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The EFTofLSS: an overview, latest developments, and going forward

Based on several works with L. Senatore, P. Zhang, Y. Donath, M. Lewandowski, et al.

<https://github.com/pierrexzyz/pybird>

Theoretical Modelling of LSS, Edinburgh, 2024/6/3

What is this for?

- We are just starting to get a wealth of data. What's the end goal?
- Understanding the universe, which means measuring known and detecting unknown physics across a wide range of energy scales (neutrino masses, PNG, dynamical DE, light mediators, relics)
- As with any experimental information, we struggle for
 - **Precision**: more volume, more galaxies, more time
 - **Accuracy**: less and less systematics, and a reliable interpretation of the data
- EFTofLSS gives us just that – analytical understanding / parametrization of the system based on good old effective theory

The *EFTofLSS*: a humble approach

- Basic dofs and symmetries: CDM smoothed density and momentum, translations, rotations, diffs
- Physical cutoff of the theory: $k_{\text{NL}}, k_{\text{R}}$
- Expansion parameter: basically $k/k_{\text{NL}}, k/k_{\text{R}}$
- Do perturbation theory, where possible.
Resum non-perturbative effects
- Add biasing scheme to get to observable. Add eventual known systematics
- Apply to data. Analysis issues (priors, anyone?) will hopefully subside

Start from dark matter

Equations of motion for dark matter

$$\dot{\delta} + \frac{1}{a\bar{\rho}} \partial_i \pi^i = 0$$

$$\dot{\pi}^i + 4H\pi^i + \frac{\bar{\rho}}{a} \partial_i \Phi = -\frac{\partial_j}{a} \left(\frac{2M_{\text{Pl}}^2}{a^2} \left(\partial_i \Phi \partial_j \Phi - \frac{1}{2} \delta_{ij} (\partial\Phi)^2 \right) + \frac{\pi^i \pi^j}{\rho} + \tau^{ij} \right)$$

EFT stress-tensor $\tau^{ij} = \tau_{\text{ct}}^{ij} + \tau_{\epsilon}^{ij}$

$$\begin{aligned} \tau_{\text{ct}}^{ij} = & c_1 \left(\frac{\partial^i \partial^j \delta^{(1)}}{\partial^2} + \frac{\partial_k \partial^i \partial^j \delta^{(1)}}{\partial^2} \frac{\partial_k \delta^{(1)}}{\partial^2} \right) + c_3 \delta^{ij} \left(\delta^{(1)} + \partial_k \delta^{(1)} \frac{\partial_k \delta^{(1)}}{\partial^2} \right) \\ & + c_2 \left(\frac{\partial^i \partial^j \delta^{(2)}}{\partial^2} - \frac{\partial_k \partial^i \partial^j \delta^{(1)}}{\partial^2} \frac{\partial_k \delta^{(1)}}{\partial^2} \right) + \dots \end{aligned}$$

$$\tau_{\epsilon}^{ij} = \epsilon_1^{ij} + \partial_k \epsilon_1^{ij} \frac{\partial_k \delta^{(1)}}{\partial^2} + \epsilon_3^{ijkl} \frac{\partial_k \partial_l \delta^{(1)}}{\partial^2} + \dots$$

$$\left\langle \epsilon_a^{ij}(\vec{k}) \epsilon_b^{kl}(\vec{k}') \right\rangle' = c_{a,b}^{(1)} \delta_K^{ij} \delta_K^{kl} + c_{a,b}^{(1)} \delta_K^{i(k} \delta_K^{l)j} + \mathcal{O}(k^2/k_{\text{NL}}^2)$$

Bias expansion

Write all contractions of $r_{ij} = \frac{2}{3\Omega_m \mathcal{H}^2} \partial_i \partial_j \Phi$ $p_{ij} = -\frac{1}{f\mathcal{H}} \partial_i v_j$

$$\begin{aligned} \delta_h(\vec{x}, t) = & \int^t dt' H(t') [c_\delta(t, t') \delta(x_{\text{fl}}, t') + c_\theta(t, t') \theta(x_{\text{fl}}, t') \\ & + c_{\delta^2}(t, t') \delta^2(x_{\text{fl}}, t') + c_{\delta\theta}(t, t') \delta\theta(x_{\text{fl}}, t') + c_{\theta^2}(t, t') \theta^2(x_{\text{fl}}, t') \\ & + c_{r^2}(t, t') r^2(x_{\text{fl}}, t') + c_{rp}(t, t') rp(x_{\text{fl}}, t') + c_{p^2}(t, t') p^2(x_{\text{fl}}, t') \\ & + c_{\delta^3}(t, t') \delta^3(x_{\text{fl}}, t') + c_{\delta^2\theta}(t, t') \delta^2\theta(x_{\text{fl}}, t') + c_{\delta\theta^2}(t, t') \delta\theta^2(x_{\text{fl}}, t') + c_{\theta^3}(t, t') \theta^3(x_{\text{fl}}, t') \\ & + c_{r^3}(t, t') r^3(x_{\text{fl}}, t') + c_{r^2p}(t, t') r^2p(x_{\text{fl}}, t') + c_{rp^2}(t, t') rp^2(x_{\text{fl}}, t') + c_{p^3}(t, t') p^3(x_{\text{fl}}, t') \\ & + c_{r^2\delta}(t, t') r^2\delta(x_{\text{fl}}, t') + c_{r p\delta}(t, t') r p\delta(x_{\text{fl}}, t') + c_{p^2\delta}(t, t') p^2\delta(x_{\text{fl}}, t') \\ & + c_{r^2\theta}(t, t') r^2\theta(x_{\text{fl}}, t') + c_{r p\theta}(t, t') r p\theta(x_{\text{fl}}, t') + c_{p^2\theta}(t, t') p^2\theta(x_{\text{fl}}, t') \\ & + c_{\delta^4}(t, t') \delta^4(x_{\text{fl}}, t') + c_{\delta r^3}(t, t') \delta r^3(x_{\text{fl}}, t') + c_{\delta^2 r^2}(t, t') \delta^2 r^2(x_{\text{fl}}, t') \\ & + c_{(r^2)^2}(t, t') (r^2)^2(x_{\text{fl}}, t') + c_{r^4}(t, t') r^4(x_{\text{fl}}, t')] \Big| \end{aligned}$$

