Determining the Dark Matter distribution in galaxies with Deep Learning (2111.08725)

As part of the darkmachines projects challenges: https://darkmachines.org/

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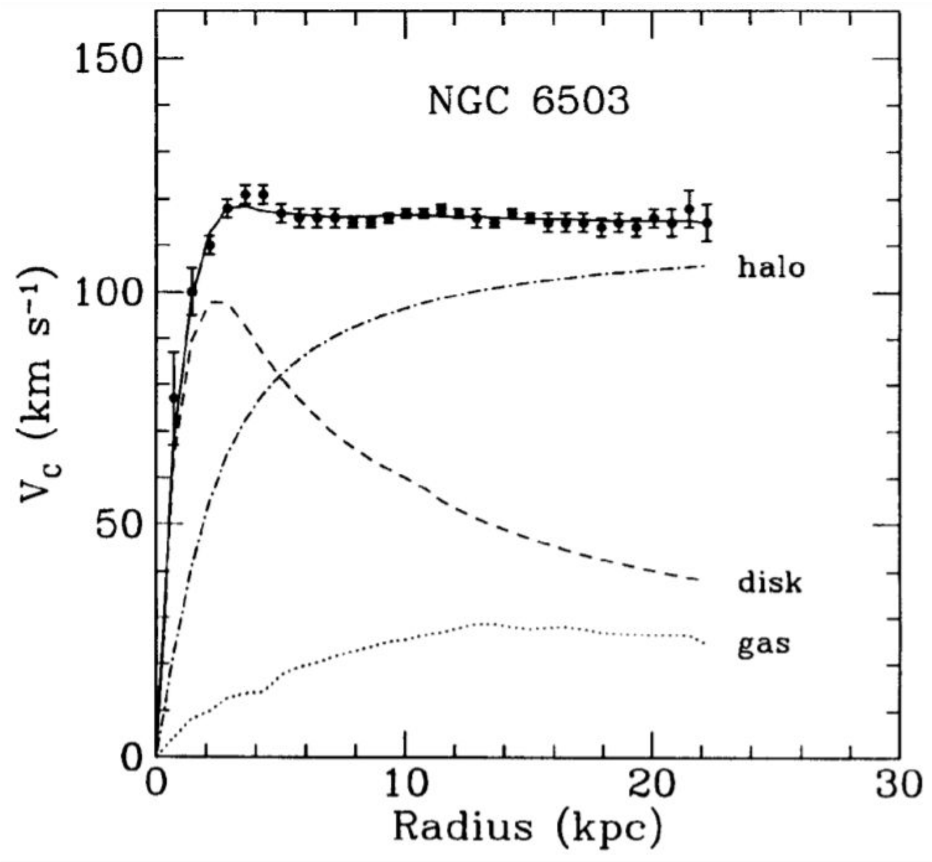
Outline

- Introduction
- Constructions of the dataset
  - TNG100 Simulations (1707.03401, 1707.03395, 1707.03395, ...)
  - SKIRT (2003.00721)
  - MARTINI (https://github.com/kyleaoman/martini)
- Results
  - Prediction of the Dark matter profile
  - Comparison between different architectures
  - Comparison between different inputs
  - Comparison with Rotation Curve method
- Conclusions and Future work

