Shrinkage Estimation of the SN Ia Host Galaxy Dust Law Distribution with a Hierarchical BayeSN SED model

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[Mandel, Thorp, Narayan, Friedman, Avelino, arXiv:2008.07538]

[Thorp, Mandel, Jones, Ward, Narayan, arXiv:2102.05678]

Science and Technology Facilities Council

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Part I: SN Ia Cosmology and the Problem of Dust

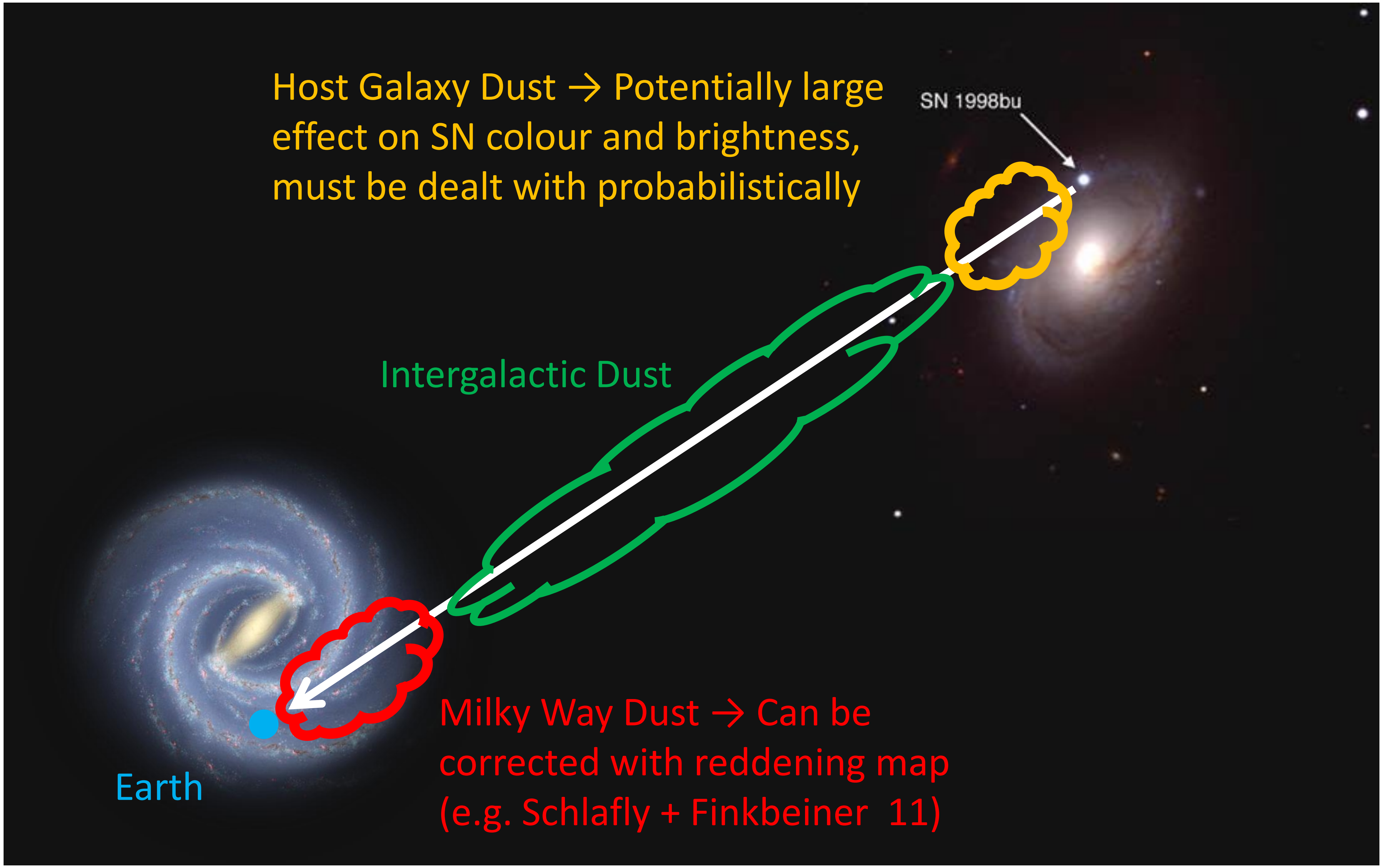
SN Ia Cosmology

- Relies on effective standardisation of SNe Ia
  → need a robust way of determining distance from photometric light curves
- Unprecedented data volume incoming
  → need to worry about details that were previously subdominant sources of error

Dust in SN Ia Host Galaxies

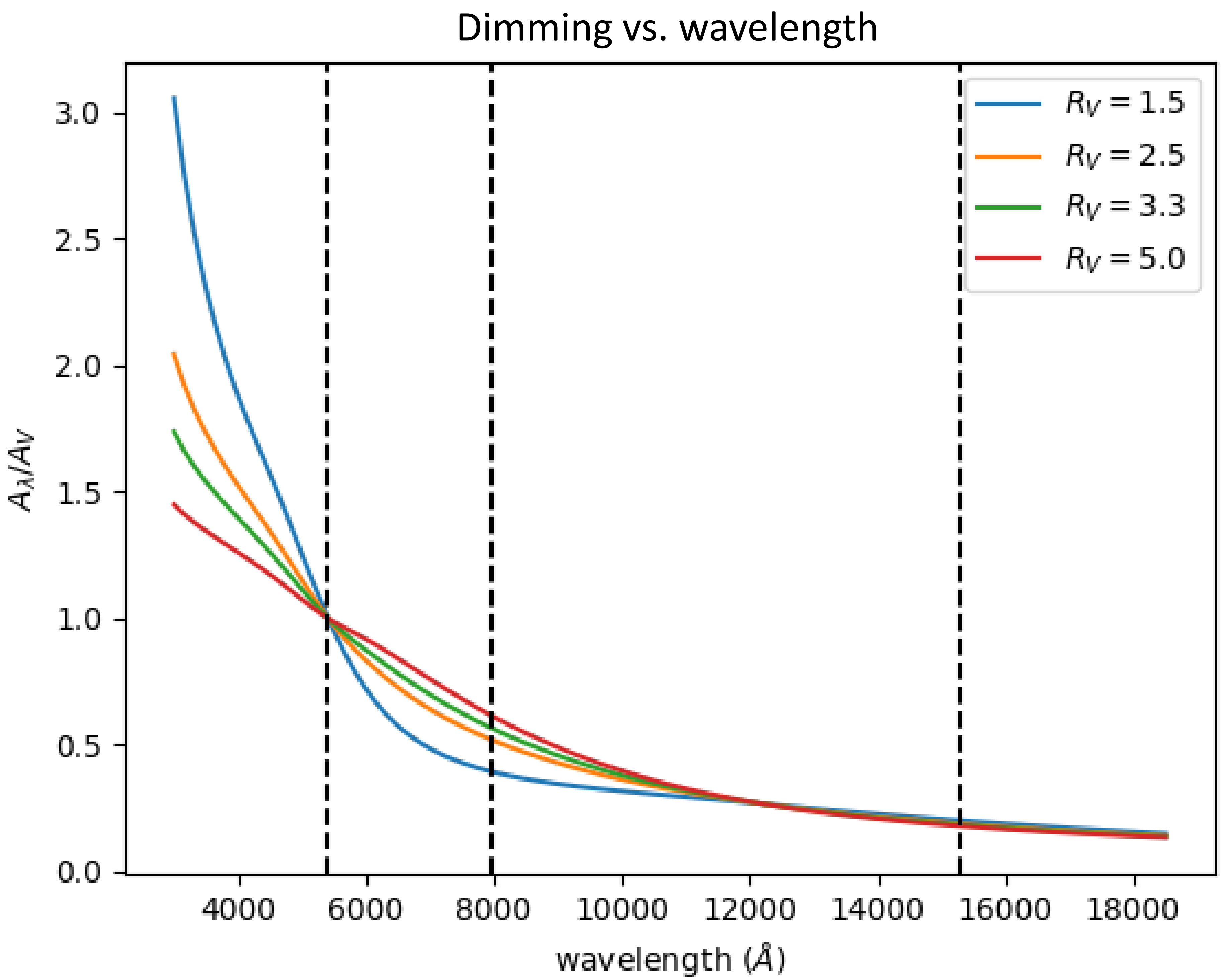
- Correctly handling dust is key to correctly estimating SN Ia distances, and potential systematic if done wrong
- Currently a lot of controversy over the dust laws in SN Ia host galaxies → particularly the distribution of R_V

