



Investigating galaxy evolution with deep learning

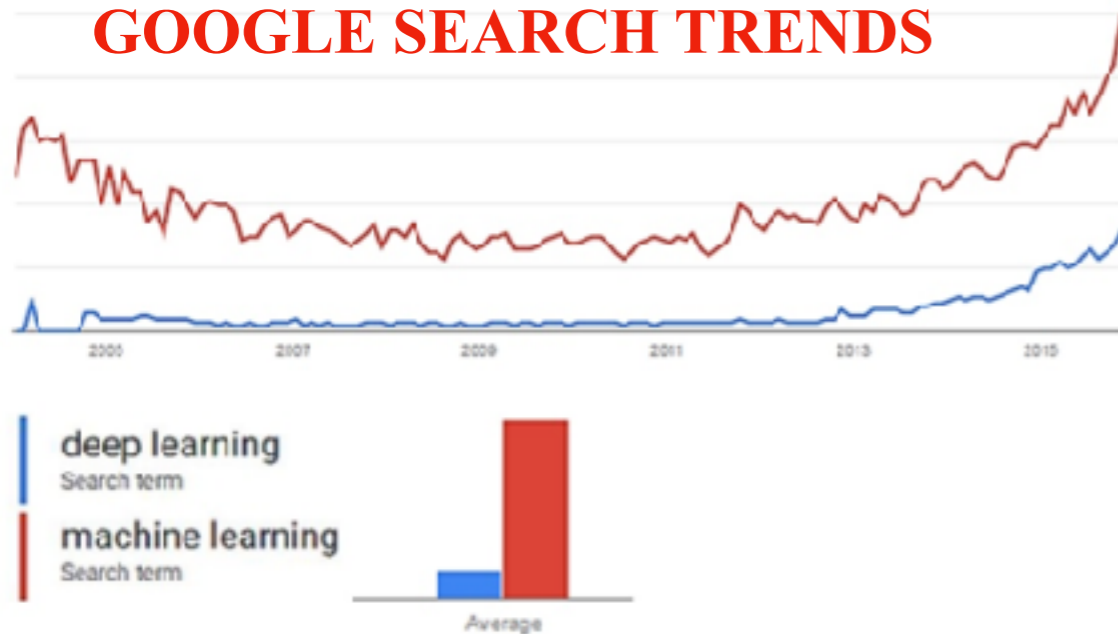
Marc Huertas-Company

Instituto de Astrofísica de Canarias
Observatoire de Paris
Université Paris Diderot
Institut Universitaire de France

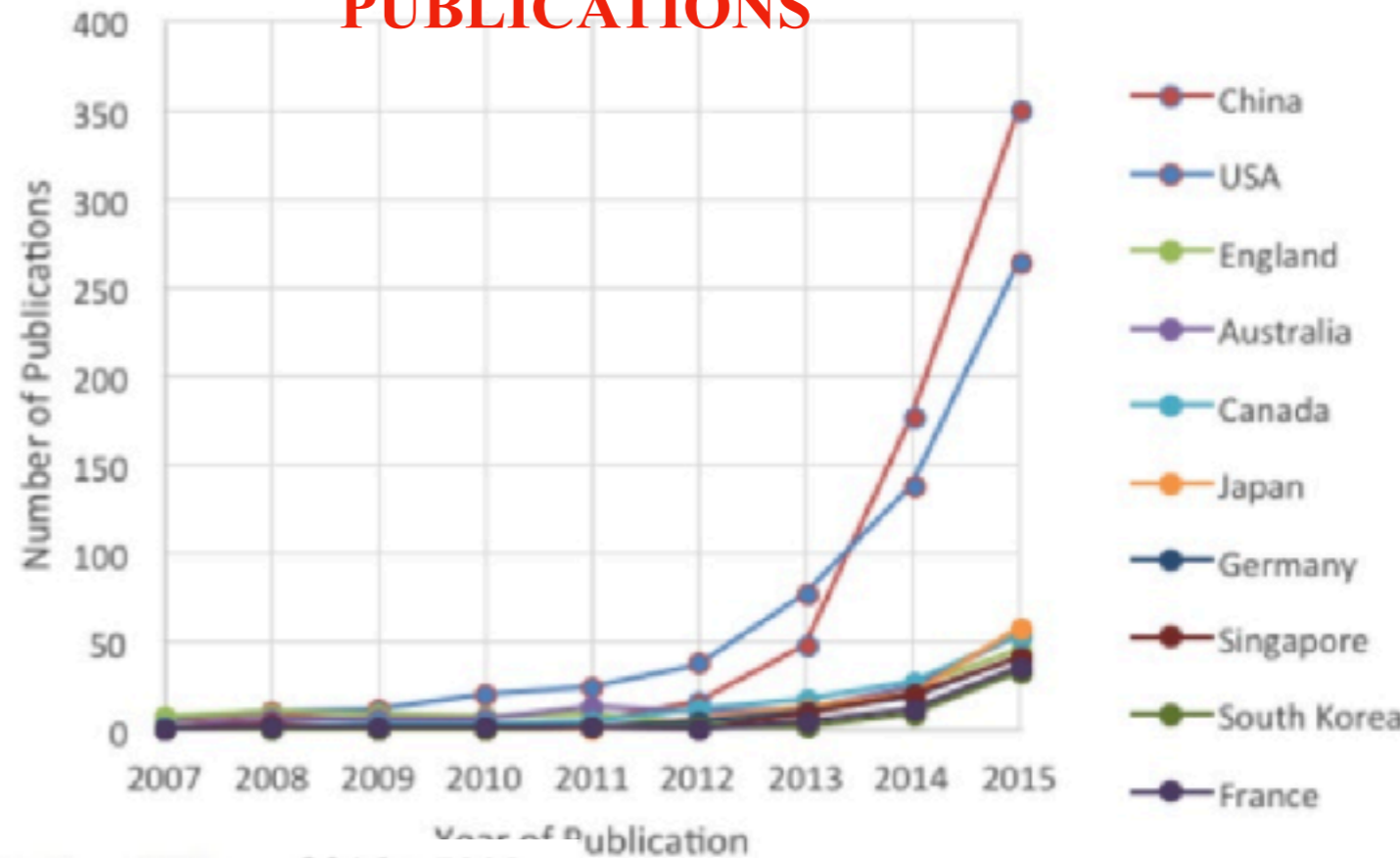
Berta Margalef-Bentabol, Fernando Caro, Christoph Lee, Alexandre Boucaud, Avishai Dekel, Joel Primack, Tom Charnock, Annalisa Pillepich, Vicente Rodriguez (+ TNG team), Emille Ishida (+ COIN initiative), Helena Dominguez-Sanchez ...

AI FEVER?

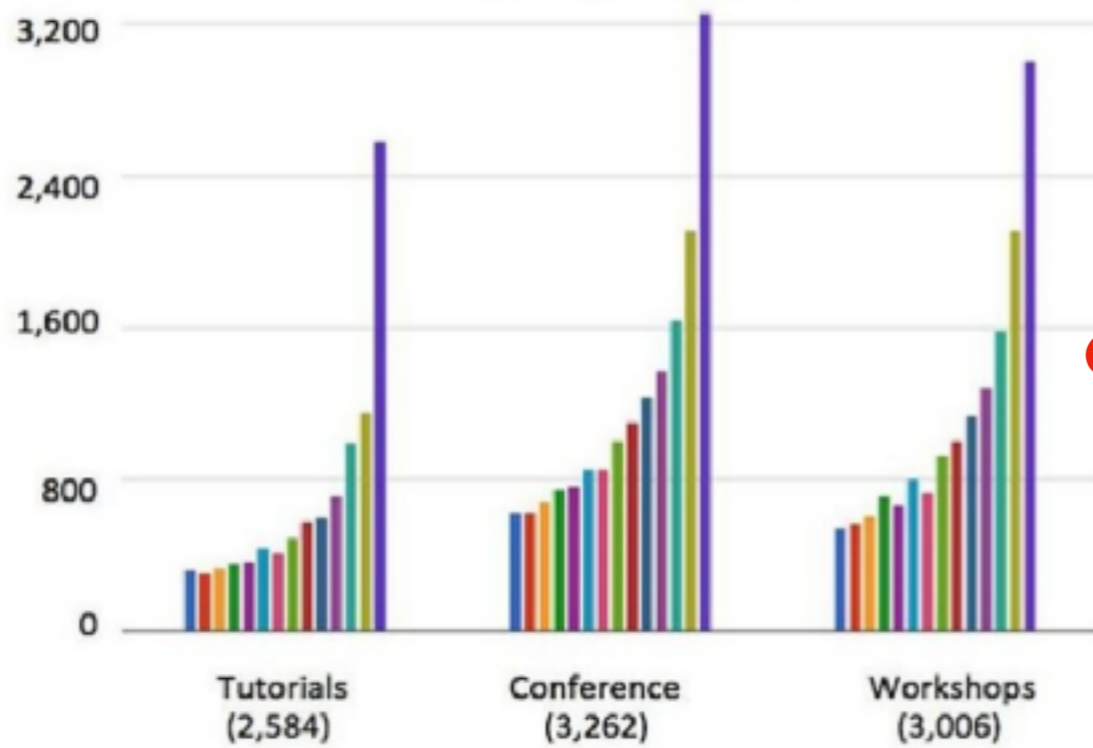
GOOGLE SEARCH TRENDS



Deep Learning PUBLICATIONS



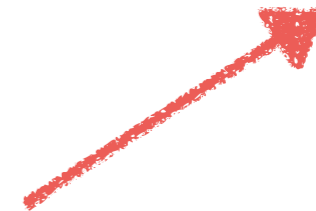
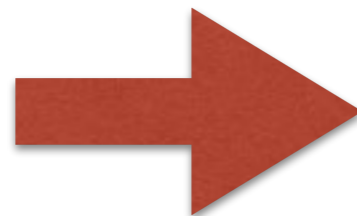
Total Registrations 3755 2016: >5000



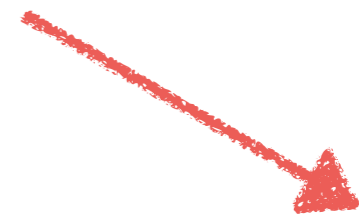
CONFERENCES

Source

BEFORE 2012....



CAT?

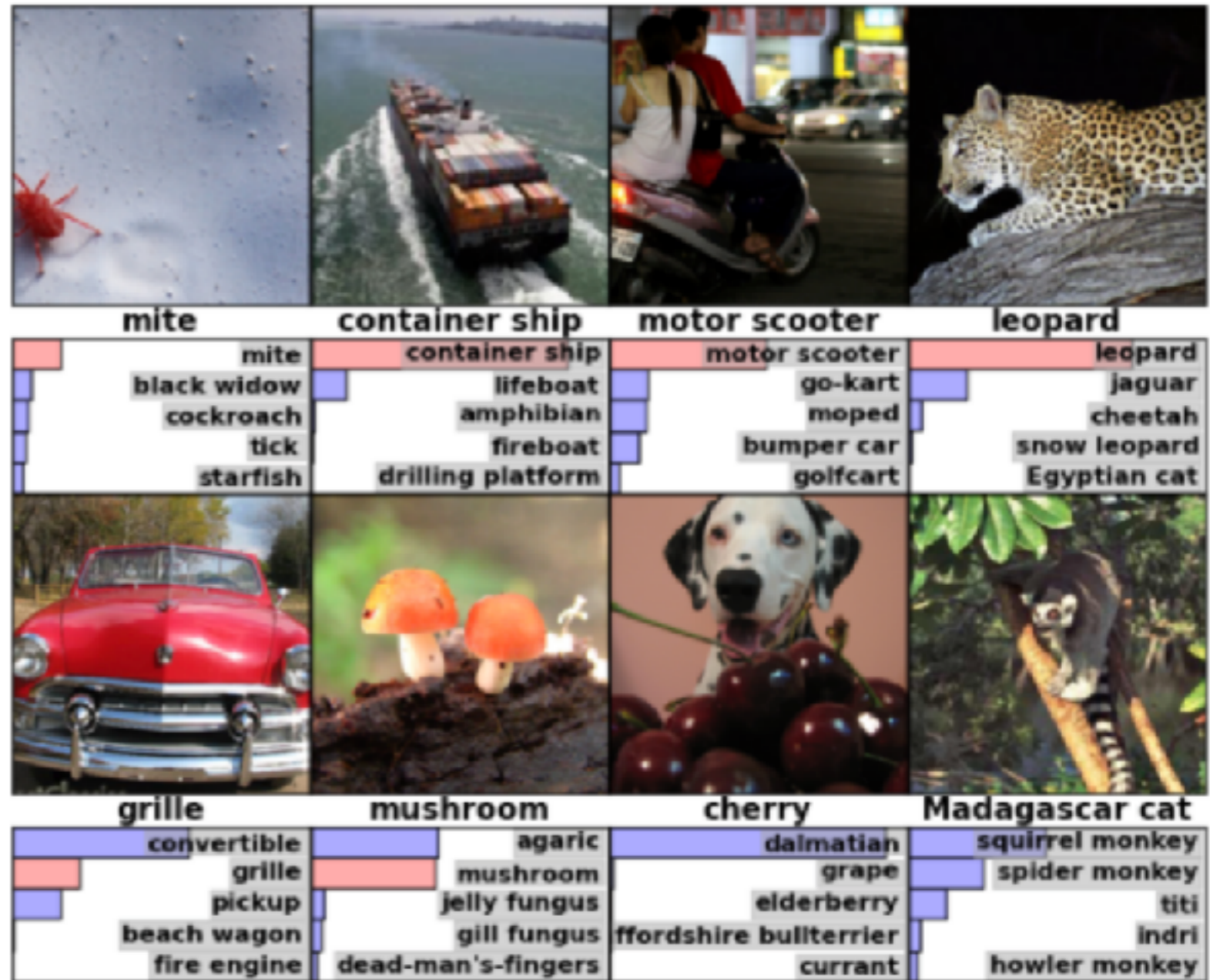
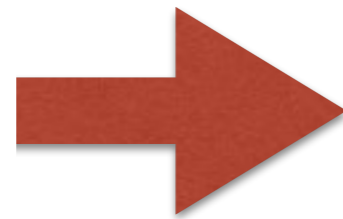


DOG?



**TRIVIAL HUMAN TASKS REMAINED
CHALLENGING FOR COMPUTERS**

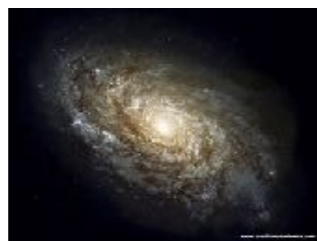
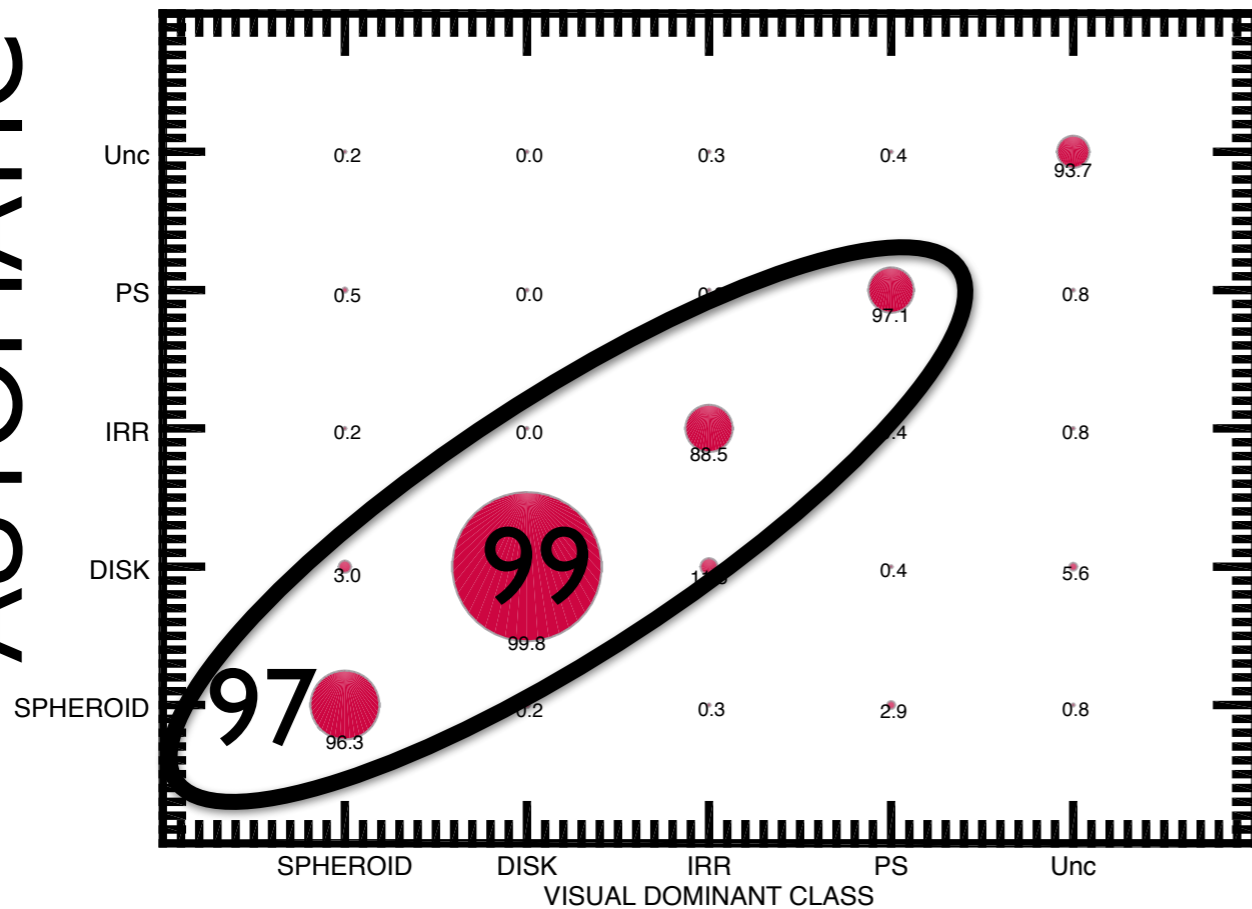
AFTER 2012



IT HAS BECOME TRIVIAL....

“OUR CATS AND DOGS”: GALAXY MORPHOLOGY

AUTOMATIC



VISUAL

CNNs

DEEP LEARNING SOLVES
THE PROBLEM
OF GALAXY MORPHOLOGICAL
CLASSIFICATION?

TALK ON WEDNESDAY AFTERNOON -

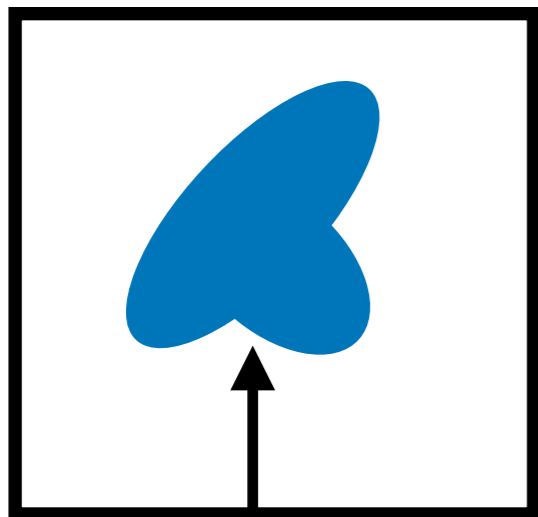
**SPECIAL SESSION
ON “MODERN” GALAXY MORPHOLOGIES**

2 TAKE HOME MESSAGES FOR TODAY

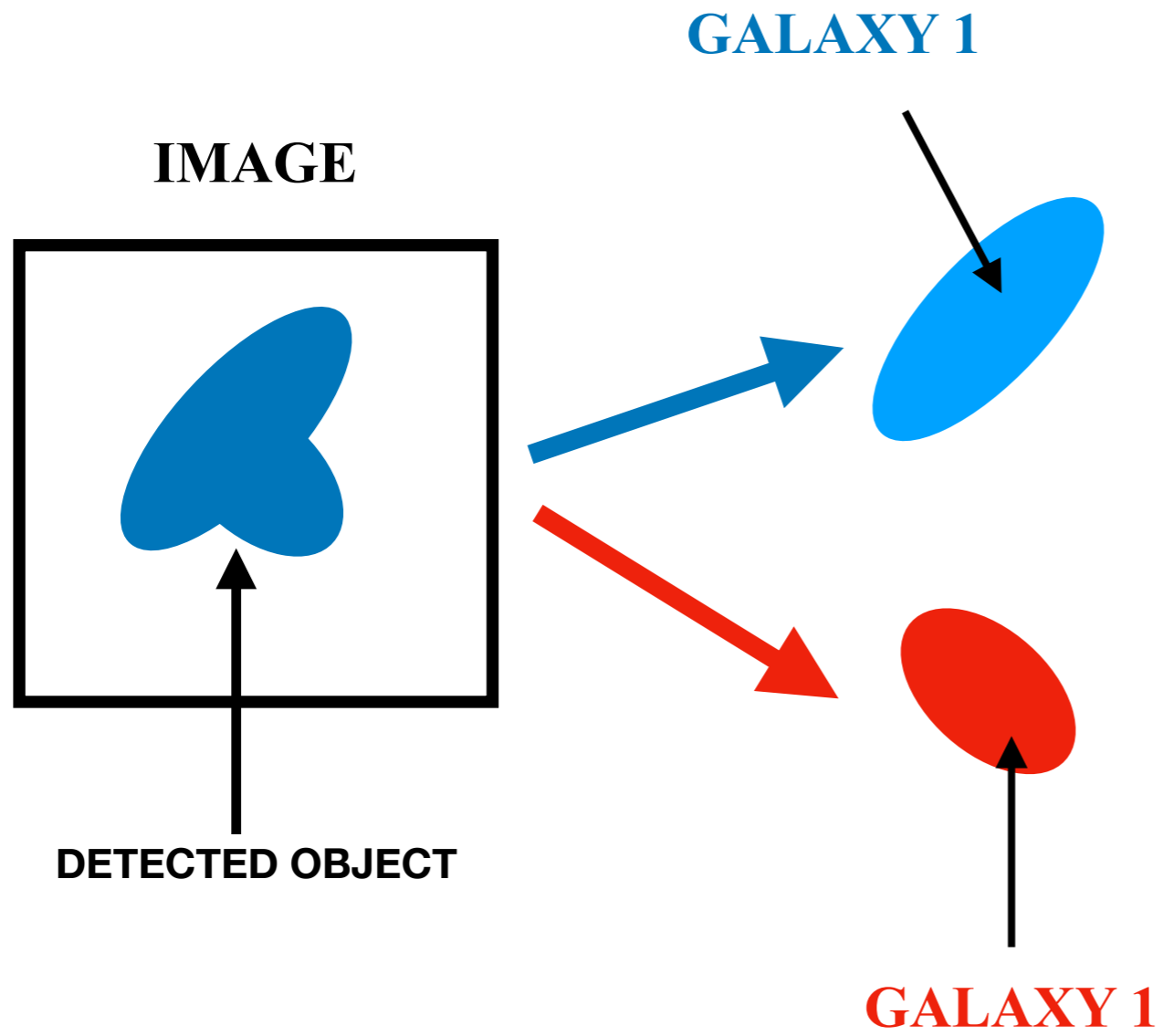
1. MOST OF THE PROCESSING WE DO ON IMAGES CAN BE DONE WITH AI - POSSIBLY MORE EFFICIENTLY AND MORE ACCURATELY