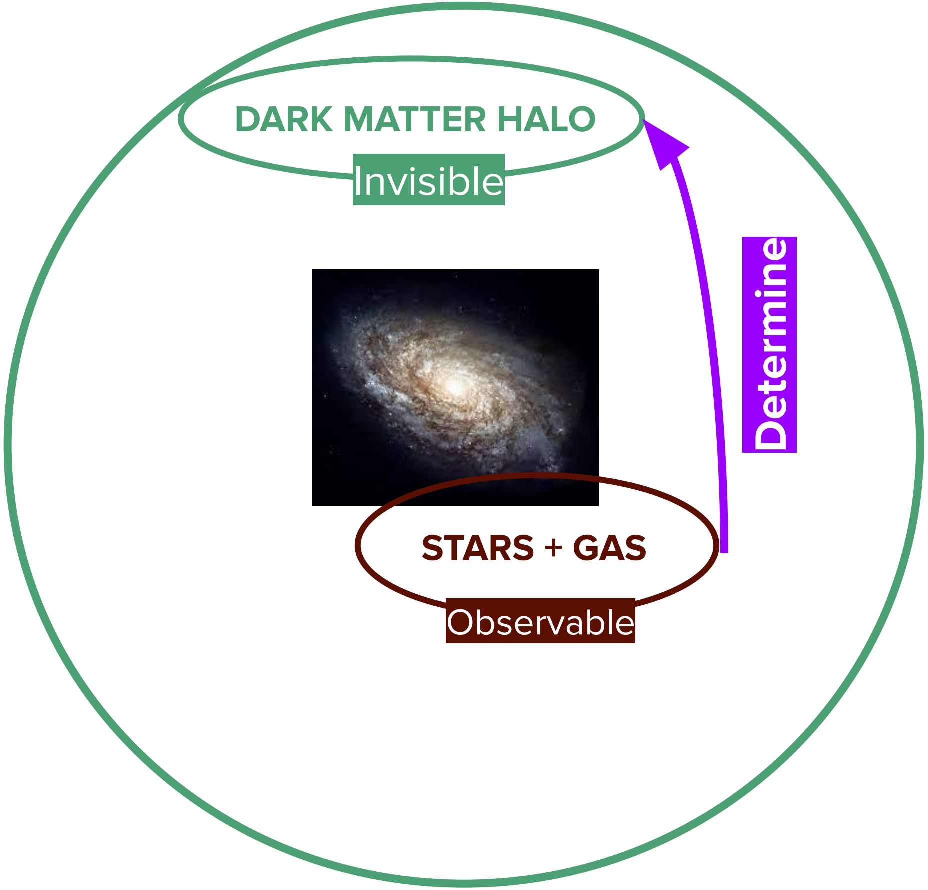
Introduction

Rotation Curves



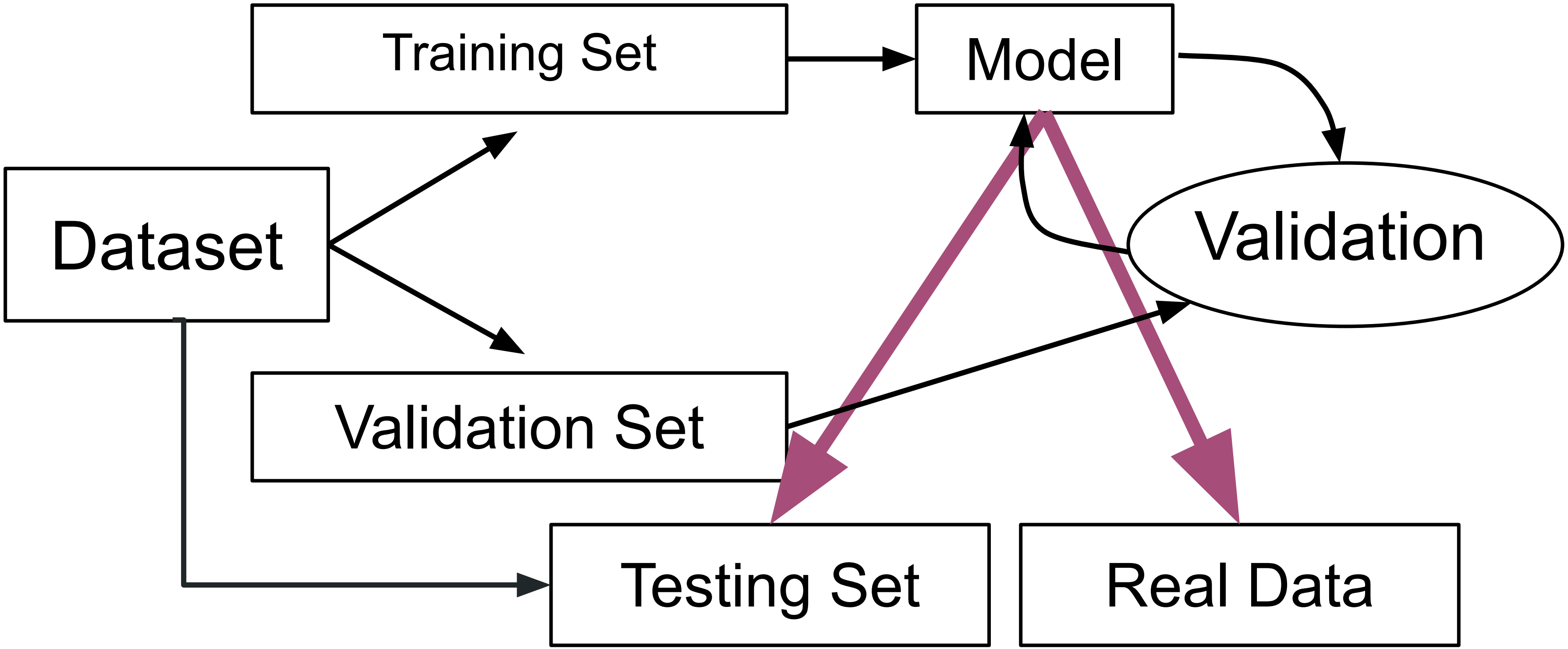
NGC 6503 Rotation Curve

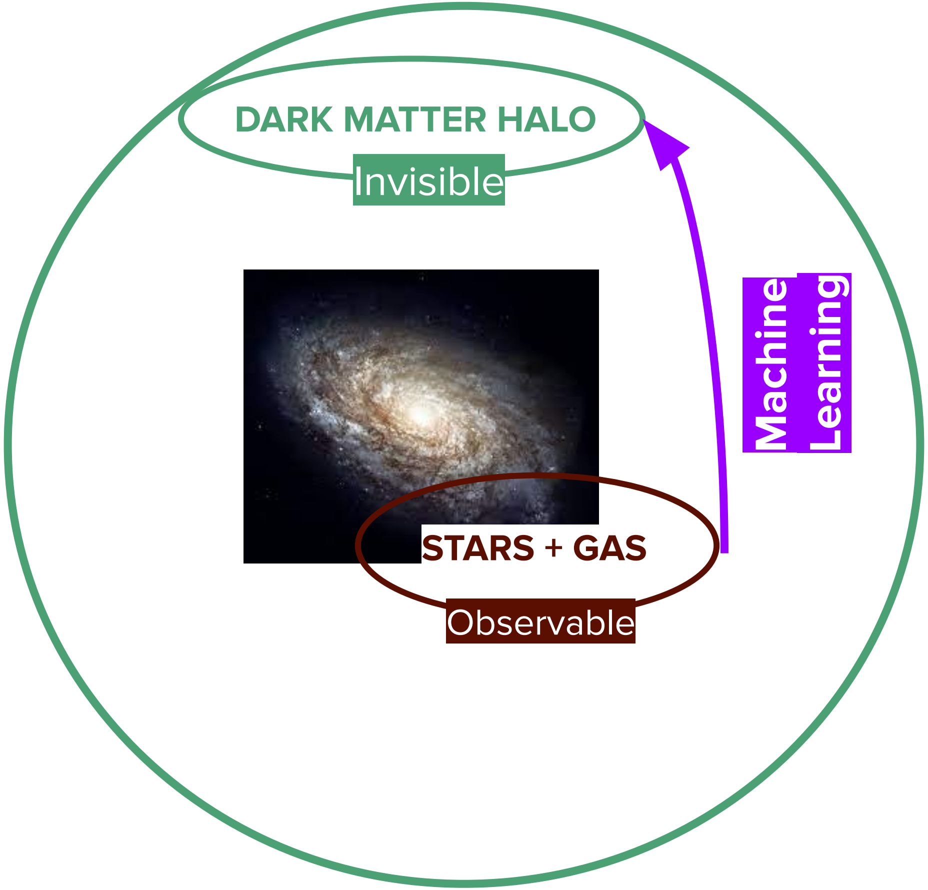
Katherine Freese 0812.4005


DARK MATTER HALO
Invisible
Determine
STARS + GAS
Observable

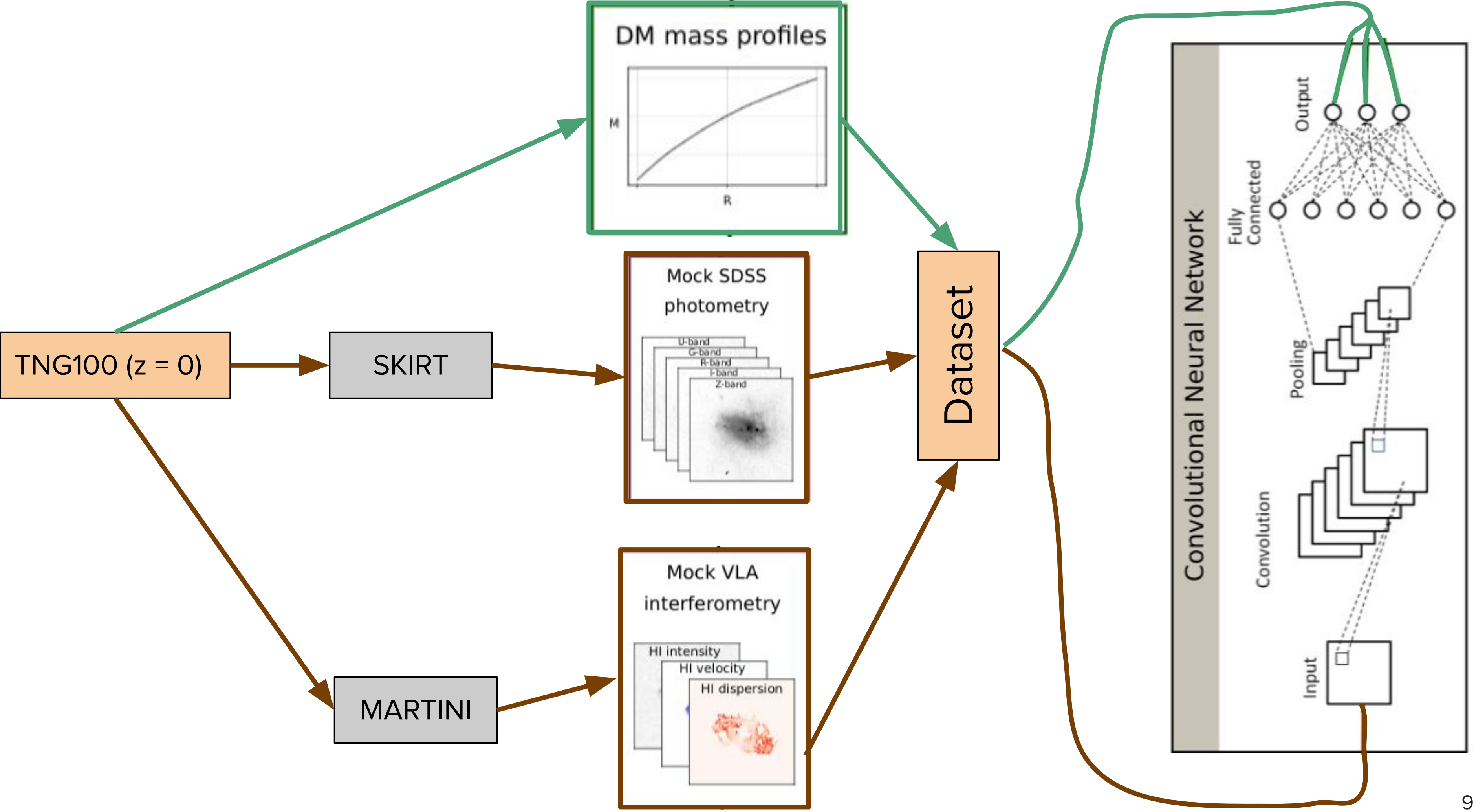
Brief introduction to Machine Learning

Supervised Learning




DARK MATTER HALO
Invisible
Machine Learning
STARS + GAS
Observable

Construction of the Dataset


DM mass profiles
M
R
TNG100 (z = 0)
SKIRT
Mock SDSS photometry
U-band
G-band
R-band
I-band
Z-band
MARTINI
Mock VLA interferometry
HI intensity
HI velocity
HI dispersion
Dataset
Convolutional Neural Network
Output
Fully Connected
Pooling
Convolution
Input

