Research Progress on the Impact of Filamentary Environments on Star Formation Activity in Galaxies: Postprint

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Abstract

Large-scale structures composed of galaxies and extending to scales of hundreds of parsecs are known as the cosmic web. Depending on morphology and galaxy density, the cosmic web is divided into structures including nodes, filaments, walls, and voids. Among these, galaxies near filaments typically have higher masses and a higher fraction of early-type red galaxies compared to those in voids. Observational and simulation results indicate that star formation activity in galaxies weakens as they approach filaments. Several factors may introduce uncertainties to this result: (1) filament structures identified by different algorithms may differ; (2) there are different methods for measuring the geometric properties of filament structures; (3) galaxies near filaments typically have larger stellar masses, higher local environmental galaxy densities, and larger host dark matter halo masses, which can also cause changes in galaxy star formation activity. This review examines algorithms for studying the cosmic web and explores the effect of filaments on star formation activity while controlling for factors such as stellar mass, galaxy density, and dark matter halo mass, in order to understand how galaxy star formation activity is influenced in filament environments.

Full Text

Preamble

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Recent Advances in the Study of Effects of Cosmic Filaments on Star Formation Activities

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Abstract

Large-scale structures composed of galaxies and extending up to hundreds of parsecs are known as the cosmic web. Based on morphology and galaxy density, the cosmic web is classified into nodes, filaments, walls, and voids. Galaxies near filaments typically exhibit higher masses and a greater proportion of early-type red galaxies compared to those in voids. Observational and simulation results indicate that star formation activity in galaxies diminishes as they approach filaments. Several factors may introduce uncertainties into these findings: (1) filament structures identified by different algorithms may vary; (2) diverse methods exist for measuring the geometric properties of filaments; and (3) galaxies near filaments generally possess larger stellar masses, reside in regions of higher local galaxy density, and inhabit more massive host dark matter halos, all of which can also influence star formation activity. This review examines algorithms for studying the cosmic web and discusses the impact of filaments on star formation activity while controlling for factors such as stellar mass, galaxy density, and halo mass, aiming to understand how galactic star formation is affected by the filamentary environment.

Keywords: cosmic filament; galaxy quenching; star formation

1 Introduction

The cosmic web represents the largest-scale structure in the observed universe, exhibiting fractal self-similarity and allowing classification of different structures across various scales. Regions with low galaxy number density are typically termed "voids," while high-density regions are called "nodes." Sparse structures or "voids"devoid of galaxies occupy nearly 95% of cosmic space [1, 2]. "Filaments" and "walls" represent structures of intermediate density, with lengths ranging from tens to hundreds of megaparsecs. Direct observations of wall structures remain limited, with notable examples including the CfA2 Great Wall [3], the Sloan Great Wall [4], and the Hercules-Corona Borealis Great Wall [5]. Evidence for cosmic filamentary structures at low redshift is abundant, including from the Sloan Digital Sky Survey (SDSS) [6]. Through Lyman-α radiation, astronomers can also map the morphology and physical properties of cosmic filaments at high redshift. Wang et al. [7] discovered a filament structure existing merely 830 million years after the Big Bang, identified by bright quasars and composed of 10 galaxies extending 3 million light-years.

Studying large-scale cosmic structures aids in understanding fundamental questions such as the Big Bang and in constructing and refining cosmological models. Cosmic inflation is generally believed to have generated tiny primordial perturbations that collapsed under gravity to form large-scale filaments. Filament structures formed in different cosmological models—such as cold dark matter and warm dark matter scenarios—would exhibit distinct morphologies. Investigating large-scale structures through observations and simulations helps constrain cosmological parameters including dark matter density, dark energy density, and the Hubble constant. The diverse large-scale environments also provide natural laboratories for studying galaxy formation and evolution. Filaments—elongated structures composed of dark matter and baryonic matter (galaxies, gas, etc.) that connect galaxies and galaxy clusters—exhibit several characteristics that distinguish galaxies in their vicinity from field galaxies: (1) galaxies in filaments have higher masses than those outside filaments. Laigle et al. [8] used data from the COSMOS survey [9] to study galaxy mass profile curves, finding that massive galaxies are distributed closer to filament centers than low-mass galaxies. Galaxies may gradually increase their mass through mergers as they travel along cosmic filaments into galaxy clusters [10]. (2) The proportion of early-type galaxies near filaments is higher, and galaxies appear redder. Kuutma et al. [11] found that the elliptical-to-spiral galaxy ratio (E/S) increases near filaments, synchronized with changes in $g-i$ color. Salerno et al. [12] demonstrated that the fraction of red galaxies is highest in clusters, intermediate in filaments, and lowest in the field. How far does the filament environment influence star formation within galaxies? Do filaments transport baryonic matter? Is the growth and evolution of filaments synchronized with galaxy mergers and evolution? Answering these questions will not only advance galaxy evolution studies but also deepen our understanding of the properties and formation processes of large-scale structures.

