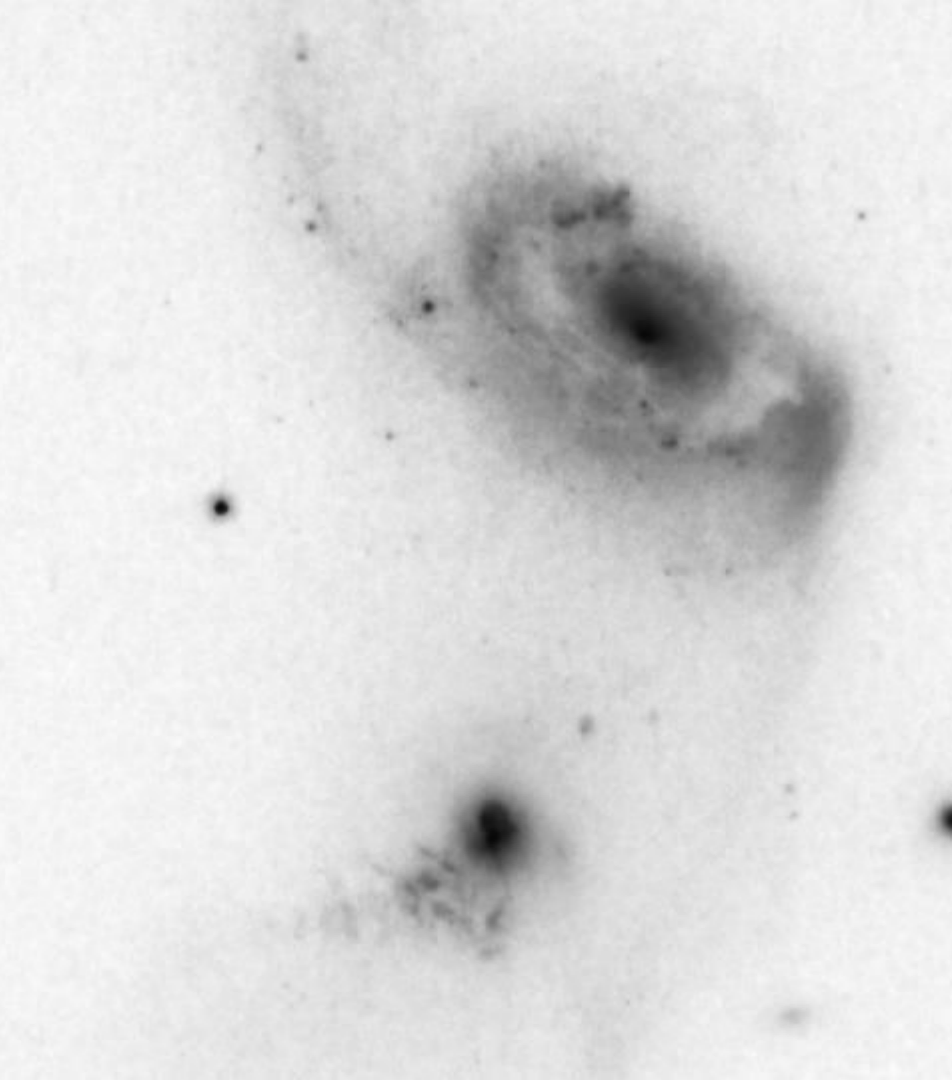
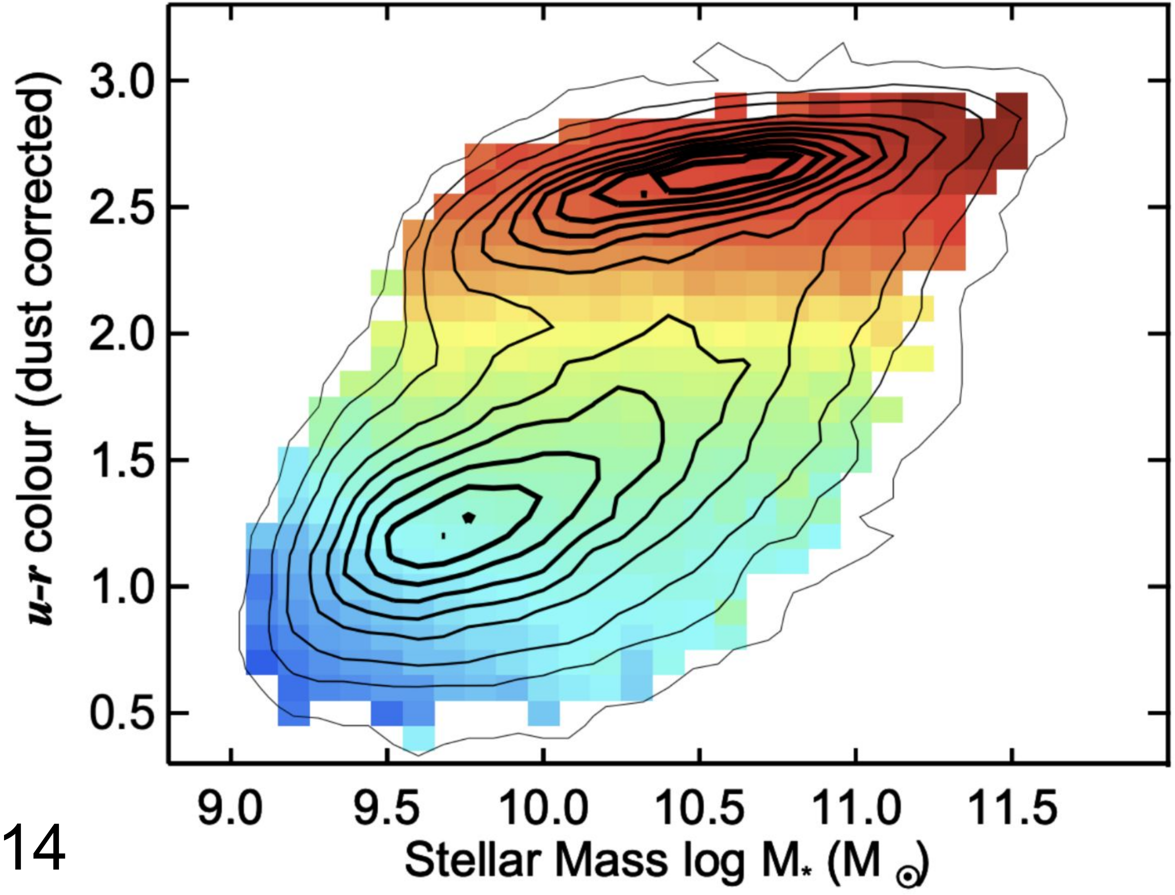
Kinematic Signatures of Galaxy Evolution

The Energetics of AGN Outflows and the Accurate Identification of Merging Galaxies

Rebecca Nevin



Galaxy properties like color are bimodal, which implies evolution



Schawinski+ 2014

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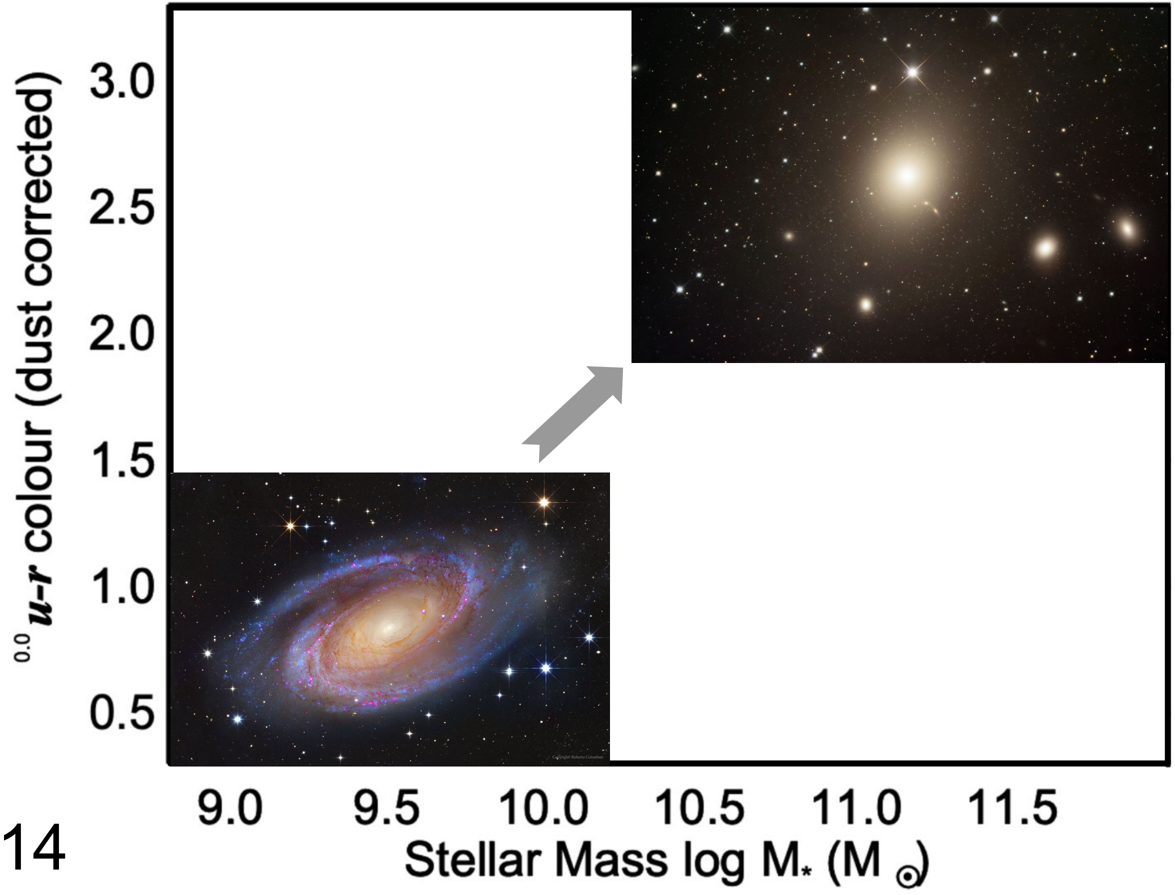


Schawinski+ 2014

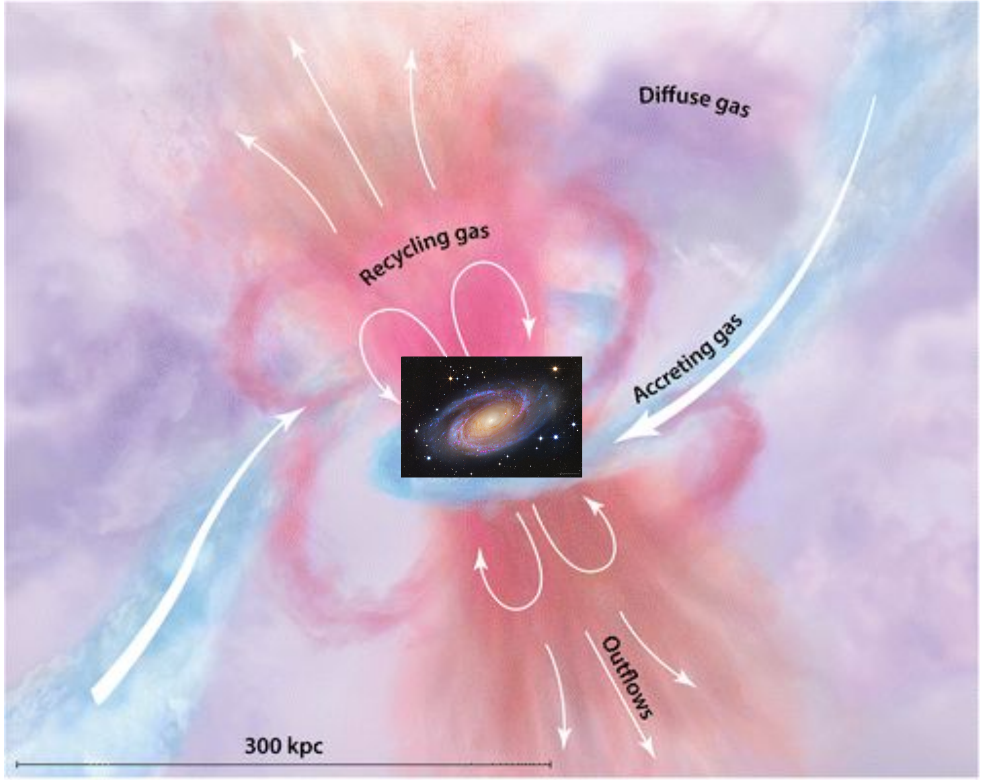
Galaxies evolve from blue spiral galaxies to quenched red elliptical galaxies

Disrupt/heat/expel/
use up gas

A complex interplay of processes drives galaxy evolution

???

Many different processes drive galaxy evolution; they operate over different time and size scales



Tumlinson+ 2017

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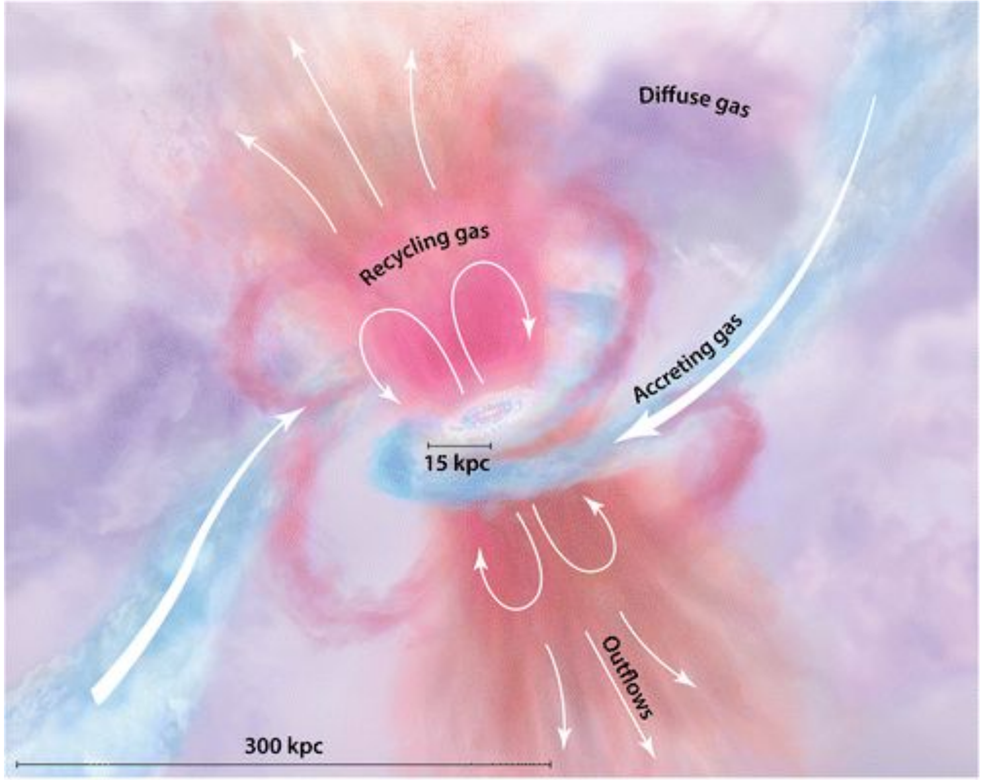
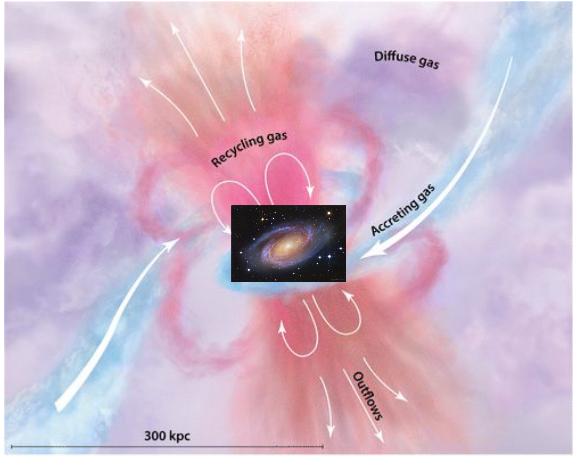
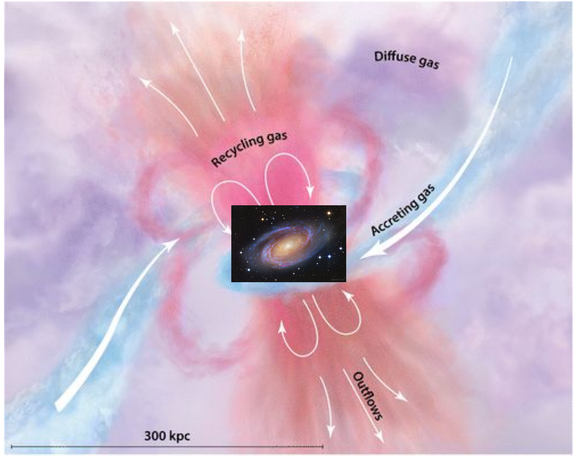


Tumlinson+ 2017

Galaxy mergers can drive evolution



Tumlinson J, et al. 2017.
Annu. Rev. Astron. Astrophys. 55:389–432



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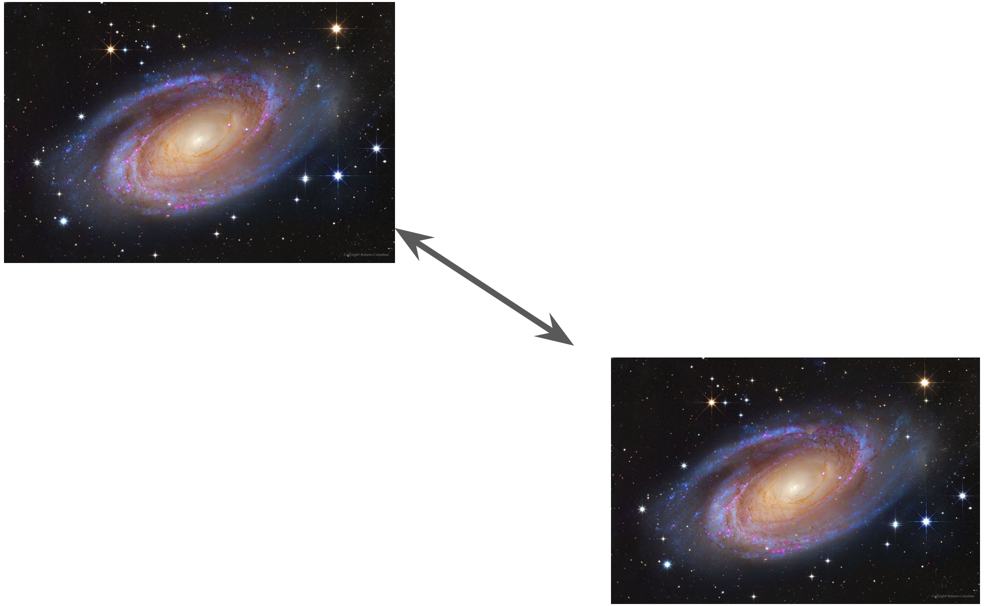

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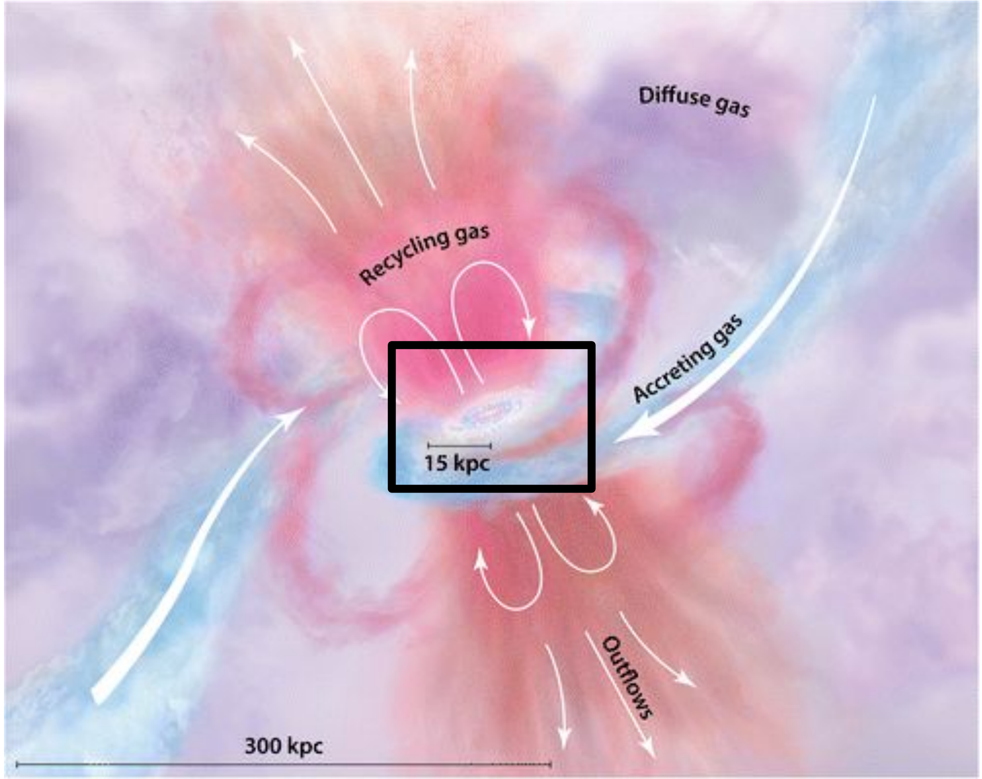
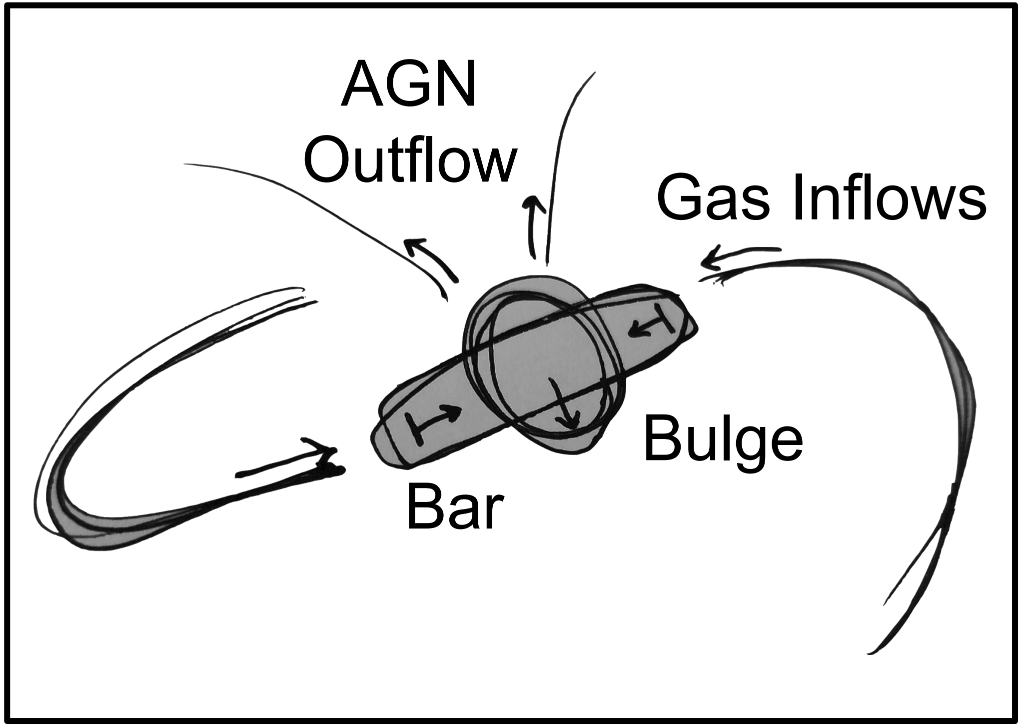
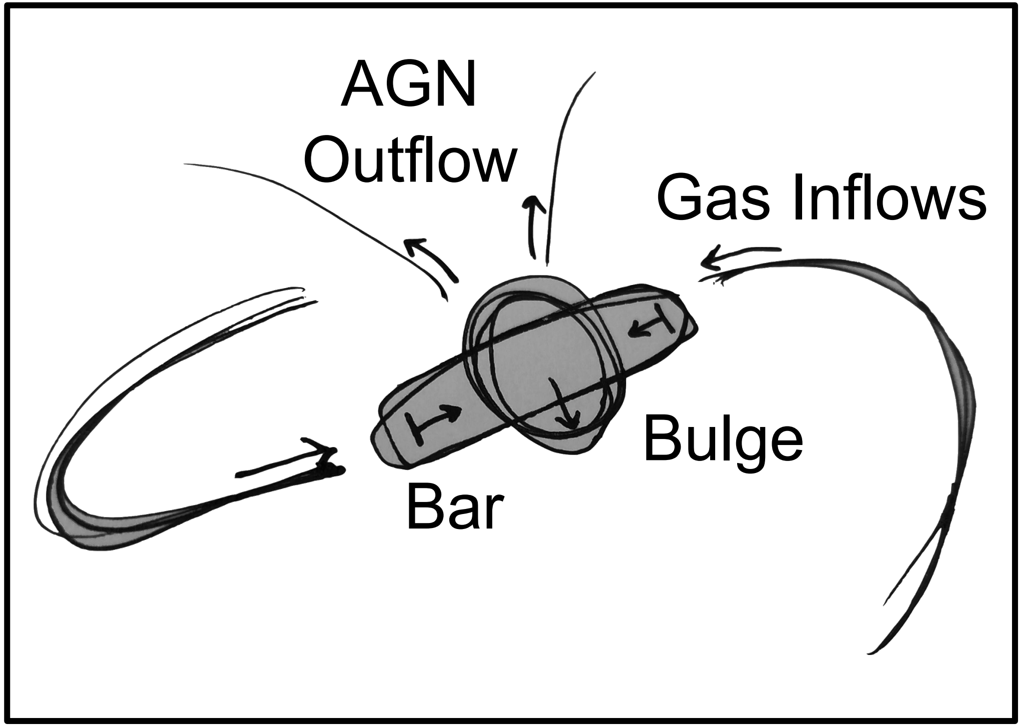


Tumlinson+ 2017


AGN
Outflow
Gas Inflows
Bulge
Bar

These evolutionary processes leave characteristic imprints on the kinematics of a galaxy



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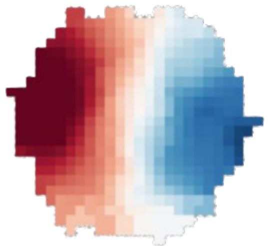

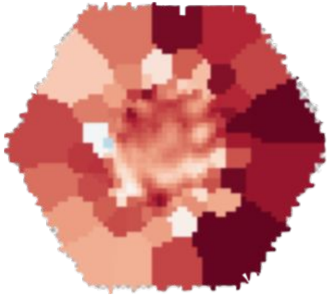

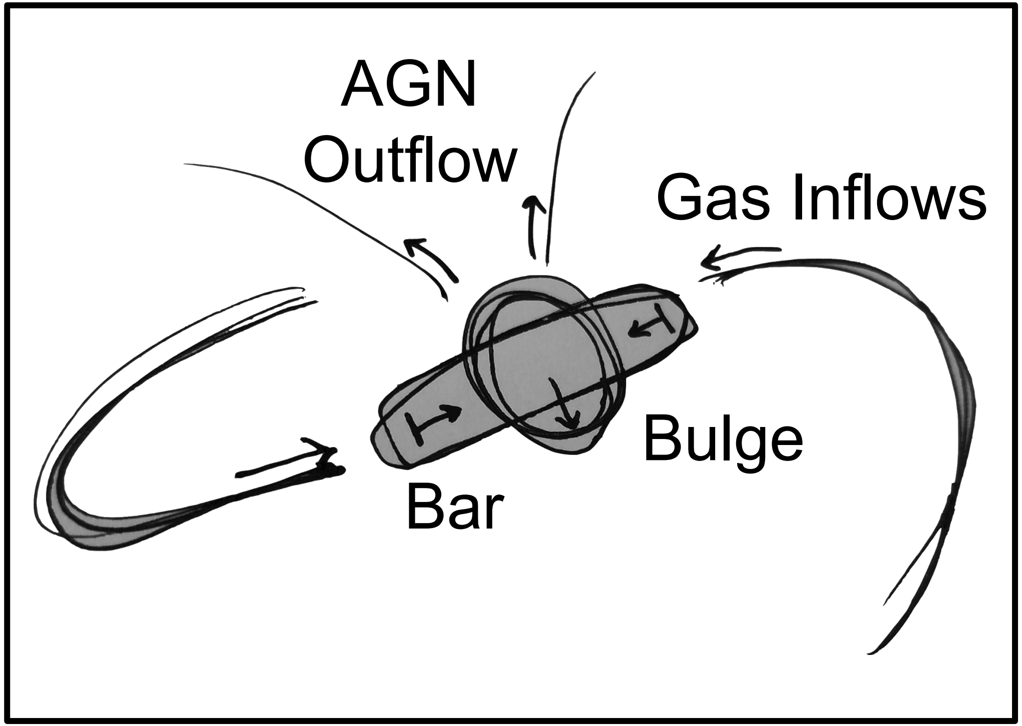

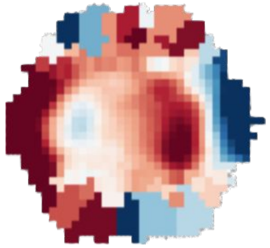

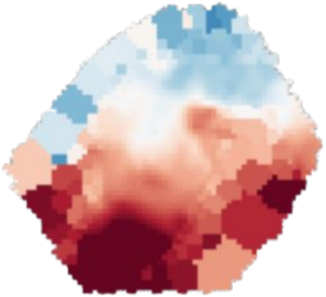

Kinematics is the hero we deserve and the hero we need right now.

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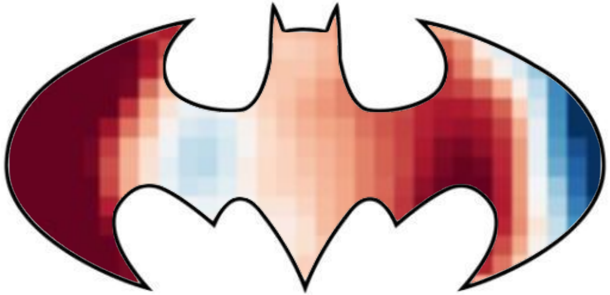
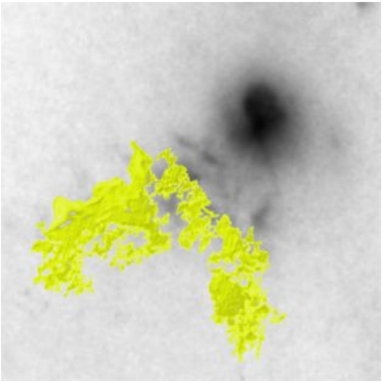
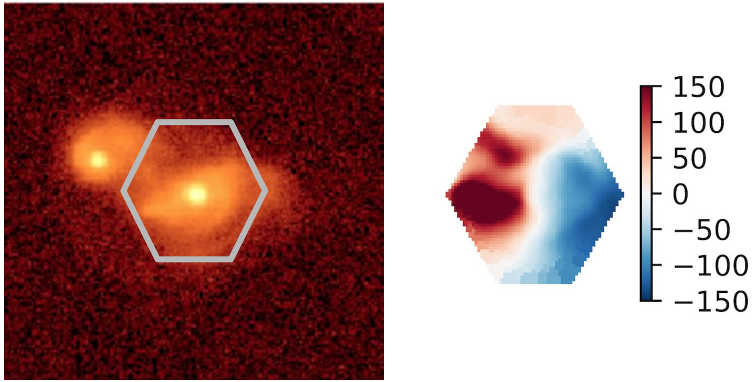


Galaxy evolution is driven by multiple processes...

AGN Feedback



Galaxy Mergers



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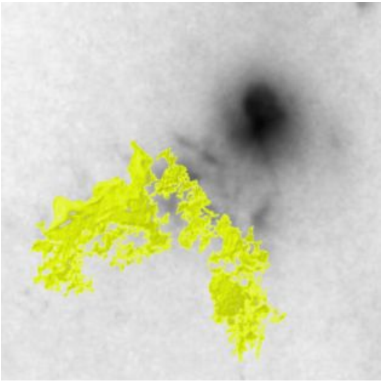

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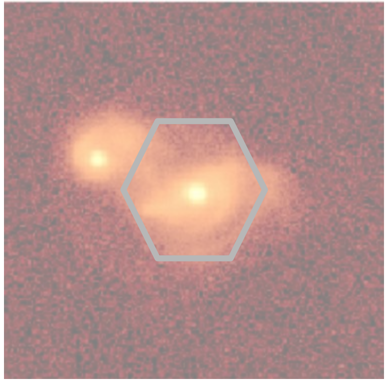
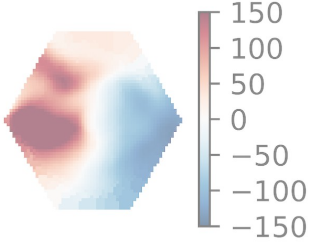
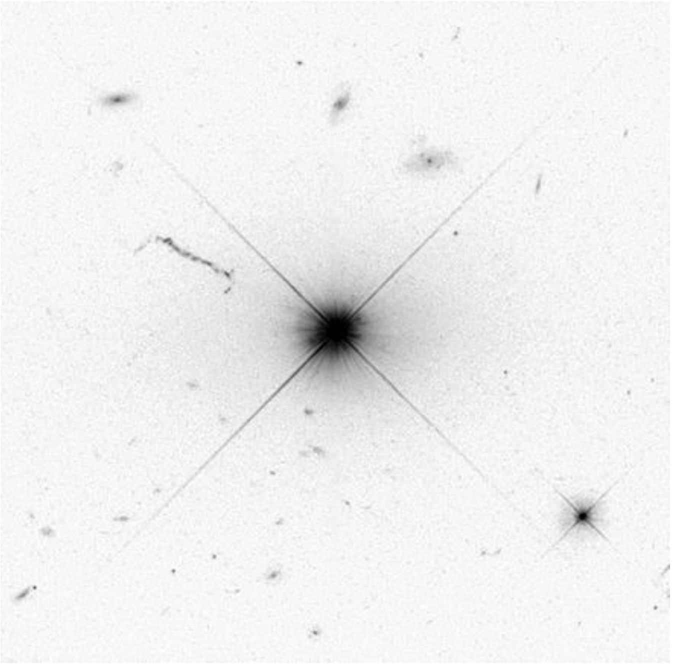




A supermassive black holes that is actively accreting enough gas is an Active Galactic Nucleus



Hubble Space Telescope

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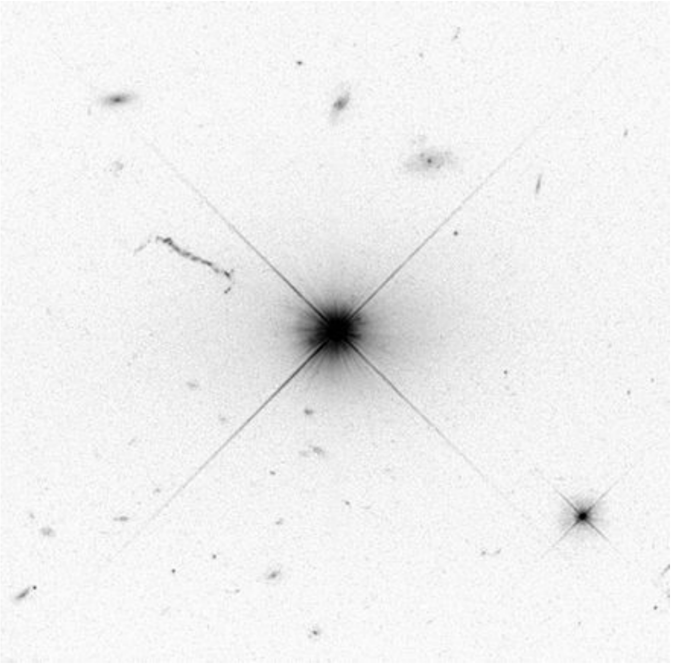

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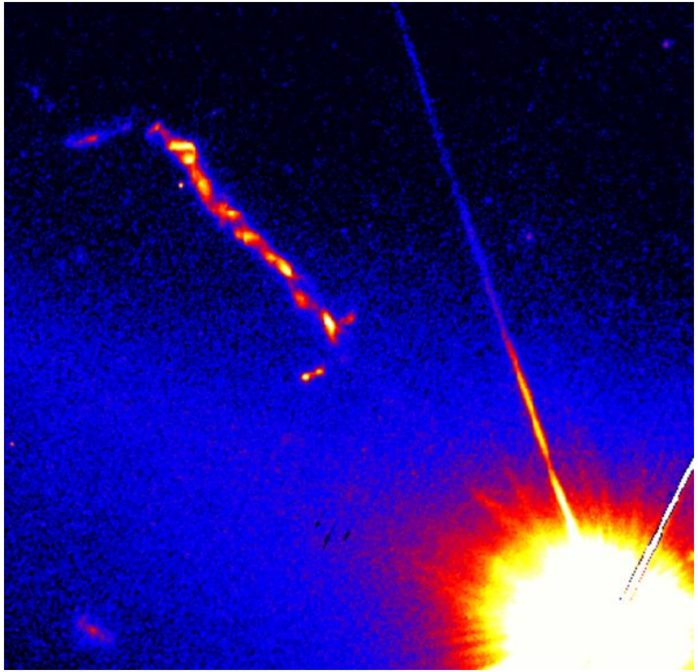
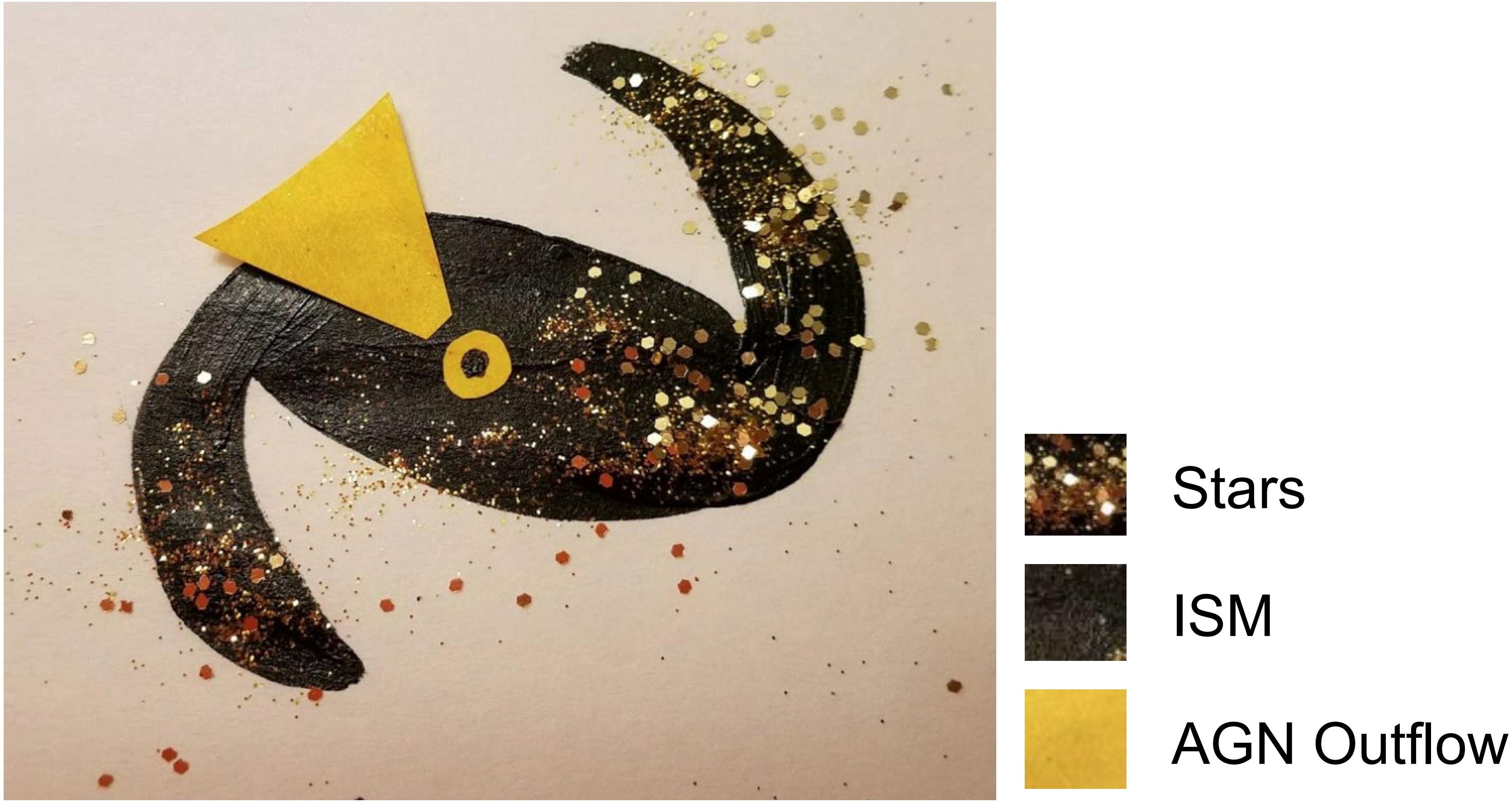


