Differentiable Modelling for Cosmology

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Precision Cosmology Post-CMB

era of large-scale structure has begun

key questions remain

law of gravity? any deviations from GR?

any hints beyond cosmological constant? w(z)?

initial conditions? what inflation?

dark matter nature?

neutrino masses?

huge model space (DM,DE,MG,inf)

multi-probe era

significantly more accurate modelling will be needed than so far...



Classical approach Model



Data



estimate PS

DESI collaboration

Summary Statistic (2pt, 3pt, ...)

Chabanier et al. 2019





Move beyond simple statistics

- two-point statistics is complete description only for Gaussian fields
- n-point functions are useful in weakly non-Gaussian case, others exist:

Wavelet Scattering Transform Mallat 2012, Cheng+2020



• alternative: 'field-level modelling': use all data without a priori compression, model observables





The forward model

Modelling challenge:

predict mapping between physical model and all observables

taking into account uncertainties, and all cross correlations

inference limitation is from modelling, not data already with current surveys!



Astronomical Survey Observables

Galaxy distribution (clustering, n-point, etc.) Gravitational Lensing (weak, strong, CMB lensing) Galaxy Clusters (optical, X-ray, tSZ) Ly-a, HI mapping

Galaxy Clusters, ...



Field-level modelling





Field-level modelling



Field-level modelling



Automatic differentiation/differentiable programming



- Computing gradients through long numerical expressions is a standard operation \bullet in machine learning (e.g. propagate gradient through NN)
- Two fundamental approaches: recursive application of chain rule
 - forward accumulation (tangent mode) \bullet
 - reverse accumulation (adjoint mode)
- JAX, but also Julia has support
- Advantage: automatic, non-approximate, fast

• Many high performance implementations exist through ML frameworks: pytorch, tensorflow,

Matching epochs in cosmological modelling

Early physics:

- GR effects (horizon+rel. species+aniso-stress)
- multi-species (CDM+baryon+photons+neutrinos)
- photon-baryon coupling + recombination
- perturbative quantity: δ and θ

Late physics:

- Newtonian gravity + small corrections
- mostly interested in mass distribution, CDM+baryons
- non-linear growth
- perturbative quantity: ψ (displacement)

choices in the literature:



Matching problem!

Eulerian

Lagrangian

Angulo & Hahn 2022 review

Differentiable Einstein-Boltzmann Solver (DISCO-EB)



Multi-species fluid of DM+baryon+photon+(massive)neutrino+DE →linear Einstein-Boltzmann solver (e.g. Ma & Bertschinger 1995, CLASS, CAMB)

~100 coupled ODEs (some stiff)

clean easily readable and extendable Python/JAX code

We use high order implicit solver from Diffrax library (Kidger 2022), supports forward and reverse mode differentiation

no need to specify Jacobian, due to autodiff

Current limitation: JAX does not support sparse matrices well

code publicly available in few weeks time, or on request: oliver.hahn@univiea.ac.at









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-0.0005-0.0010





differentiable simulations for cosmology



Differentiable Einstein-Boltzmann Solver (DISCO-EB)



OH, List & Porqueres (2023, subm. to JCAP)

Fisher matrices are just calls to autodiff:

$$F_{ij} = \sum_{\ell} \frac{\partial y(\ell)^{\top}}{\partial \theta_i} \sum_{j=1}^{\ell-1} (\ell) \frac{\partial y(\ell)}{\partial \theta_j}$$

Known/modelled precision matrix of the observables

Change of the observable w.r.t. the i-th parameter \rightarrow compute with autodiff

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Solve Vlasov-Poisson on submanifold characteristics $(q, t) \mapsto (x(q, t), p(q, t))$

$$\frac{\partial f}{\partial t} + \frac{v}{a^2} \cdot \boldsymbol{\nabla}_x f - \boldsymbol{\nabla}_x \phi \cdot \boldsymbol{\nabla}_v f = 0 \qquad \qquad \Longleftrightarrow$$



 $\mathbf{x}'' + \mathcal{H}\mathbf{x}' = -\nabla\phi$

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moment of shell-crossing

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monokinetic, single-valued

(analytic treatment possible)

multikinetic, multi-valued

(simulations, EFTs [by integrating out])

Zeldovich (1970) solution (straight lines) is exact prior to shell-crossing and outside shell-crossed regions

moment of shell-crossing

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entering the multi-stream region is non-analytic (only finitely many bounded derivatives)

monokinetic, single-valued

(analytic treatment possible)

multikinetic, multi-valued

(simulations, EFTs [by integrating out])

Zeldovich (1970) solution (straight lines) is exact prior to shell-crossing and outside shell-crossed regions

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Modelling LSS – Lagrangian perturbation theory Non-linear evolution of perturbations

Solve Vlasov-Poisson on submanifold characteristics $(\boldsymbol{q},t) \mapsto (\boldsymbol{x}(\boldsymbol{q},t), \boldsymbol{p}(\boldsymbol{q},t))$



all-order recursion relations first implemented in code

> Rampf+OH (2021) Schmidt (2021)



Modelling LSS – Lagrangian perturbation theory Non-linear evolution of perturbations

Solve Vlasov-Poisson on submanifold characteristics $(\boldsymbol{q},t) \mapsto (\boldsymbol{x}(\boldsymbol{q},t), \boldsymbol{p}(\boldsymbol{q},t))$



We want to solve this as a perturbative series (D is small parameter)

$$\Psi(\mathbf{q},\tau) = \sum_{n=1}^{\infty} D(\tau)^n \, \Psi^{(n)}(\mathbf{q})$$

Buchert (1994), Catelan (1995), Bouchet+(1995), n=3 Rampf (2012), Zheligovsky&Frisch (2014), Matsubara (2015), all order

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All order recursion fully implemented in upcoming **DISCO-DJ** module (stay tuned! List, OH et al (2024, in prep)





Modelling LSS: Numerical N-body simulations

simulation maps discrete fluid elements from Lagrangian space to Eulerian space



N-body simulations still the main work horse of LSS!

