Insights into the star formation and dust properties of galaxies from integrated spectral energy distributions

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Stephane Arnouts, Emeric Le Floc'h

Outline (1)

1) **Introduction**

(a) The key role of dust in shaping galaxy SEDs

(b) Formalism

2) Radiative transfer models of dust attenuation in galaxies

(a) Description of the models

(b) General properties of dust attenuation curves form RT models

3) The data: the Wild et al. (2011) sample

(a) How to compute attenuation curves from integrated photometry?

4) The model:

a) Stats 2: How to “guess” curves (or more generally, functions) from partially computed models?

b) The parameters of the model

Outline (2)

5) Fitting the data:

a) Results of the fit

b) Stats 3: Exploring the parameter space through MCMC

6) Discussion of the results

7) Examples / applications

8) **SFR and dust attenuation:** how to reliably infer the SFR from UV-to-near infrared colors, in absence of MIR/FIR observations?

a) The data

b) Encoding the infrared excess IRX into the (NUV-R) vs (R-K) diagram

c) Modeling

d) Discussion

9) Future developments

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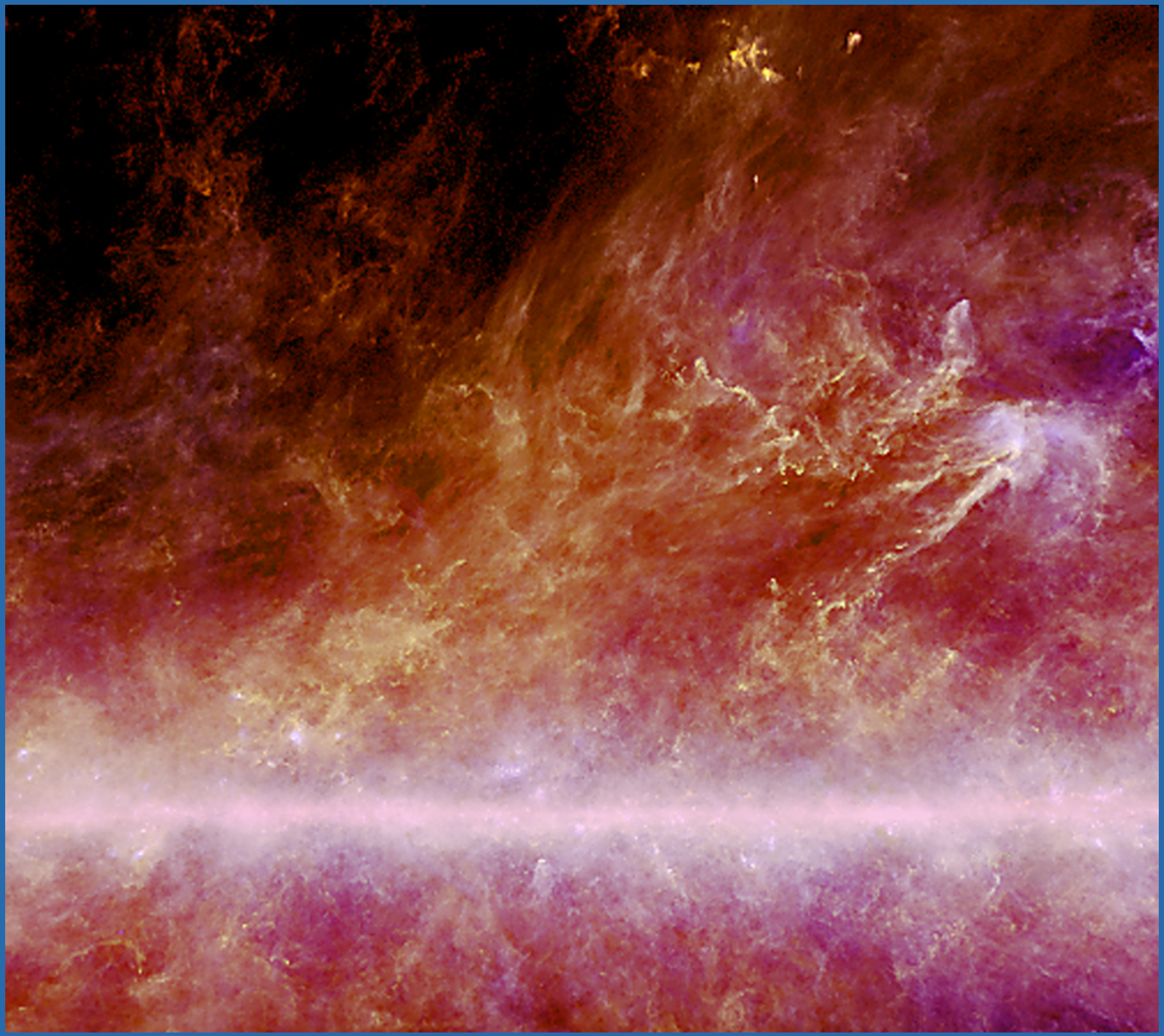