$$\vec{x}_{\text{fl}} = \vec{x} + \int_t^{t'} \frac{dt''}{a(t'')} \vec{v}(\vec{x}_{\text{fl}}(\vec{x}, t, t''), t'')$$

Then, expand in v

$$\begin{aligned} \mathcal{O}(x_{\text{fl}}(\vec{x}, t, t'), t') \approx & \mathcal{O}(\vec{x}, t') + \partial_i \mathcal{O}(\vec{x}, t') \int_t^{t'} \frac{dt_1}{a(t_1)} v^i(\vec{x}, t_1) \\ & + \frac{1}{2} \partial_i \partial_j \mathcal{O}(\vec{x}, t') \int_t^{t'} \frac{dt_1}{a(t_1)} v^i(\vec{x}, t_1) \int_t^{t'} \frac{dt_2}{a(t_2)} v^j(\vec{x}, t_2) \\ & + \partial_i \mathcal{O}(\vec{x}, t') \int_t^{t'} \frac{dt_1}{a(t_1)} \partial_j v^i(\vec{x}, t_1) \int_t^{t_1} \frac{dt_2}{a(t_2)} v^j(\vec{x}, t_2) \end{aligned}$$

MacDonald , Roy (2010)
 Senatore (2014)
 Desjaques, Jeong, Schmidt (2014)
 Many others

Bias expansion

Finally, do the time integrals, getting

$$\mathcal{O}_m^{(n)}(\vec{x}_{\text{fl}}(\vec{x}, t, t'), t') = \sum_{\alpha=1}^{n-m+1} \left(\frac{D(t')}{D(t)} \right)^{\alpha+m-1} \mathbb{C}_{\mathcal{O}_m, \alpha}^{(n)}(\vec{x}, t)$$

And remove degeneracies. At 4th order, we have

$$\begin{aligned} \delta_h(\vec{x}, t) = & b_1 \left(\mathbb{C}_{\delta,1}^{(1)}(\vec{x}, t) + \mathbb{C}_{\delta,1}^{(2)}(\vec{x}, t) + \mathbb{C}_{\delta,1}^{(3)}(\vec{x}, t) + \mathbb{C}_{\delta,1}^{(4)}(\vec{x}, t) \right) \\ & + b_2 \left(\mathbb{C}_{\delta,2}^{(2)}(\vec{x}, t) + \mathbb{C}_{\delta,2}^{(3)}(\vec{x}, t) + \mathbb{C}_{\delta,2}^{(4)}(\vec{x}, t) \right) + b_3 \left(\mathbb{C}_{\delta,3}^{(3)}(\vec{x}, t) + \mathbb{C}_{\delta,3}^{(4)}(\vec{x}, t) \right) \\ & + b_4 \mathbb{C}_{\delta,4}^{(4)}(\vec{x}, t) + b_5 \left(\mathbb{C}_{\delta^2,1}^{(2)}(\vec{x}, t) + \mathbb{C}_{\delta^2,1}^{(3)}(\vec{x}, t) + \mathbb{C}_{\delta^2,1}^{(4)}(\vec{x}, t) \right) \\ & + b_6 \left(\mathbb{C}_{\delta^2,2}^{(3)}(\vec{x}, t) + \mathbb{C}_{\delta^2,2}^{(4)}(\vec{x}, t) \right) + b_7 \mathbb{C}_{\delta^2,3}^{(4)}(\vec{x}, t) + b_8 \left(\mathbb{C}_{r^2,2}^{(3)}(\vec{x}, t) + \mathbb{C}_{r^2,2}^{(4)}(\vec{x}, t) \right) \\ & + b_9 \mathbb{C}_{r^2,3}^{(4)}(\vec{x}, t) + b_{10} \left(\mathbb{C}_{\delta^3,1}^{(3)}(\vec{x}, t) + \mathbb{C}_{\delta^3,1}^{(4)}(\vec{x}, t) \right) + b_{11} \mathbb{C}_{r^3,2}^{(4)}(\vec{x}, t) \\ & + b_{12} \mathbb{C}_{\delta^3,2}^{(4)}(\vec{x}, t) + b_{13} \mathbb{C}_{r^2\delta,2}^{(4)}(\vec{x}, t) + b_{14} \mathbb{C}_{\delta^4,1}^{(4)}(\vec{x}, t) + b_{15} \mathbb{C}_{\delta r^3,1}^{(4)}(\vec{x}, t) \end{aligned}$$

