Distilling physics from astronomical imaging

John F Wu STScI · JHU

Kavli Institute for Theoretical Physics
galevo23 conference

2023-03-21

Roadmap

I. The growth and evolution of galaxies

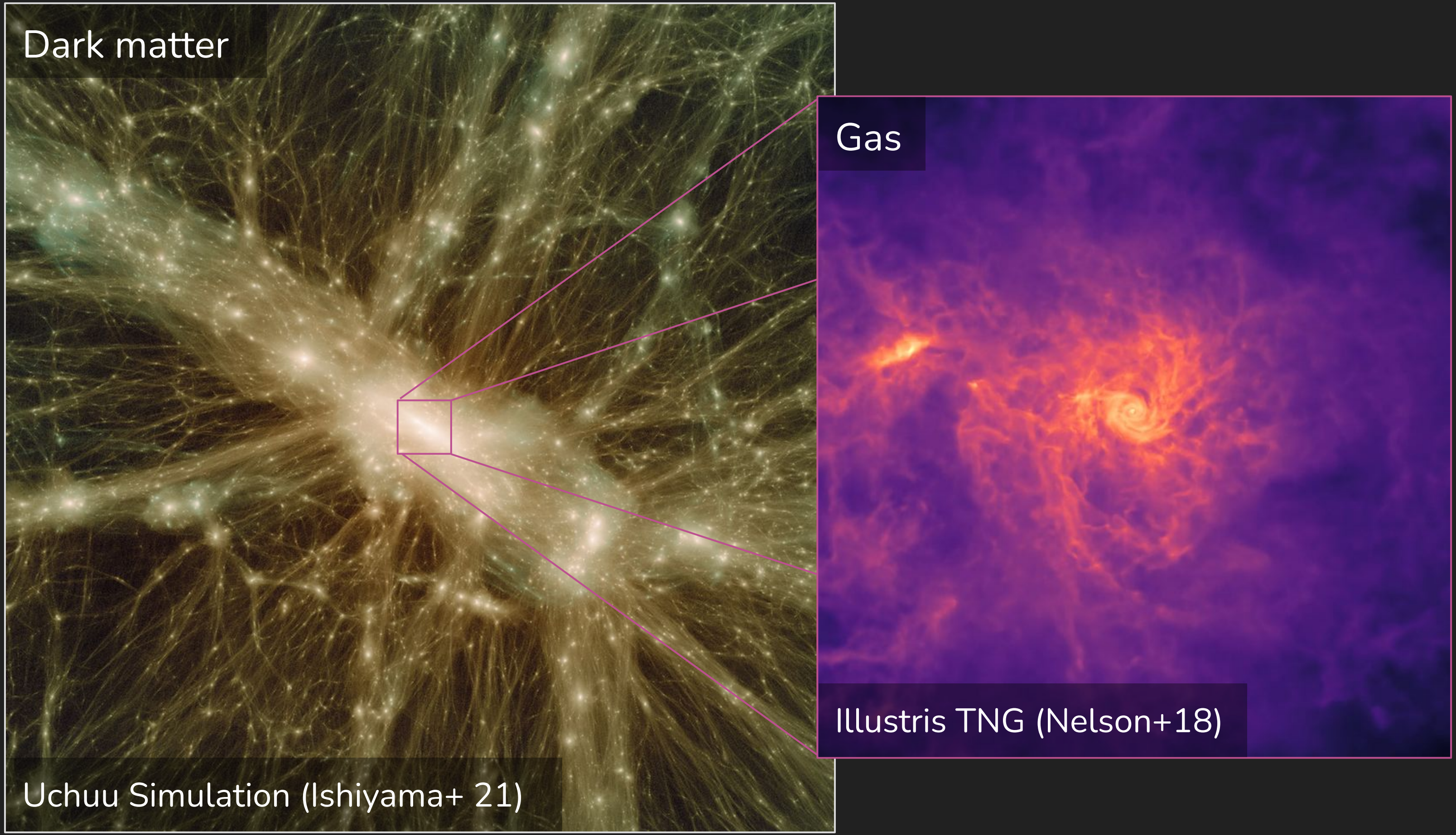
II. Convolutional neural networks

III. Extending the SAGA survey with CNNs

Roadmap

I. **The growth and evolution of galaxies**
II. Convolutional neural networks
III. Extending the SAGA survey with CNNs

Galaxies grow via gas accretion, star formation, and merging



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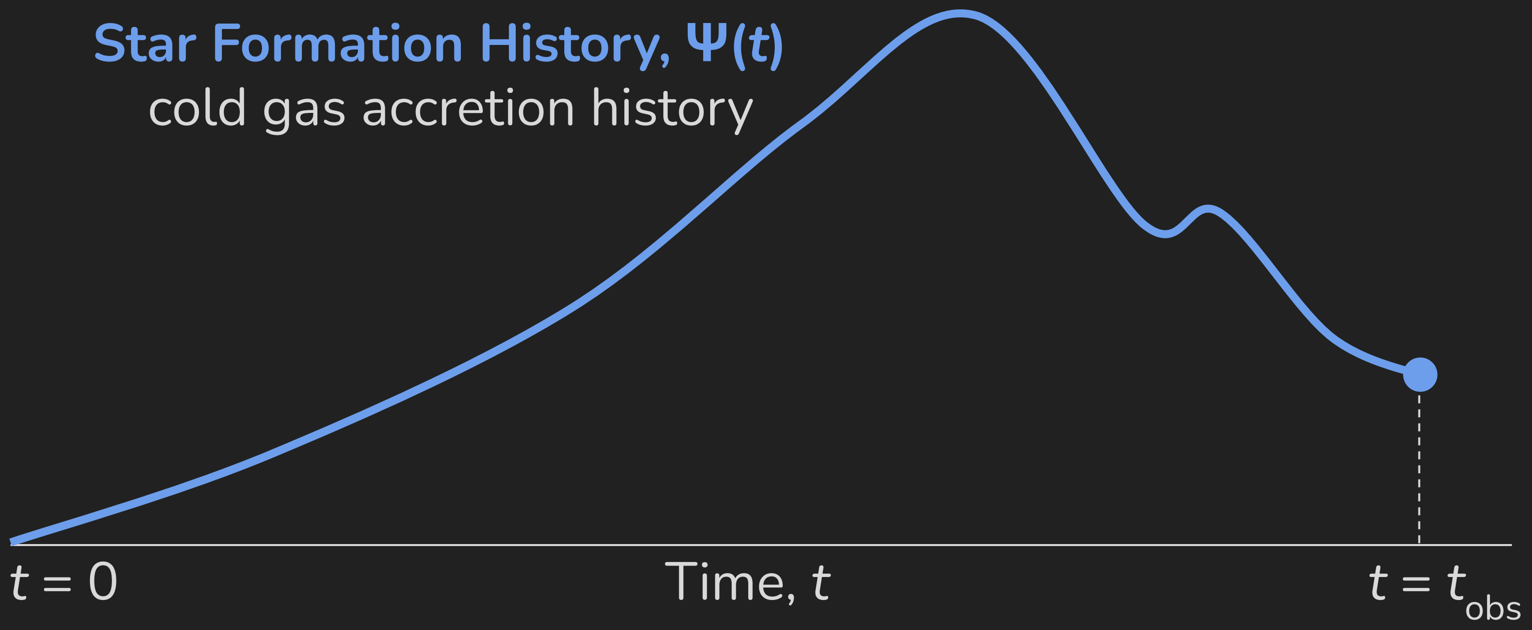

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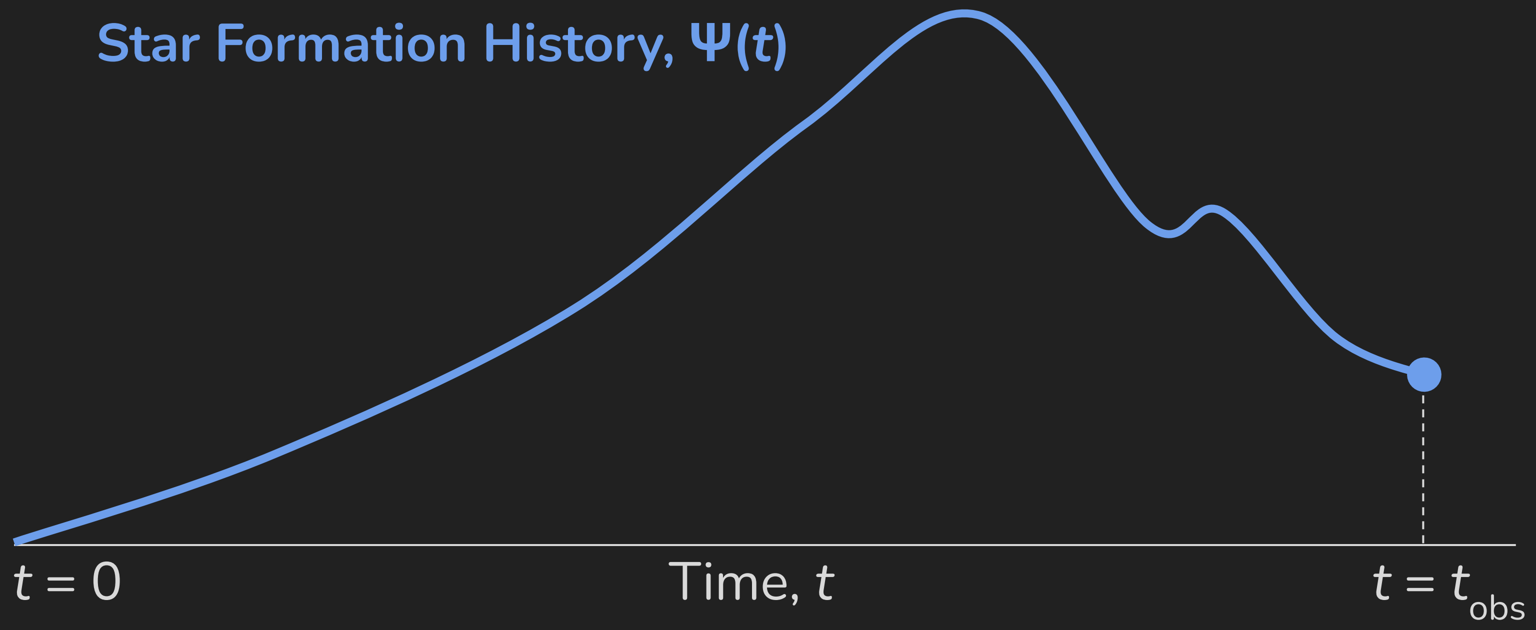
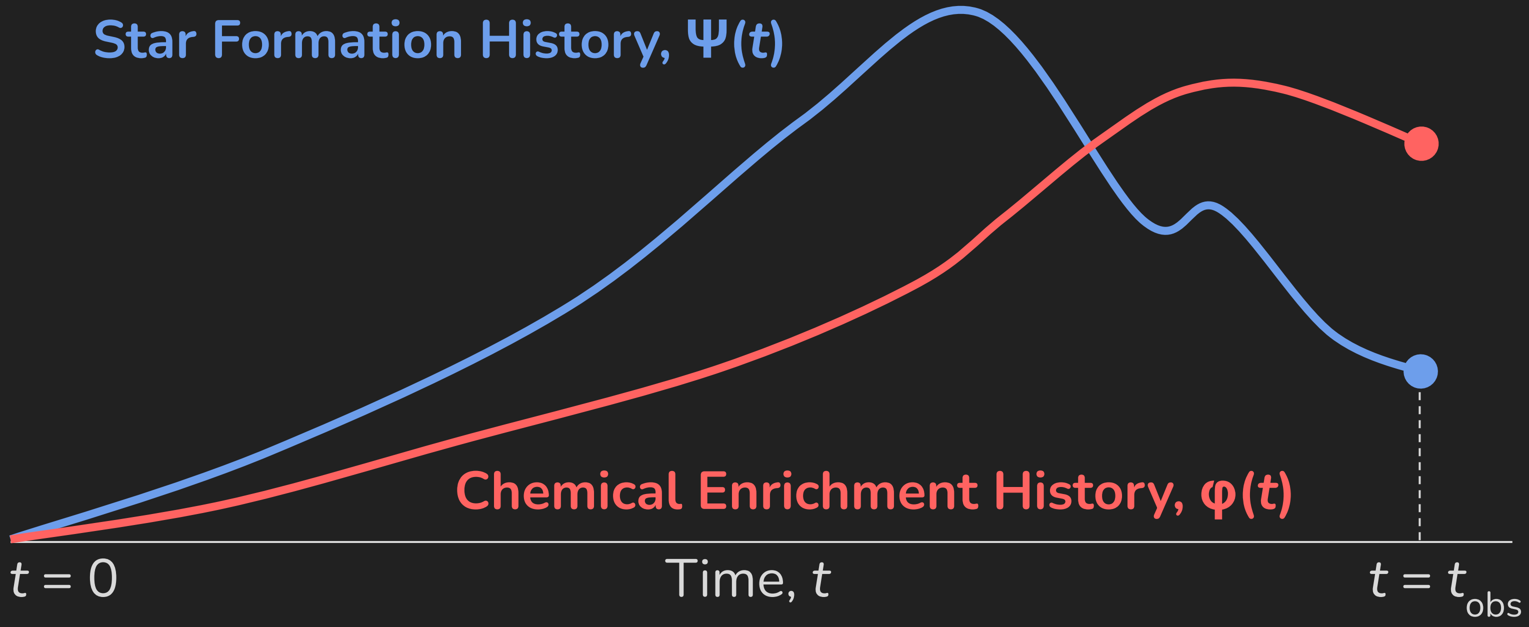


Heavy element production follows star formation

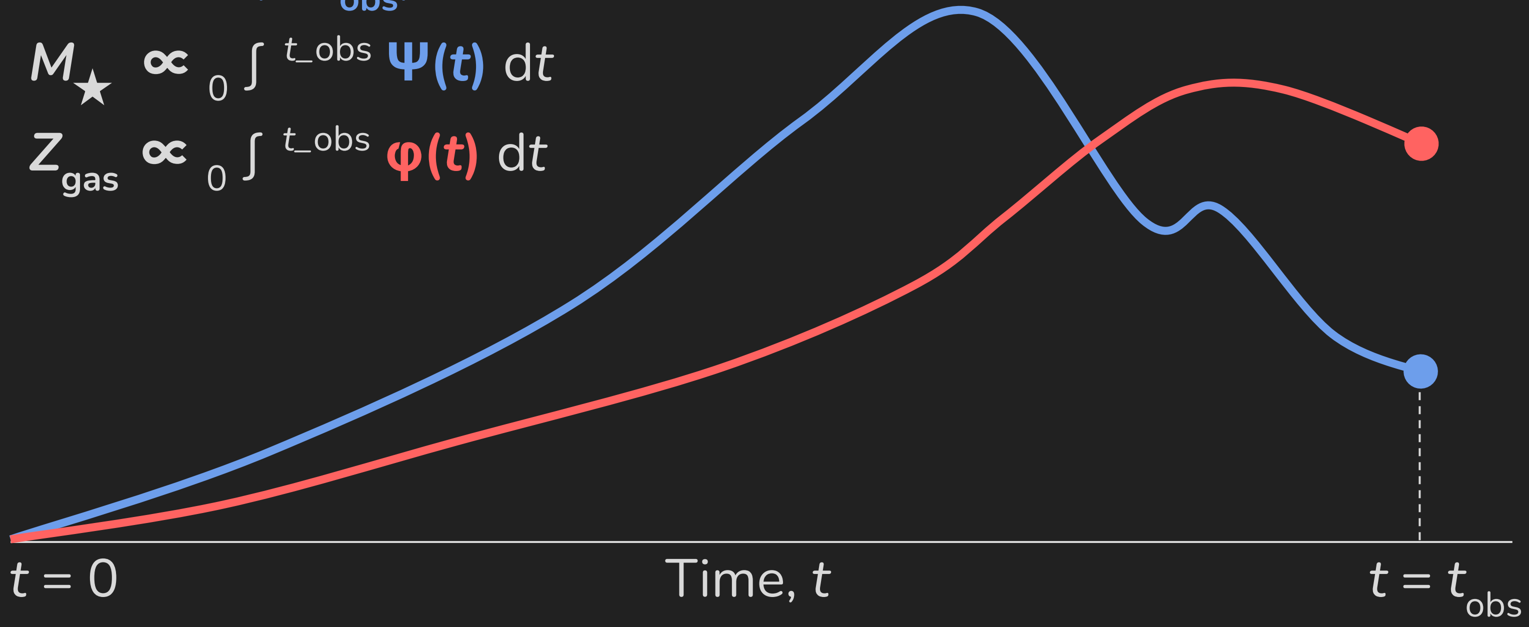


Models map physical processes to observables

$$\mathrm{SFR} = \Psi(t{=}t_{obs})$$

$$M_\star \propto \int_0^{t\_obs} \Psi(t)\,\mathrm{d}t$$

$$Z_{gas} \propto \int_0^{t\_obs} \varphi(t)\,\mathrm{d}t$$



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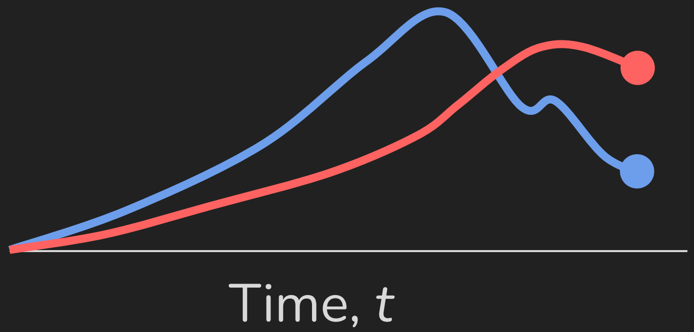