Credits: ESA and the HFI Consortium IRAS

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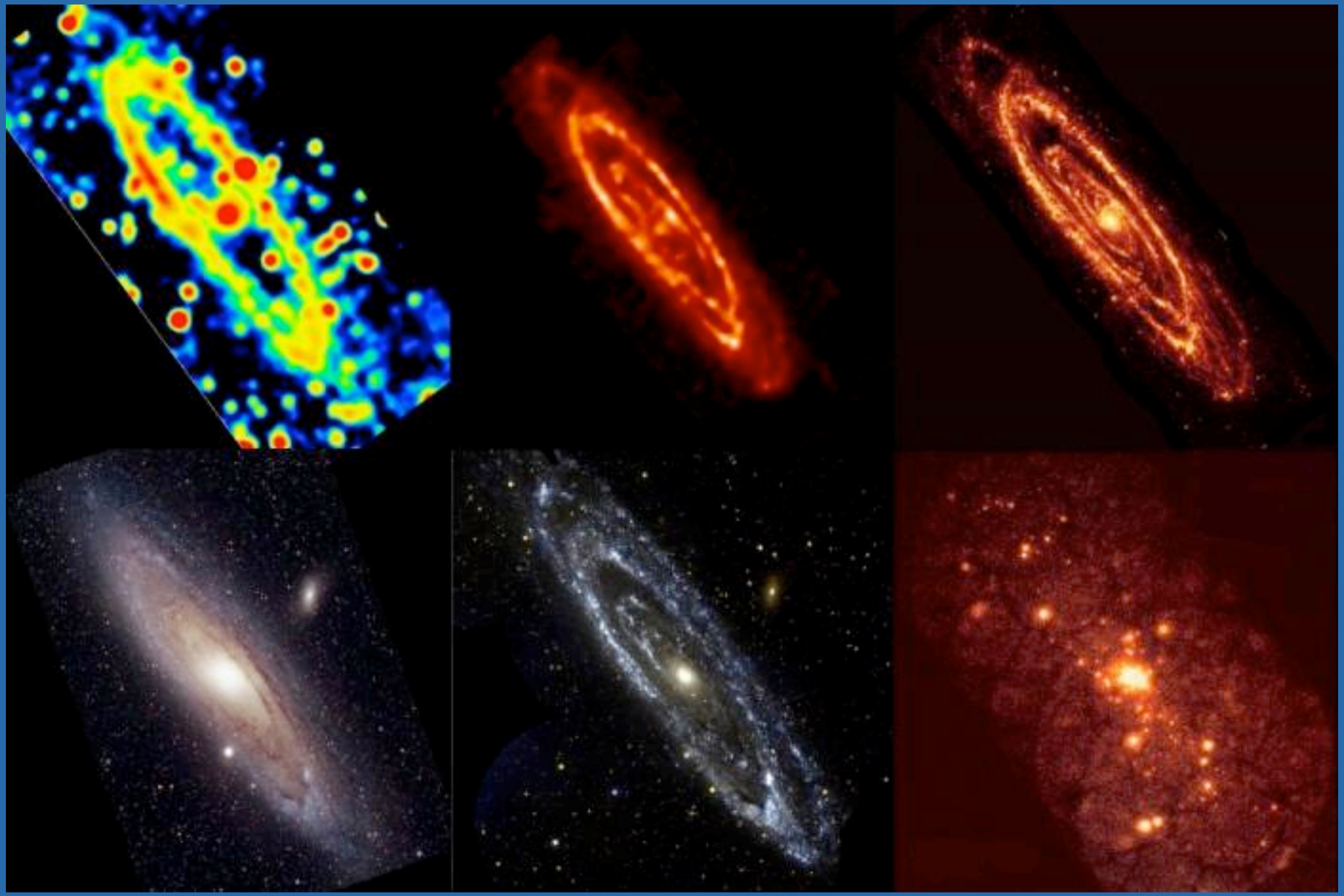
- Dust absorbs nearly half the UV-to-optical starlight, re-emitting the absorbed energy in the FIR



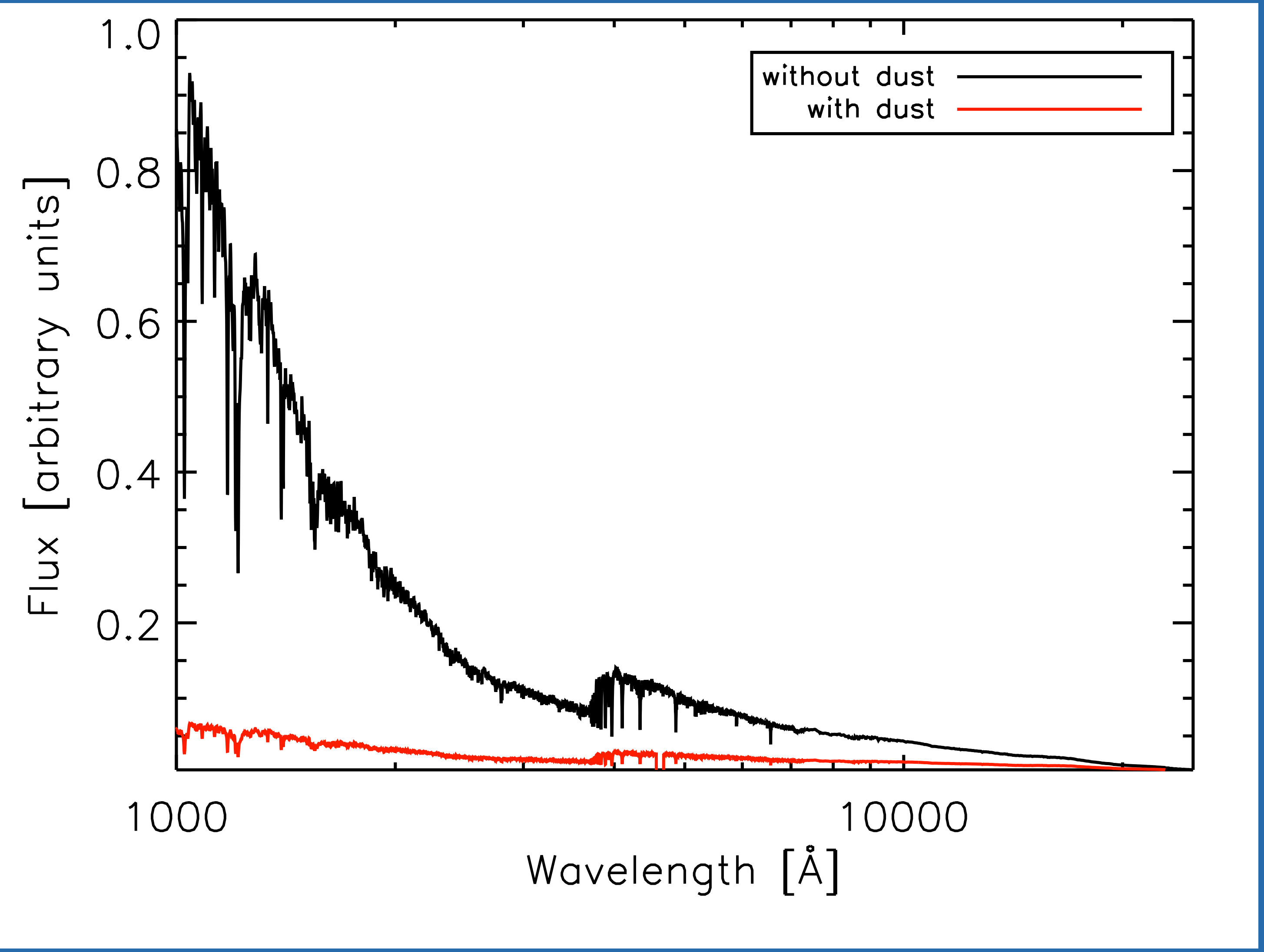
Andromeda (M31)

The key role of dust in shaping galaxies SEDs

- Dust is an ubiquitous component of the ISM

- Dust absorbs nearly half the UV-to-optical starlight, re-emitting the absorbed energy in the FIR

- To reliably estimate physical quantities (masses, SFR, SFH, ages, metallicities) from stellar and gas emission, modeling the effect of dust is critical



Dust attenuation: formalism

$$I_\lambda(\theta) = I_\lambda^0 \exp\left[-\hat{\tau}_\lambda(\theta)\right]$$

$I_\lambda(\theta)$: intensity emerging at wavelength λ in a direction θ from the normal to the equatorial plane of a galaxy

I_λ^0 : intensity produced by stars at wavelength λ (assumed isotropic)

$\hat{\tau}_\lambda(\theta)$: effective absorption optical depth at wavelength λ and inclination θ

Dust attenuation: modeling

$\hat{\tau}_\lambda(\theta)$: absorption + scattering + **geometry**

Same dust properties, but different **distributions** of dust and stars → Different attenuation laws in the **bulge**, **thick** and **thin** discs.

