Cosmic Web Reconstruction through Density Ridges

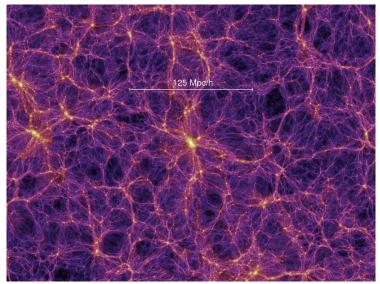
Yen-Chi Chen

Shirley Ho Peter E. Freeman Christopher R. Genovese Larry Wasserman

> Department of Statistics McWilliams Center for Cosmology Carnegie Mellon University

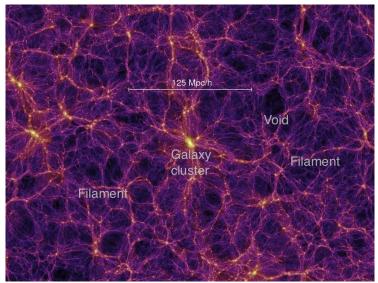
> > May 26, 2016

Cosmic Web: What Does Our Universe Look Like



Credit: Millennium Simulation

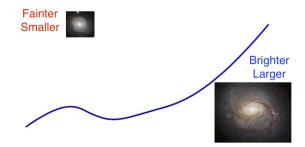
Cosmic Web: What Does Our Universe Look Like



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The Importance of Filaments

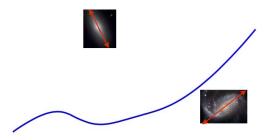
• A galaxy's brightness, size, and mass are associated with the distance to filaments.



 \rightarrow Chen et al. 'Detecting Effects of Filaments on Galaxy Properties in Sloan Digital Sky Survey III' (2015)

The Importance of Filaments

- A galaxy's brightness, size, and mass are associated with the distance to filaments.
- A galaxy's alignment is associated with filaments.



 \rightarrow Chen et al. 'Investigating Galaxy-Filament Alignment in Hydrodynamic Simulations using Density Ridges' (2015)

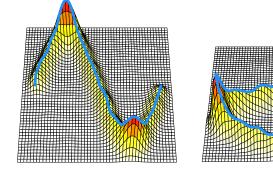
We formalize the notion of filaments as *density ridges*.

Example: Ridges in Mountains

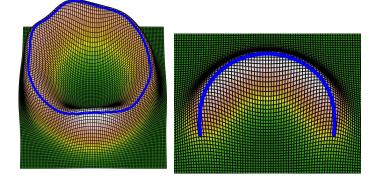


Credit: Google

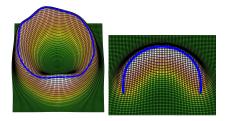
Example: Ridges in Smooth Functions



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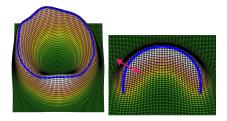


Ridges: Local Modes in Subspace



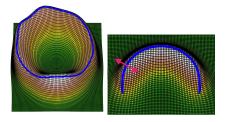
• A generalized local mode in a specific 'subspace'.

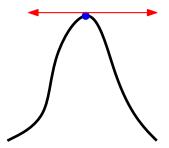
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Local modes:

$$Mode(p) = \{x : \nabla p(x) = 0, \lambda_1(x) < 0\}.$$

The dimension of a ridge is 1.

This is because ridges are points satisfying $V(x)V(x)^T \nabla p(x) = 0$.

 $V(x)V(x)^T$ has rank d-1, so there are d-1 effective constraints.

By the Implicit Function Theorem, ridges have dimension 1.

We use the plug-in estimate:

$$\widehat{R}_n = \mathsf{Ridge}(\widehat{p}_n),$$

where $\hat{p}_n = \frac{1}{nh^d} \sum_{i=1}^n K\left(\frac{x-X_i}{h}\right)$ is the kernel density estimator (KDE).