What We Mean When We Talk About Dust

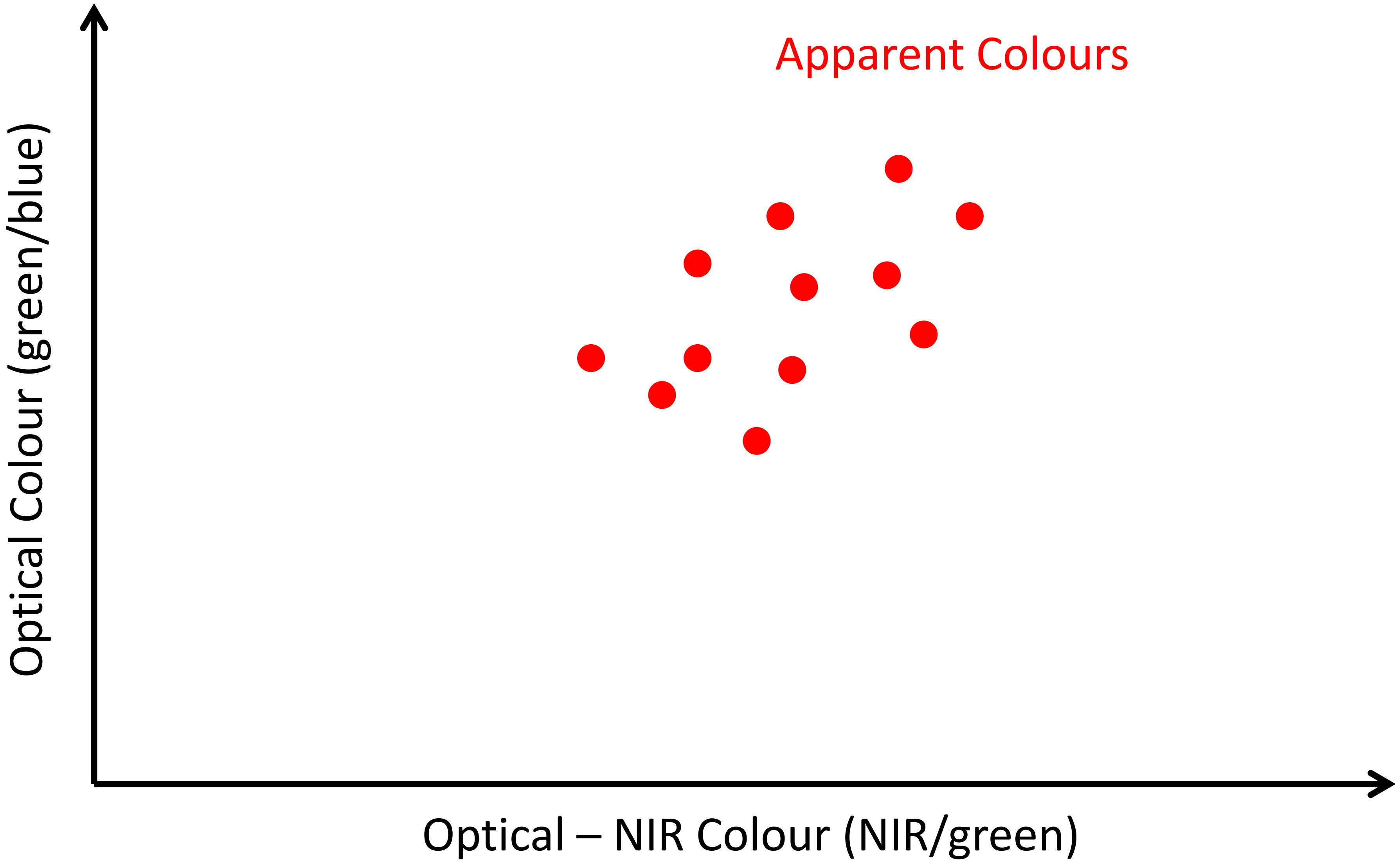


NASA/JPL-Caltech/ESO/R. Hurt
Nicholas B. Suntzeff

Effect of R_V on Fitzpatrick (1999) Dust Law



How Do We Constrain R_V?



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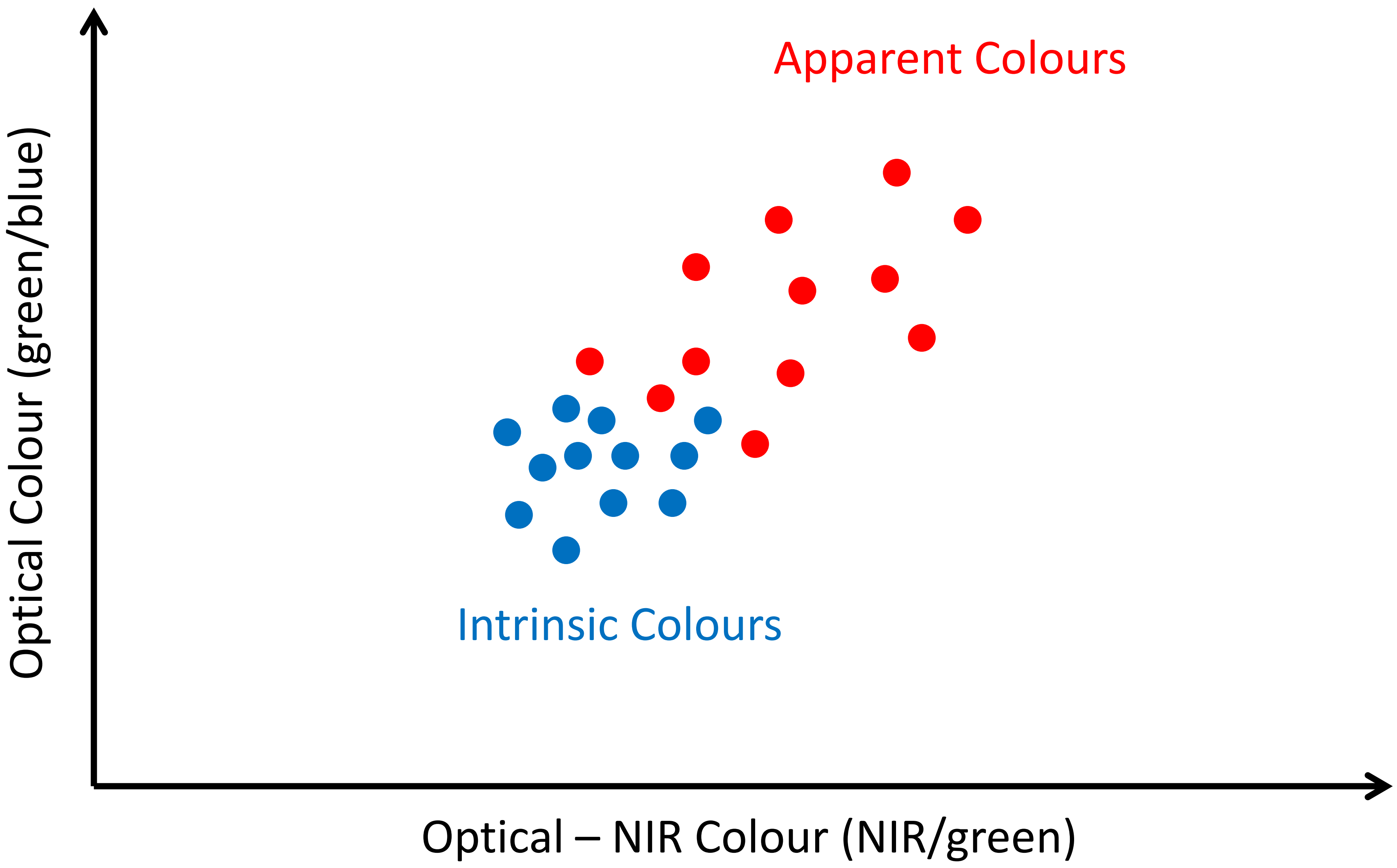

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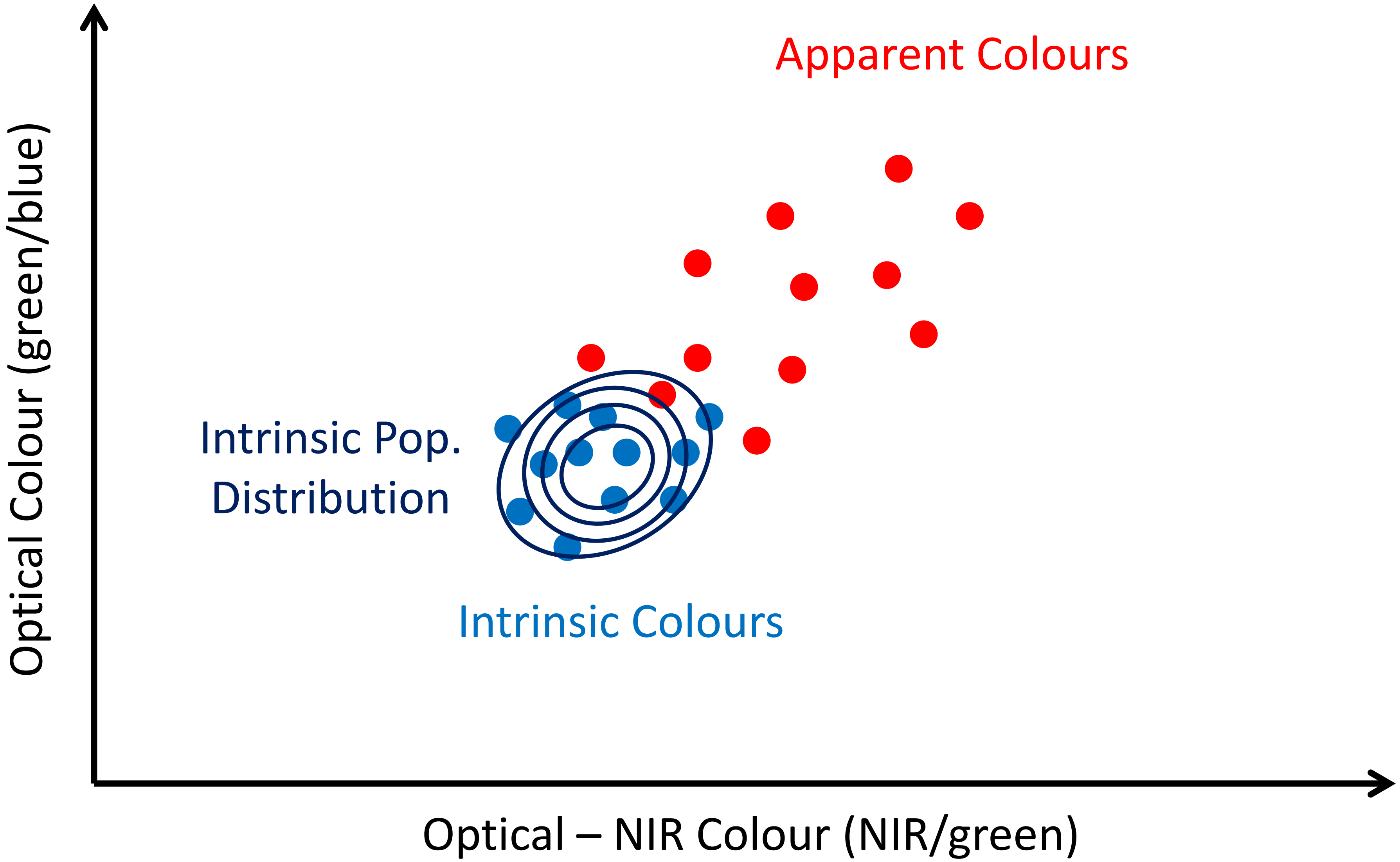