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Aim of my work: use general conclusions from **radiative transfer** (RT) models to improve dust attenuation prescriptions used in spectral analyses

↓

Includes **galaxy inclination** and different **spatial components**

Dust attenuation: effect on galaxy SED

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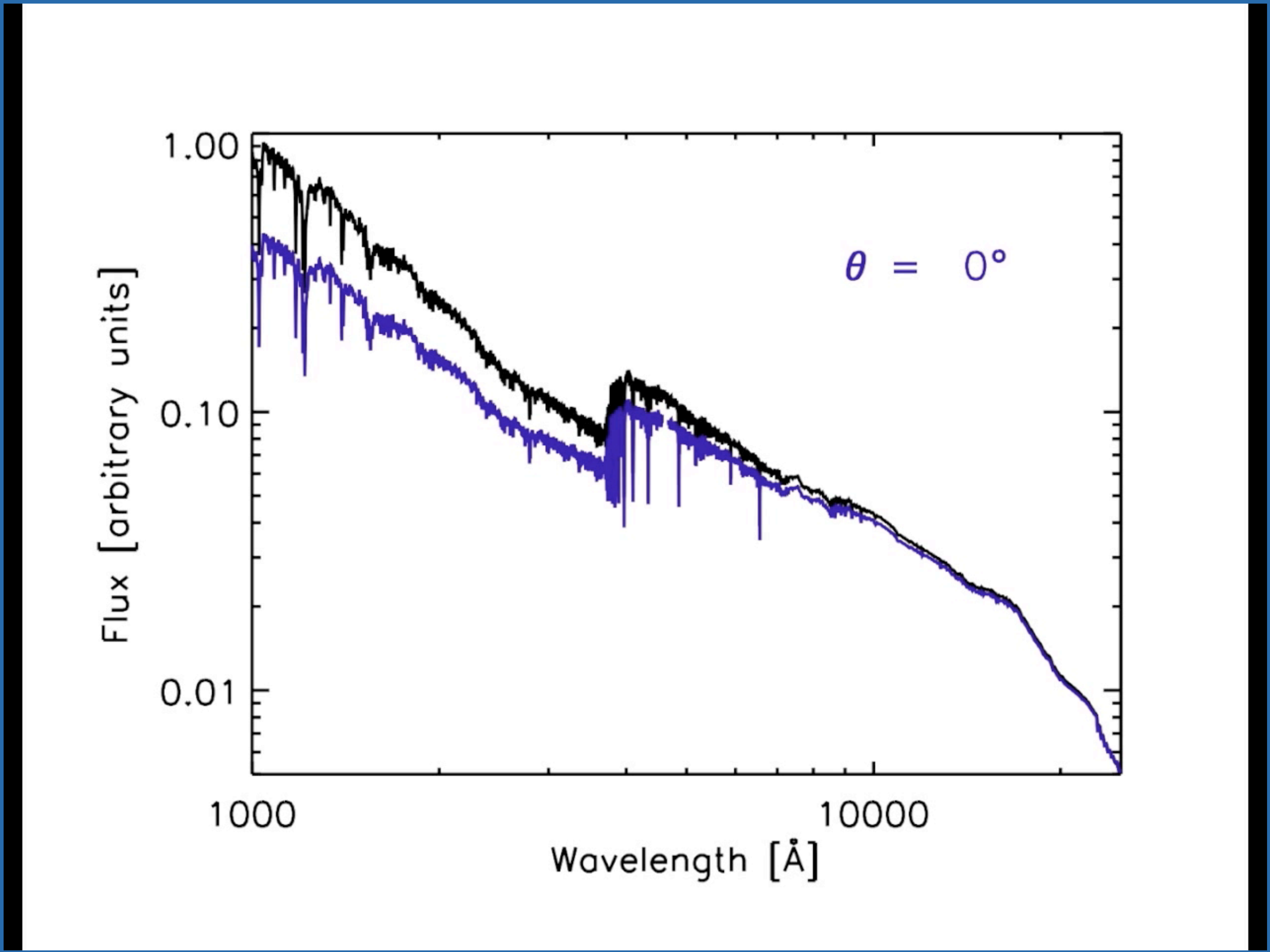

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Dust attenuation: modeling

- Comparison of different **radiative transfer models**:
  - ➡ Tuffs et al., 2004 (analytic, 3 comp.)
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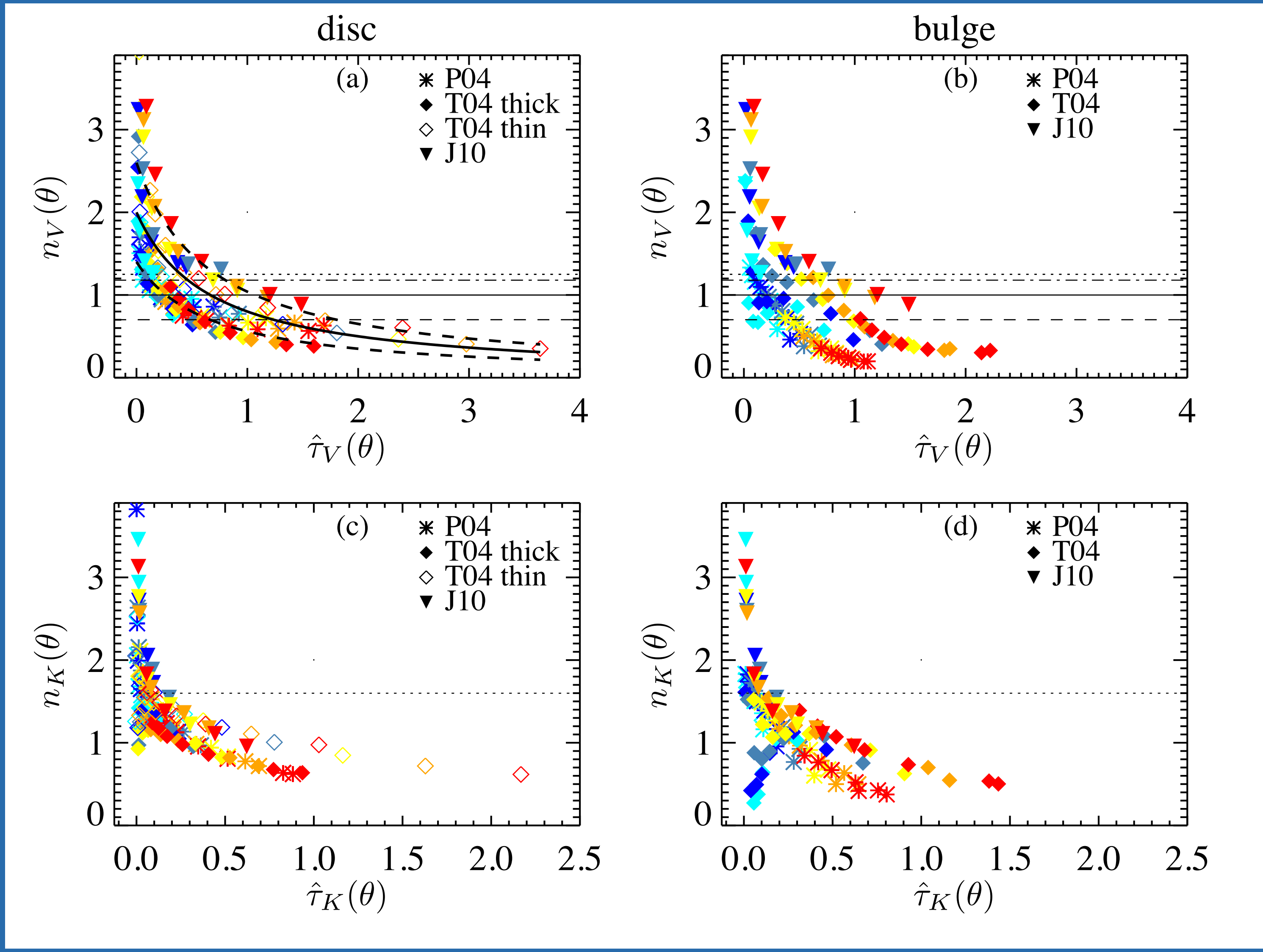
Predictions from different models are roughly consistent with each other (esp. optical)



