Machine Learning for New Physics

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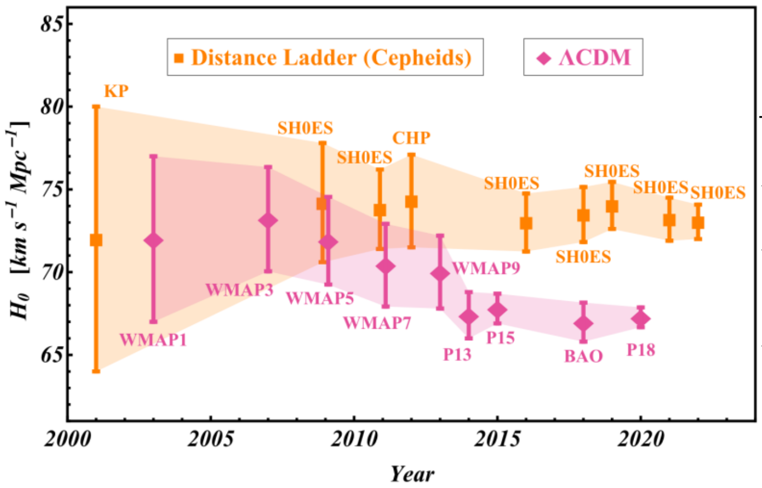
SLAC/KIPAC

