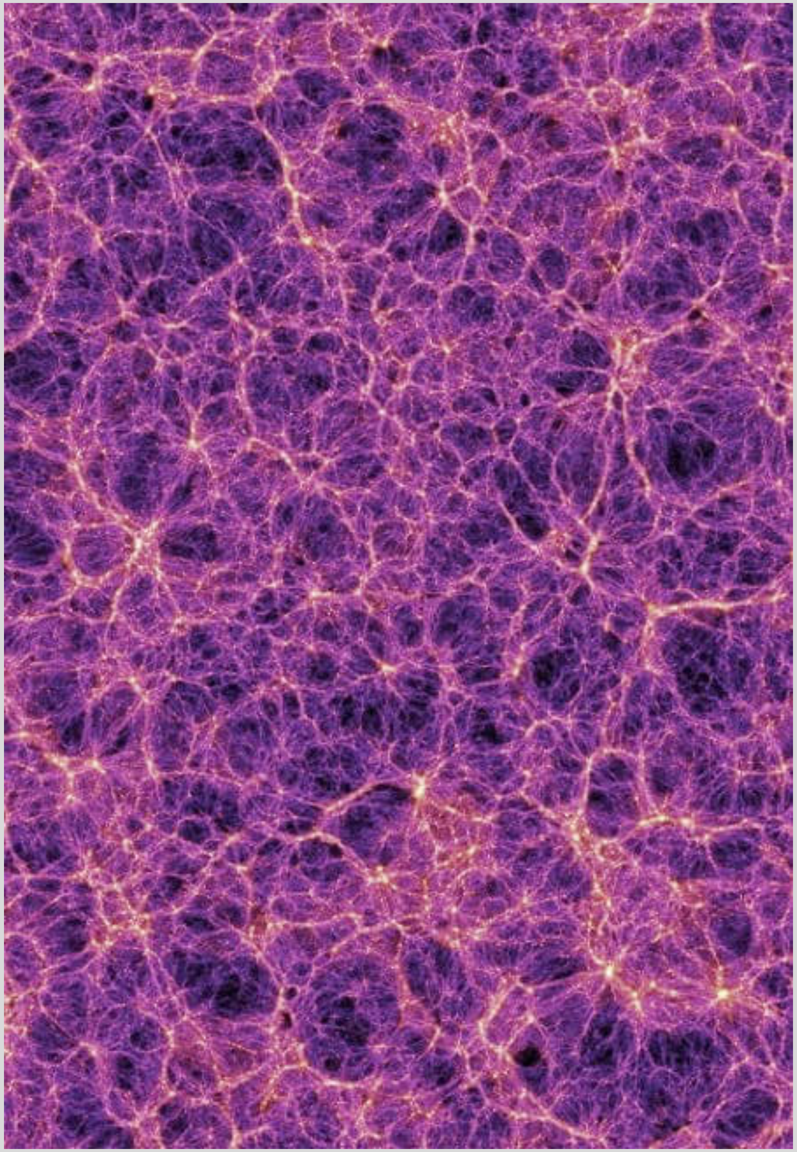
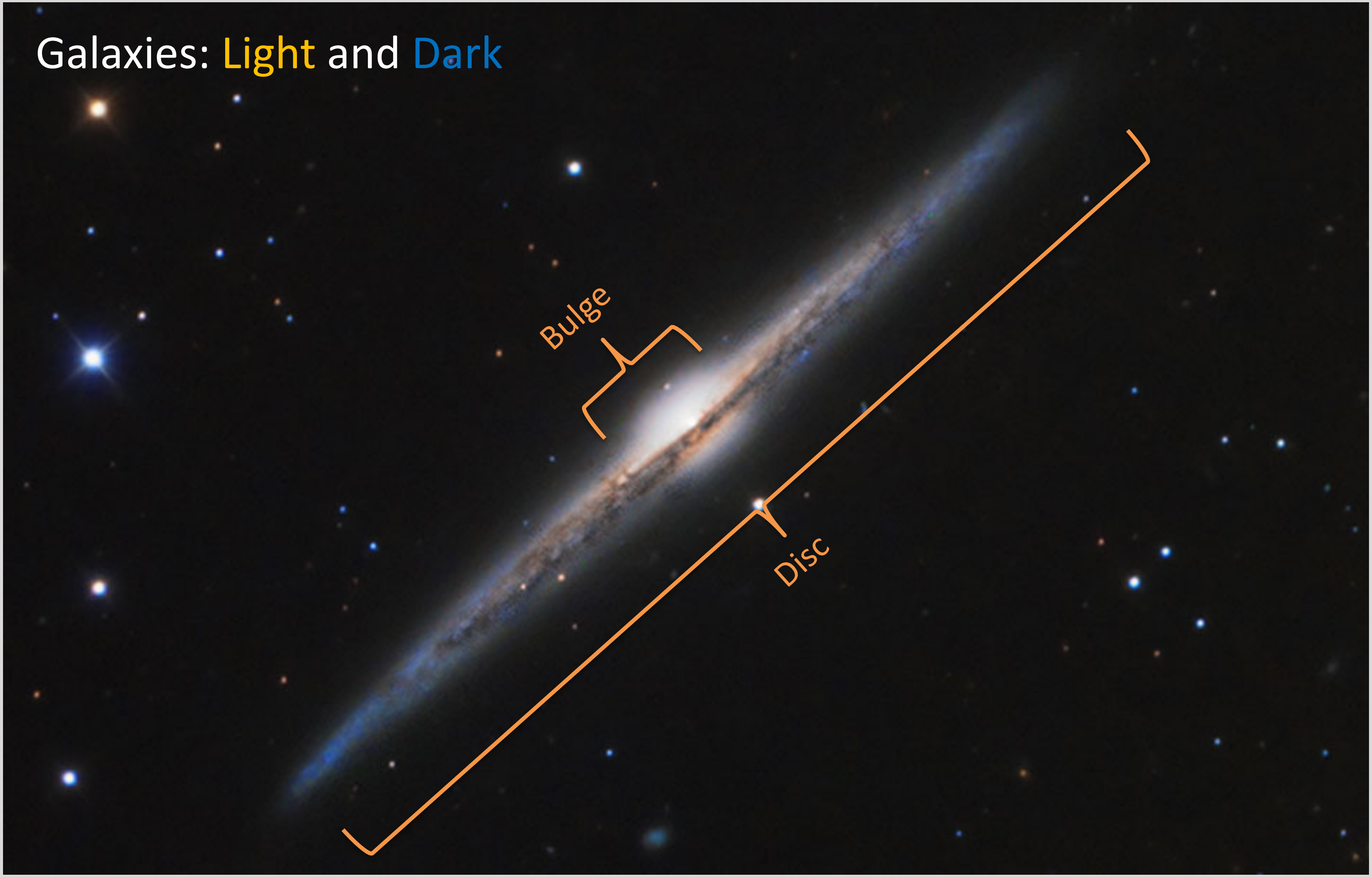


←Cosmic Microwave background

"Cosmic web" (Dark matter distribution) →



Galaxies: Light and Dark


Galaxies: Light and Dark
Bulge
Disc

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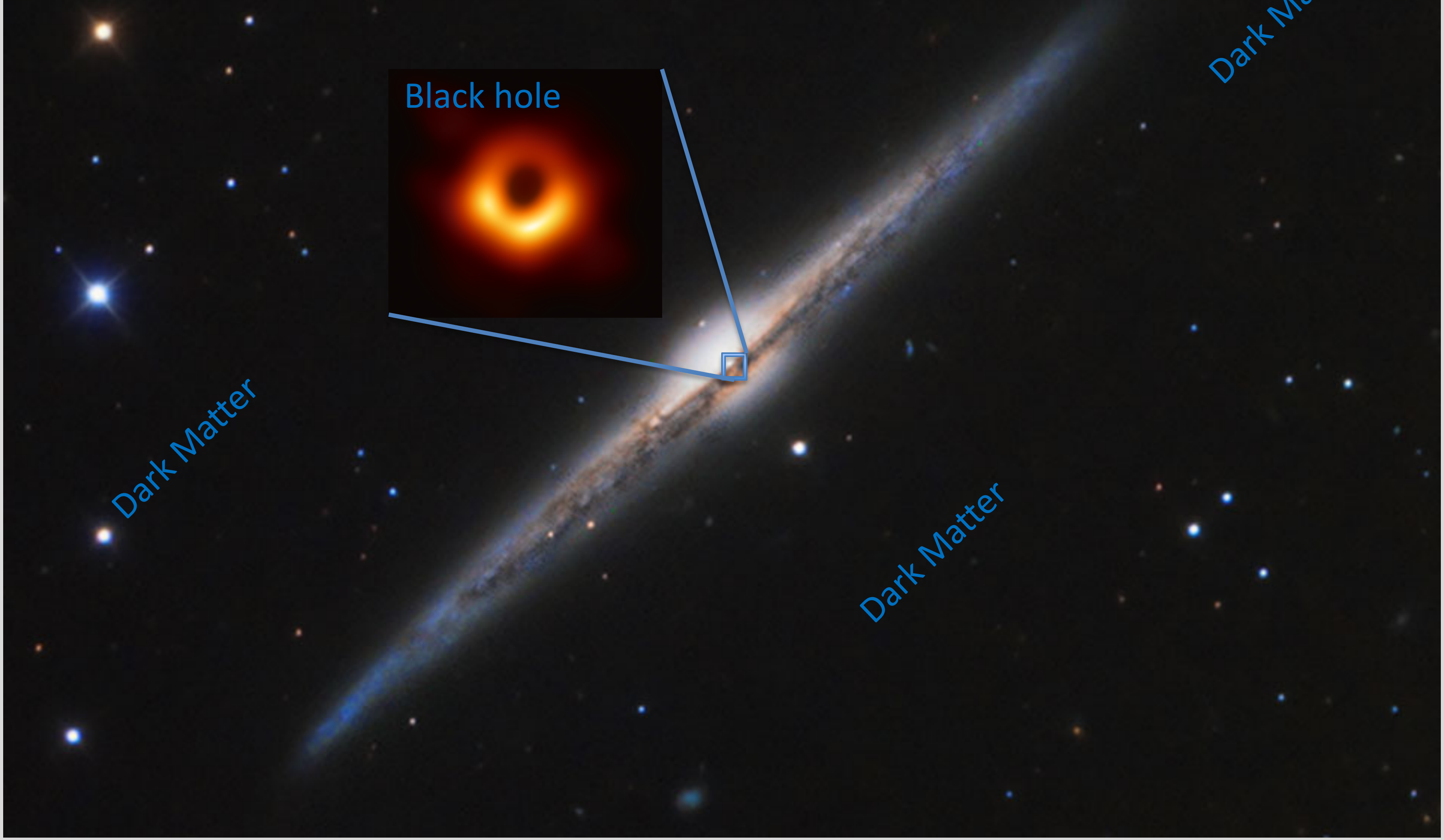
Galaxies: Light and Dark



Galaxies: Light and Dark

Bulge

Disc

Black Hole

Dark Matter

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Galaxies: Light and Dark

Bulge

Disc

Black Hole

Dark Matter

These dark components primarily interact gravitationally!