Redshift space

Finally, redshift space

$$\delta_{r,h}(\vec{k}, \hat{z}) = \delta_h(\vec{k}) + \int d^3x e^{-i\vec{k}\cdot\vec{x}} \left(\exp \left[-i \frac{(\hat{z} \cdot \vec{k})}{aH} (\hat{z} \cdot \vec{v}(\vec{x})) \right] - 1 \right) (1 + \delta_h(\vec{x}))$$

$$\begin{aligned} \delta_{r,h} = & \delta_h - \frac{\hat{z}^i \hat{z}^j}{aH \bar{\rho}_h} \partial_i \pi_h^j + \frac{\hat{z}^i \hat{z}^j \hat{z}^k \hat{z}^l}{2(aH)^2 \bar{\rho}_h} \partial_i \partial_j (\pi_h^k v^l) \\ & - \frac{\prod_{a=1}^6 \hat{z}^{i_a}}{3!(aH)^3 \bar{\rho}_h} \partial_{i_1} \partial_{i_2} \partial_{i_3} (\pi_h^{i_4} v^{i_5} v^{i_6}) + \frac{\prod_{a=1}^8 \hat{z}^{i_a}}{4!(aH)^4 \bar{\rho}_h} \partial_{i_1} \partial_{i_2} \partial_{i_3} \partial_{i_4} (\pi_h^{i_5} v^{i_6} v^{i_7} v^{i_8}) + \dots \end{aligned}$$

Scoccimarro (2004)

Lewandowski, Senatore, Prada, Zhao, Chuang (2015)

Perko, Senatore, Jennings, Wechsler (2016)

Renormalising products

Important to respect extended Galilean invariance

$$[v^i]_R \rightarrow [v^i]_R + \chi^i$$

$$[v^i v^j]_R \rightarrow [v^i v^j]_R + [v^i]_R \chi^j + [v^j]_R \chi^i + \chi^i \chi^j$$

...

$$[\delta_h]_R = \delta_h + \mathcal{O}_{\delta_h} ,$$

$$[\pi_h^i]_R = \rho_h v^i + v^i \mathcal{O}_{\rho_h} + \mathcal{O}_{\pi_h}^i ,$$

$$[\pi_h^i v^j]_R = \rho_h v^i v^j + v^i v^j \mathcal{O}_{\rho_h} + v^i \mathcal{O}_{\pi_h}^j + v^j \mathcal{O}_{\pi_h}^i + \mathcal{O}_{\pi_h v}^{ij} ,$$

$$[\pi_h^i v^j v^k]_R = \rho_h v^i v^j v^k + v^i v^j v^k \mathcal{O}_{\rho_h} + (v^i v^j \mathcal{O}_{\pi_h}^k + 2 \text{ perms.}) + (v^i \mathcal{O}_{\pi_h v}^{jk} + 2 \text{ perms.}) + \mathcal{O}_{\pi_h v^2}^{ijk} ,$$

$$\begin{aligned} [\pi_h^i v^j v^k v^l]_R &= \rho_h v^i v^j v^k v^l + v^i v^j v^k v^l \mathcal{O}_{\rho_h} + (v^i v^j v^k \mathcal{O}_{\pi_h}^l + 3 \text{ perms.}) \\ &\quad + (v^i v^j \mathcal{O}_{\pi_h v}^{kl} + 5 \text{ perms.}) + (v^i \mathcal{O}_{\pi_h v^2}^{jkl} + 3 \text{ perms.}) + \mathcal{O}_{\pi_h v^3}^{ijkl} \end{aligned}$$

Scoccimarro (2004)

Lewandowski, Senatore, Prada, Zhao, Chuang (2015)

Perko, Senatore, Jennings, Wechsler (2016)

GDA, Donath, Lewandowski, Senatore (2022)

New momentum counterterm

At 4th order in redshift space, must have

$$\delta_r(\vec{x}) \supset \frac{1}{H\bar{\rho}} \hat{z}^i \hat{z}^j \partial_i \pi^j(\vec{x}) \sim \hat{z}^i \hat{z}^j \frac{\partial_i \partial_j \partial_k \partial_m}{k_{\text{NL}}^2 \partial^2} \left(\frac{\partial_k \partial_l}{H^2} \Phi(\vec{x}) \frac{\partial_l \partial_m}{H^2} \Phi(\vec{x}) \right)$$

It absorbs the following B_{411} piece

$$B_{411}^r|_{\text{UV}} \supset \frac{2(c_5 - c_3)}{99} \frac{f(k_1^2 - k_2^2)^2 (k_1^2 + k_2^2) (k_1 \mu_1 + k_2 \mu_2)^2}{k_{\text{NL}}^2 k_1^2 k_2^2 k_3^2} P_{11}(k_1) P_{11}(k_2) + 2 \text{ perms.}$$

Questions of scale

$$P_{1\text{-loop tot.}}^{r,h}(k, \hat{k} \cdot \hat{z}, a) = D(a)^2 P_{11}^{r,h}(k, \hat{k} \cdot \hat{z}) + D(a)^4 (P_{22}^{r,h}(k, \hat{k} \cdot \hat{z}) + P_{13}^{r,h}(k, \hat{k} \cdot \hat{z}))$$

It depends on 4 biases, and the following UV

$$P_{13}^{r,hct}(k, \hat{k} \cdot \hat{z}) = 2K_1^{h,r}(\vec{k}; \hat{z}) P_{11}(k) \frac{k^2}{k_{\text{NL}}^2} \left(c_{\text{ct}} + c_{r,1}(\hat{k} \cdot \hat{z})^2 + c_{r,2}(\hat{k} \cdot \hat{z})^4 \right)$$

$$P_{22}^{r,h,\epsilon}(k, \hat{k} \cdot \hat{z}) = \frac{1}{\bar{n}} \left(c_1^{\text{St}} + c_2^{\text{St}} \frac{k^2}{k_{\text{NL}}^2} + c_3^{\text{St}} \frac{k^2}{k_{\text{NL}}^2} f(\hat{k} \cdot \hat{z})^2 \right)$$