Search for new physics with cosmological surveys

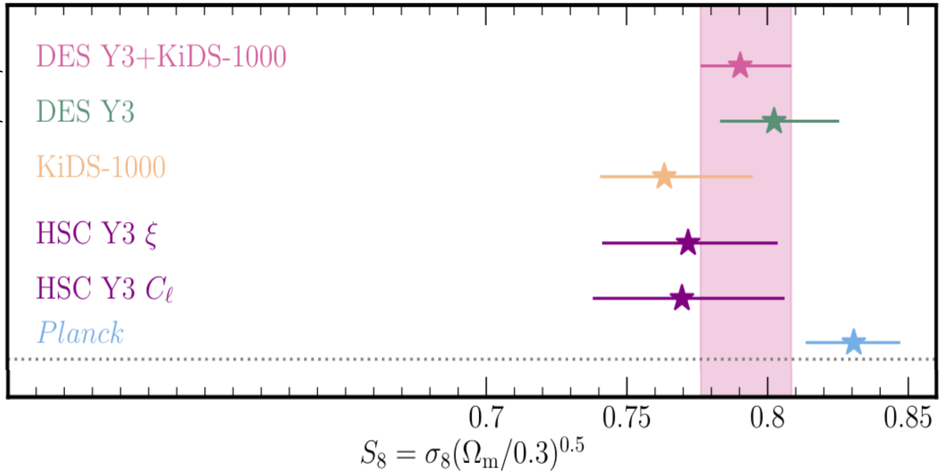
The H_0 tension



Perivolaropoulos, Skara, New A R, 2022

The σ_8 tension

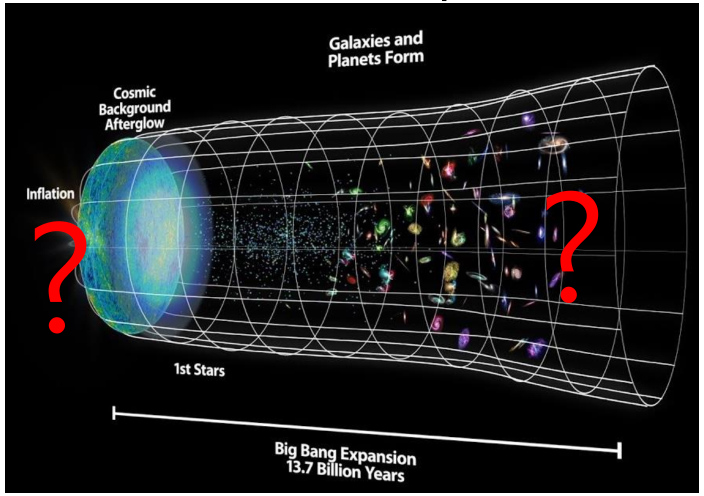
DES Collaboration, OJA, 2023



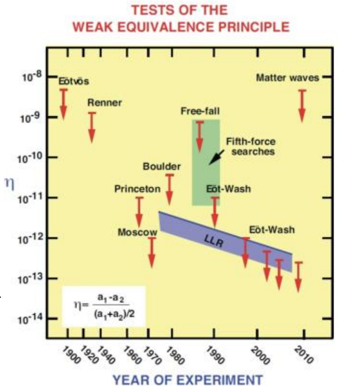
Neutrinos, dark matter

Sandbox Studio, Chicago with Ana Kova

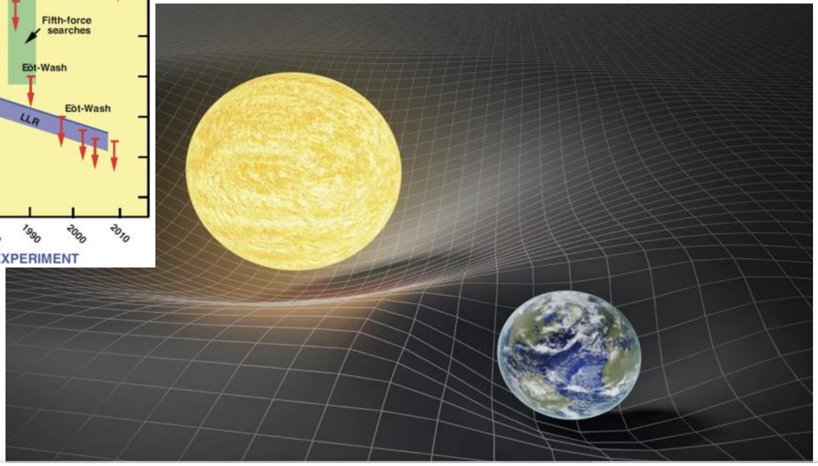
Accelerated expansion

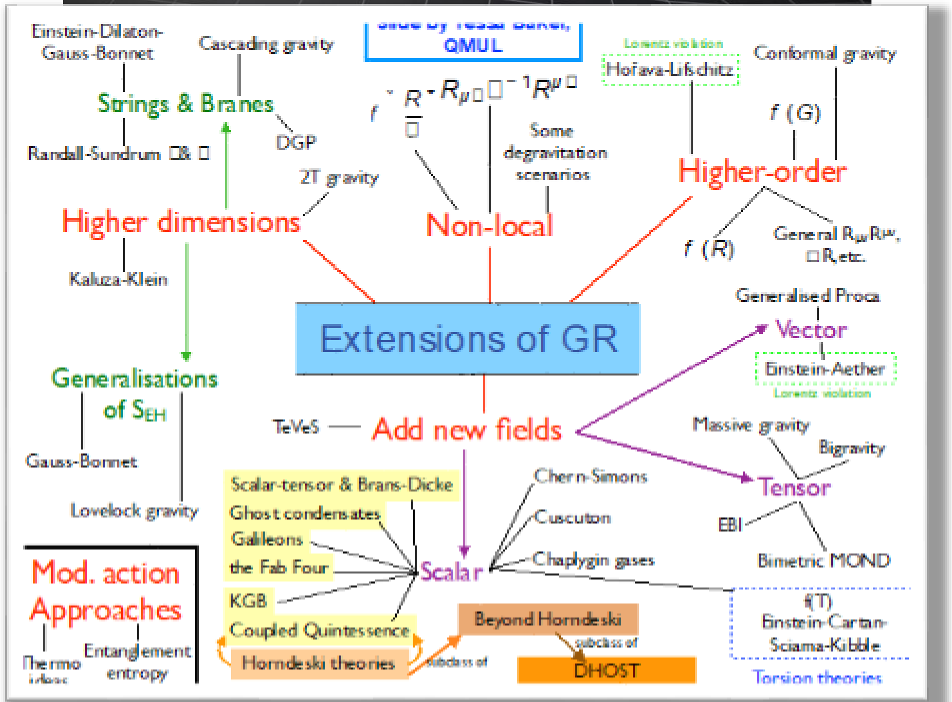


Tests of gravity on cosmological scales

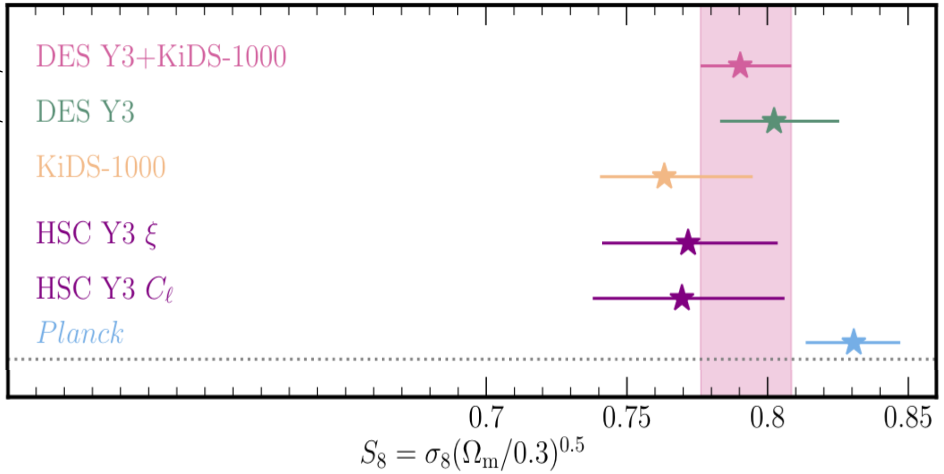


Will, 2006



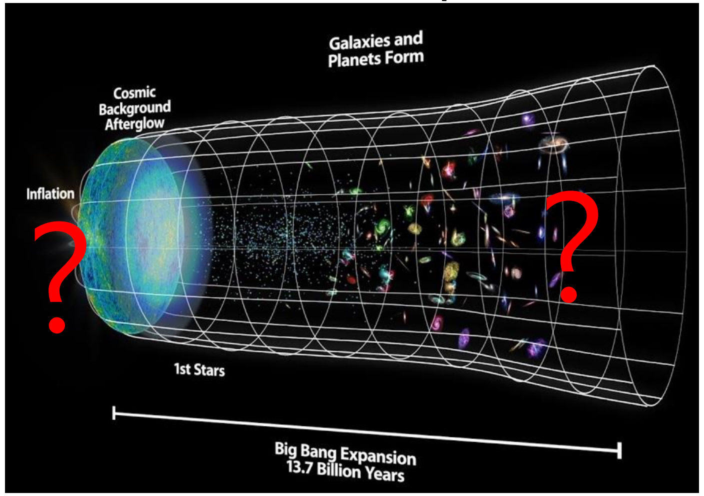


