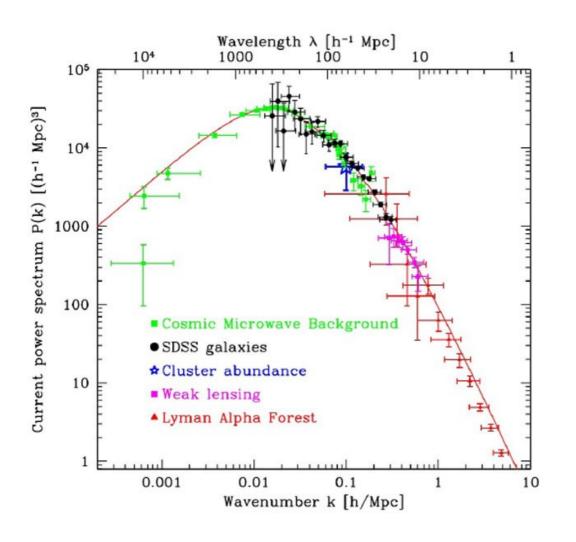
Two point correlation function

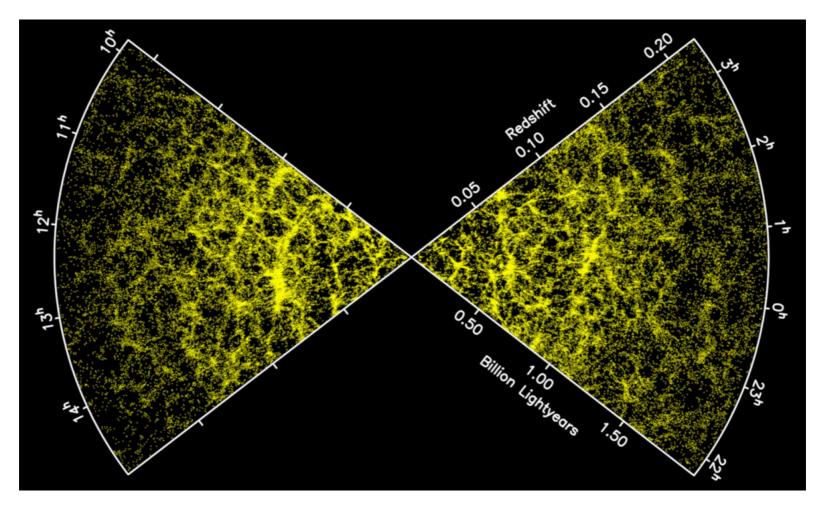


Gustavo Niz

U. de Guanajuato

2018

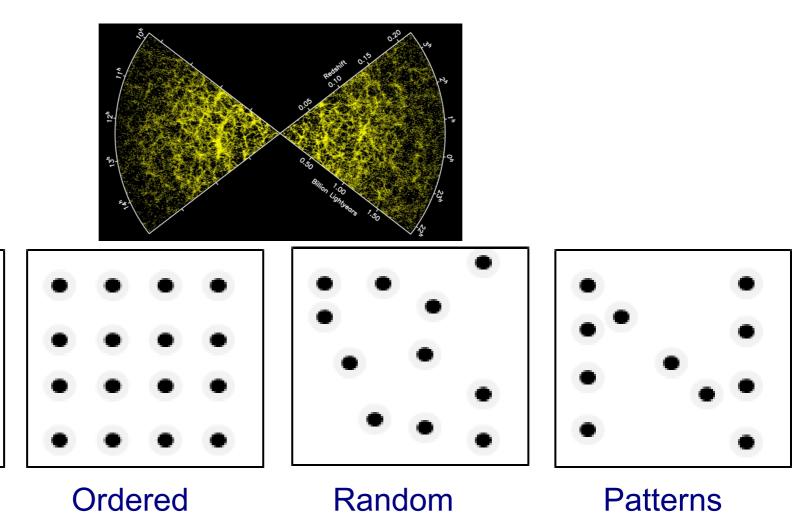
LSS



