Using Minkowski Functionals to Analyze CMB Lensing

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What is Minkowski Functionals?

Euler's formula for convex polyhedra



V + F - E = 2

vertices faces edges

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Euler's formula for convex polyhedra



V + F - E = 2

vertices faces edges

8 + 6 - 12 = 2

Euler's formula for general surface







Euler's formula for general surface



2 + 4 - 4 = 2

vertices

edges faces



10 + 6 - 16 = 0

edges vertices faces



0 + 4 - 4 = 0

faces

vertices

edges

Euler's formula for general surface



6 + 8 - 12 = 2



faces edges



faces

16 + 13 - 29 = 0

vertices

edges



8 + 8 - 16 = 0

faces

vertices

edges

$V + F - E = \chi$ edges faces vertices Euler characteristic

$\chi = 2$ (# of disconnected parts) – η (# of **holes**)

non – orientable $\eta = \begin{cases} 1 \\ 2 \end{cases}$ orientable



 $\chi = 4$



 $\chi = 0$



Minkowski Functionals (MFs)

• morphological descriptors

d	1	2	3
V_0 V_1 V_2 V_3	$egin{array}{c} { m length} & \chi & \ - & $	area circumference χ -	volume surface area total mean curvature χ

- Minkowski Functionals of excursion sets
- Define a threshold value ν
- $\phi > \nu \rightarrow$ white, $\phi < \nu \rightarrow$ Black









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excursion sets

 χ = # of isolated white parts – # of isolated black parts





Analysis of 2D scalar field Φ

- Minkowski Functionals of excursion sets
- Define a **threshold value** ν
- $\phi > \nu \rightarrow$ white, $\phi < \nu \rightarrow$ Black









Note: This is not a one to one plot, just for demonstration

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MFs are idea descriptors of CMB Lensing

- Relatively straightforward to evaluate
- Sensitive to all higher order correlations (great for non-Gaussian field)





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Likelihood

 $-2 \ln \mathcal{L}(data | \Theta) = \sum_{i,j} \mu_i \overset{\downarrow}{C_{ij}} \overset{-1}{\mu_j} \mu_j$

$$\mu_i = V_n^{obs}(\nu_i) - V_n^{th}(\nu_i, \Theta)$$

$$\uparrow$$
Planck observation theory prediction

Likelihood

covariance matrix

$$-2\ln\mathcal{L}(data|\Theta) = \sum_{i,j} \mu_i \dot{C}_{ij}^{-1} \mu_j$$

$$\mu_i = V_n^{obs}(\nu_i) - V_n^{th}(\nu_i, \Theta)$$

↑
Planck observation
theory prediction

MFs from maps

Numerically •

$$V_0 = \int_{\Sigma} d\Omega$$
 at

rea

 $\kappa dl = -1$



 $V_1 = \frac{1}{4} \int_{\partial \Sigma} dl$

circumference

$$V_2 = \frac{1}{2\pi} \int_{\partial \Sigma} \kappa dl \qquad \mathbf{X}$$

 χ = # of isolated white parts – # of isolated black parts

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Planck observation
theory prediction

- N-body simulations + ray-tracing
- Perturbative approach

$$V_i = V_i^G + V_i^{(1)} \ \sigma + V_i^{(2)} \ \sigma^2 + \dots$$

Likelihood

covariance matrix

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$$\begin{split} V_i &= V_i^G + V_i^{(1)} \ \sigma + V_i^{(2)} \ \sigma^2 + \dots \\ V_i^G(\nu) \propto \left(\frac{\sigma_1}{\sqrt{2}\sigma}\right)^i \ e^{-\nu^2/2\sigma^2} \ H_{i-1}(\nu/\sigma) \\ & \text{Hermite polynomials} \end{split}$$

Likelihood

covariance matrix

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Planck observation
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Prediction of MFs

- N-body simulations + ray-tracing
- Perturbative approach

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$$V_i^{\rm G}(\nu) \propto \left(\frac{\sigma_1}{\sqrt{2\sigma}}\right)^{\sigma}$$



Hermite polynomials

2nd moment (variance)

Likelihood

covariance matrix

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Planck observation theory prediction

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Hermite polynomials

2nd moment (variance)

2nd moment of field gradient

Likelihood

covariance matrix

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$$\uparrow$$
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Likelihood

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- N-body simulations + ray-tracing
- Perturbative approach

$$V_{i} = V_{i}^{G} + V_{i}^{(1)} \sigma + V_{i}^{(2)} \sigma^{2} + \dots$$

$$\uparrow$$
2nd moment
$$\uparrow$$
Power spectrum

Likelihood

covariance matrix

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- Gaussian approximation $V_i pprox V_i^G$
- Forecast constrain with Planck-like fiducial data (best-fit, noise, mask)



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- Treat low multipoles and high multipoles separately



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Summary

- Minkowski functionals describe topological and morphological properties of maps
- For non-Gaussian maps, MFs can add information that is missed by the power spectrum
- MFs are promising tools for current and future CMB lensing observations

Back up Slides

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Covariance Matrix

