Cosmology with imaging surveys – from precision to accuracy

NYU

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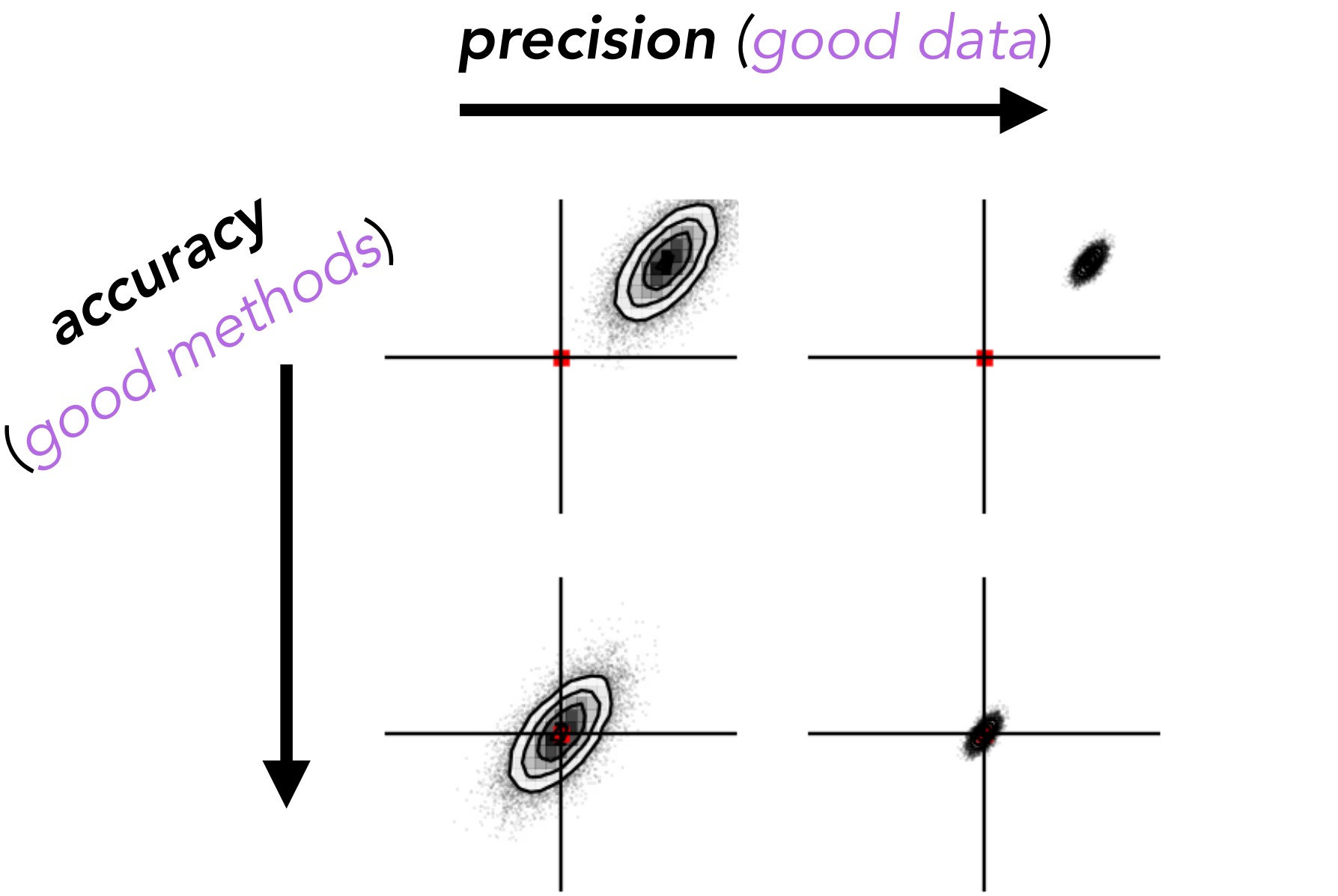
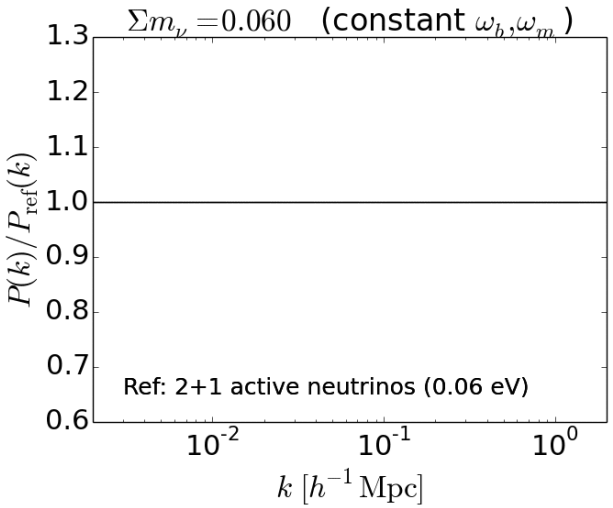