Questions of scale

- We kept one scale $k_M \simeq k_{\text{NL}}$ as the physical cutoff of the theory
But: we measured $c_{r,2}$ to be larger than others, why?
- In fact it is consistent to assume there are 2 cutoff scales for different UV operators $k_{\text{NL}} \simeq 0.7 h/\text{Mpc}$, $k_R \simeq 0.25 h/\text{Mpc}$

$$\langle \tau_{ij}(\vec{x}, t) \rangle = \left(\frac{aH}{k_{\text{NL}}^2} \right) \left(c_0 \delta_{ij} + c_s^2(t) \delta(\vec{x}, t) + c_4(t) \frac{\partial^2}{k_{\text{NL}}^2} \delta(\vec{x}, t) + \dots \right)$$

$$\delta_g(\vec{x}, t) = b_1(t) \delta^{(1)}(\vec{x}, t) + c_{ct,2}(t) \frac{\partial^2}{k_M^2} \delta(\vec{x}, t) + \dots$$

$$\langle v_i(\vec{x}, t) v_j(\vec{x}, t) \rangle = \left(\frac{aH}{k_R} \right)^2 \left[c_1(t) \delta_{ij} + \left(c_2(t) \delta_{ij} + c_3(t) \frac{\partial_i \partial_j}{\nabla^2} \right) \delta(\vec{x}, t) + \tilde{c}_r(t) \frac{\partial_i \partial_j}{k_{\text{NL}}^2} \delta(\vec{x}, t) + \dots \right]$$

Where do we stop?

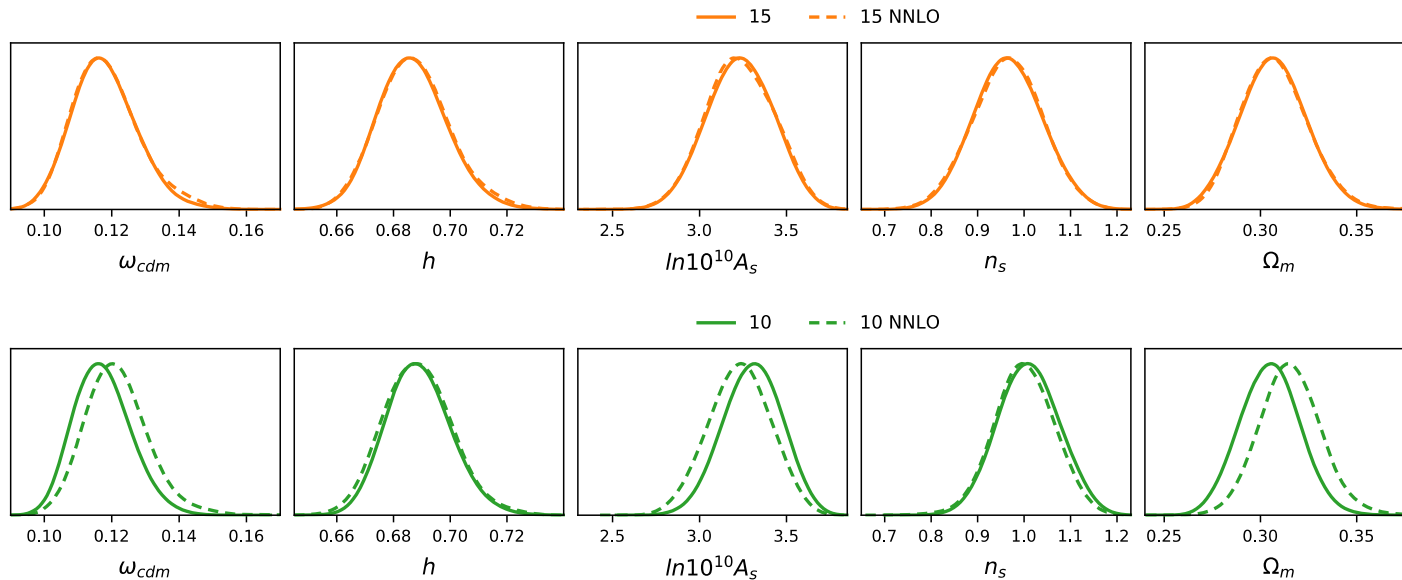
- Very important issue: **where to stop the fit?**
Usual tradeoff between *accuracy* and *precision*: smaller scales have smaller errors, but perturbative approach starts to fail
- Two avenues: **fits on simulations** and/or **adding NNLO estimate**
- On simulations, we measure theoretical error as shift of 1σ region from the truth, after combining: we stop when we reach $\sim 0.3\sigma_{\text{data}}$
Why? If we combine in quadrature, then it means we shift the result by 5%
- NNLO estimate is *an estimate of the largest neglected term*: if it is detected, then we are not allowed to use those scales

