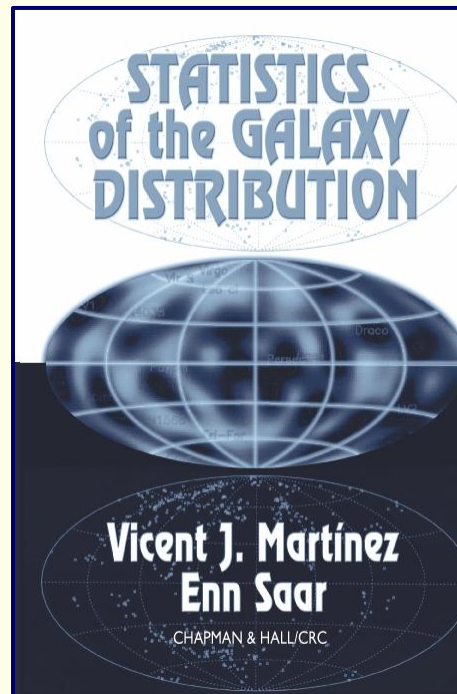


Measures of Cosmic Structure

Lecture course LSS2009
University Groningen
Apr. 2009-July 2009

Standard to
Reference:

Martinez & Saar



Ergodic Theorem

Statistical Cosmological Principle

Cosmological Principle:

Universe is Isotropic and Homogeneous

Homogeneous & Isotropic Random Field $\psi(\vec{x})$:

Homogenous

$$p[\psi(\vec{x} + \vec{a})] = p[\psi(\vec{x})]$$

Isotropic

$$p[\psi(\vec{x} - \vec{y})] = p[\psi(|\vec{x} - \vec{y}|)]$$

Within Universe one particular realization $\psi(\vec{x})$:

Observations: only spatial distribution in that one particular $\psi(\vec{x})$

Theory: $p[\psi(x)]$

Ergodic Theorem

Ensemble Averages \longleftrightarrow Spatial Averages
over one realization
of random field

- Basis for statistical analysis cosmological large scale structure
- In statistical mechanics Ergodic Hypothesis usually refers to time evolution of system, in cosmological applications to spatial distribution at one fixed time

Ergodic Theorem

Validity Ergodic Theorem:

- Proven for Gaussian random fields with continuous power spectrum

- Requirement:

spatial correlations decay sufficiently rapidly with separation

such that

many statistically independent volumes in one realization



All information present in complete distribution function $p[\psi(\vec{x})]$ available from single sample $\psi(x)$ over all space

Fair Sample Hypothesis

- Statistical Cosmological Principle
- +
- Weak cosmological principle
(small fluctuations initially and today over Hubble scale)
- +
- Ergodic Hypothesis

fair sample hypothesis
(Peebles 1980)

Discrete e.g. Continuous

Discrete & Continuous Distributions

- How to relate discrete and continuous distributions:
- Define number density $n(\vec{x})$ for a point process:

$$n(\vec{x}) = \bar{n}[1 + \delta(\vec{x})] = \sum_i \delta_D(\vec{x} - \vec{x}_i)$$

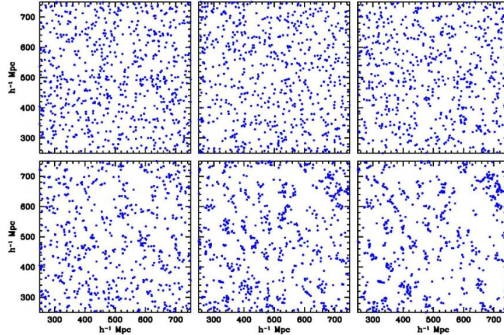
$\delta_D(\vec{x})$

Dirac Delta function

$$\left\langle \sum_i \delta_D(\vec{x} - \vec{x}_i) \right\rangle = \bar{n} \quad \text{ensemble average}$$

Correlation Functions

Correlation Functions

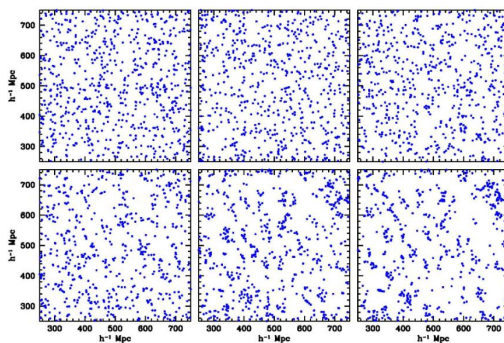


Joint probability that
in each one of
the two infinitesimal volumes
 dV_1 & dV_2 ,
at distance r ,
lies a galaxy

Infinitesimal Definition Two-Point Correlation Function:

$$dP(r) = \bar{n}^2 (1 + \xi(r)) dV_1 dV_2$$

Correlation Functions



In case of
Homogeneous & Isotropic
point process

then $\xi(\vec{r})$

only dependent on

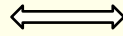
$$|\vec{r}| = r$$

Infinitesimal Definition Two-Point Correlation Function:

$$dP(r) = \bar{n}^2 (1 + \xi(r)) dV_1 dV_2$$

Correlation Functions

Discrete



Continuous

Two-point correlation function

$$dP(\vec{x}_1, \vec{x}_2) = \bar{n}^{-2} dV_1 dV_2 [1 + \xi(r_{12})]$$

$$r_{12} = |\vec{x}_1 - \vec{x}_2|$$

$$\langle \delta(\vec{x}) \rangle = 0$$

Autocorrelation function

$$\xi(r_{12}) = \langle \delta(\vec{x}_1) \delta(\vec{x}_2) \rangle$$

probability for 2 points in dV_1 and dV_2

Correlation Functions

- Gaussian (primordial and large-scale) density field:

Autocorrelation function $\xi(r)$ Fourier transform power spectrum $P(k)$

$$\xi(\mathbf{r}) = \xi(|\mathbf{r}|) = \int \frac{d\mathbf{k}}{(2\pi)^3} P_f(k) e^{-i\mathbf{k}\cdot\mathbf{r}}$$

Autocorrelation function completely specifies statistical properties of field

- First order measure of deviations from uniformity
- Nonlinear objects (halos):
 $\xi(r)$ measure of density profile
- Large Scales:
related to dynamics of structure formation via e.g. cosmic virial theorem

Correlation Functions: related measures

Other measures related to $\xi(r)$:

- Second-order intensity $\lambda_2(r) = \bar{n}^2 \xi(r) + 1$
- Pair correlation function $g(r) = 1 + \xi(r)$
- Conditional density $\Gamma(r) = \bar{n}(1 + \xi(r))$

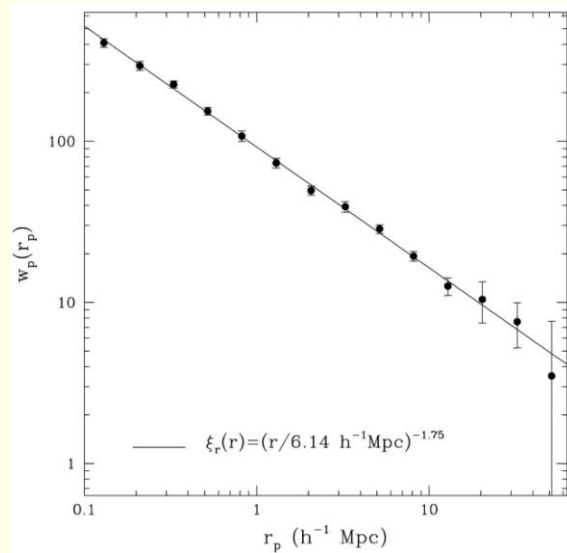
Correlation Functions: related measures

$$J_3(r) \equiv \int_0^{\infty} \xi(y) y^2 dy$$

Volume averaged correlation function $\bar{\xi}(r)$

$$\bar{\xi}(r) = \frac{3}{4\pi r^3} \int_0^r 4\pi \xi(x) x^2 dx = \frac{3J_3(r)}{r^3}$$

Power-law Correlations



$$\xi(r) = \left(\frac{r}{r_0} \right)^{-\gamma}$$

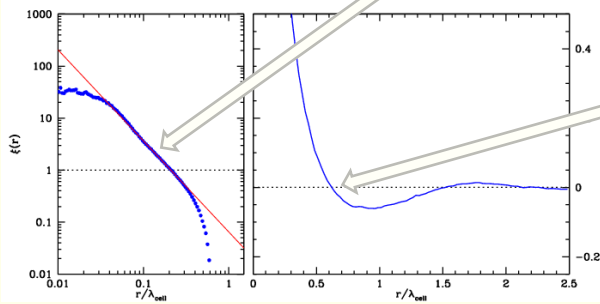
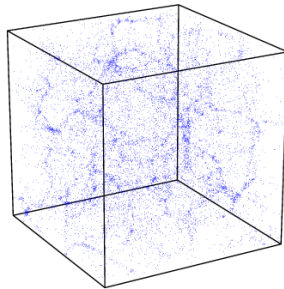
$$\gamma \approx 1.8$$

$$r_0 \approx 5 h^{-1} \text{ Mpc}$$

Totsuji & Kihara 1969

Peebles 1975, 1980, ...

Correlation Functions



$$\xi_{cc}(r) = \left(\frac{r_0}{r} \right)^\gamma$$

$$\xi(r_0) = 1$$

Clustering length/
"Correlation" length

Coherence length

$$\xi(r_a) = 0$$

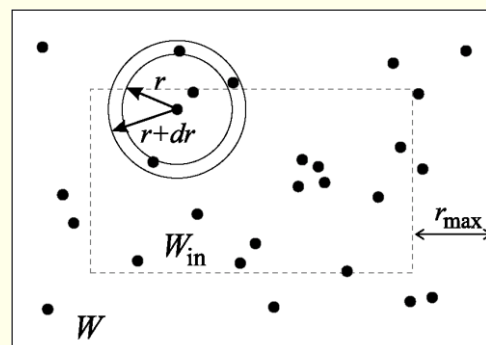
Correlation Function Estimators

Minimal Estimator

$$\hat{\xi}_{\min}(r) = \frac{V(W)}{NN_{in}} \sum_{i=1}^{N_{in}} \frac{n_i(r)}{V_{sh}} - 1$$

For galaxies close to the boundary the number of neighbours is underestimated. One way to overcome this problem is to consider as centers for counting neighbours only galaxies lying within an inner window W_{in}

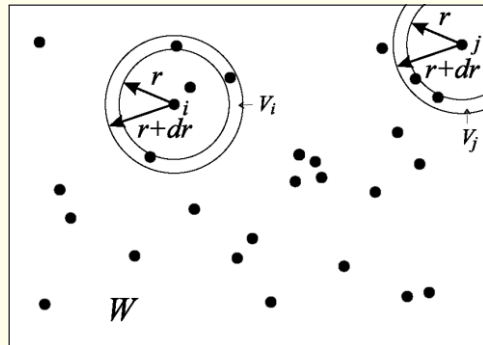
V_{sh} is the volume of the shell of width dr



Edge-Corrected Estimator

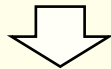
$$\hat{\xi}_{edge}(r) = \frac{V(W)}{N^2} \sum_{i=1}^{N_{in}} \frac{n_i(r)}{V_i} - 1$$

- $N_i(r)$: number of neighbours at distance in the interval $[r, r+dr]$ from galaxy i
- V_i : volume of the intersection of the shell with W
- W : when W a cube, an analytic expression for V_i can be found in Baddely et al. (1993).



Estimators Redshift Surveys

- In redshift surveys, galaxies are not sampled uniformly over the survey volume
- Depth selection:
in magnitude-limited surveys, the sampling density decreases as function of distance
- Survey Geometry
boundaries of survey often nontrivially defined:
 - slice surveys
 - non-uniform sky coverage
 - etc.