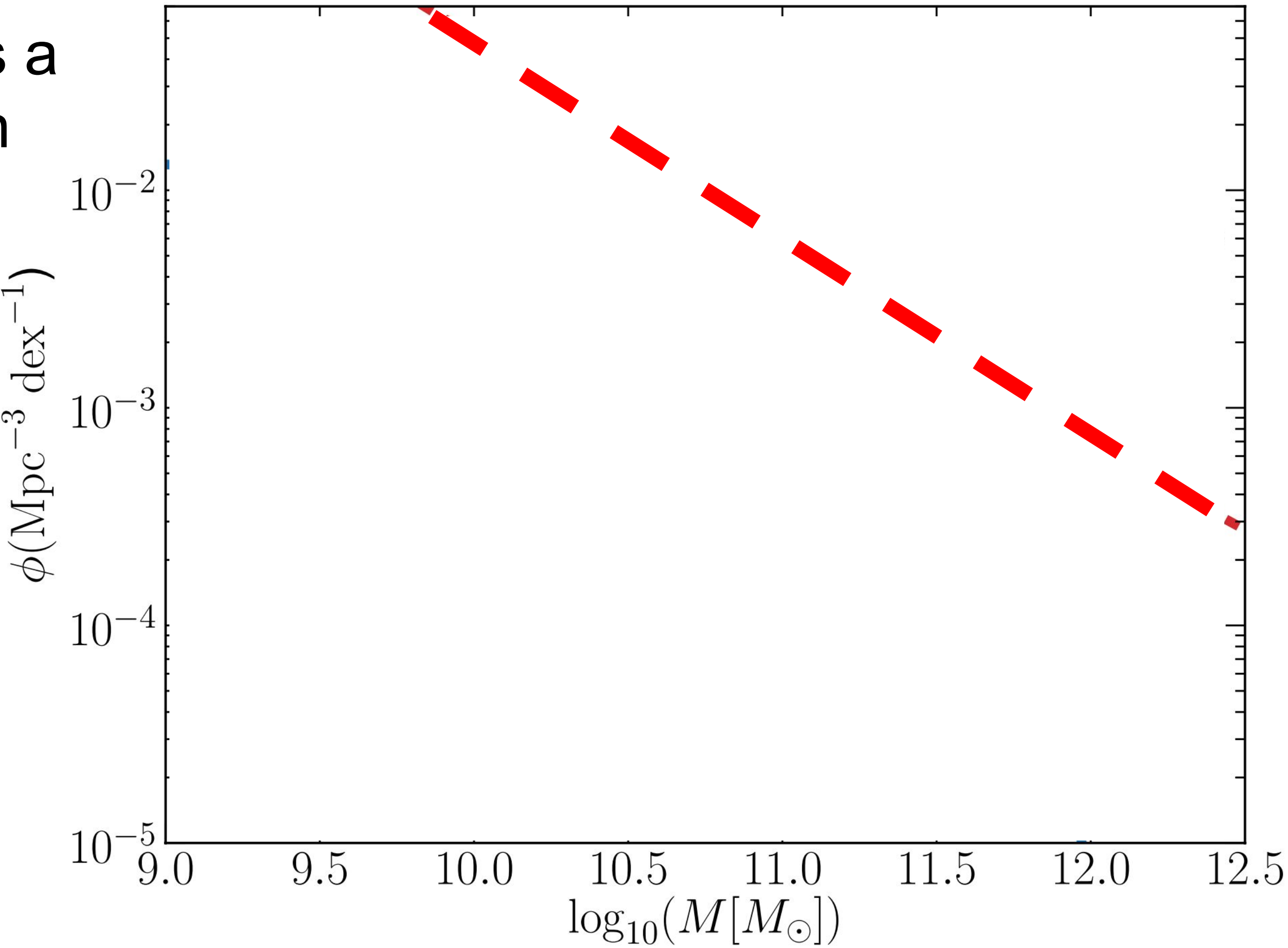
Chandra X-ray Observatory

Feedback is any process that disrupts gas and affects star formation

Feedback = Energy + must couple energy to the ISM

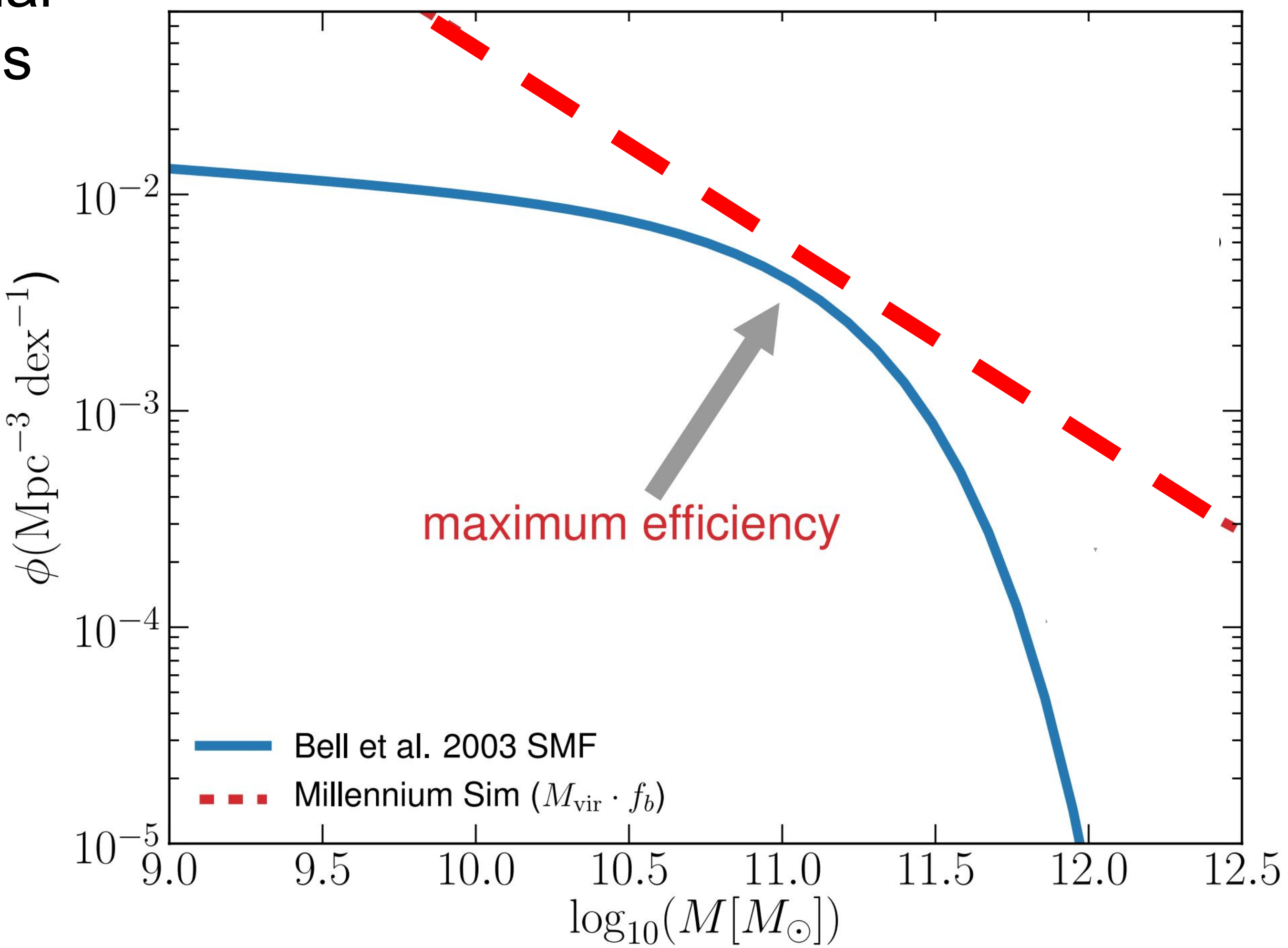


The Millennium simulation predicts a halo mass function



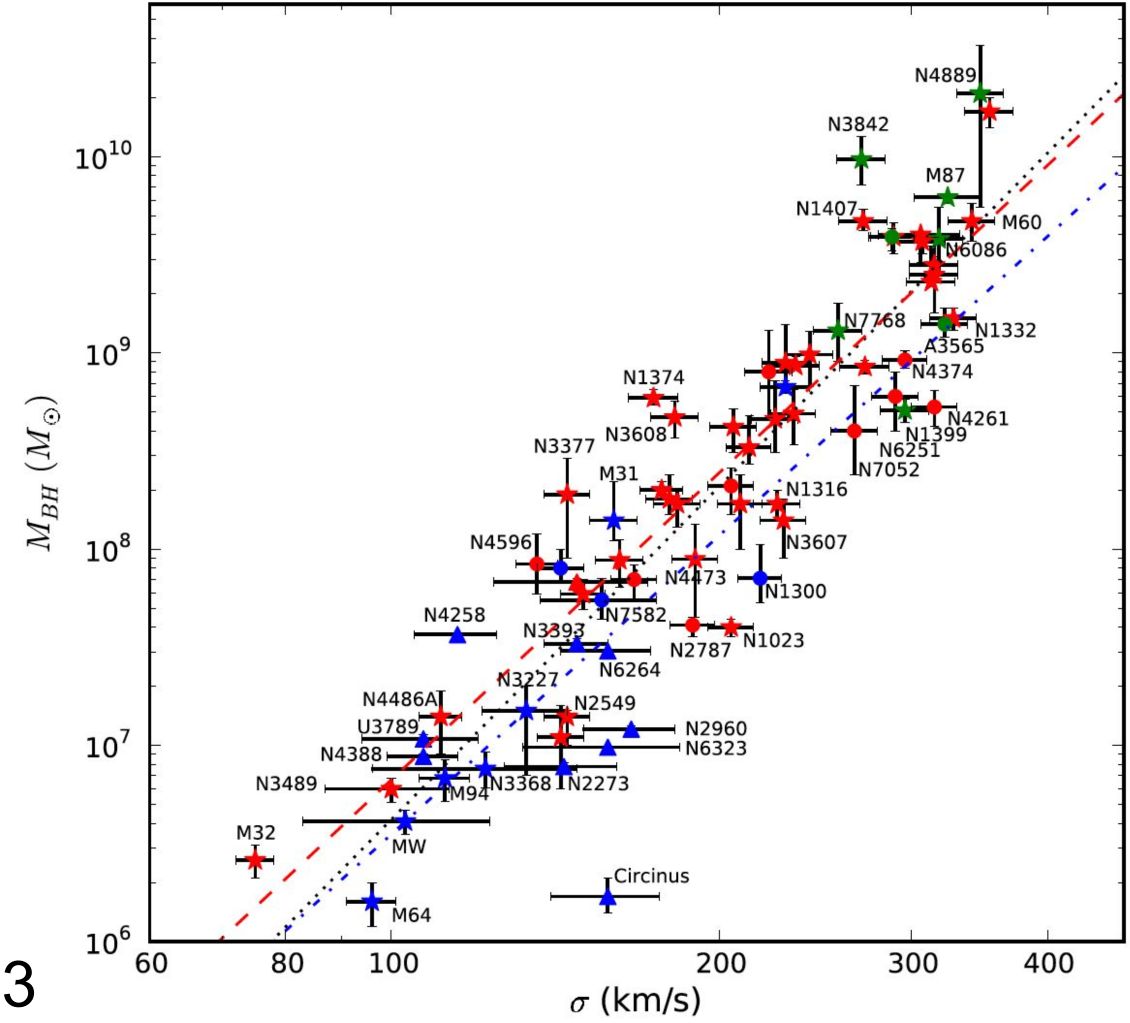
Mutch+ 2013

The observed stellar mass function does not match the predicted mass function



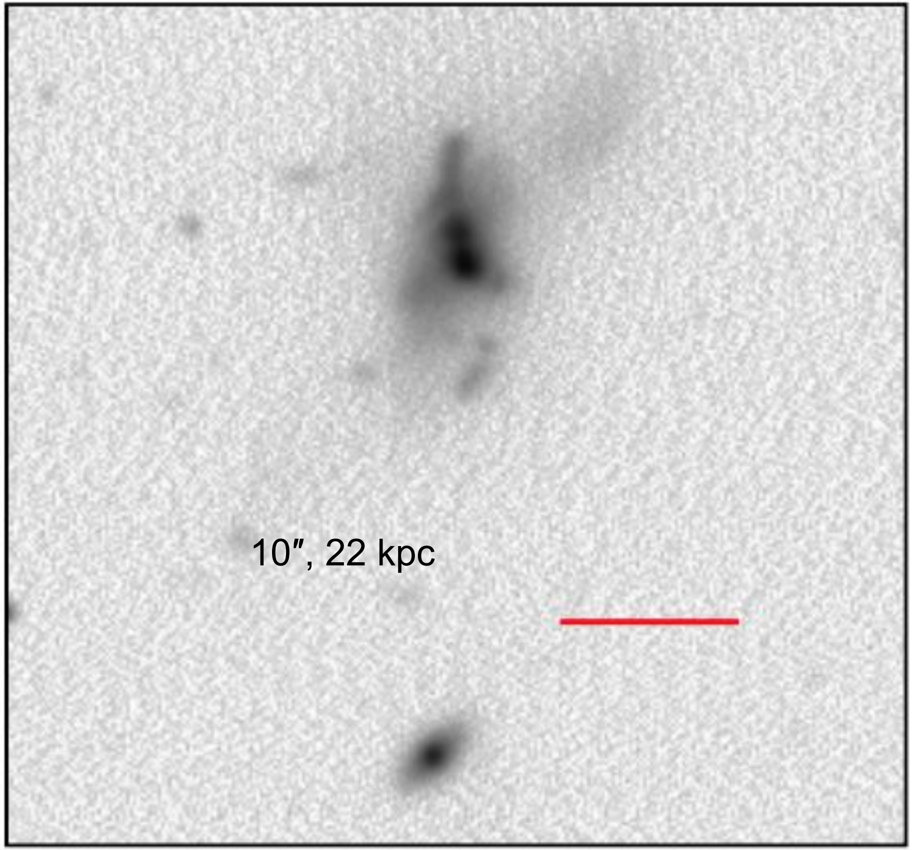
Mutch+ 2013

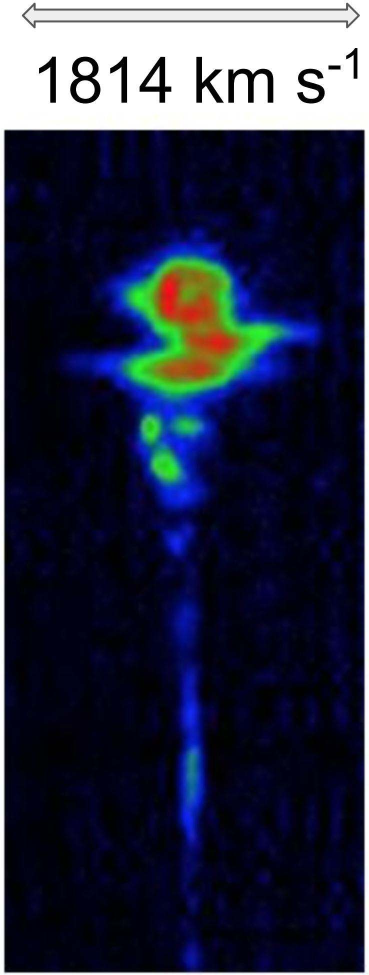
AGN scaling relations require a mechanism for feedback



McConnell & Ma 2013

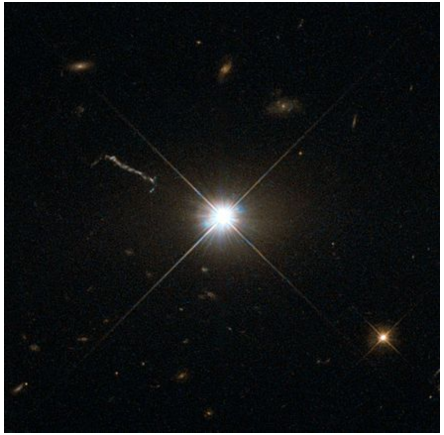
High luminosity AGN have powerful outflows

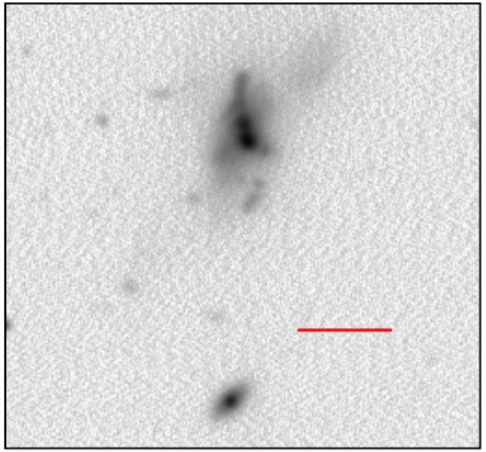


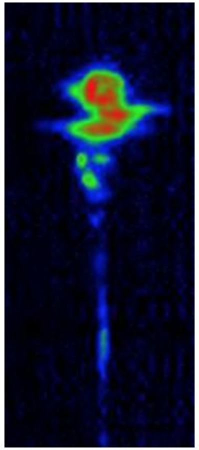


Greene+ 2011

High luminosity AGN are rare







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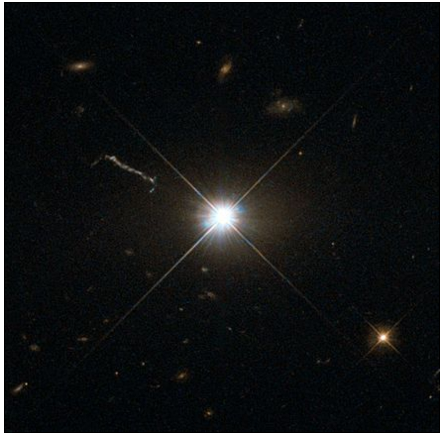
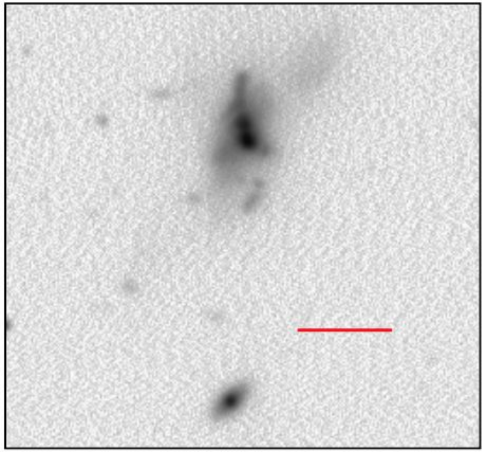
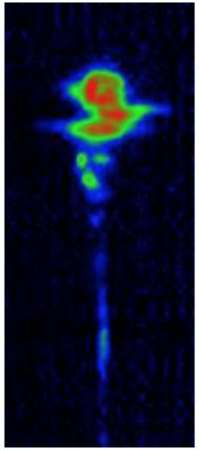
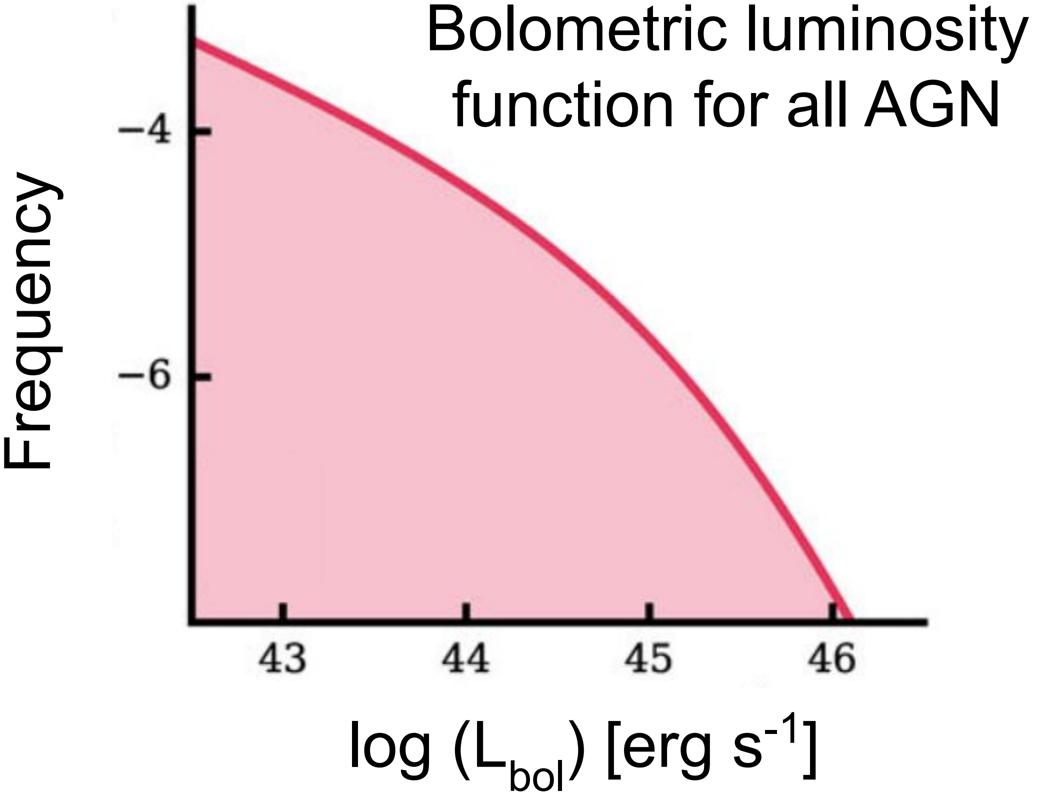


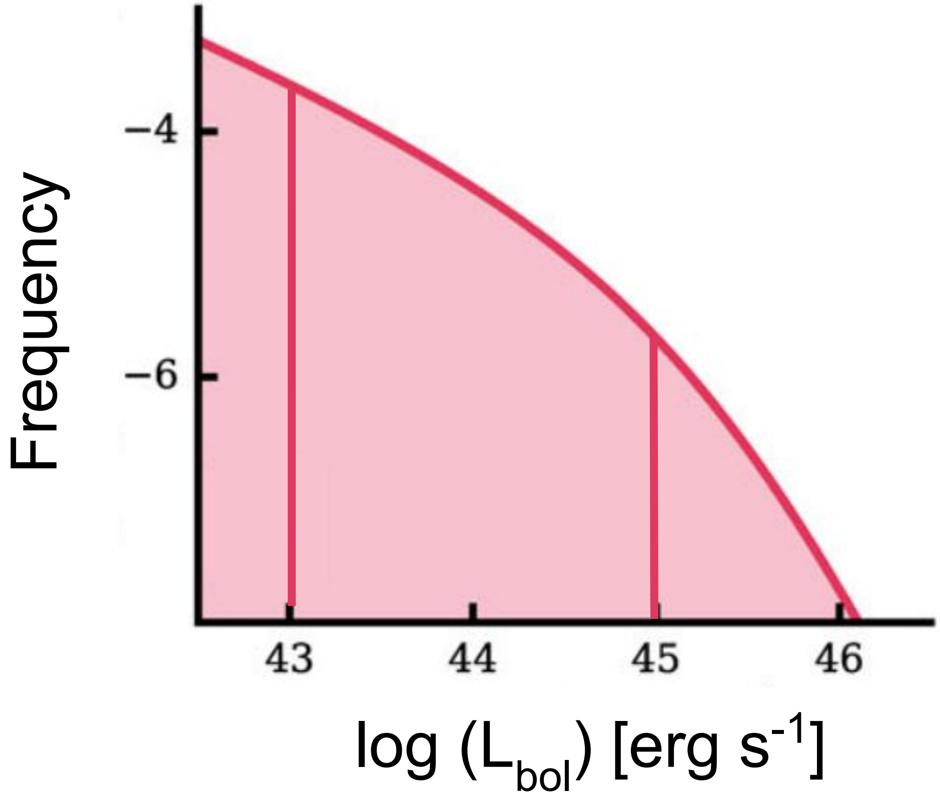






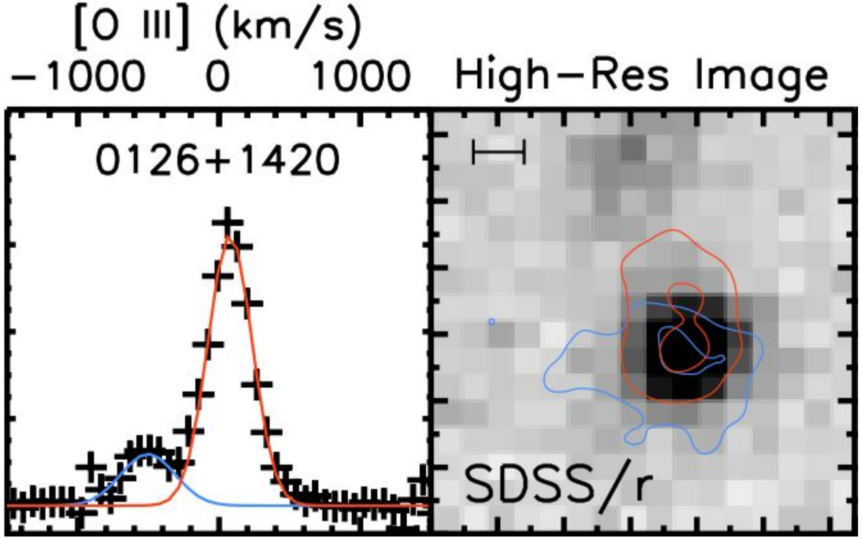
Weigel+ 2018

Moderate luminosity AGN are common

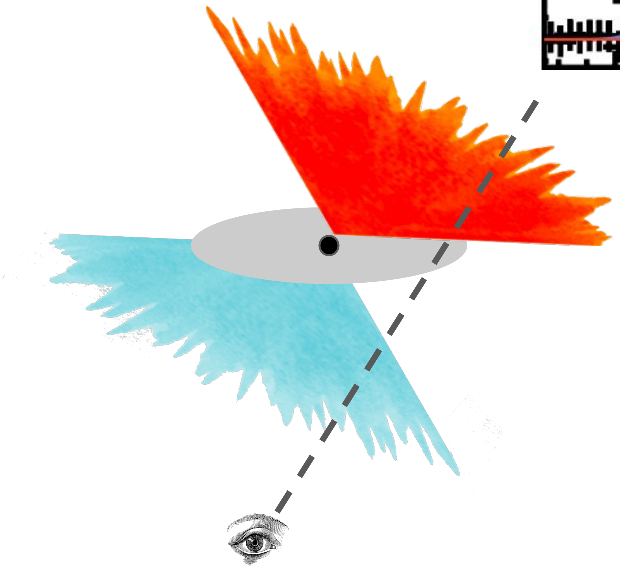


Weigel+ 2018

Double-peaked emission lines can be produced by AGN outflows



Fu+ 2012



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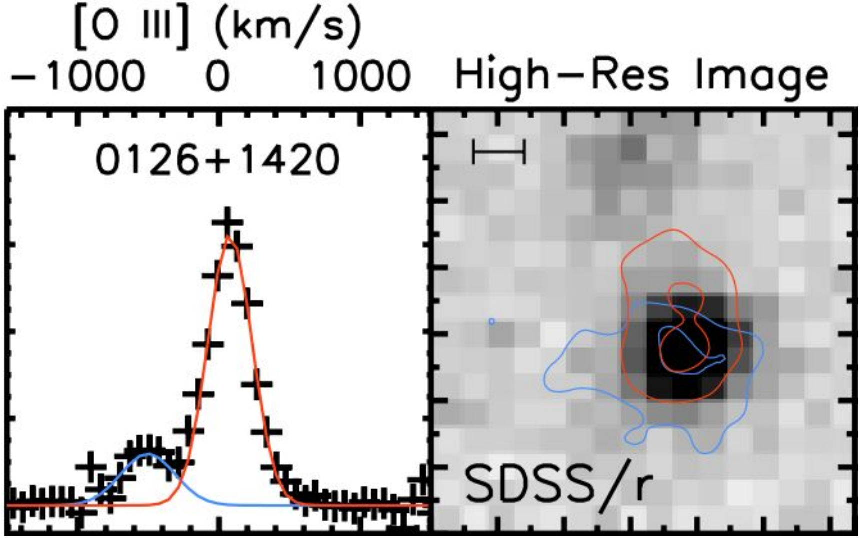
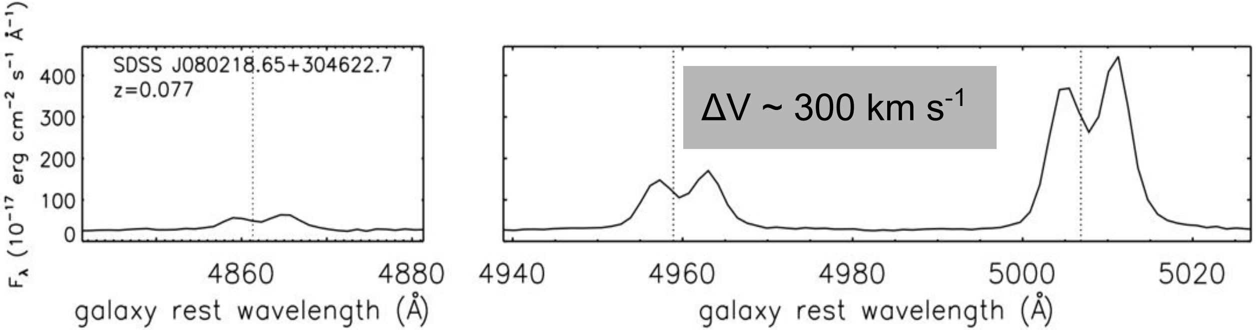
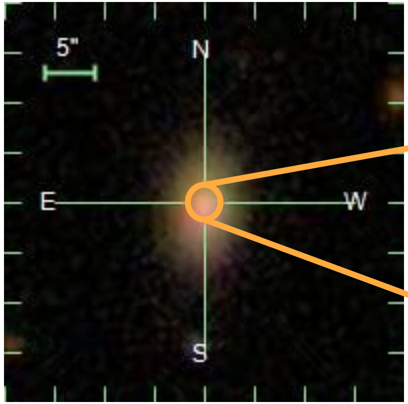


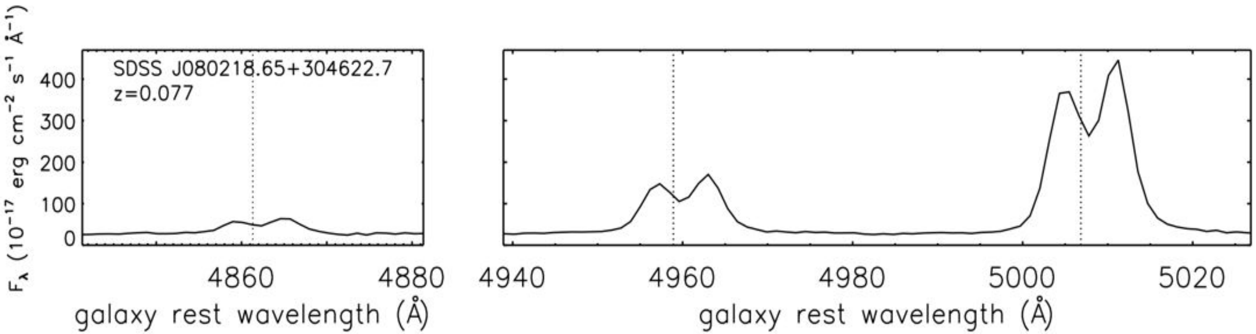
Fu+ 2012

Parent sample is 71 double peaked AGN at z < 0.1 in SDSS

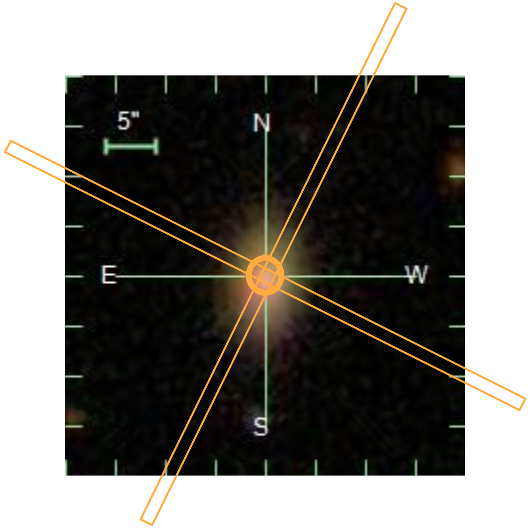


The SDSS double-peaked profiles are from integrated fiber spectra; they do not provide spatial information





With follow-up optical longslit spectra of two orthogonal PAs, I determine the kinematic origin of the double-peaked emission lines (**Nevin+ 2016**)



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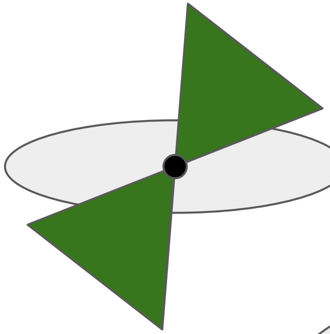
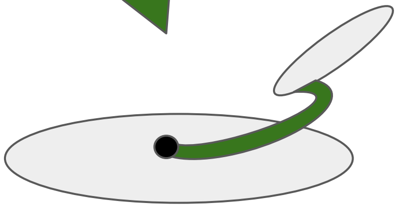
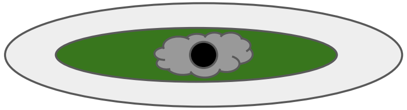
Outflow



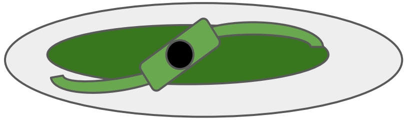
Inflow



Rotation-dominated + Obscuration



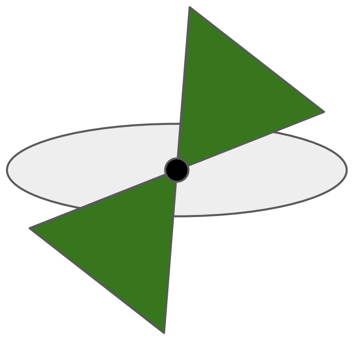
Rotation-dominated + Disturbance



The double-peaked lines in this sample are mostly produced by outflows (58/71)

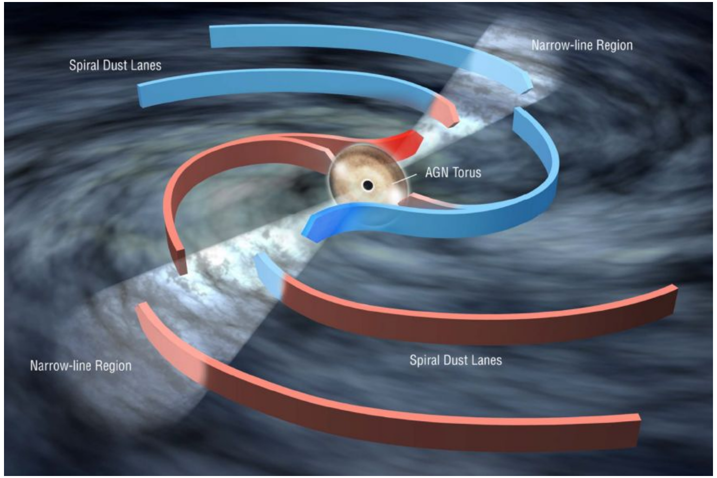
See also:
Smith+ 2011
Fu+ 2012
Müller-Sánchez+ 2015
Lyu+ 2016

Outflow

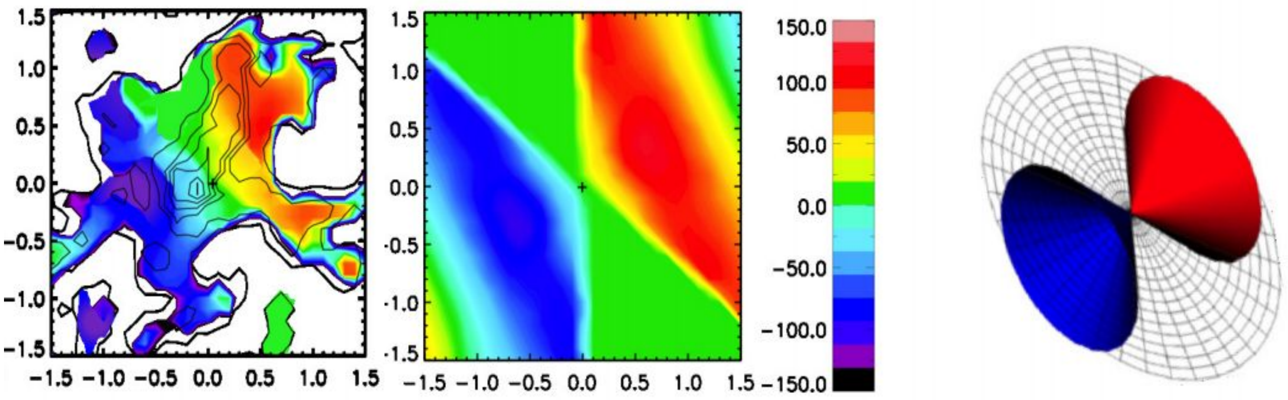


We model the 18 AGN (that are dominated by outflows on all scales) as biconical outflows

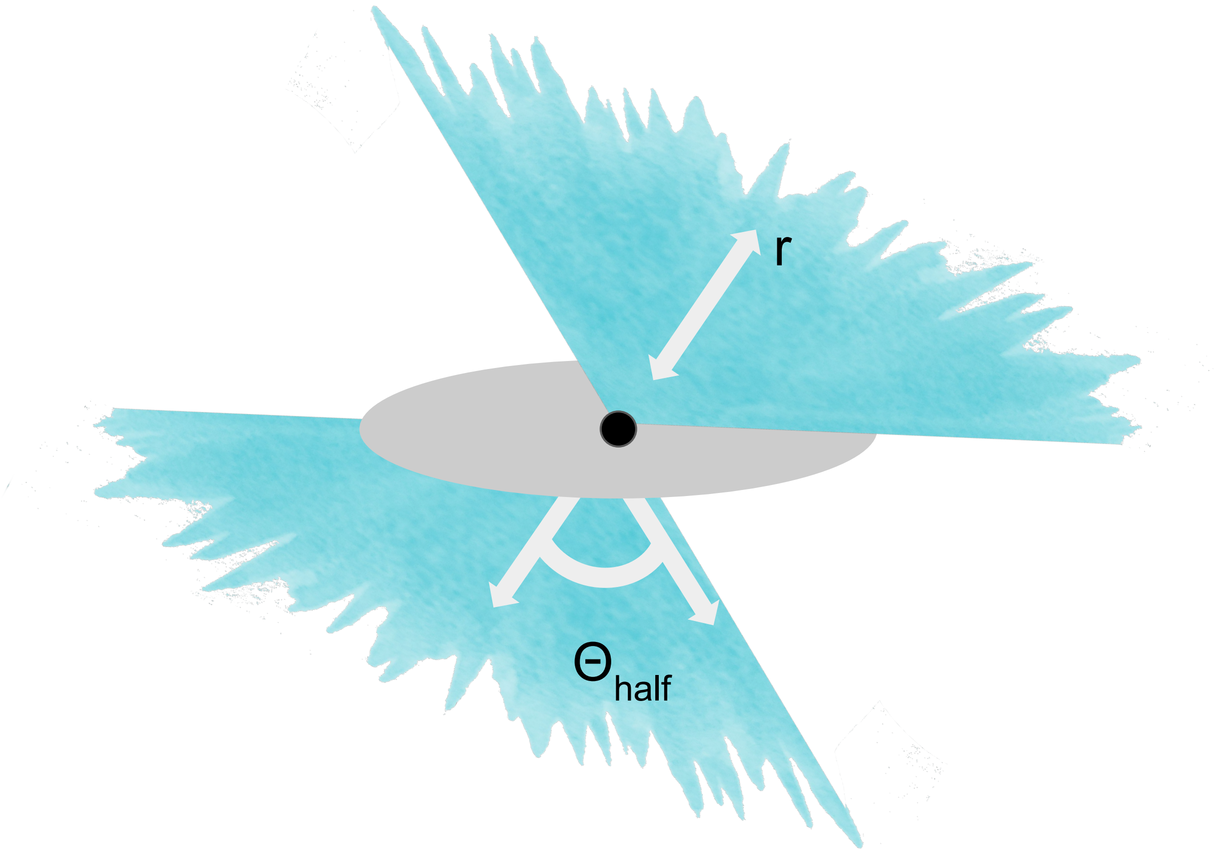
Fischer+ 2017



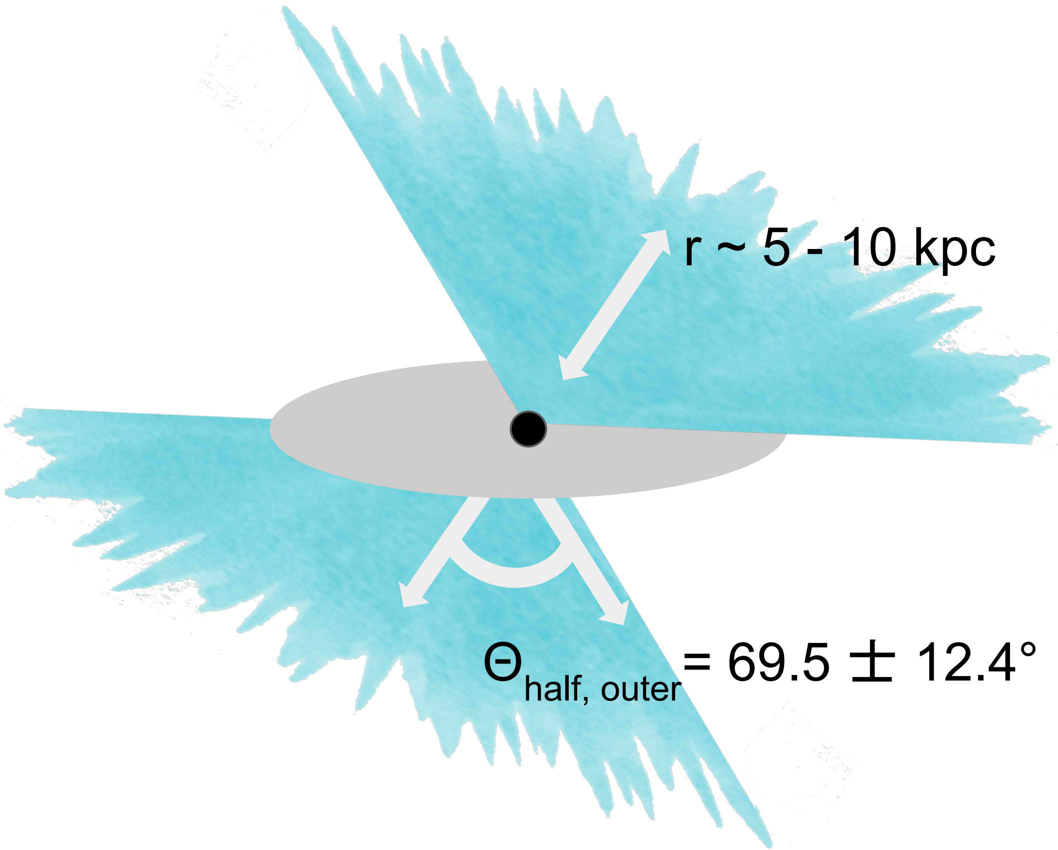
Müller-Sánchez+ 2016



I use a MCMC to determine the posterior distribution functions of the bicone parameters



The bicones are large



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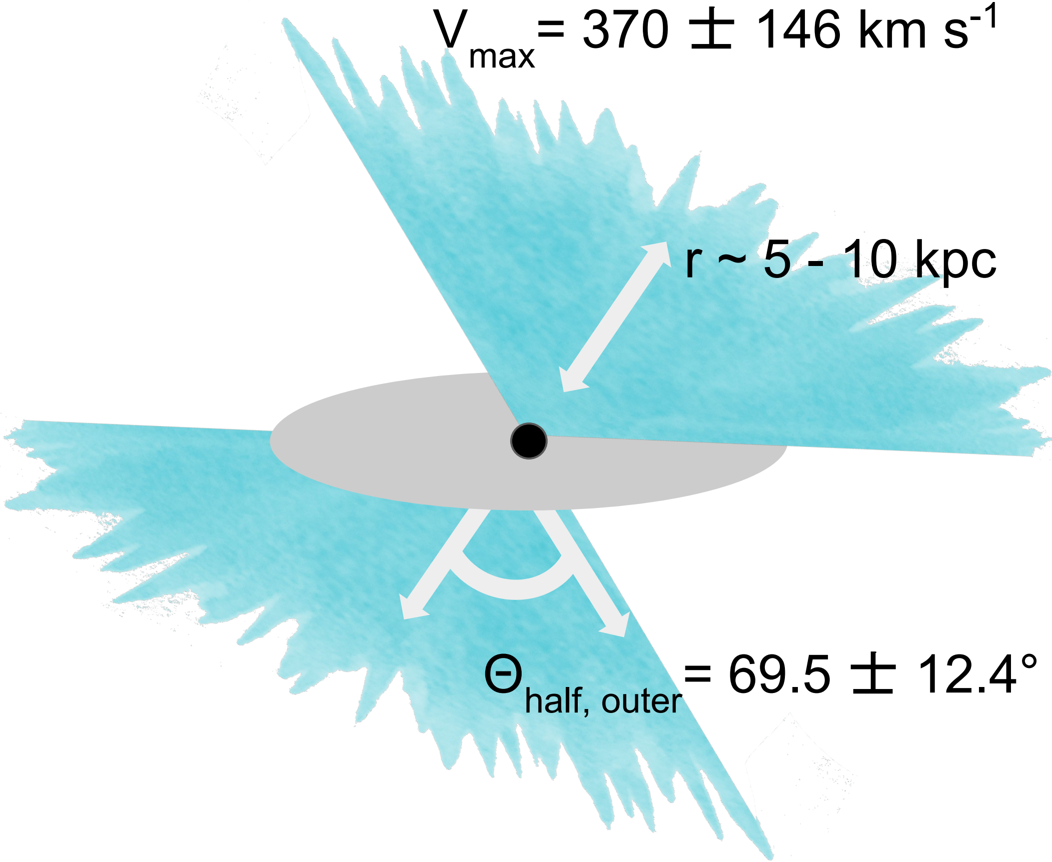
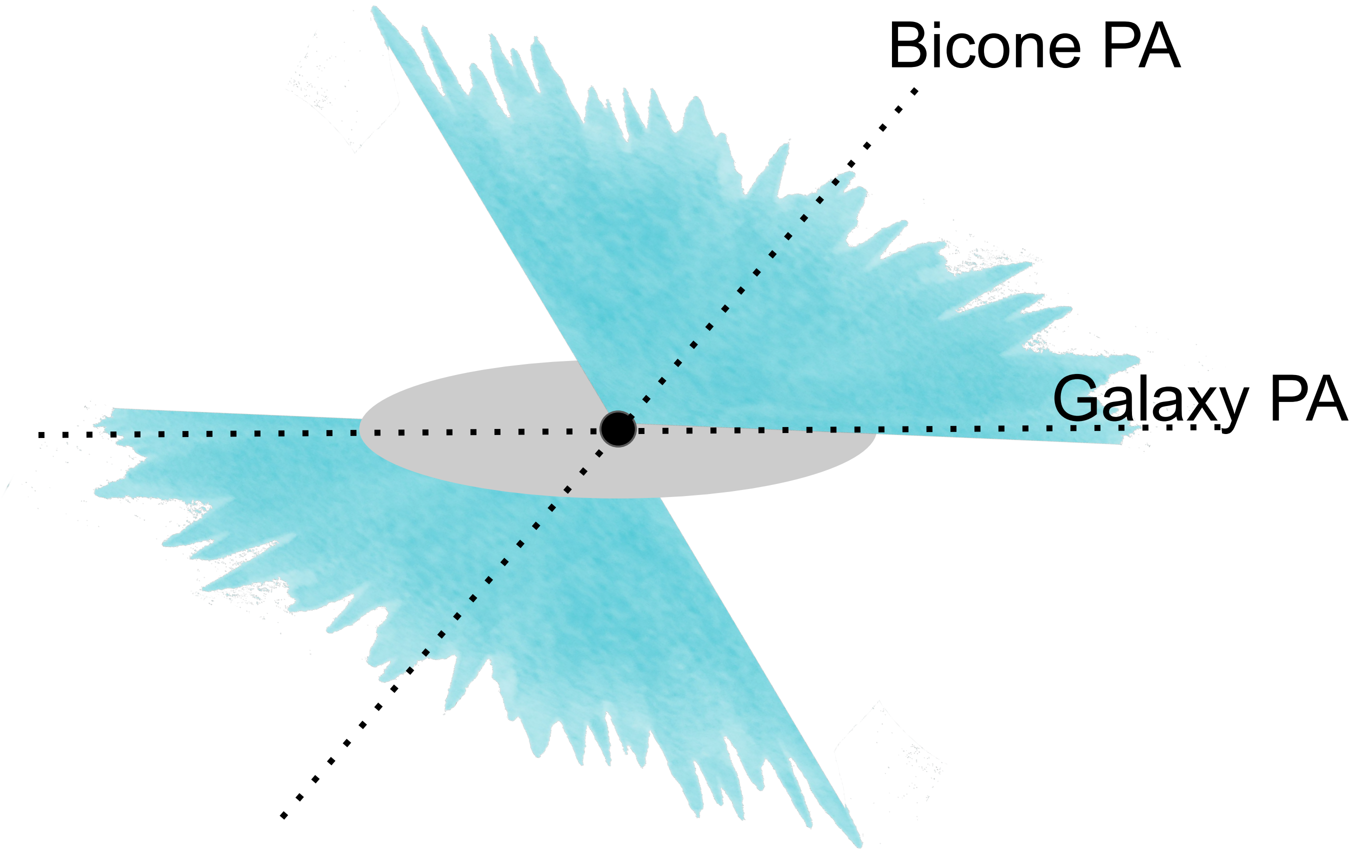
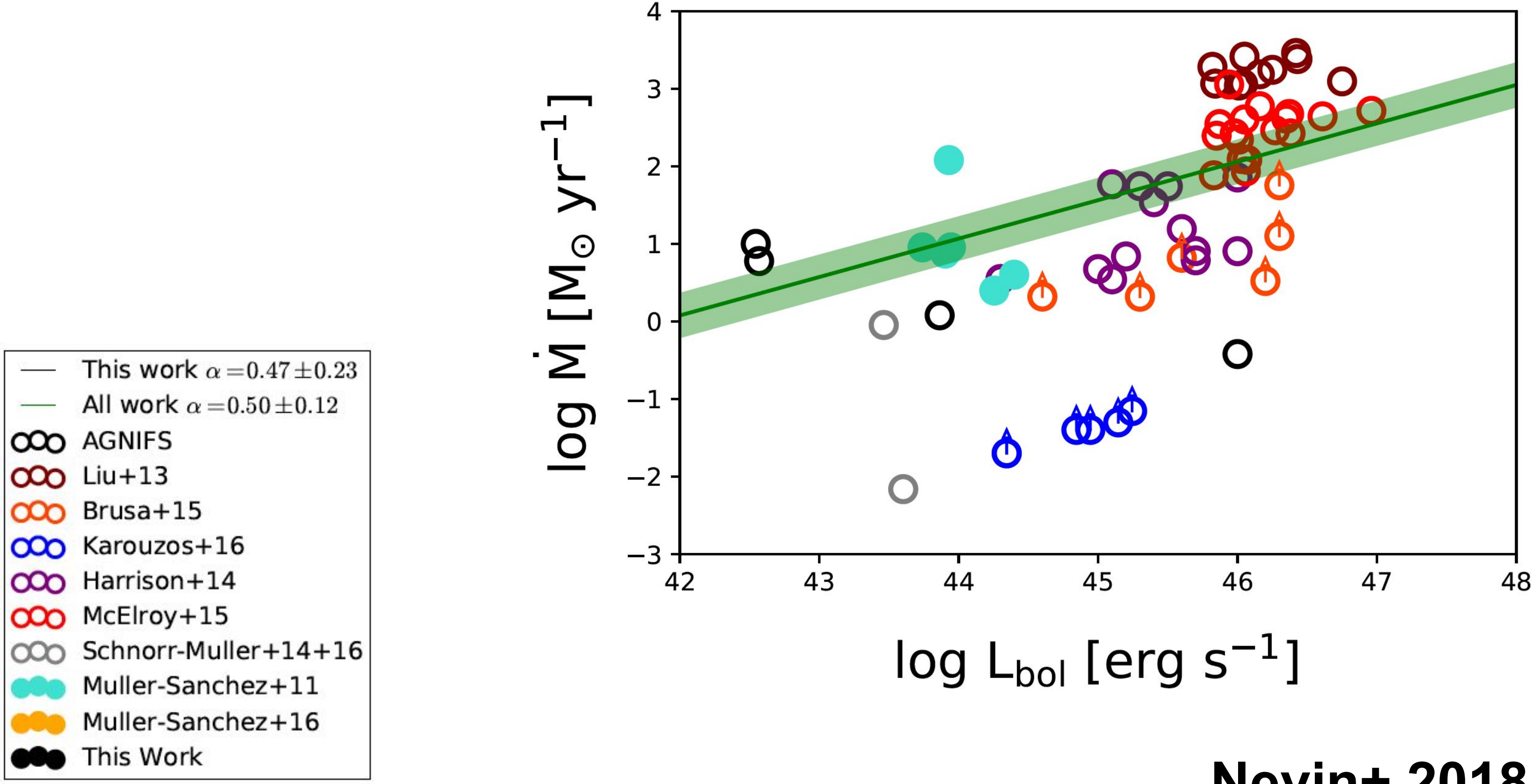


The bicones intersect the planes of their host galaxies, which increases the coupling of the bicone energy to the ISM

