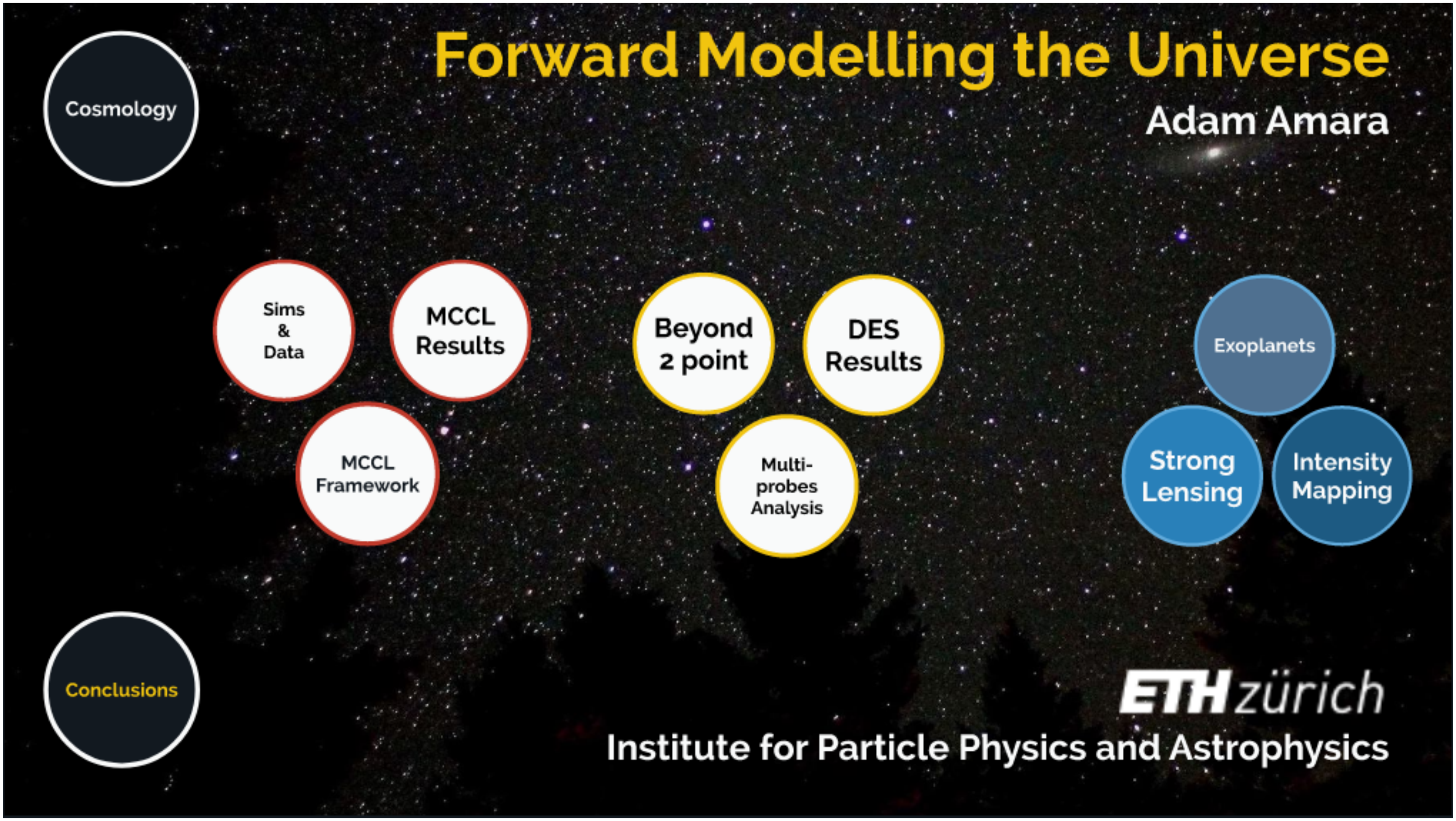

Forward Modelling the Universe
Adam Amara
Cosmology
Sims & Data
MCCL Results
MCCL Framework
Beyond 2 point
DES Results
Multi-probes Analysis
Exoplanets
Strong Lensing
Intensity Mapping
Conclusions
ETH zürich
Institute for Particle Physics and Astrophysics

MCCL Framework

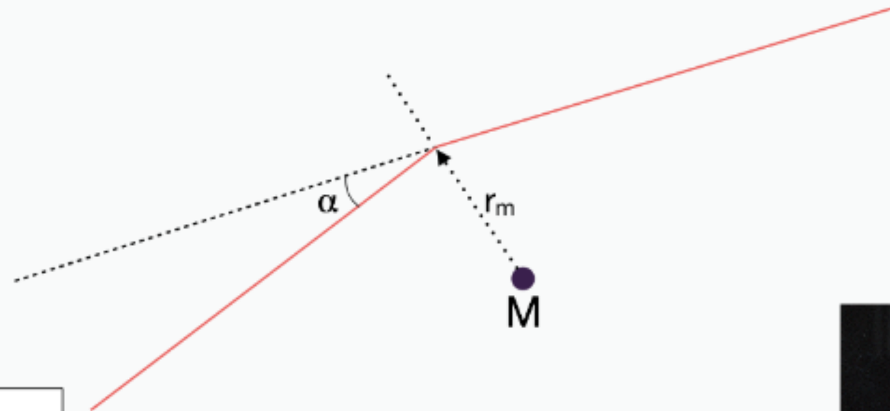
Why is weak lensing difficult to measure?

MCCL Framework

Why is weak lensing difficult to measure?

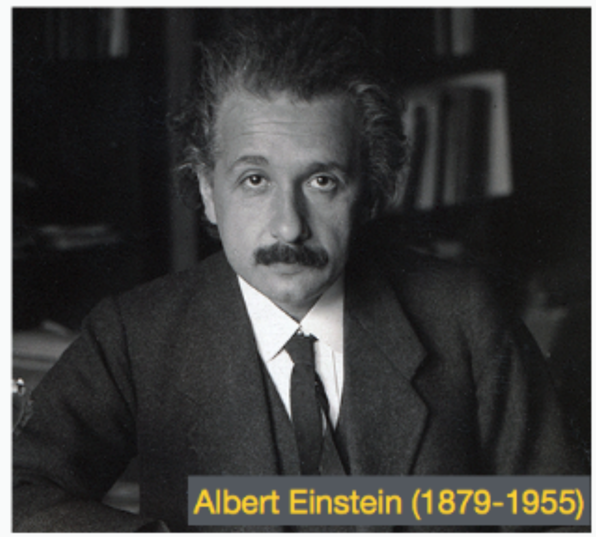
first a quick recap of lensing

Gravitational Lensing

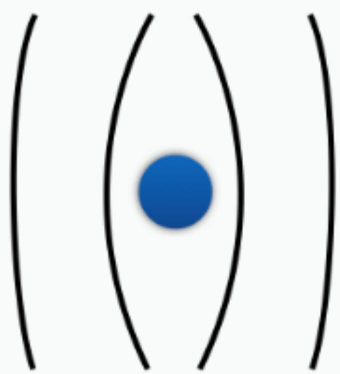


$$G_{\mu\nu} = \frac{8\pi G}{c^4} T_{\mu\nu}$$

$$\alpha = \frac{4G}{c^2} \frac{M}{r_m}$$



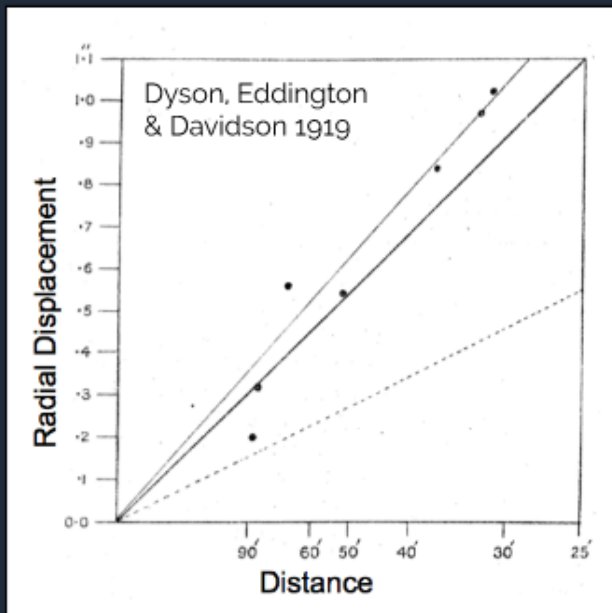
Two Limits



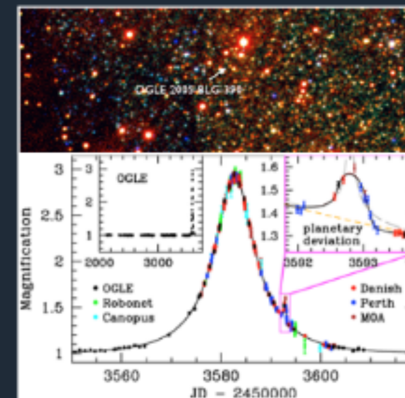
Strong Lensing:
Single object effect
Large displacements
Physics of instabilities
Sensitive System

Weak Lensing:
Lowest order - no Lensing <k> = 0
Fluctuations in density -> weak lensing
Effect is small
Collective action
Statistical physics