Clustering in survey compared with sample of Poisson distributed points, following the same sampling behaviour in depth and survey geometry

Difference in clustering between
data sample (D) and Poisson sample (R)
genuine clustering

Estimators Redshift Surveys

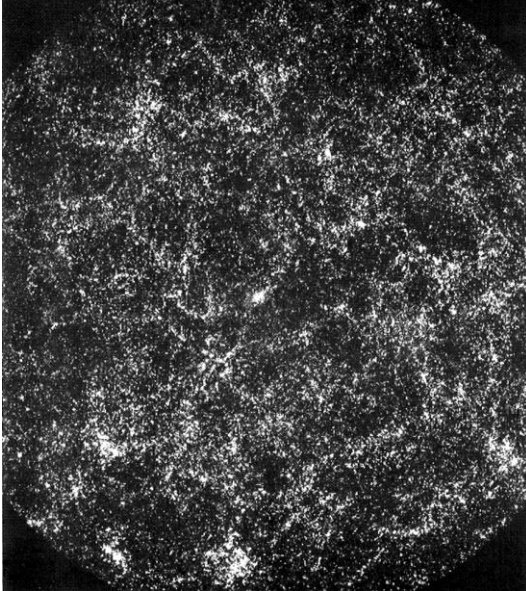
Clustering in survey compared with sample of Poisson distributed points, following the same sampling behaviour in depth and survey geometry

Difference in clustering between
data sample (D) and Poisson sample (R)
genuine clustering

- $\xi_{DP}(r) = \frac{n_R}{n_D} \frac{\langle DD \rangle}{\langle RR \rangle} - 1$ Davis-Peebles
(1983)
- $\xi_{Ham}(r) = \frac{\langle DD \rangle \langle RR \rangle}{\langle DR \rangle^2} - 1$ Hamilton
(1993)
- $\xi_{LS}(r) = 1 + \left(\frac{n_R}{n_D} \right)^2 \frac{\langle DD \rangle}{\langle RR \rangle} - 2 \frac{n_R}{n_D} \frac{\langle DR \rangle}{\langle RR \rangle}$ Landy-Szalay
(1993)

Angular
Two-point Correlation Function

Angular Correlation Function



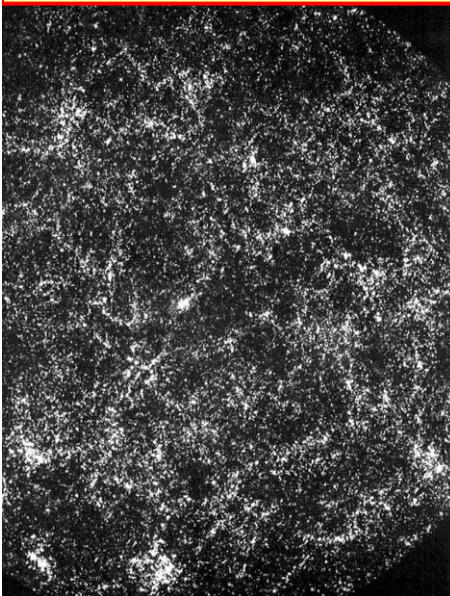
Galaxy sky distribution:

- Galaxies clustered, a projected expression of the true 3-D clustering
- Probability to find a galaxy near another galaxy higher than average (Poisson) probability
- Quantitatively expressed by 2-pt correlation function $w(\theta)$:

$$dP(\theta) = \bar{n}^2 \{1 + w(\theta)\} d\Omega_1 d\Omega_2$$

Excess probability of finding 2 gal's at angular distance θ

Angular & Spatial Clustering



$$dP(\theta) = \bar{n}^2 \{1 + w(\theta)\} d\Omega_1 d\Omega_2$$



Two-point angular correlation function is the "projection" of $\xi(r)$

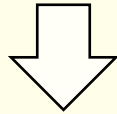
Limber's Equation:

$$w(\theta) = \frac{\iint p(\bar{x}_1) p(\bar{x}_2) x_1^2 x_2^2 dx_1 dx_2 \xi(|\bar{x}_1 - \bar{x}_2|)}{\left[\int_0^\infty x^2 p(x) dx \right]^2}$$

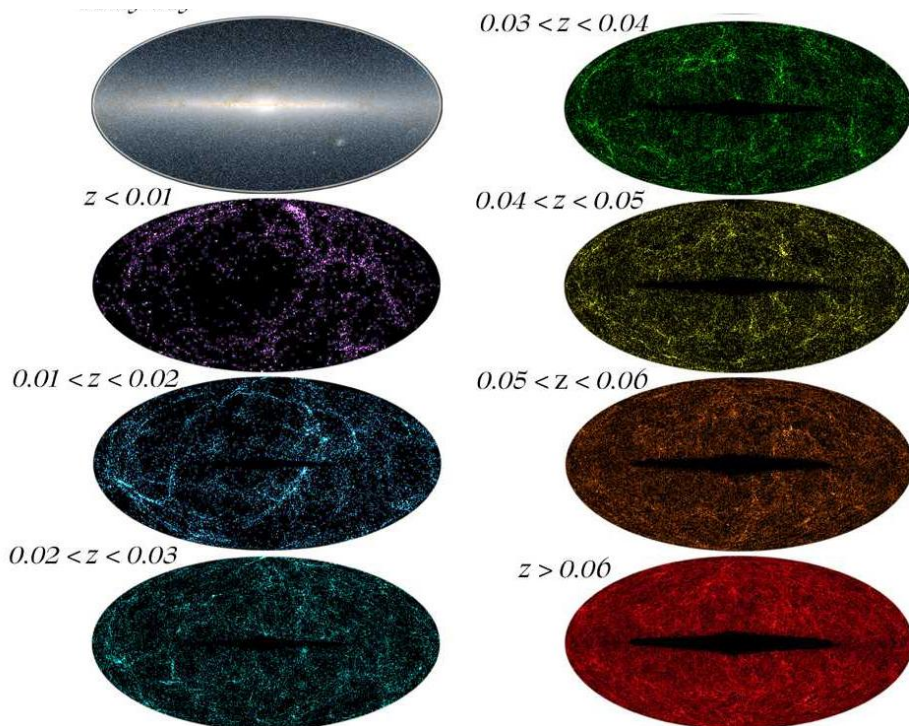
$p(x)$: survey selection function

Limber Equation

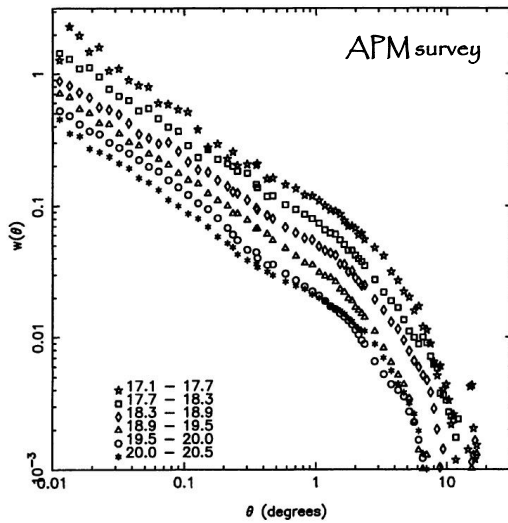
$$w(\theta) = \frac{\iint p(\vec{x}_1) p(\vec{x}_2) x_1^2 x_2^2 dx_1 dx_2 \xi(|\vec{x}_1 - \vec{x}_2|)}{\left[\int_0^\infty x^2 p(x) dx \right]^2}$$



$$\xi(r) = \left(\frac{r_0}{r} \right)^\gamma \longleftrightarrow w(\theta) = A \left(\frac{1}{\theta} \right)^{\gamma-1}$$



Angular Clustering Scaling



Two-point correlation function:

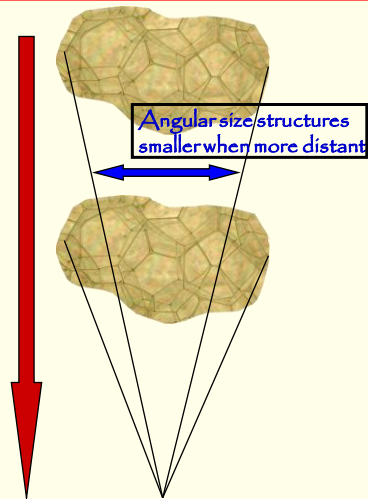
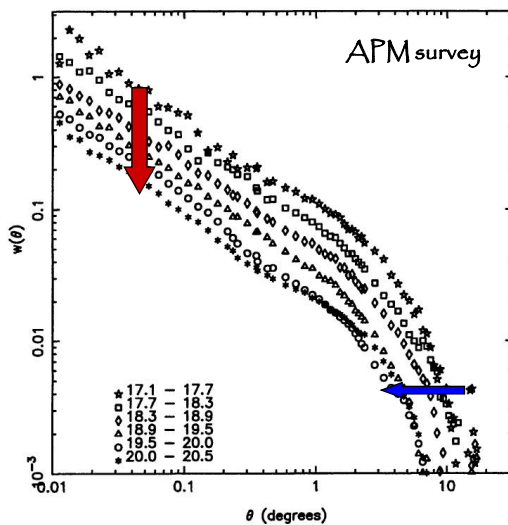
- small angles: power-law

$$w(\theta) = \left(\frac{\theta_0}{\theta} \right)^\gamma$$

$$\gamma \approx 0.8$$

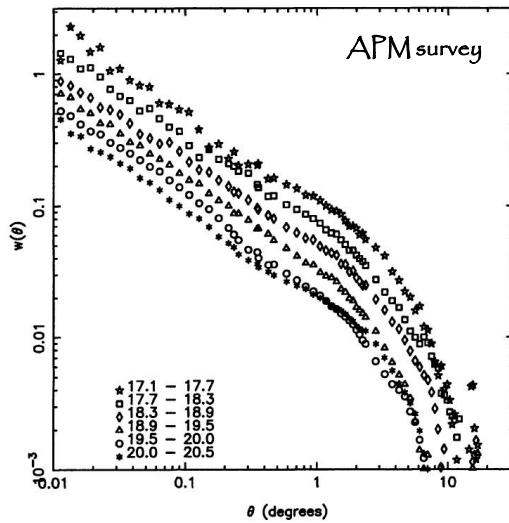
- large angles $\rightarrow 0$
i.e. to homogeneity

Angular Clustering Scaling



Projection of more layers leads to decreasing amplitude $w(\theta)$

Angular Clustering Scaling

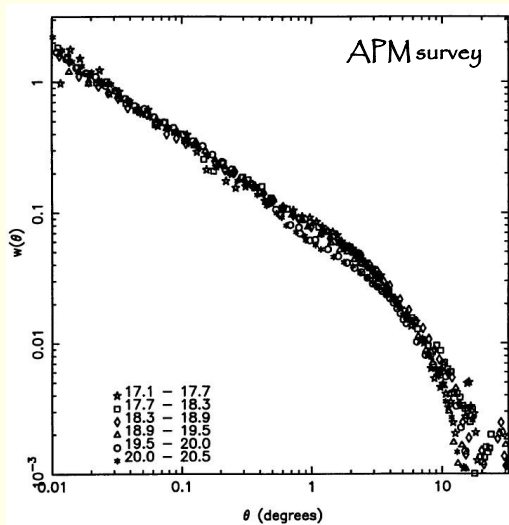


Angular size structures
smaller when more distant

Projection of
more layers
leads to
decreasing
amplitude $w(\theta)$

$$w(\theta, D_*) = \frac{1}{D_*} w(\theta D_*)$$

Angular Clustering Scaling



Angular size structures
smaller when more distant

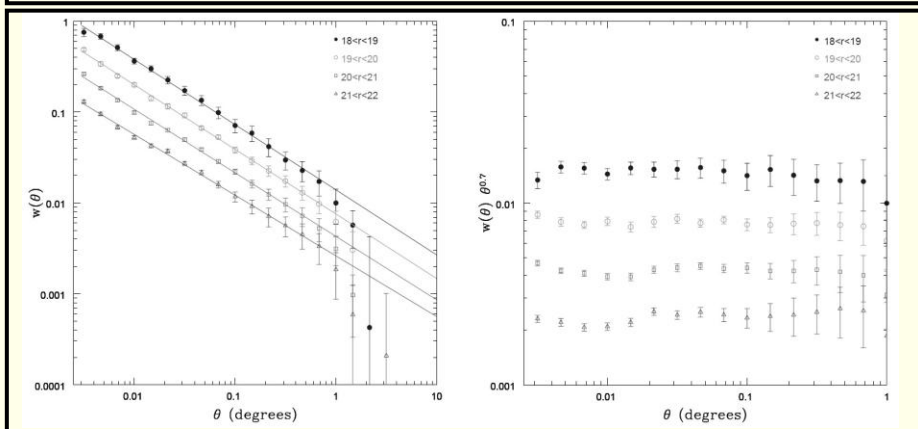
Projection of
more layers
leads to
decreasing
amplitude $w(\theta)$

$$w(\theta, D_*) = \frac{1}{D_*} w(\theta D_*)$$

Angular Clustering Scaling

The angular scaling of $w(\theta)$ is found back to even fainter magnitudes in the SDSS survey ($m=22$)