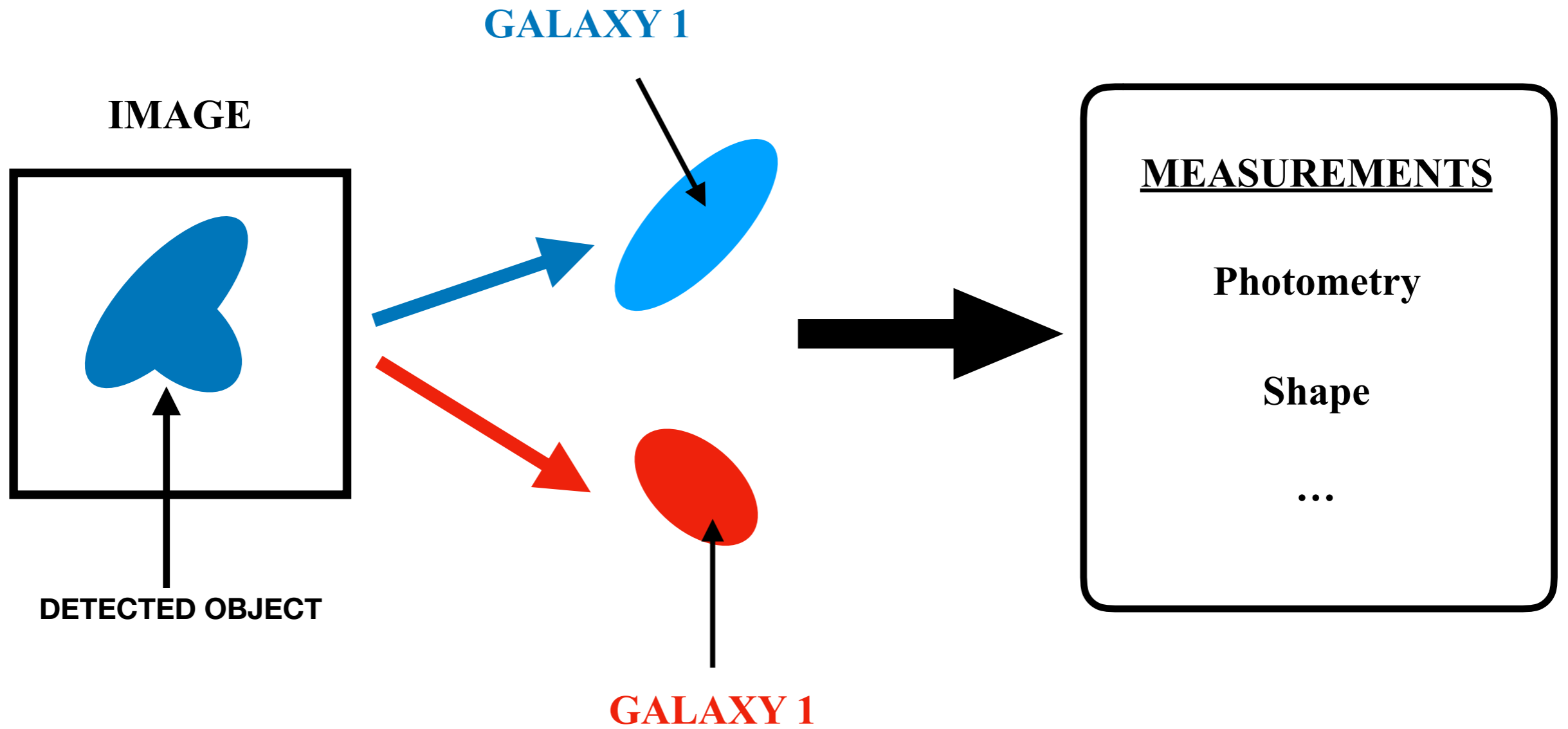
2. WE CAN LEARN SOME PHYSICS BY USING AI TO LINK SIMULATIONS AND OBSERVATIONS

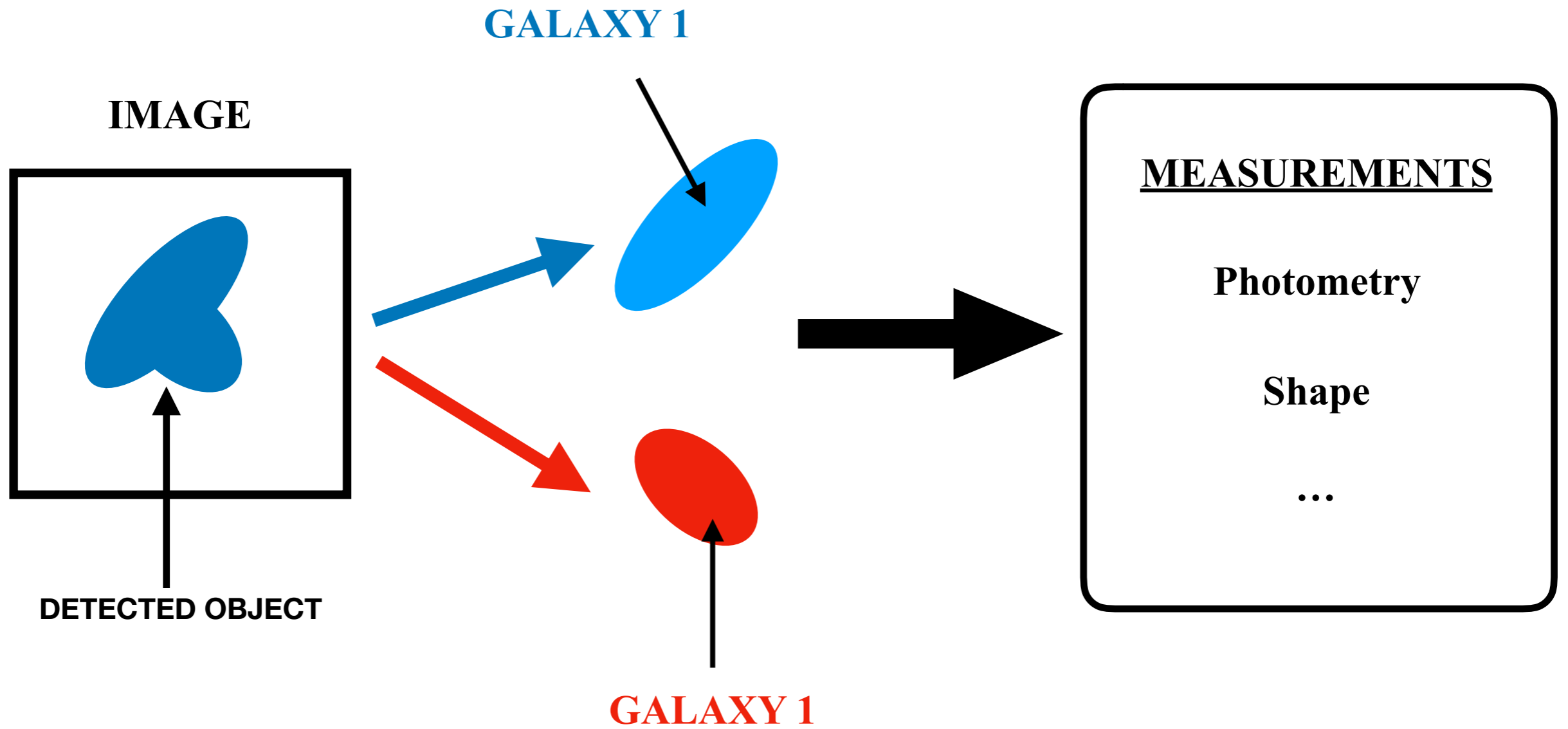
IMAGE



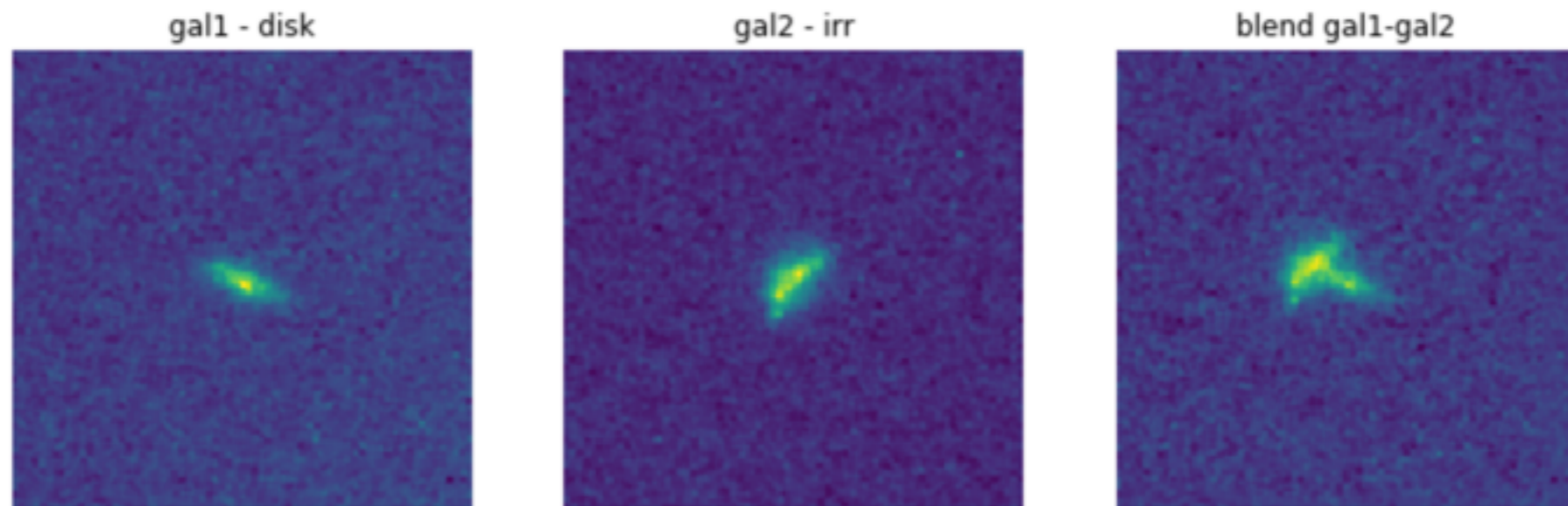
DETECTED OBJECT







**ISOLATED
GALAXIES IN
CANDELS
ARTIFICIALLY
BLENDED**



U-NET (ENCODER DECODER)

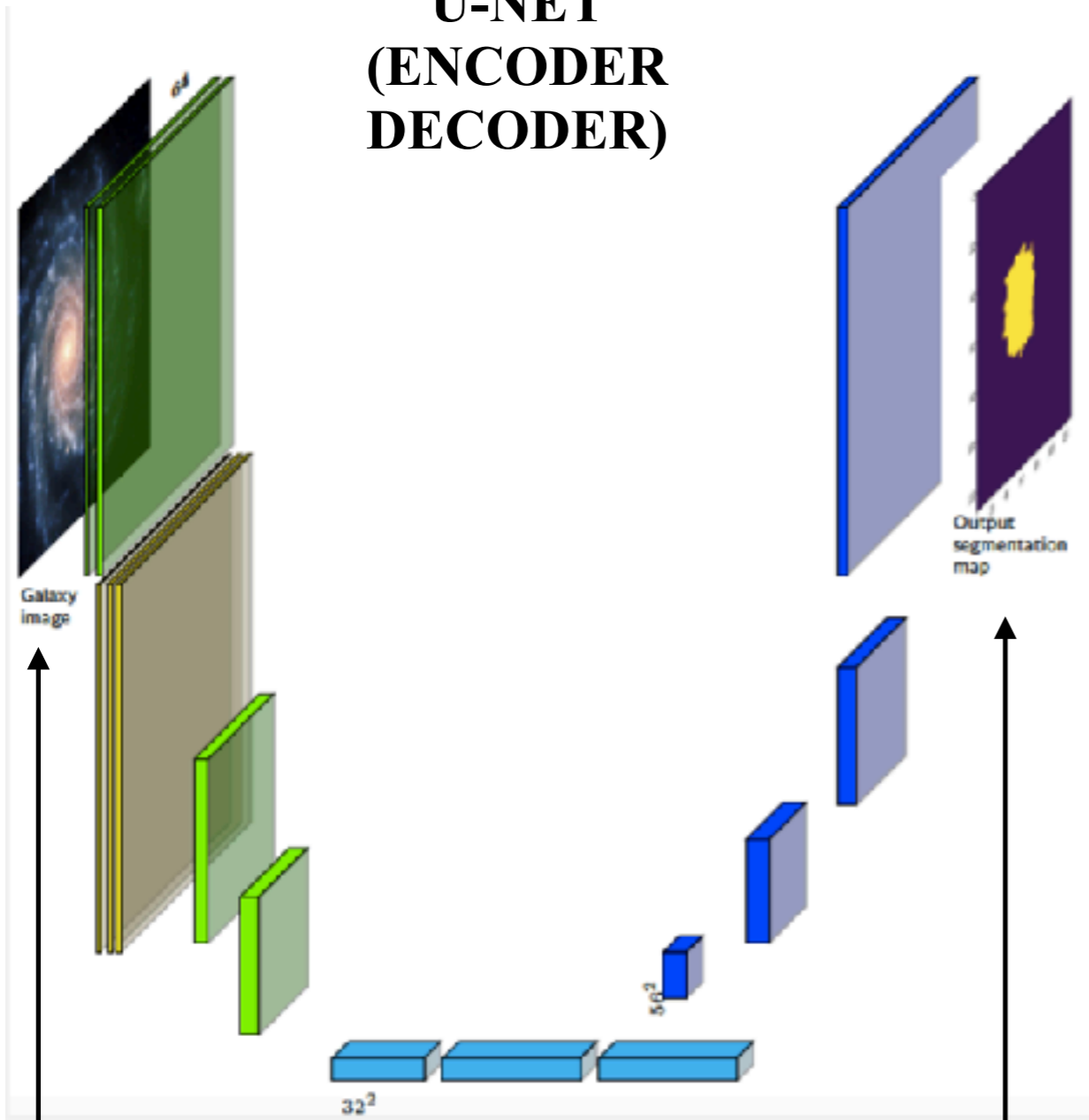
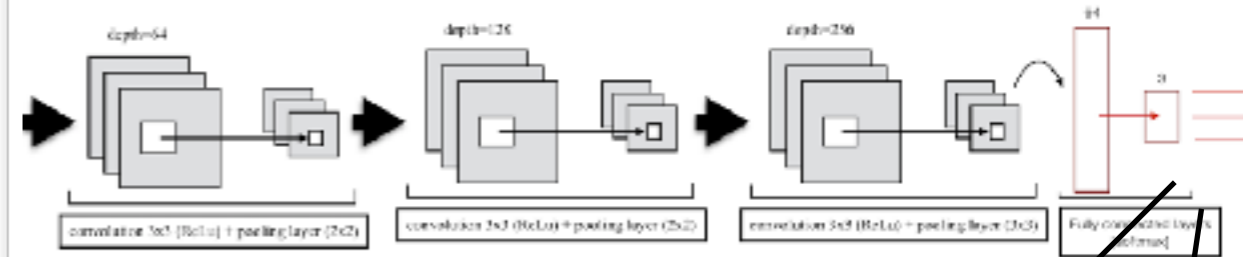


IMAGE OF
BLENDED
OBJECTS

OUTPUT
SEGMENTATION
MAP (BINARY 2
CHANNELS)

