Dark Matter in galaxies: learning with machines
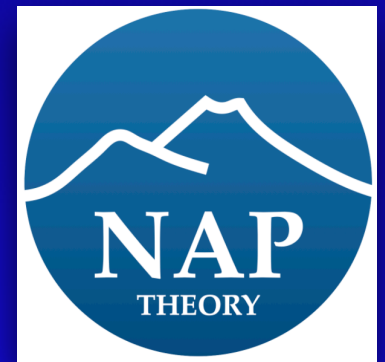
Fabio Iocco

Università Federico II, NAPOLI

In collaboration with: M. de los Rìos, M. Petac, B. Zaldivar, F. Calore, N. Bonaventura
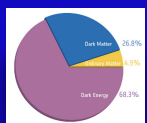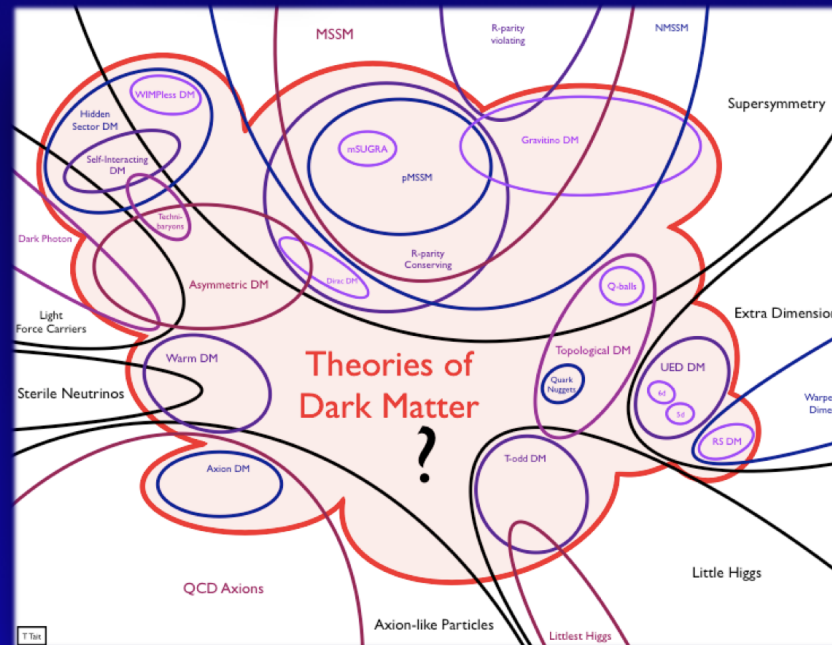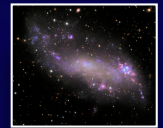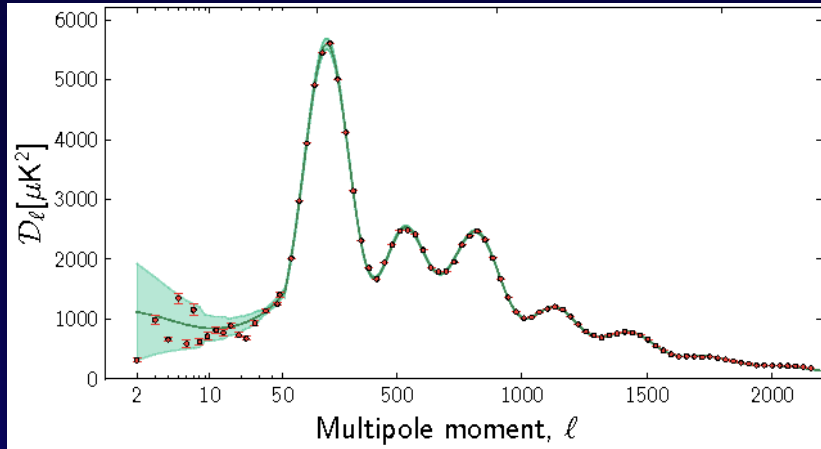
TAsP meeting
Torino, 18-19 Jan. '24

Dark Matter

Evidence over large range of scales

NATURE STILL UNKNOWN

A story of LCDM
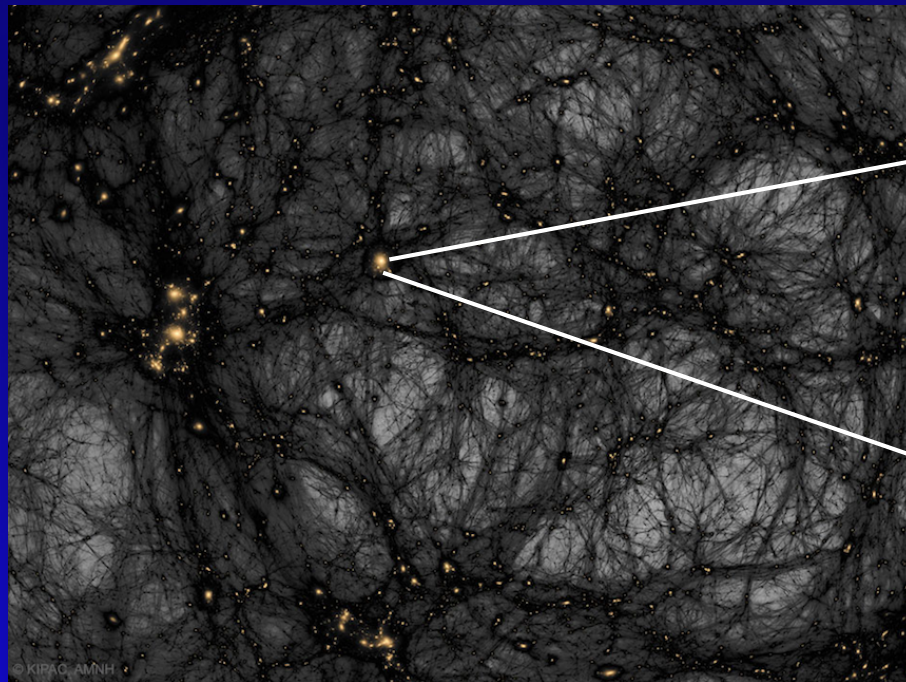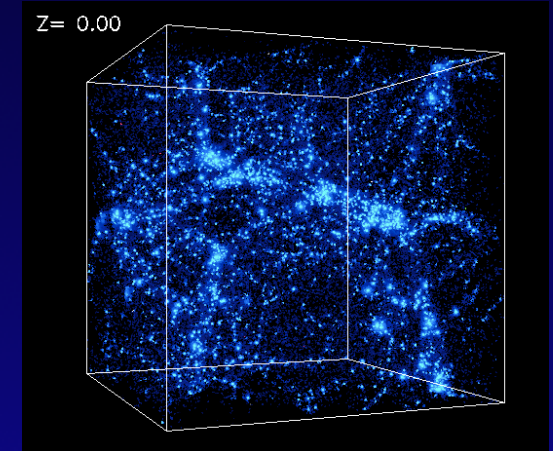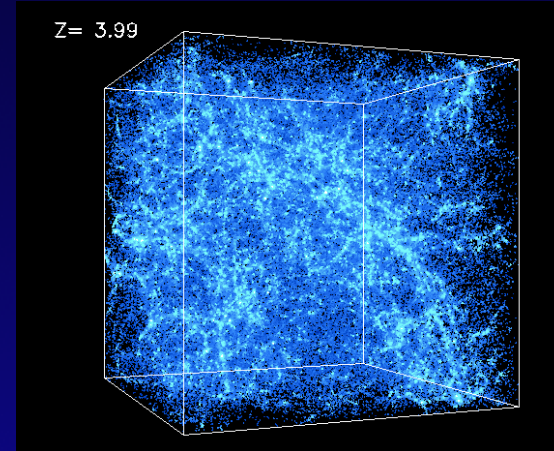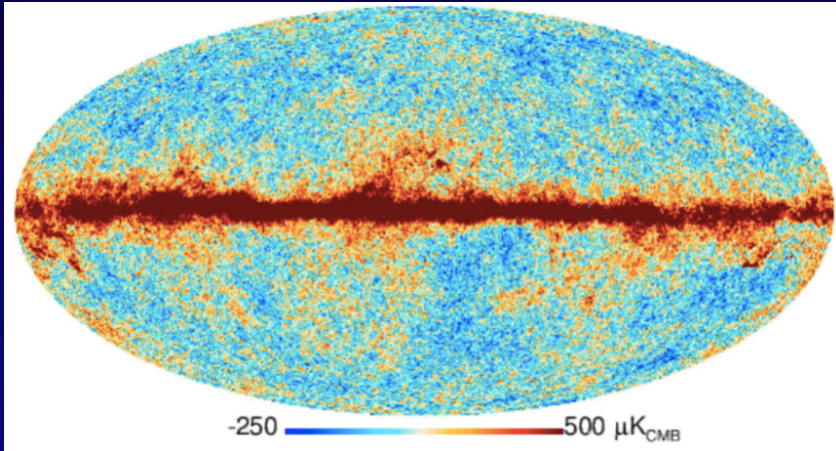# I: structure formation

