Massive multi-tracer surveys of LSS:
The sky is not the limit

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Galaxy surveys are evolving

We used to live in an era of shot ("counts") noise

[Finding galaxies was the limiting factor]
Galaxy surveys are evolving

We used to live in an era of shot ("counts") noise

We are now entering the age of cosmic variance

[Finding galaxies was the limiting factor]

[Gaining volume is the limiting factor]
Cosmological surveys are now severely limited by **cosmic variance** (and systematics)

These **error bars** have a large contribution from **cosmic variance**: in order to improve, we must increase the **volume** of our surveys

However, up to any given redshift there is only a finite volume to survey. Moreover, we are reaching closer to the limits of the observable Universe!
**Shot noise:**
finite number of **counts** of the tracers of the underlying density field

**Cosmic variance:**
finite **volume** inside which we can estimate the **amplitudes and phases** of the (Gaussian) random **modes** of the density field
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$$\left\langle \frac{\delta n_g(\bar{x})}{\bar{n}_g} \frac{\delta n_g(\bar{y})}{\bar{n}_g} \right\rangle_V \simeq b_g^2 \left\langle \delta_m(\bar{x}) \delta_m(\bar{y}) \right\rangle_V + \frac{1}{\bar{n}_g} \delta_D(\bar{x} - \bar{y})$$
Shot noise:
finite number of \textbf{counts} of the tracers of the underlying density field

Cosmic variance:
finite \textbf{volume} inside which we can estimate the \textbf{amplitudes and phases} of the (Gaussian) random \textbf{modes} of the density field

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\]

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P_g(\vec{k}) \simeq b_g^2 P_m(\vec{k}) + \frac{1}{\bar{n}_g}
\]
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\]

\[
P_g(\vec{k}) \simeq b_g^2 P_m(\vec{k}) + \frac{1}{\bar{n}_g}
\]

Clustering in units of shot noise

\[
\bar{n}_g P_g(\vec{k}) \simeq \bar{n}_g b_g^2 P_m(\vec{k}) + 1
\]
Fisher information of galaxy surveys (single type of galaxy)

Tegmark et al. (1997)

Clustering strength of galaxy type “g” in redshift space

\[ \mathcal{P}_g(\vec{x}, \vec{k}) \equiv \bar{n}_g(\vec{x}) \left[ b_g(z, k) + f(z) \mu_k^2 \right]^2 G^2(z) P_m(k) \]
Fisher information of galaxy surveys (single type of galaxy)

\[ \mathcal{P}_g(\tilde{x}, \tilde{k}) = \bar{n}_g(\tilde{x}) \left[ b_g(z, k) + f(z) \mu_k^2 \right]^2 G^2(z) P_m(k) \]

more galaxies

Information \( \sim \) \( \left( \frac{\mathcal{P}_g}{1 + \mathcal{P}_g} \right)^2 \)

Tegmark et al. (1997)

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Clustering strength of galaxy type "g" in redshift space

Are we about to hit a cosmic variance "wall"?
Fisher information in phase space

On each cell of phase space volume there is a certain amount of information about the spectrum (and other quantities), given by:

\[
F[\log P_g] \times \frac{\Delta V_x \Delta V_k}{(2\pi)^3} = \frac{1}{2} \left( \frac{P_g}{1 + P_g} \right)^2 \times \frac{\Delta V_x \Delta V_k}{(2\pi)^3}
\]

phase space volume = \Delta \mathcal{V}.
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\]

The precision (SNR) with which we can estimate the clustering strength is:

\[
\frac{\mathcal{P}_g^2}{\sigma^2(\mathcal{P}_g)} = F[\log \mathcal{P}_g] \times \Delta \mathcal{V} = \frac{1}{2} \left( \frac{\mathcal{P}_g}{1 + \mathcal{P}_g} \right)^2 \Delta \mathcal{V}
\]
Multi-tracer Fisher information matrix

\[ F[\log \mathcal{P}_\alpha, \log \mathcal{P}_\beta] = \frac{1}{4} \left[ \frac{\mathcal{P}_\alpha \mathcal{P}_\beta (1 - \mathcal{P})}{(1 + \mathcal{P})^2} + \delta_{\alpha \beta} \frac{\mathcal{P}_\alpha \mathcal{P}}{1 + \mathcal{P}} \right] \]