observational systematics are the next frontier

models

Fundamental physics:
inflation, neutrinos, dark energy, modified gravity

Dark matter & baryons
on large & small scales



observables

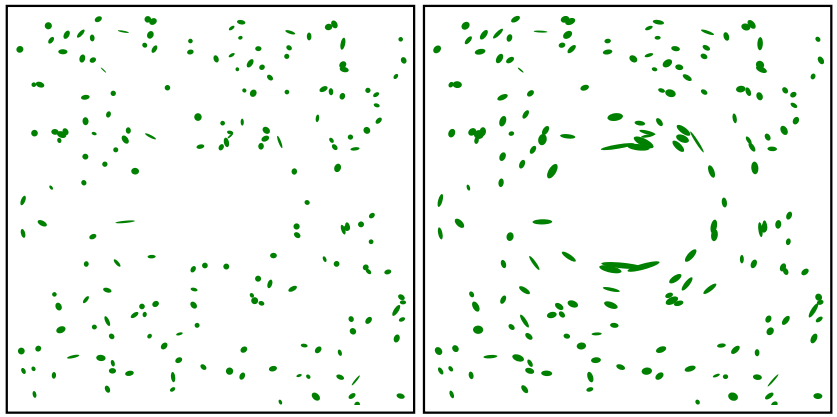
Galaxy clustering

Baryon acoustic oscillations