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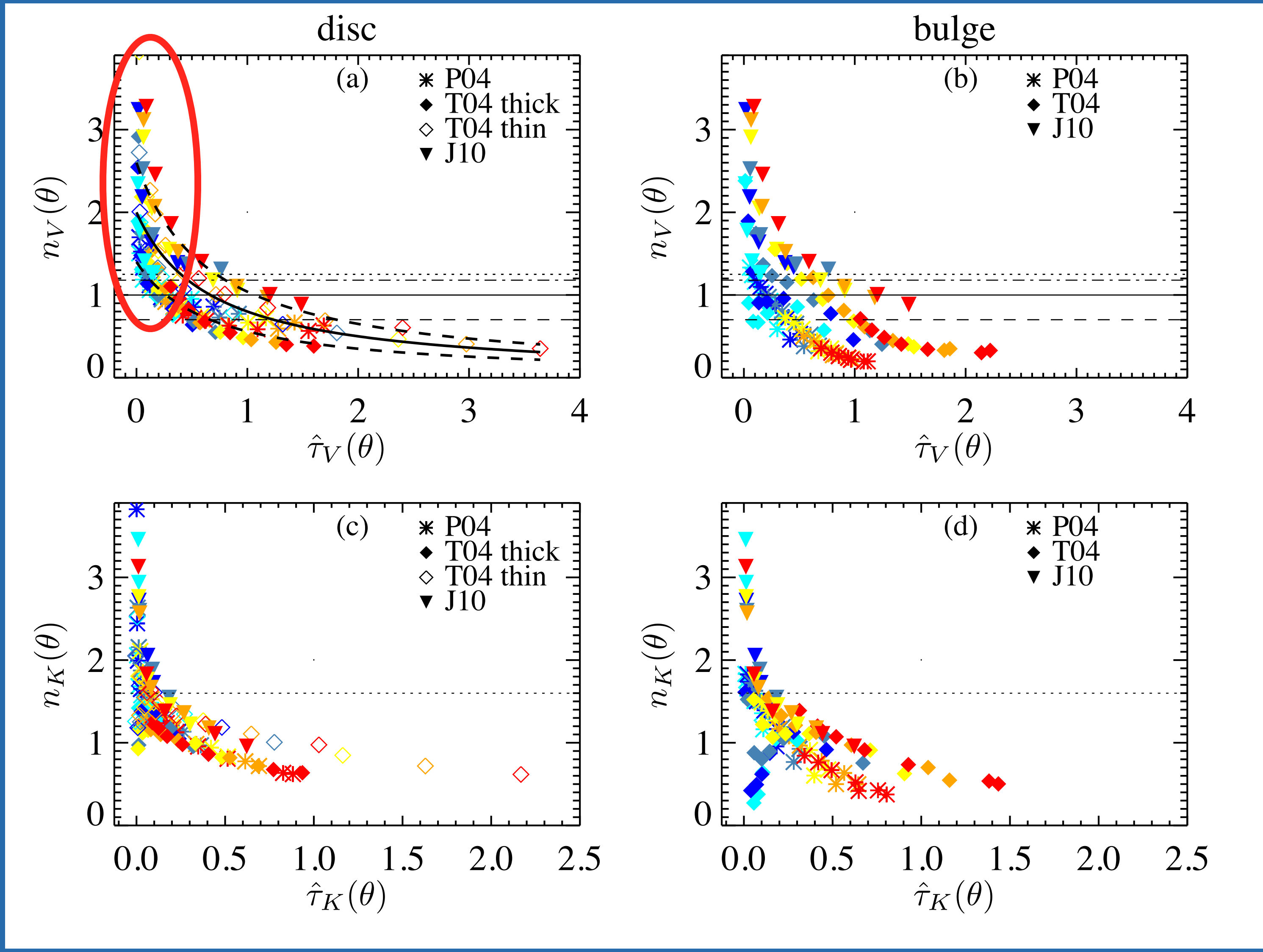