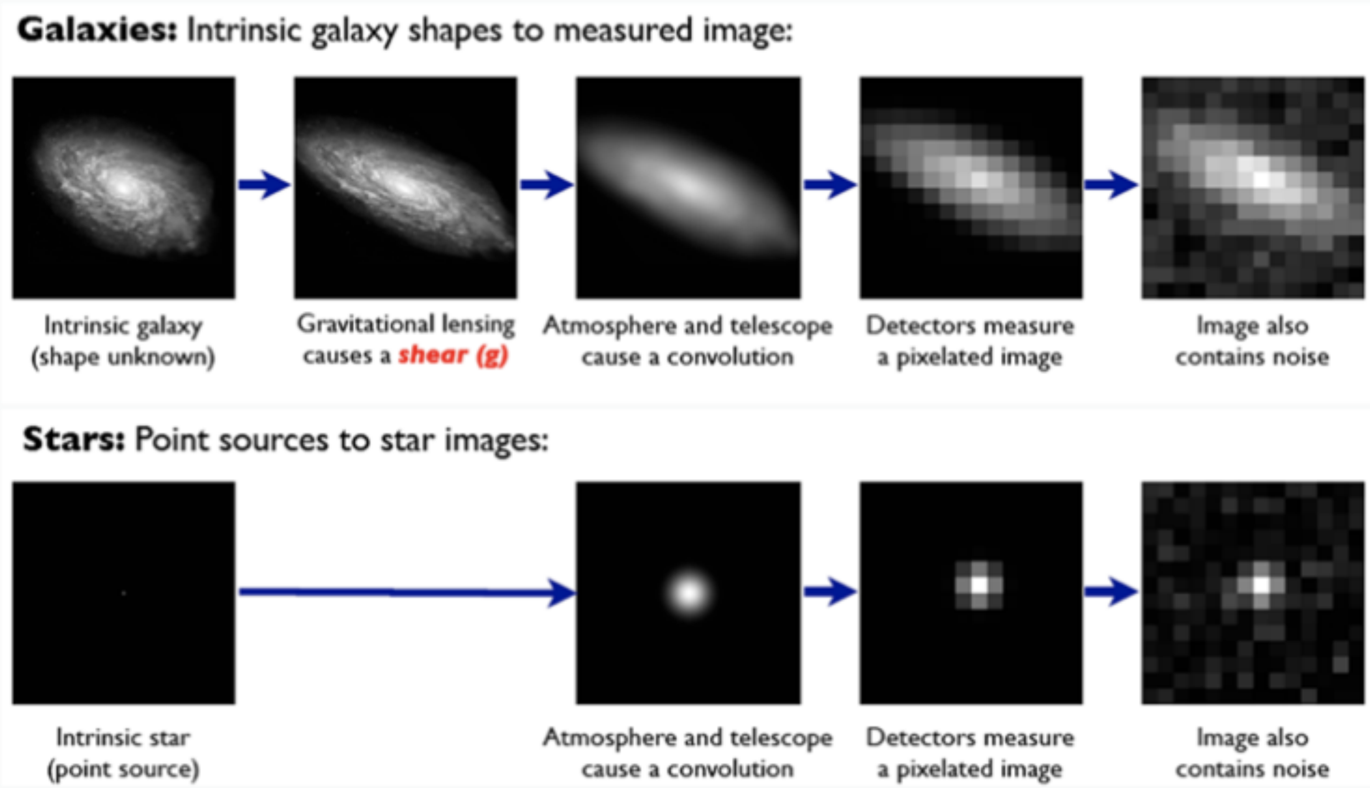
Examples of Gravitational Lenses



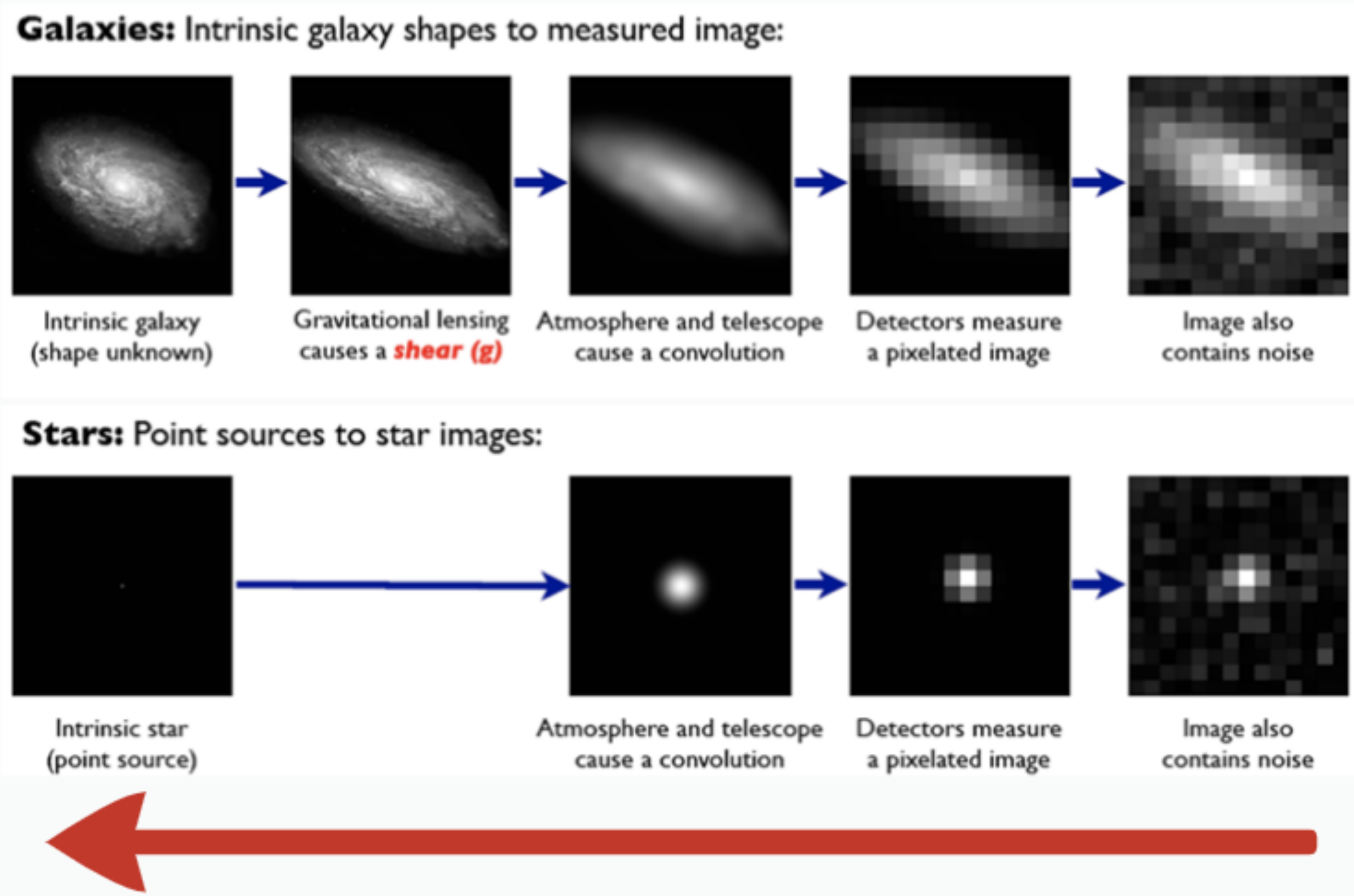
1915: General Relativity
1919: Eclipse Experiment
1937: Galaxies as Lens (Zwicky)
1979: First Galaxy Lens