age of Universe
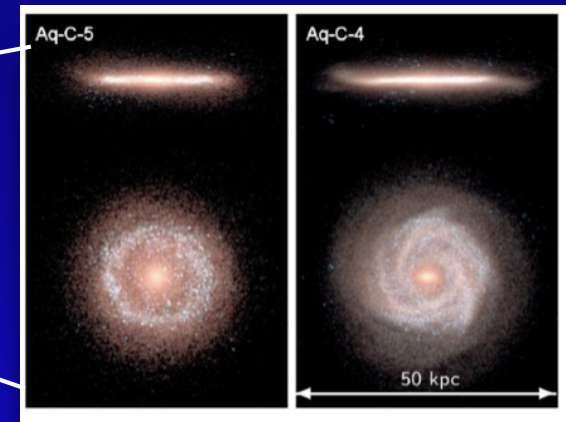
physical size

A story of LCDM
II. the single halo

A "universal" DM profile?
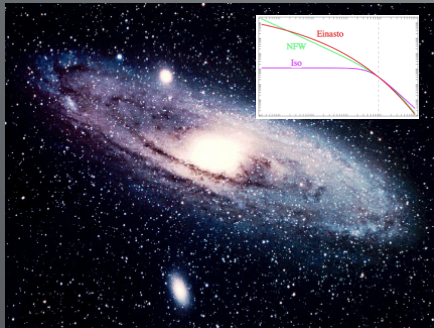
(not in scale!)
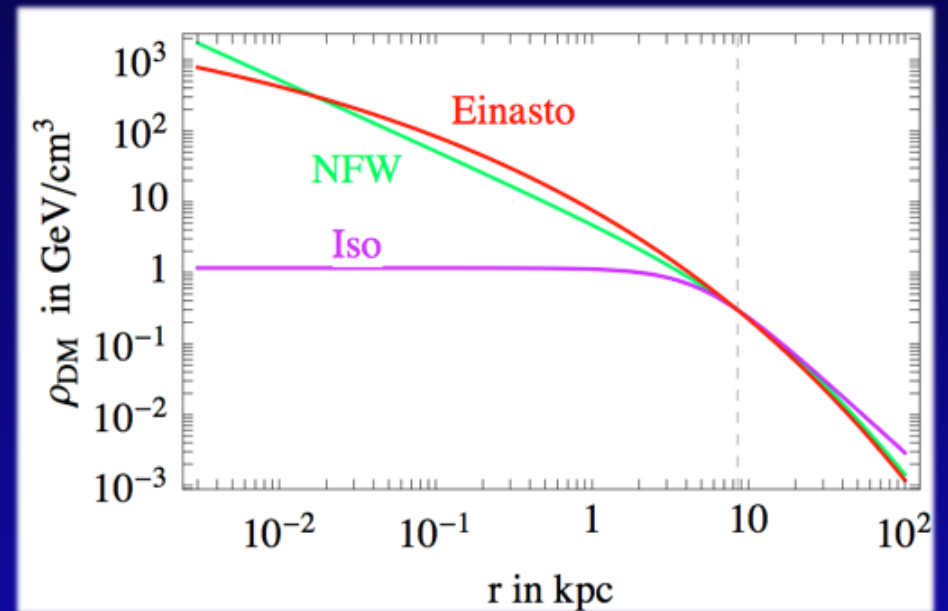
NAVARRO-FRENK-WHITE

$$\rho(R) \propto \frac{R_s}{R}\left(1 + \frac{R}{R_s}\right)^{-2}$$

A story of LCDM
III. the dark matter distribution

A "dynamical" DM profile

[Di Cintio et al., 2013]

CORE OR CUSP?
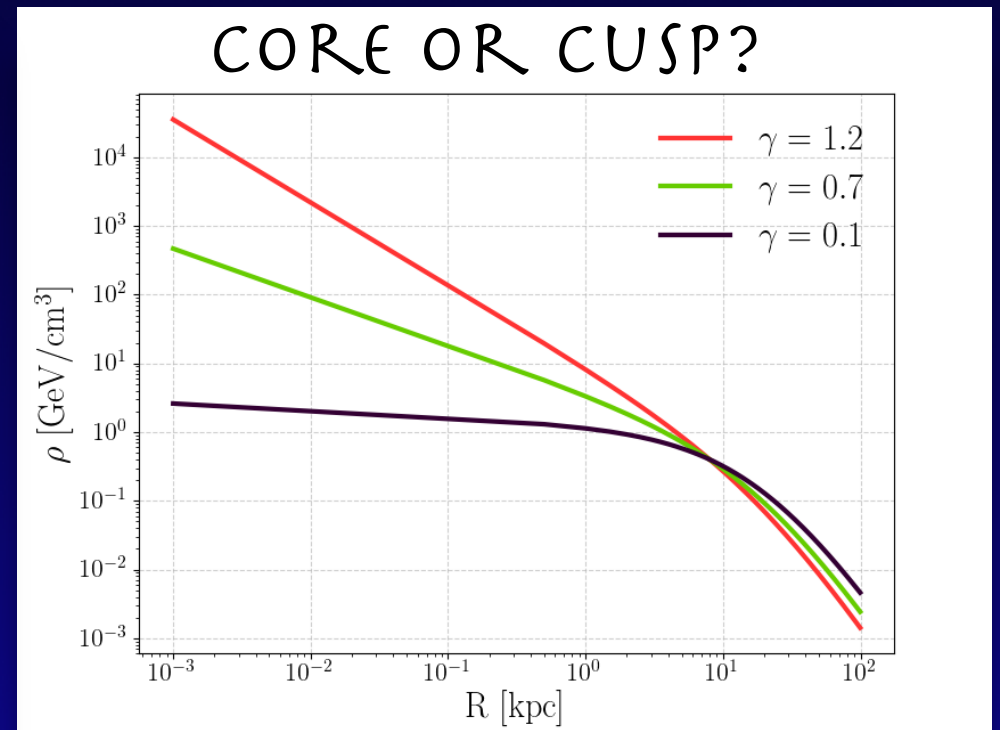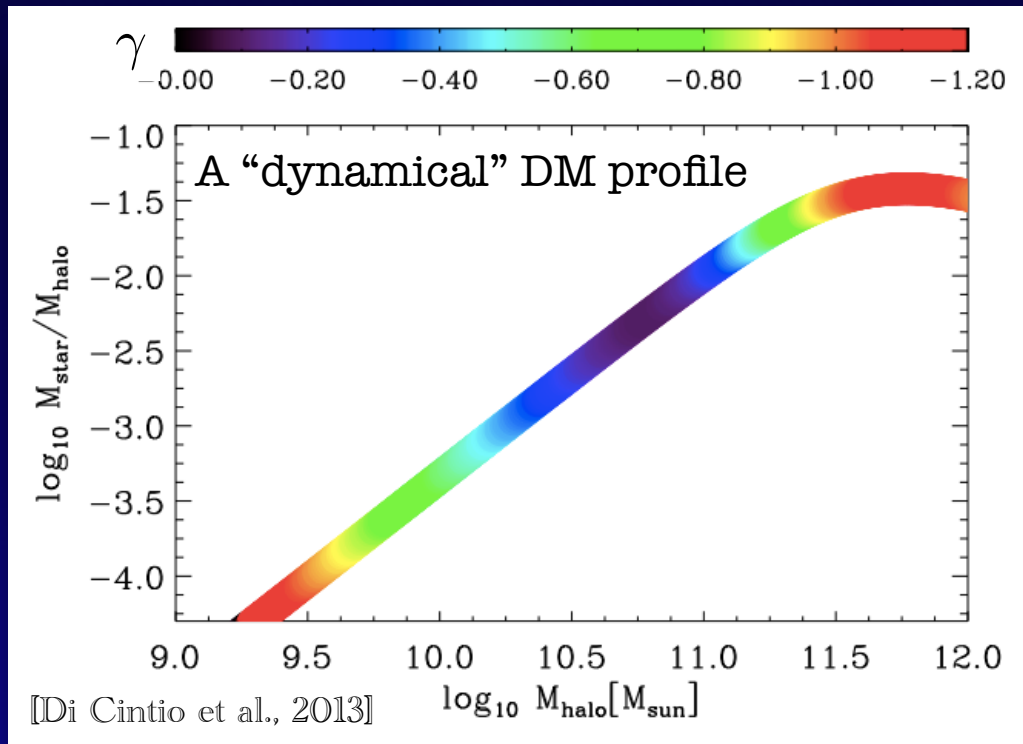
generalized NFW

$$\rho_{DM}(R) \propto \rho_0 \left(\frac{R}{R_s}\right)^{-\gamma} \left(1 + \frac{R}{R_s}\right)^{-3+\gamma}$$

