PETER MELCHIOR, JIM BOSCH, ROBERT LUPTON, DAVID SPERGEL (PRINCETON)

WFIRST & LSST

SYNERGIES AT THE PIXEL-LEVEL

MEASUREMENT PIPELINE: LEVEL 2

0a. Instrumental signature removal

0b. Image coaddition

1. Object detection

2. Object characterization

3. Deblending

MEASUREMENT PIPELINE: CURRENT STATE

0a. Instrumental signature removal

0b. Image coaddition

1. Object detection: SExtractor or likelihood coadds

2. Object characterization

3. Deblending

MEASUREMENT PIPELINE: CURRENT STATE

0a. Instrumental signature removal

0b. Image coaddition

1. Object detection: SExtractor or likelihood coadds
2. Object characterization: Direct vs model-based
3. Deblending

MEASUREMENT PIPELINE: CURRENT STATE

0a. Instrumental signature removal

0b. Image coaddition

1. Object detection: SExtractor or likelihood coadds

2. Object characterization: Direct vs model-based

3. Deblending: “Hack job” vs simultaneous/iterative modeling

MEASUREMENT PIPELINE: LIMITATIONS

0a. Instrumental signature removal

0b. Image coaddition

1. Object detection: Filters/thresholds only optimal for one kind of object

2. Object characterization:
   Undersampling for direct measures
   Too simplistic vs too complicated for models

3. Deblending:
   Heuristic criteria for direct methods
   Parameter degeneracies for model-fitting methods

PROBABILISTIC APPROACH, IN REVERSE

$$p(\theta|y) = p(y|\theta)p(\theta) = \prod_i p(y_i|\theta)p(\theta)$$

PROBABILISTIC APPROACH, IN REVERSE

$$p(\theta|y) = p(y|\theta)p(\theta) = \prod_i p(y_i|\theta)p(\theta)$$

- 3. (De-)Blending

$$p(y|\theta) = \sum_k p(y|\theta_k)$$

PROBABILISTIC APPROACH, IN REVERSE

$$p(\theta|y) = p(y|\theta)p(\theta) = \prod_i p(y_i|\theta)p(\theta)$$

- 3. (De-)Blending

$$p(y|\theta) = \sum_k p(y|\theta_k) \to \sum_k \prod_{i:S_i=k} p(y_i|\theta_k) = p(y|\theta, S)$$

PROBABILISTIC APPROACH, IN REVERSE

$$p(\theta|y) = p(y|\theta)p(\theta) = \prod_i p(y_i|\theta)p(\theta)$$

- 3. (De-)Blending

$$p(y|\theta) = \sum_k p(y|\theta_k) \rightarrow \sum_k \prod_{i:S_i=k} p(y_i|\theta_k) = p(y|\theta, S)$$

$$p(\theta, S|y) = \left[\sum_k \prod_{i:S_i=k} p(y_i|\theta_k)p(\theta_k)\right] p(S|\theta)$$

PROBABILISTIC APPROACH, IN REVERSE

$$p(\theta|y) = p(y|\theta)p(\theta) = \prod_i p(y_i|\theta)p(\theta)$$

- 3. (De-)Blending

$$p(y|\theta) = \sum_k p(y|\theta_k) \rightarrow \sum_k \prod_{i:S_i=k} p(y_i|\theta_k) = p(y|\theta, S)$$

$$p(\theta, S|y) = \left[\sum_k \prod_{i:S_i=k} p(y_i|\theta_k)p(\theta_k)\right] p(S|\theta)$$