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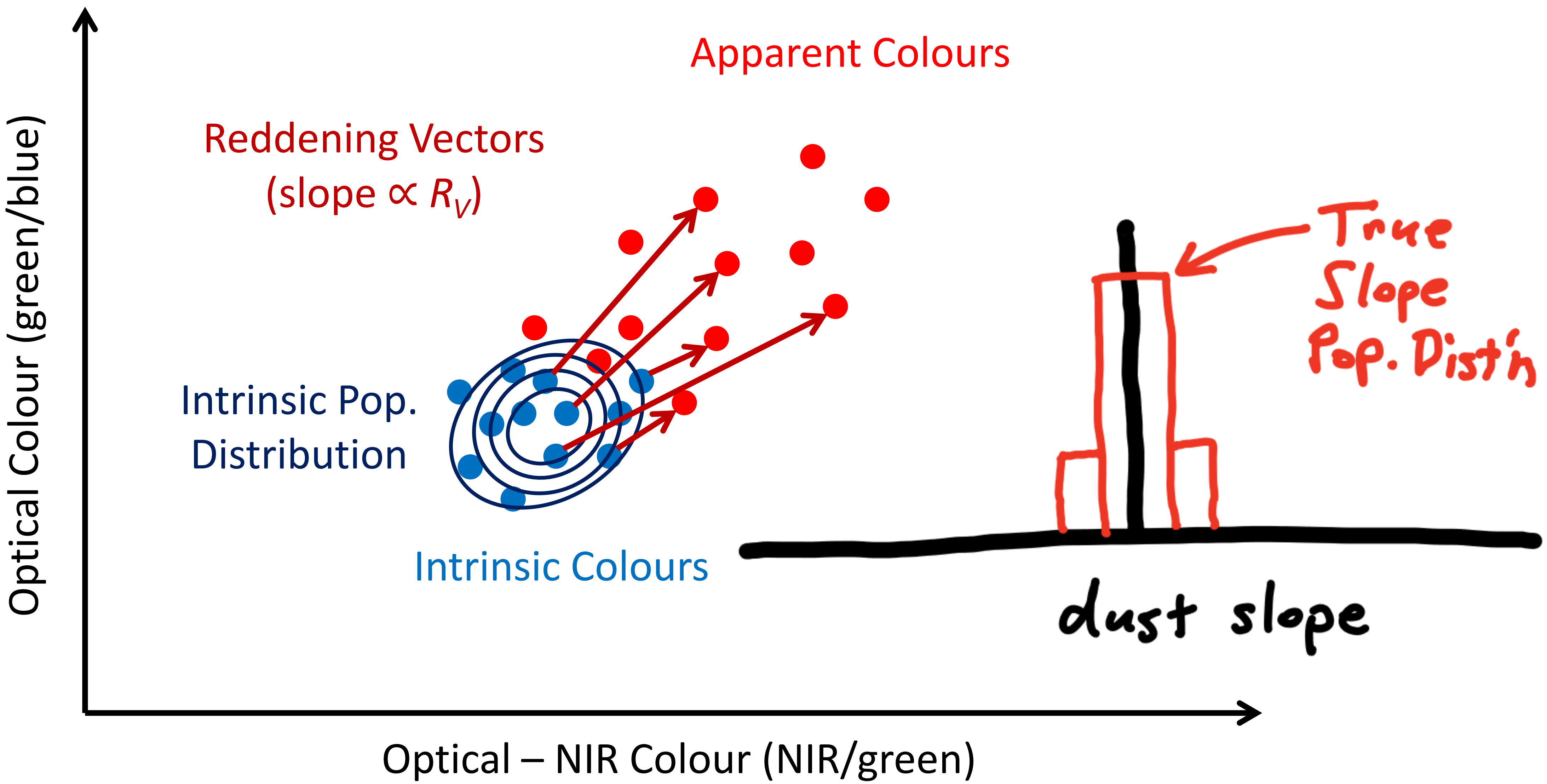

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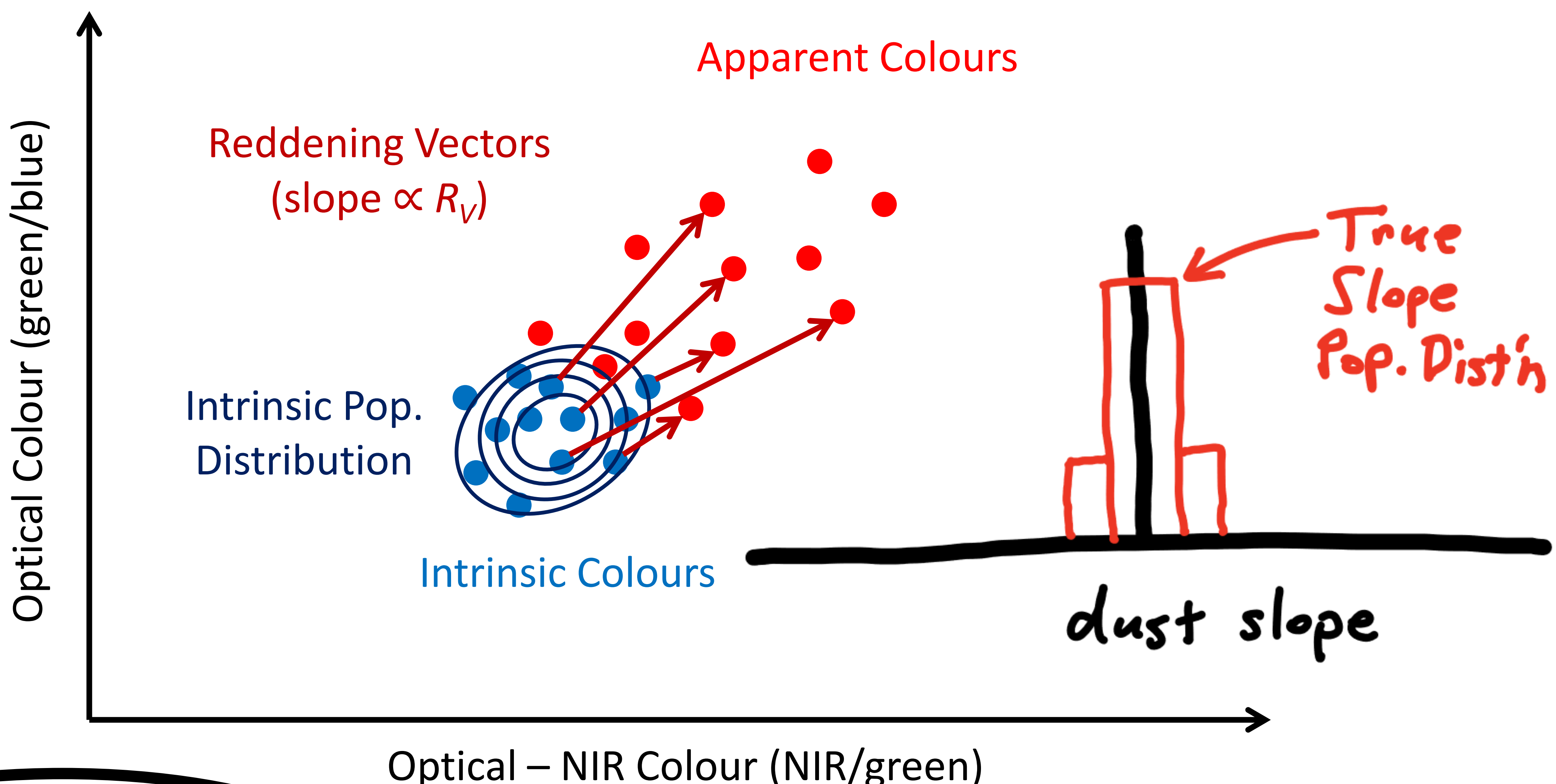
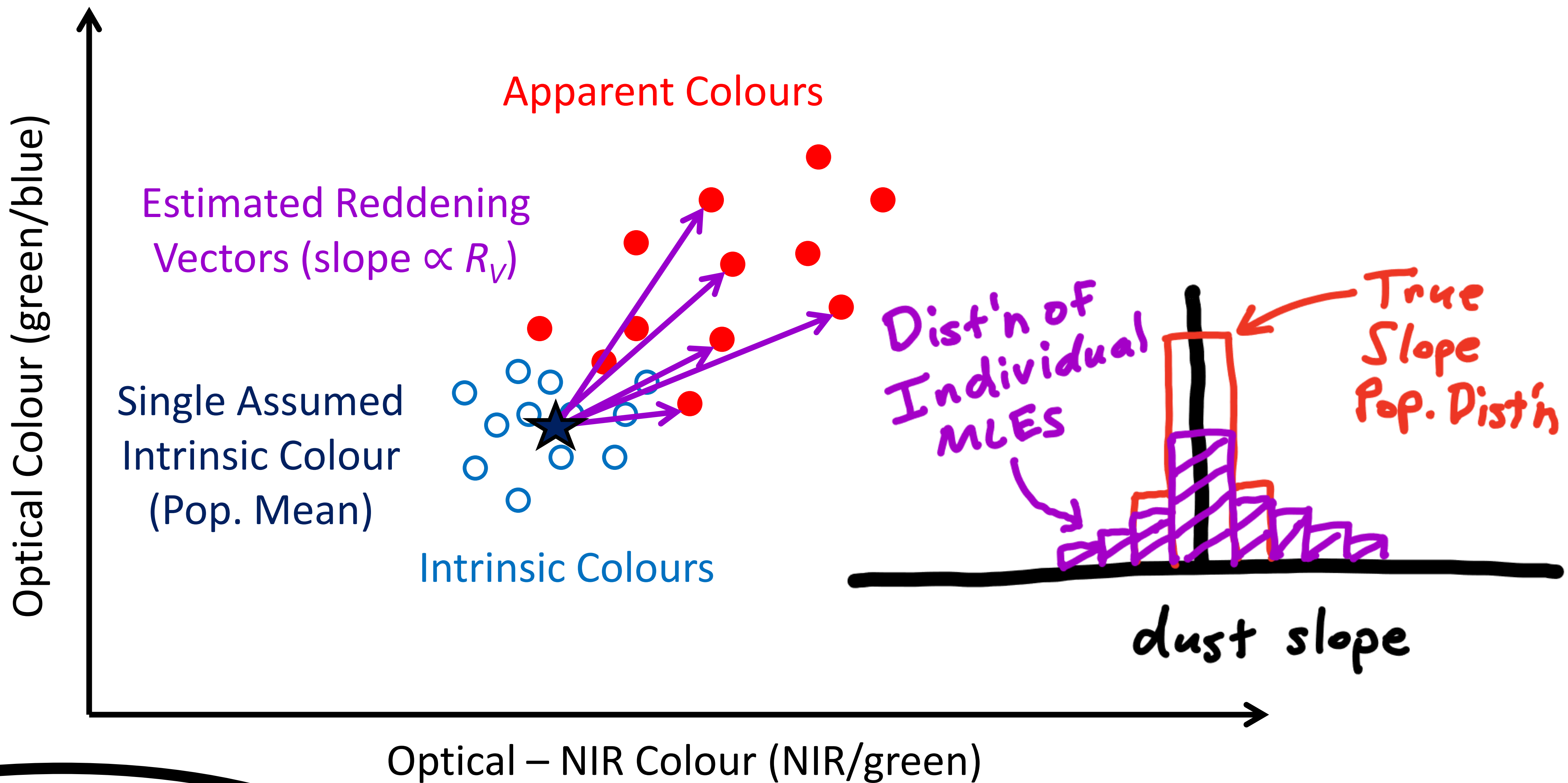