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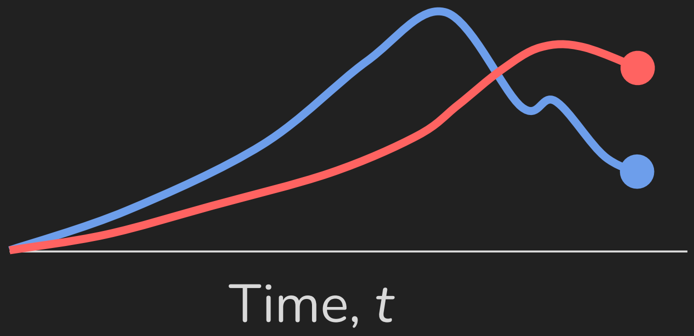

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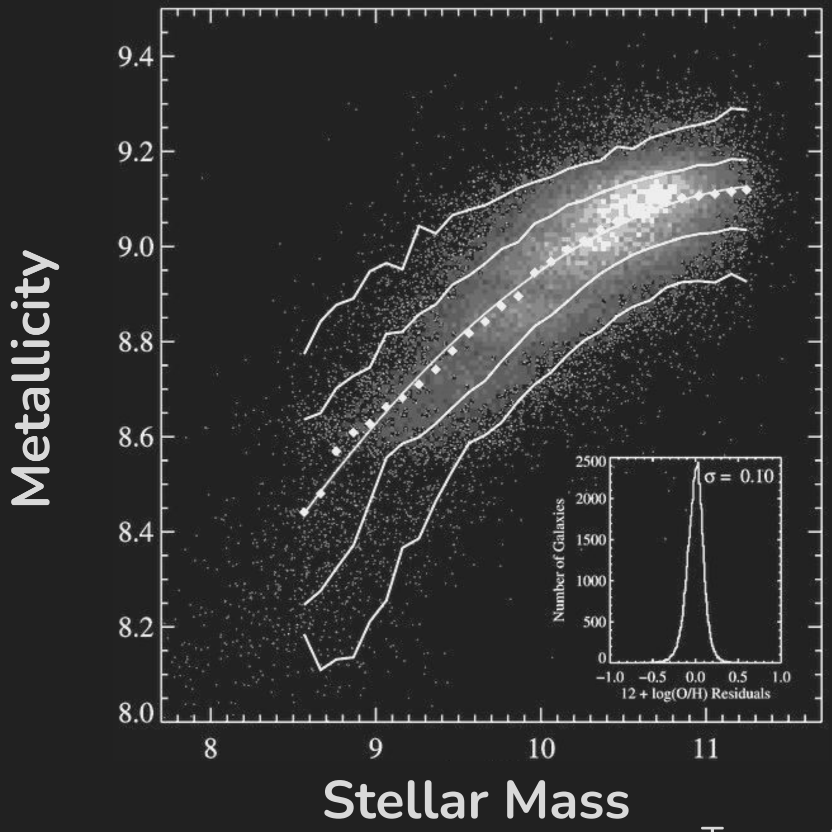
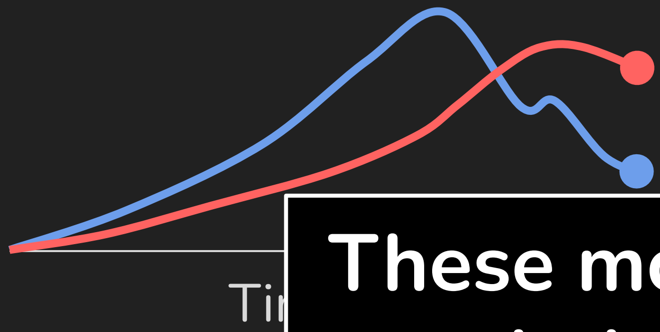


Tremonti+ 04

Models map physical processes to observables



These models don't take morphology into account!

$$M_\star \propto \int_0^{t\_obs} \Psi(t)\, dt$$

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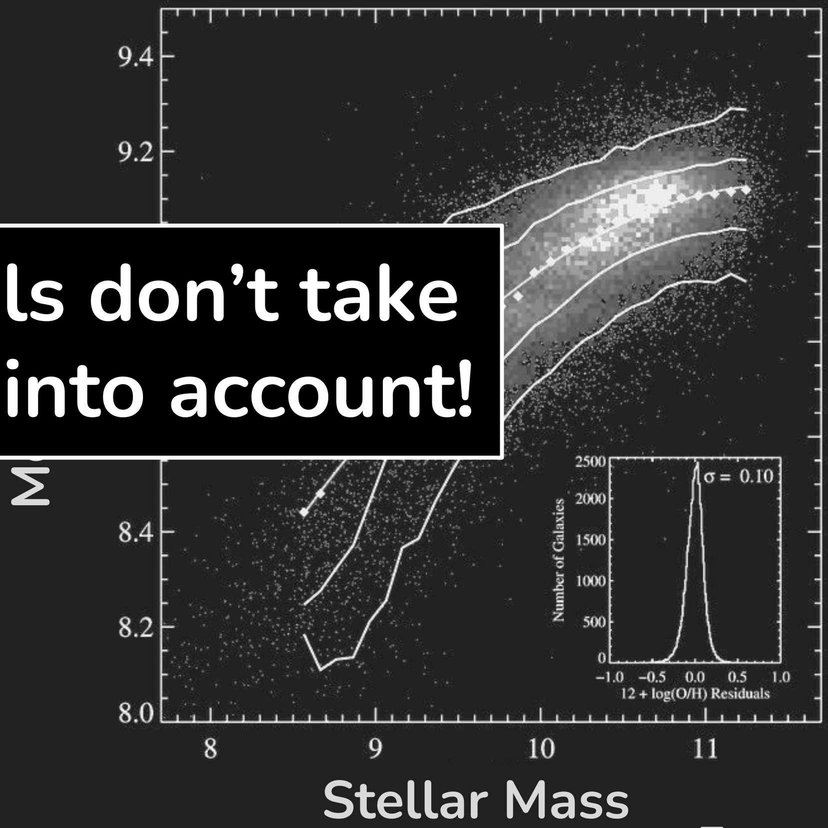
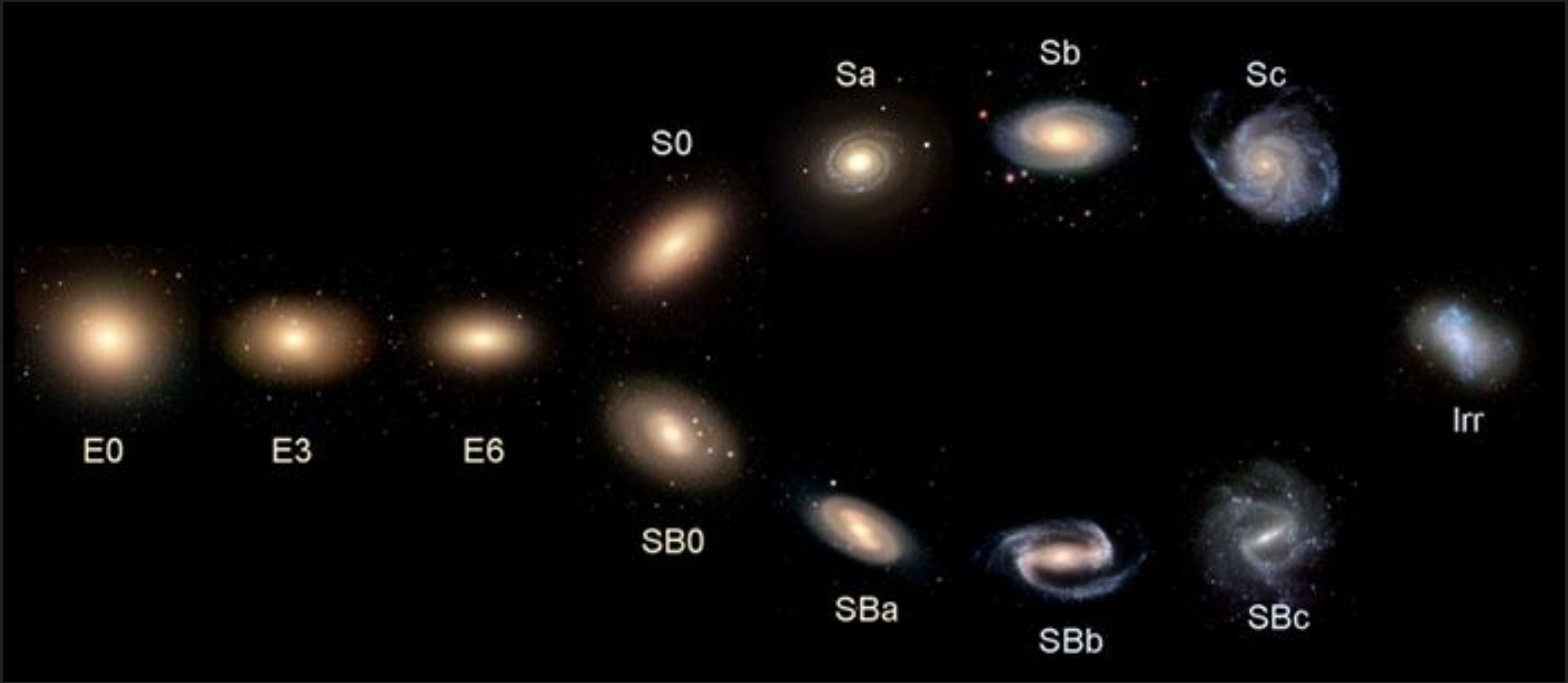


Tremonti+ 04

Physical processes are imprinted on galaxies' morphologies



U. Iowa

An image is more informative than a row in a photometric catalog

g mag	*r* mag
17.50	16.99
17.47	16.97
17.50	17.00
17.46	16.95
17.43	16.93
17.48	16.97
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Legacy Survey DR9 (Dey+ 19)

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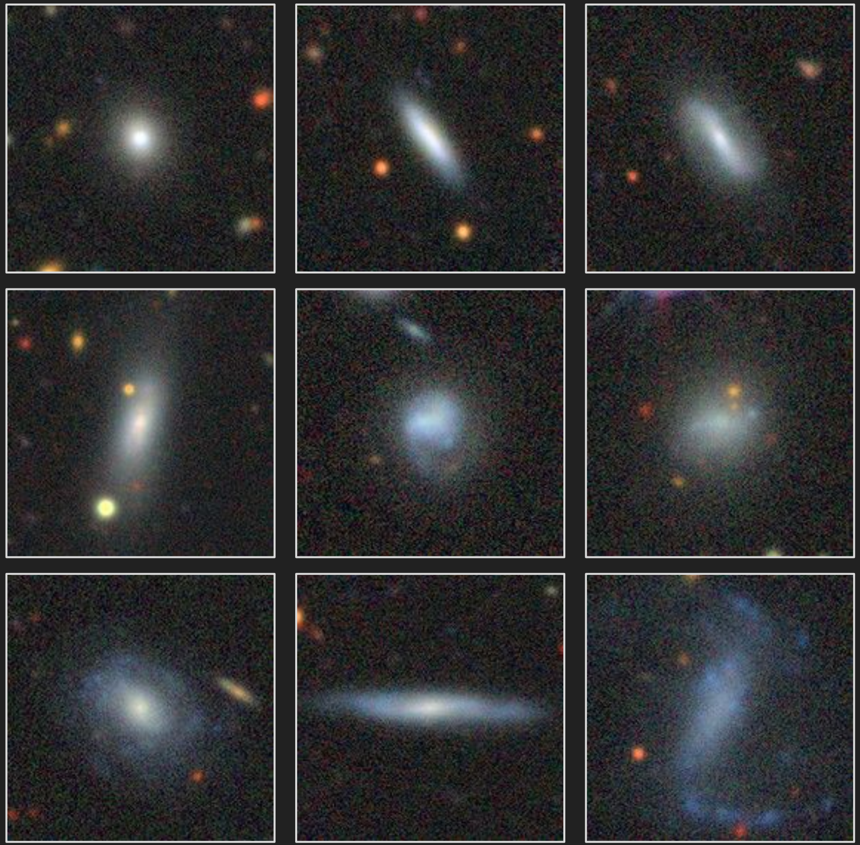

Legacy Survey DR9 (Dey+ 19)

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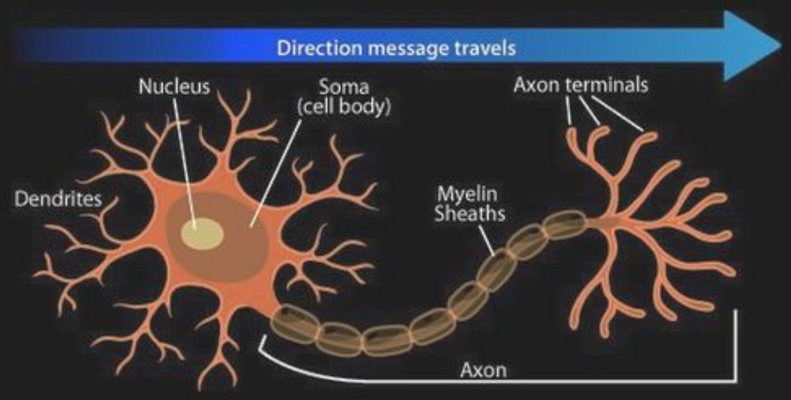
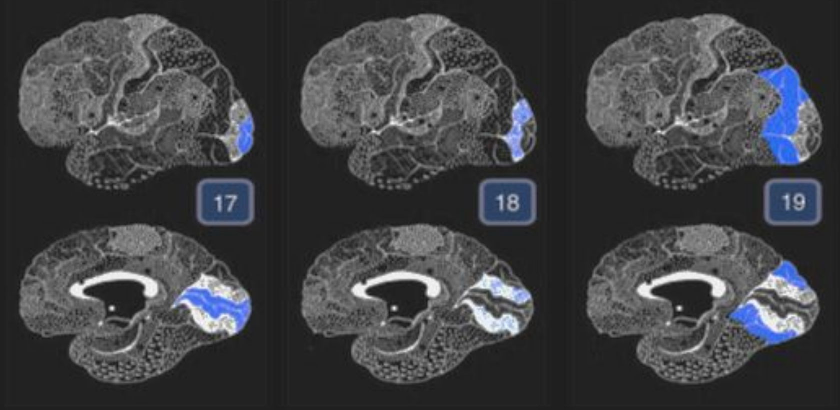
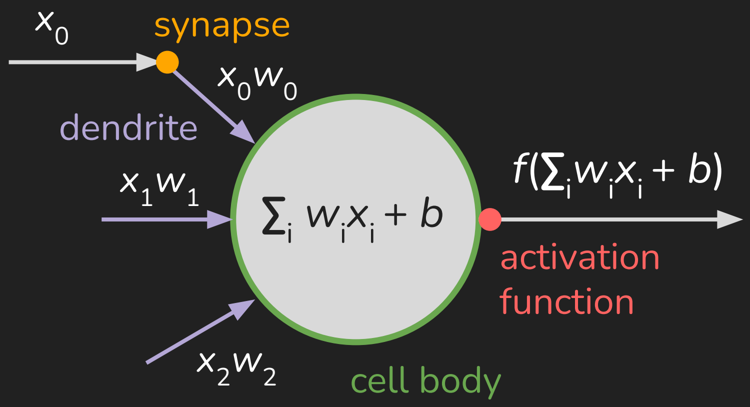
Biological neurons process and propagate signals

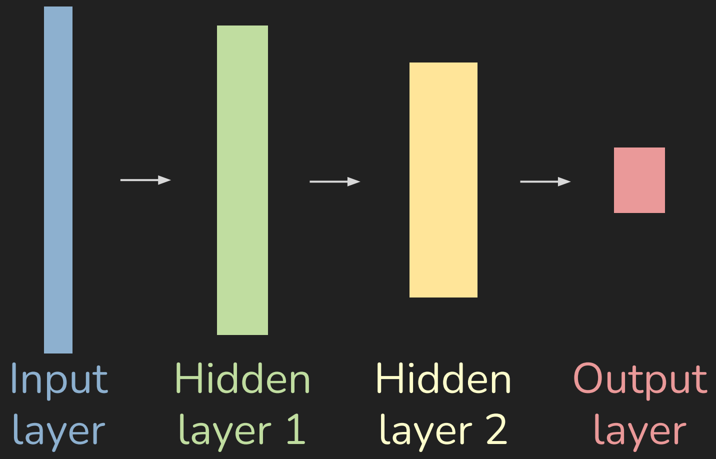




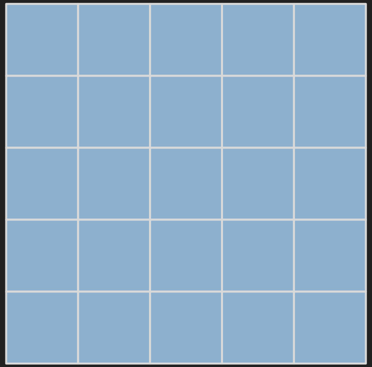
Kuzovkinet+ 18

Artificial neurons process and propagate signals!





