AUTOMATED CHARACTERIZATION OF GALAXY MORPHOLOGY

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RATIONALE

TECHNIQUES TO CHARACTERIZE

MORPHOLOGY OF GALAXIES

AT DIFFERENT SCALES

INDEX

INTRODUCTION

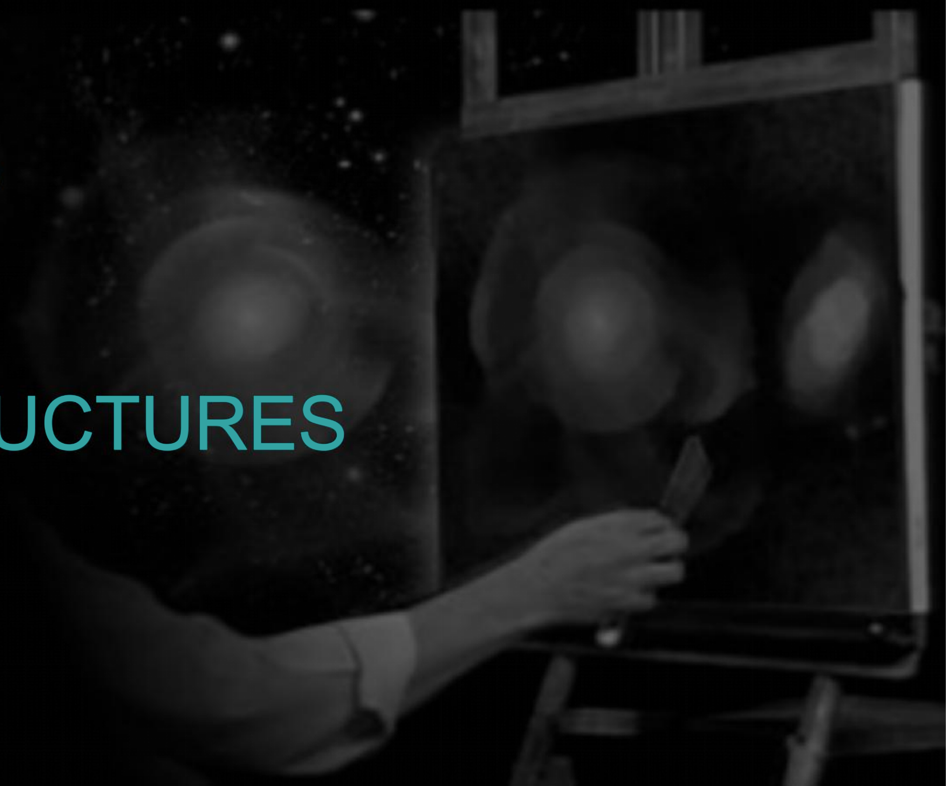
- ✪ Galaxy morphology overview
- ✪ Evolution of modelling

GLOBAL MORPHOLOGY

- ✪ Galaxy morphology in large surveys
- ✪ Machine Learning results

MORPHOLOGICAL SUB-STRUCTURES

- ✪ Merger remnants

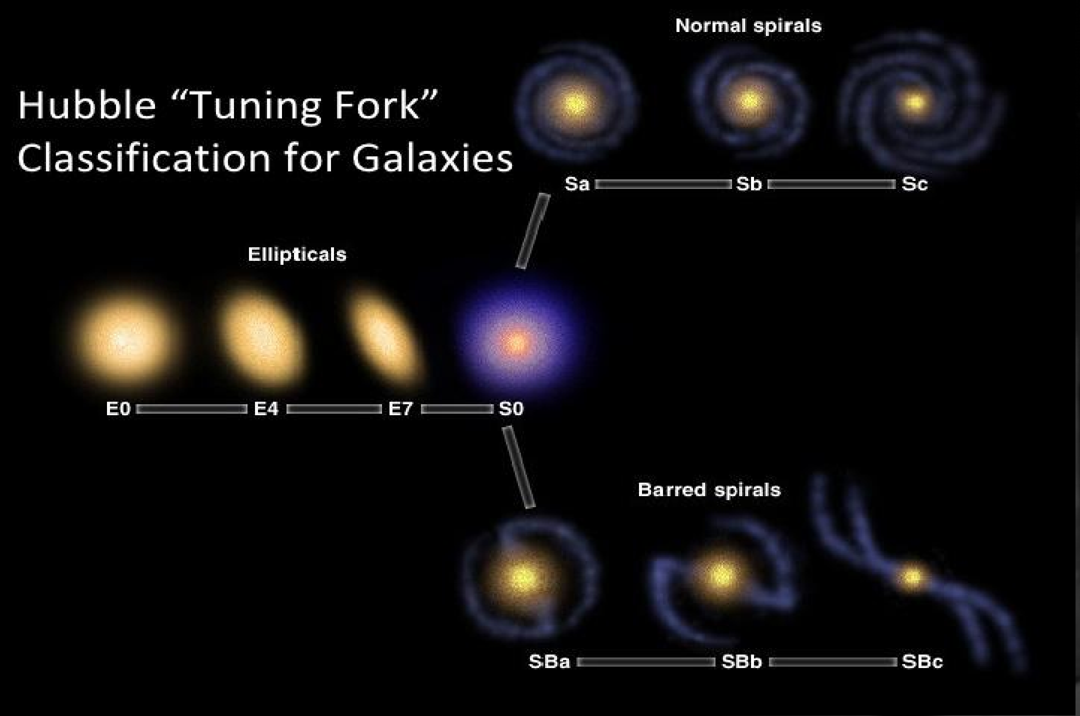


EARLY MORPHOLOGY STUDIES

- Galaxy classification by morphological type is as old as the concept of "galaxy"

  *see "**Great Debate**" - Shapley vs. Curtis, ~1920*

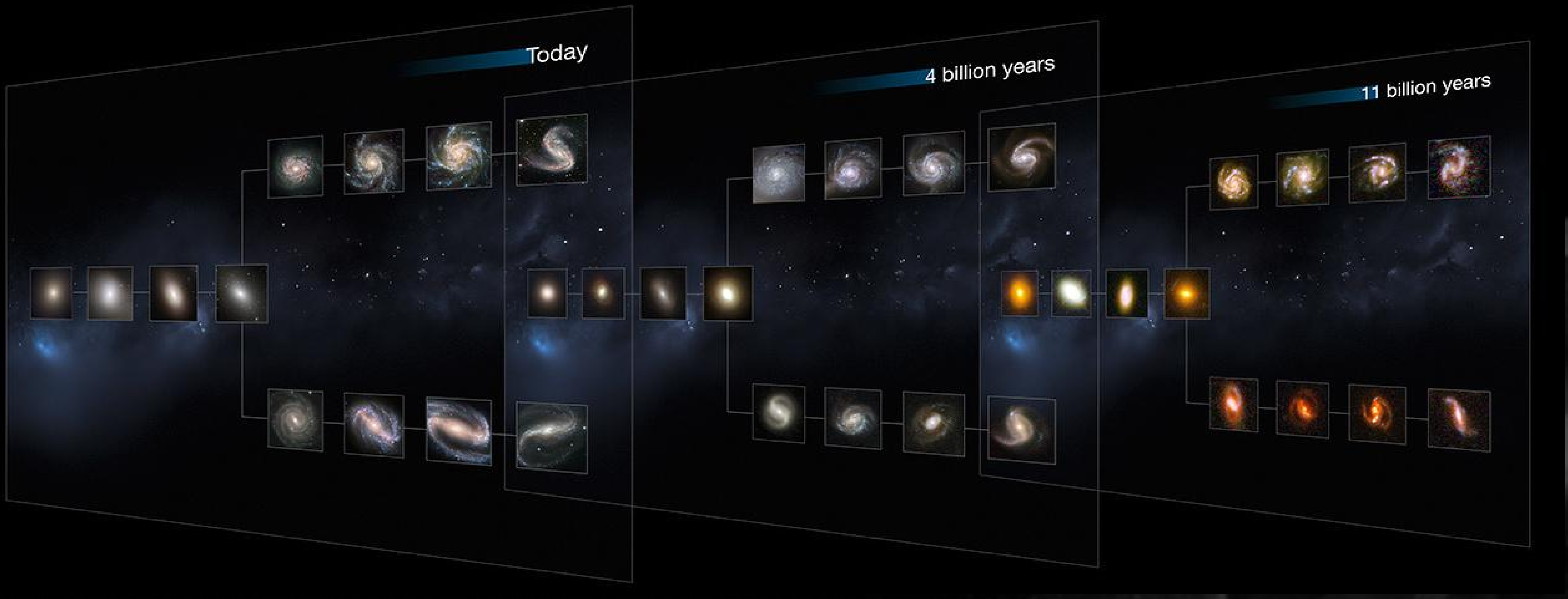
- The oldest excercise is to arrange galaxies according to a "sequence"



- The underlying idea is that there is a continuity → *evolution ?*

COSMIC EVOLUTION

- Hubble was wrong, but not so much ...
- Galaxy morphology changes in time



[STScI & NASA]

- Galaxies progressively smaller, more irregular and more compact with redshift z

MORPHOLOGY MODIFIERS

✪ The evolutionary transition between types is NOT linear

✪ Different processes / conditions simultaneusly affect the morphology of a galaxy:

- **Environment** (***nurture***)

  Interactions and mergers, gas stripping

- **Secular evolution** (***nature***)

  Internal processes, e.g.:
  - conversion of gas into stars (efficiency mostly scales with mass)
  - migration of stars (e.g. through the bar towards the bulge)