Scale-cut without simulations

- Because of scale enhancement, the largest terms are the k_R suppressed ones, for which *we actually know the functional dependence*

$$\xi_{\text{NNLO}}^\ell(s) = i^\ell \int \frac{dk}{2\pi^2} k^2 P_{\text{NNLO}}^\ell(k) j_\ell(ks)$$

$$P_{\text{NNLO}}^\ell(k) = b_{k^2 P_{\text{NLO}}}^\ell \frac{k^2}{k_{\text{M}}^2} P_{\text{NLO}}^\ell(k) + c_{r,4} b_1^2 \mu^4 \frac{k^4}{k_{\text{M,R}}^4} P_{11}(k) \Big|_\ell + c_{r,6} b_1 \mu^6 \frac{k^4}{k_{\text{M,R}}^4} P_{11}(k) \Big|_\ell$$



$s_{\text{min}} \simeq 15 \text{ Mpc}/h$

Beyond 2-pt: the 1-loop bispectrum in LSS

- Lots of work to develop the pipeline for 1-loop bispectrum
 - Biased tracers to 4th order in perturbations
 - Redshift distortions up to 4th order
 - Counterterms up to 2nd order
 - Efficient way of computing loop integrals
 - Generalization to non-Gaussian initial conditions

GDA, Lewandowski, Senatore, Zhang (2022a, 2022b)

GDA, Donath, Lewandowski, Senatore, Zhang (2022)

Philcox, Ivanov, Cabass, Simonovic, Zaldarriaga (2022a, 2022b, 2022c)

Theory Model

- Perturbation theory up to 4th order: 11 bias parameters

$$P_{11}^{r,h}[b_1] , \quad P_{13}^{r,h}[b_1, b_3, b_8] , \quad P_{22}^{r,h}[b_1, b_2, b_5] , \quad B_{321}^{r,h,(I)}[b_1, b_2, b_3, b_5, b_6, b_8, b_{10}] , \\ B_{211}^{r,h}[b_1, b_2, b_5] , \quad B_{321}^{r,h,(II)}[b_1, b_2, b_3, b_5, b_8] , \quad B_{411}^{r,h}[b_1, \dots, b_{11}] , \quad B_{222}^{r,h}[b_1, b_2, b_5]$$

- Stochastic and counterterms up to 2nd order: 30 parameters

$$P_{13}^{r,h,ct}[b_1, c_1^h, c_1^\pi, c_1^{\pi v}, c_3^{\pi v}] , \quad P_{22}^{r,h,\epsilon}[c_1^{\text{St}}, c_2^{\text{St}}, c_3^{\text{St}}] , \\ B_{321}^{r,h,(II),ct}[b_1, b_2, b_5, c_1^h, c_1^\pi, c_1^{\pi v}, c_3^{\pi v}] , \quad B_{321}^{r,h,(I),\epsilon}[b_1, c_1^{\text{St}}, c_2^{\text{St}}, \{c_i^{\text{St}}\}_{i=4,\dots,13}] , \\ B_{411}^{r,h,ct}[b_1, \{c_i^h\}_{i=1,\dots,5}, c_1^\pi, c_5^\pi, \{c_j^{\pi v}\}_{j=1,\dots,7}] , \quad B_{222}^{r,h,\epsilon}[c_1^{(222)}, c_2^{(222)}, c_5^{(222)}]$$

A numerical workhorse: FFTLog

- Integrals over the PS are challenging and slow, and the PS changes at each cosmology... We FFTLog to separate cosmology dependence

$$P_{11}(k_n) = \sum_{m=-N_{\max}/2}^{N_{\max}/2} c_m k_n^{\nu+i\eta_m}$$

$$c_m = \frac{1}{N_{\max}} \sum_{l=0}^{N_{\max}-1} P_{11}(k_l) k_l^{-\nu} k_{\min}^{-i\eta_m} e^{-2iml/N} \quad \eta_m = \frac{2\pi m}{\log(k_{\max}/k_{\min})}$$

- Then **~everything** is a matrix multiplication of the coefficients

$$P_{\sigma}(k) = k^3 \sum_{m_1, m_2} c_{m_1} k^{-2\nu_1} M_{\sigma}(\nu_1, \nu_2) k^{-2\nu_2} c_{m_2}$$

Problems with 1-loop bispectrum

- B_{222} is annoying... Number of integrals scales as N_{basis}^3 !
- Idea: change basis to one with scales
We only need $N_{\text{basis}} = 16$. We have to be careful about matching

$$P_{\text{fit}}(k) = \frac{\alpha_0}{1 + \frac{k^2}{k_{\text{UV},0}^2}} + \sum_{n=1}^{N-1} \alpha_n f(k^2, k_{\text{peak},n}^2, k_{\text{UV},n}^2, i_n, j_n)$$

$$f(k^2, k_{\text{peak}}^2, k_{\text{UV}}^2, i, j) = \frac{(k^2/k_0^2)^i}{\left(1 + \frac{(k^2 - k_{\text{peak}}^2)^2}{k_{\text{UV}}^4}\right)^j}$$

Theory model

- **Window**: use approximation (on linear term) from Gil-Marin et al. (2014)

$$B_{211}^{r,h} = 2K_1^{r,h}(\vec{k}_1; \hat{z})K_1^{r,h}(\vec{k}_2; \hat{z})K_2^{r,h}(\vec{k}_1, \vec{k}_2; \hat{z})[W * P_{11}](\vec{k}_1)[W * P_{11}](\vec{k}_2) + 2 \text{ perms. } ,$$

$$[W * P_{11}](\vec{k}) = \int \frac{d^3k'}{(2\pi)^3} W(\vec{k} - \vec{k}')P_{11}(\vec{k}')$$