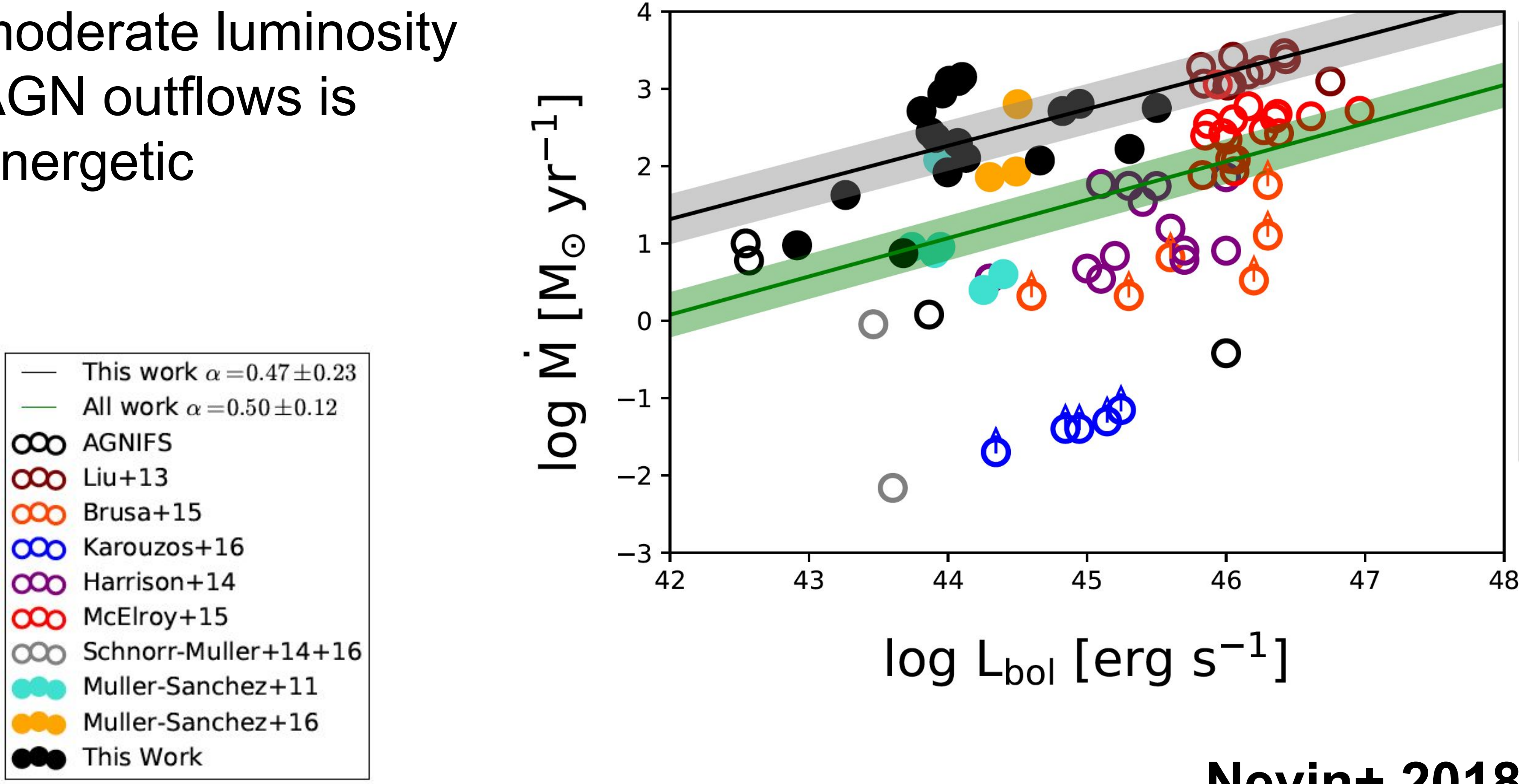




This work $\alpha = 0.47 \pm 0.23$
All work $\alpha = 0.50 \pm 0.12$
AGNIFS
Liu+13
Brusa+15
Karouzos+16
Harrison+14
McElroy+15
Schnorr-Muller+14+16
Muller-Sanchez+11
Muller-Sanchez+16
This Work
$\log \dot{M}$ [$M_\odot$ yr^{-1}]
$\log L_{bol}$ [erg s^{-1}]
4
3
2
1
0
−1
−2
−3
42
43
44
45
46
47
48

Nevin+ 2018

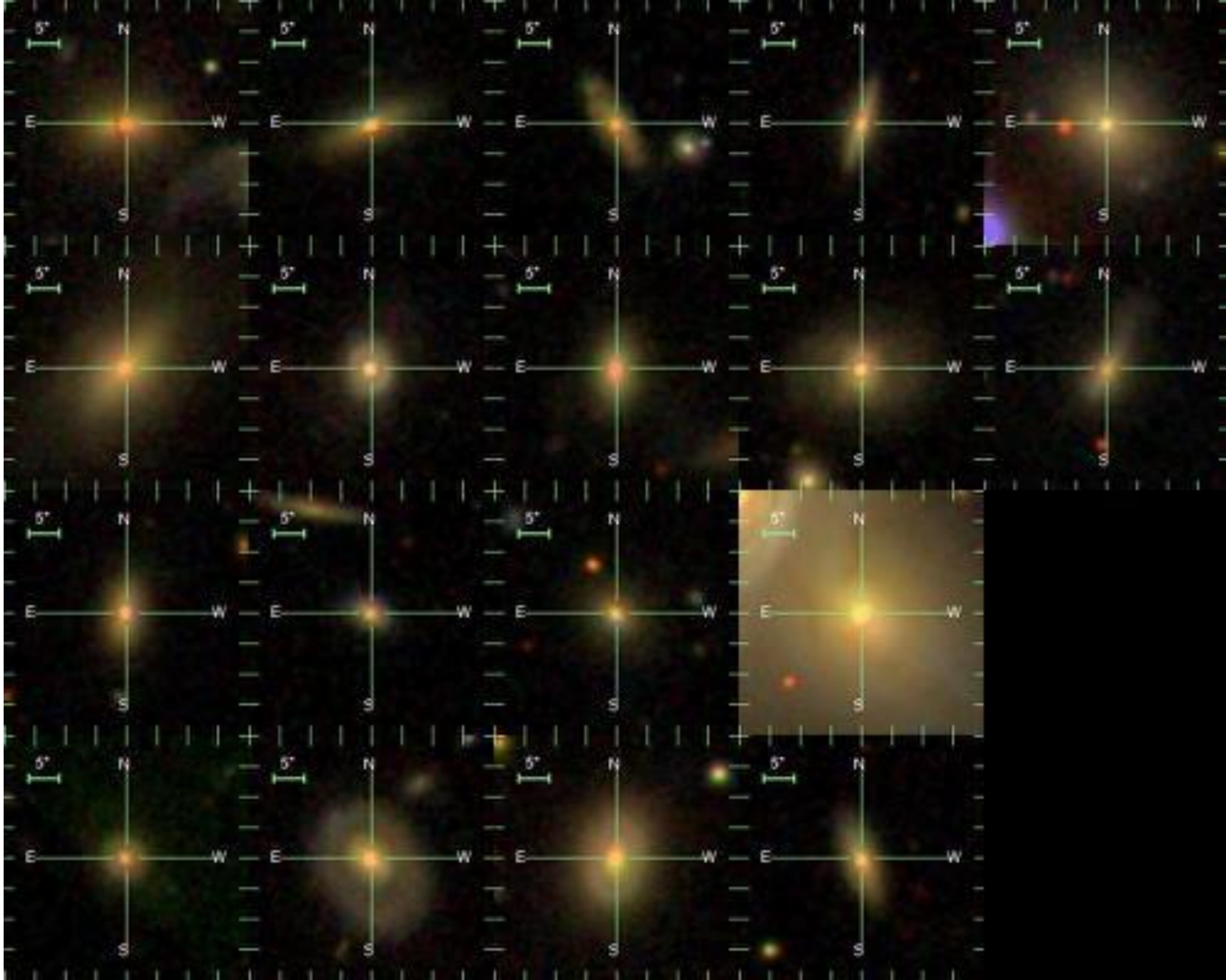
This sample of moderate luminosity AGN outflows is energetic



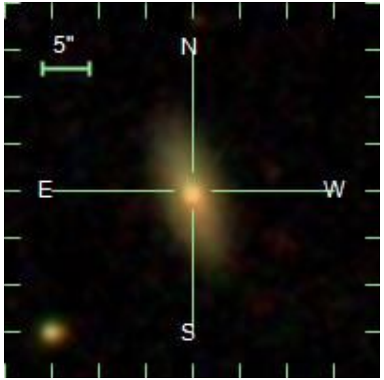
Nevin+ 2018

I measured g-r color and sSFR compared to a control sample

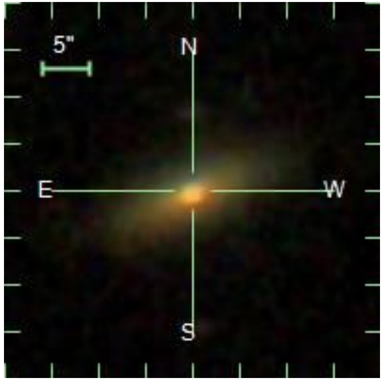
$sSFR = SFR / M_*$



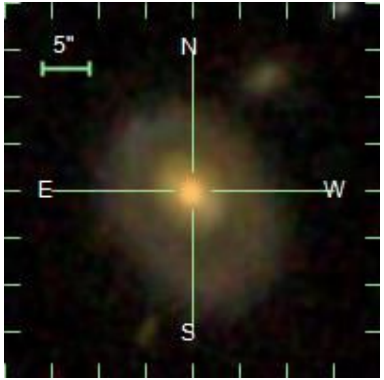
The AGN outflows are potentially impacting their host galaxies



J1606+3427



J0930+3430

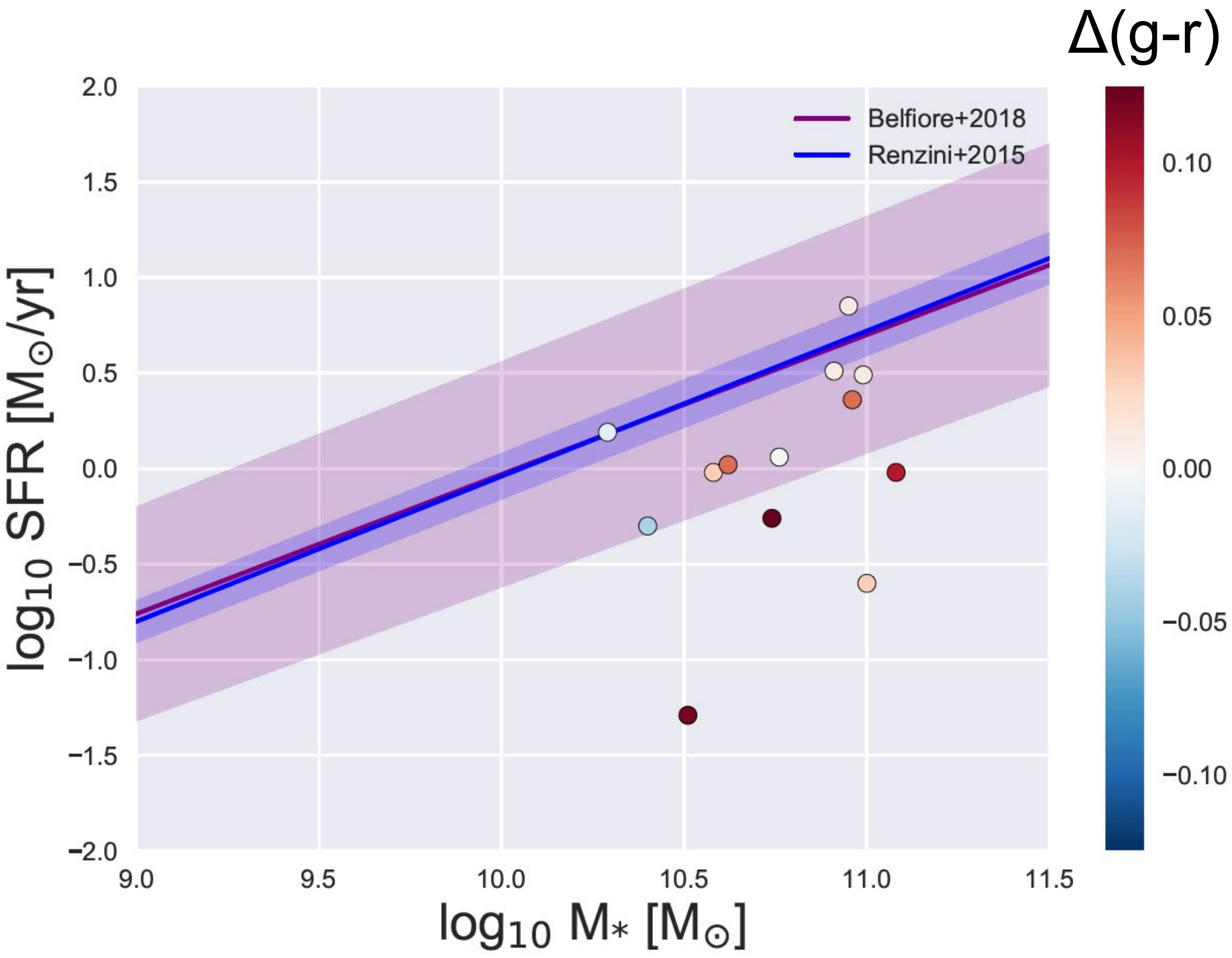


J1109+0201

3 host galaxies have lower sSFRs and/or redder

0 host galaxies have higher sSFRs and/or bluer

The moderate luminosity AGN outflows are potentially impacting their host galaxies



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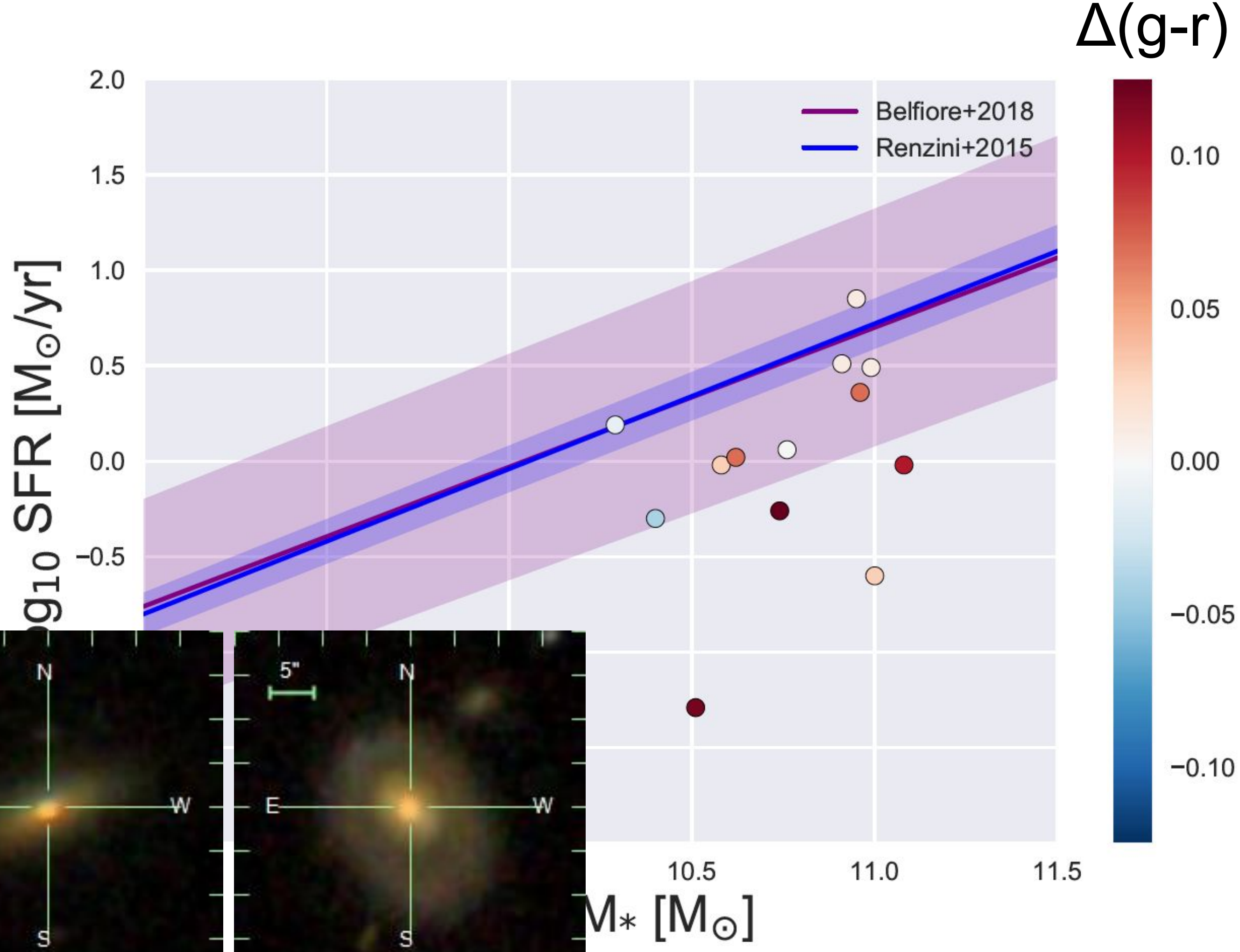
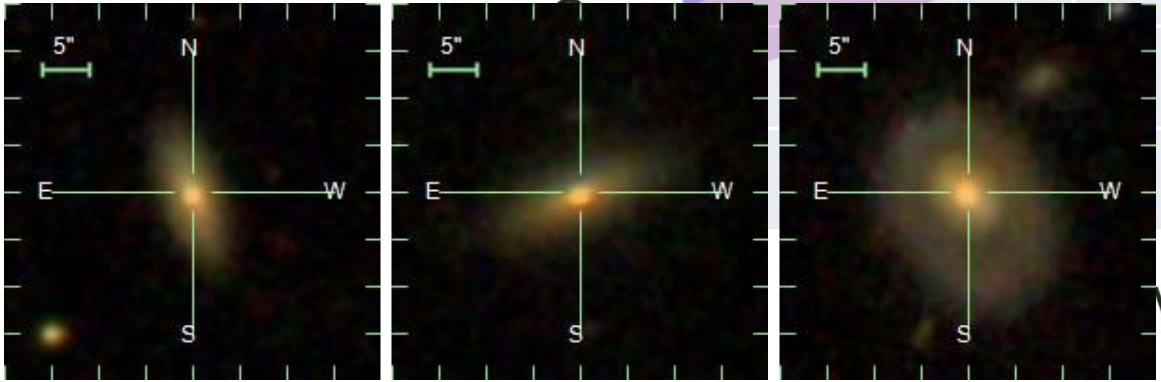
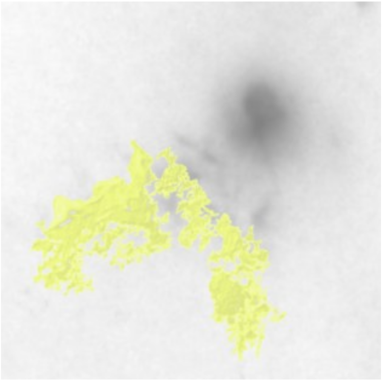


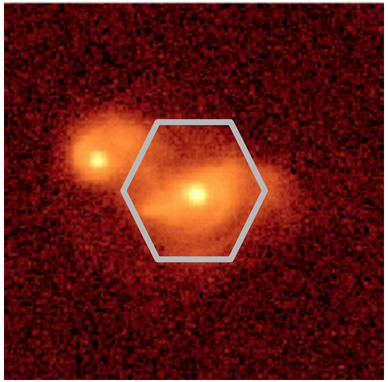


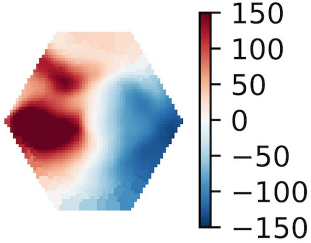
Galaxy evolution is driven by multiple processes...

AGN Feedback

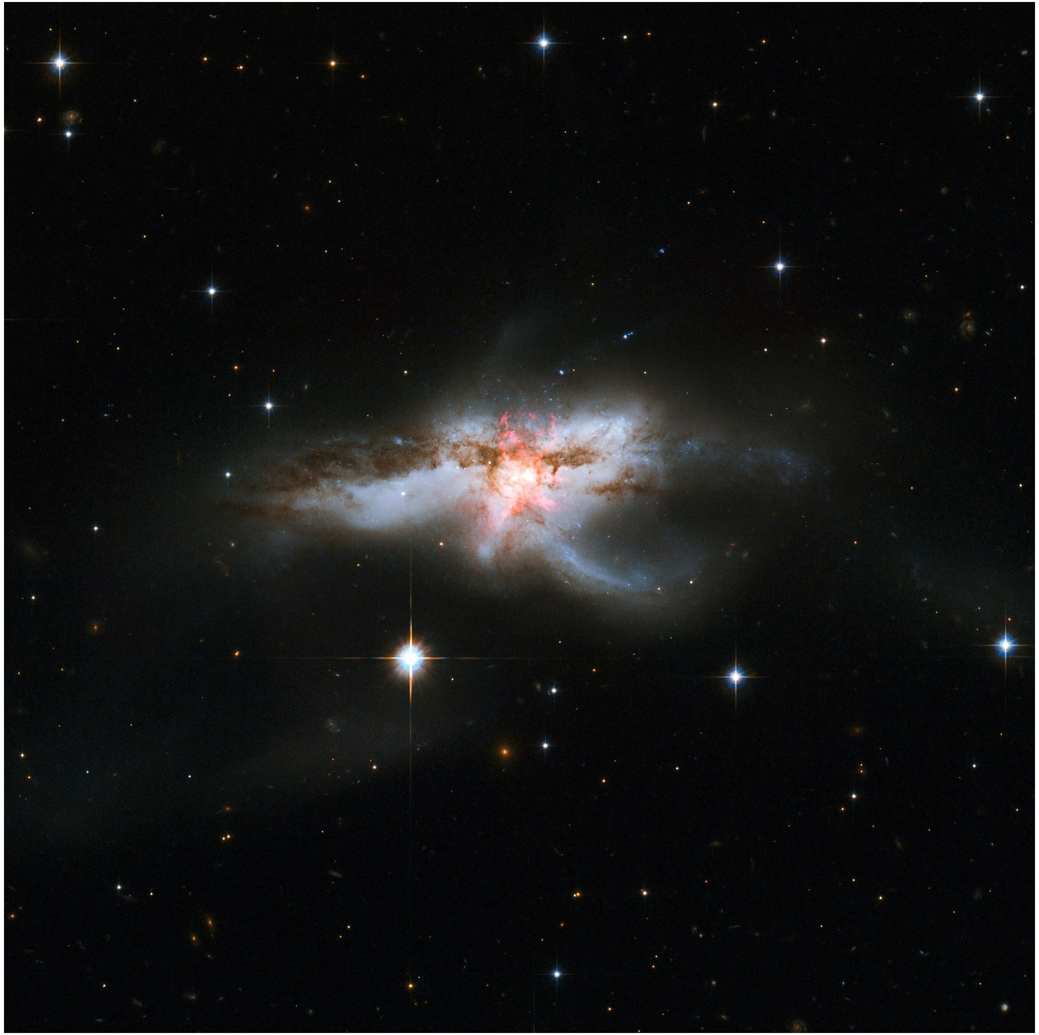


Galaxy Mergers

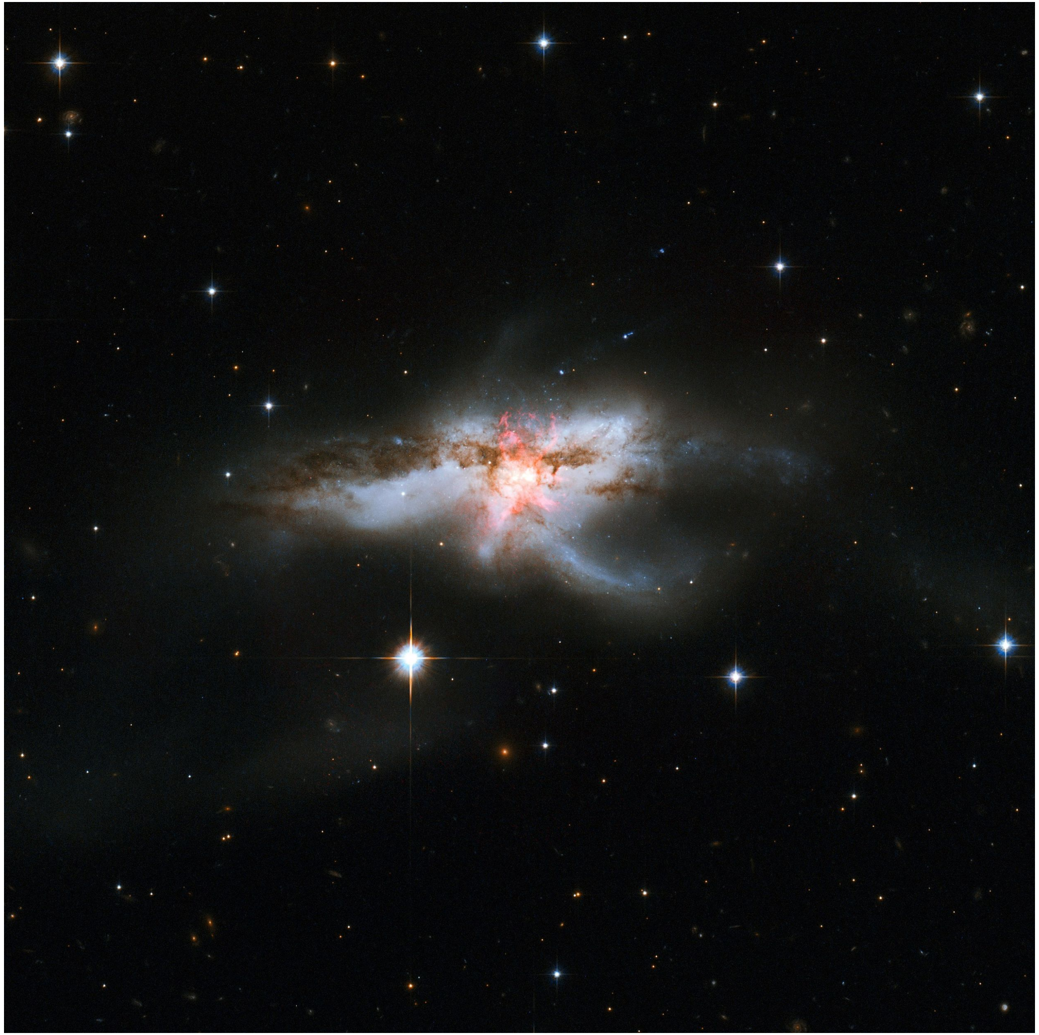




The ULIRG NGC6240 is a great example of a major merger →



Galaxy mergers can trigger important evolutionary processes such as star formation and AGN activity



It is unclear how important galaxy mergers are for driving galaxy evolution due to the difficulty of accurately identifying them

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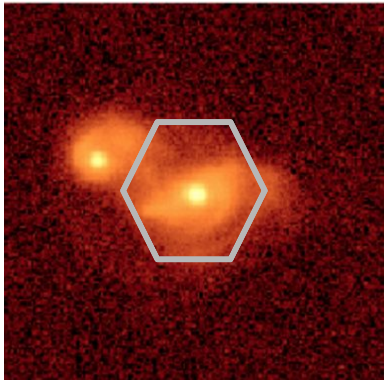
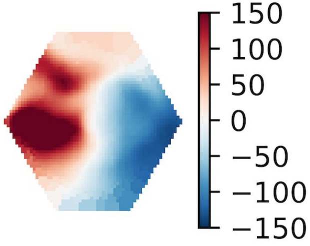
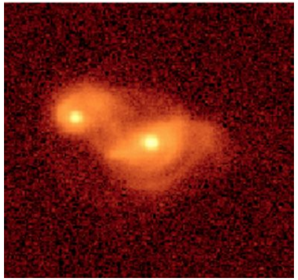
Imaging

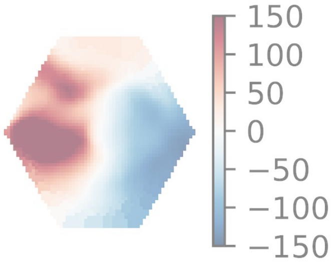


Stellar Kinematics





Imaging
of Galaxy
Mergers



Kinematics
of Galaxy
Mergers

Merging galaxies are typically identified using imaging techniques

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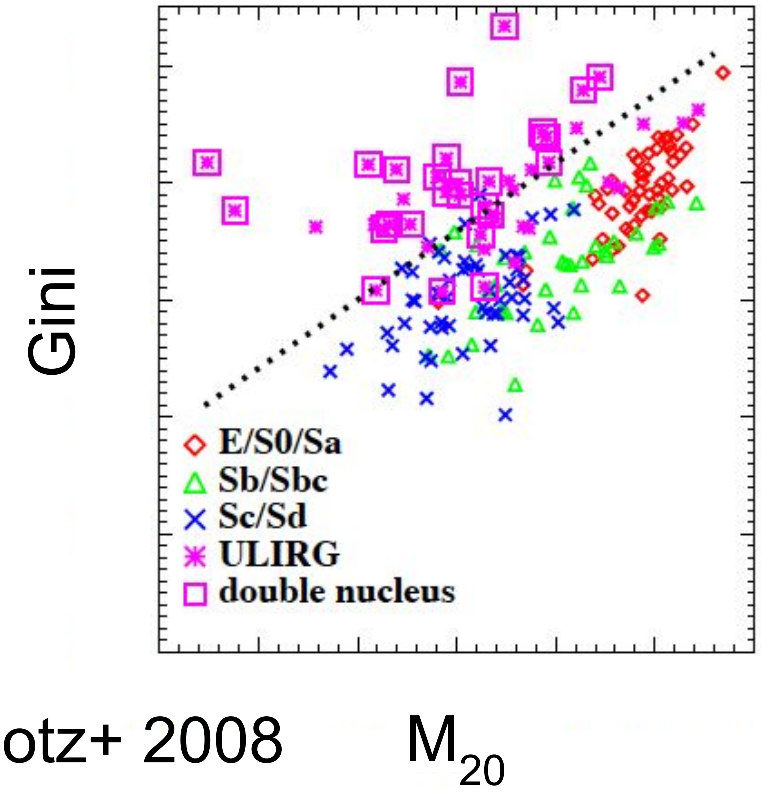
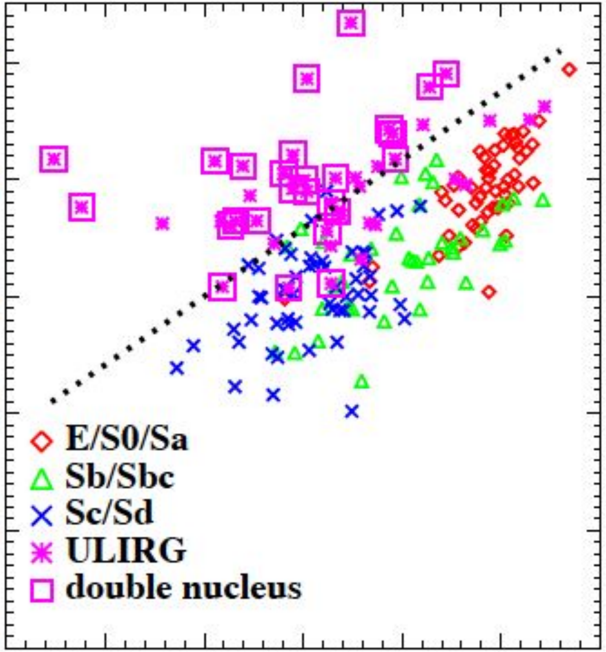


Lotz+ 2008

Merging galaxies are typically identified using imaging techniques

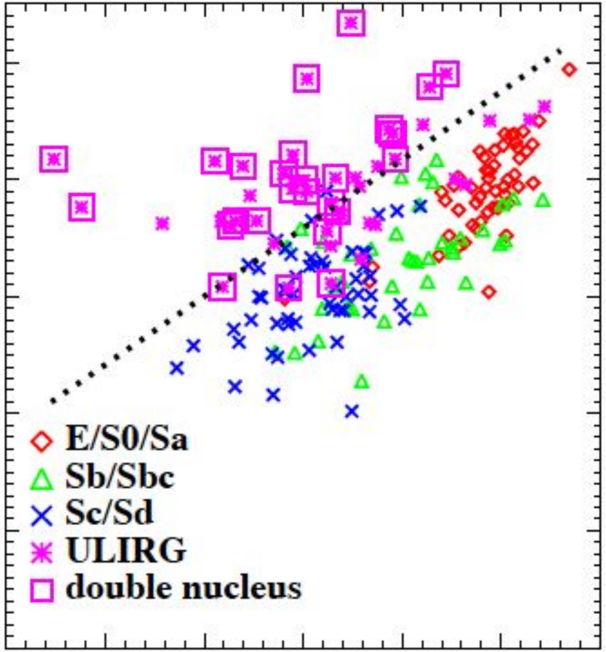
Gini



Lotz+ 2008 M_{20}

Different imaging predictors excel at identifying different types of merging galaxies

Gini



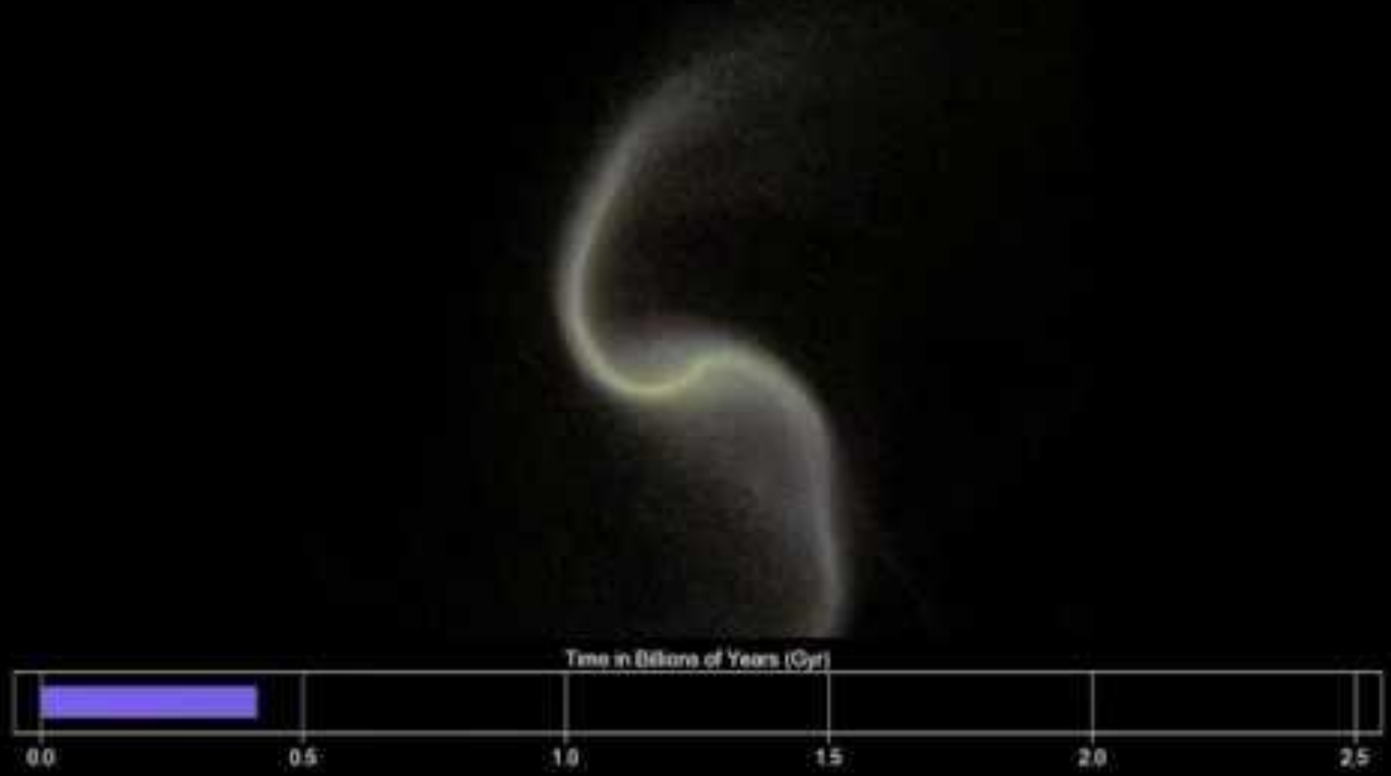
Lotz+ 2008 M_{20}

Imaging Predictors:

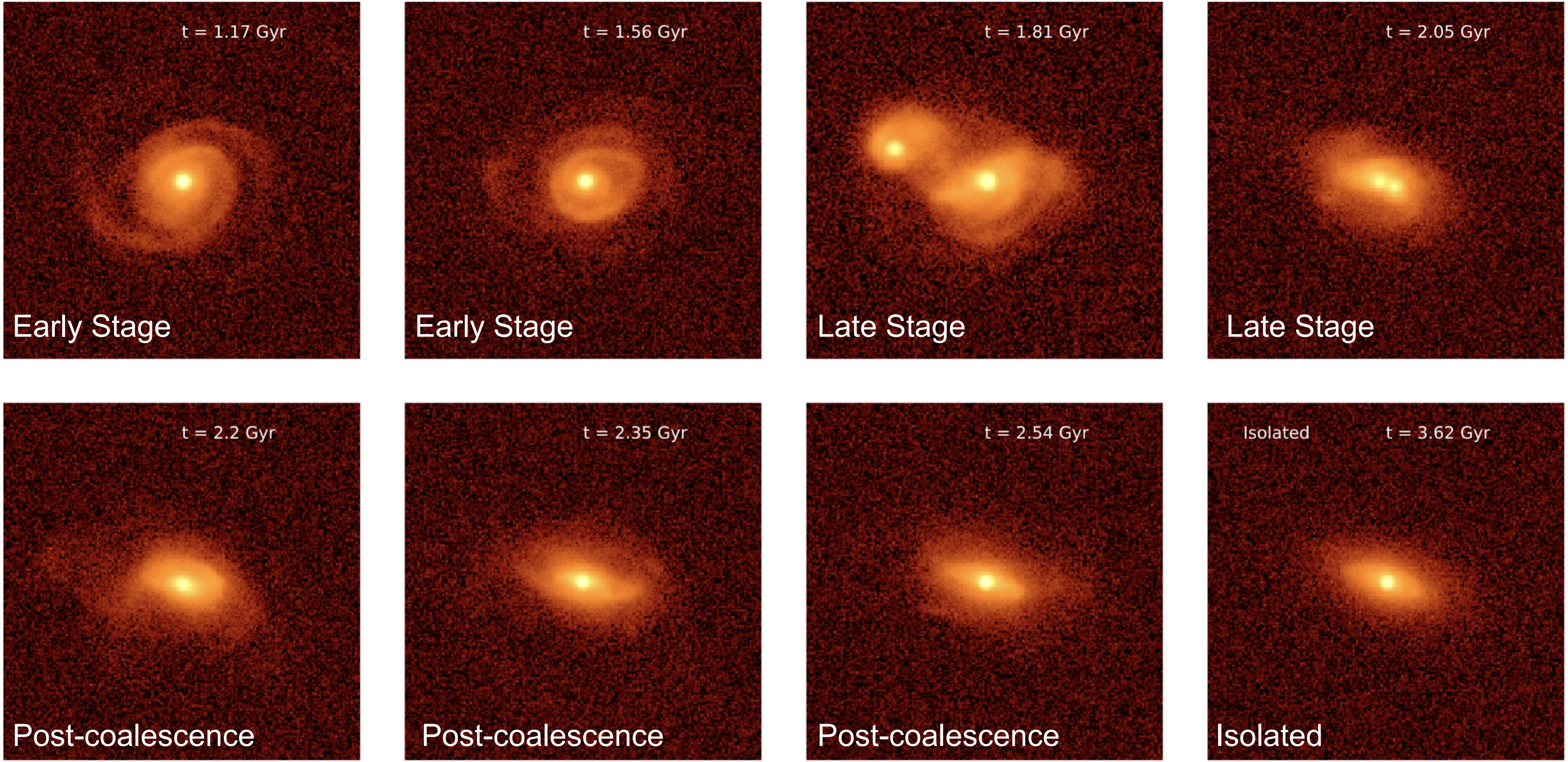
Gini
M_{20}
Concentration
Asymmetry
Shape Asymmetry
Sersic Index

Laura Blecha runs N-body hydrodynamics GADGET-3 simulations with SUNRISE dust radiative transfer

Laura Blecha runs N-body hydrodynamics GADGET-3 simulations with SUNRISE dust radiative transfer



I create mock images that match the specifications of SDSS



I cover a range of merger initial conditions

1:2, gas rich

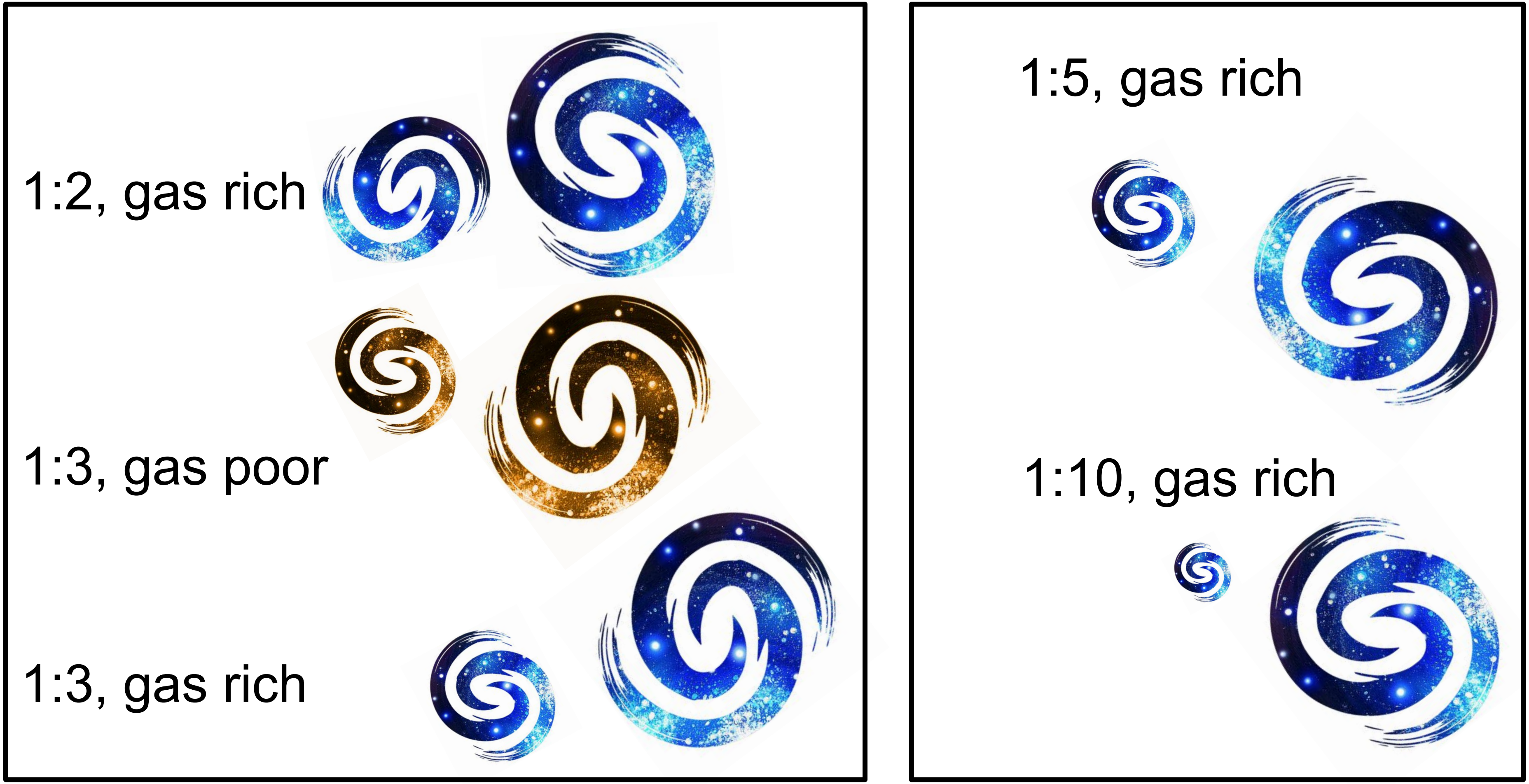
1:3, gas poor

1:3, gas rich

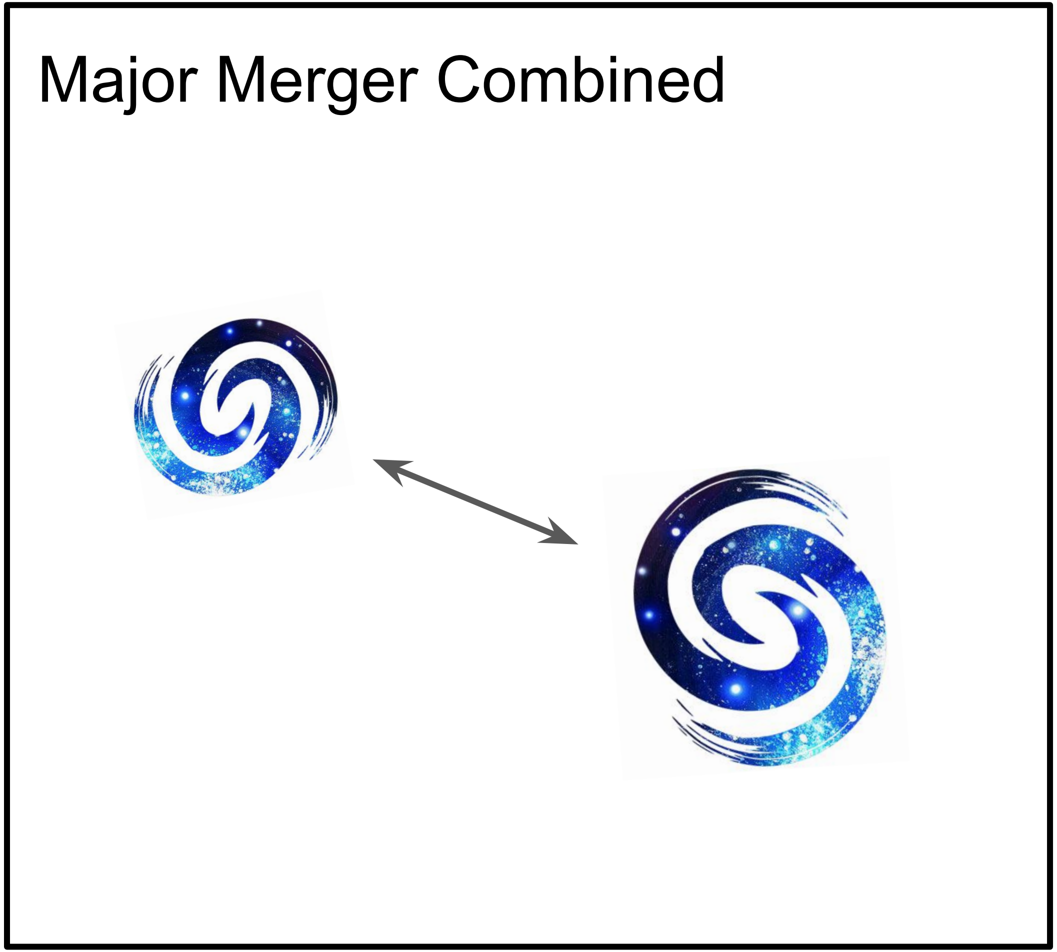
1:5, gas rich

1:10, gas rich

Mass ratio is the most important merger parameter

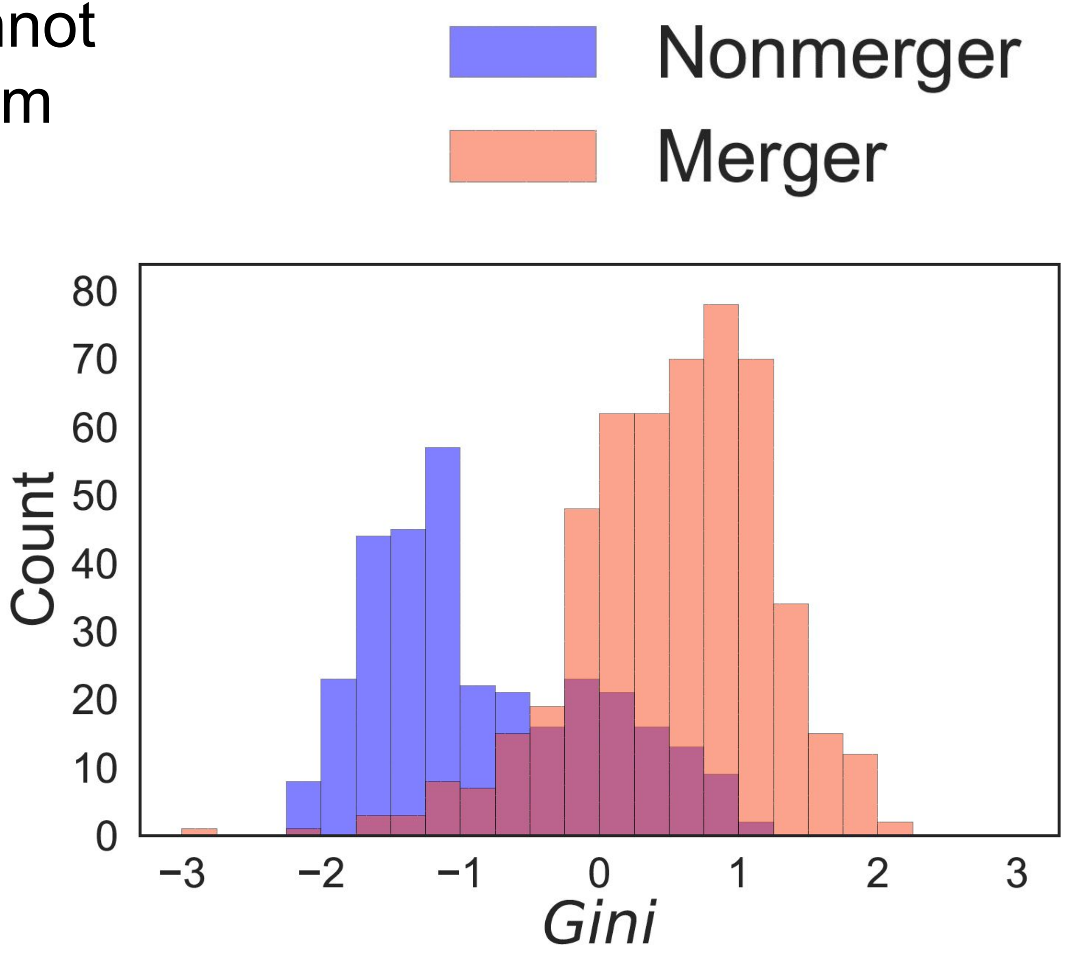


I additionally combine the major and minor mergers:

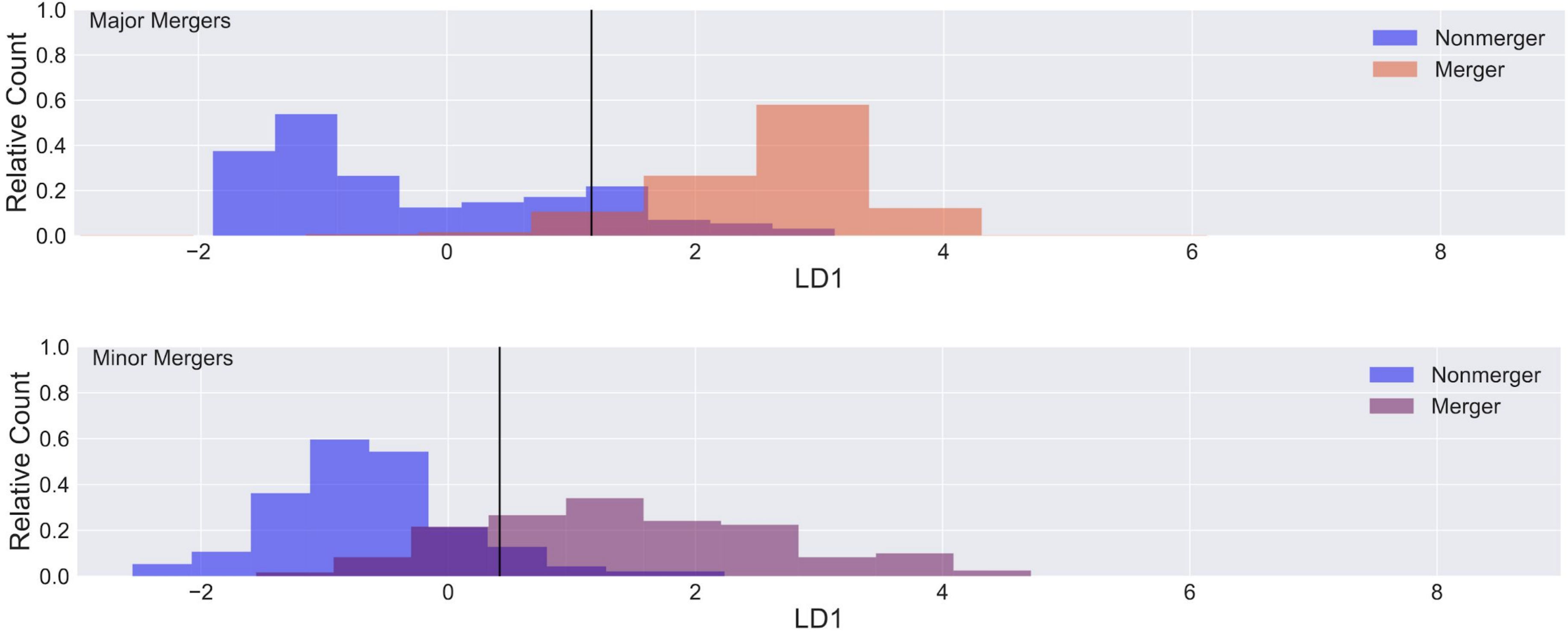


The imaging predictors cannot alone separate merging from nonmerging galaxies

Gini
M_{20}
Concentration
Asymmetry
Shape Asymmetry
Sersic Index



Linear Discriminant Analysis separates merging and nonmerging populations and assigns a probability



Nevin+ 2019

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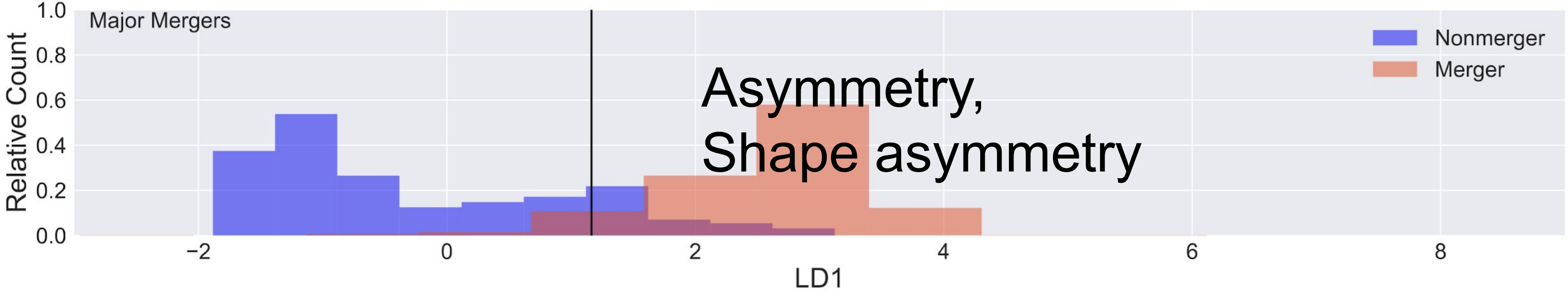
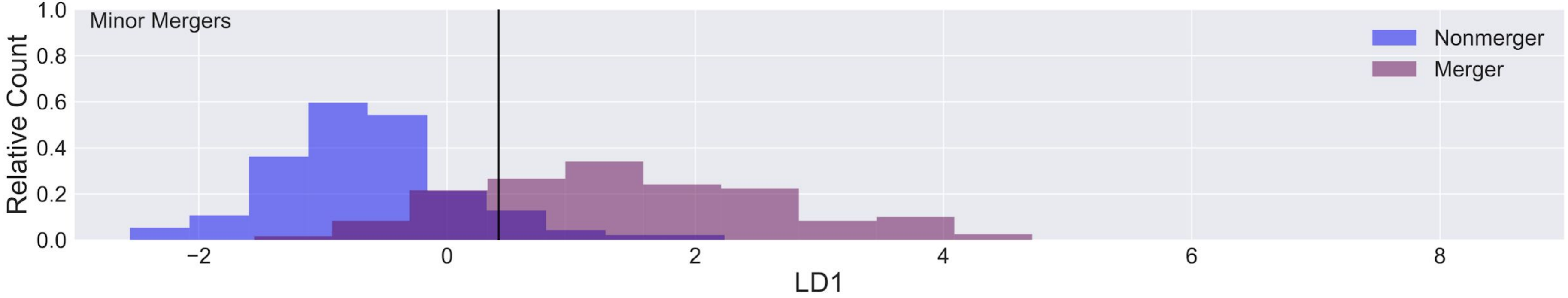
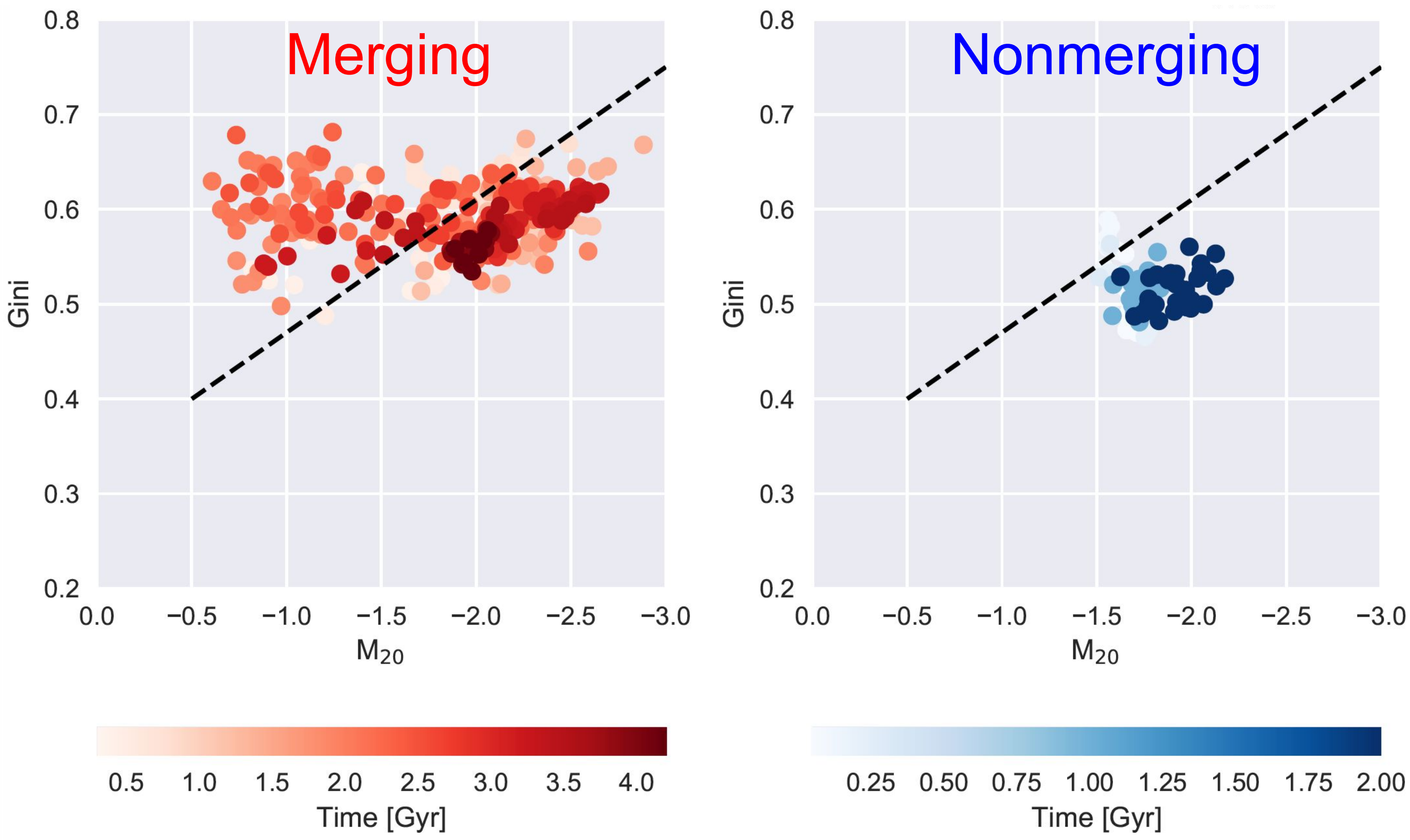


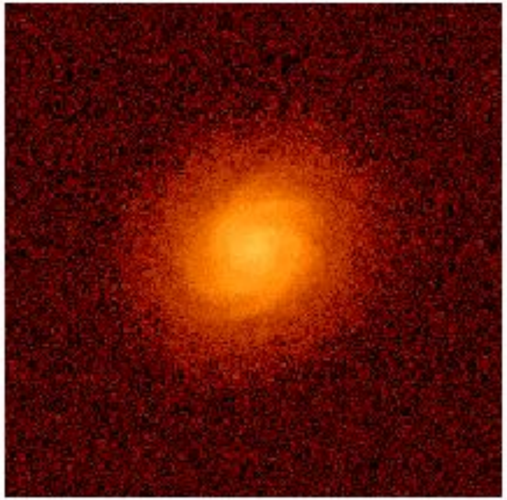


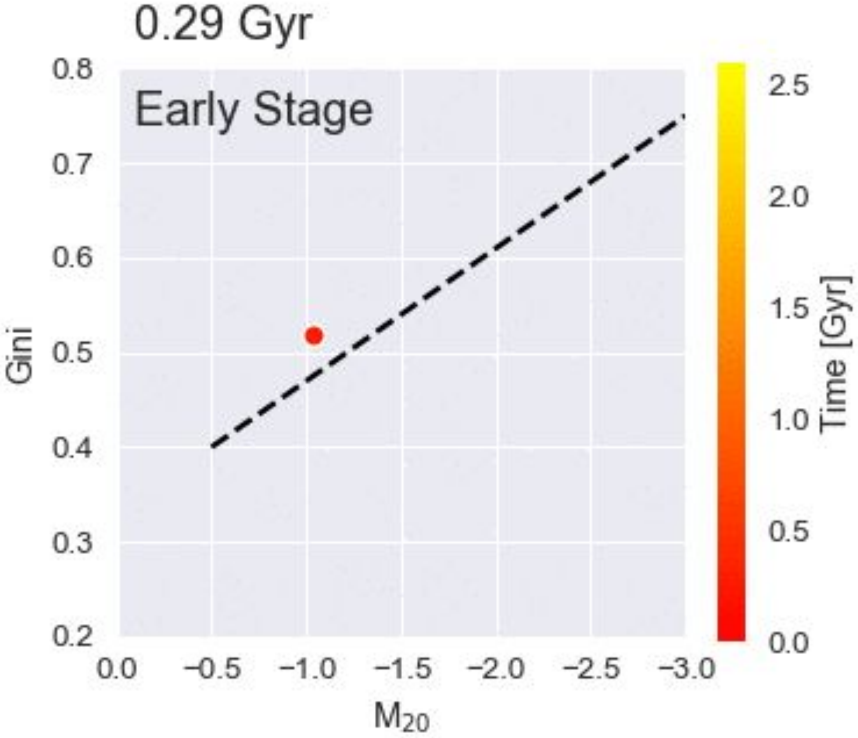
Nevin+ 2019

The imaging predictors evolve over the timeline of the merger

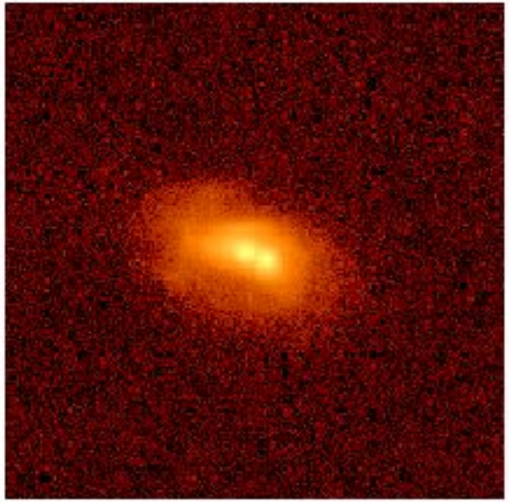


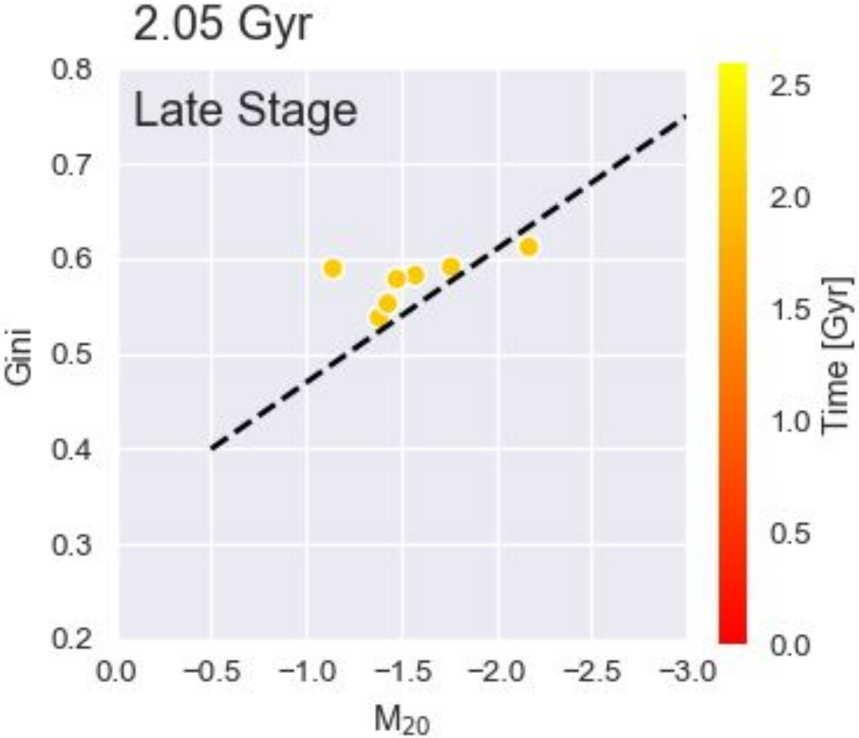
The imaging predictors evolve over the timeline of the merger



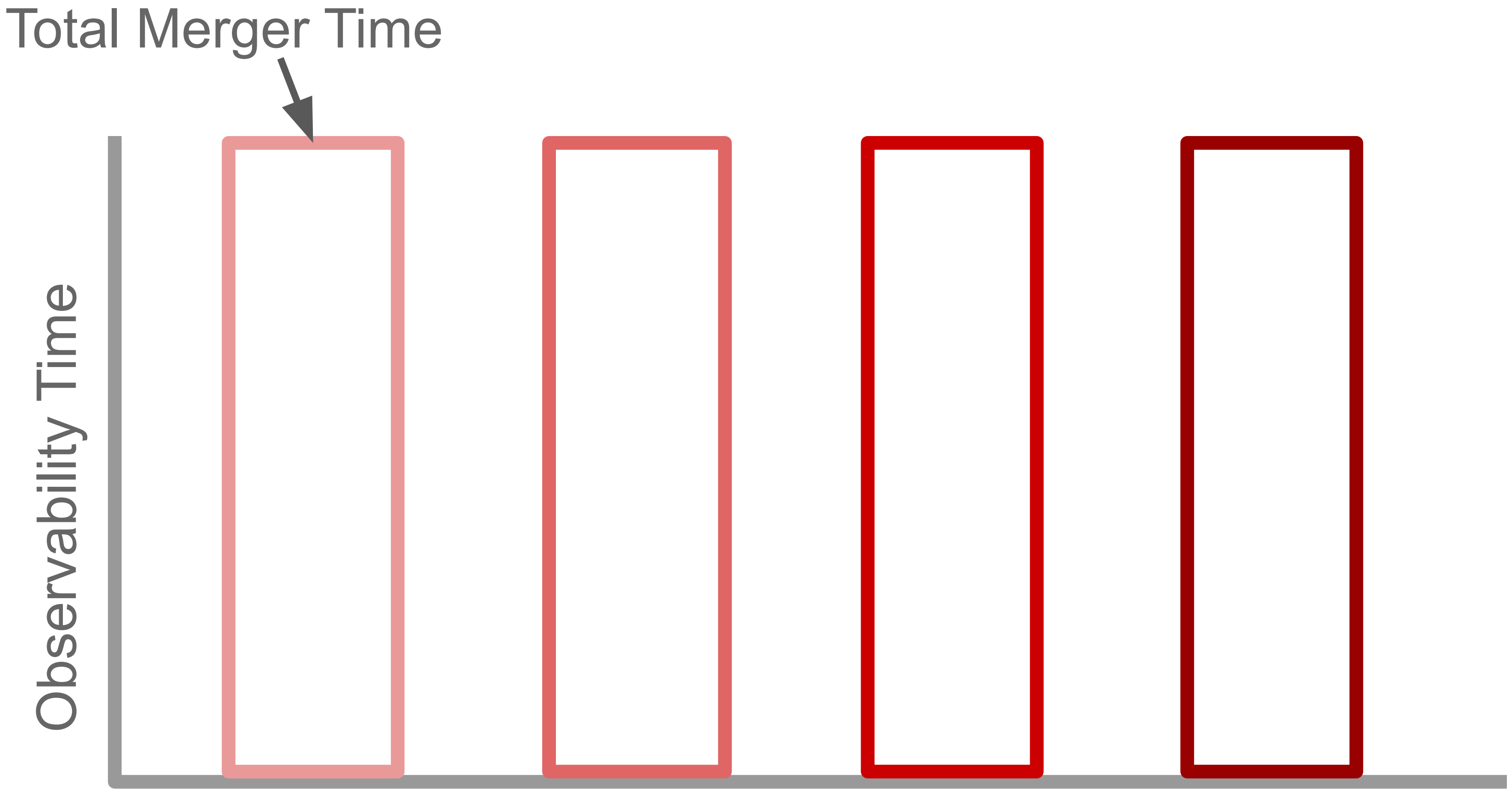


The galaxies are most disturbed in Gini-M_{20} in the late stage



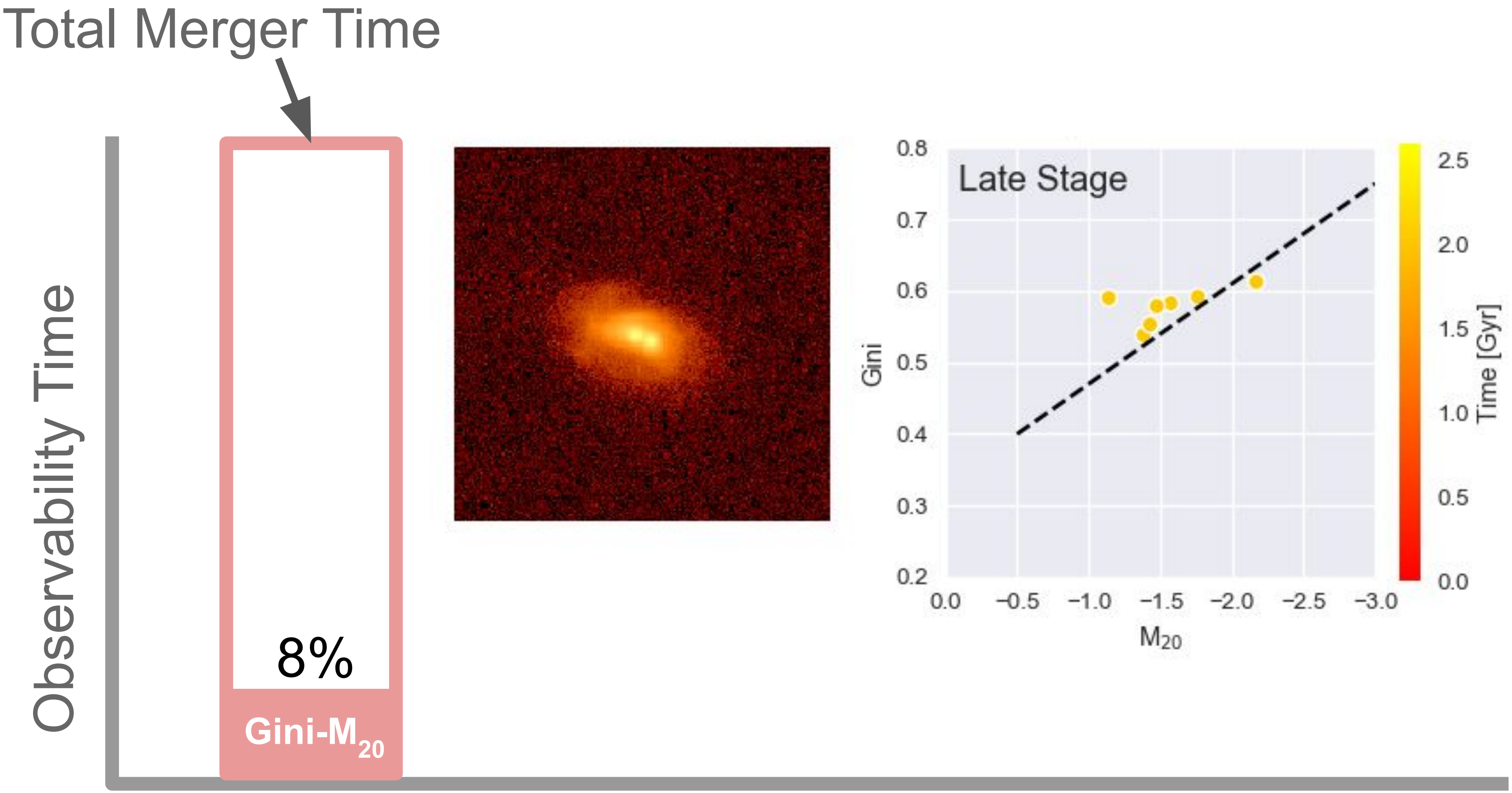


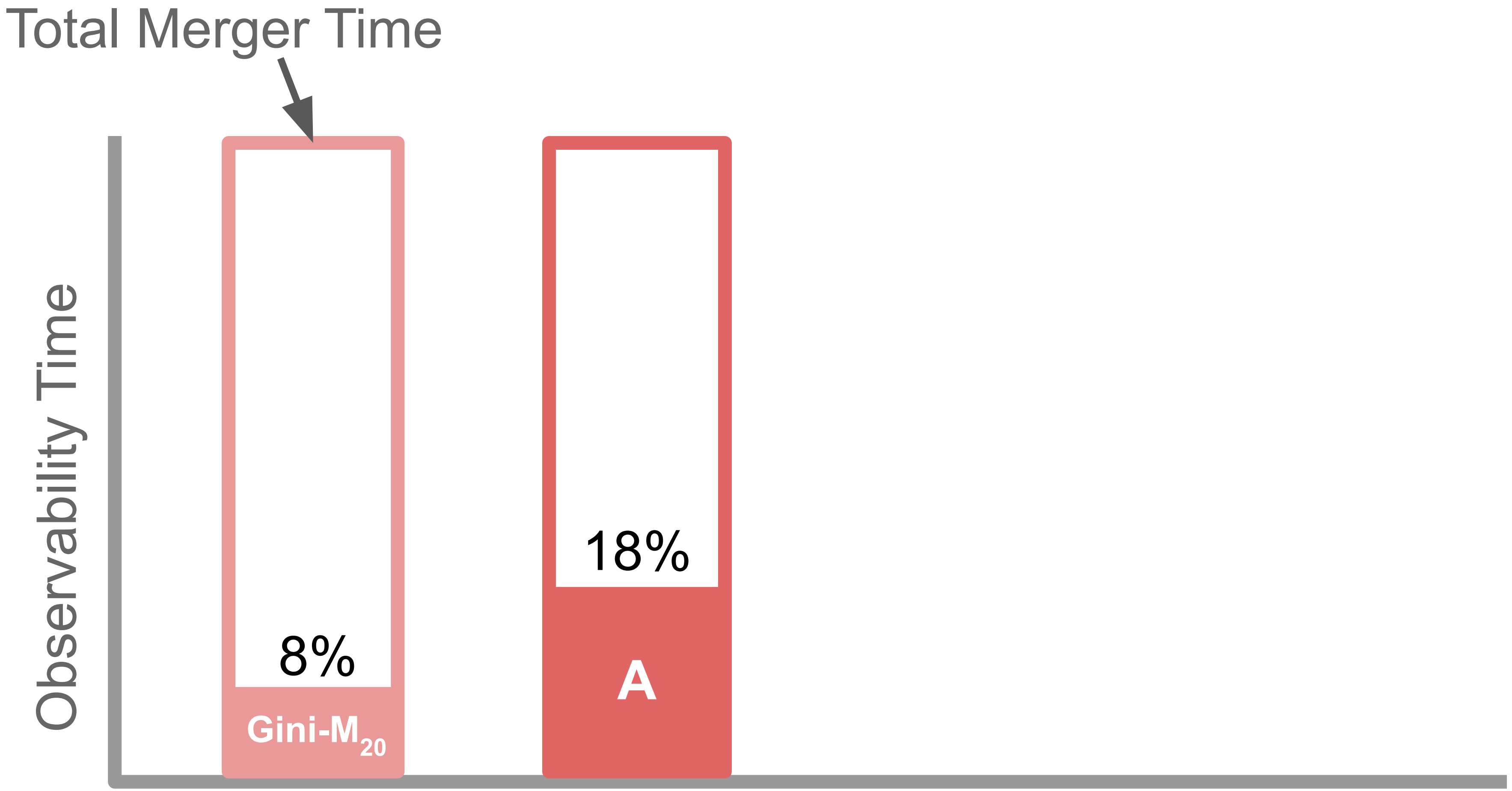
LDA has the longest timescale of merger observability (compare to other methods)

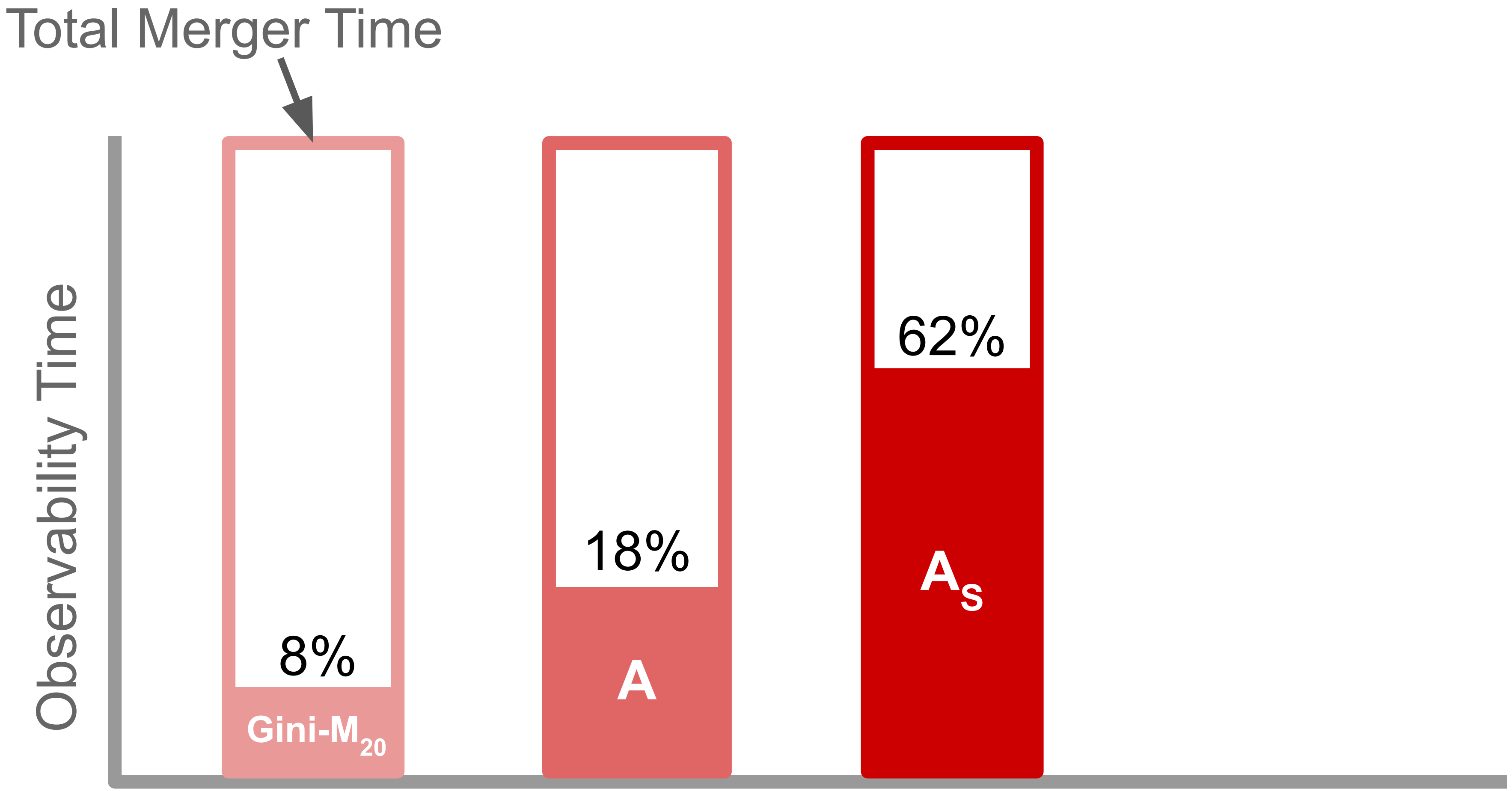


Total Merger Time
Observability Time

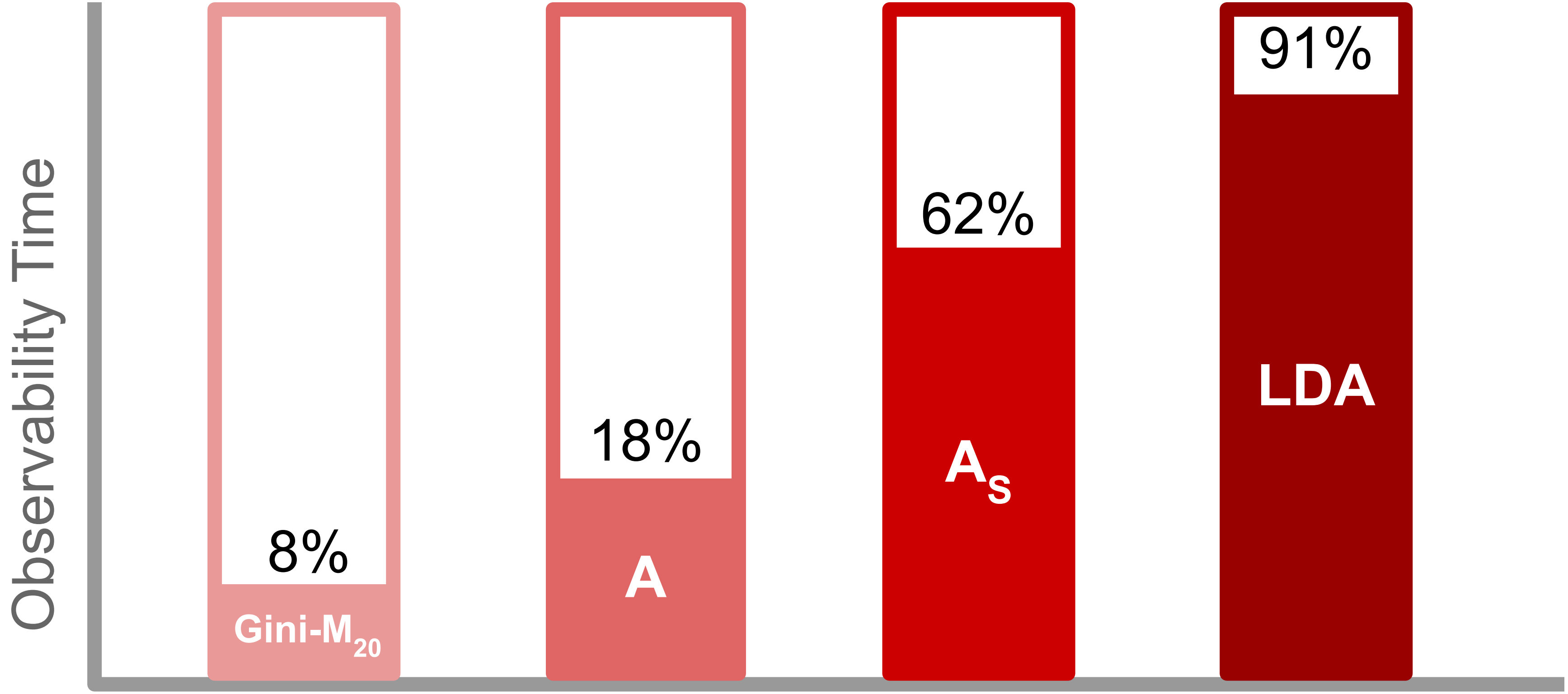

Total Merger Time
Observability Time
8%
Gini-M_{20}


Total Merger Time
Observability Time
8%
Gini-M20
Late Stage
Gini
M20
Time [Gyr]
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
2.5
2.0
1.5
1.0
0.5
0.0

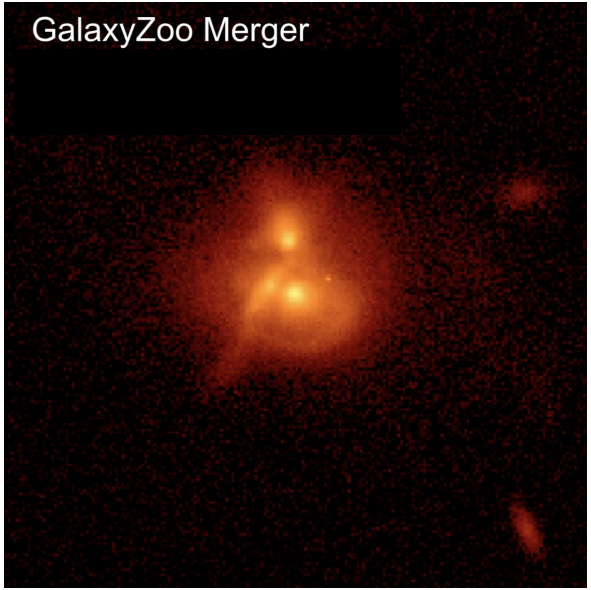

Total Merger Time
Observability Time
8%
Gini-M_{20}
18%
A

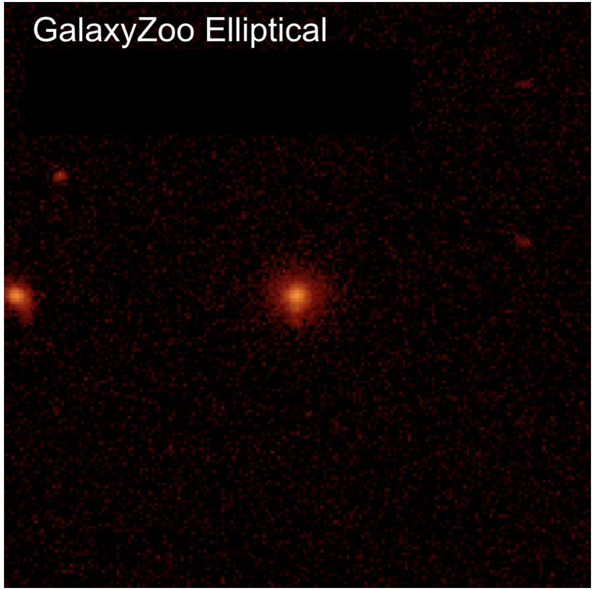

Total Merger Time
Observability Time
8%
Gini-M20
18%
A
62%
As

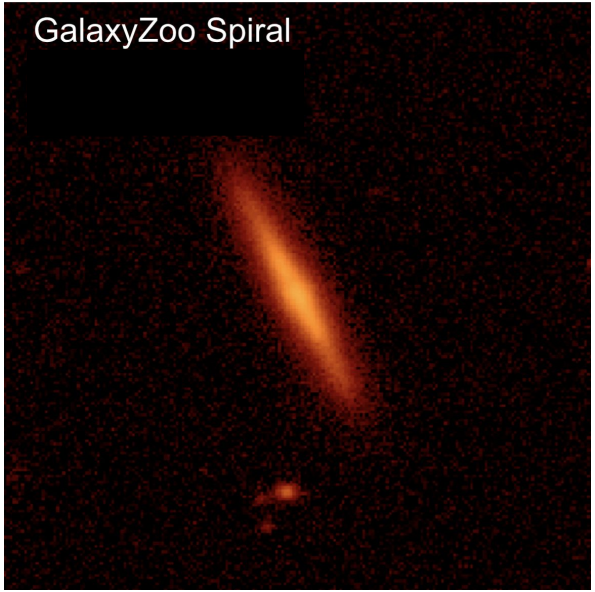
The merger observability timescale is maximized for the LDA technique



I create a test sample of ~150 ‘superclean’ SDSS galaxies from GalaxyZoo







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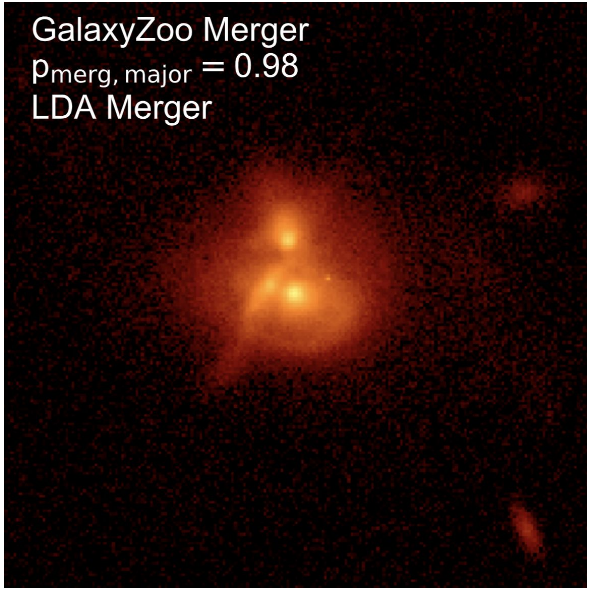
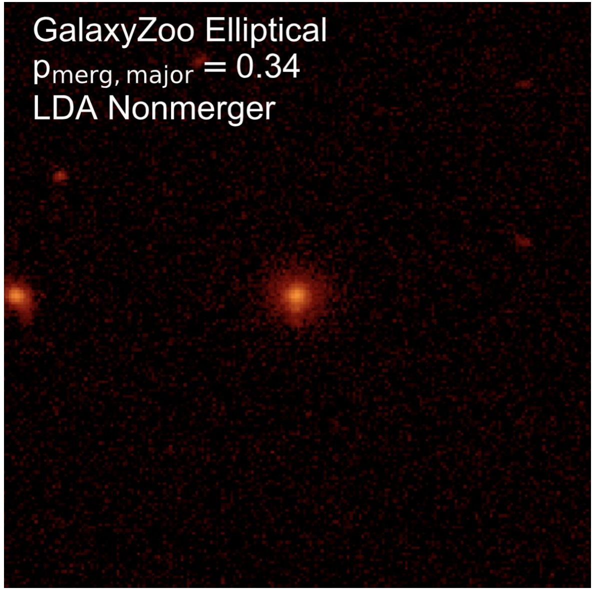
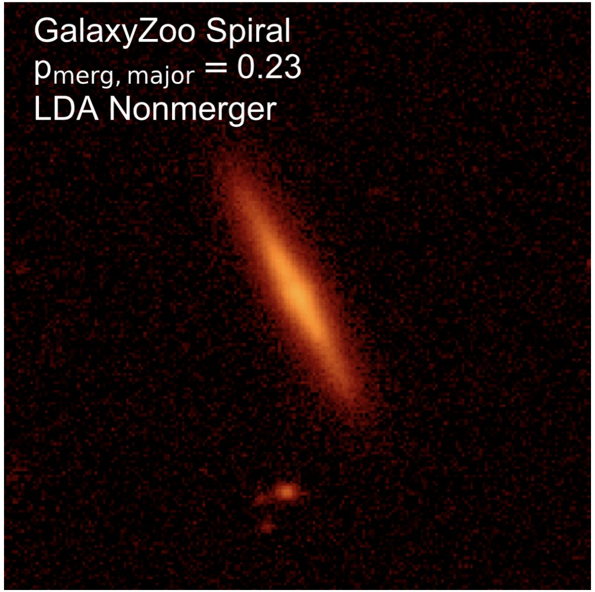
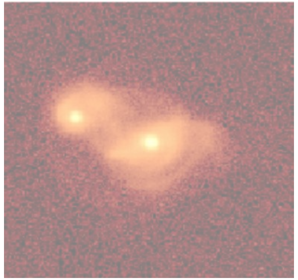
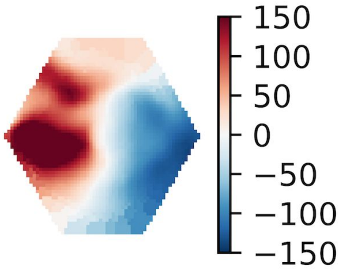






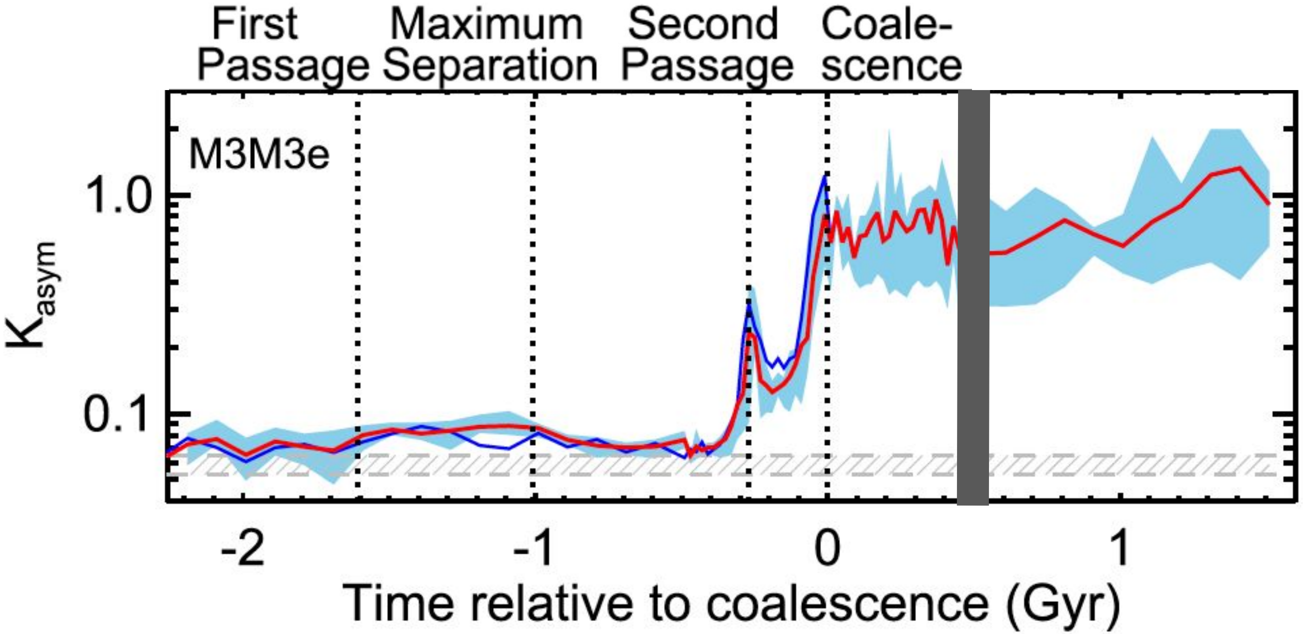


Imaging
of Galaxy
Mergers



Kinematics
of Galaxy
Mergers

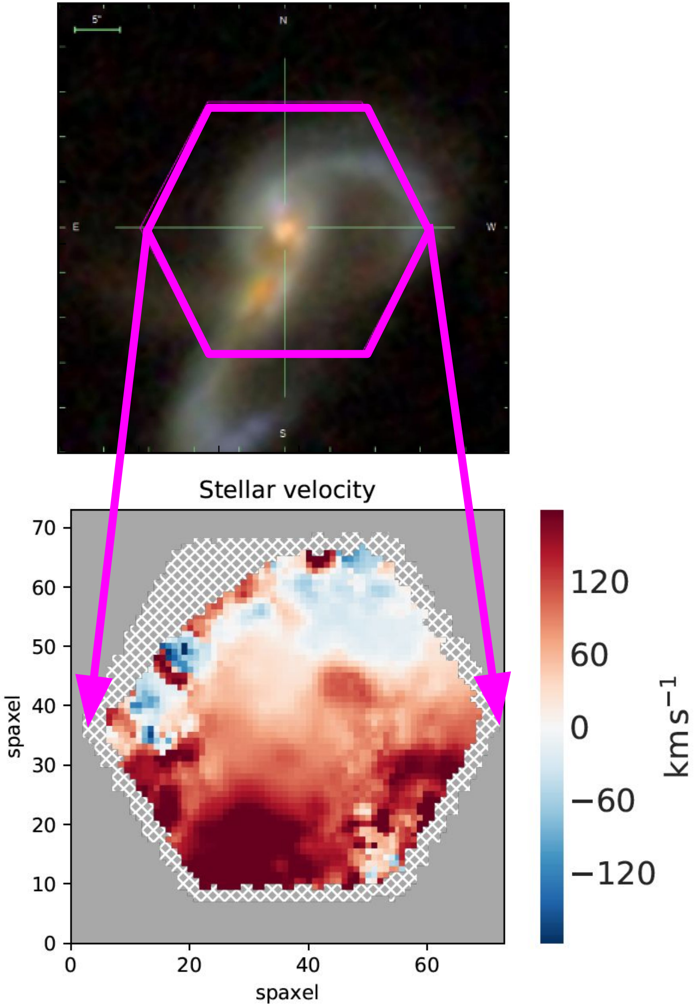
The kinematic predictors can remain disturbed for longer