We use *dynamics* to trace them

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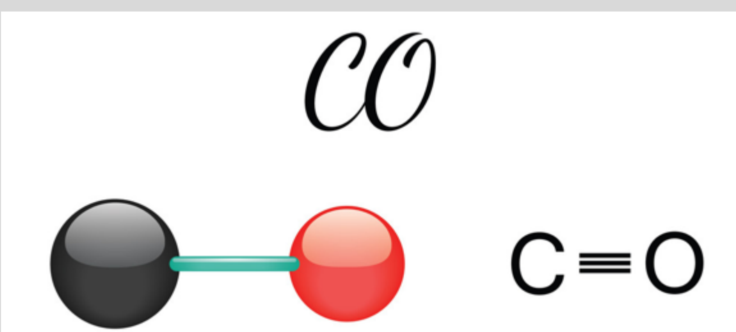
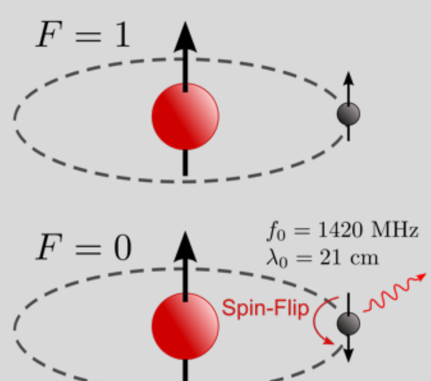
How do we measure galaxy dynamics?

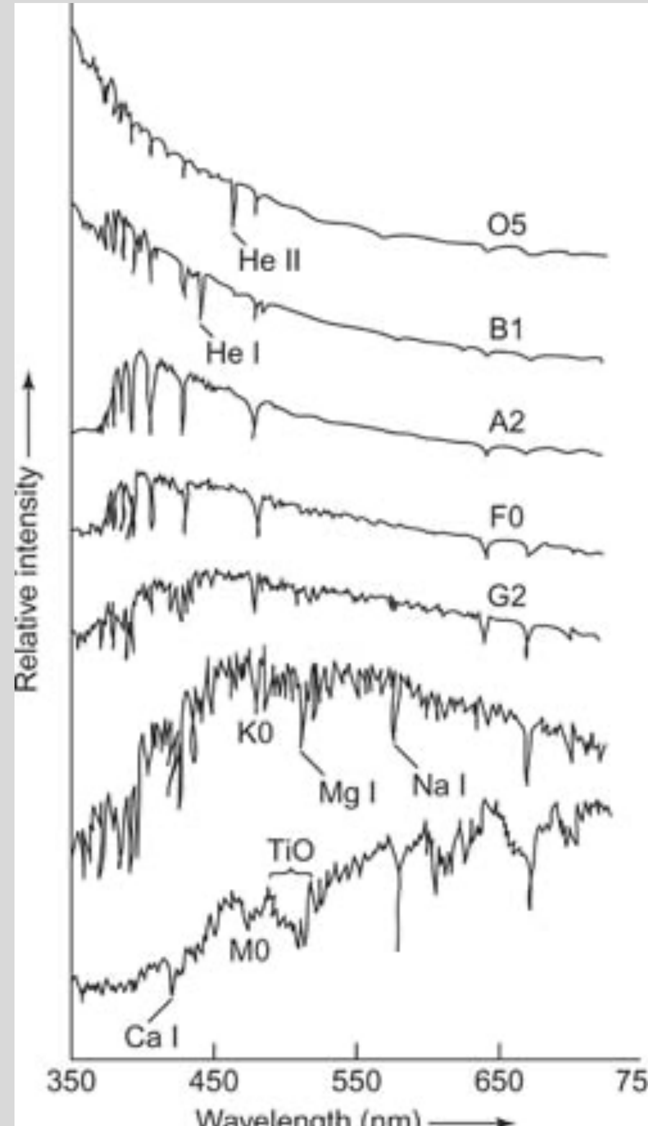
→ Spectroscopy!

- We need to observe some spectral feature with a known wavelength – then via its doppler shift reveal its motion

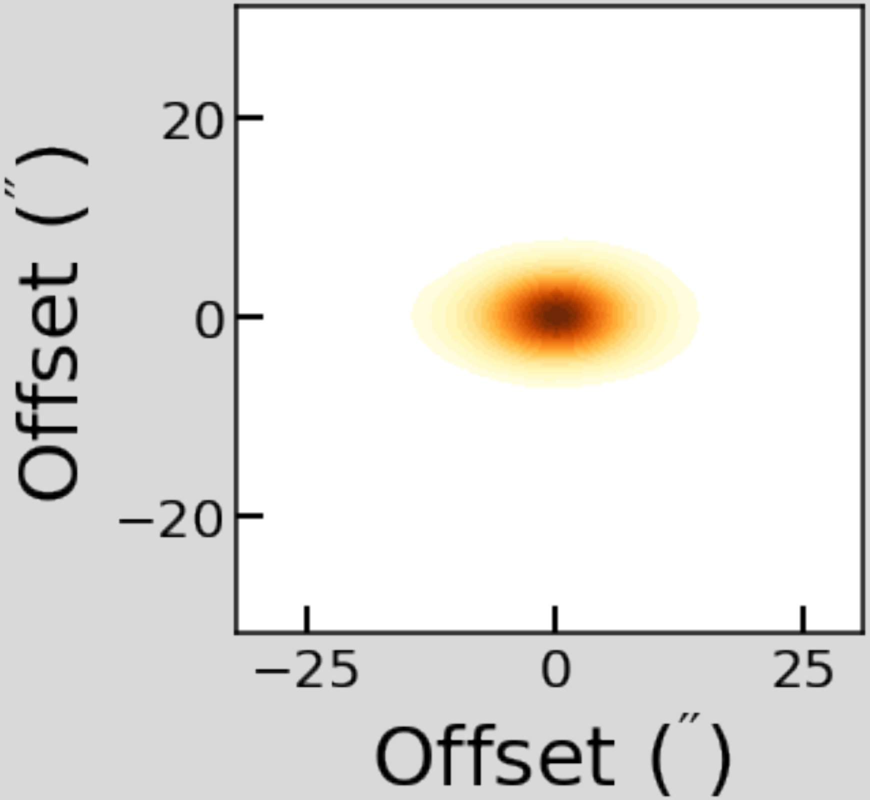
  → Emission/absorption lines from stars, atoms and molecules

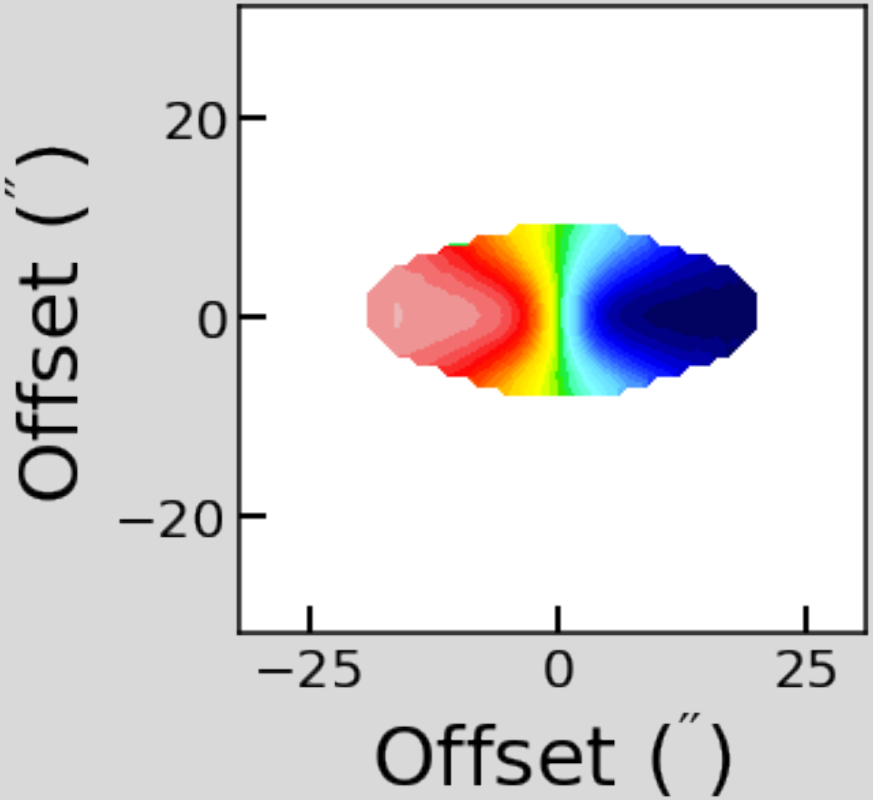






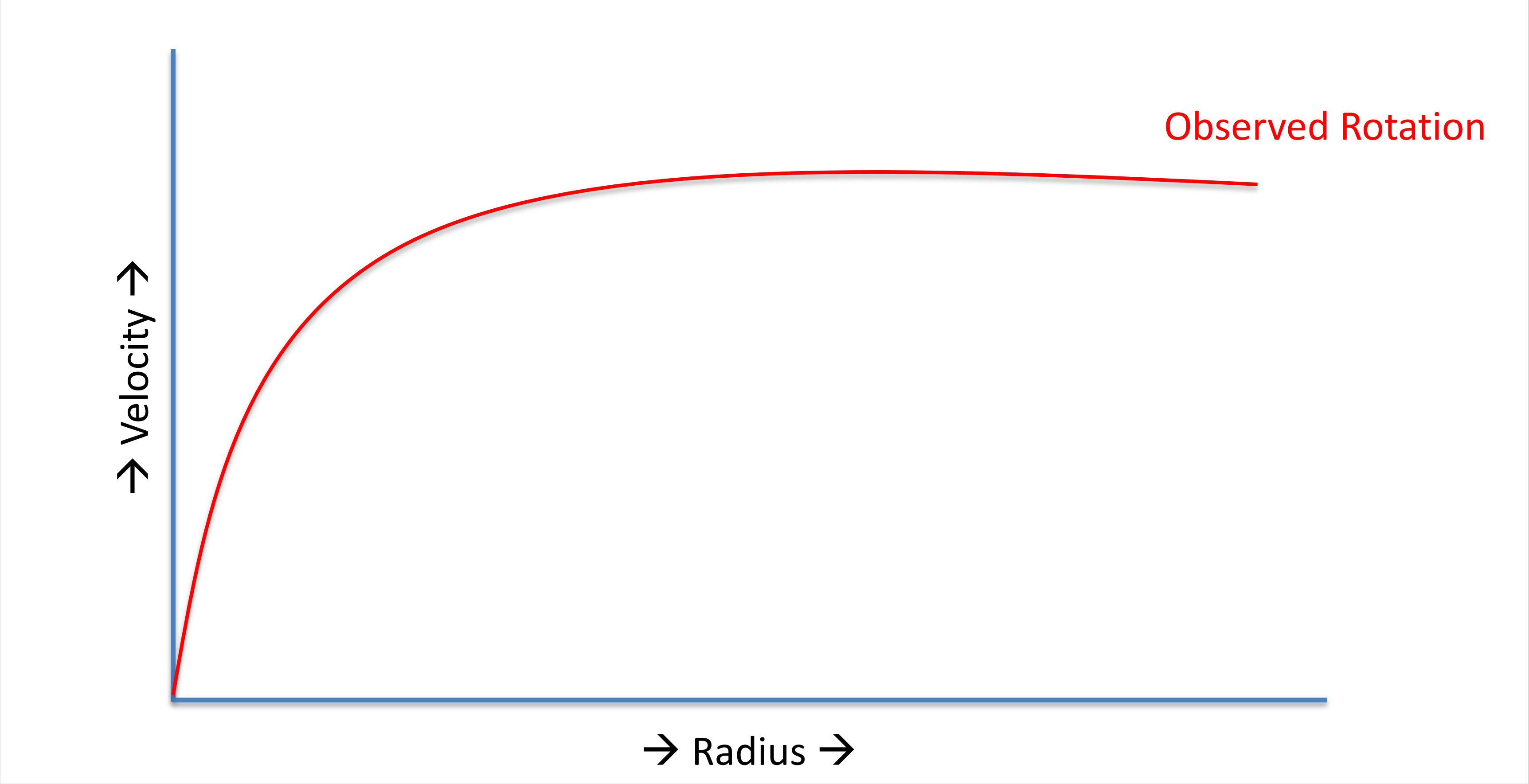
Spectroscopy via the doppler effect only lets us measure the *line-of-sight* component of the gas/stellar motions