Clear evidence that there are no significant large structures on scales $> 100\text{-}200$ Mpc



Redshift Space Distortions

Redshift Distortions

- In reality, galaxies do not exactly follow the Hubble flow:

In addition to the cosmological flow, there are locally induced velocity components in a galaxy's motion:

$$cz = Hr + v_{pec}$$

the galaxy's peculiar velocity v_{pec}

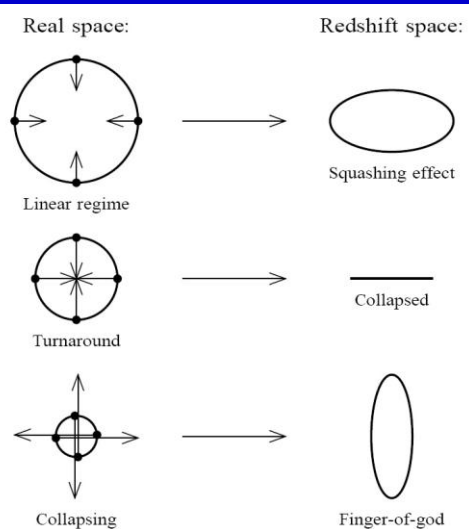
- As a result, maps on the basis of galaxy z do not reflect the galaxies' true spatial distribution

Redshift Distortions

Origin of peculiar velocities:

three regimes

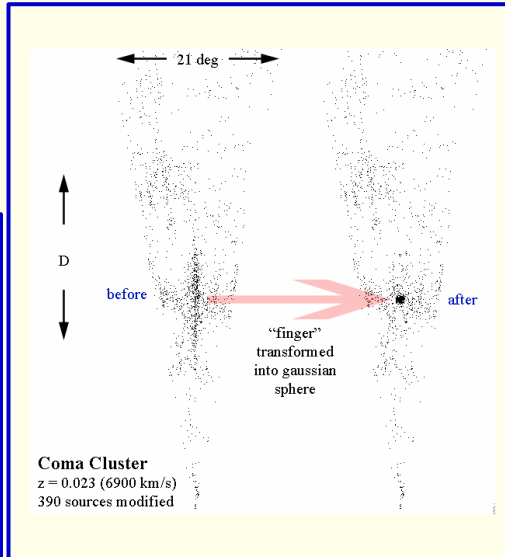
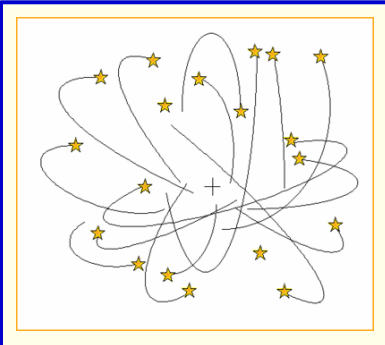
- very high-density virialized cluster (core) regions: "thermal" motion in cluster, up to > 1000 km/s
"Fingers of God"
- collapsing overdensity (forming cluster): inflow/infall velocity
- Large scales: (linear, quasi-linear) cosmic flow, manifestation of structure growth



Fingers of God

$$cz = Hr_{clust} + \frac{\vec{v}_{gal} \cdot \vec{r}_{gal}}{r_{gal}}$$

Galaxy velocity
component along
line of sight



Fingers of God

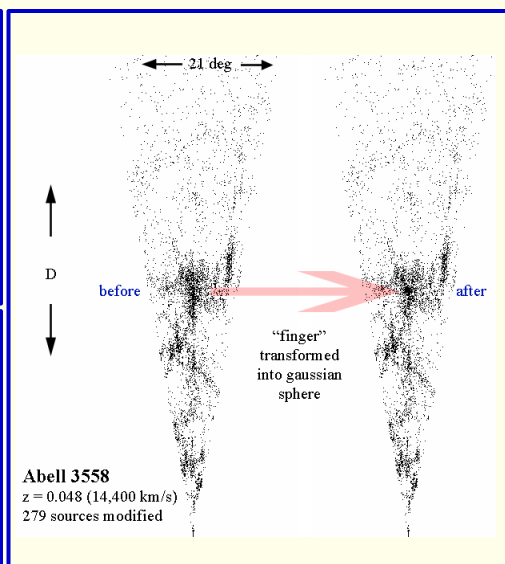
Clusters of galaxies:

Mass: 10^{14} - $10^{15} M_{\odot}$
Radius: ~ 1.5 Mpc
Overdensity $\Delta \sim 1000$

Thermal velocity: ~ 1000 km/s

Internal cluster galaxy velocities
visible in projection along line of sight

→ "Finger of God"



Nonlinear Infall Pattern

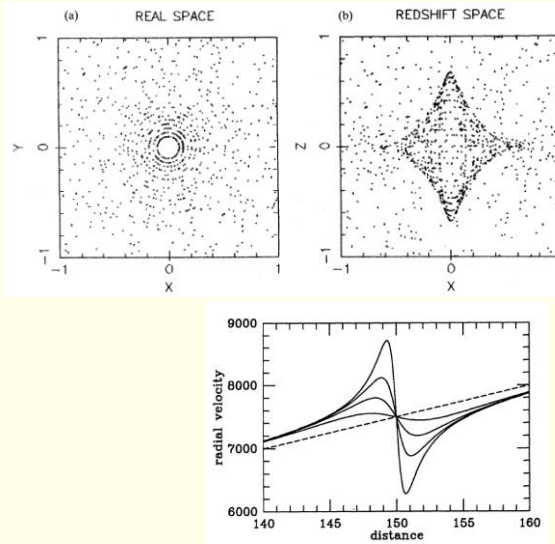
Cluster Infall:

Matter in surroundings falling in onto cluster:

- infall velocities up to 1000 km/s radially declining:
- velocities decrease as distance to cluster centre increases
- projected radial velocity function of angle & distance wrt. cluster centre.



- triple-value region redshift space:
 - within turnaround radius, a particular redshift may correspond to 3 spatial positions



Nonlinear Infall Pattern

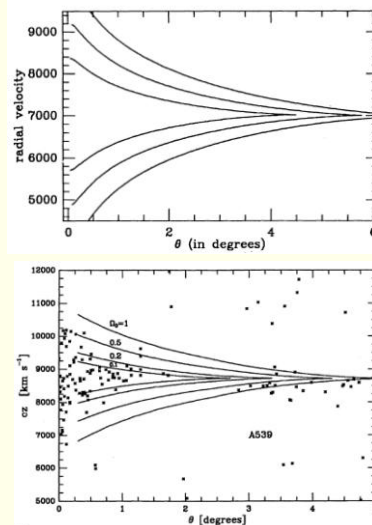
Cluster Caustics:

Three-value region cluster infall:

Projection onto restricted cone-shaped redshift space regions around clusters

Enclosed within caustic surfaces

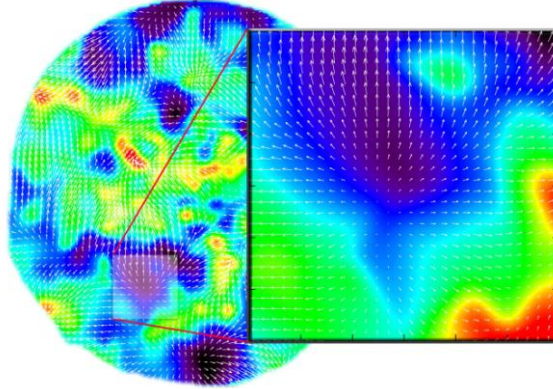
Position caustics dependent on Ω_m



Large Scale Flows

Large-Scale Flows:

- On large (Mpc) scales, structure formation still in linear regime
- Structure buildup accompanied by displacement of matter:
 - Cosmic flows
- Directly related to cosmic matter distribution
- In principle possible to correct for this distortion, i.e. to invert the mapping from real to redshift space
- Condition: entire mass distribution within volume should be mapped



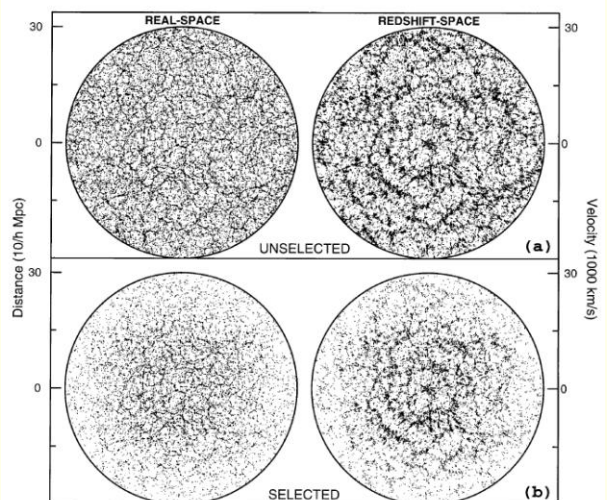
$$\mathbf{v}(\mathbf{x}, t) = \frac{H}{4\pi} \frac{f(\Omega_m)}{b} a \int d\mathbf{x}' \delta_{gal}(\mathbf{x}', t) \frac{(\mathbf{x}' - \mathbf{x})}{|\mathbf{x}' - \mathbf{x}|^3}$$

Large Scale Flows

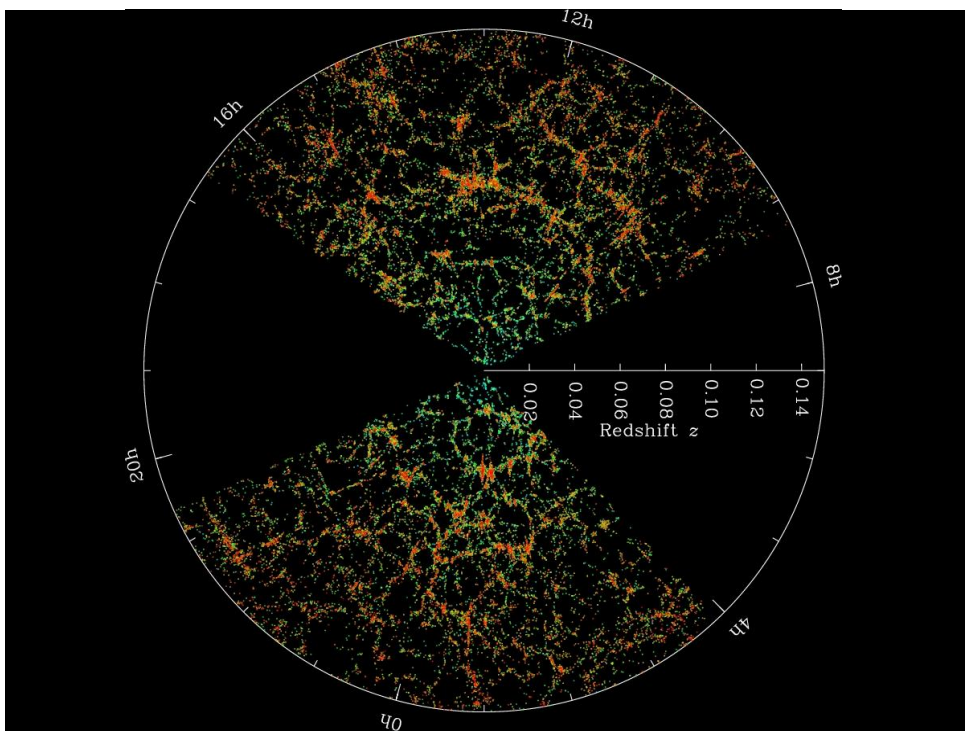
Large-Scale Flows:

The induced large scale peculiar velocities translate into extra contributions to the redshift of the galaxies

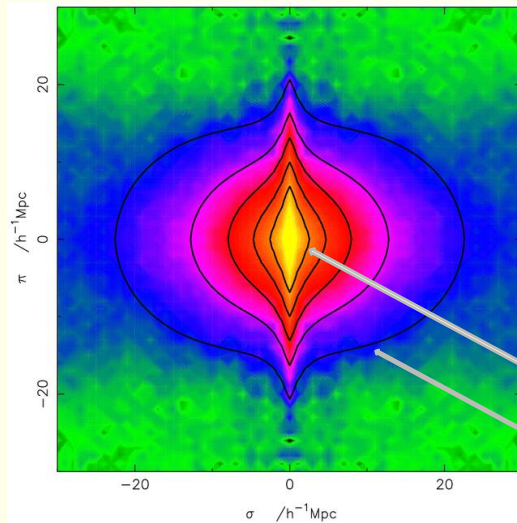
Compare "real space" structure vs. "redshift space" structure



Correlation Functions: Redshift Space



sky-redshift space 2-pt correlation function $\xi(\sigma, \pi)$



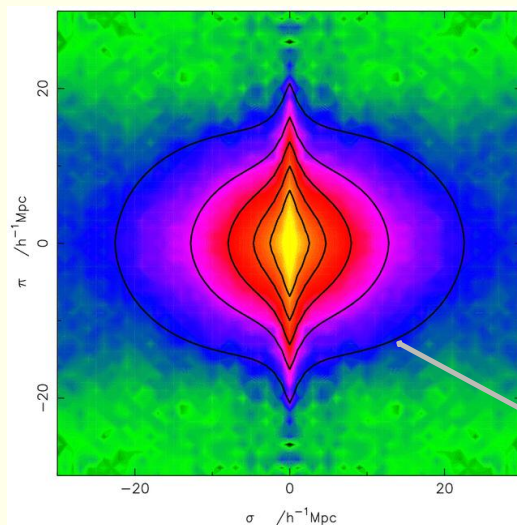
Correlation function determined
in sky-redshift space:

$$\xi(\sigma, \pi)$$

sky position: $\sigma = (\alpha, \delta)$
redshift coordinate: $\pi = cz$

Close distances:
distortion due to non-linear
Finger of God
Large distances:
distortions due to large-scale
flows

Redshift Space Distortions Correlation Function

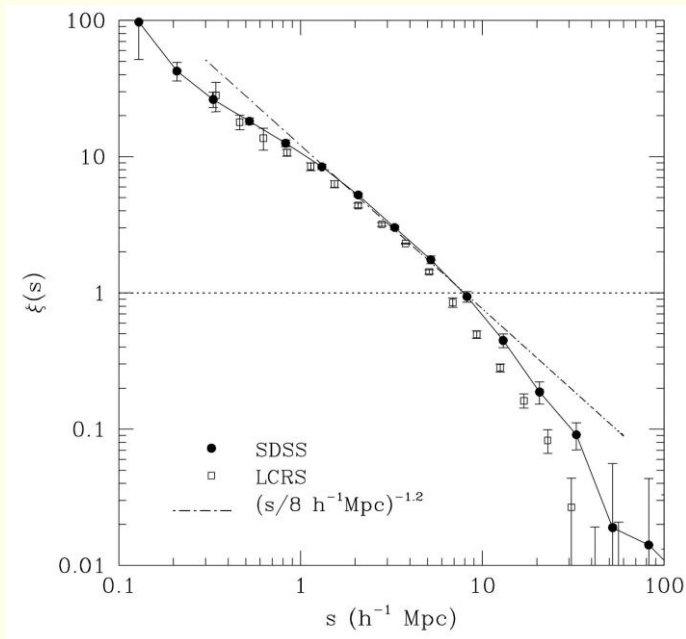


On average, $\xi_s(s)$ gets amplified
wrt. $\xi_r(r)$

Linear perturbation theory
(Kaiser 1987):

$$\xi_s(s) = \left(1 + \frac{2}{3}\Omega^{0.6} + \frac{1}{5}\Omega^{1.2}\right)\xi_r(s)$$

Large distances:
distortions due to large-scale
flows



Measurement
Spatial 2pt-Correlation Function

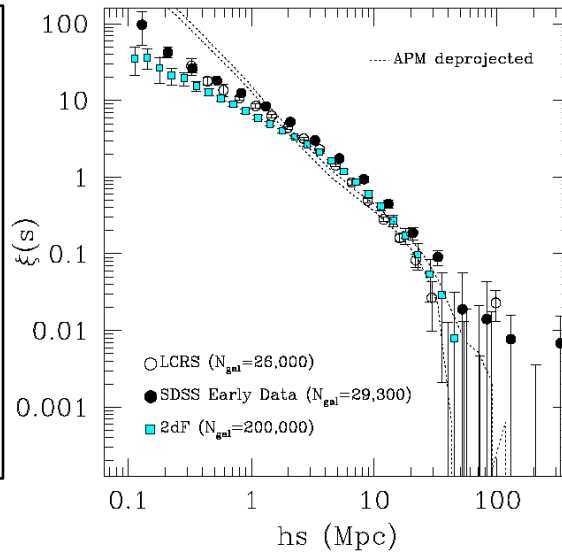
Deprojected Spatial Correlations

2pt correlation function
not an ideal power-law:

Halo Model:

Two-point correlation function
combination of

- 1) small-scale correlations,
due to galaxies inside
one dark matter halo
- 2) large scale correlations
between dark matter halos



Convergence to Homogeneity

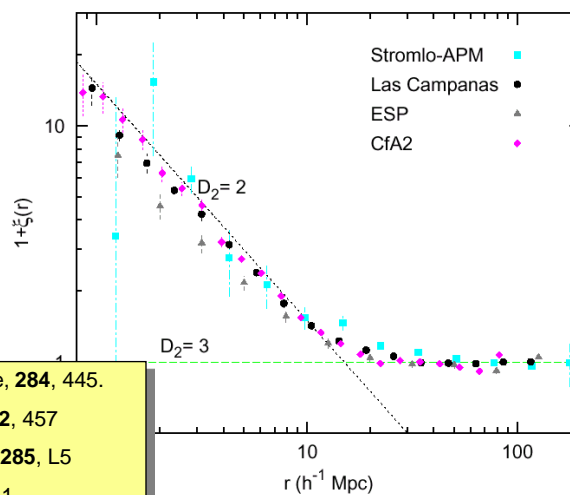
The correlation function
 $g(r)=1+\xi(r)$

Stromlo-APM, Las Campanas
CfA2, ESP redshift surveys.

The fractal behavior at small
scales disappears at larger
distances, providing evidence
for a gradual transition to
homogeneity.

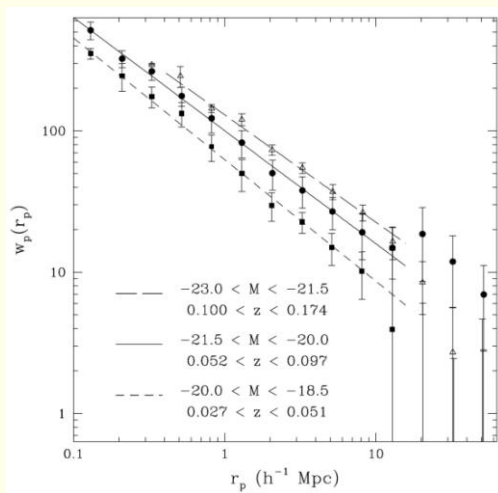
Plot from Martínez, 1999, *Science*, **284**, 445.

- (1) Loveday *et al.*, 1995, *ApJ*, **442**, 457
- (2) Tucker *et al.*, 1997, *MNRAS*, **285**, L5
- (3) Guzzo *et al.*, 2000, *AA*, **355**, 1



Luminosity Dependence Correlation Functions

Galaxy Luminosity Dependence



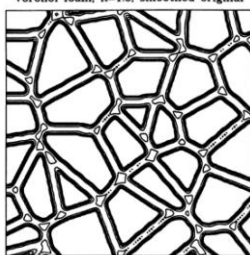
SDSS
correlation function

for galaxies in different
luminosity bins

Spatial Structure & Correlation Functions

Structural Insensitivity

Voronoi foam, R=1.6, smoothed original



2-pt correlation function is highly insensitive to the geometry & morphology of weblike patterns:

compare 2 distributions with same $\xi(r)$, cq. $P(k)$, but totally different phase distribution

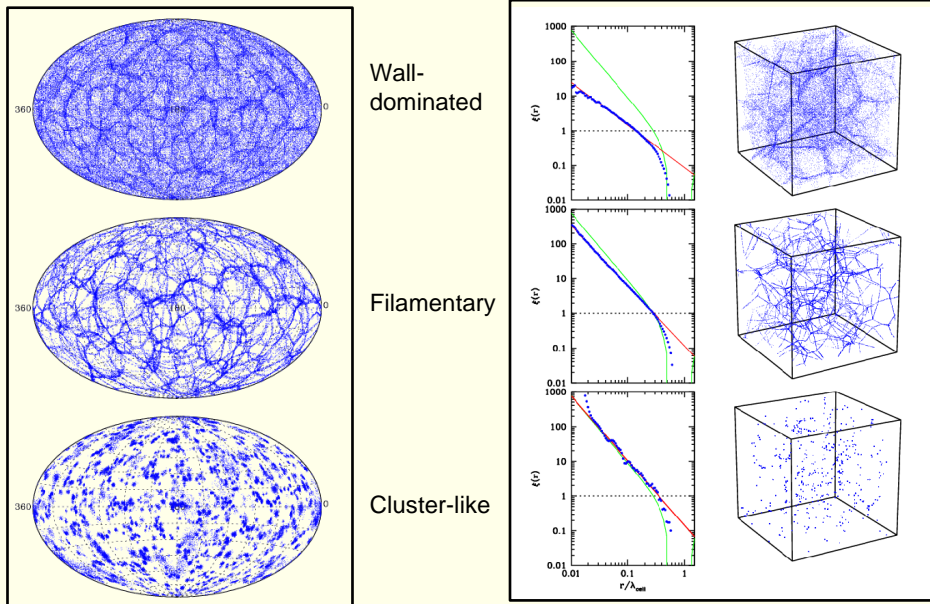
Voronoi foam, R=1.6, random phases



In practice, some sensitivity in terms of distinction Field, Filamentary, Wall-like and Cluster-dominated distributions:

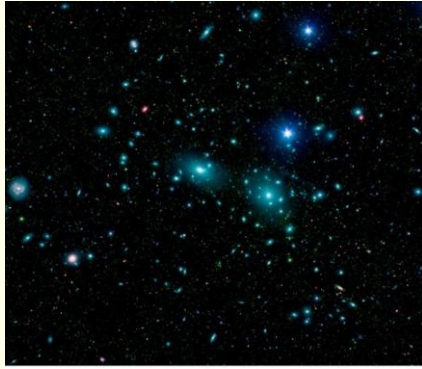
because of different fractal dimensions

Structural Sensitivity



Cluster
Correlation Functions

Clusters of Galaxies



Coma Cluster



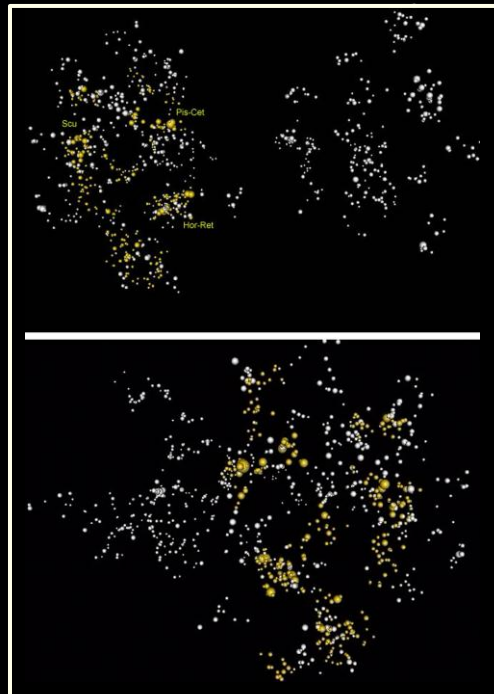
Perseus Cluster

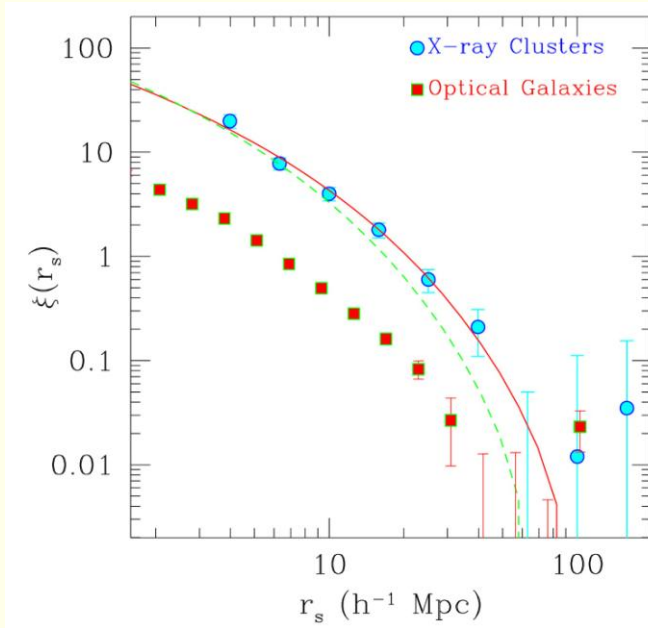
Clustering of Clusters

Clusters cluster much more strongly than galaxies:

- clustering defines superclusters !
- also power-law 2-pt correlation fct.
- same power law slope $\gamma \sim 1.8$
- much higher correlation length r_0 :

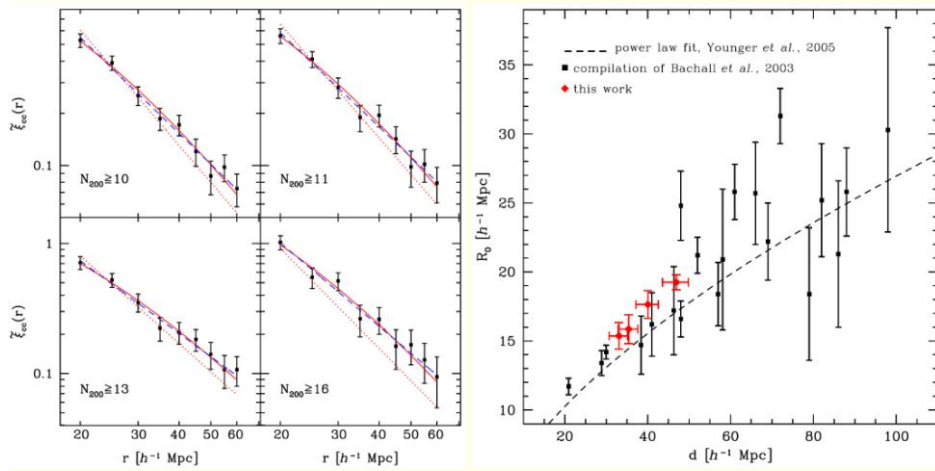
$$r_0 \sim 15\text{-}25 \text{ h}^{-1} \text{ Mpc}$$





Richness-Dependent Cluster Correlations

More massive clusters are systematically more strongly clustered than lower mass ones.



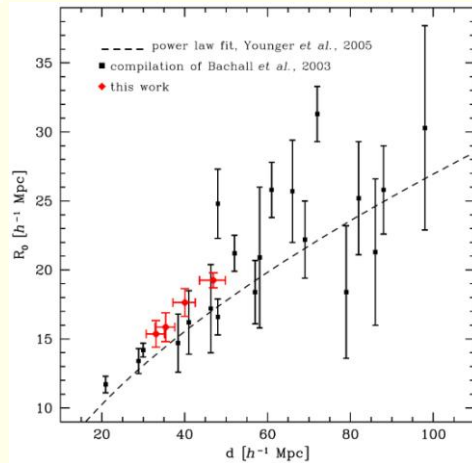
Richness-Dependent Cluster Correlations

More massive clusters are more systematically more strongly clustered than lower mass ones:

simple model:
Szalay & Schramm 1985

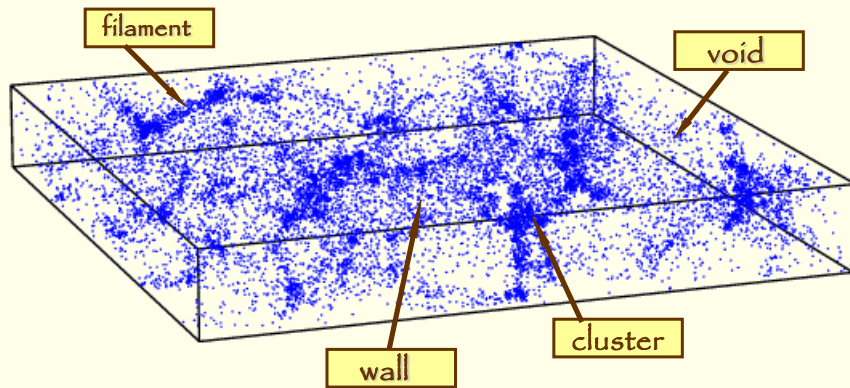
$$\xi_{cc}(r) = \beta \left(\frac{L(r)}{r} \right)^\gamma$$

$$L(R) = n^{-1/3}$$

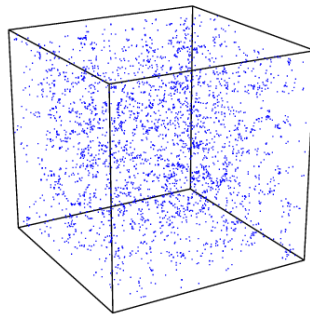


Scaling of
Cluster Correlation Functions:
a geometric model

Voronoi Models: Templates for the Cosmic Web

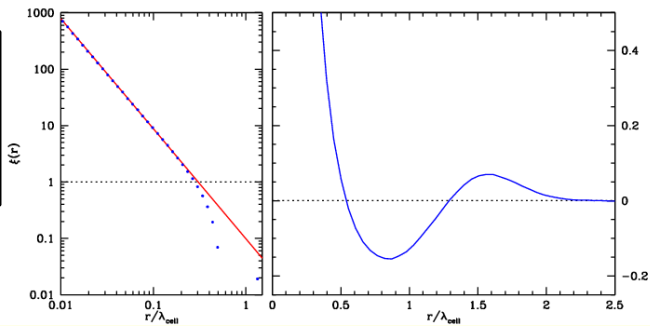


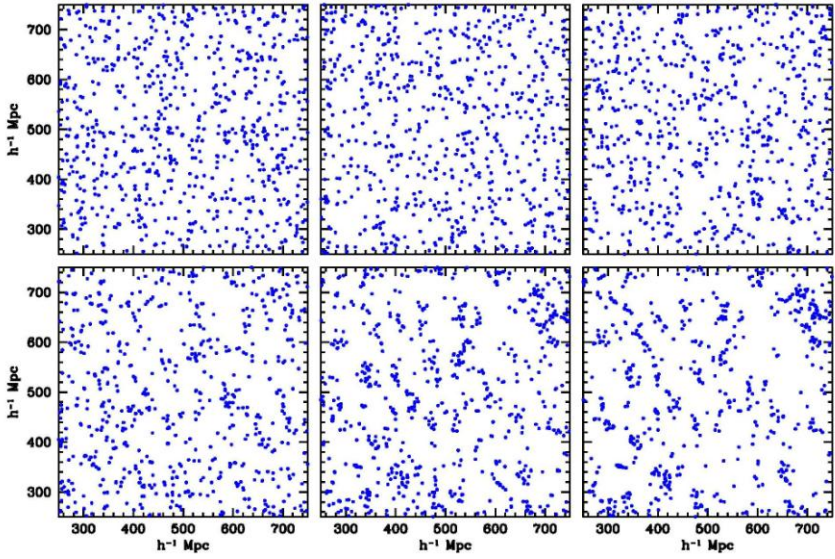
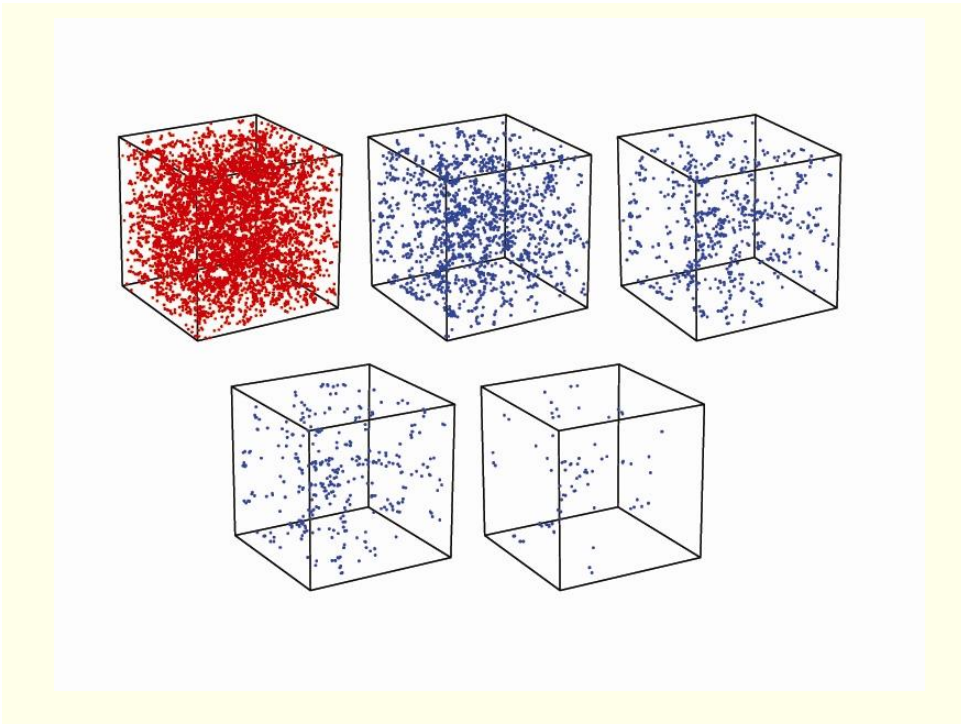
Perfect
Power-law clustering
Voronoi vertices



