

Cosmic Web Reconstruction through Density Ridges

Yen-Chi Chen

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

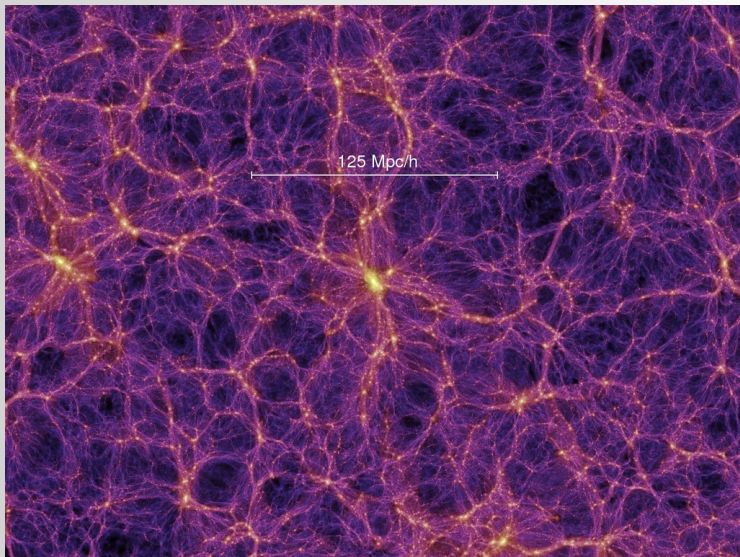
Department of Statistics
McWilliams Center for Cosmology
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February 12, 2015

- Introduction to Cosmic Web
- Statistical Model and Algorithm
- Filament Coverage and Uncertainty Measures
- Scientific Applications
- Summary

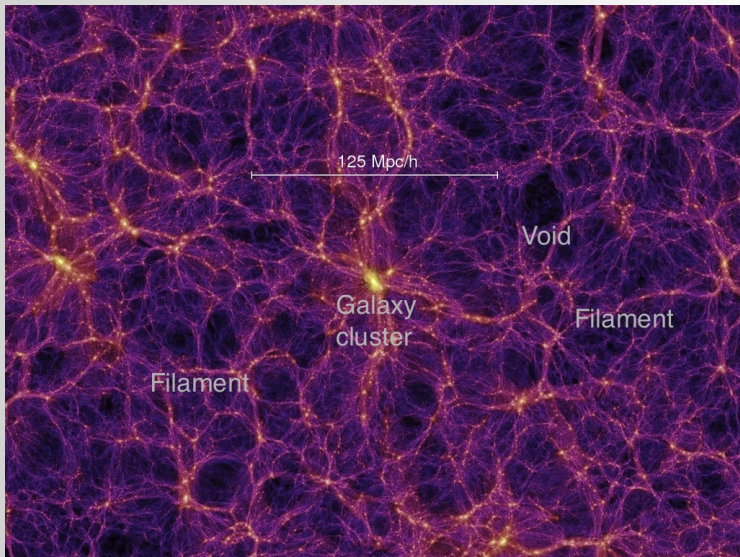
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Cosmic Web: What Does Our Universe Look Like



Credit: Millennium Simulation

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Focus of the Research: Filaments

Why filament?

- Galaxies tend to concentrate around filaments.

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- Brightness of galaxies is influenced by filaments.

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- Galaxies tend to concentrate around filaments.
- Brightness of galaxies is influenced by filaments.
- Shape of galaxies is correlated with filaments.

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A Glance at our Universe

(Loading)

Statistical Model for Filaments: Density Ridges

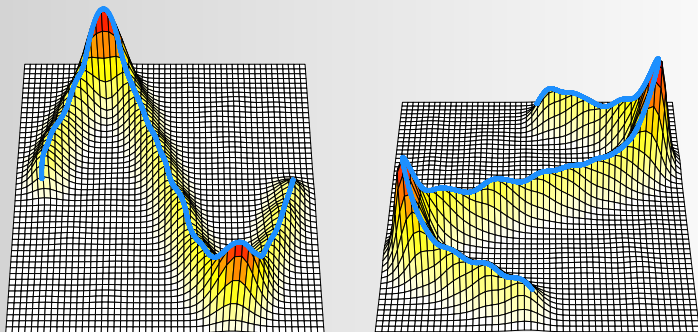
Formally, we define a filament to be a **ridge** of the density.