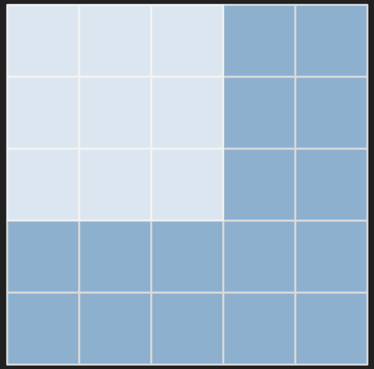
Convolutional layers are just morphological feature finders



Input image

$(x_0, x_1, \ldots)$

Convolutional layers are just morphological feature finders



Input image $\otimes$ morphological feature

$(x_0, x_1, \dots)$ $(w_0, w_1, \dots)$

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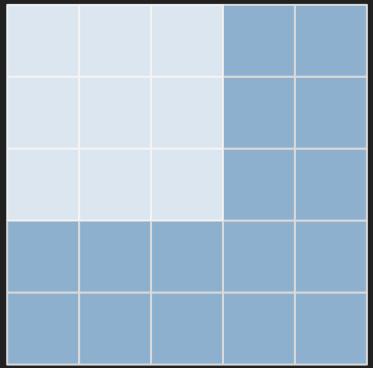

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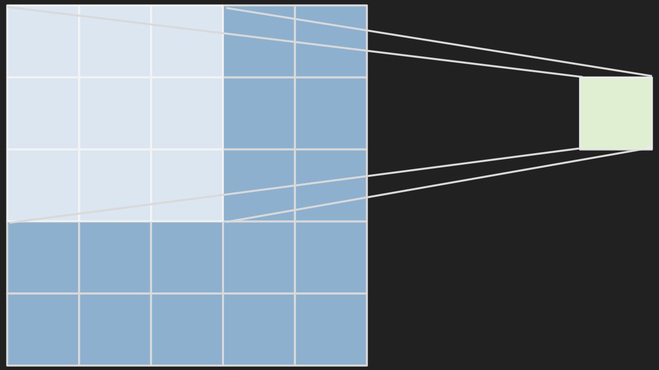
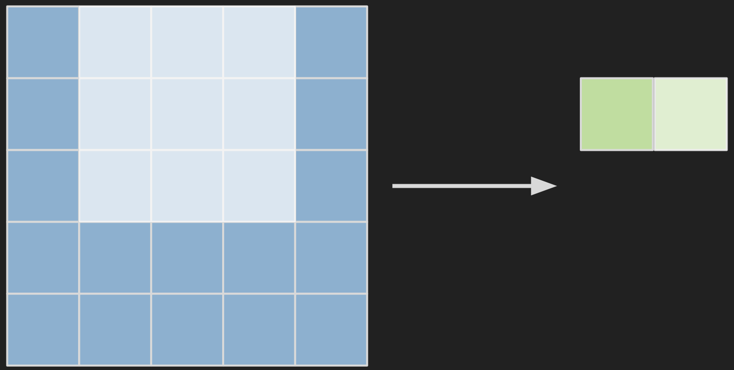


Input image ⊗ morphological feature ⟶ map of features

$(x_0, x_1, \ldots)$ $(w_0, w_1, \ldots)$ $f(\sum_i w_i x_i + b)$

Convolutional layers are just morphological feature finders



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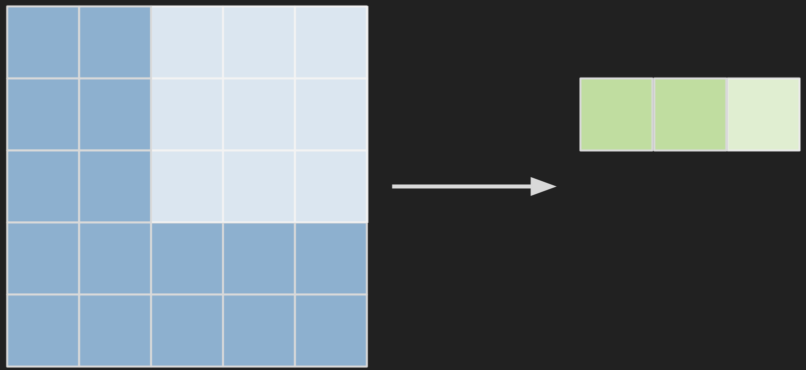

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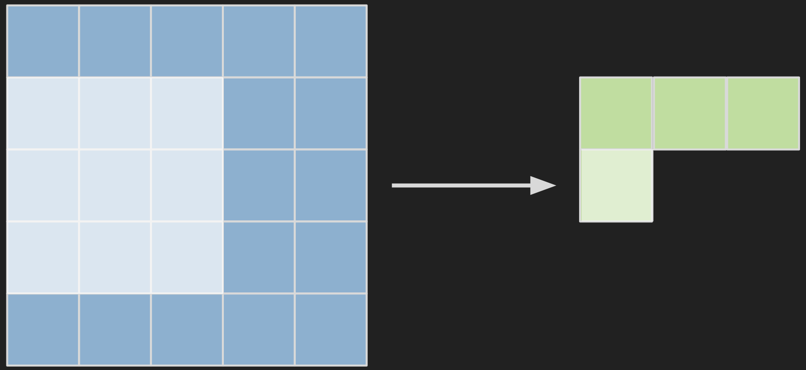

Input image ⊗ morphological feature → map of features

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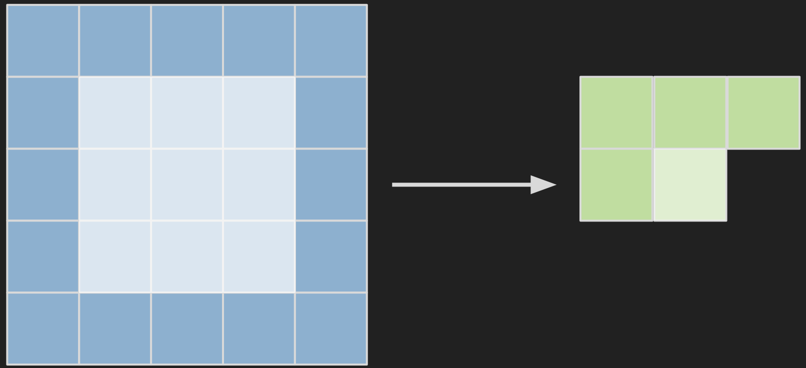

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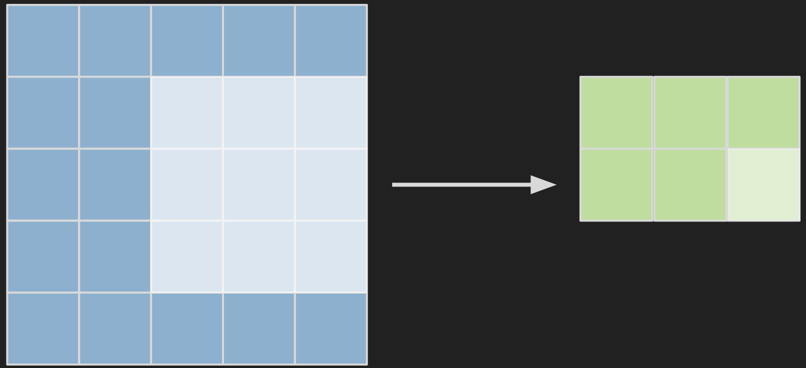

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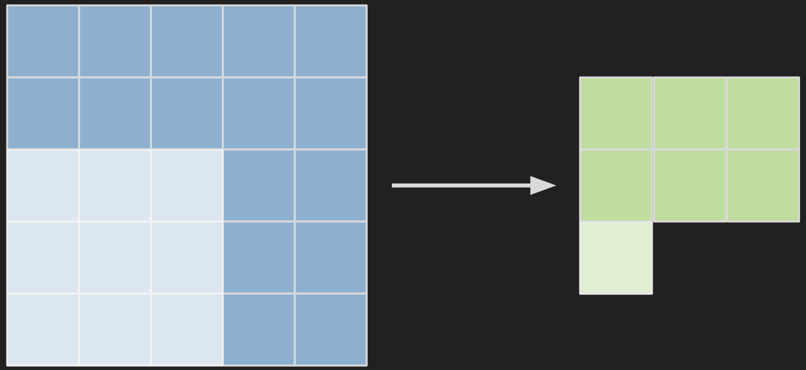

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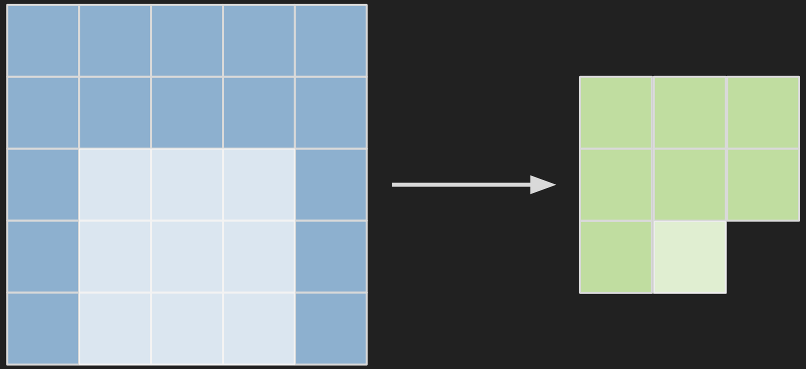

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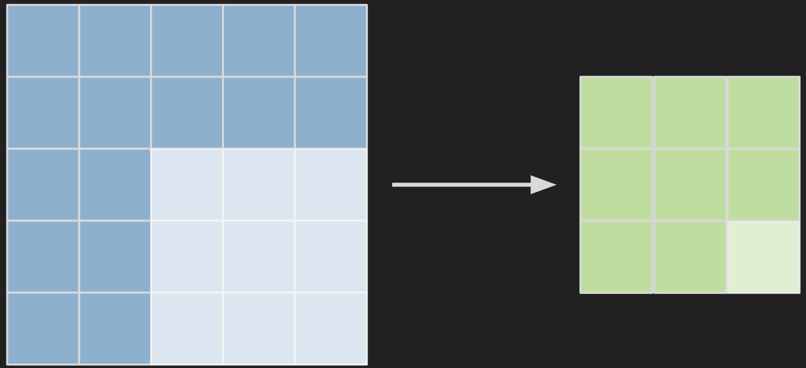

Input image $\otimes$ morphological feature $\longrightarrow$ map of features

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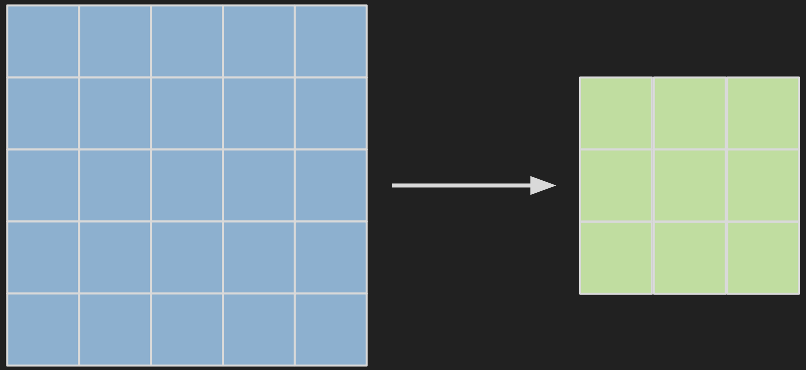
CNNs are just sequential morphological feature finders



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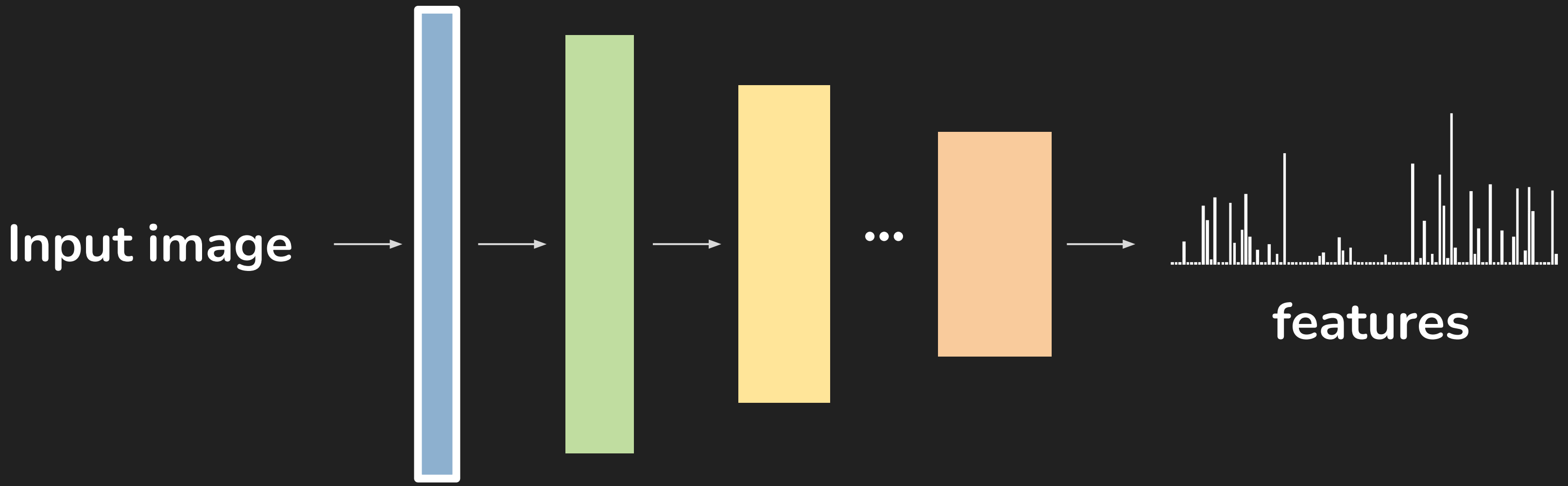

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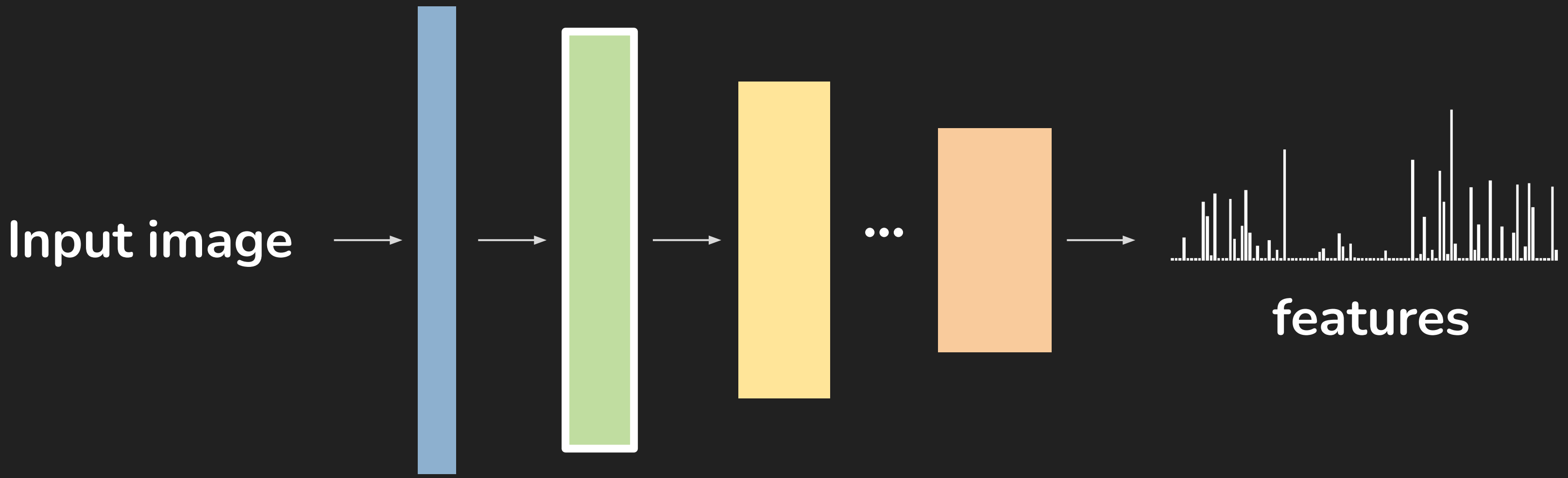

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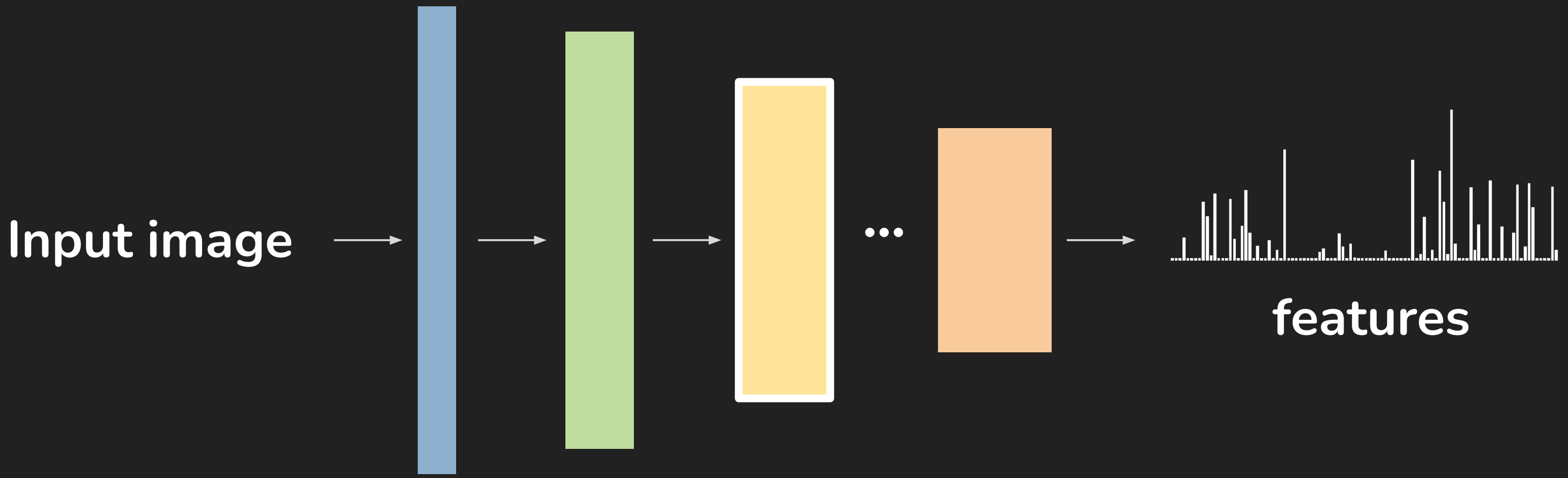