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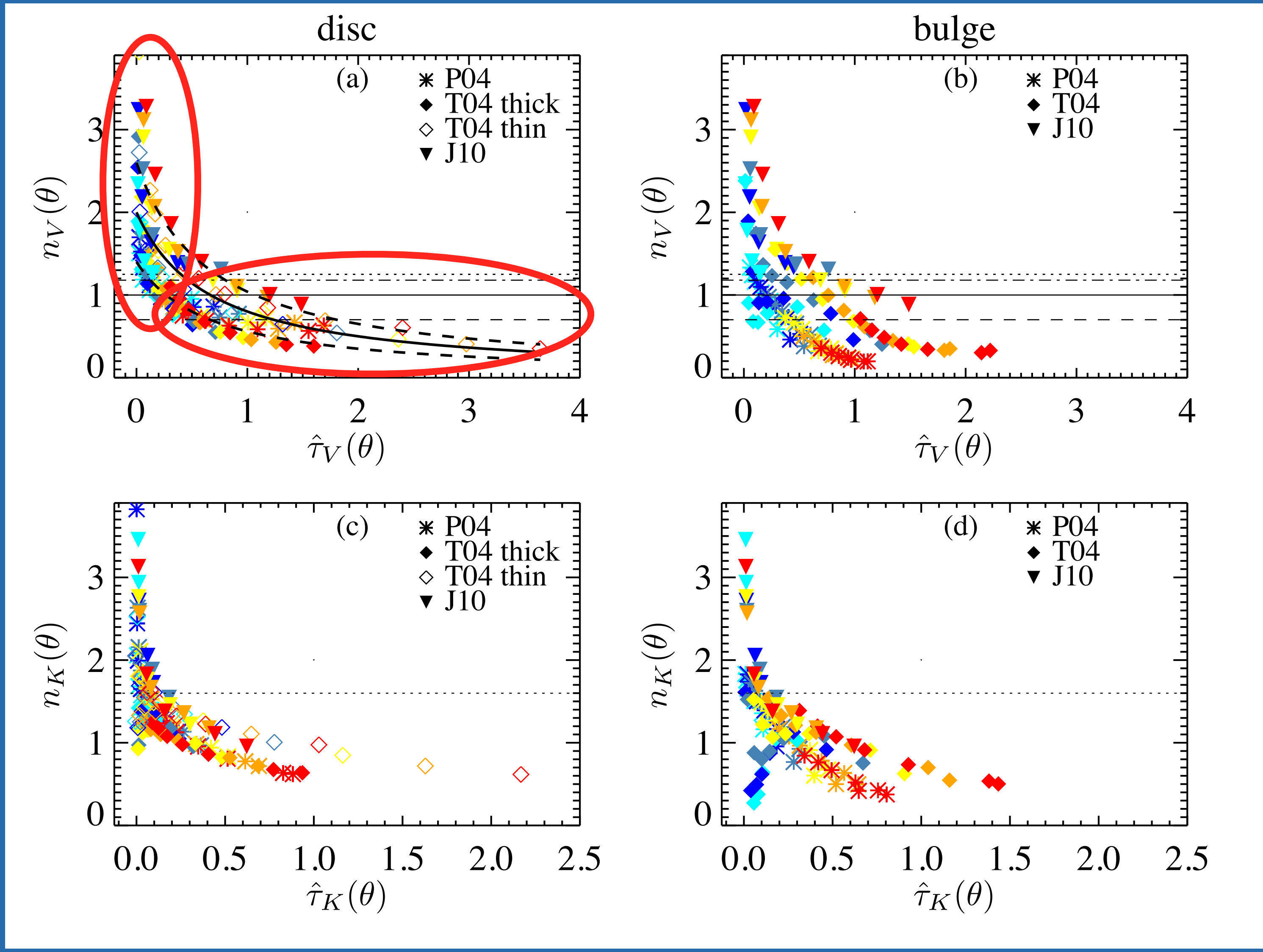

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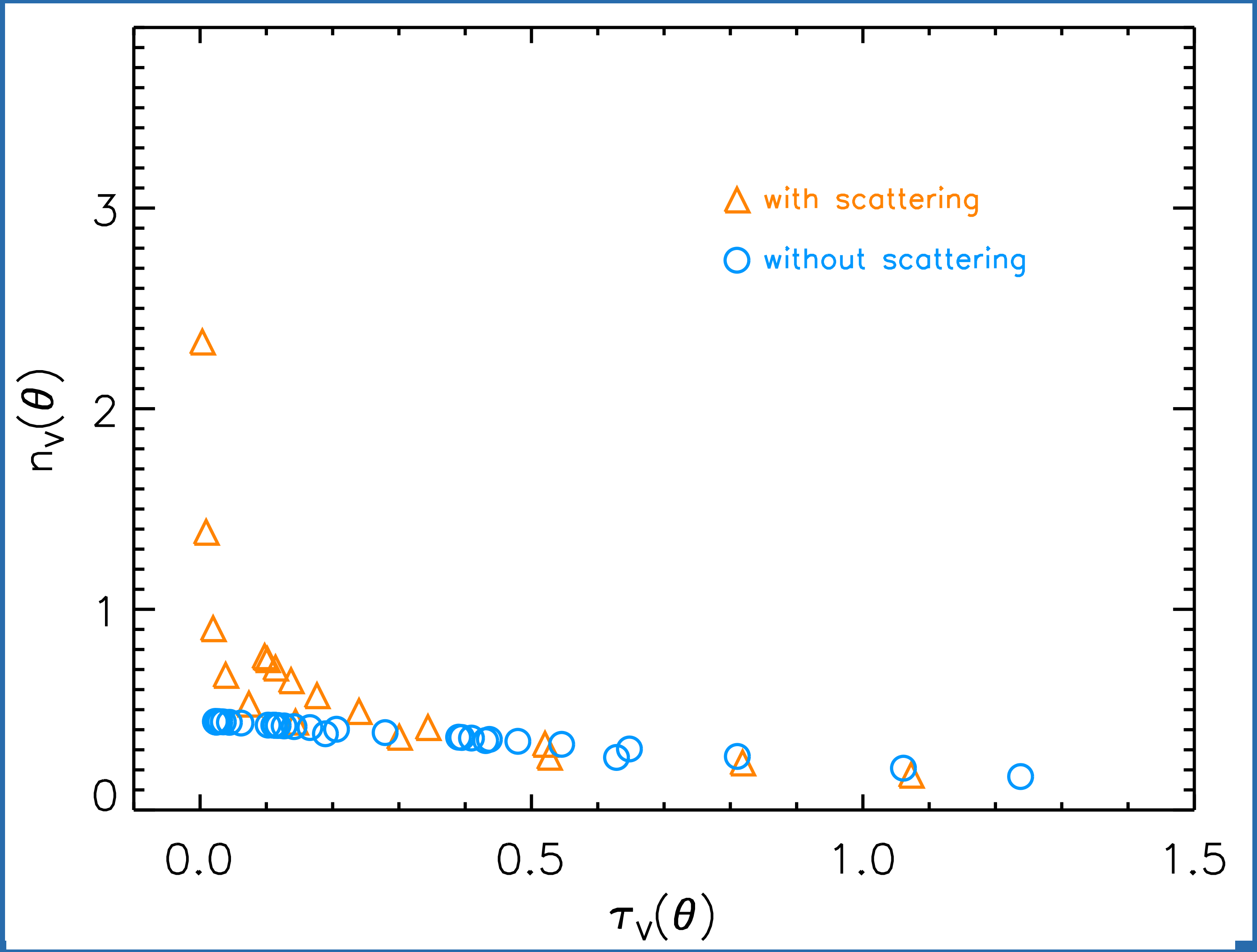