Information is lost → Dynamics becomes *kinematics*

Galaxy kinematics allow us to trace out the *gravitational potential* of the system, and reveal the presence of dark components



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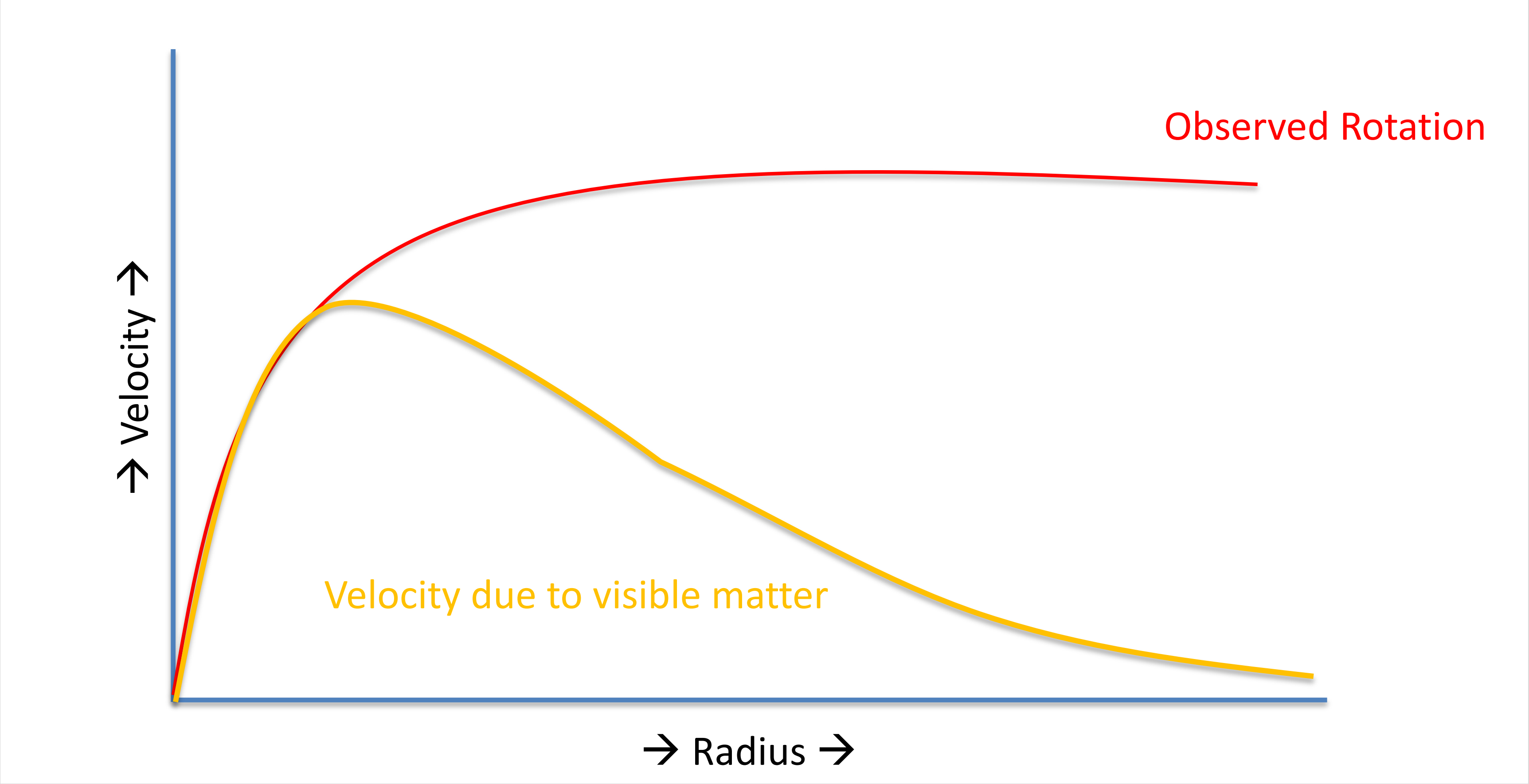

Dynamical probes of galaxy evolution with machine learning

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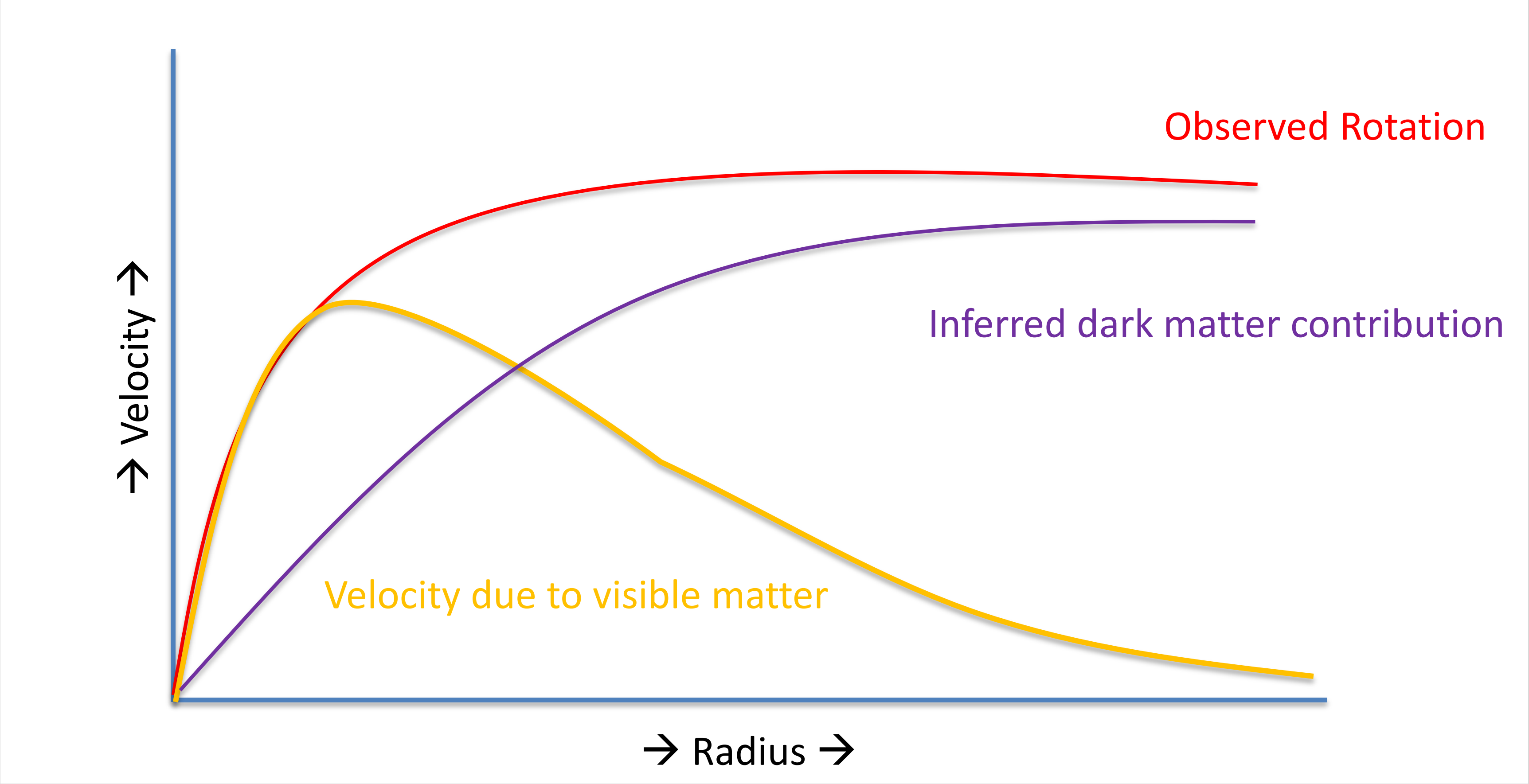