Section 2 enumerates several algorithms for identifying filamentary structures. Section 3 reviews research progress on the influence of filamentary environments on galactic star formation activity. Subsection 3.1 summarizes observations and simulations showing decreased star formation activity near filaments. Subsection 3.2 discusses studies of filament quenching mechanisms after controlling for variables such as halo mass and local galaxy density field, including ranking of variable importance using random forests. Subsection 3.3 explores the possibility that the cosmic web may facilitate star formation activity through gas transport. Section 4 provides a summary and outlook.

2 Overview of Algorithms for Identifying Cosmic Web Structures

Libeskind [13] summarized several algorithms for finding cosmic web structures in their study. As a supplement, this review examines the most commonly used DisperSE (Discrete Persistent Structures Extractor) algorithm and also discusses Sconce, MCPM, the Bisous model, and simple connection network algorithms, comparing their advantages and disadvantages with a summary provided in Table 1 .

2.1 DisperSE

The widely used structure finder DisperSE can extract persistent topological features such as peaks, voids, and walls, and trace filaments connecting them [14]. DisperSE begins with field data—a set of discrete points from galaxy coordinates, halo positions, or dark matter particles in simulations. It then tessellates the field using DTFE (Delaunay Tessellation Field Estimator) [15] and computes smoothed density fields by averaging adjacent values (from the two nearest vertices) at each tessellation vertex. Structures in the density field are identified as functions on a Morse-Smale complex. Points where the density function gradient equals zero are critical points, comprising maxima, minima, and saddle points. In DisperSE, filaments are one-dimensional structures—one-manifolds of ascending or descending gradient—composed of two integral lines (curves tangent to the gradient field at each point) emanating from a given saddle point and connecting to two maxima.

Topological structures in data may be unstable. For instance, data noise can create temporary structures, while smoothing at different scales may cause them to disappear. DisperSE identifies and quantifies the significance of these structures by measuring topological persistence [16]. It calculates the persistence ratio between pairs of critical points (e.g., a maximum and saddle point) and removes points with occurrence probabilities below a set threshold in random fields. Lower thresholds enable detection of more filamentary structures.

2.2 Sconce

For two- and three-dimensional discrete point coordinates, Zhang et al. [17] developed two Python packages (DirSCMS, DirLinSCMS) to identify filamentary structures. The Sconce algorithm operates through two processes: (1) computing density fields on regularly spaced grid points using a directional kernel density estimator in spherical coordinates [18, 19] with appropriate smoothing bandwidth parameters (larger bandwidth yields smoother density fields); and (2) directly locating density ridges—comprising local density maxima in the normal direction as defined by the Hessian matrix—through an iterative gradient-ascent-like process. Sconce effectively avoids spurious filament structures caused by the "fingers of God" effect [20] when converting redshift to comoving distance, and can simultaneously construct filaments parallel and perpendicular to the line of sight in three-dimensional space.

Zhang et al. [17] compared filament structures identified by Sconce and DisperSE in their Figure 4 [Figure 4: see original paper]. They found that in high-declination regions of the celestial sphere, DisperSE yields irregular filamentary structures potentially containing numerous spurious components, though it excels at identifying short filamentary "tendrils." In contrast, Sconce achieves higher recovery precision for filaments, showing clear advantages in locating long filaments while avoiding errors that may arise from reconnecting short filamentary segments.

2.3 MCPM

The Monte Carlo Physarum Machine (MCPM) [21] draws inspiration from Jones [22] and emulates the efficient network-forming behavior of the slime mold *Physarum polycephalum* when foraging for food [23]. In the algorithm, "slime mold" moves along "chemoattractant" paths, depositing its own trail at each time step to find optimal transport networks. MCPM adapts this model to three dimensions, sampling possible paths probabilistically so that routes leading to smaller deposits may still be traversed. This approach' s advantage lies in its ability to reasonably interpolate low-density regions of the cosmic web. MCPM has been applied to analyze galaxy and fast radio burst data [21, 24], advancing studies of intergalactic neutral hydrogen and thermally ionized gas in the cosmic web.