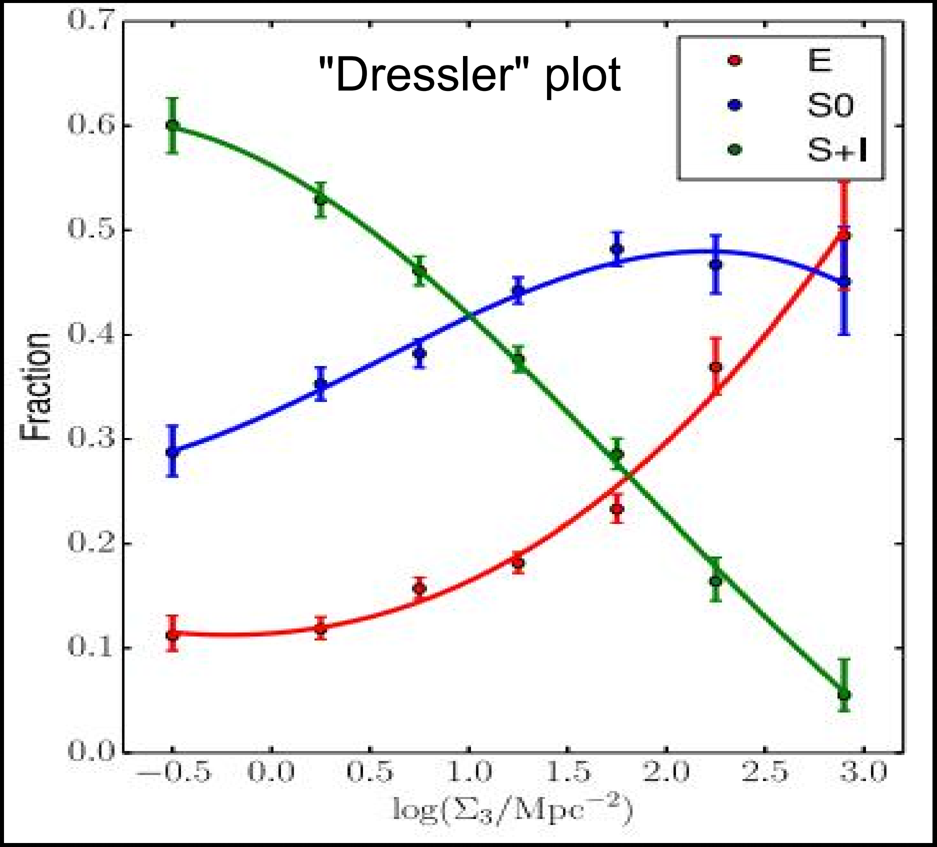
+ **Feedback processes**

  Regulation of star-formation by super-novae and active galactic nucleii

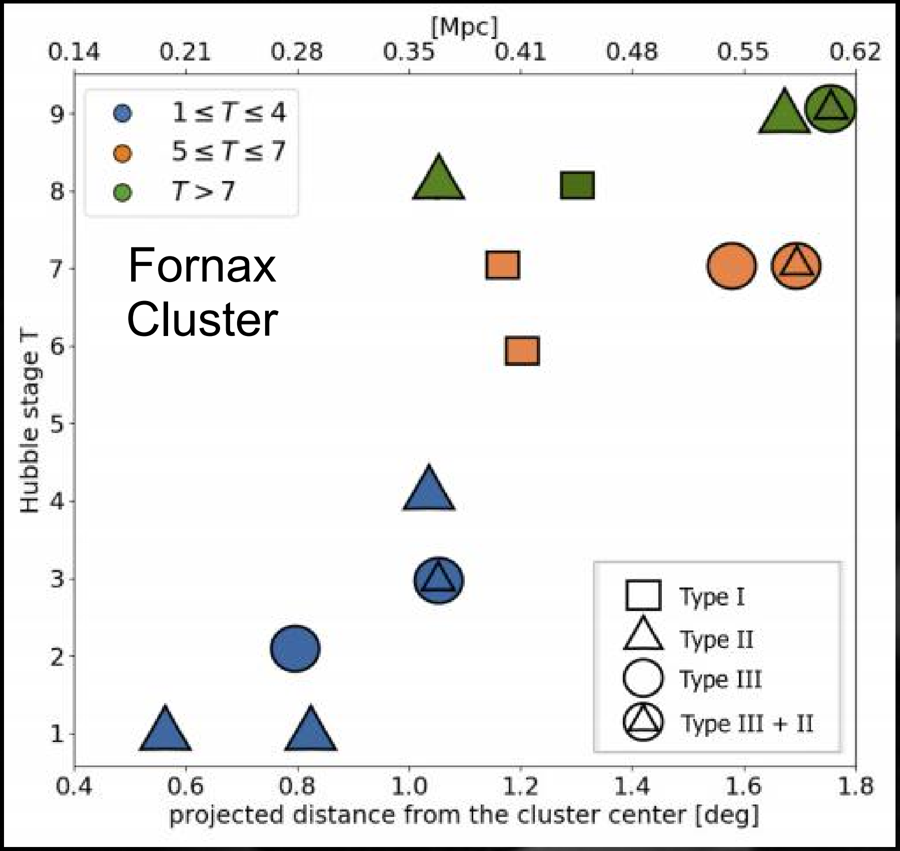
→ ***LET'S SEE A FEW EVIDENCES***

MORPHOLOGY - ENVIRONMENT

✪ Morphology relates to **environment** density



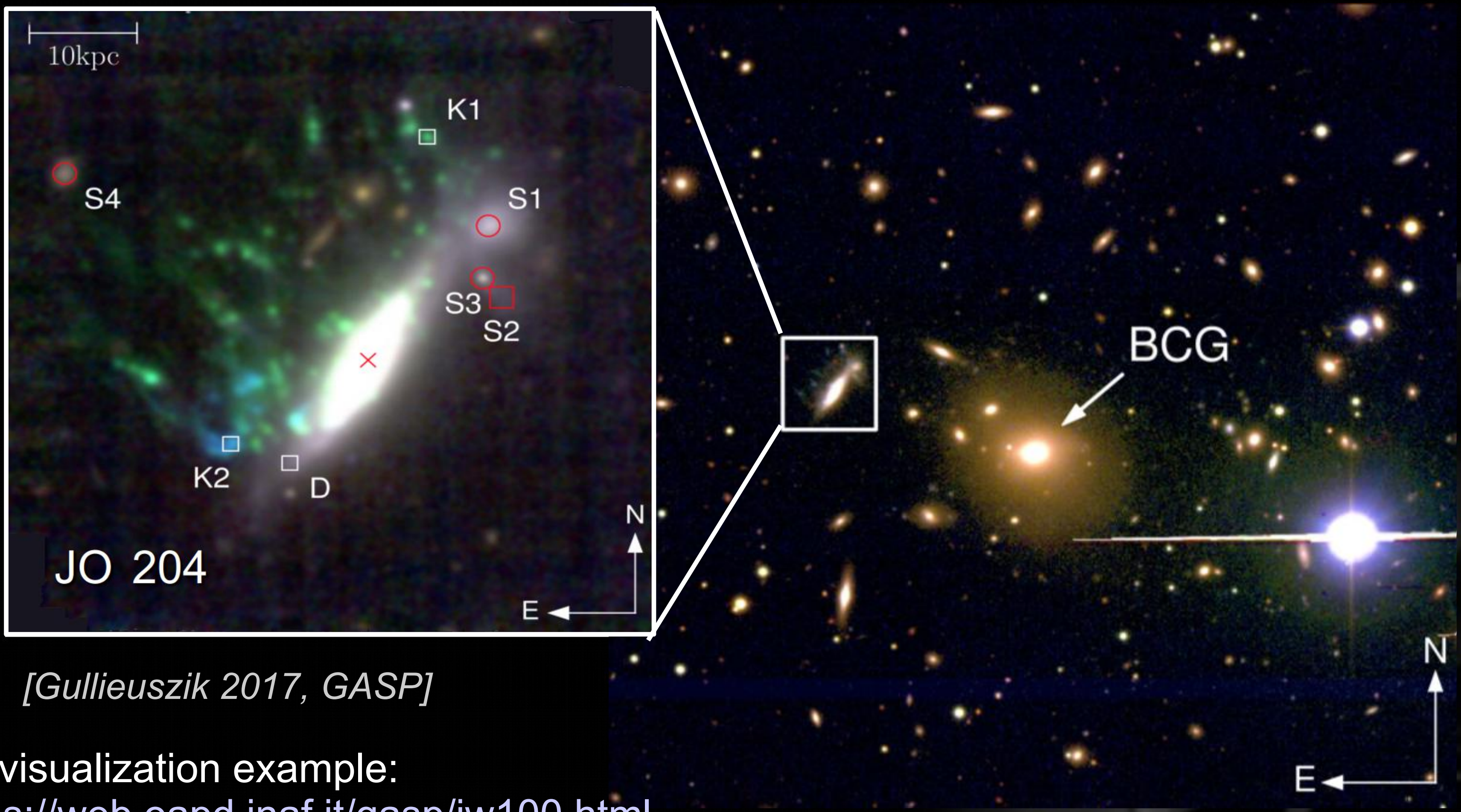
[Houghton 2015]



[Raj 2019]

GAS STRIPPING

✪ Galaxies infalling into a cluster lose gas due to "**ram-pressure**"
(e.g. see Jellyfish galaxies)

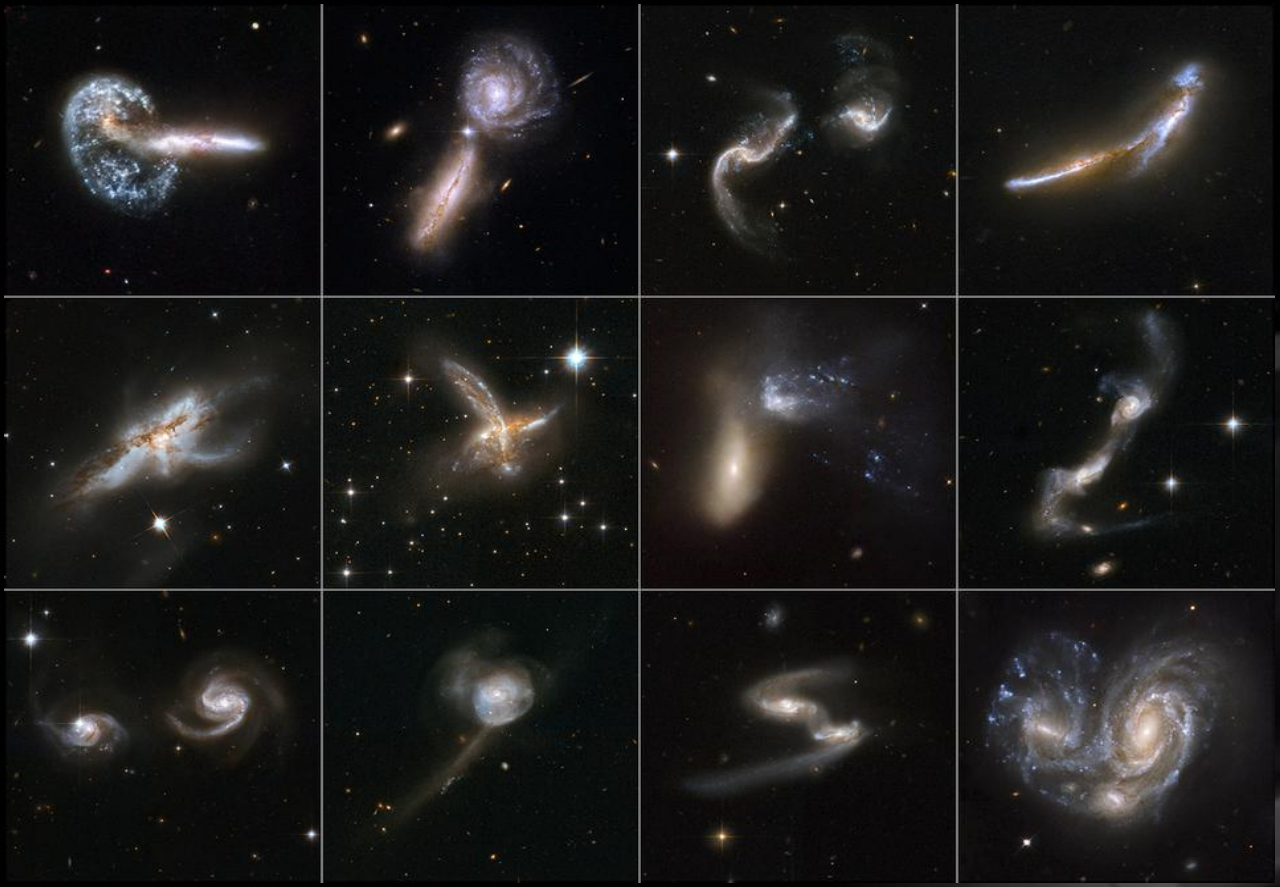


[Gullieuszik 2017, GASP]

3D visualization example:
https://web.oapd.inaf.it/gasp/jw100.html

GALAXY INTERACTIONS

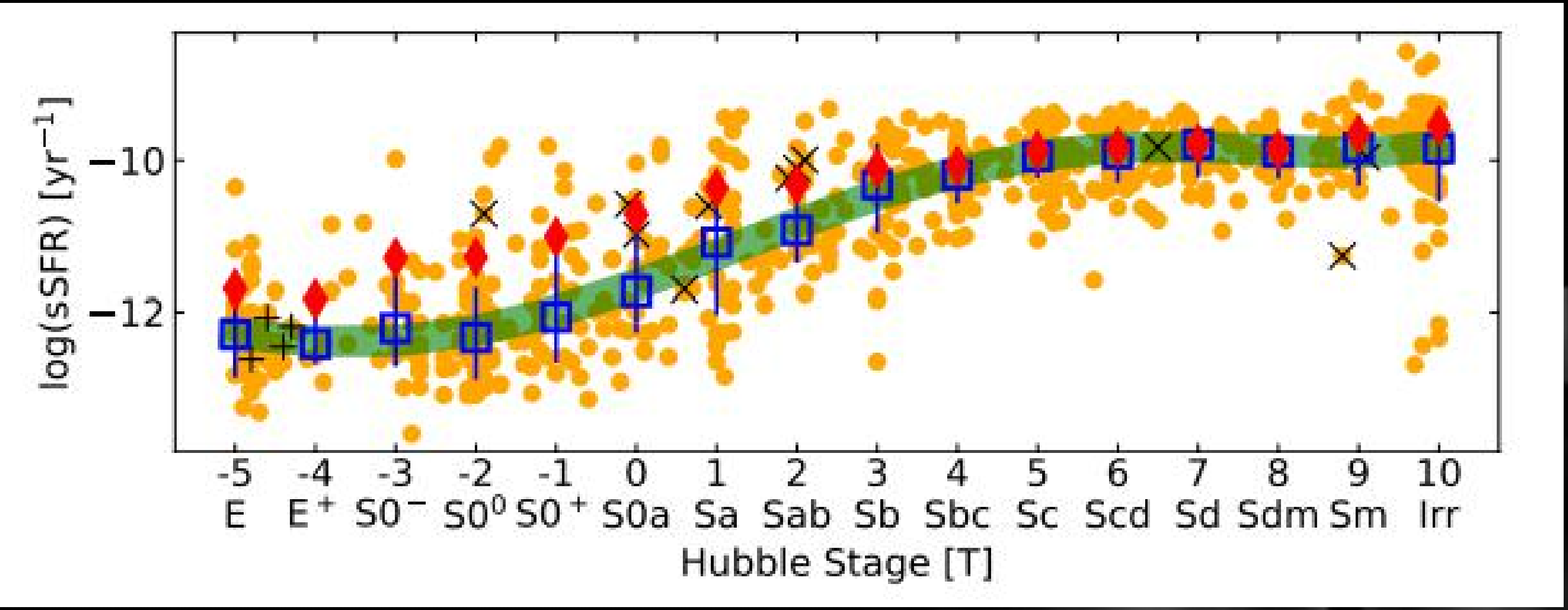
- Galaxy interactions (fly-bys / mergers) disturb morphologies in countless ways
  (e.g. see Arp catalogue of "peculiar" galaxies)



[STScI & NASA]

MORPHOLOGY - SECULAR EVOLUTION

✪ Morphology relates to **star-formation** activity



[Nersesian 2019]

