Probabilistic Modeling to Measure Dark Energy

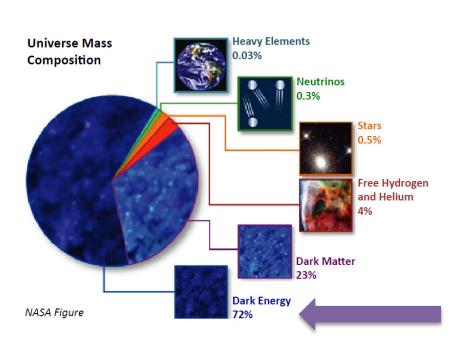
Data Science Workshop 2018

Physics Division, LLNL August 7, 2018 Collaborators: Will Dawson, Josh Meyers D. Bard, N. Golovich, D. Hogg, D. Lang, P. Marshall, K. Ng, K. Shah



Michael D. Schneider

Science driver: The expansion of the universe is accelerating, but we know almost nothing about the mechanism – "Dark Energy"



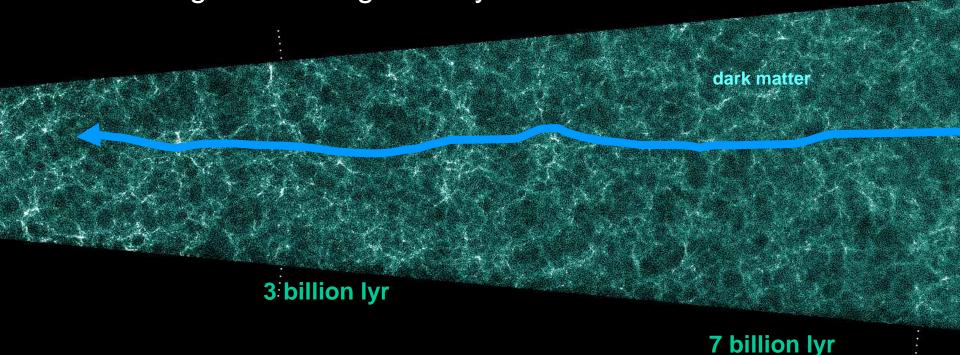
What causes cosmic acceleration?

Three possibilities:

- The universe is filled with a negativepressure component that gives rise to 'gravitational repulsion': Dark Energy
- The theory of General Relativity (gravity) is wrong on cosmic distance scales
- 3. The universe is inhomogeneous and only apparently accelerating, due to large-scale structure (unlikely given current data)

Path to the greatest prize in physics: Reconciliation of gravity and quantum mechanics. Gravitational lensing traces mass structure vs cosmic time

– A promising dark energy probe that is sensitive to both
structure growth and geometry

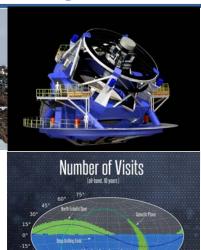


The Large Synoptic Survey Telescope (LSST) will be a primary dark energy instrument in the next decade

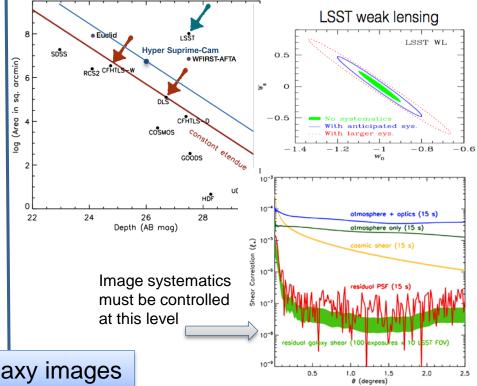
The LSST gravitational lensing measurement of dark energy is systematics limited



- DOE/NSF project
- 3.2Gpix camera
- 2π steradians
- 10 sq. deg. FOV
- 30 sec visits every night for 10 years
- 15Tb / night
- Commissioning start: FY20
- 15-years of LLNL contributions