VANILLA CNN

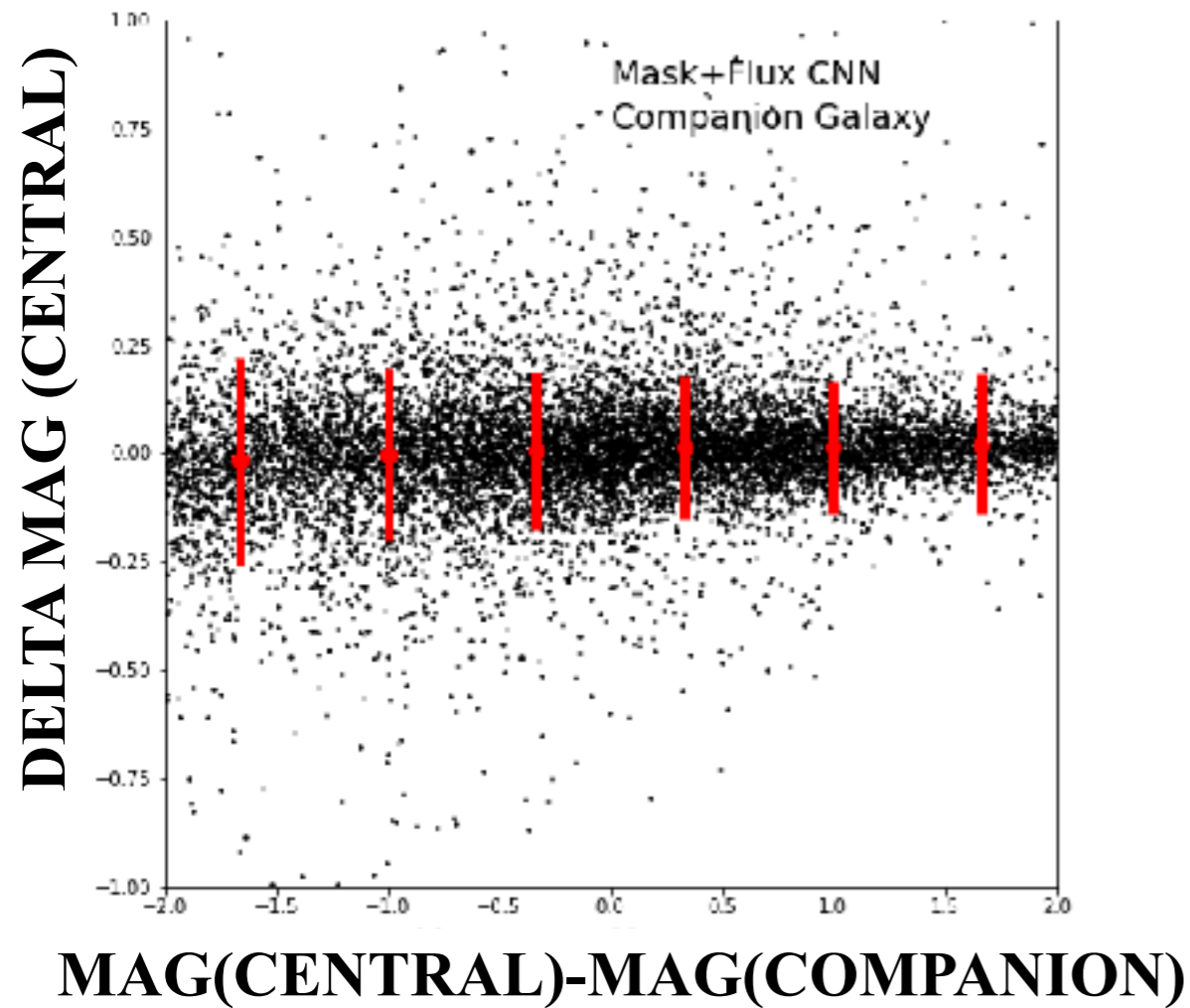


FLUX
GALAXY 1

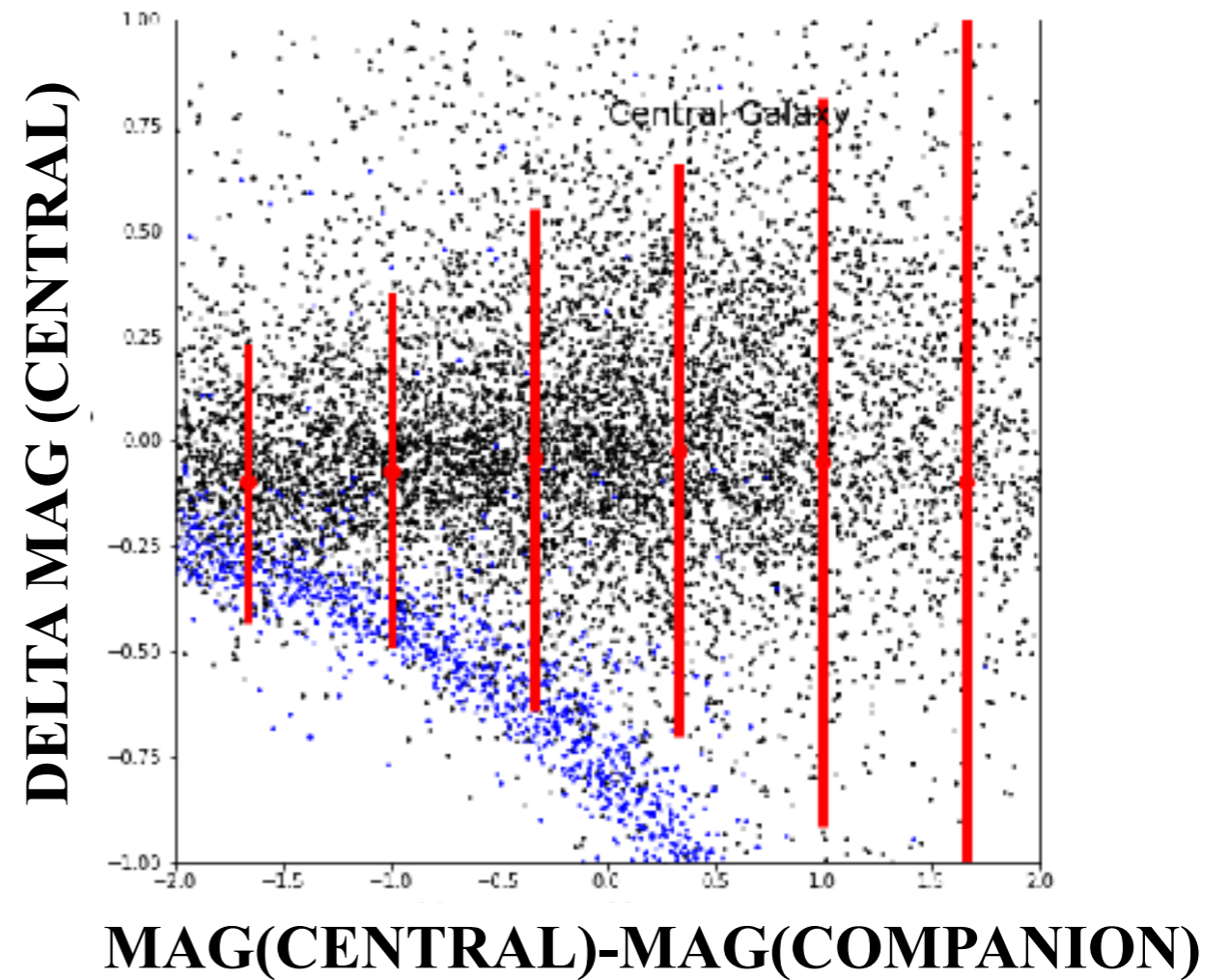
FLUX
GALAXY 2

PHOTOMETRY OF BLENDED SOURCES

U-NET+CNN

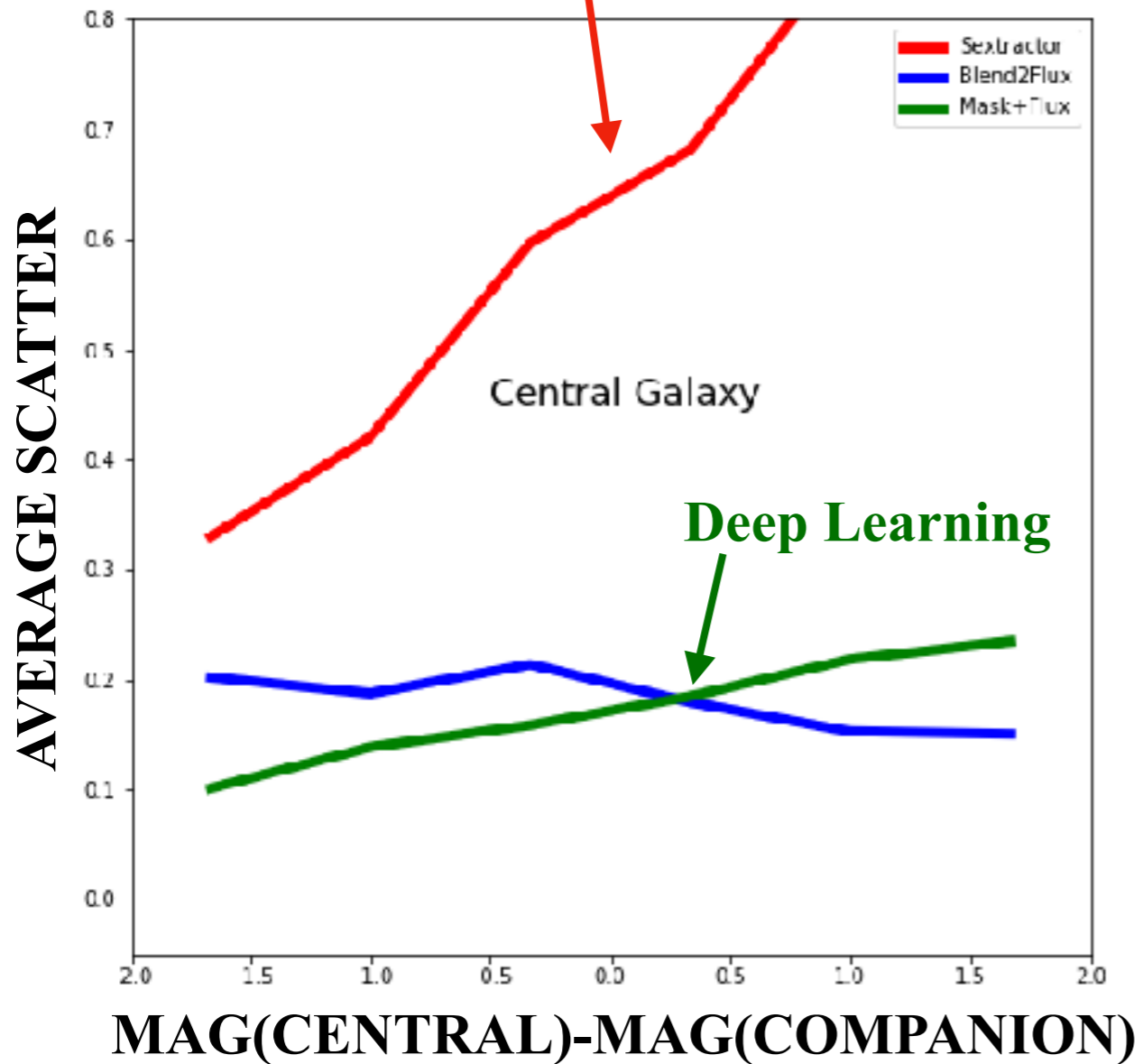


SExtractor

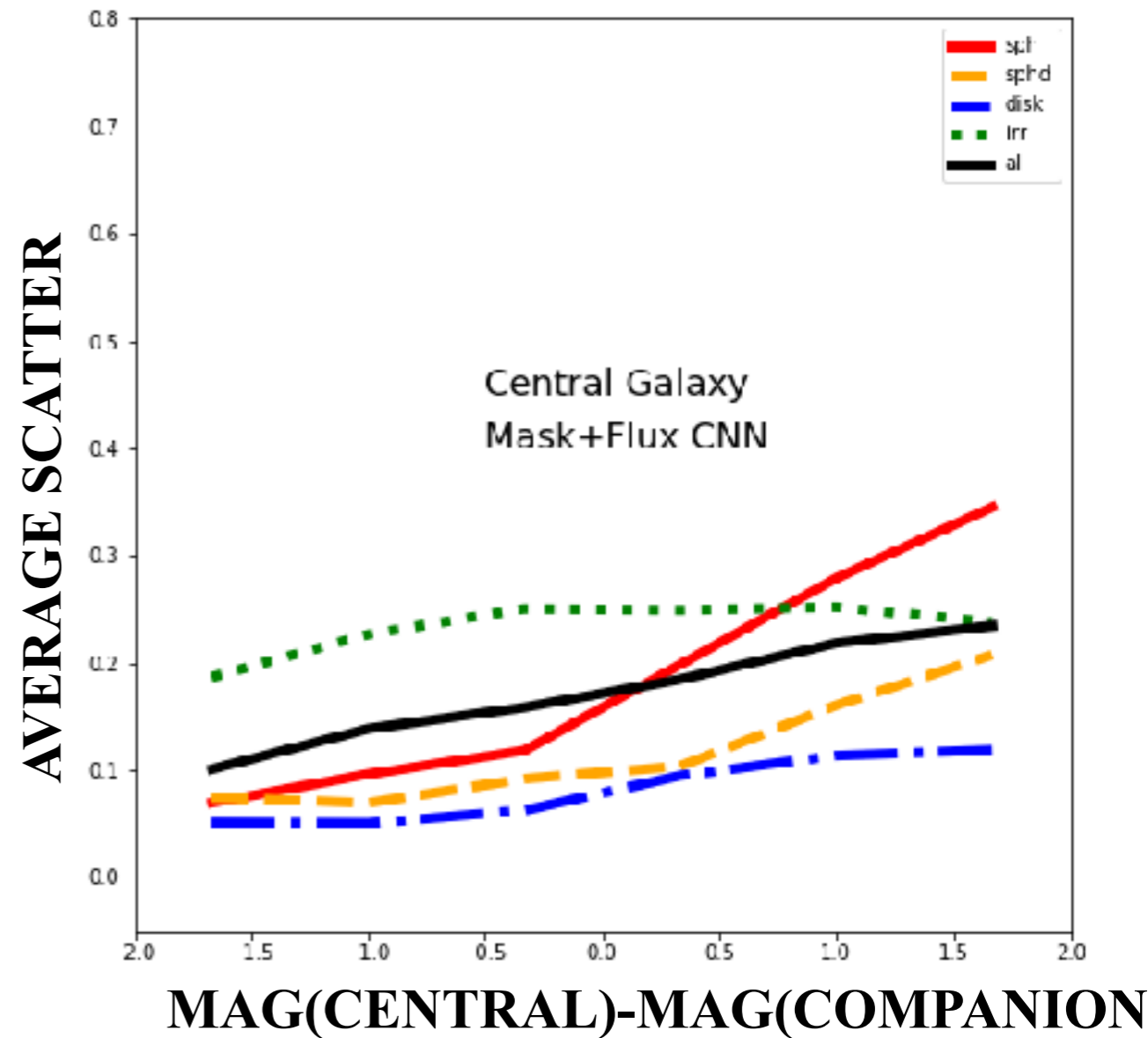


PHOTOMETRY OF BLENDED SOURCES

SExtractor



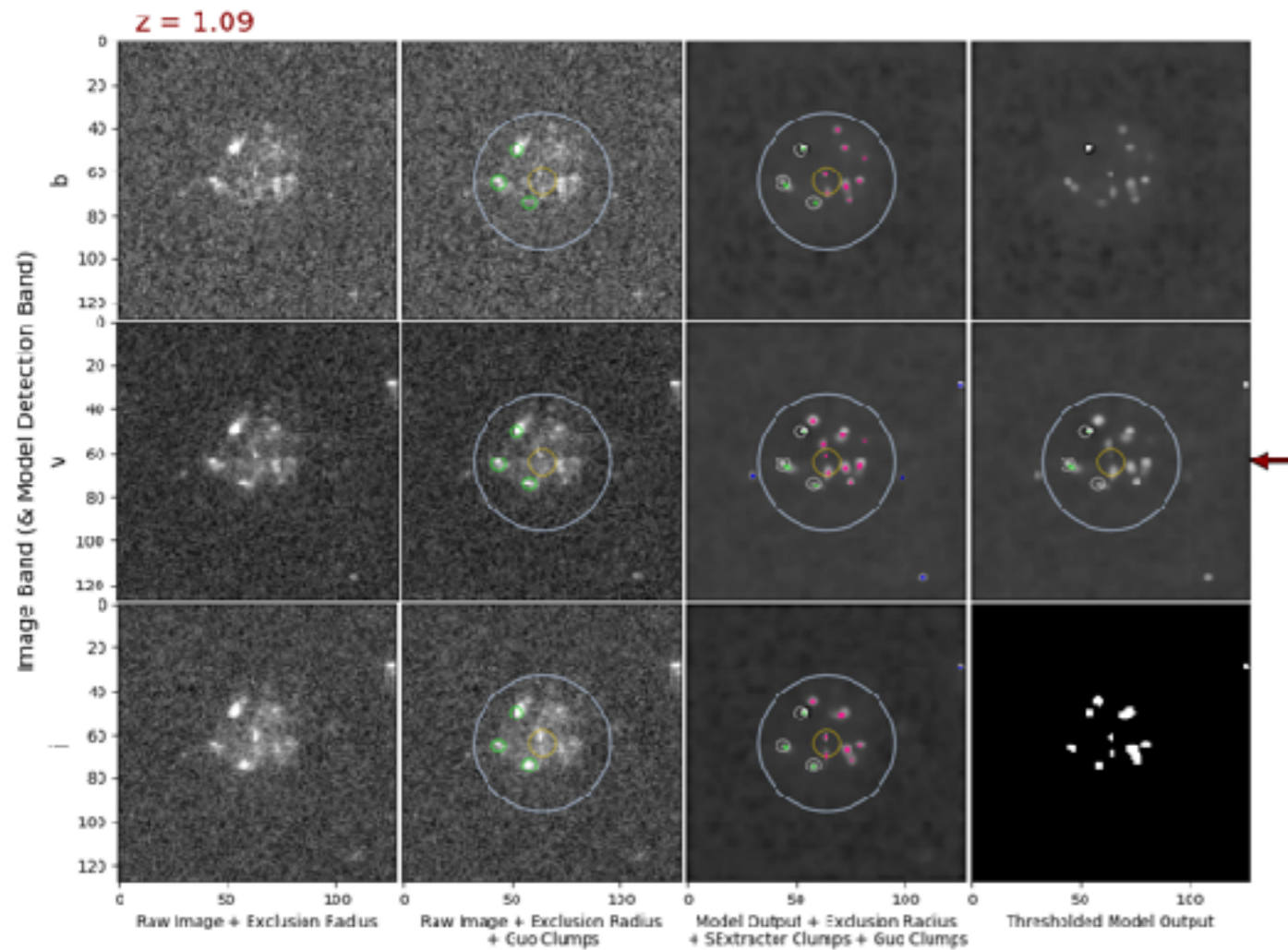
CONSTANT <0.2 SCATTER. A FACTOR
3-4 BETTER THAN SExtractor



REASONABLE BEHAVIOR FOR
DIFFERENT MORPHOLOGIES

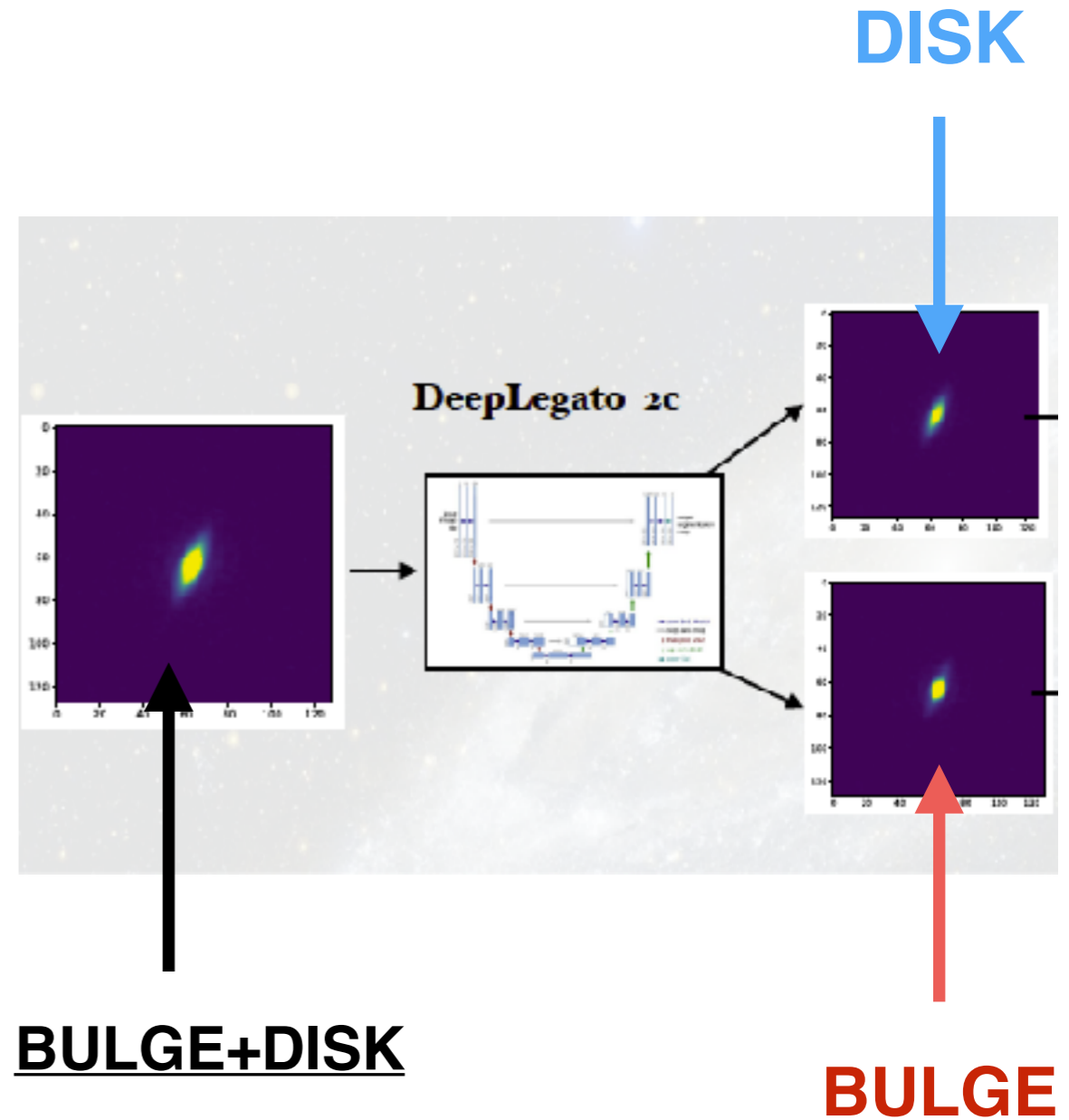
SIMILAR APPROACHES CAN BE USED FOR...

DETECTION OF CLUMPS IN HIGH REDSHIFT GALAXIES



Lee, MHC+19

BULGE-DISK DECOMPOSITIONS



Tuccillo, MHC+19

**THEORY /
SIMULATIONS**



**Illustris, EAGLE,
Horizon-AGN ...**

[FULL 3D EVOLUTION HISTORY]

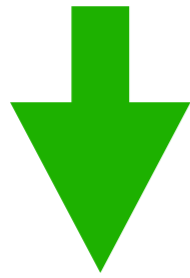
AI TO LINK THEORY AND OBSERVATION IN THE DATA SPACE

**THEORY /
SIMULATIONS**



**Illustris, EAGLE,
Horizon-AGN ...**

[FULL 3D EVOLUTION HISTORY]



**PROJECT HYDRO
SIMS IN
THE
“OBSERVATIONAL
PLANE”**

**ASSUMPTIONS OF MASS
TO LIGHT CONVERSION**

+ DUST

+PSF

+ NOISE

**AI TO LINK THEORY AND
OBSERVATION
IN THE DATA SPACE**

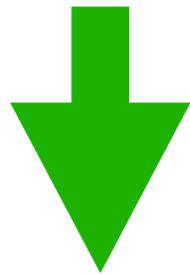
**THEORY /
SIMULATIONS**



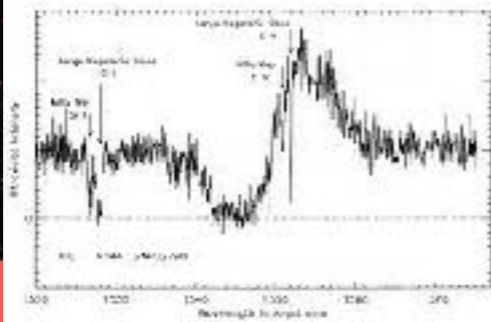
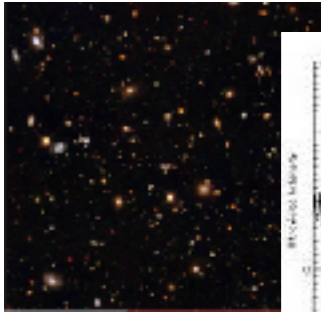
**Illustris, EAGLE,
Horizon-AGN ...**

AI TO LINK THEORY AND OBSERVATION IN THE DATA SPACE

[FULL 3D EVOLUTION HISTORY]



**PROJECT HYDRO
SIMS IN
THE
“OBSERVATIONAL
PLANE”**



**MOCK
OBSERVATIONS**



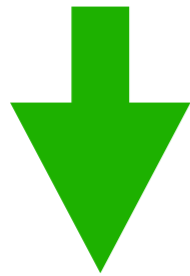
**THEORY /
SIMULATIONS**



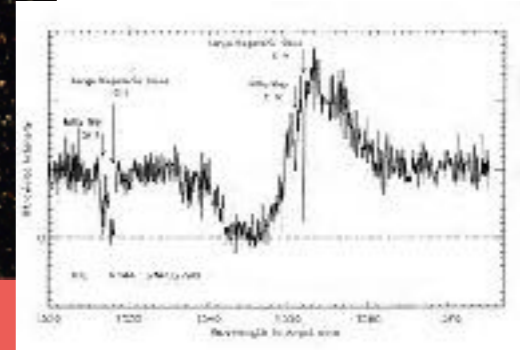
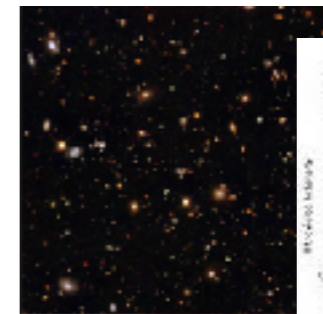
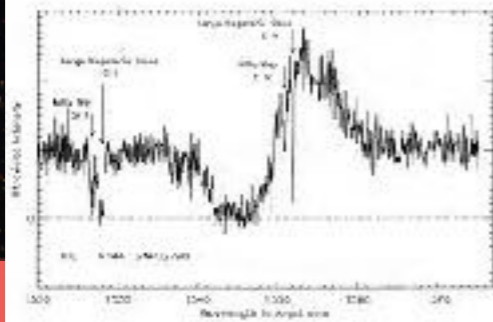
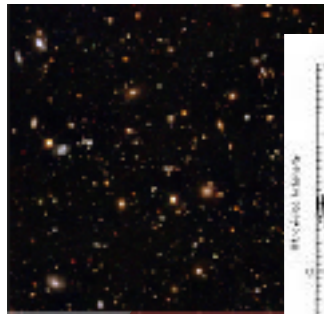
**Illustris, EAGLE,
Horizon-AGN ...**

AI TO LINK THEORY AND OBSERVATION IN THE DATA SPACE

[FULL 3D EVOLUTION HISTORY]



**PROJECT HYDRO
SIMS IN
THE
“OBSERVATIONAL
PLANE”**



**MOCK
OBSERVATIONS**



OBSERVATIONS



**MACHINE (DEEP)
LEARNING**

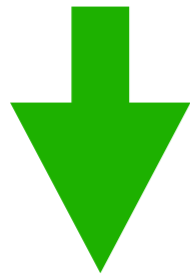
**THEORY /
SIMULATIONS**



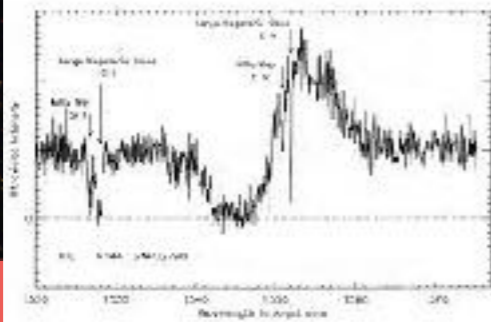
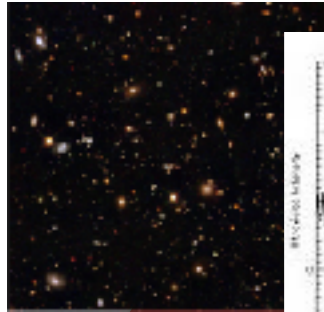
**Illustris, EAGLE,
Horizon-AGN ...**

AI TO LINK THEORY AND OBSERVATION IN THE DATA SPACE

[FULL 3D EVOLUTION HISTORY]

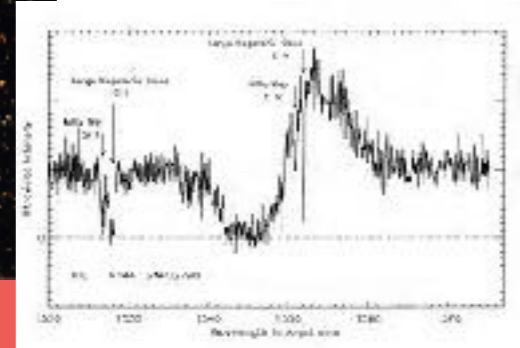
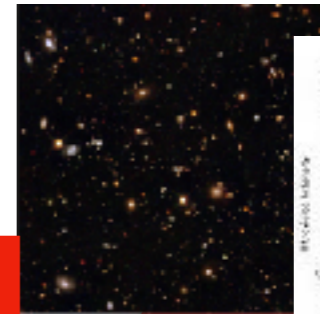