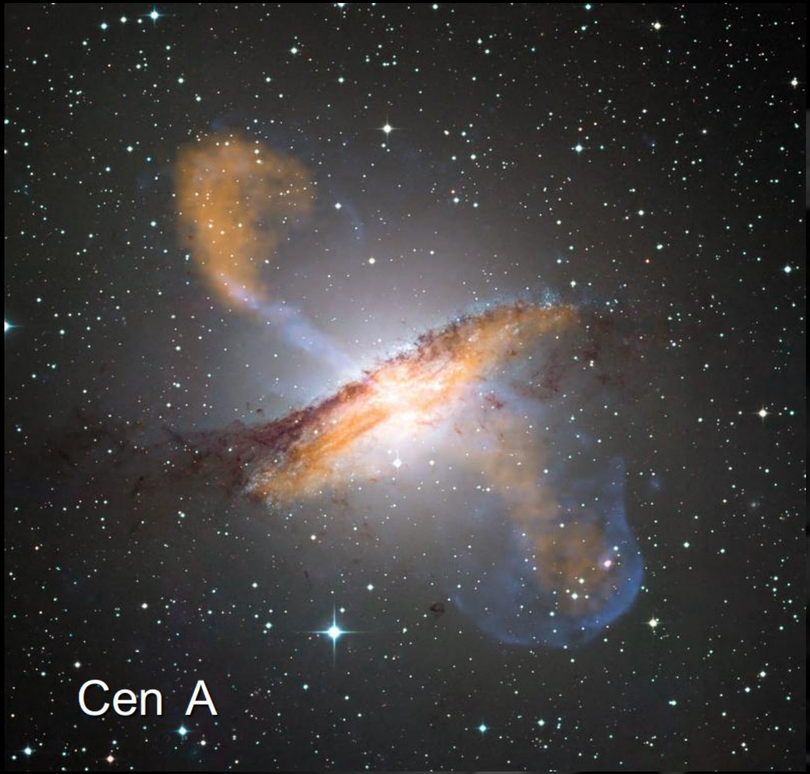
✪ The correlation goes both ways:

- new stars alter galaxy appearance
- formation of bulge stabilizes disk and reduces SF
  (see "Morphological quenching" - Martig 2009)

MORPHOLOGY - FEEDBACK PROCESSES

✪ **Feedback** from strong episodic star-formation and Active Galactic Nucleii (AGNs) regulate gas concentration (the source of new stars)

- Strong Super-Nova winds can remove gas from the galaxy
- AGN jets can prevent the infall of new gas



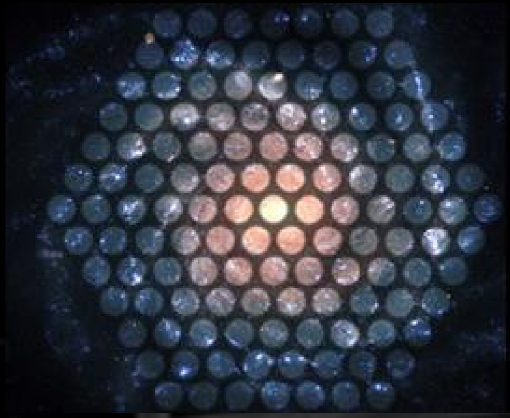
[Dietmar & Torsten 2011]

[ESO]

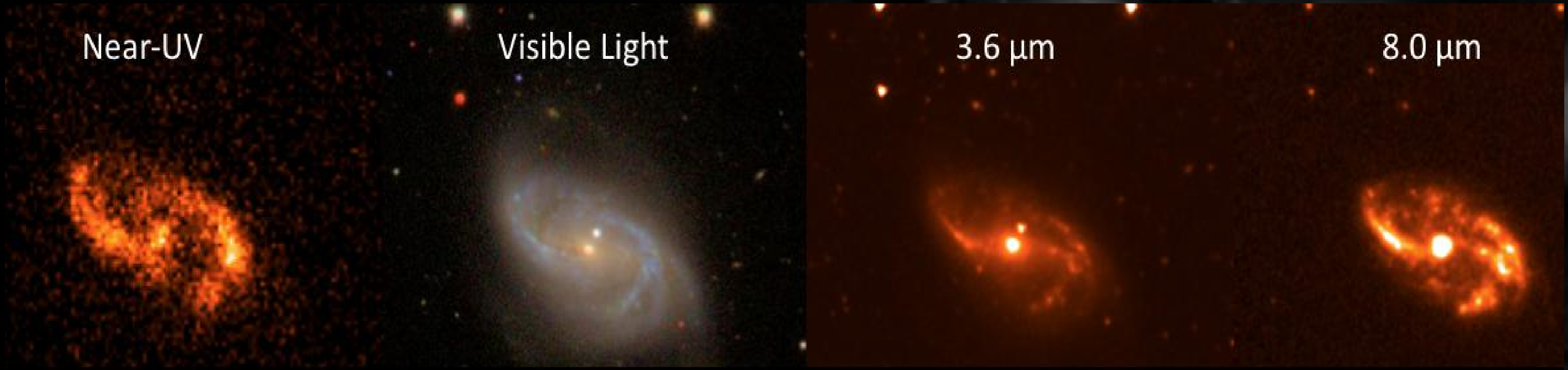
STUDYING MORPHOLOGY = STUDYING GALAXY EVOLUTION

- ✪ Galaxy morphology is a fundamental tool to study galaxy evolution

- ✪ Even spectral information is now integrated w/ spatial info
  → development of IFUs
  (e.g. MANGA survey)



- ✪ Morphology at different wavelengths provide info about emission processes

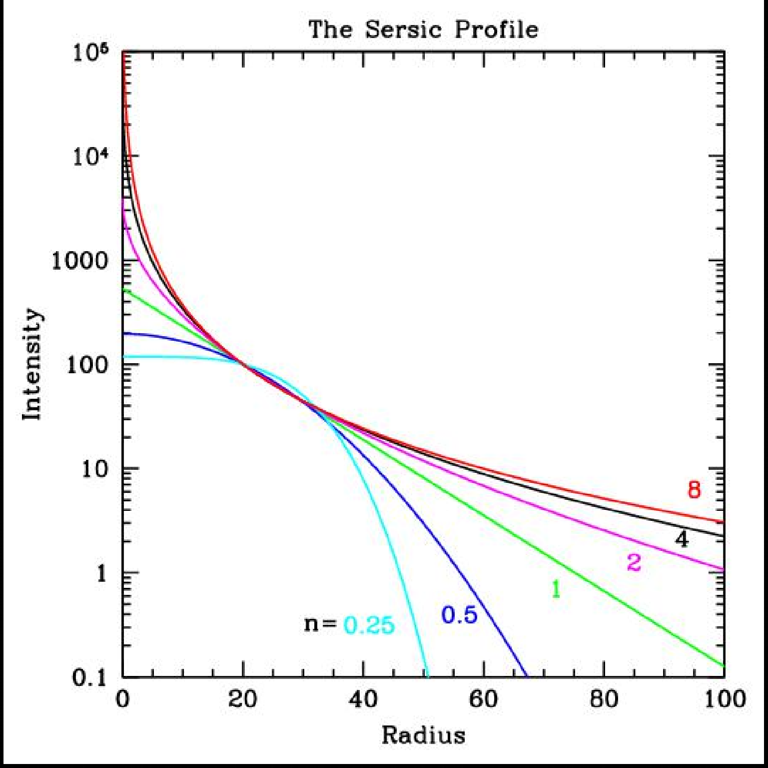


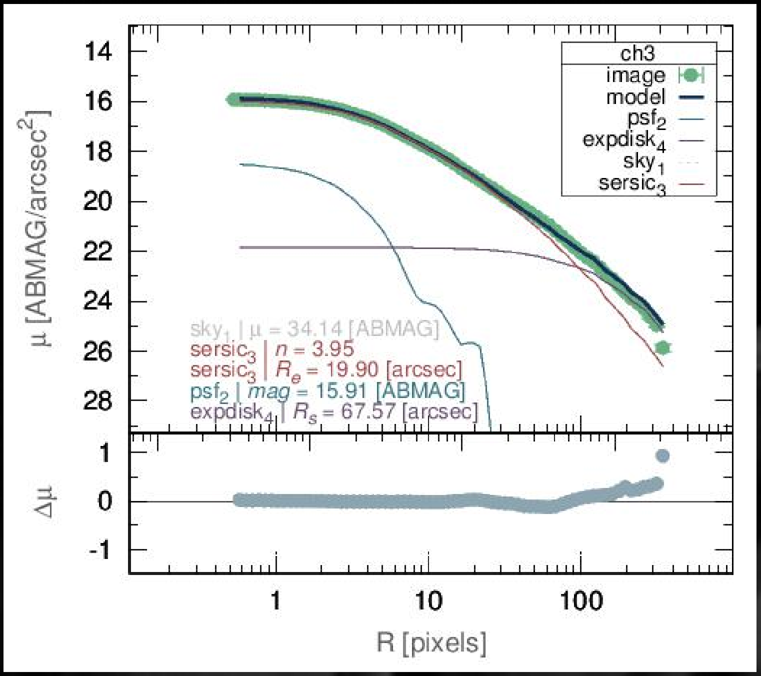
[SFRS collaboration]

MORPHOLOGY PARAMETRIZATION

- One common method to define morphology is the **bulge** / **disk** decomposition via fit to parametric functions

$$\Sigma(r) = \Sigma_e \, exp \left[-k \, (r/r_e)^{1/n}\right]$$





[Peng 2010]

- This can be done in 1D or 2D

- Allows to calculatea **B** / **D** ratio
  → Hubble sequence as a **B** / **D** sequence

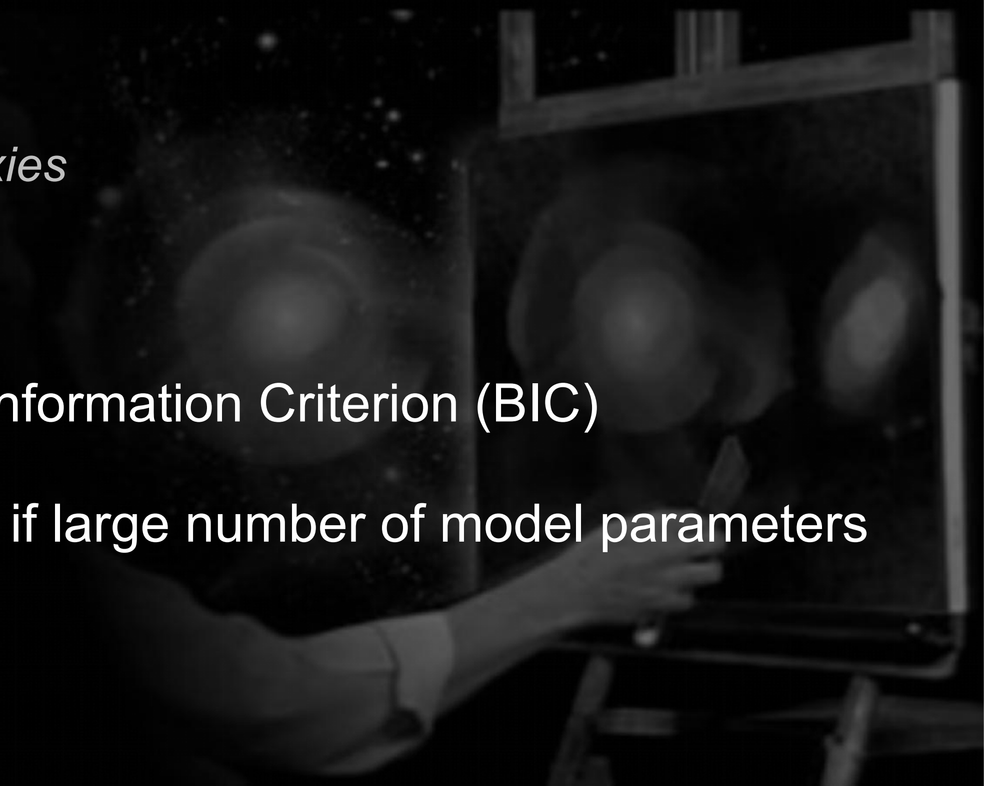
THE DRAMA OF BEST FIT MODEL

✪ Problem with parametric modelling → choice of best-fit components

WHICH PARAMETRIC MODEL BEST REPRESENTS THE DATA ?

✪ likelihood (e.g. χ^2) smaller for models with more parameters → risk of overfitting

✪ Several approaches in the literature:



- F-test

  Simard (2011): fit of 1.2 milion SDSS galaxies

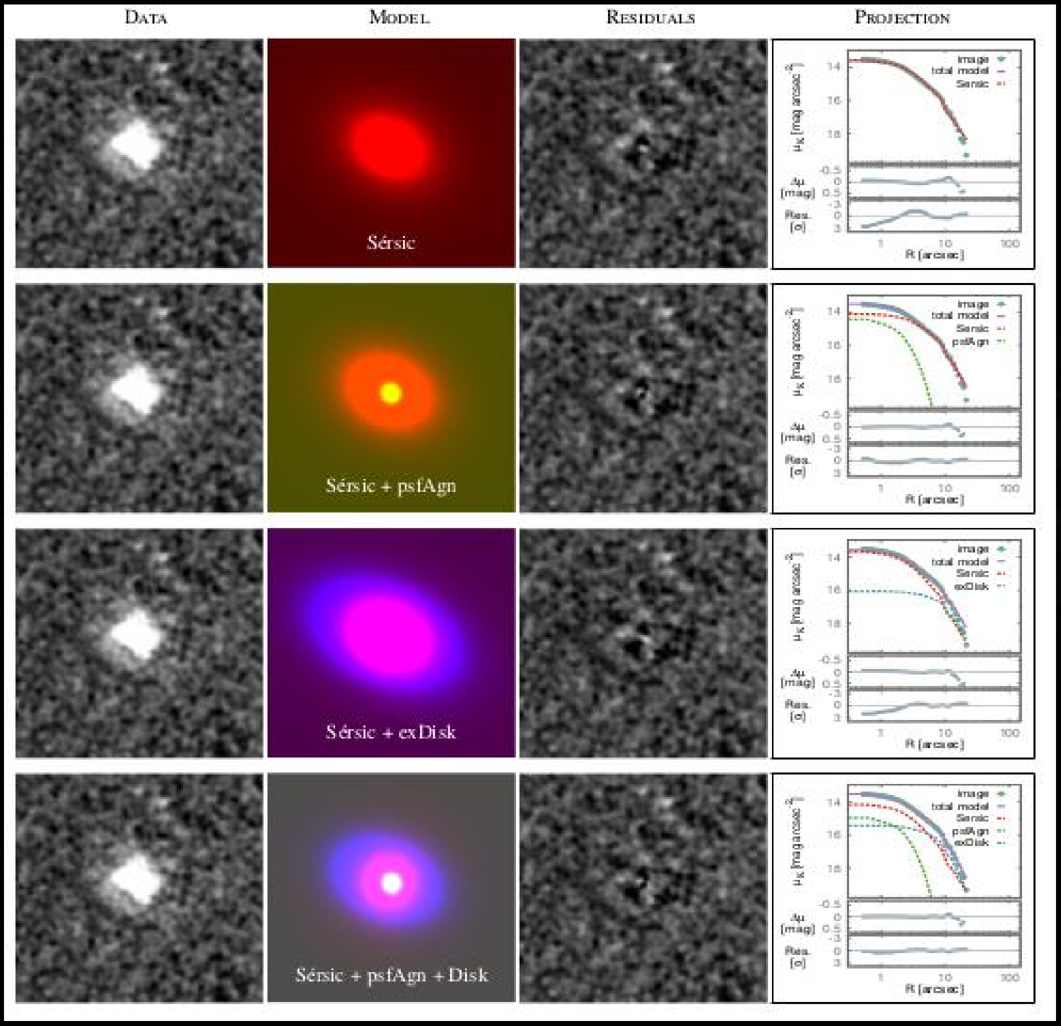
  Shortcome: Models must be nested

- Likelihood penalizers - e.g. Bayesian Information Criterion (BIC)

