**ZACHARY SLEPIAN** EINSTEIN & CHAMBERLAIN FELLOW LAWRENCE BERKELEY NATIONAL LABORATORY & BERKELEY CENTER FOR COSMOLOGICAL PHYSICS



## TRIANGULATING THE UNIVERSE'S LAWS AND CONTENTS WITH THE 3-POINT CORRELATION FUNCTION

FUERTEVENTURA COSMOLOGY SUMMER SCHOOL CANARY ISLANDS 19 SEPTEMBER 2017

## OUTLINE Why? Data landscape Four areas 3PCF can help with

### How?

How do we measure it, model it, and match model to measurement?

> Synthetic approach History + cutting edge

MAJOR QUESTIONS IN COSMOLOGY

How do galaxies form?

What is the full theory of gravity?

What are the initial conditions?

What is the nature of dark energy?

WHAT IS THE DATA LANDSCAPE?

Current: BOSS, eBOSS, DES (photo)

Future: Dark Energy Spectroscopic Instrument (DESI)

+other spectroscopic: Euclid, WFIRST

+other photometric: LSST

## SDSS

CMASS sample

### 2.4 m at Apache point





## DARK ENERGY SPECTROSCOPIC INSTRUMENT





5k robotic positioners: reconfigure in ~1 minute

### BOSS and eBOSS ~I million galaxies each

## DESI will get 30 million spectra: ELGs, LRGs, Quasars



## How will we use this data to answer the key questions?

## Make a 3-D map of the distribution of galaxies



## Search for patterns



## **Search for patterns**



### Isotropic

Laws of physics: same everywhere and in all directions This is what we mean by laws

### Galaxy clustering will be so too\*

Need a way to mod out translations and rotations

## CORRELATION FUNCTIONS

2-point correlation function (2PCF): count excess pairs of galaxies over random



For a Gaussian Random Field density, the 2PCF, or its Fourierspace analog the power spectrum, contains all the information

Intuitively: Gaussian has a mean and variance—2 parameters

We know cosmic mean density, and 2PCF is a generalization of the variance (zero-lag  $\xi$  is the variance)

But I am here to talk about the 3PCF . . . excess triangles over random

### because Universe is not just a GRF!

I) non-linear structure formation

### and

2) possible primordial non-Gaussianity

## RECENT LARGE-SCALE 3PCF

**SDSS:** Nichol+2006: 37k LRGs 2, 3 and 4:1, 40 Mpc/h, Kulrkarni+2007, 51k SDSS DR3 LRGs, 1, 2, 3:1, 30 Mpc/h Gaztanaga+2009: 40k DR7 LRGs, 2-3sigma BAO Marin 2011: 106k DR7 LRGs, 2:1, 90 Mpc/h McBride 2011a, b: 220k galaxies SDSS DR6, 2:1, 27 Mpc/h Guo+2014: DR7 LRGs 1, 2, 3:1, 40 Mpc/h Guo+2015: DR11 CMASS LRGs, 2:1, 40 Mpc/h Slepian+ 2016a,b, 2017: 800k DR12 CMASS LRGs, all configs. up to 180 Mpc/h

WiggleZ: Marin+2013: 1, 2, and 3:1, 90 Mpc/h.

2dFGRS: Jing & Borner 2004: 60k, 40 Mpc/h Wang+2004: 250k, 20 Mpc/h.

### PARAMETRIZATION & ESTIMATOR



## MULTIPOLE BASIS



Color shows # of triangles with given side lengths; angle dependence is projected onto Legendre polynomial  $P_1$ 

Basis proposed by Szapudi 2004, developed in several papers by Slepian & Eisenstein (2015, 16, 17)

The 3PCF is computationally expensive: if you have 10 friends, choosing two to take to lunch is 10 X 9 = 90, but choosing 3 is 10 X 9 X 8 = 720—you are doublebooked!