Bridle, AA+ 2008



Bridle, AA+ 2008



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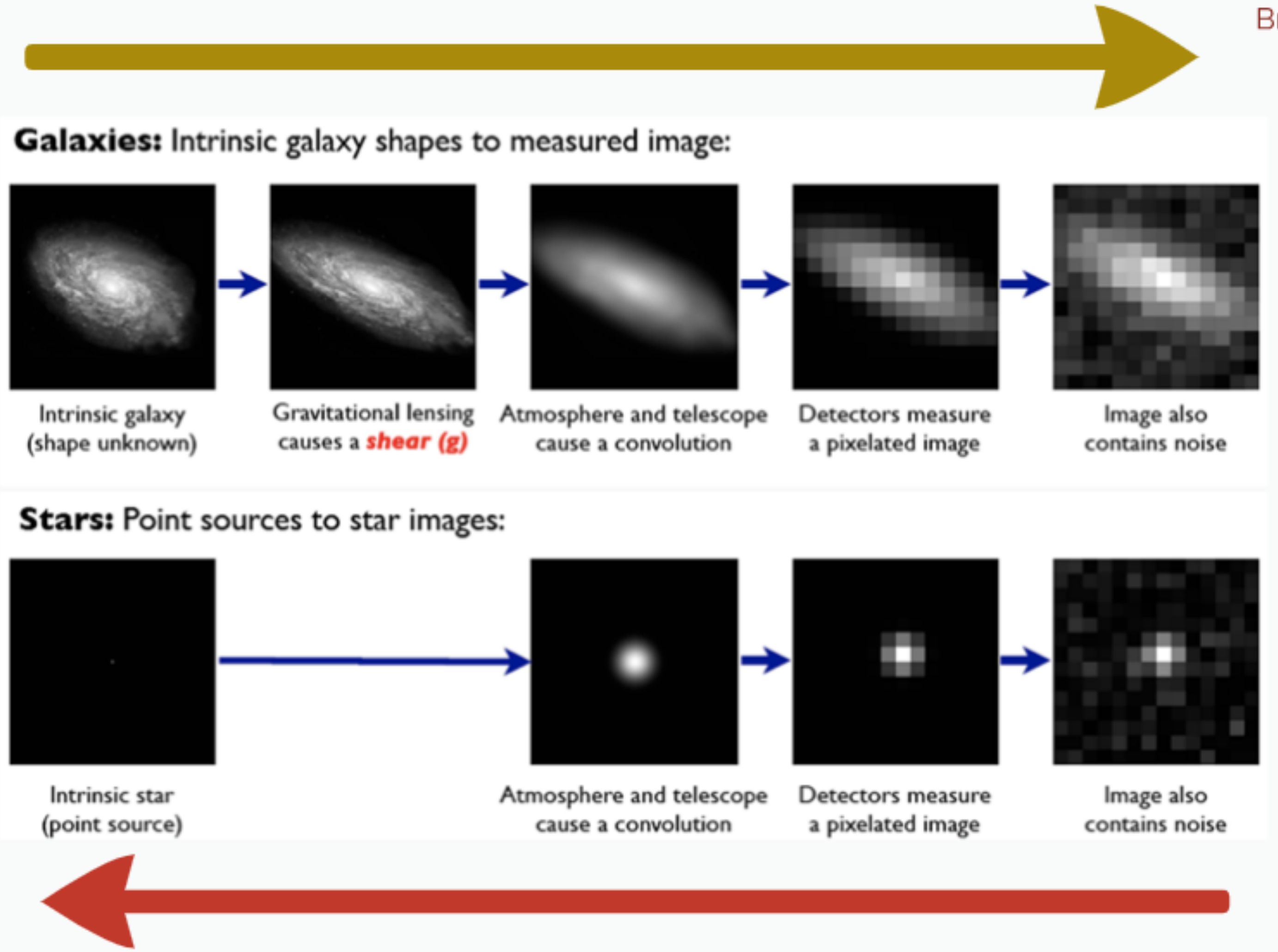
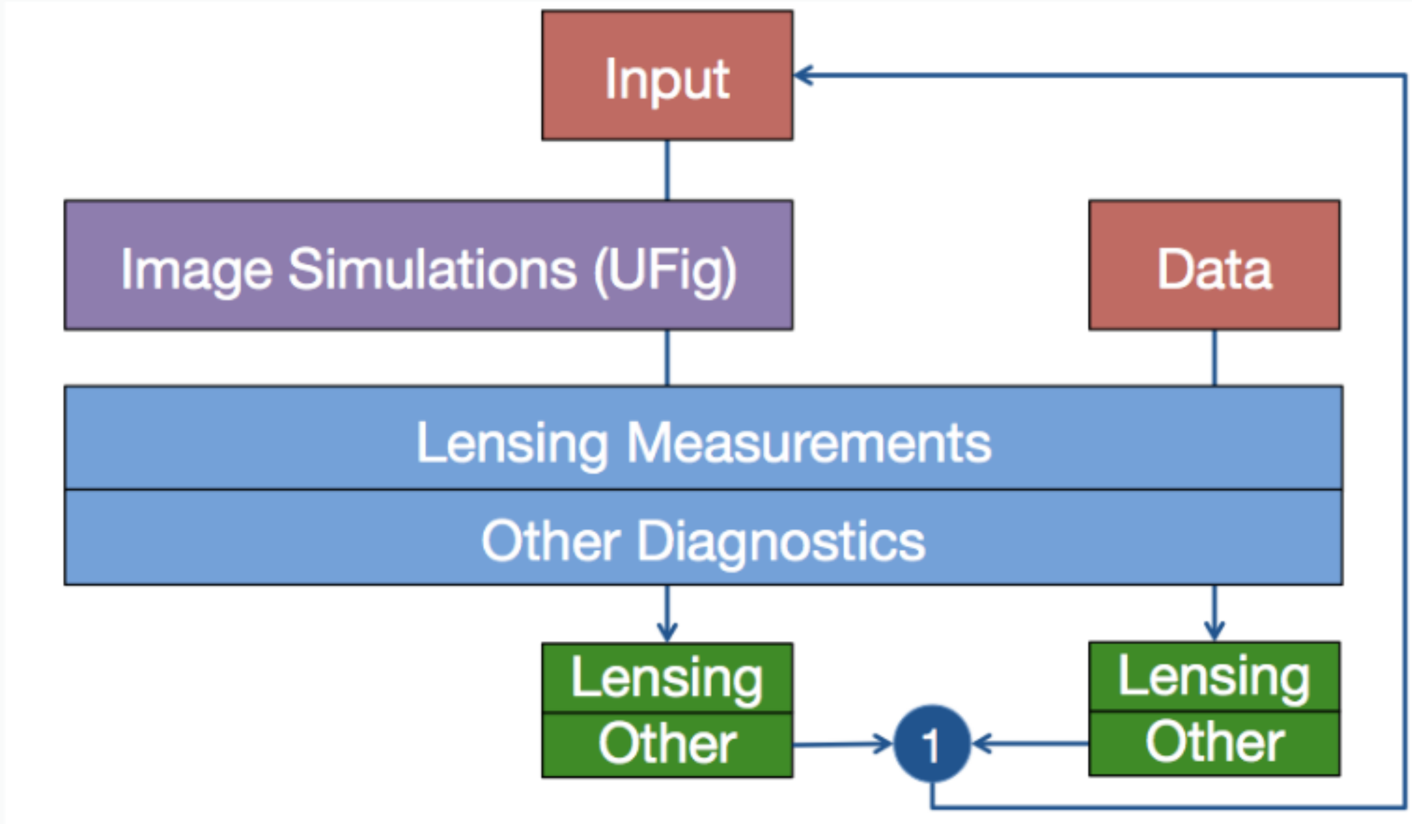
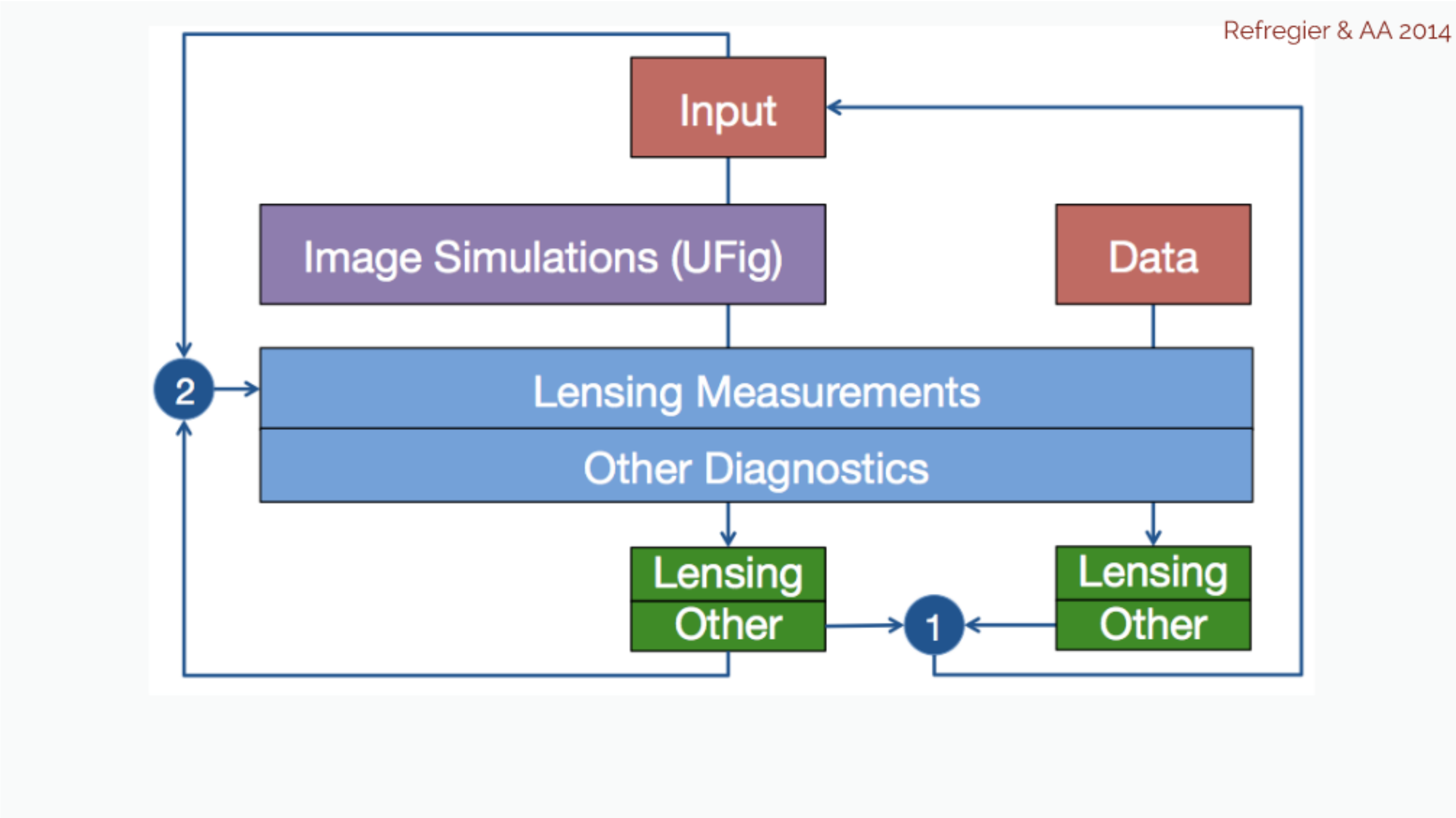
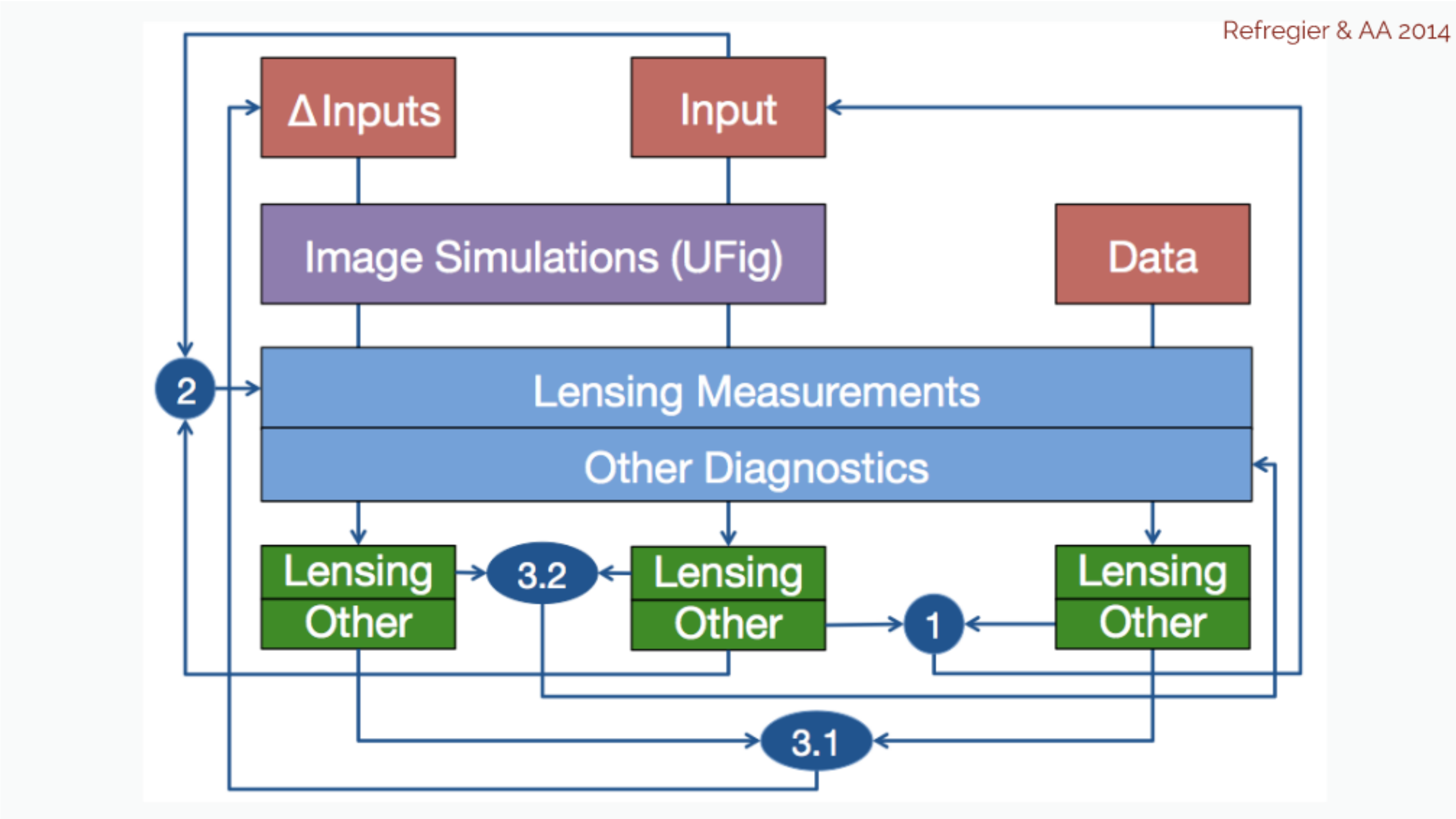