Example: Ridges in Mountains

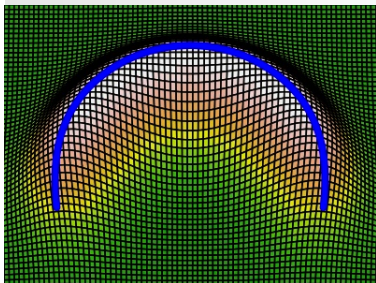
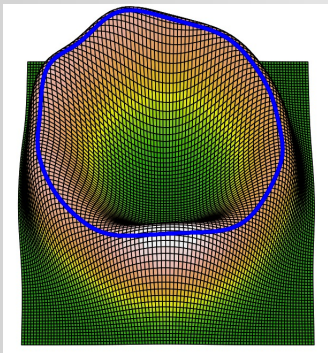


Credit: Google

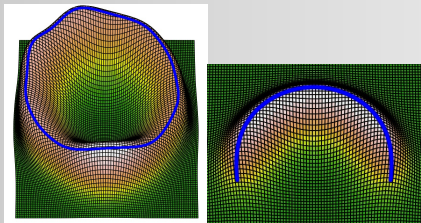
Example: Ridges in Smooth Functions



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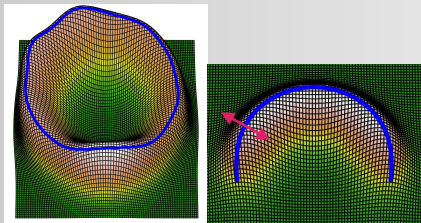


Ridges: Local Modes in Subspace



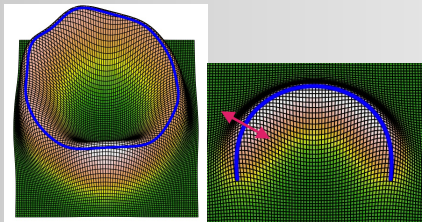
- A generalized local mode in a specific 'subspace'.

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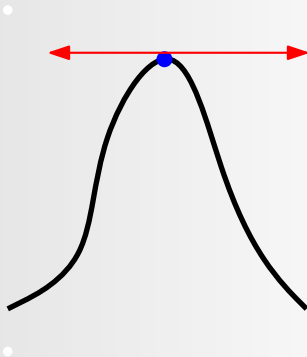


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Formal Definition of Density Ridges

- $p(x)$: a density function.

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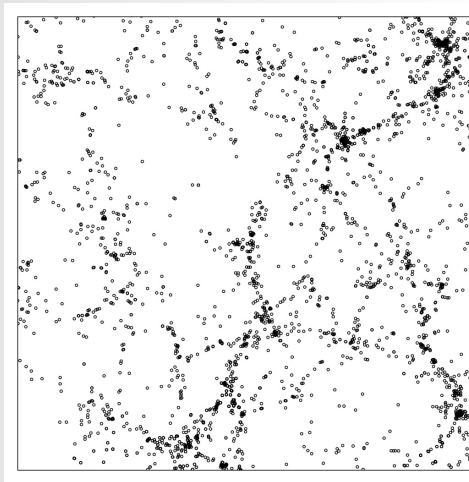
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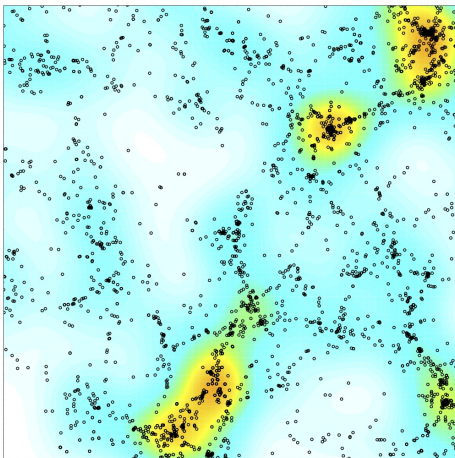
- In practice, we estimate p by the kernel density estimator \hat{p}_n .