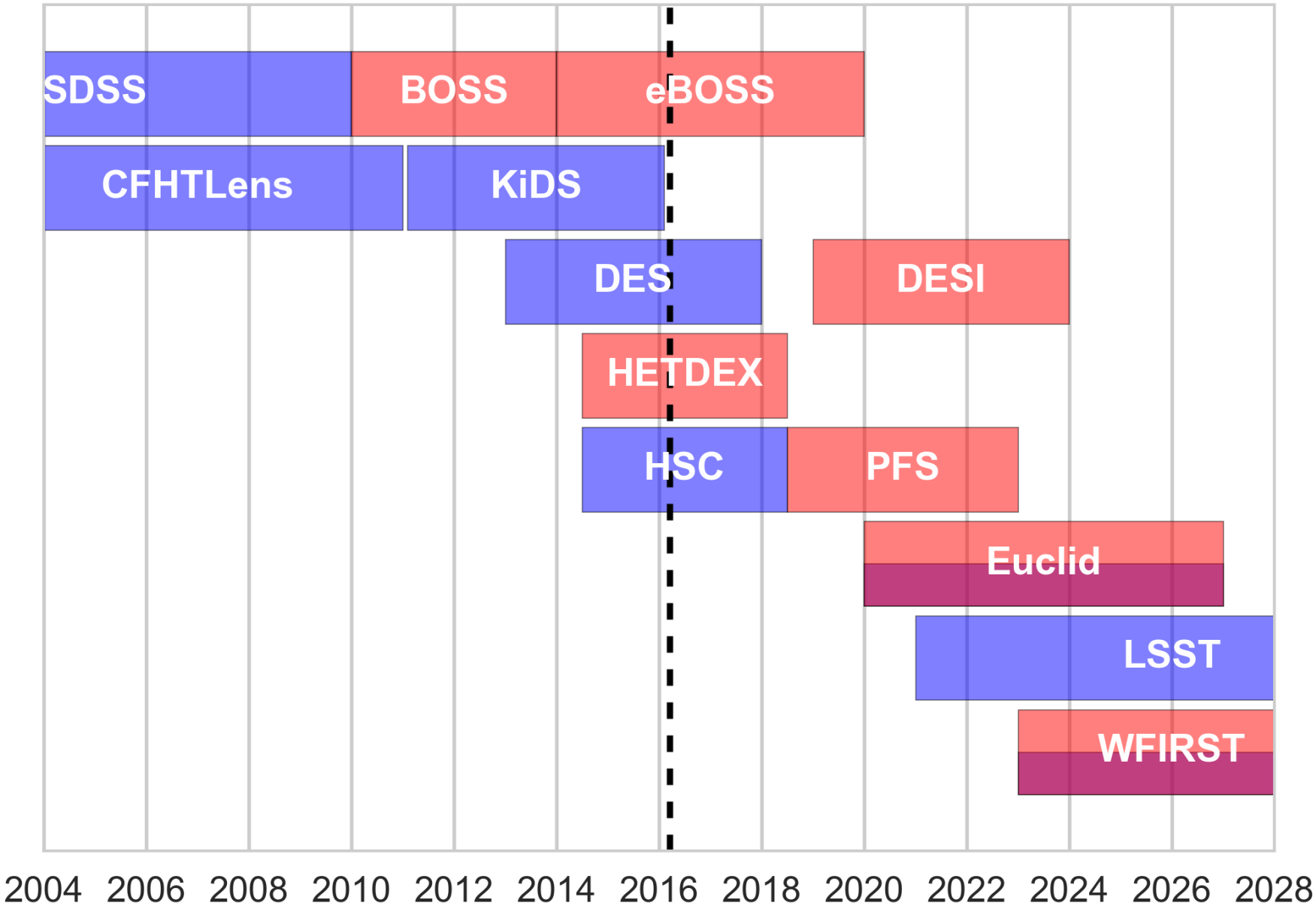
Redshift-space distortions

Gravitational lensing

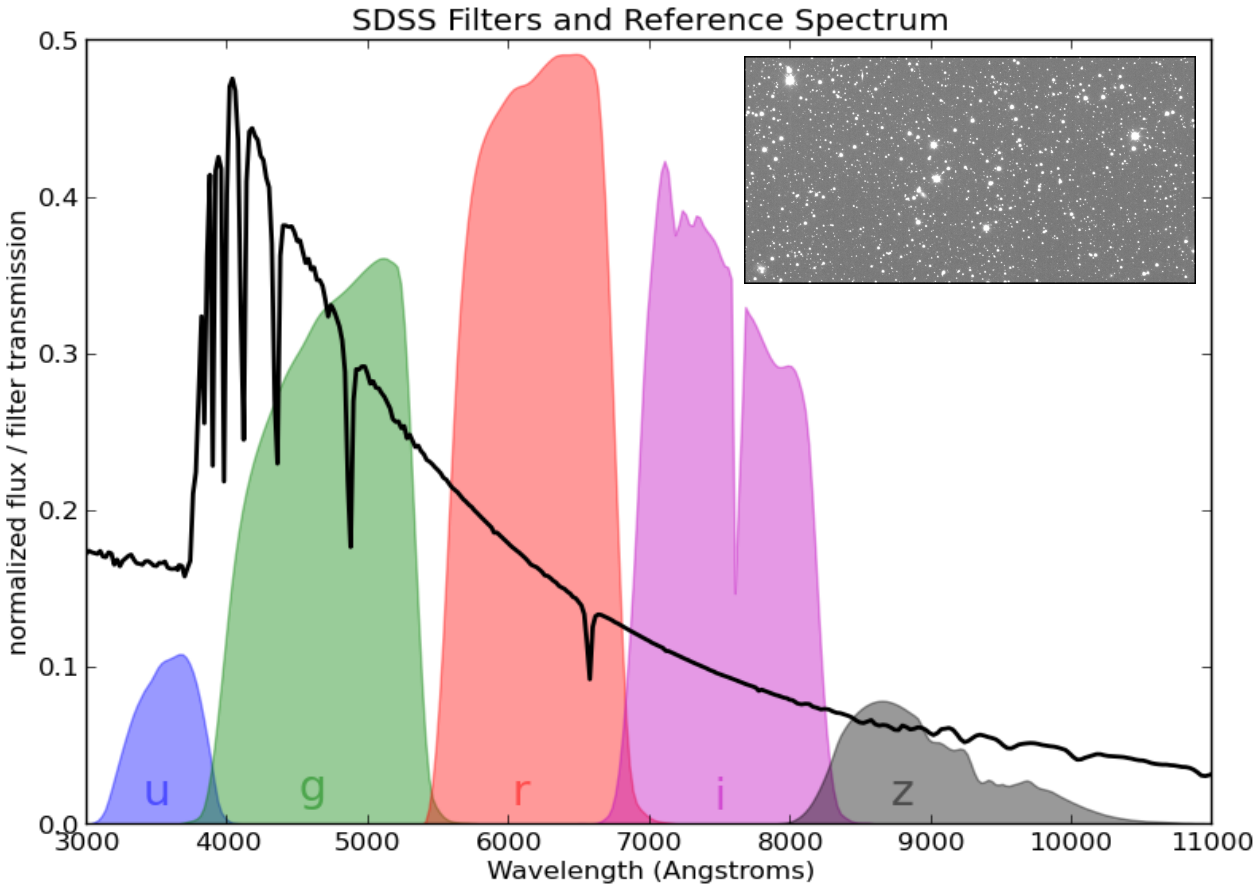
Galaxy clusters



experimental landscape



photometric galaxy surveys



✓ CCD images

✓ deep

✓ shear

✗ no types

✗ no redshifts

***Challenge**: construct uniform, pure galaxy