For large N, N<sup>3</sup> vs. 2PCF's N<sup>2</sup>

## WHY USE THE 3PCF?

I) Galaxy formation: biasing

2) Gravity: RSD

3) Initial Conditions: Primordial Non-Gaussianity

4) Dark Energy: BAO

## BIASING

$$\delta_g = b_1 \delta_m + b_2 [\delta_m^2 - \langle \delta_m^2 \rangle] + b_t S_{ij} + b_v [v_{bc}^2 - \langle v_b c \rangle^2]$$
  
$$\delta_m = \delta_{lin} + \delta^{(2)} + \delta^{(3)} + \cdots$$

## Linear bias is like the contrast on a photocopier, or the volume on a speaker

## One can also see biases as derivatives with respect to different parameters

Historical: Dekel & Rees 1987 PT review: Bernardeau+2002

Biasing review: Desjacques+2016

# WHY CAN'T WE JUST USE THE 2PCF?



Could just fix σ<sub>8</sub> from CMB, but if we want it and b<sub>1</sub> from LSS, need to break the degeneracy

$$\frac{\xi_{gg}^2}{\zeta_{ggg}} = b_1$$

## RSD AFFECT ON BIAS? RSD also enter so as to be degenerate with the linear bias



Take ratio of observed 3PCF to DM simulations that have been RSD-ed using their velocities (McBride+2011a,b) But builds sim-dependence into reported results, and not a simple ratio if biases other than b<sub>1</sub>  $\begin{array}{ll} {\sf REMARKABLY} & . & . \\ {\sf 2PCF:} & \xi_{gg} \propto \sigma_8^4 b_1^4 (1 + \frac{4}{3}\beta) + \mathcal{O}(\beta^2) \\ \\ {\sf 3PCF:} & \zeta_{ggg} \propto \sigma_8^4 b_1^3 (1 + \frac{4}{3}\beta) + \mathcal{O}(\beta^2) \end{array}$ 

 $\beta = f/b_1 \qquad \qquad f = d\ln D/d\ln a \approx \Omega_{m,eff}^{0.55}(z)$ 

So ratio argument still works (but again, assuming only linear biasing) BUT LET'S BE MORE REALISTIC We'd like to study bias terms beyond linear: quadratic, tidal tensor, relative velocity, etc.

This is where the 3PCF has a key advantage over the 2PCF

These bias terms enter the 3PCF at leading (4th) order in the linear density field but are sub-leading in the 2PCF

## A BIAS MACHINE

So in the 2PCF, you are using one curve to look for many parameters each of which is producing a *small* fractional change to the total signal

In the 3PCF, you are using many triangle configurations to look for these parameters and each can produce an order unity change to the signal

## IN REAL SPACE



**3PCF** split out by bias and multipole moments, as function **of 2** triangle sides

## N REDSHIFT SPACE



Recent work: high-precision constraints on relative velocity biasing, linear bias, hints at tidal tensor bias w/BOSS (Slepian+16a,b,17)



## RSD



Fingers of God along I.o.s. due to infall (Jackson 1972) and on larger scales, transverse Kaiser pancakes (Kaiser 1987); review: Hamilton (1998) PROBING GRAVITY Large-scale RSD are generated by coherent growth of structure and can be used to probe gravity

$$\beta = f/b_1 \qquad \qquad f = d \ln D/d \ln a \approx \Omega_{m,eff}^{0.55}(z)$$

Exponent of 0.55 is assuming GR: it has a different value for other theories (Linder 2005; Raccanelli +2013) WHAT ARE OUR OPTIONS? Use multipoles of 2PCF/power spectrum, or wedges in angle to line of sight

Try the grueling push to higher k? Hand+2017 shows this is very hard: 19 free parameters roughly get you to k = 0.4 h/Mpc but this only buys 15-30% improvement on  $f\sigma_8$  relative to k = 0.2 h/Mpc

## OR...

Open up the use of the 3PCF. There are lots of triangles, and lots of ways for each side to project onto the line of sight

But . . . as we've seen, the sphericallyaveraged (isotropic) 3PCF has  $\beta$ degenerate with linear bias!

Why not use anisotropic 3PCF?

## PNG

## Generically, inflation predicts some deviation from GRF initial conditions

 $\Phi(\vec{x}) = \Phi_G(\vec{x}) + f_{NL}^{loc} [\Phi_G^2(\vec{x}) - \langle \Phi_G^2(\vec{x}) \rangle]$ 

 $\Phi$  is the Bardeen's curvature perturbation, G for Gaussian

This is a bit analogous to non-linear biasing, or a Taylor series!