2.4 Bisous Model and Connection Network Algorithms

Some algorithms identify cosmic web structures through geometric connectivity properties combined with statistical methods, without requiring density field interpolation, smoothing, or estimation. The Bisous model proposed by Tempel et al. [25] assumes galaxies cluster within small cylinders that combine into filaments when neighboring cylinders align in similar directions. Each small cylinder is characterized by four parameters: central coordinates, height, base radius, and direction vector. The model then computes a probability density field based on the Poisson distribution probability density function, using system energy as the primary parameter (equivalent to total Gibbs energy in physics, determined by cylinder positions, alignment, and connectivity in the galaxy field). Filaments are finally extracted from regions with high probability density. The Bisous model can accurately identify filaments while considering network connectivity, though implementation is complex.

Hong and Dey [26] proposed that two galaxies are considered connected when their separation is smaller than a given "linking length." First, large random networks exhibit Poisson distribution characteristics [27]. Each random process represents a binomial trial; calculating the distribution of n points in spherical space of radius l yields a Poisson-like formula whose mean can be expressed in terms of l and n. Thus, linking lengths can be determined through Poisson distribution construction and used to identify connectivity between galaxies, with structures classified by connectivity degree at each point: voids (lowest connectivity), walls, and nodes (highest connectivity).

Martínez et al. [28] suggested first identifying "node pairs" connected by filaments, then screening filaments by calculating galaxy overdensity. Specifically, node pairs must satisfy constraints where both projected and line-of-sight distances between two points are below given values, while the projected distance must exceed the sum of the two halos' virial radii to ensure clear structures. Rectangles are then constructed between node pairs (height along line-of-sight, base in projection plane) and galaxy overdensity is computed by comparing the number of galaxies within the rectangle to that in a field region of equivalent spatial and redshift range. Structures with overdensity greater than 1 are identified as filaments. Both methods are fast, intuitive, and computationally inexpensive, though Hong and Dey' s method is highly parameter-dependent (linking length) and cannot directly construct filamentary networks. Martínez et al.' s approach relies on threshold parameters for line-of-sight and projected distances and requires high-precision galaxy position and redshift data, as measurement errors may affect results. It is currently applied primarily to distinguishing cosmic web environments where galaxies reside.

3 Galaxy Quenching in Cosmic Web Environments

The evolution from star-forming "blue galaxies" to star-formation-quenched "red galaxies" occurs relatively rapidly on cosmological timescales, with the transitional stage termed the "green valley," appearing as a narrow distribution in color-magnitude diagrams [29]. Galaxy quenching mechanisms are complex, influenced by intrinsic properties such as mass and morphology, as well as external environments including dark matter halos, local galaxy density, and large-scale structure. Dressler [30] established the famous relationship between environmental density and galaxy morphology, showing that cluster galaxies are more likely to be elliptical compared to field galaxies which are typically spiral. Jaffé et al. [31] studied ram pressure stripping mechanisms of neutral hydrogen gas in galaxy clusters by plotting observed galaxies on velocity-phase diagrams according to neutral hydrogen detection and color classification [32]. Lotz et al. [33] simulated orbital "preprocessing" of galaxies in clusters, finding that most satellite galaxies with radial velocity directions are rapidly quenched by gas stripping effects [34] during their first infall. Whether similar quenching processes occur in cosmic filaments—structures with densities lower than clusters but higher than voids—remains to be tested.

3.1 Galaxy Quenching in Filaments: Observational and Simulation Results

Various observations and simulations have examined changes in galactic star formation activity when approaching filaments. Several statistical indicators commonly measure these variations: (1) galaxy colors, such as $u - r > 1.8$ for red galaxies [36], or classifications on $g{-}r/u{-}g$ diagrams like $(g{-}r) > 0.234(u{-}g) + 1.03$ [37]; (2) specific star formation rate $sSFR$ (the ratio of star formation rate to stellar mass), which exhibits a bimodal distribution highly consistent with color diagrams [38] and thus provides rapid quenching diagnostics; and (3) the quenched fraction—the proportion of quenched galaxies in a sample. Below we introduce several studies applying different statistical indicators to observe environmental variations in star formation activity.