catalog with redshift estimates*

spectroscopic

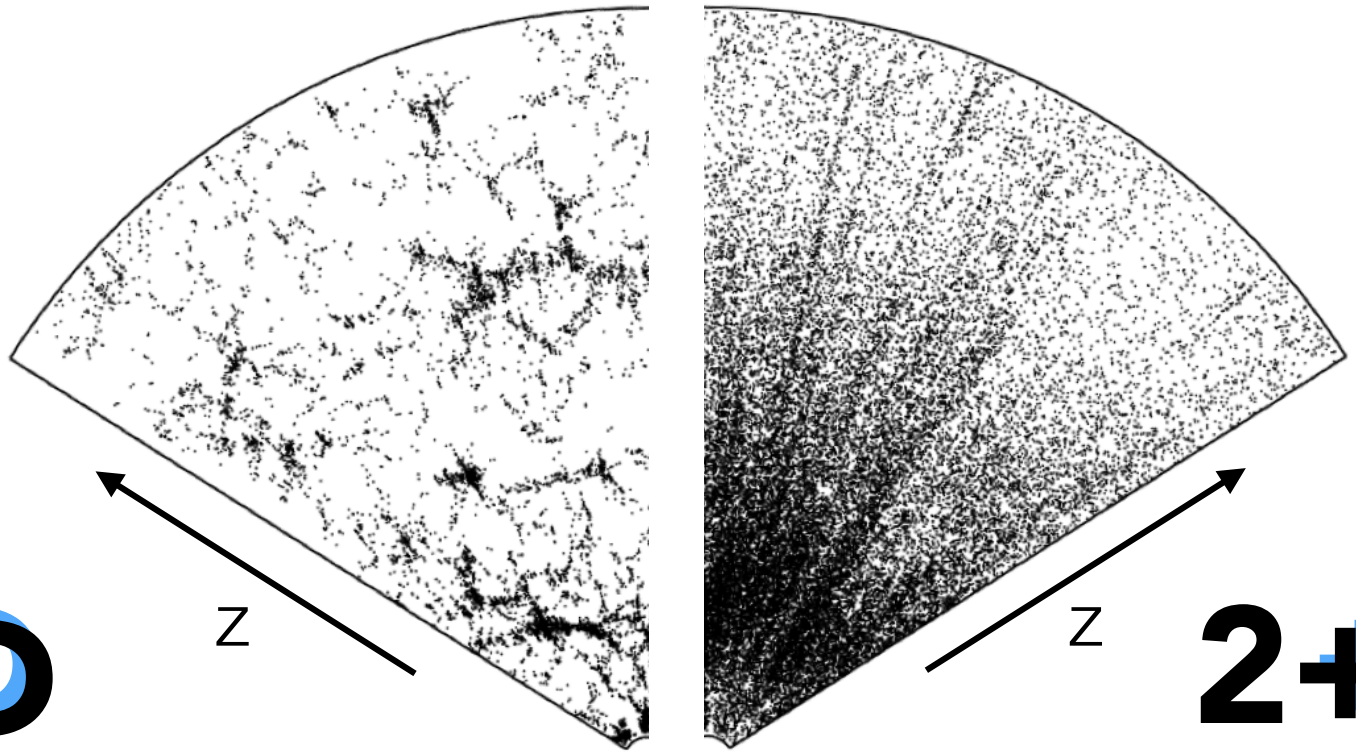
✓ types + redshifts

✗ shallow

photometric

✗ no types / redshifts

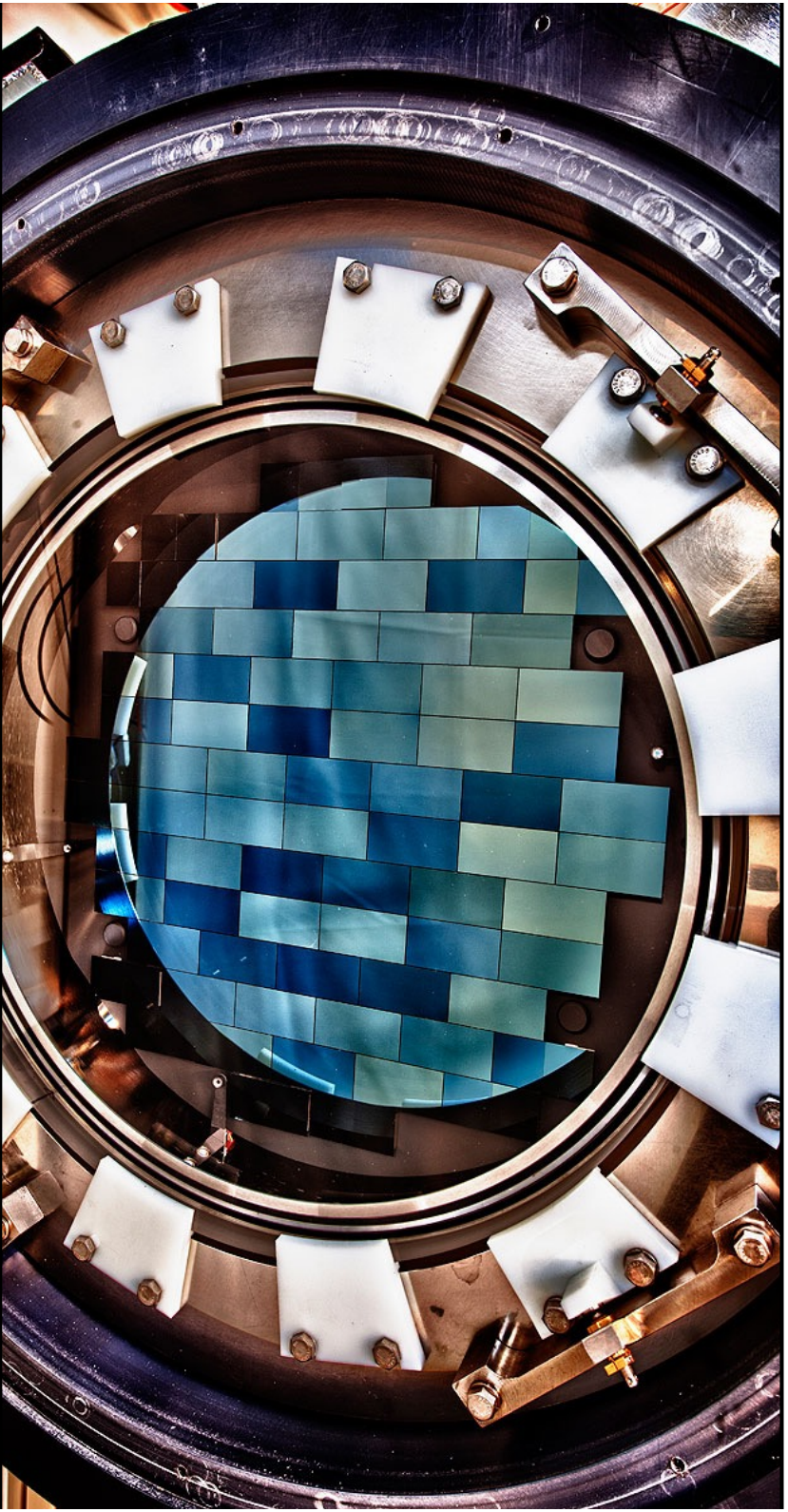
✓ deep



3D

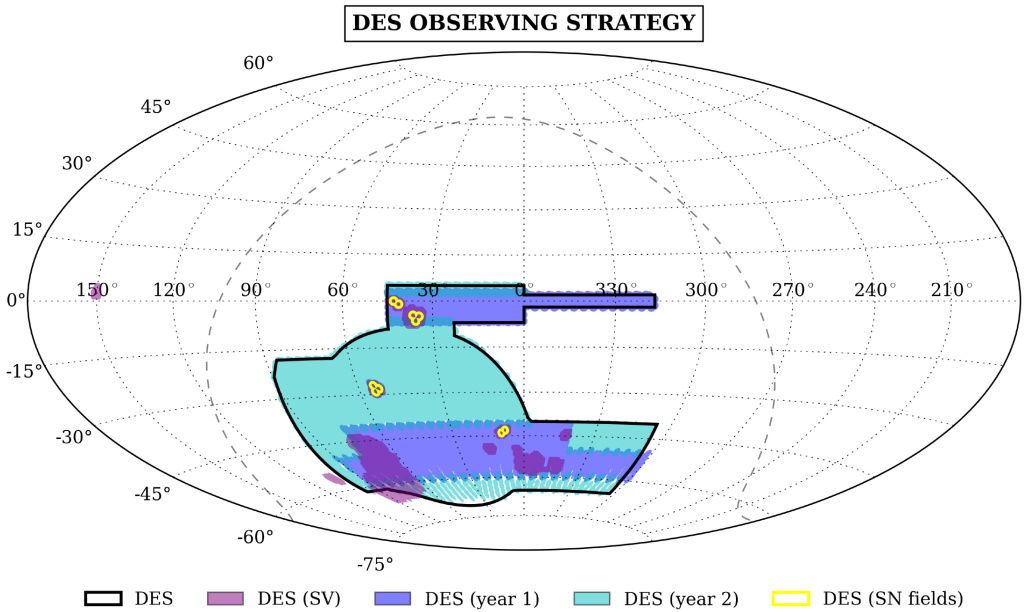
2+1D

credit: Aragon-Calvo et al (2014)



