Opportunities and Challenges in "big data" cosmology

Masahiro Takada (Kavli IPMU) Also ask Leander Thiele ...







Decoding galaxy survey data

Each galaxy carries

- positions (RA, dec, z)
- shapes (~2 comps)
- luminosity
- stars, gas, dust, metallicity, .
- star formation history
- super massive blackholes

Subaru HSC data

Big data cosmology

~10^9 galaxies (RO LSST) (each galaxy carries >10 information)
~100 (Gpc/h)^3 volume (DESI, PFS) (~1,000 (Gpc/h)^3 volume in principle)
~10^7 Fourier modes at least (kmax~0.3h/Mpc) wavelengths + redshift

Subaru HSC data

A 3D map of the universe with Dark Energy Spectroscopic Instrument (DESI) (0<z<3.5)

Credit: Claire Lamman/DESI





We need to be ready ...

Rubin Observatory LSST (Chile): 2025-



CI AG

Cosmic structure formation: time-evolution of primordial perturbations





Small scales



Multi-components maps (many observables in the same large-scale structure)



Omori 2022

A hint of new physics beyond ACDM – discovery potential



A hint of new physics beyond ACDM – discovery potential



Kim+24 (DESI+ACT)

Planck PR4 CMB aniso.

ACT DR6 CMB lensing + BAO Planck PR4 CMB lensing + BAO ACT+Planck CMB lensing + BAO SPTPol CMB lensing + BAO $ACT DR6 + Planck PR4 \times DESI LRGs$ ACT DR6 x DESI LRG8 *Planck* PR4 x DESI LRGs ACT DR6 + Planck PR4 x unWISEACT DR4 x DES MagLim $DES-Y3 \times SPT + Planck PR3$ DES-Y3 galaxy lensing + BAO KiDS-1000 galaxy lensing + BAO HSC-Y3 galaxy lensing (Fourier) + BAOHSC-Y3 galaxy lensing (Real) + BAO

neutrino mass





Kim+24 (DESI+ACT)

Discovery potential and Opportunities for AI/ML in fundamental cosmology

- Cosmic expansion (dark energy, H0 tension, curvature)
- Growth of cosmic structures (S8 tension, modified gravity)
- Primordial non-Gaussianity (inflation physics) (+parity violation)
- Neutrino mass (note: synergy with particle physics)
- Nature of dark matter

Discovery potential and Opportunities for AI/ML

- Cosmic expansion (dark energy, H0 tension, curvature)
 - Galaxy surveys: BAO, supernovae, GW sirens, [weak lensing (WL)]
- Growth of cosmic structures (S8 tension, modified gravity)
 - Galaxy surveys: WL, galaxy clustering, redshift space distortion (RSD), galaxy clusters
- Primordial non-Gaussianity (inflation) (+parity violation)
 - Galaxy surveys: power spectrum, bispectrum, intrinsic alignments, WL
- Neutrino mass (note: synergy with particle physics)
 - Galaxy surveys: galaxy clustering, WL, galaxy clusters
- Nature of dark matter
 - small-scale probes Lyman-alpha, dwarf galaxies, microlensing, ...



Late-time universe: non-Gaussian (fluctuations) field

Power spectrum is not sufficient





Credit: Claire Lamman/DESI

Challenges in fundamental cosmology – opportunities for ML

- How can we extract the maximum amount of information from galaxy survey data?
 - Can we recover the information of the initial Gaussian field? (angular 2D + redshift in the light-cone volume)
 - Up to which k_max can we use for cosmology?
 - Systematic effects: baryonic effects, observational systematics (Galactic dust) ...
 - Properties of galaxies (which are impossible to accurately model from first principles) or very small-scale data can be used for cosmology
- How can we combine multi-wavelength data and/or –probes to obtain improved cosmological constraints, mitigating the systematic effects?
 - Weak lensing (WL), galaxies, X-ray, tSZ, kSZ, intensity mapping (e.g., HI), GW, ...