**PROJECT HYDRO
SIMS IN
THE
“OBSERVATIONAL
PLANE”**



TEST

TRAIN



**MOCK
OBSERVATIONS**



OBSERVATIONS



**MACHINE (DEEP)
LEARNING**

**THEORY /
SIMULATIONS**



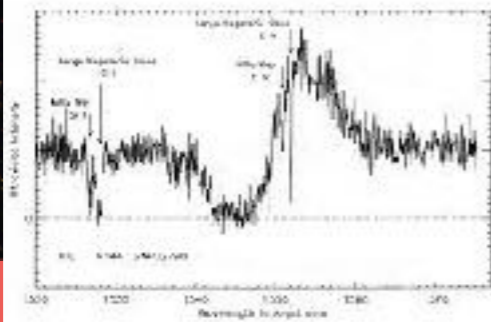
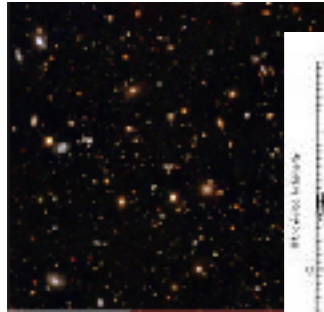
**Illustris, EAGLE,
Horizon-AGN ...**

AI TO LINK THEORY AND OBSERVATION IN THE DATA SPACE

[FULL 3D EVOLUTION HISTORY]

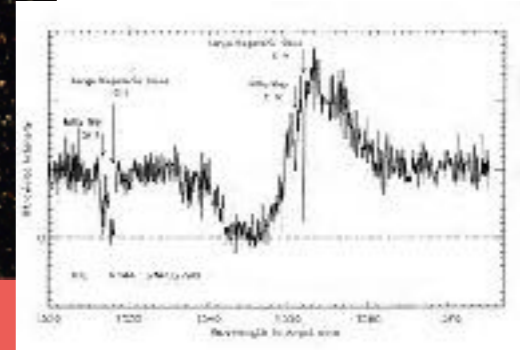
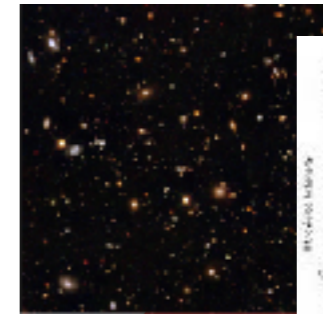


**PROJECT HYDRO
SIMS IN
THE
“OBSERVATIONAL
PLANE”**



TRAIN

TEST



**MOCK
OBSERVATIONS**

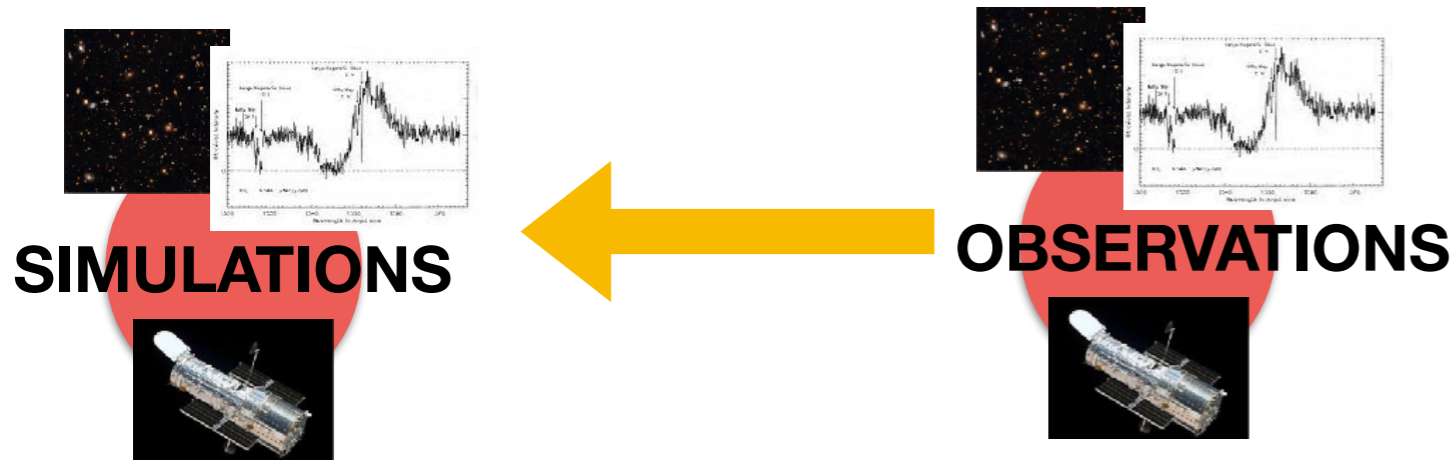


OBSERVATIONS



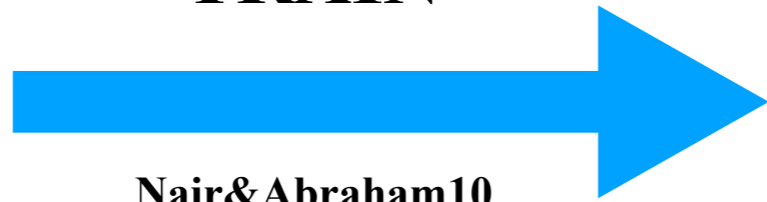
**MACHINE (DEEP)
LEARNING**

**HOW REALISTIC
ARE ILLUSTRIS
TNG
MORPHOLOGIES?**



**SDSS
DR7**

TRAIN



Nair&Abraham10
GZOO

**CNN MODEL
TO ESTIMATE GALAXY “VISUAL”
MORPHOLOGY**

Dominguez-Sanchez+18

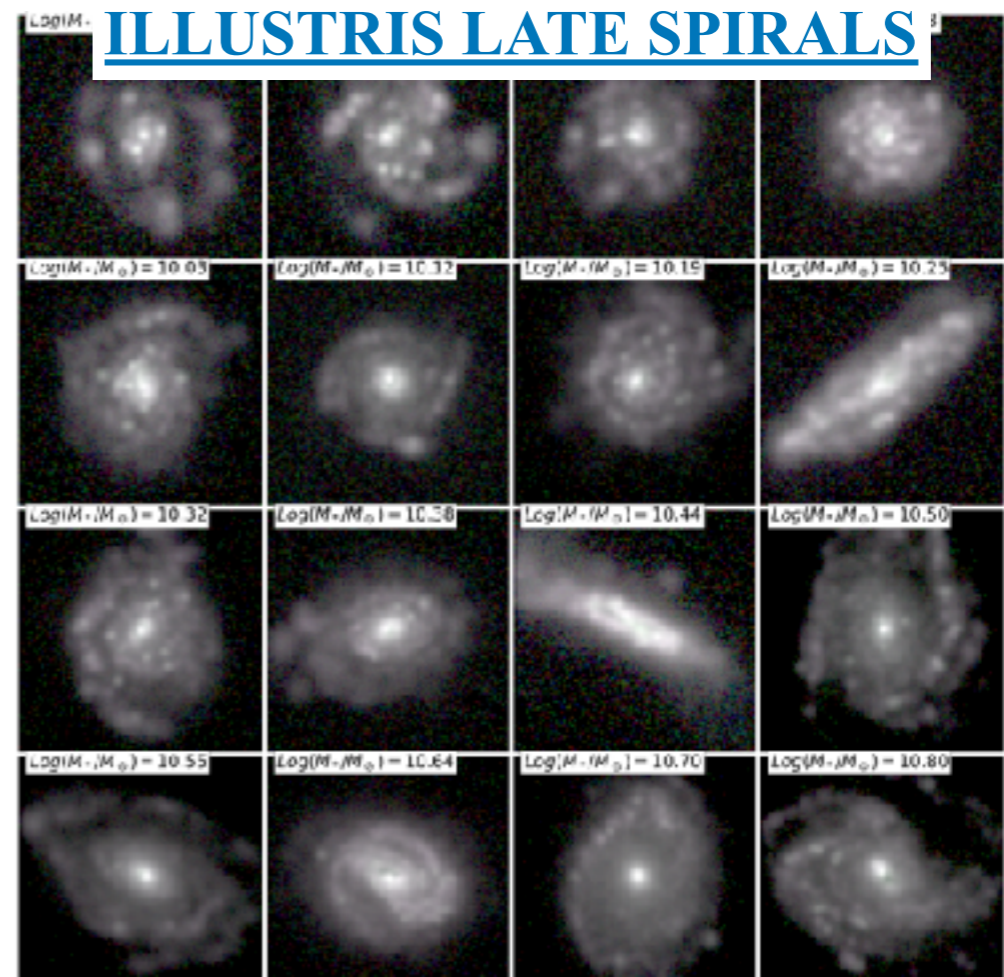
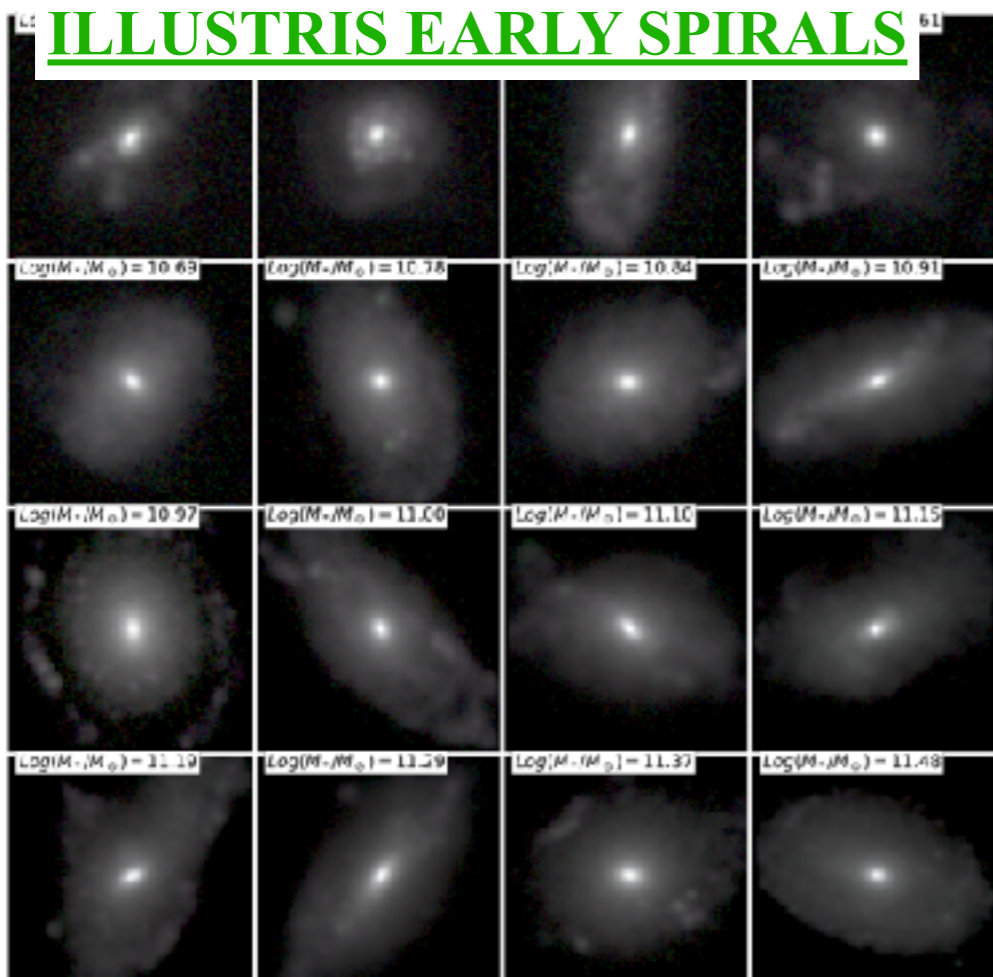
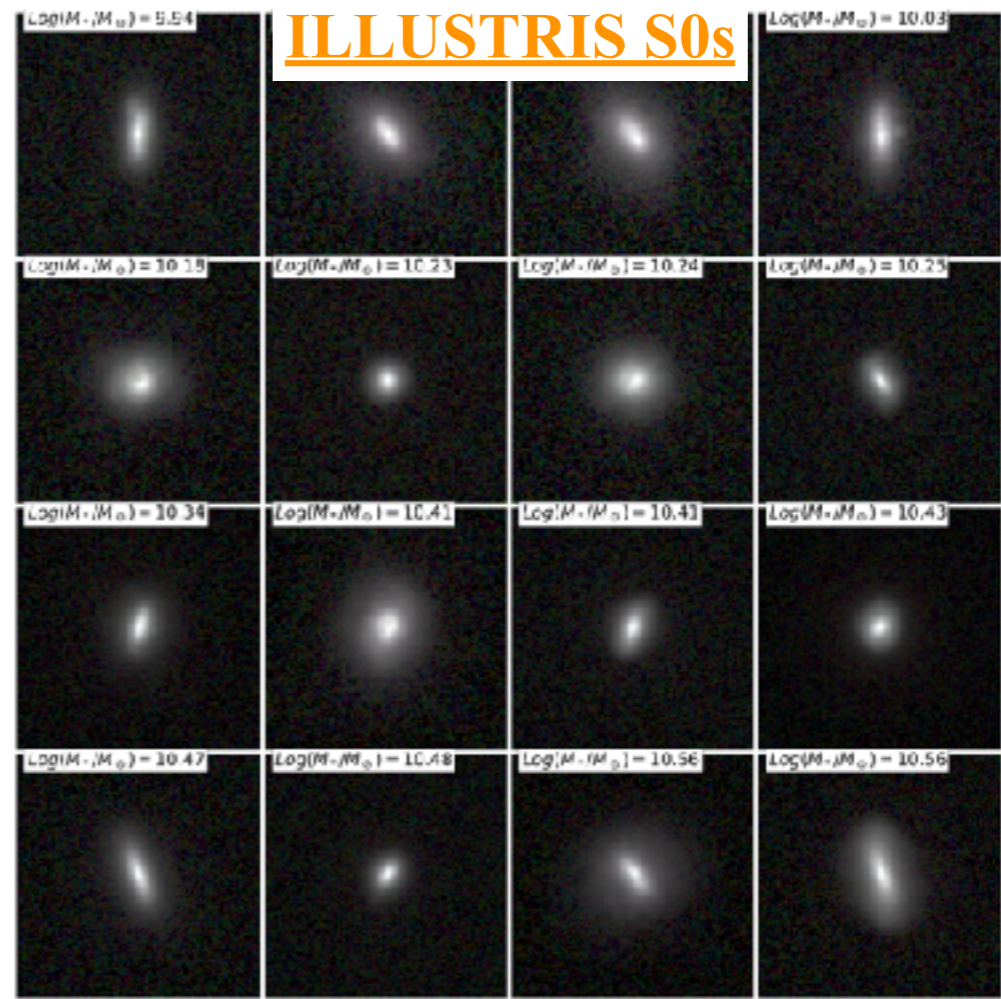
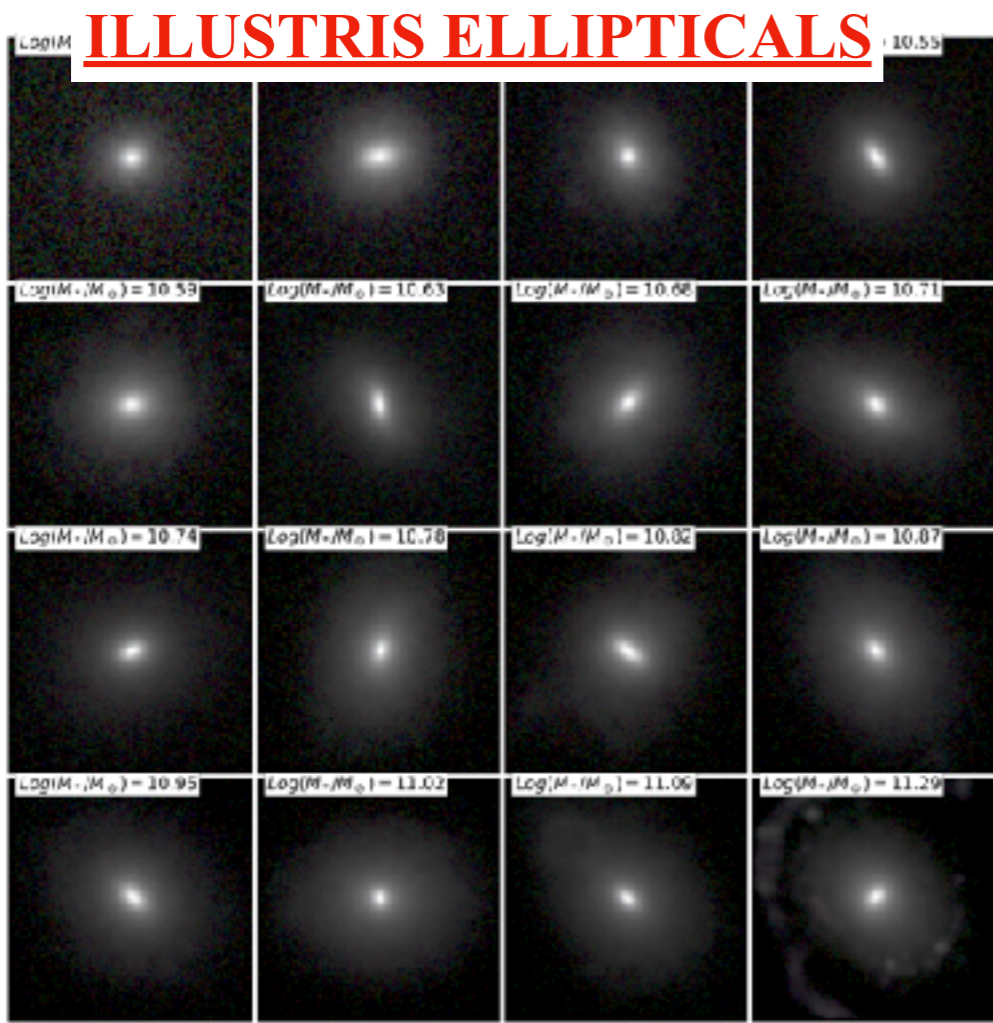
**ILLUTRIS
TNG**