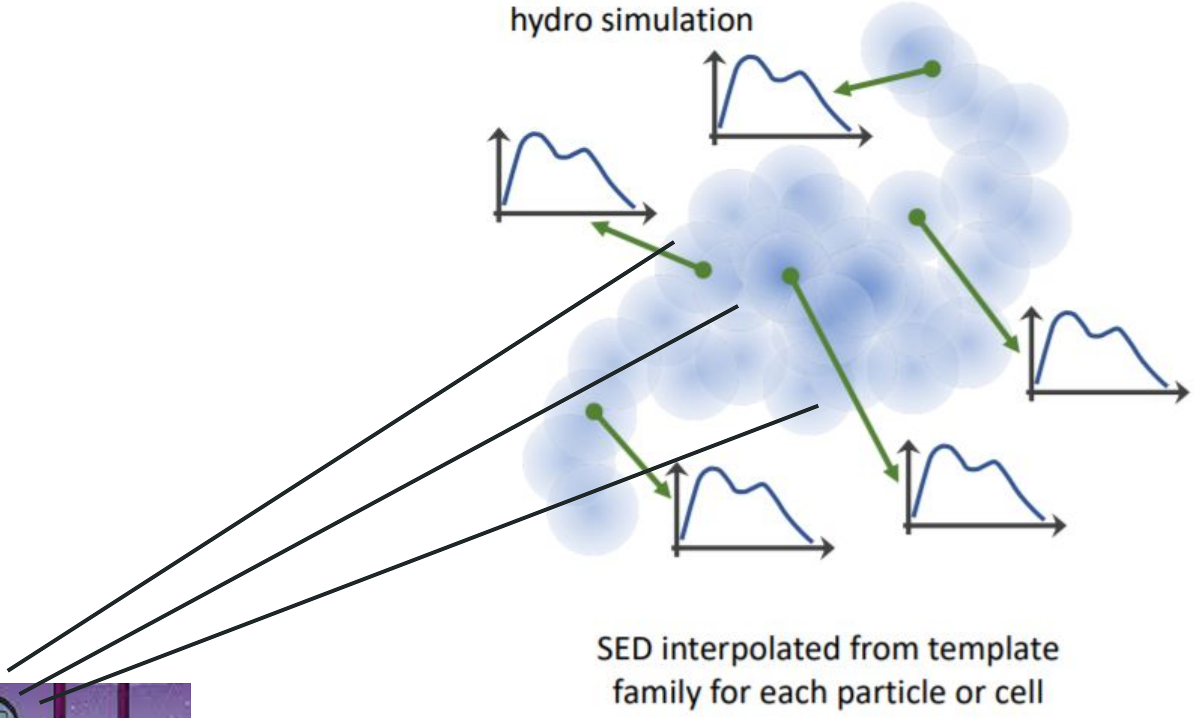
TNG100 Simulation

- 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

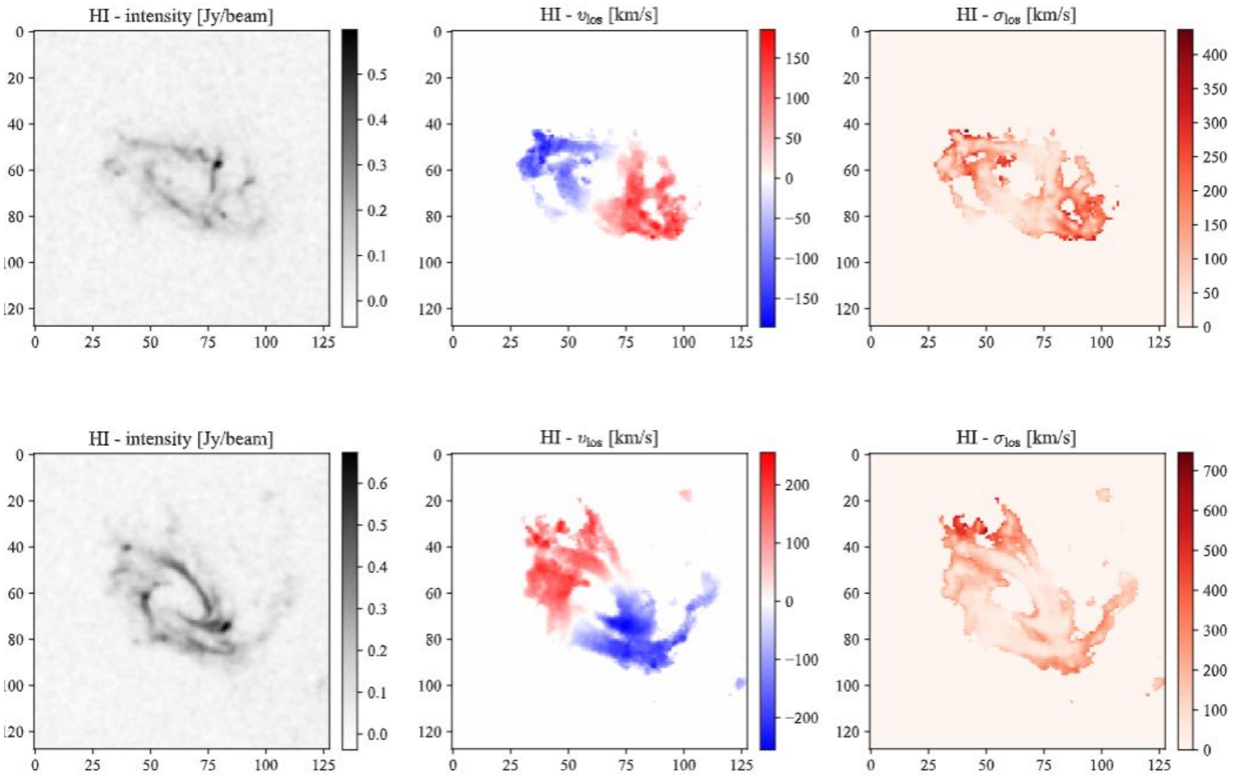
SKIRT* (2003.00721, skirt.ugent.be)

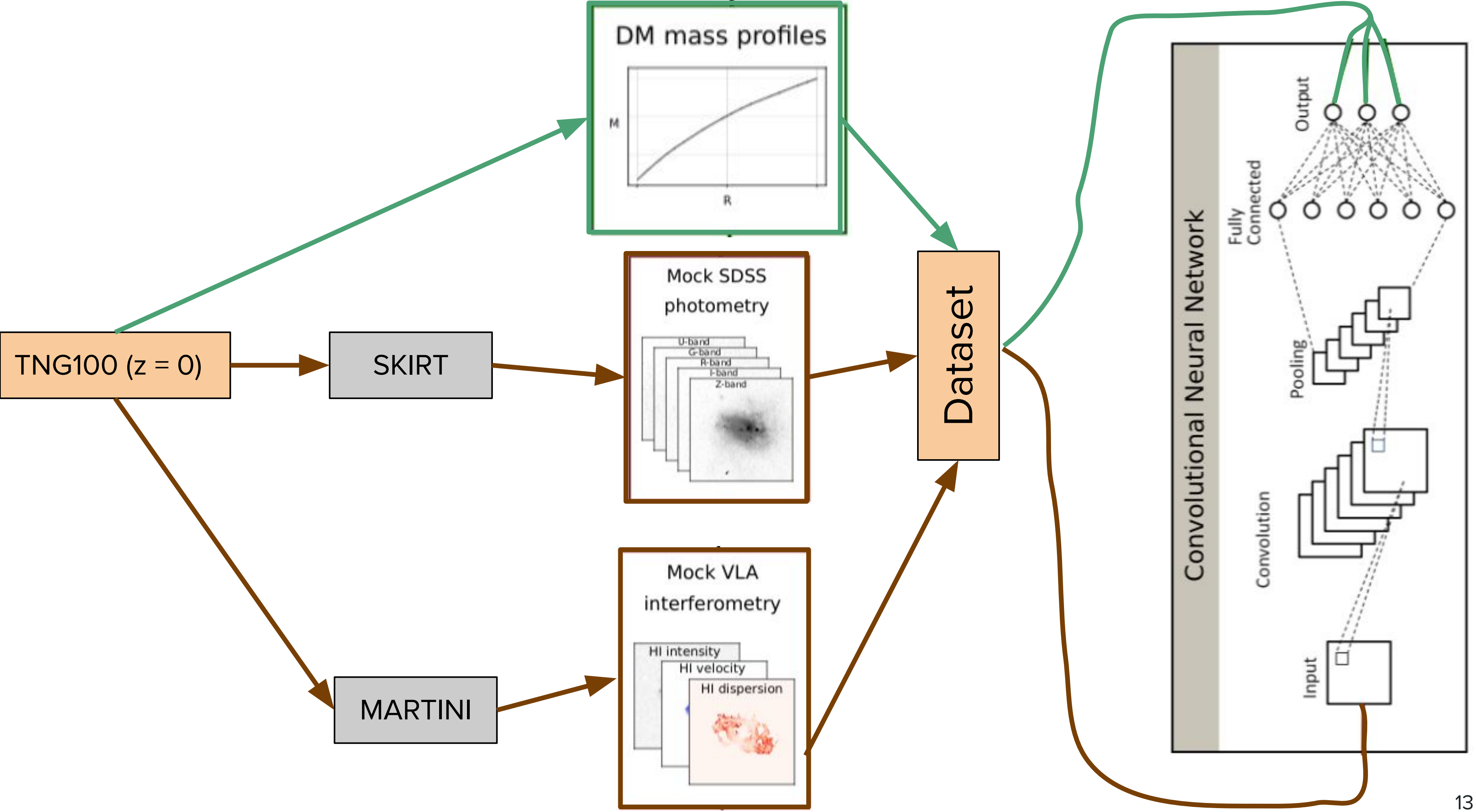
Radiative transfer code which emulates the stellar emissions and subsequent light-ray propagation to the observer, taking into account the absorption and re-emission by dust.



MARTINI

Allows for the creation of synthetic resolved HI line observations (i.e. data cubes) directly from the snapshot of a hydrodynamic simulation, and its posterior analysis.