1 Rawdata



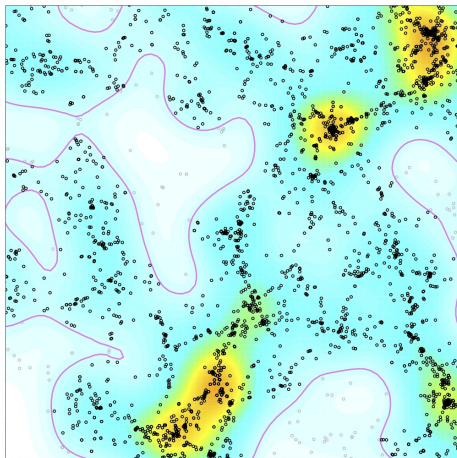
Algorithm

- 1 Rawdata
- 2 Density Reconstruction



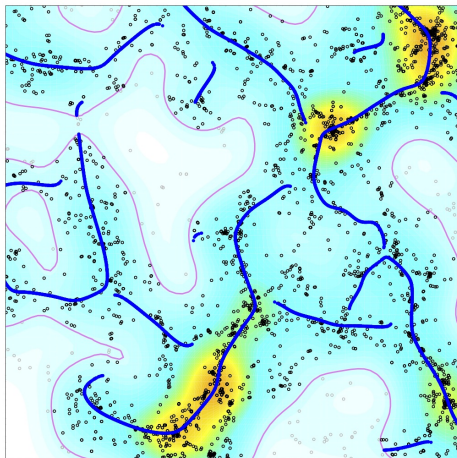
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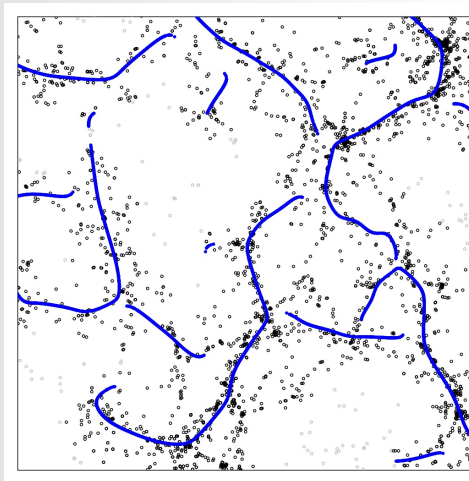
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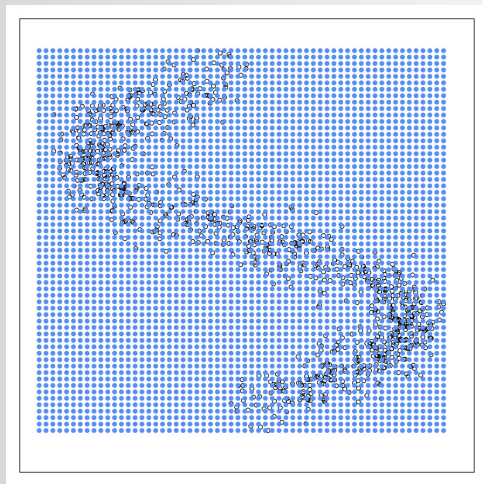


Algorithm

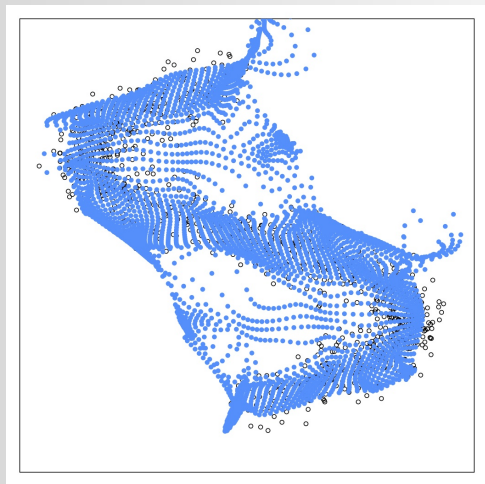
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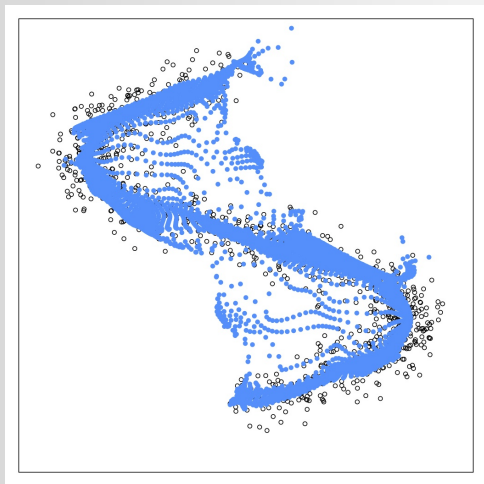
SCMS: Ridge Recovery Algorithm