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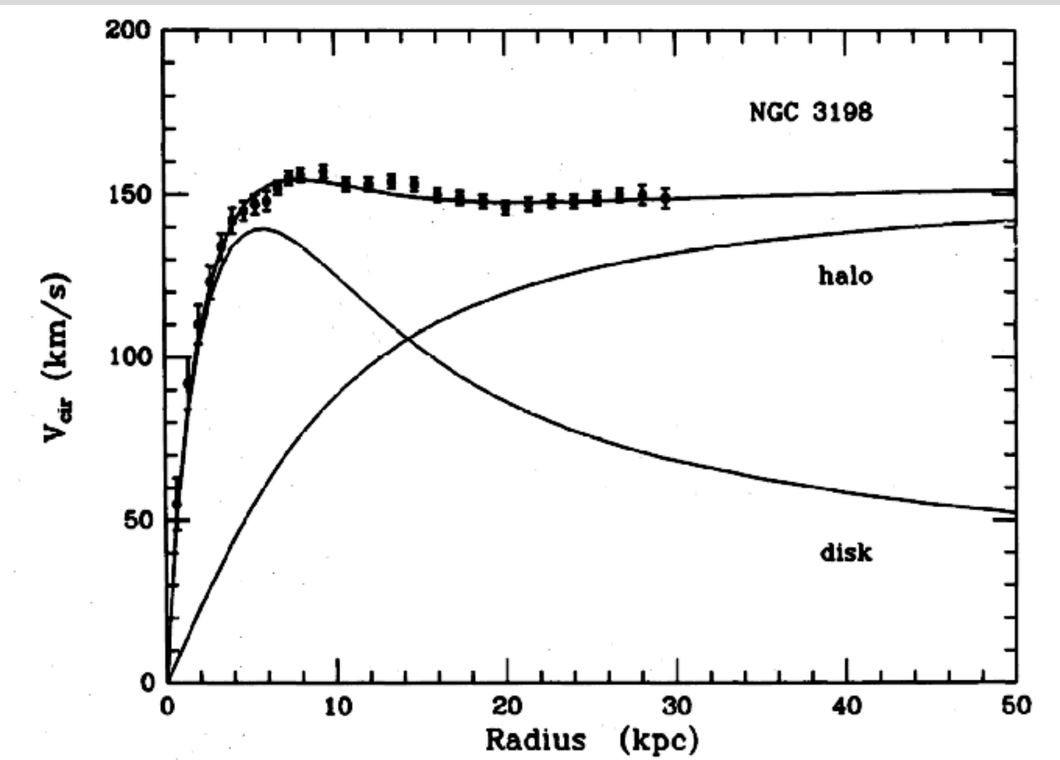
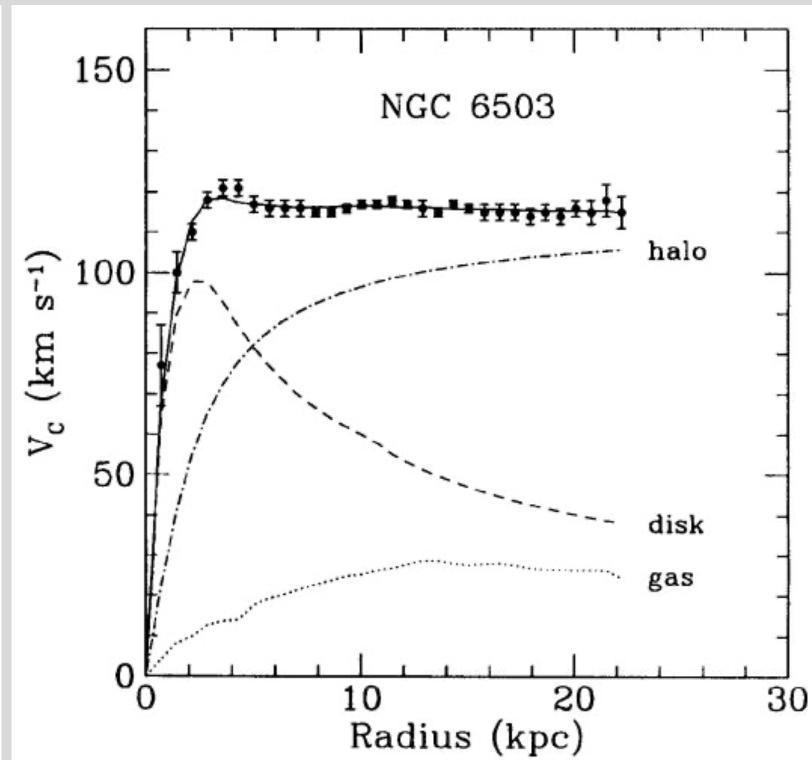
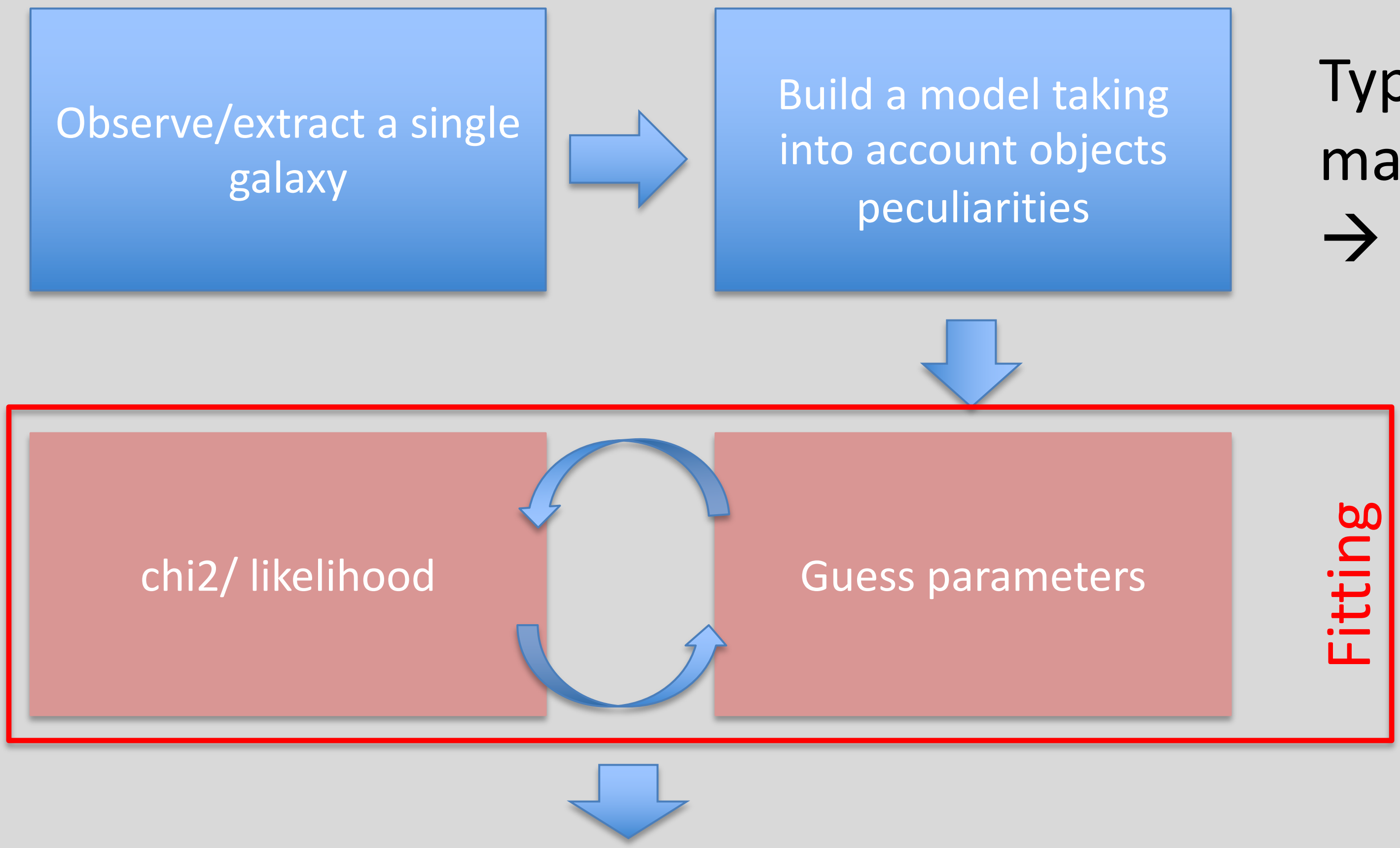




Typical workflow



Typically involves manual choices
→ Human time

Minutes, Hours, or days of computer time

Best fit *+ uncertainties* → Science

Kinematic modeling like this is key to revealing the dark matter properties of galaxies: but the future poses big challenges → Big Data!

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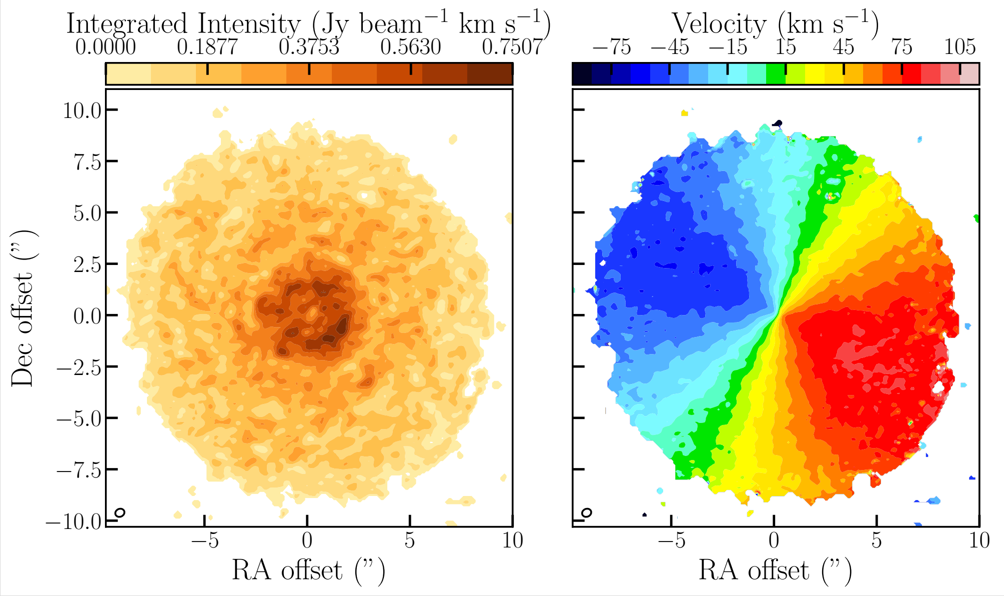
- In order to cope with the many millions of sources detected by e.g. SKA need to develop *fast*, robust kinematic fitting tools

→ *Machine learning*

Dawson et al. 2021 MNRAS, 503, 1, 574



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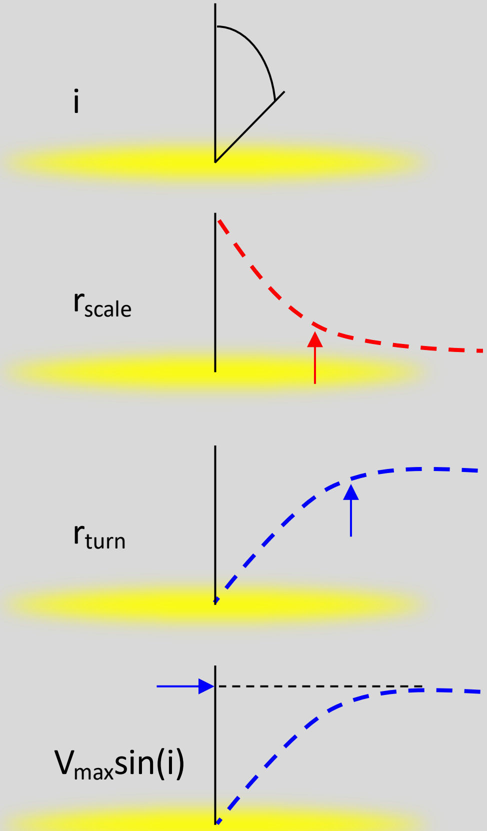
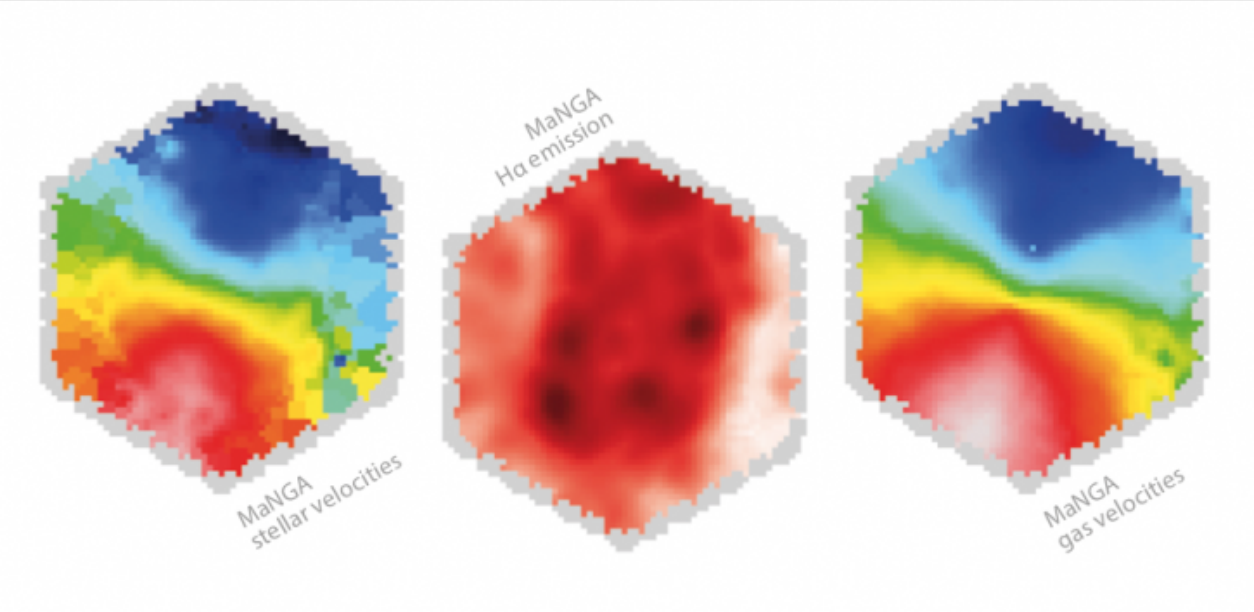


Dynamical probes of galaxy evolution with machine learning

To do this we use:

Self-supervised, physics-aware, Bayesian neural networks

Dawson et al. 2021 MNRAS, 503, 1, 574



Dynamical probes of galaxy evolution with machine learning

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Good for extracting information from images/cubes