There can also be equilateral contributions (Fourier space), motivated by higher derivative and DBI inflationary models

> Sefusatti & Komatsu 2007 also: Baumann notes

## PNG

Creminelli & Zaldarriaga: squeezed limit PNG in single-field inflation is suppressed by (I - n<sub>s</sub>) ~ 0 for scale invariant perturbations

PNG will be a major goal of post-DESI LSS

Why? The CMB has led so far, but is more or less saturated at f<sub>nl</sub> ~ 5 modulo a slight improvement from polarization

But f<sub>nl</sub> is very hard with the 2PCF, in particular getting to order 1, where theory indicates is interesting

## DESI-2 PROJECTION



FIG. 16. Local non-Gaussianity constraints, for 14000 sq. deg. with uniform comoving density out to  $z_{\text{max}}$ , for different numbers of "ELGs" (objects with bias 0.84D(0)/D(z)) and "LRGs" (objects with bias 1.7D(0)/D(z)). Bias is always capped to be no greater than the bias expected if the objects lived in the most massive halos with this number density.

#### Forecast: Pat McDonald for DESI-2 WG

## 3PCF AND PNG

The 3PCF is the leading-order statistic sensitive to PNG

### A complication is that Dalal (2008) showed scale-dependent bias in the power spectrum can also reveal PNG

But signature is on large scales, and again . . . one curve, many parameters, many possible systematics on large scales (survey boundary, dust), also cosmic variance

So 3PCF will still be vital for a robust detection

### BARYON ACOUSTIC OSCILLATIONS: A STANDARD RULER



z ~ |-0

(roughly 7 billion years ago to today)

### BAO METHOD WITH THE 2PCF



Cole et al. 2005 Eisenstein et al. 2005 Figure: Anderson et al. 2014

### BAO IN THE 3PCF



## THE FIRST HIGH-SIGNIFICANCE BAO DETECTION IN THE 3PCF



Measure distance to z = 0.57 (6 billion years in the past) with 1.7% precision: first use of BAO method in 3PCF

Data: Slepian+1607.06097, 1512.02231,1607.06098 Model: SE1607.03109

### BUT A COMPLICATION . . .

Comparing unreconstructed 2PCF with 3PCF, 3PCF is like making BOSS 10% longer—seems like a win, for zero extra dollars and not much computer time!

But Schmittfull+2015 shows density field reconstruction brings this info nearly fully into 2PCF

Slepian+2017 confirmed this empirically using mocks pre and post-recon

But mocks don't have systematics; data does Valuable to have an independent method of getting this information

### AND IN SOME CASES . . .

Sampling is so sparse that you don't have enough info on the density to do reconstruction: e.g. quasars

In these cases, 3PCF is the only way to access this additional BAO information

-eBOSS quasar BAO search underway right now! (Peter Choi, Graziano Rossi, ZS, David Schlegel, Shirley Ho, Daniel Eisenstein) -z~I.5—not many points on the Hubble diagram there, and will be a pathfinder for DESI WE'VE DISCUSSED WHY

**Now: how? Three challenges** 

I) Measurement (N<sup>3</sup>)
 2) Modeling
 3) Matching measurement to model (covariance)

Previous algorithms: kd-tree (Moore+2001, Gray+2001, used in McBride, Marin, others; Zhang & Pen 2005 also uses a tree. Not ideal for galaxy surveys which are sparse.