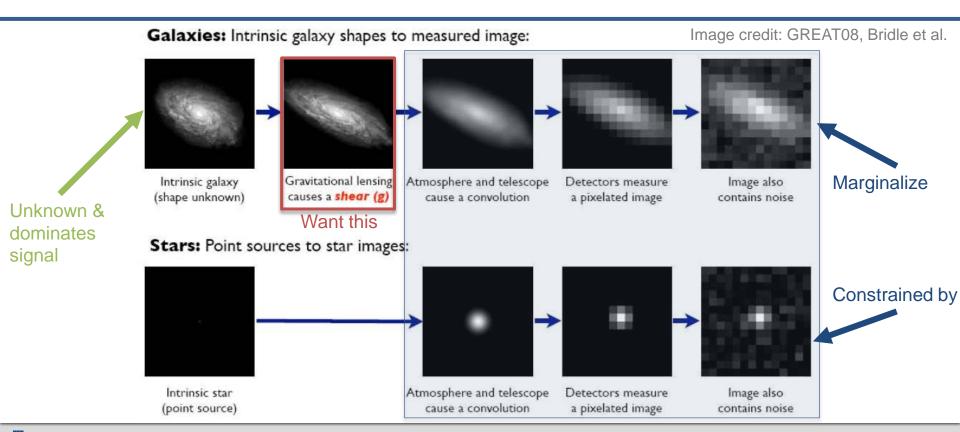




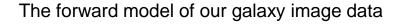


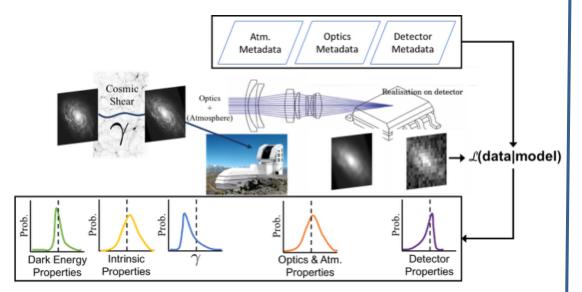


Weak lensing of galaxies: the forward model

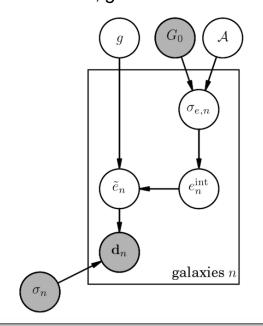


Our solution: Hierarchical Bayesian forward models of the image data





A simplified probabilistic graphical model for galaxy image data with cosmic shear, *g*

