Forward Modelling in Cosmology

Alexandre Refregier
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

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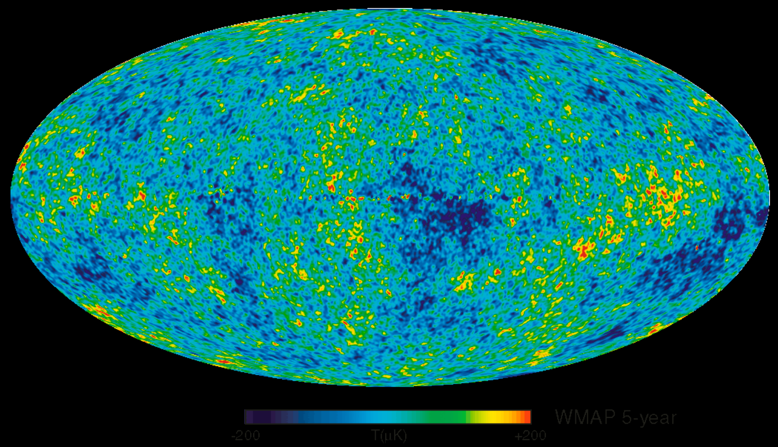
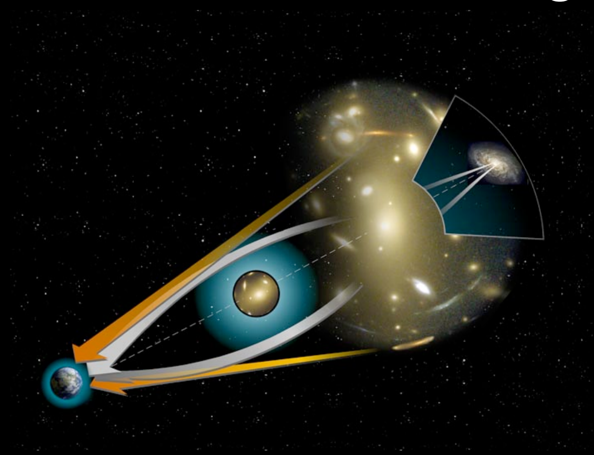
Cosmological Probes

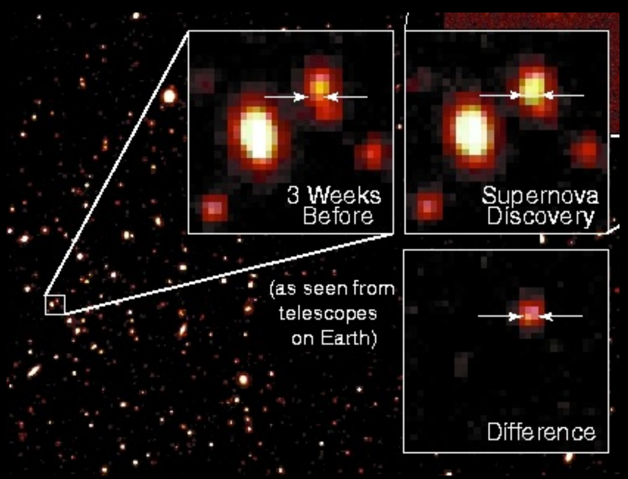
Cosmic Microwave Background



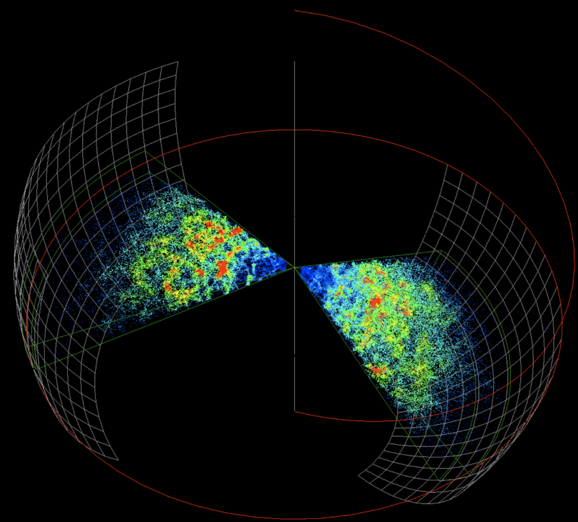
Gravitational Lensing



Supernovae



Galaxy Clustering



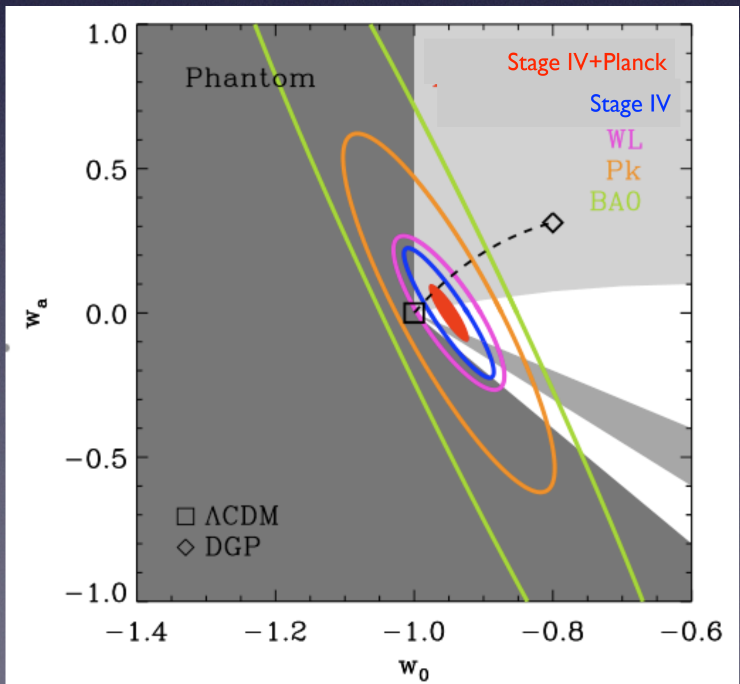
Wide-Field Instruments

CMB		Planck, SPT, ACT, Keck
VIS/NIR	Imaging	VST, DES, Pann-STARRS, LSST Euclid, WFIRST, Subaru Boss, Wigglez, DESI, HETDEX
	Spectro	
Radio		LOFAR, GBT, Chimes, BINGO, GMRT, BAORadio, ASKAP, MeerKAT, SKA