  Shortcome: Likelihood over-penalized if large number of model parameters *(e.g. Andrae 2010)*

EXCESS VARIANCE

- In Bonfini 2019, MNRAS, sub. we modelled SFRS sample → 6 models each



- Fit residuals seems identical
- We used the **Excess Variance** *(Vaughan 2003)*

$$\sigma^2_{XS} = \sigma^2_{objects} - \sigma_{sky}{}^2$$

$$\delta\sigma^2_{XS} = \sqrt{\frac{2}{N_{objects}} \cdot (\sigma_{sky}{}^2)^2}$$

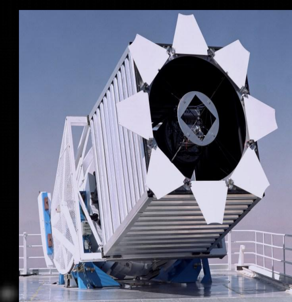
Variance in the residuals at the area of an object, after removing variations due to the background

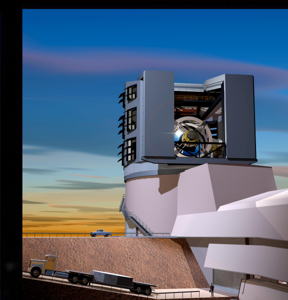
- The best-fit model automatically determines B / D decomposition

NEW CHALLENGES

- Deeper surveys show extended morphologies *(more on this later...)*
- Incoming surveys will observe orders of magnitudes more galaxies

[Duc 2018, MATLAS]





	SDSS DR14	LSST
N galaxies	2×10^8	2×10^{10}
limit r_{mag}	23	25

➡ NECESSITY FOR AUTOMATION IS OUT OF QUESTION !

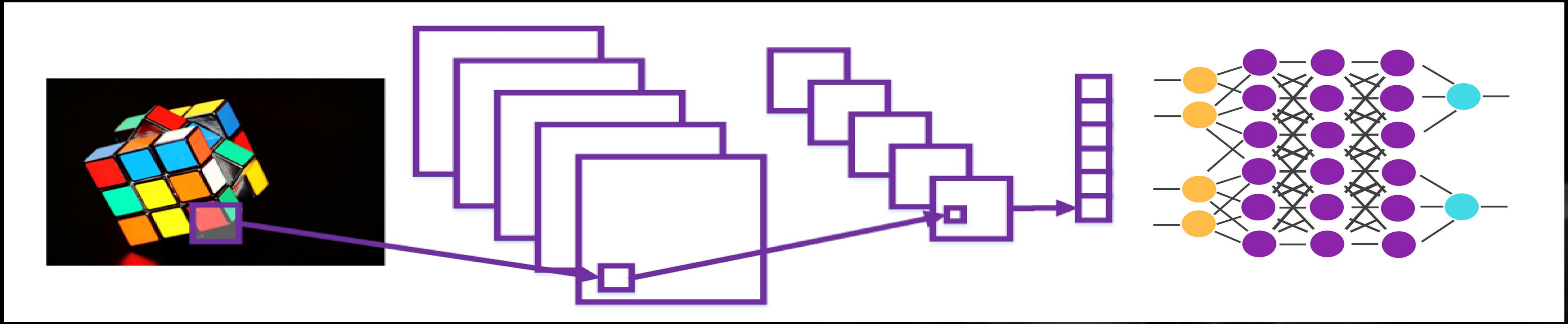
✪ **Machine Learning** (**ML**) techniques are a promising solution

✪ Supervised ML need labels ➡ Galaxy Zoo (***citizen science***) was a milestone

... AND SUDDENLY, DEEP LEARNING !

✪ ~2014 and on ➡ **Deep Learning** explodes in galaxy morphology
(To be fair ... SExtractor already implemented Neural Networks - Bertin, 2010)

✪ Mostly based on **Convolutional Neural Networks** (**CNNs**)



Convolution **Pooling** **Flattening** **Dense Layers**

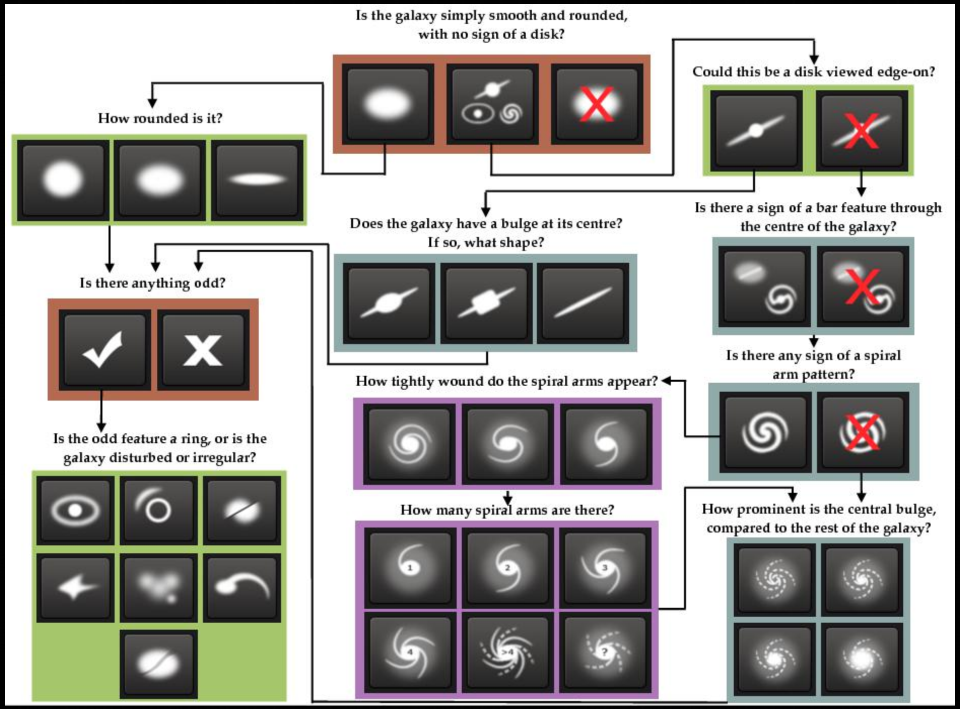
- **Convolution filter ➡ Scan the image to detect different features**
- **Pooling ➡ Reduce dimensionality to increase abstraction**
- **Flattening ➡ Encodes features into variables**
- **Dense Layers ➡ Feature classifier**

✪ **Many papers, list is growing ➡ presenting a few ...**

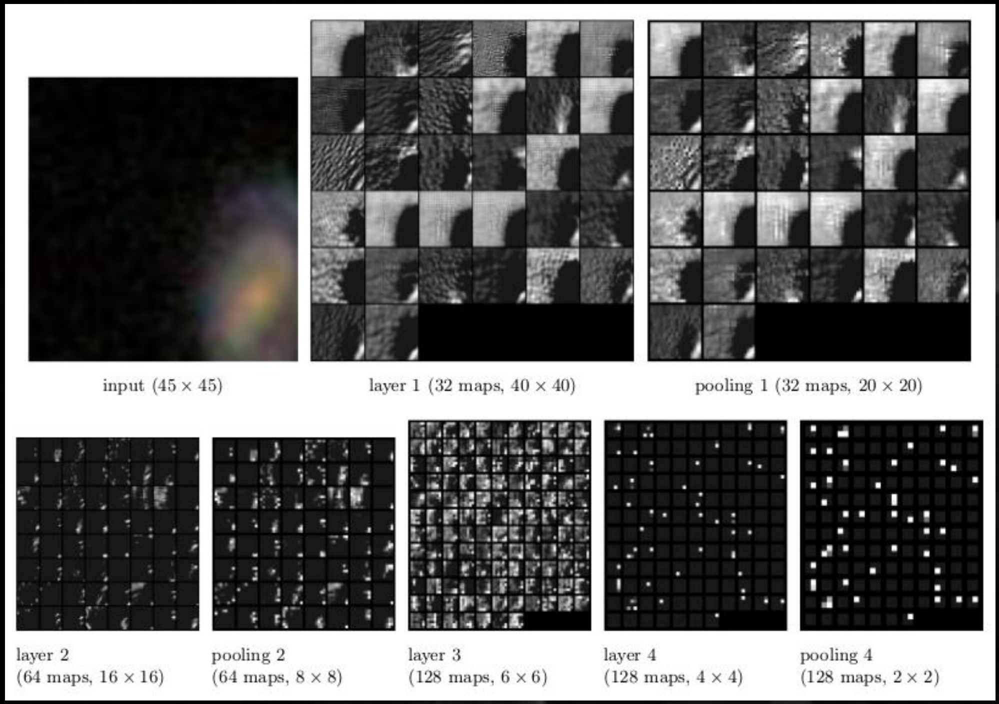
SDSS CLASSIFICATION

✪ Dieleman (2015) ➡ calculate probabilities for the 37 Galaxy Zoo possible answers

- ▸ ***training***: *classification of 61,578 JPEG images from SDSS with GZ labels*
- ▸ ***architecture***: *"standard CNN"*



[Willett 2013]

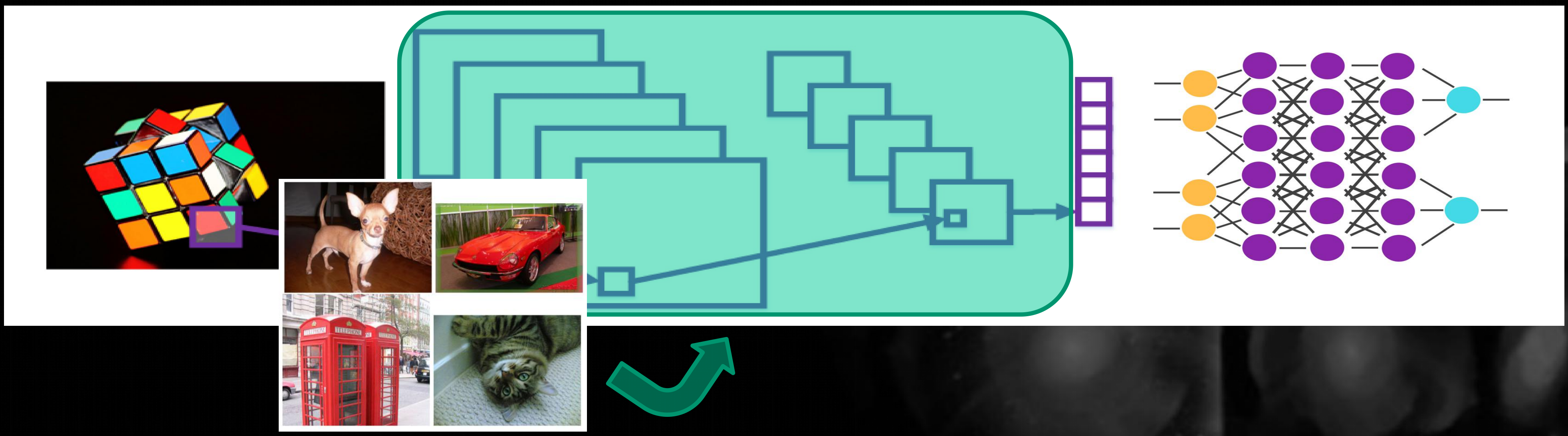


[Dieleman 2015]

✪ Accuracy as high as 99% for some questions

CNN - TRANSFER LEARNING

- ✪ Ackermann (2017) ➡ identify mergers
  - *training*: *classification of ~4000 JPEG images from SDSS with GZ labels*
  - *architecture*: *CNN with "transfer learning"*
- ✪ Transfer learning is used when few (e.g. <10,000) examples are available



- ✪ Merger sample created with this model reproduces expected mergers:
  - *mass function*
  - *color distribution*