Clustering strengths of each galaxy type: \( \mathcal{P}_\alpha \)

Total clustering strength of a survey: \( \mathcal{P} \equiv \sum_\alpha \mathcal{P}_\alpha \)
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\[ F = \frac{1}{2} \left( \frac{\mathcal{P}}{1 + \mathcal{P}} \right)^2 \]

1 tracer
Multi-tracer Fisher information matrix

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\[ F = \frac{1}{2} \left( \frac{\mathcal{P}}{1 + \mathcal{P}} \right)^2 \Rightarrow \frac{1}{4} \left( \frac{\mathcal{P}_1^2 (1 - \mathcal{P})}{(1 + \mathcal{P})^2} + \frac{\mathcal{P}_1 \mathcal{P}_2 (1 - \mathcal{P})}{(1 + \mathcal{P})^2} \right) \]

\textbf{1 tracer} \hspace{3cm} \textbf{2 tracers}
Multi-tracer Fisher information matrix

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F[\log \mathcal{P}_\alpha, \log \mathcal{P}_\beta] = \frac{1}{4} \left[ \mathcal{P}_\alpha \mathcal{P}_\beta (1 - \mathcal{P}) \frac{1}{(1 + \mathcal{P})^2} + \delta_{\alpha\beta} \frac{\mathcal{P}_\alpha \mathcal{P}}{1 + \mathcal{P}} \right]
\]

Clustering strengths of each galaxy type:

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Total clustering strength of a survey:

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\[
F = \frac{1}{2} \left( \frac{\mathcal{P}}{1 + \mathcal{P}} \right)^2 \Rightarrow \frac{1}{4} \left( \frac{\mathcal{P}_1^2 (1 - \mathcal{P})}{(1 + \mathcal{P})^2} + \frac{\mathcal{P}_1 \mathcal{P}_2 (1 - \mathcal{P})}{1 + \mathcal{P}} \frac{1}{(1 + \mathcal{P})^2} + \frac{\mathcal{P}_2^2 (1 - \mathcal{P})}{(1 + \mathcal{P})^2} \right) \Rightarrow \frac{1}{4} \left( \begin{array}{ccc}
\frac{\mathcal{P}_1^2 (1 - \mathcal{P})}{(1 + \mathcal{P})^2} & \frac{\mathcal{P}_1 \mathcal{P}_2 (1 - \mathcal{P})}{1 + \mathcal{P}} & \frac{\mathcal{P}_1 \mathcal{P}_2 (1 - \mathcal{P})}{1 + \mathcal{P}} \\
\frac{\mathcal{P}_1 \mathcal{P}_2 (1 - \mathcal{P})}{1 + \mathcal{P}} & \frac{\mathcal{P}_2^2 (1 - \mathcal{P})}{(1 + \mathcal{P})^2} & \frac{\mathcal{P}_2 \mathcal{P}_3 (1 - \mathcal{P})}{1 + \mathcal{P}} \\
\frac{\mathcal{P}_1 \mathcal{P}_2 (1 - \mathcal{P})}{1 + \mathcal{P}} & \frac{\mathcal{P}_2 \mathcal{P}_3 (1 - \mathcal{P})}{1 + \mathcal{P}} & \frac{\mathcal{P}_3^2 (1 - \mathcal{P})}{(1 + \mathcal{P})^2} + \frac{\mathcal{P}_3 \mathcal{P}}{1 + \mathcal{P}} \\
\end{array} \right)
\]

1 tracer

2 tracers

3 tracers

So... are we in fact gaining any information by splitting galaxies into sub-types, or are we just "shuffling it around"?
Multi-tracer Fisher information matrix

Yes, we **gain** information.
In fact, with **multiple tracers** the Fisher matrix is **unbounded**!
Yes, we **gain** information.
In fact, with **multiple tracers** the Fisher matrix is **unbounded**!