Impact on Cosmology

Amara et al. 2008

	Δw_p	ΔW_a	$\Delta\Omega_m$	$\Delta\Omega_\Lambda$	$\Delta\Omega_b$	$\Delta\sigma_8$	Δn_s	Δh	DE FoM
Current+WMAP	0.13	-	0.01	0.015	0.0015	0.026	0.013	0.013	~10
Planck	-	-	0.008	-	0.0007	0.05	0.005	0.007	-
Weak Lensing	0.03	0.17	0.006	0.04	0.012	0.013	0.02	0.1	180
Imaging Probes	0.018	0.15	0.004	0.02	0.007	0.0009	0.014	0.07	400
Stage IV	0.016	0.13	0.003	0.012	0.005	0.003	0.006	0.020	500
Stage IV+Planck	0.01	0.066	0.0008	0.003	0.0004	0.0015	0.003	0.002	1500
Factor Gain	13	>15	13	5	4	17	4	7	150



Stage IV Surveys will challenge all sectors of the cosmological model:

- Dark Energy: w_p and w_a with an error of 2% and 13% respectively (no prior)
- Dark Matter: test of CDM paradigm, precision of 0.04eV on sum of neutrino masses (with Planck)
- Initial Conditions: constrain shape of primordial power spectrum, primordial non-gaussianity
- Gravity: test GR by reaching a precision of 2% on the growth exponent ($d\ln_m/d\ln a_m$)

→ Uncover new physics and map LSS at 0<z<2: Low redshift counterpart to CMB surveys

Challenges

Current:

Radiation-Matter transition

High-precision Cosmology era with CMB

Next stage:

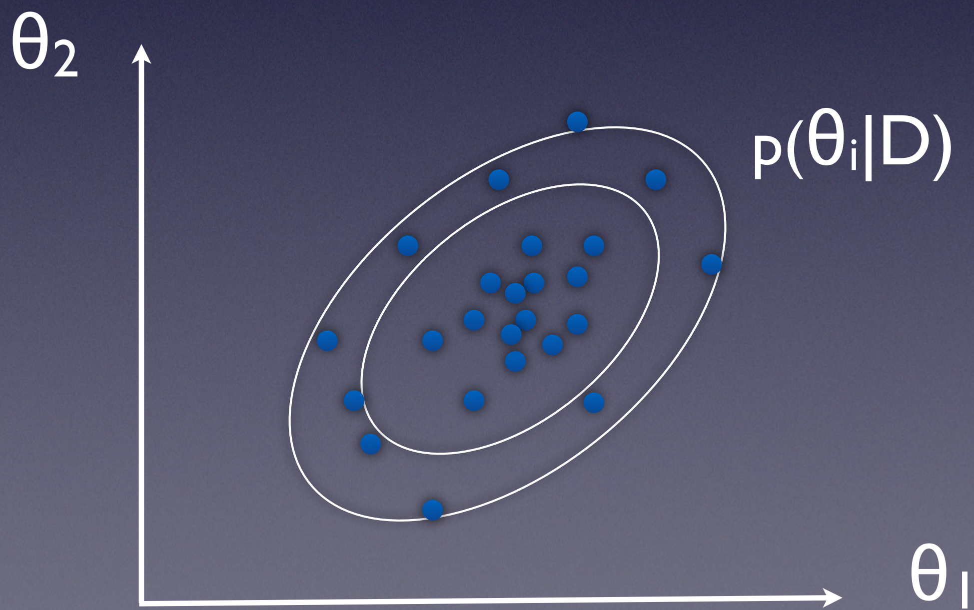
Matter-Dark Energy transition

High-precision Cosmology with LSS surveys, different from CMB:

- 3D spherical geometry
- Multi-probe, Multi-experiments
- Non-gaussian, Non-Linear
- Systematics limited
- Large Data Volumes

Bayesian Parameter Estimation

- Bayesian inference: $p(\theta|y)=p(y|\theta)\times p(\theta)/P(y)$
- In practice: Evaluation of $p(y|\theta)$ is expensive, N_θ is large (≥ 7)
- MCMC: produce a sample $\{\theta_i\}$ distributed as $p(\theta|y)$ (e.g. CosmoMC Lewis & Bridle 2002, CosmoHammer, Akeret+ 2012)

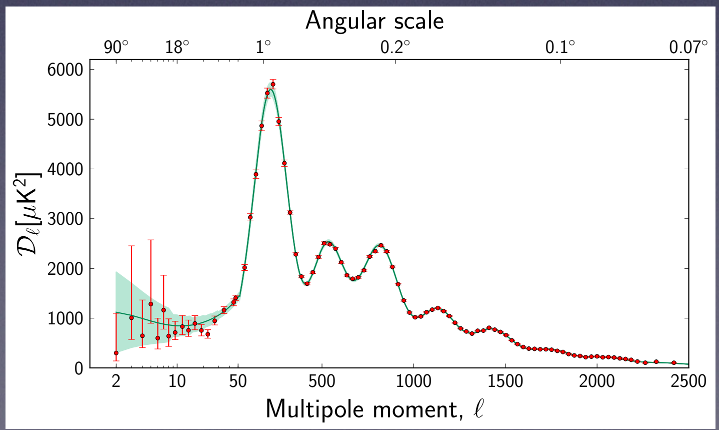


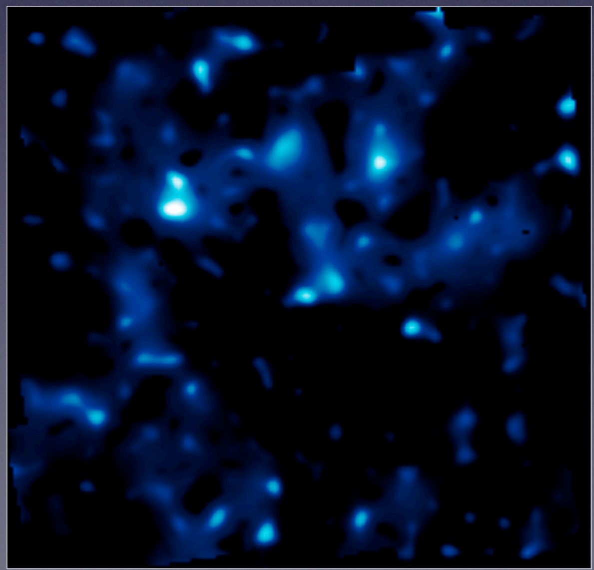
Forward Modelling

- Bayesian inference relies on the computation of the likelihood function p(y|θ)