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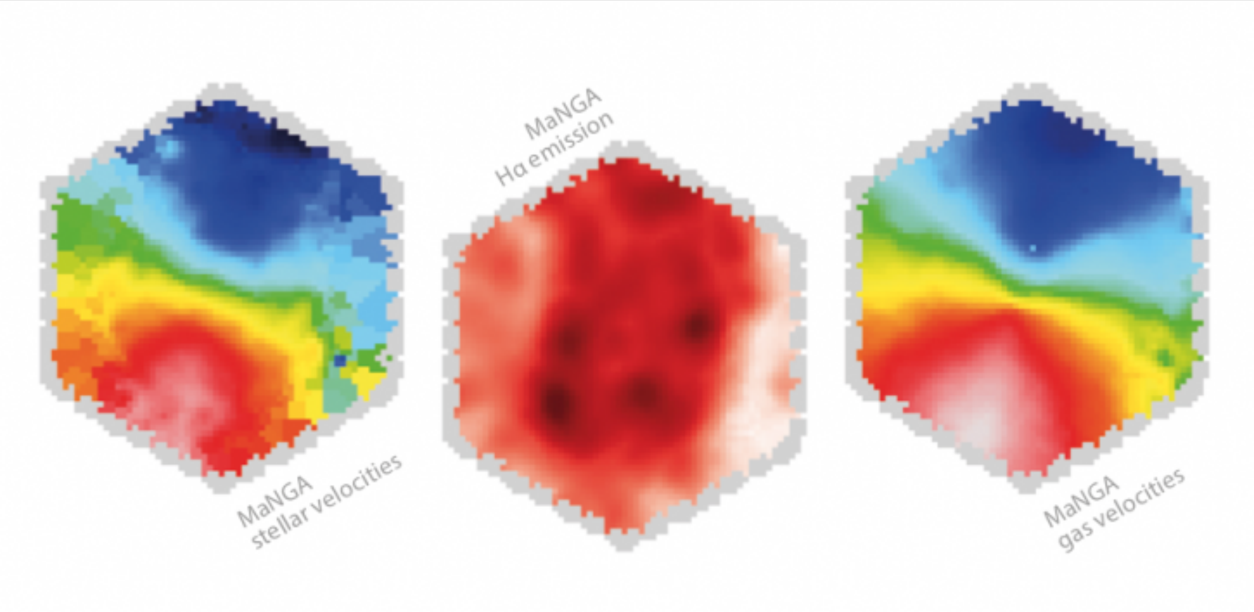

Dynamical probes of galaxy evolution with machine learning

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Doesn't require a labelled training set, can train as your survey expands and improve predictions

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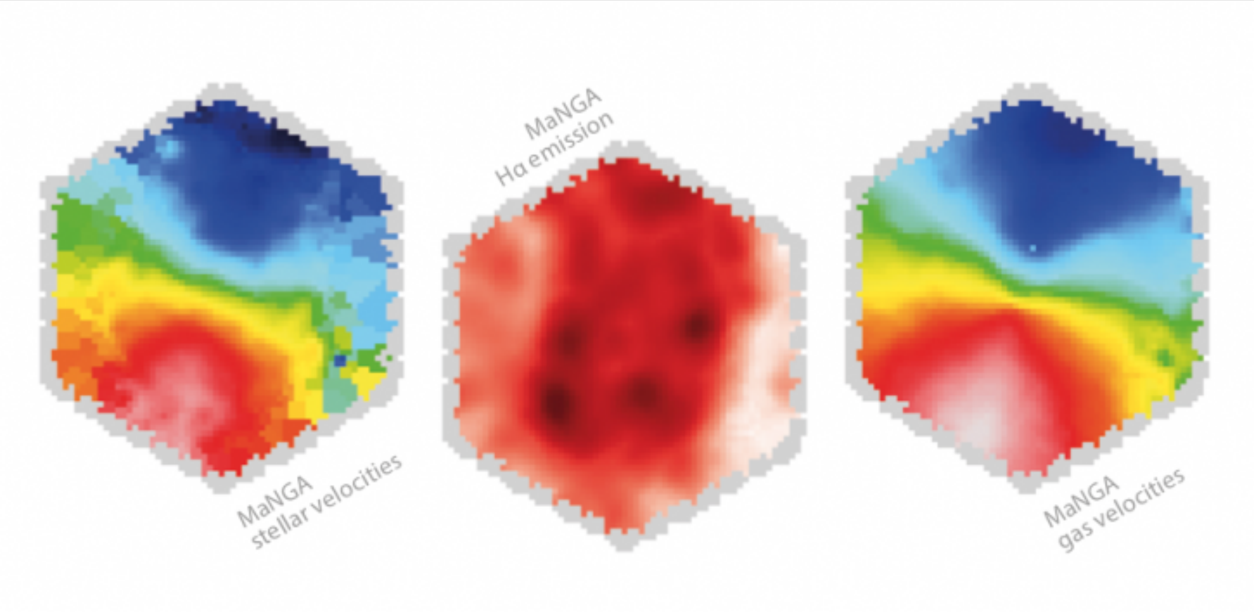

Dynamical probes of galaxy evolution with machine learning

To do this we use:

Self-supervised, physics-aware, Bayesian neural networks

- **Self-supervised:** Doesn't require a labelled training set, can train as your survey expands and improve predictions
- **Bayesian:** Gives error estimates!
- **Neural networks:** Good for extracting information from images/cubes

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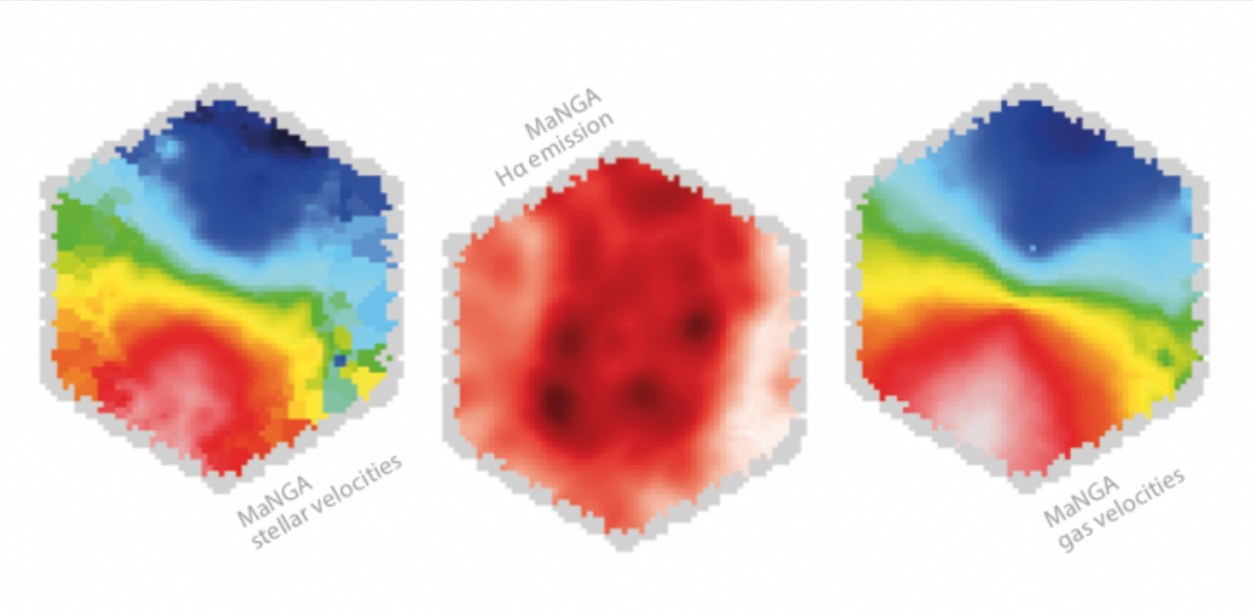

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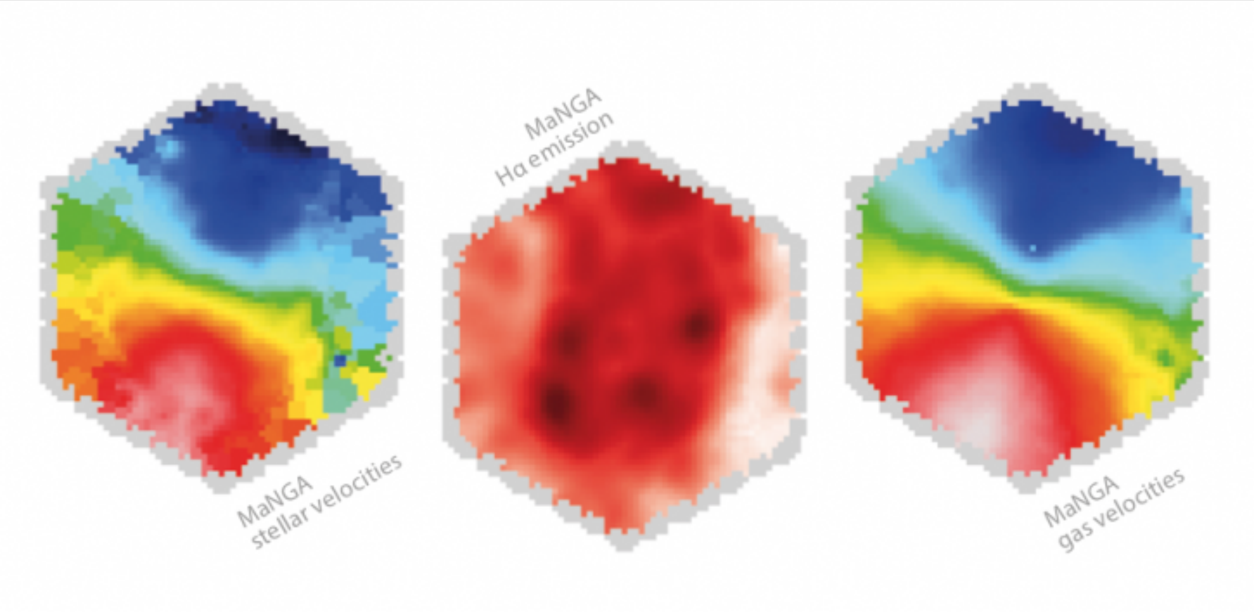
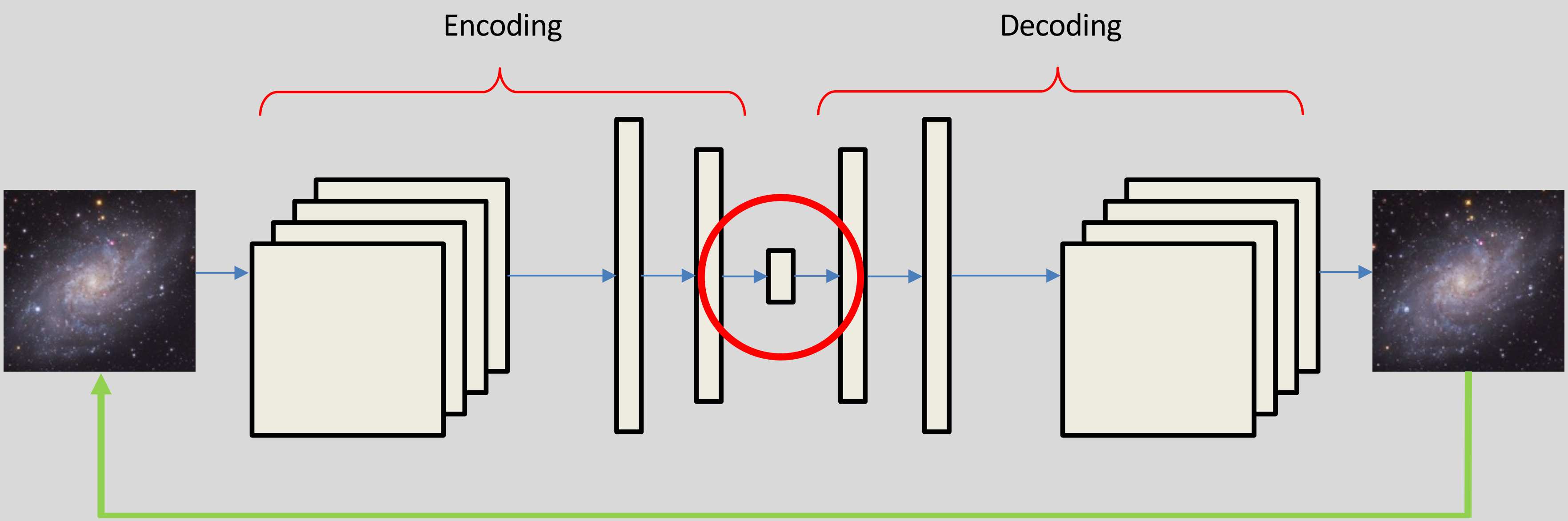
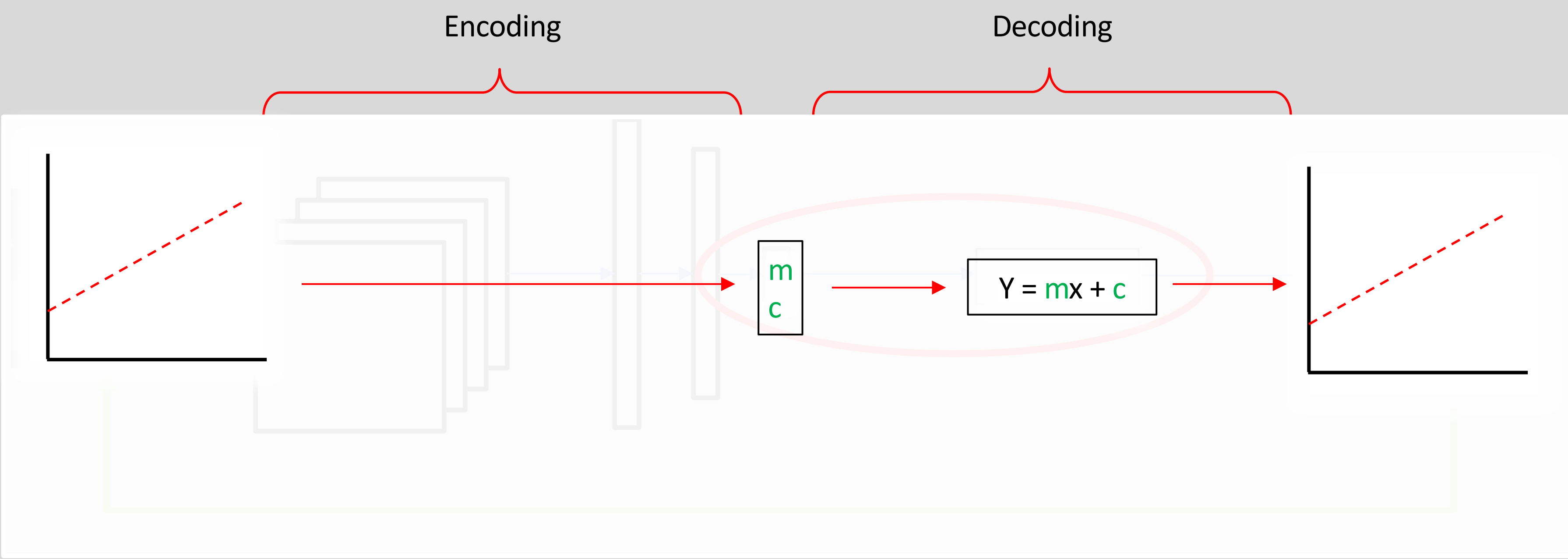