Cosmology with galaxy surveys, compared to particle experiments

• Pros

- Can use accurate theory, on large or quasi nonlinear scales: cosmological linear and perturbation theory (can recover the primordial information)
- Can simulate the universe in computers; Can make mocks of a galaxy survey
- Various datasets: multi probes & multi-wavelength data
- All data (even raw data) are public; anyone can get great science with a better method
- Cons
 - Can't replicate the same survey (sample variance), unlike experiments in the lab
 - Simulations, especially hydrodynamical simulations, are still expensive (~trillion particle N-body sim takes ~10M CPU hours, for a single cosmological model)
 - (Unknown) systematic effects
 - No Feynman diagram ...



Summary statistics: conventional approach

• How can we extract the maximum amount of cosmological information?



Oguri & Miyazaki 24 (HSC weak lensing map)

2-point correlation function $\langle f(\mathbf{x}_1)f(\mathbf{x}_2)\rangle$ Power spectrum (Fourier space) 3pt $\langle f(\mathbf{x}_1)f(\mathbf{x}_2)f(\mathbf{x}_3)\rangle$ Bispectrum 4pt $\langle f(\mathbf{x}_1)f(\mathbf{x}_2)f(\mathbf{x}_3)f(\mathbf{x}_4)\rangle$ Trispectrum

Summary statistics: conventional approach

- How can we extract the maximum amount of cosmological information?
- Q: Up to what n-point correlations should we measure?



Oguri & Miyazaki 24 (HSC weak lensing map)

- Challenges
 - The measurements of >3pt functions are not easy (WL bispectrum hasn't yet measured
 - Constructing accurate modes of >3pt functions are expensive (but not impossible)
 - Need to include observational effects (survey window, masks, ...)

Field level inference

DE, PNG, neutrino mass

How can we extract the maximum amount of cosmological information?



Credit: Minh Nguyen



Field level inference

DE, PNG, neutrino mass

How can we extract the maximum amount of cosmological information?



Simulation based inference (SBI)

How can we extract the maximum amount of cosmological information?



Simulation based inference

DE, PNG, neutrino mass

How can we extract the maximum amount of cosmological information? Hahn+21

- Hope: we can use the data on small (higher kmax) scales to obtain cosmological constraints
- Can extend the method to multiprobe and/or wavelength data
- The SBI method is now feasible for some datasets, e.g., the SDSS covering 1 (Gpc/h)^3



Simulation based inference

DE, PNG, neutrino mass

• How can we extract the maximum amount of cosmological information?

Challenges

- SBI needs to simulate galaxy survey, with the same volume, and to use many realizations to model the sample variance effect
- Still computationally very expensive: impossible to simulate a DESI-like survey of >100 (Gpc/h)^3 with the required spatial resolution
- Interpretability and reproducibility



An example of using ML for cosmology

Al-assisted super-resolution cosmological simulations



Li, Ni+ PNAS 21

We also need a faster sampler for cosmology inference (~100 parameters for LSST)

For example, MCLMC





Microcanonical HMC



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Robnik+2022

Microcanonical HMC converges while conserving energy

Many more opportunities for the use of ML/AI in astrophysics

- E.g., see the following websites
 - <u>Machine Learning for Astrophysics</u>
 - <u>Center for Computational Astrophysics</u>
 - <u>The NSF AI Institute for Artificial Intelligence and Fundamental Interactions</u>
 <u>(IAIFI) (at MIT)</u>
 - <u>SkIA</u>

• . . .

• <u>Smsharma</u>: A community sourced list of papers and resources on simulations-based inference (cosmology/astrophysics dominates the papers)

Summary (discussion items)

- Fundamental cosmology: many exciting opportunities & discovery potential
 - Dark energy (modified gravity), primordial non-Gaussianity (inflation physics), neutrino mass, dark matter ...
- Big data cosmology or data driven cosmology: we don't yet have an optimal methodology for extracting the full information
 - Summary statistics ⇔ Field-level inference (explicit LF inference ⇔ LF-free inference)
 - Simulation based inference
 - Faster sampler for cosmological parameter inference
 - Emulation of simulation data or posterior distribution
- ML/AI methods are clearly needed for big data cosmology
 - Many opportunities and Many challenges