

Are galaxies in compact groups special?

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ABSTRACT

We investigate the properties of galaxies in compact groups (CGs) and compare them to a control sample of galaxies.

Key words. galaxies: clusters: general – catalogs

1. Introduction

2. Data

2.1. Samples

We use the compact groups and control samples we built in our previous article Tricottet et al. (2025). We nevertheless briefly recall here how they were built. Explain. Contrarily to our previous article, though, we remove CGs that we classified as *split* following Zheng & Shen (2021). In this process, our initial compact group sample of 78 groups reduced to 62.

We use the SDSS DR 16 to retrieve masses, star formation rates (SFRs) and morphologies of galaxies assessed in Galaxy Zoo Lintott et al. (2011). We specifically extracted fields `sfr_tot_p50`, `specsfr_tot_p50` and `lgm_tot_p50` from the `galSpecExtra` table, and `p_el_debiased` and `p_cs_debiased` from the `zooSpec` table.

2.2. sSFR

To build a general star formation classification that could be uniformly applied to all our samples, we extracted galaxies from the SDSS DR 16 through the query displayed in listing 1.

```

1      SELECT
2          s.specObjID,
3          s.z,
4          p.petroMag_r,
5          p.objID,
6          g.sfr_tot_p50, g.specsfr_tot_p50, g.
7              lgm_tot_p50,
8              l.h_alpha_eqw, l.h_beta_eqw, l.
9                  oiii_5007_eqw, l.nii_6584_eqw,
10                 l.h_alpha_flux, l.h_beta_flux, l.
11                     oiii_5007_flux, l.nii_6584_flux,
12                     z. p_el_debiased AS p_E,
```