DES (2013-2018) — The Dark Energy Survey

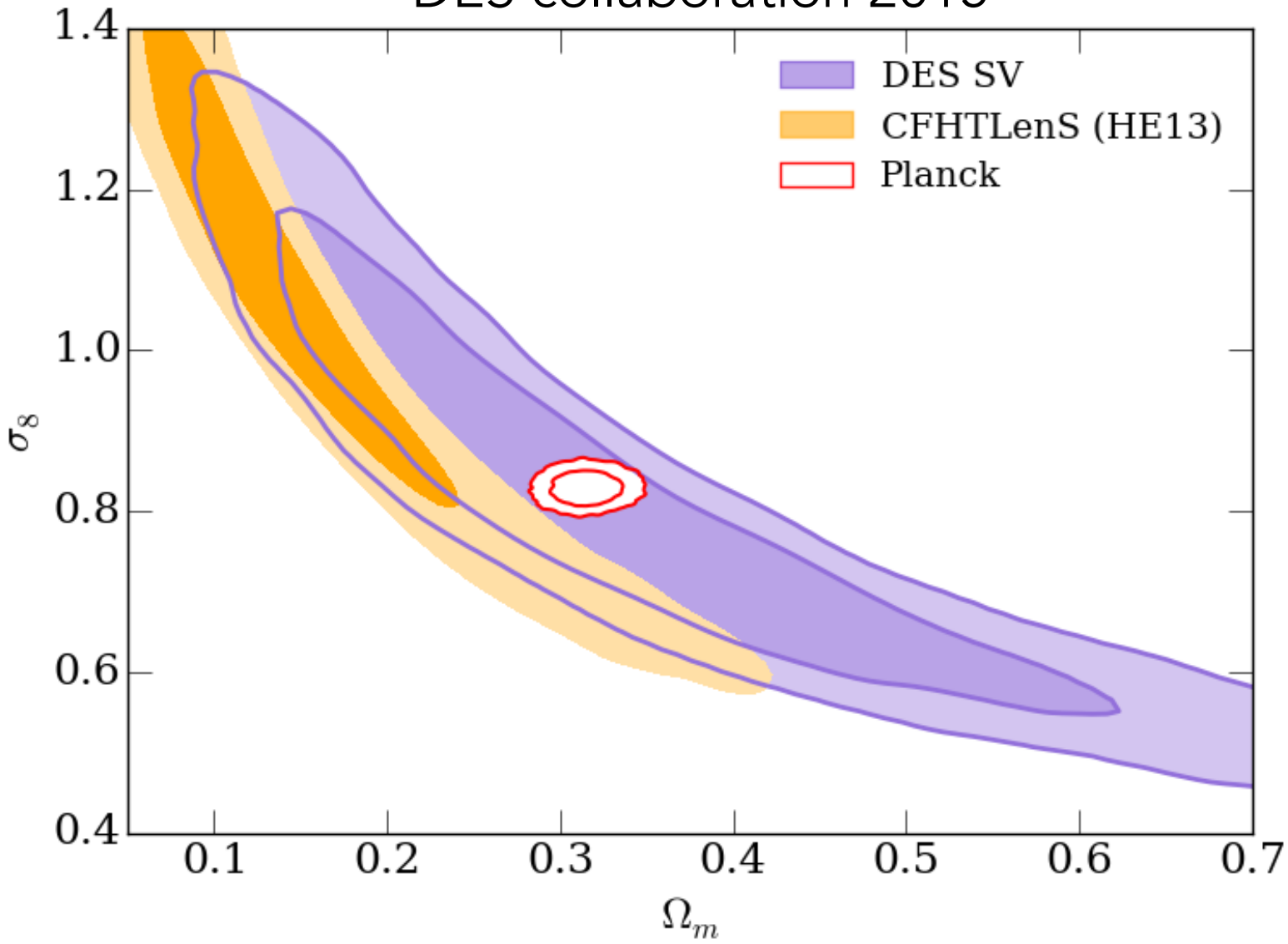
4 standard observational probes:
galaxy clustering, galaxy lensing,
supernovae, clusters
+ **cross-correlations**



Over 60 papers already — some highlights:

- **Galaxy-Galaxy Lensing**, *Clampitt et al*, arXiv:1603.05790
- **Cosmology constraints from shear peak statistics**, *Kacprzak et al*, arXiv:1603.05040
- **Weak lensing by galaxy throughs**, *Gruen et al*, arXiv:1507.05090
- **Mapping spatial systematics**, *Leistedt et al*, arXiv:1507.05647
- **Detection of the kinematic Sunyaev-Zel'dovich effect (DES Y1)**, *Soergel et al*, arXiv:1603.03904
- **DECam Search for an Optical Counterpart to the First Advanced LIGO Gravitational Wave Event GW150914**, *Soares-Santos et al*, arXiv:1602.04198
- **Cosmology from Cosmic Shear**, arXiv:1507.05552
- **CMB lensing tomography**, T. *Giannantonio et al*, arXiv:1507.05551
- **Wide-Field Lensing Mass Maps**, *Chang et al*, arXiv:1505.01871

DES collaboration 2015



Data vectors available at http://deswl.github.io/

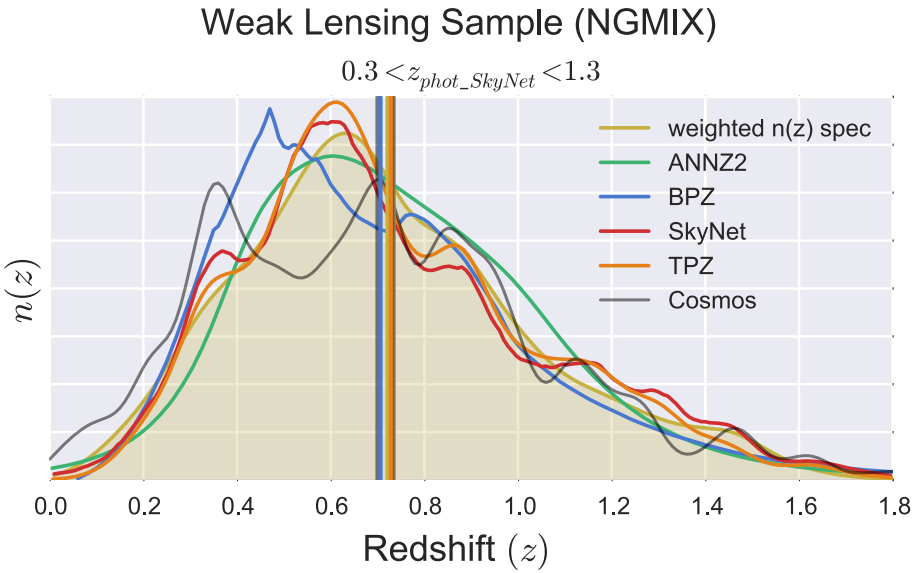
First BAO and multi-probe cosmology coming soon!

photometric redshifts

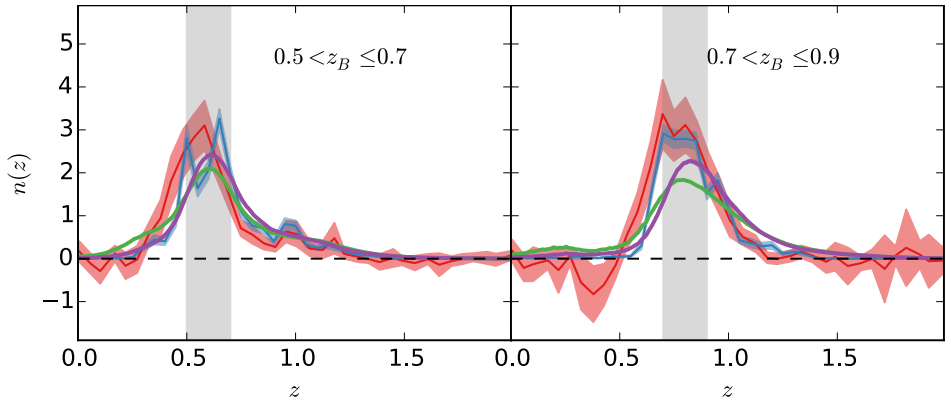
for galaxy clustering & cosmic shear

State of the art

DES SV data
(arXiv:1507.05909)