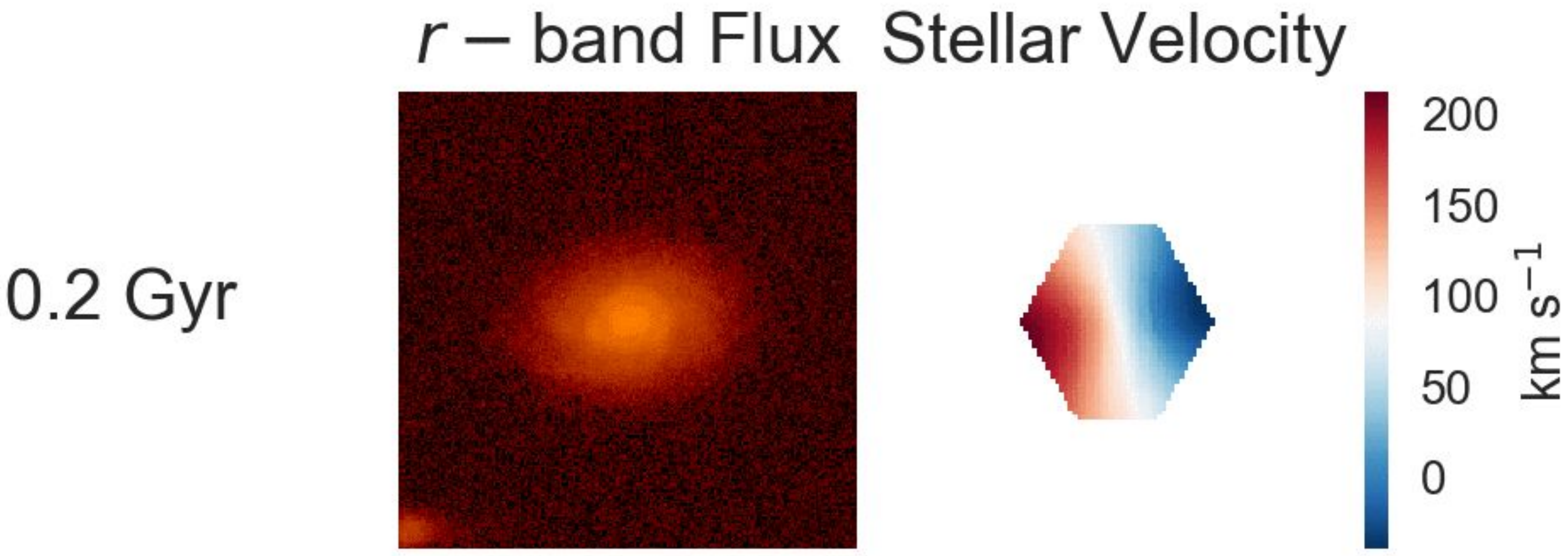
Hung+ 2016

SDSS-IV’s Mapping Nearby Galaxies at Apache Point:

Integral Field Spectroscopy and imaging of >10,000 galaxies
z ~ 0.03

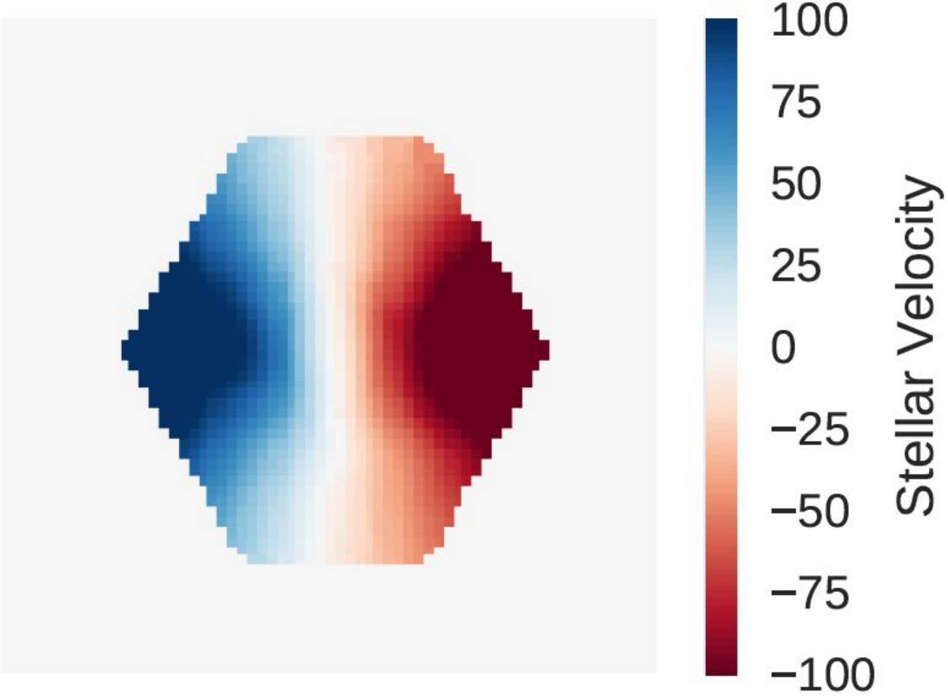


I create mock stellar kinematic maps to match the specifications of MaNGA

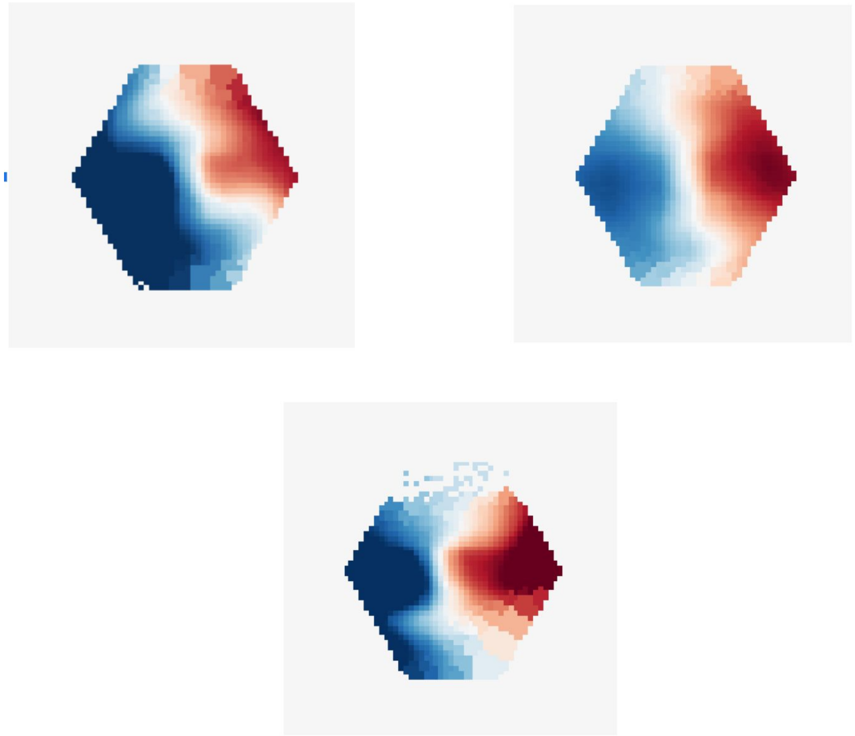


I extract kinematic predictors for use in the LDA

Isolated Galaxy



Merging Galaxy

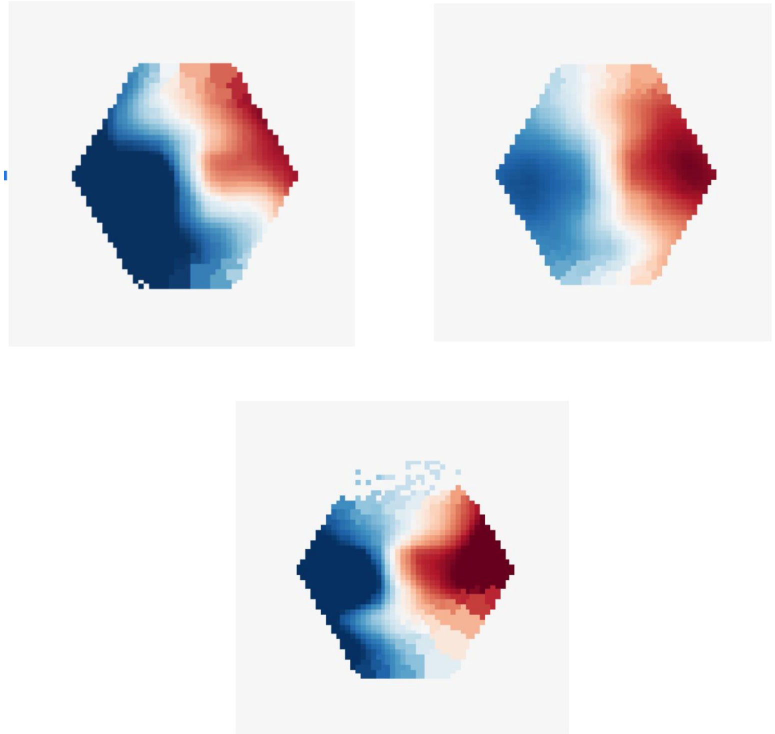


I extract kinematic predictors for use in the LDA

Kinematic Predictors:

- The difference between the imaging and kinematic PA (**ΔPA**)
- The asymmetry in the velocity maps (**V_{asym}**)
- The asymmetry in the velocity dispersion maps (**σ_{asym}**)
- **Kinemetry residuals**
- The specific angular momentum (**λ_R**)
- The asymmetry in the Radon profile (**A**, **A_2**)

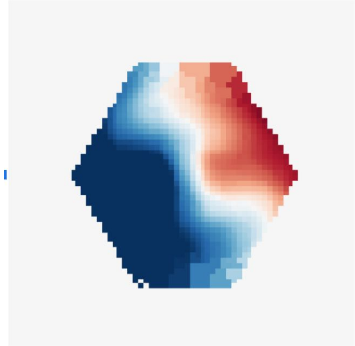
Merging Galaxy

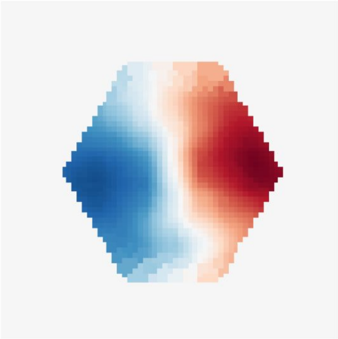


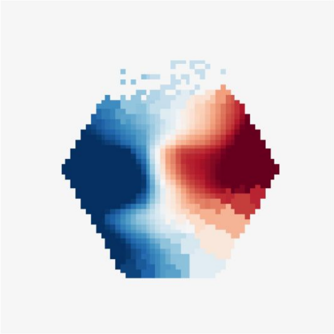
I combine the kinematic predictors into one LDA technique that combines their individual strengths

Kinematic Predictors:

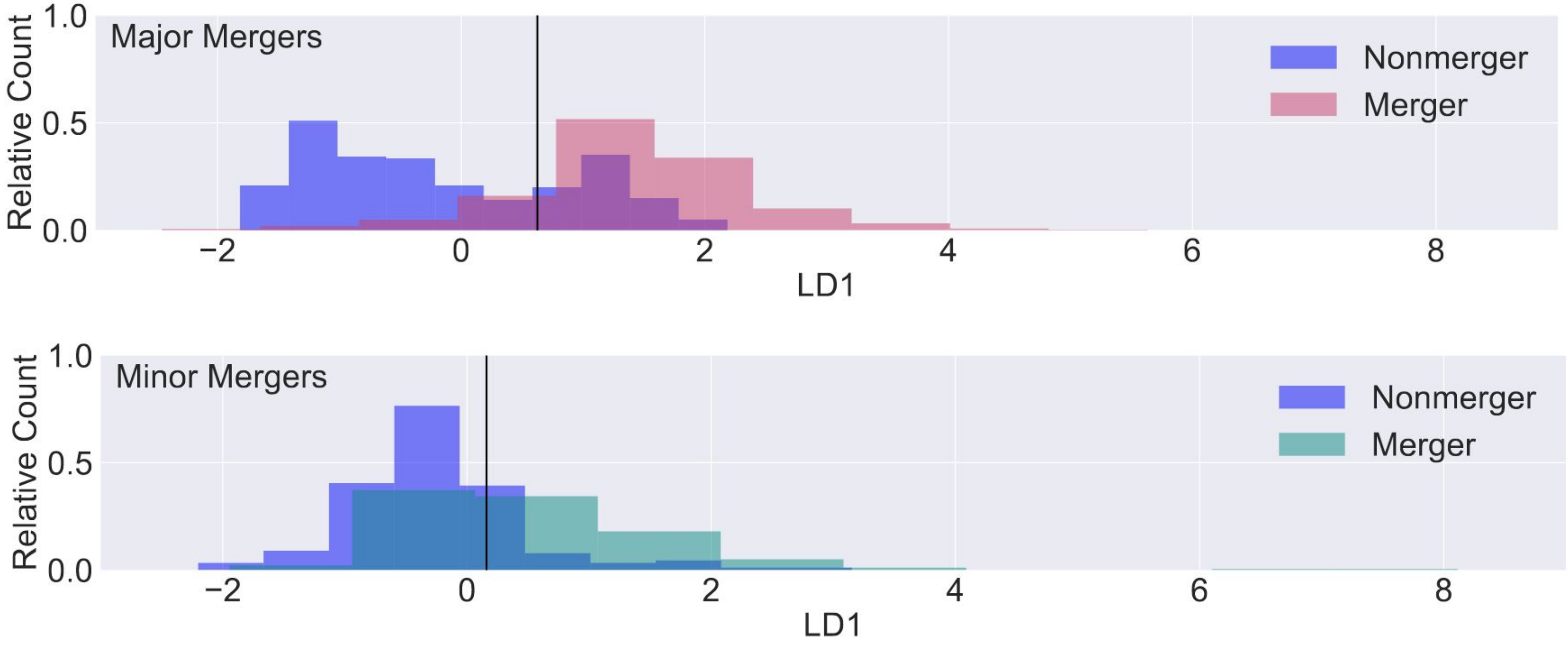
ΔPA
V_{asym}
σ_{asym}
Kinemetry residuals
λ_R
A
A_2







The major and minor merger rely on different predictors but have the same accuracy



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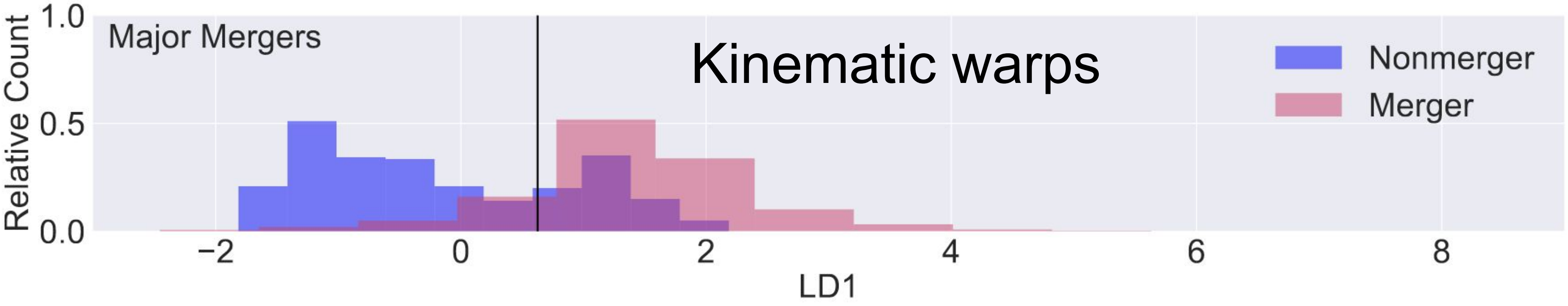
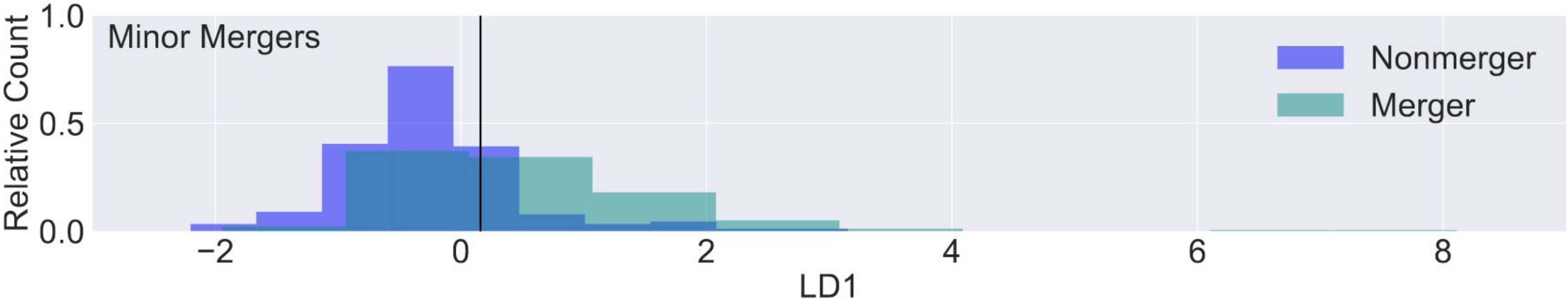
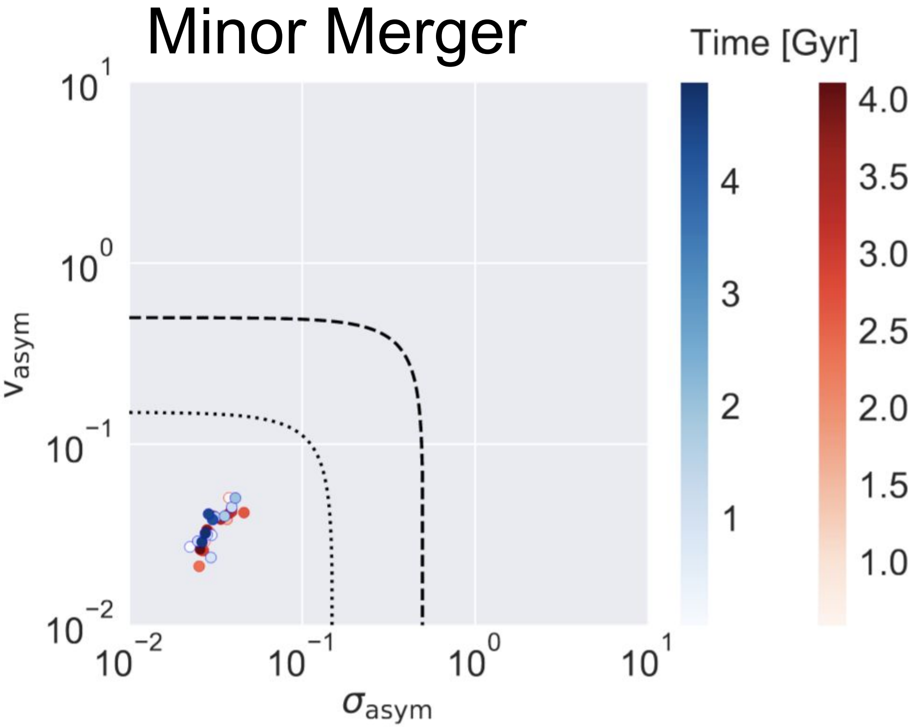




The major and minor merger classifications are different; the major mergers are more precise



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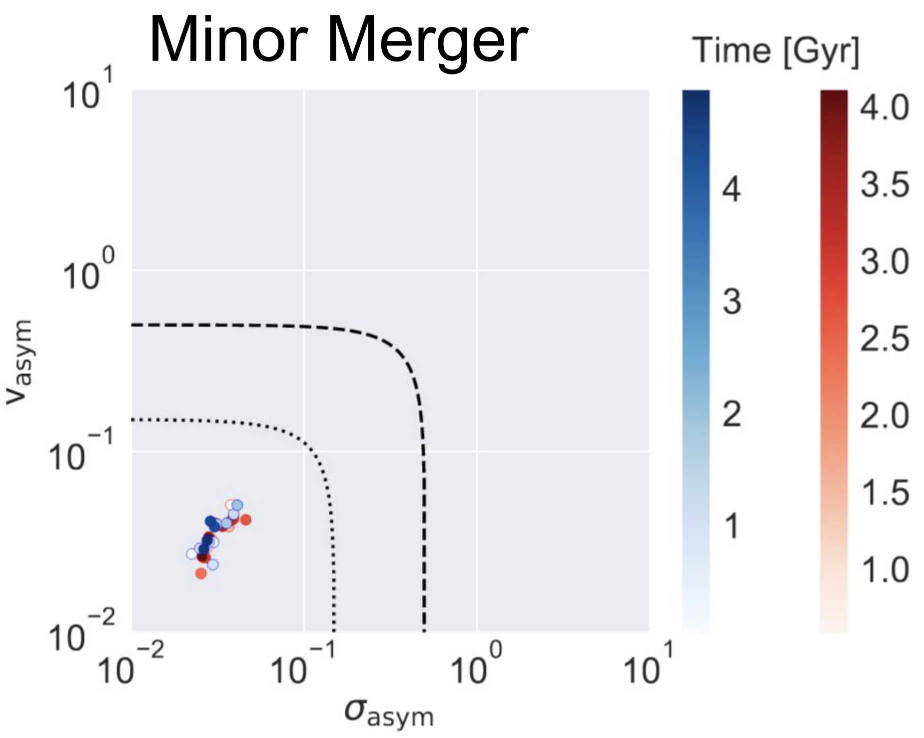
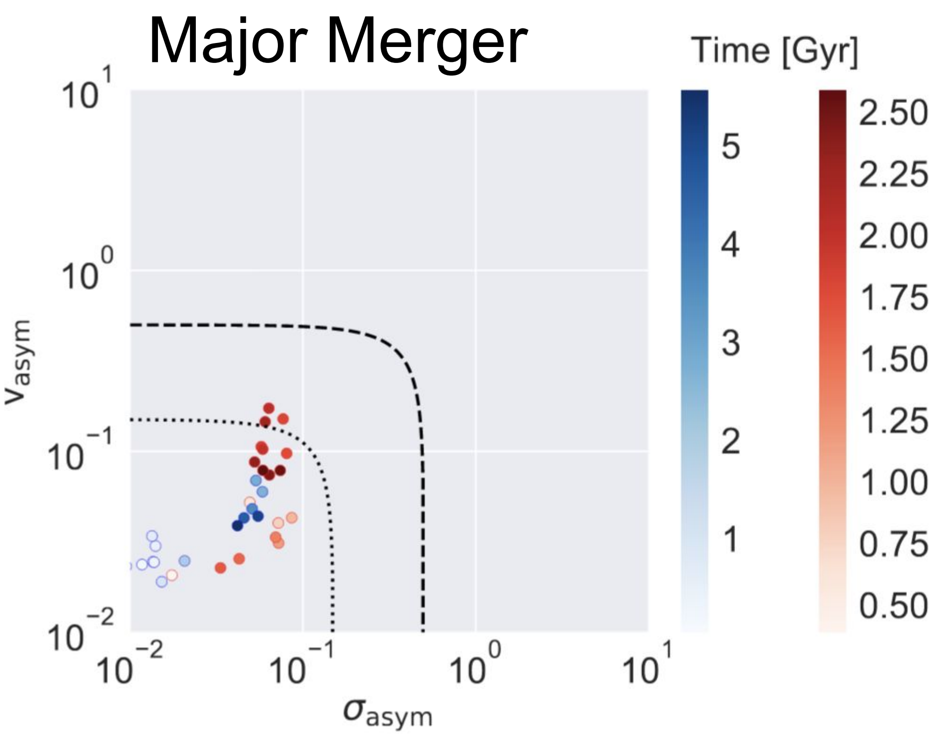
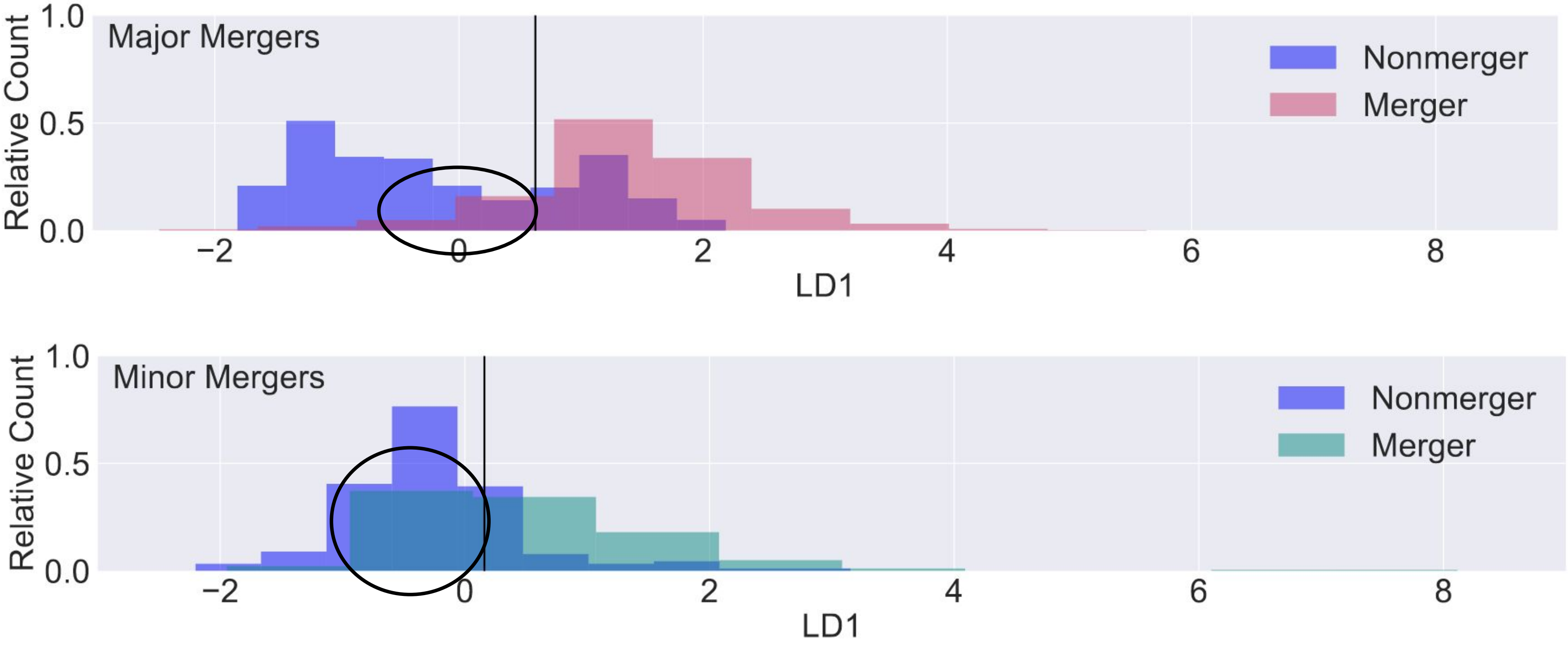
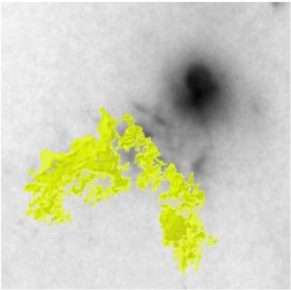


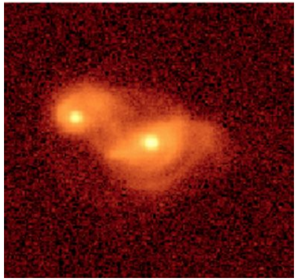


The kinematic classifications have a significant number of false negatives

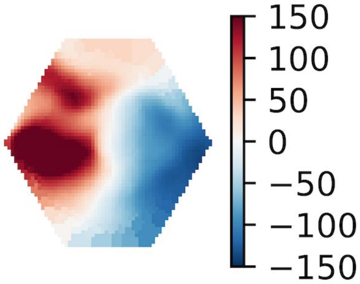




AGN
Feedback

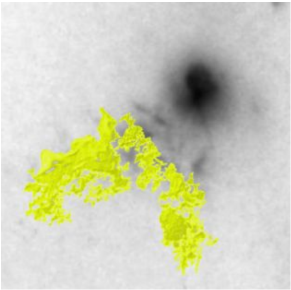


Imaging
of Galaxy
Mergers



Kinematics
of Galaxy
Mergers

- Most double-peaked AGN are outflows **(Nevin+ 2016)**
- Moderate-luminosity AGN outflows can drive feedback in their host galaxies **(Nevin+ 2018)**



AGN
Feedback

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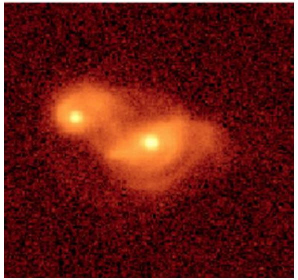
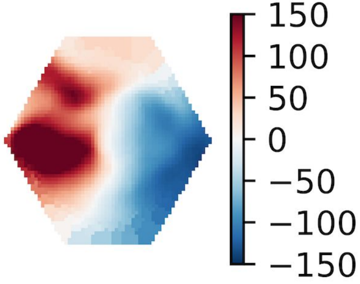
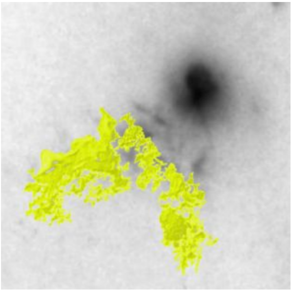


Imaging
of Galaxy
Mergers

- Combining imaging predictors leads to more accurate and precise merger identification **(Nevin+ 2019)**



Kinematics
of Galaxy
Mergers



AGN Feedback

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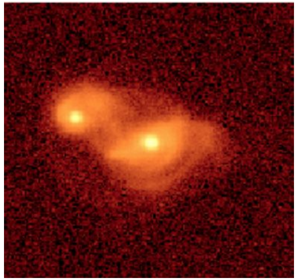
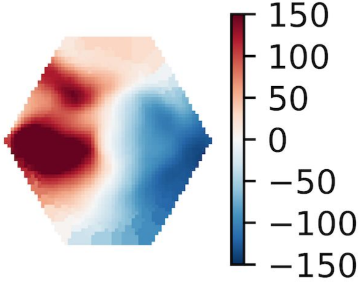


Imaging of Galaxy Mergers

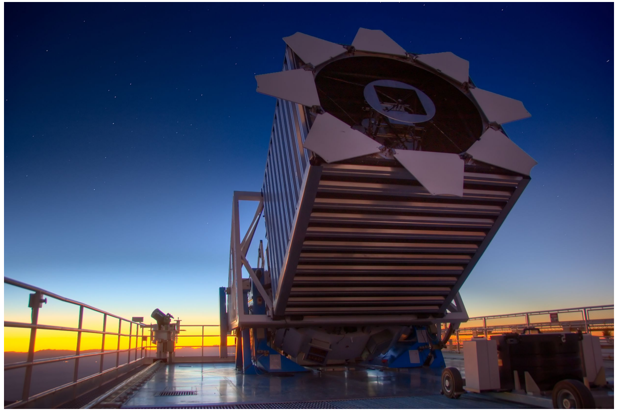
- Combining imaging predictors leads to more accurate and precise merger identification **(Nevin+ 2019)**



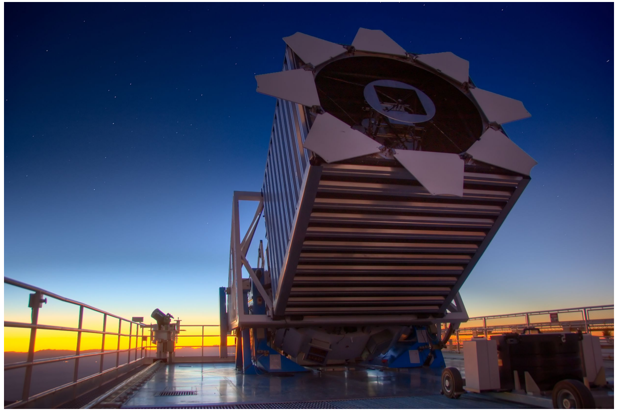
Kinematics of Galaxy Mergers

- Combining kinematic predictors leads to more accurate and precise merger identification **(Nevin+ 2019 in prep)**
- Not as good as imaging

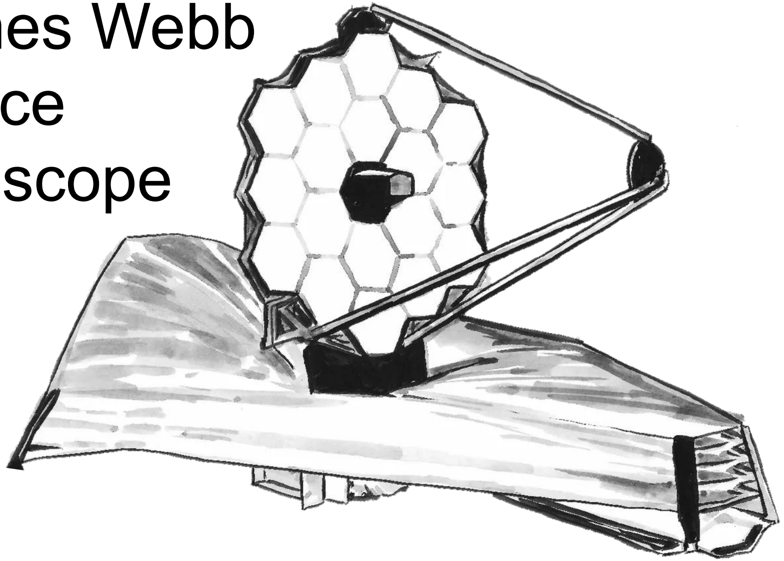
This technique can be applied to MaNGA and other imaging and kinematic surveys

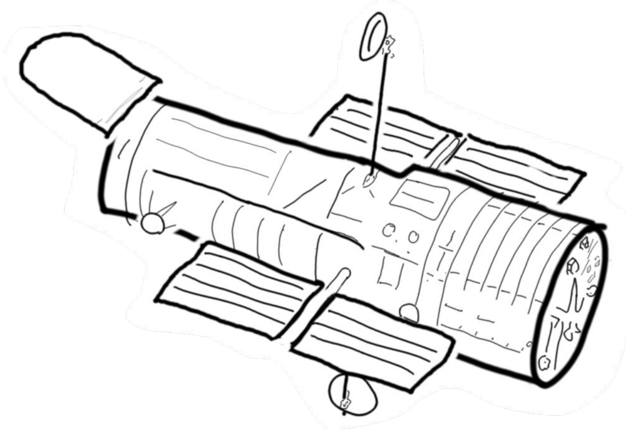


This technique can be applied to MaNGA and other imaging and kinematic surveys



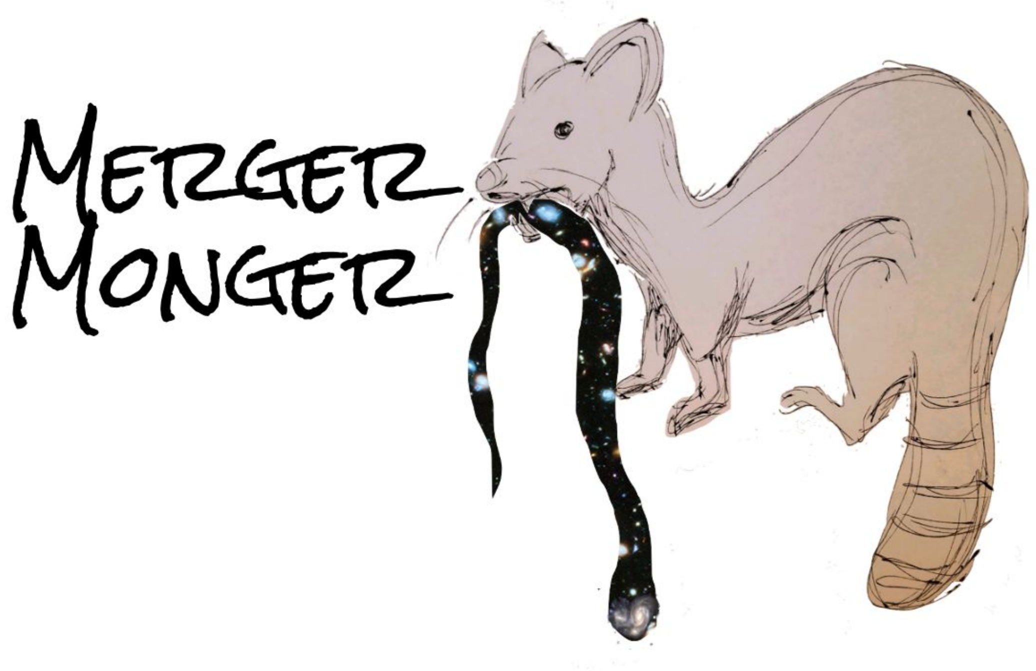
James Webb Space Telescope





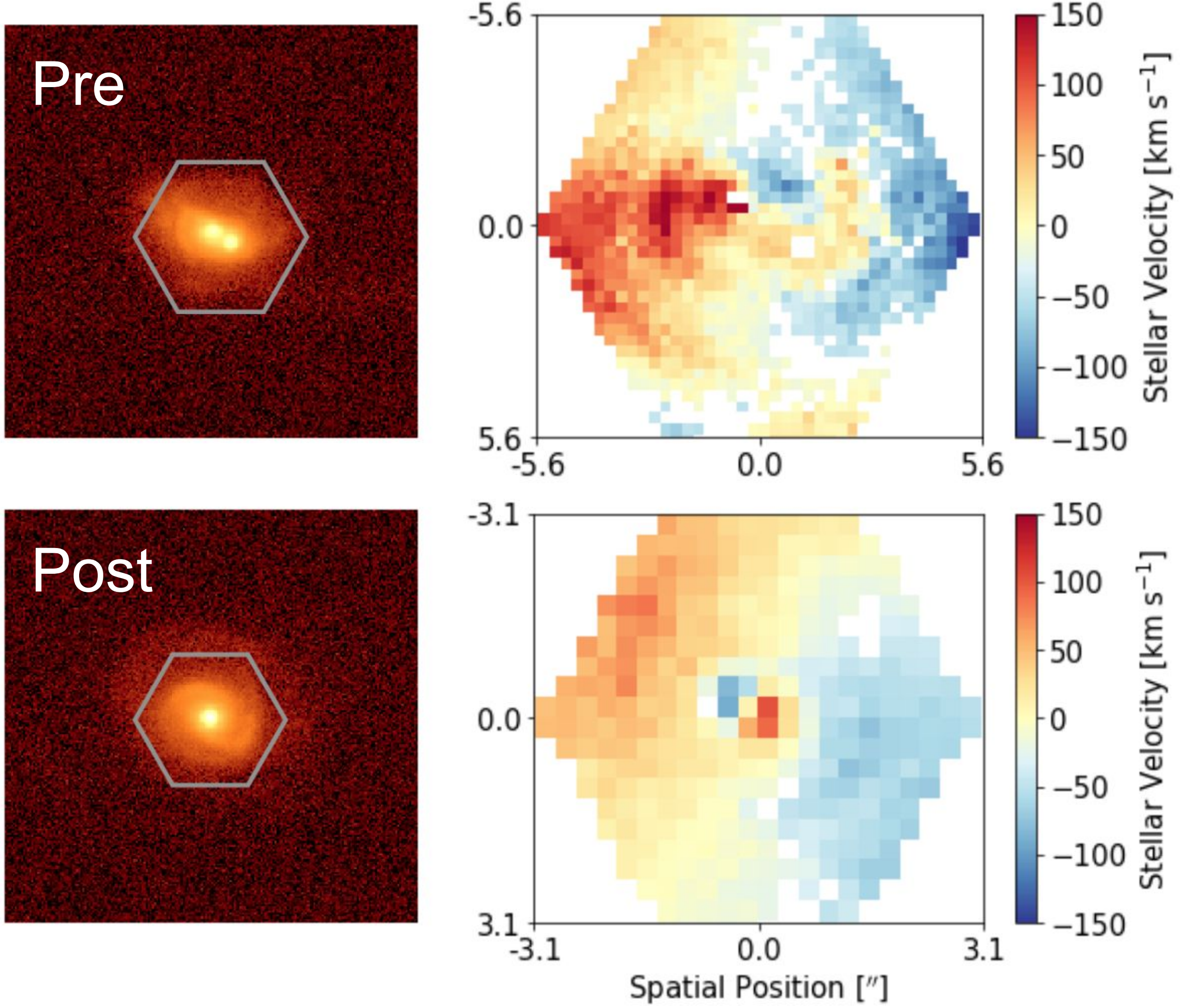
HST

This technique will be publicly available in a Github repository:

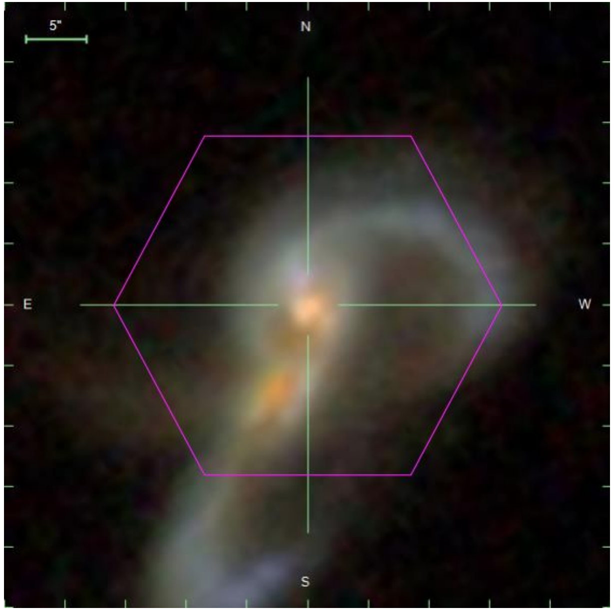


Mongoose credit: Briana Ingermann

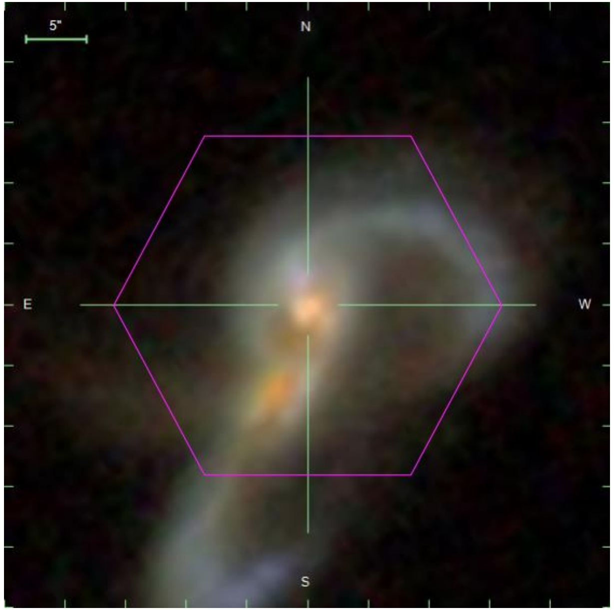
I will split the classification further into pre and post-coalescence mergers



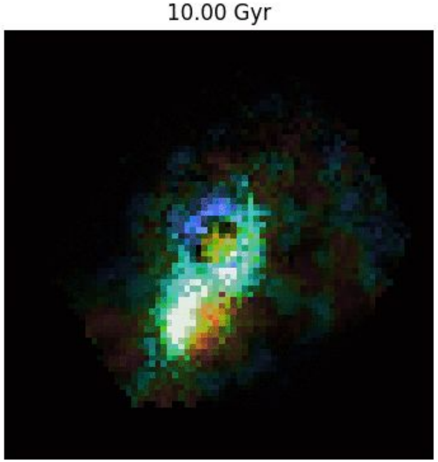
Explore how star formation history and metallicity change for different types of mergers (in radial bins)



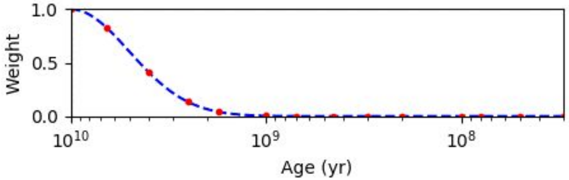
Explore how star formation history and metallicity change for different types of mergers (in radial bins)



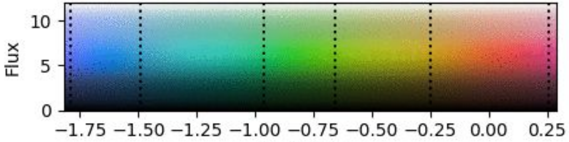
Animation by Tom Peterken



Stellar age (yr)