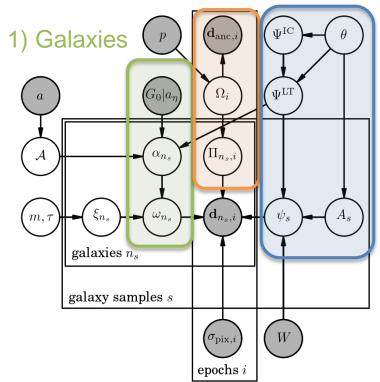


arXiv:1411.2608

Precision control of systematics via forward modeling and marginalization

2) PSFs 3) Cosmology

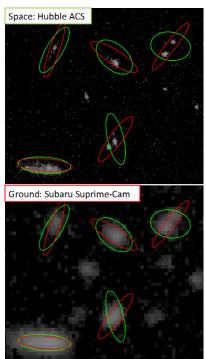
Parameter	Description
	•
$\boldsymbol{\theta}$	Cosmological parameters
$\Psi^{ ext{IC}}$	Initial conditions for the 3D gravitational potential
$\Psi^{ m LT}$	Late-time 3D gravitational potential
ψ_s	2D lens potential (given source photo- z bin s)
A_s	Parameters for the line-of-sight source distribution
$\Pi_{n_s,i}$	PSF for galaxy n_s observed in epoch i
Ω_i	Observing conditions in epoch i
$\{{\omega_n}_s\}$	Galaxy model parameters; $n_s = 1, \ldots, n_{\text{gal},s}$
$\{lpha_{n_s}\}$	Parameters for the distribution of $\{\omega_{n_s}\}$
$\{{m \xi_n}_s\}$	Scaling parameters for $\{\omega_{n_s}\}$
m, au	Hyperprior parameters for $\{\xi_{n_s}\}$
$\mathcal A$	Hyperparameter for $\{\alpha_{n_s}\}$ classifications
$\overline{\{\mathbf{d}_{n_s,i}\}}$	Pixel data for galaxies $n_s = 1, \ldots, n_{\text{gal},s}$ in epoch i
$G_0 a_\eta$	Prior specification for $\{\alpha_{n_s}\}$
s	Source sample (e.g., photo- z bin)
W	Survey window function
$\mathbf{d}_{\mathrm{anc},i}$	Ancillary data for PSF in epoch i
\boldsymbol{p}	Prior params. for observing conditions
\boldsymbol{a}	Prior params. for \mathcal{A}
$\sigma_{\mathrm{pix},i}$	Pixel noise r.m.s. in epoch i
I	Model selection assumptions

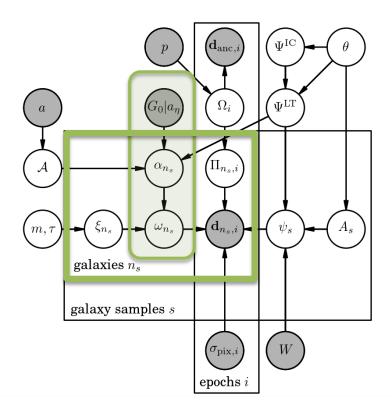


Naïve approach is intractable

Galaxy models be joint fitted to all

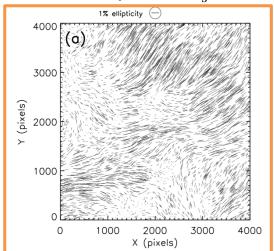
available epochs i

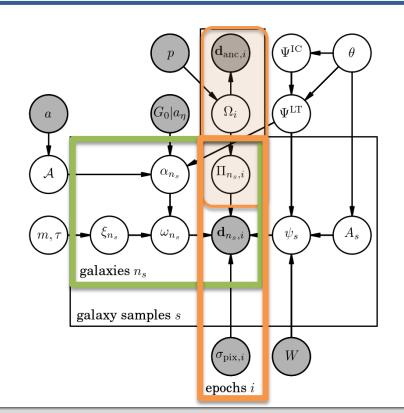




Naïve approach is intractable

- 1. Galaxy models be joint fitted to all available epochs i
- 2. PSF models must be joint fitted to all galaxies in an exposure n_s