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```

11             z. p_cs_debiased      AS p_S
12             FROM SpecObj AS s
13             JOIN PhotoObj AS p ON s.bestObjID = p
14             .objID
15             JOIN galSpecExtra AS g ON s.specObjID
16             = g.specObjID
17             JOIN galSpecLine AS l ON s.specObjID
18             = l.specObjID
19             JOIN zooSpec AS z ON s.specObjID = z.
20             specObjID
21             WHERE s.z BETWEEN 0.005 AND 0.0452
22             AND (p.petroMag_r - p.extinction_r <=
23                   17.77)
24             AND s.class = 'GALAXY'
25             AND g.lgm_tot_p50 > -1000
```

Listing 1. Query used for selecting spectral & photometric data from the SDSS

We select non-AGN galaxies by first placing them on the classical BPT diagnostic of Veilleux & Osterbrock (1987) and requiring measured values of both emission-line ratios

$$\log_{10}(\text{[N II]}\lambda 6584/\text{H}\alpha) \text{ and } \log_{10}(\text{[O III]}\lambda 5007/\text{H}\beta).$$

A galaxy is flagged as an AGN if it satisfies either

$$\log_{10} \frac{\text{[N II]}}{\text{H}\alpha} > 0,$$

or if it lies above the empirical demarcation of Kauffmann et al. (2003):

$$\log_{10} \frac{\text{[O III]}}{\text{H}\beta} > \frac{0.61}{\log_{10}(\text{[N II]}/\text{H}\alpha) - 0.05} + 1.3,$$

in which case it is removed from the non-AGN sample. All remaining galaxies—including those with missing line ratios—are retained as non-AGN. The non-AGN selection process is shown on figure 1.

We identify the galaxies having a `specsfr_tot_p50` of -9999 in the SDSS as quenched (for graphic representation purposes, we give it here an arbitrary low value

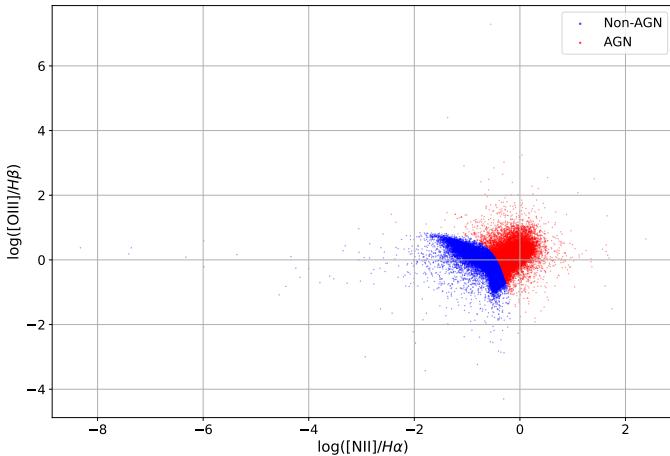


Fig. 1. BPT diagram showing our separation between ordinary and AGN galaxies

of $10^{-16.0}$ Gyr $^{-1}$). We then consider the other ones and sort them between the star-forming and passive populations using a two-component Gaussian Mixture Model (GMM) in the $\log M_*$ - $\log \text{sSFR}$ plane. Its parameters determined by minimizing the Kullback–Leibler divergence between the empirical and model densities Kullback & Leibler (1951); McLachlan & Peel (2000). For any trial parameter vector θ , we reconstruct the mixture means $\{\mu_i\}$, covariances $\{\Sigma_i\}$, and weights $\{w_i\}$ via a Cholesky-like decomposition and logistic mapping, optionally constraining the second component’s mean to isolate the passive population Dempster et al. (1977). The KL divergence is estimated by constructing a 2D histogram of the data and summing $p_{\text{data}} \ln(p_{\text{data}}/p_{\text{GMM}})$, with a small regularization ϵ to avoid singularities Tojeiro et al. (2009); Bisigello et al. (2018). We optimize θ via L-BFGS-B (with fallback to Nelder–Mead) over multiple guided and random initializations, selecting the solution with lowest divergence Pedregosa et al. (2011); Bishop (2006). Initial means are seeded by a median split in $\log \text{sSFR}$ to improve convergence and robustness against local minima Rousseeuw (1987). In the final fit, one component