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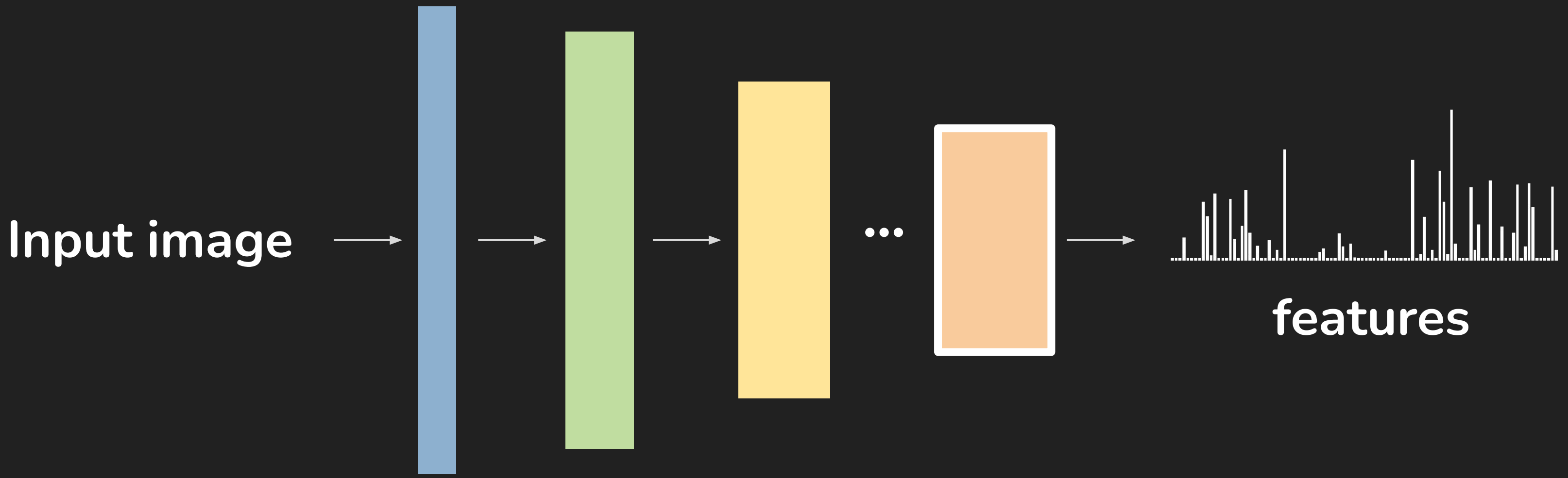

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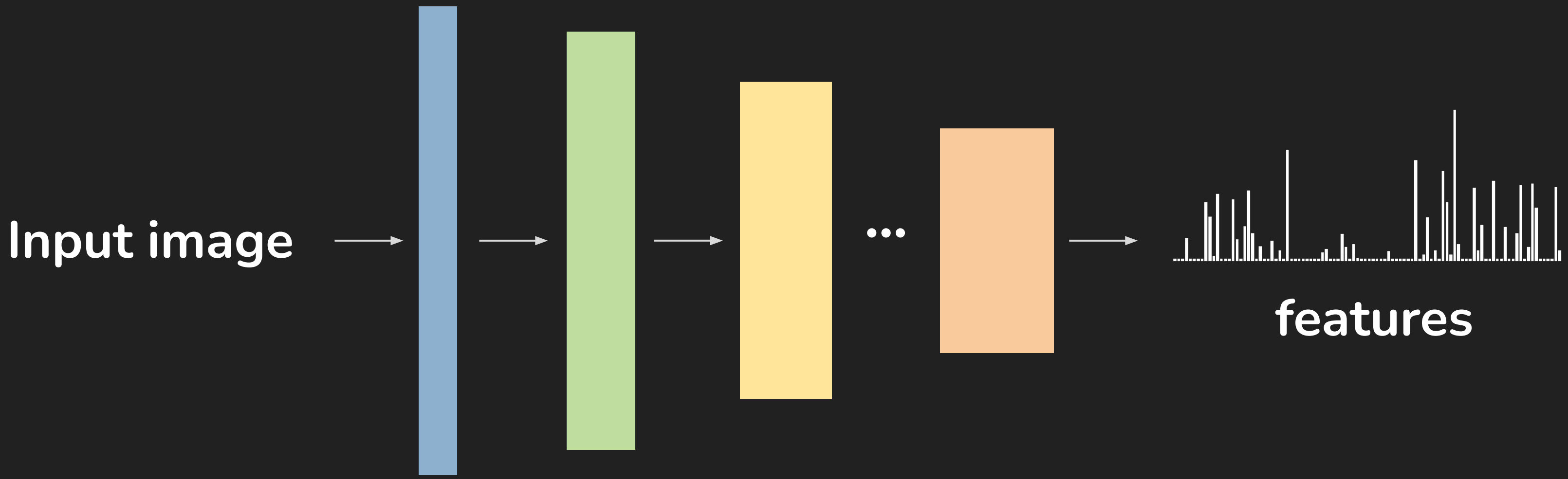

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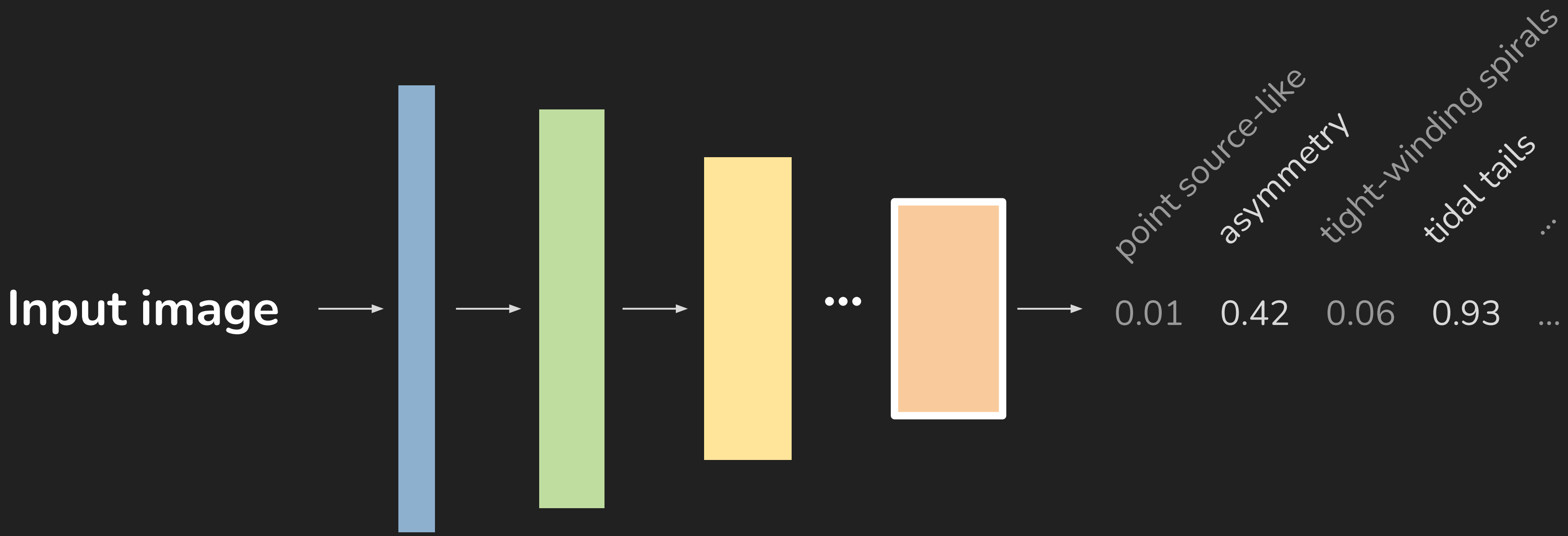

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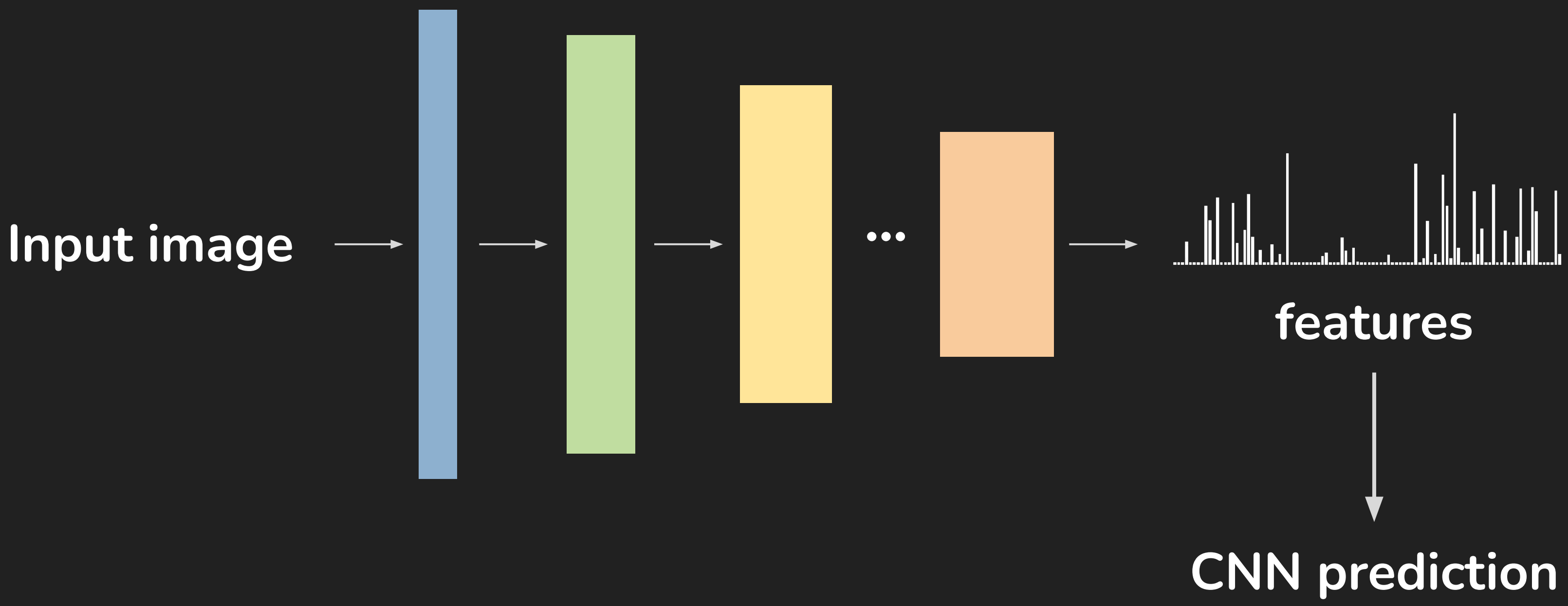

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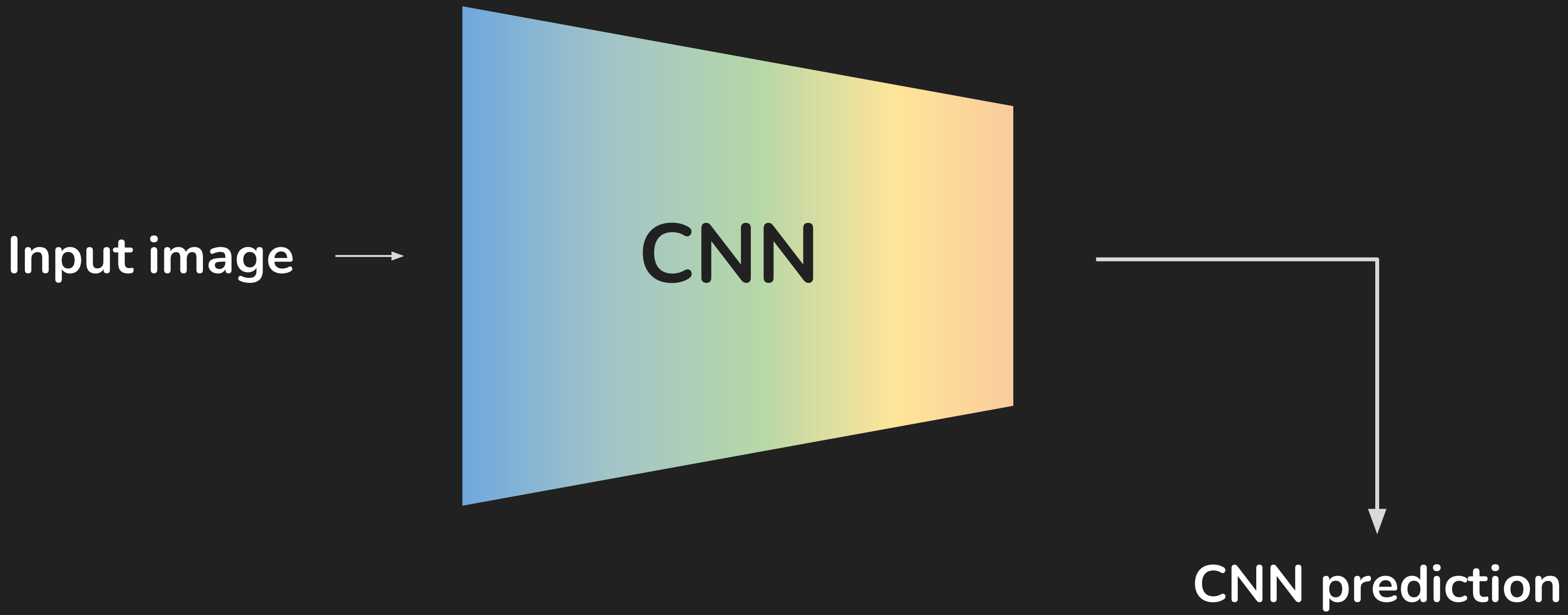
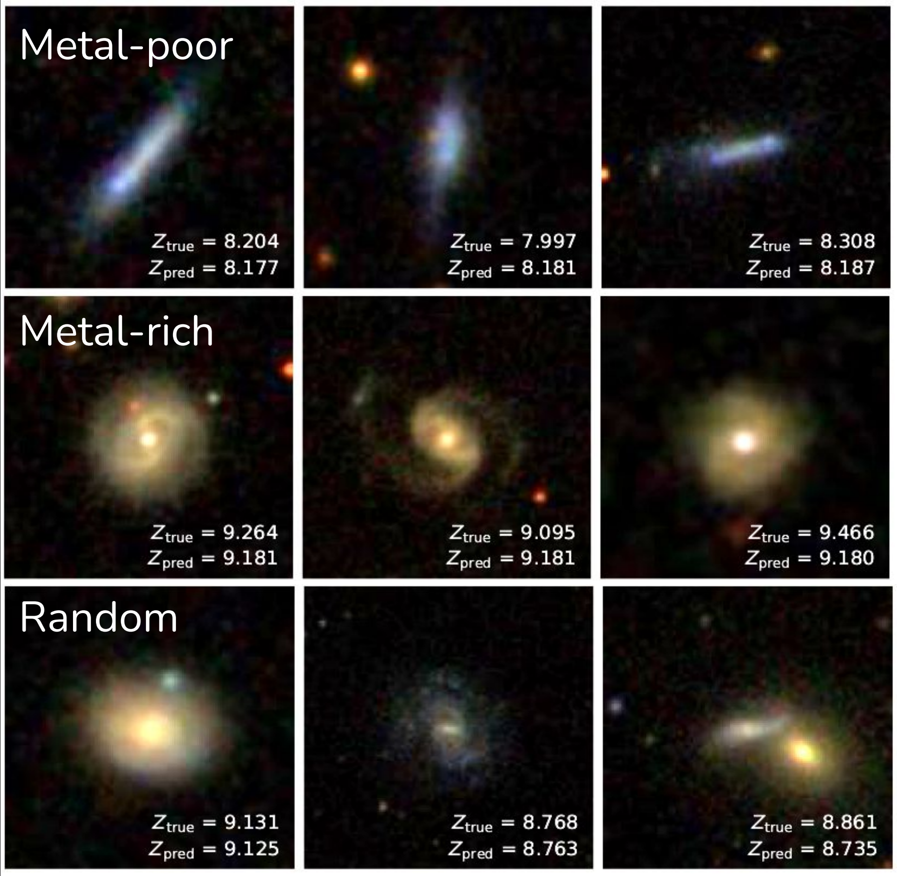
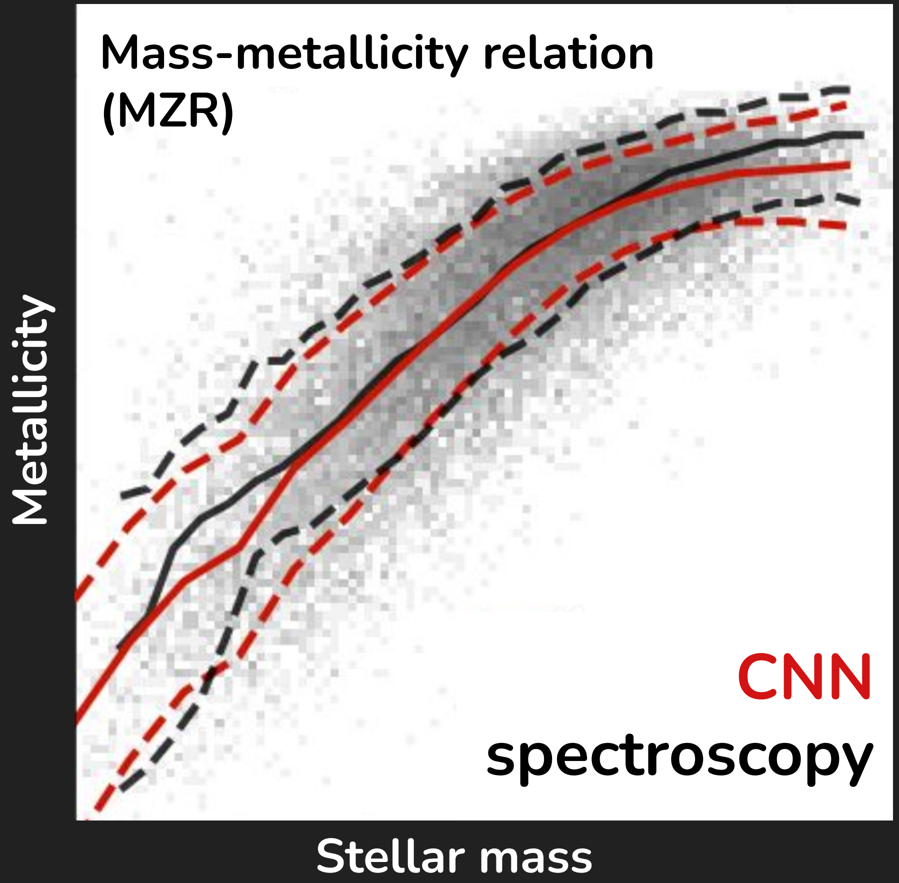


CNNs can estimate spectroscopic properties like metallicity!