A story of LCDM
IV. the small scale problems

Cusp vs core

Missing satellite

Too big to fail
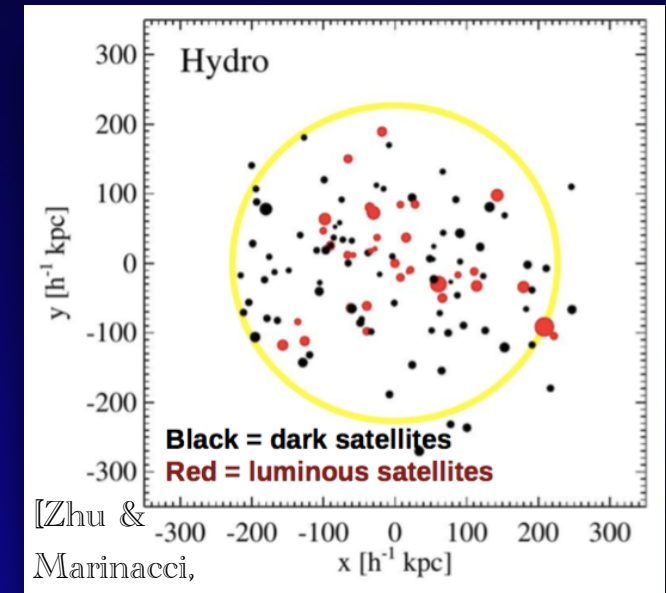
Diversity of RCs
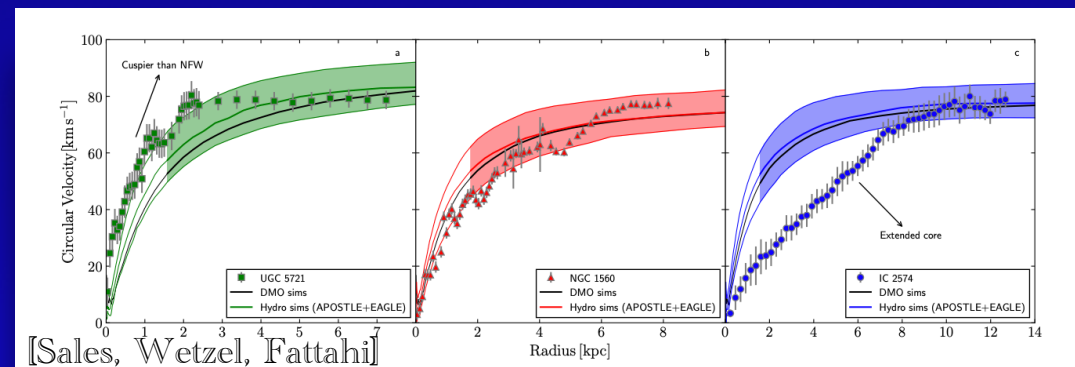
(each their own way…)

Inferring the DM distribution in disk galaxies: the Rotation Curve method

Fitting a pre-assigned shape on top of luminous
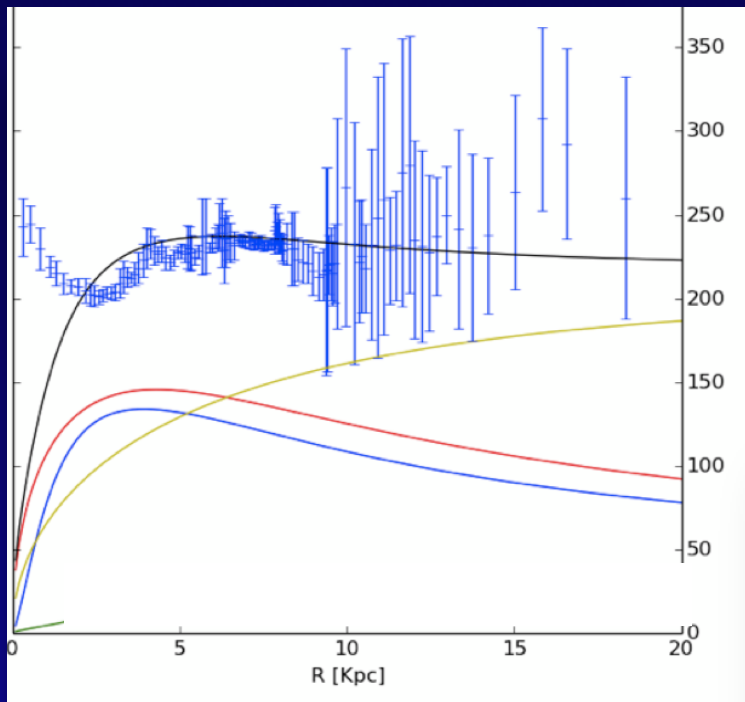
gNFW
$$\rho_{DM}(R) \propto \rho_0 \left(\frac{R}{R_s}\right)^{-\gamma} \left(1 + \frac{R}{R_s}\right)^{-3+\gamma}$$
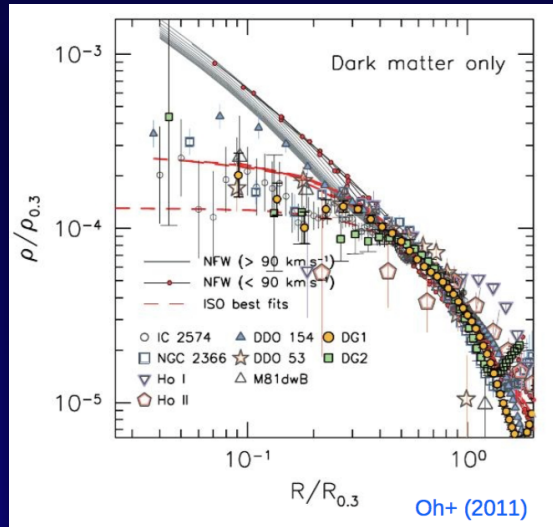
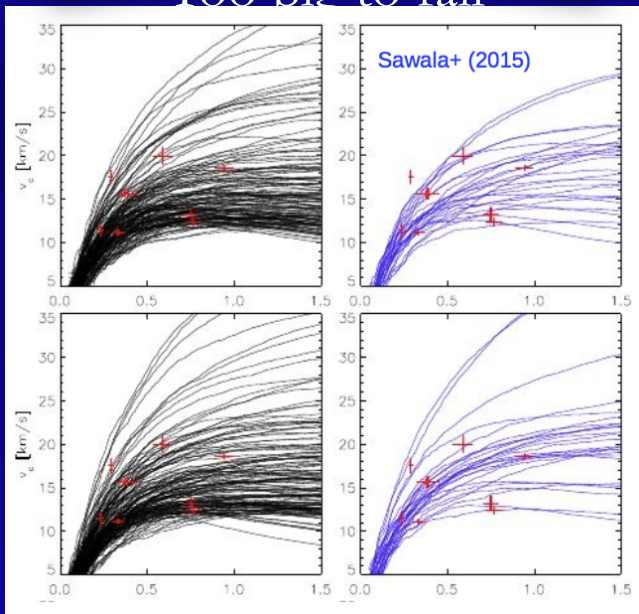$$\rho_{DM}(R) \propto \rho_0 \exp\left[-\frac{2}{\gamma}\left(\left(\frac{R}{R_s}\right)^{\gamma} - 1\right)\right]$$
Einasto
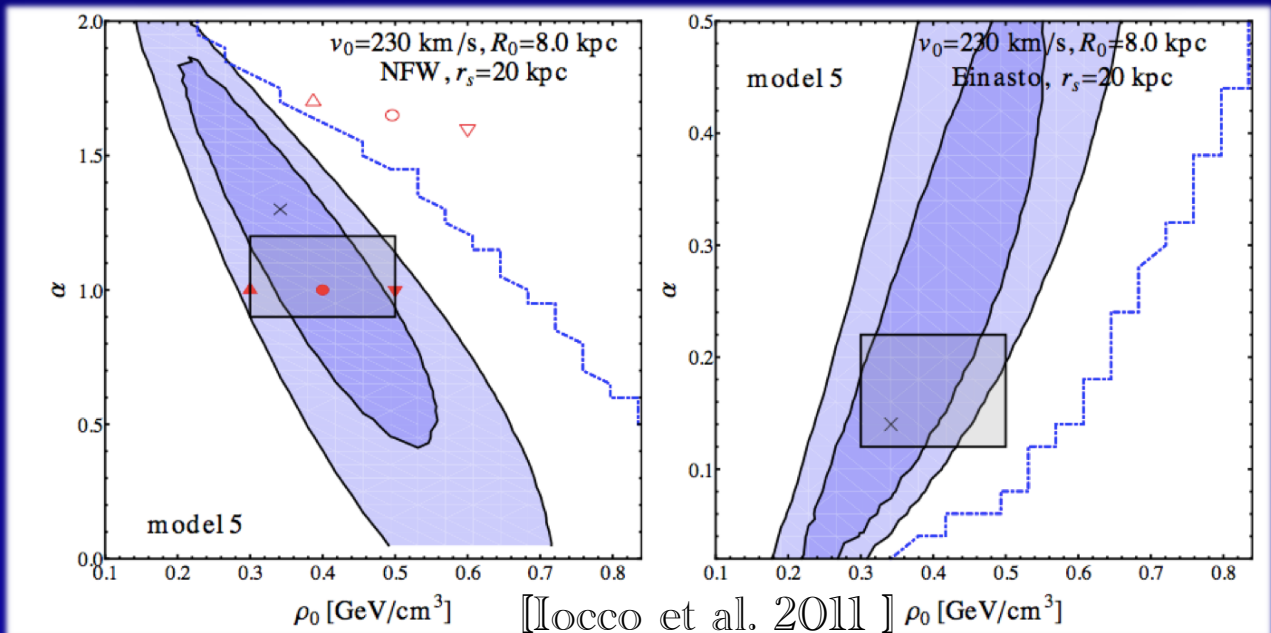
[many autors, e.g. Iocco et al. 2011]