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Mock VLA
interferometry
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HI velocity
HI dispersion
Dataset
Convolutional Neural Network
Input
Convolution
Pooling
Fully
Connected
Output

Results

Comparison between different architectures

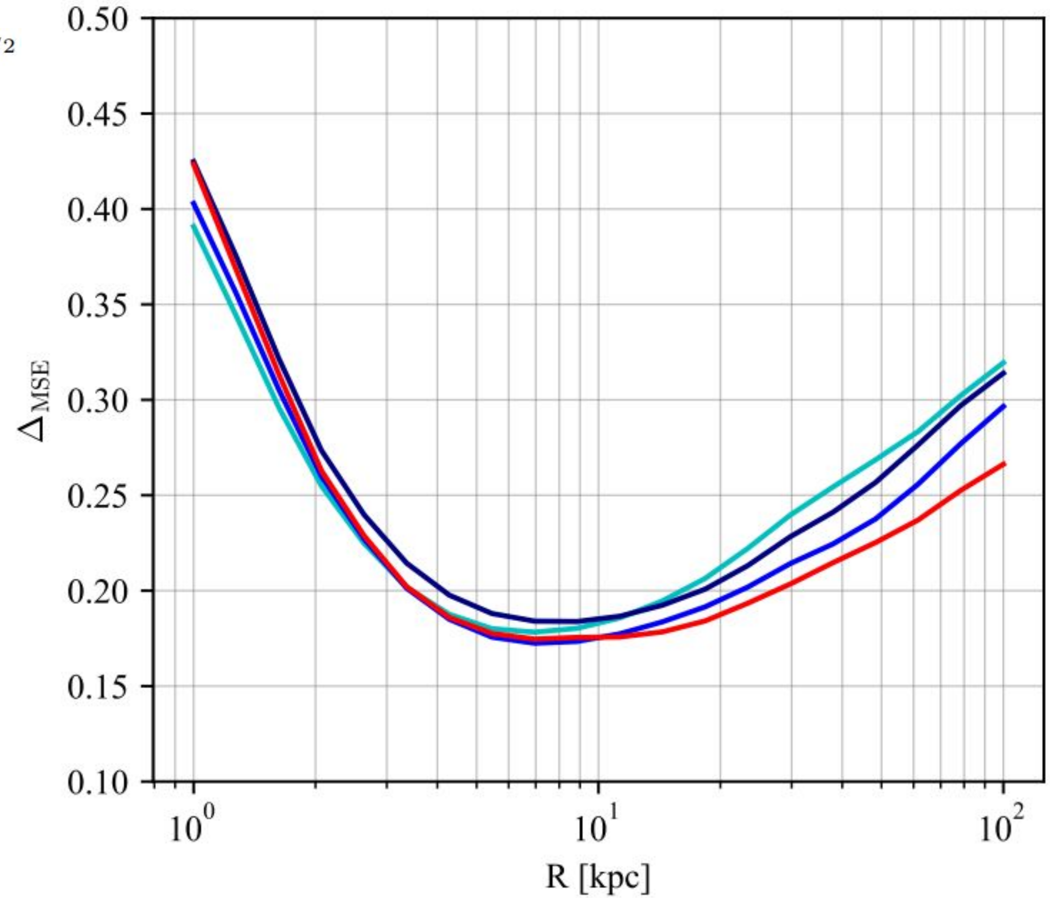
$$\Delta_{\mathrm{MSE}}(R_i) = \left[\frac{1}{N}\sum_{j=1}^{N}\left(\frac{\mu_j(R_i) - \hat{\mu}_j(R_i)}{\hat{\mu}_j(R_i)}\right)^2\right]^{1/2}$$