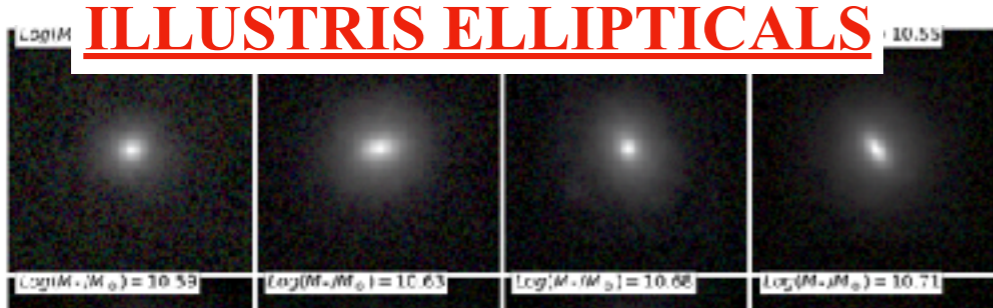


**MOCK
SDSS
GALAXIES**

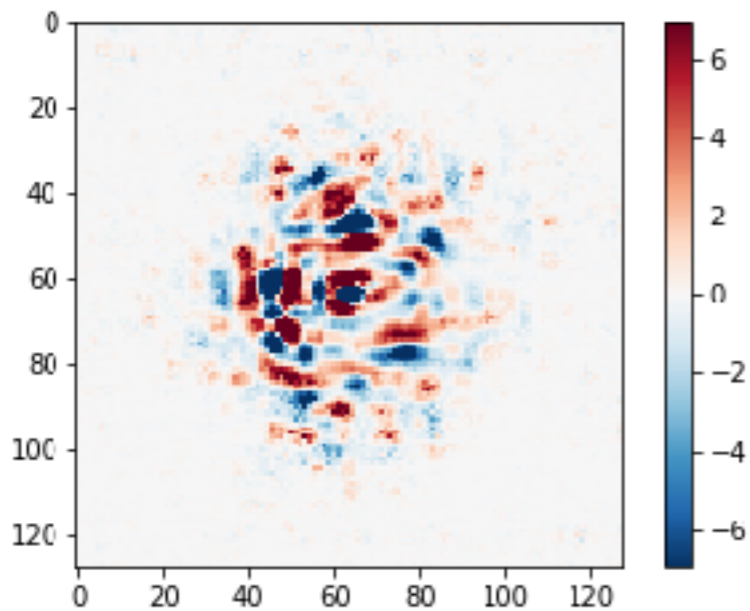
CLASSIFY



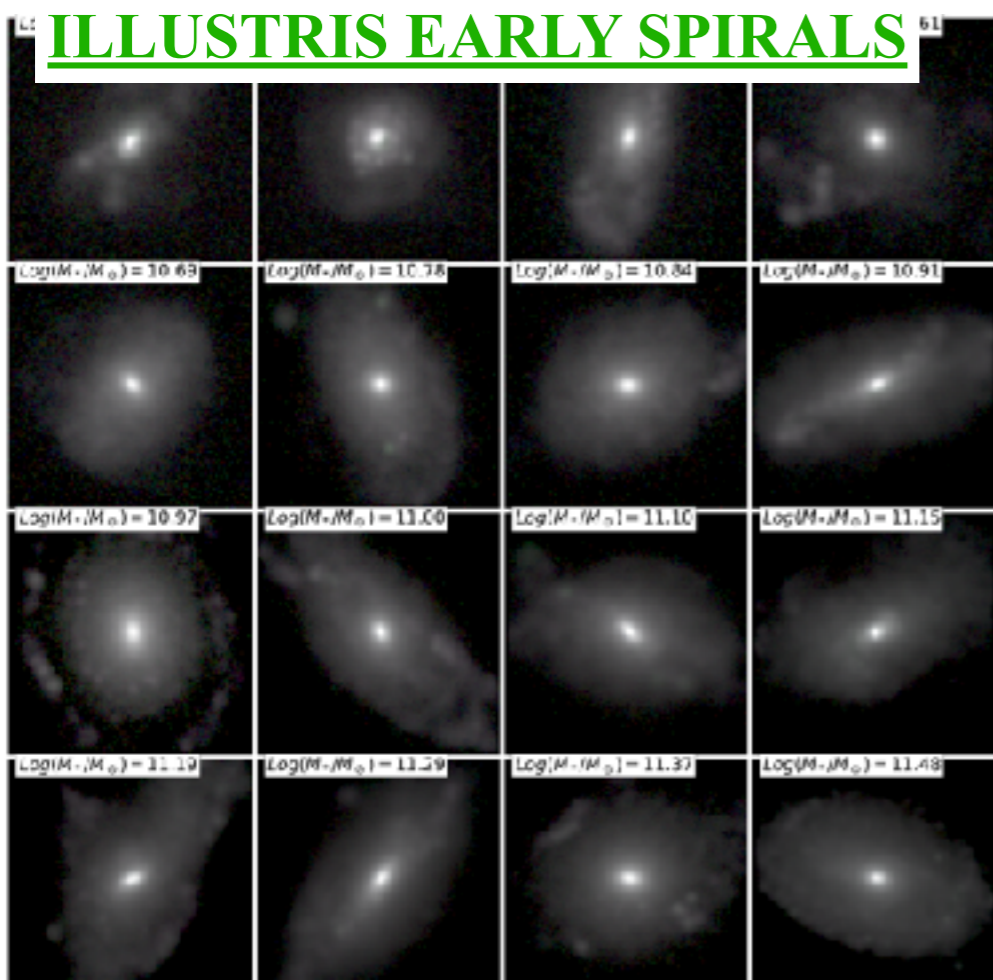




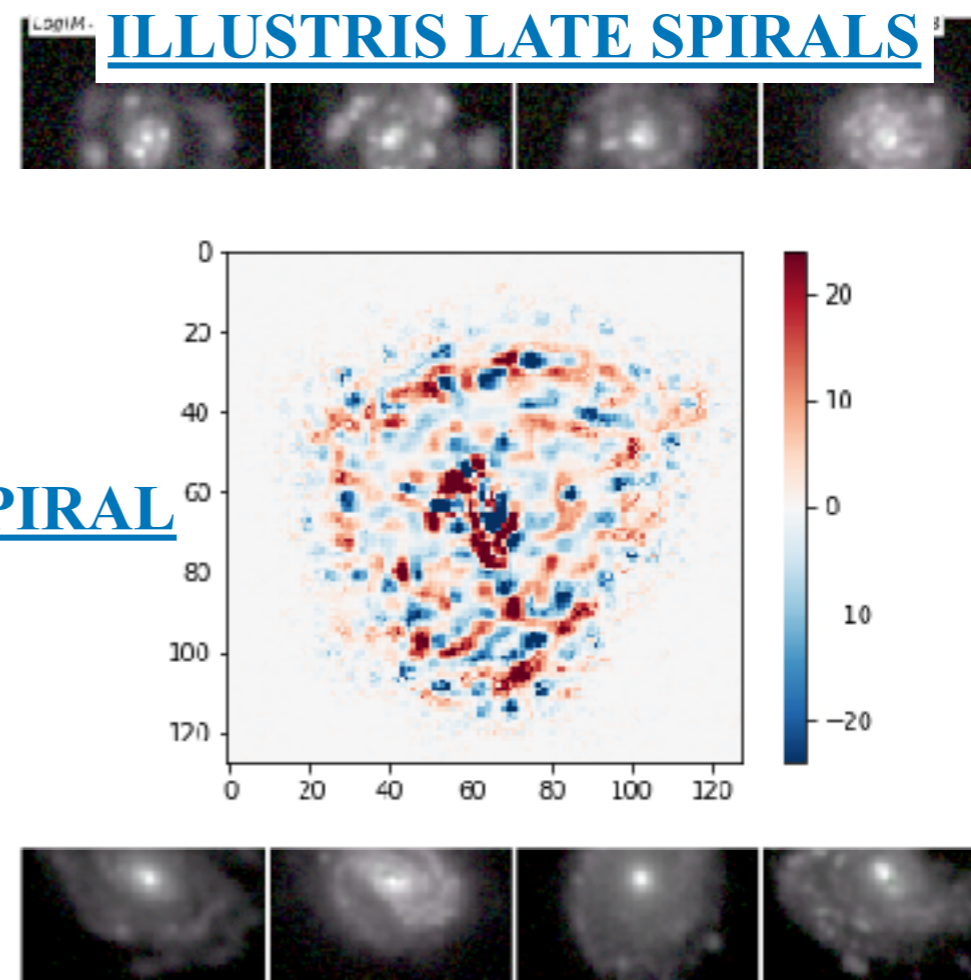
ELL



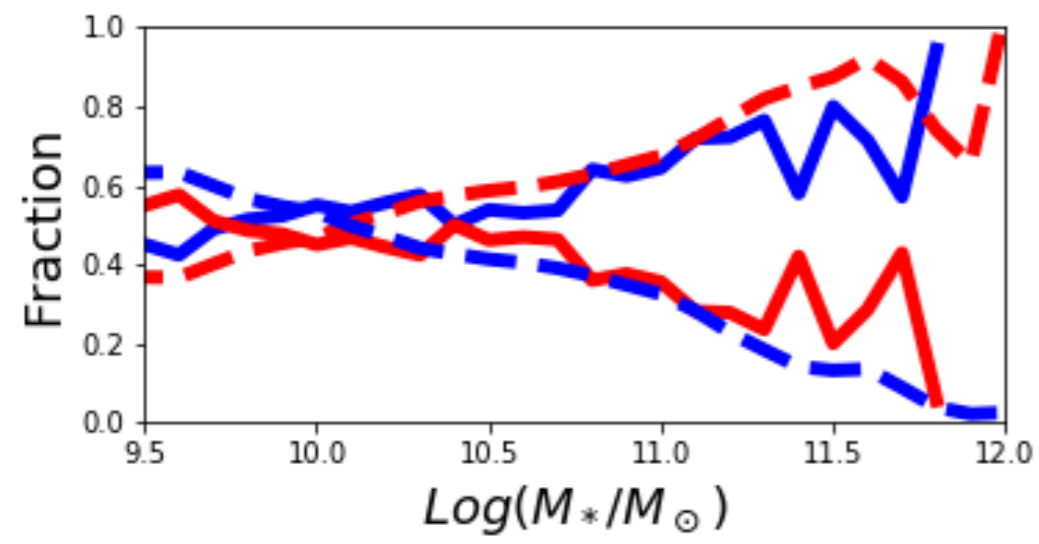
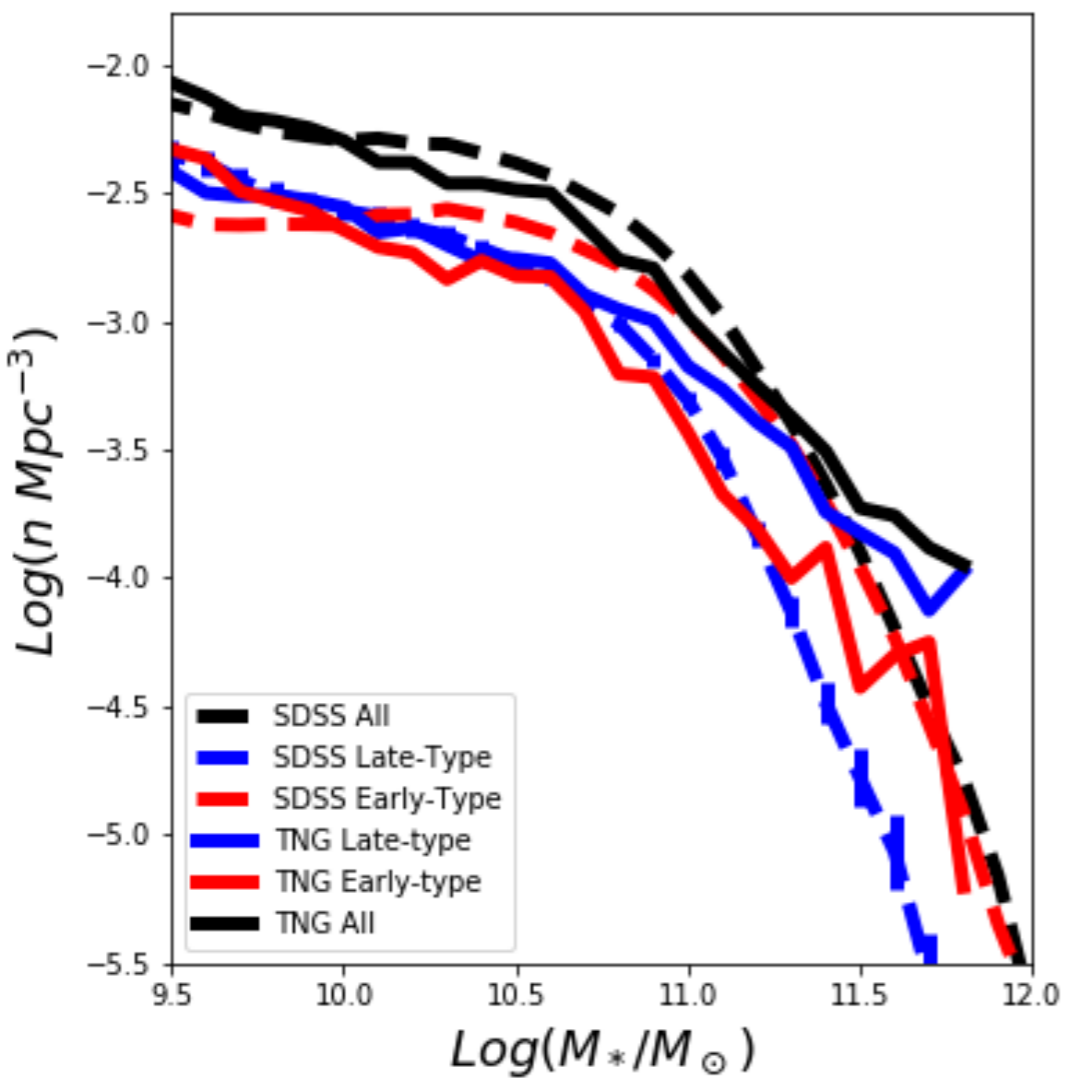
**ATTRIBUTION
TECHNIQUES
PROVIDE SOME
INFORMATION
BUT STILL
RATHER LIMITED**



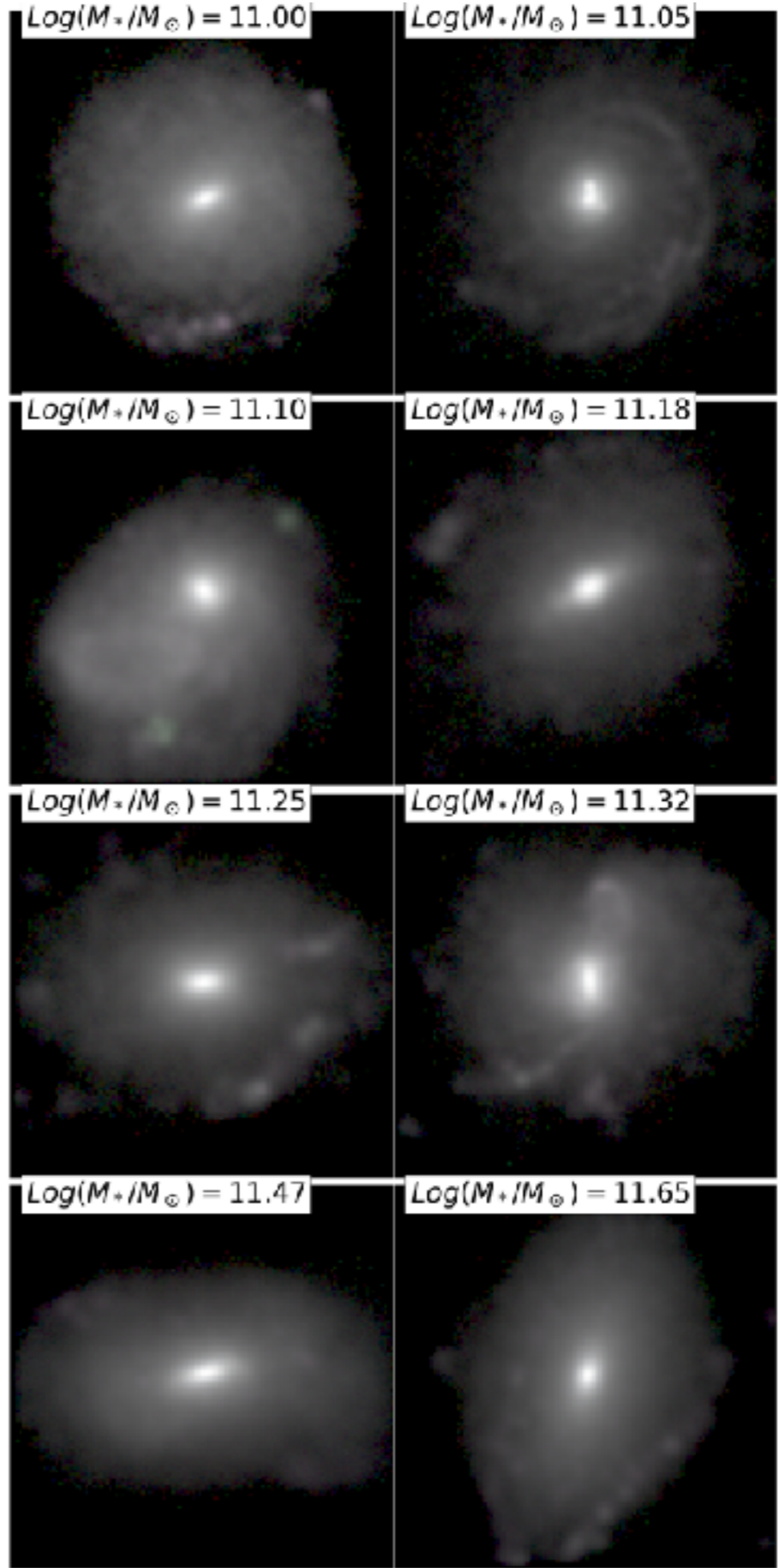
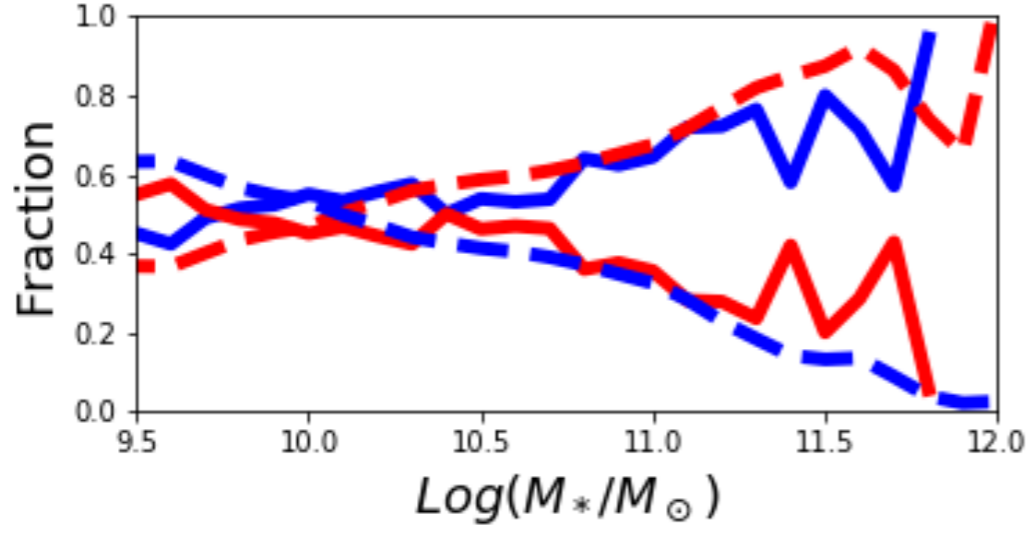
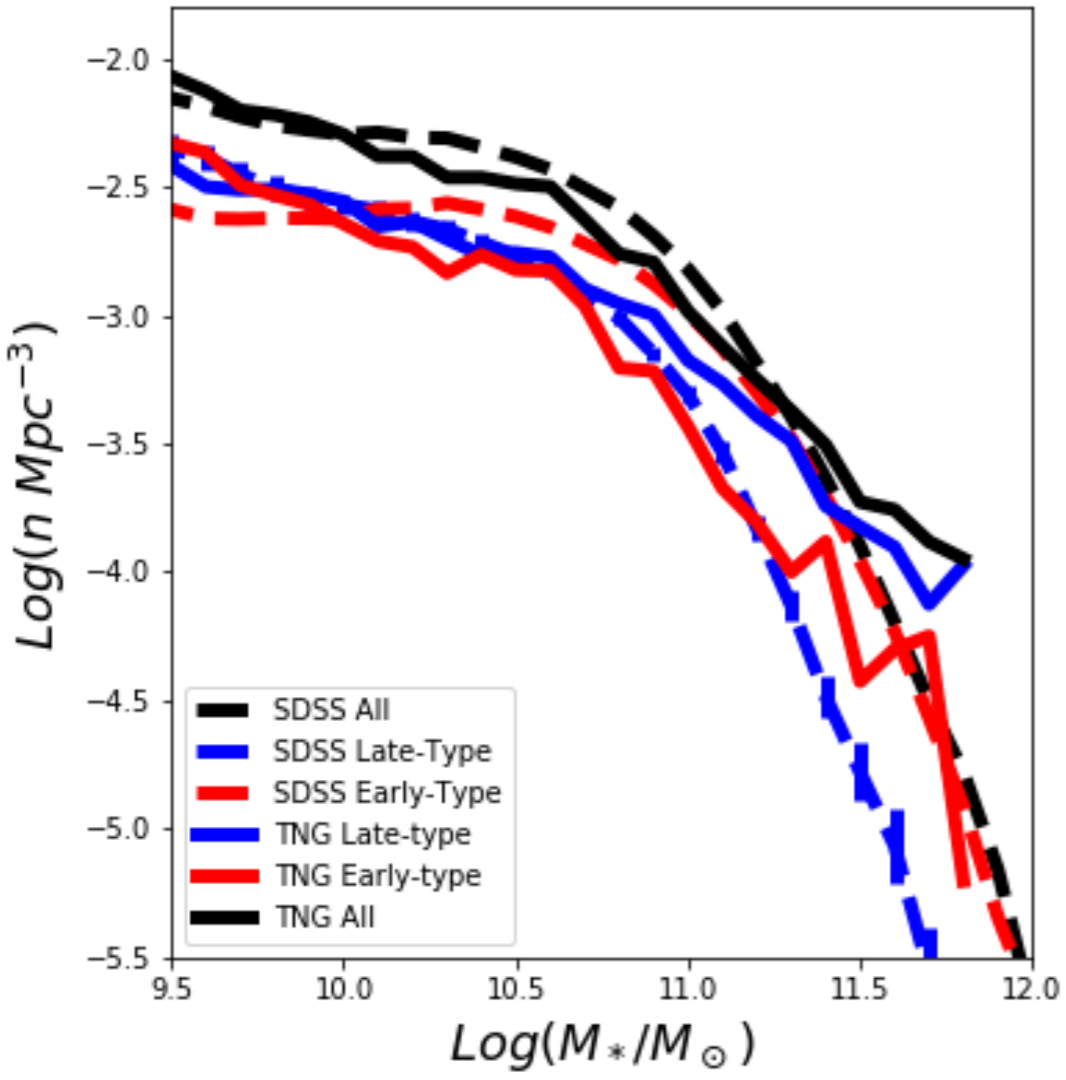
SPIRAL



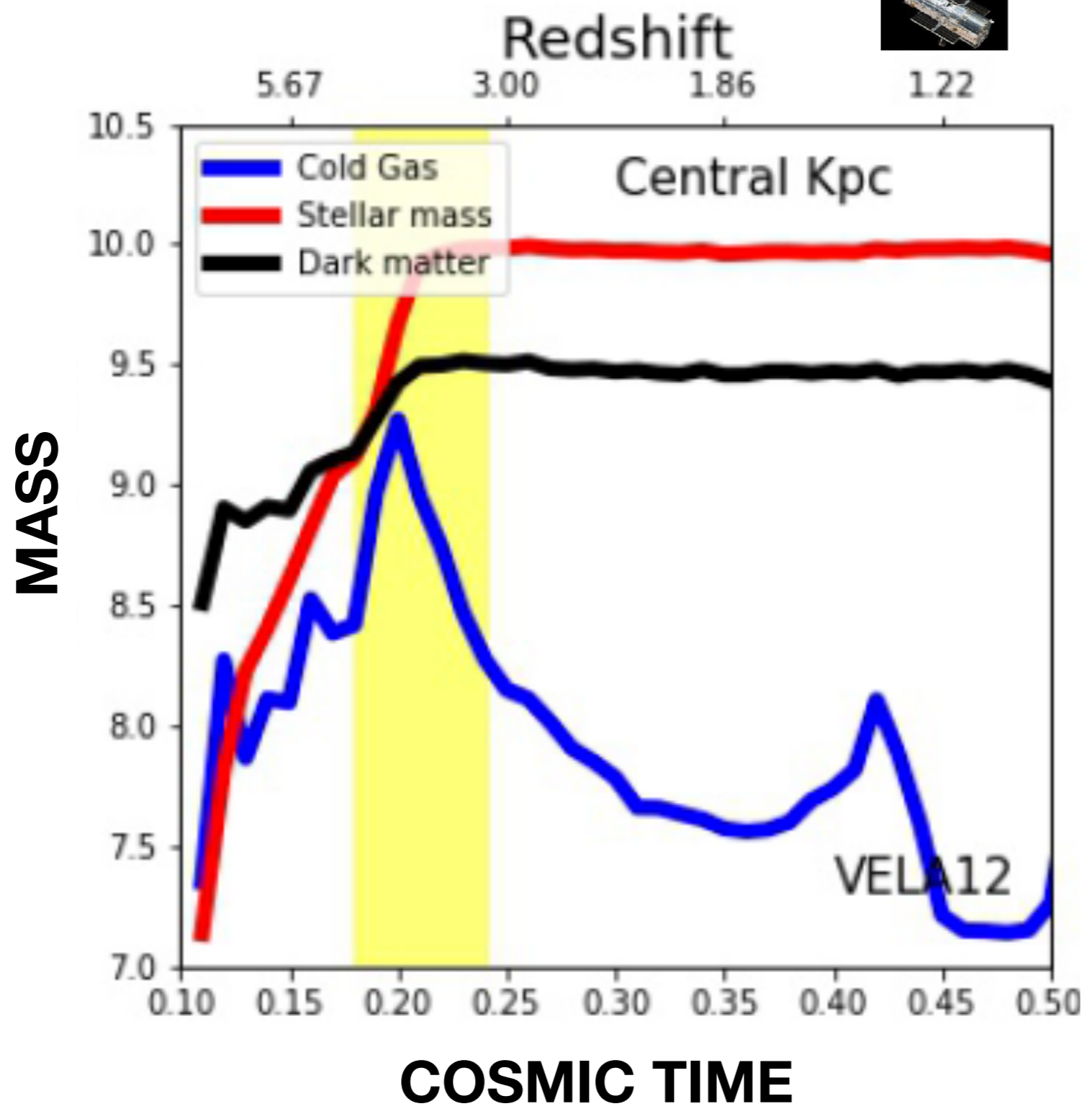
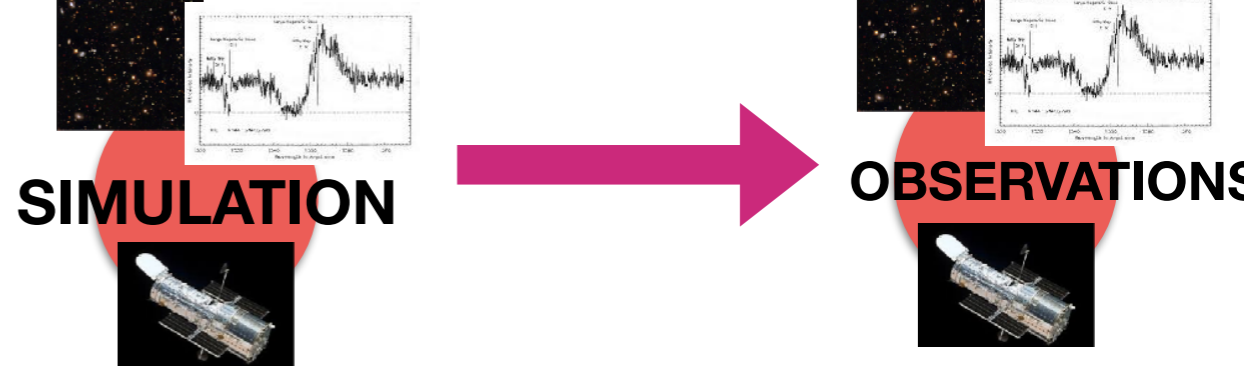
THE HIGH MASS END OF THE STELLAR MASS FUNCTION OF ILLUSTRIS TNG IS DOMINATED BY DISKS