### ISOTROPIC 3PCF ALGORITHM

#### 3-point correlation function (3PCF): excess triangles over random



Color represents # of triangles with given side lengths; in this panel, angle dependence is projected onto P<sub>1</sub> 3PCF basis: Szapudi 2004, also Verde+2000 Algorithm: SE1506.02040, SE1506.04746

## Around each galaxy, compute a<sub>lm</sub> in spherical shells/radial bins



gals j in bin

SE1506.02040, SE1506.04746

NOW ORDER N ABOUT EACH GALAXY, SO N<sup>2</sup> OVERALL CAN BE EVEN FASTER WITH FOURIER TRANSFORMS ADVANTAGES OF THE ALGORITHM 500X FASTER THAN A TRIPLET COUNT FOR 700K GALAXY TEST CASE

ONLY 6X SLOWER THAN COMPUTING A 2-POINT FUNCTION

HIGHLY ENABLING FOR USE OF 3PCF IN COSMOLOGY ALREADY

ANISOTROPIC 2PCF WITH ROTATING LOS FOR FREE BECAUSE GEOMETRY IS THE SAME

### PROBING REDSHIFT-SPACE DISTORTIONS: ANISOTROPIC 3PCF



-Ran at scale on CORI
-9,600 nodes, 5.6 sustained PF
-80% peak for instruction mix
-Obtain harmonic coefficients
with matrix algebra libraries
3PCF for 2 billion haloes in 20 minutes





Algorithm: SE17.; Implementation: Friesen+(incl. ZS) 17, accepted ACM: SC'17 conference; First use on data (BOSS): Nugent+17 in prep.

### HANDLING RSD

## This improved algorithm will enable us to extract information on RSD from the 3PCF

Also allows computing 3PCF for entire observable Universe (100 bn galaxies) in time it took me to fly here (~17 hours)

## MODELING THE ISOTROPIC 3PCF

$$\begin{split} \ell &= 0: \ b_1^3 \bigg\{ \frac{34}{21} \left[ 1 + \frac{4}{3}\beta + \frac{1154}{1275}\beta^2 + \frac{936}{2975}\beta^3 + \frac{21}{425}\beta^4 \right] \\ &+ \gamma \left[ 1 + \frac{2}{3}\beta + \frac{1}{9}\beta^2 \right] \bigg\} \xi_1^{[0]} \xi_2^{[0]} \\ &+ b_1^3 (7\beta^2 + 3\beta^3) \kappa_0(r_1, r_2) \\ \ell &= 1: \ -b_1^3 \left[ 1 + \frac{4}{3}\beta + \frac{82}{75}\beta^2 + \frac{12}{25}\beta^3 + \frac{3}{35}\beta^4 \right] \\ &\times \left[ \xi_1^{[1+]} \xi_2^{[1-]} + \xi_2^{[1+]} \xi_1^{[1-]} \right] \\ &+ b_1^3 (7\beta^2 + 3\beta^3) \kappa_1(r_1, r_2) \\ \ell &= 2: \ b_1^3 \bigg\{ \frac{8}{21} \left[ 1 + \frac{4}{3}\beta + \frac{52}{21}\beta^2 + \frac{81}{49}\beta^3 + \frac{12}{35}\beta^4 \right] \\ &+ \frac{32\gamma}{945}\beta^2 \bigg\} \xi_1^{[2]} \xi_2^{[2]} + b_1^3 (7\beta^2 + 3\beta^3) \kappa_2(r_1, r_2) \\ \ell &= 3: \ -b_1^3 \left[ \frac{8}{75}\beta^2 + \frac{16}{175}\beta^3 + \frac{8}{315}\beta^4 \right] \left[ \xi_1^{[3+]} \xi_2^{[3-]} + \xi_2^{[3+]} \xi_1^{[3-]} \\ &+ b_1^3 (7\beta^2 + 3\beta^3) \kappa_3(r_1, r_2) \\ \ell &= 4: \ b_1^3 \left[ -\frac{32}{3675}\beta^2 + \frac{32}{8575}\beta^3 + \frac{128}{11025}\beta^4 \right] \xi_1^{[4]} \xi_2^{[4]} \\ &+ b_1^3 (7\beta^2 + 3\beta^3) \kappa_4(r_1, r_2) \\ \ell &\geqslant 5: \ b_1^3 (7\beta^2 + 3\beta^3) \kappa_4(r_1, r_2) \end{split}$$