DEEP LEARNING AND STRUCTURAL PARAMETERS

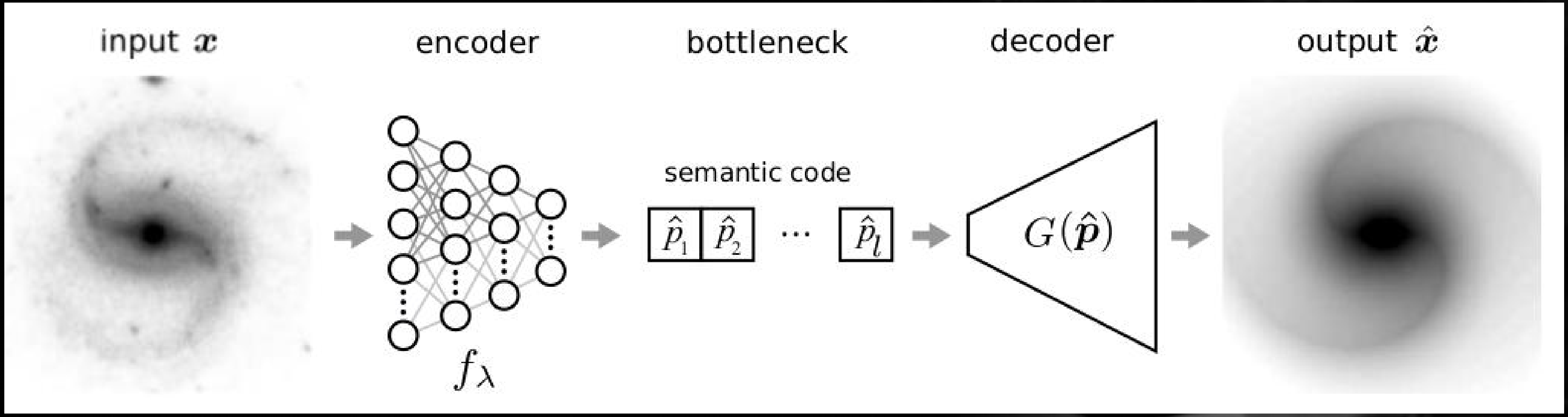
✪ Tuccillo (2017) ➡ obtain structural parameters (e.g. effective radius, Sersic n)

- ***training***: *re-produce parameters used to generate artificial galaxies*
- ***architecture***: *"standard" CNN*

Performance ~ GALFIT ("industry standard" for parametric fitting)

✪ Aragon-Calvo (2019) ➡ obtain structural parameters via self-supervised learning

- ***training***: *re-produce parameters used to generate artificial galaxies*
- ***architecture***: *"semantic autoencoder"*



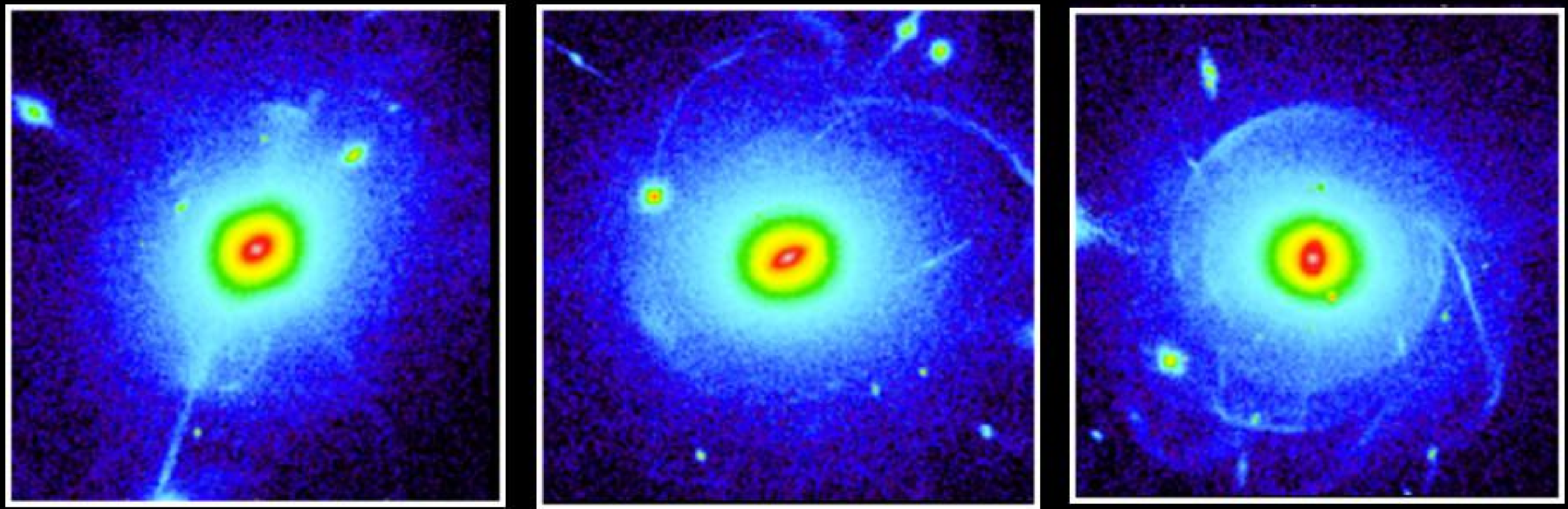
[Aragon-Calvo 2019]

Performance - Model undistinguishable from input !

GALAXY SUB-STRUCTURES

- Deep imaging is revealing that galaxies present **fine structures**
- These are the imprint of “recent” mergers

TAILS **SREAMS** **SHELLS**



[MATLAS collaboration]

- Different features are associated with different interaction events (major/minor, gas-rich/gas-poor, etc.)

GALAXY SUB-STRUCTURES: FINE STRUCTURES

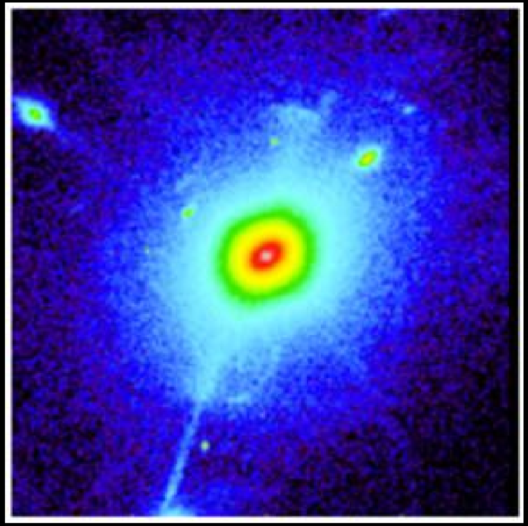
- Machine Learning proven to be efficient in classifying global morphology, i.e.: ***elliptical*** *vs.* ***spiral***

- Classifying ***individual*** **fine structure** features is way more challenging
  (e.g. Walmsley 2018; 76% completeness)

➡ ***THESE FEATURES MUST BE PROPERLY CHARACTERIZED BEFORE APPLYING MACHINE LEARNING***

FINE STRUCTURES - TIDAL TAILS

TAILS



- Origin:

  major mergers, mostly disrupted disk

- Features:
  - long and diffuse
  - same color as parent disk
  - relatively faint (μ < 25 mag/arcsec^2)

[Robert Gendler]

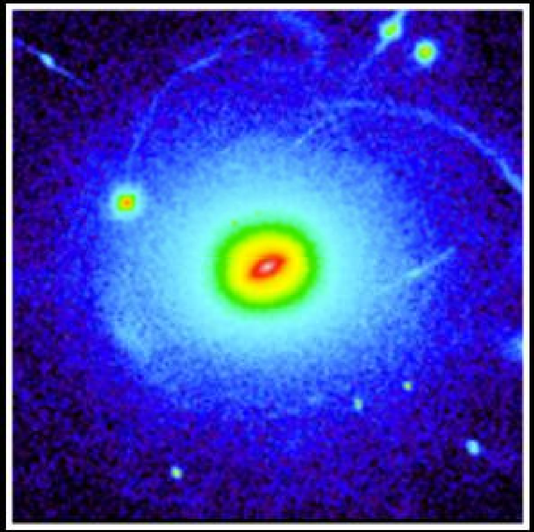
FINE STRUCTURES - STREAMS

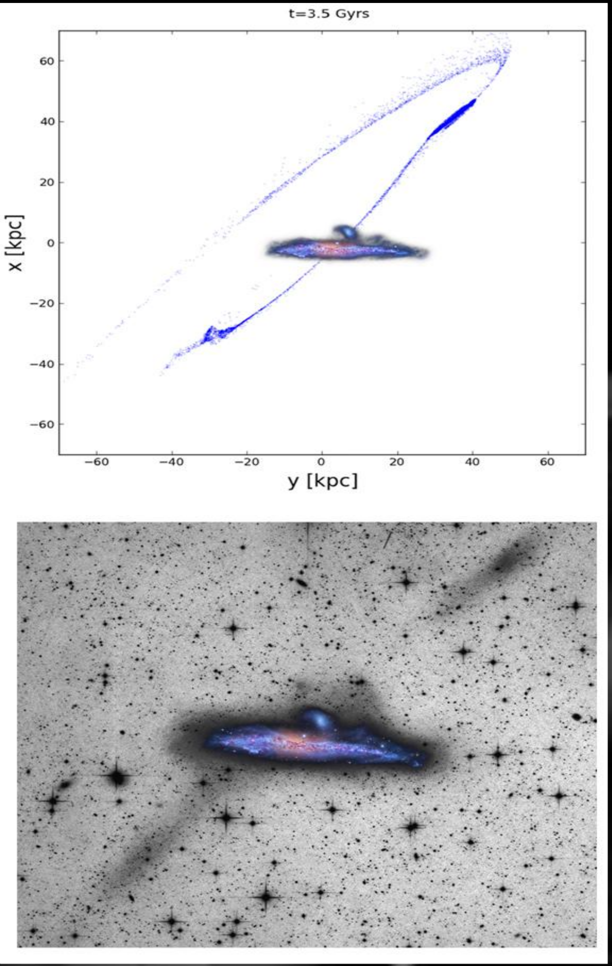
- Origin:

  disrupted satellites

- Features:
  - narrow and curved
  - blue colors (g-r = 0.8)
  - very faint ($\mu < 26$ mag/arcsec^2)

STREAMS





[Martinez-Delgado et al. 2015]

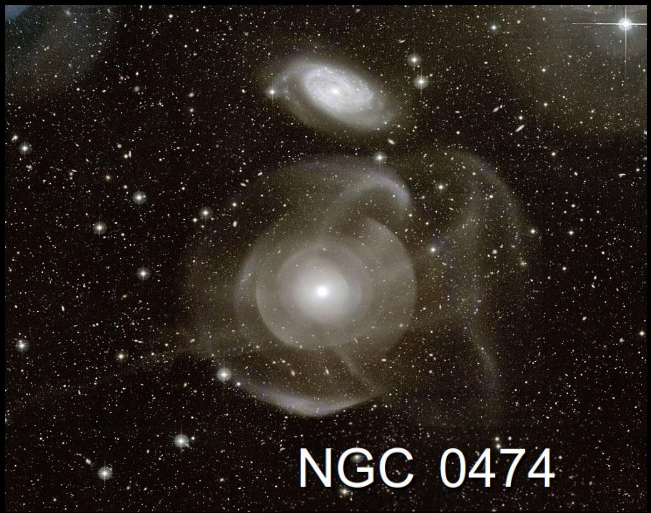
FINE STRUCTURES - SHELLS

- Origin:

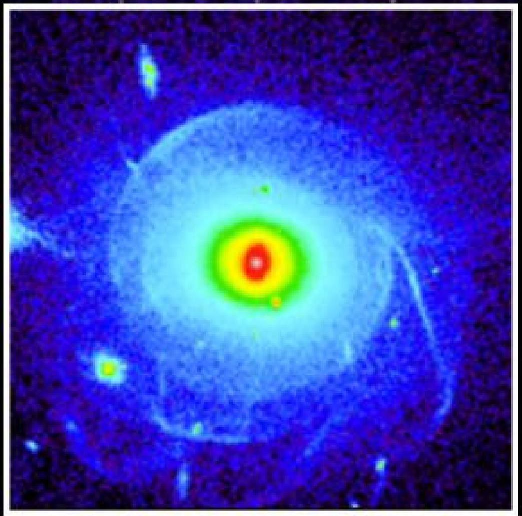
intermediate/major dry (gas-poor) mergers

(Prieur 1990; but see Peirani 2010 for wet mergers)

- Features:
  - ▸ concentric arcs
  - ▸ red colors (no star-formation)
  - ▸ relatively bright (μ < 23 mag/arcsec^2)