A standard Convolutional Autoencoder (revisited)



A Self-supervised, Physics-aware Neural Network

(Aragon-Cavlo (2019) arXiv:1907.03957v1)



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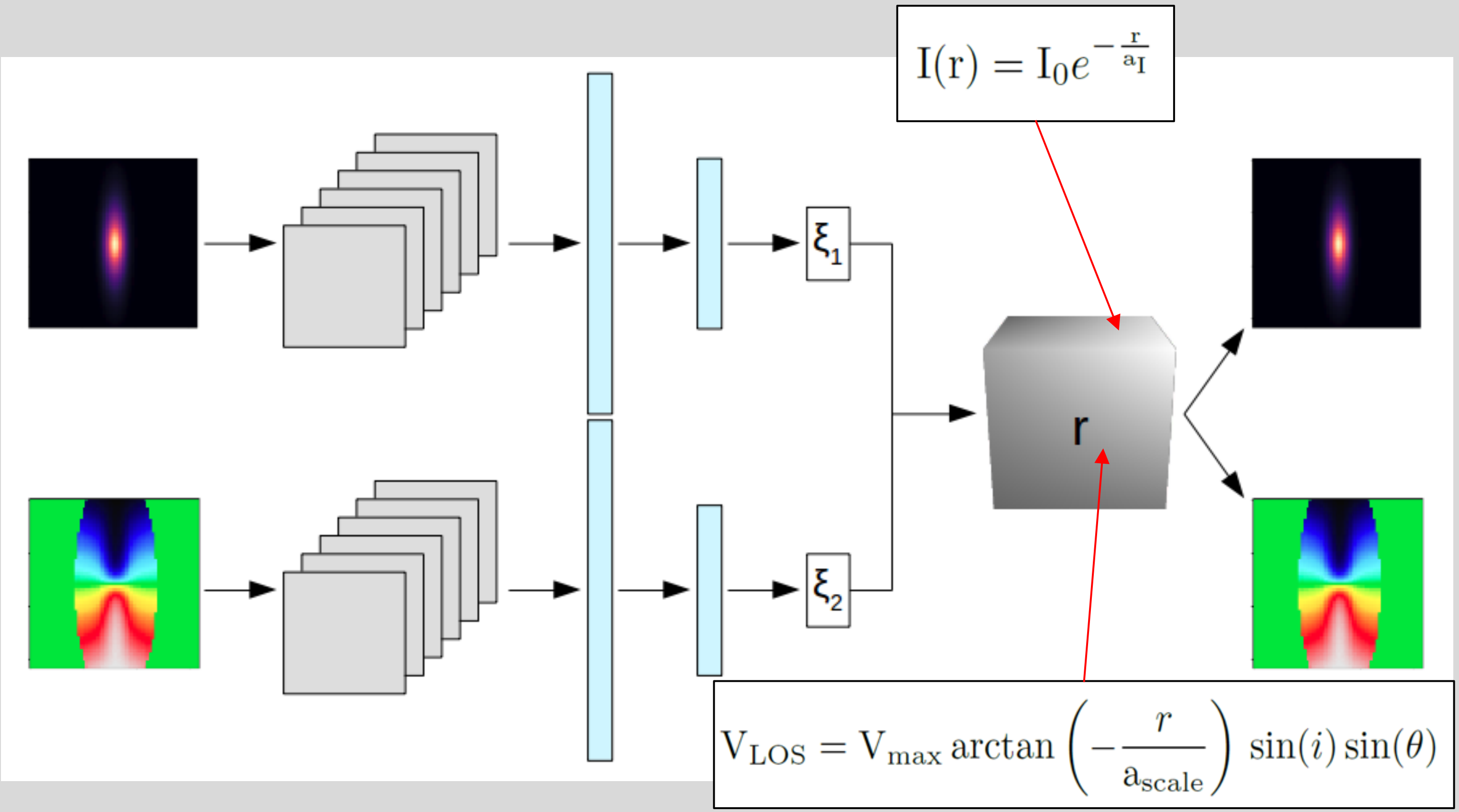

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Model using exponential disc/arctan velocity functions

Note: Any functional form would work!

$$V(r) = \frac{2V_{\max}}{\pi} \arctan\left(\frac{r}{R_{\text{turn}}}\right)$$

$$\Sigma(r) = I_o e^{\frac{-r}{R_{\text{scale}}}}$$

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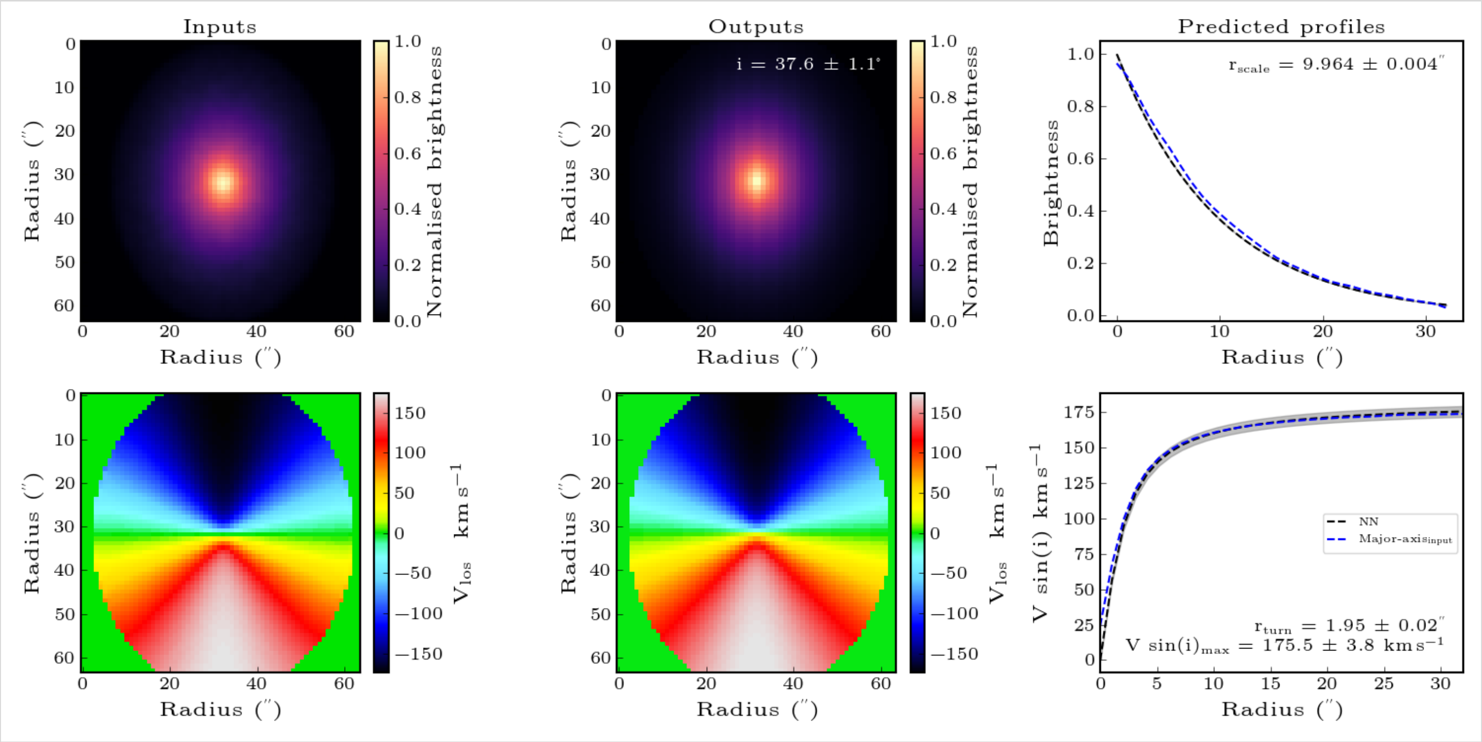
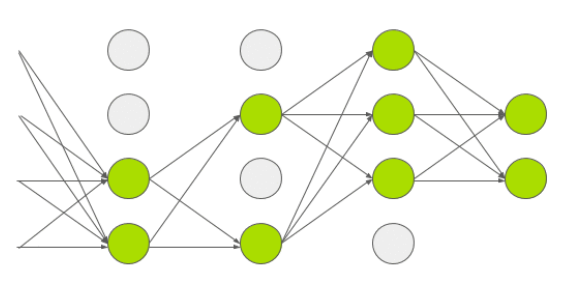