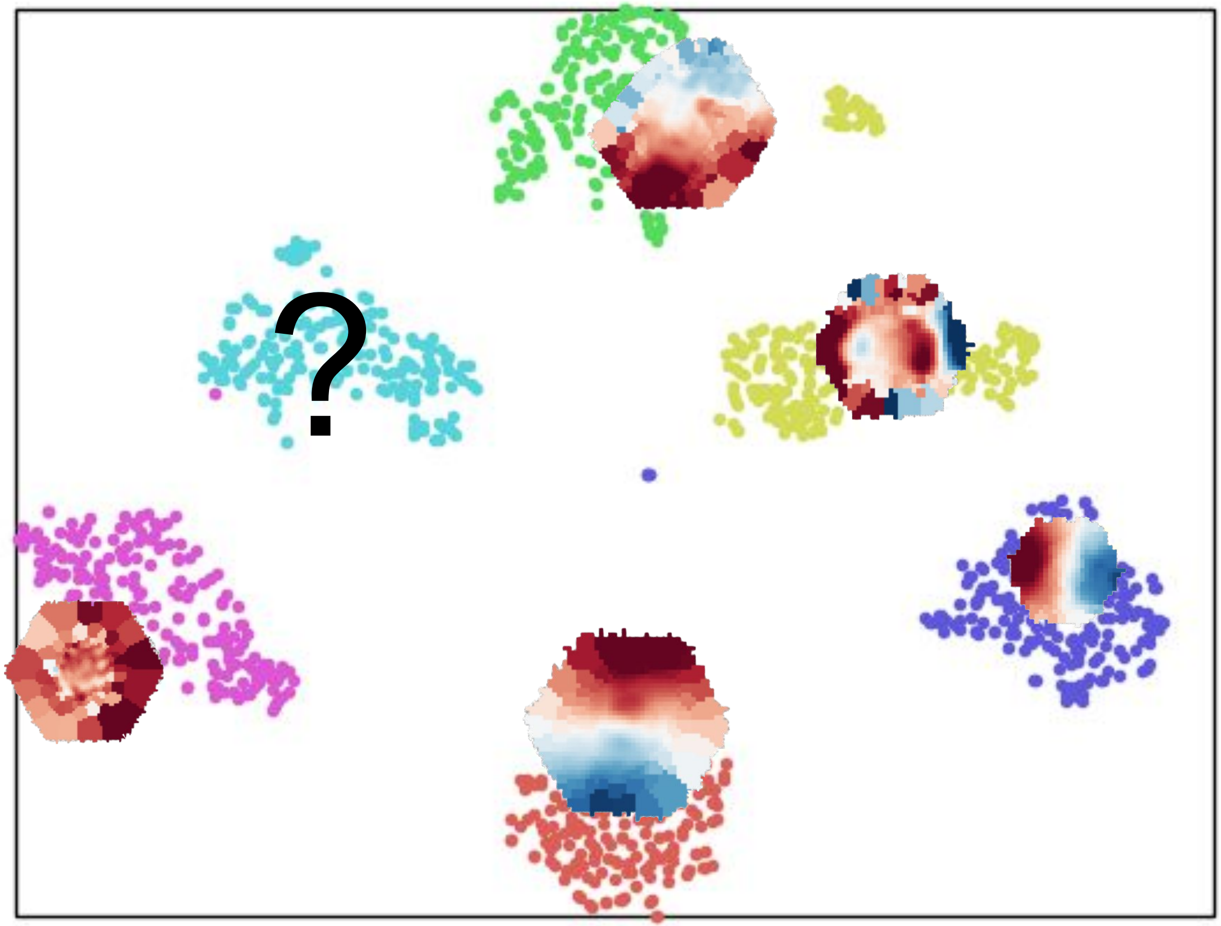


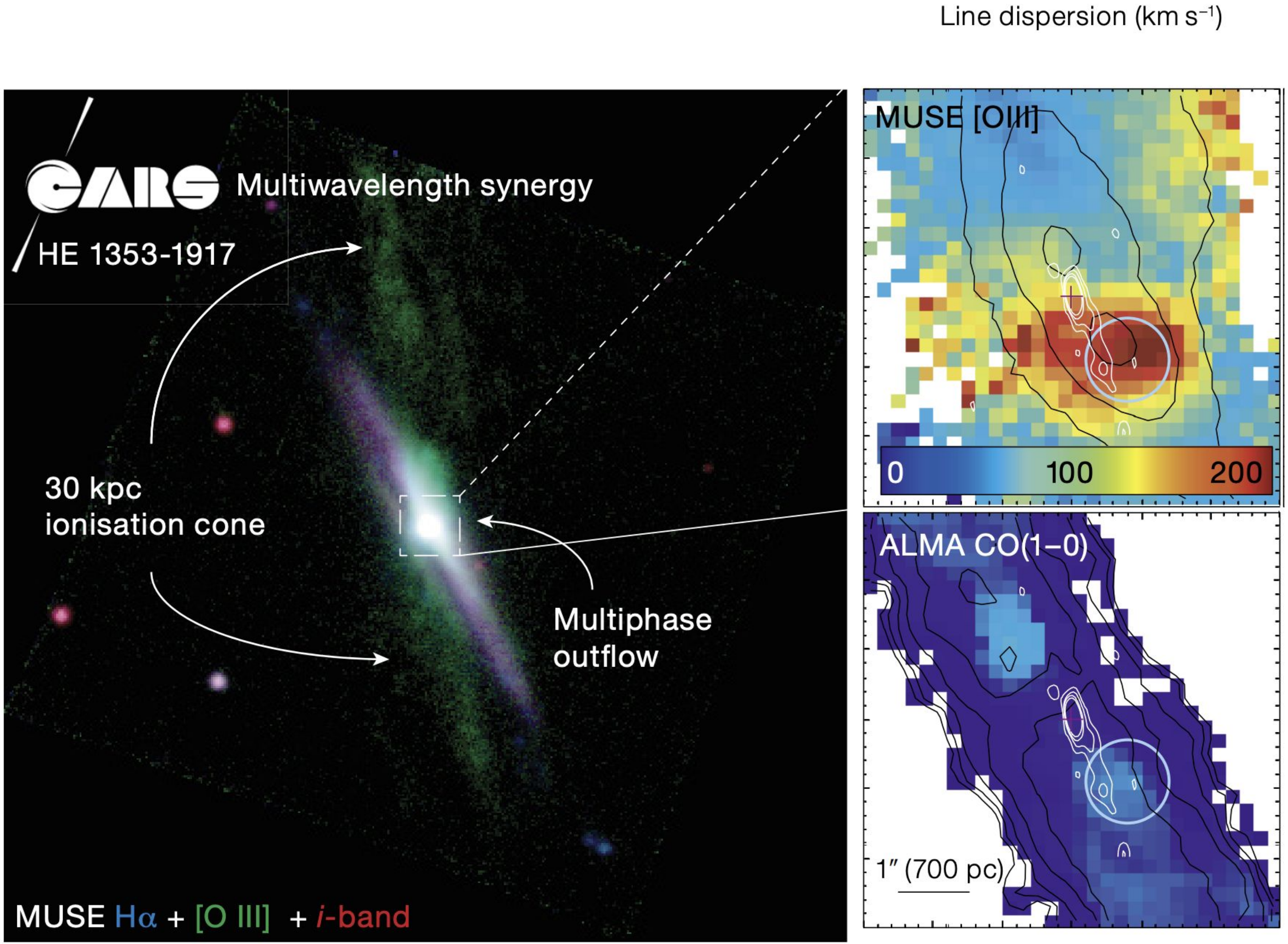
Metallicity



Less metals More metals

There's a lot of opportunity for exploration here, using the statistical might of MaNGA

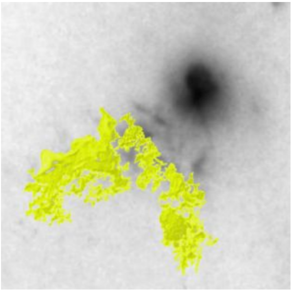




Husemann, Tremblay+ 2017

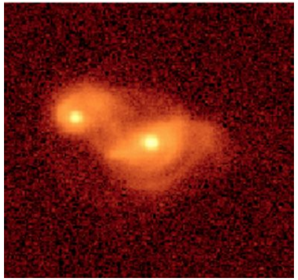

COLORADO


ALL Jeeps.
ALL
NIGHT
WRECK



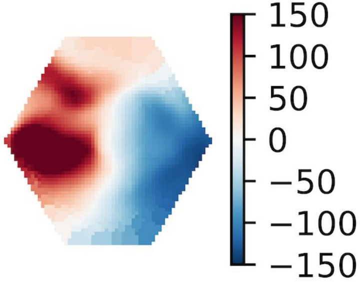
AGN Feedback

- Most double-peaked AGN are outflows **(Nevin+ 2016)**
- Moderate-luminosity AGN outflows can drive feedback in their host galaxies **(Nevin+ 2018)**



Imaging of Galaxy Mergers

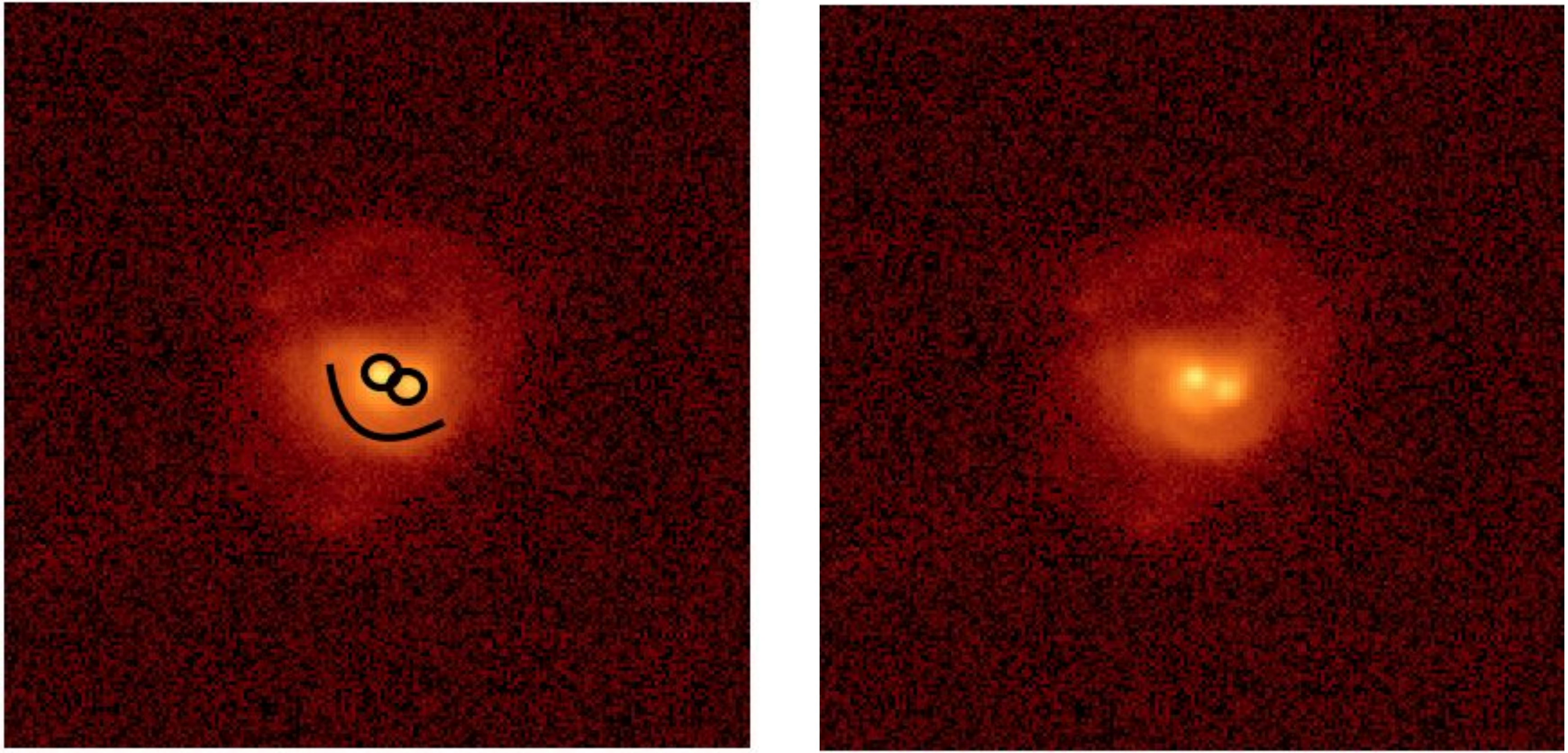
- Combining imaging predictors leads to more accurate and precise merger identification **(Nevin+ 2019)**



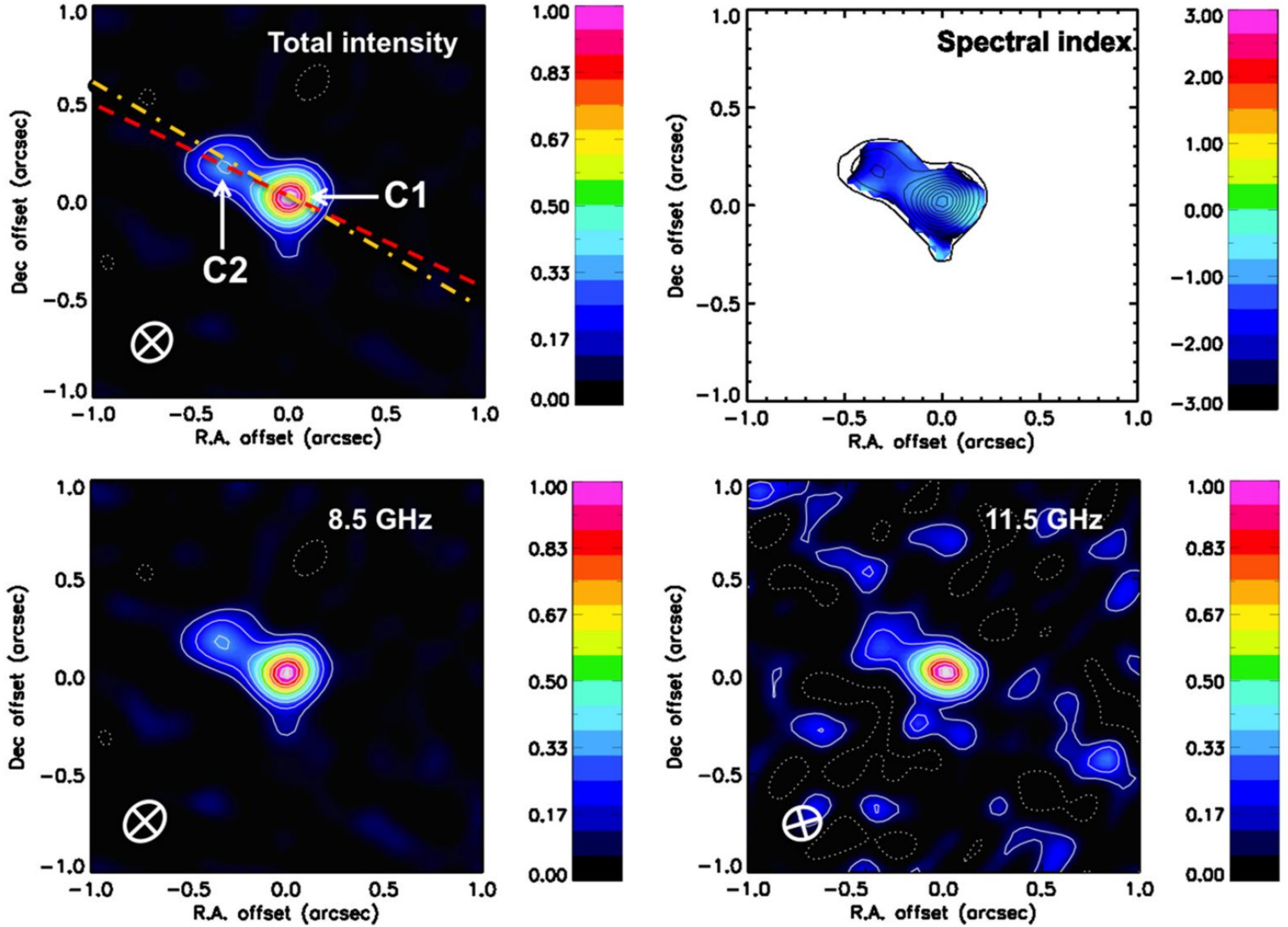
Kinematics of Galaxy Mergers

- Combining kinematic predictors leads to more accurate and precise merger identification **(Nevin+ 2019 in prep)**
- Not as good as imaging

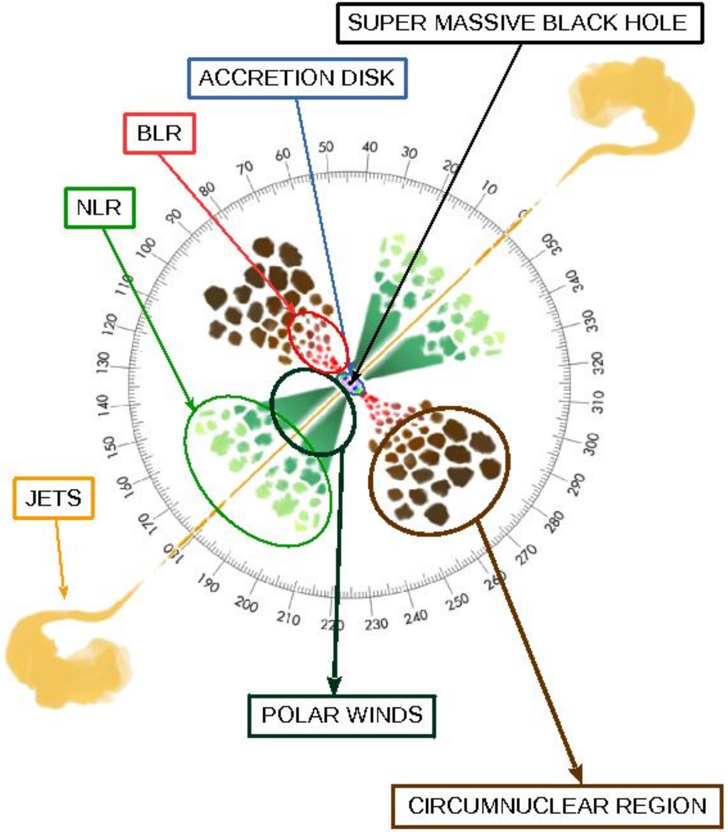
This slide will be for picture acknowledgement



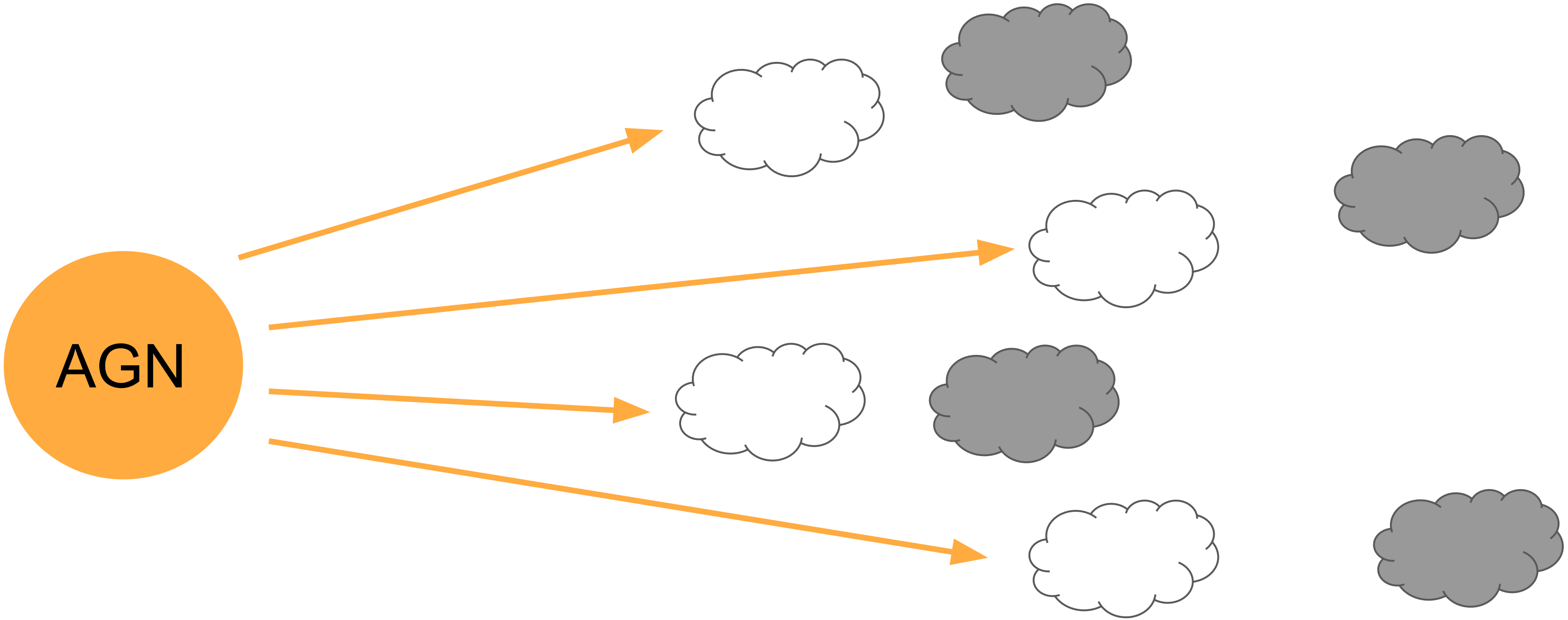
Extra Material from Chapter 2



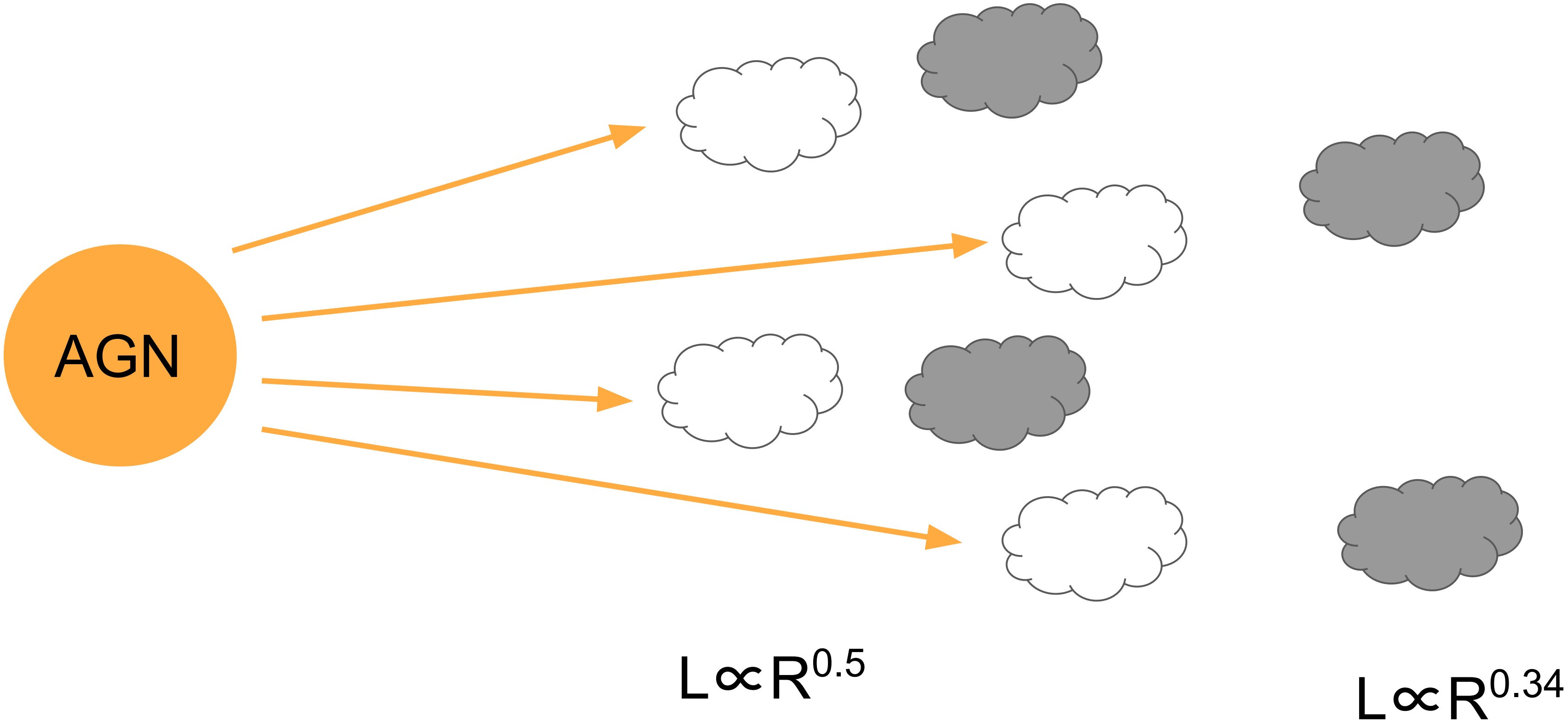
Total intensity
C1
C2
Spectral index
8.5 GHz
11.5 GHz
Dec offset (arcsec)
R.A. offset (arcsec)

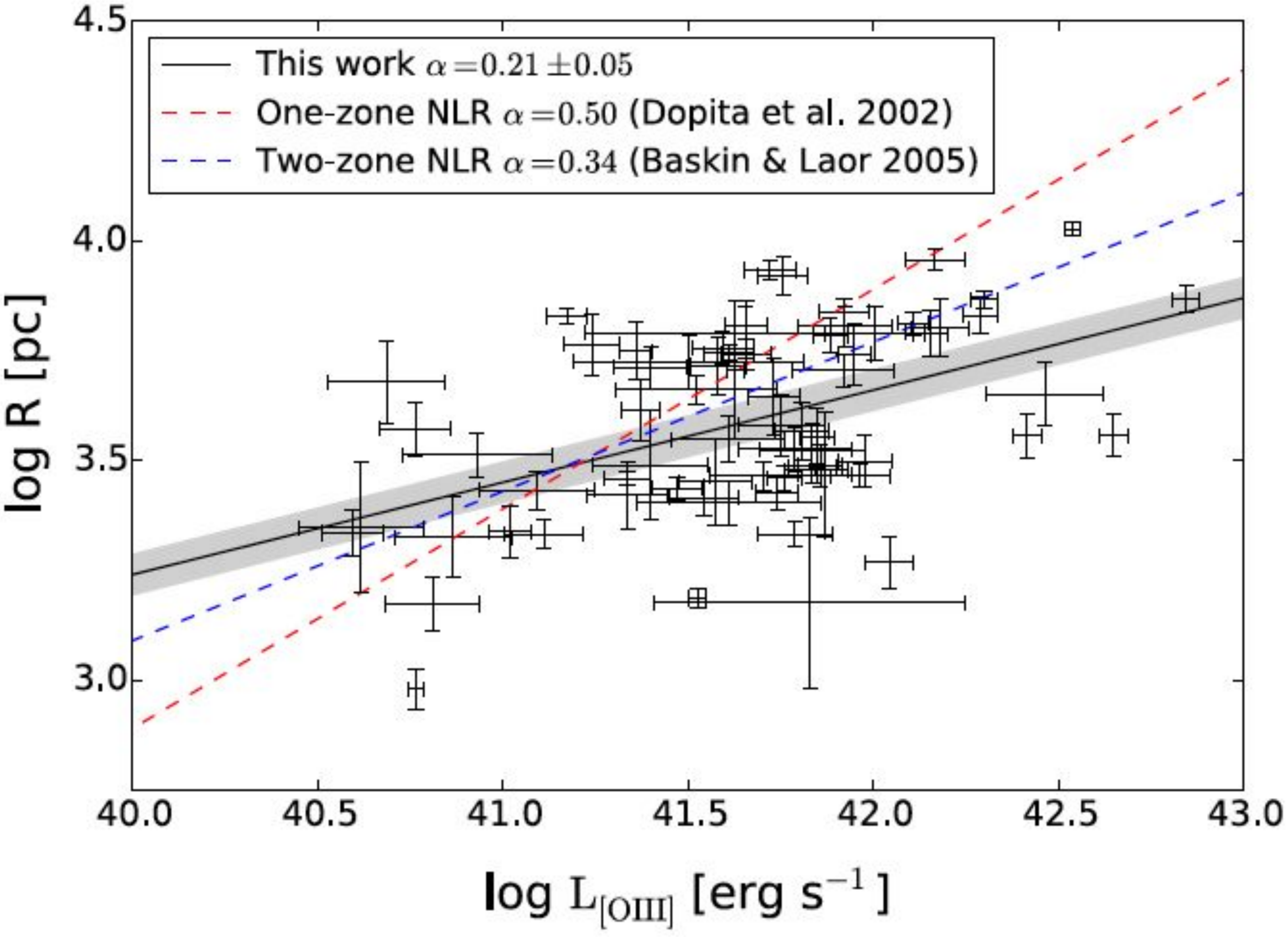

SUPER MASSIVE BLACK HOLE
ACCRETION DISK
BLR
NLR
JETS
POLAR WINDS
CIRCUMNUCLEAR REGION

Ionization v Matter-bounded



Ionization v Matter-bounded




This work $\alpha = 0.21 \pm 0.05$
One-zone NLR $\alpha = 0.50$ (Dopita et al. 2002)
Two-zone NLR $\alpha = 0.34$ (Baskin & Laor 2005)
4.5
4.0
3.5
3.0
log R [pc]
40.0
40.5
41.0
41.5
42.0
42.5
43.0
log $L_{[OIII]}$ [erg s^{-1}]

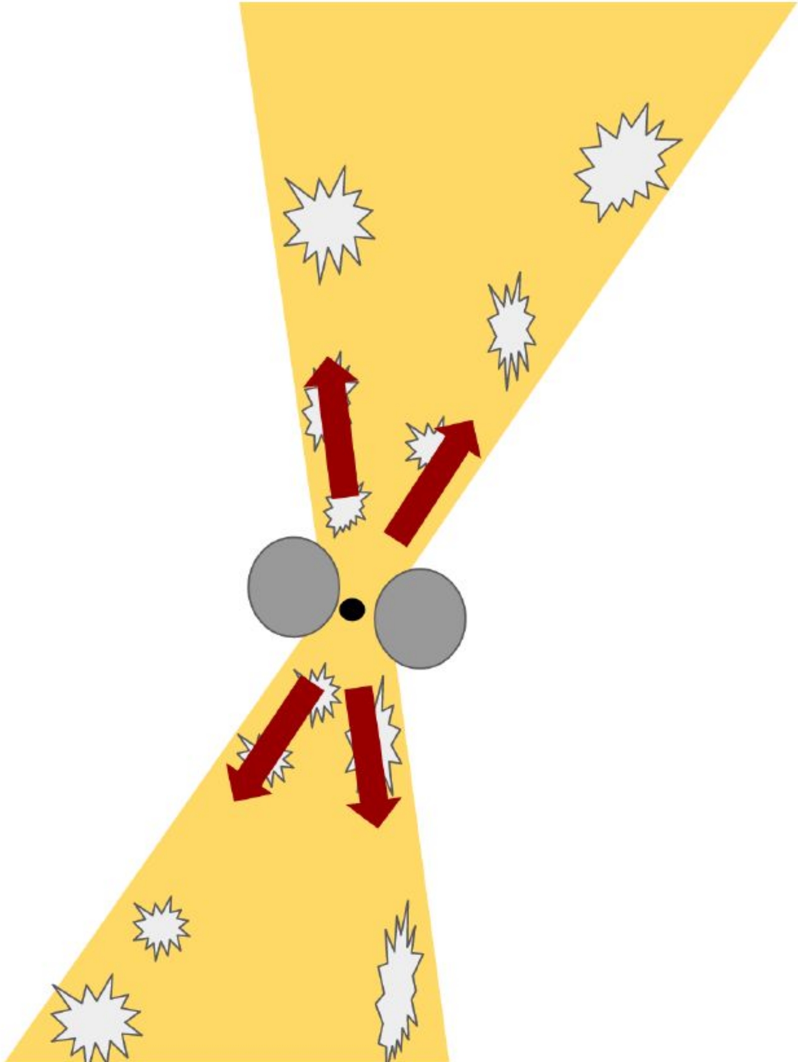
The size of the NLR (R_{NLR}) is related to the luminosity of the central AGN (ionizing source), this relationship can probe the ionization conditions in the NLR

$$U = \frac{n_\gamma}{n_e} = \frac{1}{4\pi R_{\mathrm{NLR}}^2 c n_e} \int_{\nu_0}^{\infty} \frac{L_\nu}{h\nu} d\nu$$

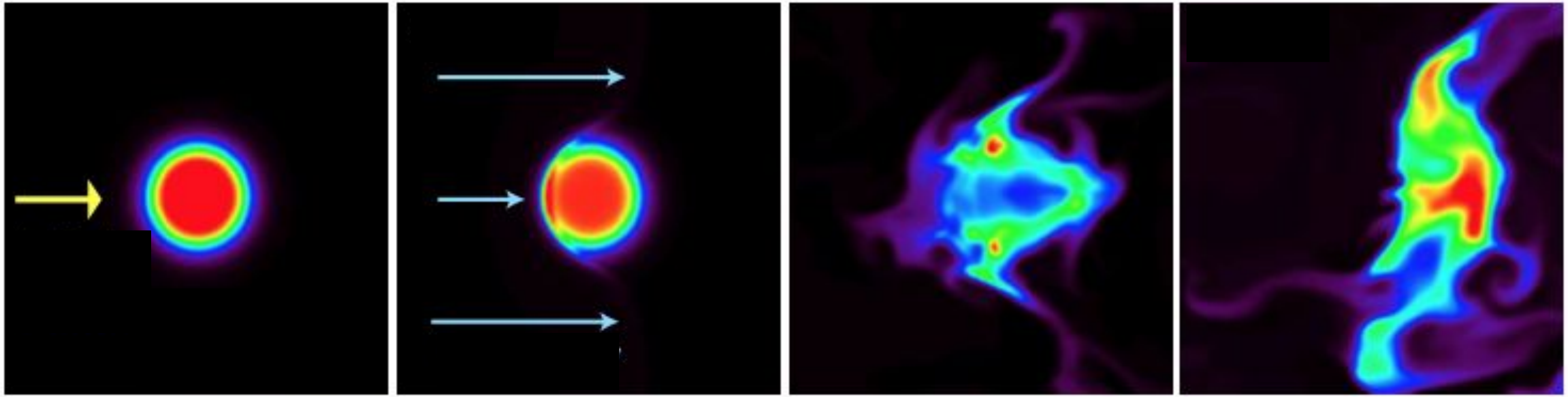
$$R_{NLR} \propto L^{0.5}_{[OIII]} \, (U \, n_e)^{-0.5}$$

Extra Material from Chapter 3

Everything is clumpy

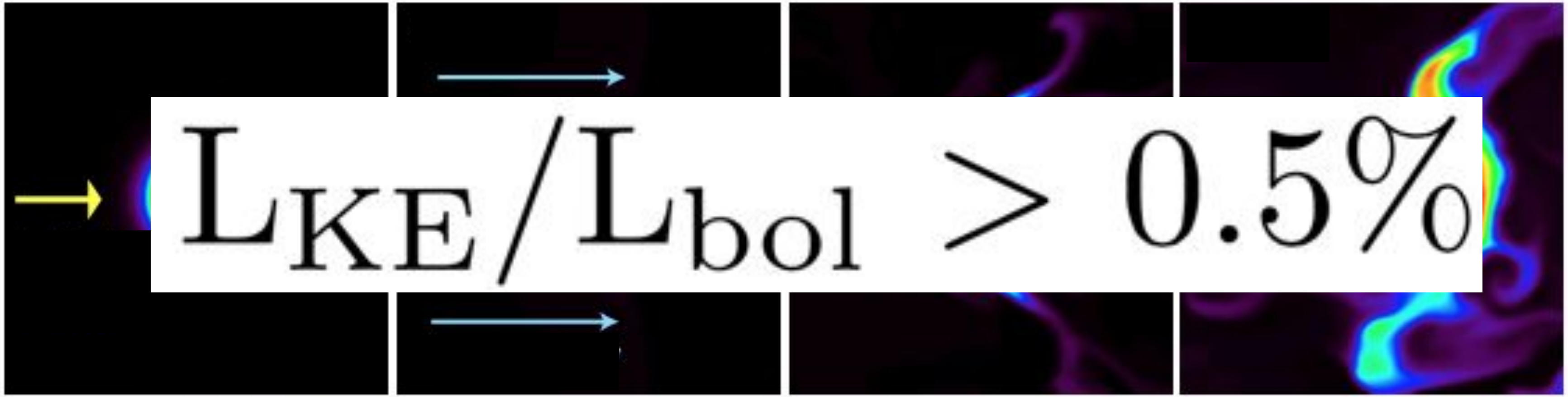


The outflow energy can disrupt cold molecular gas in a two stage feedback model



Hopkins & Elvis 2010

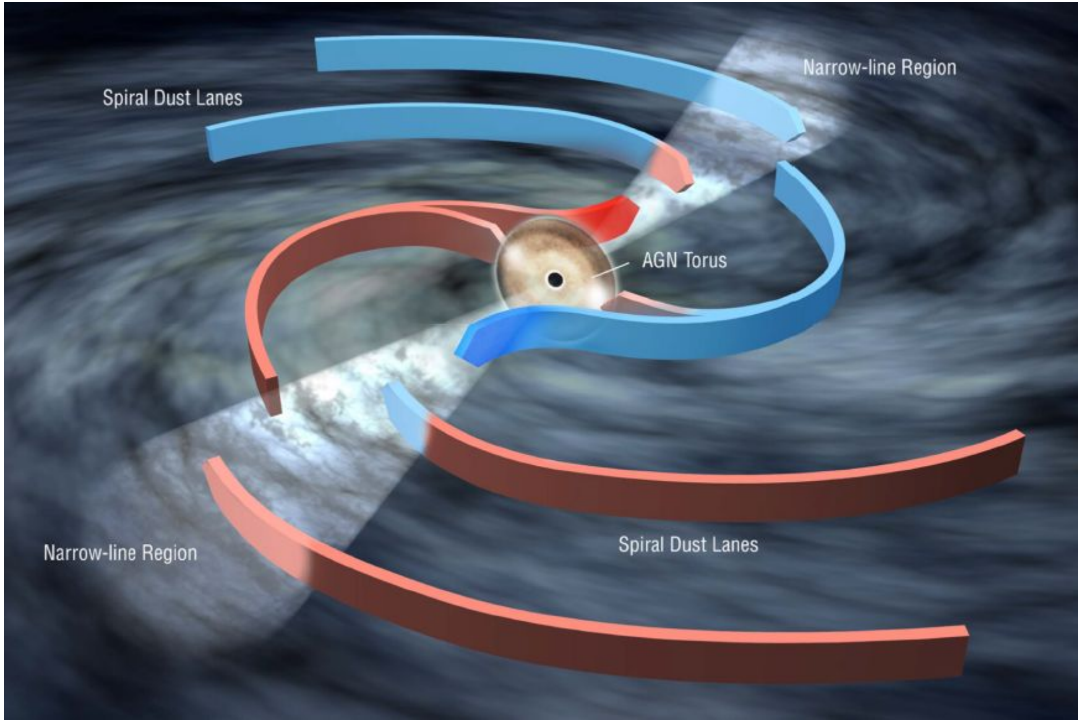
The outflow energy can disrupt cold molecular gas in a two stage feedback model



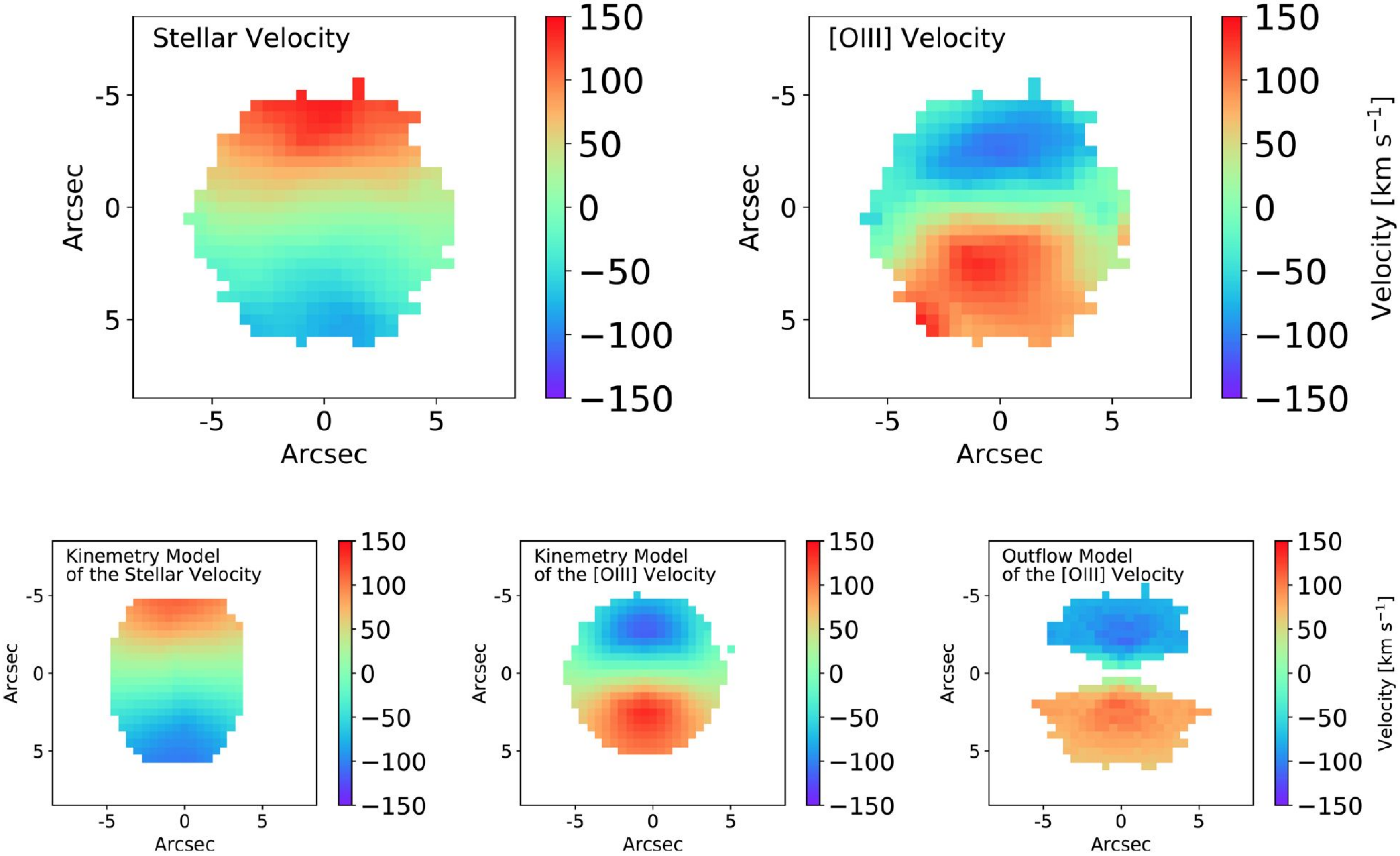
$$L_{KE}/L_{bol} > 0.5\%$$

Hopkins & Elvis 2010

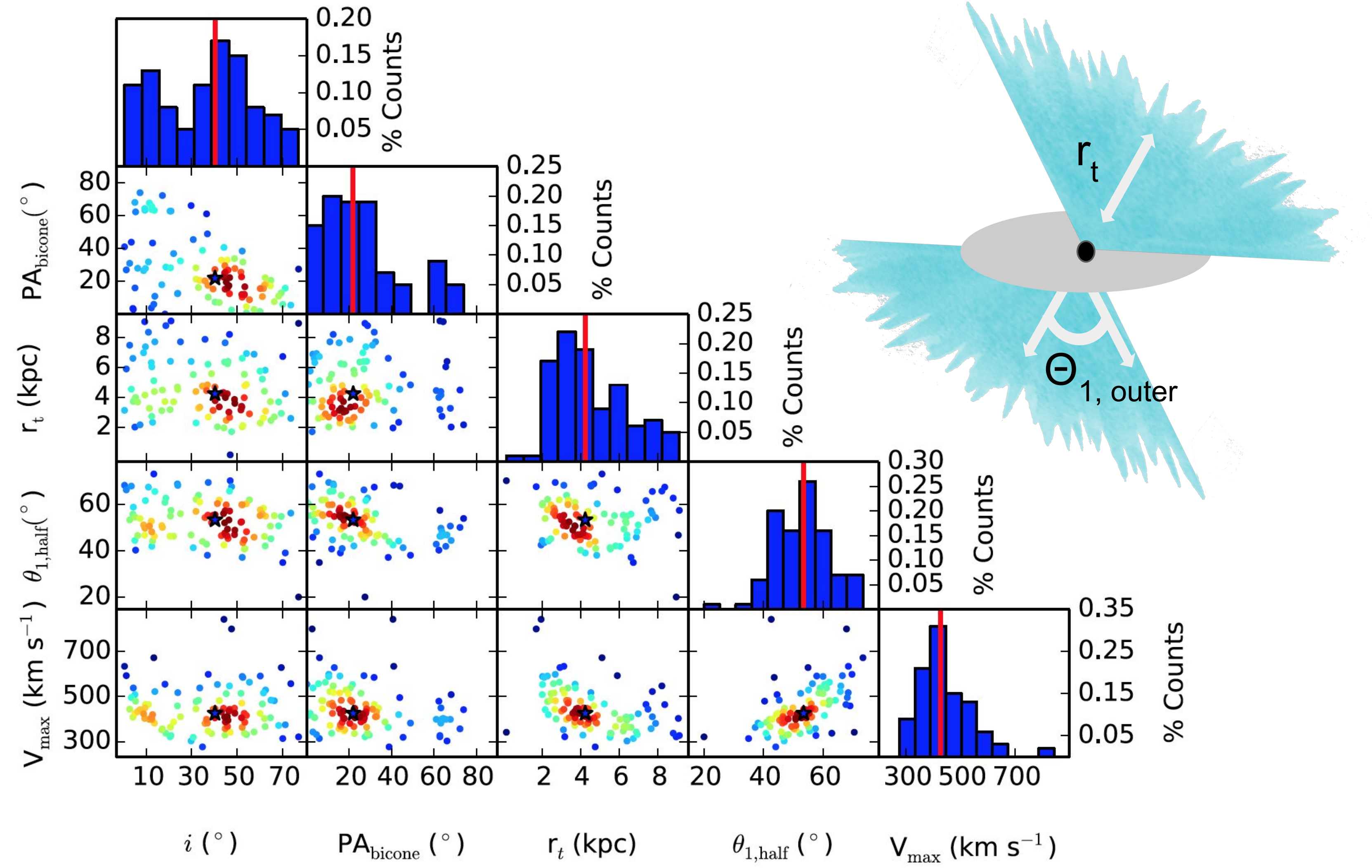
Rotation on large scales - No



Fischer+ 2017



Stellar Velocity
[OIII] Velocity
Velocity [km s^{-1}]
Arcsec
150
100
50
0
−50
−100
−150
Kinemetry Model
of the Stellar Velocity
Kinemetry Model
of the [OIII] Velocity
Outflow Model
of the [OIII] Velocity

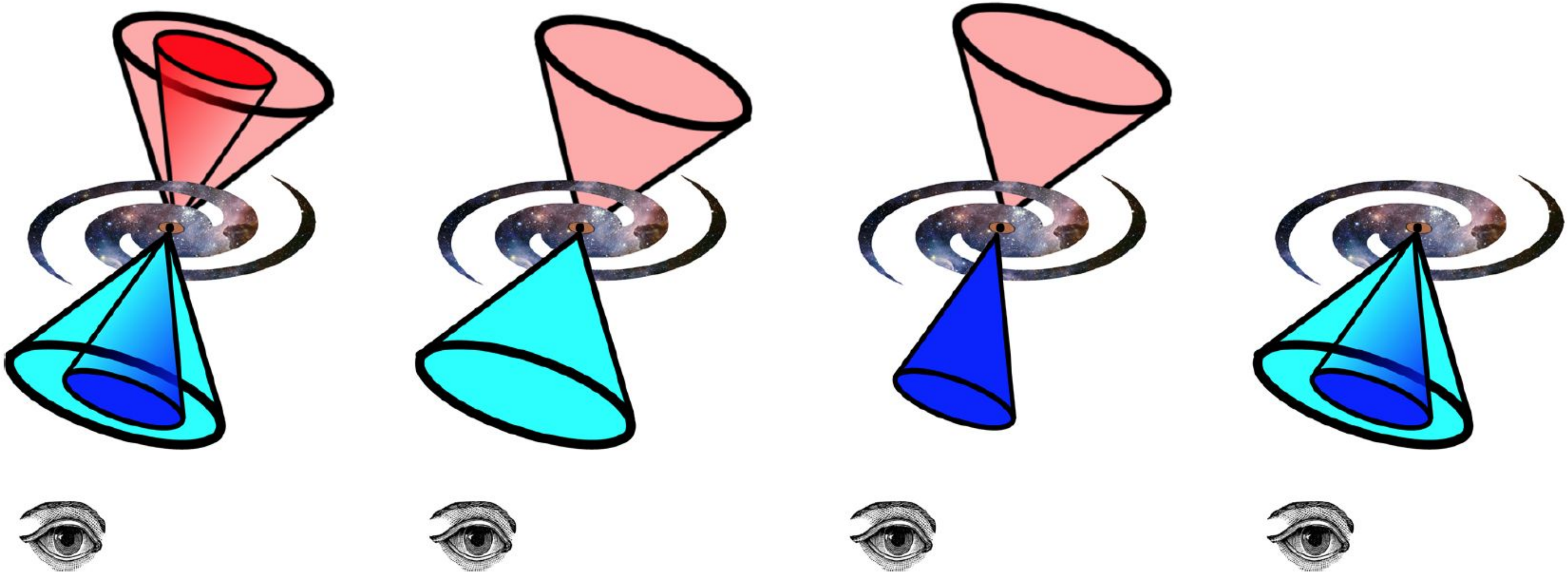

% Counts
$PA_{bicone}(^\circ)$
r_t (kpc)
$\theta_{1,half}(^\circ)$
V_{max} (km s^{-1})
i ($^\circ$)
PA_{bicone} ($^\circ$)
r_t (kpc)
$\theta_{1,half}$ ($^\circ$)
V_{max} (km s^{-1})
r_t
$\Theta_{1,\ outer}$