The σ_8 tension



DES Collaboration, OJA, 2023

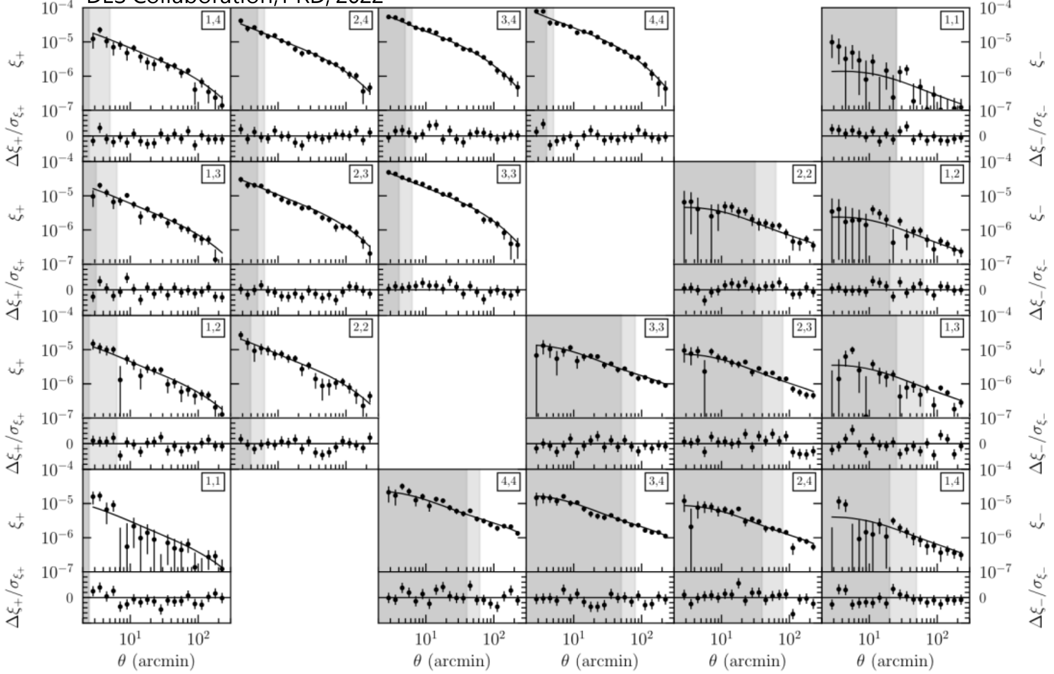
Accelerated expansion



Current search of new physics with galaxy surveys

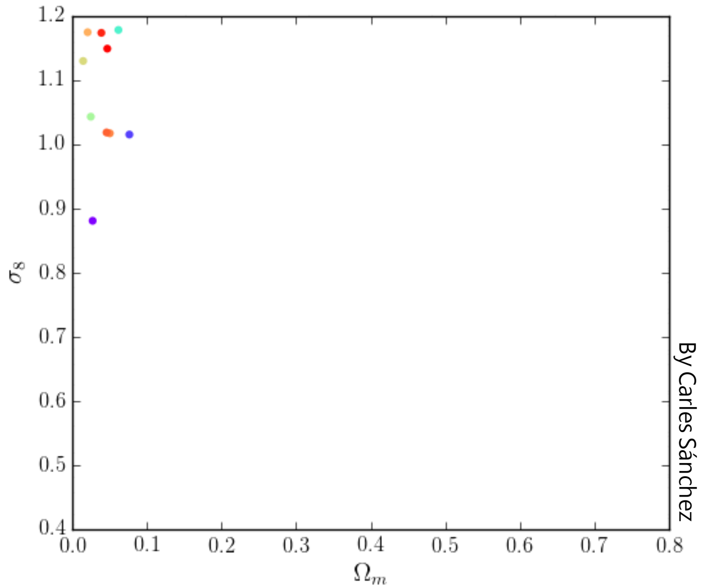
Precise measurements of summary statistics

DES Collaboration, PRD, 2022



Parameter estimation: likelihood sampling

$$L(D|p) \sim \exp\left(-\frac{1}{2}[(D - M(p))^T C^{-1}(D - M(p))]\right)$$



By Carles Sánchez

Samplers comparison in
Lemos, Weaverdyck et al (incl. AF), MNRAS, 2023
=> **Polychord** validated for DES Y3 3x2pt sampling