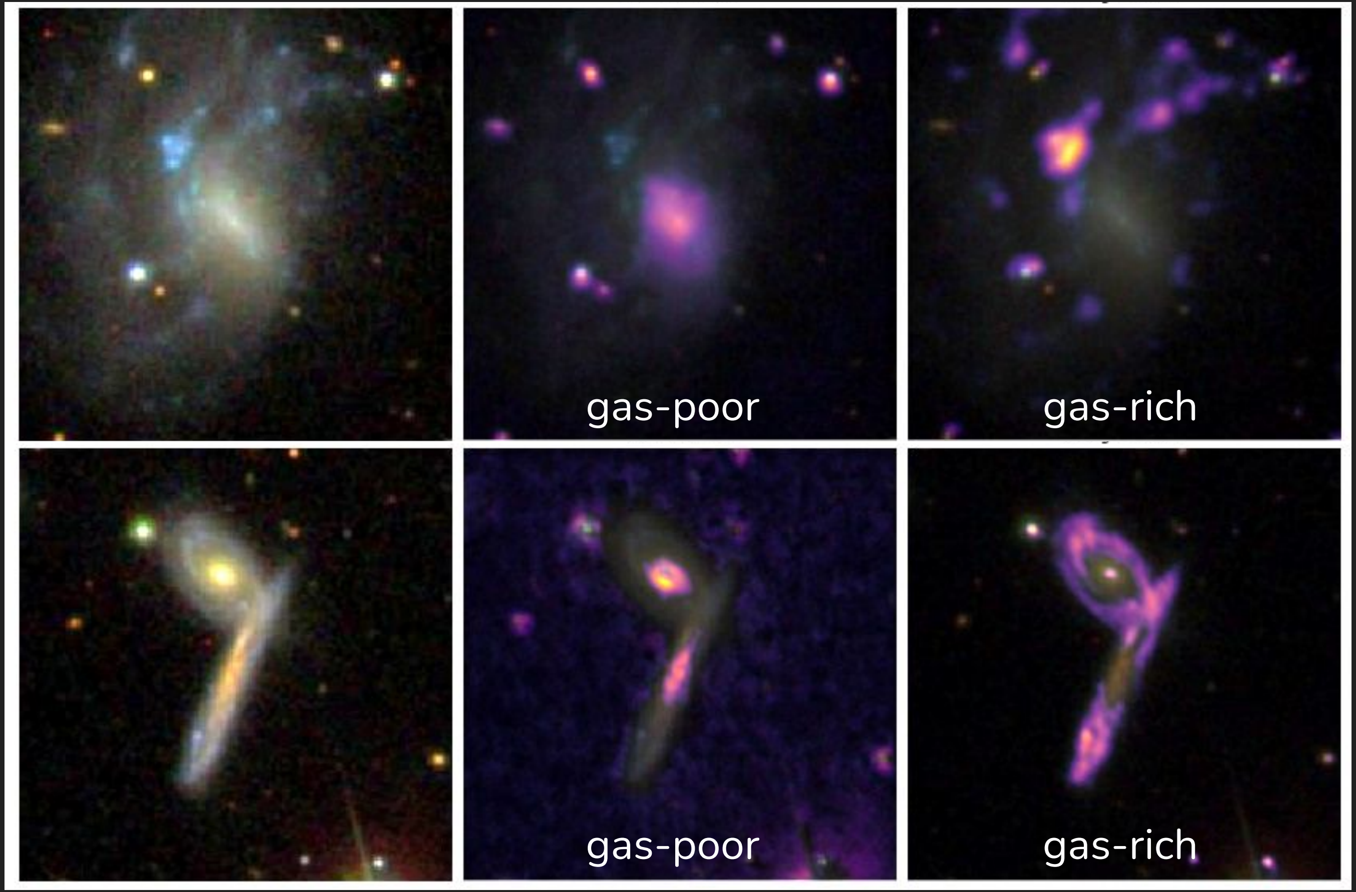
Wu & Boada 19

Re-constructing the MZR *without any spectroscopy*



Wu & Boada 19

We know what CNNs are "looking" at!



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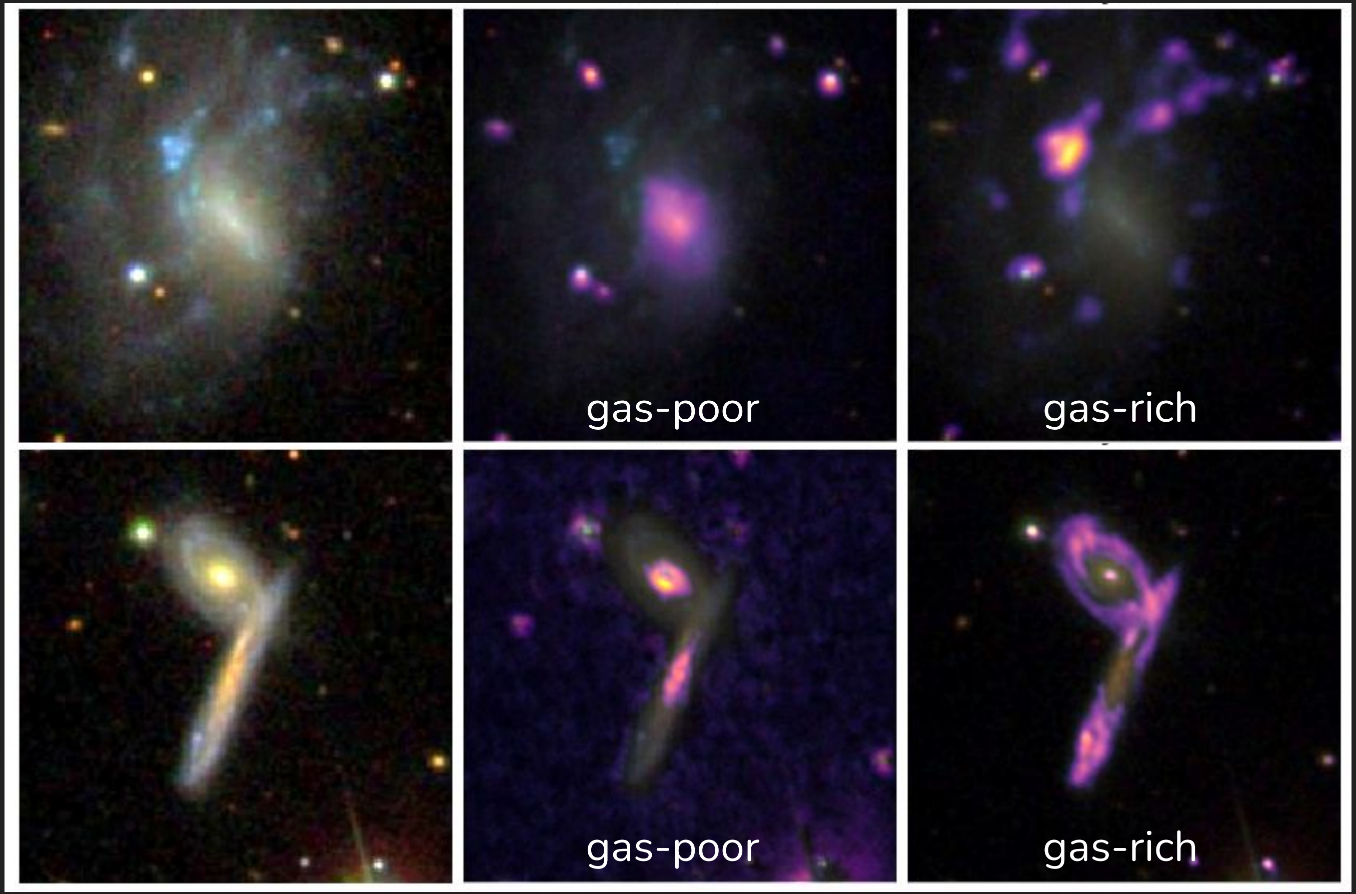
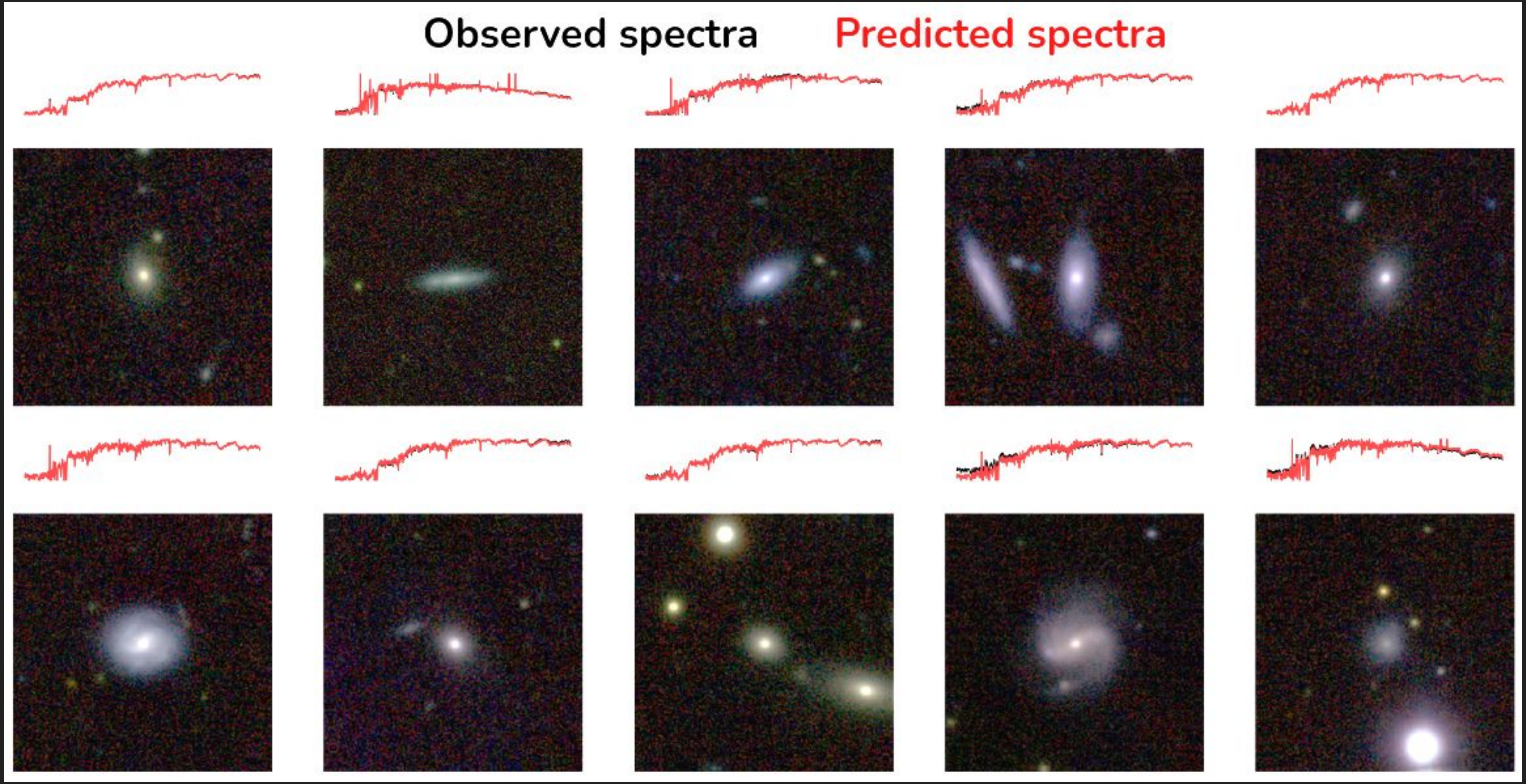


Wu 20

Predict the entire optical spectrum from PS1 imaging



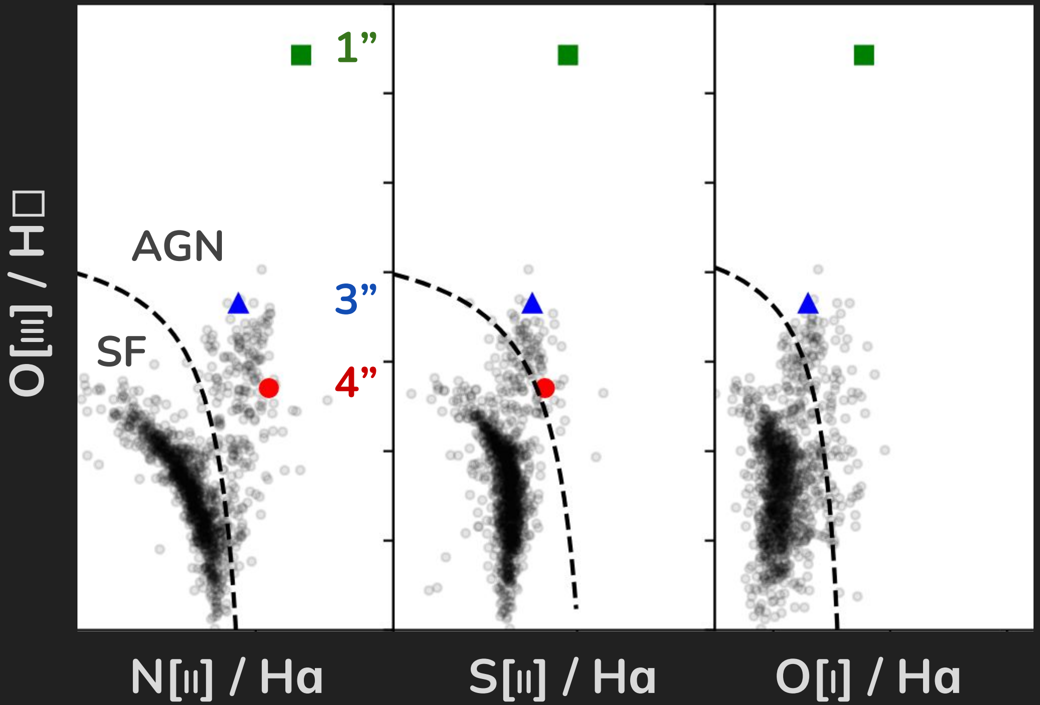
Wu & Peek 20

Passing the test: a weak AGN detected in a bizarre galaxy

70 kpc

Holwerda+ 21

Passing the test: a weak AGN detected in a bizarre galaxy



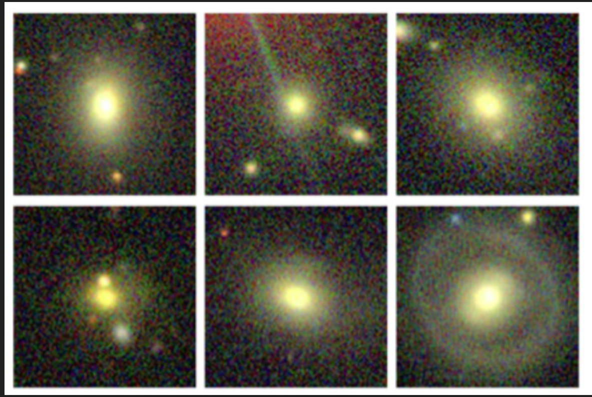
■ VIRUS-P + KPNO 2.1m + Mount Lemmon 60in

▲ **CNN prediction**

● MMT Binospec

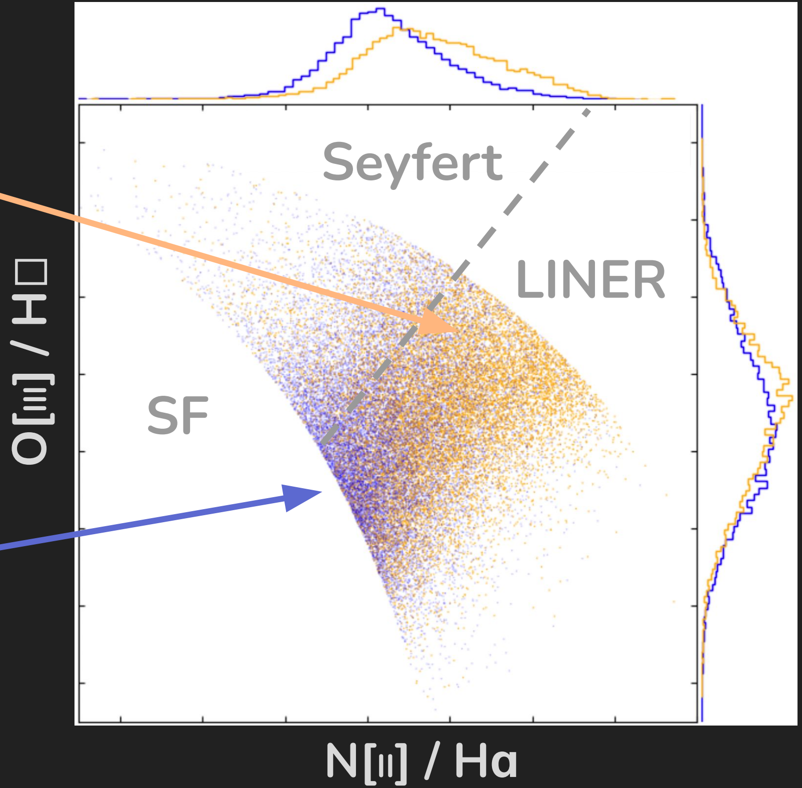
Holwerda+ 21

Identifying LINERs from spectral composites with CNNs?