$$p(\theta|y) = \sum_S p(\theta, S|y)p(S)$$

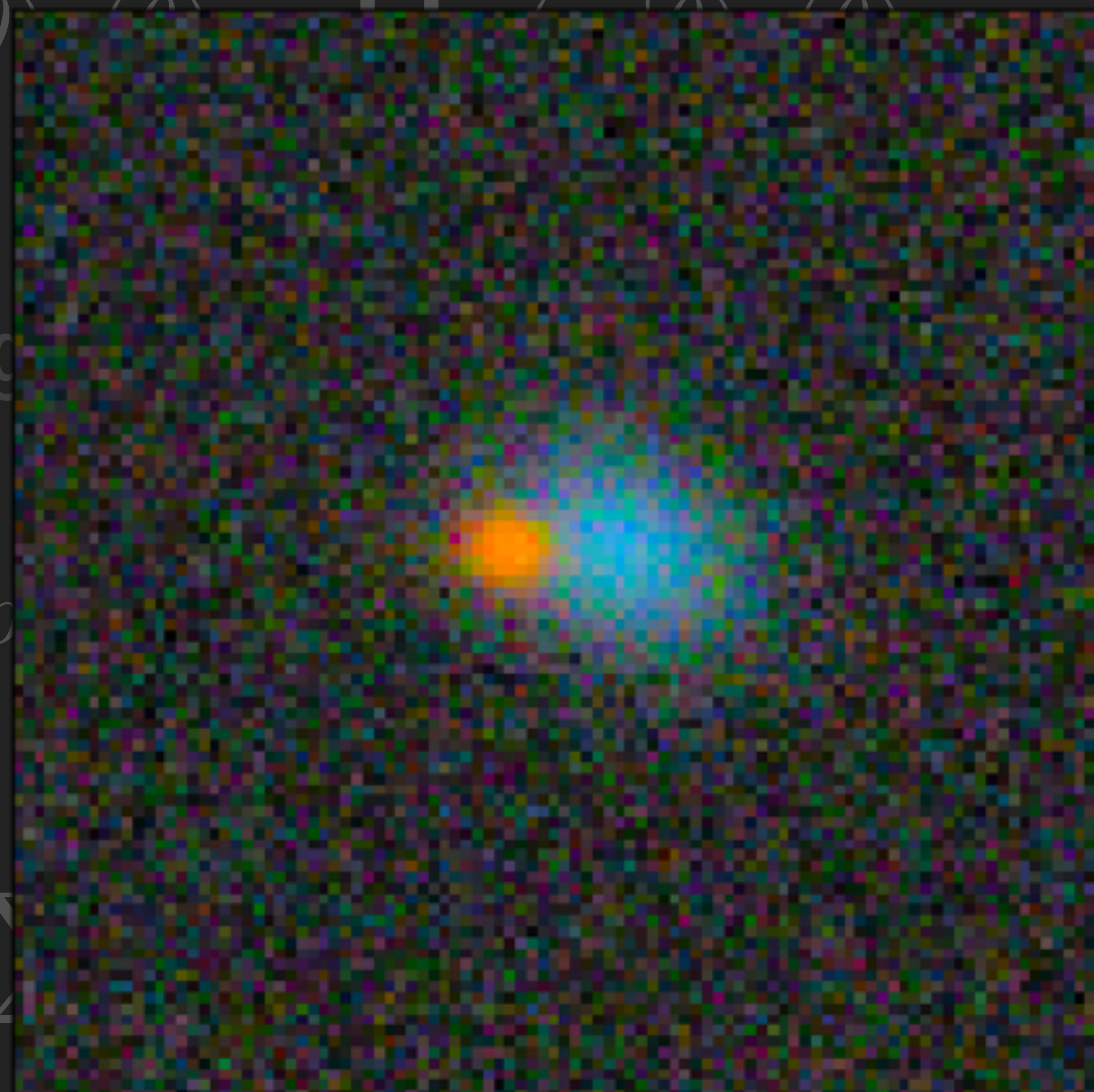
PROBABILISTIC APPROACH, IN REVERSE

$$p(\theta|y) = p(y|\theta$$

- 3. (De-)Blending

$$p(y|\theta) = \sum_k p \qquad = p(y|\theta, S)$$

$$p(\theta, S|y) = \Big[\qquad |\theta)$$



$$p(\theta|y) = \sum_S p(\theta, S|y) p(S)$$

THE CASE FOR GROUND & SPACE

DES data from Melchior et al. (2015)