Refregier & AA 2014

Refregier & AA 2014




Refregier & AA 2014
Input
Image Simulations (UFig)
Data
2
Lensing Measurements
Other Diagnostics
Lensing
Other
1
Lensing
Other

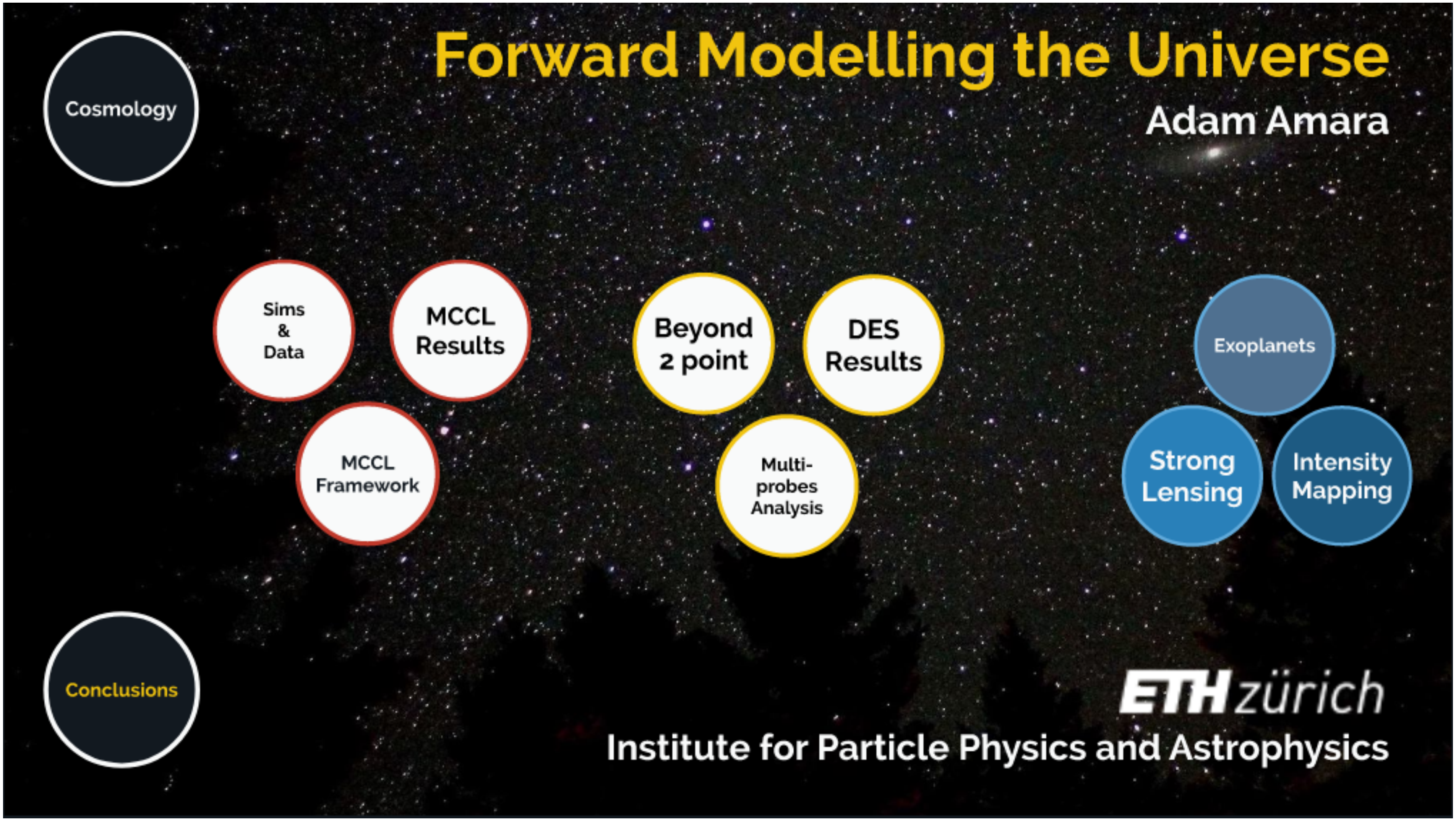

Refregier & AA 2014
ΔInputs
Input
Image Simulations (UFig)
Data
2
Lensing Measurements
Other Diagnostics
Lensing
Other
3.2
Lensing
Other
1
Lensing
Other
3.1

Key Features

- For each analysis of data we will need to analyses lots of simulations
- The analysis pipeline therefore needs to be fast
- The simulation pipeline needs to be fast also
- The MCCL method takes a holistic end-to-end approach

MCCL Team

+ earlier contributions:
Joel Berge, Lukas Gamper, Chihway Chang,
Laurence Gamper and Joel Akeret



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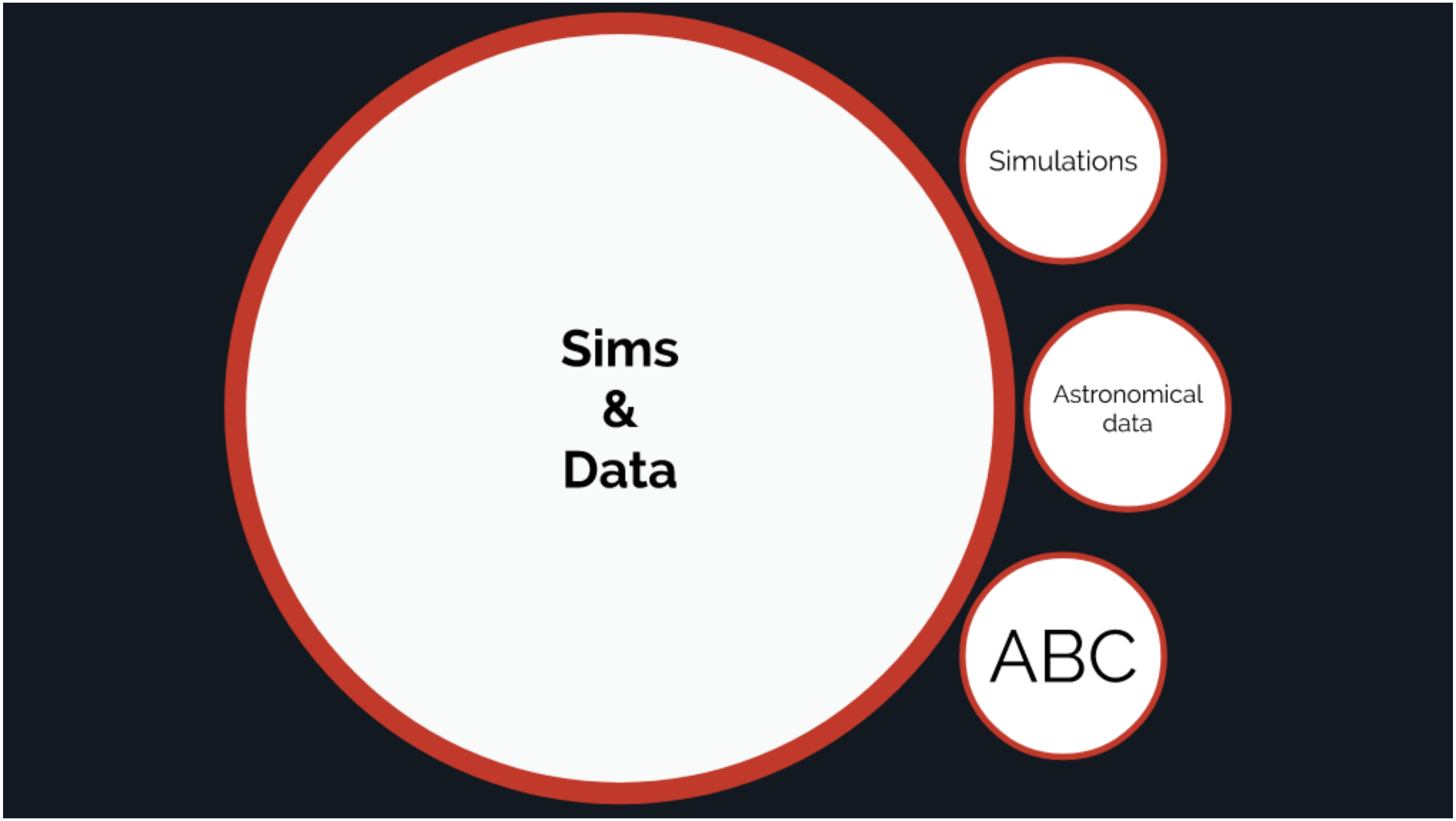