- **Binning** effect is important: it is performed (together with AP) exactly on the linear part, loop terms are small
- Effect of approximations are small

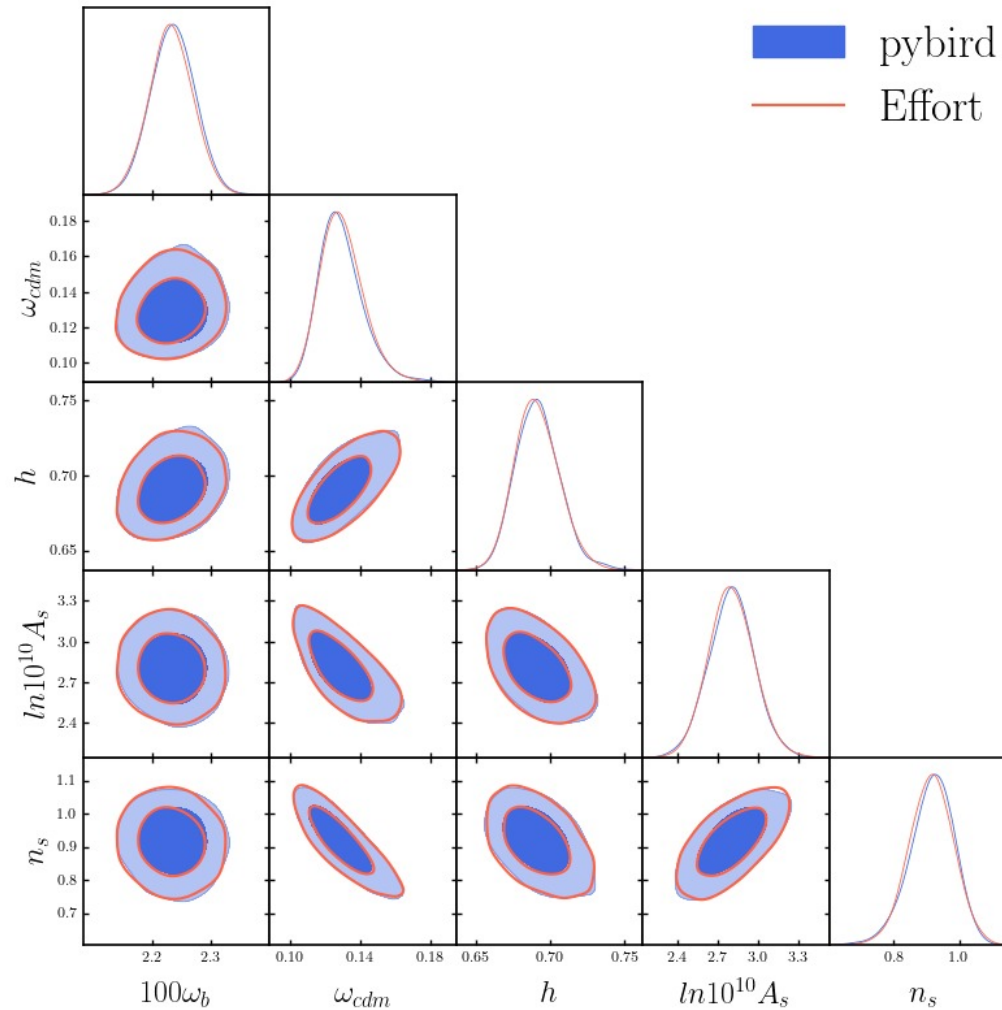
$\Delta_{\text{shift}}/\sigma_{\text{stat}}$	Ω_m	h	σ_8
$P_\ell + B_0$: base - w/ NNLO	-0.03	-0.09	-0.03
$P_\ell + B_0$: base - w/o B_0 window	0.11	-0.05	0.01
$P_\ell + B_0 + B_2$: base - w/o B_0, B_2 window	0.51	0.09	0.02

Emulate the theory: Effort.jl

- Pybird, CLASS-PT, Velocileptors, CLASS-OneLoop have been developed by (more or less) millennials, but we are already too old for the cool kids of today
- We managed to compute things in $\sim O(\text{sec})$, and built likelihood for efficient sampling, but there can be a better way
- **Emulate the theory!** For 2-pt very easy. Moreover, one can afford more precision in the code, since the NN is trained only once. Each evaluation takes $\sim O(100 \mu\text{sec})$
- And, **we can differentiate on parameters!** So one can easily do minimization, profile likelihoods, and we can use differentiable samplers

Emulate the theory: *Effort.jl*

BOSS 4sky



A note on priors

- In Bayesian analysis, data update our belief on the model and its parameters. Must start from a probability measure on parameters. *There is no “uninformative prior”*.
- And what if data are not precise enough?

The status of LSS EFT analysis: two manifestly equivalent implementations of the manifestly correct theory on manifestly the same data produce manifestly different results. [#cosmology](#)

Priors on counterterms? The encarnation of the devil on Earth.



A note on priors

- “Typically”, data determine well cosmological parameters. We put a large uniform prior on them: akin to frequentist maximum likelihood approach.
- On the EFT parameters?
We know they have to be small, but not much more: except for a few, we center them at 0 with $\sigma=2$.
- Other choices are possible, as long as they cover the physically allowed region, but *EFT parametrization stays the same*.
“West Coast” and “East Coast” parameters are a *linear transformation of each other*. **Prior choice is, however, different**.
- Now, best fits are unchanged, since both priors cover the allowed region. 1d projected posteriors are slightly different, due to different projection effects.

