pop-cosmos: **Comprehensive forward modelling of photometric galaxy surveys**

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centre



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Large Scale Structure Cosmology

- Map the matter distribution in the universe using spectra or photometry of galaxies
- Galaxy clustering (positions), or weak lensing (shapes) sensitive to cosmological parameters
- But... need redshifts



SDSS: Blanton et al. (2003)

Coming Soon...

- 18,000 deg²
- Deep imaging in *ugrizy*
- 10 year LSST survey
- Single epoch: $r \leq 24$ mag; 10 year co-add: r < 26.9 mag
- Billions of galaxies: impossible to get spectra
- Need *photometric* redshifts



VERA C. RUBIN BSERVATORY





Credit: Rubin Observatory

Photometry



Graham et al. (2017)



Photometric Redshifts We need accurate characterisation of n(z) in tomographic bins



KiDS: Loureiro et al. (2022)

















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Solution over physical properties and z on synthesis

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- 5. Apply selection
- 6. Compare model fluxes to data

pop-cosmos framework

How do we represent a galaxy? **Stellar Population Synthesis (SPS)**







What should our population model be? A score-based diffusion model



(t = 0)

differential equation

iid Gaussian noise (t = T)



What goes into the data model? Uncertainty, noise, and calibration



Student's-t error model





















data model





data model





data model





data model





What data will we use? **COSMOS2020 (Weaver et al. 2022)**

- Has $\approx 140,000$ galaxies with r < 25
- Wide and narrow bands
- Coverage from near-UV to mid-IR



Results

Photometric Predictions





Redshift Distribution Predicted population-level n(z)



Alsing et al. (2024)



Stellar Mass Function We get more than just redshifts!



Alsing et al. (2024)





data model



data model



40







What's else can we do? Using pop-cosmos as a prior for Bayesian photo-z estimation...





Thorp et al. (in prep.)

Summary pop-cosmos

- Comprehensive forward model for galaxy photometry
- Flexible non-parametric population model
- Gives us redshift distribution, and can be used to make predictions for other surveys
- Tons of information about galaxy demographics on a huge sample with minimal selection (see the talk + poster by Sinan Deger!)







Extra Slides

Photometric Predictions Colour marginals



Photometric Predictions Magnitude marginals



Alsing et al. (2024)





Fundamental Metallicity Relation Gas metallicity vs. mass vs. SFR



Alsing et al. (2024)



Star Forming Sequence SFR vs. mass in redshift slices



Alsing et al. (2024)

Mass-Metallicity Relation



Mass-Metallicity Relation Gas metallicity vs. mass







Alsing et al. (2024)











Validation **Data-space validation using Q-Q and P-P plots**



Thorp et al. (2024)



Image Based Selection

- Some galaxy surveys have image-level selection (e.g. based on shape, PSF)
- We can train a conditional density estimator $P(\text{image property} | \varphi)$ to learn a model for the relevant image-level summary statistics given **SPS** parameters
- Allows us to forward model these catalogs without simulating full images



KiDS: Kuijken et al. (2015)



Our stellar population synthesis parameters \approx Prospector- α

$$\begin{split} \varphi &= \begin{bmatrix} \log_{10}(M/M_{\odot}), \text{ stellar mass} \\ & \Delta \log_{10}(\text{SFR}), \text{ star forming history (\times 7)} \\ & \tau_1, \tau_2, n, \text{ dust attenuation} \\ & \ln(f_{\text{AGN}}), \ln(\tau_{\text{AGN}}), \text{ active galactic nuclei} \\ & \log_{10}(Z/Z_{\odot}), \text{ stellar metallicity} \\ & \log_{10}(Z_{\text{gas}}/Z_{\odot}), \log_{10}(U_{\text{gas}}) \end{bmatrix} \text{ gas metallicity + ionisation} \end{split}$$



Assembly of simple stellar / populations from initial mass function, isochrones, and stellar spectra



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Star formation history / evolution



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Star formation history / evolution

Dust attenuation and emission



Assembly of simple stellar populations from initial mass function, isochrones, and stellar spectra

Star formation history / evolution

Dust attenuation and emission

Assembly of composite stellar populations



Our uncertainty model Mixture density network (see Bishop 2006)

 $s \sim N(0,1)$ $\sigma = \mu(f) + \Sigma(f) \odot s$ dense neural network (2 layers, 128 hidden units, tanh activation)



More on diffusion models Variance-exploding SDE



 $\mathbf{x}(t=T) \sim P_T(\mathbf{x}) \equiv N(0,1)$



$$s(\mathbf{x}, t) = \nabla_{\mathbf{x}} P_t(\mathbf{x}) \qquad \begin{array}{l} \text{score} \\ \text{function} \\ \mathbf{d}\mathbf{x} = g(t) \, \mathbf{d}\mathbf{w} \qquad \begin{array}{l} \text{Browniar} \\ \text{motion} (\mathbf{w}) \\ \mathbf{d}\mathbf{x} = -\frac{1}{2}g^2(t) \, \nabla_{\mathbf{x}} P_t(\mathbf{x}) \, \mathbf{d}t \\ \\ g^2(t) = \frac{\mathbf{d}\sigma^2(t)}{\mathbf{d}t} \\ \\ \sigma(t) = \sigma_0 (\sigma_T / \sigma_0)^{t/T} \\ \\ \sigma_0 = 0.01, \ \sigma_T = 6, \ T = 1 \end{array}$$