$$\rho = \bar{\rho}(1+\delta)$$

$$\delta \ll 1$$

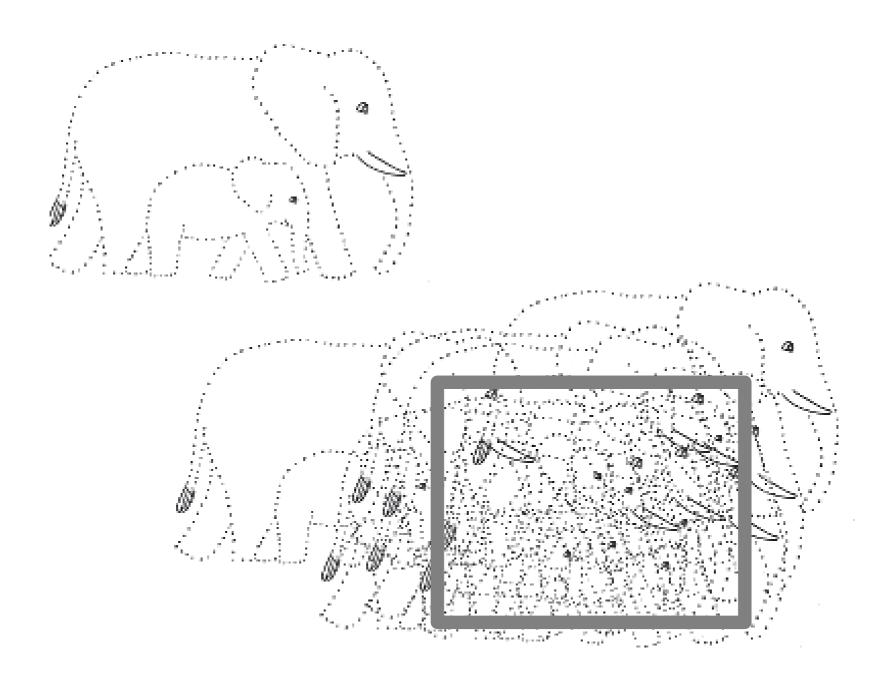
Info in the LSS



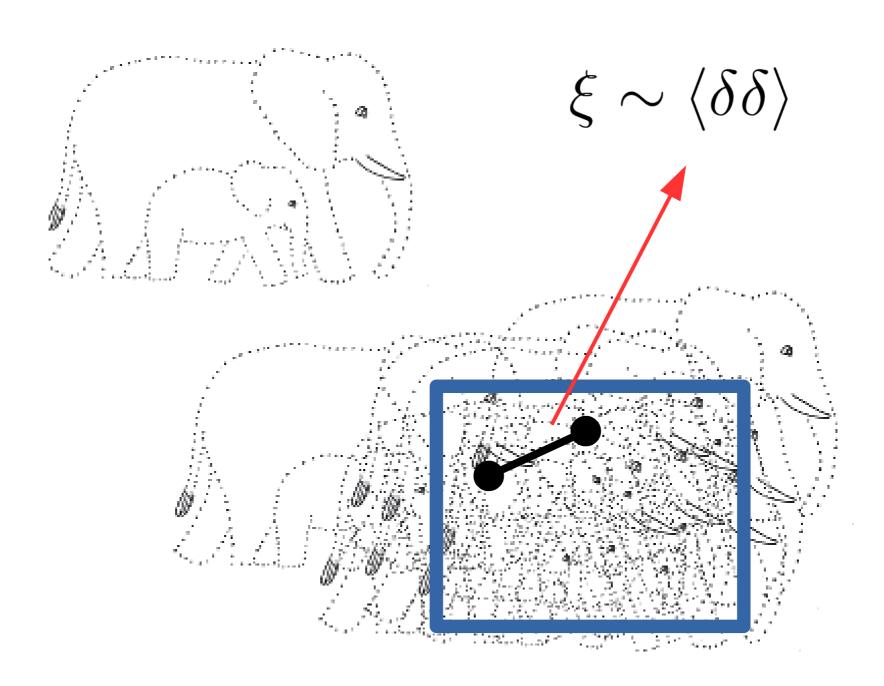
Does the distribution of galaxies in the LSS contains info like this?