- In some situations the likelihood is unavailable or intractable (eg. non-gaussian errors, non-linear measurement processes, complex data formats such as maps or catalogues)

- Simulation of mock data sets may however be done through forward modelling





mag	r50	class	ellip
23.5	2.3	0.11	0.23
22.1	1.2	0.89	0.02
24.1	3.2	0.76	0.54
24.2	4.3	0.45	0.65
22.7	3.1	0.91	0.32

Approximate Bayesian Computation

review: Turner & Zandt 2012, see also: Akeret et al. 2015

- Consider reference data set y and simulation based model with parameters θ which can generate simulated data sets x
- Define:
  - Summary statistics S to compress information in the data
  - Distance measure $\rho(S(x),S(y))$ between data sets
  - Threshold ε for the distance measure
- Sample prior $p(\theta)$ and accept sample θ^* if $\rho(S(x),S(y))<\varepsilon$, where x is generated from model θ^*
- ABC approximation to posterior: $p(\theta|y) \simeq p(\theta|\rho(S(x),S(y))<\varepsilon)$
- Use Monte Carlo sampler with sequential ε to sample ABC posterior (eg. ABC Population Monte Carlo)

Gaussian Toy Model

Akeret et al. 2015

Data set y: *N* samples drawn from gaussian distribution with known σ and unknown mean θ

Summary statistics: *S(x)*=<*x*>

Distance: ρ*(x,y)* = |<*x*>-<*y*>|

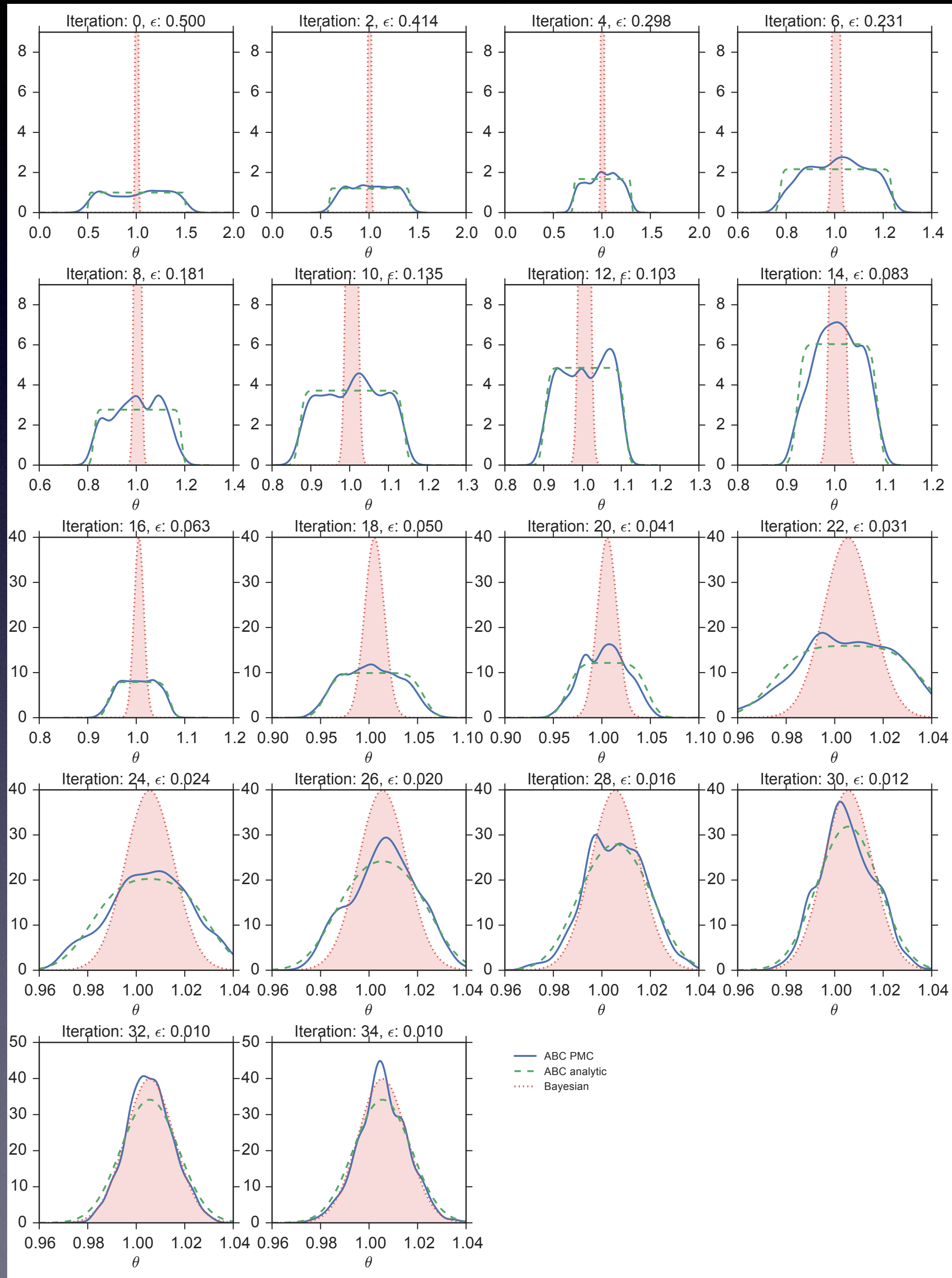
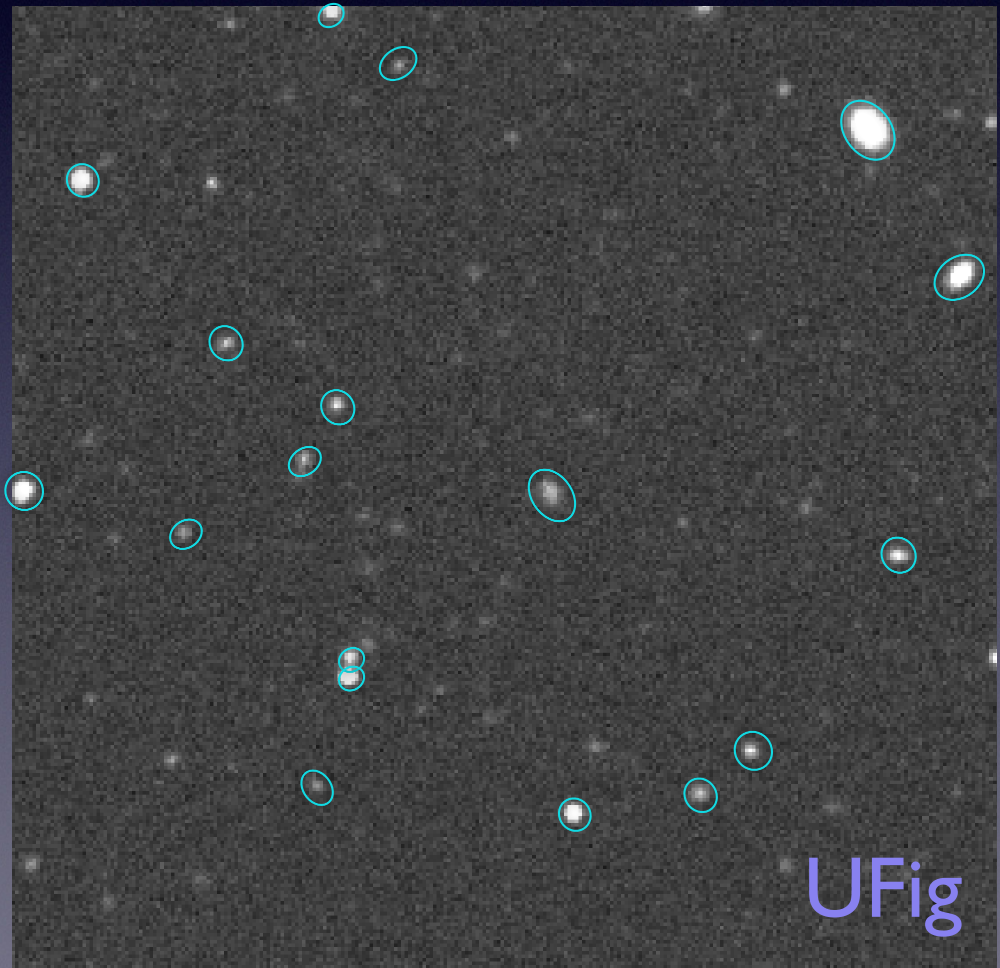