THE HIGH MASS END OF THE STELLAR MASS FUNCTION OF ILLUSTRIS TNG IS DOMINATED BY DISKS

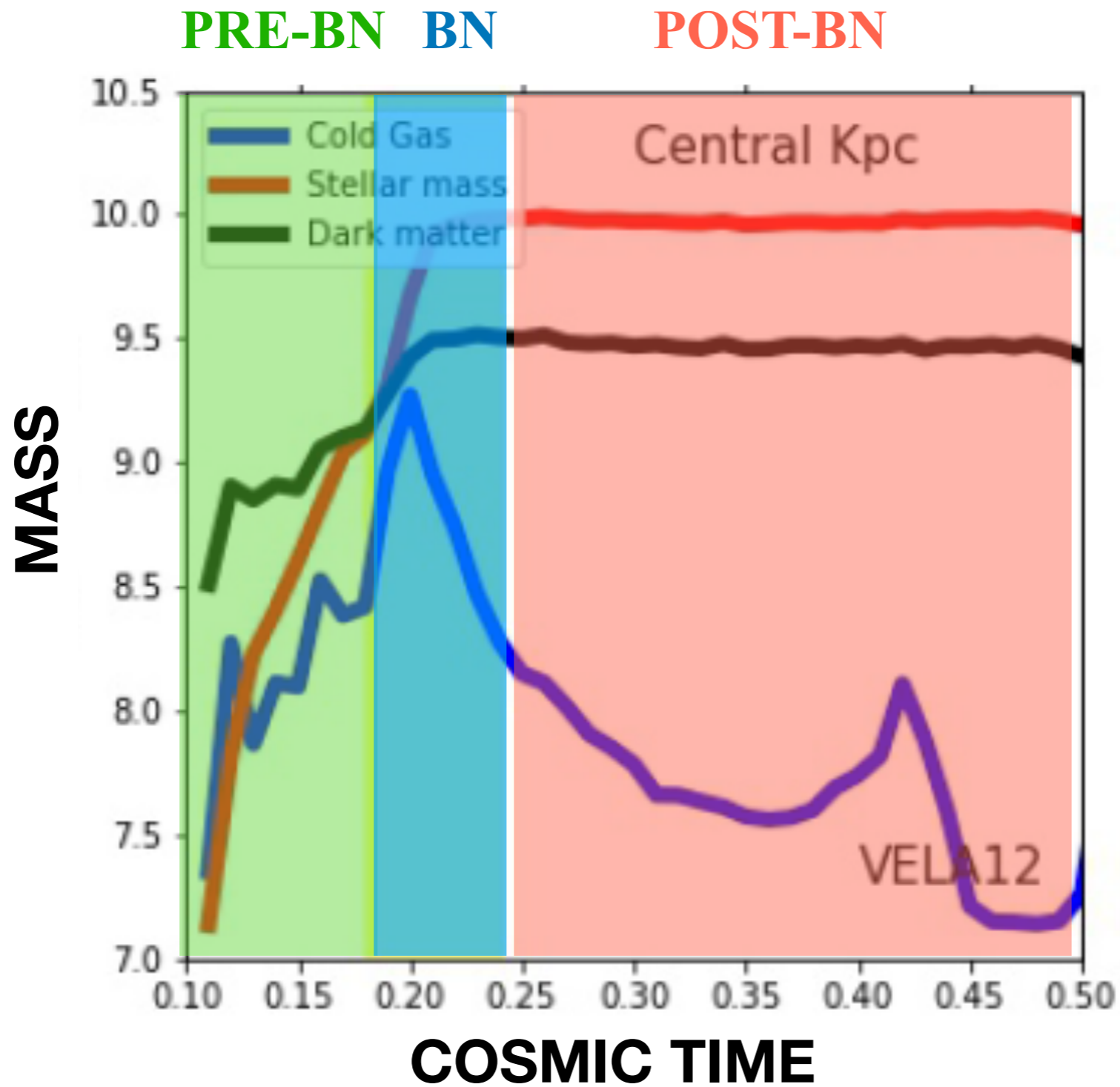


IDENTIFYING COMPACTION IN THE VELA ZOOM-IN OF SIMULATIONS



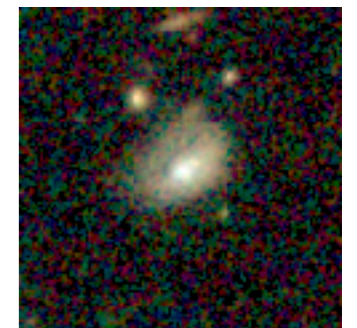
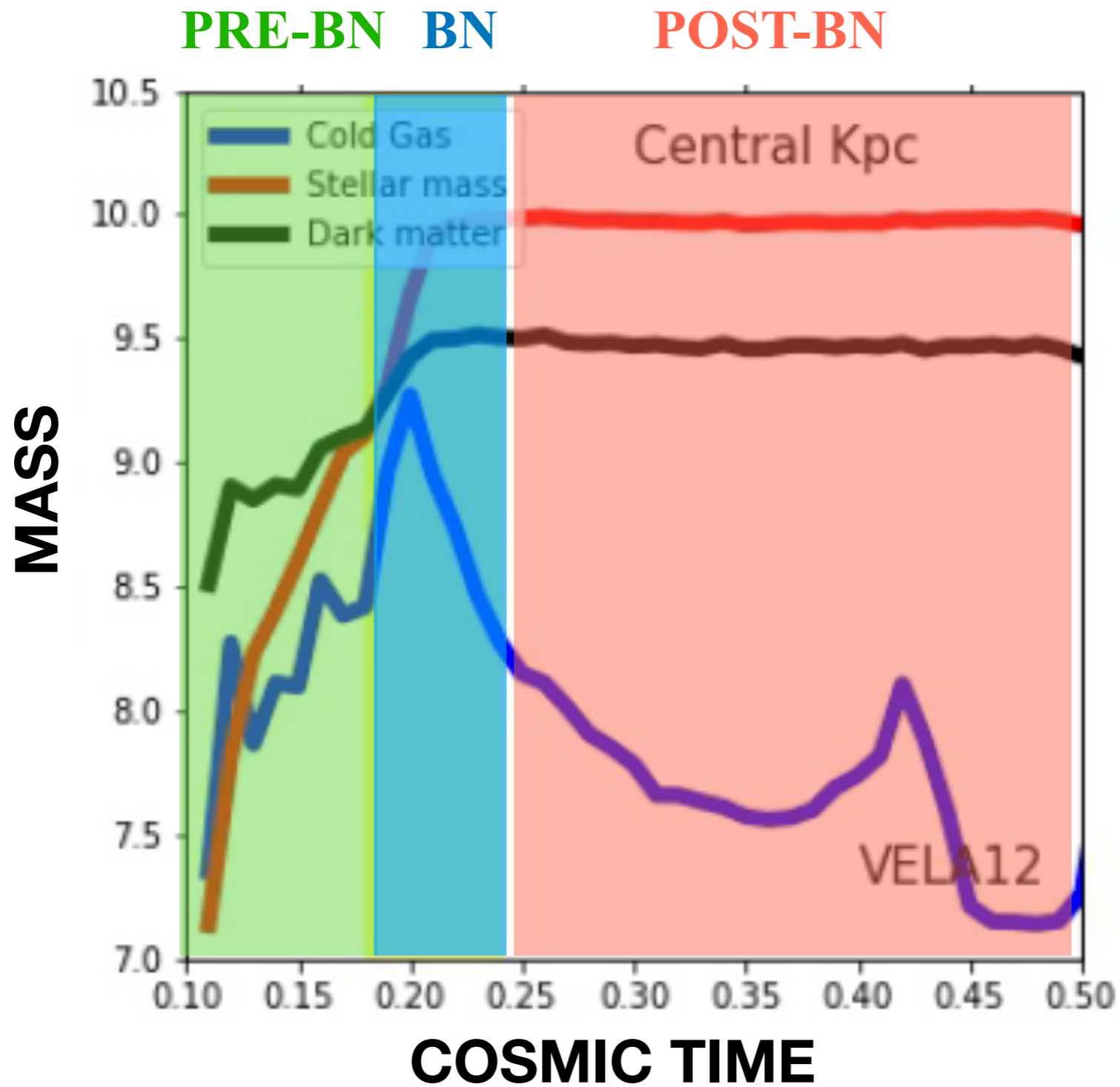
VELA suite of hydro simulations [Ceverino, Dekel+]

IDENTIFYING COMPACTION IN THE VELA ZOOM-IN OF SIMULATIONS

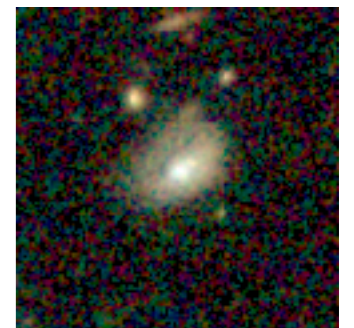
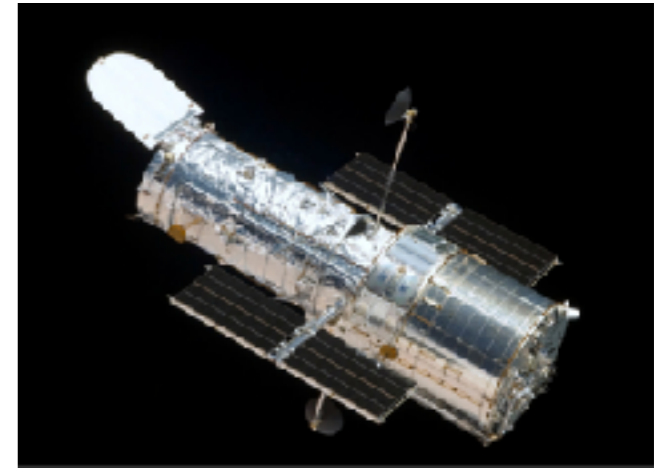
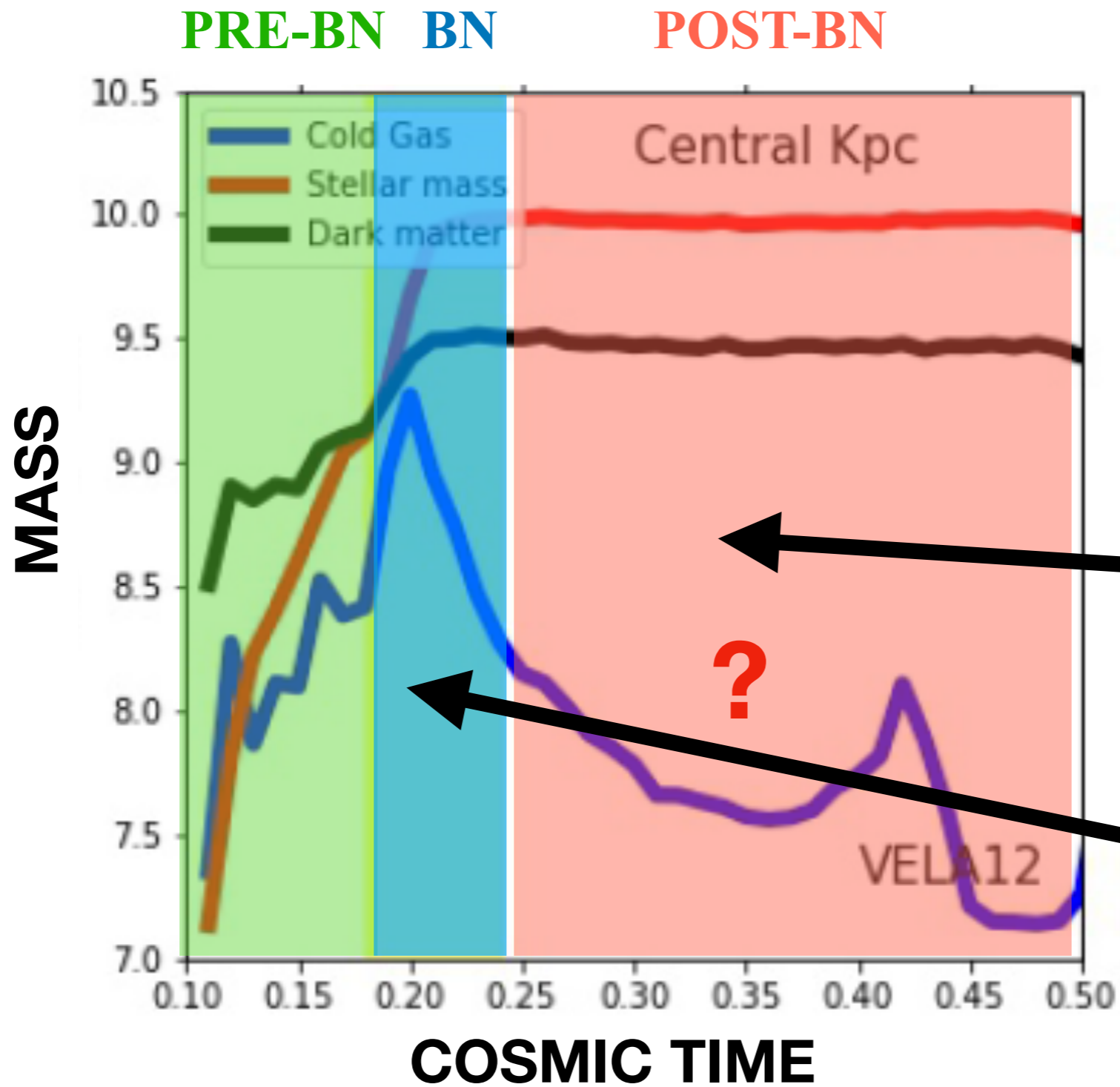


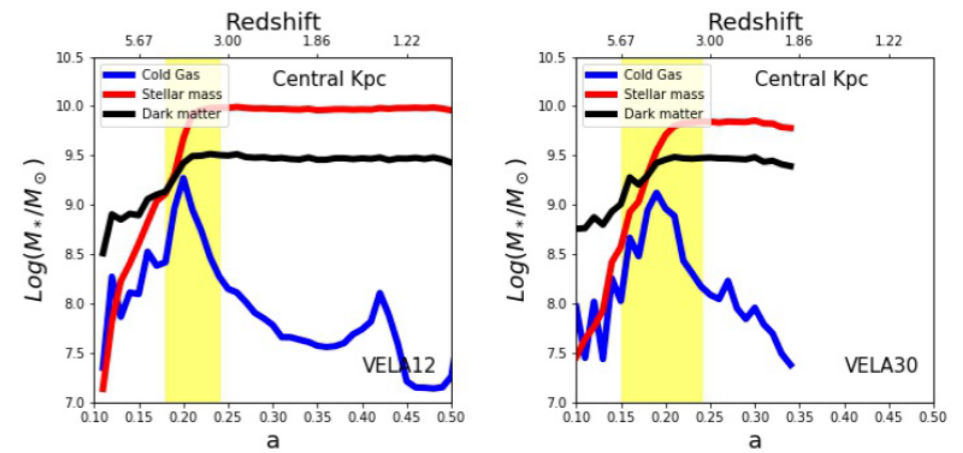
**LABELLING
EXCLUSIVELY
BASED ON
THE FULL HISTORY
OF THE GALAXY
FROM ADVANCED
NUMERICAL
SIMULATIONS
BASED ON PHYSICAL
PRINCIPLES**

IN THE OBSERVATIONS WE ONLY HAVE ONE SNAPSHOT OF A GALAXY AT A GIVEN TIME

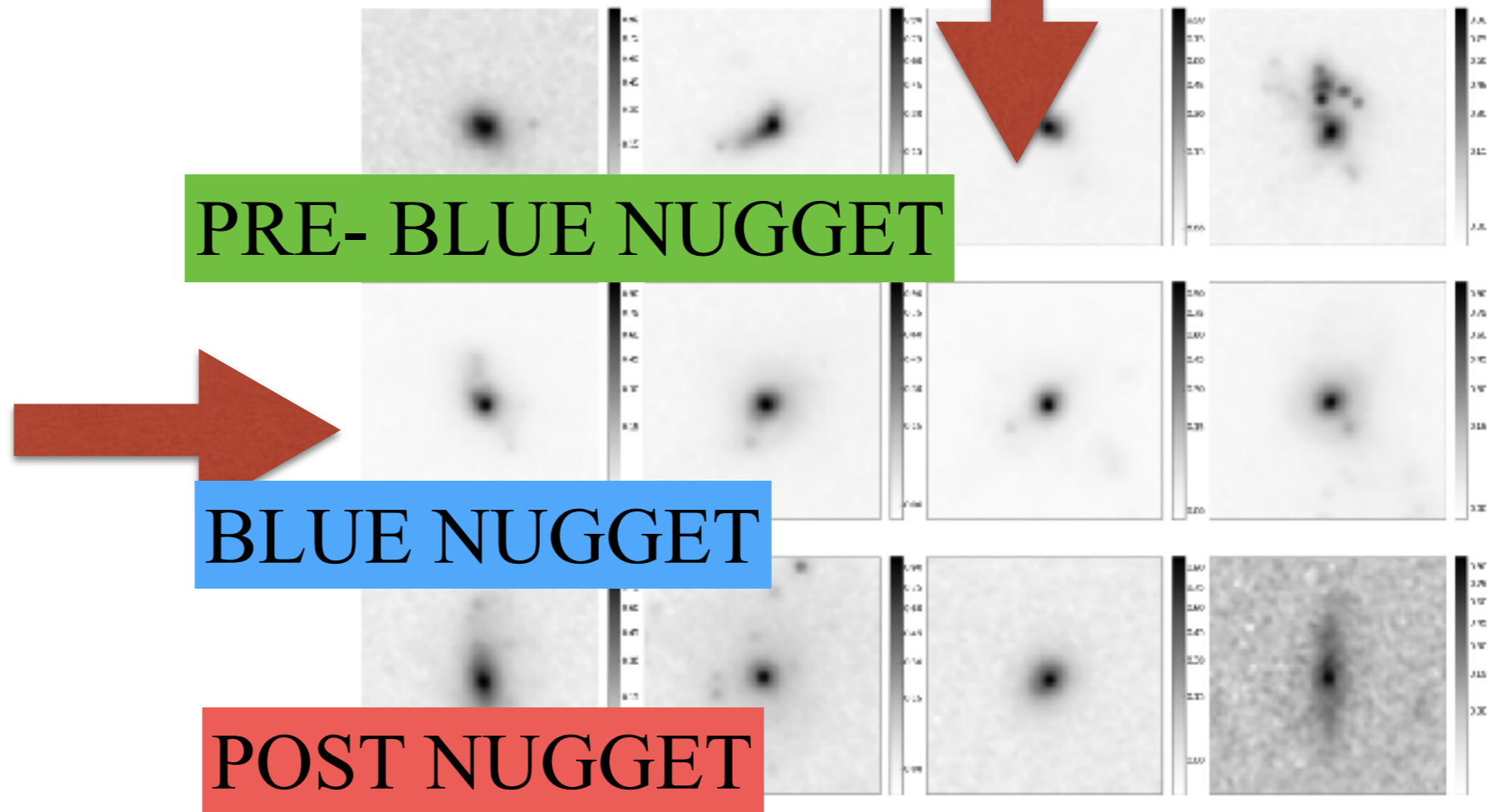
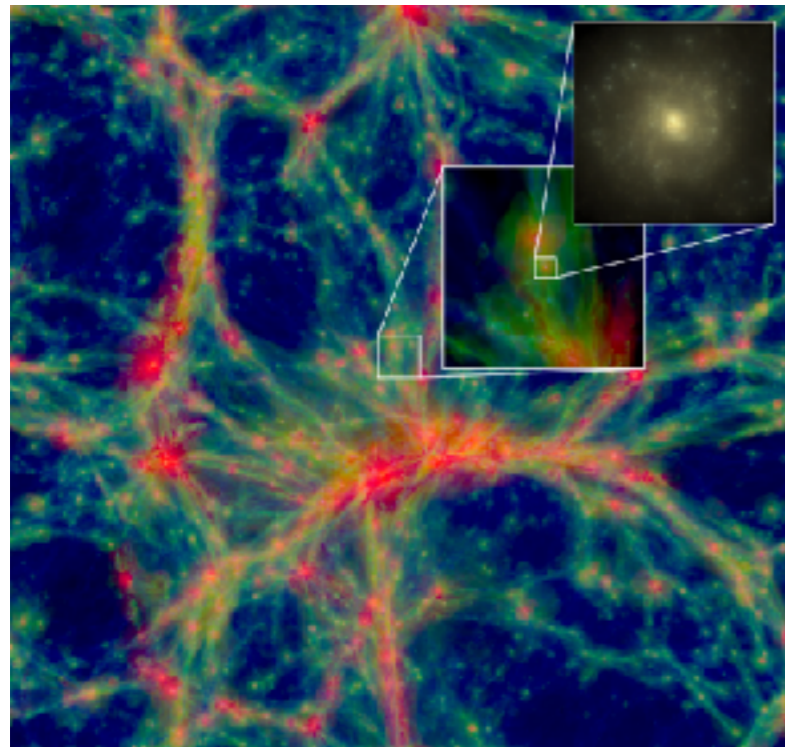


HOW CAN WE ESTIMATE THE PHASE FROM A UNIQUE IMAGE?





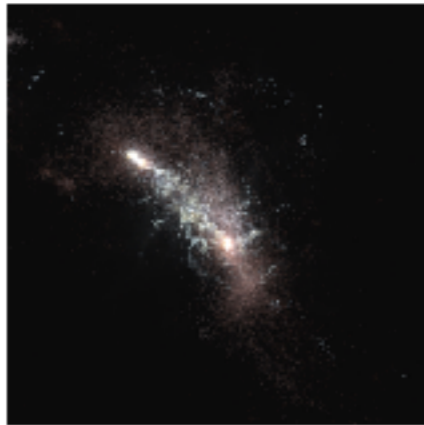
USE THE FORMATION HISTORY OF EACH GALAXY
TO LABEL IMAGES ...