Architecture A

Architecture B

Architecture C

ResNet50



Comparison between different inputs

SDSS I

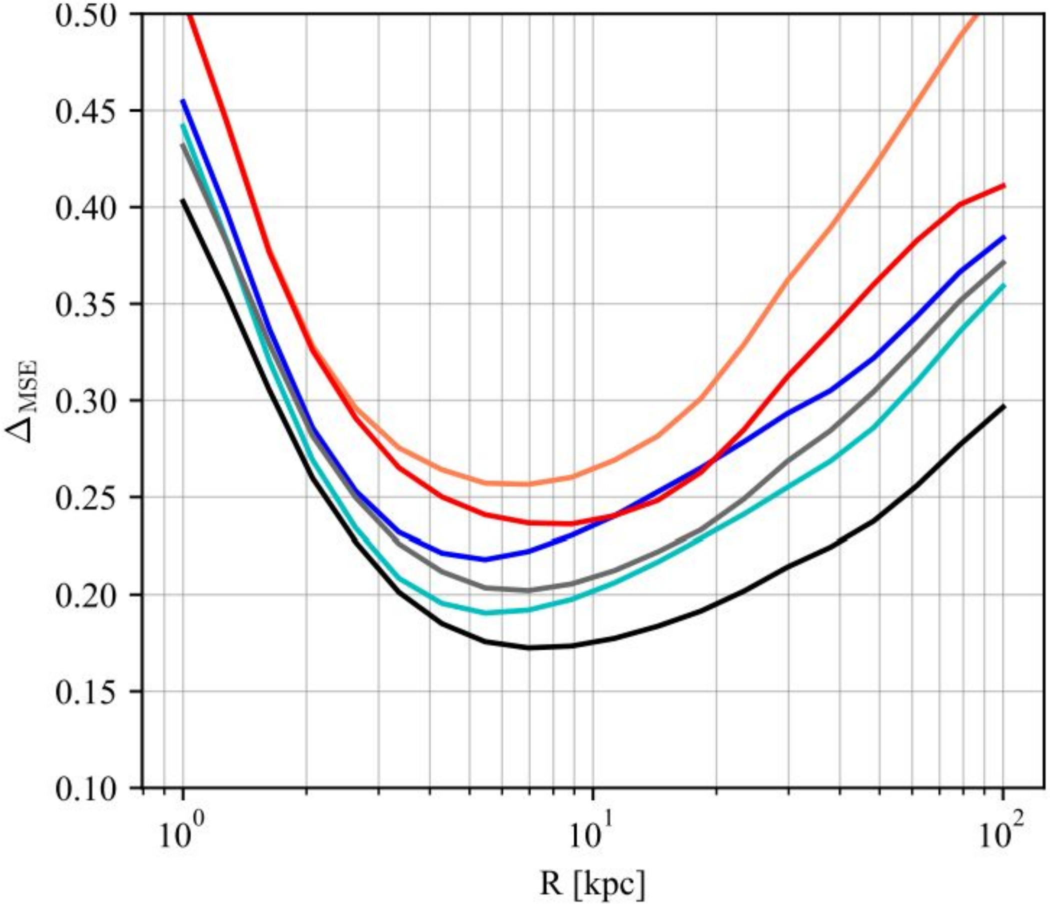
SDSS URZ

V_{HI}

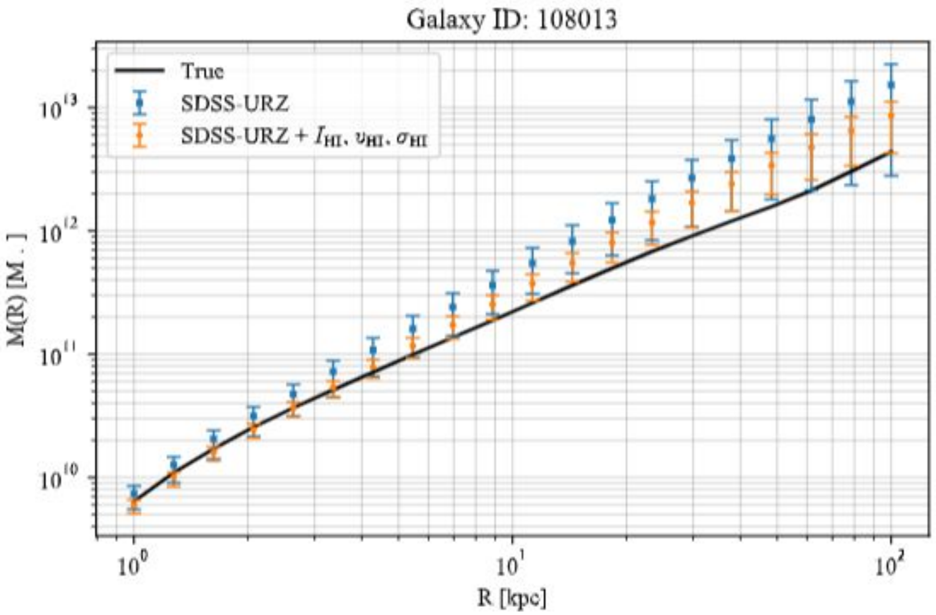
$I_{HI} + V_{HI} + \sigma_{HI}$

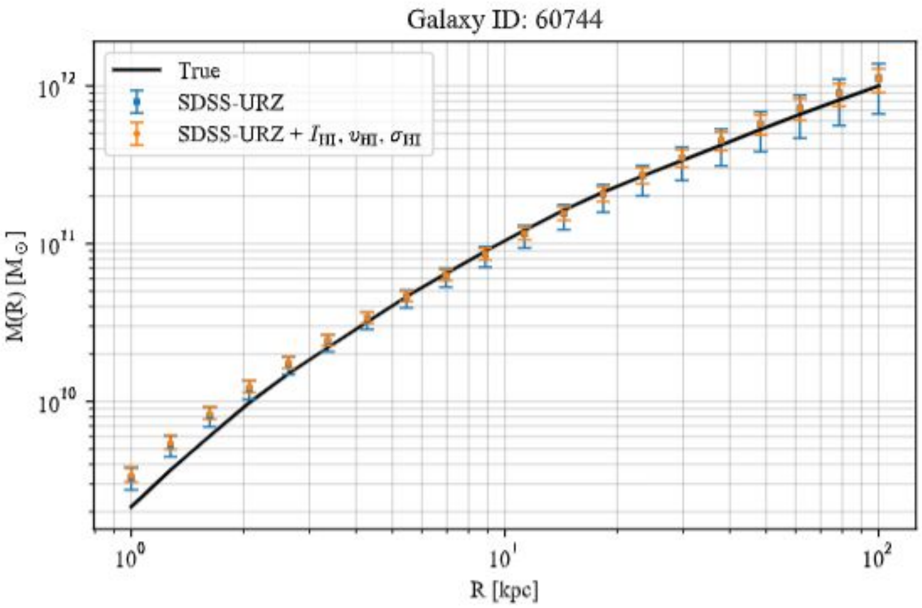
SDSS URZ + V_{HI}

SDSS URZ + $I_{HI} + V_{HI} + \sigma_{HI}$



Prediction of the dark matter profile





Conclusions and Future work

- Our algorithm is able to reconstruct the DM distribution profile with high performance throughout the extension of the galaxy.

- The highest performance is achieved in the intermediate regions with a mean square error below 0.2 using all the photometric and spectroscopic information.

- Even in the absence of spectroscopic information, our method is able to recover the dark matter profile with a mean square error below 0.3 in the intermediate regions.

- Our reconstruction of the DM distribution is completely data-driven, and does not need any assumption on the shape nor the functional form of the DM profile.

- The method developed here is applicable to different types of galaxies since it does not rely on explicit physical assumptions regarding the dynamical state of the system.

Conclusions and Future work

- We will make a comparison with the dark matter profile obtained through the traditional rotation curve analysis for the simulated galaxies.

- Study the robustness of our results to the hydrodynamical cosmological simulation.

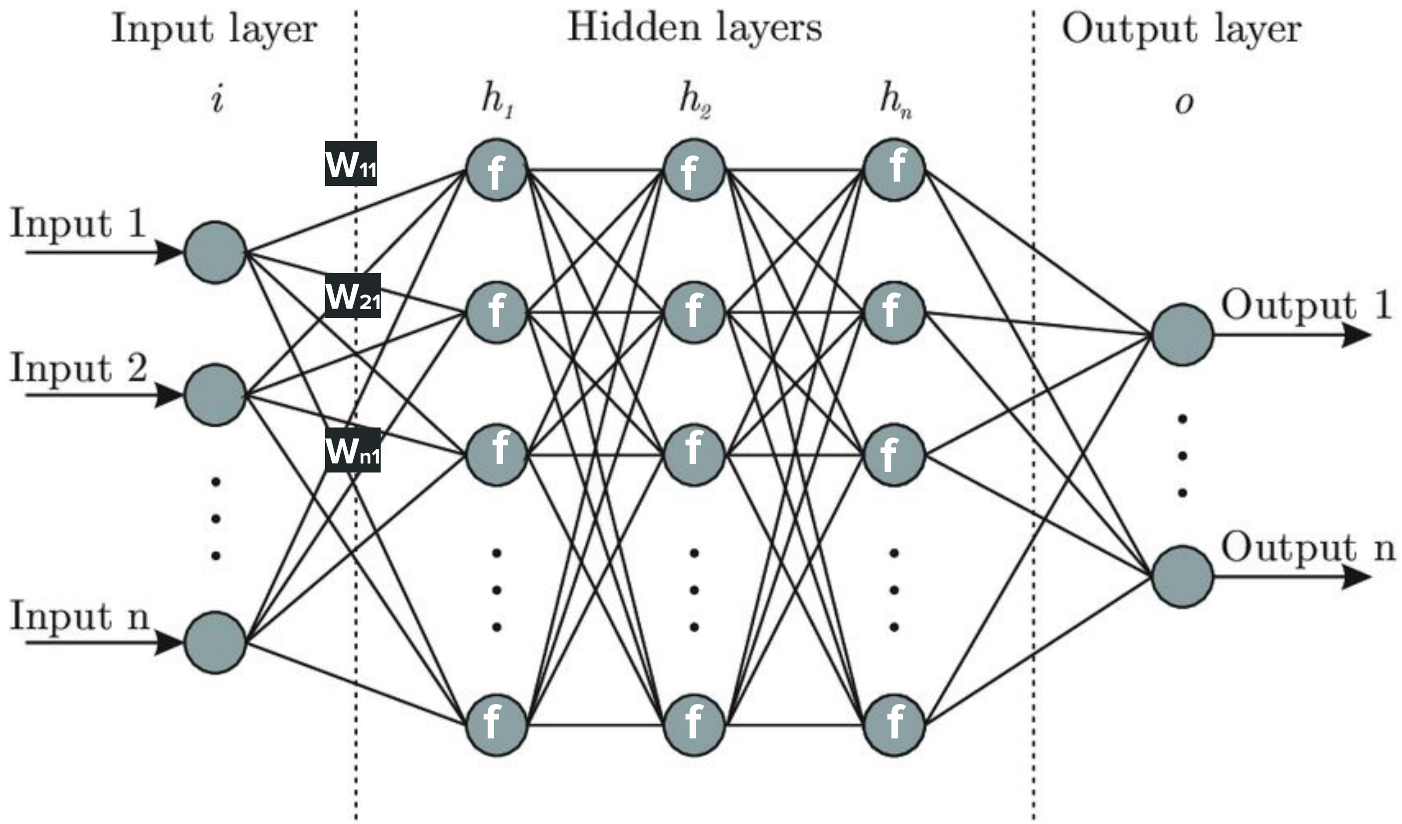
- Apply our method to real galaxies and compare the results with other estimations.