Clusters

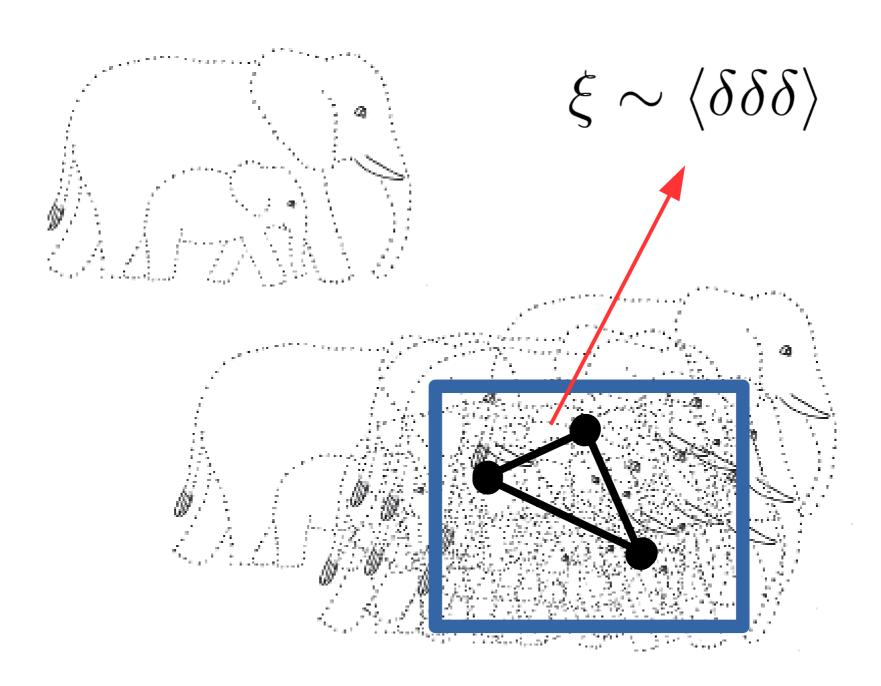
Understading distributions



Understading distributions



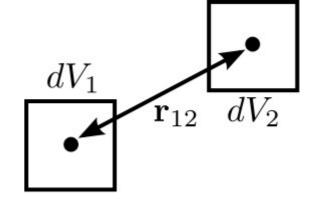
Understading distributions

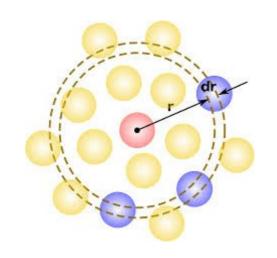


Formally

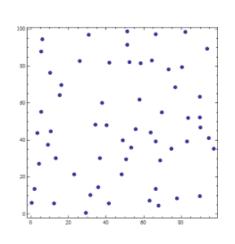
Usual to consider N-point correlation functions