Kuutma et al. [11] used data from SDSS Data Release 10 [39] and Galaxy Zoo classifications to analyze changes in the elliptical-to-spiral ratio (E/S) and $g-i$ color from 10 $\mathrm{Mpc}\cdot h^{-1}$ to 0.1 $\mathrm{Mpc}\cdot h^{-1}$ from filaments. Their Figure 3 [Figure 3: see original paper] revealed that brighter galaxies tend to become redder when approaching filaments, while fainter galaxies show no significant change beyond error bars. The E/S ratio increases near filaments, synchronized with $g-i$ color changes. They proposed that morphological transformation might cause color index variations. However, the trend of reddening near filaments persists even after distinguishing galaxy morphology in brighter galaxy samples, being more pronounced for spiral galaxies.

Malavasi et al. [35] used IllustrisTNG [40–42] simulation data at redshift 0 to study the dependence of stellar mass, star formation rate (SFR), and $sSFR$ on distance to filaments, as shown in Figure 1a [Figure 1: see original paper]. They identified the cosmic web (including filament segment positions and node locations) using the DisperSE algorithm and considered three distance variables: (1) distance to the nearest node on the cosmic web (density maxima and bifurcation points identified by DisperSE) (d_{cp}); (2) distance to the nearest filament segment midpoint (d_{fil}); and (3) distance from the nearest filament point (the galaxy’ s projection onto its nearest filament) to one of the two critical points connecting that filament (d_{skel}). Regardless of the calculation method, all three galactic properties show strong dependence on cosmic web distance variables.

Similarly, Hasan et al. [43, 44] analyzed the relationship between galaxy $sSFR$ and filament distance using IllustrisTNG data, extending the redshift range to 4 and distinguishing central from satellite galaxies. Their study revealed that cosmic web influence on $sSFR$ only emerges beginning at redshift 2, being negligible at higher redshifts, and primarily affects satellite galaxies while central galaxies experience only minimal environmental quenching.

Observational evidence exists for cosmic environmental influence on galaxy quenching at higher redshifts. Salerno et al. [12] selected galaxies from the VIMOS Extragalactic Survey [45] in the redshift range $0.43 \sim 0.89$, classified them by cosmic environment, and compared how quenched fractions vary with stellar mass across environments. They found quenched fractions are lowest in field and infall regions, intermediate in filaments, and highest in groups, as shown in Figure 2 [Figure 2: see original paper]. However, Salerno et al. neither calculated galaxy distances to filaments nor statistically accounted for other potential quenching factors.

Both observational and theoretical studies show declining trends in multiple star formation indicators from 10 $\mathrm{Mpc}\cdot h^{-1}$ to 0.1 $\mathrm{Mpc}\cdot h^{-1}$ from filaments, with simulations extending this influence to redshifts $1 \sim 2$. Simulations indicate this trend is dominated by satellite galaxies, while observations reveal it primarily appears in lower-luminosity galaxies (typically satellites are less luminous than central galaxies). Satellite galaxies, having smaller stellar masses and residing closer to halo outskirts, may be more susceptible to environmental effects. However, since star formation rate variations are more pronounced in low-luminosity galaxies, observational biases may exist, requiring further evidence to investigate the scope and mechanisms of large-scale environmental quenching.

3.2 Results from Studies Controlling for Influence Variables

Galactic stellar mass, local environment (i.e., halo mass), and the local galaxy density field all influence star formation activity, with considerable degeneracy among these parameters. Proximity to filaments typically corresponds to larger stellar mass, more massive halos, and higher galaxy density, making it crucial to separate these effects in studies.

A tight correlation exists between star formation rate and stellar mass [46]. Hydrodynamic simulations generally agree that feedback from supermassive black holes (SMBHs) or active galactic nuclei (AGN) is key to quenching massive galaxies [47, 48]. AGN feedback can be triggered under various conditions, such as black hole accretion and galaxy mergers [49, 50], heating gas through powerful jets and causing quenching. Most environmental quenching studies (including those in Section 3.1) control for stellar mass.

