Machine Learning and Morphological Measurement of Galaxies

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Introduction

Motivation

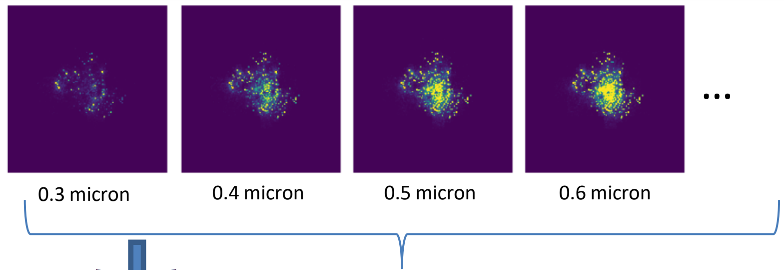
Now we can have pretty galaxy images with the JWST, but pretty images are not the end of a story. Many **morphological measurements of a galaxy** (measurements of shape, physical appearance of a galaxy) **require multiple steps of calculation**. In this project **Machine Learning (ML)** is used to bypass such steps and as **a new method** of calculating **half-mass radius (r50).**

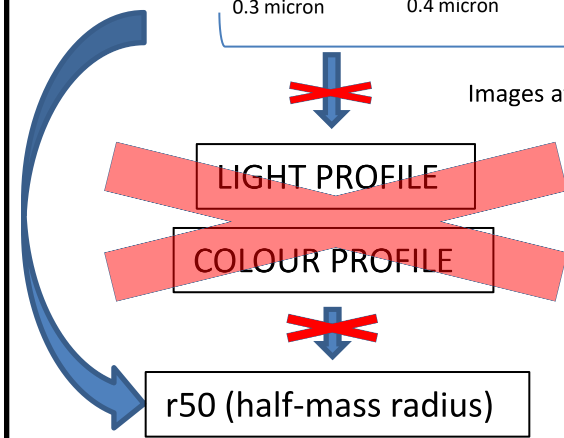
Why Machine Learning (ML)?

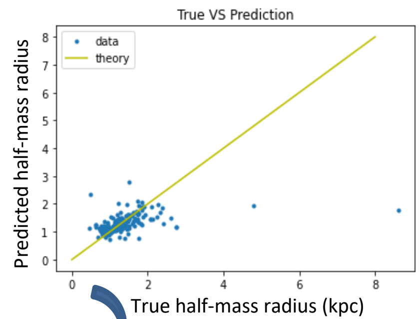
ML allows to skip some steps. **It can take in raw images as input and predict their corresponding r50 as output.** The **additional advantage** of skipping those steps is that there is **no need of pre-assumptions**.

What is half-mass radius (r50)?

Half-mass radius (r50) in this project is **radius of a galaxy that contains 50% of stellar mass.** It is widespread morphological measurement, one of key characteristics a galaxy has.

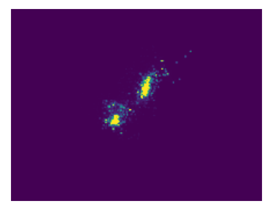






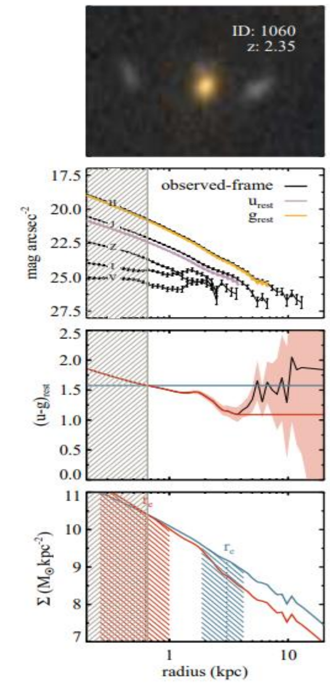
Performance of the CNN

The yellow line represents perfect match between true r50 values and predictions from the CNN. It shows that **the trained CNN works decently overall, except maybe when true r50 is big (> 4)**. But this might be because the **test image itself is not a good example** of a normal galaxy. The image on the right is one of galaxies that has a quite inaccurate prediction. This **galaxy consists of two separate bodies** unlike others. Perhaps this caused its **unusual size of r50** and made **the CNN to produce the wrong estimation** .