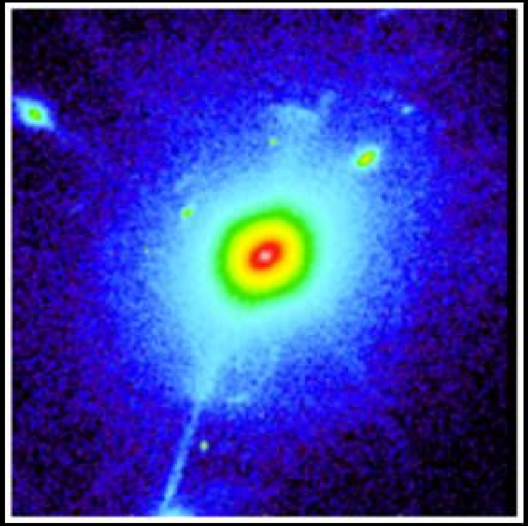
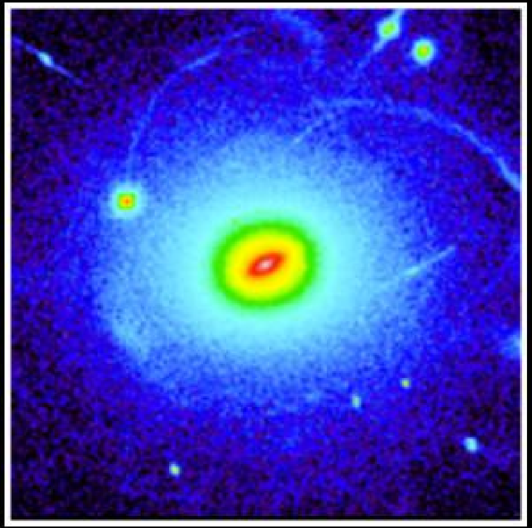
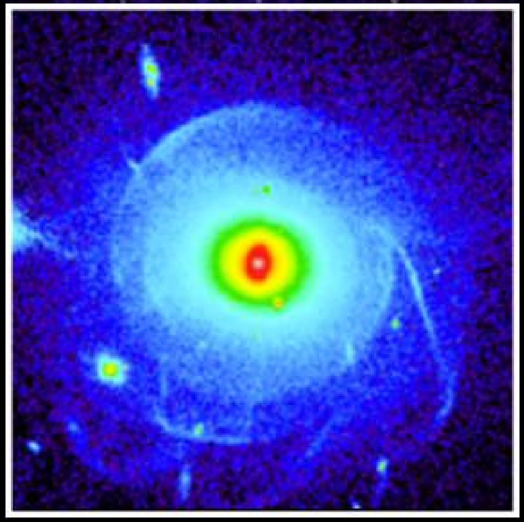
SHELLS



[P.A. Duc]

TIMESCALE COMPARISON – FINE STRUCTURES

- Disappearance of **fine structres** strongly depends on the type

TAILS	SREAMS	SHELLS
		
1-2 Gyr	1-2 Gyr	1-4 Gyr

- Values from idealized and cosmological simulations
  e.g ILLUSTRIS (Pop et al. 2017)

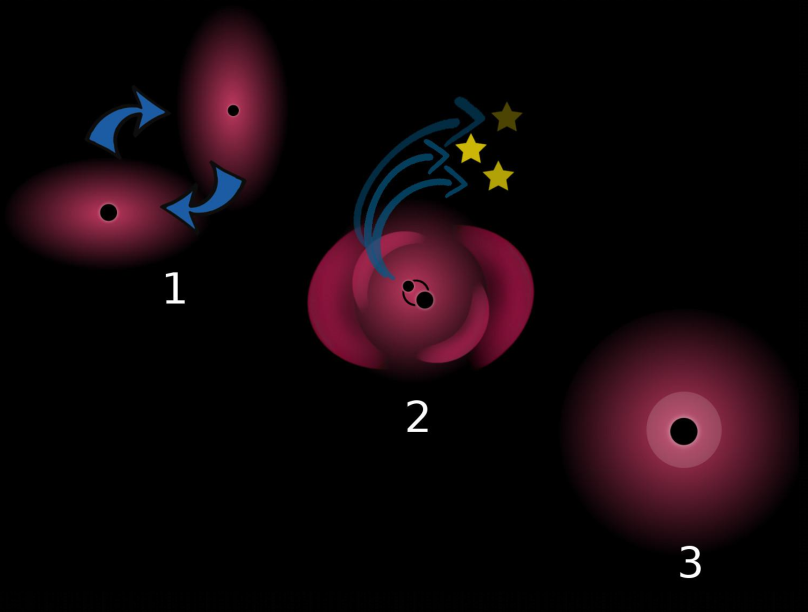
FINE STRUCTURES AS TIME PROXY

✪ Fine structures trace **time elapsed** from the last interaction event

➡ can be used as **time proxy**

✪ Extremely valuable for Early-Type Galaxies (ETGs) - uniform stellar populations

In Bonfini 2018, we used them to "time" the evolution of **cores**



⬅ **cores** are central deficit of stars
due to the action of a
Super Massive Black Hole (SMBH) binary

CONNECTING FINE STRUCTURES WITH CORES

✪ Fine structures trace **time elapsed** from the last interaction event

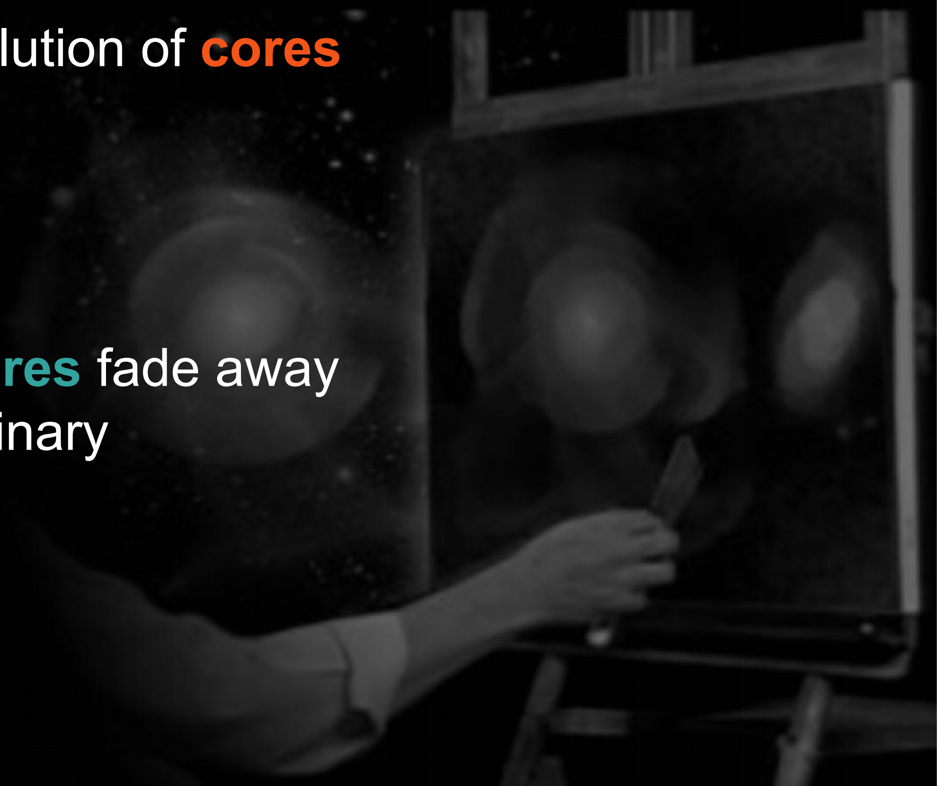
➡ can be used as **time proxy**

✪ Extremely valuable for Early-Type Galaxies (ETGs) - uniform stellar populations

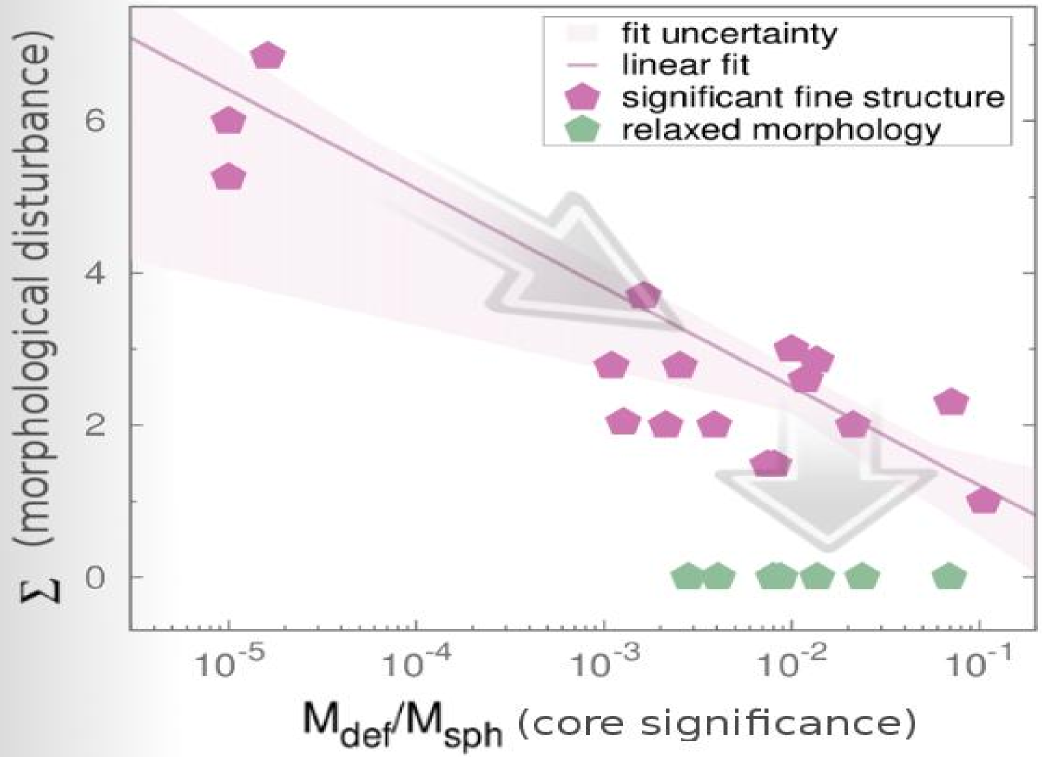
In Bonfini 2018, we used them to "time" the evolution of **cores**

✪ Following the merger which created an ETG:

- stellar orbit relax and **fine structure features** fade away
- **core** progressively excavated by SMBH binary



RESULTS



[Cartoon adapted from Bonfini 2018]

NEXT STEP

- Unfortunately, up to now fine structures only semi-qualitatively classified (i.e. "**by eye**")

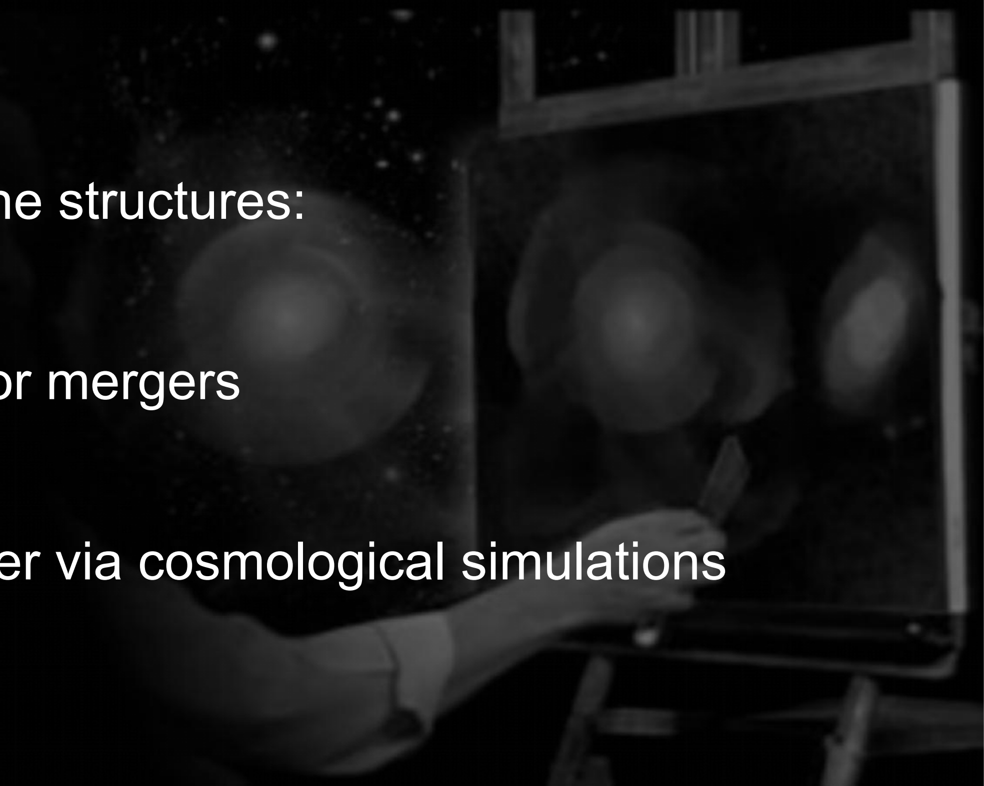
➡ NEED FOR AN AUTOMATED CLASSIFICATION

- We are working on it ! How ?

  - Sample: deep exposure ETG data

  - Define an automated metric to estimate fine structures:
    - robust
    - independent of image depth
    - able to distinguish between gas-rich/poor mergers

  - Calibrate fine structure *vs.* age from merger via cosmological simulations



NEXT STEP – EXTREMELY DEEP IMAGING DATA

$\mu_g \sim 28 - 31$ mag/arcsec^2 !!