[Iocco et al. 2011]

The Rotation Curve method requires a lot of (fortunate) conditions
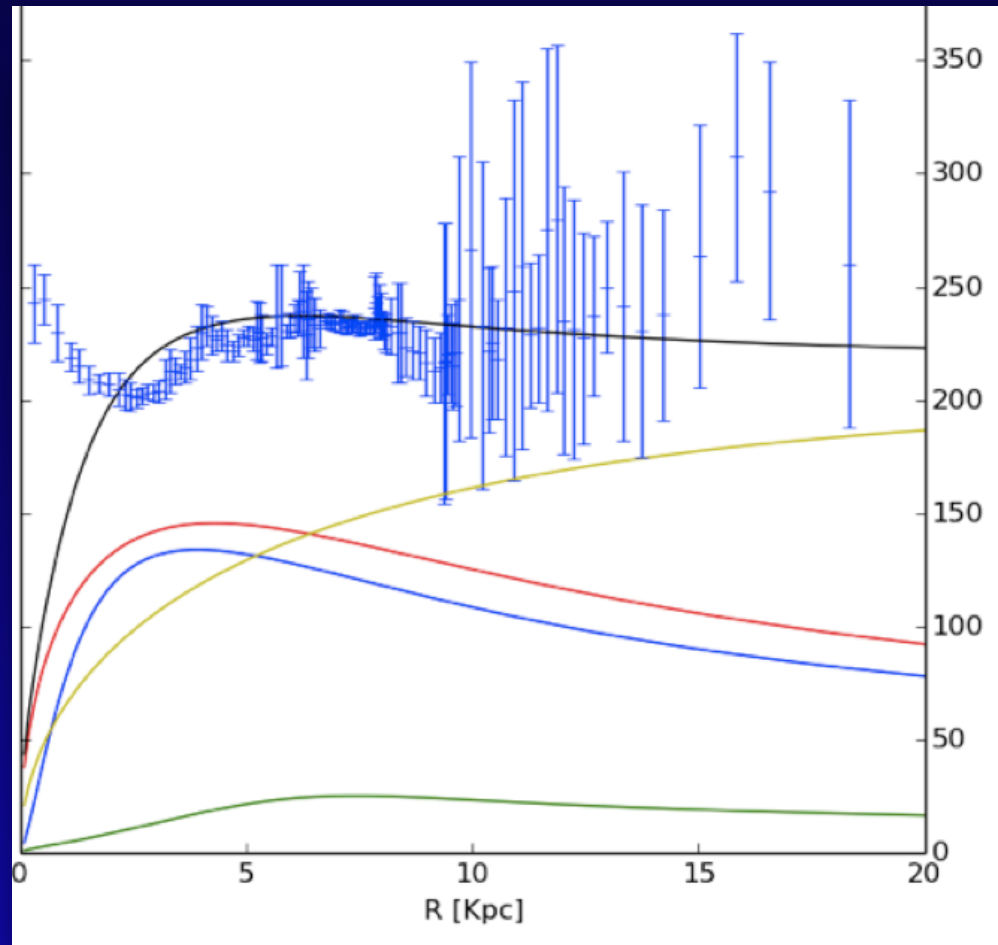
("all happy families are alike")

The Rotation Curve method, an example: the Milky Way

[Iocco, Pato, Bertone, Nature Physics 2015]
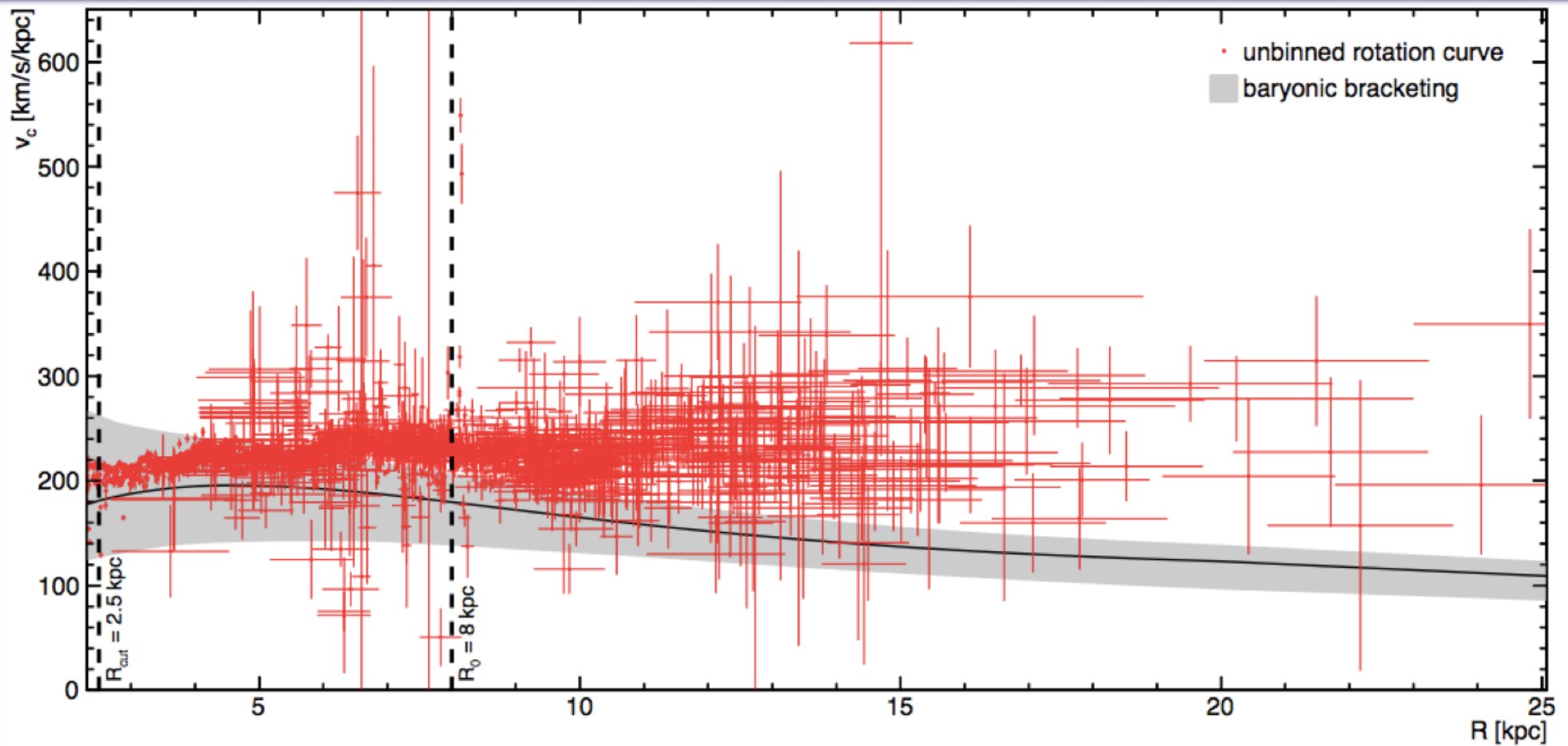
The Rotation Curve method, an example: the Milky Way

