Primordial Features from Linear to Nonlinear Scales

Florian Beutler

In collaboration with Matteo Biagetti, Daniel Green, Anze Slosar & Benjamin Wallisch

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Inflation in one plot

Baumann (2009)

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Testing inflation through primordial features

No features

\[ P(k) = \frac{2\pi^2}{k^3} P_{\zeta,0}(k) = \frac{2\pi^2 A_s}{k^3} \left( \frac{k}{k_*} \right)^{n_s-1} \]
Testing inflation through primordial features

\[
\frac{\Delta P_\zeta(k)}{P_\zeta,0(k)} = A_{\text{lin}} \sin \left( \omega_{\text{lin}} k + \phi_{\text{lin}} \right)
\]

- Sharp Features
- Starobinsky (1992)
- Adams, Cresswell & Easther (1997)

\[
\omega_{\text{lin}} = 271.8 \text{ Mpc}
\]
Testing inflation through primordial features

Logarithmic features

\[ \Delta P_\zeta(k) = A_{\log} \sin \left( \omega_{\log} \log\left(\frac{k}{k_*}\right) + \phi_{\log} \right) \]

[Resonant features]
Chen, Easther & Lim (2008)
Silverstein & Westphal (2008)
Flauger, McAllister, Pajer & Westphal (2010)

...
Non-linear gravitational evolution

\[ P_g(k) = b_1^2 \left[ e^{-k^2 \Sigma_{nl}^2/2} P_{\text{lin}}(k) + P_{\text{MC}}(k) \right] \]

\[ P_{\text{MC}}(k) \approx 2 \int F_2^2(k-q, q) P_{\text{lin}}(|k-q|) P_{\text{lin}}(q) d^3q \]

Heavens & Matarrese (1998), McDonald (2006), Smith et al. (2007), Carlson et al. (2009)
Blas et al. (2016)
Density-field reconstruction

\[ \nabla \cdot \Psi + \frac{f}{b} \nabla \cdot (\Psi_s \hat{s}) = -\frac{\delta g}{b} \quad \text{with} \quad f = \frac{d \ln D}{d \ln a} \]

Schmittfull, FB et al. (2016)

\[ \Sigma_{\text{post-recon}}^{\text{nl}} < \Sigma_{\text{pre-recon}}^{\text{nl}} \]

\[ P_{\text{post-recon}}^{\text{MC}} \approx 0 \]

Eisenstein et al. (2007), Padmanabhan et al. (2009)

Padmanabhan et al. (2012) . . .
Fitting the BAO

Model for the BAO

\[ P(k) = P_{nw}(k) + e^{-k^2 \Sigma_{nl}^2/2}P_{BAO}(k/\alpha) \]

Add broadband nuisance terms

\[ A(k) = a_1 k + a_2 + \frac{a_3}{k} + \frac{a_4}{k^2} + \frac{a_5}{k^3} \]

\[ P_{\text{fit}}(k) = \frac{B^2}{(1 + (k\Sigma_{\text{FOG}})^2/2)^2}P(k) + A(k) \]

Marginalize to get \( \mathcal{L}(\alpha) \).
Modelling the BAO

Ding, Vlah, FB et al. (2018)

→ 2 simulations with the same phase but based on $P_{\text{lin}}$ and $P_{\text{nw}}^{\text{lin}}$
→ Allows to measure the BAO (almost) without sample variance
Modelling the BAO

\[ \alpha = \alpha_\parallel^{1/3} \alpha_\perp^{2/3} \]

Ding, Vlah, FB et al. (2018)
Modelling the BAO

Ding, Vlah, FB et al. (2018)

\[ \alpha = \alpha_{||}^{1/3} \alpha_{\perp}^{2/3} \]
Baryon Acoustic Oscillations in BOSS DR12

→ 2 independent $8\sigma$ detections
→ 1% distance constrains (1.5% in $D_A(z)$ and $\sim 2.5\%$ in $H(z)$)

FB et al. (2017)
Feature damping

Linear Feature

- Damping factor of linear features equal to BAO damping for $\omega_{\text{lin}} \gtrsim 75$ Mpc

Logarithmic Feature

- Damping factor of log features approx. equal to BAO damping for $\omega_{\text{log}} \gtrsim 10$

\[
P(k) = P_{\text{nw}}(k) + e^{-k^2 \Sigma^2_{\text{nl}} / 2} \left[ P_{\text{BAO}}^w(k/\alpha) \right]
\]
Feature damping

**Linear Feature**

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**Logarithmic Feature**

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\[
P(k) = P_{\text{nw}}(k) + e^{-k^2\Sigma_{\text{nl}}^2/2} \left[ P_{\text{BAO}}^w(k/\alpha) + P_{\text{lin,log}}^w(k) + P_{\text{BAO}}^w(k/\alpha)\delta P_{\zeta}^{\text{lin,log}}(k) \right]
\]
Feature constraints from BOSS DR12 and Planck

BOSS

BOSS vs. Planck

BOSS + Planck
Feature constraints from BOSS DR12 and Planck

BOSS

BOSS vs. Planck

BOSS + Planck
Feature constraints from BOSS DR12 and Planck

BOSS

BOSS vs. Planck

BOSS + Planck
Forecasts for primordial feature constraints

→ LSS dominates on small frequencies, while the CMB can access higher frequencies
→ DESI/Euclid are going to beat even CVL-CMB experiments
Many well motivated inflationary models introduce features in the primordial power spectrum.

And we know how to detect features → BAO.

Constraints on primordial features from LSS are already better than Planck for a large frequency range.

Future LSS constraints from DESI and Euclid will push into a parameter space, which is even beyond a CVL-CMB experiment.
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Fourier-space vs. configuration space

Linear Feature

Logarithmic Feature

$P_w(k) / P_{nw}(k)$

$k \,[h \, \text{Mpc}^{-1}]$

$r^2 \xi(r) \,[\text{Mpc}^2]$

$r \,[\text{Mpc}]$
S/N after Density-field reconstruction

\[
(S/N)^2 = \sum_{k_1, k_2 \leq k_{\text{max}}} C^{-1}(k_1, k_2) P_m(k_1) P_m(k_2)
\]

Sugiyama, FB et al. (in prep.)

Seo, FB et al. (2016)
Dependence on fiducial cosmology

\[ \alpha = \alpha_{\parallel}^{1/3} \alpha_{\perp}^{2/3} \]

Carter, FB et al. (2019)
Transfer of power

\[ \omega_{\text{lin}} = 100 \text{ Mpc} \]

\[ \omega_{\text{lin}} = 400 \text{ Mpc} \]

\[ \omega_{\text{lin}} = 900 \text{ Mpc} \]

\[ \omega_{\text{log}} = 10 \]

\[ \omega_{\text{log}} = 40 \]

\[ \omega_{\text{log}} = 80 \]

\[ [C_\ell - C_{\text{fid}}]/C_{\text{fid}}] \]

\[ [P(k) - P_{\text{fid}}(k)]/P_{\text{fid}}(k) \]

\[ k = \ell/D_A [h^{-1} \text{ Mpc}] \]