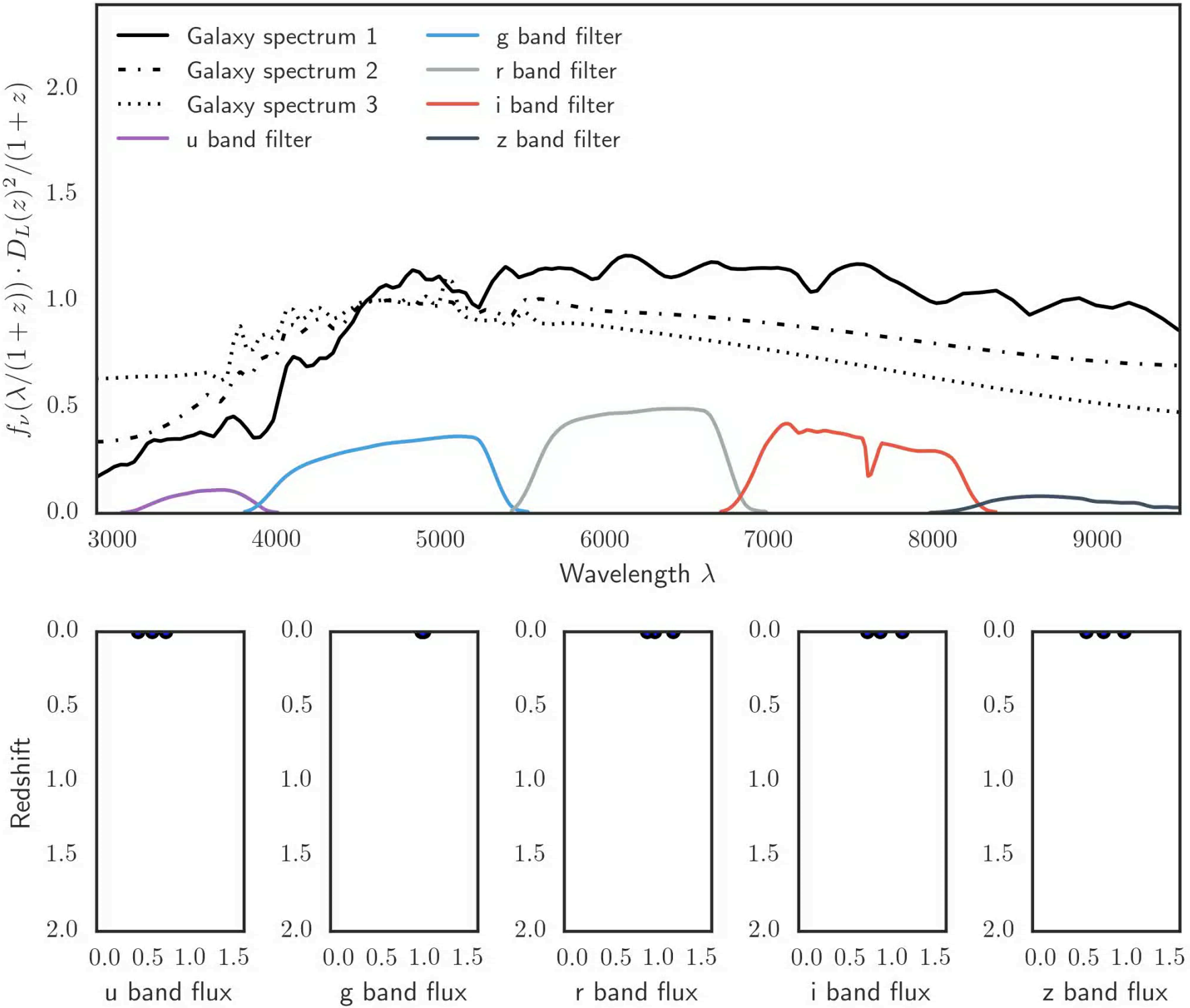


KIDS data
(arXiv:1606.05338)



Ongoing surveys don't meet
photo-z requirements

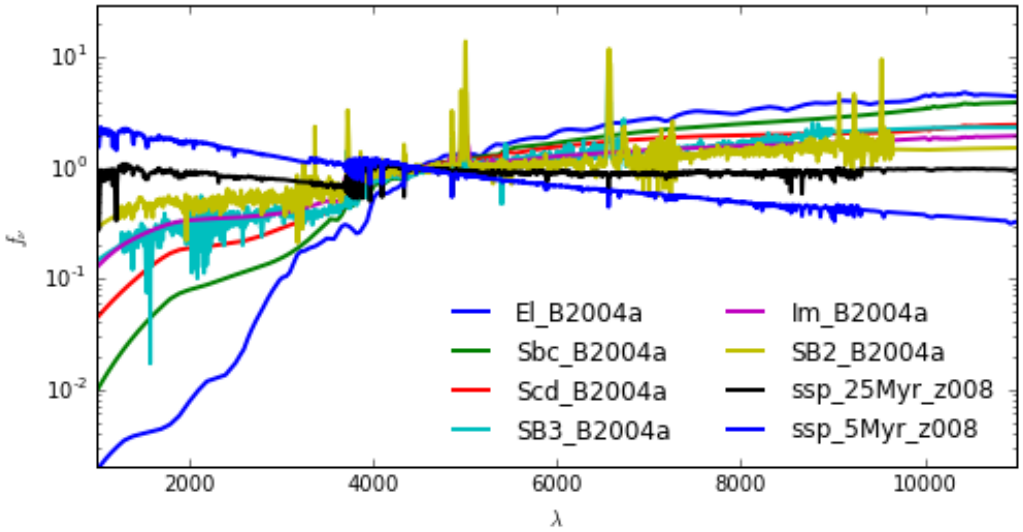
LSST requires
insanely precise photo-z's


Galaxy spectrum 1
Galaxy spectrum 2
Galaxy spectrum 3
u band filter
g band filter
r band filter
i band filter
z band filter
$f_\nu(\lambda/(1+z)) \cdot D_L(z)^2/(1+z)$
Wavelength λ
Redshift
u band flux
g band flux
r band flux
i band flux
z band flux

template fitting

- ✓ *physical model*
- ✓ *probabilistic*
- ✗ *need template set*
- ✗ *hard to capture data complexity*
- ✗ *sensitive to priors*