#### Multipoles of the 3PCF; γ is b<sub>2</sub>/b<sub>1</sub>, tidal tensor can also be added easily

Key: write model in terms of I-D and 2-D integrals of power spectrum

$$\begin{split} \xi_i^{[n]} &= \int \frac{k^2 dk}{2\pi^2} P(k) j_n(kr_i) \\ \xi_i^{[n\pm]} &= \int \frac{k^2 dk}{2\pi^2} k^{\pm 1} P(k) j_n(kr_i); \end{split}$$

$$\begin{aligned} \kappa_{\ell}(r_1, r_2) &= \frac{64}{77175} \bigg[ 9I_{1\ell}(r_1, r_2) - 14I_{3\ell}(r_1, r_2) \\ &+ 5I_{5\ell}(r_1, r_2) \bigg], \end{aligned}$$

$$egin{aligned} I_{\mathcal{L}\ell}(r_1,r_2) = &\sum_{l_1} (-1)^{l_1+\ell} (2l_1+1)(2\ell+1) \left( egin{aligned} l_1 & \ell & \mathcal{L} \ 0 & 0 & 0 \end{array} 
ight)^2 \ & imes \int r dr f_{\ell l_1}(r_1;r) f_{\ell l_1}(r_2;r), \end{aligned}$$

#### Makes predictions quite fast to compute: eventually, embed in MCMC?

Scoccimarro Couchman Frieman 1999: base model see also Rampf & Wong 2012 Slepian & Eisenstein 2016, 1607.03109



## MATCHING MEASUREMENT TO MODEL

Requires the covariance. Very high-d matrix, and inverse is dominated by smallest eigenvalue, which is noisiest

Thus if estimating from mocks, need >> I mock/dimension to render it invertible: demands an impossible number of mocks

Instead: analytically compute dominant, GRF covariance and use mocks to fit for 2 free parameters (shot noise and volume)

Analytic template is smoothly invertible

### Isotropic covariance

$$\begin{aligned} \operatorname{Cov}_{ll'}(r_1, r_2; r_1', r_2') &= \frac{4\pi}{V} (2l+1)(2l'+1)(-1)^{l+l'} \\ &\times \int r^2 dr \sum_{l_2} (2l_2+1) \begin{pmatrix} l & l' & l_2 \\ 0 & 0 & 0 \end{pmatrix}^2 \\ &\times \Big\{ (-1)^{l_2} \xi_0(r) \Big[ f_{l_2 ll'}(r; r_1, r_1') f_{l_2 ll'}(r; r_2, r_2') \\ &+ f_{l_2 ll'}(r; r_2, r_1') f_{l_2 ll'}(r; r_1, r_2') \Big] + (-1)^{(l+l'+l_2)/2} \\ &\times \Big[ f_{ll}(r; r_1) f_{l'l'}(r; r_1') f_{l_2 ll'}(r; r_2, r_1') \\ &+ f_{ll}(r; r_2) f_{l'l'}(r; r_1') f_{l_2 ll'}(r; r_1, r_2') \\ &+ f_{ll}(r; r_2) f_{l'l'}(r; r_1') f_{l_2 ll'}(r; r_1, r_1') \Big] \Big\}. \end{aligned}$$

$$f_{ll}(r;r_1) = \int \frac{k^2 dk}{2\pi^2} P(k) j_l(kr_1) j_l(kr)$$

$$f_{l_2ll'}(r;r_1,r_1') = \int \frac{k^2 \mathrm{d}k}{2\pi^2} P(k) j_l(kr_1) j_{l'}(kr_1') j_{l_2}(kr).$$

#### In terms of I and 2-D integrals of the power spectrum





## WHAT ABOUT CROSS COVARIANCE?

### How do we combine fitted parameter values (e.g. linear bias) from the 3PCF with those from the 2PCF?

Use analytic auto-covariance to fit them separately, then use mocks to form the low-d (2N<sub>params</sub>) cross-covariance matrix and combine parameters weighted by its inverse

Used this approach with BAO results from BOSS 3PCF

### SUMMARY

The 3PCF is a uniquely powerful probe of galaxy biasing and primordial non-Gaussianity

Beyond-linear biasing enters at leading order. 3PCF is also the leading order statistic sensitive to PNG

It has discovery potential in both of these areas

**3PCF also has potential to add to standard 2PCF analyses on RSD and BAO**