MacLachlan, private communication

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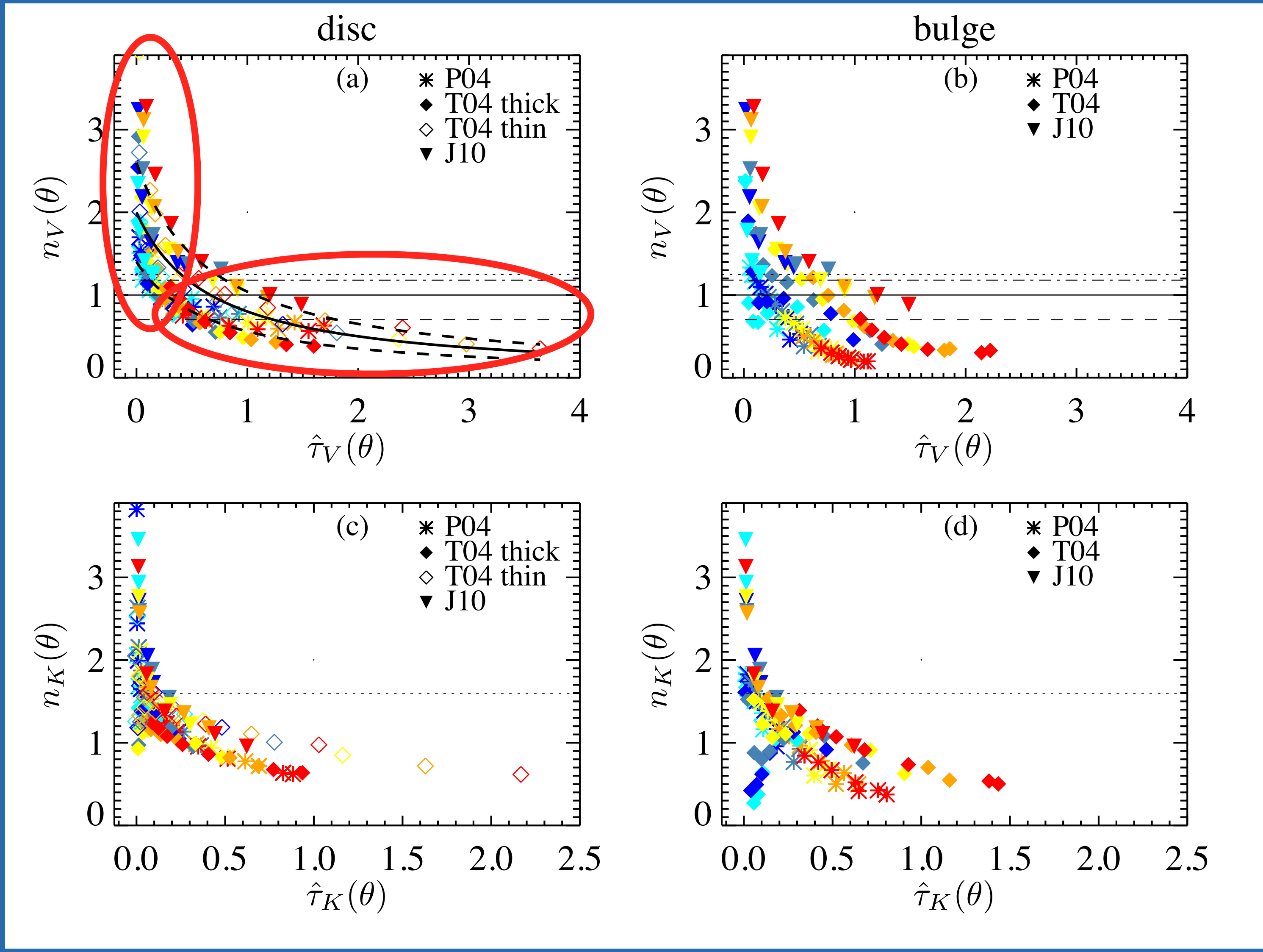

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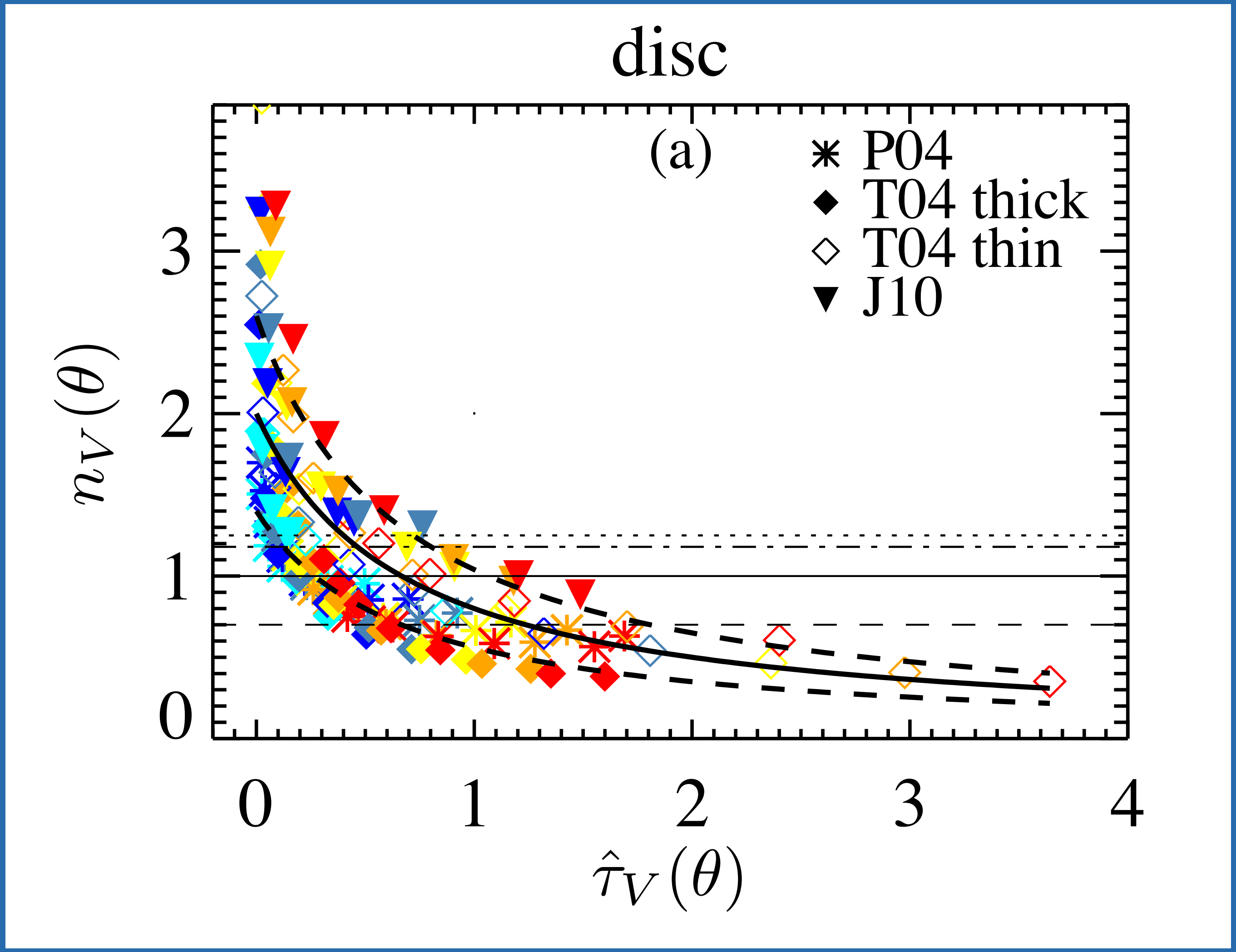
Dust attenuation: modeling