Ugly galaxy

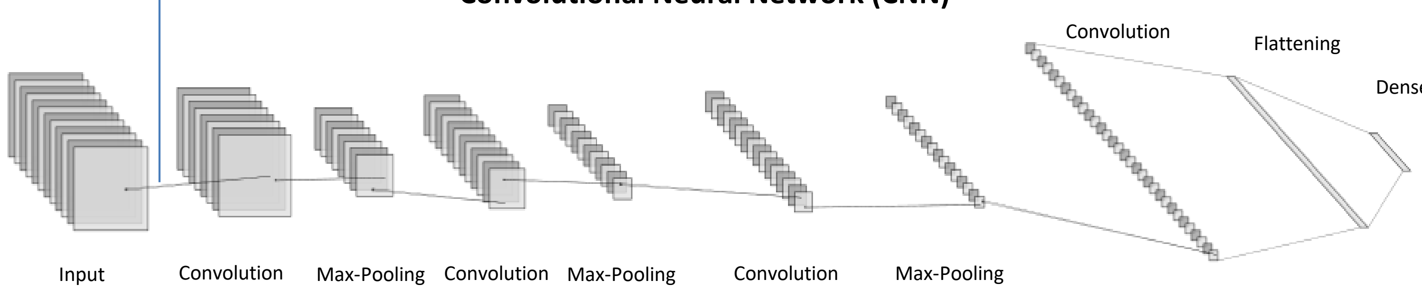
The traditional way



(Szomoru et al., 2012)

This is a usual way of calculating stellar mass profile. From the top: (Image → brightness profile → color profile → mass profile)

Convolutional Neural Network (CNN)



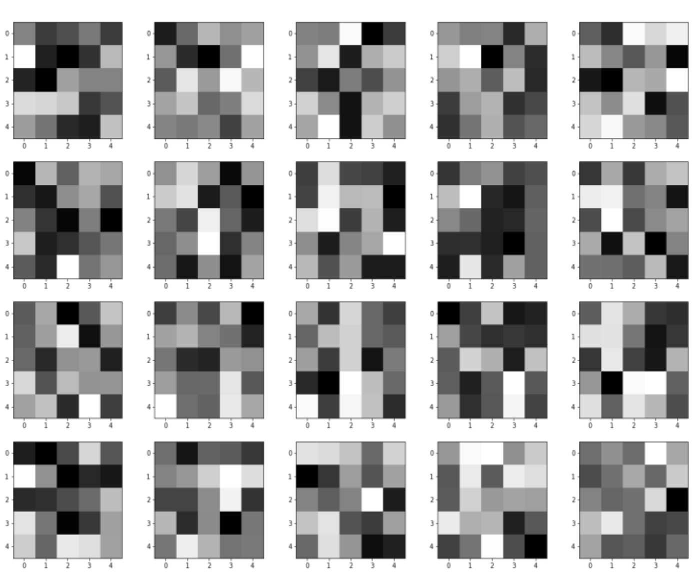
Convolutional Neural Network or CNN is a type of artificial neural network that has particularly **good performance with image inputs.** The above figure is a visualization of the CNN used in this project, and the followings are the names and functions of each layer.

- **Convolutional layer:** A layer with multiple **filters convolving across the input images** and **capturing key features**
- **Max Pooling layer:** A layer that decreases size of the convolution and **helps to capture larger features** in next convolutional layer
- **Fully connected layer:** Usually the last layer of CNN. It **takes information from previous layers and predicts output** (which is r50 in this project)

How does it learn?

In this project **artificial neural network (ANN)** is used and it has fairly conceptually simple way to 'learn' from training data. When an ANN is built, **two things are needed** other than shapes of each layer; a loss function and an optimizer. A **loss function** is a function that **quantifies errors** in an ANN's predictions. An **optimizer** is a method of **improving weights and biases** (changeable parameters of ANN) based of the loss function. As a result an ANN can improve its parameters for better predictions and hence 'learning'.

Filters



How does convolutional layer work?

What is this figure?

The figure on the left is a part of the **set of filters** of the first convolutional layer. Each column is a set of filters for each image at different wavelength. These filters convolve across the images and **captures features that are similar to their shapes.**

Why multiple convolutional layers?

There are 4 convolutional layers in the CNN for this project. Technically there can be only one convolutional layer with a lot of different filters to do the same calculation with similar accuracy. However, machine learning with **only one layer** of neural network to solve fairly complicated problems would often **require tremendous amount of time**. It is like measuring size of the Earth with a meter stick.

At each convolutional layer filters capture different level of features. For example, first layer captures shapes of edges of a galaxy, next layer captures more general shapes such as combination of the edges from the previous layer, and so on.

Future Prospects

This project shows that **machine learning can be used widely in making measurements** of celestial objects. The same or similar pipeline can be applied to train the CNN for **other morphological measurements**, perhaps even for **images that are** currently considered as **too distorted** to make any measurements.

Reference

- Szomoru, D., Franx, M., van Dokkum, P. G., Trenti, M., Illingworth, G. D., Labbe, I., & Oesch, P. (2013). The Stellar Mass Structure of Massive Galaxies from z= 0 to z= 2.5: Surface Density Profiles and Half-mass Radii. *The Astrophysical Journal*, *763*(2), 73.