Both observational data [51-53] and theoretical simulations [54, 55] reveal that galaxies may redden or quench in massive halos. The mechanism involves virial shock heating of infalling gas from the intergalactic medium in halos above a critical mass of $10^{12} M_{\odot}$, preventing accreted gas from directly fueling star formation [56]. Additionally, AGN feedback efficiency correlates with halo mass. Lin et al. [57] used SDSS-IV MaNGA survey [58] data to classify quenching as inside-out or outside-in. External mechanisms like ram pressure stripping or gas exhaustion typically cause outside-in quenching, while AGN feedback produces the opposite trend (inside-out). They found inside-out quenching dominates, with its fraction increasing alongside both stellar mass (at fixed halo mass) and halo mass (at fixed stellar mass). Some studies control for halo mass to determine whether filament environments independently affect star formation. Perez et al. [59] used TNG300-1 data to separate galaxies into red and blue populations and three halo mass bins ($M_{\rm halo} < 10^{11.5} M_{\odot} \cdot h^{-1}$, $10^{11.5} M_{\odot} \cdot h^{-1} < M_{\rm halo} < 10^{12.5} M_{\odot} \cdot h^{-1}$, $M_{\rm halo} > 10^{12.5} M_{\odot} \cdot h^{-1}$), plotting galaxy distributions (Figure 3). They found that in low-mass halos, more blue galaxies appear in filament peripheries (galaxy-to-filament distances of $1.2 \sim 2$ Mpc $\cdot\, h^{-1}$), while the opposite trend occurs in massive halos: blue galaxies concentrate in filament centers (distances $0 \sim 0.1$ Mpc $\cdot\, h^{-1}$), with red galaxies dominating filament peripheries—still reflecting local halo effects.

O' Kane et al. [60] used SDSS DR8 data to study scatter in the star formation main sequence (MS) as a measure of star formation suppression. After matching galaxy stellar masses across environments, they found higher suppression in filament galaxies, demonstrating environmental influence. However, this effect nearly disappeared after simultaneously matching both stellar mass and local galaxy density, indicating degeneracy between filament environment and local density field effects. As shown in Figure 1b [Figure 1: see original paper], Malavasi et al. [35] also analyzed dependence on the local density field: as density increases, galaxy mass increases while SFR and $sSFR$ decrease, with different galaxy-to-filament distances having minimal impact on results. When ρ_{DTFE} lies between $10 \sim 10^3$ Mpc^{-3}, $sSFR$ increases slightly with density over a small range. Figure 1c [Figure 1: see original paper] illustrates the degeneracy between local density and filament distance. To separate these variables' effects on galaxy property distributions, they proposed a "shuffling" method: dividing the density field into numerous small intervals, randomly shuffling galaxy properties (SFR, mass, etc.) among galaxies within each interval 1,000 times while preserving galaxy-to-filament distances (d_{cp}, d_{skel}, d_{fil}), then recombining the intervals. This randomizes the relationship between galaxy properties and filament distance within each interval while maintaining the overall relationship between properties and local density field, thereby controlling for density. They calculated differences between original results (H_0) and shuffled averages (H_R), normalized by the root-mean-square error of the original results. The differences are nearly zero across all filament distances, suggesting that filament distance effects on quenching cannot be distinguished from local density field effects.

Song et al. [61] used HORIZON-AGN data, simultaneously considering local density field and halo mass effects. Using 0.4 times the halo virial radius as a standard ($d_{\mathrm{fil}} = 0.4R_{\mathrm{h,vir}} = d_{\mathrm{cut}}$), they distinguished galaxies on filaments from those near filaments. At fixed local density, they found that galaxies on filaments have universally higher halo mass, galaxy mass, and SFR than those near filaments, with a discontinuous jump occurring very close to filaments (see their Figure 8 [Figure 8: see original paper]). To remove halo mass effects, they fitted the SFR-M_{halo} relation and computed residuals from this primary relationship (see their Figure 7 [Figure 7: see original paper]). The SFR residuals increase when approaching filaments but decline from approximately $10^{0.5}R_{\mathrm{h,vir}}$, indicating that galaxies experience quenching near filaments.

To compare the importance of different variables for galaxy quenching and identify the most predictive parameters for star formation activity, researchers can employ the random forest method. Random forest is a machine learning approach for classifying complex data. The dataset is divided into training and test sets, with multiple subsets constructed through random sampling from the training set. Each subset builds a decision tree to learn which feature parameters best classify the data (in galaxy quenching studies, "star-forming" versus "quenched" categories). The probability of randomly selecting a class at each node can be used to compute Gini impurity [62]; higher Gini impurity indicates poorer classification ability. If a feature parameter effectively reduces Gini impurity, it is important for galaxy quenching. Weighted averaging of Gini impurity changes across decision trees yields variable importance. Bluck et al. [37] analyzed MaNGA data, finding bulge mass to be the most predictive photometric parameter (among bulge mass, disk mass, total stellar mass, and B/T morphology), while central stellar velocity dispersion becomes more important when spectroscopic data are available. Goubert et al. [63] compared several simulation datasets, discovering that central black hole mass best predicts quenching for central and massive satellite galaxies, whereas halo mass is optimal for low-mass satellites. Random forest algorithms have limitations, being significantly affected by input data quality and completeness, and may overfit training data—particularly with very large numbers of trees or improper model tuning—necessitating multiple approaches to investigate these questions.