Fit of relation between optical slope $n_V(\theta)$ and V-band effective optical depth $\hat{\tau}_V(\theta)$



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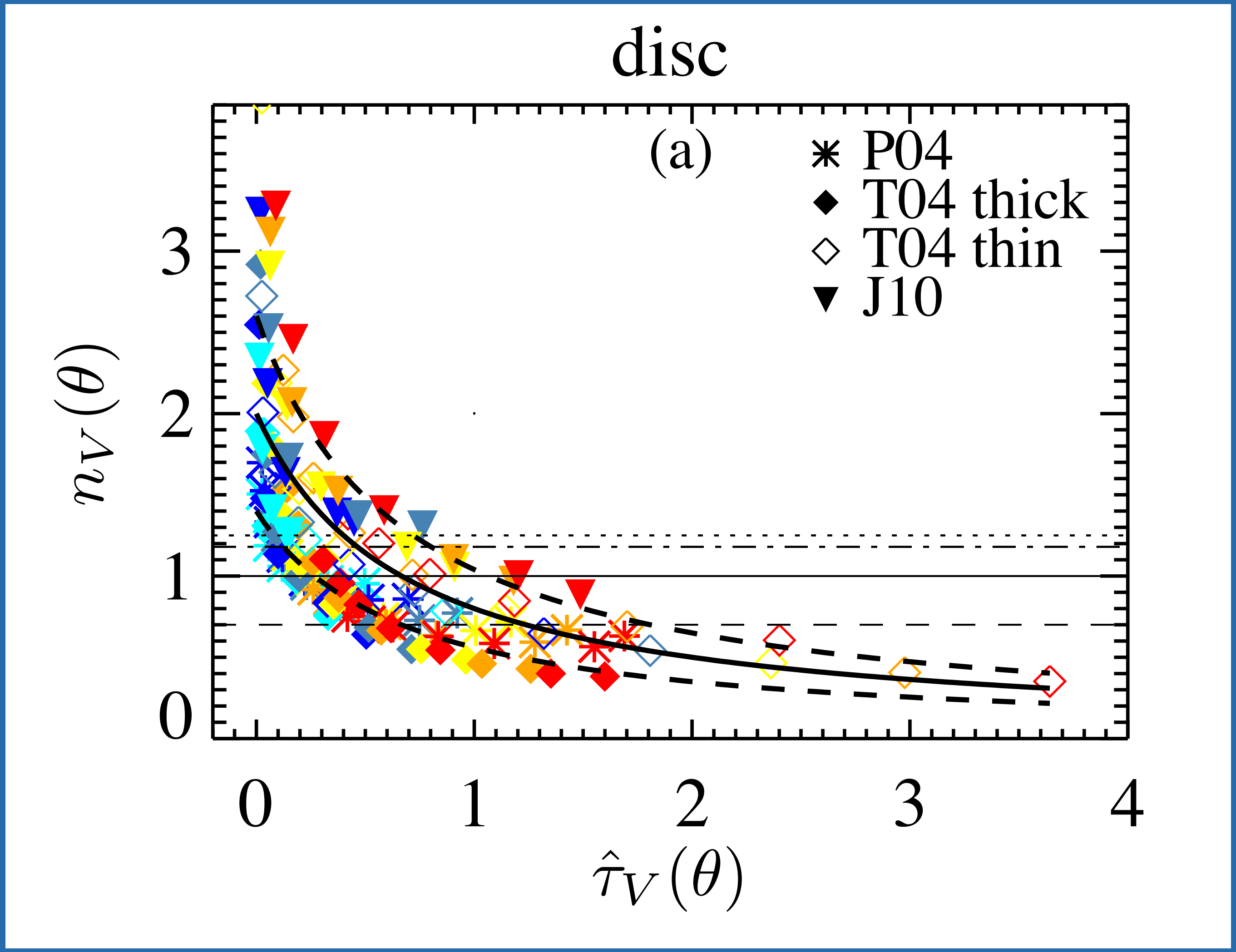

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- Account for effect of inclination and spatial distribution of dust and stars
- Based on MW-type dust
- Valid for quietly star-forming disc

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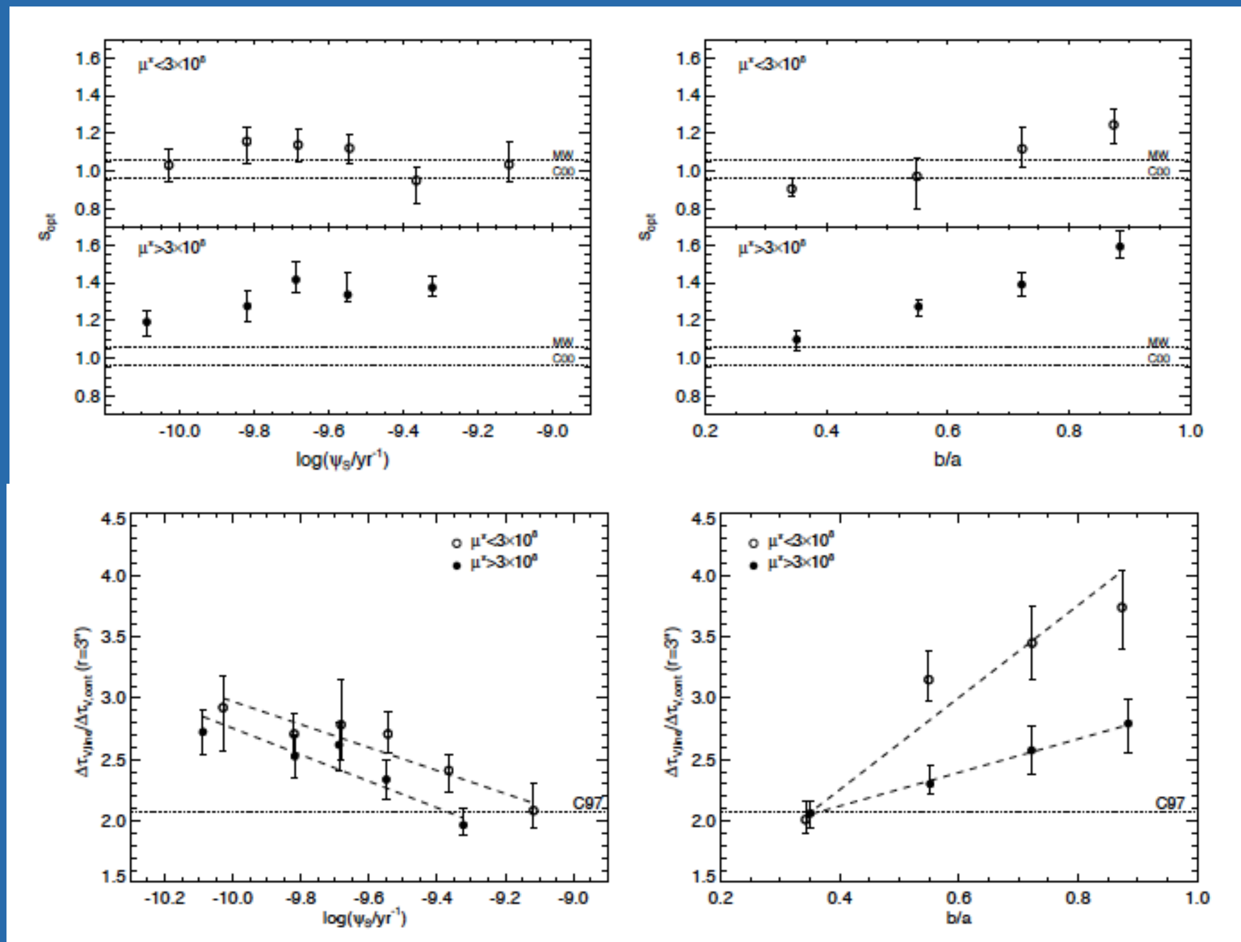