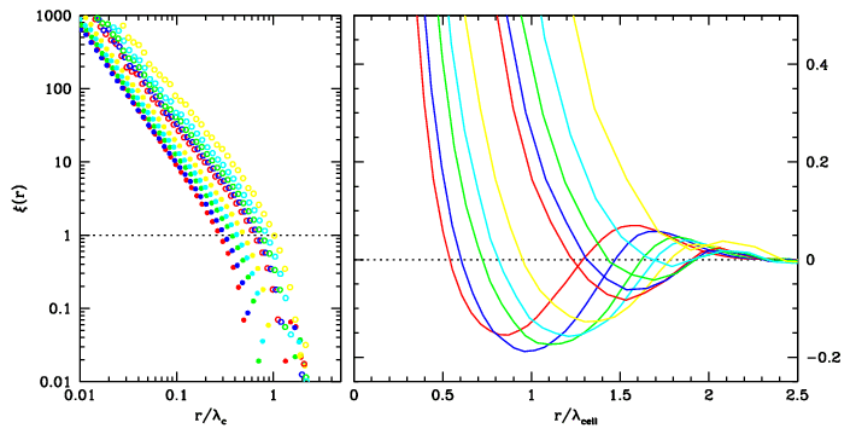
$$\xi_{vv}(r) = \left(\frac{r_0}{r}\right)^\gamma$$

$\gamma = 1.95; \quad r_0 \approx 0.3 \lambda_c$



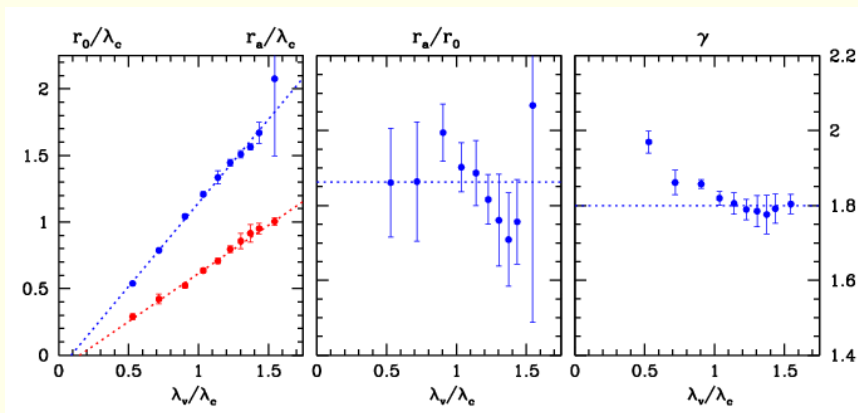


Self-similar Clustering



As function of mass, the correlation length r_0 and coherence length r_a increase unanimously.

Self-similar Clustering



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Higher Order Correlation Functions:

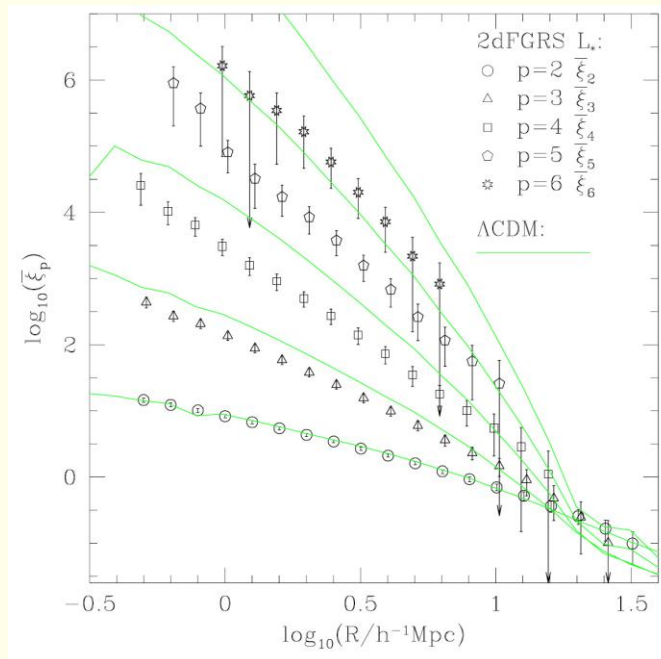
N-point correlation functions

- N-point correlation function

$$\xi^{(n)}(\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n)$$

- Probability function of finding an n-tuplet of galaxies in n specified volumes dV_1, dV_2, \dots, dV_n

$$dP(\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n) = \bar{n}^n [1 + \xi^{(n)}] dV_1 dV_2 \dots dV_n$$

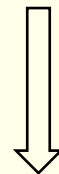


3-point correlation functions

3-point correlation function

$$dP(\vec{x}_1, \vec{x}_2, \vec{x}_3) = \bar{n}^{-3} [1 + \xi^{(3)}] dV_1 dV_2 dV_3$$

$$[1 + \xi^{(3)}] = \left\langle \prod_i (1 + \delta_i) \right\rangle$$



$$[1 + \xi^{(3)}] = 1 + \xi(r_{12}) + \xi(r_{13}) + \xi(r_{23}) + \zeta(\vec{r}_1, \vec{r}_2, \vec{r}_3)$$

3-point correlation functions

3-point correlation function

$$[1 + \xi^{(3)}] = 1 + \xi(r_{12}) + \xi(r_{13}) + \xi(r_{23}) + \zeta(\vec{r}_1, \vec{r}_2, \vec{r}_3)$$

reduced 3-point correlation function

$$\zeta(\vec{r}_1, \vec{r}_2, \vec{r}_3) = \langle \delta_1 \delta_2 \delta_3 \rangle$$

excess correlation over that described by the 2-pt contributions

- $\zeta \neq 0$: non-Gaussian density field
- Hierarchical ansatz (Groth & Peebles 1977)

$$\zeta(\vec{r}_1, \vec{r}_2, \vec{r}_3) = Q(\xi_{12}\xi_{23} + \xi_{23}\xi_{31} + \xi_{31}\xi_{12})$$

Power Spectrum

Power Spectrum

- Directly measuring clustering in Fourier space:
 - More intuitive physically: separating processes on different scales
 - Theoretical model predictions are made in terms of power spectrum
 - Amplitudes for different wavenumbers are statistically orthogonal

Power Spectrum $P(k)$

$$\delta(\mathbf{x}) = \int \frac{d\mathbf{k}}{(2\pi)^3} \hat{\delta}(\mathbf{k}) e^{-i\mathbf{k}\cdot\mathbf{x}}$$

$$\begin{aligned} (2\pi)^3 P(k_1) \delta_D(\mathbf{k}_1 - \mathbf{k}_2) &\equiv \langle \hat{f}(\mathbf{k}_1) \hat{f}^*(\mathbf{k}_2) \rangle \\ &\quad \updownarrow \\ P(k) &\propto \langle \hat{f}(\mathbf{k}) \hat{f}^*(\mathbf{k}) \rangle \end{aligned}$$

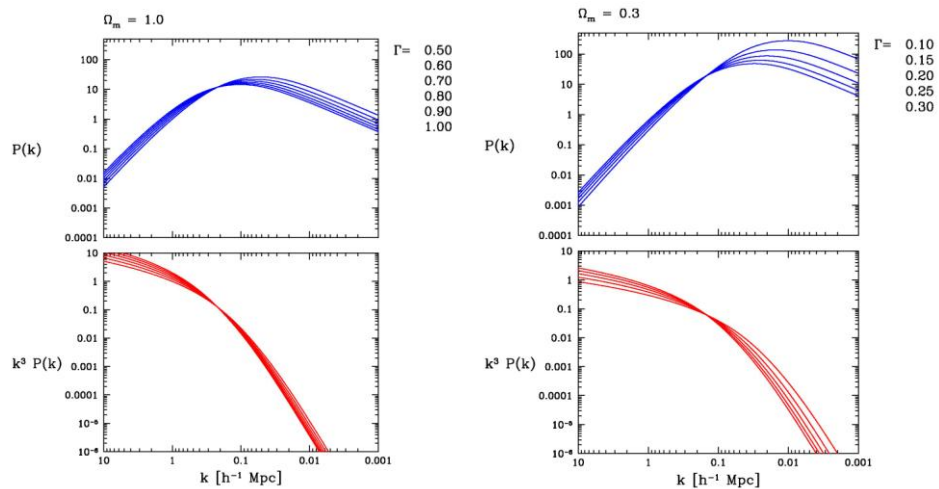
CDM Power Spectrum $P(k)$

$$P_{\text{CDM}}(k) \propto \frac{k^n}{[1 + 3.89q + (16.1q)^2 + (5.46q)^3 + (6.71q)^4]^{1/2}} \times \frac{[\ln(1 + 2.34q)]^2}{(2.34q)^2}$$

$$q = k/\Gamma$$

$$\Gamma = \Omega_{m,0} h \exp\left\{-\Omega_b - \frac{\Omega_b}{\Omega_{m,0}}\right\}$$

Power Spectrum $P(k)$



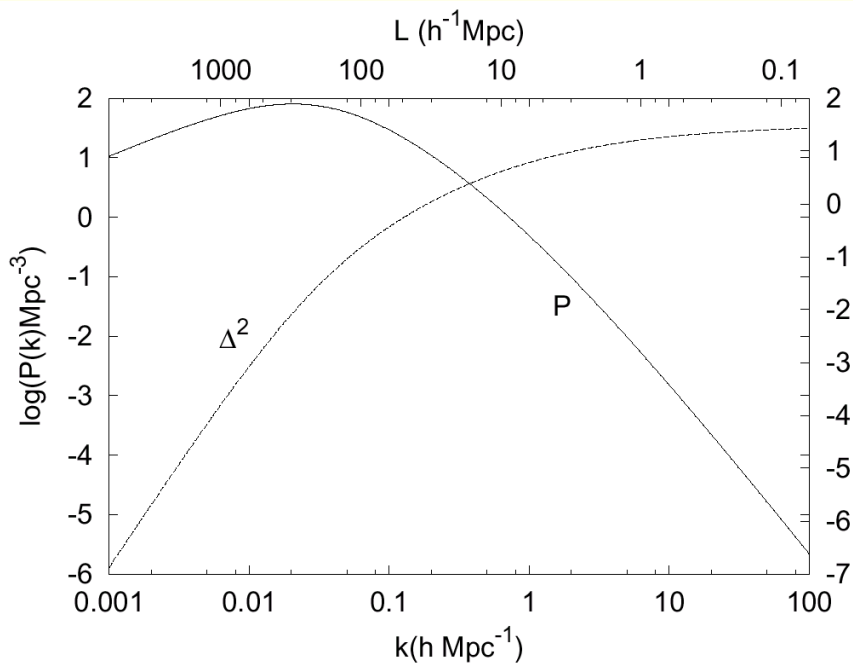
Power Spectrum - Correlation Function

$$P(k) = \int d^3 r \xi(\vec{r}) e^{i\vec{k}\cdot\vec{r}}$$

$$\xi(\vec{r}) = \int \frac{d^3 k}{(2\pi)^3} P(k) e^{-i\vec{k}\cdot\vec{r}}$$

Isotropy: $\xi(r) = 4\pi \int_0^\infty \frac{k^2 dk}{(2\pi)^3} P(k) \frac{\sin(kr)}{kr}$