What to do?

- Just wait. Sooner or later data will just not care about the priors
- Perturbativity prior

$$\mathcal{P}_P = \frac{1}{2N_{\text{bins}}^P} \sum_{i \in \text{bins}_P} \left(\frac{P_{1\text{-loop}}^h(k_i)}{\sigma_P^{\text{P.P.}}(k_i)} \right)^2 \quad \mathcal{P}_B = \frac{1}{2N_{\text{bins}}^B} \sum_{i \in \text{bins}_B} \left(\frac{B_{1\text{-loop}}^h(k_1^i, k_2^i, k_3^i)}{\sigma_B^{\text{P.P.}}(k_1^i, k_2^i, k_3^i)} \right)^2$$

$$\sigma_P^{\text{P.P.}}(k) \sim S^P(k) P_{1\text{-loop}}^{k_{\text{max}}}, \quad \sigma_B^{\text{P.P.}}(k_1, k_2, k_3) \sim S^B(k_1, k_2, k_3) B_{1\text{-loop}}^{k_{\text{max}}}$$

$$S_{1\text{-loop}}^P(k) \sim b_1^2 P_{11}(k) \left(\frac{k}{k_{\text{NL}}} \right)^{3+n(k)} \quad S_{1\text{-loop}}^B(k_1, k_2, k_3) \sim B_{211}^h(k_1, k_2, k_3) \sum_{i=1}^3 \left(\frac{k_i}{k_{\text{NL}}} \right)^{3+n(k_i)}$$

- Get some controlled UV information.
We used some old fitting formulas from simulations.
Now, the idea is to do a dedicated search. As a first step, fitting HOD. But have to marginalise over them.

Getting new physics

- As if we didn't have enough parameters...
- We can get new physics *in a model-independent way*: bootstrap
- Impose symmetries, and parametrize the kernels with basic building blocks
- Modifications from, e.g., EFT of DE

$$G_2(\vec{k}_1, \vec{k}_2) = 2\beta(\vec{k}_1, \vec{k}_2) + d_1^{(2)} \gamma(\vec{k}_1, \vec{k}_2)$$

$$G_3(\vec{k}_1, \vec{k}_2, \vec{k}_3) = 2\beta(\vec{k}_1, \vec{k}_2)\beta(\vec{k}_{12}, \vec{k}_3) + d_5^{(3)} \gamma(\vec{k}_1, \vec{k}_2)\gamma(\vec{k}_{12}, \vec{k}_3) - 2 \left(d_{10}^{(3)} - h \right) \gamma(\vec{k}_1, \vec{k}_2)\beta(\vec{k}_{12}, \vec{k}_3) \\ + 2(d_1^{(2)} + 2d_{10}^{(3)} - h)\beta(\vec{k}_1, \vec{k}_2)\gamma(\vec{k}_{12}, \vec{k}_3) + d_{10}^{(3)} \gamma(\vec{k}_1, \vec{k}_2)\alpha_a(\vec{k}_{12}, \vec{k}_3) + \text{cyc.}$$

3x2pt

- Photometric part of surveys will also play a big part in the future of LSS — e.g., for Euclid lensing is as important as clustering
- Why can't we apply the EFTofLSS to 3x2pt analysis?
Yes we can!
- Some systematics can be dealt with in an EFT-like way: baryonic effects and intrinsic alignments
- Main practical challenges: determine the scale cuts, and keep the number of free parameters under control

Projection integrals

$$w^i(\theta) = \int \frac{dl l}{2\pi} J_0(l\theta) \frac{2}{\pi} \int dk k^2 \int d\chi_1 \int d\chi_2 f_{\delta_g}^i(\chi_1) f_{\delta_g}^j(\chi_2) P_{gg}(k, z(\chi_1), z(\chi_2))$$

$$\gamma_t^{ij}(\theta) = \int \frac{dl l}{2\pi} J_2(l\theta) \frac{2}{\pi} \int dk k^2 \int d\chi_1 \int d\chi_2 f_{\delta_g}^i(\chi_1) f_{\kappa}^j(\chi_2) P_{gm}(k, z(\chi_1), z(\chi_2))$$

$$\xi_+^{ij}(\theta) = \int \frac{dl l}{2\pi} J_0(l\theta) \int d\chi \frac{f_{\kappa}^i(\chi) f_{\kappa}^j(\chi)}{\chi^2} P_{mm} \left(\frac{l}{\chi}; z(\chi) \right)$$

$$\xi_-^{ij}(\theta) = \int \frac{dl l}{2\pi} J_4(l\theta) \int d\chi \frac{f_{\kappa}^i(\chi) f_{\kappa}^j(\chi)}{\chi^2} P_{mm} \left(\frac{l}{\chi}; z(\chi) \right)$$

Power spectra and parameters

- Standard EFTofLSS expressions for the P_{mm} , P_{mg} , P_{gg} .
- However, we are integrating parameters with unknown time dependence!
- Assume parameter is almost constant over the bin, so each redshift bin combination now has its own parameters, e.g.