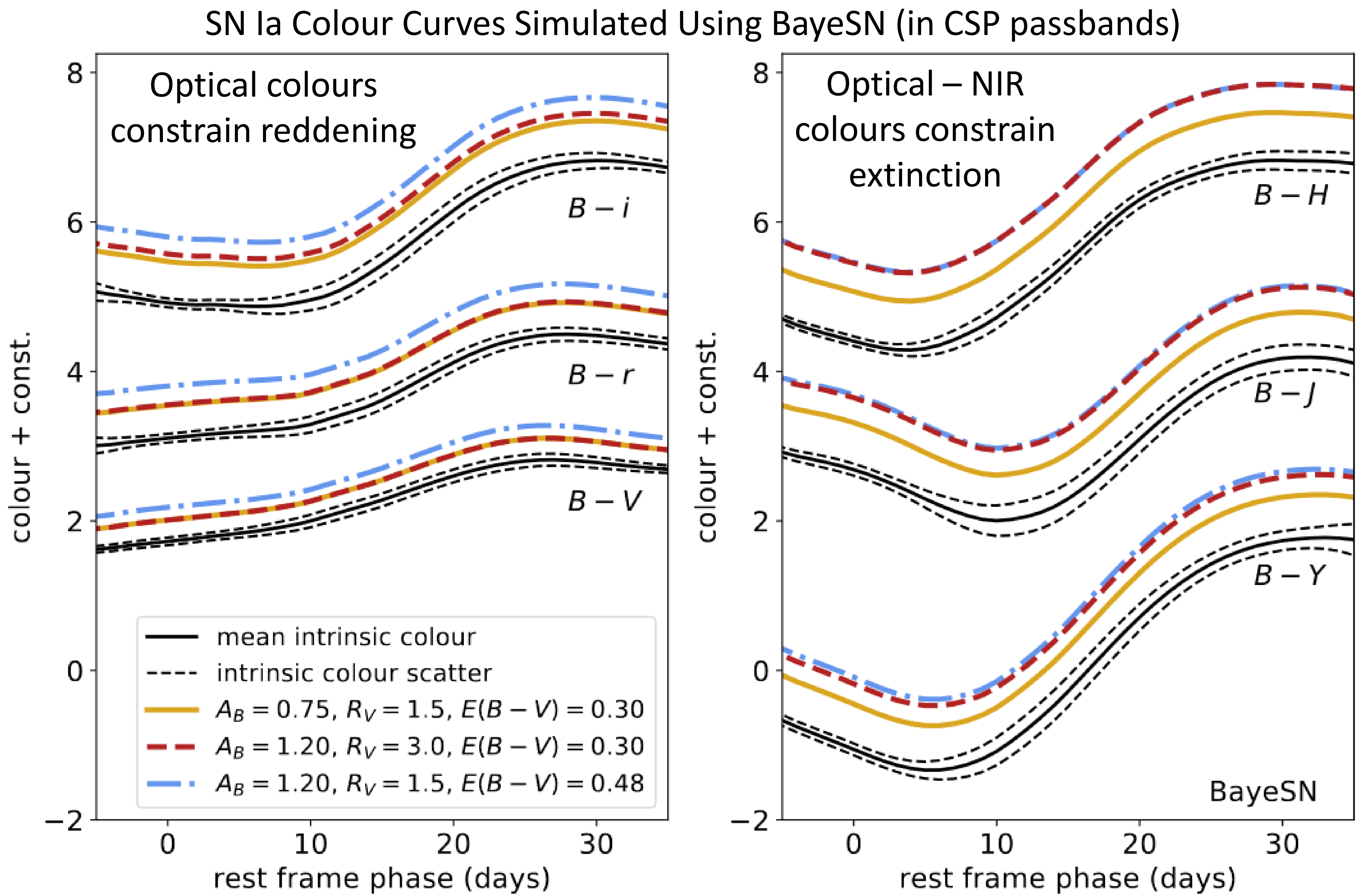
Need to account for intrinsic colour scatter when inferring R_V

How Do We (Not) Constrain R_V?



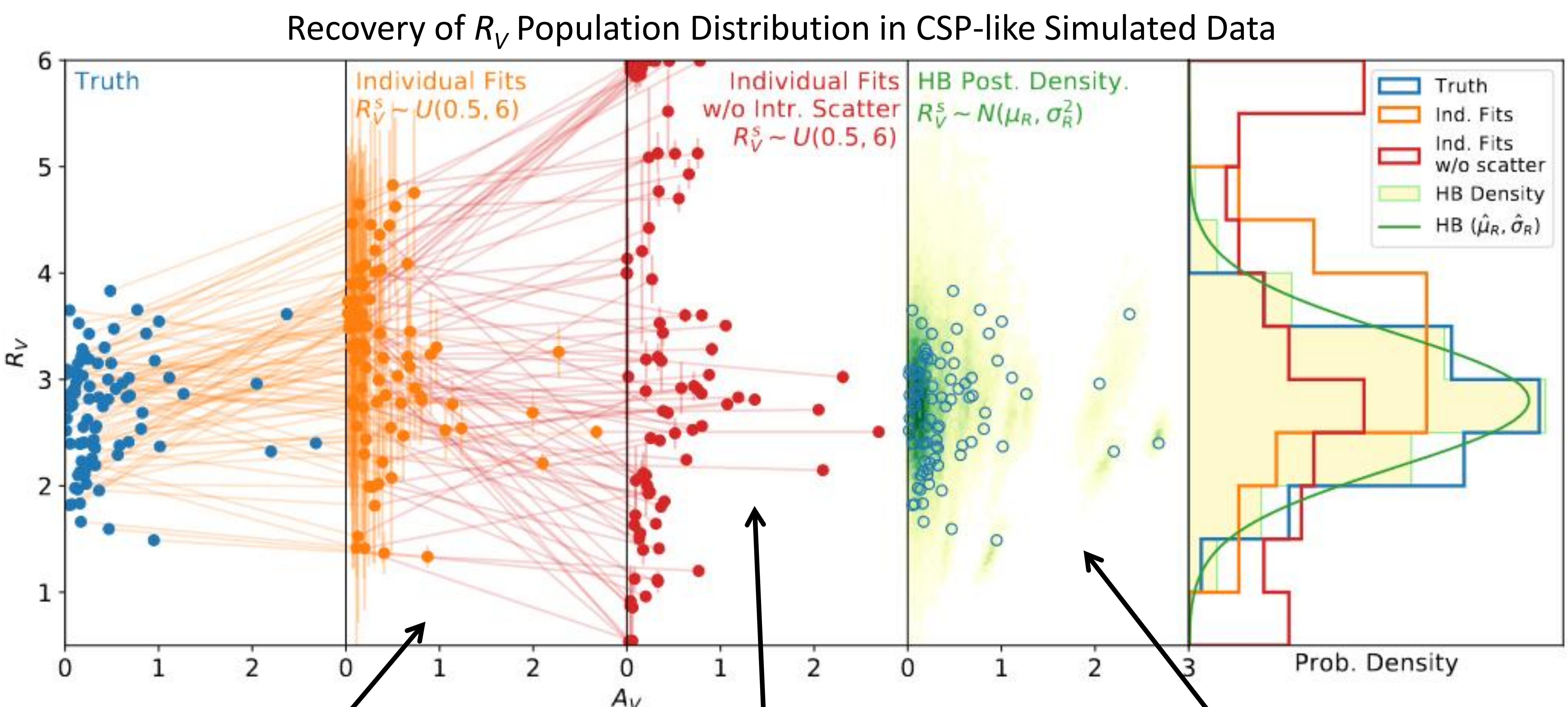
Otherwise width of R_V distribution will be overestimated!