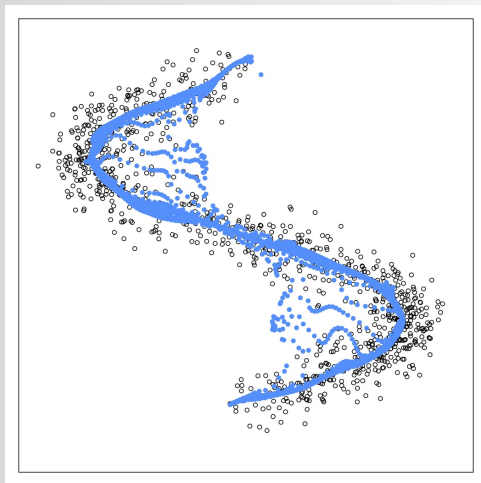
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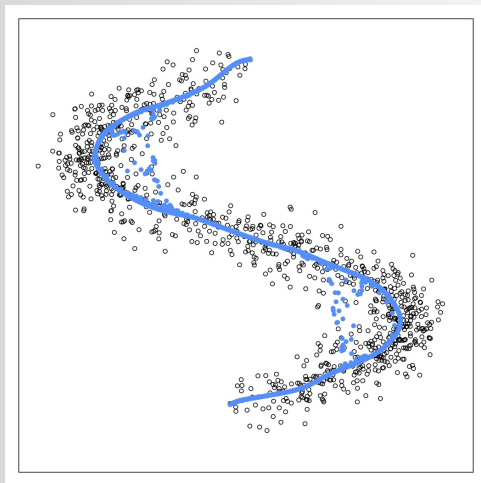
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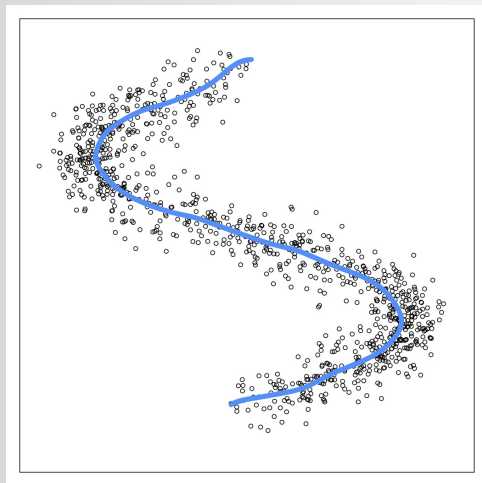
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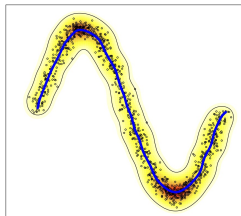
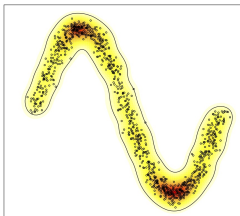
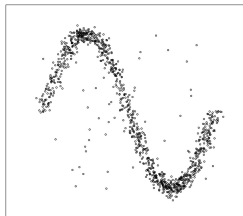
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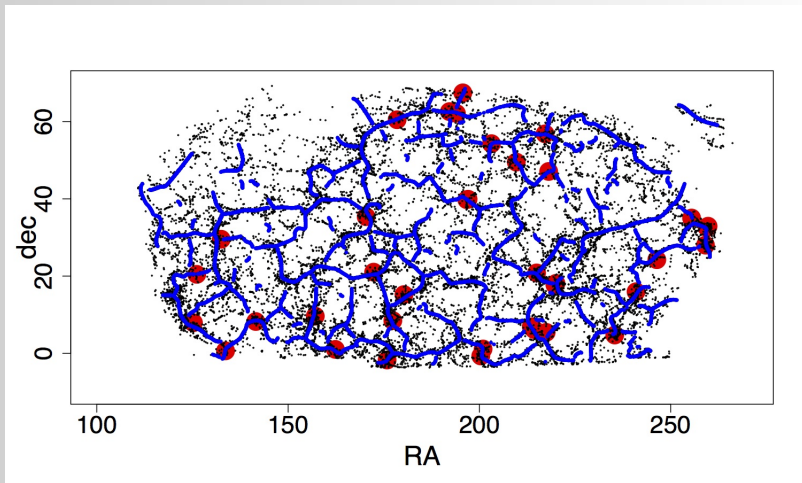
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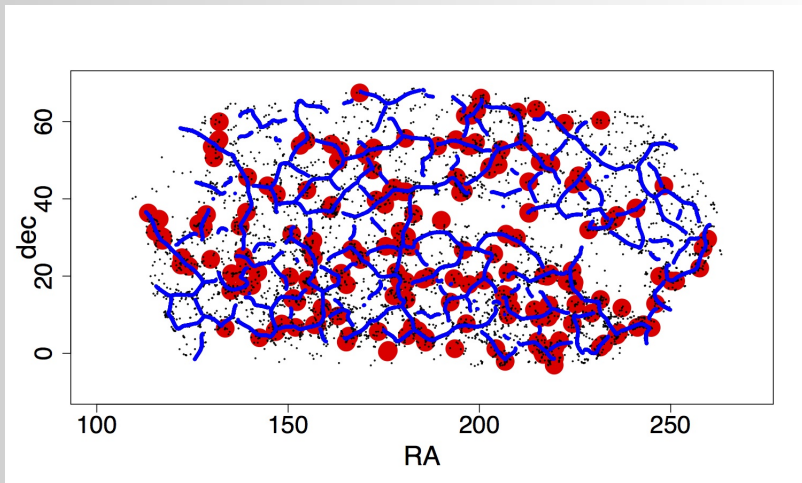
Summary for the Algorithm