We can **diagonalize** the multi-tracer Fisher matrix by changing variables:

⇒ **Hyper-spherical coordinates**!

\[
\begin{align*}
\mathcal{P}_1 &= x^2 \\
\mathcal{P}_2 &= y^2 \\
\mathcal{P}_3 &= z^2 \\
\end{align*}
\]  \quad \leftrightarrow \quad 
\begin{align*}
\frac{r^2}{\mathcal{P}} &= \frac{\mathcal{P}_3}{\mathcal{P}_1 + \mathcal{P}_2} \\
\tan^2 \theta &= \frac{\mathcal{P}_2}{\mathcal{P}_1} \\
\tan^2 \phi &= \\
\end{align*}
\]
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⇒ **Hyper-spherical coordinates**!

\[
\begin{align*}
\mathcal{P}_1 &= \begin{cases} x^2 \\ y^2 \\ z^2 \end{cases} \\
\mathcal{P}_2 &= \begin{cases} x^2 \\ y^2 \\ z^2 \end{cases} \\
\mathcal{P}_3 &= \begin{cases} x^2 \\ y^2 \\ z^2 \end{cases}
\end{align*}
\]

\[
\begin{align*}
\begin{bmatrix}
\mathcal{P}_1 \\
\mathcal{P}_2 \\
\mathcal{P}_3
\end{bmatrix}
&= 
\begin{bmatrix}
x^2 \\
y^2 \\
z^2
\end{bmatrix}
\quad \Longleftrightarrow \quad 
\begin{bmatrix}
r^2 \\
\tan^2 \theta \\
\tan^2 \phi
\end{bmatrix}
= 
\begin{bmatrix}
\mathcal{P} \\
\mathcal{P}_3 / (\mathcal{P}_1 + \mathcal{P}_2) \\
\mathcal{P}_2 / \mathcal{P}_1
\end{bmatrix}
\end{align*}
\]
Multi-tracer Fisher information matrix

In “spherical” coordinates (i.e., using the total clustering strength and the relative clustering strengths) the Fisher matrix becomes diagonal!

E.g.: three species of tracers

\[
F_{Sp} = \left\{ \begin{array}{ccc}
\frac{1}{2} \left( \frac{\mathcal{P}}{1+\mathcal{P}} \right)^2 & 0 & 0 \\
0 & \frac{1}{4} \frac{\mathcal{P}^2}{1+\mathcal{P}} \sin^2 \theta \cos^2 \theta & 0 \\
0 & 0 & \frac{1}{4} \frac{\mathcal{P}^2}{1+\mathcal{P}} \sin^2 \theta \sin^2 \phi \cos^2 \phi \\
\end{array} \right\}
\]
Multi-tracer Fisher information matrix

In “spherical” coordinates (i.e., using the total clustering strength and the relative clustering strengths) the **Fisher matrix becomes diagonal**!

E.g.: three species of tracers

\[
F_{Sph} = \begin{pmatrix}
\frac{1}{2} \left( \frac{P}{1+P} \right)^2 & 0 & 0 \\
0 & \frac{1}{4} \frac{P^2}{1+P} \sin^2 \theta \cos^2 \theta & 0 \\
0 & 0 & \frac{1}{4} \frac{P^2}{1+P} \sin^2 \theta \sin^2 \phi \cos^2 \phi
\end{pmatrix}
\]

Total clustering: 
\[
< 1/2
\]
Multi-tracer Fisher information matrix

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E.g.: three species of tracers

\[
F_{Sph} = \begin{bmatrix}
\frac{1}{2} \left( \frac{\mathcal{P}}{1+\mathcal{P}} \right)^2 & 0 & 0 \\
0 & \frac{\mathcal{P}^2}{4(1+\mathcal{P})} & \frac{\mathcal{P}^2}{4(1+\mathcal{P})} \\
0 & \frac{\mathcal{P}^2}{4(1+\mathcal{P})} & \frac{\mathcal{P}^2}{4(1+\mathcal{P})}
\end{bmatrix}
\]

Total clustering: \( < 1/2 \)