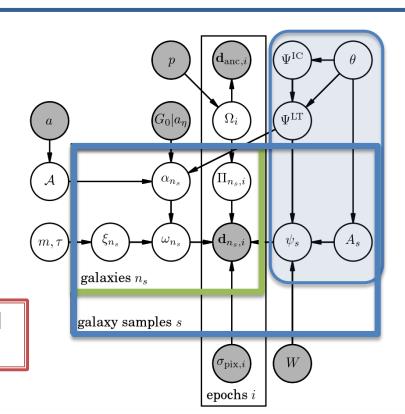




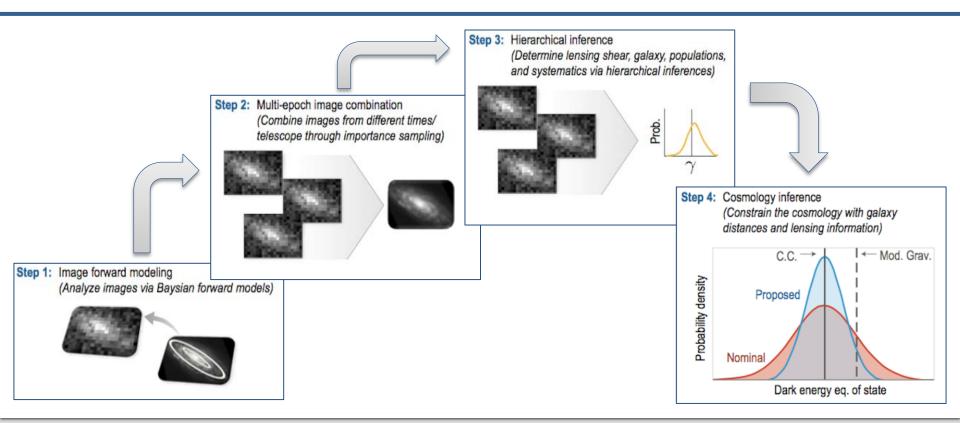
Naïve approach is intractable

- 1. Galaxy models be joint fitted to all available epochs i
- 2. PSF models must be joint fitted to all galaxies in an exposure n_s
- Cosmology must be joint fitted to all galaxy samples & epochs

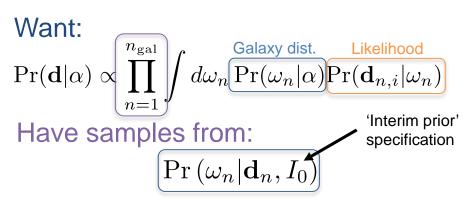
The principled inference requires fitting all pixels of all surveys simultaneously



We have developed a tractable 'divide & conquer' computational approach for the complete statistical model for multiple imaging surveys



Importance Sampling allows tractable divide & compute: The pseudo-marginal likelihood

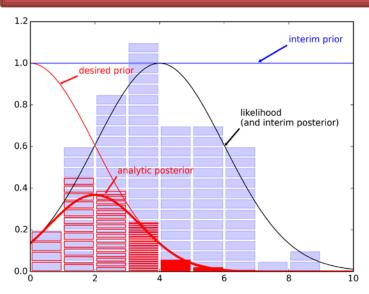


Importance sampling:

$$\Pr(\mathbf{d}_n|\alpha) \approx \frac{Z_n}{K} \sum_{k} \frac{\Pr(\omega_{nk}|\alpha)}{\Pr(\omega_{nk}|I_0)},$$

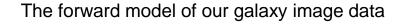
$$\Pr(\mathbf{d}|\alpha) = \prod_{n=1}^{n_{\text{gal}}} \Pr(\mathbf{d}_n|\alpha).$$

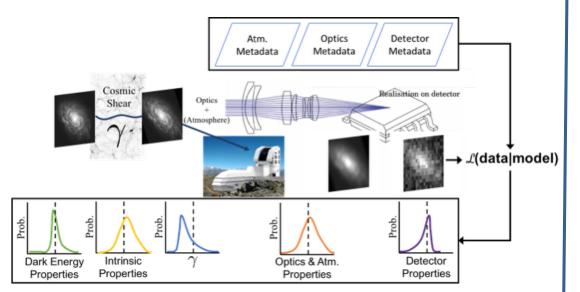
Ongoing research question: How many interim samples are needed?



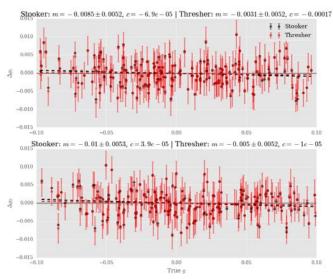
Credit: J. Meyers

Our hierarchical Bayesian forward models can meet LSST systematics tolerances for galaxy shear when the model is accurate enough





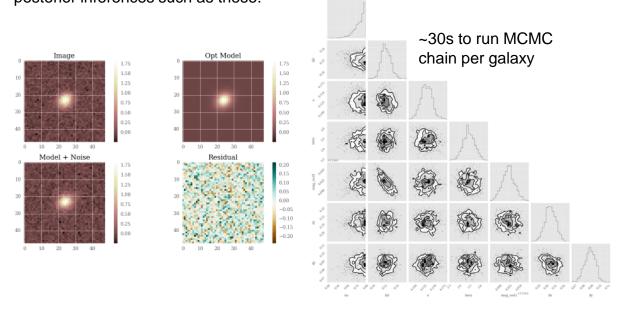
Our approach works:



Sensitivity analyses with (simplified) galaxy simulation suites show biases well below LSST tolerances.