Delta-power $\Delta^2(k) = \frac{1}{2\pi^2} P(k) k^2$



Power Spectrum Estimators

Estimators of $P(k)$

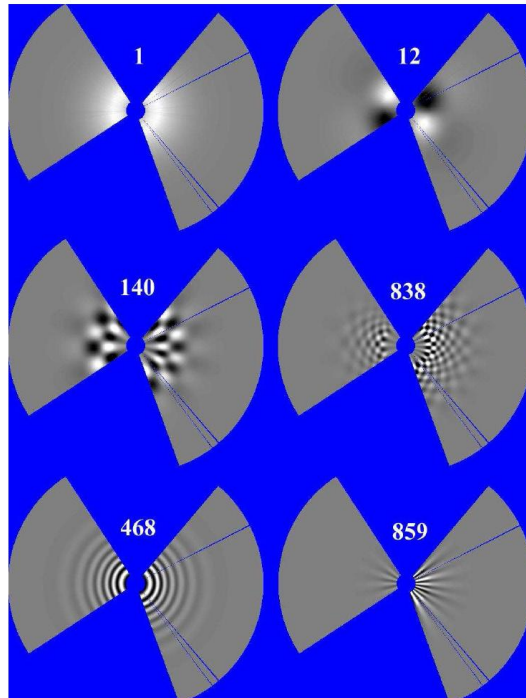
- Direct estimator
- Pixelization and maximum likelihood
- Karhunen-Loève (signal-to-noise) transform
- Quadratic compression
- Bayesian
- Multiresolution decomposition

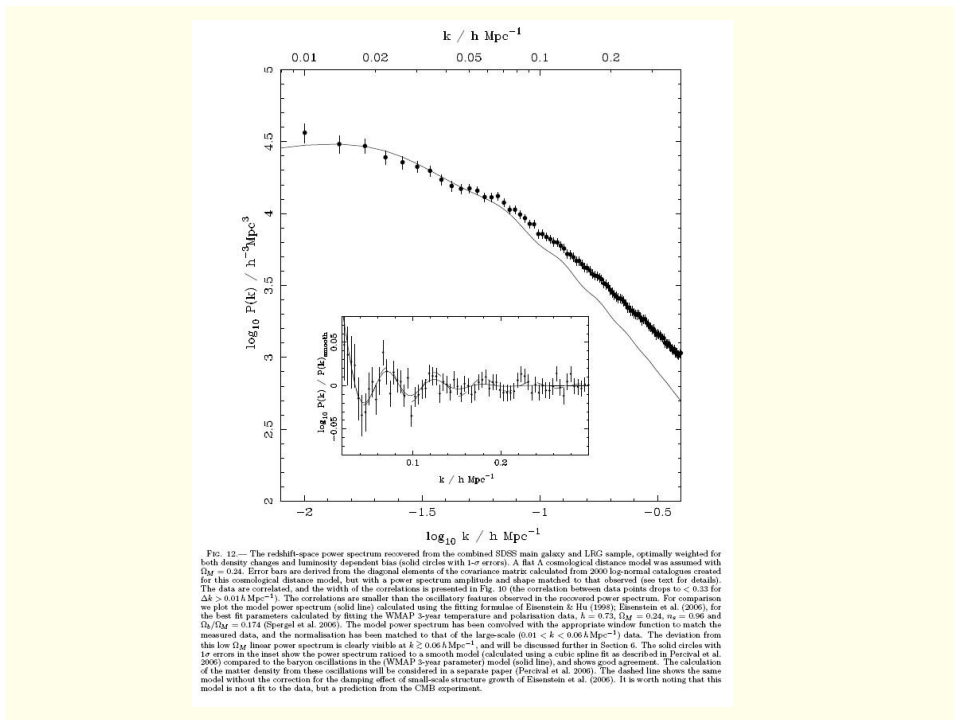
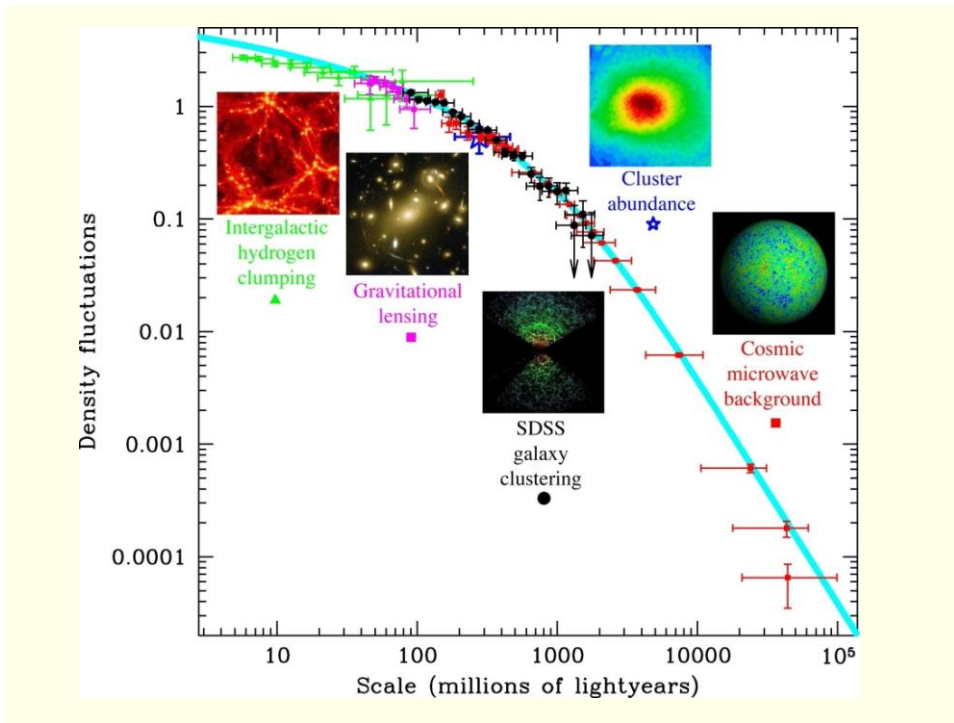
Tegmark, Hamilton, Strauss, Vogeley, and Szalay, (1998),
Measuring the galaxy power spectrum with future redshift
surveys, ApJ, **499**, 555

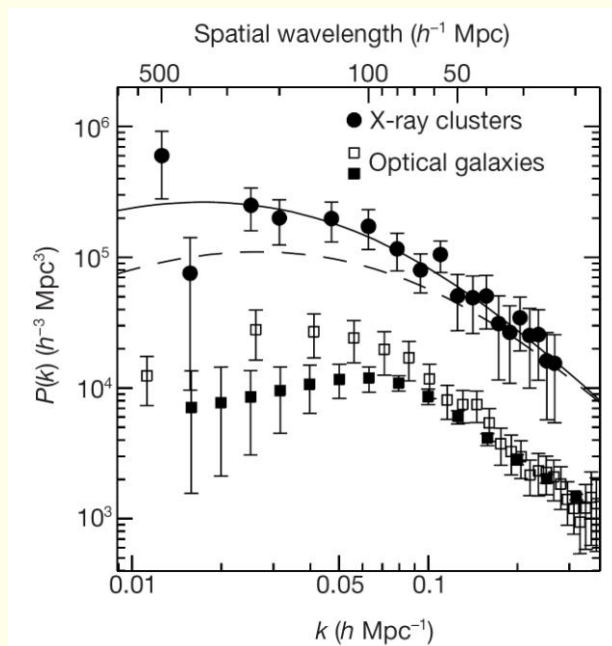
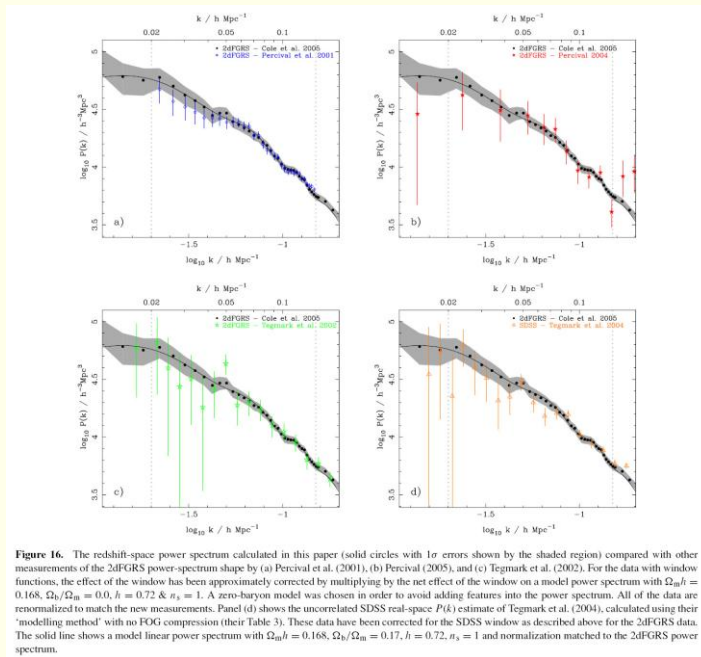
Karhunen-Loève

Decomposition in series of
orthogonal
signal-noise eigenfunctions

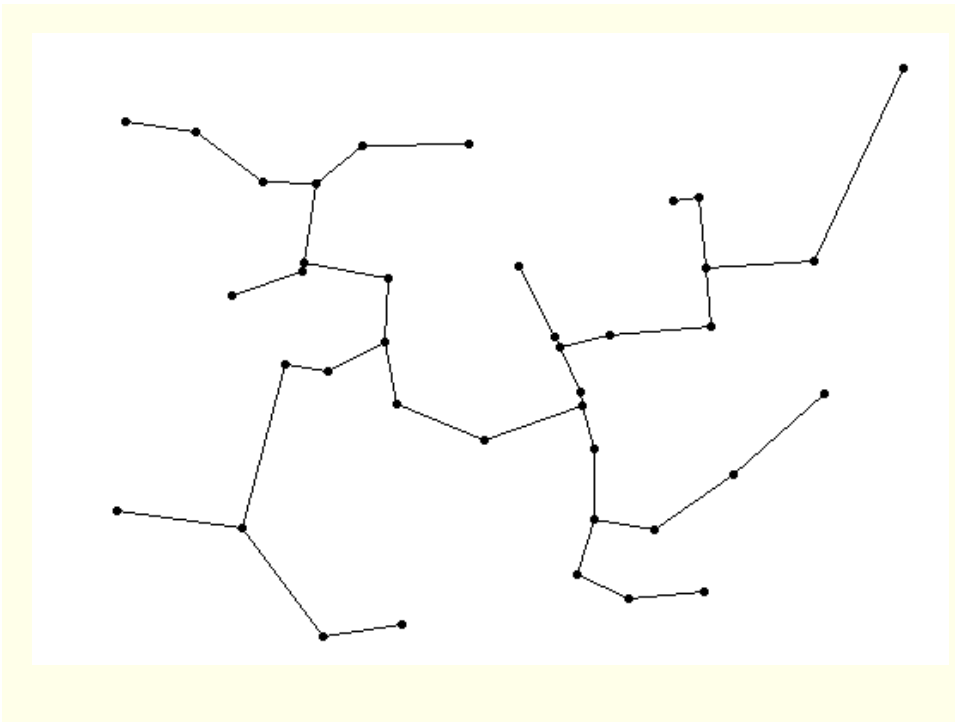
Vogeley & Szalay 1995







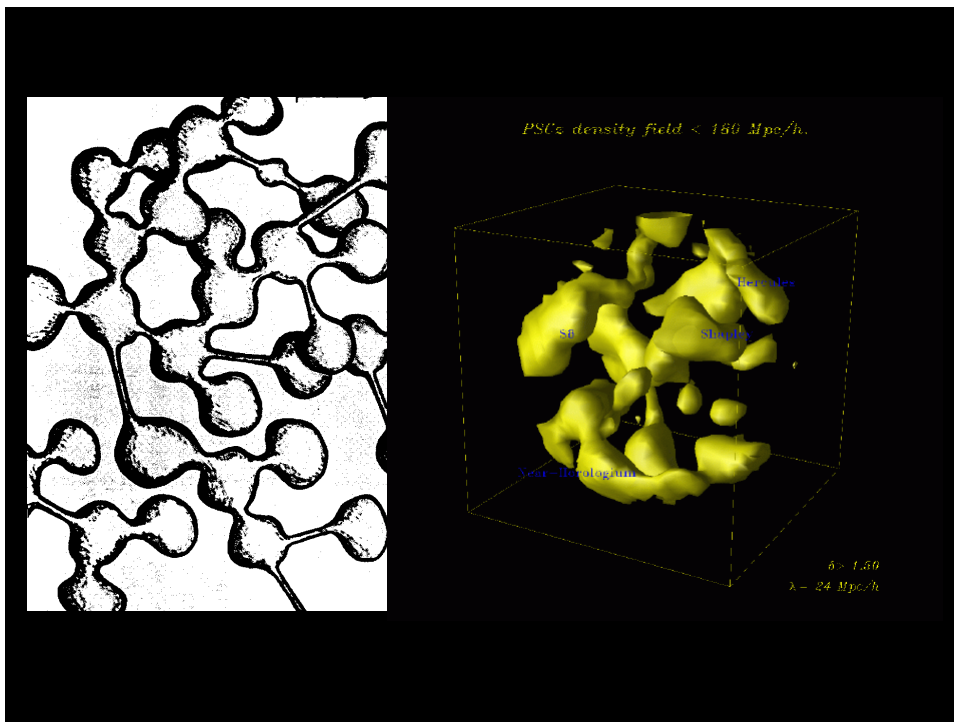
Minimal Spanning Tree



Topology

Topology and the Morphology of LSS

- Deals with *Excursion Sets*, i.e. regions where a field exceeds a certain level usually given in terms of the *rms* fluctuation.
- This could be the temperature field on the CMB Sky or the density field traced by galaxies.
- In general the excursion set will consist of a number of disjoint pieces which may be simply or multiply connected.