Sims
&
Data
Simulations
Astronomical
data
ABC

Simulations

Simulations (generative models) are the backbone of a forward modelling approach

Forward modelling has been done in other areas (high enegry particle physics and CMB)

Applying these ideas to the late-time universe allows for new inovations (complex fields and modern methods)

UCat

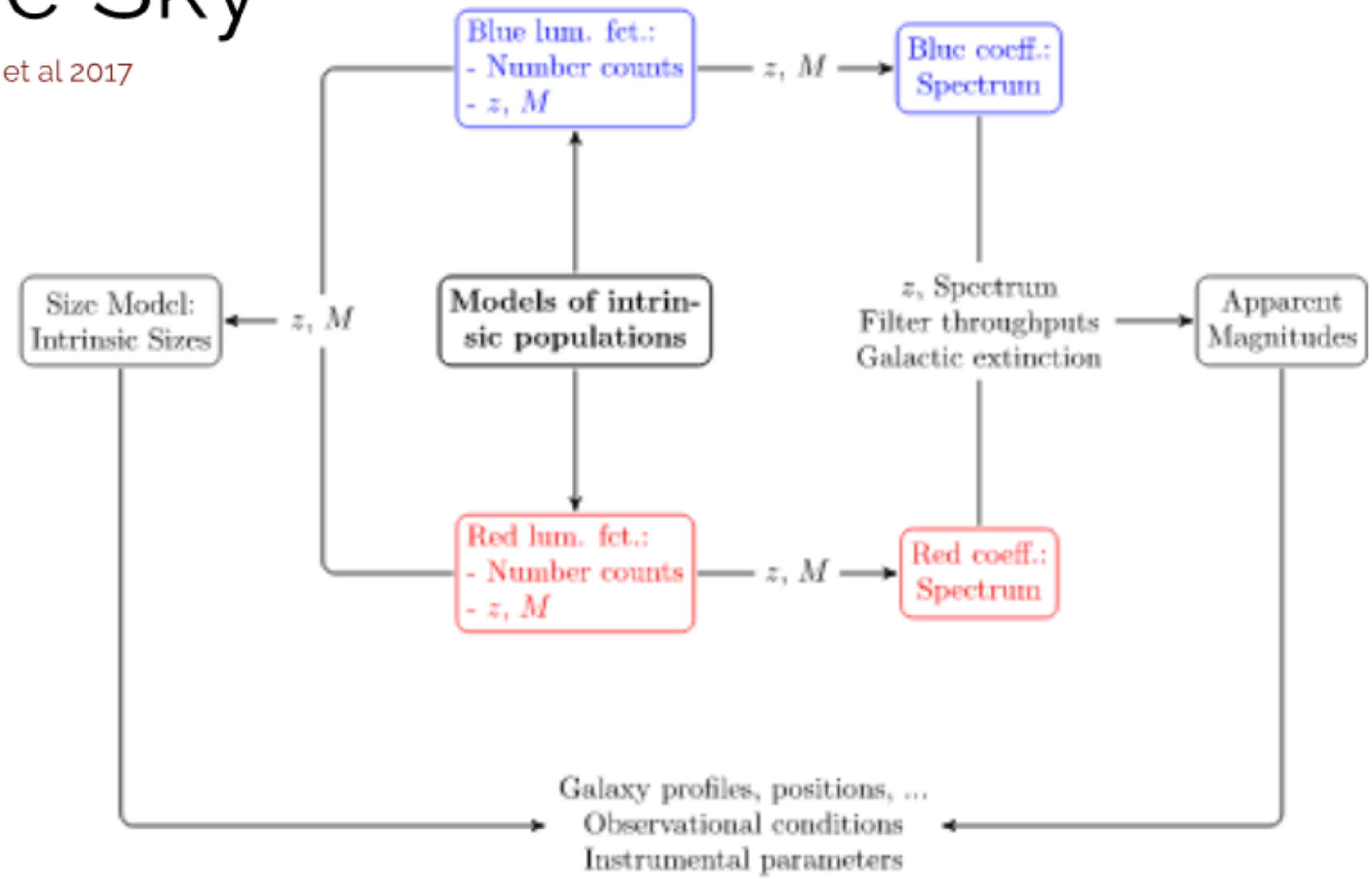
UFig

USpec

UFalcon

The Sky

Herbel et al 2017



UCat

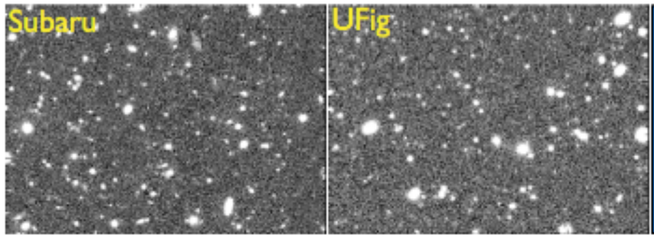
UFig

USpec

UFalcon

Image Rendering

Berge et al 2013



Speed the driving factor

As fast as SExtractor (or faster)
Subaru Image (0.25 deg2,R~26,10kx8k) generated in:
- 30sec on a laptop
- 30μsec per galaxy

HOPE: A Python Just-In-Time compiler for astrophysical computations

Akeret et al 2014
http://hope.phys.ethz.ch

	Python (NumPy)	Numba	Cython	Nuitka (NumPy)	PyPy (NumPy)	numexpr (8 cores)	HOPE	C++
Fibonacci	57.4	65.7[a]	1.1	26.7	21.1	—	1.1	**1.0**
Quicksort	79.4	—[b]	4.6	61.0	45.8	—	1.1	**1.0**
Pi sum	27.2	**1.0**	1.1	13.0	**1.0**	—	**1.0**	**1.0**
10^{th}order	2.6	2.2	2.1	1.2	12.1	1.4	1.1	**1.0**
Simplify	1.4	1.5[ab]	1.8	1.4	23.2	0.6	**0.015**	1.0
Pairwise distance	1357.8 (8.7)	1.8	**1.0**	1247.7 (9.5)	277.8 (60.4)	—	1.7	**1.0**
Star PSF	265.4	250.4[a]	46.2	234.6	339.5	—	2.2	**1.0**

Several image simulatin tools in WL:
Phosim, Balrog, GalSim

UCat

UFig

USpec

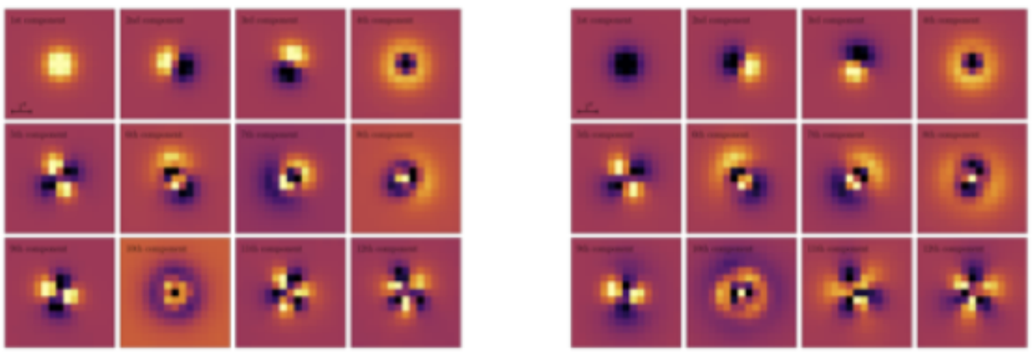
UFalcon

PSF modeling with deep learning

Herbel et al 2018

UFig includes modeling of several instrumental and observational features.
One important example is the PSF:

$$\theta''_i = A_{ij}\theta'_j + D_{ijk}\theta'_j\theta'_k + E_{ijkl}\theta'_j\theta'_k\theta'_l.$$



Paulin-Henriksson, AA+ 2008
Paulin-Henriksson, Refregier & AA 2009
AA+ 2010
Cypriano, AA+ 2010
Voigt, Bridle, AA+2012
Kacprzak,..., AA+2012
Refregier, Kacprzak, AA+ 2012
Refregier & AA 2014