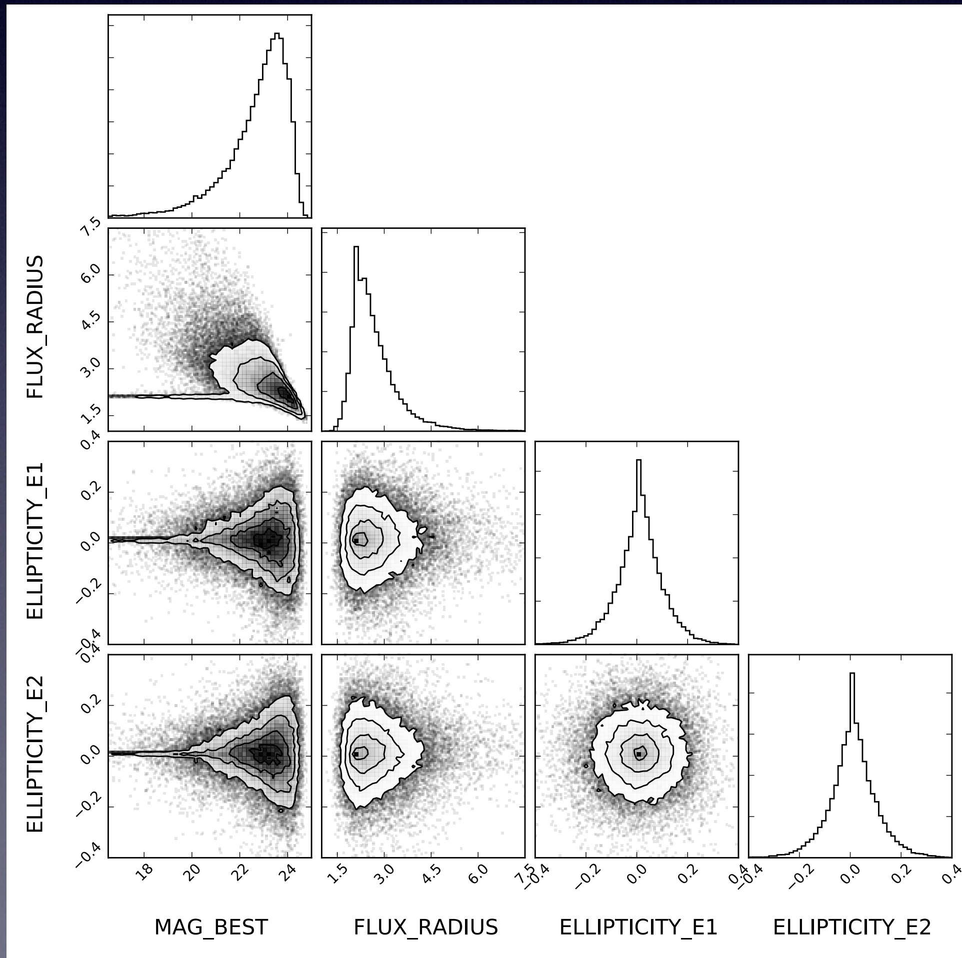
Image Modelling

UFig: Ultra Fast Image Generator   Bergé et al. 2013, Bruderer et al. 2015

data *y*: SExtractor catalogue   Bertin & Arnouts 1996

model: parametrised distribution of intrinsic galaxy properties





ABCPMC

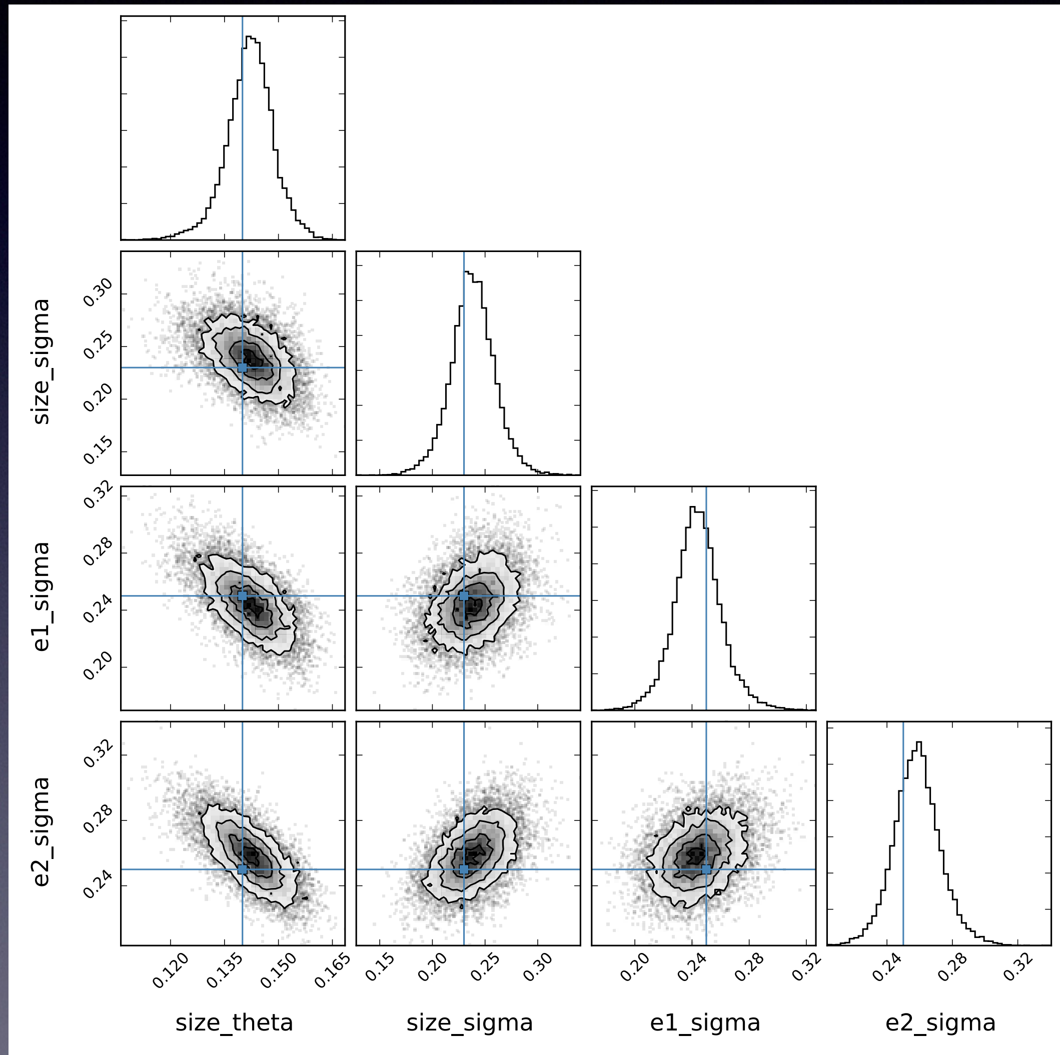
Akeret et al. 2015

Mahalonobis distance:

$$S(y) = \sqrt{(y-\mu_y)^T \Sigma_y^{-1} (y-\mu_y)}$$

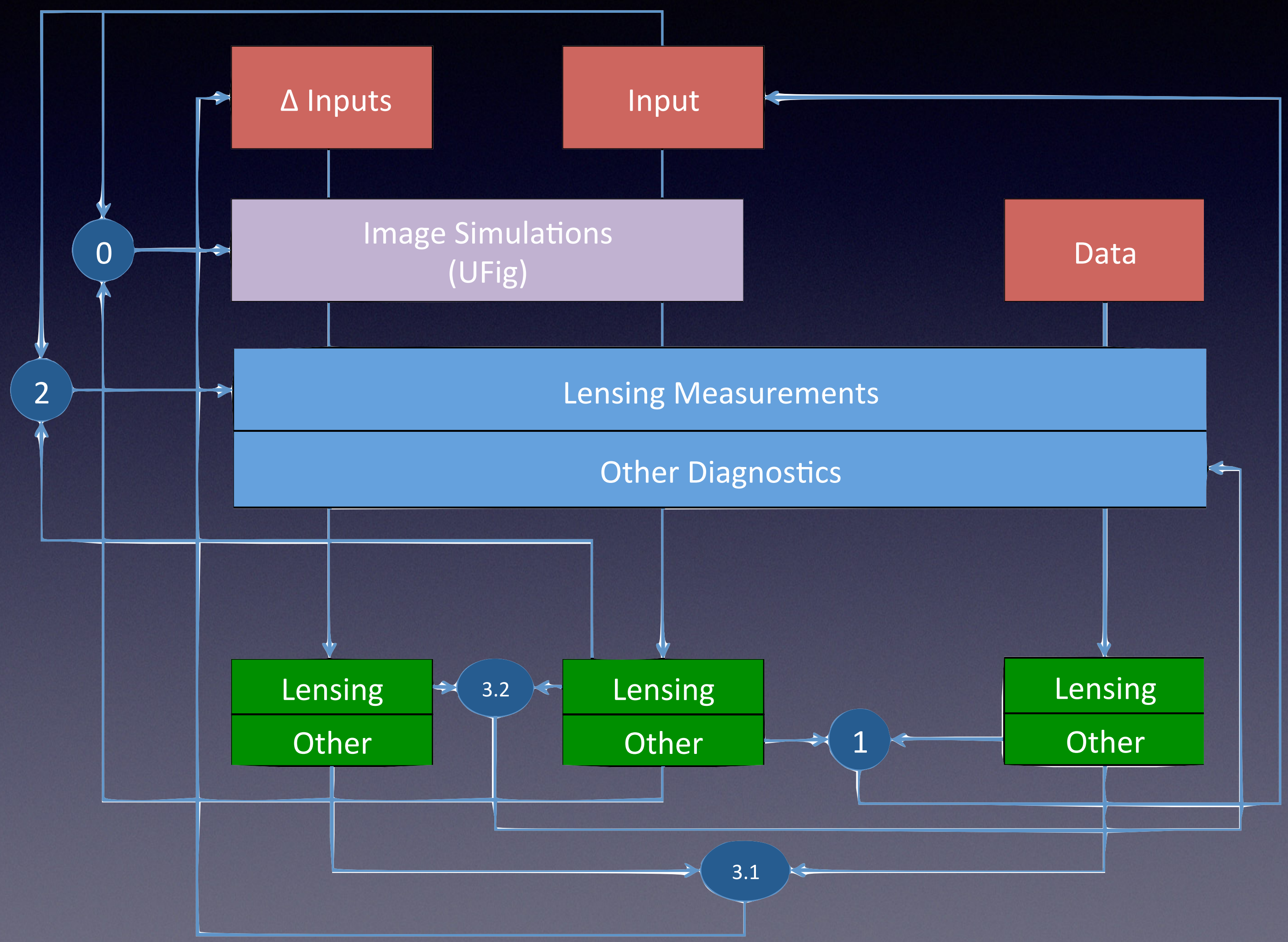
$$S(x) = \sqrt{(x-\mu_y)^T \Sigma_y^{-1} (x-\mu_y)},$$

ρ(S(x),S(y))= 1D KS distance



Monte-Carlo Control Loops

Refregier & Amara 2013



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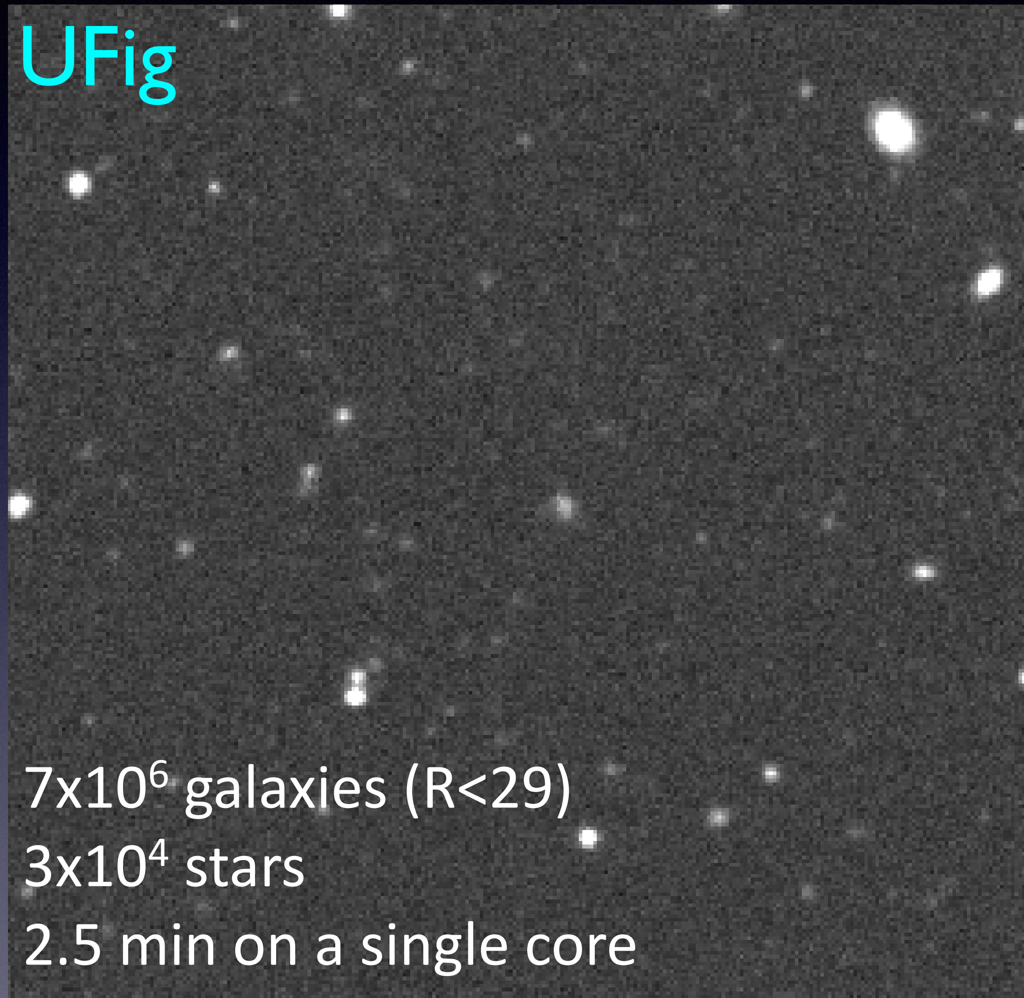
UFig Ultra Fast Image Generator

Bergé et al. 2013; Bruderer et al. 2015



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HOPE

Akeret et al. 2014

- Just-In-Time compiler for astrophysical computations
- Makes Python as fast as compiled languages
- HOPE translates a Python function into C++ at runtime
- Only a @jit decorator needs to be added