¹Ozertem, Umut, and Deniz Erdogmus. "Locally defined principal curves and surfaces." JMLR (2011).

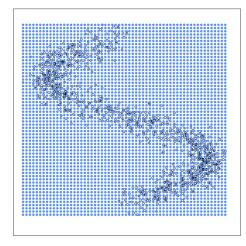
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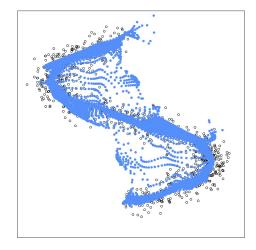
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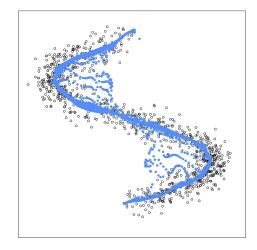
- In general, finding ridges from a given function is hard.
- The Subspace Constraint Mean Shift¹ (SCMS) algorithm allows us to find \hat{R}_n , ridges of the KDE.

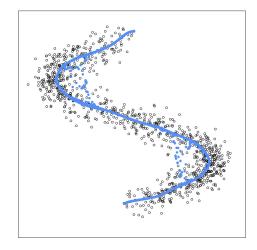
 $^{^1 \}textsc{Ozertem},$ Umut, and Deniz Erdogmus. "Locally defined principal curves and surfaces." JMLR (2011).

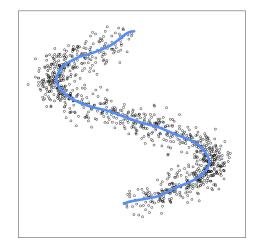


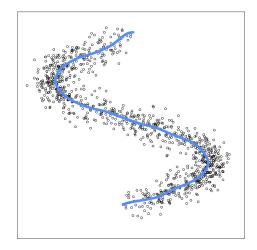




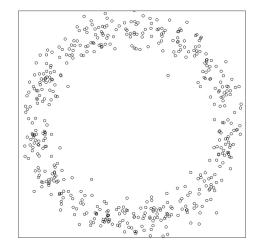


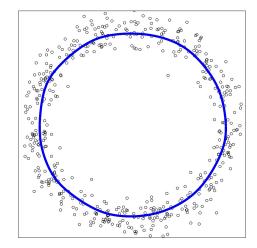


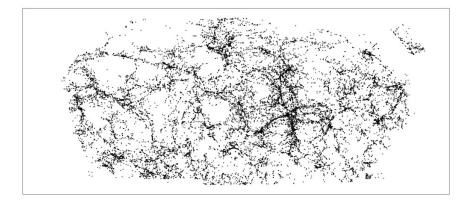


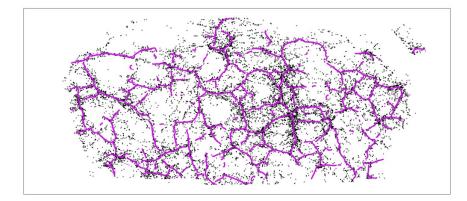


SCMS moves blue mesh points by gradient ascent and a projection.

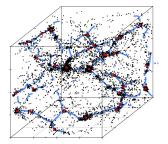


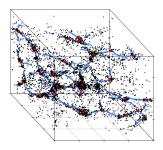






3D Example for Estimated Ridges





Blue curves: density ridges. Red points: density local modes.

Uncertainty of Ridges

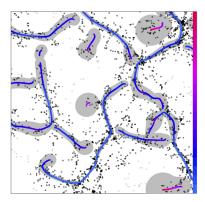
We use the bootstrap to estimate the uncertainty of ridges (filaments).

Basic idea: comparing original ridges and bootstrap ridges.

Uncertainty of Ridges

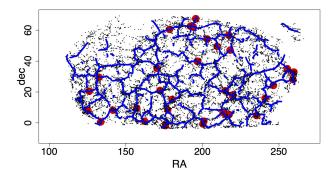
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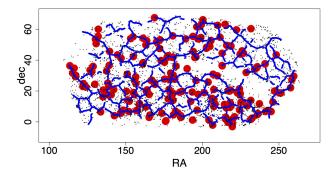
SDSS: Comparing to Clusters

• Blue: filaments. Red: galaxy clusters (redMaPPer).