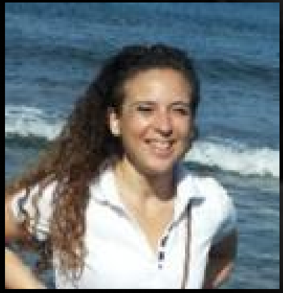
MATLAS

Mass Assembly of early-Type GaLAxies with their fine Structures

P.I: *P.-A. Duc (Observatoire Astronomique de Strasbourg)*

VEGAS

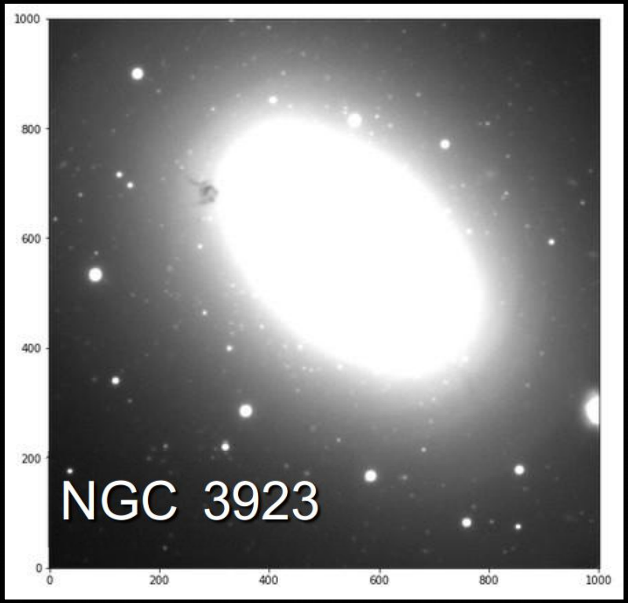
VST survey of Early-type GAlaxieS



P.I: E. Iodice *(INAF – Osservatorio Astronomico di Capodimonte)*

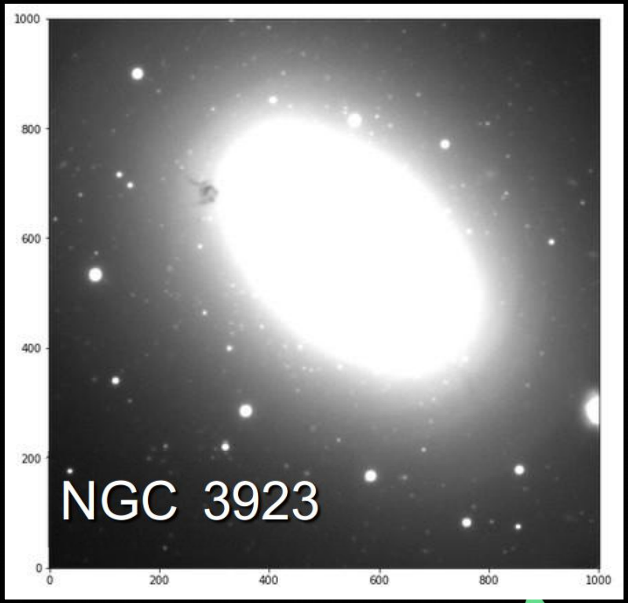
NEXT STEP – DETECTION ROUTINE

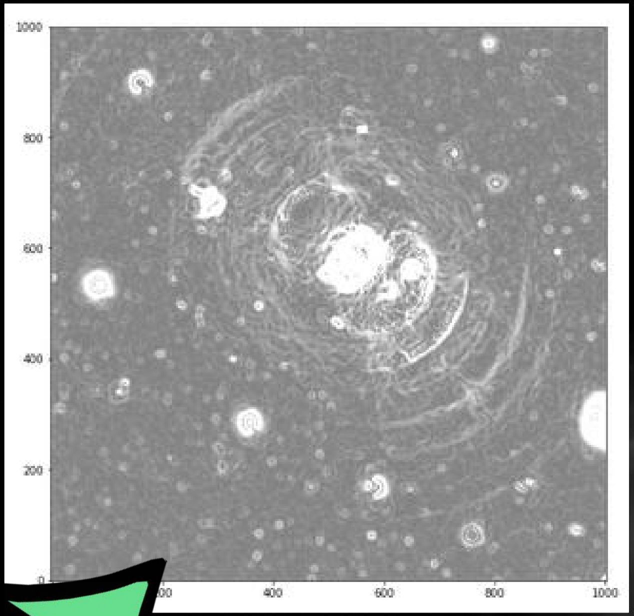
- Automated detection of shells in our deep images