$$dP = \bar{n}^2 (1 + \xi^{(2)}(\mathbf{r_{12}})) dV_1 dV_2$$

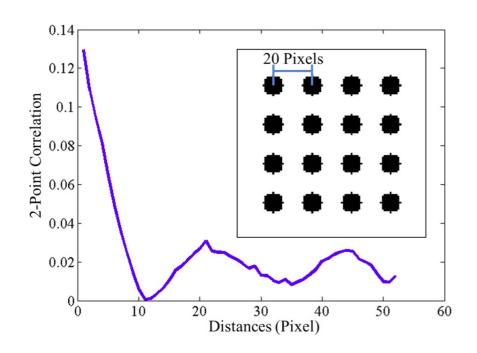


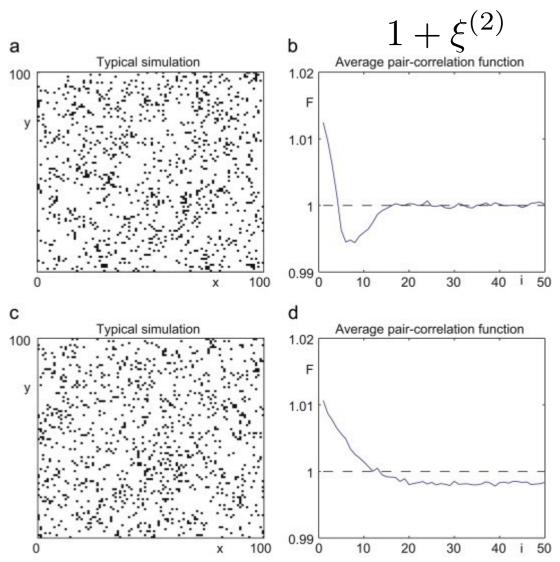


Excess correlation over the random pairs



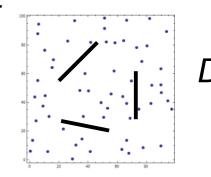
examples

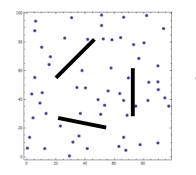




Practial way to do it over sample data (Estimator of Peebles-Hauser)

$$\xi^{(2)}(r) = \frac{DD(r)}{RR(r)} - 1 = \frac{DD(r) - RR(r)}{RR(r)}$$

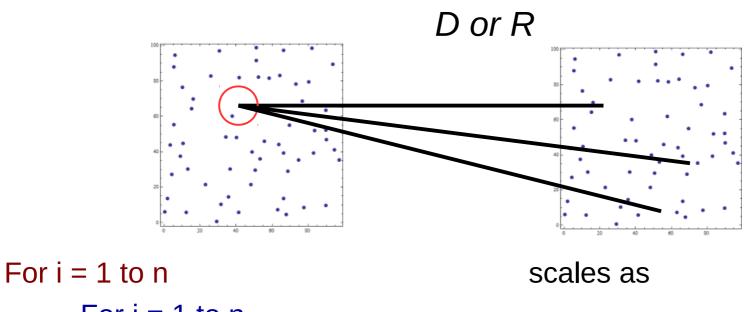




If no. of particles in R and D are not equal:

$$\xi^{(2)} = \frac{N_D(N_D - 1)}{N_R(N_R - 1)} \frac{DD}{RR} - 1 \equiv \frac{1}{N_{est}^2} \frac{DD}{RR} - 1$$

Algorithm & computing time



For
$$j = 1$$
 to n
distance(r)

histo(bin of r)+=1

$$\mathcal{O}(n^2)$$

Can do better (eg. kd tree, FFT)

 $\mathcal{O}(n\log(n))$

Biased estimator!

$$\delta = \frac{n - \bar{n}}{\bar{n}}$$



Sample is volume finite

$$\langle \; , \; \rangle = \int dV$$

• *W(r)*: indicator function

no. points =
$$\langle W(r)n(r)\rangle$$

Uncertainity in mean density and 1-pt function

$$\bar{\delta} = \frac{\langle W(r)\delta(r)\rangle}{\langle W(r)\rangle} \qquad \Psi = \frac{\langle \langle W(r)W(r)\delta(r)\rangle\rangle}{\langle \langle W(r)W(r)\rangle\rangle}$$

2-pt function is

$$\xi^{2}(r) = \frac{\langle \langle W(r)W(r)\delta(r)\delta(r)\rangle \rangle}{\langle \langle W(r)W(r)\rangle \rangle}$$

$$\xi_{PH}^{(2)} = \frac{\xi_{true}^{(2)}(x_1, x_2) + \Psi(x_1) + \Psi(x_2) - 2\bar{\delta} - \bar{\delta}^2}{(1 + \bar{\delta})^2}$$