THE CASE FOR GROUND & SPACE

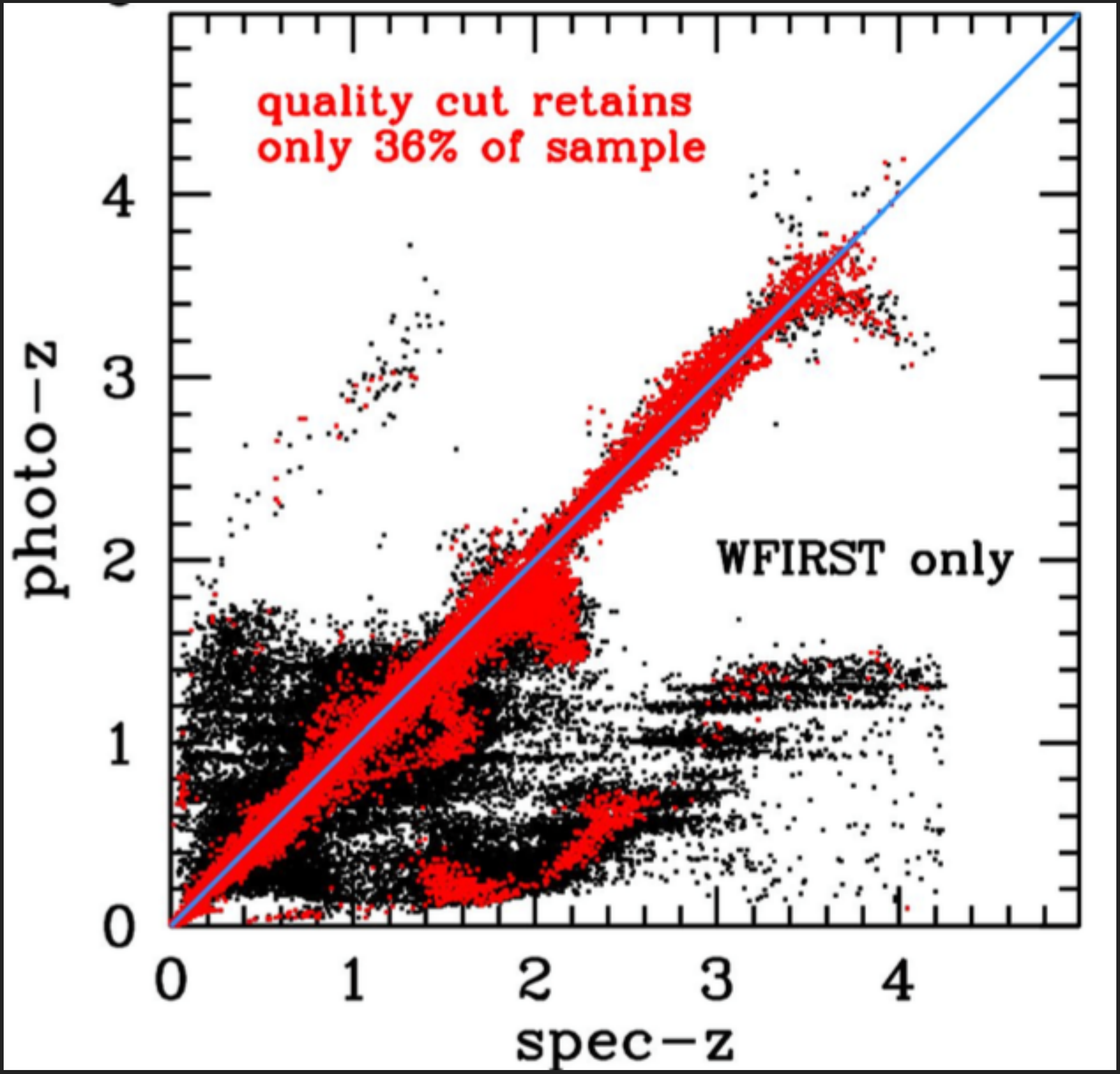
CLASH WFC3/IR data, image by Dan Coe

PIXEL-LEVEL SYNERGIES

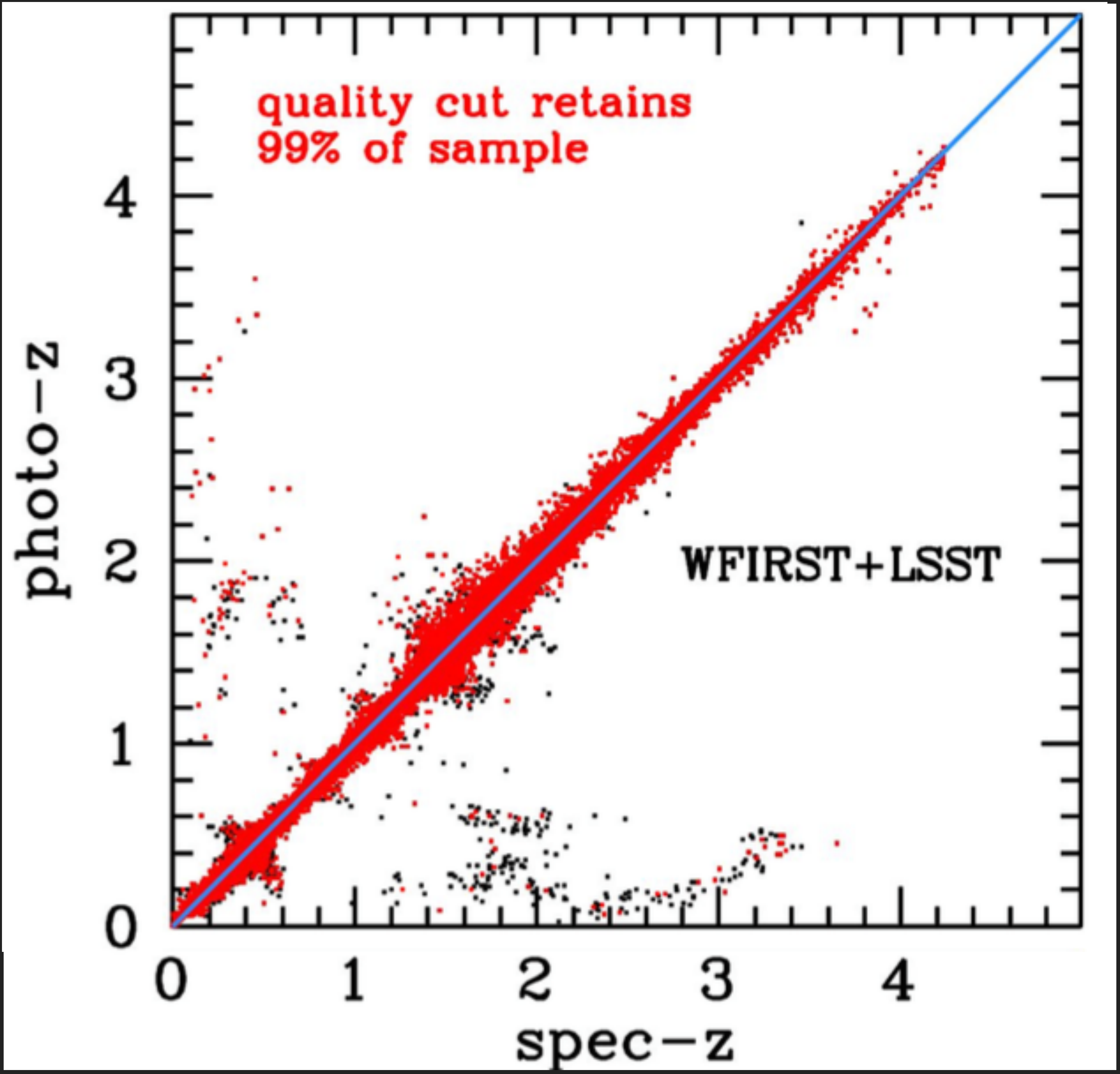
$$p(\theta, S|y) = \left[\sum_k \prod_{i:S_i=k} p(y_i|\theta_k)p(\theta_k)\right] p(S|\theta)$$

- Object characterization
  WFIRST benefits from LSST through color-morphology priors
  LSST benefits from sharp likelihood peaks in WFIRST bands