Relative clusterings: information \( \sim \mathcal{P} = \sum_{\alpha} \bar{n}_\alpha b^2_\alpha P_m \)
- unbounded
- extra information!
Very simple example: two types of tracers of large-scale structure

\[ \mathcal{F}_1 = \frac{1}{2} \left( \frac{\mathcal{P}_1 + \mathcal{P}_2}{1 + \mathcal{P}_1 + \mathcal{P}_2} \right)^2 \]

\[ \mathcal{F}_2 = \frac{1}{4} \frac{\mathcal{P}_1 \mathcal{P}_2}{1 + \mathcal{P}_1 + \mathcal{P}_2} \]

\[ \mathcal{F}_1, \mathcal{F}_2 \]

\[ \mathcal{P}_1, \mathcal{P}_2 \]
Very simple argument: cosmic variance is only inherited through the spectrum

By comparing the clustering between different tracers of large-scale structure (e.g.: LRGs, ELGs, etc.), we can measure with arbitrary accuracy* the physical parameters that determine the different clustering strengths:

\[
P_1 = n_1 (b_1 + f \mu_k^2)^2 P(k; z)
\]

\[
P_2 = n_2 (b_2 + f \mu_k^2)^2 P(k; z)
\]
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\mathcal{P}_1 = n_1 (b_1 + f \mu_k^2) P(k; z)
\]
\[
\mathcal{P}_2 = n_2 (b_2 + f \mu_k^2) P(k; z)
\]

\[
\frac{\mathcal{P}_1}{\mathcal{P}_2} = \frac{n_1 (b_1 + f \mu_k^2)}{n_2 (b_2 + f \mu_k^2)}
\]

Cosmic variance does not apply:
- * bias
- * RSDs
- * PNG

The key: very high numbers of distinct types of tracers (red galaxies, blue galaxies, emission-line galaxies, quasars, etc.)
Galaxies are more than just a nice redshift!

Just give me the goddamn z already!
J-PAS

Javalambre Physics of the Accelerated Universe Astrophysical Survey

- New site - OAJ, mainland Spain
- Two new telescopes (2.5m & .8m) dedicated to surveys
- An innovative strategy: imaging in 54 narrow-band filters
- Benitez et al., 1403.5237 – http://j-pas.org

Images & low-resolution ($R\sim60$) spectra of everything ($i<\sim22.5$)

> 8500 $\text{deg}^2$!

- Dark energy
- Galaxy evolution
- LSS & BAOs
- Supernovas
- Clusters
- QSOs
Joint Spain + Brazil project; total cost ~ € 45 million

Two telescopes:
2.5 m and 0.8 m

1.2 Gpixel camera,
FoV 3°

Science data
beginning in 2015
(running 'til 2020/21)
Main telescope - T250 (2.5m)

M1 = 2.5m
FoV = 3 deg = 476 mm at FP
Effective coll. area = 3.89 m²
Etendue = 27.5 m² deg²

Plate scale = 22.67″/mm = 0.22″/pix
Focal length = 9098 mm (F#3.5)
Type = Ritchey Chrétien-like
Mount = Alt-azimuthal
Focus = Cassegrain
Field corrector = 3 lenses
Mass = 45.000 Kg

On lab (AMOS)
c. 2012

On site
March 2014
Camera - JPCam

* Array of 14 large-format CCDs from E2V
* 9.216 x 9.216 pixels (1.2 Gpix camera!)
* QE > 80% (400–900 nm)
Camera JPCam - completed by Q4/2014-Q1/2015
Some pics

- OAJ
- M106
- OAJ
- M27
Datacube: 54 narrow-band + 7 broad-band filters

z-photo: $\sigma_z \sim 0.002-0.003 \ (1+z)$
neart-spectroscopic accuracy & precision

J-PAS:
an R~60 IFU
over 8500 deg$^2$, down to $i\sim23$!
J-PAS: an 8500 deg$^2$ IFU