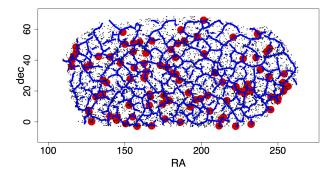
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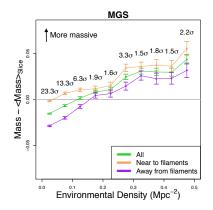


SDSS: Filament Effects VS Environments

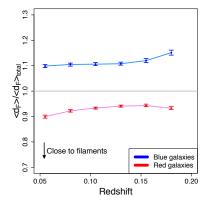
Do filaments have an extra effect other than environments?

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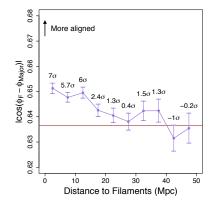
Do filaments have an extra effect other than environments? \longrightarrow Yes!



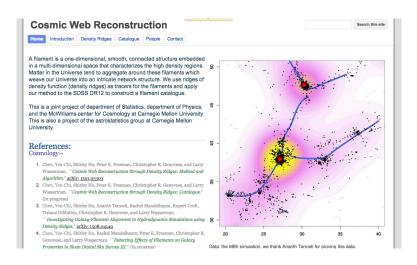
SDSS: Color



SDSS: Alignment

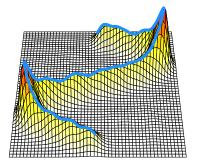


A Filament Catalogue for the SDSS



https://sites.google.com/site/yenchicr/

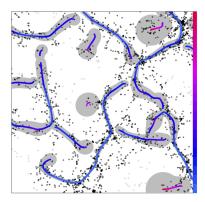
1 Model: density ridges.



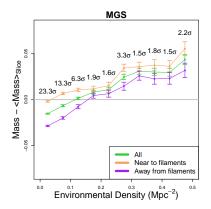
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- **2** Algorithm: SCMS.



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- Model: density ridges.
- Algorithm: SCMS.
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- Applications in various problems.

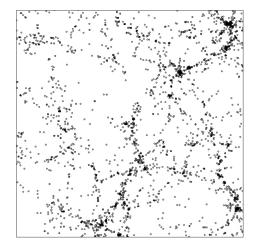


Thank you!

- Chen, Yen-Chi, Shirley Ho, Peter E. Freeman, Christopher R. Genovese, and Larry Wasserman. "Cosmic Web Reconstruction through Density Ridges: Method and Algorithm." To appear in Monthly Notices of the Royal Astronomical Society.
- Chen, Yen-Chi, et al. "Investigating Galaxy-Filament Alignments in Hydrodynamic Simulations using Density Ridges." arXiv preprint arXiv:1508.04149 (2015).
- Chen, Yen-Chi, Christopher R. Genovese, and Larry Wasserman. "Asymptotic theory for density ridges." The Annals of Statistics 43.5 (2015): 1896-1928.
- Conroy, Charlie, James E. Gunn, and Martin White. "The propagation of uncertainties in stellar population synthesis modeling. I. The relevance of uncertain aspects of stellar evolution and the initial mass function to the derived physical properties of galaxies." The Astrophysical Journal 699.1 (2009): 486.
- 5. Eberly, David. Ridges in image and data analysis. Vol. 7. Springer Science & Business Media, 1996.
- Genovese, Christopher R., et al. "Nonparametric ridge estimation." The Annals of Statistics 42.4 (2014): 1511-1545.
- 7. Ozertem, Umut, and Deniz Erdogmus. "Locally defined principal curves and surfaces." The Journal of

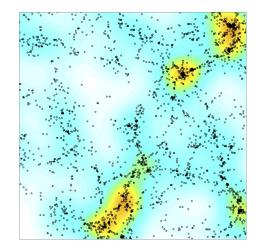
Machine Learning Research 12 (2011): 1249-1286.