Generated by classical kinematic modelling tool

Generated by network

Making it quasi-Bayesian



Monte Carlo dropout

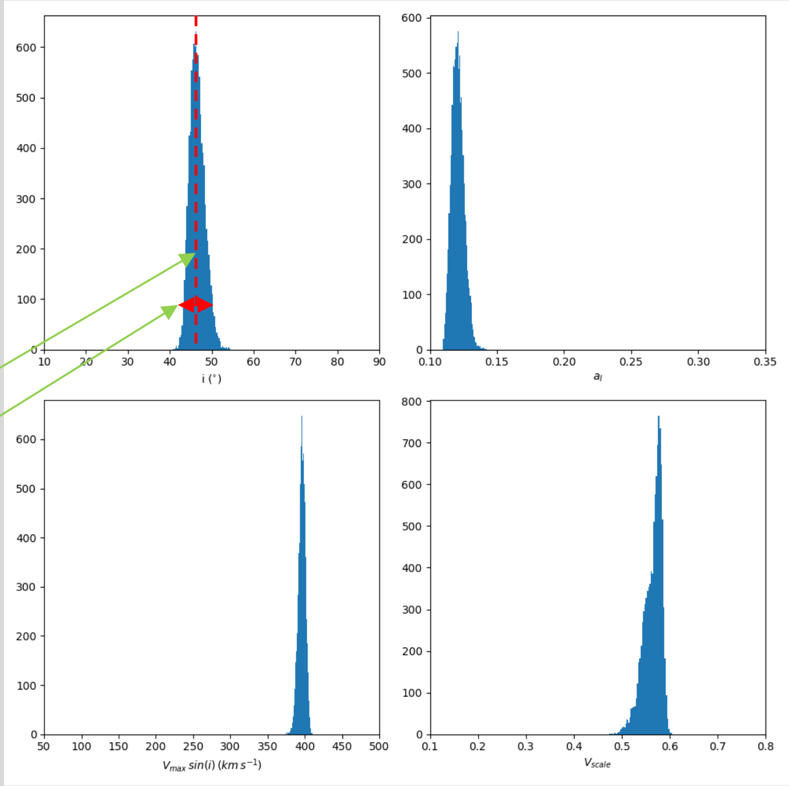
$$P(k|x,D) = \int P(k|x,w)\, P(w,D)\, dw$$

$$P(w|D) \approx q^*$$

$$P(k|x,D) = \int P(k|,x,w)\, q^*\, dw$$

$$k = \frac{1}{T}\sum_t P(k|x,w_t)$$

$$\sigma = \frac{1}{T}\sum_t |k - k_t|$$



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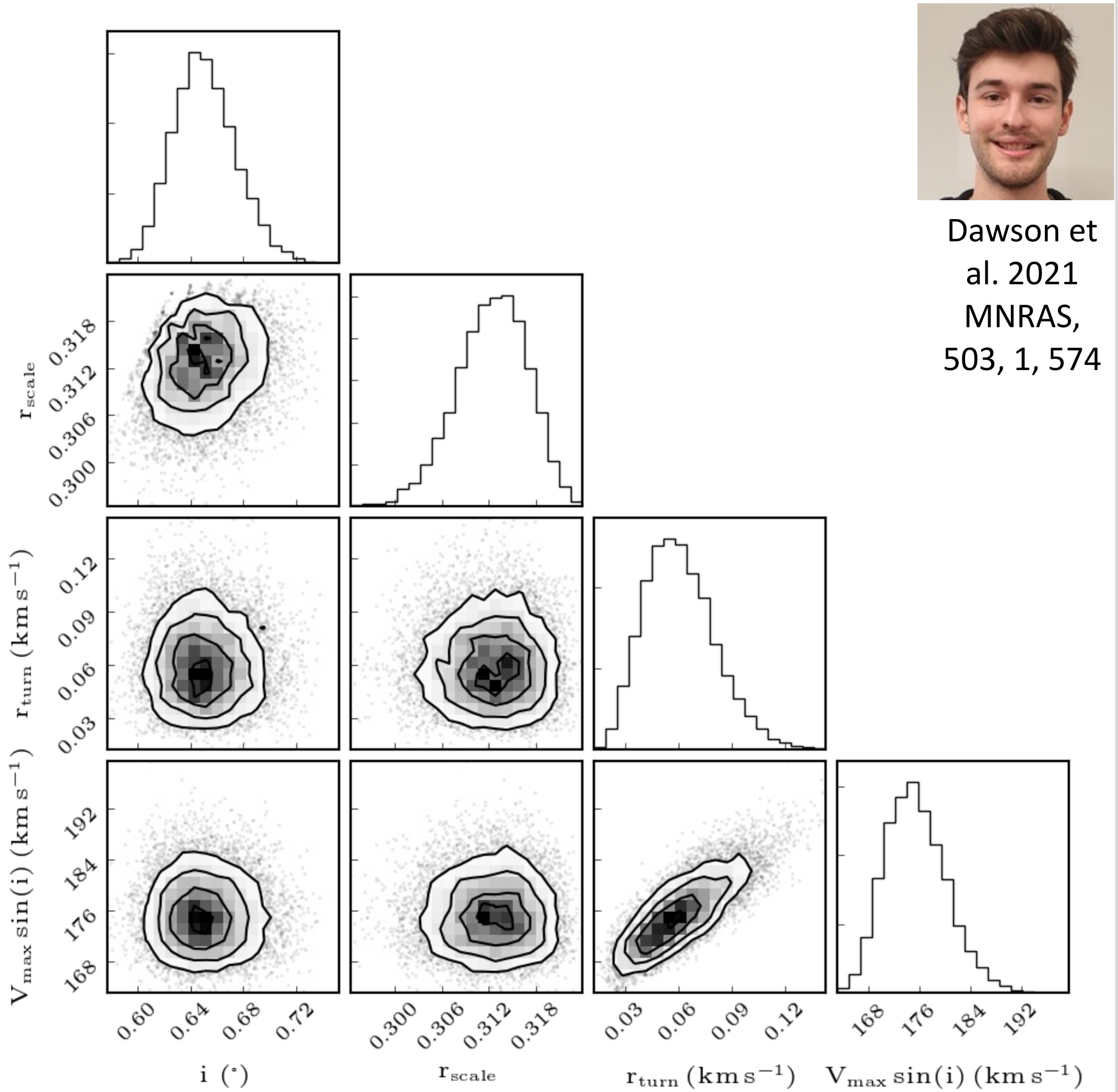
Using monte-carlo dropout we also get estimates of the posterior probability distribution for each parameter!

Classical analyses would take ~hours to get this with MCMC on multi-core machines. Here 25 seconds on a single GPU core for 10,000 realizations.



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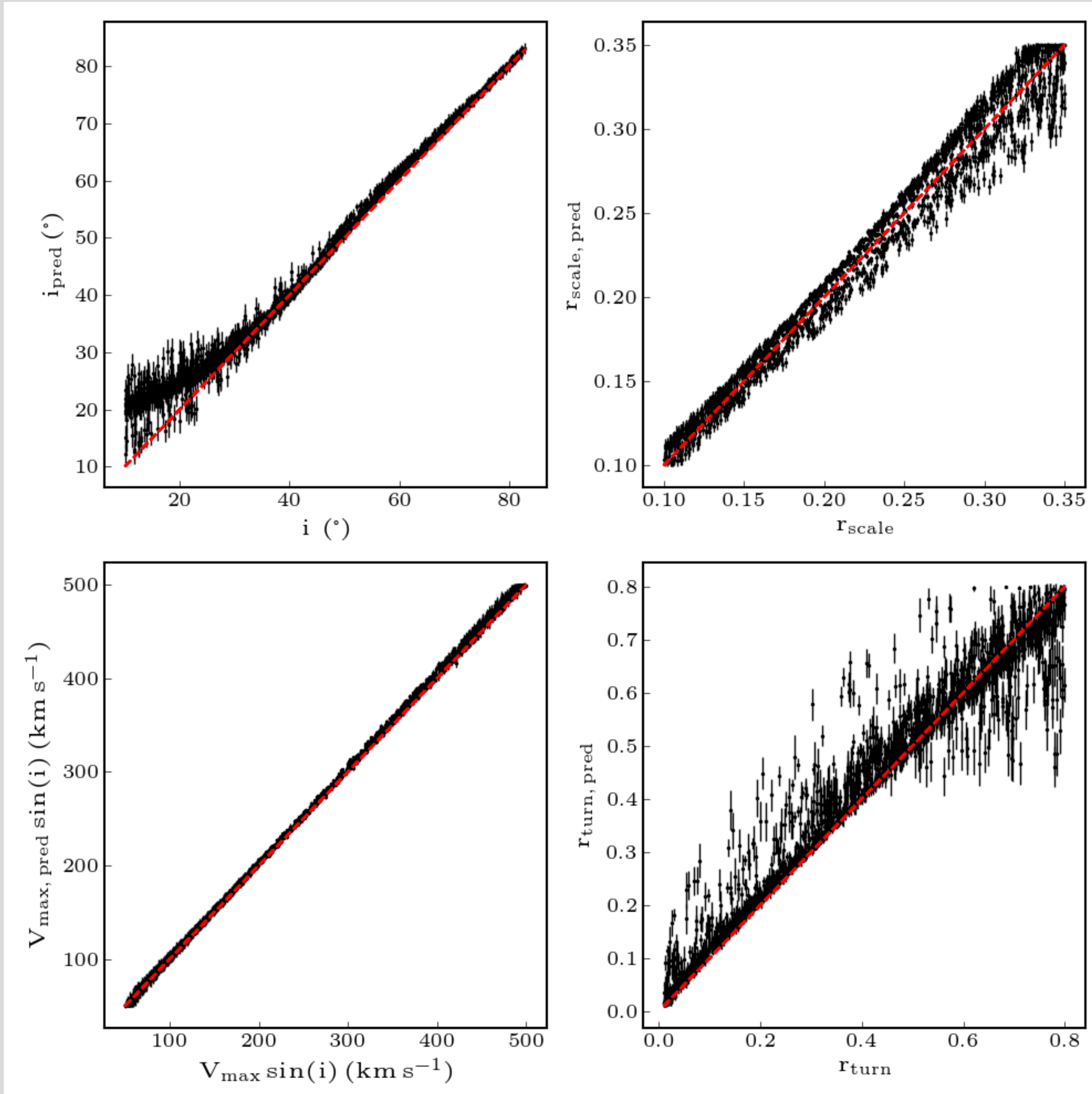
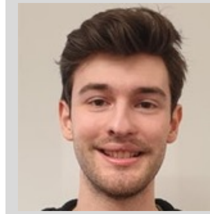
On synthetic data can retrieve the required parameters (inclination, rotation curve Vmax and scale lengths) very well!