3.3 Phenomena and Mechanisms of Cosmic Web Enhancing Star Formation

Galárraga-Espinosa et al. [64] studied the "filament connectivity" of central galaxies with masses above $10^8 M_\odot$ in the TNG50-1 simulation—defined as the number of filaments connected to a galaxy. As shown in Figure 4a, to simultaneously control for stellar mass and local density, they divided galaxies into four groups (A, B, C, D). Figure 4b plots $sSFR$ versus filament connectivity. For groups A and B (lower stellar mass), $sSFR$ increases significantly with connectivity, indicating that more filaments enhance star formation activity. They interpret this effect through the work of Kereš et al. [66]: low-mass galaxies' host halos may lack sufficient mass to sustain shock heating effects, allowing cold gas to flow along filaments into central galaxies. Meanwhile, groups C and D show almost no variation with connectivity, suggesting that in massive galaxies, star formation is more likely regulated by internal processes independent of cold gas inflow through filaments. This may relate to the work of Gabor and Davé [67], who found using hot gas quenching models that while red galaxies often reside in denser environments, many isolated red central galaxies exist in hot halos.

Kraljic et al. [65] found markedly different filament connectivity for star-forming versus inactive galaxies, with inactive galaxies showing higher connectivity (Figure 4c). Galárraga-Espinosa et al. argued that Kraljic et al.'s study only demonstrates environmental differences between galaxy populations without explaining how intrinsic galaxy properties vary with environment. Additionally, with improved simulation resolution, their study focused on identifying fine filamentary structures. Both studies used DisperSE to find filaments, but Kraljic et al. input galaxy coordinates while Galárraga-Espinosa et al. used dark matter particle coordinates, with the latter potentially better suited for identifying fine structures—a major distinction from previous research.

The physical picture suggested by these studies warrants further discussion. Bulichi et al. [68] found through Simba simulations [69] that while changes in central galaxy star formation activity near filament centers are negligible, the amount of H_2 gas available for star formation increases. Nelson et al. [70] noted that gas transport within halos (gas flow from CGM into galaxies) is significantly affected by hydrodynamic simulation numerical schemes. Nevertheless, some observational data provide potential evidence for cold gas storage in filamentary structures. Kleiner et al. [71] analyzed neutral hydrogen content (the ratio of neutral hydrogen mass to galaxy mass) in galaxies near filament backbones in the local universe, finding higher neutral hydrogen content in more massive galaxies ($> 10^{11} M_\odot$). Odekon et al. [72] used neutral hydrogen data from the ALFALFA survey [73] to analyze star-forming galaxies with masses $10^{8.5} M_\odot \sim 10^{10.5} M_\odot$, discovering higher neutral hydrogen content in galaxies located in filaments and tendrils compared to voids. Sinigaglia et al. [74] selected star-forming galaxies with masses $> 10^{9.6} M_\odot$ at redshift 0.37 from the COSMOS survey, finding significantly higher neutral hydrogen content in filament galaxies compared to field and cluster galaxies. Cosmic web structures may transport cold gas to central galaxies, delaying their quenching processes driven by halo mass and black hole feedback [75].

4 Summary and Outlook

This review examined cosmic web studies and research on galaxy quenching in filamentary environments. Algorithms including DisPerSE, Sconce, MCPM, and Poisson-distribution-based networks have been used to identify and quantify cosmic web structures. Although observations at redshifts $0 \sim 1$ and simulations at redshifts $0 \sim 2$ provide evidence for diminished star formation activity near filaments—manifesting as redder colors, decreased $sSFR$, and increased quenched fractions—some studies suggest the filament effect is weak or uncertain after separating central and satellite galaxies and controlling for variables including halo mass and local galaxy density. Alternative perspectives propose that filaments may supply gas to nearby galaxies, triggering increased SFR. However, direct simulation of gas and star formation activity in large-scale structure studies remains challenging due to strong dependencies on specific numerical schemes.