A Rawdata



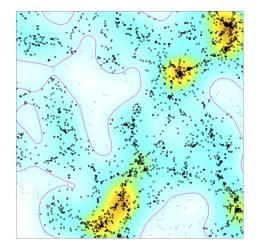
Algorithm

- A Rawdata
- ② Density Reconstruction



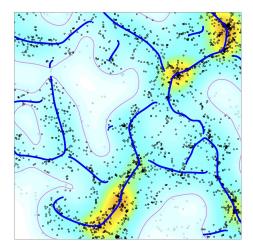
Algorithm

- Rawdata
- ② Density Reconstruction
- O Thresholding

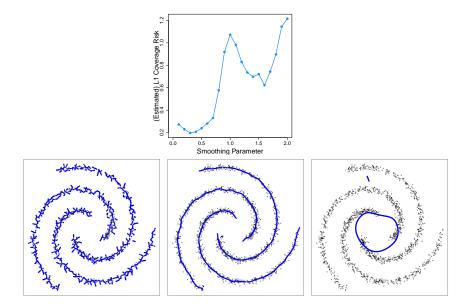


Algorithm

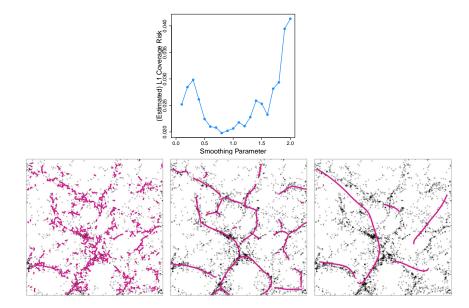
- Rawdata
- **2** Density Reconstruction
- O Thresholding
- O Ridge Recovery



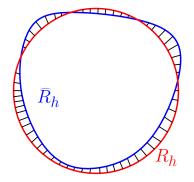
Bandwidth Selection



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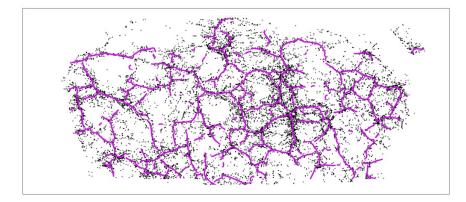


 L_1 distance are like the area of the shady regions. We estimate this distance by data splitting or the bootstrap. Reference: **Chen** et al. 'Optimal Ridge Detection using Coverage Risk' (NIPS 2015). We can generalize ridges to higher dimensions. Pick $V_r(x) = [v_{r+1}(x), \cdots, v_d(x)].$ We define

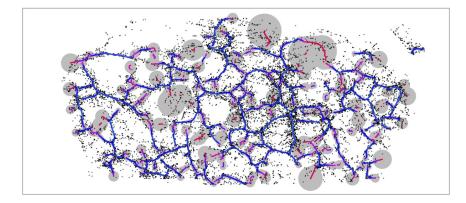
$$r$$
-Ridge $(p) = \{x : V_r(x)V_r(x)^T \nabla p(x) = 0, \lambda_{r+1}(x) < 0\}.$

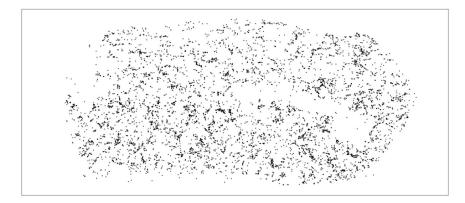
 $V_r(x)$ is a $d \times (d - r)$ matrix. There are d - r constraints. By Implicit Function Theorem, *r*-ridges are *r*-manifolds. In Astronomy, r = 2 can be used to model 'Cosmic Sheets (Walls)'. r = 0 coincides with the definition of local modes.