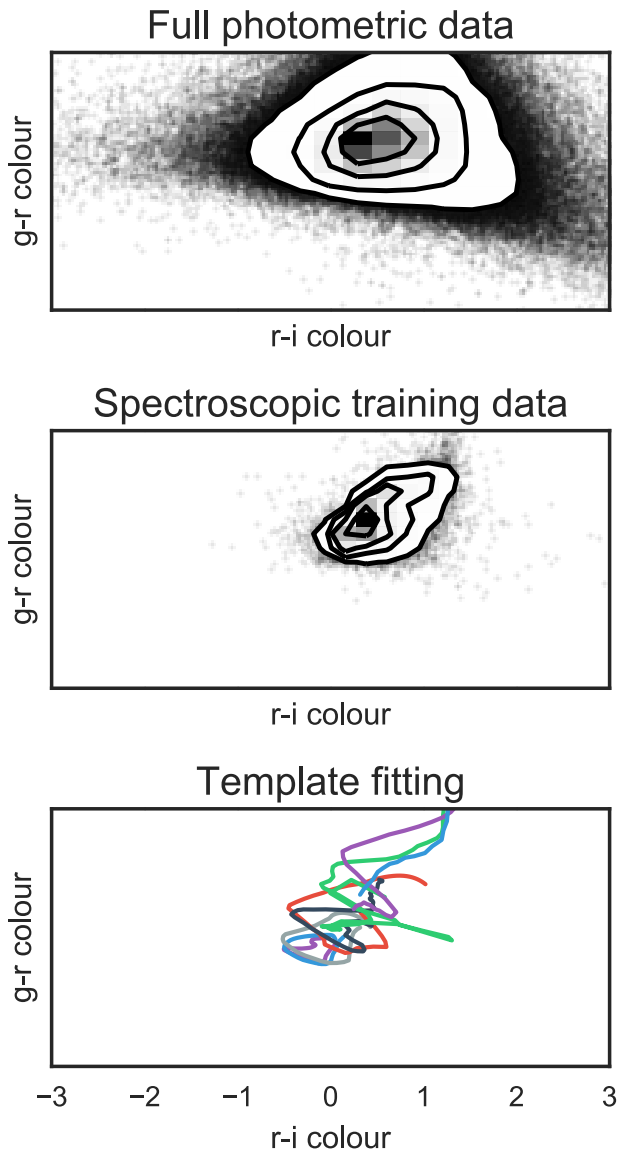
template set (CWW)



likelihood function

$$p(\{\hat{F}_b\}|z,t) = \prod_b \mathcal{N}(\hat{F}_b, F_b^{\rm mod}(z,t), \sigma_{\hat{F}_b})$$

machine learning



✓ *captures data complexity*

✓ *very flexible*

✗ *no physical model, solves for flux=>z, cannot extrapolate*

✗ *not probabilistic*

✗ *requires representative training data*

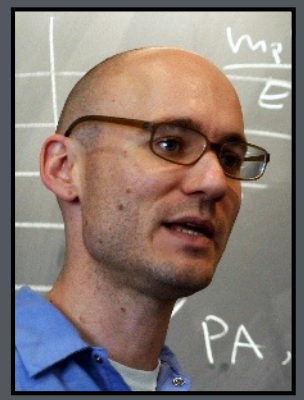
Will **never** have representative spectroscopic data

Galaxy SED models are not flexible/precise enough

Only deep spectroscopic & many-band surveys available

photometric redshifts with heterogeneous, incomplete training

with David Hogg (NYU)



New method: DELIGHT^{TM}

Template space: all SEDs fitting training galaxies

Pairwise comparisons: $p(\underbrace{\{\hat{F}'_b\}|z'}_{\text{target}}, t_i) = p(\{\hat{F}_b\}|z', \underbrace{z, \{\hat{F}_b\}}_{\text{training}})$

Tractable via **Gaussian Process** fitting/predicting fluxes while encoding physics of redshift

Training need not to be representative, only *diverse*.

Can consistently combine training sets (=use more data)

Why is Boris algorithm so good?

Hong Qin[1,2], Shuangxi Zhang[1], Jianyuan Xiao[1], Jian Liu[1], Yajuan Sun[3] and William M. Tang[2]