PHOTOMETRY-ONLY SYNERGIES



PHOTOMETRY-ONLY SYNERGIES

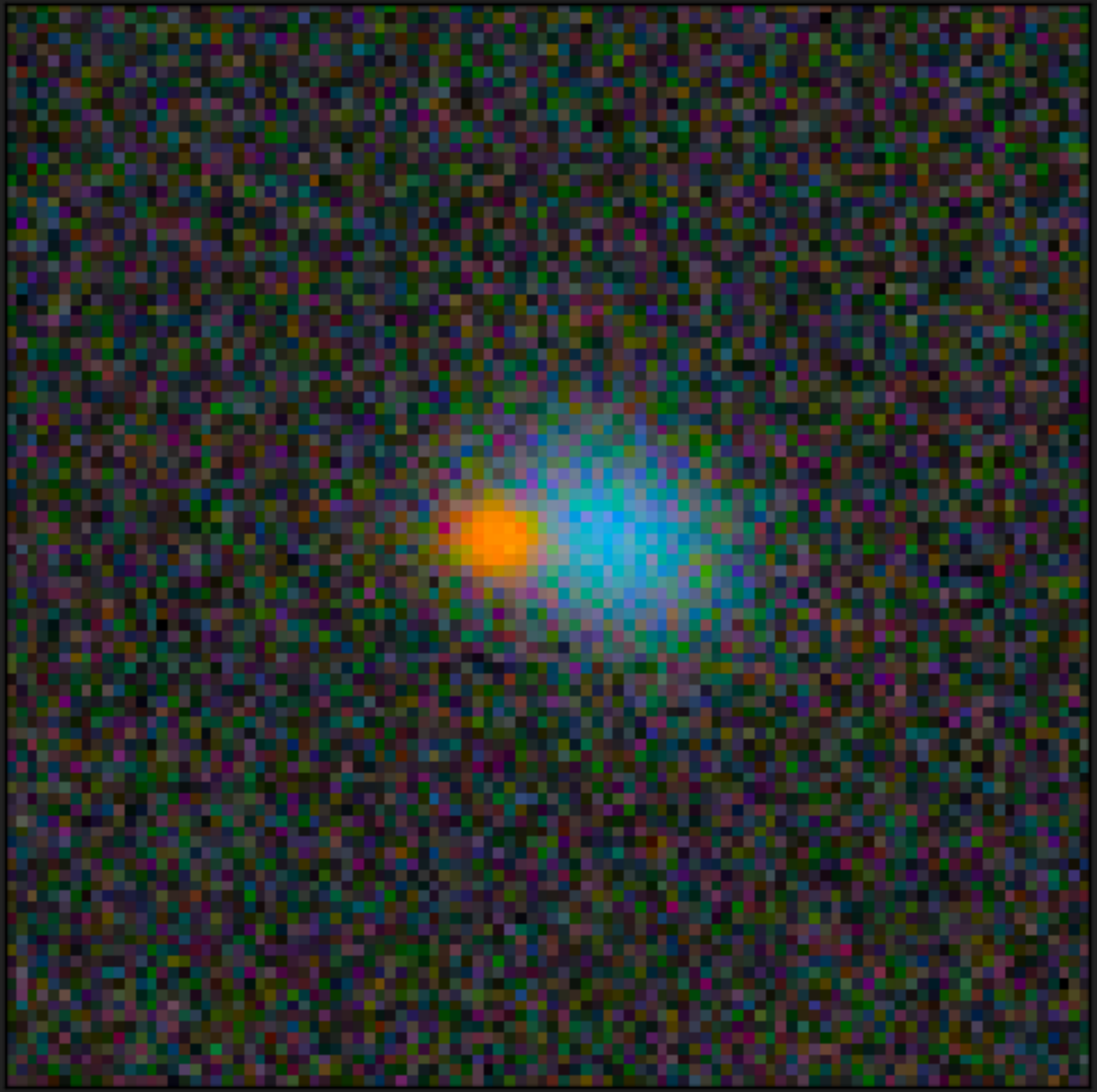


BENEFIT OF COLOR-MORPHOLOGY MODELS

- single Sersic-type galaxies, convolved with constant Gaussian PSF
- SEDs and morphologies from late-type and early-type galaxy
- simple template redshifts from 3-band photometry