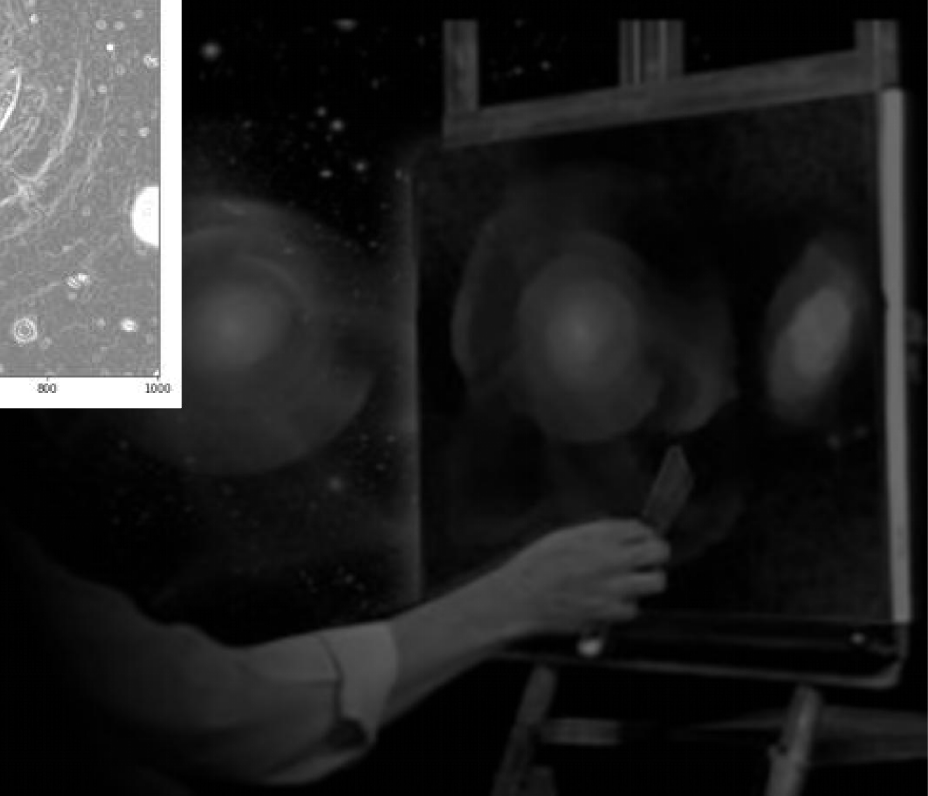


DETECTION ROUTINE

- Model subtraction + edge detection

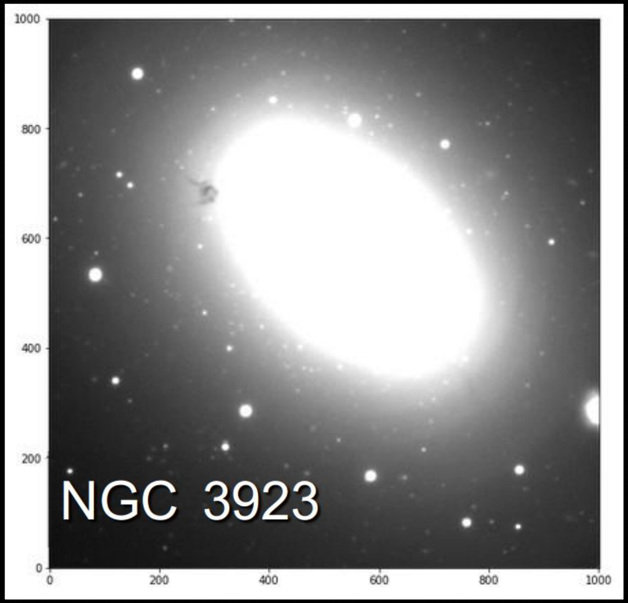


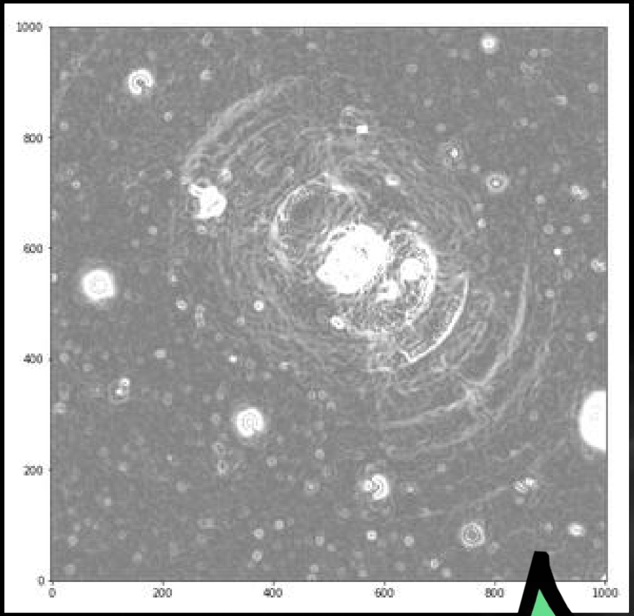


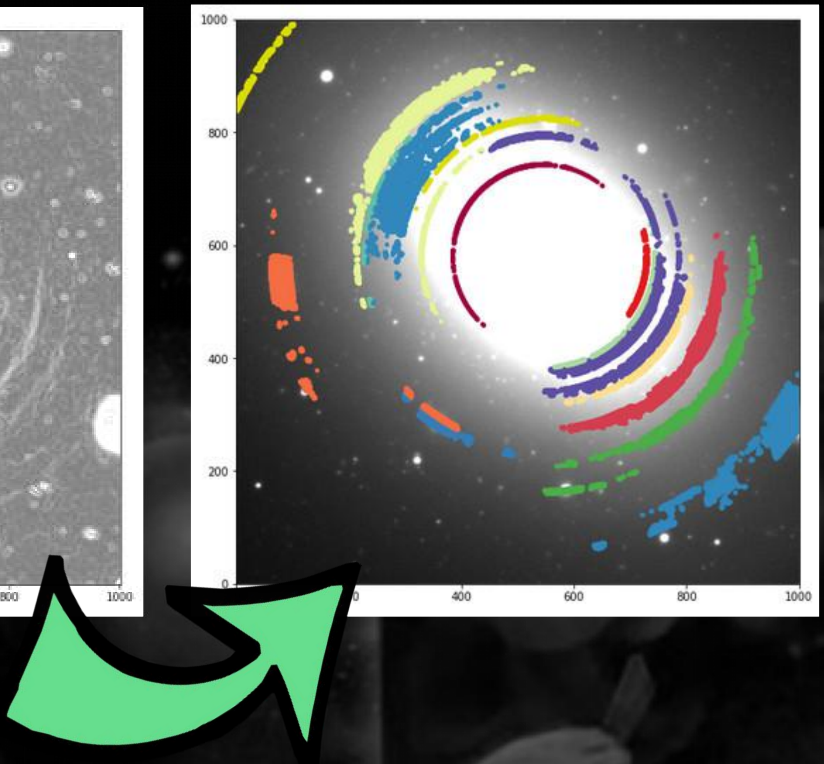


DETECTION ROUTINE

- Clustering analysis

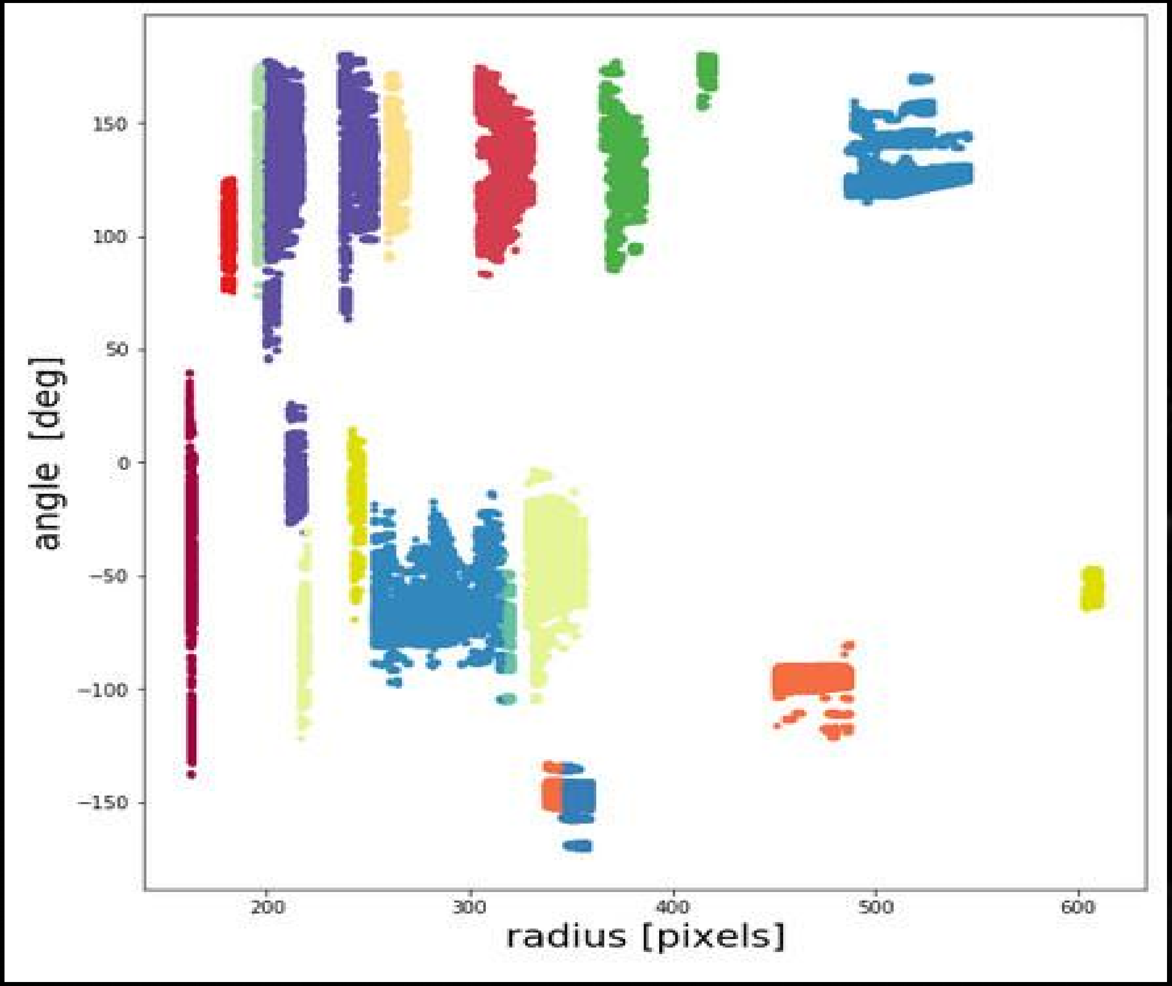




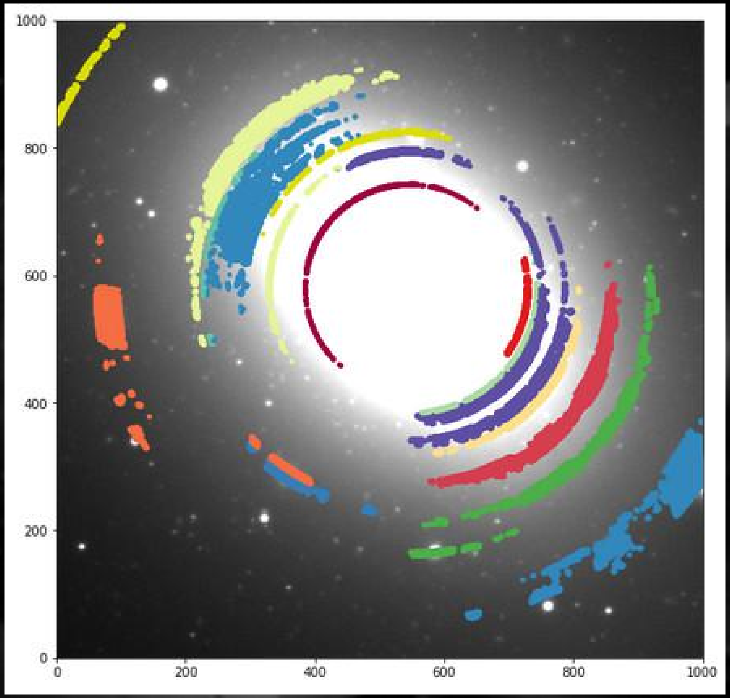


DETECTION ROUTINE

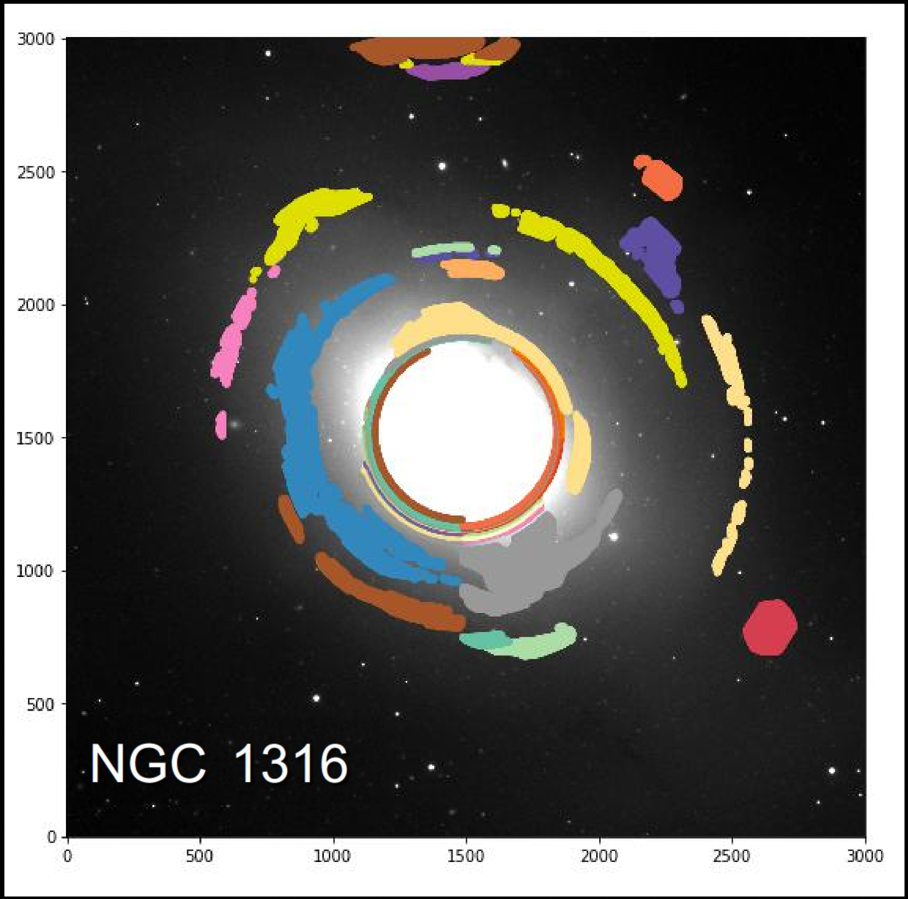
- In polar coordinates → shells are vertical (further screening if necessary)

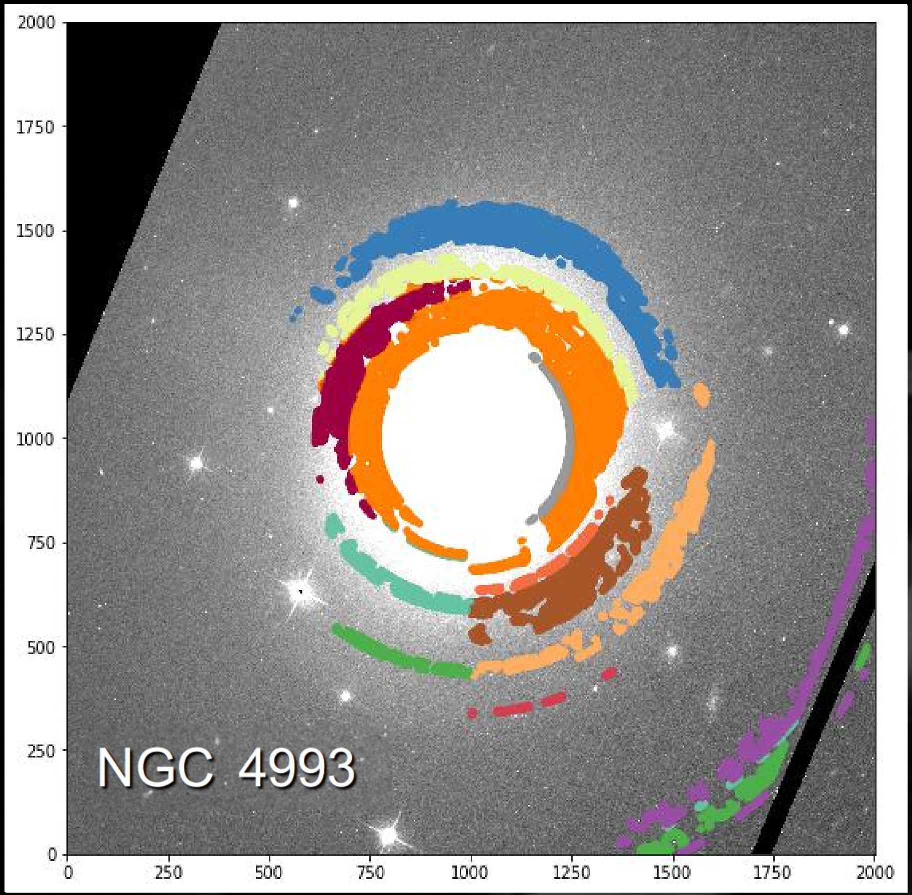


- Now trivial to automatically get:
  - shells number
  - shells radii
  - shells angular apertures

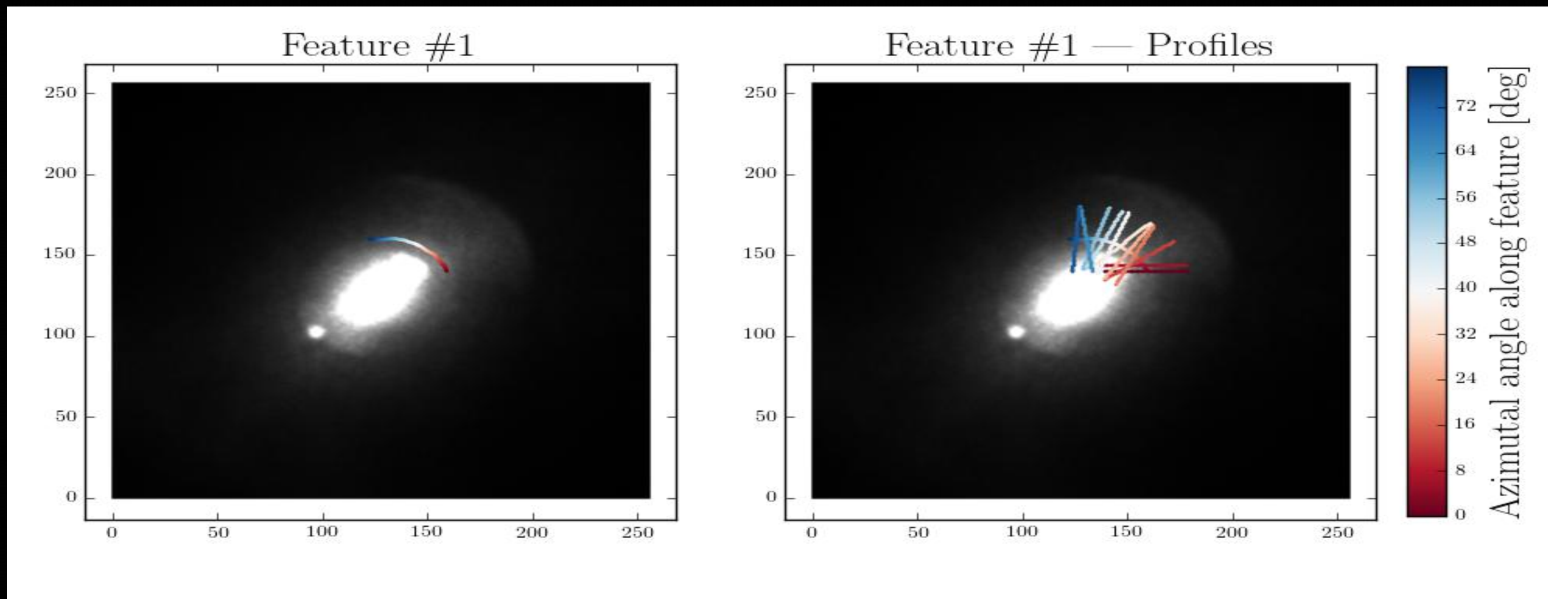


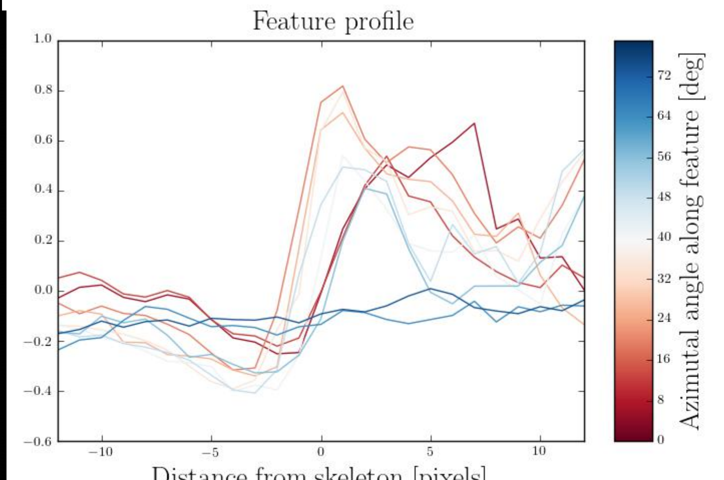
COUPLE MORE EXAMPLES





AUTOMATED PROFILING - FILTER





FilTER

The Filament Trait-Evaluated Reconstruction

Georgia Panopoulou

CALTECH, postdoc

TAKE-HOME POINTS

✪ Morphology is still a fundamental tool for galaxy evolution

✪ Machine Learning (ML) provides fast / efficient classifiers

✪ <u>Sub-structures</u> represent the next challenge

BUT

ML not applicable yet because poorly characterized

✪ Our work on fine structures will provide:

- ▸ automated parametrization
- ▸ fundamental input to design dedicated ML networks

THANK YOU ! (FOR NOT FALLING ASLEEP)