Theory error in non-linear simulations under control (without including astrophysics effects)

Gravity only LCDM predictions for matter distribution in the Universe have essentially no theory error any more





the 10¹² particle frontier:

|--|

Year	Simulation	Code	Supercomputer	Cores [10 ³]	$N_{\rm p}$ [10 ¹²]	Box $[h^{-1}$ Gpc]	Algorit
2014	Dark Sky [916]	2HOT	Titan, USA	20	1.1	8	FMM
2017	TianNu [469]	CUBEP ³ M	Tianhe-2, China	331	2.97	1.2	PM-PM
2017	Euclid Flagship [201]	PKDGRAV3	PizDaint, Switzerland	4	2.0	3.	Tree-FN
2019	Outer Rim [917]	HACC	Mira, USA	524	1.07	3.0	Tree-P
2019	$\operatorname{Cosmo-}\pi$ [613]	CUBE	π 2.0, China	20	4.39	3.2	PM-PI
2020	Ushuu [918]	GreeM	ATERUI-II, Japan	<40	2.0	2.0	Tree-P
2020	Last Journey [919]	HACC	Mira, USA	524	1.24	3.4	Tree-P

+ Farpoint (2021)



Feng+2016: FastPM idea: modify time integrator to get 1LPT agreement **Can do better:** second order LPT (2LPT) can be written

 $X_{i}(D) = X_{i}^{n} + [D - D_{n}]\psi_{i}^{n,(1)} + d_{D}X_{i}(D) = \psi_{i}^{n,(1)} + 2[D - D_{n}]\psi_{i}^{n,(2)}$ $d_{D}^{2}X_{i}(D) = 2\psi_{i}^{n,(2)} = \text{const.}$

$$\left[D - D_n \right]^2 \boldsymbol{\psi}_i^{n,(2)}$$

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> $X_{i}(D) = X_{i}^{n} + [D - D_{n}]\psi_{i}^{n,(1)} +$ $d_D X_i(D) = \psi_i^{n,(1)} + 2[D - D_n]\psi_i^{n,(1)}$ $d_D^2 X_i(D) = 2\psi_i^{n,(2)} = \text{const.}$ i.e. acceleration can be made constant

This can be matched in various ways to yield new integrators that can reproduce 2LPT.

$$\left[D - D_n \right]^2 \boldsymbol{\psi}_i^{n,(2)}$$

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Growing mode plane wave



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Growing mode plane wave



Comparison of methods

Initial conditions





Reference (Camels)



Performed using the Gadget-3 simulation code [Springel+ 2005]

- accurate TreePM forces
- thousands of timesteps

Density field when universe was 1/3of the current size in each dimension





see also https://github.com/eelregit/pmwd by Yin Li see also <u>https://github.com/Differentiable</u> UniverseInitiative/JaxPM by François Lanusse et al see also FlowPM by Seljak & collaborators



Unifying LPT and N-body...(but UV-complete!)

PowerFrog integrator is asymptotically consistent with 2LPT for $a \rightarrow 0$, so can start at a=0 as we do in LPT **Residual of single PowerFrog step from** $a=\infty$ **to** a=0.05**,** wrt. nLPT:



 $100 {
m Mpc}/h$

This is only possible after controlling **all** discreteness effects in the N-body simulation, otherwise:



y



Curing Discreteness Noise in N-body and Fragmentation

spurious fragmentation is well-known phenomenon in N-body sims with cut-off



Schandarin et al. 2012

(also quadratic tetrahedra)

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Ondaro-Mallea et al. 2023



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Ondaro-Mallea et al. 2023





Field-level inference: reconstruction

Task: given a (simulated) late-time density field, reconstruct initial conditions $\mathbb{P}(\Phi \mid \delta) \propto \mathbb{P}(\delta \mid \Phi) \mathbb{P}(\Phi)$

> **True** label (initial conditions)



forward model (Lagrangian perturbation theory)

Mean reconstruction



Resulting observation (late-time density field)



survey mask





Field-level inference: reconstruction

$\mathbb{P}(\Phi \mid \delta) \propto \mathbb{P}(\delta \mid \Phi) \mathbb{P}(\Phi)$

Example: drawing posterior samples (PhD thesis of Lukas Winkler)



Here, we use a **No U-Turn Sampler (NUTS)** – a variant of Hamiltonian Monte Carlo – provided by the BlackJax library https://blackjax-devs.github.io/blackjax/.

see also work by BORG collaboration





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Summary

- Diff'able model = prediction + dprediction/d{parameters,ICs,...}
- Differentiable models allow new ways of confronting data -> beyond simple summary statistics
- DISCO-DJ new contender:
 - DISCO-EB Einstein-Boltzmann solver
 - "easy" forecasting, add your models
 - currently still too slow for MCMC analysis (work in progress...)
- DISCO-DJ LSS model (optimized PM solver, see also JaxPM, pmwd, FlowPM)
 - will directly integrate with EB module (differentiate through both)
 - nLPT recursion
 - new PT-informed time integrators+discreteness suppression
 - currently only single GPU, multi-GPU is WIP

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