Why Use Optical + NIR Data?



Thorp + Mandel, in prep.

Why Use Hierarchical Bayes?



Recovery of R_V values from fits to each SN individually: overdispersed point estimates, but reasonable uncertainties

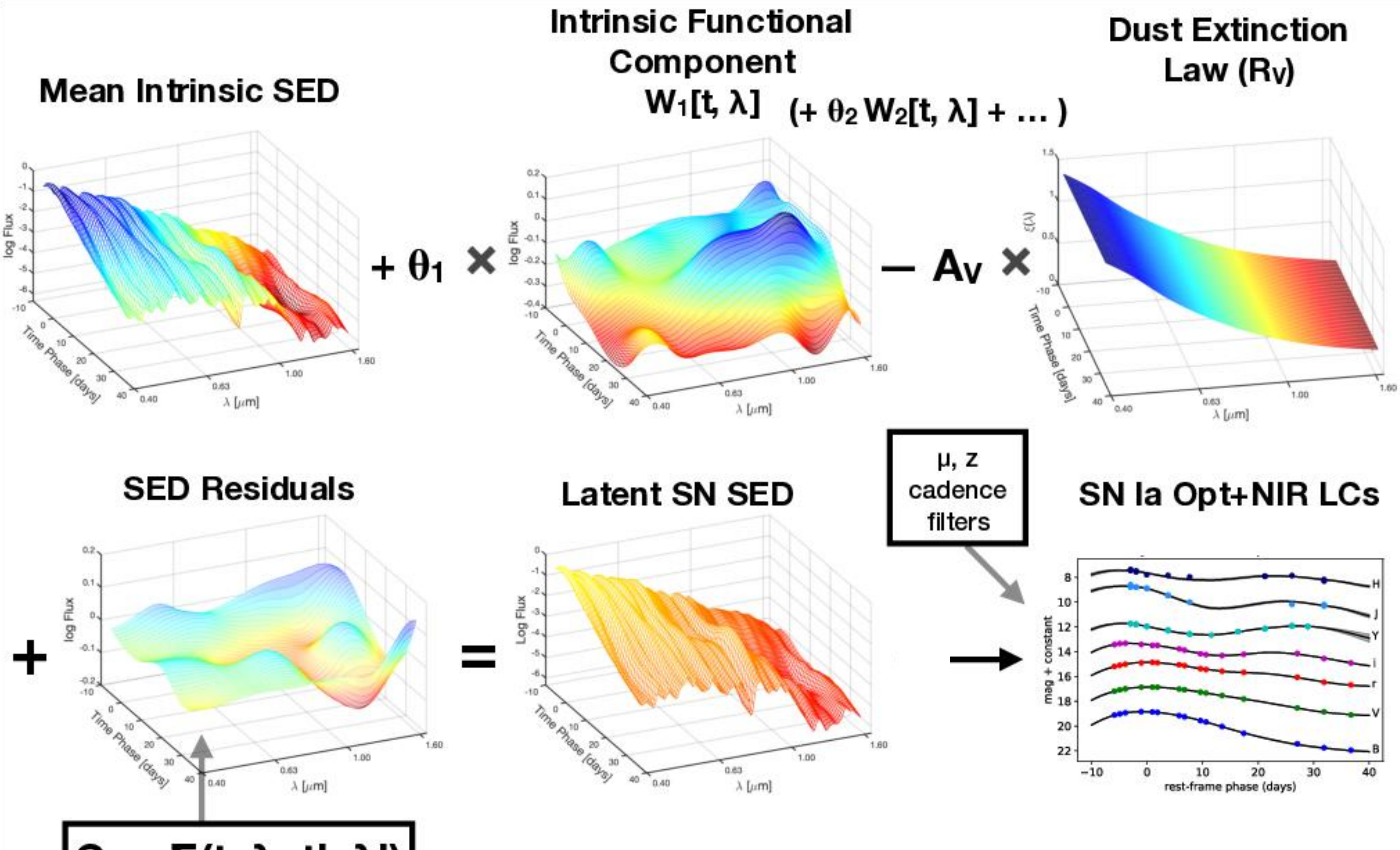
Same again, but ignoring intrinsic colour scatter: overdispersed and overconfident

Hierarchical Bayes: effectively captures true population distribution

Thorp + Mandel, in prep.

Part II: Results Using the BayeSN Hierarchical Model for SN Ia SEDs

The BayeSN SED Model

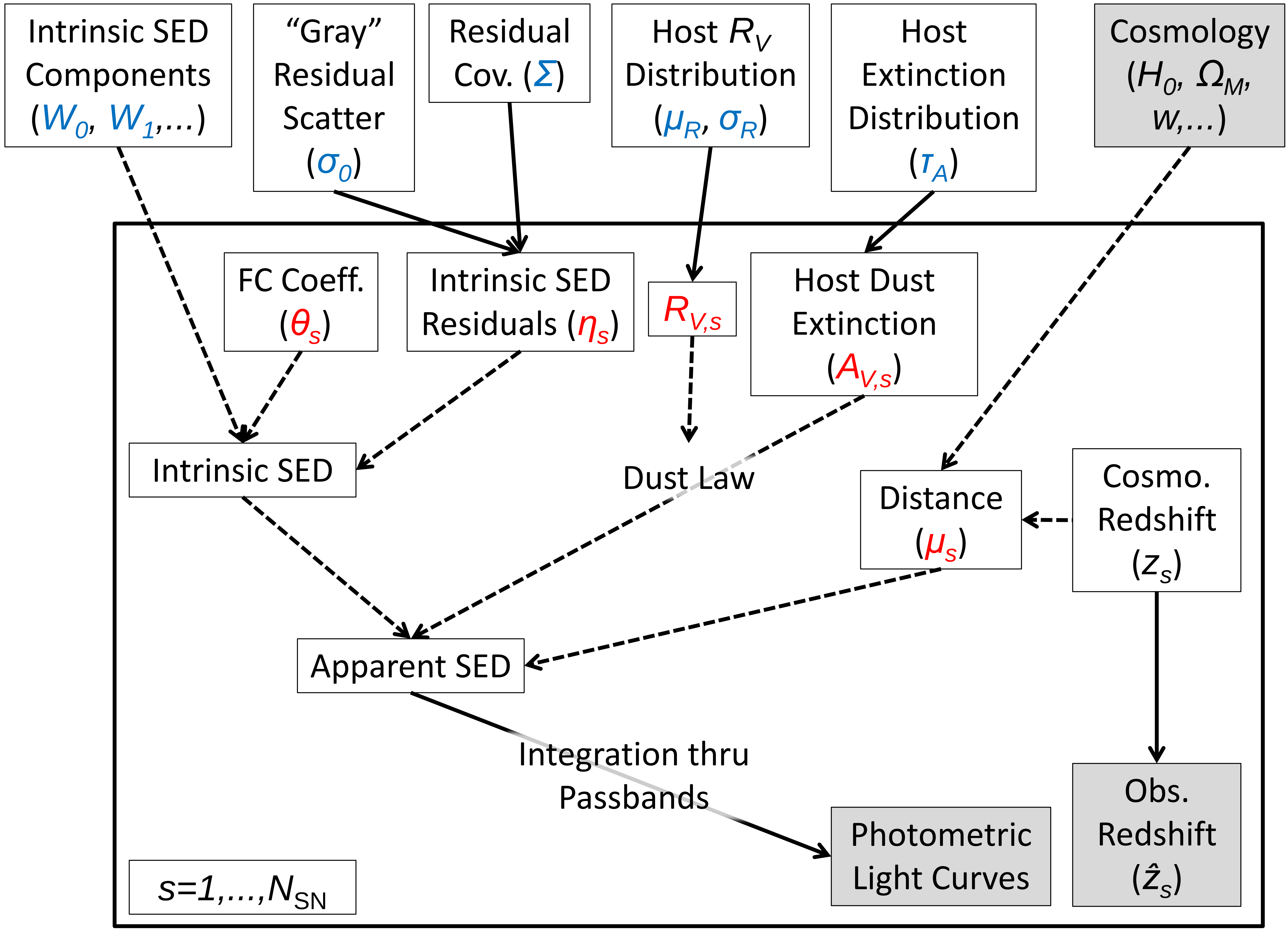


Mandel+22 [arXiv:2008.07538]