Milky Way edge-on

dark halo

~8 kpc

bulge/bar

Sun

Galactic Centre

gas disk
stellar disk

200 kpc

not to scale!
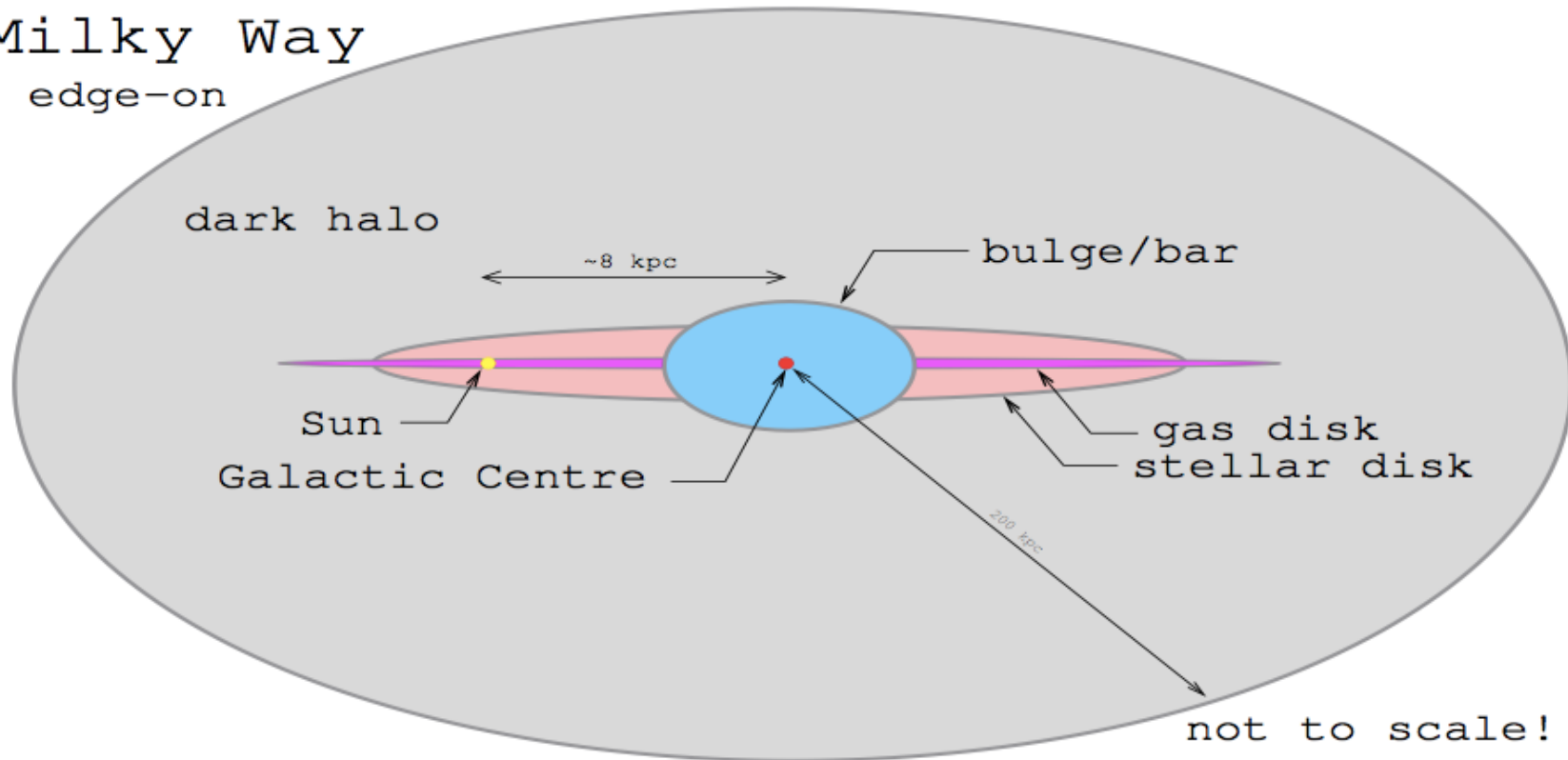
bulge — tilted bar

disk — thin+thick

gas — H_2, HI, HII

Courtesy of Miguel Pato

The rationale of our machine algorithms (Convolutional Neural Networks

Choice of galaxies in our database

TNG100 Simulation

- Planck cosmology
- 106.5 Mpc by side
- 1820^3 DM particles
- 1820^3 hydrodynamic cells
- DM resolution 7.5 *10^6 M☉
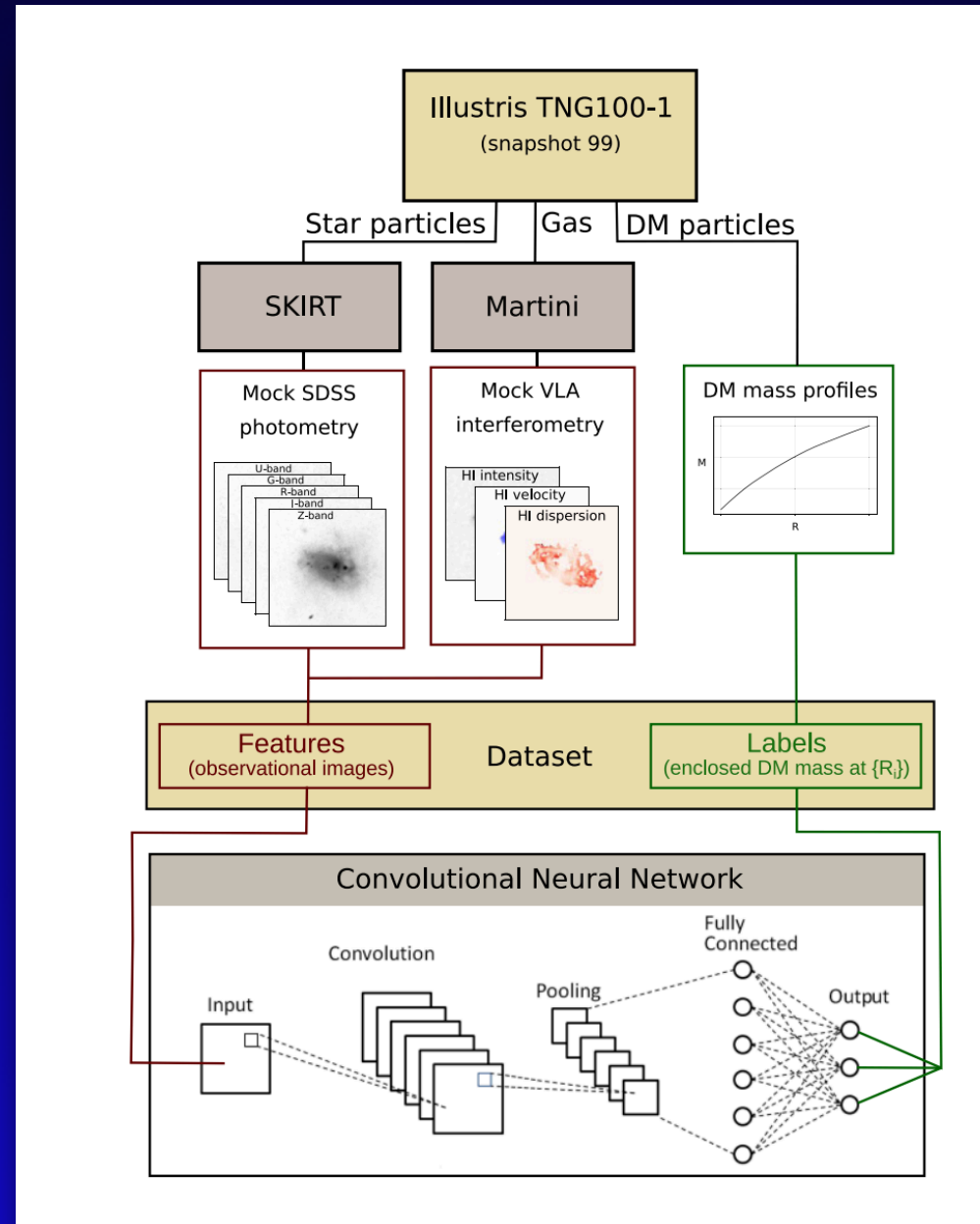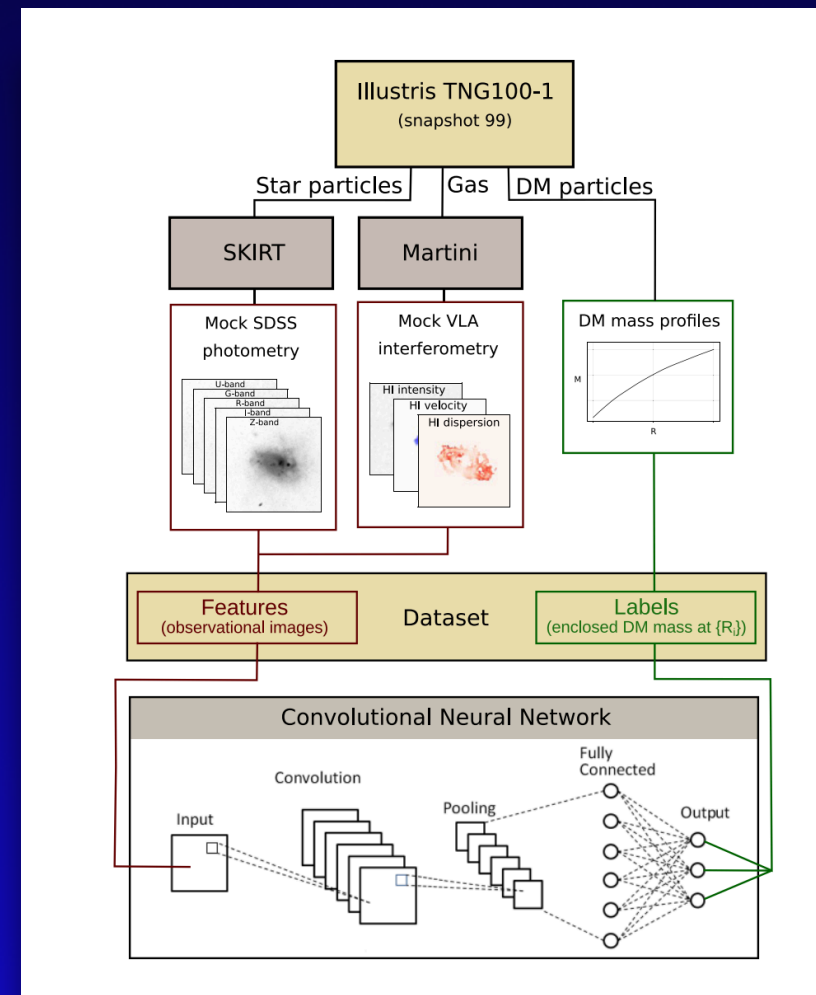- Baryon resolution 1.4*10^6 M☉
- 136 snapshots from z=127 to z=0