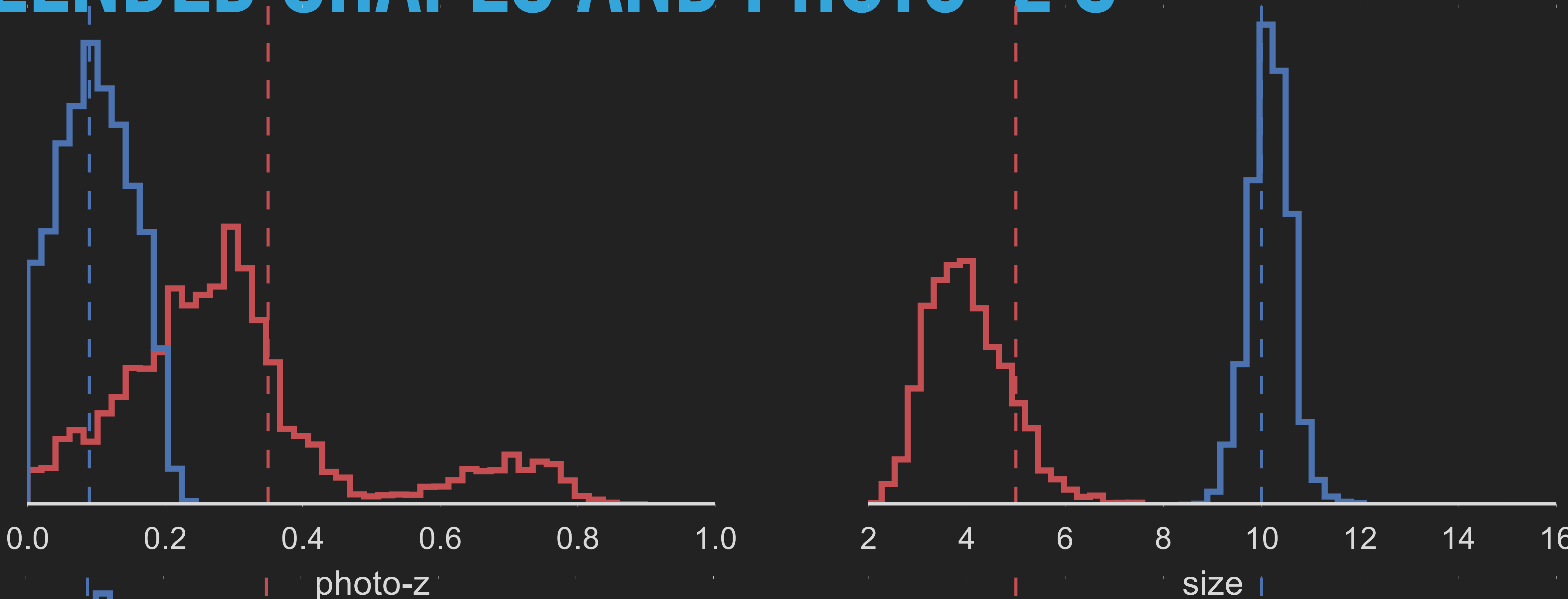
BENEFIT OF COLOR-MORPHOLOGY MODELS

- single Sersic-type galaxies, convolved with constant Gaussian PSF
- SEDs and morphologies from late-type and early-type galaxy
- simple template redshifts from 3-band photometry