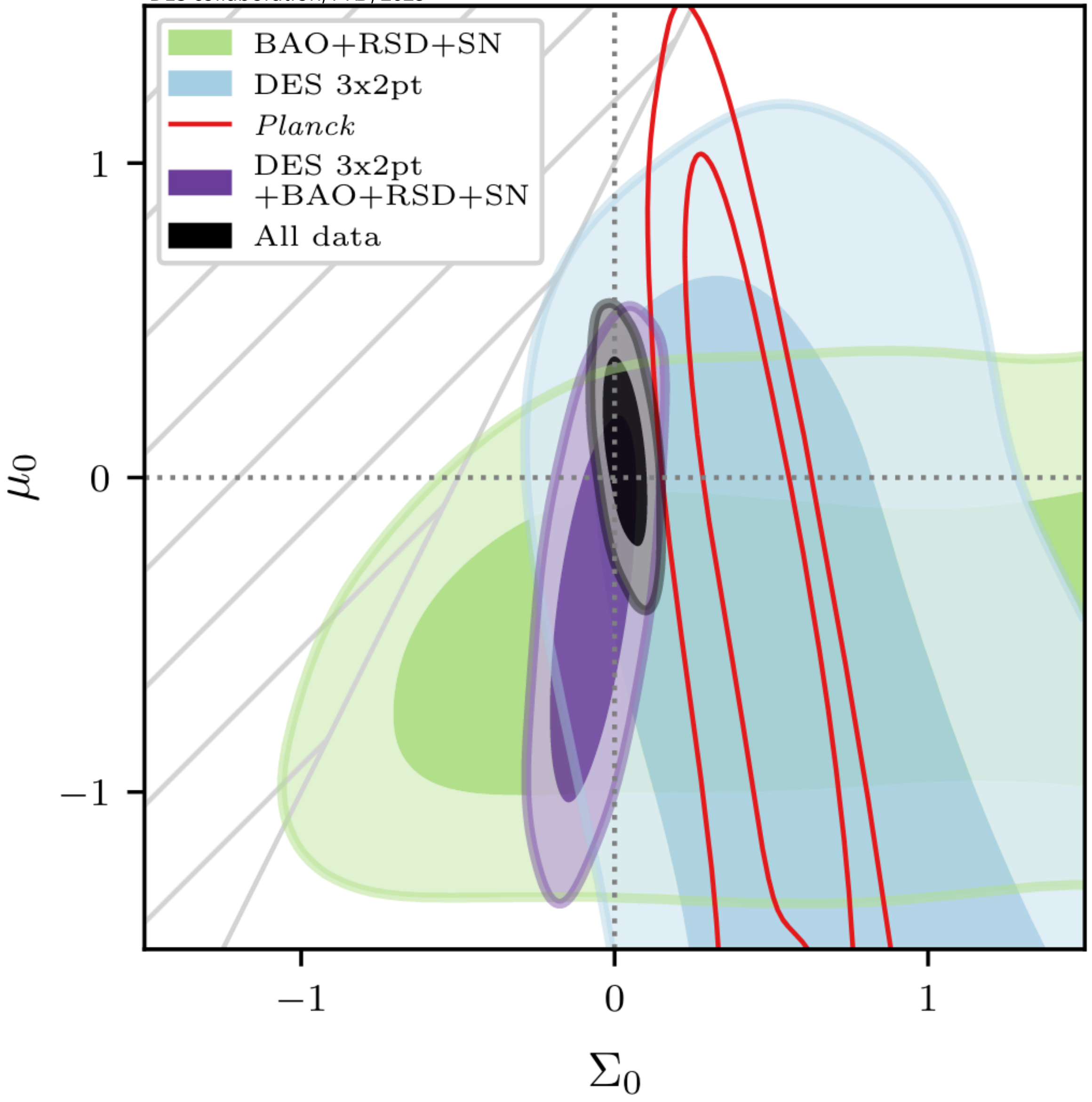
The case of beyond-ΛCDM models with DES Y3 weak lensing

DES Y3 extensions (co-leads Jessie Muir and **AF**):
DES collaboration, PRD, 2023