| Property	Criterium
Simulation snapshot	$99\ (z=0)$
Stellar mass	$10^{10}\ M_\odot \leq M_\star \leq 10^{12}\ M_\odot$
Star formation rate	$SFR \geq 0.1\ M_\odot/\mathrm{yr}$
Central galaxy	$SubhaloParent = 0$
Cosmological origin	$SubhaloFlag = 1$

Illustris TNG100-1 (snapshot 99)

Star particles | Gas | DM particles

SKIRT | Martini

Mock SDSS photometry
- U-band
- G-band
- R-band
- I-band
- Z-band

Mock VLA interferometry
- HI intensity
- HI velocity
- HI dispersion

DM mass profiles

Dataset
Features (observational images) | Labels (enclosed DM mass at {R_i})

Convolutional Neural Network
Input — Convolution — Pooling — Fully Connected — Output

[deLosRios, Petac,
Zaldivar, Calore,
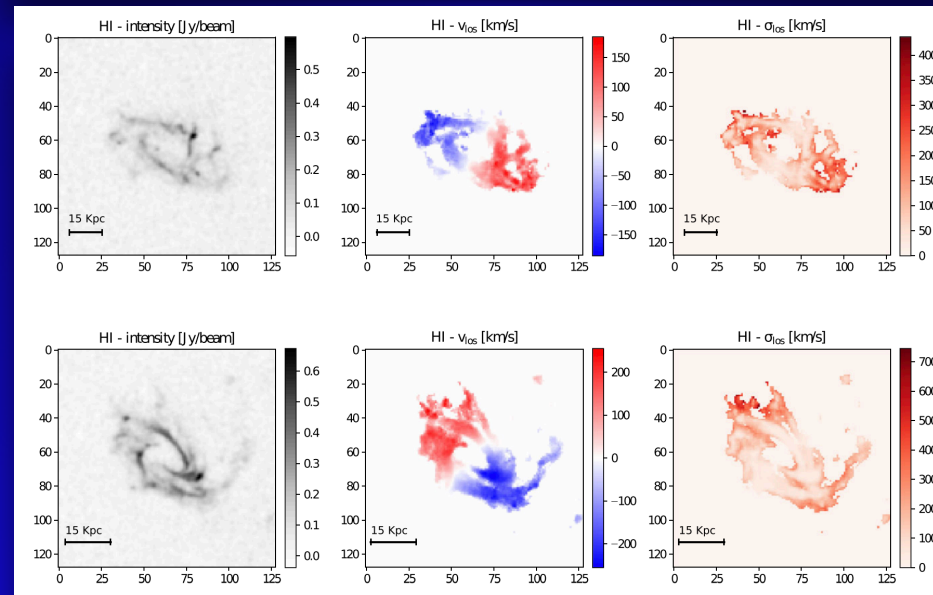Bonaventura, FI
arXiV:2111.08725]