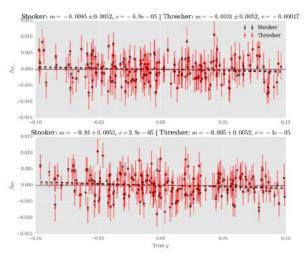
Accurate modeling in an MCMC framework is more computationally demanding than traditional approaches – but still tractable

Every data point on the right is inferred from thousands of galaxy image model posterior inferences such as these:



LSST data volume: 4 billion galaxies, each seen 1000 times

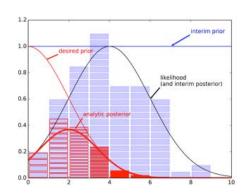
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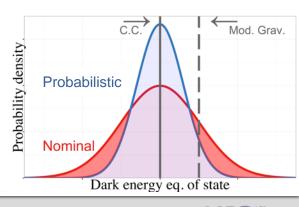


Sensitivity analyses with (simplified) galaxy simulation suites show biases well below LSST tolerances

Summary

- Cosmic shear is systematics limited & signal is dominated by PSF and astrophysics
 - A probabilistic approach is warranted to infer a small signal and mitigate biases
- A hierarchical probabilistic model for cosmic shear can trade bias for variance, but also can increase precision by learning latent structure in the galaxy distribution.
- Importance sampling methods allow tractable approaches to a probabilistic forward model of LSST & WFIRST imaging
 - With billions of galaxies and hundreds of epochs per galaxy modeling LSST or WFIRST imaging requires an approach to separating analyses of data subsets, even though statistically correlated
- We are able to sample from a probabilistic model with multiple hierarchies to marginalize both correlated image systematics and astrophysical properties of galaxies.



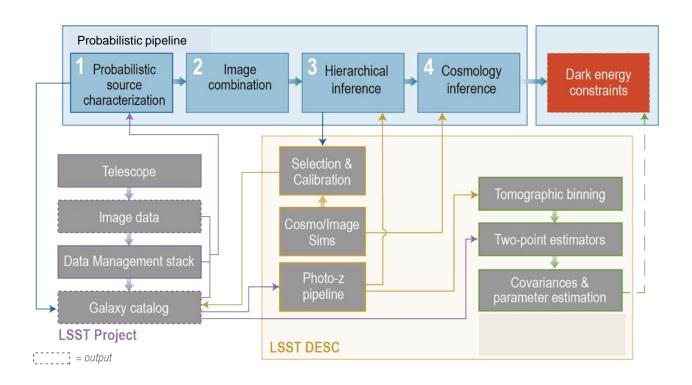




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The probabilistic weak lensing workflow plan for LSST



How do we combine multiple observations of the same galaxy?

Naïvely we must joint fit all epochs simultaneously

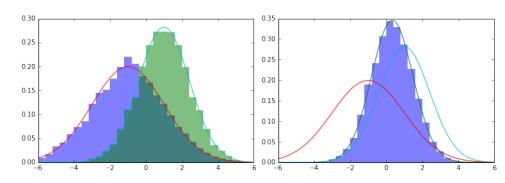
Problem: Imagine we have fit pixel data from LSST year 1. How do we incorporate year 2 observations without redoing (expensive) calculations?

Solution: Consider single-epoch samples as draws from a multi-modal importance sampling distribution:

arXiv:1511.03095

Generalized Multiple Importance Sampling

Elvira, Martino, Luengo, & Bugallo



Multiple importance sampling (MIS) via weighted pseudo-marginals

- 1. Sample from the conditional posterior for each epoch individually
- 2. Evaluate the ratio of the conditional posterior for each epoch *i* to that of the MIS sampling distribution

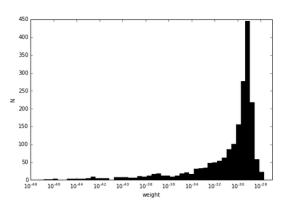
'cross-pollination' needed:

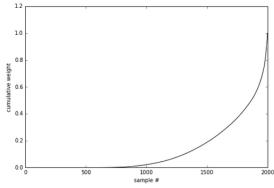
Evaluate the likelihood of epoch ${\bf i}$ given model parameter samples from epoch ${\bf j}$, for all combinations of ${\bf i}$, ${\bf j}$.