Two-walled symmetric bicone

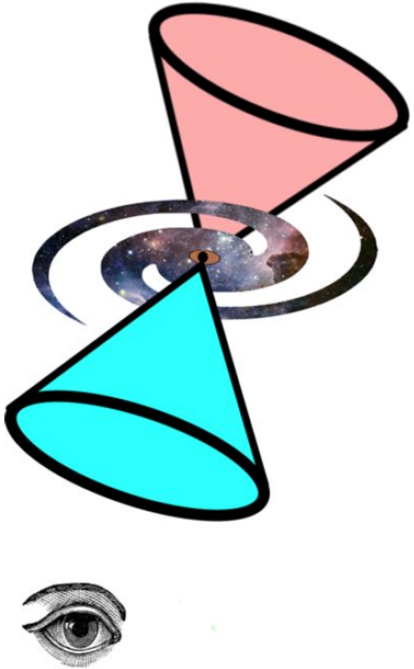
One-walled symmetric bicone

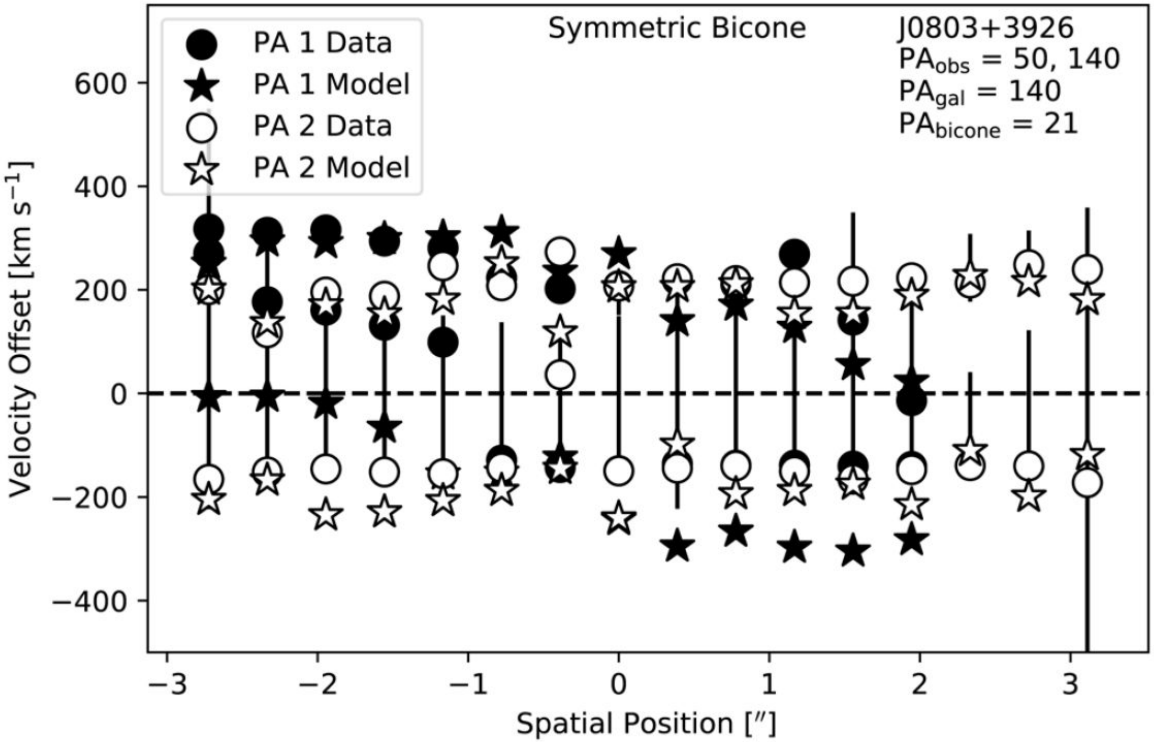
One-walled asymmetric bicone

Two-walled nested bicone



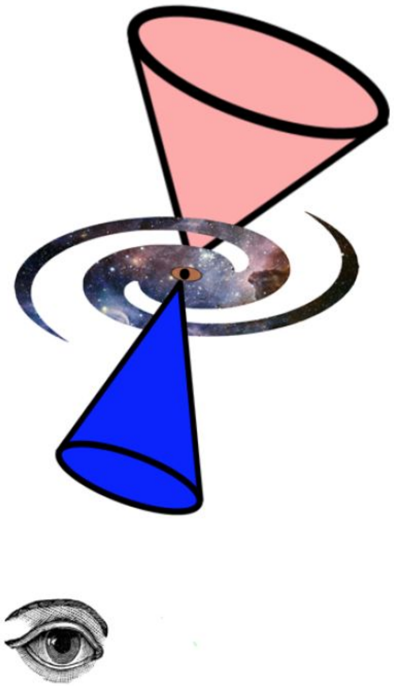
One-walled
symmetric bicone

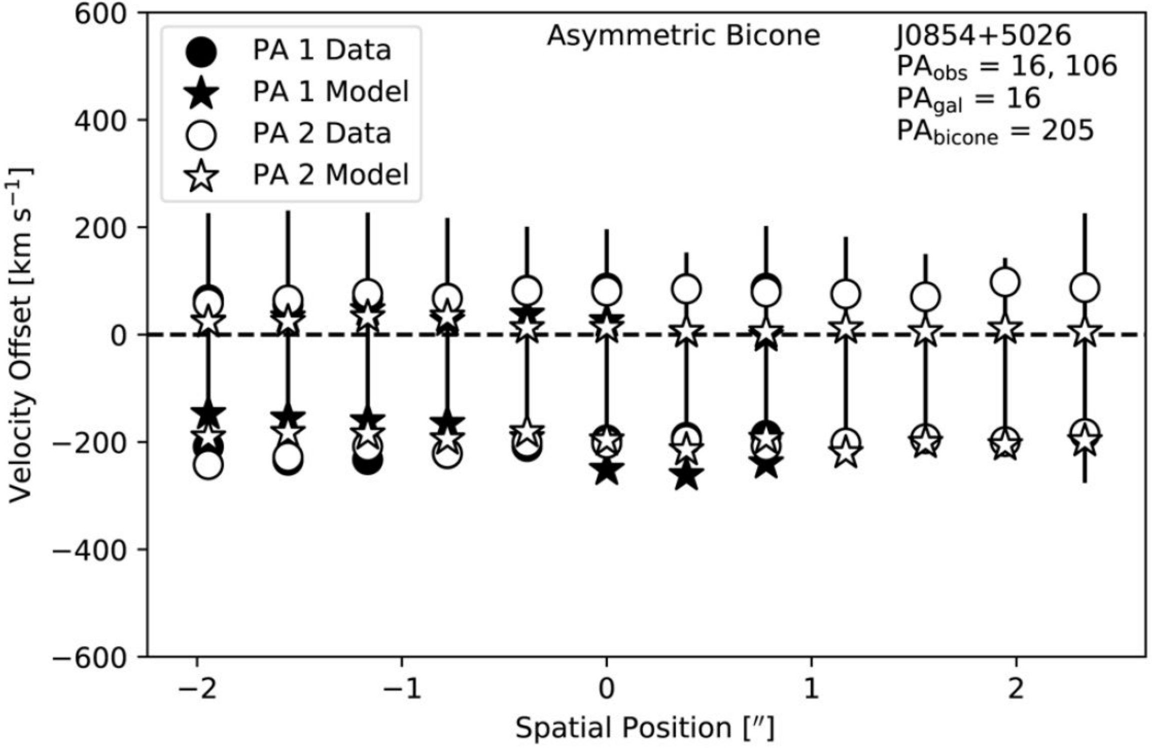




One-walled

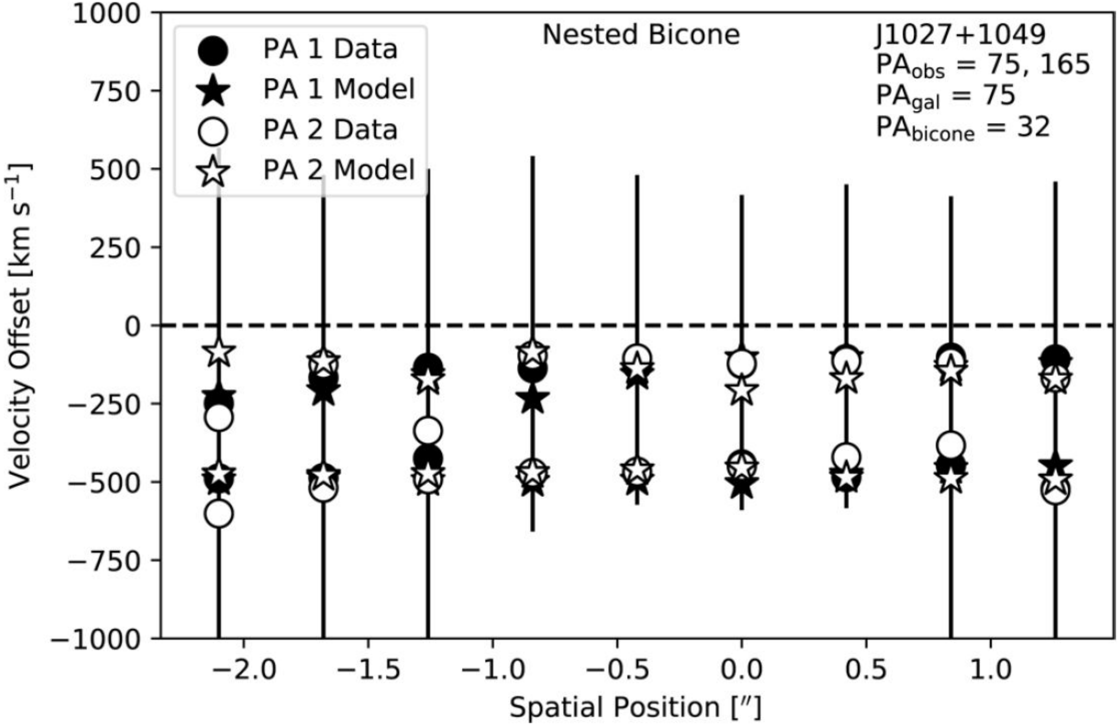
asymmetric bicone



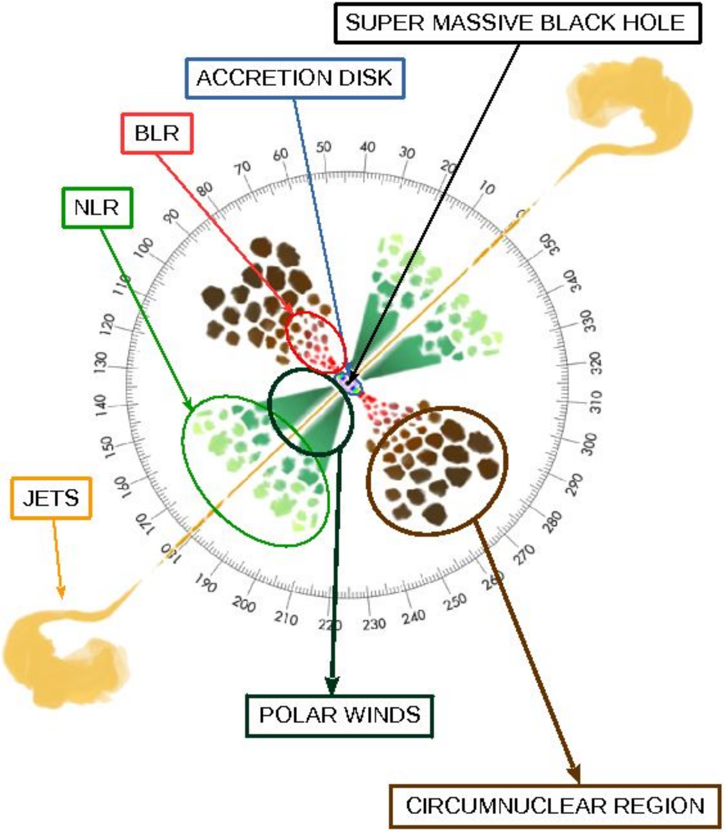


Two-walled

nested bicone



Type 1 vs Type 2 AGN - the picture is not this clear



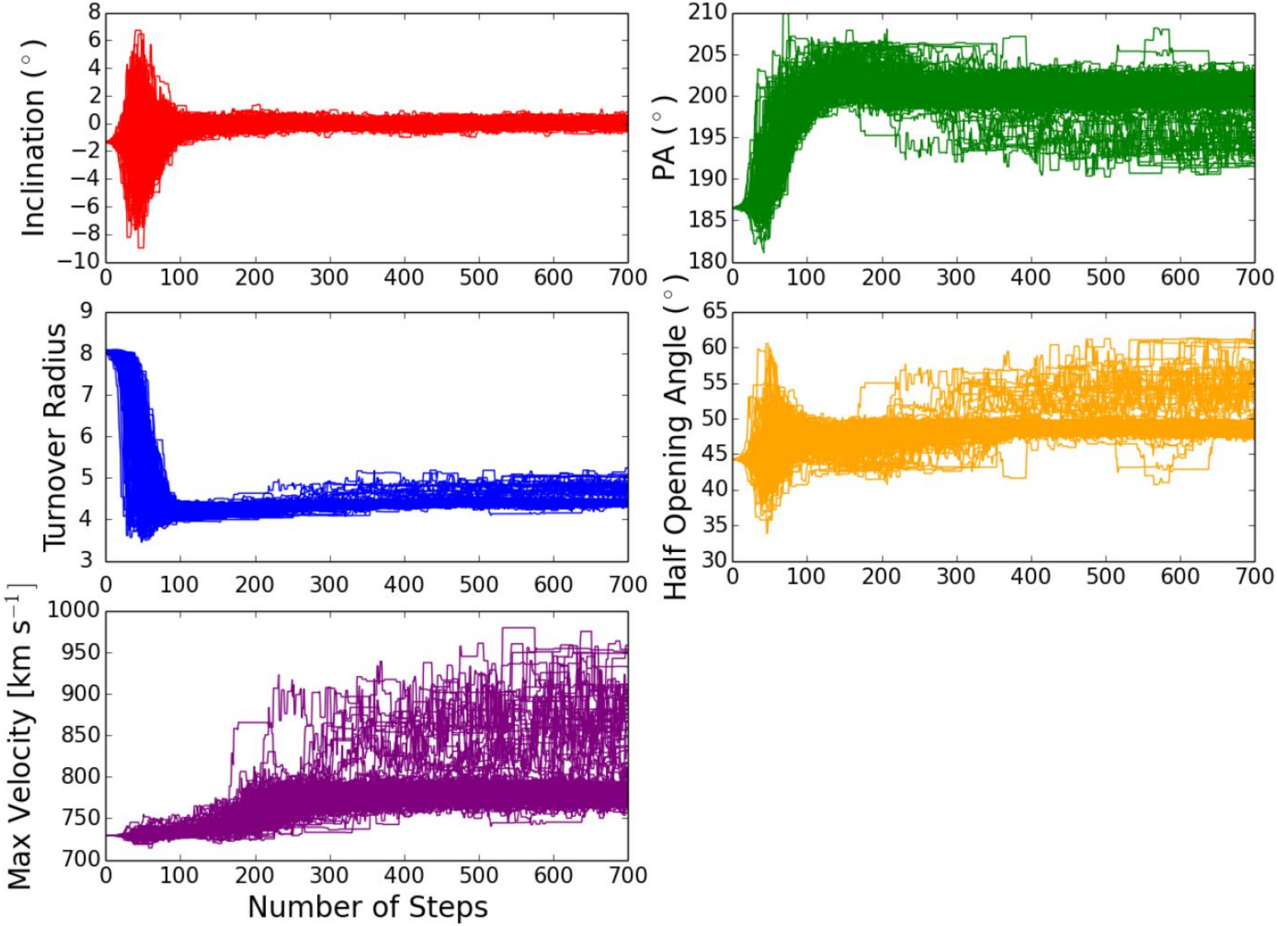
Energetics

$$\dot{\mathrm{M}} = m_{\mathrm{p}} n_{\mathrm{e}} V_{\mathrm{max}} f (A_1 + A_2)$$

$$A = \pi r \sqrt{h^2 + r^2} \qquad r = r_t \sin(\theta_{\mathrm{half}})$$

$$L_{\mathrm{KE}} = \frac{1}{2} \dot{\mathrm{M}} V_{\mathrm{max}}^2$$

(Practical) identifiability



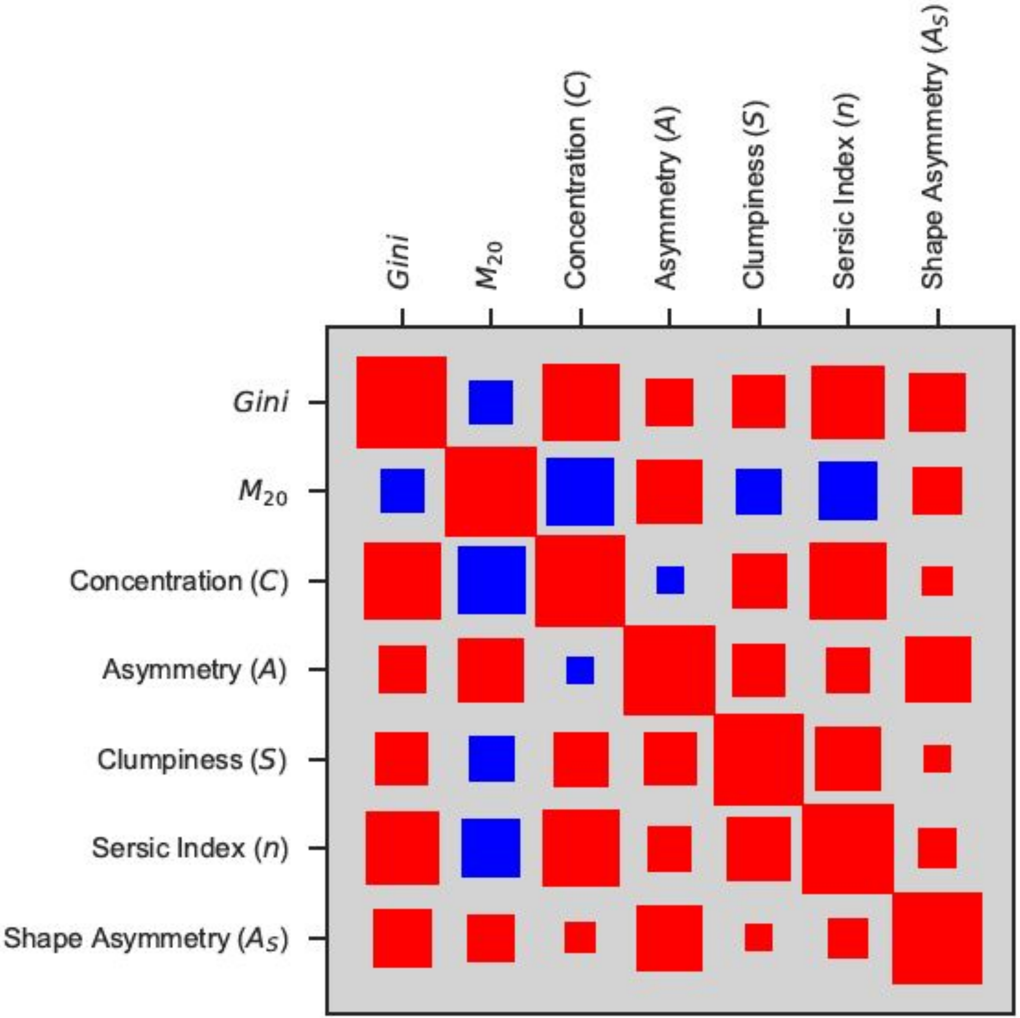
OFAT sensitivity analysis

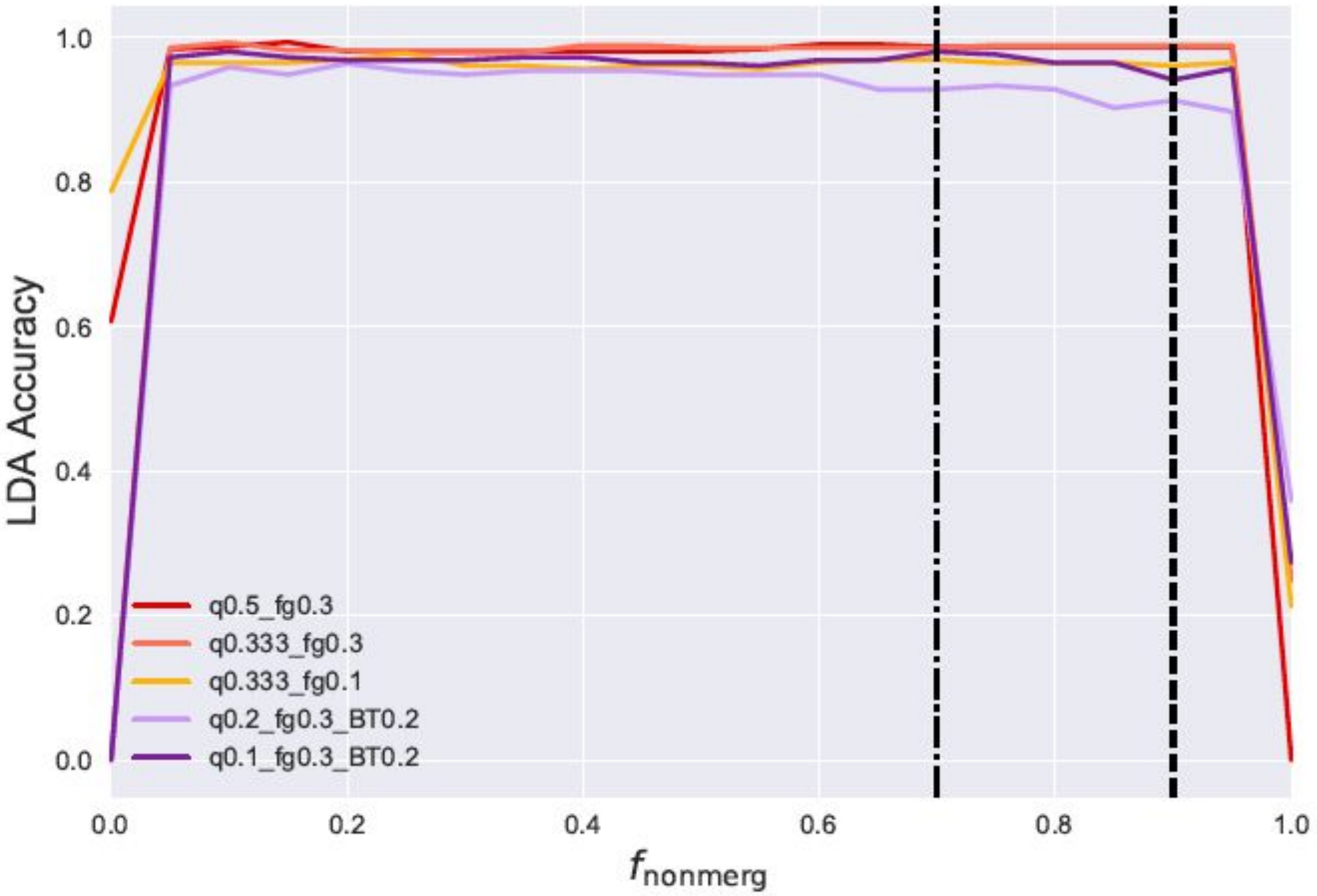
- How much does the reduced-chi change with each parameter/ which are the least sensitive parameters?
- PA is least sensitive
- Half opening angles are most sensitive

Things I could do with the bicones (if I had time)

- Expand sample to other analytic models (right now restricted to two walls)
- What is happening with the radio jets? - need to expand sample to do this
- Small scale observations of torus structure to figure out Type 1 vs Type 2 problem
- HST imaging please
- Investigate the role of shocks
- Entrained vs accelerated in situ - probably need 100s of pc scale observations, right now we are just seeing the kpc-scale
- ALMA molecular gas (small-scale outflow?)
- Estimability = terrifying
- Stellar velocities for comparison’s sake - we sort of did this with H alpha

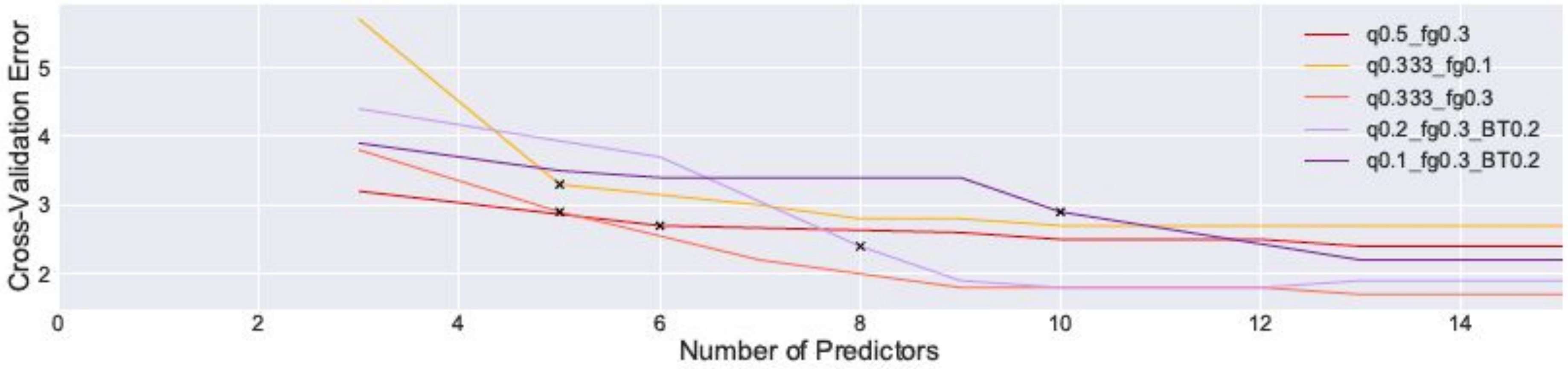
Extra material from Chapter 4


Gini
M_{20}
Concentration (C)
Asymmetry (A)
Clumpiness (S)
Sersic Index (n)
Shape Asymmetry (A_S)

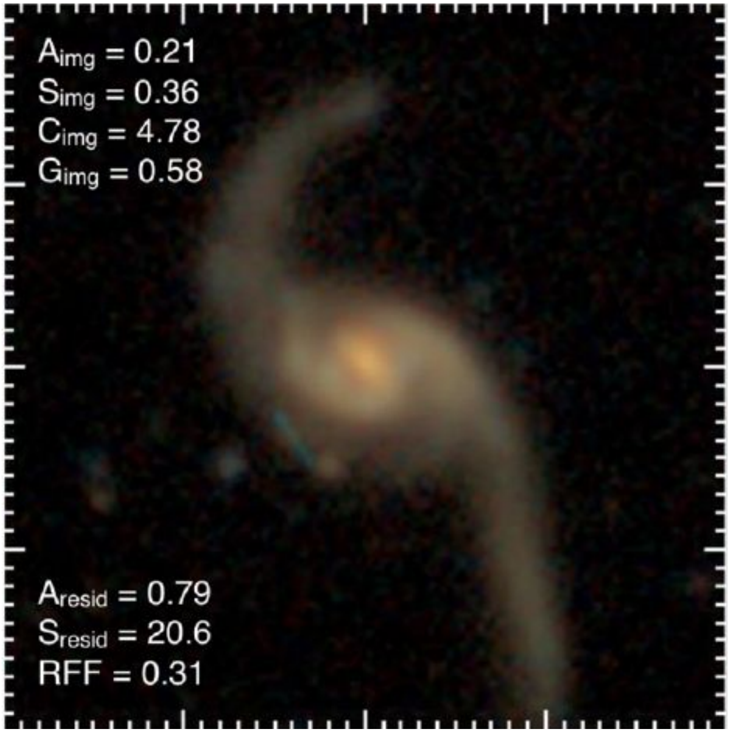


LDA Accuracy
f_{nonmerg}
0.0
0.2
0.4
0.6
0.8
1.0
q0.5_fg0.3
q0.333_fg0.3
q0.333_fg0.1
q0.2_fg0.3_BT0.2
q0.1_fg0.3_BT0.2

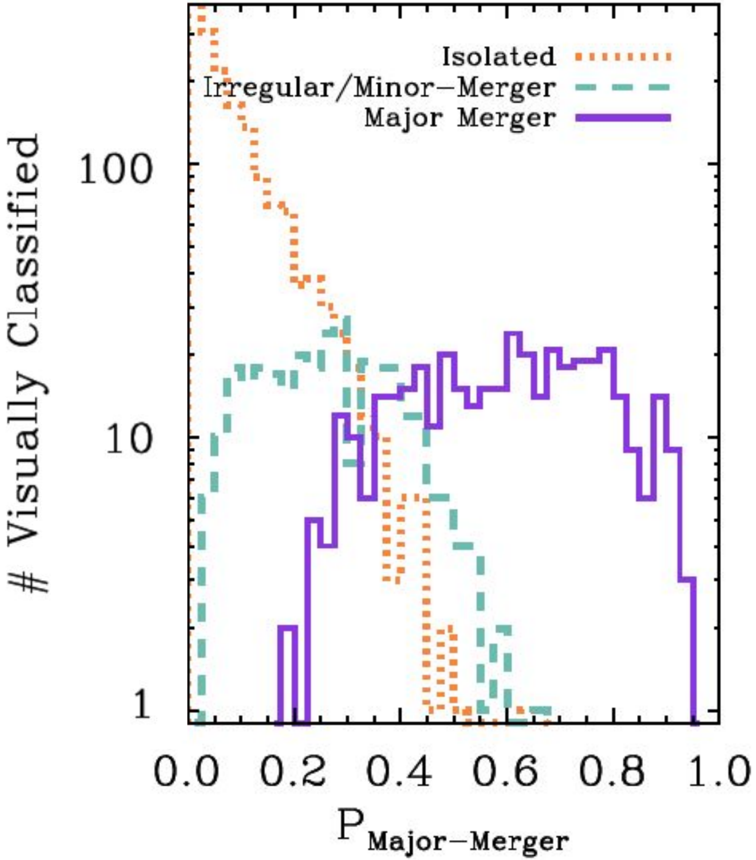
A forward stepwise selection selects which predictors to use and a k-fold cross-validation determines the error on each coefficient



Combining imaging predictors is a more effective tool



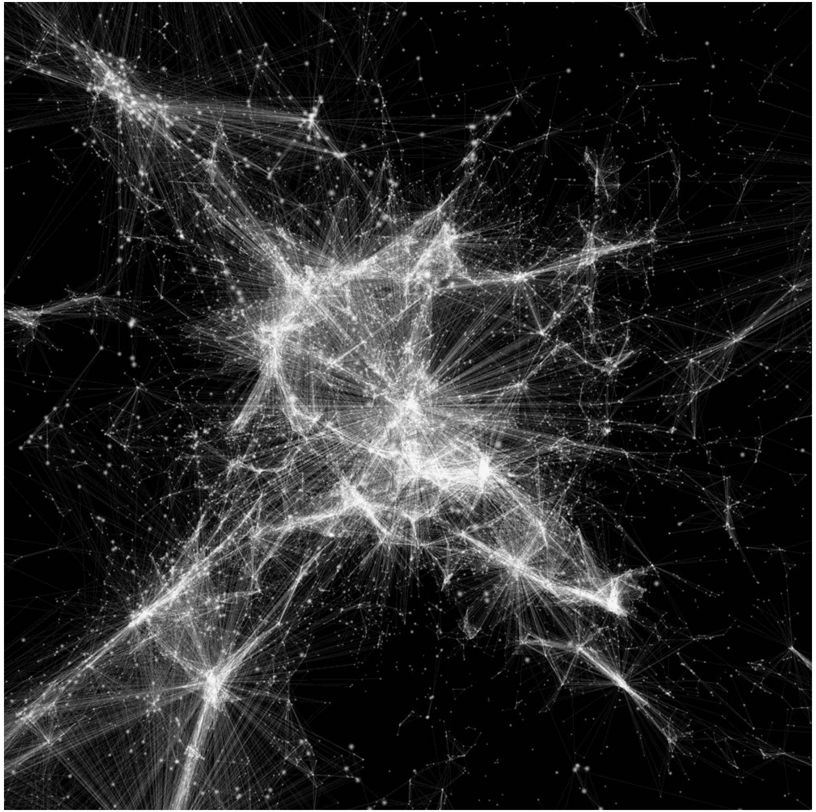
Goulding+ 2018



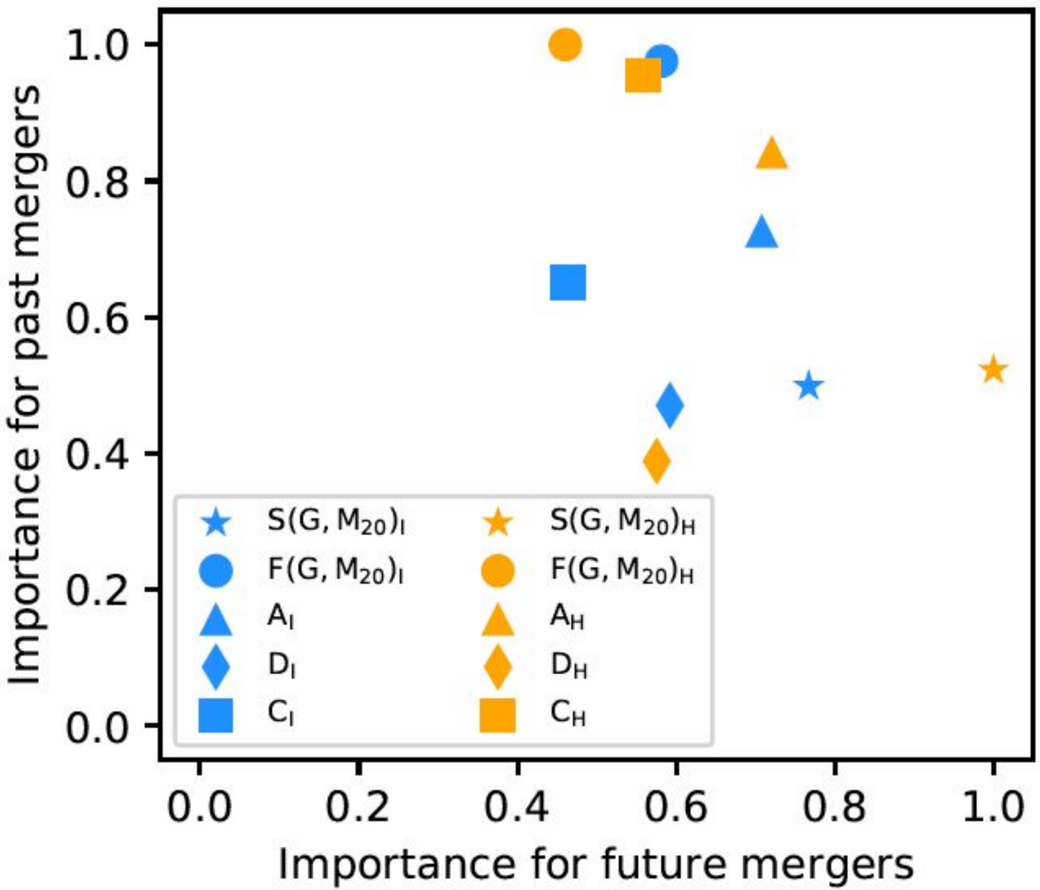
Linear Discriminant Axis #1 (LD1) is a linear combination of all input predictors and interaction terms

$$\begin{aligned}
\mathrm{LD1}_{\mathrm{major}} = \quad & 3.49 \times Gini + 4.32 \times M_{20} - 1.01 \times C + 6.09 \times A + 8.08 \times A_S \\
& - 7.67 \times Gini * A - 7.66 \times Gini * A_S - 4.74 \times M_{20} * C - 2.89 \times M_{20} * A \\
& - 1.34
\end{aligned}$$

Cosmological (zoom) simulations incorporate a range of galaxy morphologies assembled over cosmic time

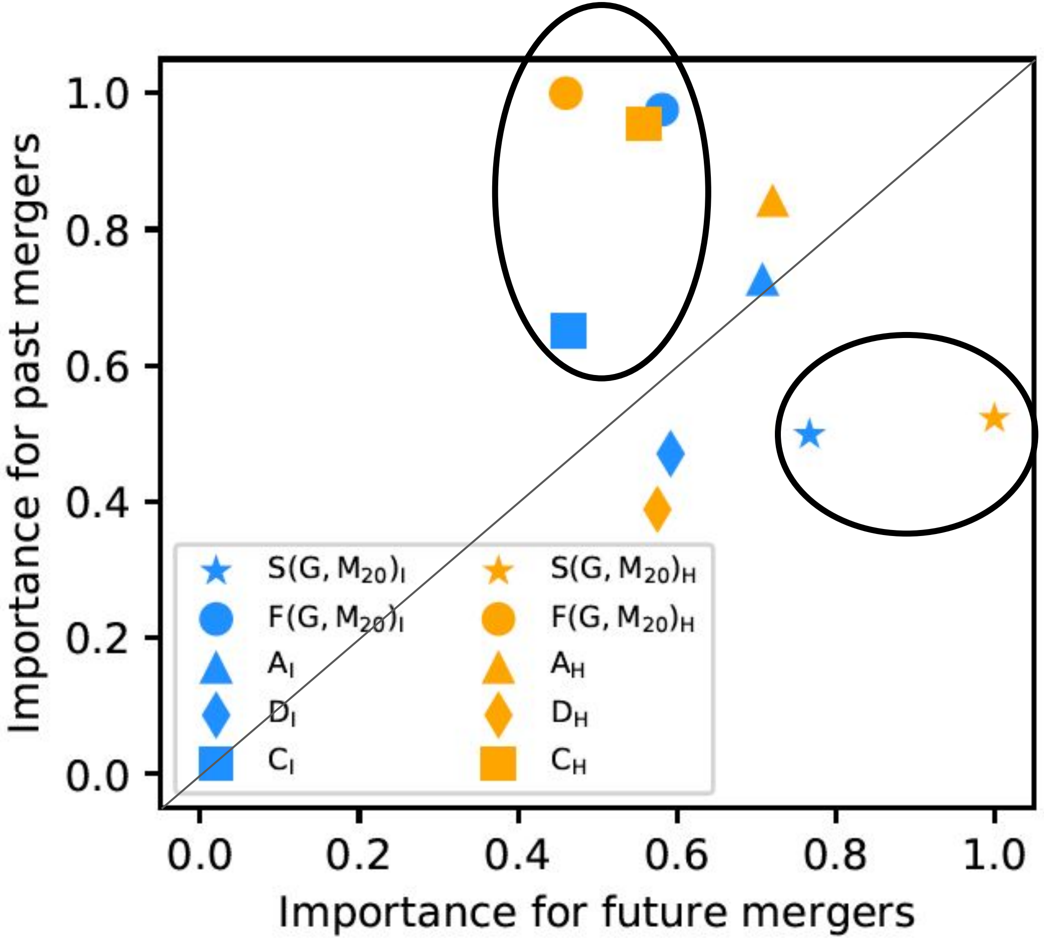


Other work with cosmological zoom simulations has found similar results



Snyder+ 2018

Other work with cosmological zoom simulations has found similar results



Snyder+ 2018

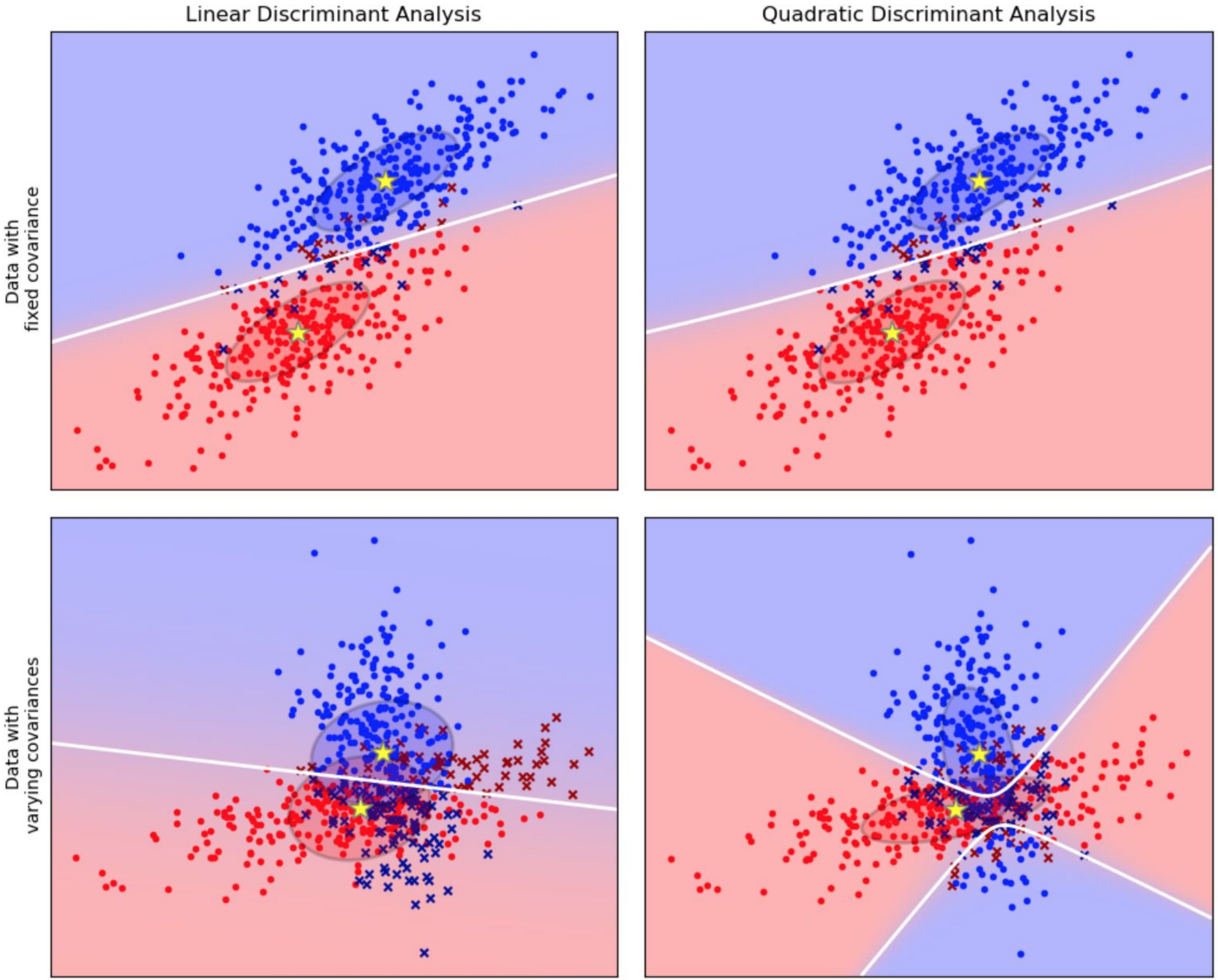
Mathematical Formalism of LDA

Bayes likelihood with discriminant scores:

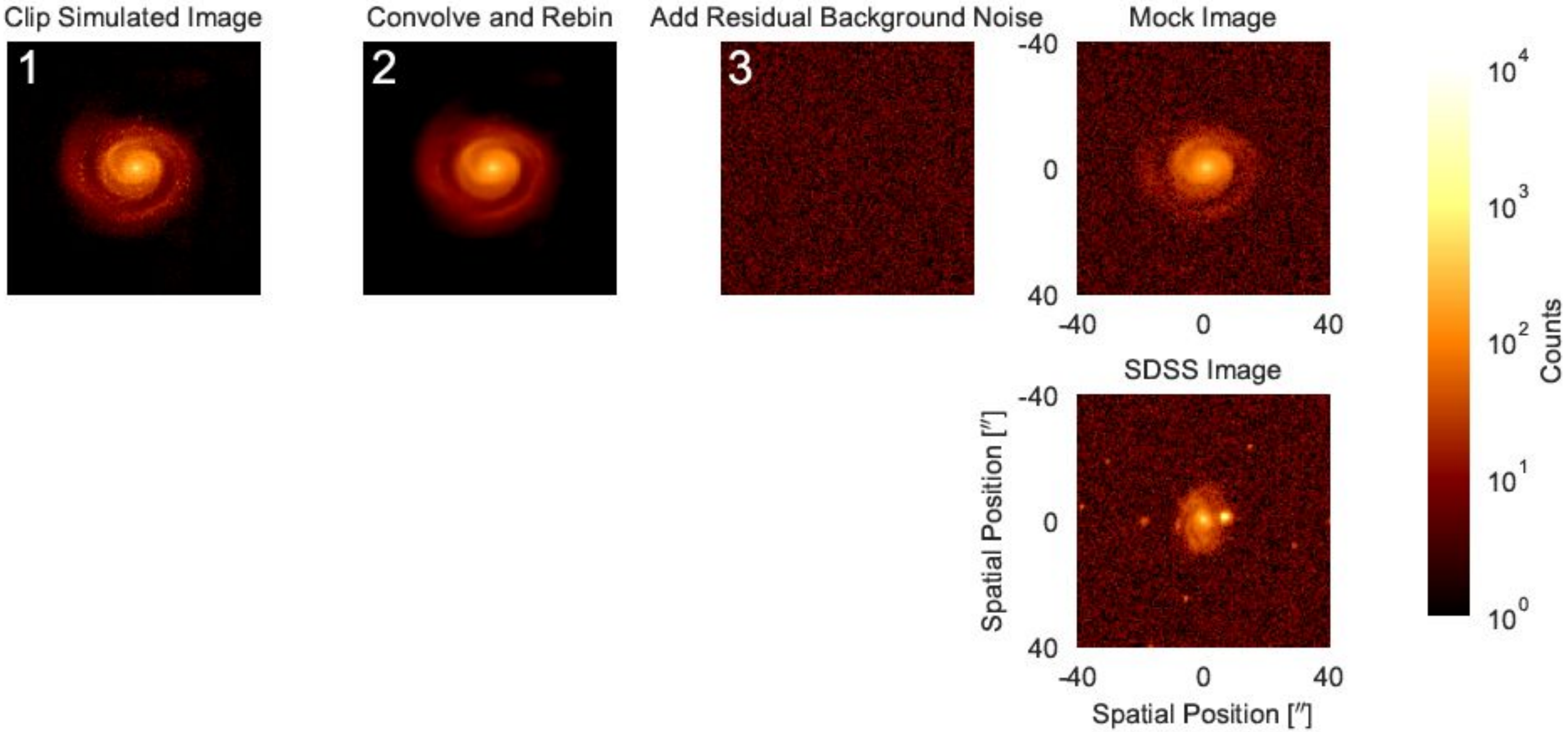
$$p(\pi_0|x) = \frac{e^{\hat{\delta}_0(x)}}{e^{\hat{\delta}_0(x)} + e^{\hat{\delta}_1(x)}}$$

Assumes multivariate normality and homoscedasticity:

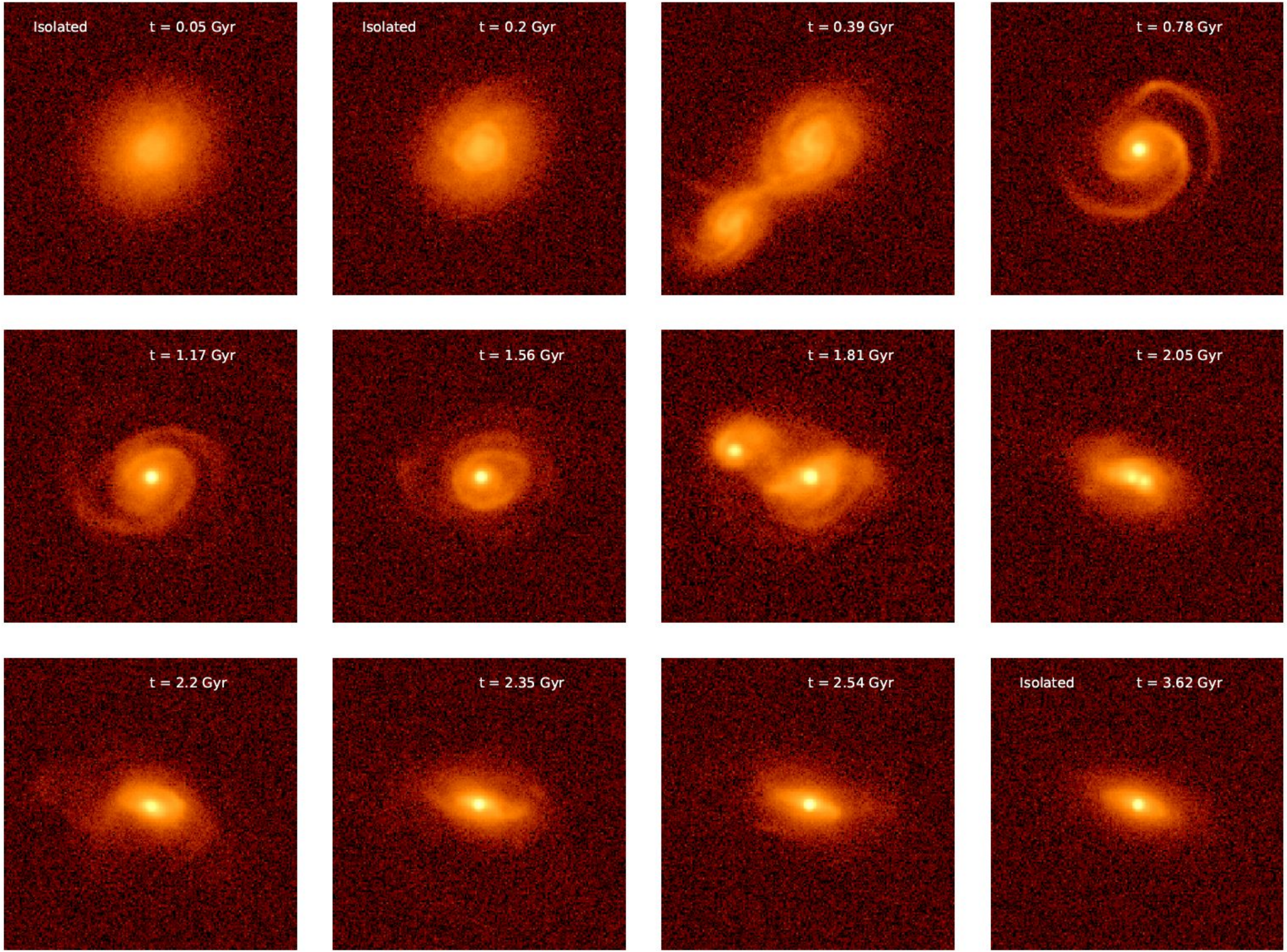
$$\hat{\delta}_0(x) = x^T \Sigma^{-1} \hat{\mu}_0 - \frac{1}{2}\hat{\mu}_0^T \Sigma^{-1} \hat{\mu}_0 + \log(\hat{\pi}_0)$$