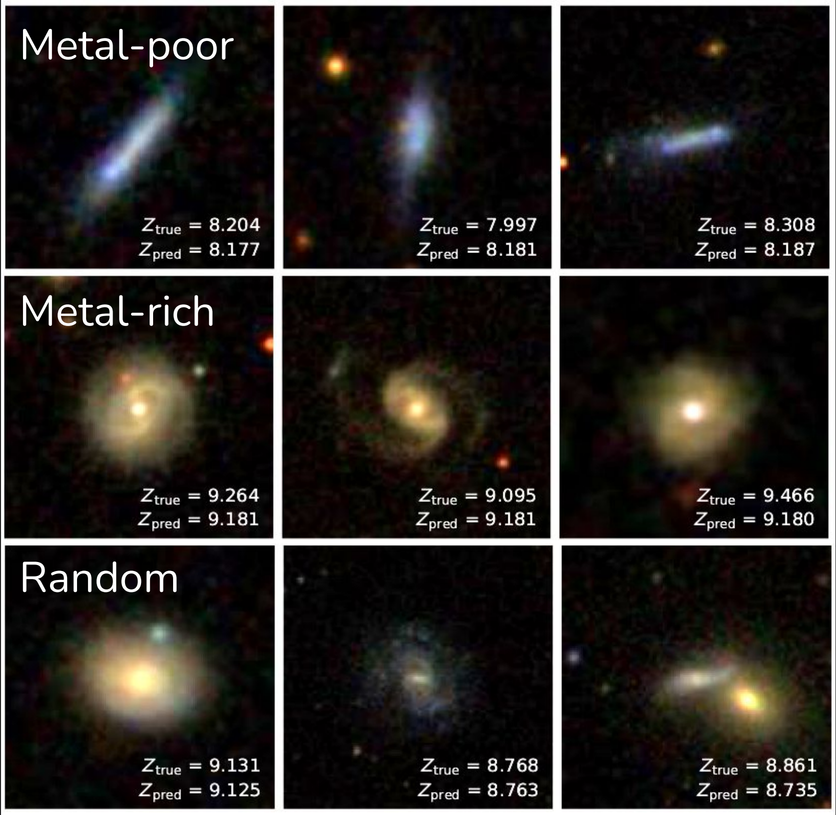
AGN?

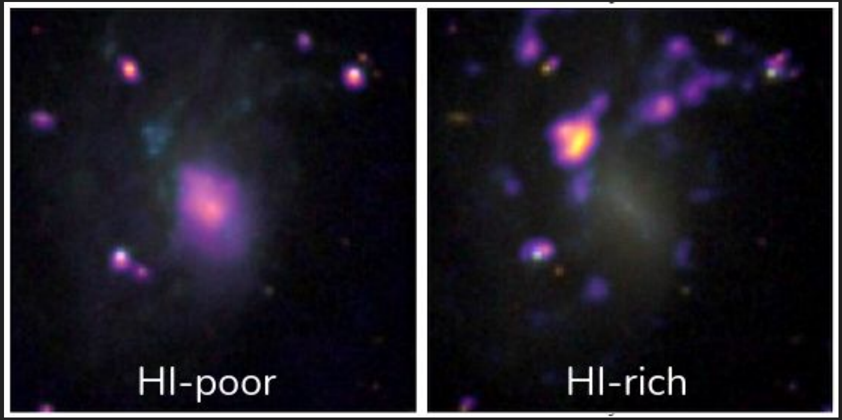
SF?

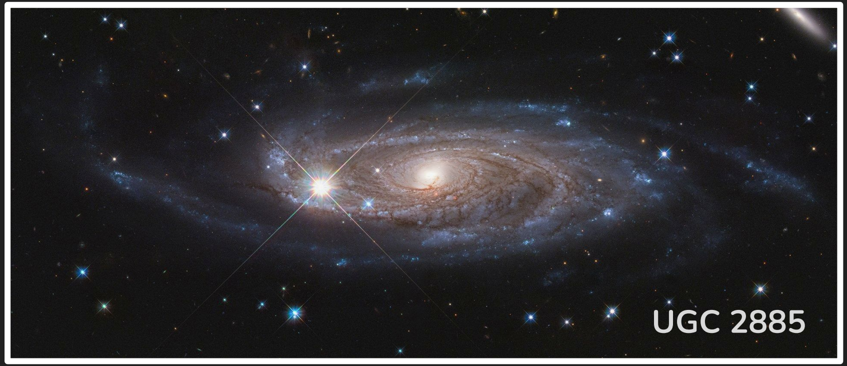


Guo, **Wu**, & Sharon 22

Just a sample of what can be done with CNNs...







Wu & Boada 19; **Wu** 2020; **Wu** & Peek 2020; Holwerda+ 21; Guo, **Wu**, & Sharon 22

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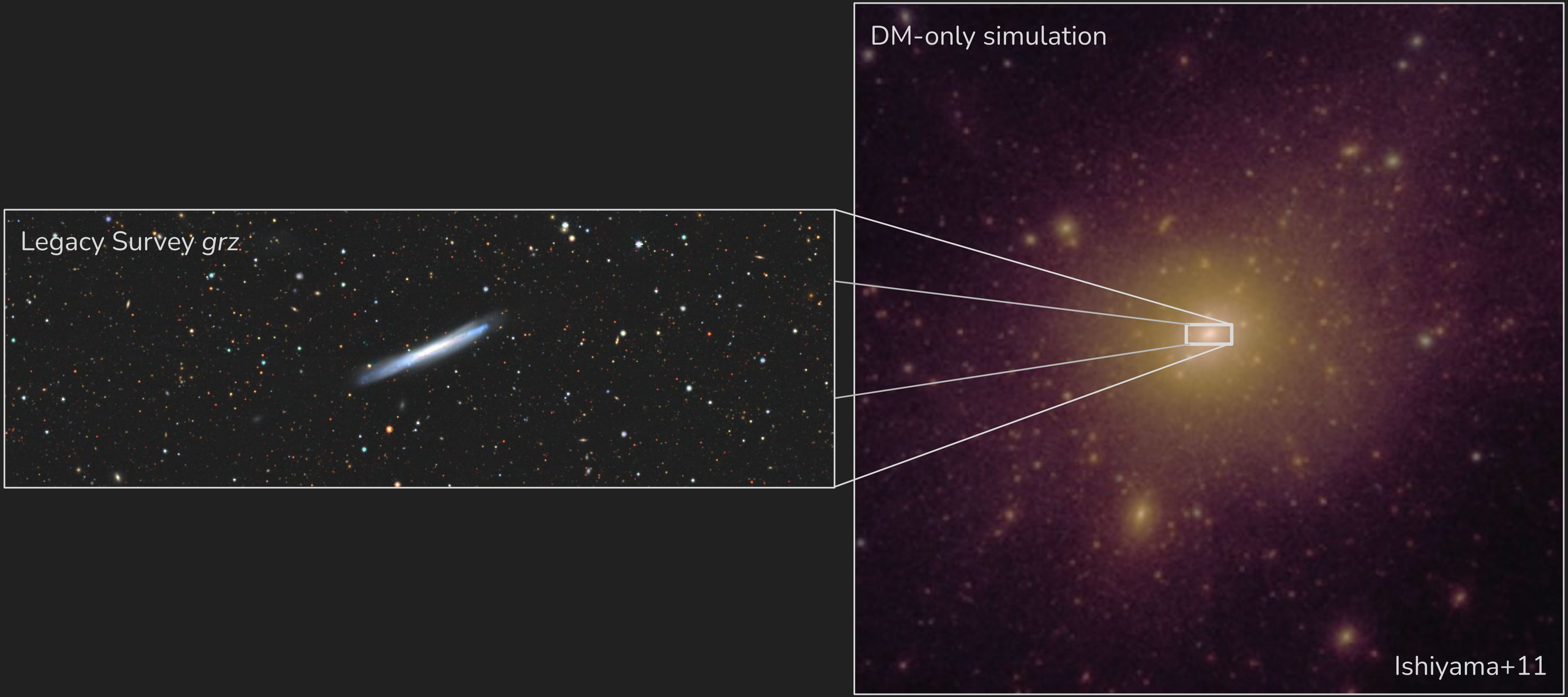
Identifying dwarf satellites is hard...

… but important for galaxy formation theory.



SAGA is the premier spectroscopic survey of low-z satellites

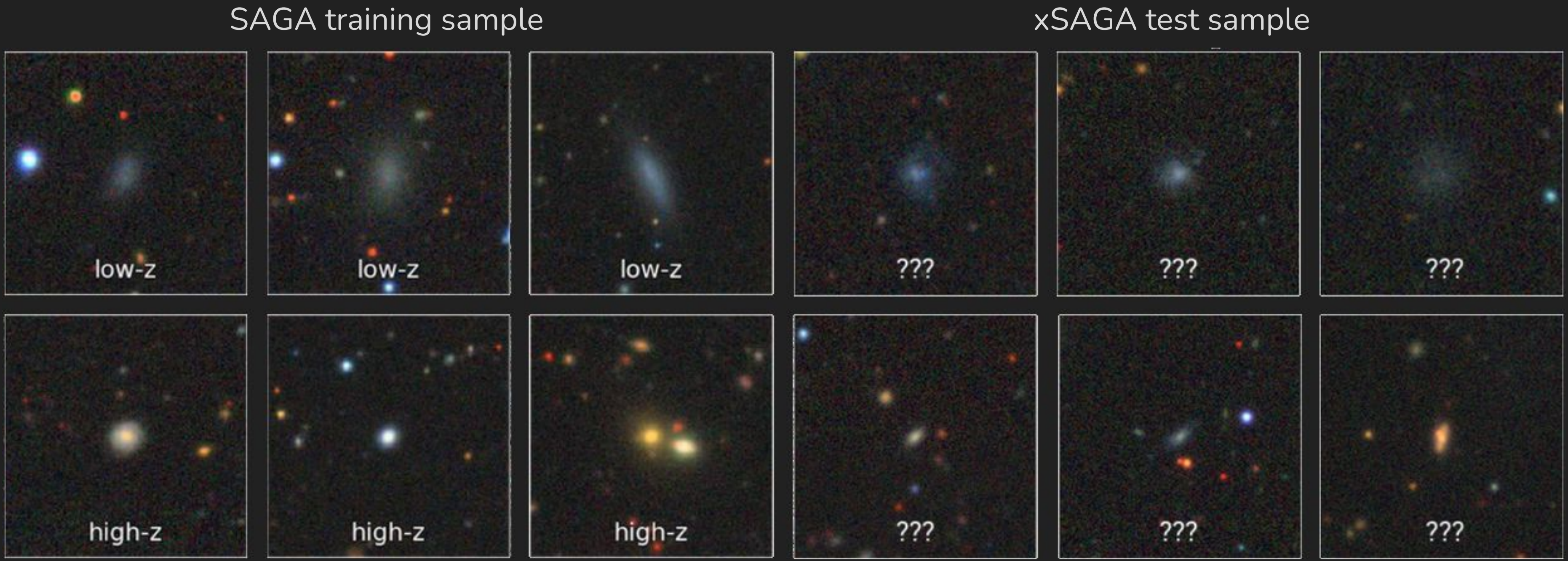
66 new satellites around 36 hosts, using 25,372 spectra; *many more on the way!*