A standard scatter / gather operation

Multiple importance sampling enables streaming data analysis Efficiency is significantly enhanced by using old data as a sampling 'prior'

- Draw parameter samples from first epoch under a nominal interim prior
- Draw samples from subsequent epochs with a prior informed by previous epoch samples
- Simulation studies show:
 - ~10% of samples have significant weight when combining 200 epochs in streaming fashion





Probabilistic cosmological mass mapping

Interpolate the unobserved lensing potential with GP

$$\psi_s \sim GP(0,\Sigma),$$

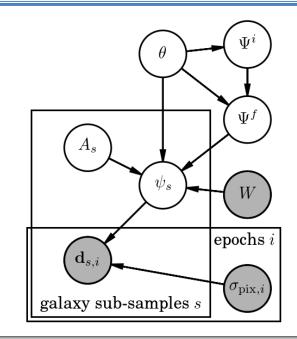
 $\kappa, \gamma_1, \gamma_2$ are the second (spatial) derivatives of ψ_s

$$Cov(\psi_{,ij}(\vec{x}),\psi_{,k\ell}(\vec{y})) = \Sigma_{,x_ix_jy_ky_\ell}(\vec{x},\vec{y}).$$

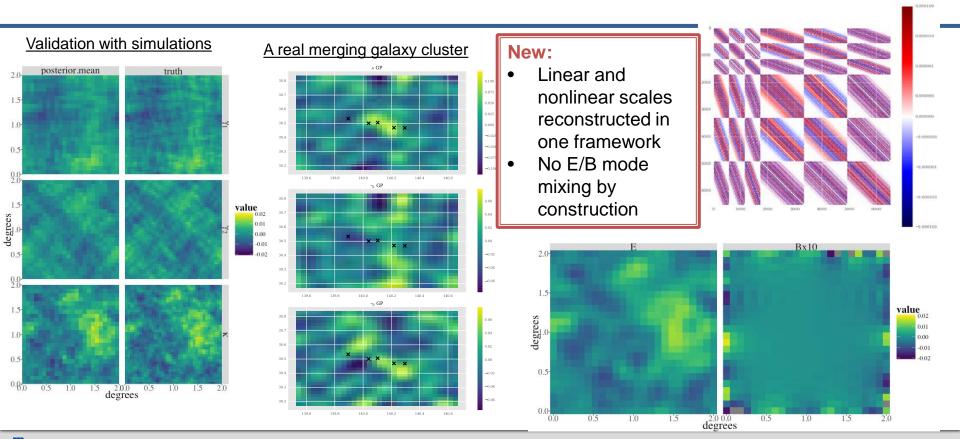
GP kernels of $\kappa, \gamma_1, \gamma_2$ are linear combinations of the 4th (spatial) derivatives of the kernel of ψ_s

Zero E/B mode mixing by construction

Objective: infer the 3D gravitational potential of the initial conditions



Hierarchical inference of cosmological lensing mass distributions



Marginalizing PSFs: MIS makes this tractable

- LSST will have ~200 epochs per object per filter
 - We aim to marginalize the PSF $\prod_{n,i}$ in every epoch
 - The marginalization is constrained by:
 - Consistency of PSF realizations over the focal plane for each epoch
 - Consistency of the underlying source model across epochs
- Simplest approach (statistically, not computationally): Infer galaxy models given all epoch imaging simultaneously
 - "Interim" samples are of size: ~10 galaxy params + 200 * ~4 PSF params = ~1k parameters!