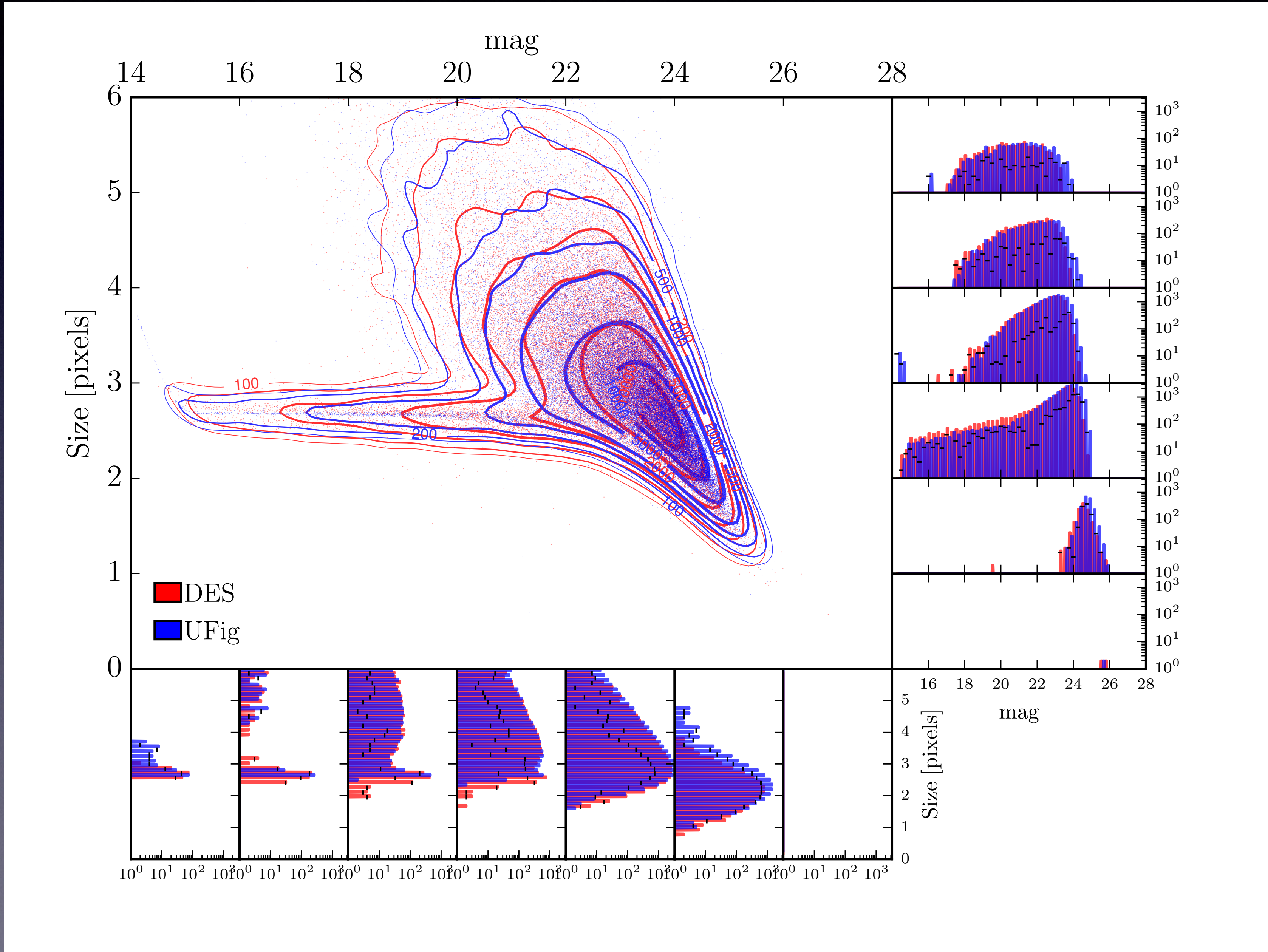
```
@hope.jit
def improved(x, y):
    return x**2 + y**4
```