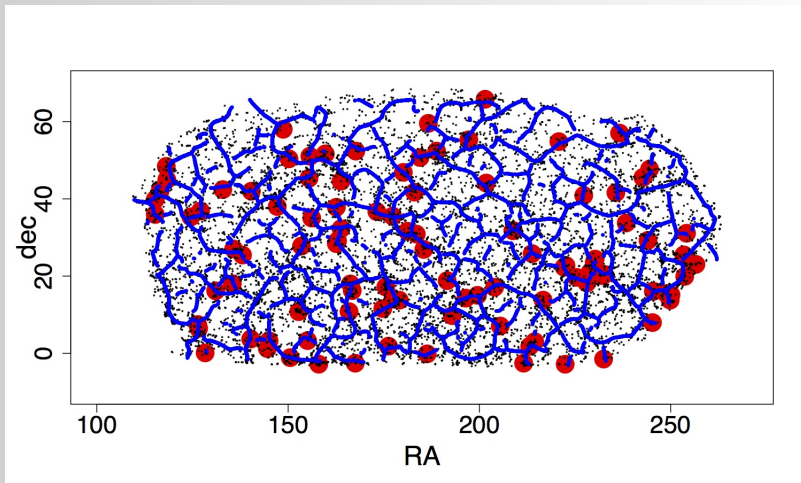
Density Ridges on the SDSS data



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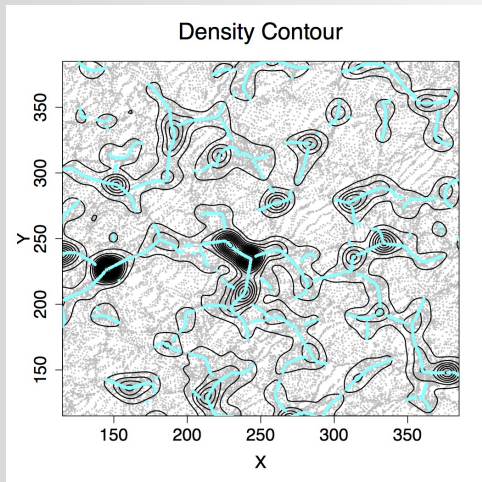
Simulation: Consistency for Density Ridges

- To evaluate the quality of our method, we use the N-body simulation.

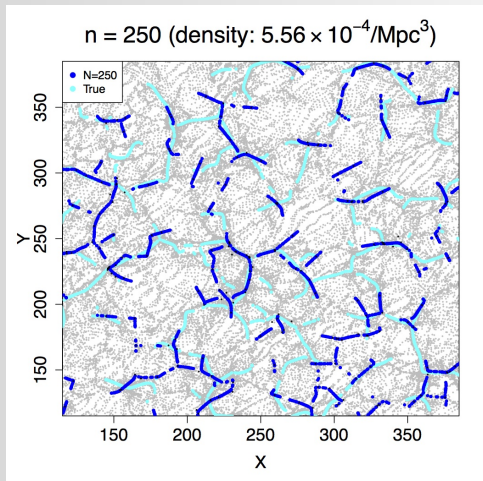
Simulation: Consistency for Density Ridges

- To evaluate the quality of our method, we use the N-body simulation.
- We define 'true' filaments as applying our method to 'all' galaxies in the simulation.
- We subsample part of the galaxies from the simulation.

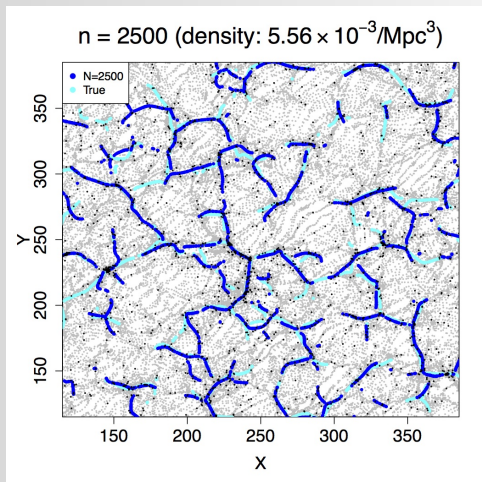
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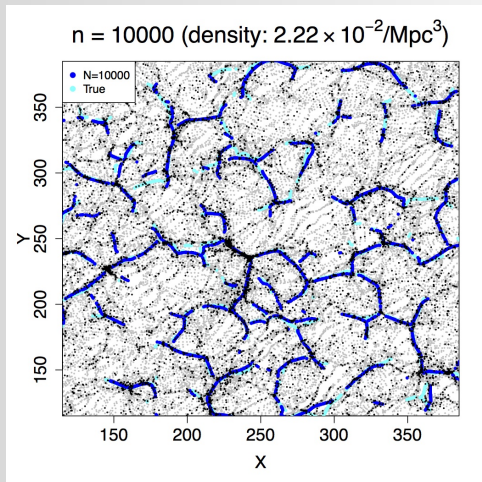
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Filament Coverage

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- *Filament coverage* provides a simple way to attain this.
- **True positive coverage:**

$$TP(r) = \frac{\text{length}(R \cap \widehat{R}_n \oplus r)}{\text{length}(R)}.$$

- **False positive coverage:**

$$FP(r) = 1 - \frac{\text{length}(\widehat{R}_n \cap R \oplus r)}{\text{length}(\widehat{R}_n)}.$$

- R and \widehat{R}_n are the 'true' filaments and estimated filaments.