Future research can address several questions through new simulation techniques and high-redshift observational data:

(1) **Filament structure formation mechanisms:** With high-redshift observational projects such as the James Webb Space Telescope (JWST), wide-field surveys like the Euclid mission, and the future Nancy Grace Roman Space Telescope, researchers can study galaxy distribution and evolution in different filament environments, further exploring the origin and formation mechanisms of filamentary structures and cosmic environments at high redshift.

(2) **Long-term connections between filament environments and galaxy evolution:** Through large-scale simulations such as MilleniumTNG, we can investigate galaxy evolution processes within cosmic filaments and explore the long-term effects of different filament environments on galaxy evolution.

(3) **Connections between environment and internal star formation mechanisms:** With high-resolution simulations like FIRE (Feedback In Realistic Environments), we can explore how filament environments affect internal processes such as AGN feedback and cold gas flows in the circum-

galactic medium, studying how cosmic filaments influence central galaxy star formation efficiency through cold gas transport.

References

[1] Kauffmann G, Fairall A P. MNRAS, 1991, 248: 313
[2] Platen E, van de Weygaert R, Jones B J T. MNRAS, 2007, 380: 551
[3] Geller M J, Huchra J P. Science, 1989, 246: 897
[4] Gott III J R, Jurić M, Schlegel D, et al. ApJ, 2005, 624: 463
[5] Horvath I, Hakkila J, Bagoly Z. https://arxiv.org/abs/1311.1104, 2013
[6] York D G, Adelman J, Anderson J, John E, et al. AJ, 2000, 120: 1579
[7] Wang F, Yang J, Hennawi J F, et al. ApJL, 2023, 951: L4
[8] Laigle C, Pichon C, Arnouts S, et al. MNRAS, 2018, 474: 5437
[9] Scoville N. From Z-Machines to ALMA: (Sub)Millimeter Spectroscopy of Galaxies ASP Conference Series, USA: National Radio Astronomy Observatory, 2007, 375: 166
[10] Malavasi N, Arnouts S, Vibert D, et al. MNRAS, 2017, 465: 3817
[11] Kuutma T, Tamm A, Tempel E. A&A, 2017, 600: L6
[12] Salerno J M, Martínez H J, Muriel H. MNRAS, 2019, 484: 2
[13] Libeskind N I, van de Weygaert R, Cautun M, et al. MNRAS, 2018, 473: 1195
[14] Sousbie T, Pichon C, Kawahara H. MNRAS, 2011, 414: 384
[15] Schaap W E, van de Weygaert R. A&A, 2000, 363: L29
[16] Edelsbrunner, Letscher, Zomorodian. Discrete & computational geometry, 2002, 28: 511
[17] Zhang Y, de Souza R S, Chen Y C. MNRAS, 2022, 517: 1197
[18] Hall P, Watson G, Cabrera J. Biometrika, 1987, 74: 751
[19] García-Portugués E. Journal of Multivariate Analysis, 2013, 120: 1655
[20] Jackson J C. MNRAS, 1972, 156: 1P
[21] Burchett J N, Elek O, Tejos N, et al. ApJL, 2020, 891: L35
[22] Jones J. Artificial life, 2010, 16: 127
[23] Adamatzky A. Physarum machines: computers from slime mould: Vol. 74. Singapore: World Scientific, 2010: 1
[24] Simha S, Burchett J N, Prochaska J X, et al. ApJ, 2020, 901: 134
[25] Tempel E, Stoica R S, Martínez V J, et al. MNRAS, 2014, 438: 3465
[26] Hong S, Dey A. MNRAS, 2015, 450: 1999
[27] Erdös P, Rényi A. Publ Math Inst Flung Acid, 1959, 3: 159
[28] Martínez H J, Muriel H, Coenda V. MNRAS, 2016, 455: 127
[29] Bell E, Balogh M, Gray M, et al. Spitzer Proposal, 2004, 142: 3294
[30] Dressler A. ApJ, 1980, 236: 351
[31] Jaffé Y L, Smith R, Candlish G N, et al. MNRAS, 2015, 448: 1715
[32] Gunn J E, Gott III J R. ApJ, 1972, 176: 1
[33] Lotz M, Remus R S, Dolag K, et al. MNRAS, 2019, 488: 5370
[34] Annunziatella M, Mercurio A, Biviano A, et al. A&A, 2016, 585: A160
[35] Malavasi N, Langer M, Aghanim N, et al. A&A, 2022, 658: A113
[36] Kraljic K, Arnouts S, Pichon C, et al. MNRAS, 2018, 474: 547