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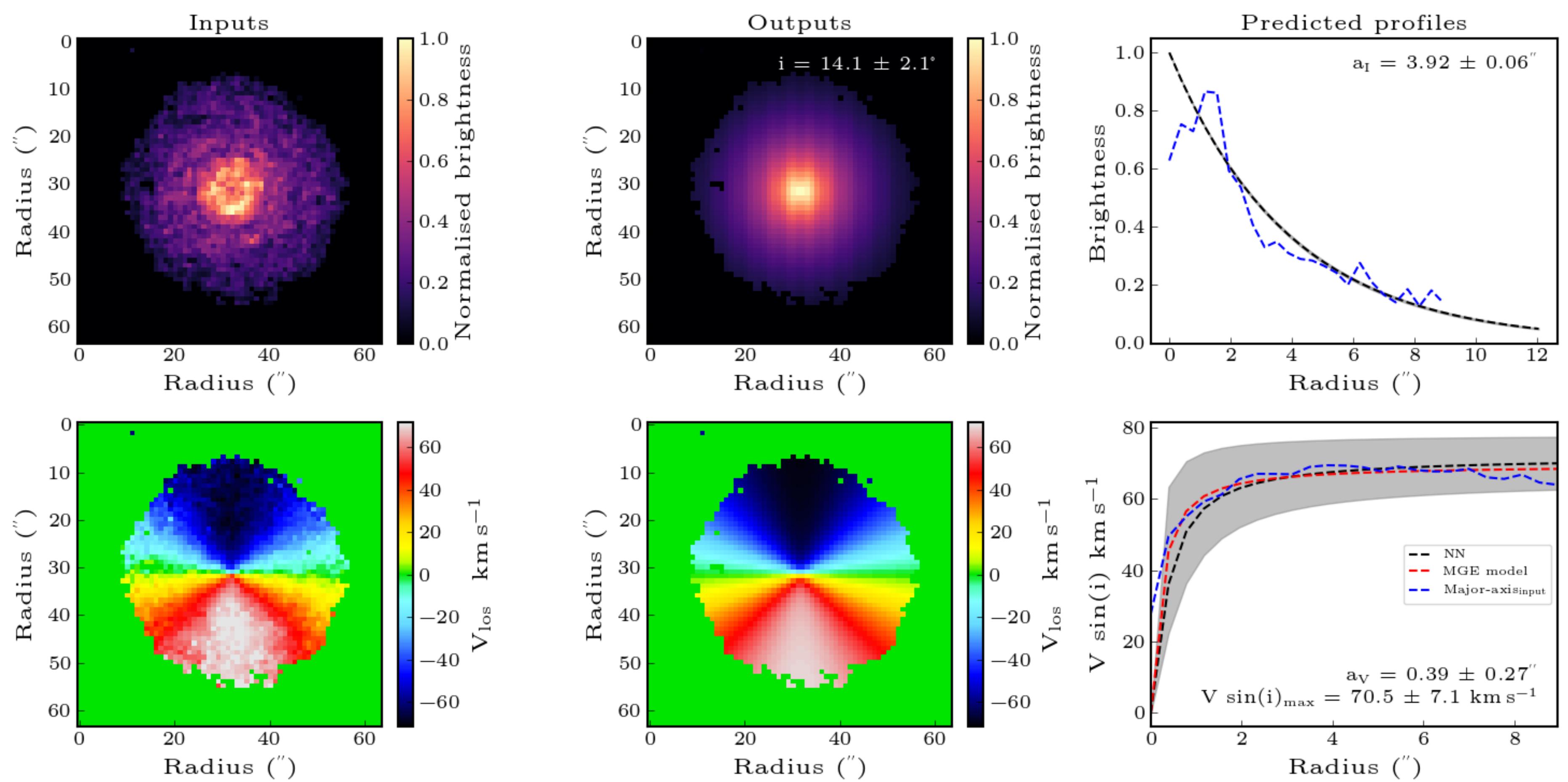
Works well on real data too



CO (NGC1387 – WISDOM)

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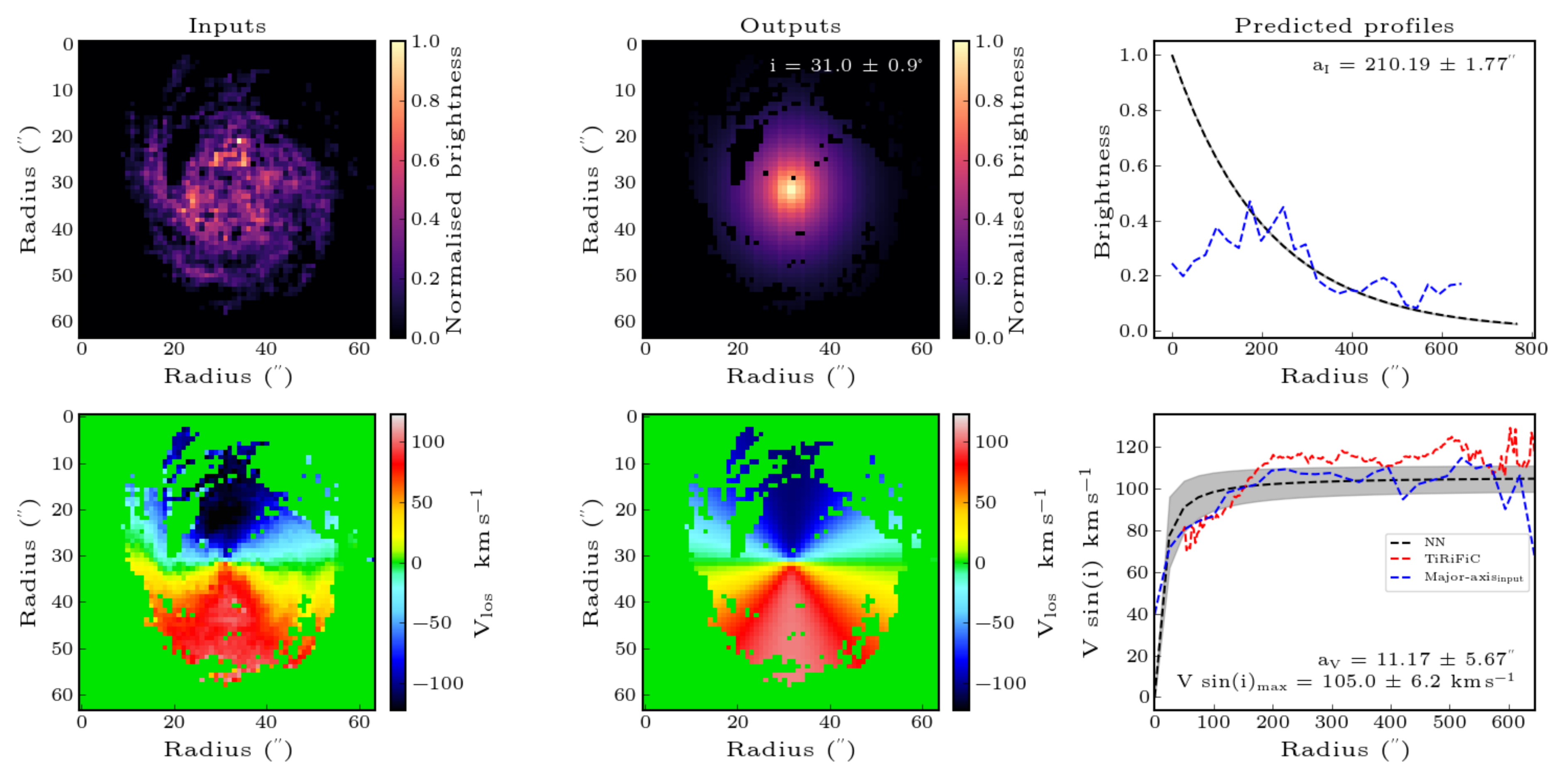
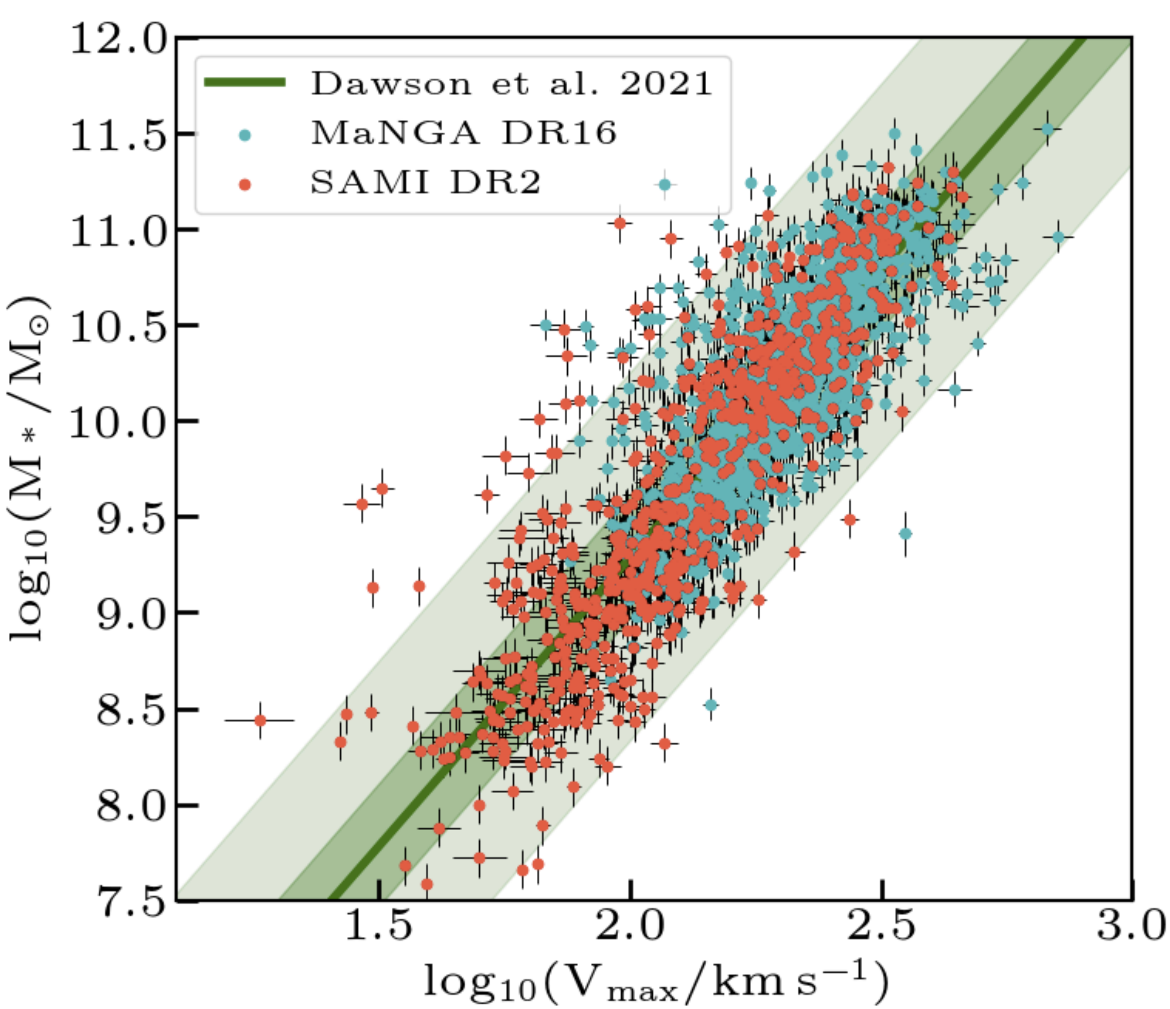
Works well on real data too (even when some assumptions are violated! e.g. non exponential discs)



HI (NGC6946 – THINGS)

Dynamical probes of galaxy evolution with machine learning

… and can be applied at scale! Here over 2000 galaxies *with errors*!



- Known relation retrieved with low intrinsic scatter
- Took ~2 hours on a single GPU.
- Classical methods would have taken ~1.2 *years!*

- Self-supervised, physics aware neural networks can be very powerful tools!
  - where the physics is understood, but you need speed, they could be a good solution for you!

- Next generation facilities like the Square Kilometer array can use such tools to probe the *dark sector*, and the physics of our universe

- See Dawson et al. 2021 MNRAS, 503, 1, 574 for more