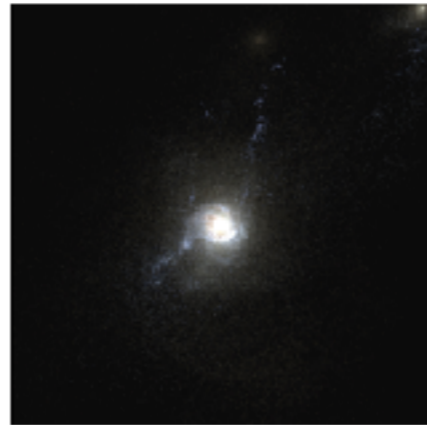
PROJECT THE 3D OBJECT TO GENERATE “MOCK”
IMAGES
AS OBSERVED BY HUBBLE

[COSMOLOGICAL
SIMULATION]

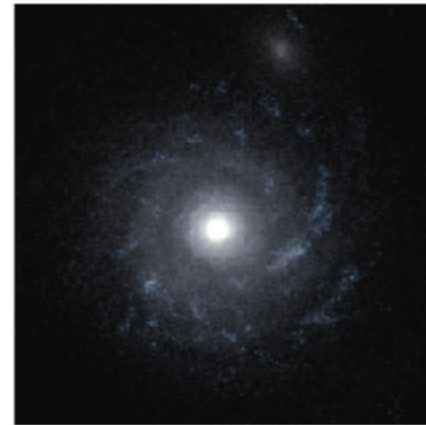
Pre-Blue-Nugget-Stage



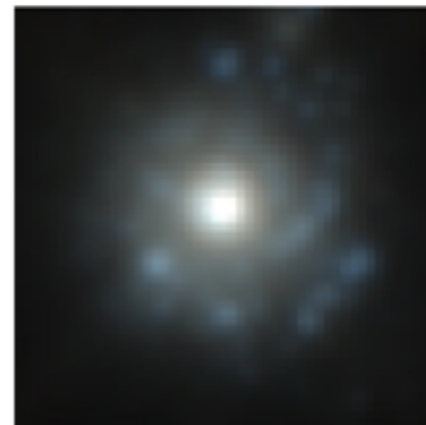
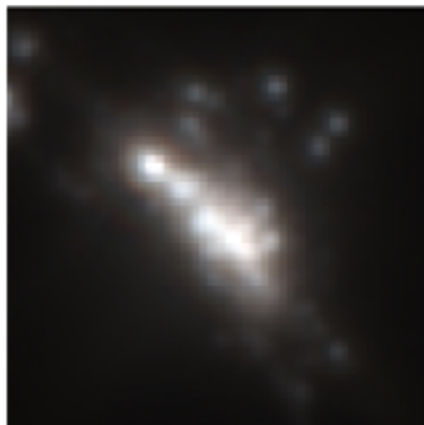
Blue-Nugget-Stage



Post-Blue-Nugget-Stage



VELA HIGH RESOLUTION

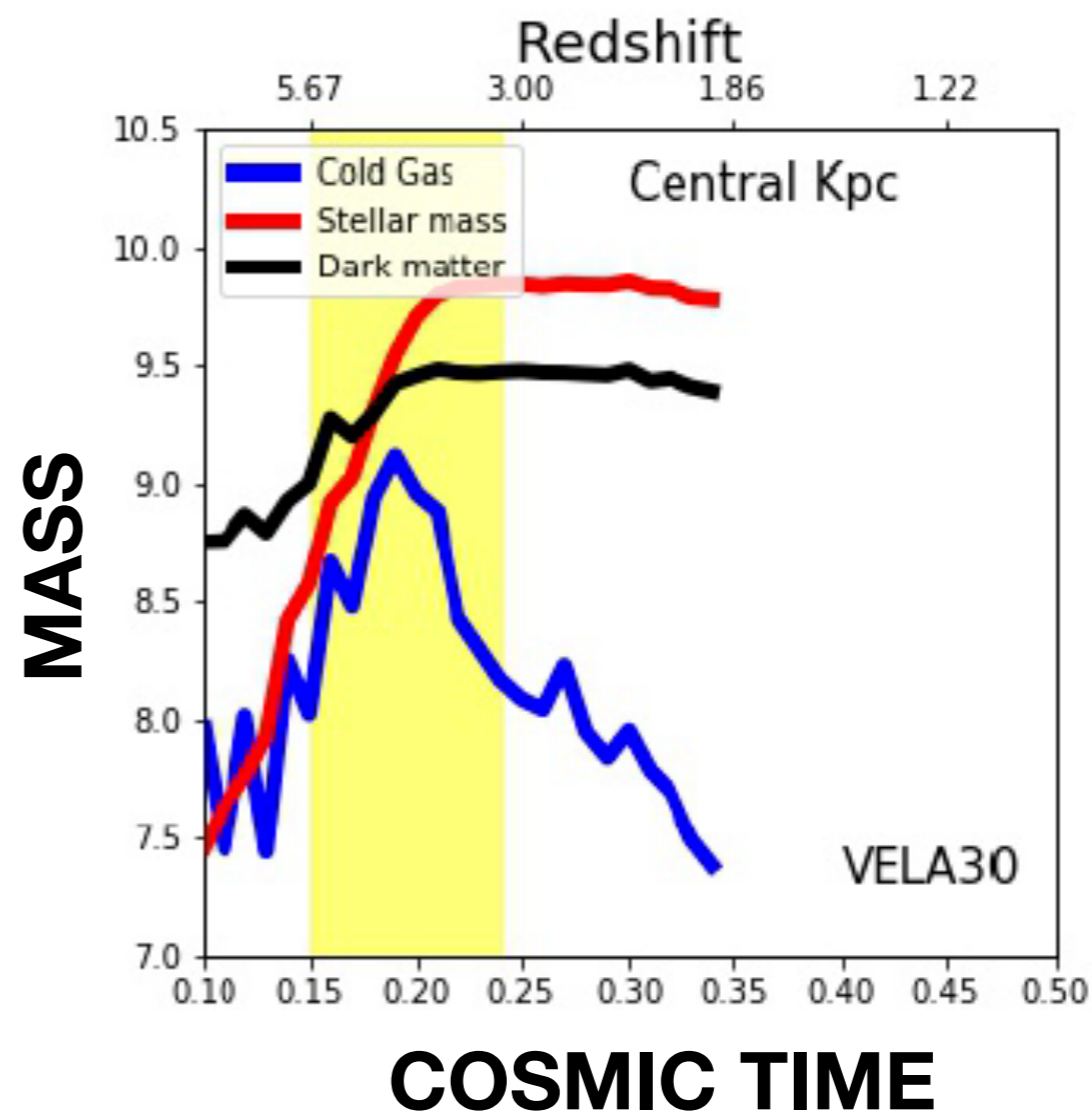
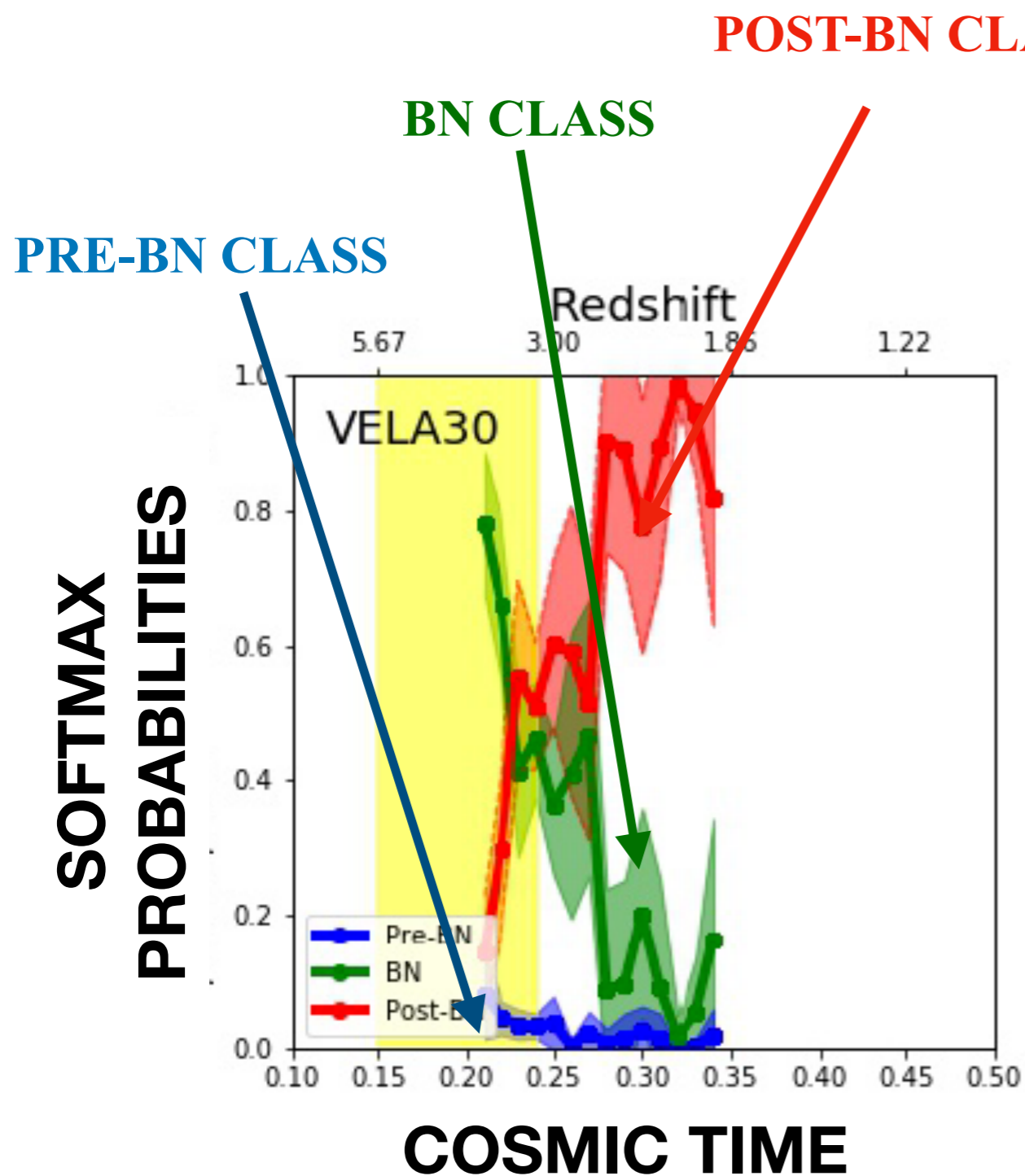


VELA HST RESOLUTION



CANDELS

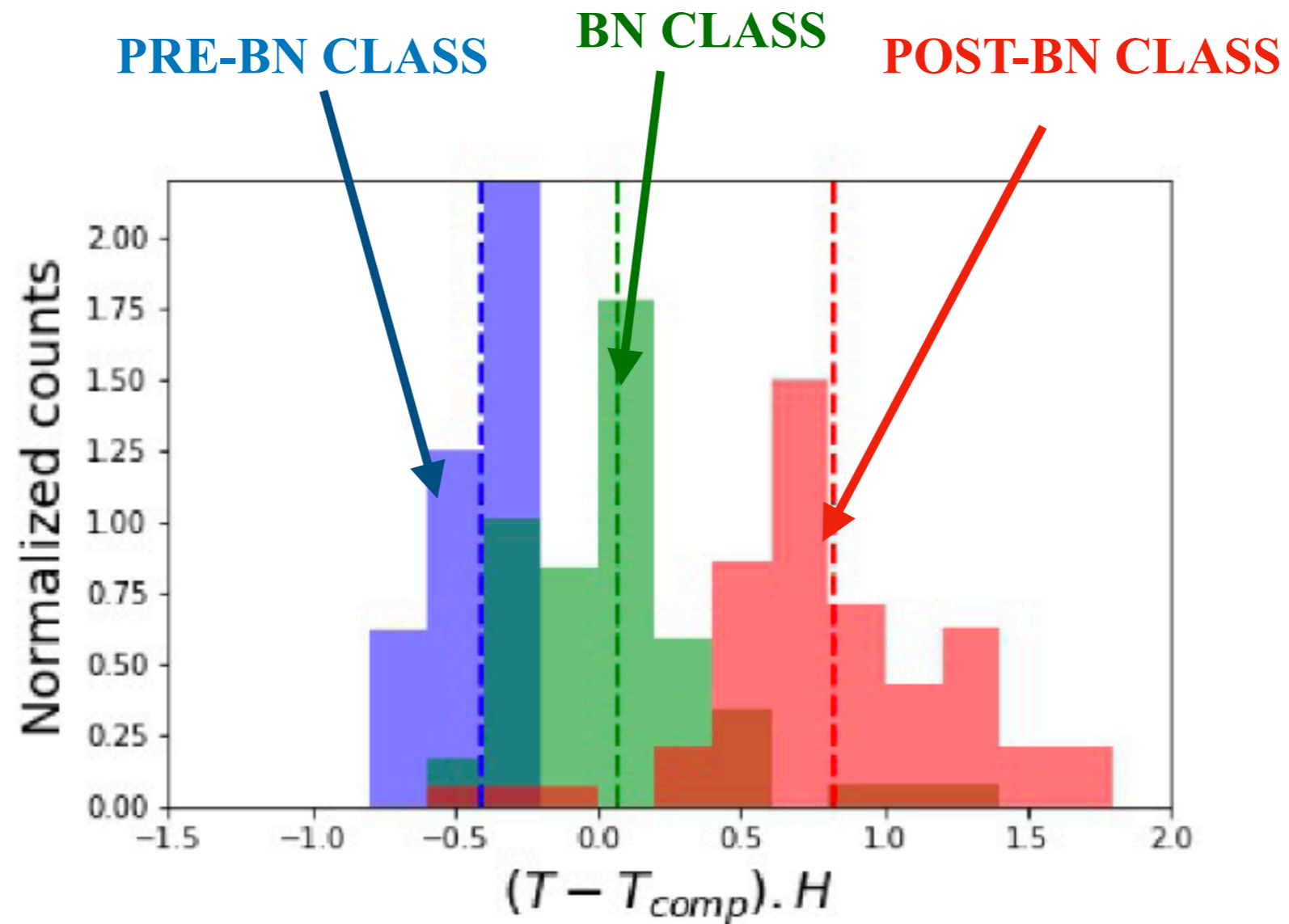
THE OUTPUT SOFTMAX PROBABILITY TRACKS THE GAS MASS



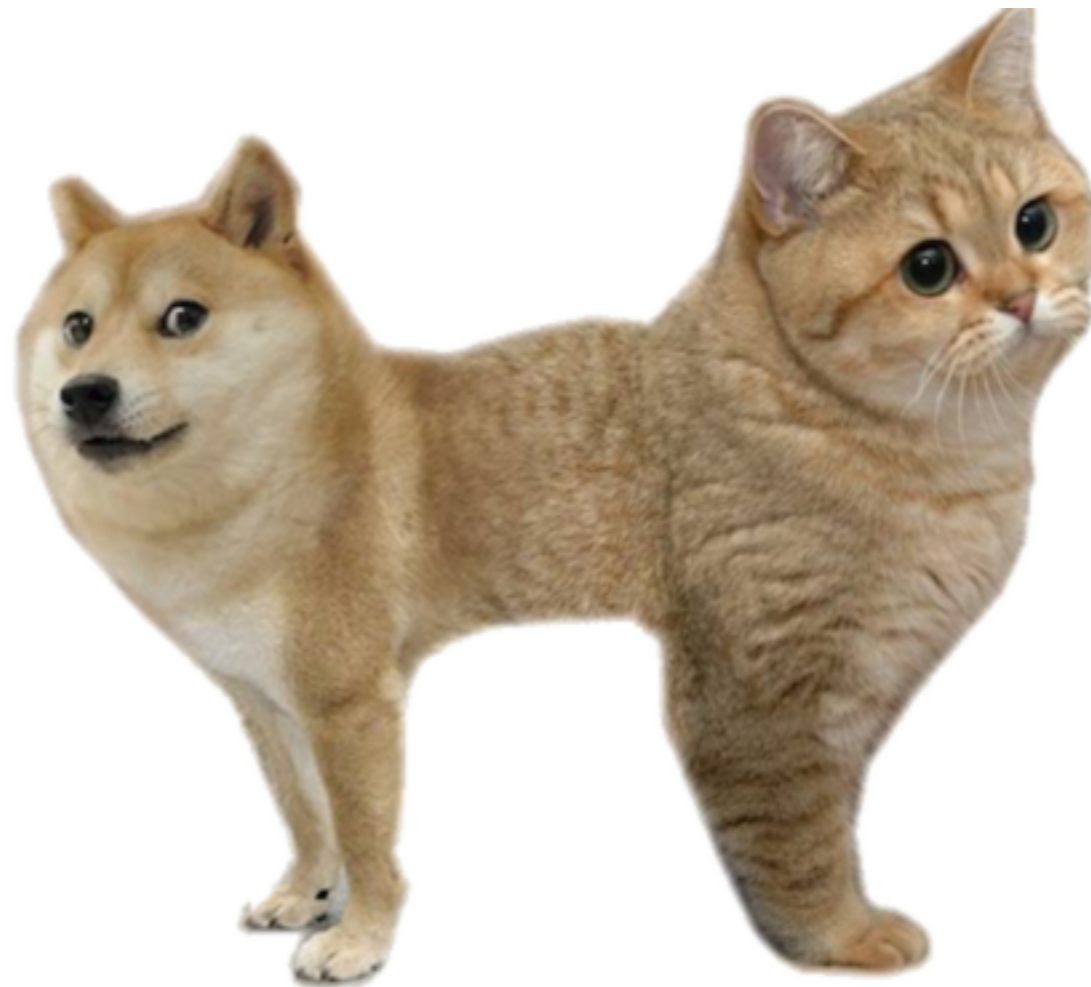
DEEP LEARNING

SIMULATION

CONSTRAINTS ON THE OBSERVABILITY TIMESCALE



CAPTURING THE MODEL UNCERTAINTY



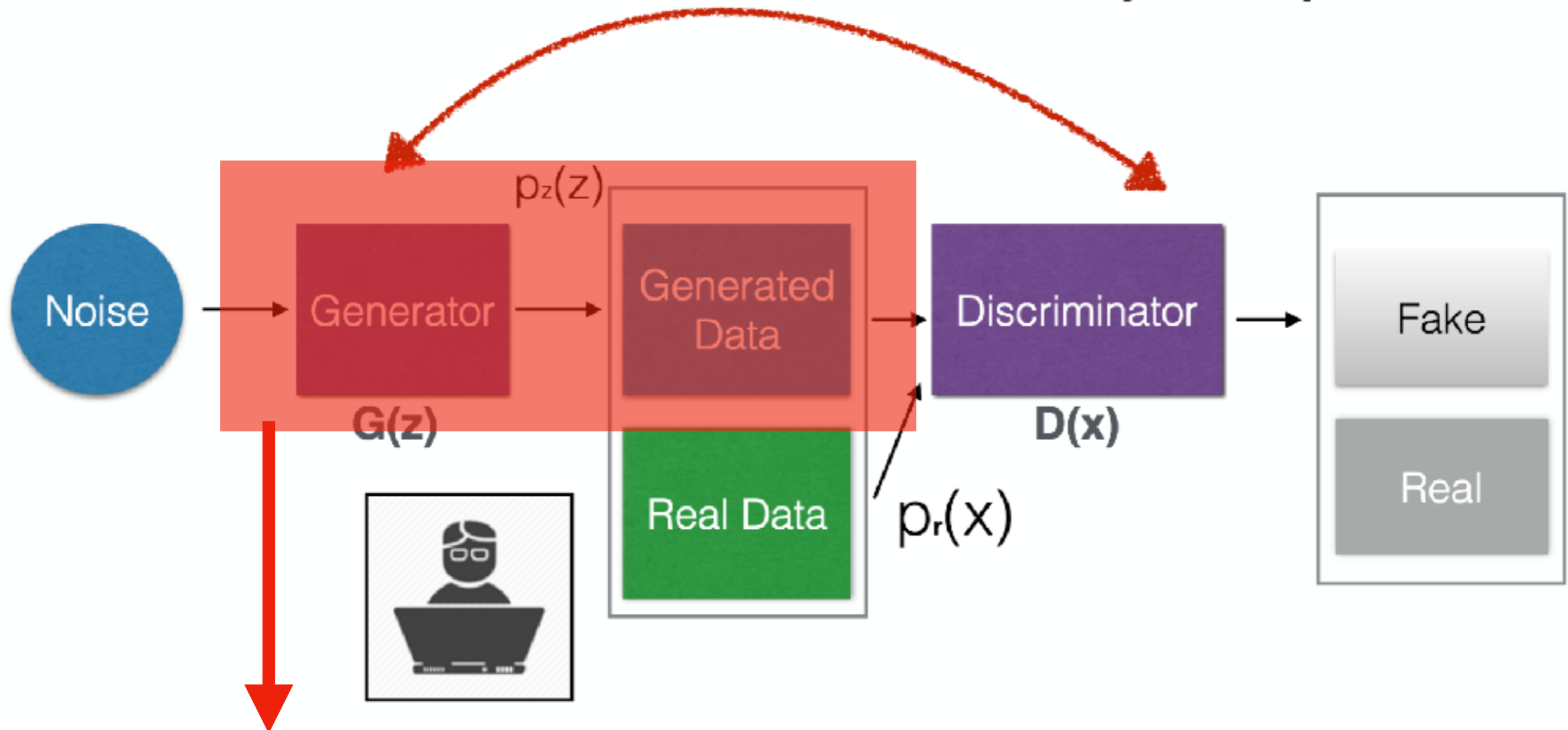
SEVERAL OPTIONS EXIST IN THE LITTERATURE...