[37] Bluck A F L, Maiolino R, Brownson S, et al. A&A, 2022, 659: A160
[38] Wetzel A R, Tinker J L, Conroy C. MNRAS, 2012, 424: 232
[39] Ahn C P, Alexandroff R, Allende Prieto C, et al. ApJS, 2014, 211: 17
[40] Nelson D, Pillepich A, Springel V, et al. MNRAS, 2018, 475: 624
[41] Pillepich A, Nelson D, Hernquist L, et al. MNRAS, 2018, 475: 648
[42] Springel V, Pakmor R, Pillepich A, et al. MNRAS, 2018, 475: 676
[43] Hasan F, Burchett J N, Abeyta A, et al. ApJ, 2023, 950: 114
[44] Hasan F, Burchett J N, Hellinger D, et al. ApJ, 2024, 970: 177
[45] Franzetti P, Garilli B, Guzzo L, et al. A&A, 2014, 566: A100
[46] Brinchmann J, Charlot S, White S D M, et al. MNRAS, 2004, 351: 1151
[47] Sijacki D, Springel V, Di Matteo T, et al. MNRAS, 2007, 380: 877
[48] Feldmann R, Quataert E, Hopkins P F, et al. MNRAS, 2017, 470: 1050
[49] Di Matteo T, Springel V, Hernquist L. Nature, 2005, 433: 604
[50] Johansson P H, Burkert A, Naab T. ApJL, 2009, 707: L184
[51] Balogh M L, Navarro J F, Morris S L. ApJ, 2000, 540: 113
[52] De Propris R, Colless M, Peacock J A, et al. MNRAS, 2004, 351: 125
[53] Blanton M R, Berlind A A. ApJ, 2007, 664: 791
[54] Weinmann S M, van den Bosch F C, Yang X, et al. MNRAS, 2006, 366: 2
[55] Kimm T, Somerville R S, Yi S K, et al. MNRAS, 2009, 394: 1131
[56] Birnboim Y, Dekel A. MNRAS, 2003, 345: 349
[57] Lin L, Hsieh B C, Pan H A, et al. ApJ, 2019, 872: 50
[58] Bundy K, Bershady M A, Law D R, et al. ApJ, 2015, 798: 7
[59] Perez N R, Pereyra L A, Coldwell G, et al. MNRAS, 2024, 528: 3186
[60] O' Kane C J, Kuchner U, Gray M E, et al. MNRAS, 2024, 534: 1682
[61] Song H, Laigle C, Hwang H S, et al. MNRAS, 2021, 501: 4635
[62] Pedregosa F, Varoquaux G, Gramfort A, et al. Journal of Machine Learning Research, 2011, 12: 2825
[63] Goubert P H, Bluck A F L, Piotrowska J M, et al. MNRAS, 2024, 528: 4891
[64] Galárraga-Espinosa D, Garaldi E, Kauffmann G. A&A, 2023, 671: A160
[65] Kraljic K, Pichon C, Codis S, et al. MNRAS, 2020, 491: 4294
[66] Kereš D, Katz N, Weinberg D H, et al. MNRAS, 2005, 363: 2
[67] Gabor J M, Davé R. MNRAS, 2015, 447: 374
[68] Bulichi T E, Davé R, Kraljic K. MNRAS, 2024, 529: 2595
[69] Davé R, Anglés-Alcázar D, Narayanan D, et al. MNRAS, 2019, 486: 2827
[70] Nelson D, Vogelsberger M, Genel S, et al. MNRAS, 2013, 429: 3353
[71] Kleiner D, Pimbblet K A, Jones D H, et al. MNRAS, 2017, 466: 4692
[72] Crone Odekon M, Hallenbeck G, Haynes M P, et al. ApJ, 2018, 852: 142
[73] Giovanelli R, Haynes M P, Kent B R, et al. AJ, 2005, 130: 2598
[74] Sinigaglia F, Rodighiero G, Elson E, et al. ApJL, 2022, 935: L13
[75] Kotecha S, Welker C, Zhou Z, et al. MNRAS, 2022, 512: 926

Note: Figure translations are in progress. See original paper for figures.