- $\sim 1.3 \times 10^7$ LRGs up to $z<1.1$ - $\sigma_z \sim 0.003(1+z)$
- $\sim 10^8$ ELGs up to $z<1.3$ - $\sigma_2 \sim 0.0025(1+z)$
- $> 2 \times 10^8$ galaxies (generic) to $z<1.3$ - $\sigma_z \sim 0.01(1+z)$
- $\sim 2 \times 10^6$ QSOs up to $z<4$ - $\sigma_z \sim 0.0015(1+z)$
- $> 10^5$ clusters & groups
- $\sim 10^4$ supernovas (no need of spectroscopic follow-up!)
- Serendipitous discoveries & more
- 54 narrow-band images of everything down to $r\sim22.5$

Footprint:

- $\sim$SDSS
Massive & deep multi-tracer survey with J-PAS

@ k=0.1 h/Mpc

See also:
* GAMA - Blake et al., MNRAS 2013 : $P_\alpha > 10$ for $z<0.25$
* Radio galaxies & SKA - Ferramacho et al., MNRAS 2014
* 21cm intensity mapping - Bull et al., arXiv:1405.1452
1. Conditional errors
PNG ($f_{\text{NL}}$ local) and matter growth rate ($f\sigma_8$) benefit from multi-tracer analysis

![Graphs showing conditional errors for $f_{\text{NL}}$ and $f\sigma_8$](image-url)
1. Conditional errors
PNG ($f_{\text{NL}}$ local) and matter growth rate ($f\sigma_8$) benefit from multi-tracer analysis

The BAO distance scales, not so much…
For **high number densities** (~low redshifts), the contribution from the **relative clustering strengths** dominates the (Fisher) information of **bias-related quantities**

\[
matter \text{ growth rate } f \sigma_8
\]

\[
f_{NL}
\]

\[
\text{Relat.} = \text{Fisher information from relative clustering strengths}
\]

\[
\text{Total} = \text{Total fisher information (absolute + relative)}
\]
2. Marginalized errors
Prior knowledge of the bias of the tracers (from, e.g., lensing) suppresses the degradation due to marginalization \(\text{wrt}\) bias

No prior on bias
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No prior on bias

Weak (~20\%) prior on bias
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Prior knowledge of the bias of the tracers (from, e.g., lensing) suppresses the degradation due to marginalization \textit{wrt} bias.

No prior on bias
Weak (~20%) prior on bias
Strong (~5%) prior on bias
$f_{\text{NL}}$ is almost unaffected: the k-dependence of $\Delta b_{\text{NL}} \sim f_{\text{NL}} \times k^{-2}$ helps break the degeneracy with bias.

Cumulative uncertainty on $f_{\text{NL}}$ when the redshift slices are combined.

No prior on bias.

1σ error: ~2
$f_{NL}$ is almost unaffected: the $k$-dependence of $\Delta b_{NL} \sim f_{NL} \times k^{-2}$ helps break the degeneracy with bias

Cumulative uncertainty on $f_{NL}$ when the redshift slices are combined

No

Weak (~20%) prior on bias

$1\sigma$ error: ~2
$f_{NL}$ is almost unaffected: the k-dependence of $\Delta b_{NL} \sim f_{NL} \times k^{-2}$ helps break the degeneracy with bias.

Cumulative uncertainty on $f_{NL}$ when the redshift slices are combined

Cumulative uncertainty on $f_{NL}$ when the redshift slices are combined

- LRGs
- ELGs
- quasars
- Combined

No
Weak (~20%)
Strong (~5%) prior on bias

1σ error: ~2
Conclusions

• In the new *age of cosmic variance*, multi-tracer surveys (e.g., J-PAS) will be far superior to single-tracer surveys of large-scale structure.

• These tracers of LSS can be different types of galaxies, galaxies of different luminosities, QSOs, or even the DM halos themselves.

• Boost from multi-tracer analysis kicks in for very large number densities of the tracers (total $\geq 10^{-2} h^3 \text{Mpc}^{-3}$).

• New horizons for constraining modified gravity & inflation.

• Actual data is right around the corner (next ~5-7 years).

• Difficulties: covariance of the biases; non-linearities and modelling or RSDs; assembly bias; cross-covariances…

• What multi-tracer analysis can tell us about the bispectrum?