The Gauss-Bonnet Theorem

$$2\pi\chi(M) = \int_M k dA + \int_{\partial M} k_g ds + \sum_{i=1}^n (\pi - \alpha_i)$$

Two dimensional manifold M with boundary ∂M ; k is the Gaussian curvature of M ; k_g is the geodesic curvature of ∂M ; the boundary is piecewise smooth, having n vertices

The quantity χ is the Euler-Poincaré characteristic of M and is a topological invariant...

Topology in 2D

For a 2D excursion set defined on a flat plane,

$$2\pi\chi = \int k_g ds = \int \frac{ds}{R_1 R_2}$$

In 2D, this gives the *number of isolated regions minus the number of holes in such regions*..

Lots of isolated regions: $\chi > 0$, like “meatballs”

One isolated region with lots of holes: $\chi < 0$, like “Swiss cheese”

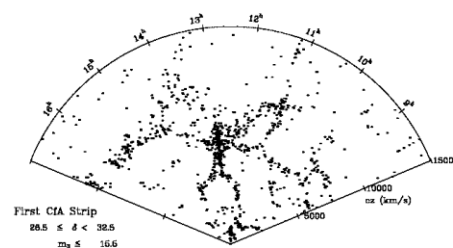
The Usefulness of χ

The mean value of χ can be calculated analytically for Gaussian random fields (test of GRF hypothesis?)

In 3D the mean level is characterised by $g > 0$ (a sponge)

In 2D the mean level has $\chi = 0$.

There is no 2D equivalent of a sponge!



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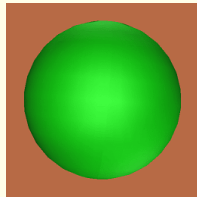
Topology in 3D

For a 3D excursion bounded by a 2D surface

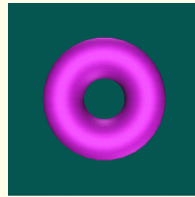
$$2\pi\chi = \int k \, dA = 4\pi(1 - g)$$

In 2D, it is typical to refer to the *genus*, g , which is the number of “handles”

$g=0$



$g=1$



Topological Genus

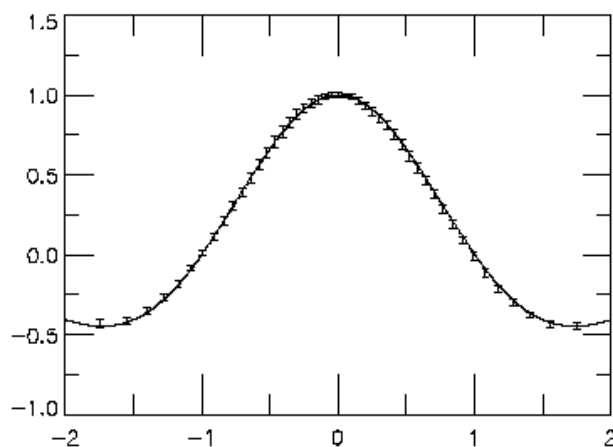


FIG. 3.— The average genus curve for 50 realizations of a Gaussian random field with $P(k) \sim k^{-1}$ together with the expected analytical result (solid line). Error bars are 1σ deviations.

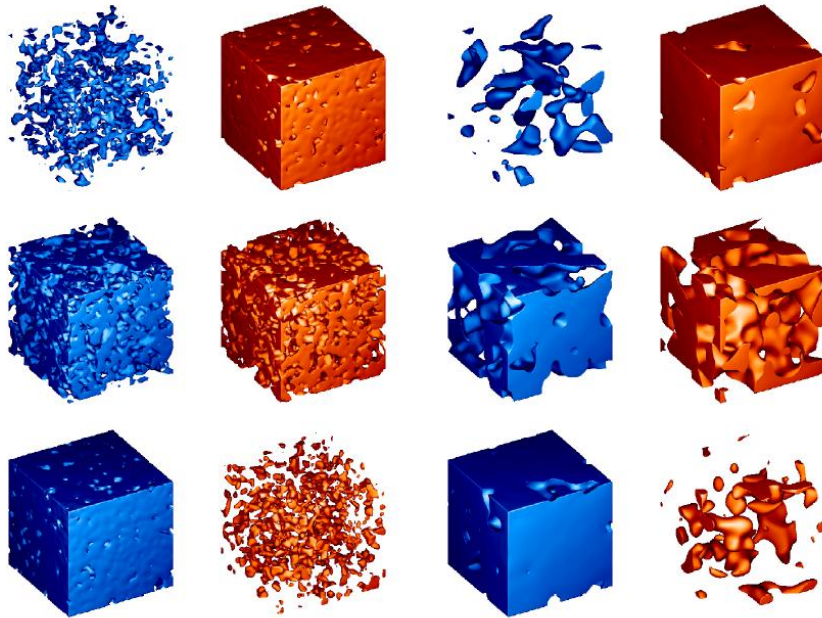


FIG. 1.— Spatial distribution of the low- (left column) and high density (right column) regions for a realization of a Gaussian random field, with comparatively little smoothing. The upper pair shows the 7% low, 93% high density regions, the middle pair stands for 50%–50%, and the lower pair shows the 93% low-density, 7% high-density case.

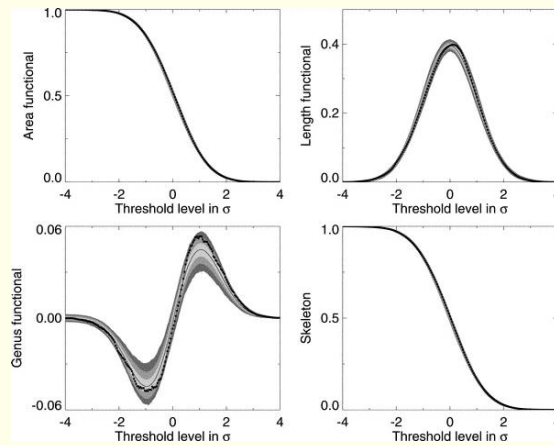
FIG. 2.— Spatial distribution of the low- (left column) and high density (right column) regions for a realization of a Gaussian random field, with heavy smoothing. The upper pair shows the 7% low, 93% high density regions, the middle pair stands for 50%–50%, and the lower pair shows the 93% low-density, 7% high-density case.

Minkowski functionals

- More recently this has been put on a much more rigorous footing using Minkowski functionals.
- In d dimensions there are $(d+1)$ invariants satisfying additivity, continuity, translation invariance and rotation invariance.
- In 3D, for example, these are:

volume,
 area,
 mean curvature,
 Euler-Poisson characteristic χ

Minkowski functionals in 2D (area, length and χ)



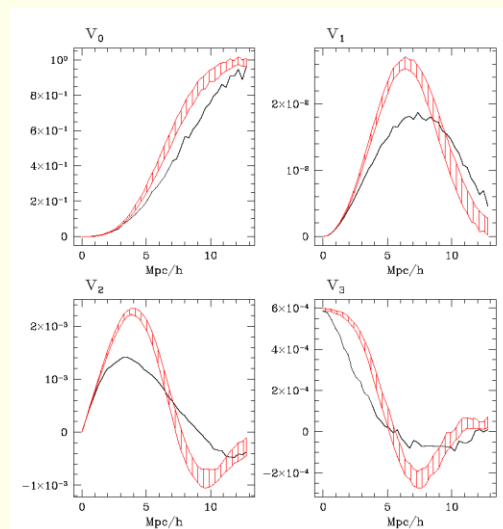
Minkowski functionals

In R^3 four functionals:

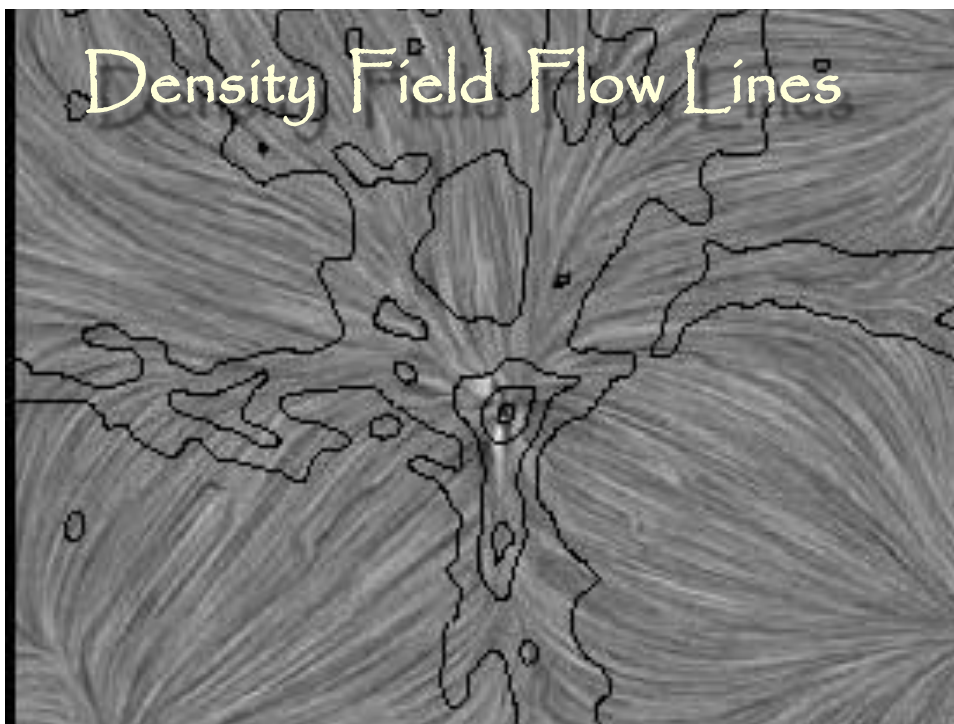
volume V
 surface area A
 integral mean curvature H
 Euler-Poincare characteristic χ

These are the Minkowski Functionals

Kerscher & Martínez (1998),
 Bull. Int. Statist. Inst. 57-2, 363



Morse Theory



Density Field Flow Lines

Density Field:
Flow Lines

$$\vec{\nabla} f$$

Density Field Flow Lines

$$\vec{\nabla} f = 0$$

Critical Points:

- Maxima
- Minima
- Saddle Points (of various signature)