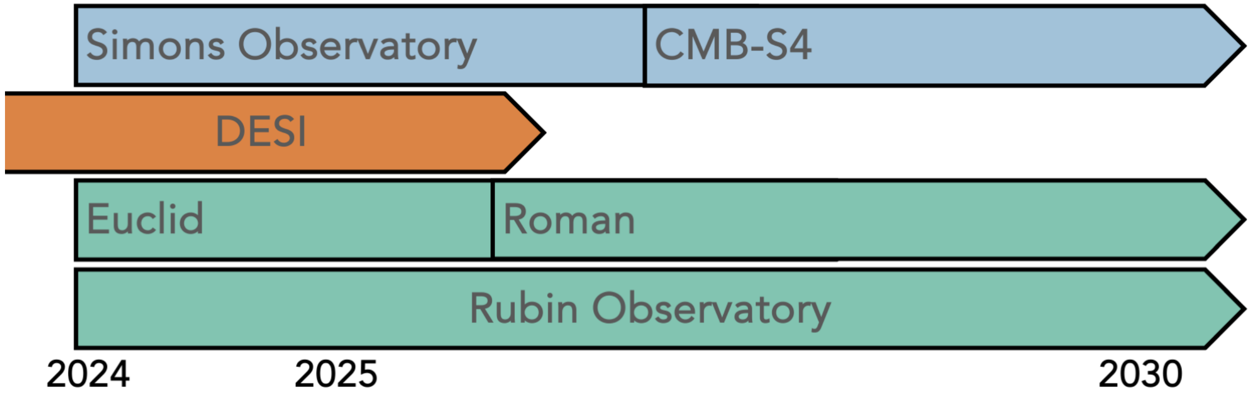
Robust analysis of 7 models:

- Blinded analysis:
  - tests of systematics,
  - scale cuts validation.
- 6 cosmological parameters + **extended parameters** + 22 nuisance parameters.
- Run **700+** chains on HPC
  Use of NERSC, TACC, GATTACA @ JPL, Sherlock @ Stanford.

DES collaboration, PRD, 2023



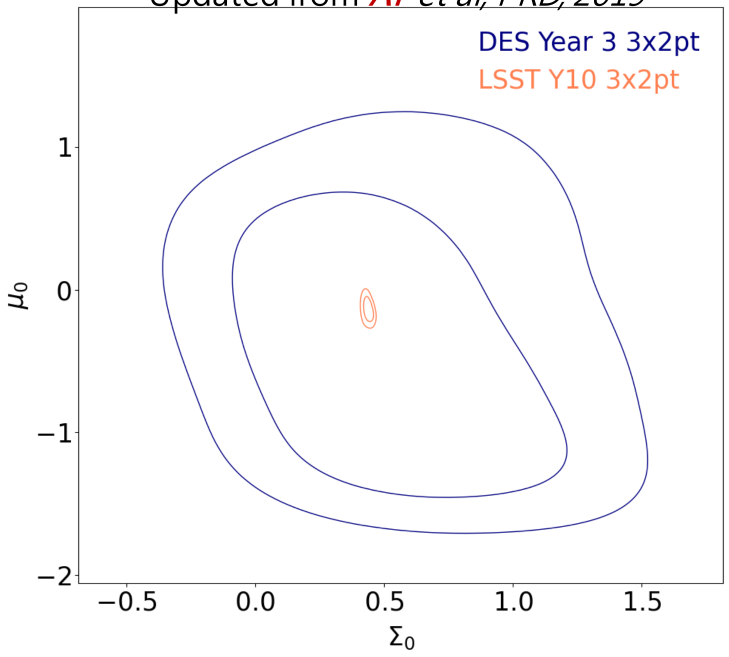
The Stage-IV experimental landscape



Goals are:
- Dark energy, modified gravity,
- Cosmic inflation.

Baseline analyses will still rely on **parameter** estimation from precise measurements of **summary statistics**.

Updated from *AF et al, PRD, 2019*



Challenges and where Machine Learning can help

Challenges:
- More complex **parameter space**,
- Expensive **likelihood evaluation**.

➔ ML to enable **faster analysis** of measurements to constrain new physics parameters

Emulators of summary statistics

CosmoPower
A. Spurio Mancini et al, MNRAS, 2022
Application to f(R): REACTEMU-FR
A. Spurio Mancini and Bose, OJA, 2023

Being used in DES Y6 (by Sujeong Lee) but need to retrain to adapt to our parameter space.

Improving the **sampling** in a large parameter space

Nautilus: inference using deep learning
J. Lange, 2023

Great improvements for DES Y6 shear but polychord still performs better for 3x2pt.

How to explore theory space with future surveys?