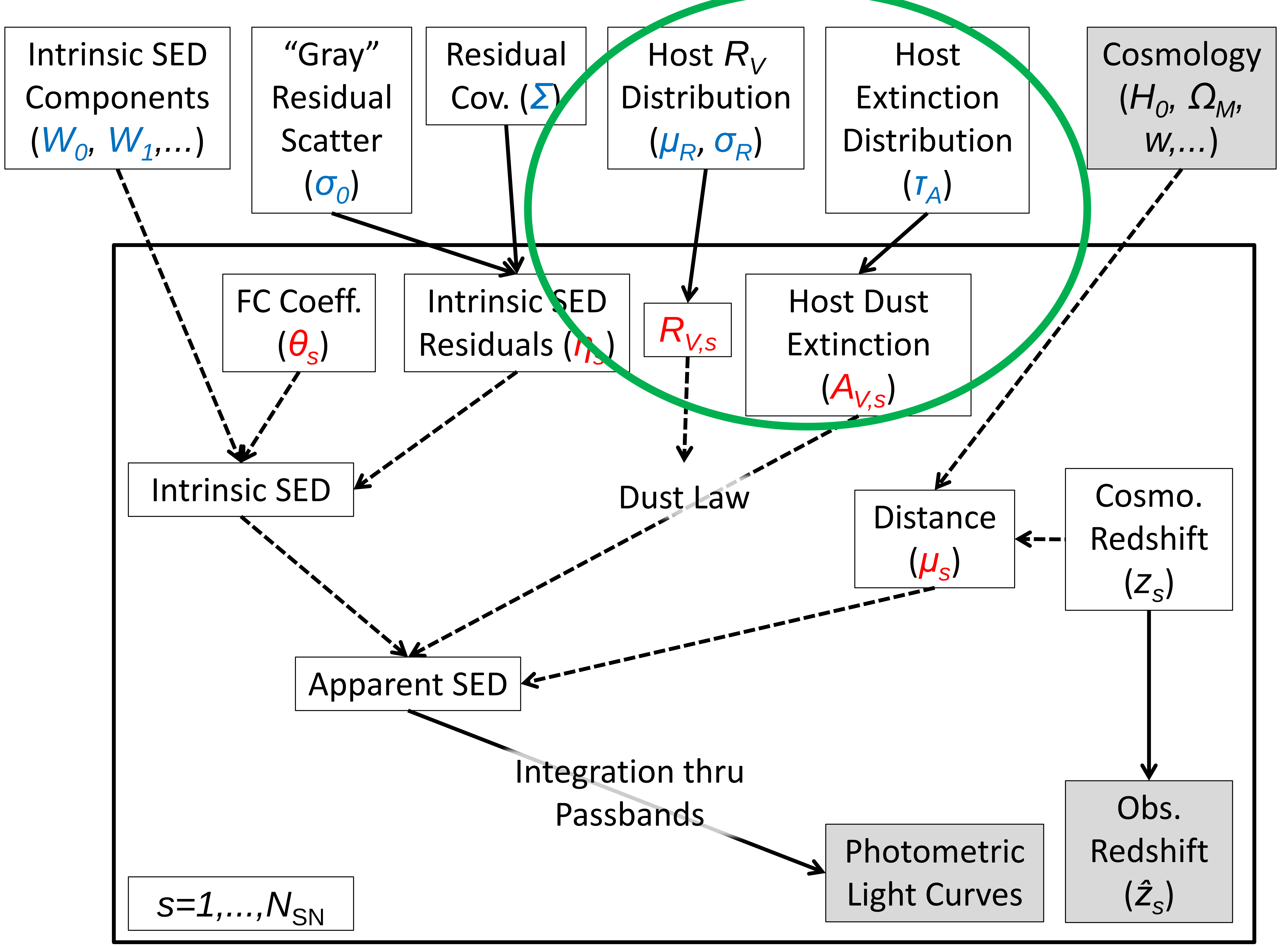
The BayeSN SED Model

$$-2.5\log_{10}[S_s(t, \lambda_r)/S_0(t, \lambda_r)] = M_0 + W_0(t, \lambda_r) + \theta_s W_1(t, \lambda_r) + \delta M_s + \varepsilon_s(t, \lambda_r) + A_{V,s}\xi(\lambda_r; R_V)$$

$$\eta_s = \delta M_s + \varepsilon_s(t, \lambda_r)$$



Intrinsic SED Components (W_0, W_1,...)
"Gray" Residual Scatter (σ_0)
Residual Cov. (Σ)
Host R_V Distribution (μ_R, σ_R)
Host Extinction Distribution (τ_A)
Cosmology (H_0, Ω_M, w,...)
FC Coeff. (θ_s)
Intrinsic SED Residuals (η_s)
$R_{V,s}$
Host Dust Extinction ($A_{V,s}$)
Intrinsic SED
Dust Law
Distance (μ_s)
Cosmo. Redshift (z_s)
Apparent SED
Integration thru Passbands
Photometric Light Curves
Obs. Redshift ($\hat{z}_s$)
s=1,...,N_{SN}



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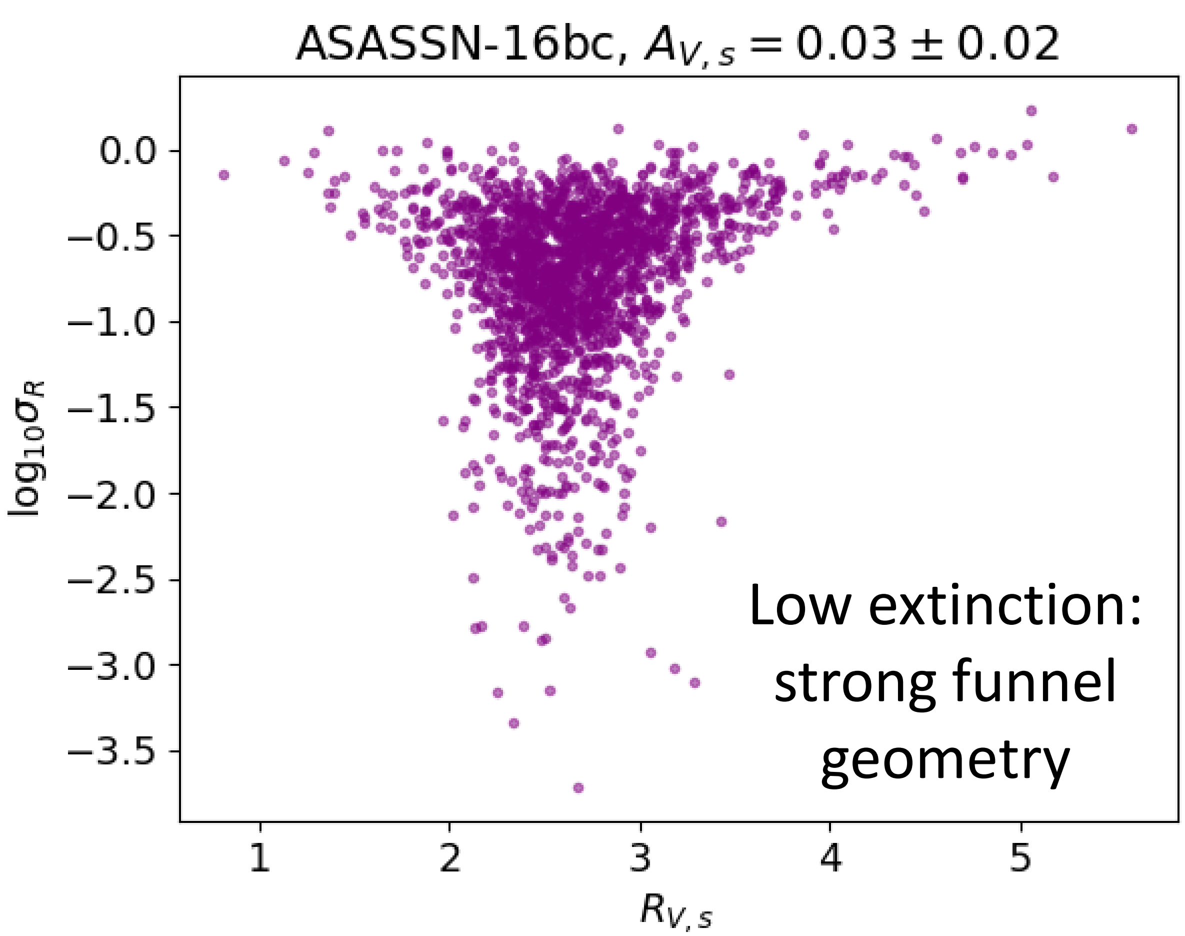
$s=1,\ldots,N_{SN}$