Illustration: Filament Coverage

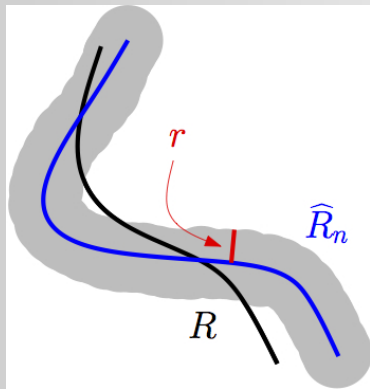


Figure: $TP(r)$

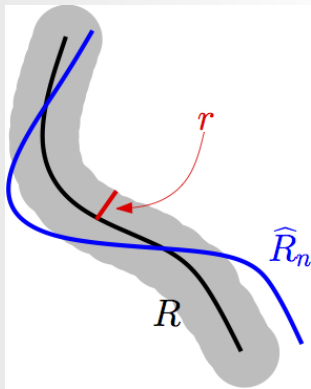
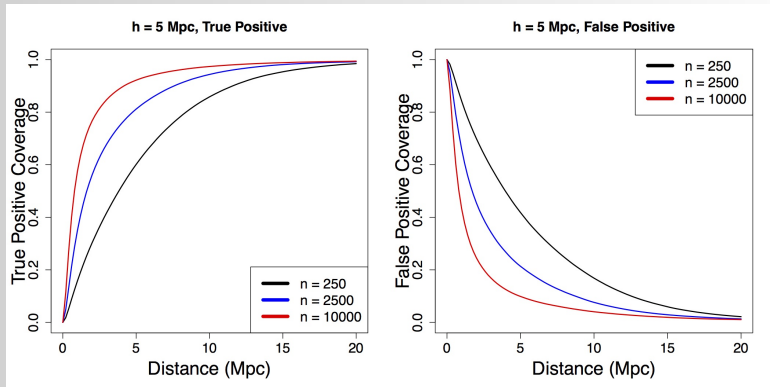


Figure: $1 - FP(r)$

Filament Coverage



The Need for Uncertainty Measure

- Filament coverage gives a (global) evaluation for filaments.
- We have no idea about the local uncertainty along filaments.
- Moreover, filament coverage requires the knowledge of truth.

Uncertainty Measures

Let R and \widehat{R}_n be the true filaments and the estimated filaments. For each $x \in R$, we define the **(local) uncertainty measure** as

$$\rho_n^2(x) = \mathbb{E}(d^2(x, \widehat{R}_n)),$$

where $d(x, A)$ is the projection distance from point x to a set A .

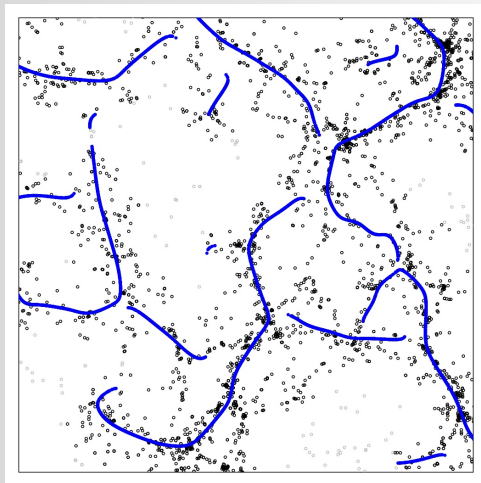
Remark:

- This is analogous to the mean square error.

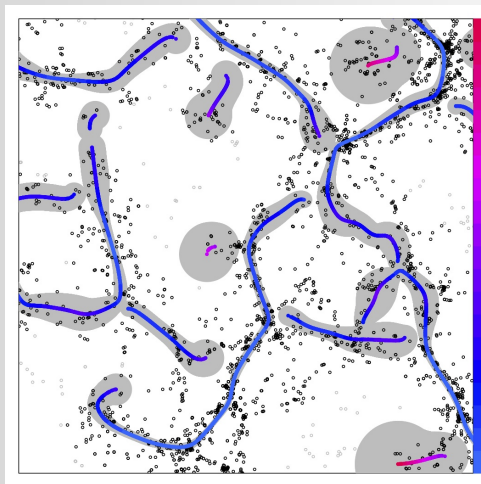
Estimating Uncertainty Measures

We apply the local uncertainty measure to our estimated filaments and use the *bootstrap* to evaluate the errors.