THANK YOU

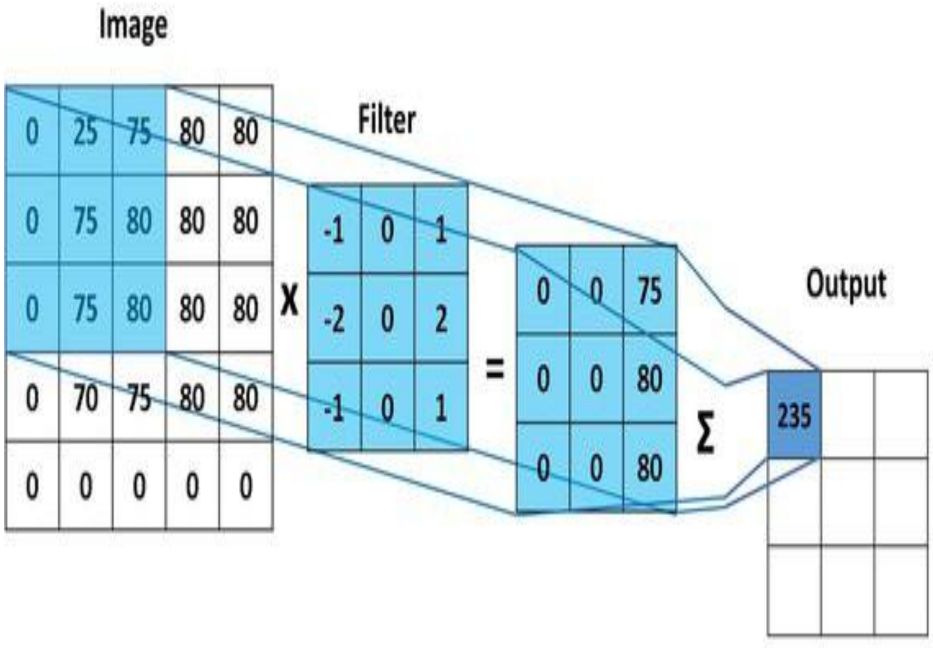
Back-up Slides

Brief introduction to Machine Learning

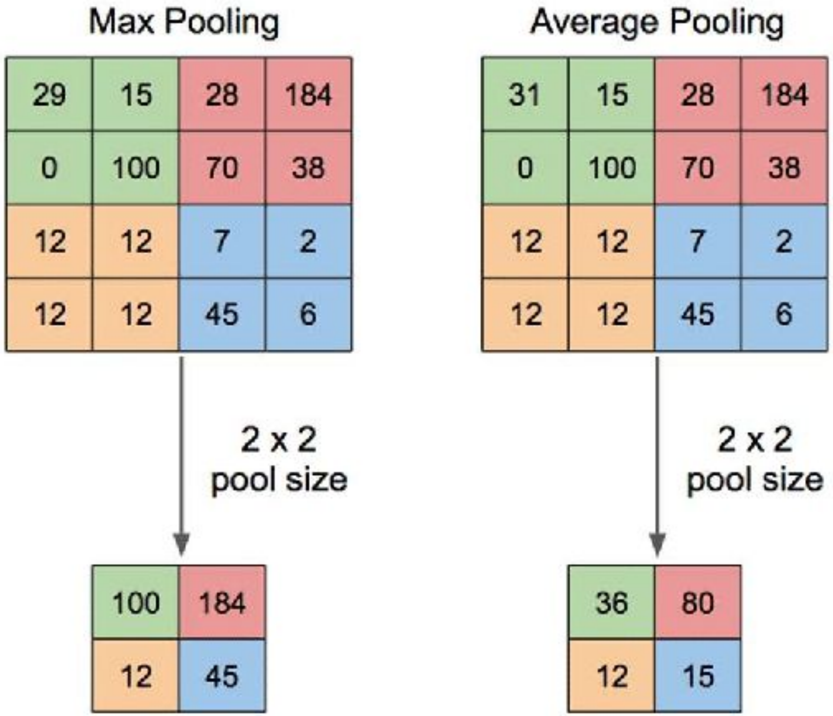
Neural Networks

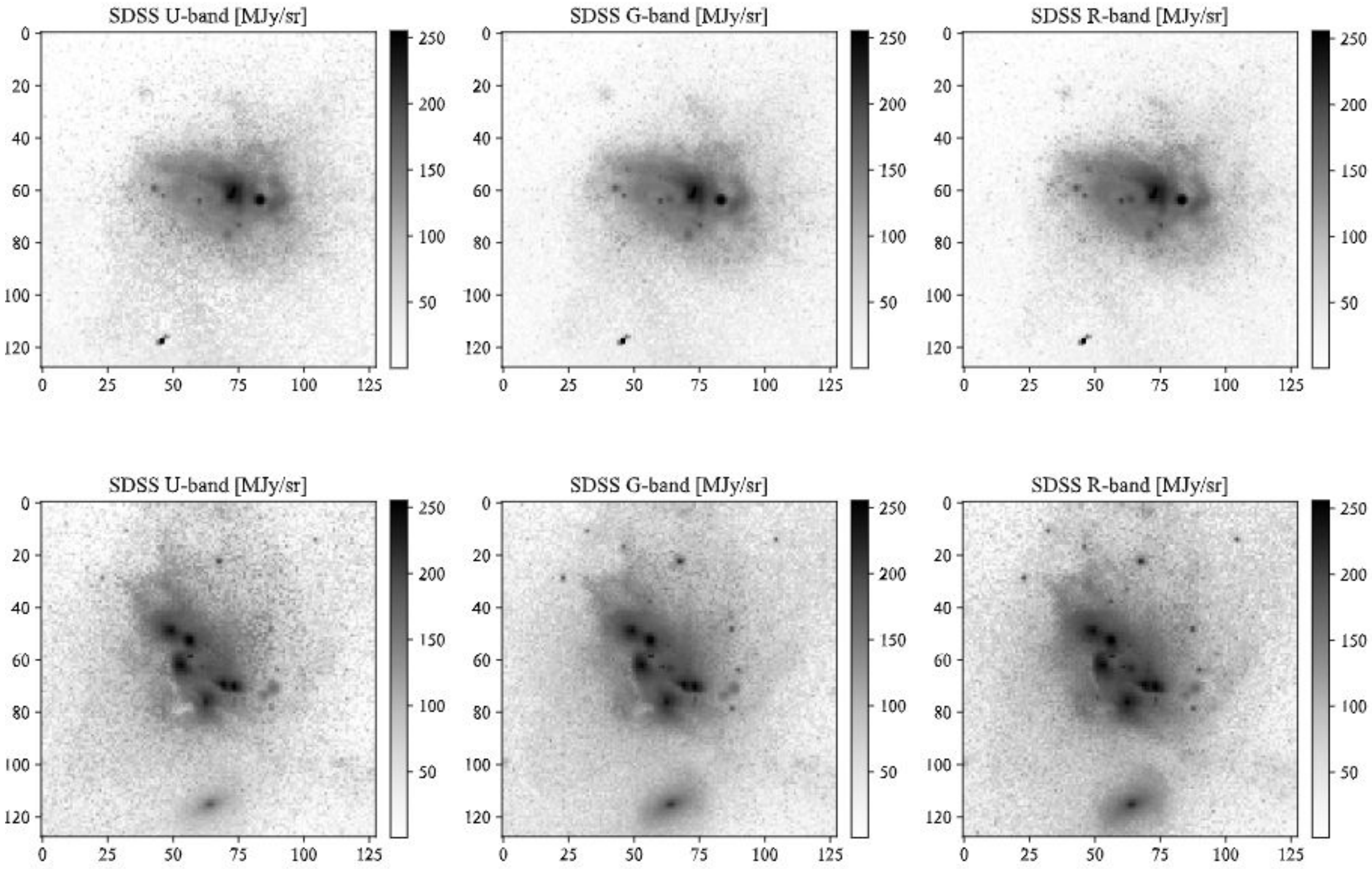


Convolutional layers



Pooling layers



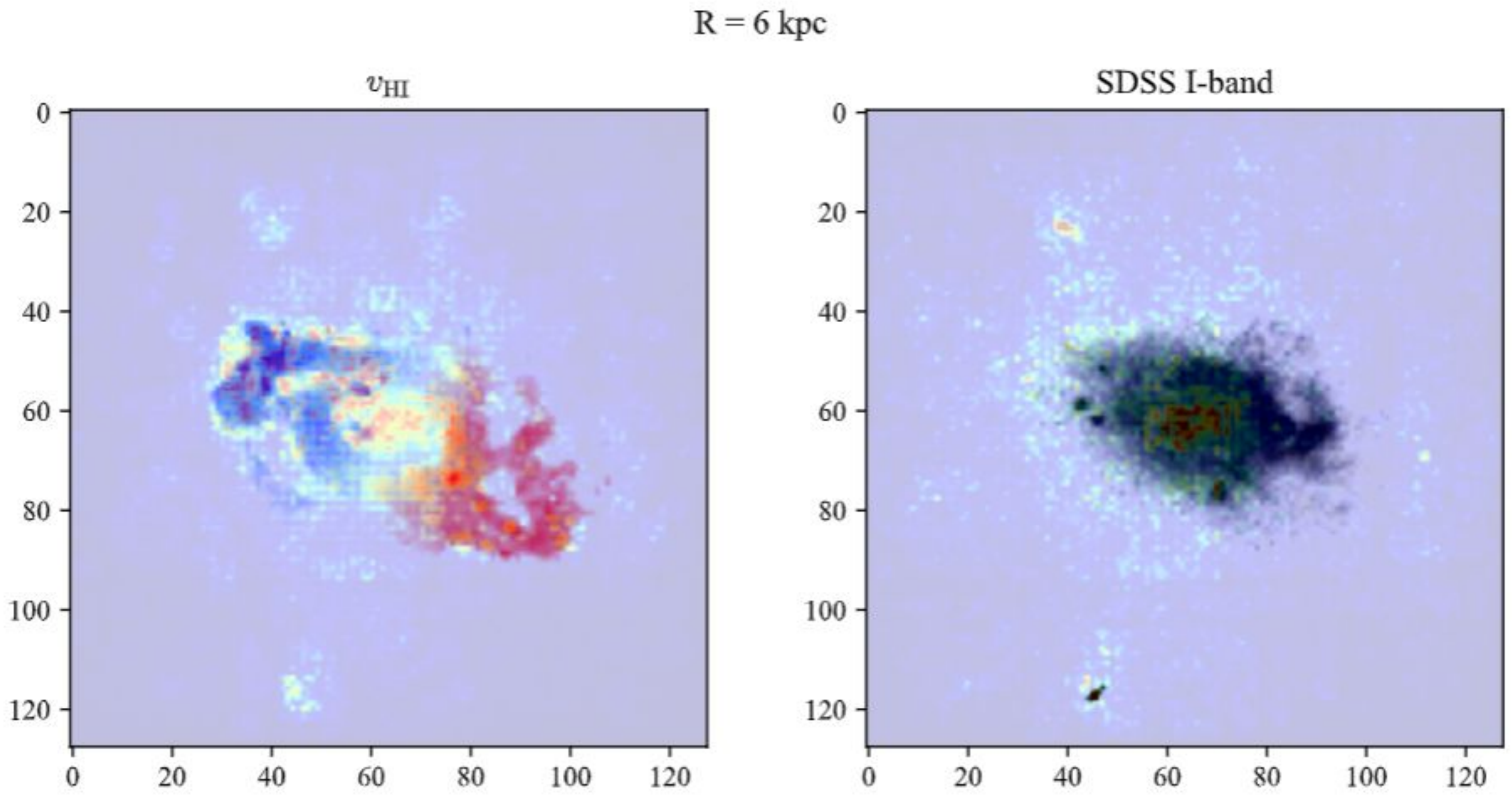

SDSS U-band [MJy/sr]
SDSS G-band [MJy/sr]
SDSS R-band [MJy/sr]
0
20
40
60
80
100
120
0
25
50
75
100
125
250
200
150
100
50
SDSS U-band [MJy/sr]
SDSS G-band [MJy/sr]
SDSS R-band [MJy/sr]

Layer	Details
2D convolution	64 kernels, 5×5 px kernel size, 2 px stride, ReLU activation
2D max pooling	2 px pooling
Dropout	50% dropout fraction
Batch normalization	
2D convolution	128 kernels, 5×5 px kernel size, 2 px stride, ReLU activation
2D max pooling	2 px pooling
Dropout	50% dropout fraction
Batch normalization	
2D convolution	256 kernels, 5×5 px kernel size, 2 px stride, ReLU activation
Batch normalization	
Dense	256 units, ReLU activation
Dropout	50% dropout fraction
Batch normalization	
Dense	128 units, ReLU activation
Dropout	50% dropout fraction
Batch normalization	
Dense	64 units, ReLU activation
Dropout	50% dropout fraction
Batch normalization	
Dense (output)	20 units, linear activation

Results

Understanding the results

$$S_{ij} \equiv \frac{\partial y}{\partial x_{ij}}$$



Results

Understanding the results