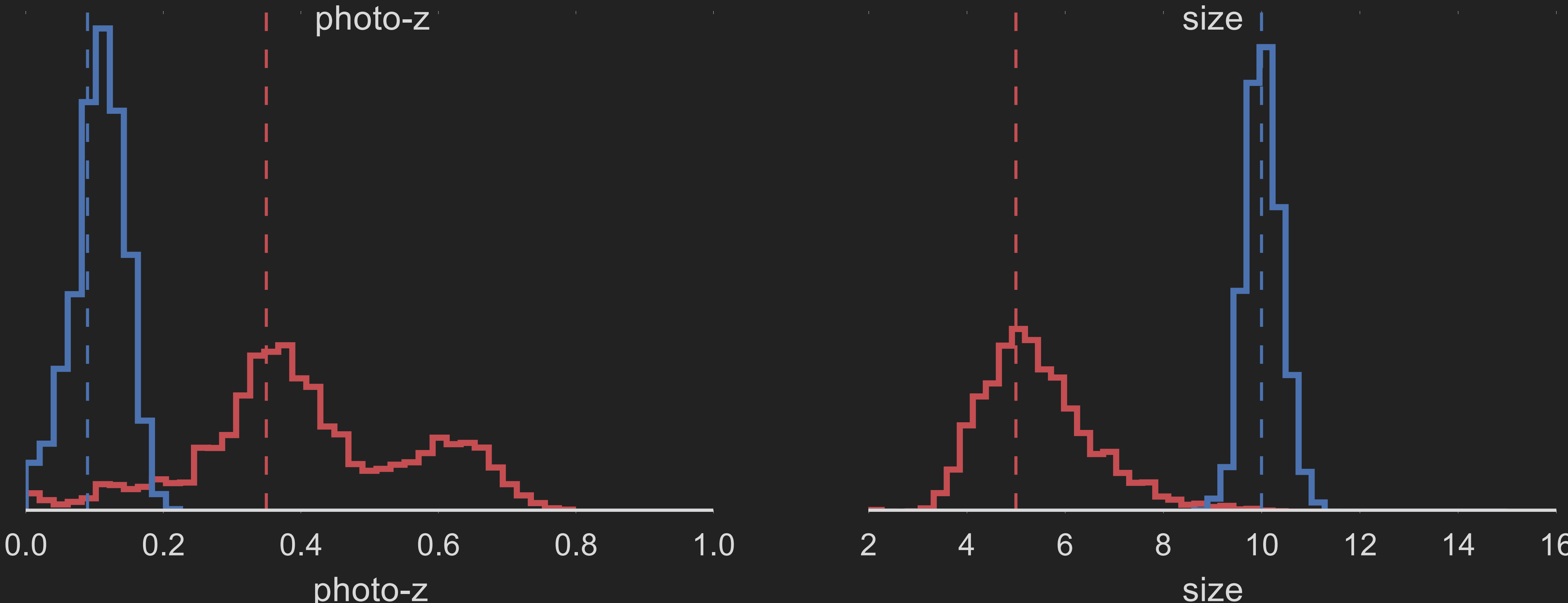


BLENDED SHAPES AND PHOTO-Z'S

2)



3)



WHERE DOES THE MODEL/PRIOR COME FROM?

- HSC & COSMOS/CANDLES
- Galsim simulations with HST image input

Methodology

- Extended bulge+disc model (based on ngmix)
- Hierarchical inference on model mis-specification
- SOMs (Masters)
- Decorrelation network (Schaefer)

PIXEL-LEVEL SYNERGIES 2

$$p(\theta, S|y) = \left[\sum_k \prod_{i:S_i=k} p(y_i|\theta_k)p(\theta_k)\right] p(S|\theta)$$

- Object characterization
  WFIRST benefits from LSST through color-morphology priors
  LSST benefits from sharp likelihood peaks in WFIRST bands

- Segmentation
  LSST benefits from WFIRST through superior resolution
  In HLS directly from a segmentation posterior, otherwise from a prior

DETECTION

$$p(\theta, S|y) = \left[\sum_k \prod_{i:S_i=k} p(y_i|\theta_k)p(\theta_k)\right] p(S|\theta)$$

- faint or diffuse features remain undetected: ICL, UDGs …
- undetected / unresolved features contaminate others
- Reversible-jump / product-space methods available if model type is specified
- Extension to several model types tricky
- Large number of likelihood evaluations to converge to stationary solution

CONSEQUENCES

- Propagation of unknowns to parameters uncertainties: blending, per-object parameters, detection
- Undersampling irrelevant (if PSF can be determined)
- Adjustment of pixel resolution not necessary
- Reliance on models for color-morphology in optical+IR
- CPU-hungry (even when done cleverly)

JOINT PIXEL PROCESSING OF LSST & WFIRST

- Complex models become norm: more flexible and properly behaved
- LSST DM plans to store posterior samples in DB
- Coadd-level combination likely sufficient
- Feasible data volumes, shipping analysis to computing facility
- Iterative runs for periodic improvements in models and priors
- maximum benefits in HLS, outside indirectly from segmentation prior
- Extending HLS immediately helpful for both surveys