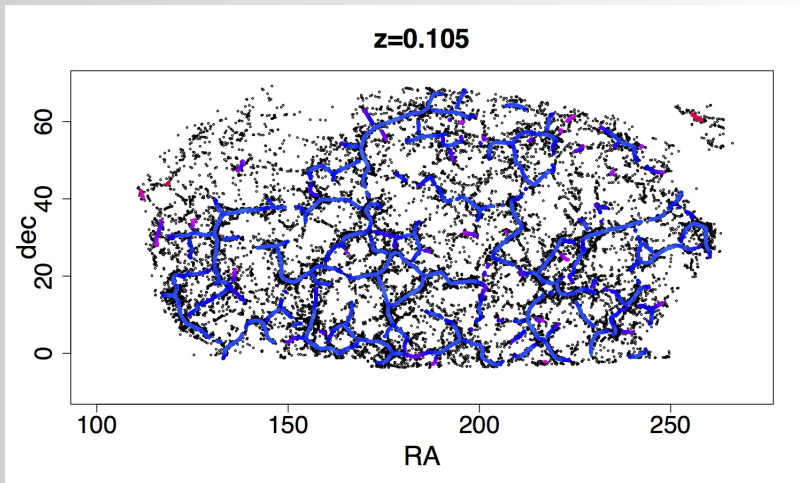
Real Data Evaluation



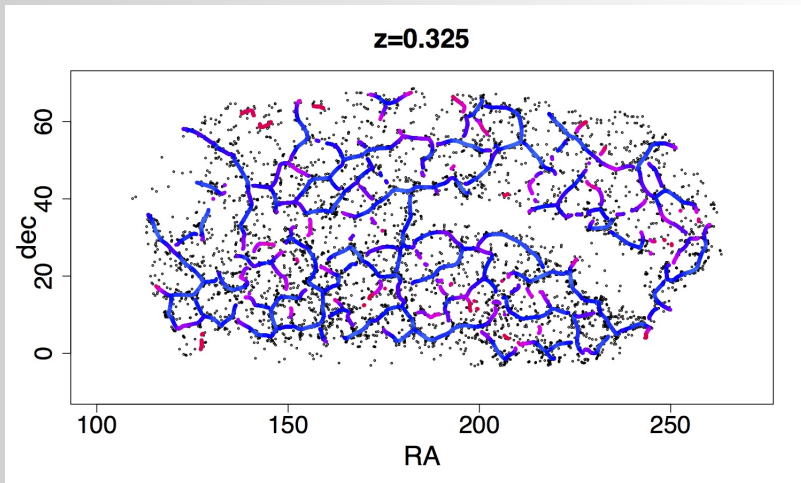
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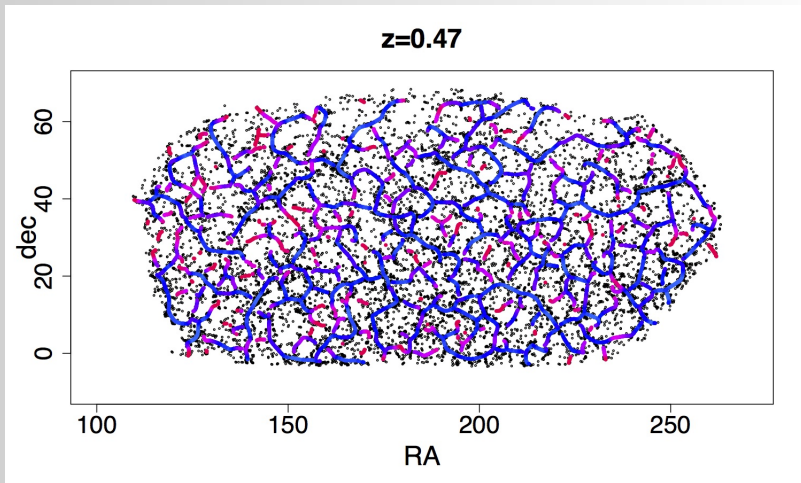
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- Goal: We want to see if galaxies close to filament are brighter than those away from filaments.