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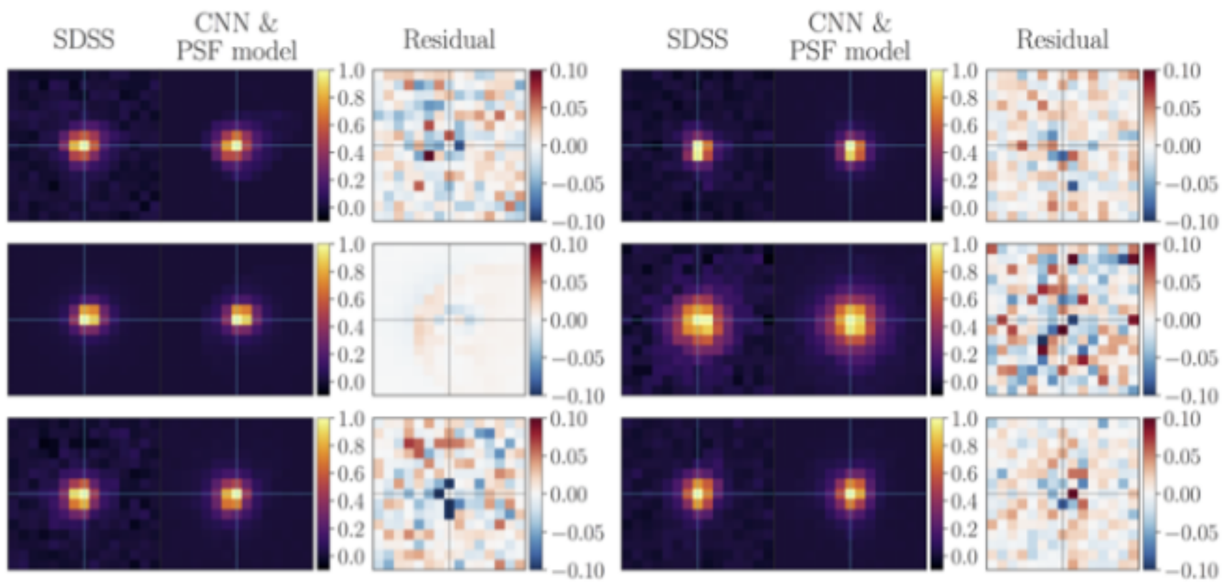


UCat

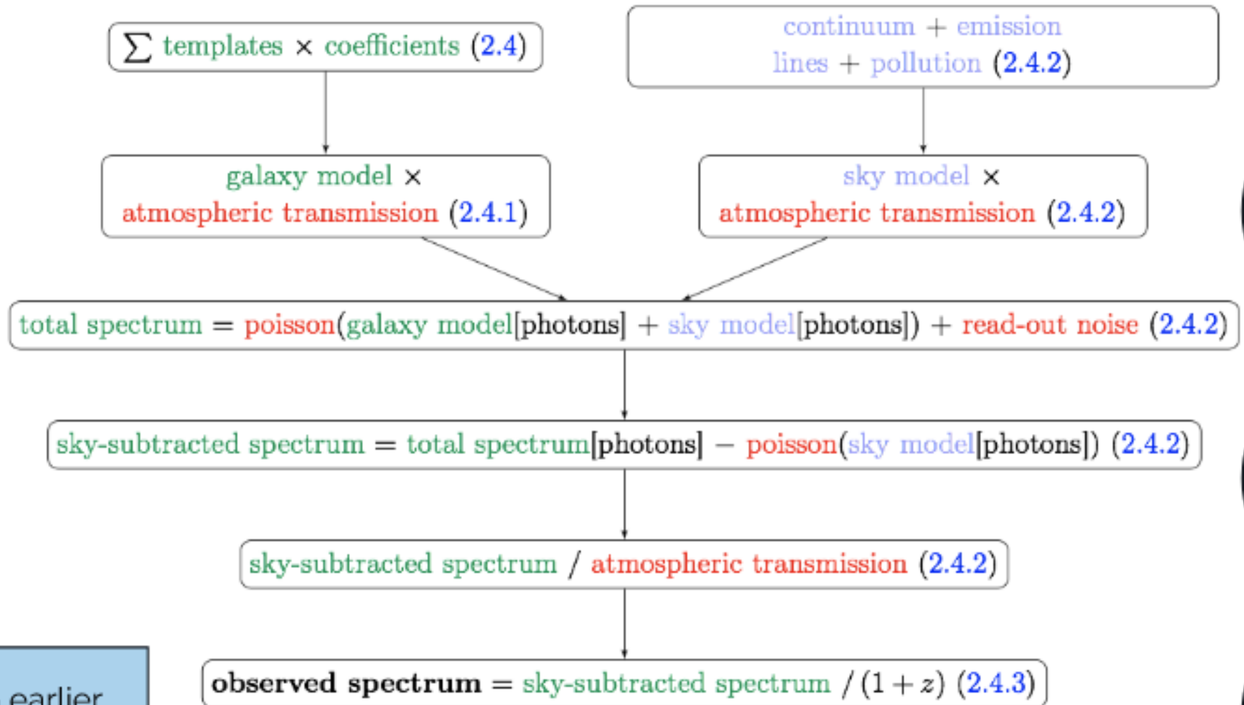
UFig

USpec

UFalcon

Rendering Spectra

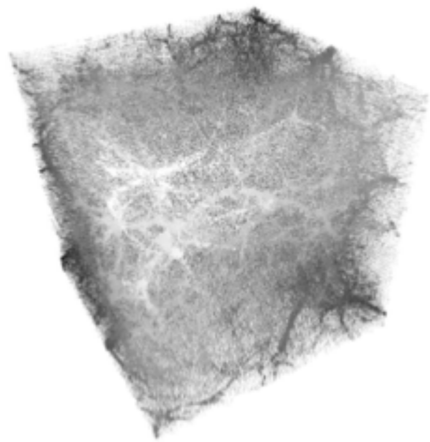
Fagioli et al (in prep 2018)

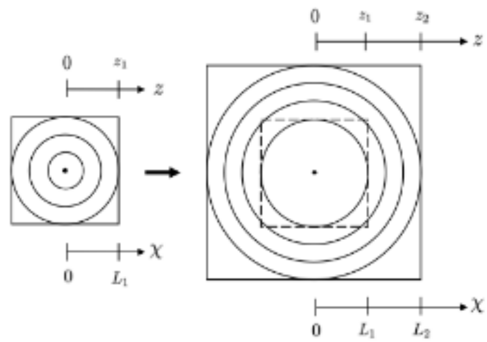


Building from SPOKES, an earlier work on a spectroscopic simulator for DESSpec and DESI (Nord et al 2016).

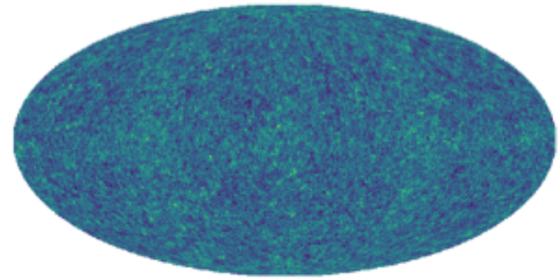
Cosmology

Sgier et al (2018)

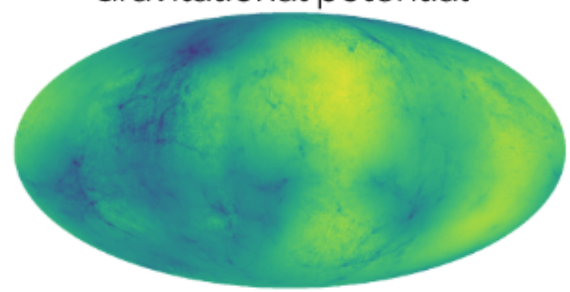




Lensing convergence



Gravitational potential



UCat

UFig

USpec

UFalcon

Gadget — 4 days

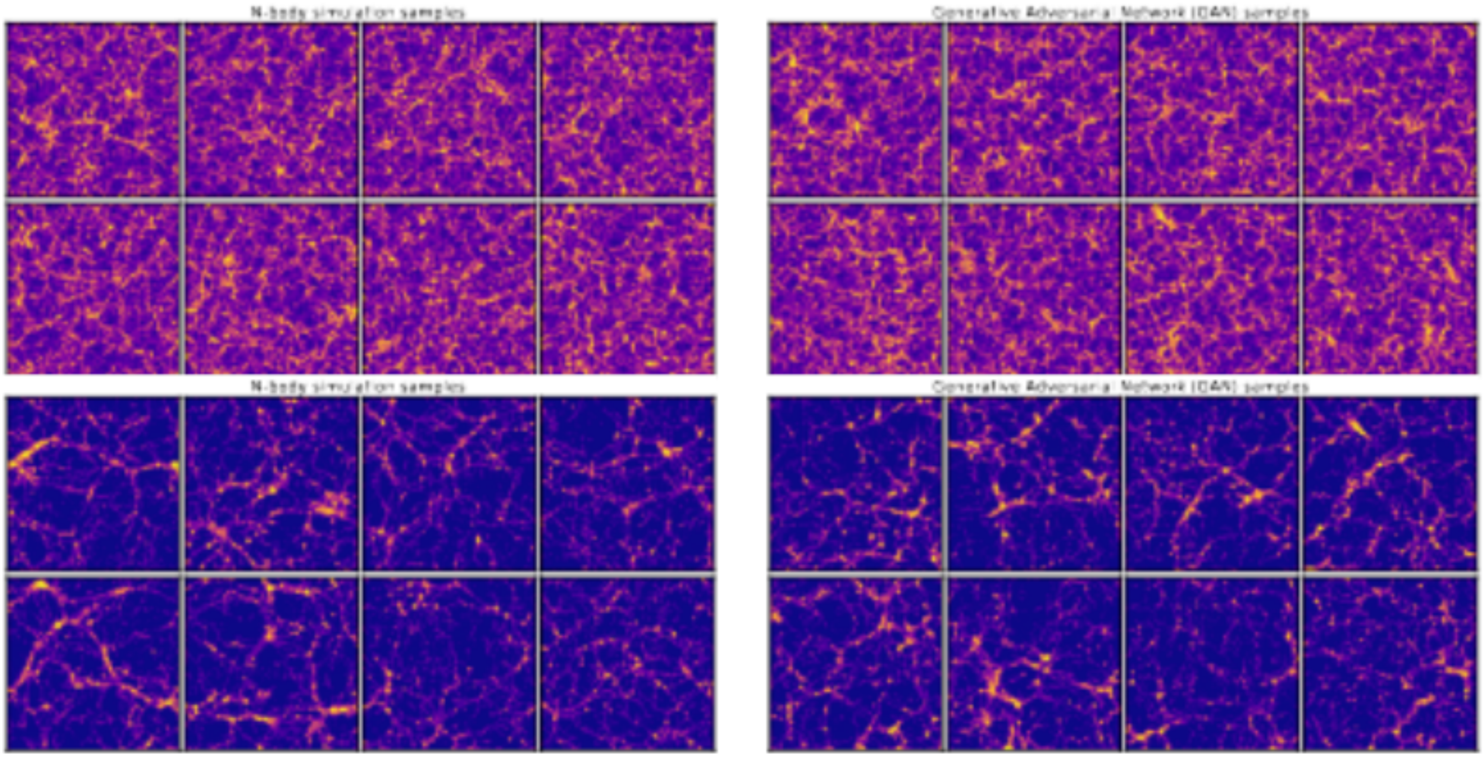
L-PICOLA (N-Body + LPT) — 3 hours

→ Lightcone → Observable fields → covariance

Tassev, Zaldarriaga, Eisenstein (2013), Howlett et al. (2015)

Cosmology

Rodriguez et al (in prep 2018)



Possible future: GANs? Instead of days and hours, we could generate thousands a second!!