+ VIEW AFFILIATIONS

Phys. Plasmas **20**, 084503 (2013); http://dx.doi.org/10.1063/1.4818428

DELIGHT™

Theory: machine learning + template fitting

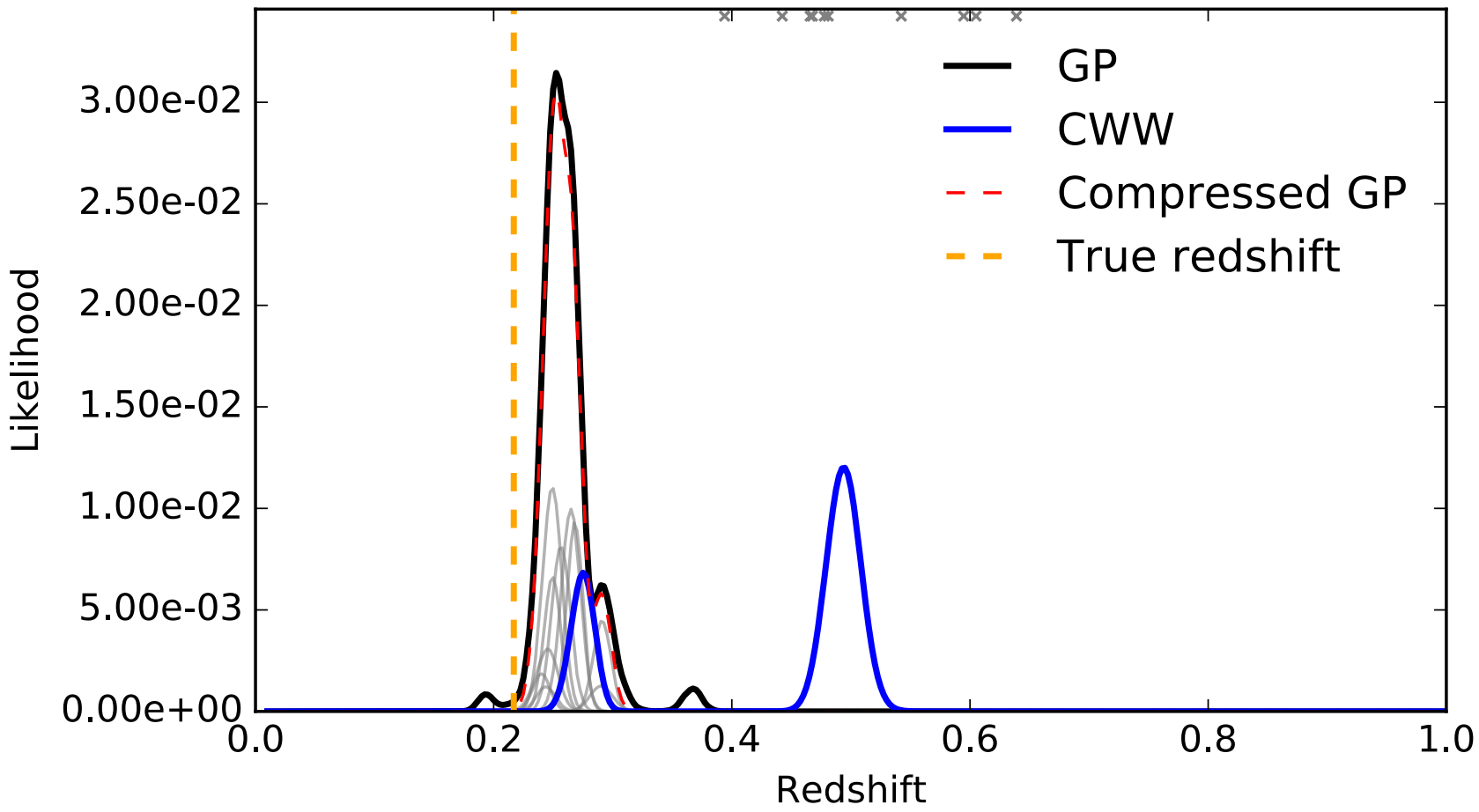
Meaning: interpretable model & PDFs

Speed: fast to train, re-train, apply to data

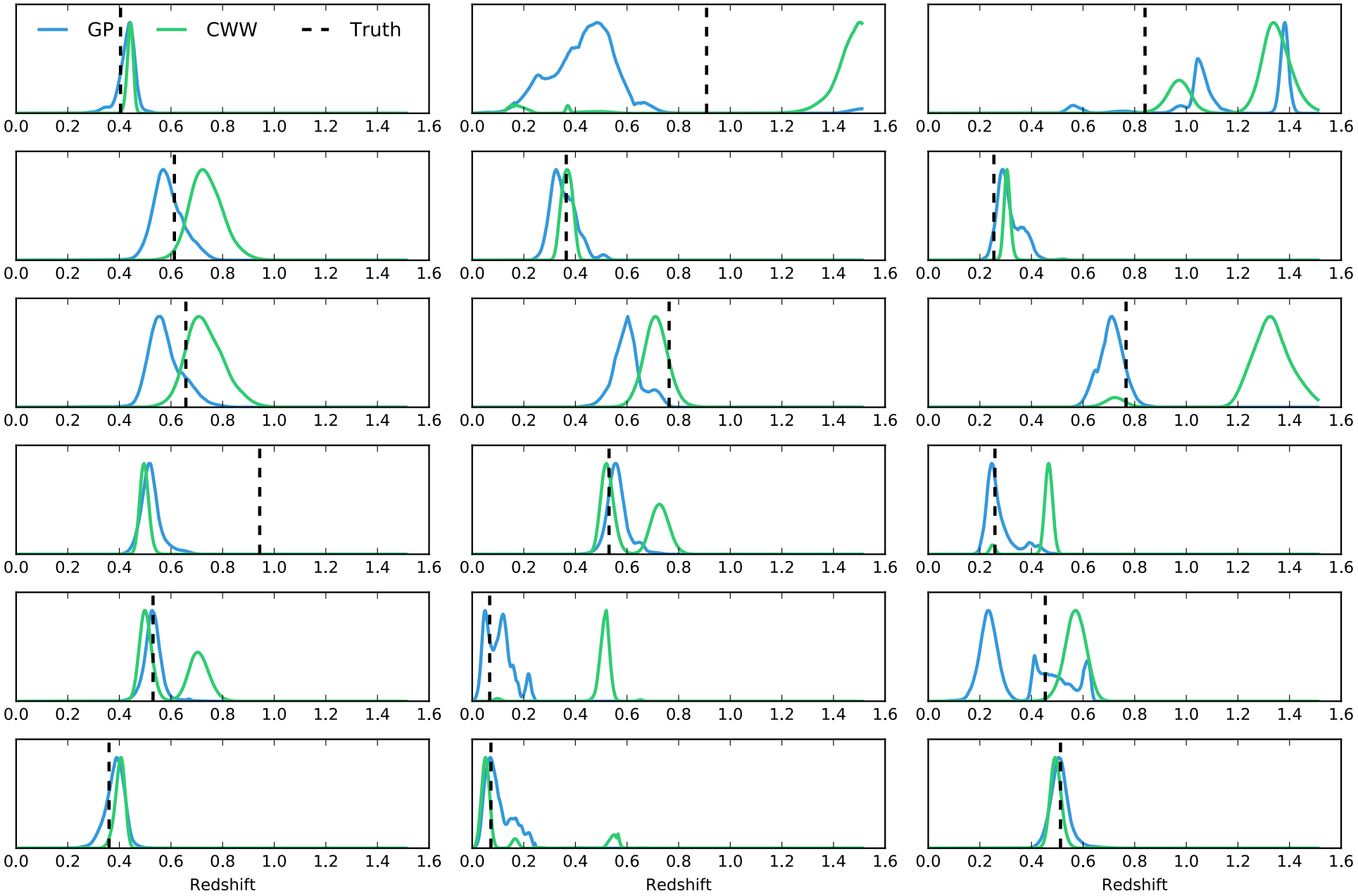
Storage: no need to store tabulated PDFs

Flexibility: hyperparameters optimization

Example: SDSS griz data with unrepresentative training set



Robust redshift probability distributions



What's next?

Robust redshifts for galaxy clustering/cosmic shear

Populating cosmological simulations
with realistic galaxy fluxes, types & redshifts

Density + velocity field reconstructions
with photometric and spectroscopic surveys

Conclusions

Imaging surveys

diverse science: fundamental physics, astrophysics
systematics limited — require exquisite photo-z's

DELIGHT

data-driven method with physics & machine learning
delivers accurate, interpretable redshifts probabilities

The future: LSST

exploit deep, diverse, non-overlapping training sets
capture & propagate redshift uncertainties