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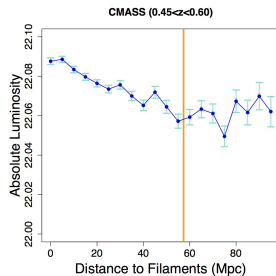
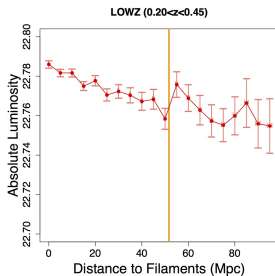
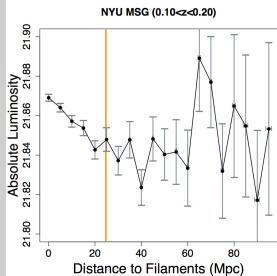
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- We analyze three datasets (at different ranges of redshifts).

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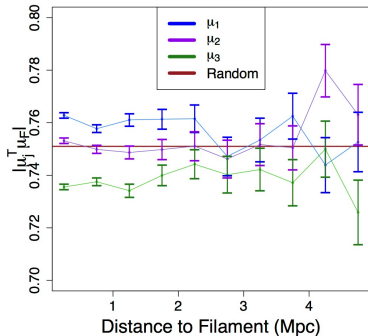
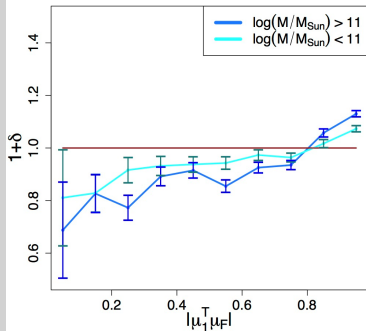
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- We analyze the massive blackhole dataset (a simulation dataset).

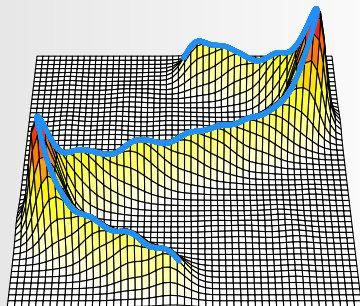
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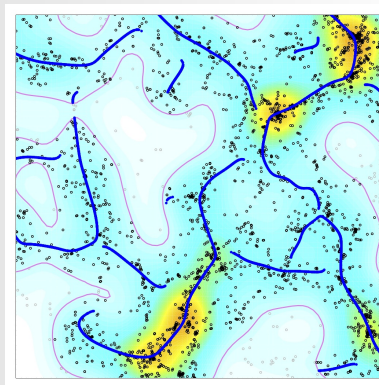
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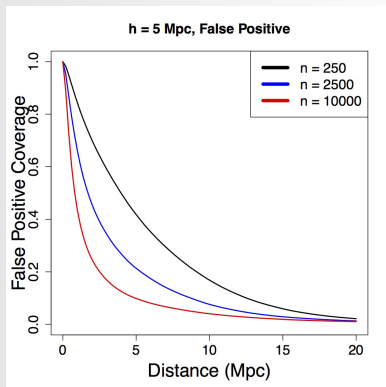
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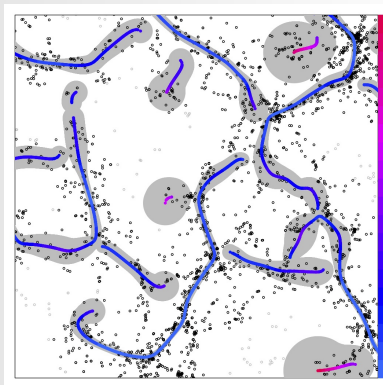
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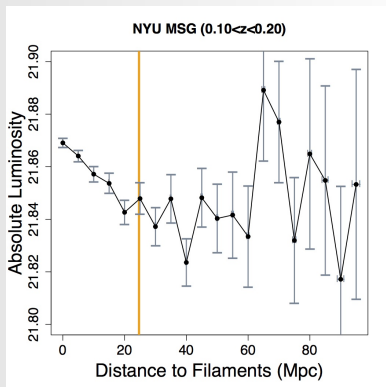
Summary

- 1 Model: density ridges.
- 2 Algorithm: SCMS.
- 3 Consistency: filament coverage.
- 4 Errors: uncertainty measures.



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- 2 Algorithm: SCMS.
- 3 Consistency: filament coverage.
- 4 Errors: uncertainty measures.
- 5 Application: galaxy luminosity, alignment.



Thank you!

1. Chen, Yen-Chi, Shirley Ho, Peter E. Freeman, Christopher R. Genovese, and Larry Wasserman. "Cosmic Web Reconstruction through Density Ridges: Method and Algorithm." arXiv preprint arXiv:1501.05303 (2015).
2. Chen, Yen-Chi, Christopher R. Genovese, and Larry Wasserman. "Asymptotic theory for density ridges." arXiv preprint arXiv:1406.5663 (2014).
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5. Genovese, Christopher R., et al. "Nonparametric ridge estimation." The Annals of Statistics 42.4 (2014): 1511-1545.
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