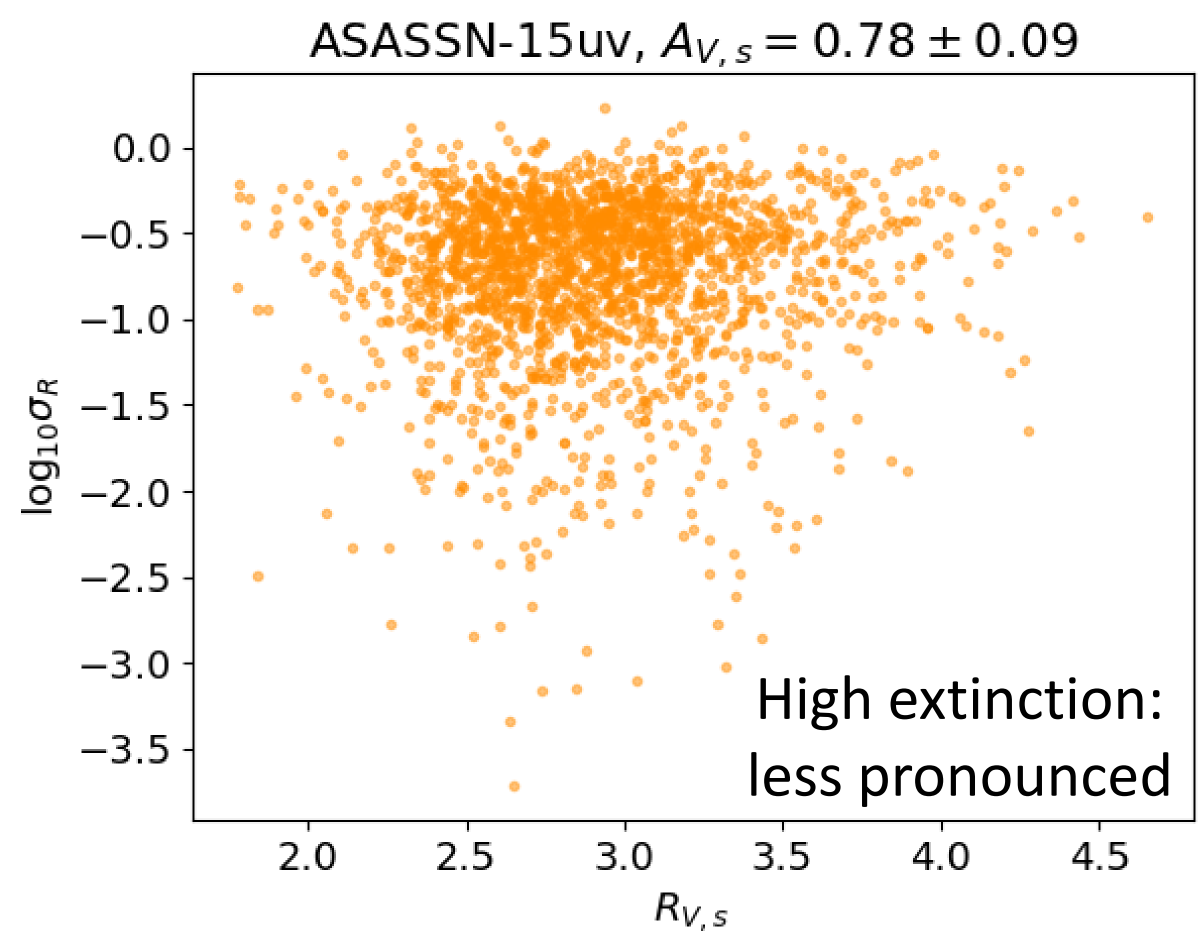
Performing the Inference

- Implement hierarchical model in Stan
- Uses HMC to sample joint posterior of global and supernova-level parameters
- Check convergence using standard diagnostics (G-R, divergences, etc.)

Computational Challenges

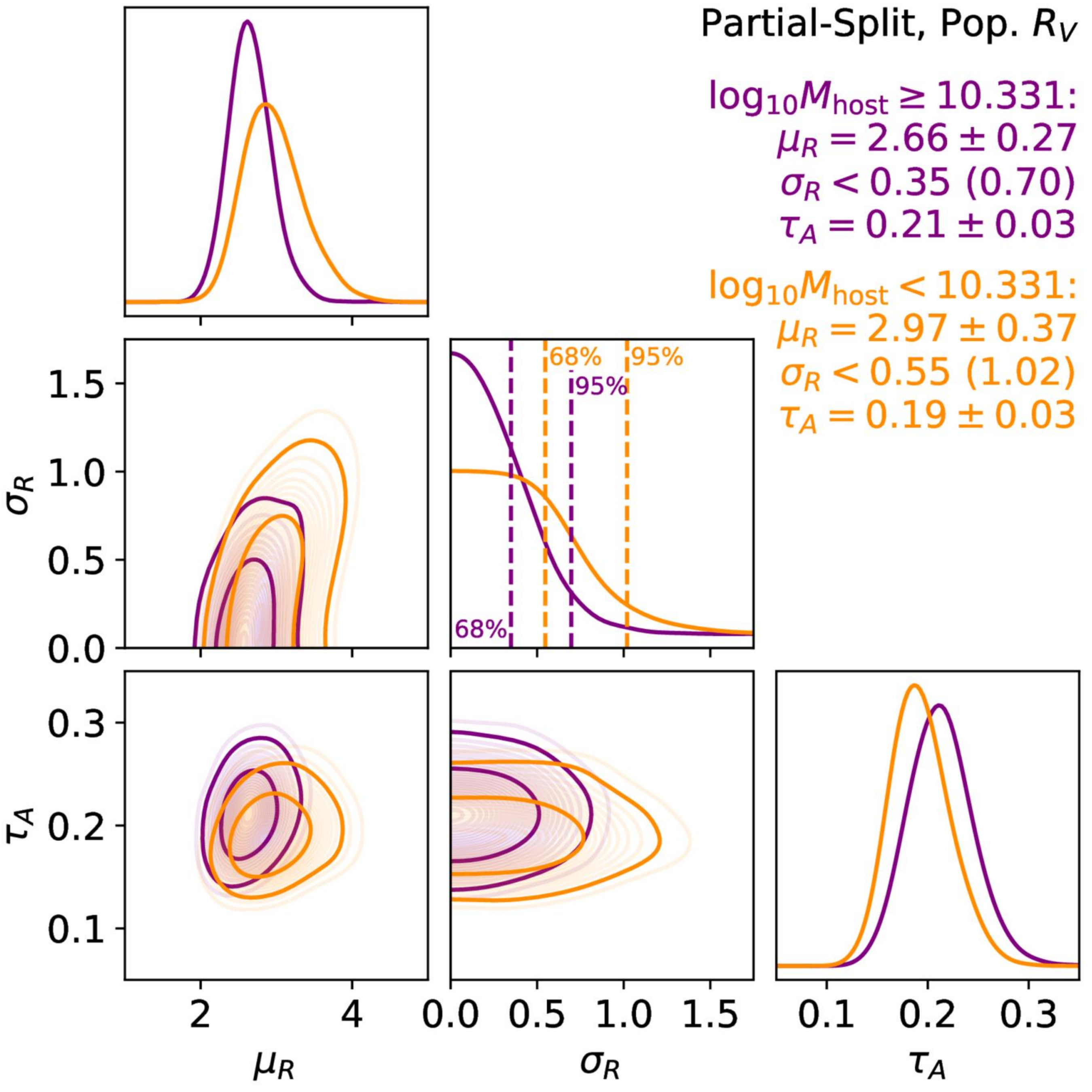
- Modelling R_V population distribution creates difficult posterior geometry
  → non-centred parameterisation!



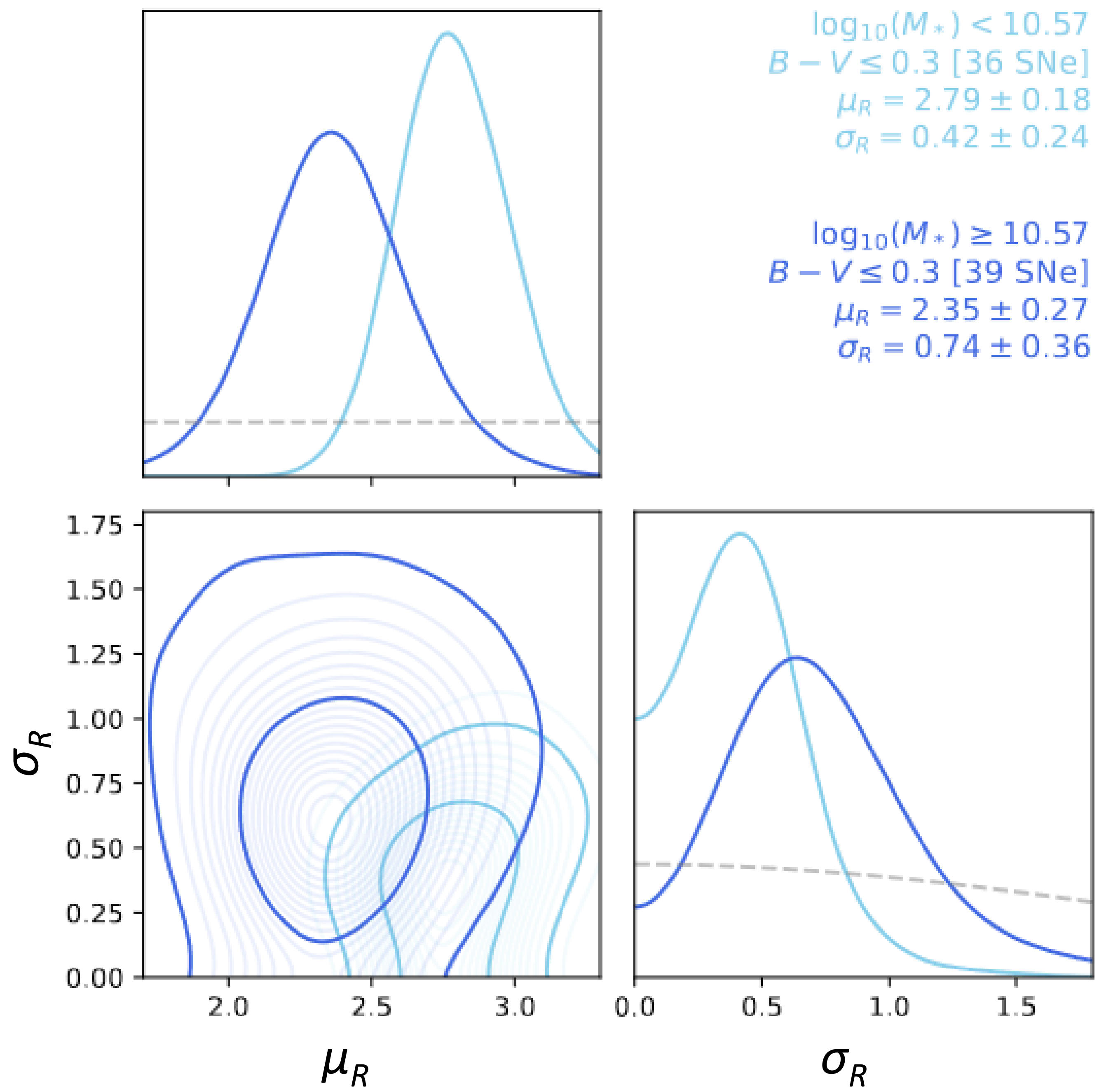


BayeSN Results on Low-*z* Data

R_V pop. distribution inference from Foundation



R_V pop. distribution inference from CSP



Thorp+21 [arXiv:2102.05678]

Thorp + Mandel, in prep.