A flavor of what machines "see"
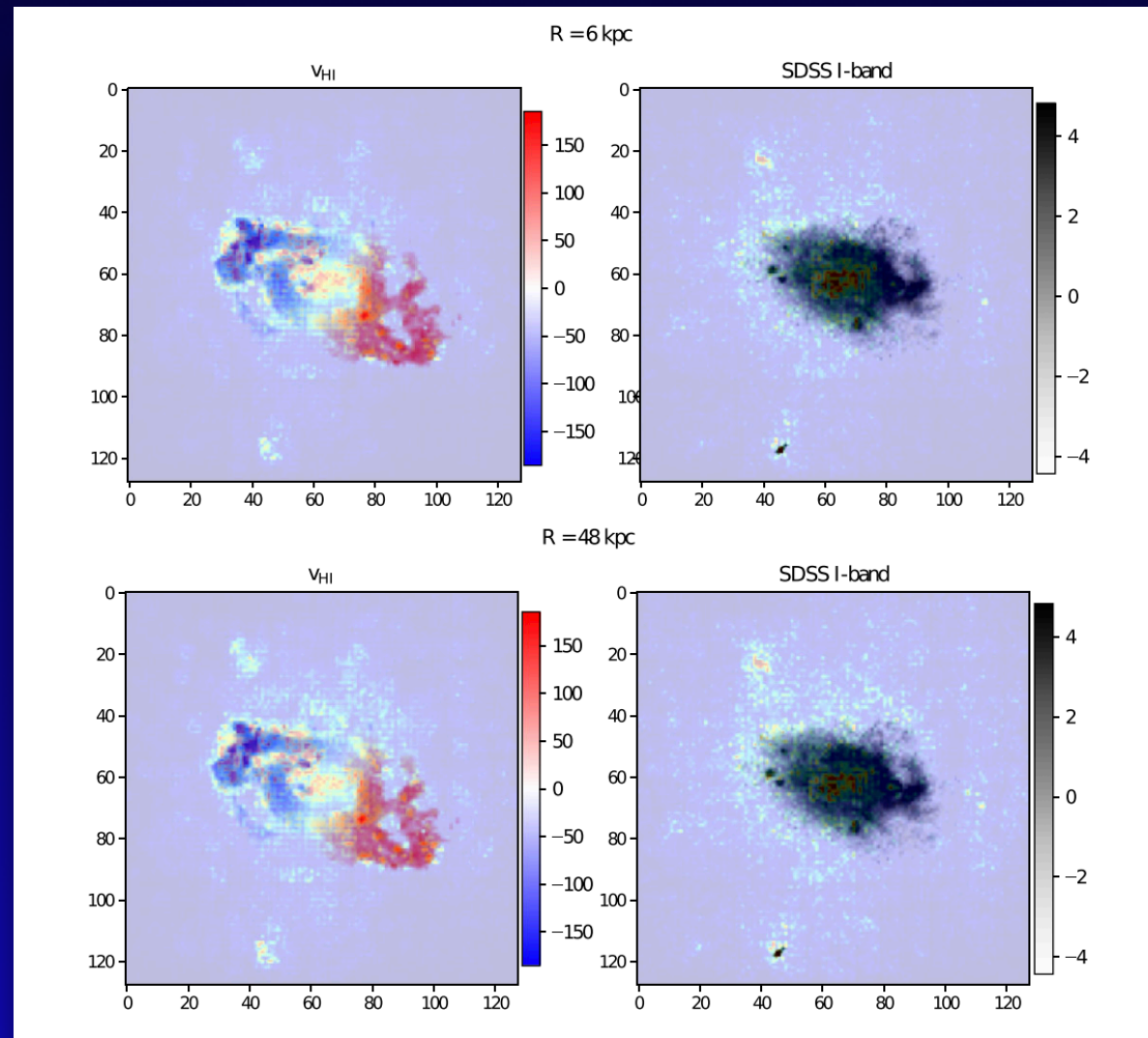

Photometry
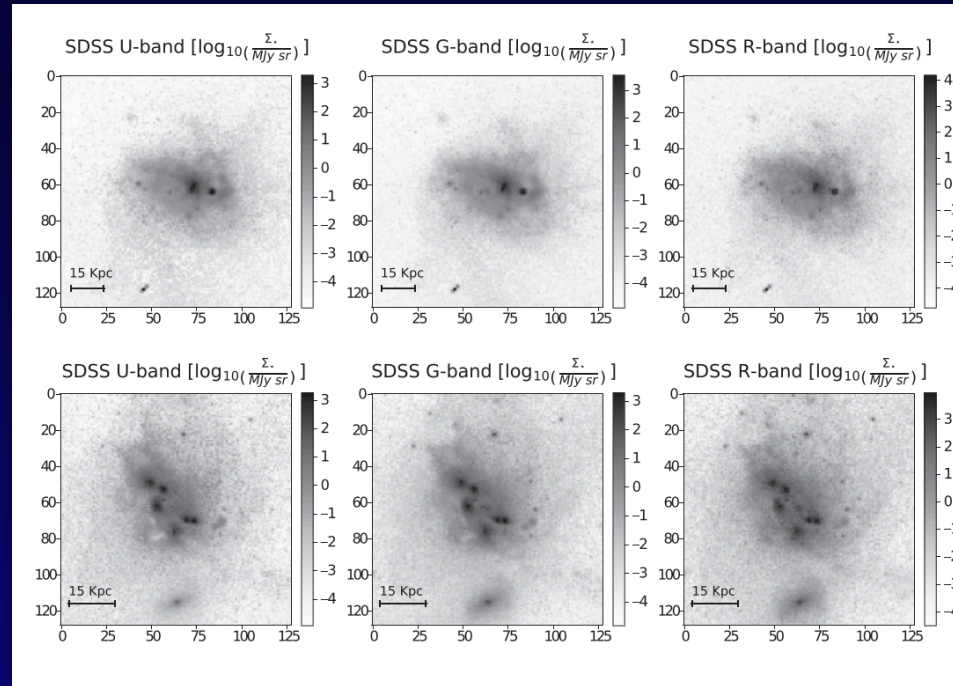
Baryons

Spectroscopy

Velocity
(total potential)

[deLosRios, Petac,
Zaldivar, Calore,
Bonaventura, FI
arXiV:2111.08725]

A flavor of what machines "see"
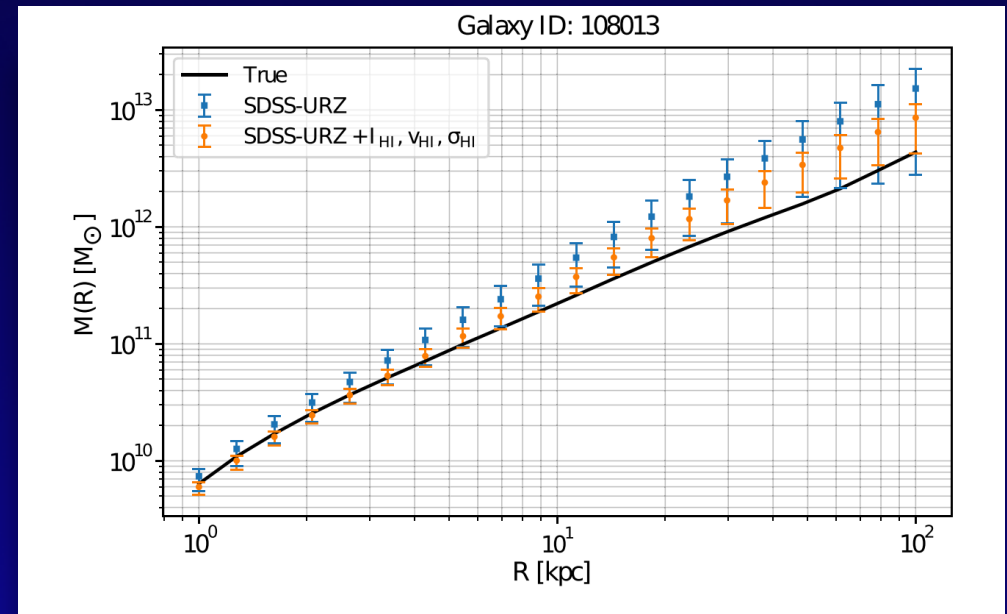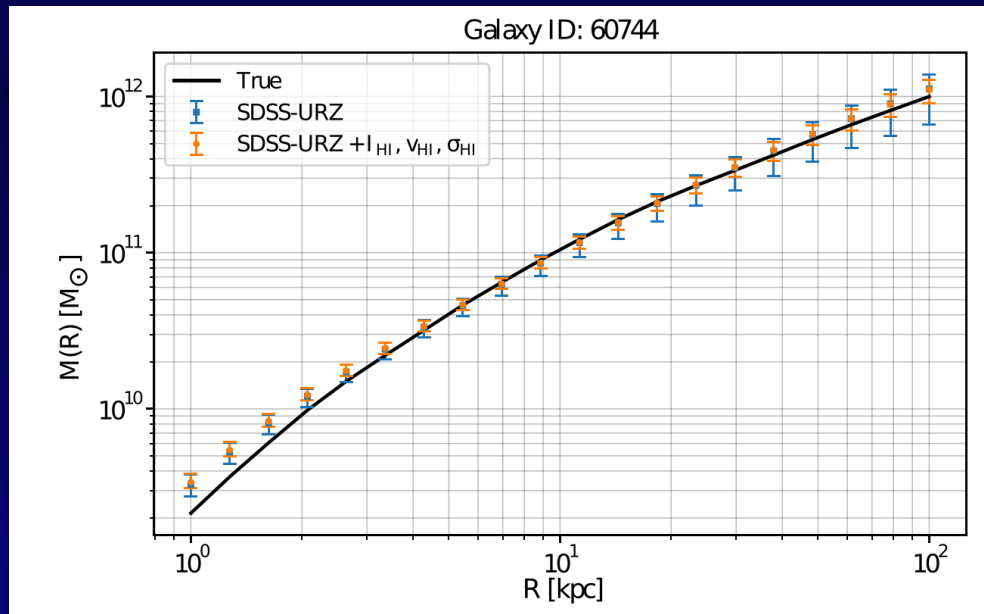