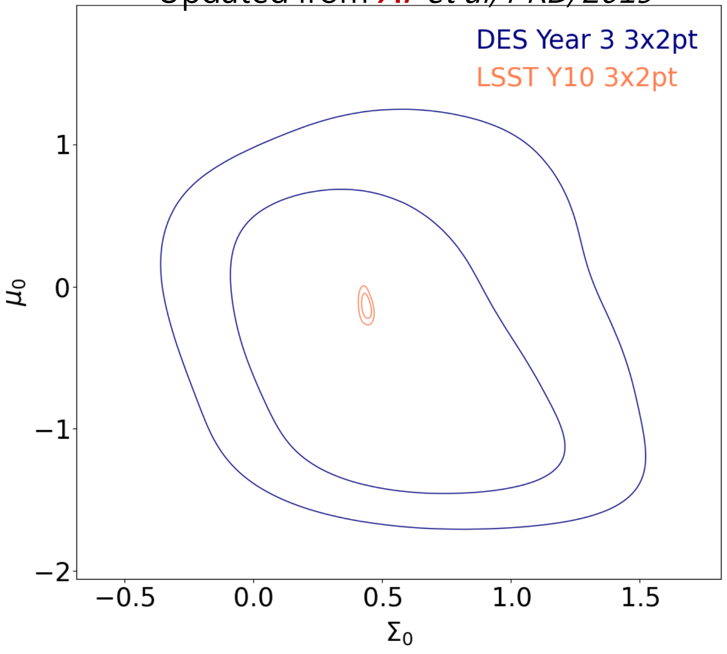
Ishak et al, 1905.09687, 2019

Grading	Physical motivation	Viability + Consistency	Maturity + Calculability	Information content	Accessibility to LSST
1	Well-motivated, including stability & lack of ghosts	Interesting model parameters not yet ruled out; all LSST observables can be calculated consistently	Can calculate anything that can be calculated in LCDM+GR	General features say something substantial about new fundamental physics	Decisive constraints possible with LSST (possibly when combined with other surveys)
2	Interesting "why not" physics, new terms/interactions stable without miraculous cancellations or fine-tunings	Interesting model parameters not yet ruled out; multiple LSST observables can be calculated consistently	Full non-linear N-body calculations possible	General features say something substantial about new physics	Strong constraints from more than one LSST observable
3	Maybe not natural, but addressing a specific observational anomaly	Some model parameters not yet ruled out; at least two LSST observables can be calculated consistently	Quasi-linear calculations possible	Models an interesting (but possibly speculative) physical possibility	Useful constraints from at least one LSST observable
4	May be unnatural, but have appealing features	Some model parameters not yet ruled out; LSST observables cannot be calculated consistently	Linear calculations possible	Models features of a broad class of theories, but may not be physically interesting	Mildly useful constraints (possibly when combined with other surveys)
5	Unnatural models (but some authors choose to work on them still)	Model is already (practically) ruled out	Only background calculations possible	Little applicability beyond the specific theory	Little chance of useful observational constraints

Arai et al, 2212.09094, 2022

	2nd-order	Diff-invariance	Metric only	DOFs
General Relativity	✓	✓	✓	2
Modified gravity with a scalar DOF (Sec. 2.1)				
Horndeski	✓	✓	×	$2+1$
DHOST	×	✓	×	$2+1$
$f(R)$	×	✓	✓	$2+1$
Modified gravity with a massive graviton (Sec. 2.2)				
dRGT	✓	×	✓	5
Mass-varying/quasi-dilaton	✓	×	×	$5+1$
Translation breaking	✓	×	✓	5
Lorentz-violating	✓	×	✓	5 or 2
Bigravity	✓	✓	×	$2+5$
Modified gravity with a vectorial DOF (Sec. 2.3)				
Generaized Proca	✓	✓	×	$2+3$
Extended vector	×	✓	×	$2+3$
Modified gravity based on non-Riemannian geometry (Sec. 2.4)				
Metric-affine	✓	✓	×	N/A
Modified gravity without new DOF (Sec. 2.5)				
Cuscuton	✓	✓	×	2
Minimally modified	✓	×	✓	2