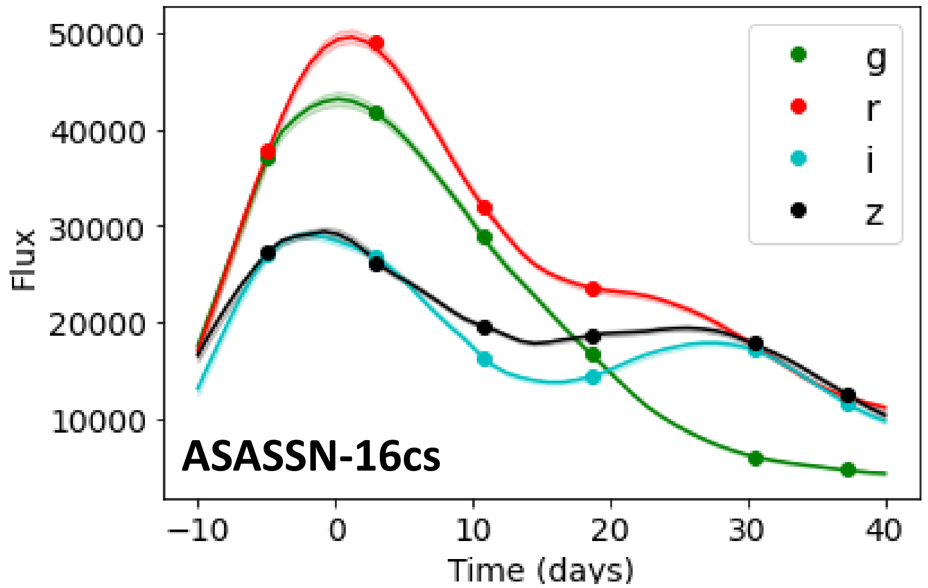
Headline Results

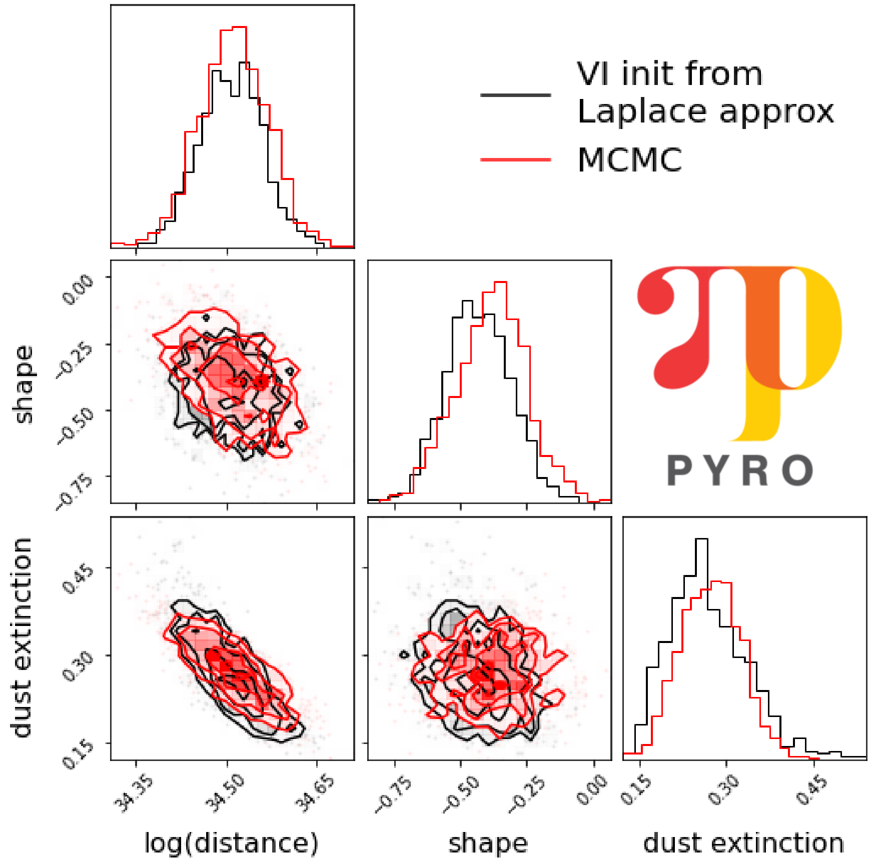
- Hierarchical Bayesian approach lets us perform robust inference of R_V distribution in SN Ia host galaxies
- Favour small to moderate R_V distribution width, without strong dependence on host galaxy stellar mass

Other BayeSN Activities

- H_0 w/ SN Ia siblings (Sam Ward)
- H_0 from optical+NIR (Suhail Dhawan)
- Improving scalability using variational inference (Ana Sofía Uzsoy)

Variational-BayeSN fit to Foundation DR1 Light Curve





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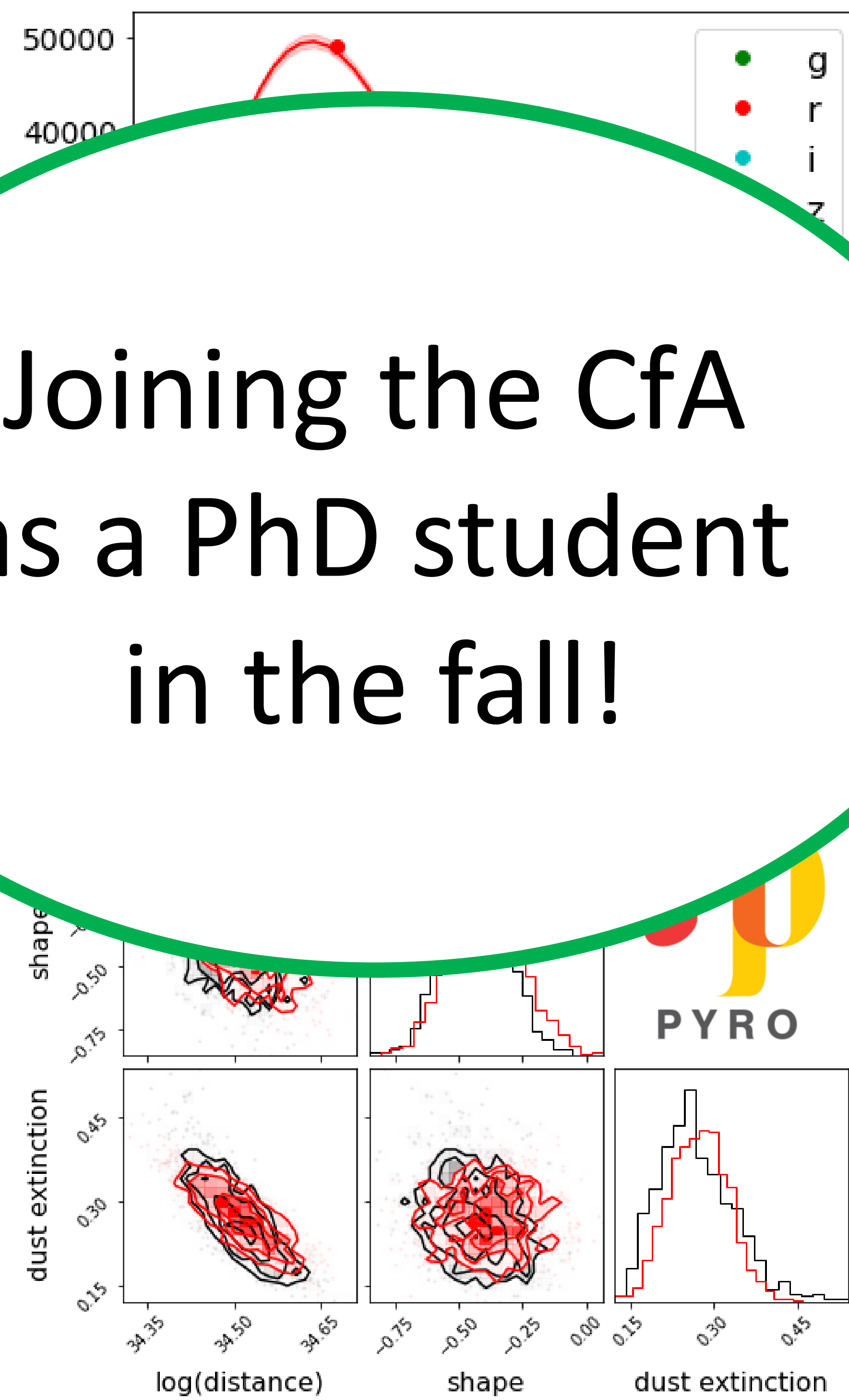

Joining the CfA as a PhD student in the fall!

Future Goals

- Scaling to LSST sized datasets whilst retaining Bayesian advantages (already making good progress with VI)
- Figuring out seamlessly integrated Bayesian treatment of selection effects
- Longer term... fully hierarchical cosmological analysis → SN photometry to cosmology with a single Bayesian model