Spectroscopy   Photometry

Let's open the box

No analytic approximation, no profile shape, etc…

It's always about the performance
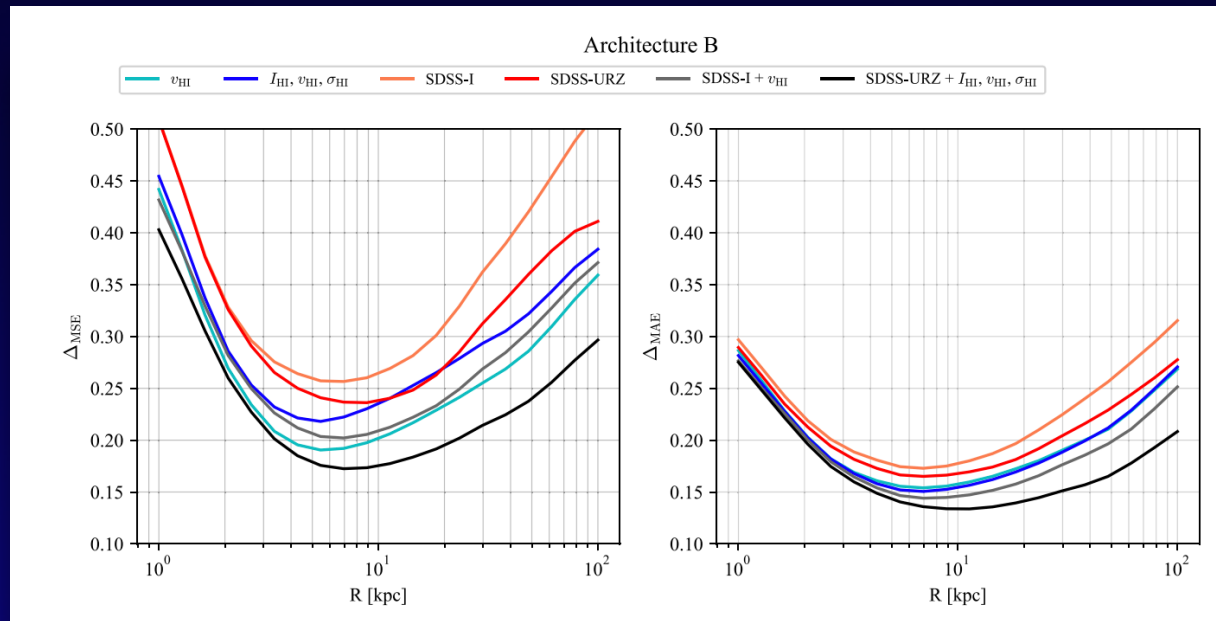
$$\Delta_{\mathrm{MSE}}(R_i) = \left[\frac{1}{N} \sum_{j=1}^{N} \left(\mu_j(R_i) - \hat{\mu}_j(R_i) \right)^2 \right]^{1/2}$$
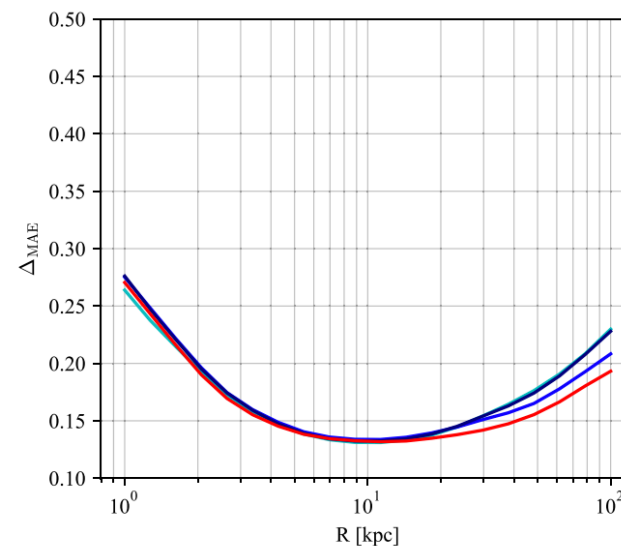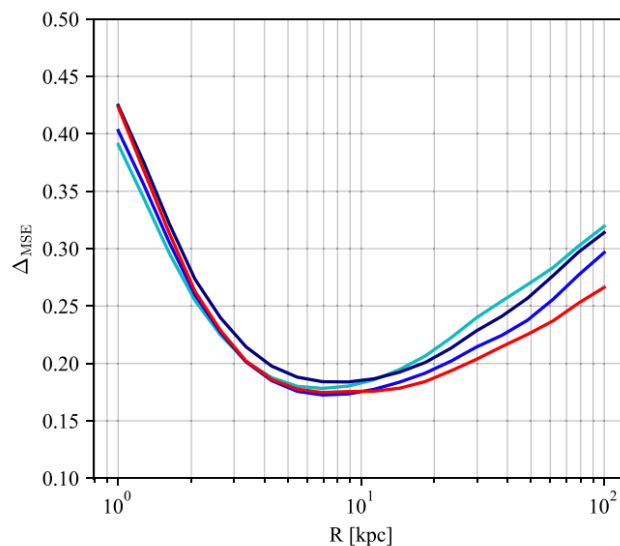
$$\Delta_{\mathrm{MAE}}(R_i) = \frac{1}{N} \sum_{i=j}^{N} \left| \mu_j(R_i) - \hat{\mu}_j(R_i) \right|$$

[deLosRios, Petac
Zaldivar, Calore,
Bonaventura, FI
arXiV:2111.08725]

Rotation Curves vs Machines

[deLosRios, Petac, Zaldivar, Calore, Bonaventura, FI, arXiV:2111.08725]
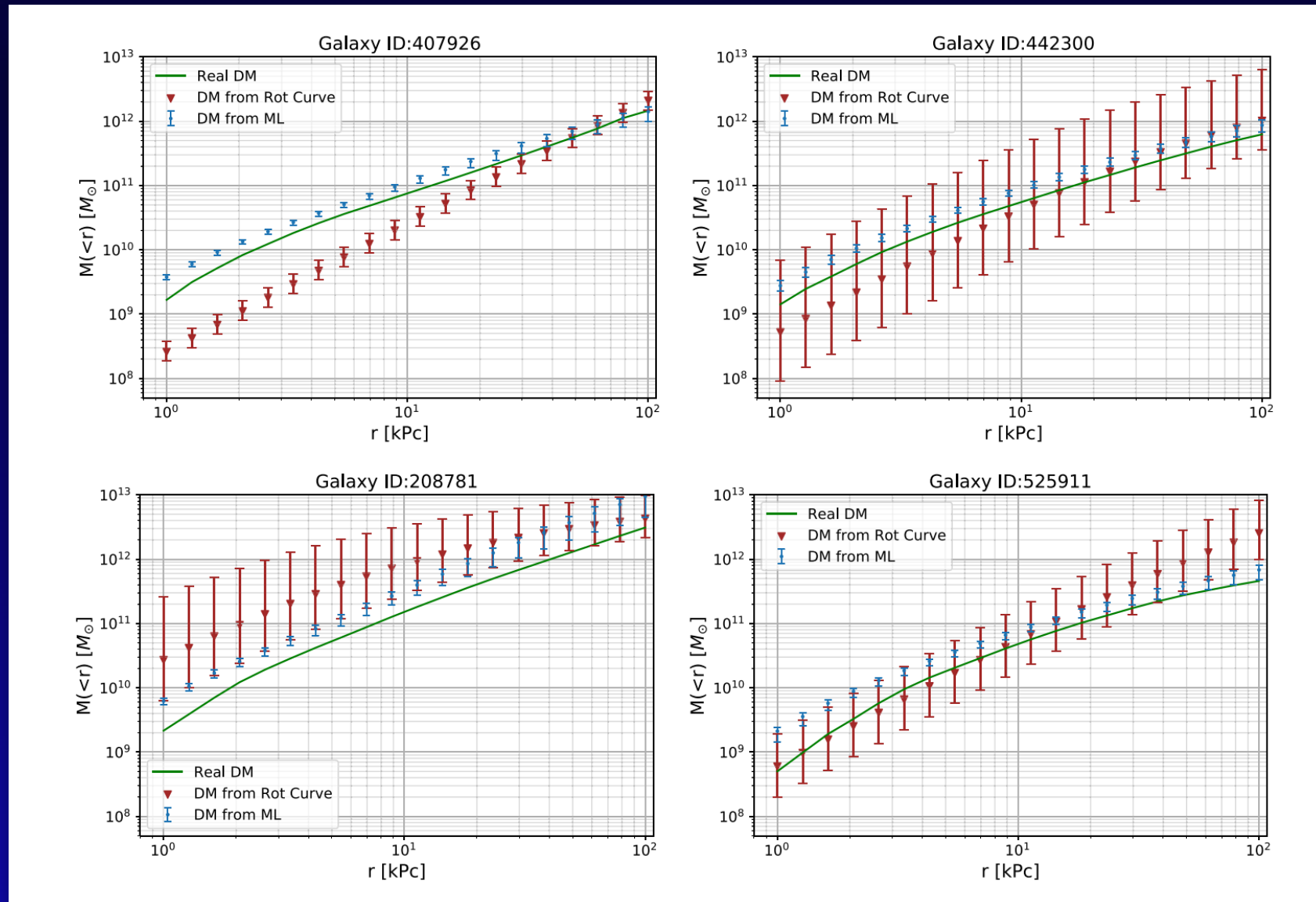
Cuncta stricte

- Deep learning algorithms do actually reconstruct the DM amount and distribution, <u>within a synthetic environment</u> (simulations)

- CNNs seem to perform better than Rotation Curve method (more statistics and detailed study needed)

- This is only the beginning. ML evolving faster than one can account. Idea stands, new results only can grow.

- Still to be released on "real world" targets