R

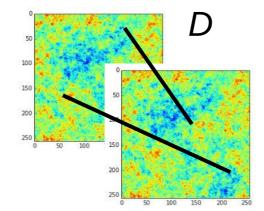
Better estimators

Hamilton

$$\xi_H^{(2)}(r) = \frac{DD(r)RR(r)}{DR(r)^2}$$

Landy-Szalay

$$\xi_H^{(2)}(r) = \frac{DD(r)RR(r)}{DR(r)^2} \qquad \xi_{LZ}^{(2)}(r) = \frac{DD(r) + RR(r) - 2DR(r)}{RR(r)}$$



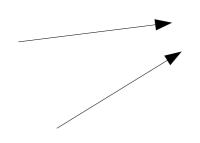
Biased estimator properties

Davis-Peebles

$$\xi_{DP}^{(2)}(r) = \frac{1}{N_{est}} \frac{DD(r)}{DR(r)} - 1 \qquad \Longrightarrow \qquad \xi_{DP}^{(2)} = \frac{\xi_{true}^{(2)} + \Psi(1 - \bar{\delta}) - \bar{\delta}}{(1 + \Psi)(1 + \bar{\delta})}$$

Hamilton

$$\xi_H^{(2)}(r) = \frac{DD(r)RR(r)}{DR(r)^2}$$



Corrections are second order in $\bar{\delta}$ or higher in the numerator for both!

Landy-Szalay

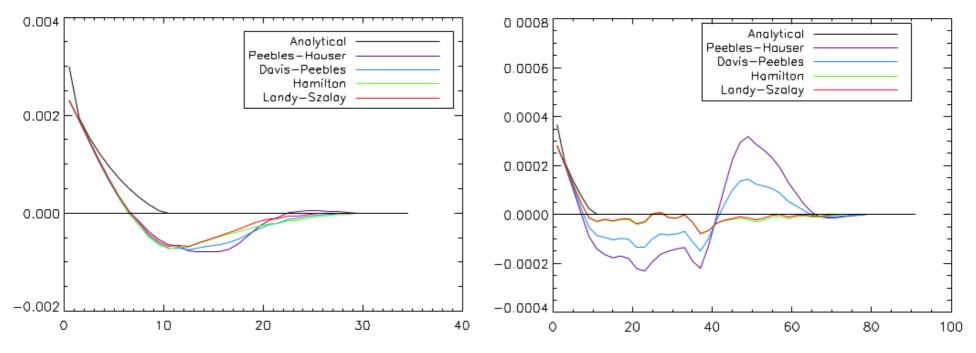
$$\xi_{LZ}^{(2)}(r) = 1 + \frac{1}{N_{est}^2} \frac{DD(r)}{RR(r)} - 2\frac{1}{N_{est}} \frac{DR(r)}{RR(r)}$$

Integral constraint

Over a finite box, we don't use the real average density, which leads to a correction in the estimator, at first order, given by

$$\xi_X^{(2)} = \xi_{true}^{(2)} - K$$

$$K = \frac{1}{V^2} \int_V \int_V \xi_X^{(2)}(x_1, x_2) d^3 x_1 d^3 x_2$$



Further reading: https://arxiv.org/abs/1311.3280 https://arxiv.org/abs/1009.1232

Next lecture: power spectrum

Fourier transform

$$\xi(\mathbf{x}) = \frac{1}{(2\pi)^d} \int_V P(\mathbf{k}) e^{-i\mathbf{k}\cdot\mathbf{x}} d^d\mathbf{k}$$
 Dimensionless
$$\Delta^2(\mathbf{k}) \sim k^d P(\mathbf{k})$$
 Dimensionfull

Correlation function

Stat. Isotropy

$$\xi(\mathbf{r}) = \xi(r)$$

Intuitive

Modes (linear) dependent

Power spectrum

$$P(\mathbf{k}) = P(k)$$

Theory

independent

Systematics drive them apart these Fourier cousins