UCat

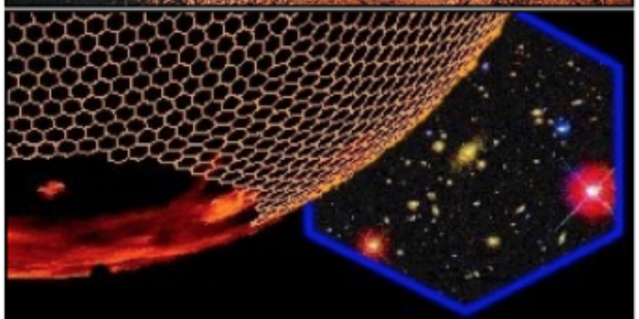
UFig

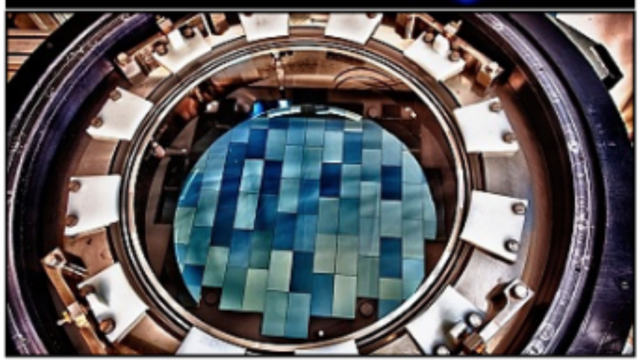
USpec

UFalcon

Astronomical data

In a **multi-probe**, **multi-experiment** era,
we need to combine several data sets.

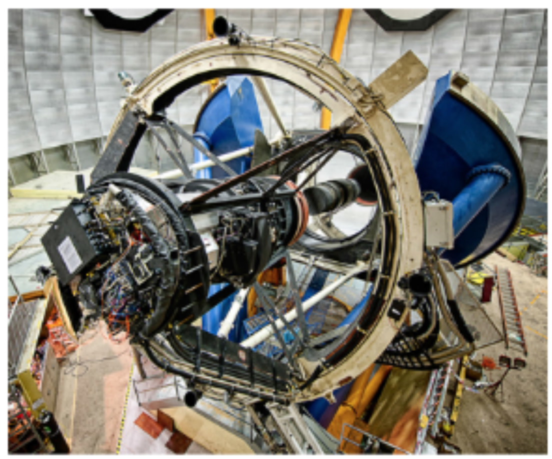


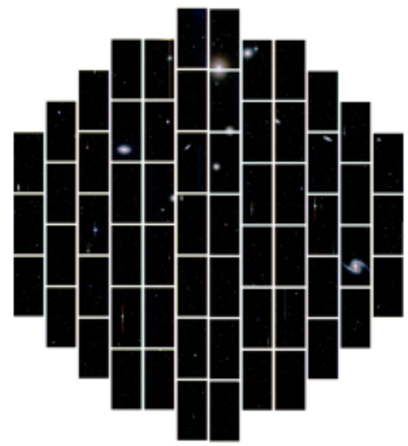


The Dark Energy Survey

First light
12 September 2012

Cosmology targeted experiment





DES
(Broad Band)

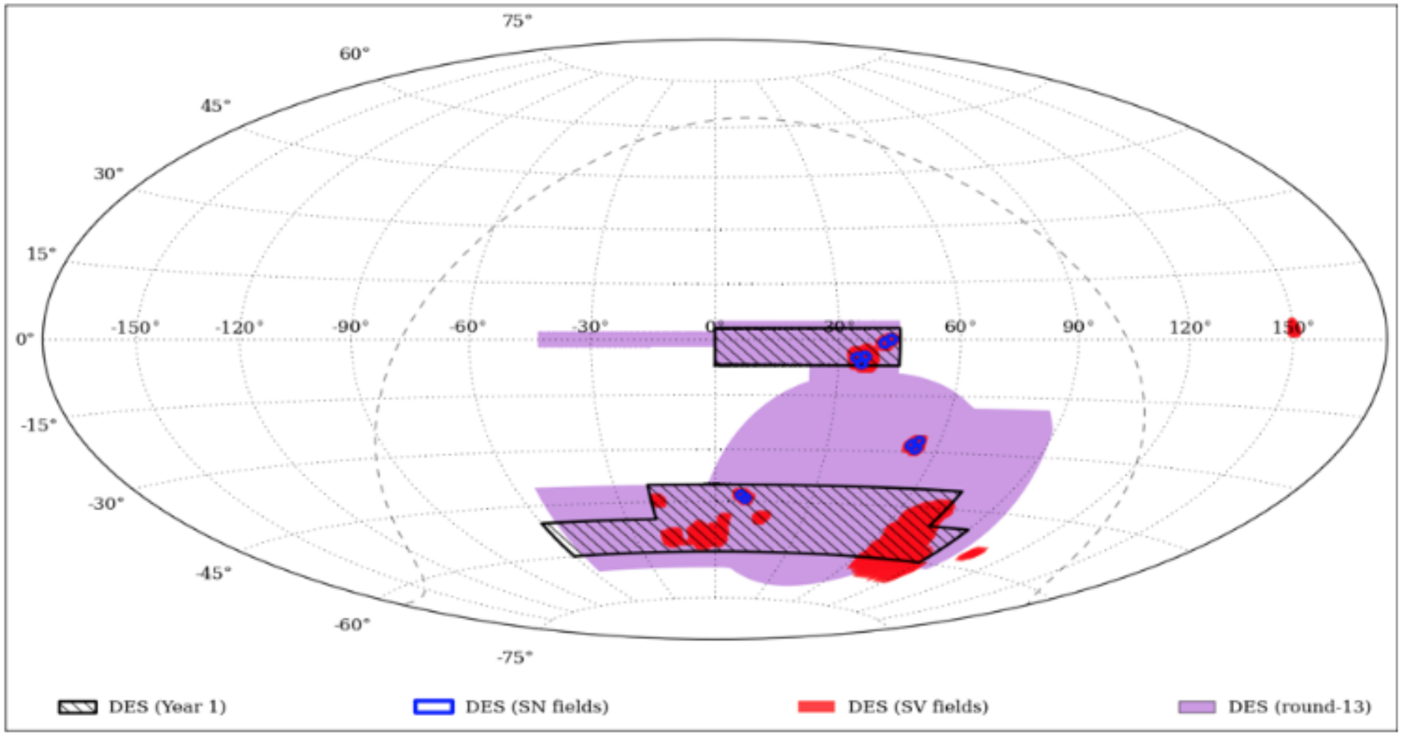
Subaru
(Broad Band)

PAU
(Narrow Band)

Spectroscopic Samples

Sloan
(Spectra)

Survey footprint



DES (Broad Band)

Subaru (Broad Band)

PAU (Narrow Band)

Spectroscopic Samples

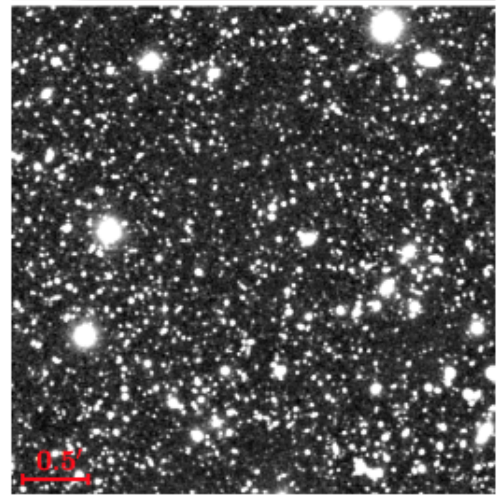
Sloan (Spectra)

Deep Broad Band

Publically available data
e.g. Suprime-Cam of COSMOS field

- 1.85 square degrees
- four bands (g+, r+, i+, z+)
- depth in r band ~27

(for more details see Capak et al 2008)



DES
(Broad Band)

Subaru
(Broad Band)

PAU
(Narrow Band)

Spectroscopic Samples

Sloan
(Spectra)

PAU - Physics of the Accelerating Universe

DES
(Broad Band)

Subaru
(Broad Band)

PAU
(Narrow Band)

Spectroscopic
Samples

Sloan
(Spectra)

PAU Survey Collaboration

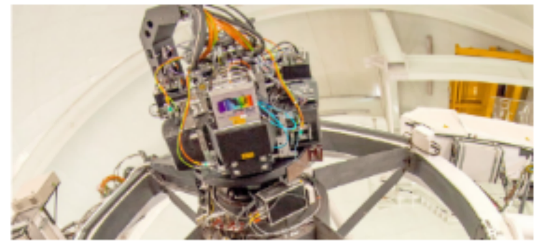
using PAUCam - 40 narrow band imaging
(13 nm wide in steps of 10 nm)