Geha+ 17, Mao+21

A CNN robustly selects low-z galaxies

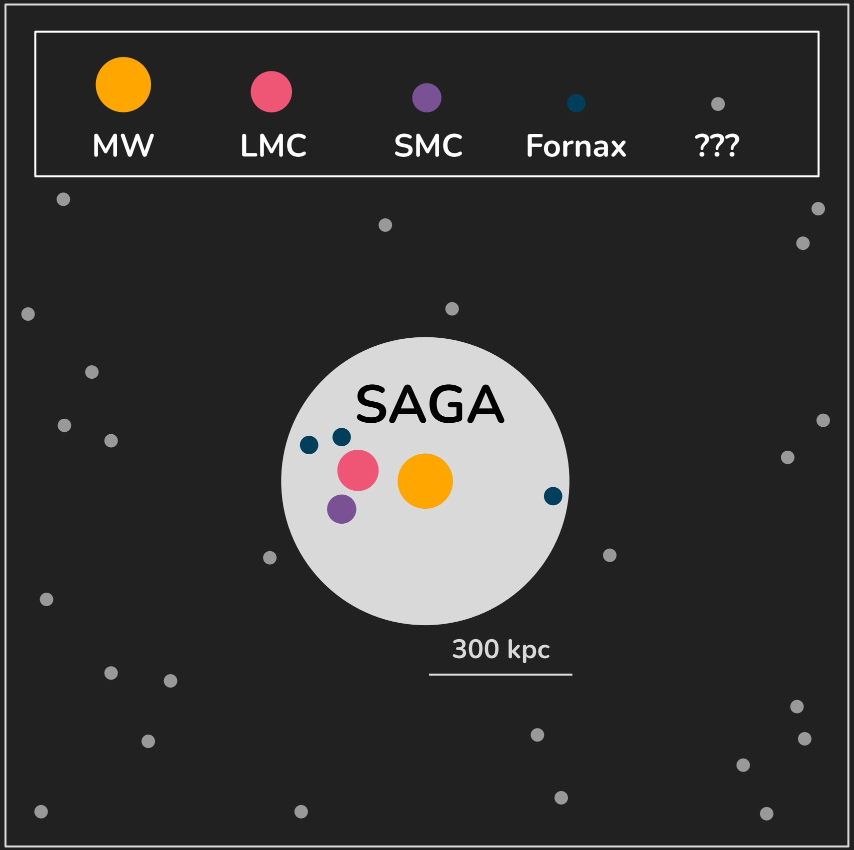
SAGA training sample

A CNN robustly selects low-z galaxies

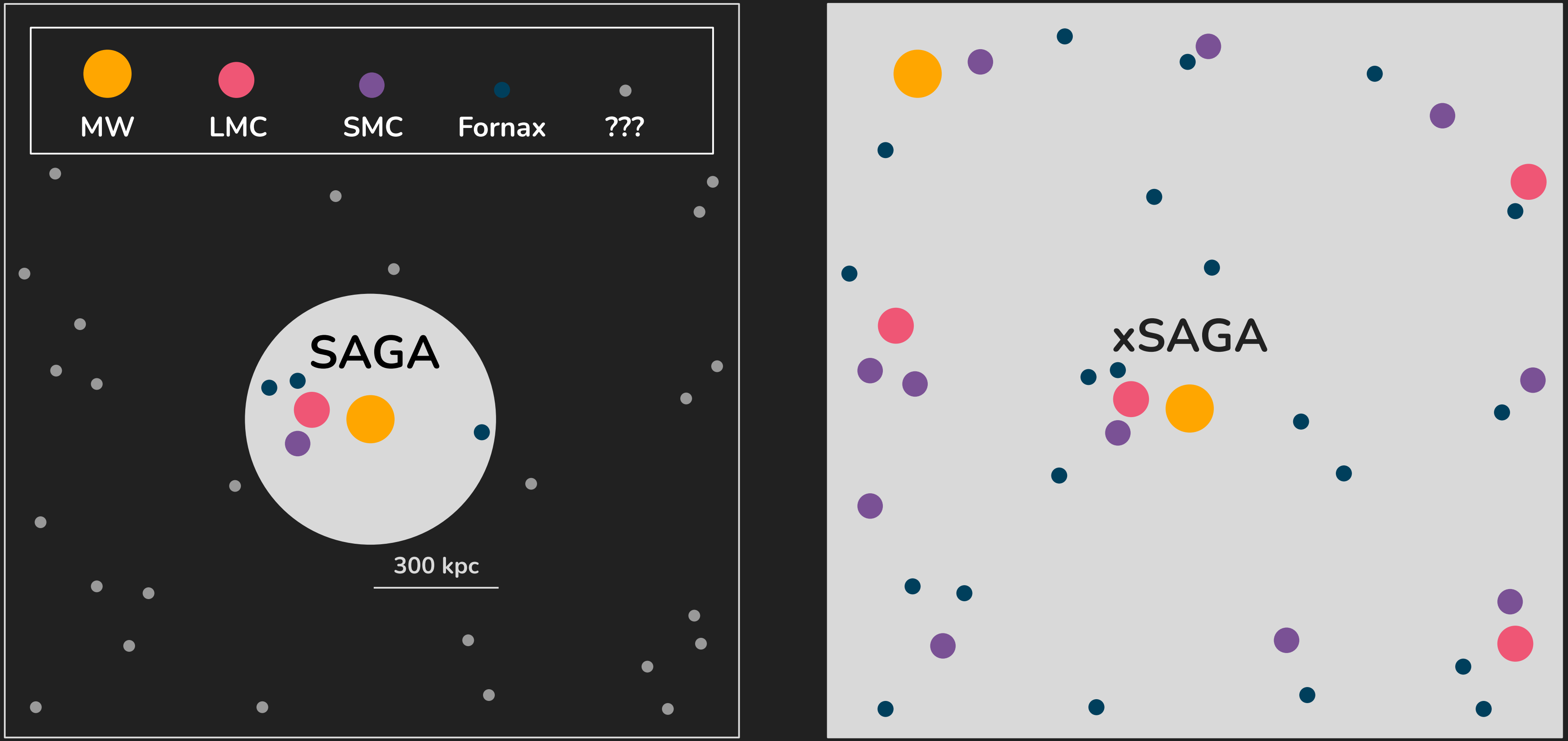


Wu+ 22

xSAGA: extending the SAGA survey with deep learning

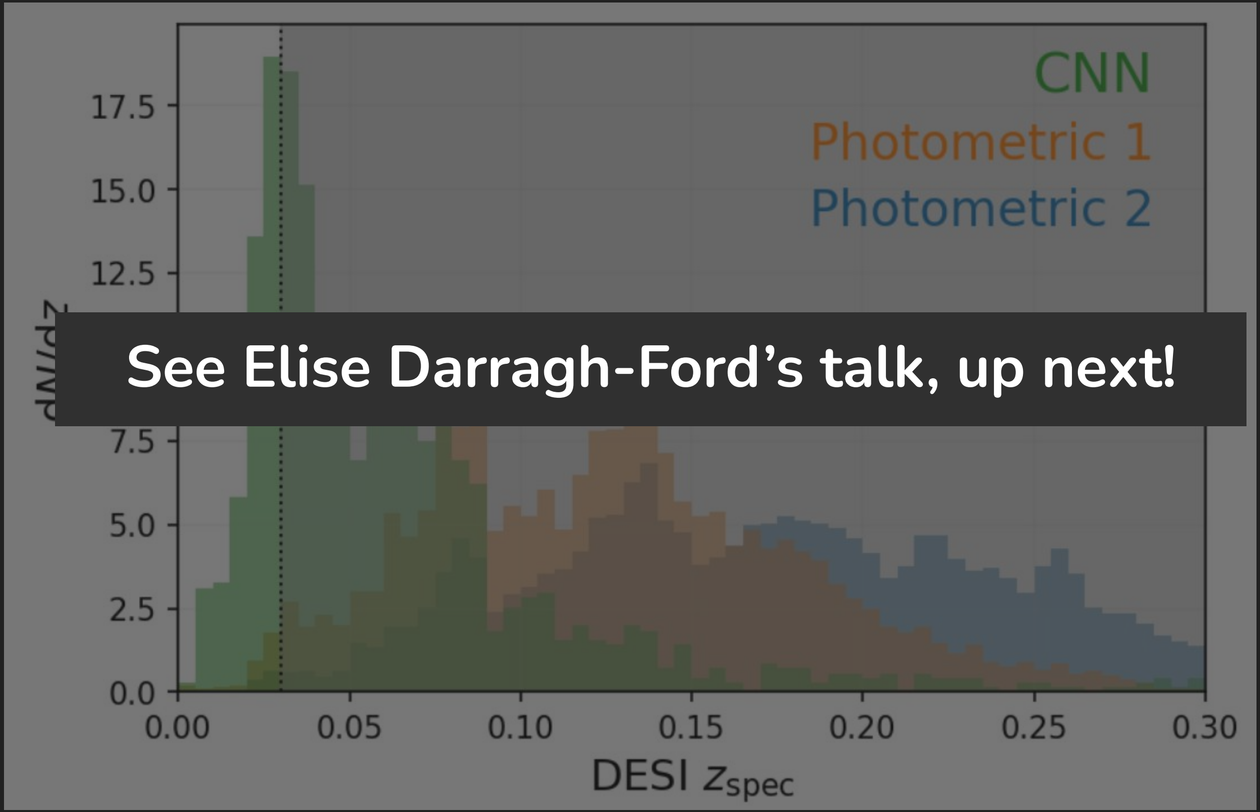


xSAGA: extending the SAGA survey with deep learning



CNN

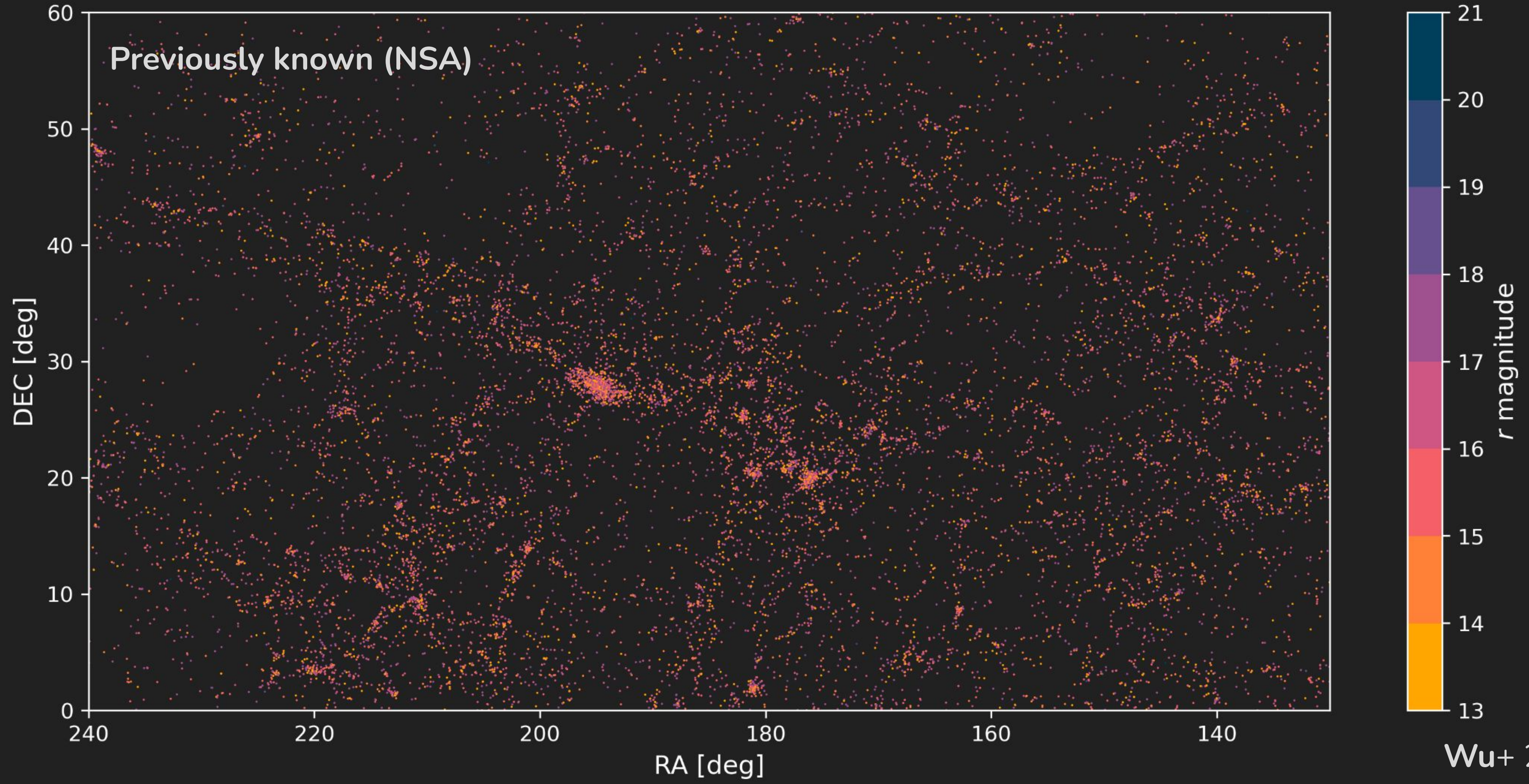
We can *validate* CNN performance with observations!



See Elise Darragh-Ford's talk, up next!

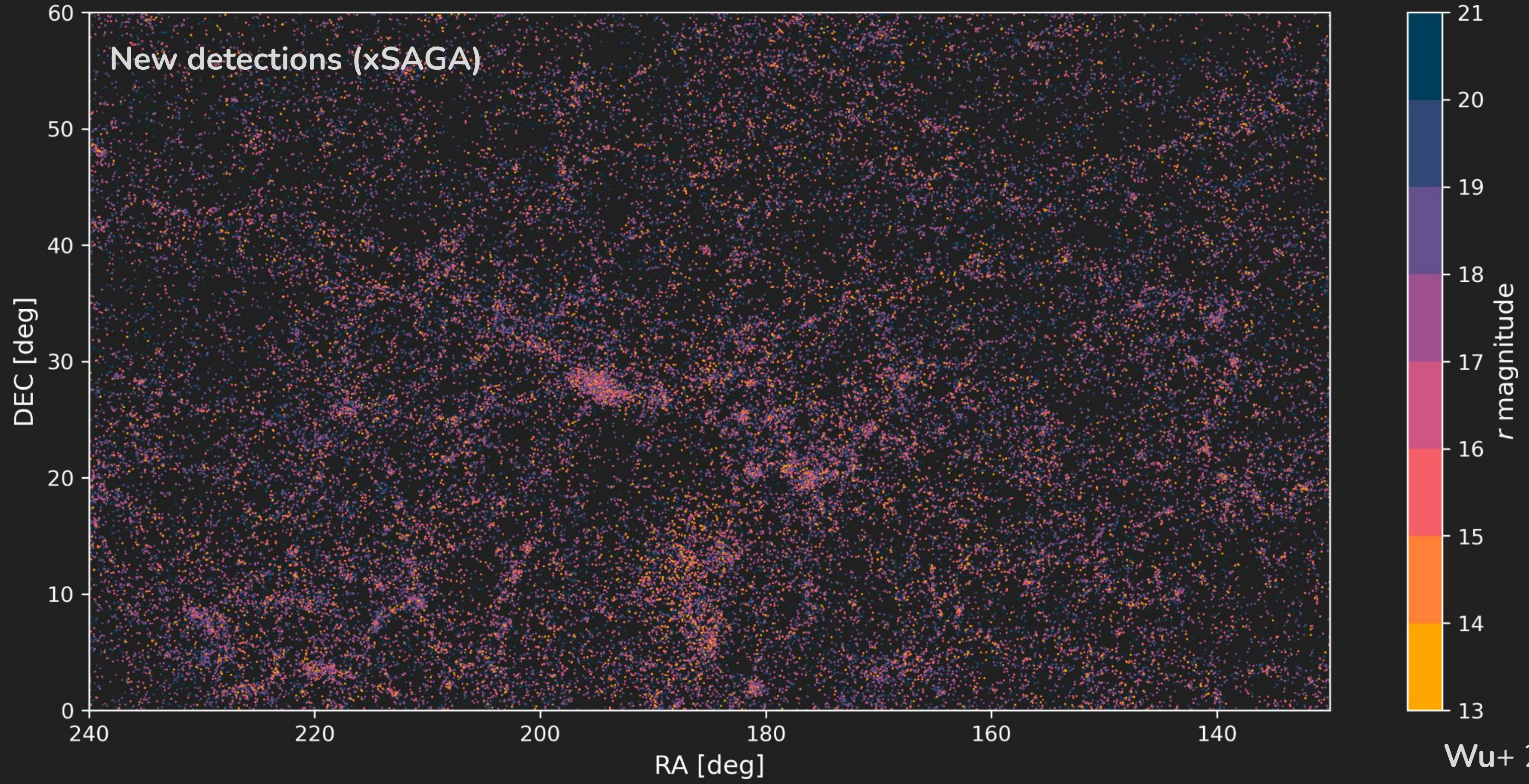
Darragh-Ford+ 22

SDSS found bright $z < 0.03$ galaxies



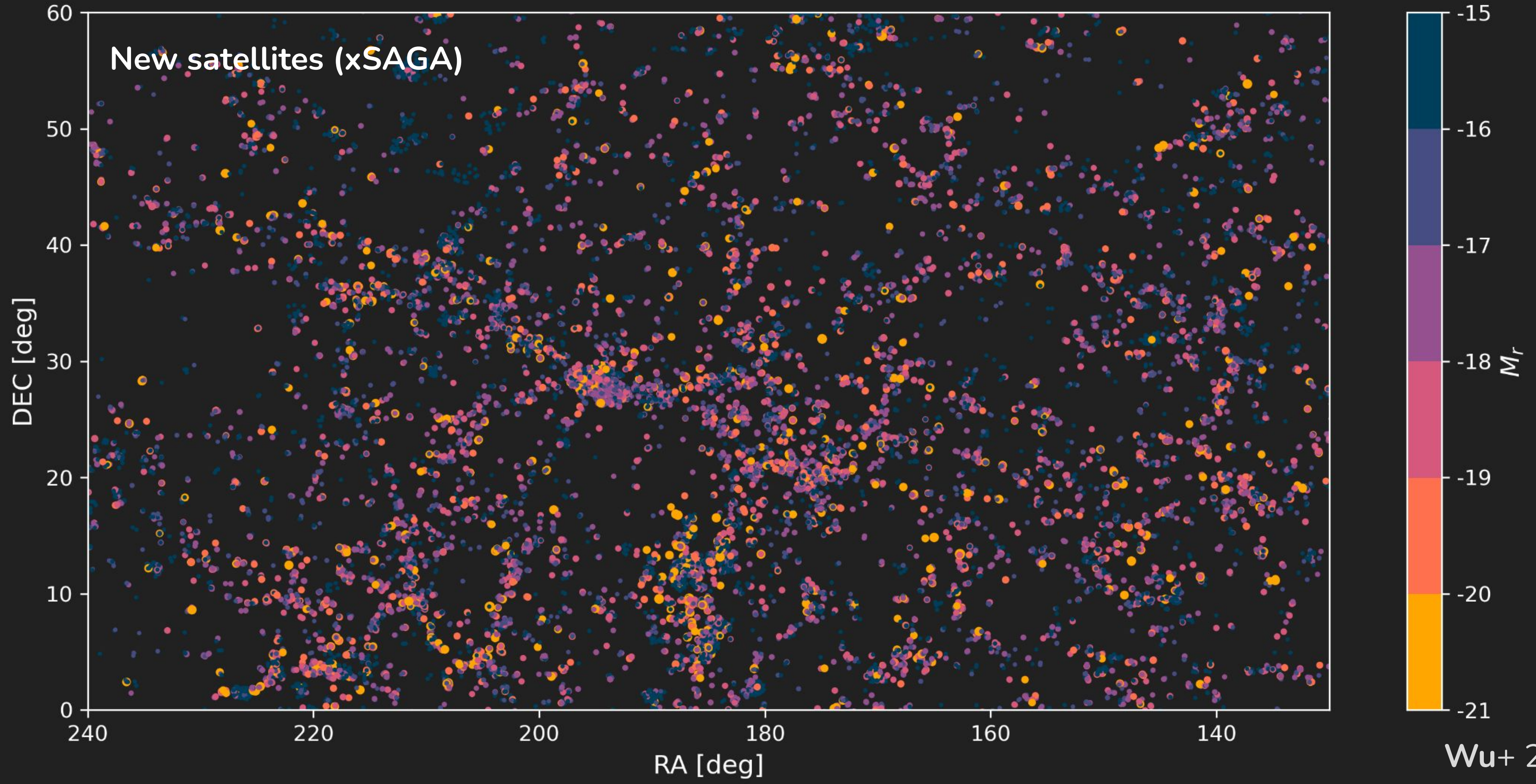
Wu+ 22

xSAGA found >100k low-z candidates with a CNN



Wu+ 22

xSAGA: >100x as many satellite systems as before

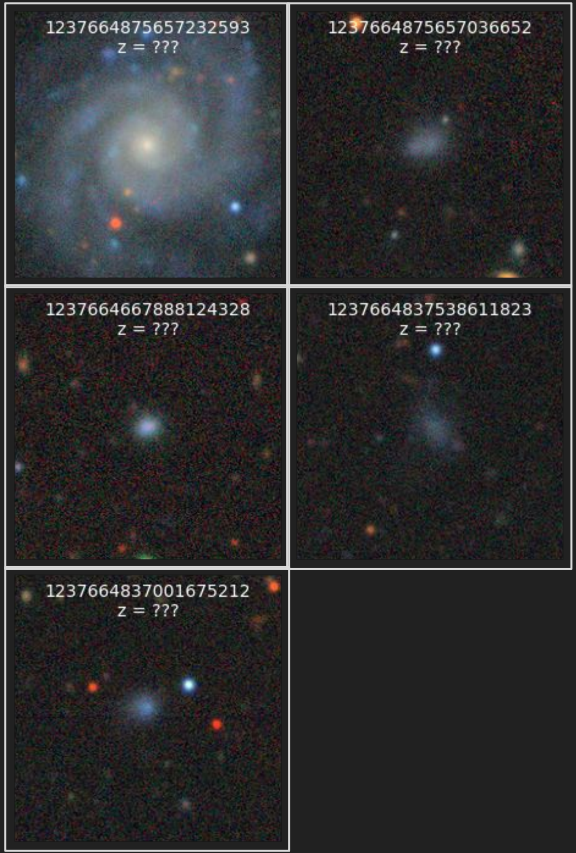


Wu+ 22

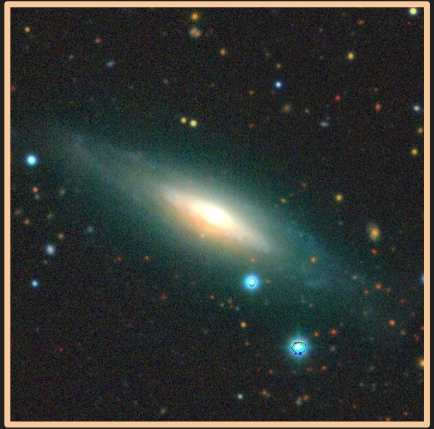
Studying satellites around Milky Way analogs