Linear Discriminant Analysis
Quadratic Discriminant Analysis
Data with
fixed covariance
Data with
varying covariances



Clip Simulated Image
1
Convolve and Rebin
2
Add Residual Background Noise
3
Mock Image
SDSS Image
-40
0
40
Spatial Position ["]
Spatial Position ["]
10^4
10^3
10^2
10^1
10^0
Counts



Isolated
t = 0.05 Gyr
Isolated
t = 0.2 Gyr
t = 0.39 Gyr
t = 0.78 Gyr
t = 1.17 Gyr
t = 1.56 Gyr
t = 1.81 Gyr
t = 2.05 Gyr
t = 2.2 Gyr
t = 2.35 Gyr
t = 2.54 Gyr
Isolated
t = 3.62 Gyr

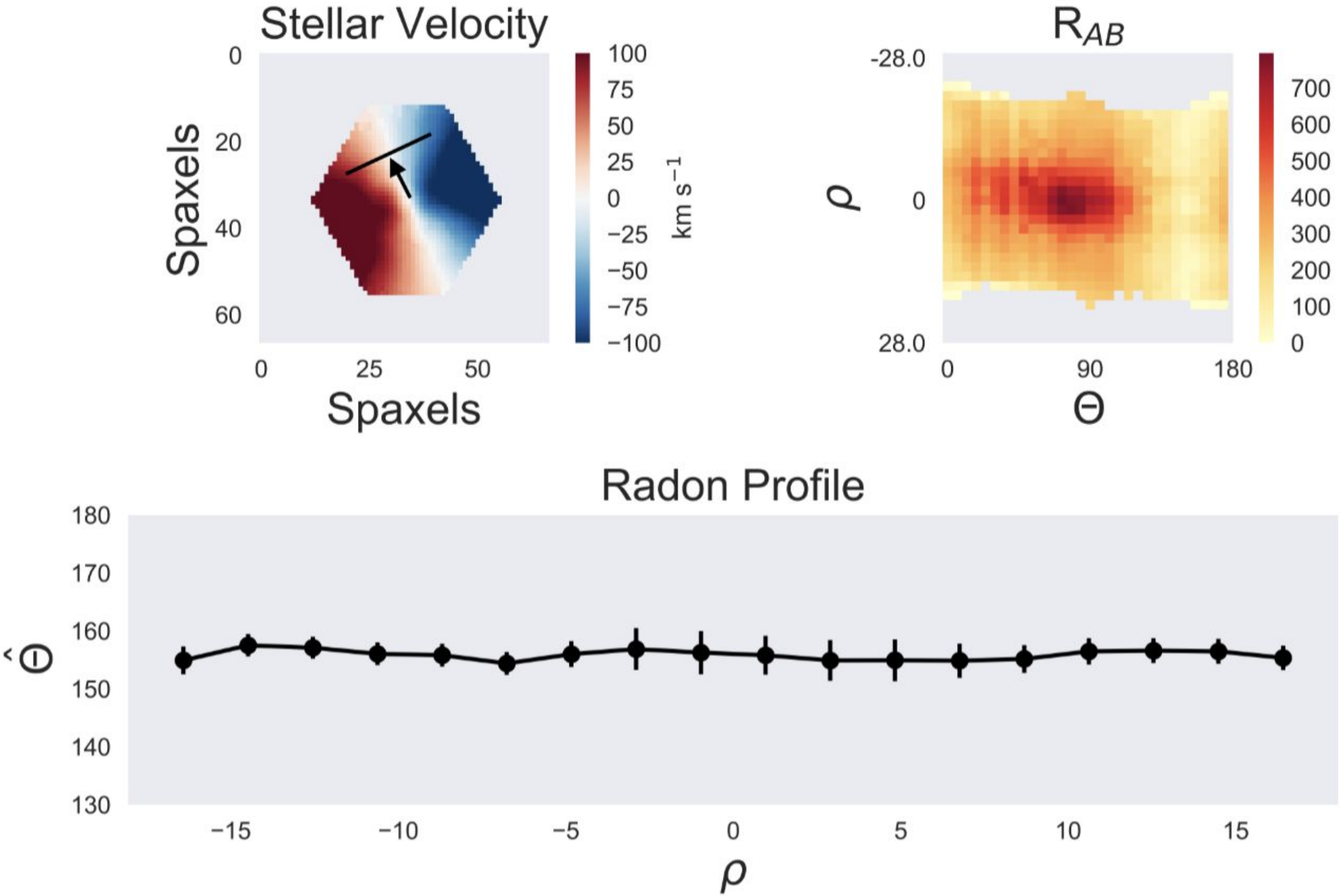
X-terms

I was wrong but it affects the analysis section

Things I could do with the imaging classification

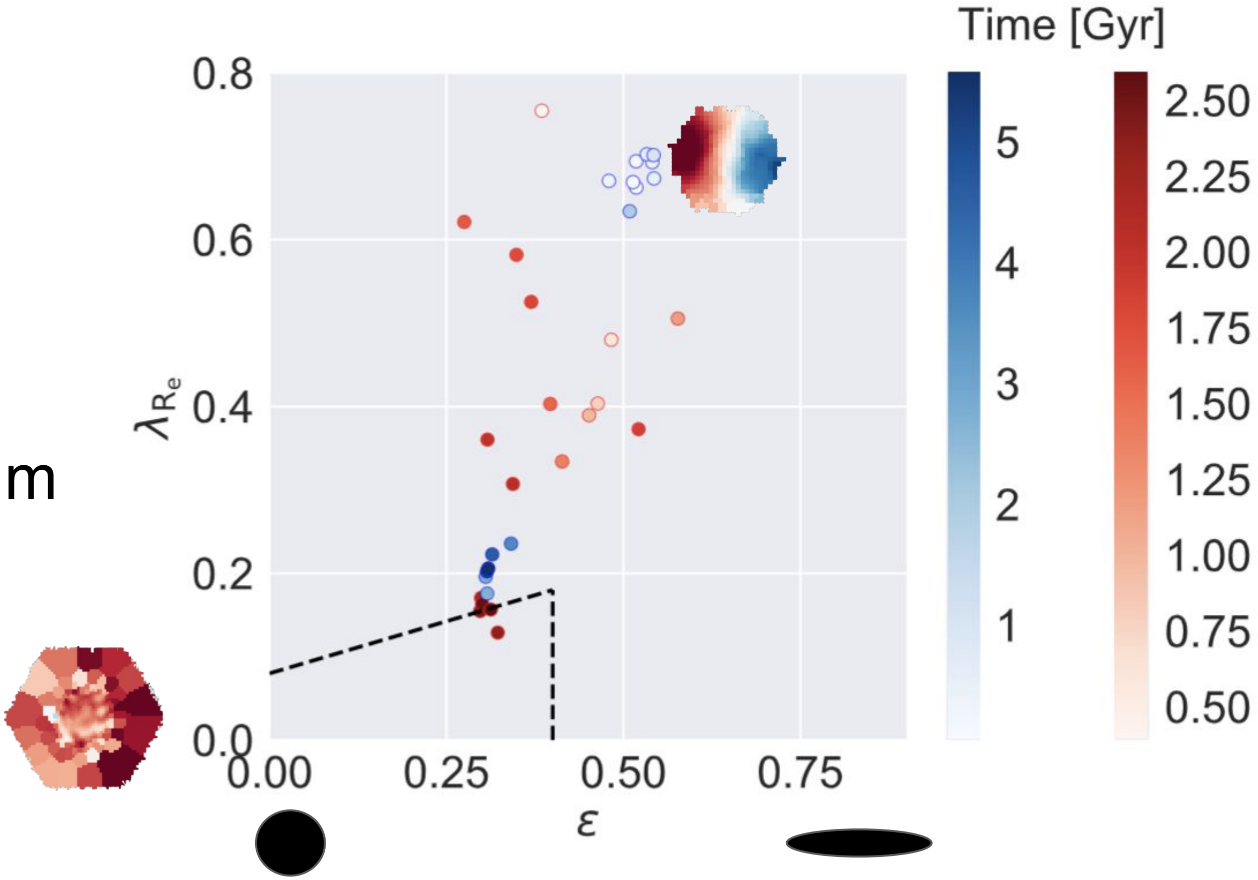
- Double-check most important terms (mostly consistent)
- Run the logistic regression with and without the interaction terms
- Focus on disk-dominated effects when applying to SDSS imaging
- Double-check AGN on vs off broadband images
- HST higher z project
- Looking at multiple different bands
- Adjusting machine learning technique

Extra material from Chapter 5


Stellar Velocity
Spaxels
0
20
40
60
0
25
50
Spaxels
100
75
50
25
0
−25
−50
−75
−100
km s^{-1}
R$_{AB}$
-28.0
0
28.0
ρ
0
90
180
Θ
700
600
500
400
300
200
100
0
Radon Profile
180
170
160
150
140
130
$\hat{\Theta}$
−15
−10
−5
0
5
10
15
ρ

The kinematic predictors evolve non-linearly with time

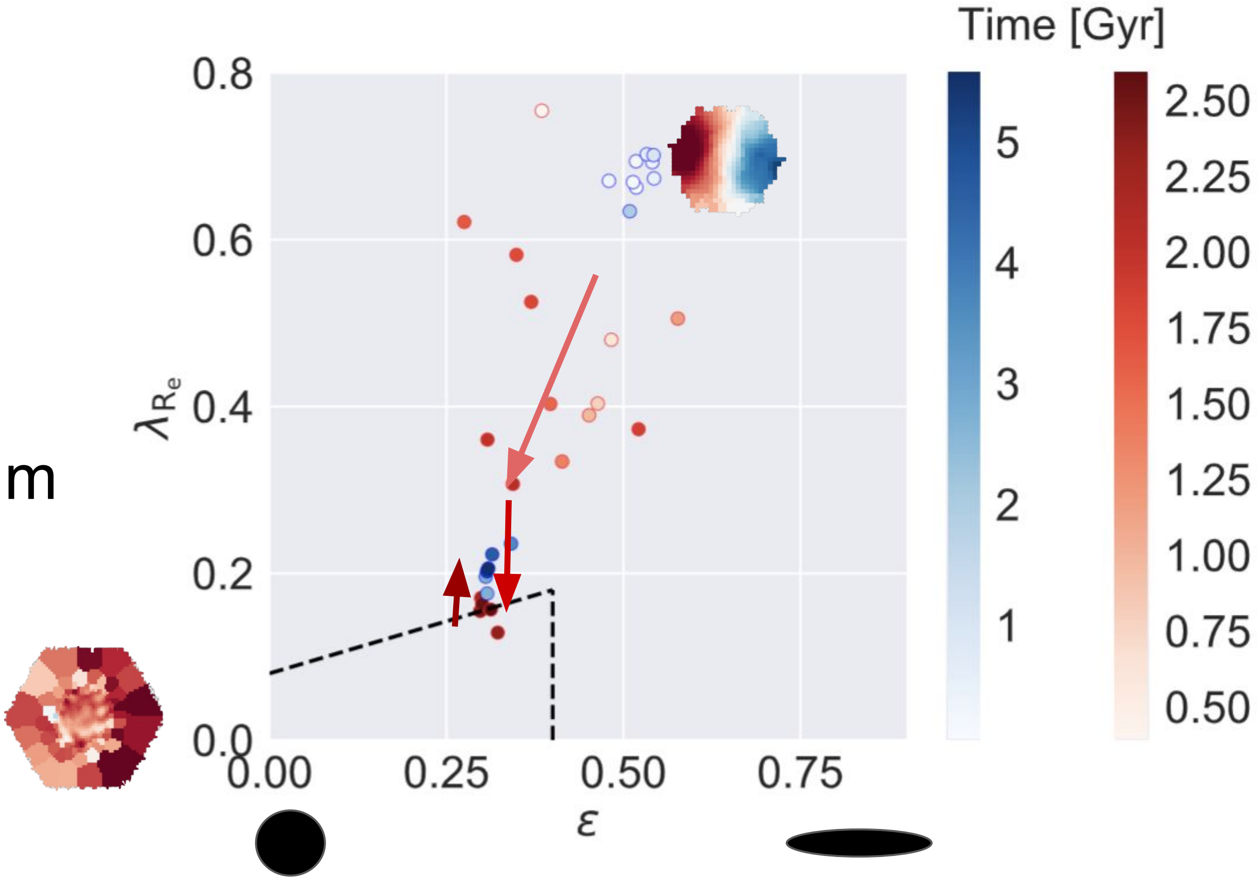
Specific angular momentum



Ellipticity

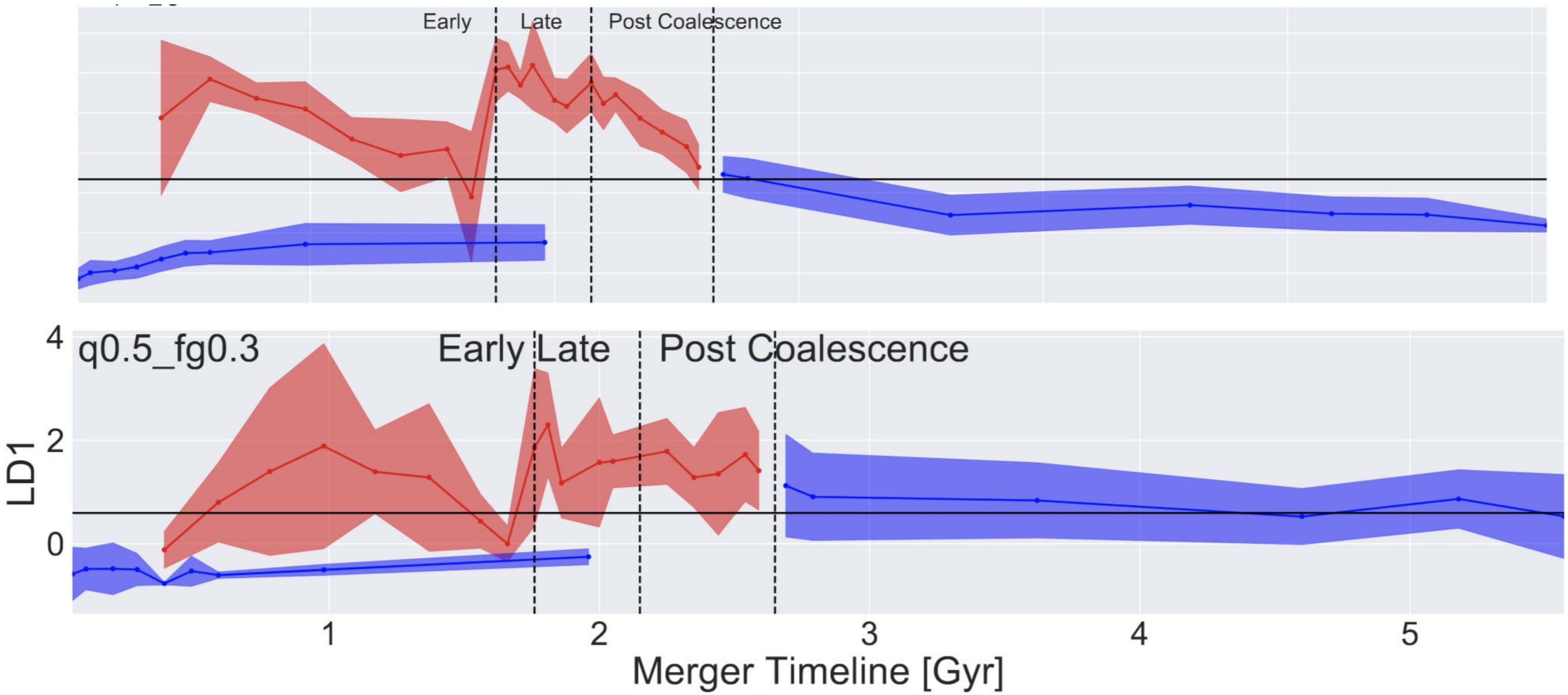
The kinematic predictors evolve non-linearly with time

Specific angular momentum



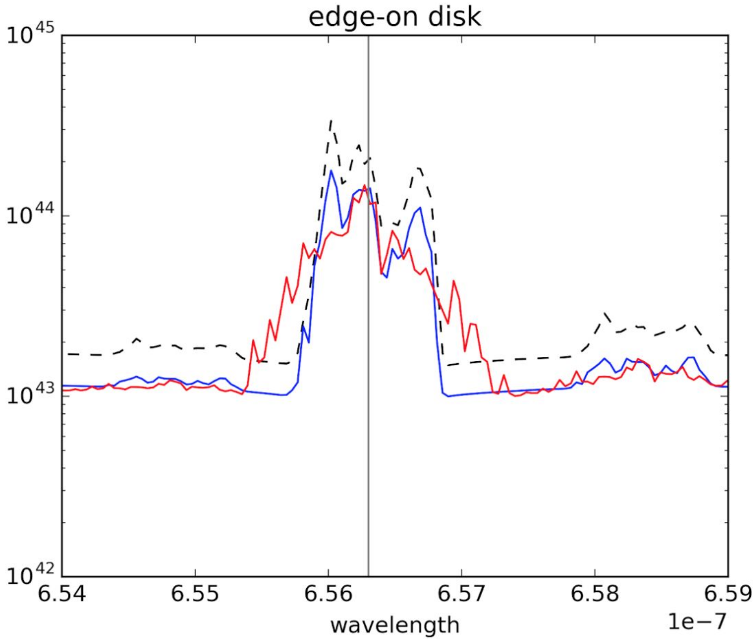
Ellipticity

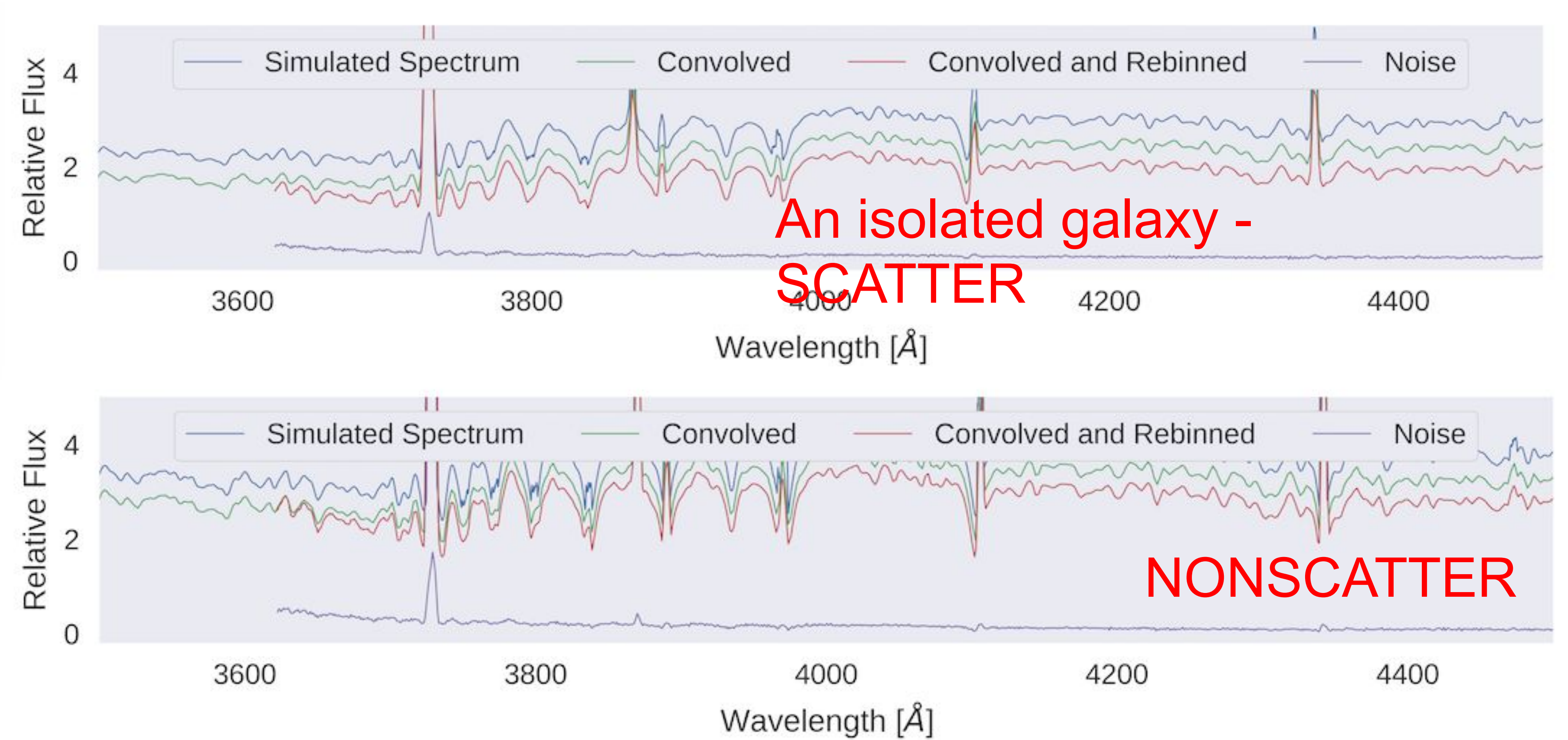
The imaging technique is more accurate and precise

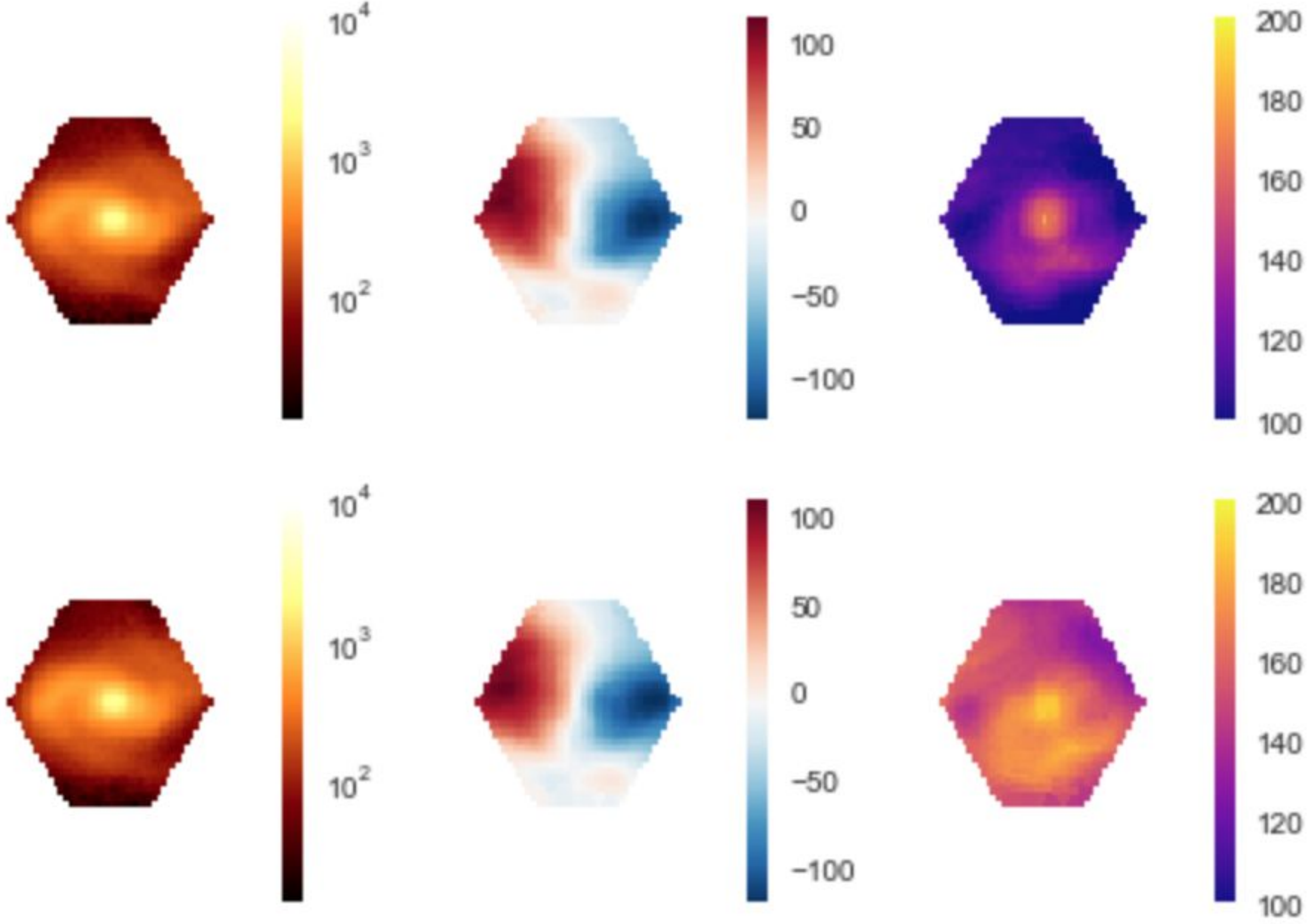


SCATTER v NONSCATTER

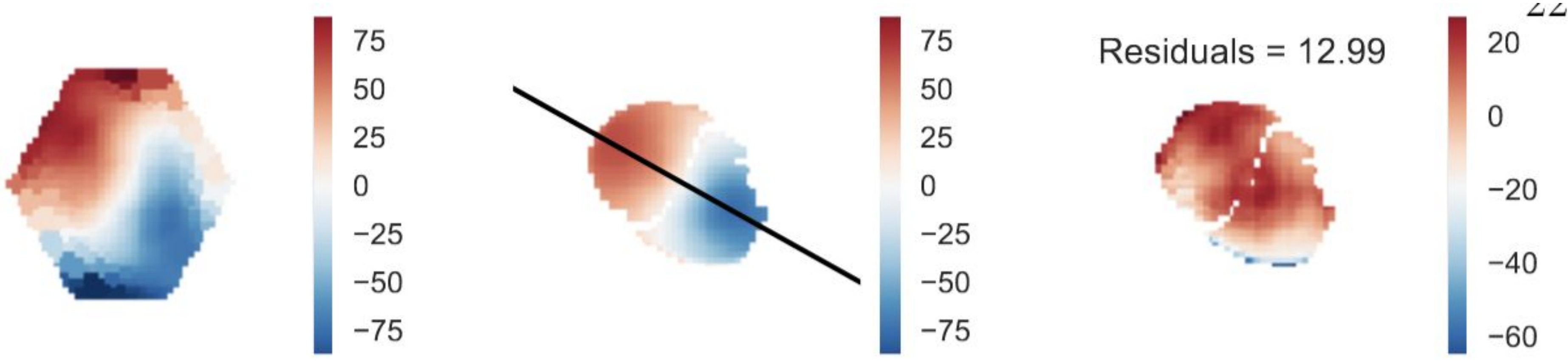
Dust problems, we got em

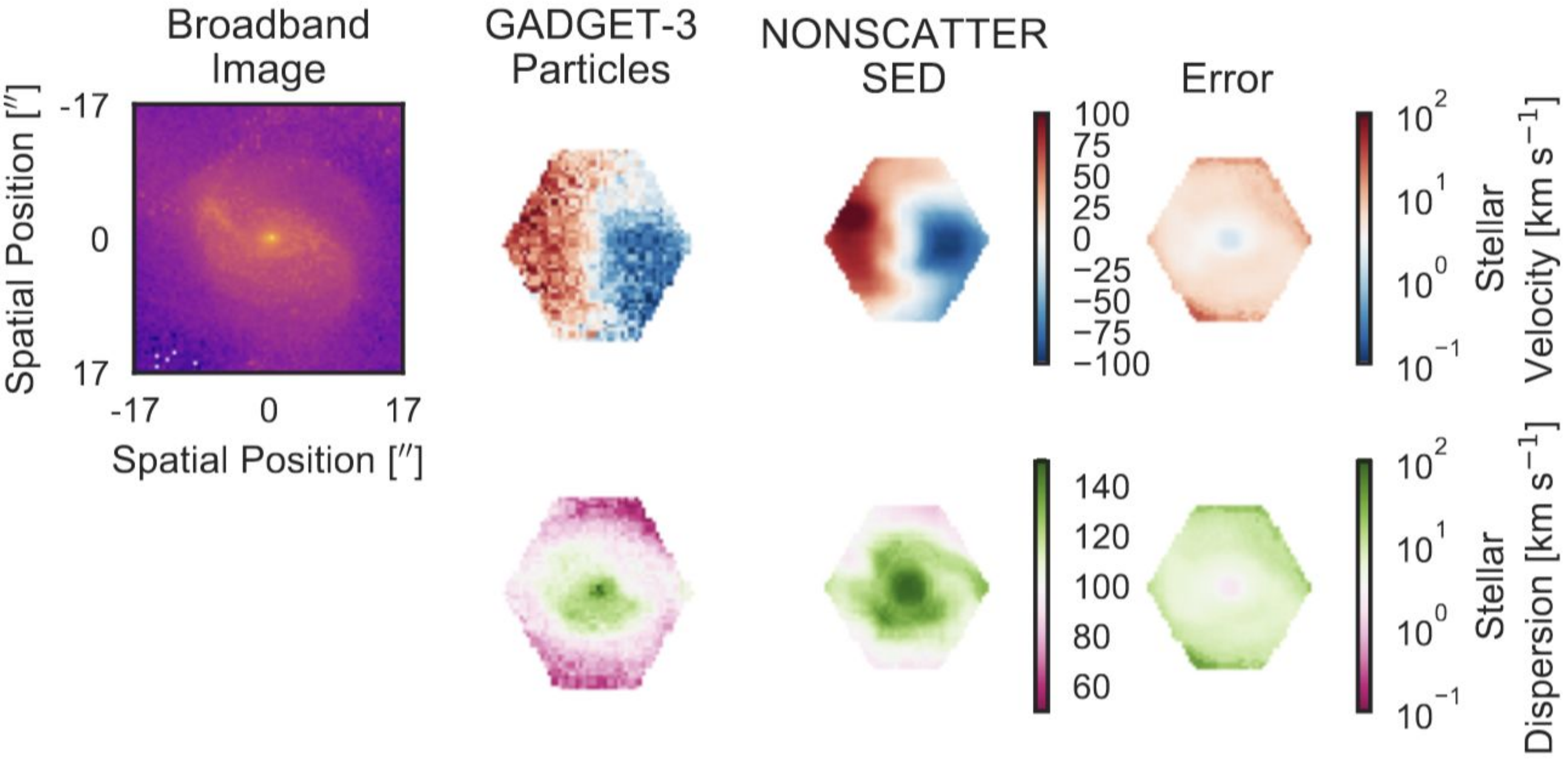



Simulated Spectrum
Convolved
Convolved and Rebinned
Noise
Relative Flux
0
2
4
3600
3800
4000
4200
4400
Wavelength [Å]
An isolated galaxy -
SCATTER
Simulated Spectrum
Convolved
Convolved and Rebinned
Noise
Relative Flux
0
2
4
3600
3800
4000
4200
4400
Wavelength [Å]
NONSCATTER

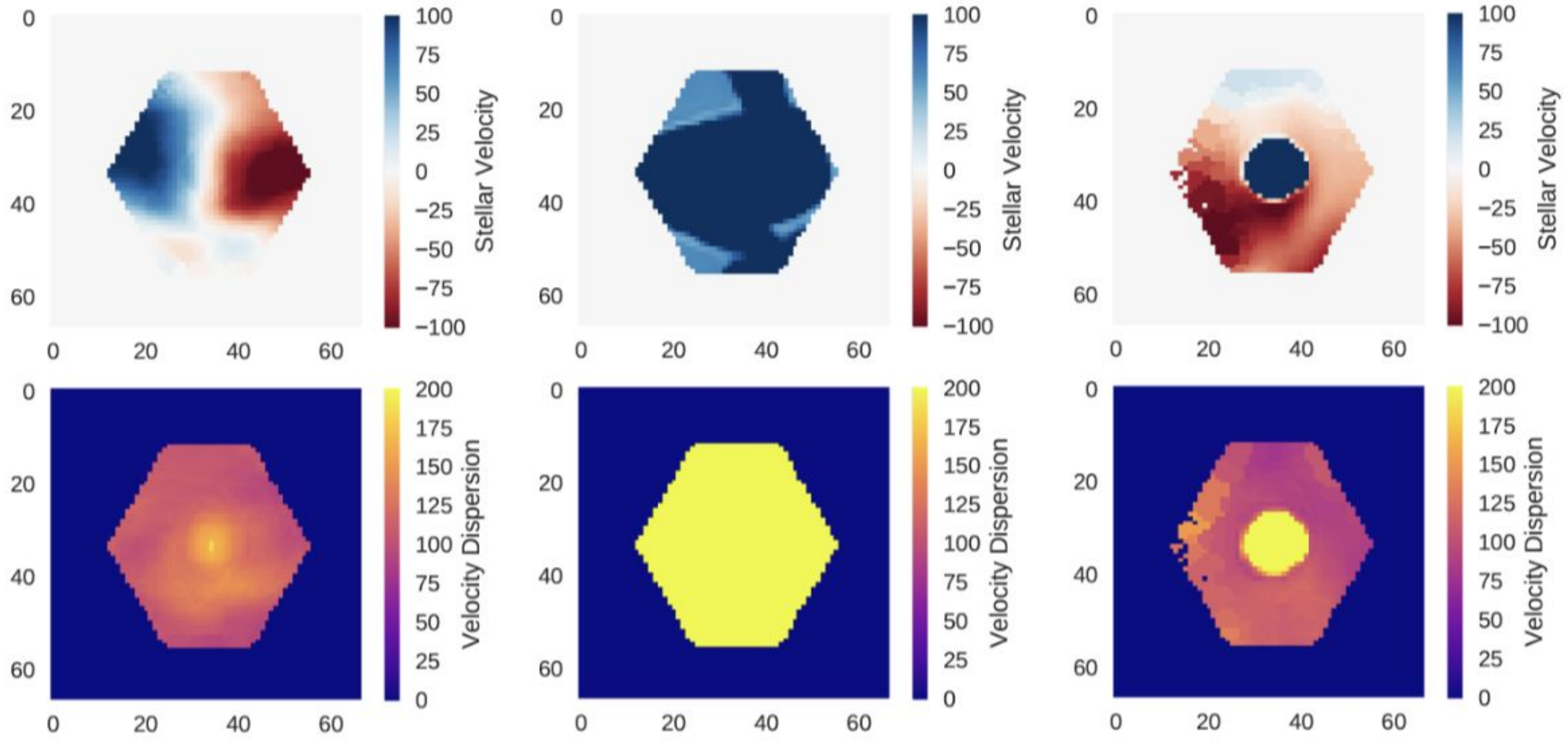

10^4
10^3
10^2
100
50
0
−50
−100
200
180
160
140
120
100
10^4
10^3
10^2
100
50
0
−50
−100
200
180
160
140
120
100

Problems with kinemetry

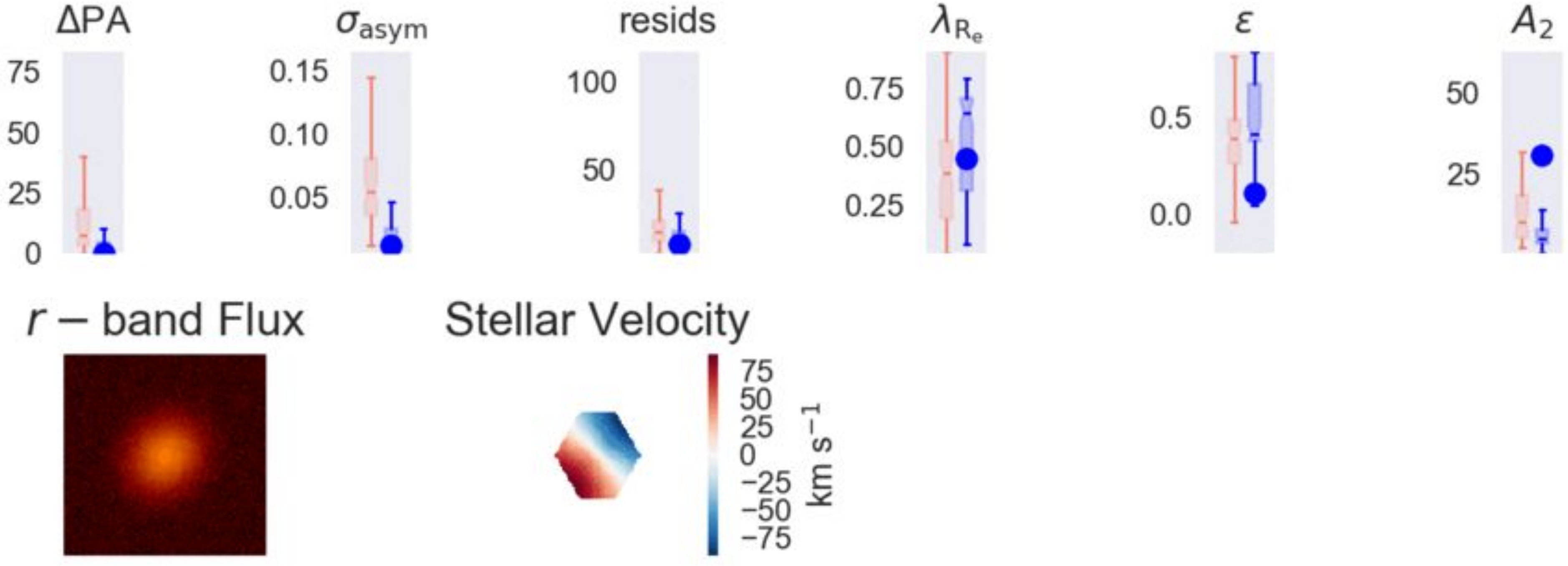


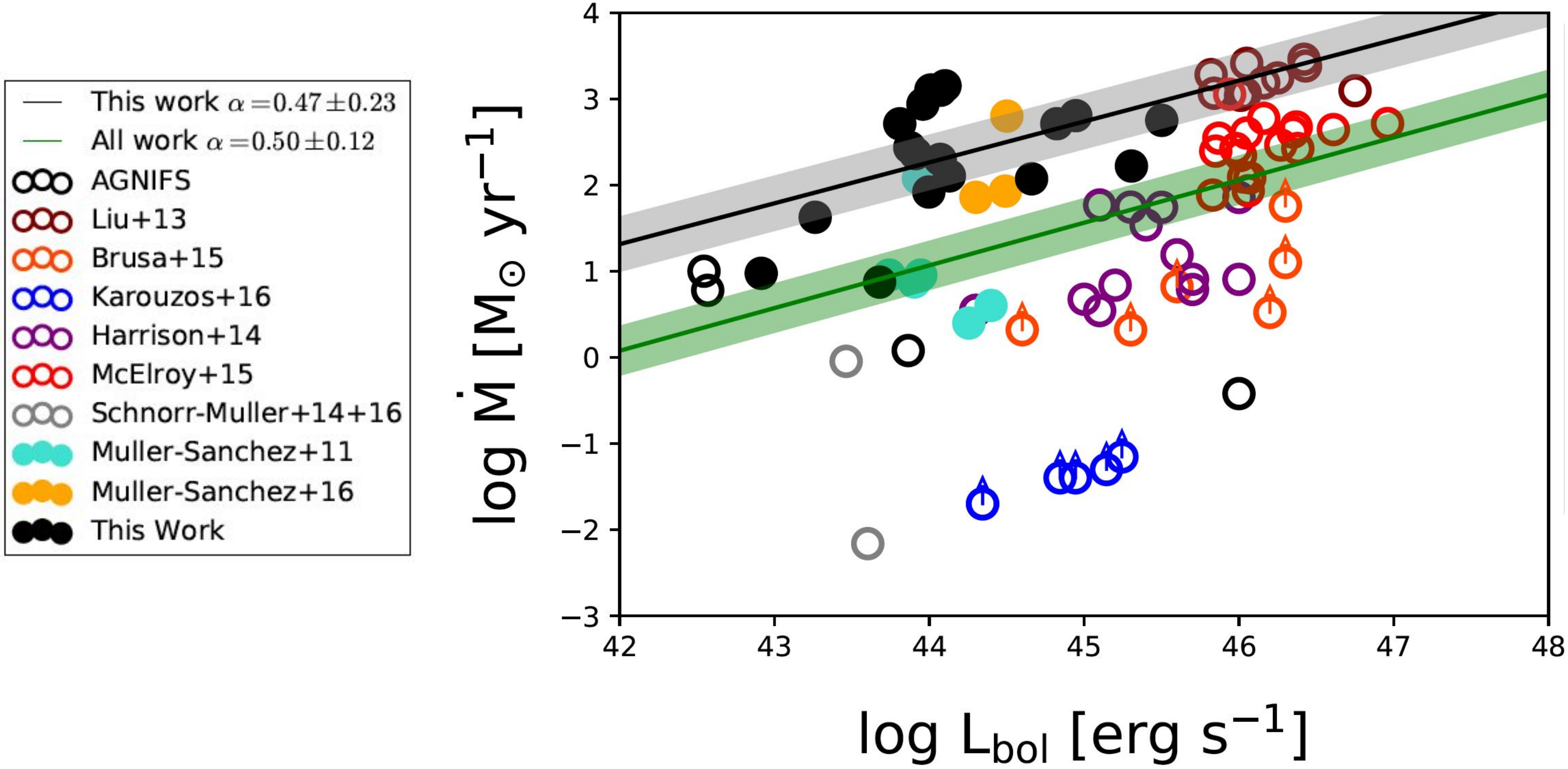


Broadband Image
GADGET-3 Particles
NONSCATTER SED
Error
Spatial Position ['']
Spatial Position ['']
-17
0
17
-17
0
17
100
75
50
25
0
−25
−50
−75
−100
10^2
10^1
10^0
10^{-1}
Stellar Velocity [km s^{-1}]
140
120
100
80
60
10^2
10^1
10^0
10^{-1}
Stellar Dispersion [km s^{-1}]



Stellar Velocity
Velocity Dispersion


ΔPA
0
25
50
75
$\sigma_{\rm asym}$
0.05
0.10
0.15
resids
50
100
$\lambda_{\rm R_e}$
0.25
0.50
0.75
ϵ
0.0
0.5
A_2
25
50
r − band Flux
Stellar Velocity
75
50
25
0
−25
−50
−75
km s^{-1}


This work $\alpha = 0.47 \pm 0.23$
All work $\alpha = 0.50 \pm 0.12$
AGNIFS
Liu+13
Brusa+15
Karouzos+16
Harrison+14
McElroy+15
Schnorr-Muller+14+16
Muller-Sanchez+11
Muller-Sanchez+16
This Work
$\log \dot{M}\ [M_\odot\ yr^{-1}]$
$\log L_{bol}\ [erg\ s^{-1}]$
4
3
2
1
0
−1
−2
−3
42
43
44
45
46
47
48

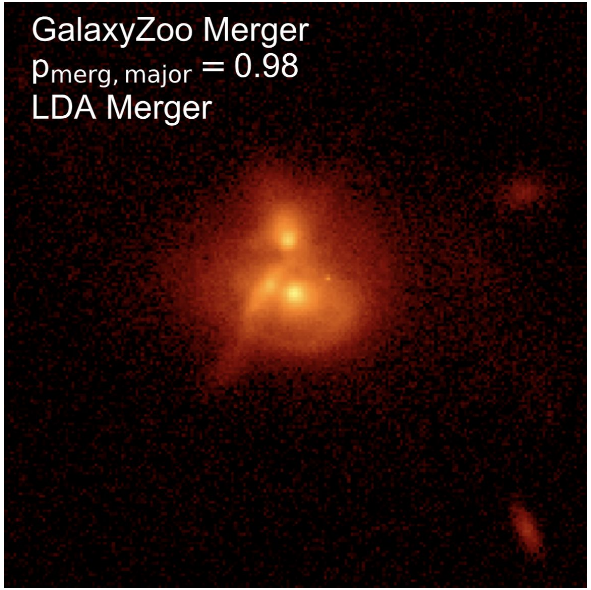
Nevin+ 2018

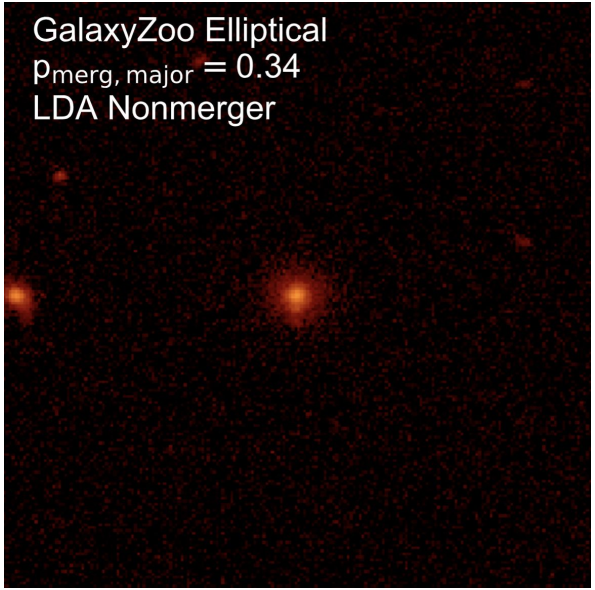
Real MaNGA AGN w/ hole

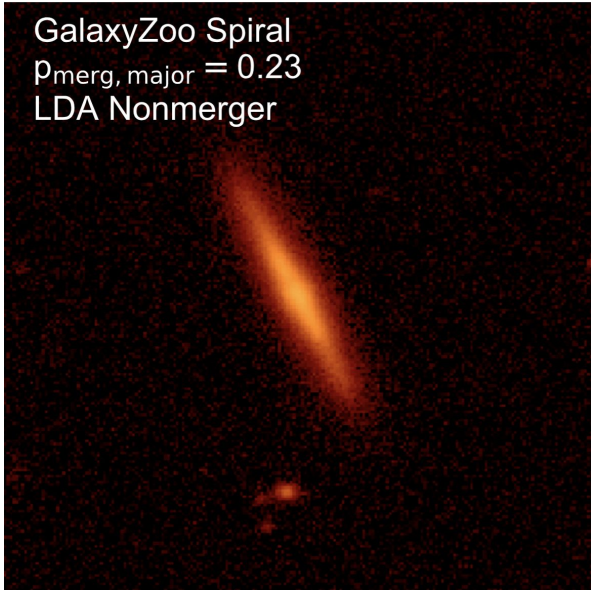
Things I could do with the kinematic classification

- Multiwavelength AGN PSF tool - this could also fix MaNGA's problem
- Kinemetry - is this a failed statistic or the tool itself?
- SCATTER v NONSCATTER - can we go back to SCATTER and fix the bug?
    - Does it affect the analysis to change the velocity dispersion
- Logistic regression with interaction terms
- Could possibly add some terms that work more with velocity dispersion - like the difference between the center of the galaxy (kinematic vs photometric) and the center of the 2D gaussian fit to the velocity dispersion

The classification differs for elliptical galaxies - only apply to a limited range of B/T mass ratio - model with Galfit?







Things I could do with the merger classification

- Discuss differences and limitations of the models
- Disky models = not as accurate for elliptical type galaxies
- Adjust end time - could kinematics prolong the technique beyond 0.5 Gyr after final coalescence?
- How to test if this is applicable for MaNGA galaxies?
  - Carefully test if selected mergers are biased - i.e., only brightest, nearby galaxies
- Collaborate on samples of Illustris?
- Additional