NO TIME TO TALK ABOUT BNNs

GENERATIVE ADVERSARIAL NETWORKS

(Goodfellow+)

TWO COMPETING NETWORKS

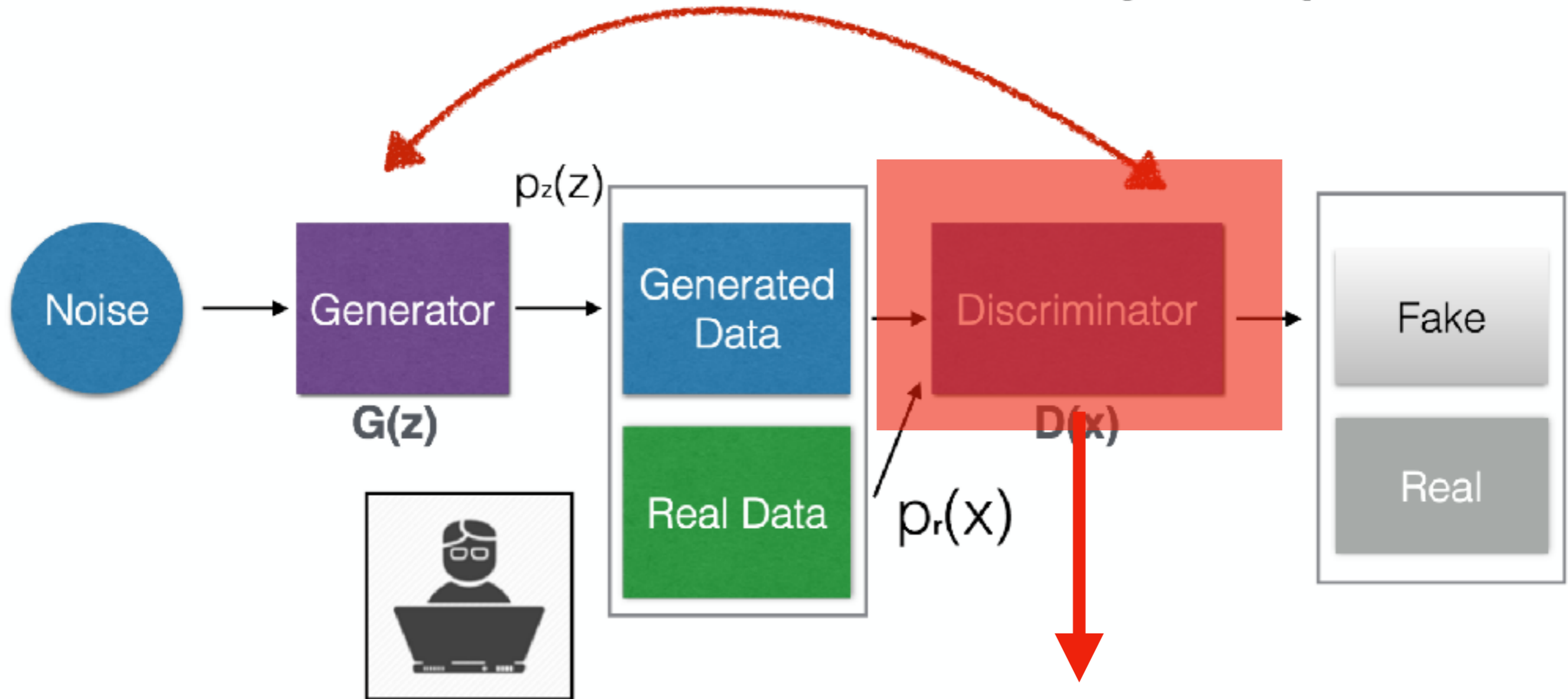


Every 2 iterations the generator is trained to force the discriminator to classify as real

GENERATIVE ADVERSARIAL NETWORKS

(Goodfellow+)

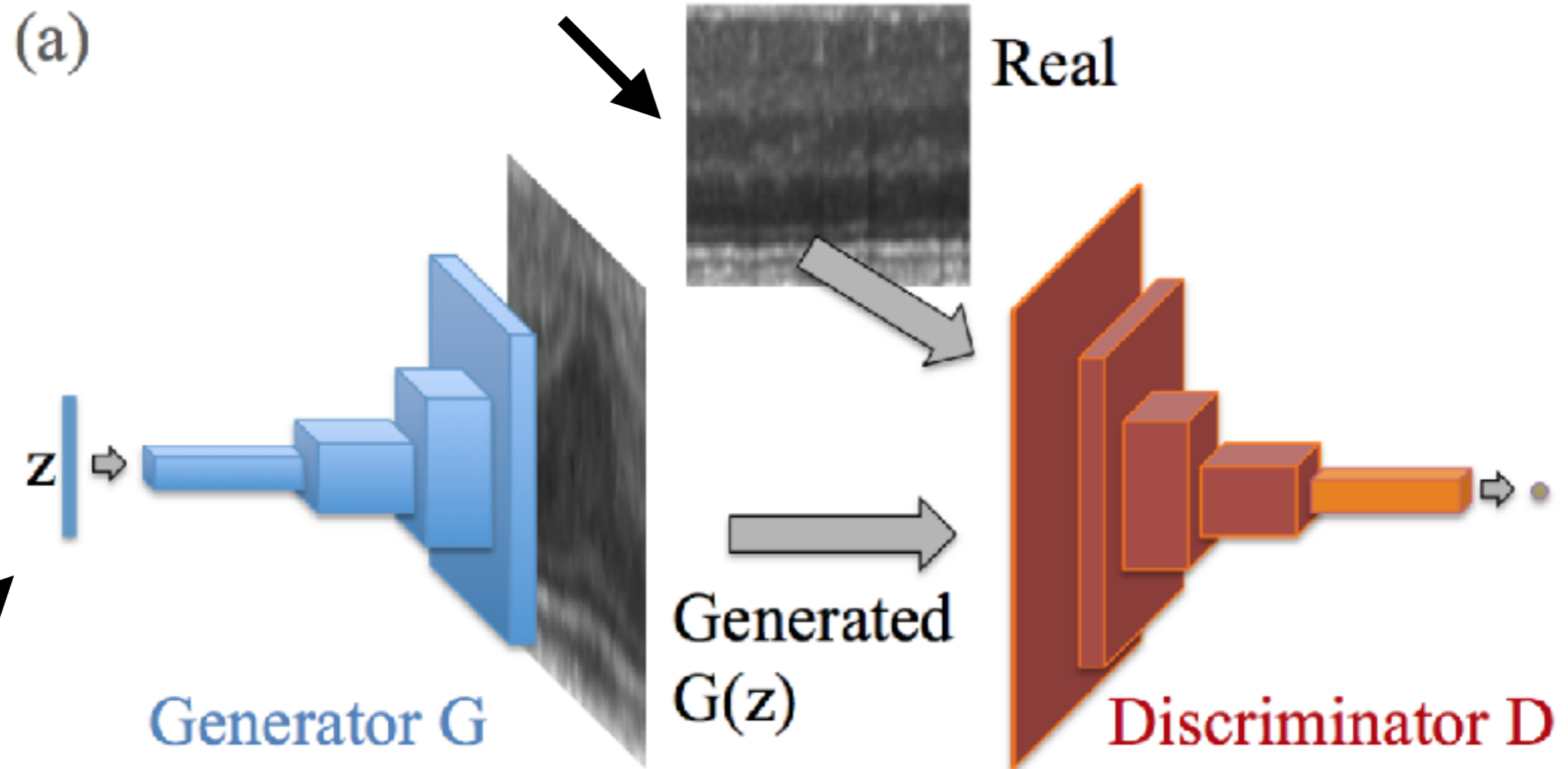
TWO COMPETING NETWORKS



Every 2 iterations the discriminator is trained to force to distinguish between real and fake

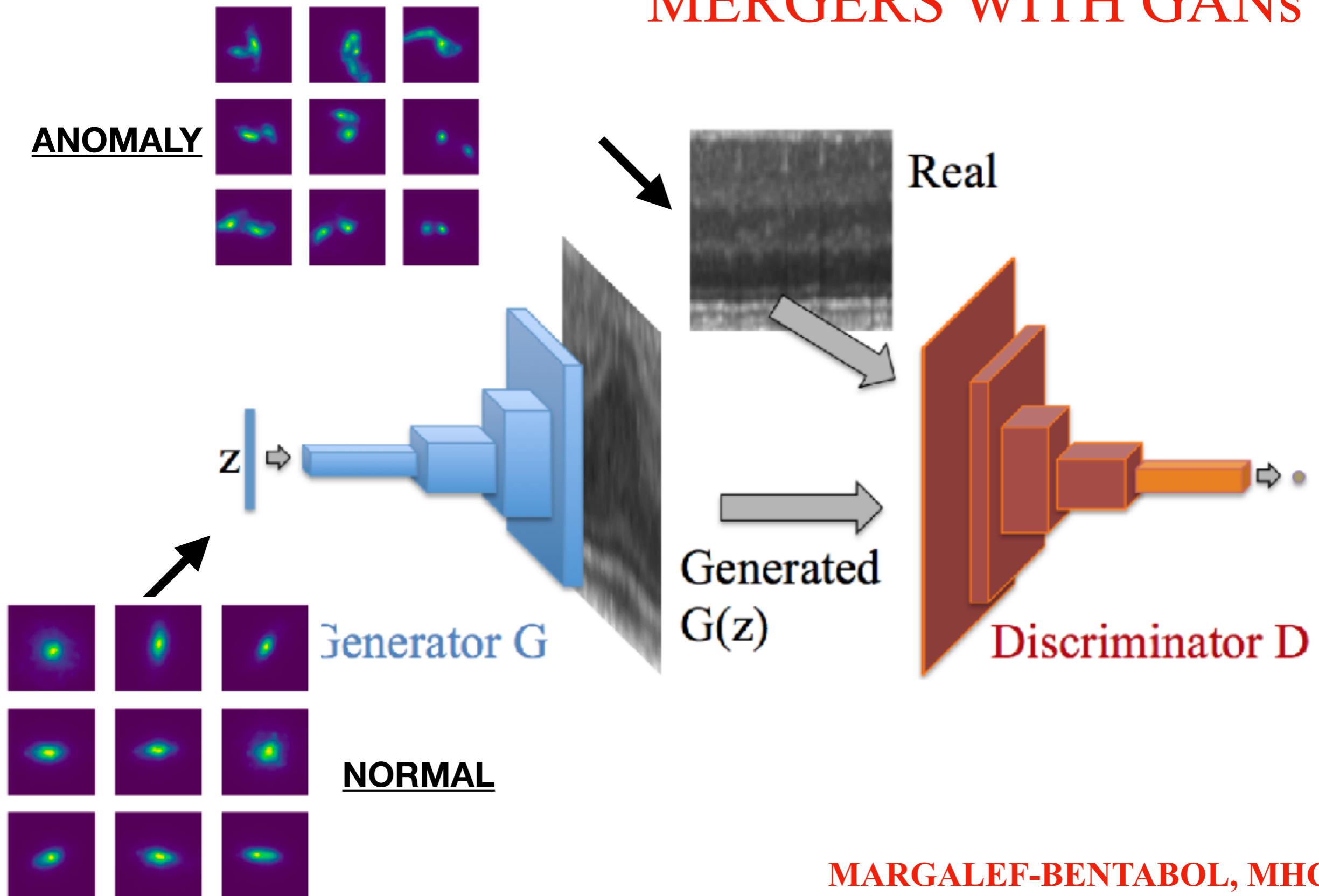
ANOMALY DETECTION WITH GANs

OBSERVATIONS

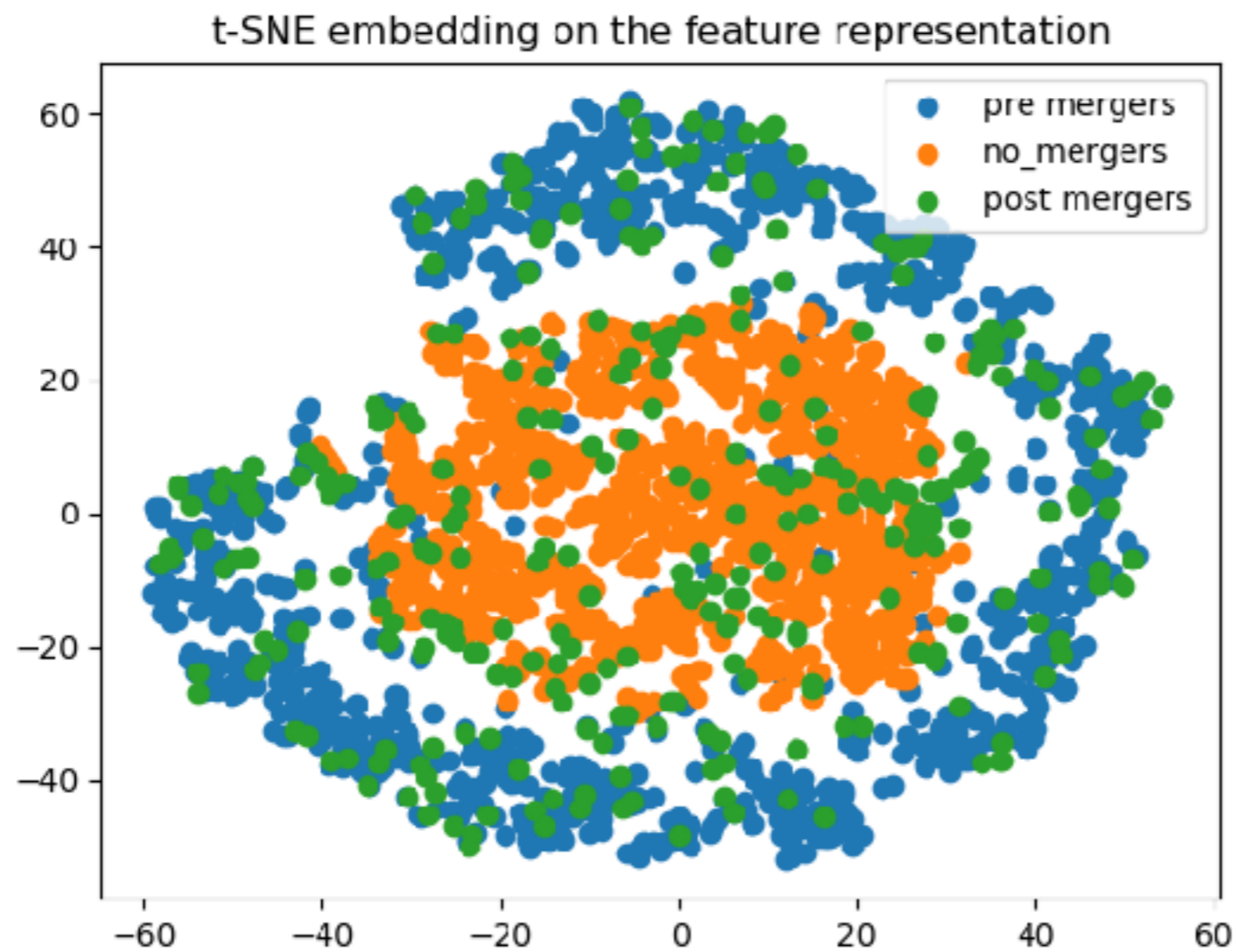


SIMULATIONS [EAGLE, Illustris,
FIRE, VELA...]

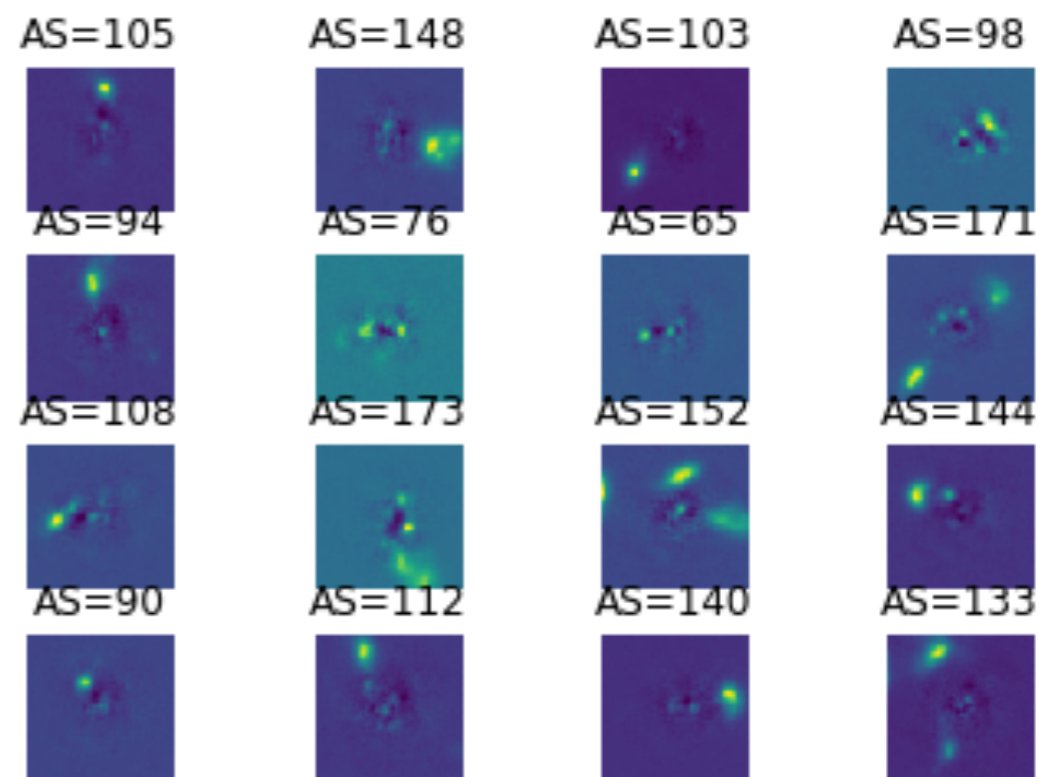
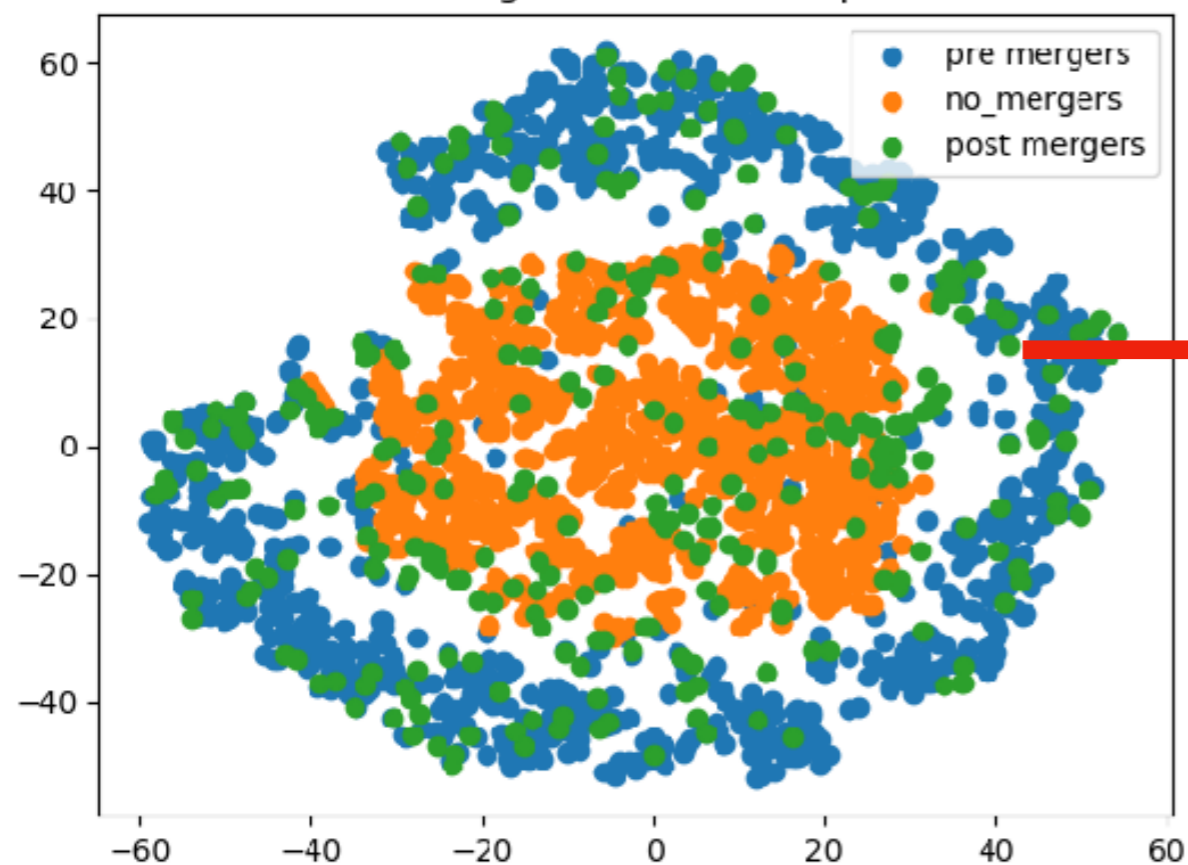
A PROOF-OF-CONCEPT CASE: UNSUPERVISED DETECTION OF MERGERS WITH GANs



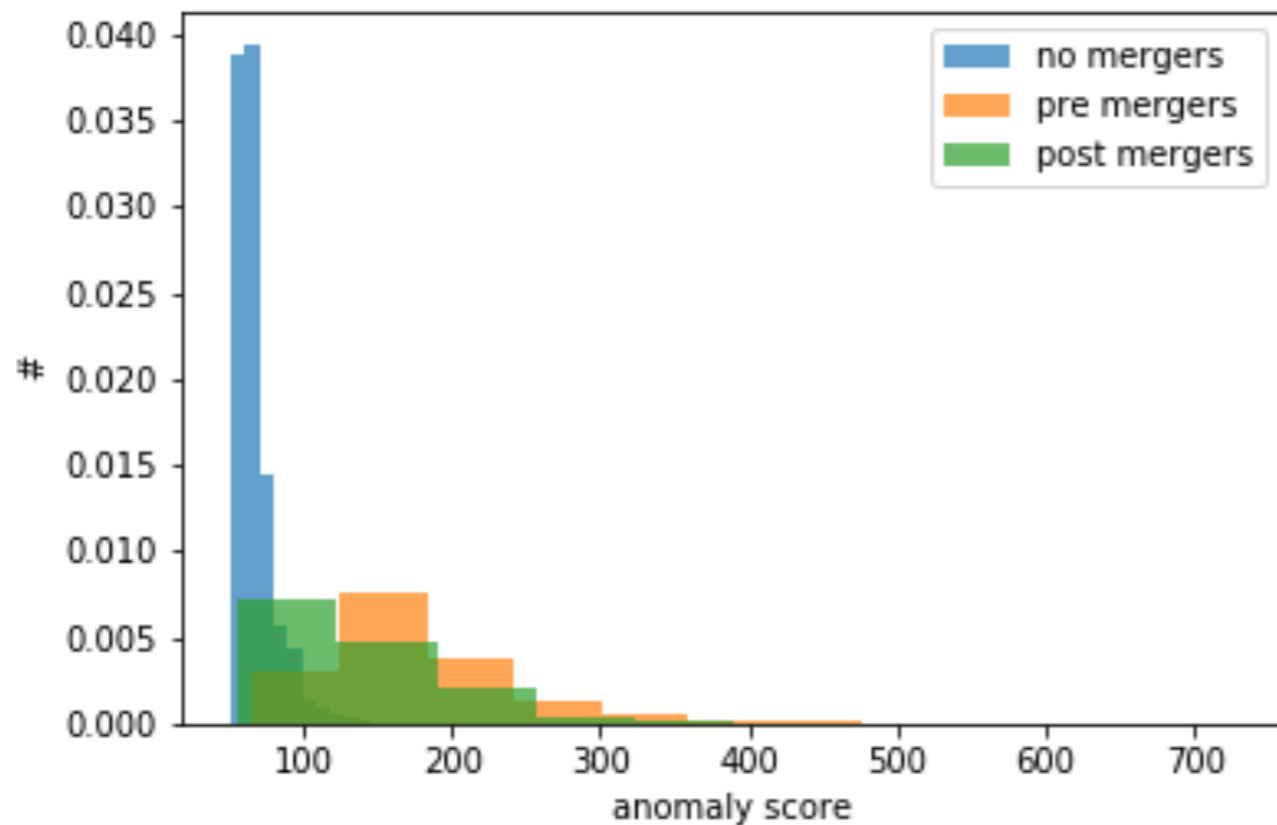
MERGERS OCCUPY A DIFFERENT REGION IN THE GAN GENERATED LATENT SPACE



t-SNE embedding on the feature representation



(RECONSTRUCTED - ORIGINAL)



“ANOMALY SCORE”

**2 TAKE HOME
PROVOCATIVE ?
MESSAGES FOR TODAY**

1. MOST OF THE PROCESSING WE DO ON IMAGES CAN BE DONE WITH AI - POSSIBLY MORE EFFICIENTLY AND MORE ACCURATELY

DETECTION, PHOTOMETRY, PHOTOZ's, MORPHOMETRY ...

2. WE CAN LEARN SOME PHYSICS BY USING AI TO LINK SIMULATIONS AND OBSERVATIONS

WITH SUPERVISED ML GOING BACK AND FORTH FROM SIMS TO DATA

WITH UN-SUPERVISED ML TO MEASURE SIMILARITIES