spectroscopically confirmed

no redshift confirmed



NSAID 407998
$z = 0.029$



NGC 1234
$z = 0.020$

Studying satellite groups and their dwarfs

NGC 5326 $z = 0.008$

spectroscopically confirmed   no redshift confirmed

Finding satellites is really really hard

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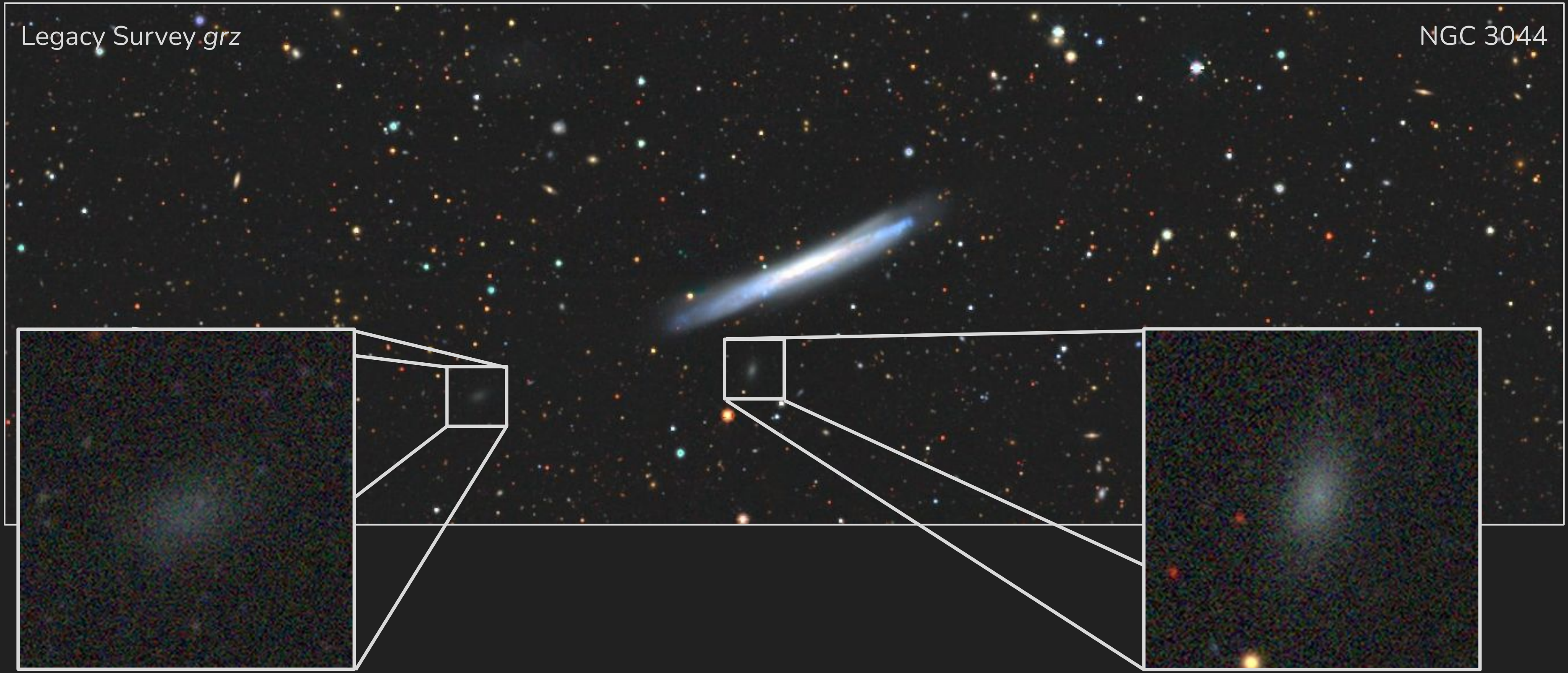
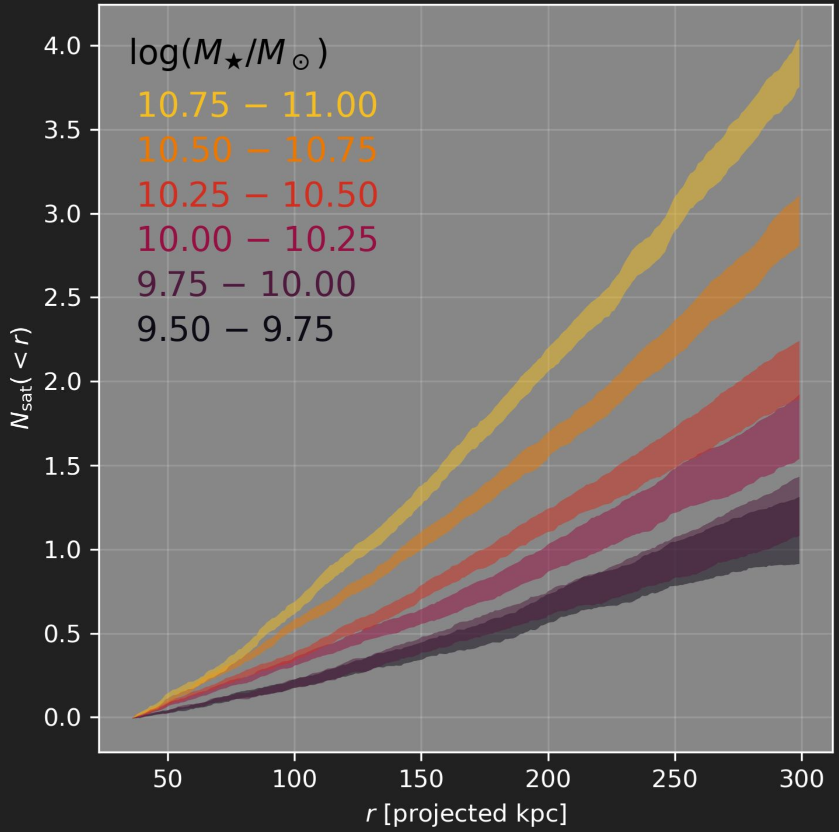


1. The first statistics on satellite radial profiles with host mass!



Wu+ 22

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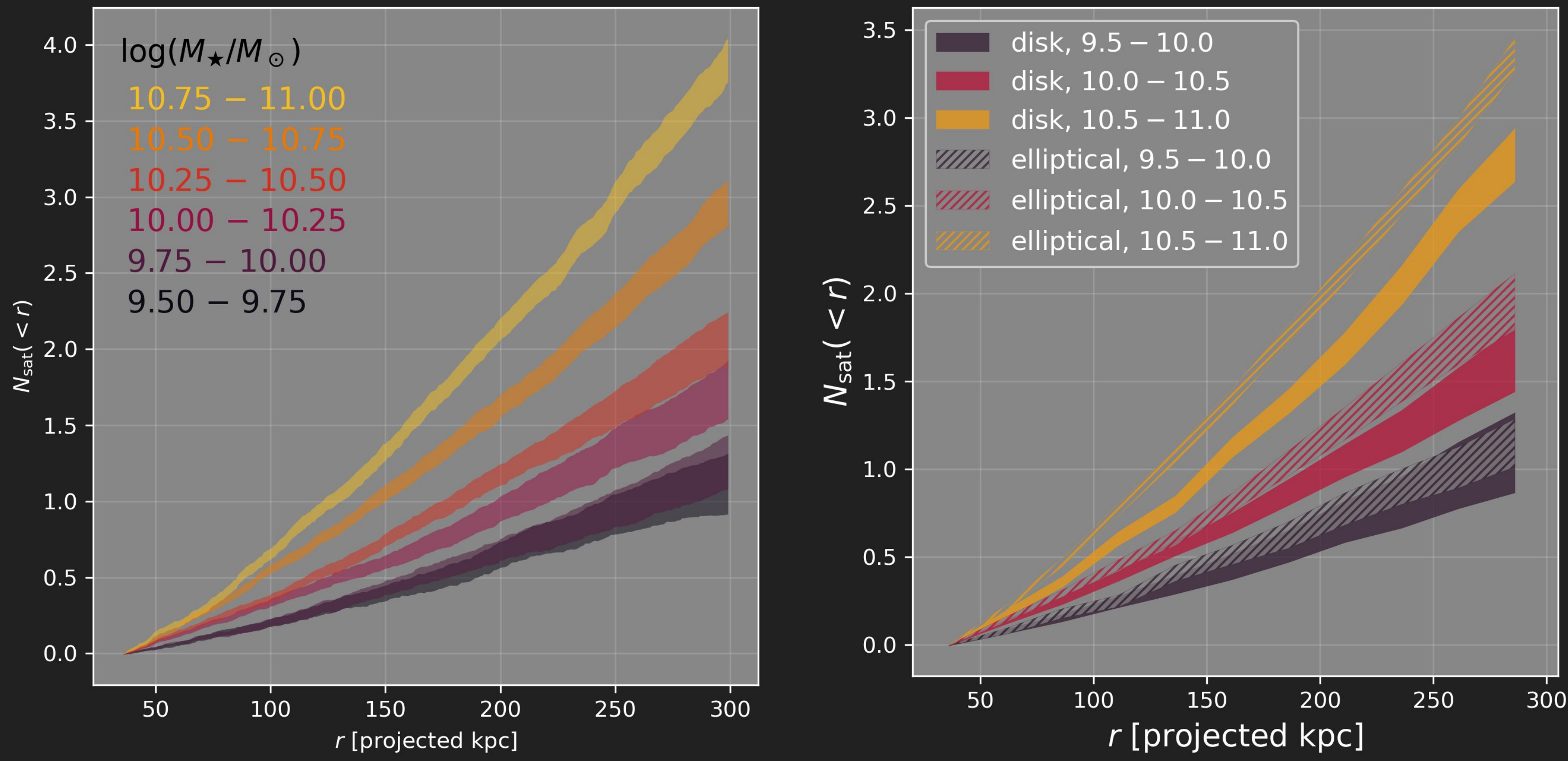
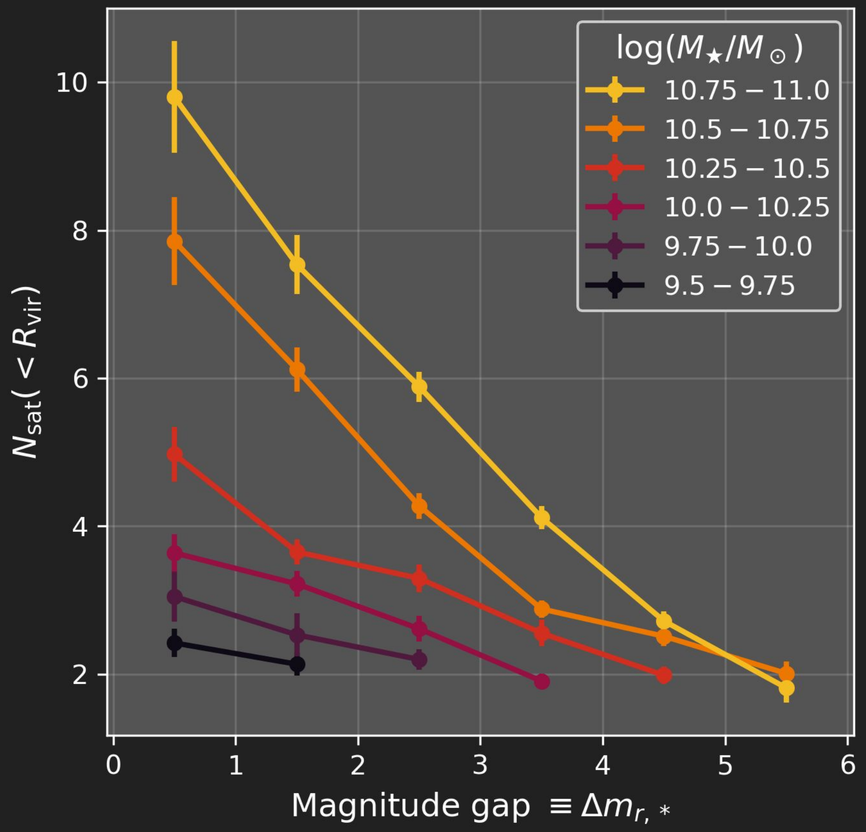


Wu+ 22

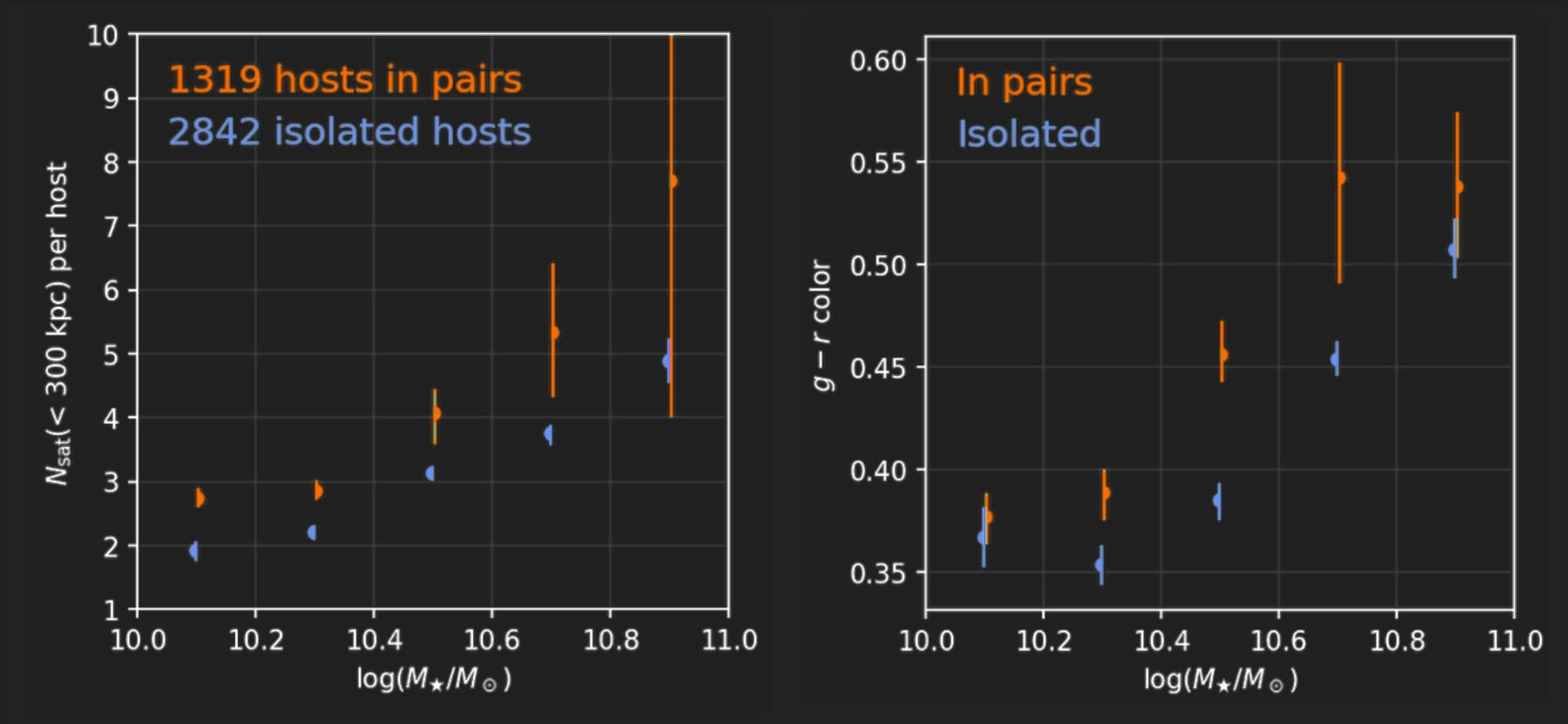
2. Satellites probe the halo accretion history



Time since last halo accretion event ⟶

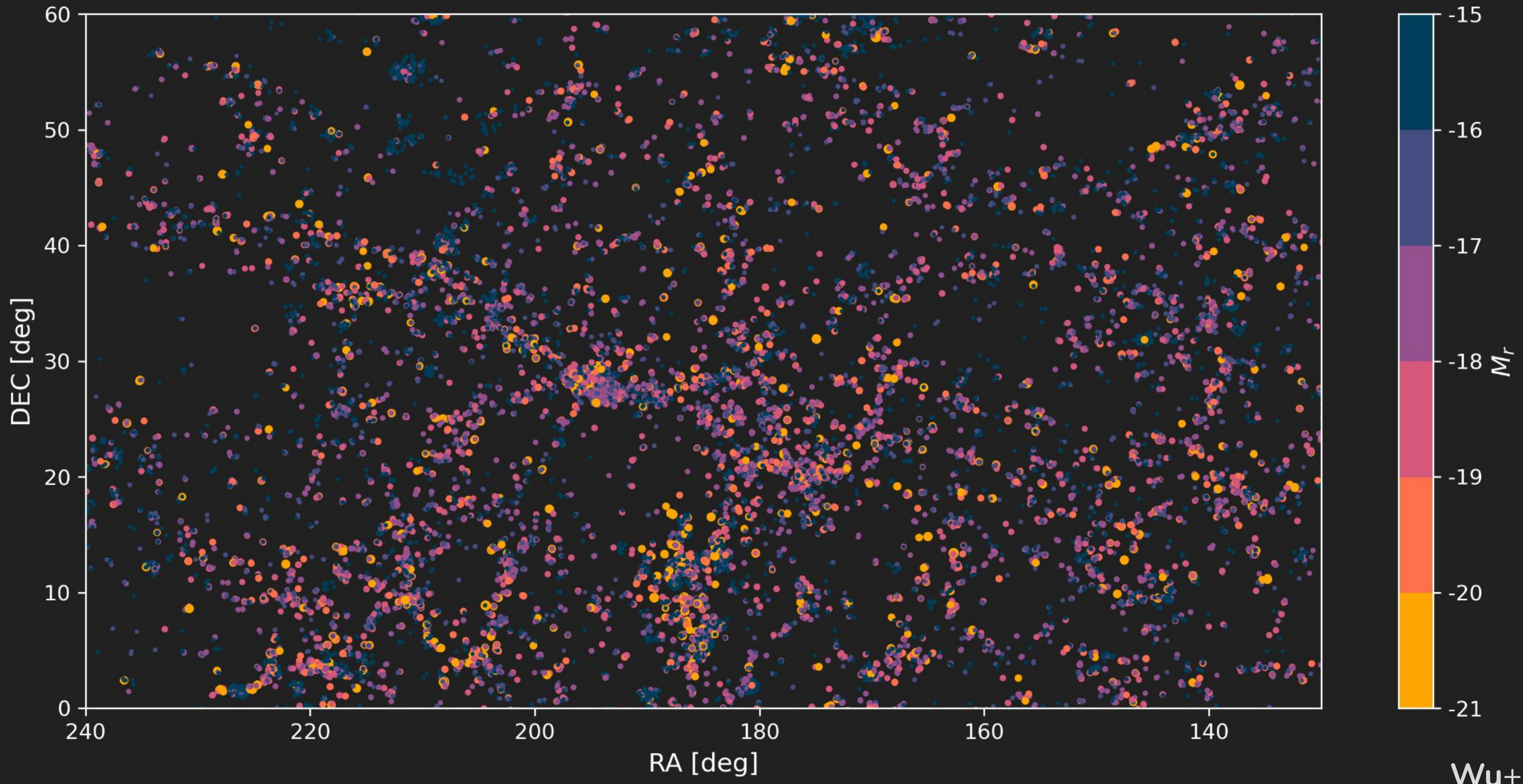
Wu+ 22

3. Isolated and paired hosts have different satellite populations



Wu+ *in prep*

xSAGA already scientifically productive, more on the way!



Wu+ 22

Summary

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II. The morphologies of galaxies tells us about their physical properties and their formation history.

III. xSAGA gives us an entirely new way to study substructure of the low-redshift cosmos.