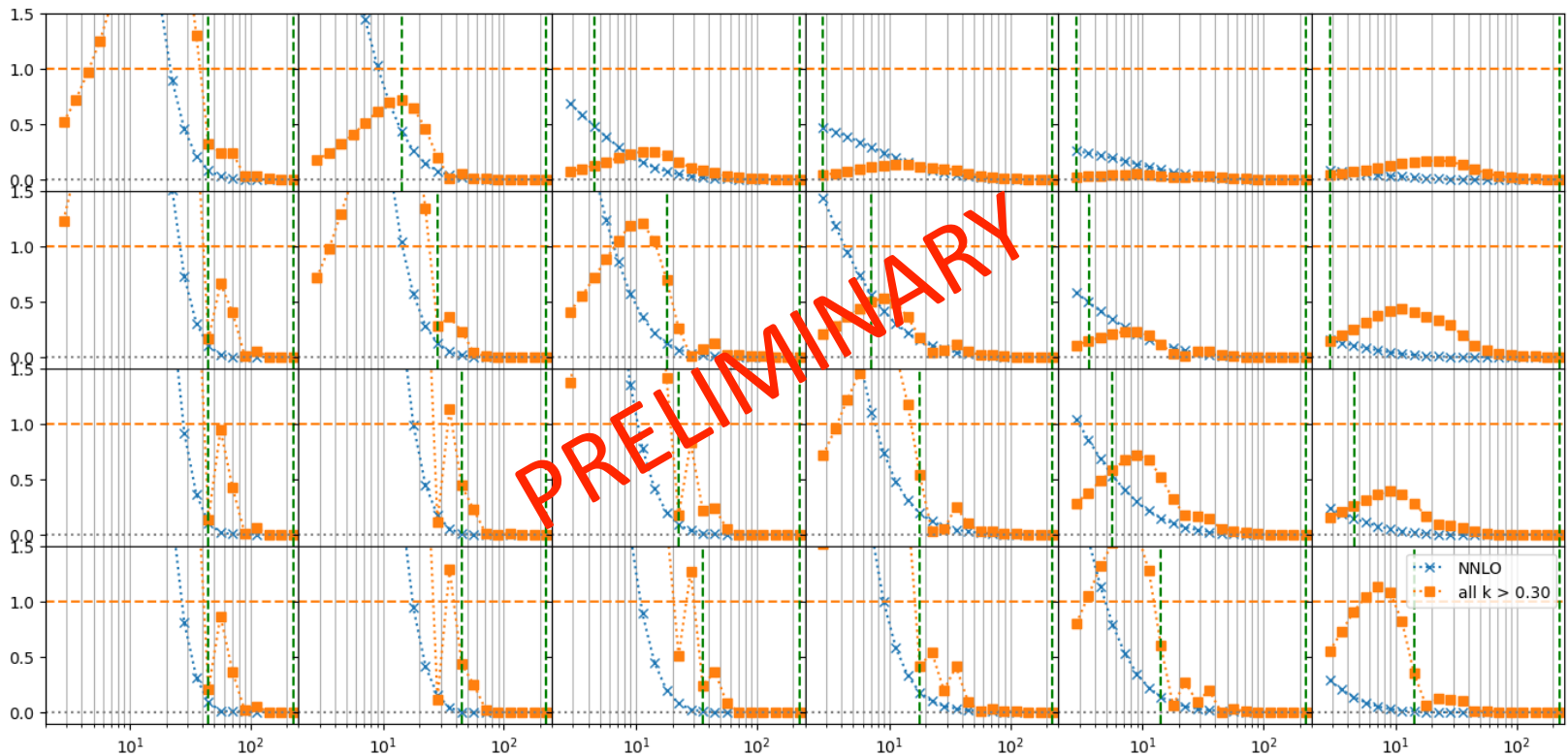
$$\xi_{+/-}^{ij}(\theta) \supset 2 \frac{c_{+/-}^{ij}}{k_{\text{NL}}^2} \int \frac{dl l}{2\pi} J_{0/4}(l\theta) \int d\chi \frac{f_{\kappa}^i(\chi) f_{\kappa}^j(\chi)}{\chi^2} D_+^2(z) P_{11} \left(\frac{l}{\chi} \right) \frac{l^2}{\chi^2}.$$

- How to reduce their impact? Simple, we correlate them! After all, their time dependence is smooth and of order Hubble.

Scale cut: NNLO and UV sensitivity

$$\xi_{ab}^{\text{NNLO}}(\theta) = c_{ab}^{\text{NNLO}} \int \frac{dl l}{2\pi} J_\mu(l\theta) \int d\chi \frac{f_a(\chi) f_b(\chi)}{\chi^2} P_{ab}^{\text{NNLO}} \left(\frac{l}{\chi}, z \right)$$

$$P_{ab}^{\text{NNLO}}(k, z) = \frac{k^2}{k_M^2} P_{ab}^{\text{NLO}}(k, z)$$



Where we stand

- Power spectrum at one loop: practically settled.
 - Several codes agreeing
 - Observational effects fairly under control
 - k_{\max} determination solid
 - Analytical covariance available (Wadekar, Scoccimarro 2019)
- Bispectrum at one loop: on its way.
 - Done: one loop expression, efficient implementation, k_{\max} determination
 - Missing: independent confirmation to our analysis (see also Philcox et al. 2022), a practical treatment of the mask, a better understanding of IR-resummation
 - Approximate analytical covariance available (Salvalaggio et al, 2024)

And where do we go?

- Higher loops?
At least 5th order for 2-loop power spectrum is doable.
Integrals are complicated. Actual covariance is probably still ok.
- Higher point functions?
Now we can go up to tree-level 5pt, no difficulty in computing.
However, no estimators, and which covariance to use?
- Can we gain by doing field level analysis? (Linde, GDA, *in preparation*)
- Focus also on other observables: 21cm, Ly- α , lensing (3x2pt), ...

Thank you!