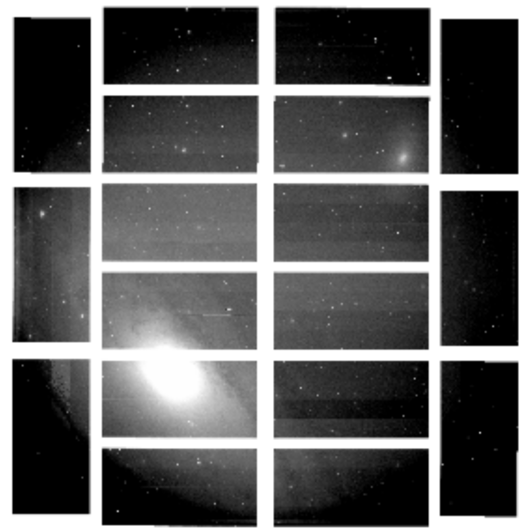
target:

- 100 square degrees
- iAB ~ 23-24

On going data collection (mostly TAC)

for more details see Castander et al 2012)





VIMOS VLT Deep Survey

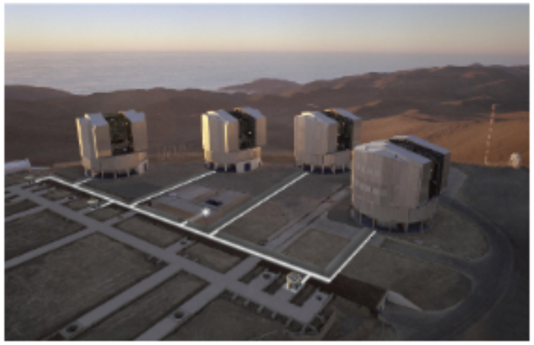
Publically available redshift sample

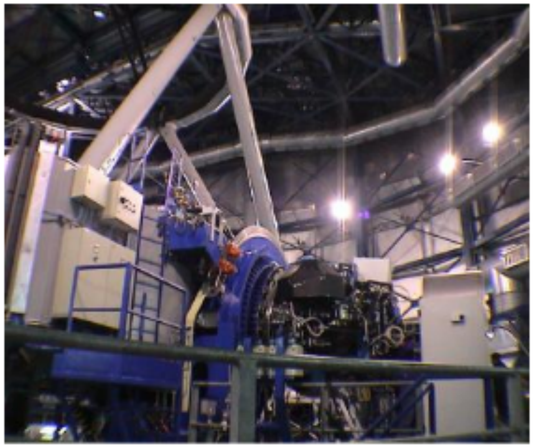
Three magnitue limited sub-surveys:

- VVDS-Wide: 17.5 < magi < 22.5
- VVDS-Deep: 17.5 < magi < 24.0
- VVDS-Ultra-Deep: 23 < magi < 24.75

Sample at the level of 10k galaxies

(see Le Fevre et al 2004 for more details)





DES (Broad Band)

Subaru (Broad Band)

PAU (Narrow Band)

Spectroscopic Samples

Sloan (Spectra)

Full spectra

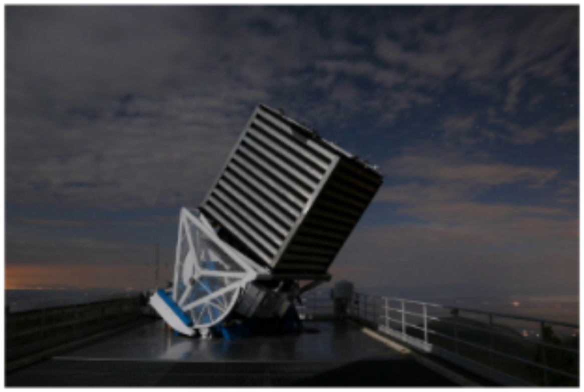
Public data as part of SDSS DR13

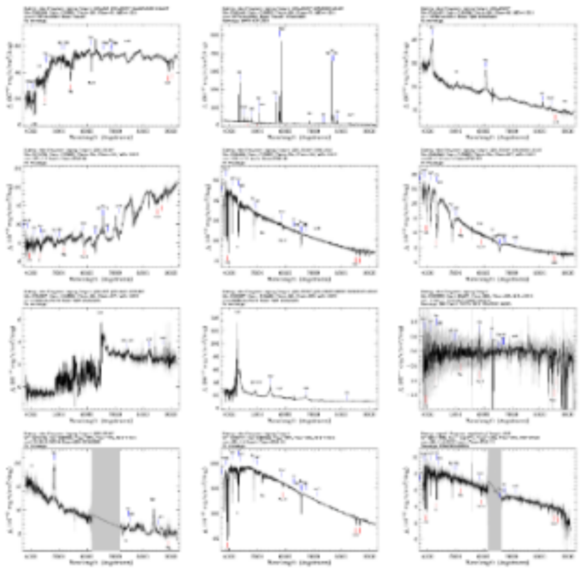
Imaging and spectroscopic data

BOSS survey (part of SDSS III)

~400 nm -> ~1000 nm

(for more details see Smee et al 2013)





DES
(Broad Band)

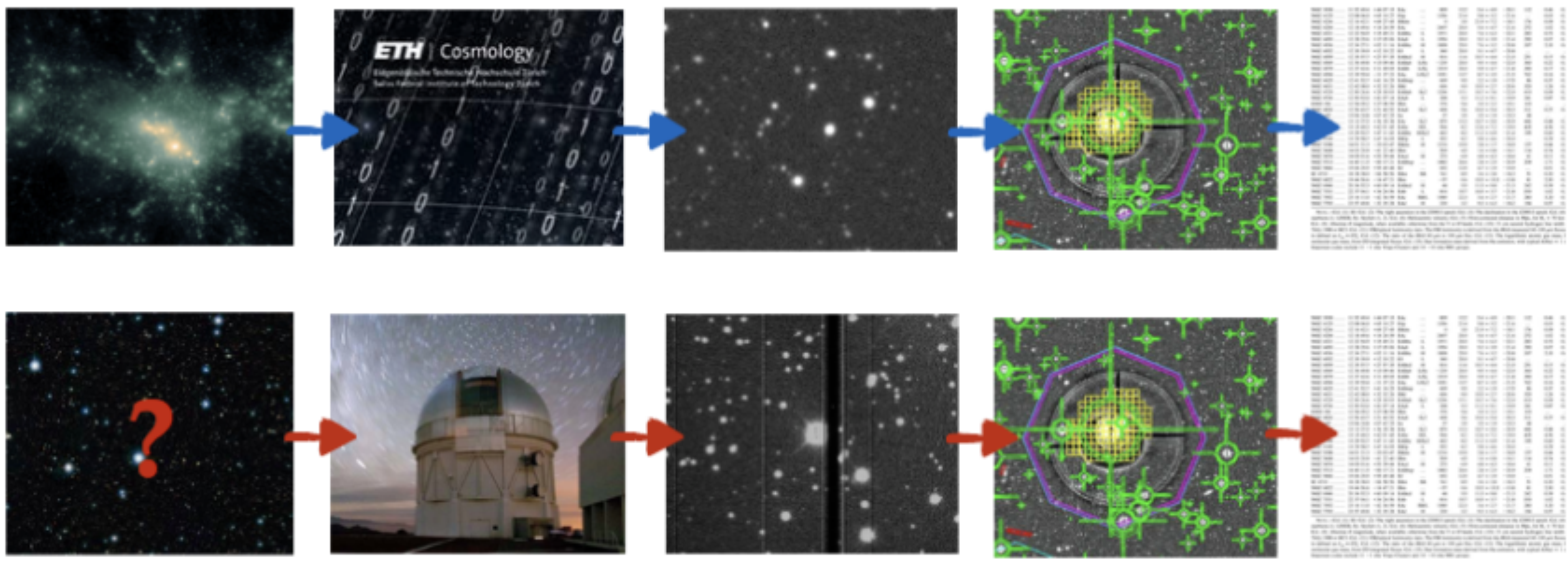
Subaru
(Broad Band)

PAU
(Narrow Band)

Spectroscopic Samples

Sloan
(Spectra)

ABC



The problem: Comparing catalogs, it is hard to calculate a likelihood. So how do we do a proper probablistic analysis? -> **Approximate Baysian Computation** (ABC)

Recap of Baysian analysis

$$p(\theta|x) = \frac{p(x|\theta)p(\theta)}{p(x)}$$

Requires a calculation of the likelihood, which accounts for the error model.

Often, we cannot calculate the likelihood, but we can simulate the data (called either forward modelling or generative models)

if x is the data and x' is the simulated (generated data):

$$p(\theta|x) \approx p(\theta|\rho(x, x')) \leq \epsilon)$$

Seems like magic, but it is right

A simple example where we want to measure the mean of a Gaussian IID process, with flat prior.

Baysian result:

$$p(\theta|x) = \left(\frac{n}{2\pi\sigma^2}\right)^{1/2} \exp\left[-\frac{n(\theta-\bar{x})^2}{2\sigma^2}\right] \quad ; \quad \mathrm{var}[\theta] = \frac{\sigma^2}{n}$$

ABC result:

$$p(\theta|\rho<\epsilon) = \frac{1}{2\epsilon}\left[\Phi\left(\frac{\bar{x}-\theta+\epsilon}{\sigma/\sqrt{n}}\right) - \Phi\left(\frac{\bar{x}-\theta-\epsilon}{\sigma/\sqrt{n}}\right)\right] \quad ; \quad \mathrm{var}[\theta|\rho<\epsilon] = \frac{\sigma^2}{n} + \frac{\epsilon^2}{3} \quad \lim_{\epsilon\to 0}$$ Baysian result

$$\Phi(t) = \left[1+\mathrm{erf}(t/\sqrt{2})\right]/2$$

Challenges

ABC method is powerful and simple, but it can be compuationally challenging. The key (again) is fast generators, efficient distances choices and clever algorithms.

- **Brute force:**
  random samples from the prior and rejection
  Simple, robust, but very time consuming
  (see Herbel et al 2017 for an example)

- **ABCPMC:**
  Population Monte Carlo that reduces the threshold in steps
  Efficient but difficult to implement
  (see Akeret et al 2015 for an example)

- **qABC:**
  ABC accelerated with quantile regression
  Excludes very unlikly parts of the prior, increases efficiency
  (see Kacprzak et al 2017 for more details)