naturally aligns with the high-sSFR “star-forming sequence,” while the other captures the low-sSFR “passive” cloud, providing a data-driven division that agrees with previous multi-Gaussian decompositions of the SFR– M_* plane Wuyts et al. (2011); Hahn et al. (2019). The decision boundaries, defined as the loci where the posterior probabilities of adjacent components are equal, provide an objective criterion for delineating star-forming from passive galaxies.

Add relevant GM parameters found by the algorithm.

The sSFR status for each sample is shown in table 1.

The probability for Star forming proportion between CG₄ and each control sample to actually come from the same underlying distribution are, estimated using Fisher exact test, 4.8×10^{-1} versus Control_{4B} sample, 2.2×10^{-1} versus Control_{4C} and 4.1×10^{-3} versus RG₄.

2.3. Morphology

Morphologies are determined via the Galaxy Zoo citizen-science decision tree, in which each galaxy image receives multiple independent volunteer classifications that are aggregated into debiased vote fractions Lintott et al.

Sample	Quenched	Passive	Starforming
CG ₄	4 (1.0 %)	128 (31.8 %)	270 (67.2 %)
Control _{4B}	32 (0.8 %)	1400 (36.3 %)	2427 (62.9 %)
Control _{4C}	31 (0.7 %)	1839 (39.1 %)	2839 (60.3 %)
RG ₄	0 (0.0 %)	149 (55.6 %)	119 (44.4 %)
<i>SDSS selection</i>	634 (1.2 %)	44192 (84.1 %)	7705 (14.7 %)

Table 1. Number of galaxies in each sSFR status for each sample.

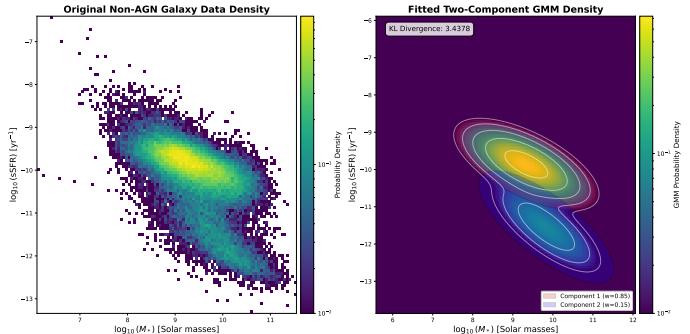


Fig. 2.

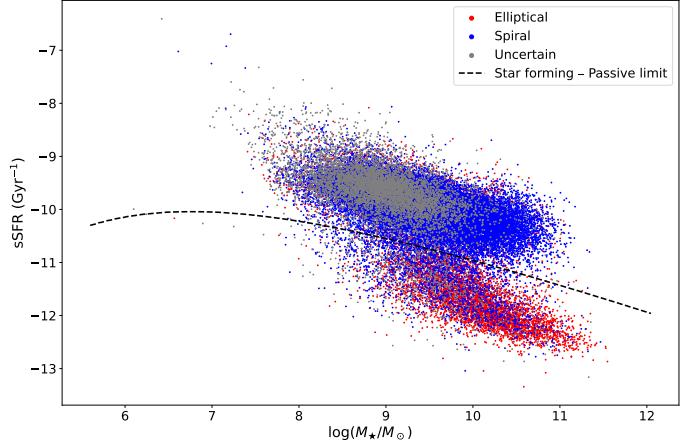
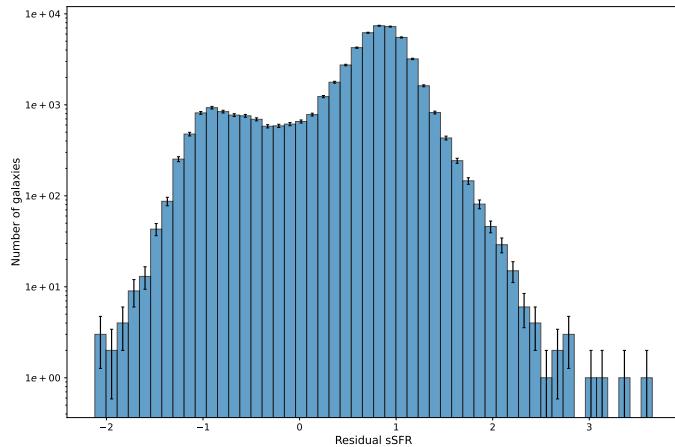
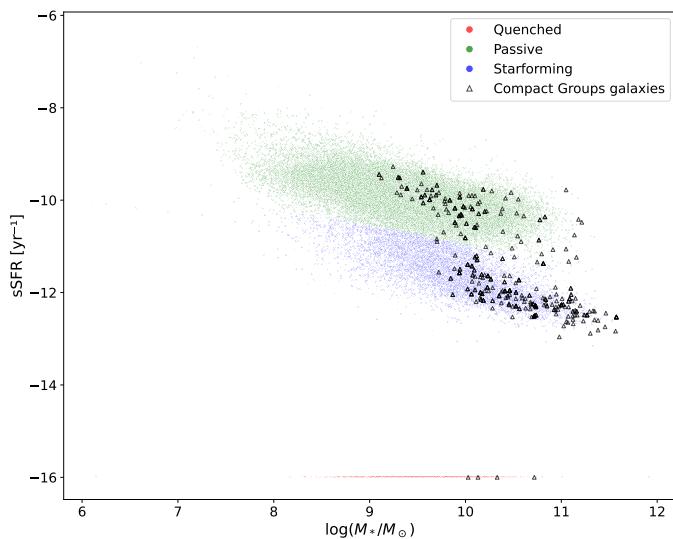


Fig. 3. sSFR vs mass, star-forming/passive limit and Zoo morphologies for the SDSS control sample, excluding quenched galaxies.

(2011). Those fractions are provided in the `zooSpecz` table of the SDSS database through the `p_el_debiased` and `p_cs_debiased` columns. We attribute to galaxies the morphology “elliptical” if the `p_el_debiased` value is greater than 0.5, and “spiral” if the `p_cs_debiased` value is greater than 0.5. Other cases are considered as “uncertain”. The morphologies found for each sample are shown in table 2. Barnard two-sided exact tests were performed to compare the fraction of each morphology between CG₄ and each control sample. The p-values found are 1.6×10^{-5} for ellipticals and 6.0×10^{-1} for spirals versus Control_{4B} sample, 7.4×10^{-2} and 6.1×10^{-1} versus Control_{4C} and 2.8×10^{-9} and 2.4×10^{-2} versus RG₄.

**Fig. 4.****Fig. 5.** sSFR and morphologies of galaxies in CG₄ and our SDSS selection. Quenched galaxies are represented at an arbitrary low value of $10^{-16.0}$ Gyr⁻¹.

Sample	Elliptical	Spiral	Uncertain
CG ₄	144 (35.8 %)	158 (39.3 %)	100 (24.9 %)
Control _{4B}	982 (25.4 %)	1465 (38.0 %)	1412 (36.6 %)
Control _{4C}	1483 (31.5 %)	1912 (40.6 %)	1314 (27.9 %)
RG ₄	37 (13.8 %)	129 (48.1 %)	102 (38.1 %)
SDSS selection	10091 (19.2 %)	34715 (66.1 %)	7725 (14.7 %)

Table 2. Number of galaxies of each morphology for each sample.

Interpolation points for sSFR classification

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