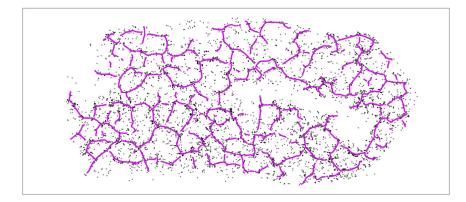
Density Ridges on the SDSS data

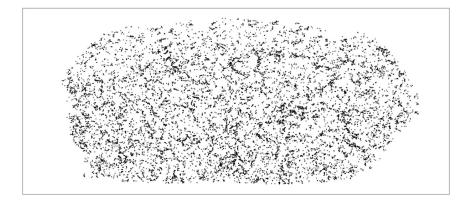


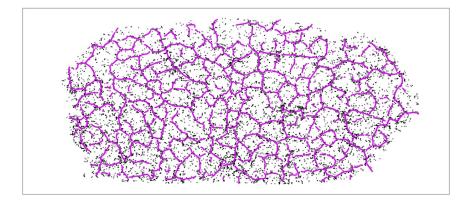
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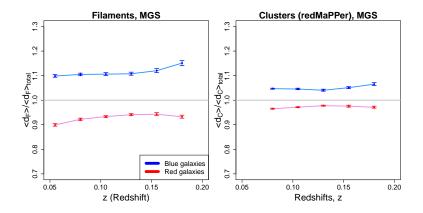






- Redshift range: 0.05 < z < 0.20 (main sample galaxy).
- Color cut: (g r) = 0.8.

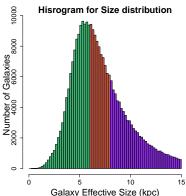
SDSS: Red and Blue Galaxies



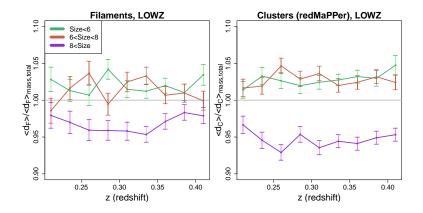
SDSS: Size for Galaxies

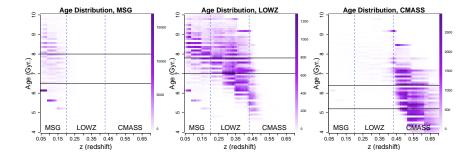
Size: Effective Radii.

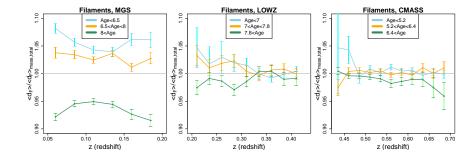
- ② Data: LOWZ (0.20 < z < 0.43)</p>
- Partitioning galaxies into three groups according to their size.

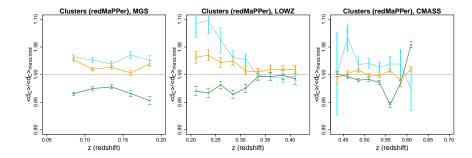


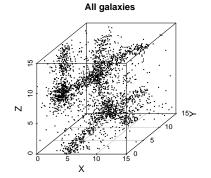
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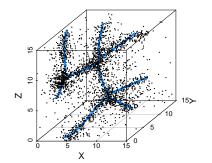




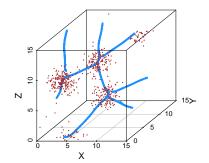




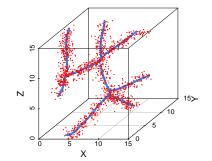




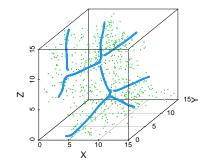
Ridges and all galaxies



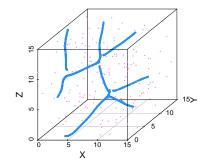
Ridges and Clusters (Voronoi)



Ridges and Filaments (Voronoi)



Ridges and Walls (Voronoi)



Ridges and Voids (Voronoi)