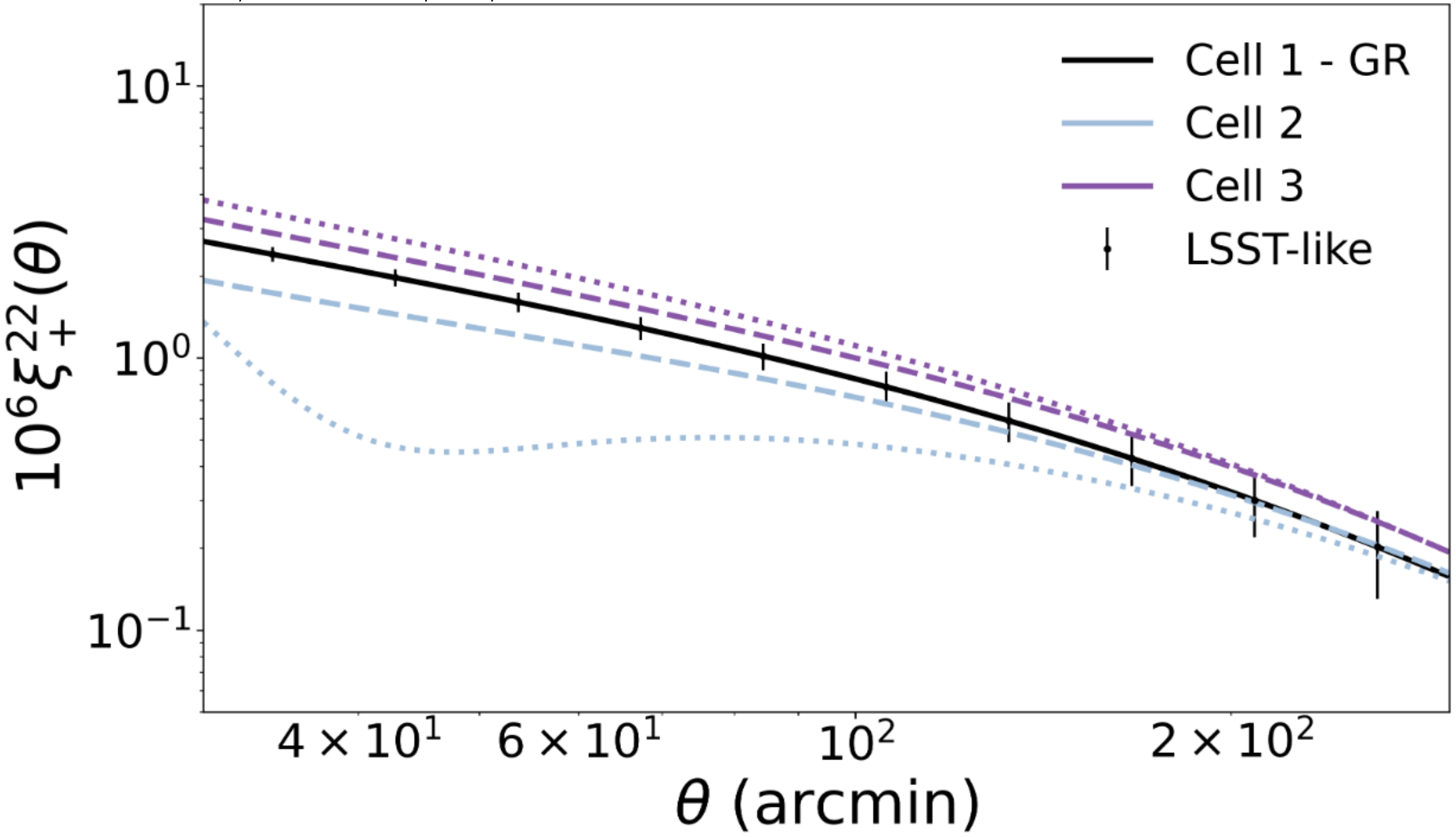
Updated from *AF et al, PRD, 2019*



Theoretical perspective to decide which model to constrain ⟺ Phenomenological parametrization, EFT, …

Gravity models impact probes differently: How do models compare at the level of probes?

AF, Hemmati et al, OJA, 2023



Map MG models onto 2D map using Self-Organizing Map

1. Producing the training set

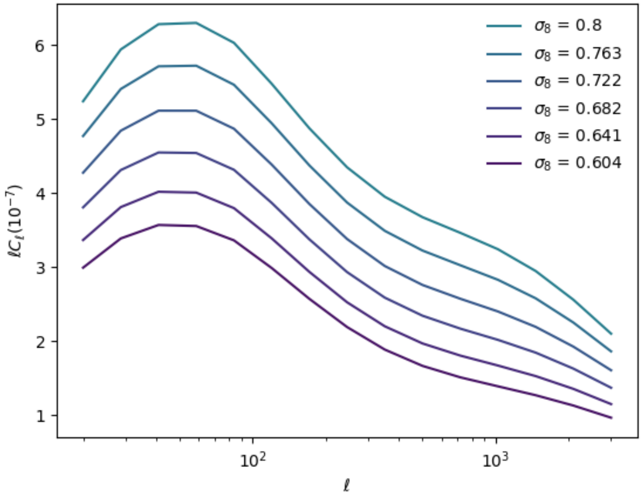
Cosmology: fixed parameters
+
Modified gravity: varying parameters
+
Vary s_8

MGCamb + CosmoSIS

Theoretical predictions of **cosmic shear**
- 5 redshift bins
- 15 values of multipole ell