- Supports numerical features commonly used in astrophysical calculations

For more information see: http://hope.phys.ethz.ch

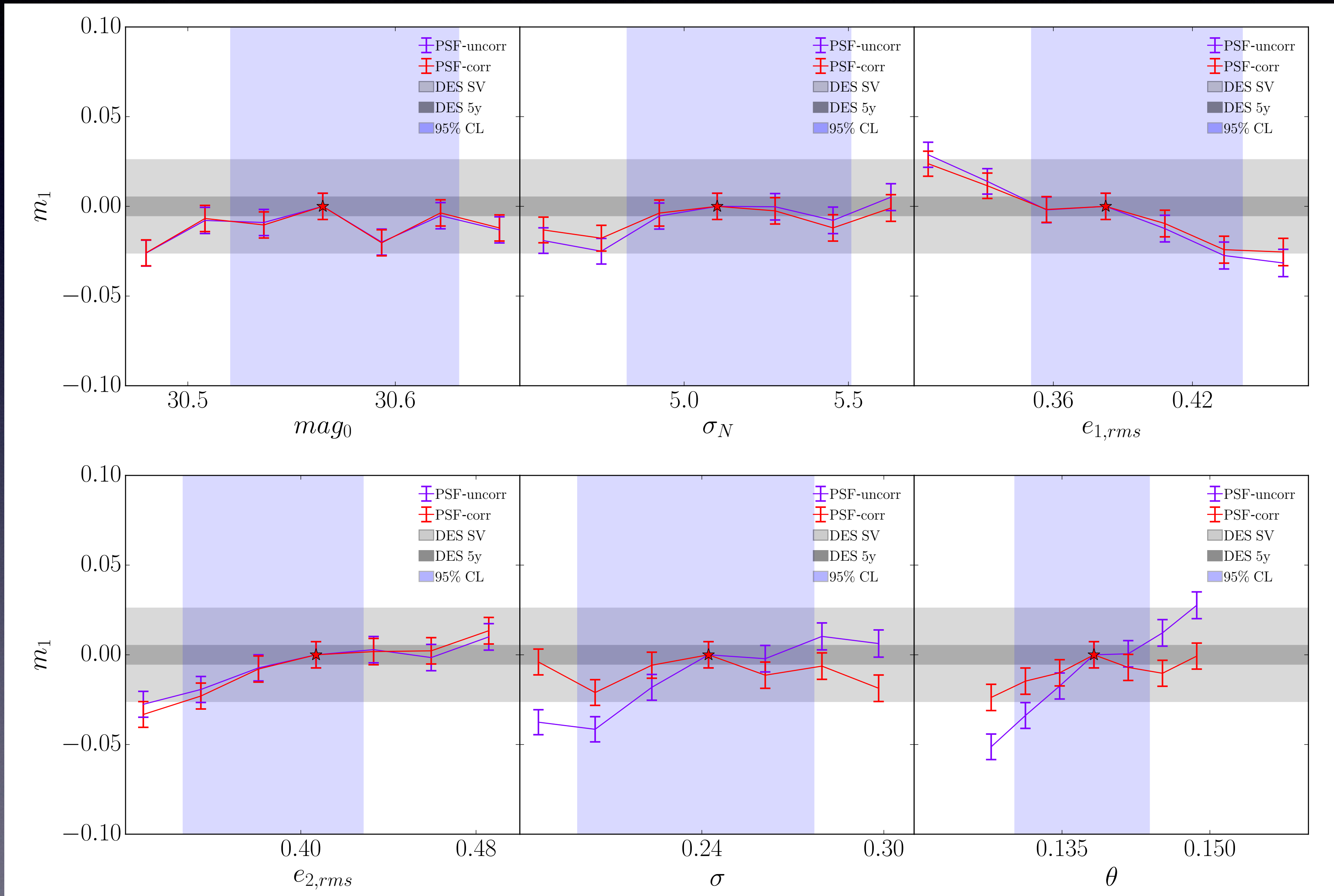
MCCL: First Implementation

Bruderer et al. 2015



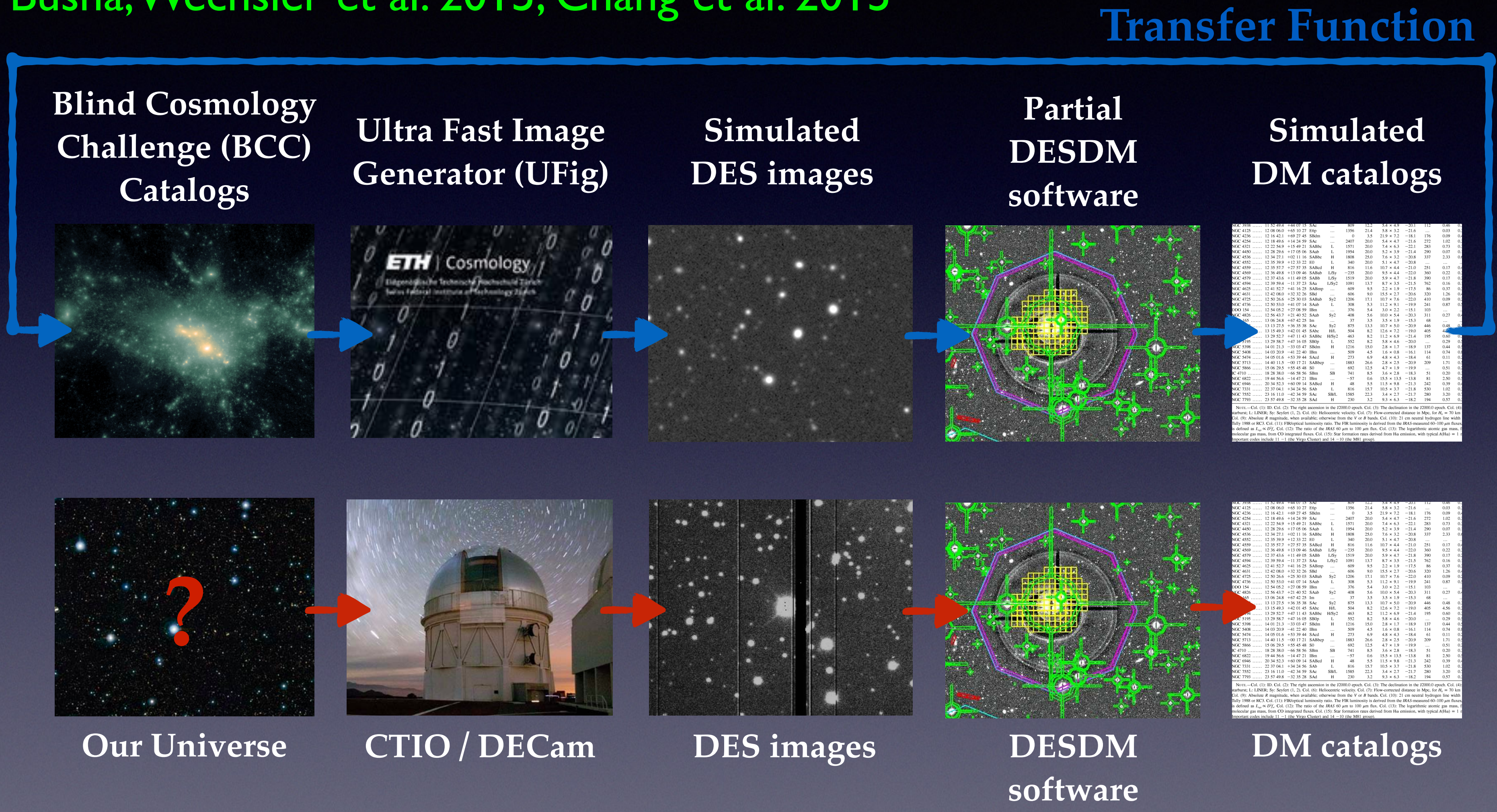
Tolerance Analysis

Bruderer et al. 2015



UFIG/BCC

Busha, Wechsler et al. 2015; Chang et al. 2015



+ Integration of spectroscopy simulations Nord et al. 2015, Nicola et al. 2015

Conclusions

- Upcoming and future LSS surveys have great promise for cosmology but will require new data analysis approaches

- Forward modelling is a promising approach to analyse complex data sets

- ABC can provide an approximation to the posterior in cases when the likelihood is not available