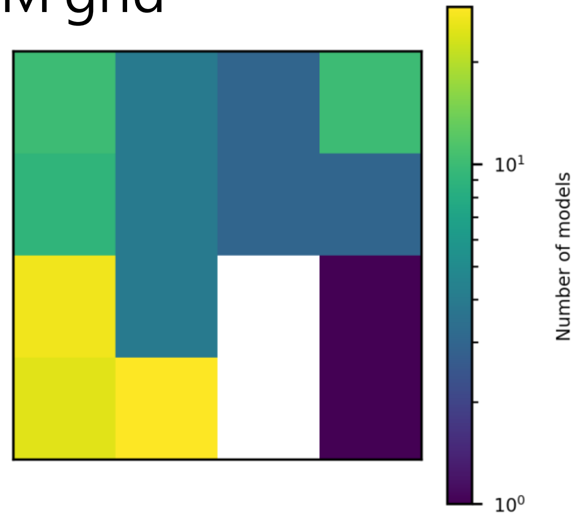
=> 225 elements per data set

2. Training the SOM



SOMPY

6x6 SOM grid

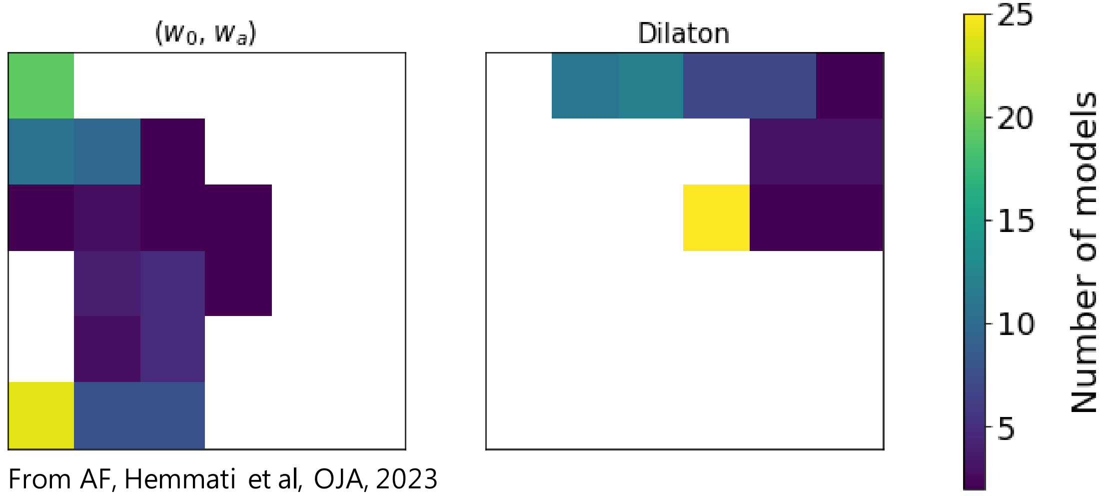


Approach proposed in *AF, Hemmati et al, OJA, 2023*

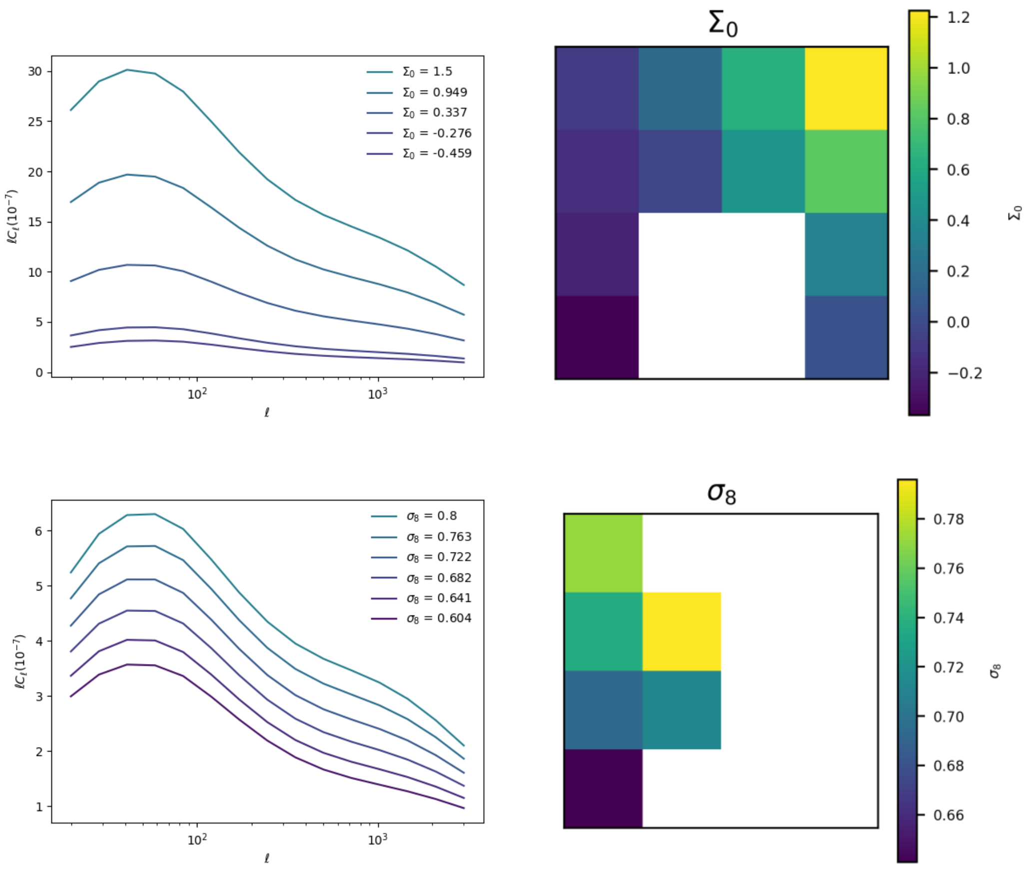
Other approach proposed in *Mancarella et al, PRD, 2022* using BNN

Understanding MG models impact on cosmic shear with SOM

- Dark energy and modified gravity should both be tested,
- Dilaton has a unique signature,
- Application to σ_8 tension.



From AF, Hemmati et al, OJA, 2023



Outlooks to enable detection of new physics with future surveys using ML

- ML to **accelerate analysis** and **decide** on theories to explore.

- **Deep learning** cosmology.
  DESLearning: Co-PIs Tomasz Kacprzak and **AF**,
  for NERSC-NESAP to accelerate the training on GPUs.

- For MG, analysis using summary statistics and deep learning:
  need **modeling developments**.