Wild et al., MNRAS 2011

- 23 000 star forming galaxies
- Optical-to-NIR photometry and optical spectra (SDSS + UKIDSS)
- High and low μ_* sub-samples to separate galaxy with/without bulge

- Wild et al. (2011) used pair matching of galaxies with different Balmer ratios to obtain attenuation curves
- Find trends between attenuation slopes and SSFR / axis ratio
- Valid only if attenuation curves are independent on $\hat{\tau}_V$
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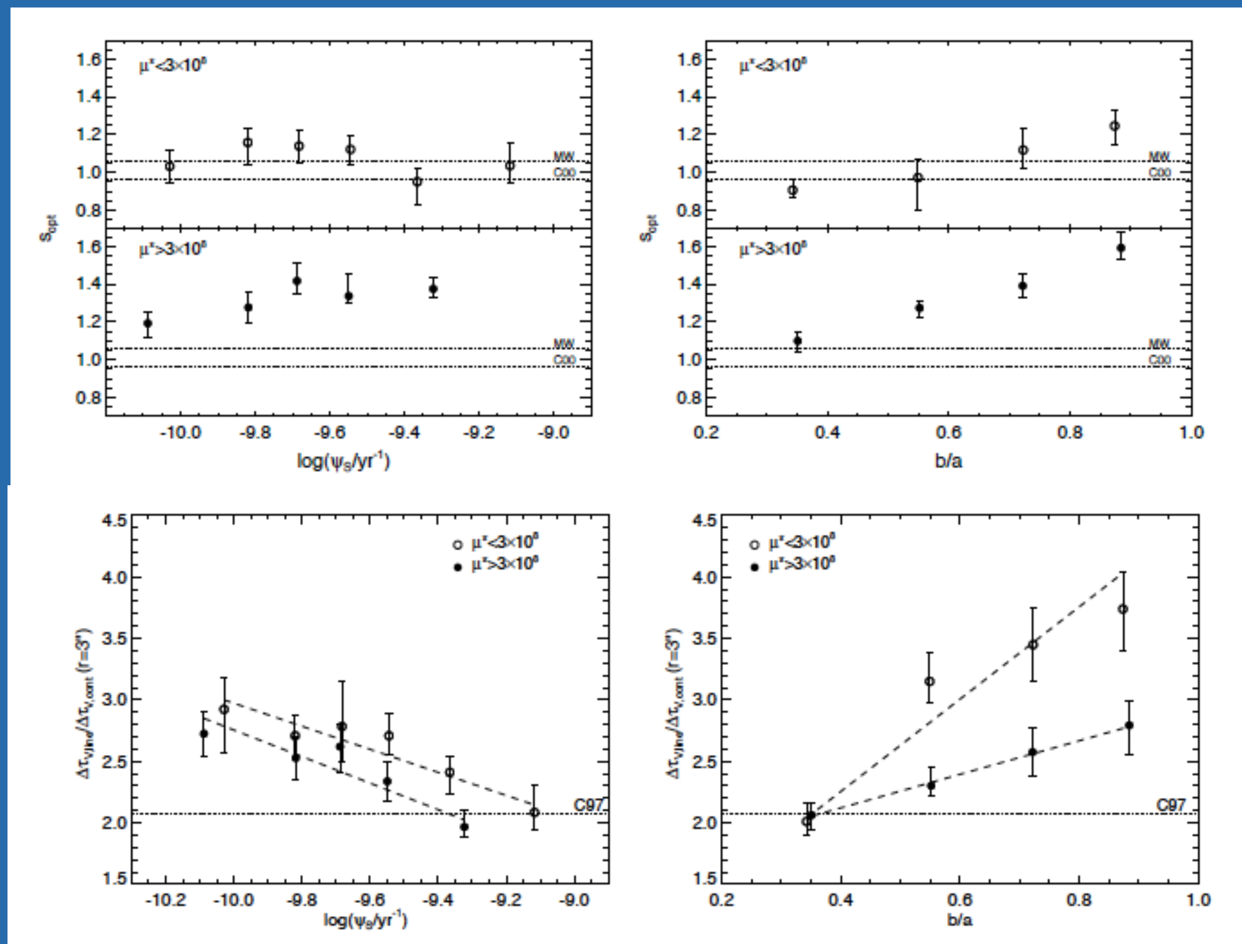

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Need of a different approach to get attenuation curves from galaxies SEDs

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Computing attenuation curves from data

- **Differential photometry** to compute attenuation curves as a function of inclination (attenuation from diffuse ISM, mainly stars older than 10 Myr):
  - normalize all the SEDs to the K-band flux (small attenuation in the K-band)
  - divide in 10 b/a bins and compute the mean SED in each bin
  - compute the ratio of the SED in any bin to the face-on one
- Works if the intrinsic SEDs are the same across the b/a bins...

+

- $H\alpha/H\beta$ ratio variation with inclination (attenuation suffered by stars younger than 10 Myr)

Computing attenuation curves from data

- Are the unattenuated SEDs constant across the b/a bins? Not really...

- Systematic variation of SSFR, 12+log(O/H), z and radius across the b/a bins

- Correct biases using a method based on importance sampling (see soon Chevallard+2012 for details!)

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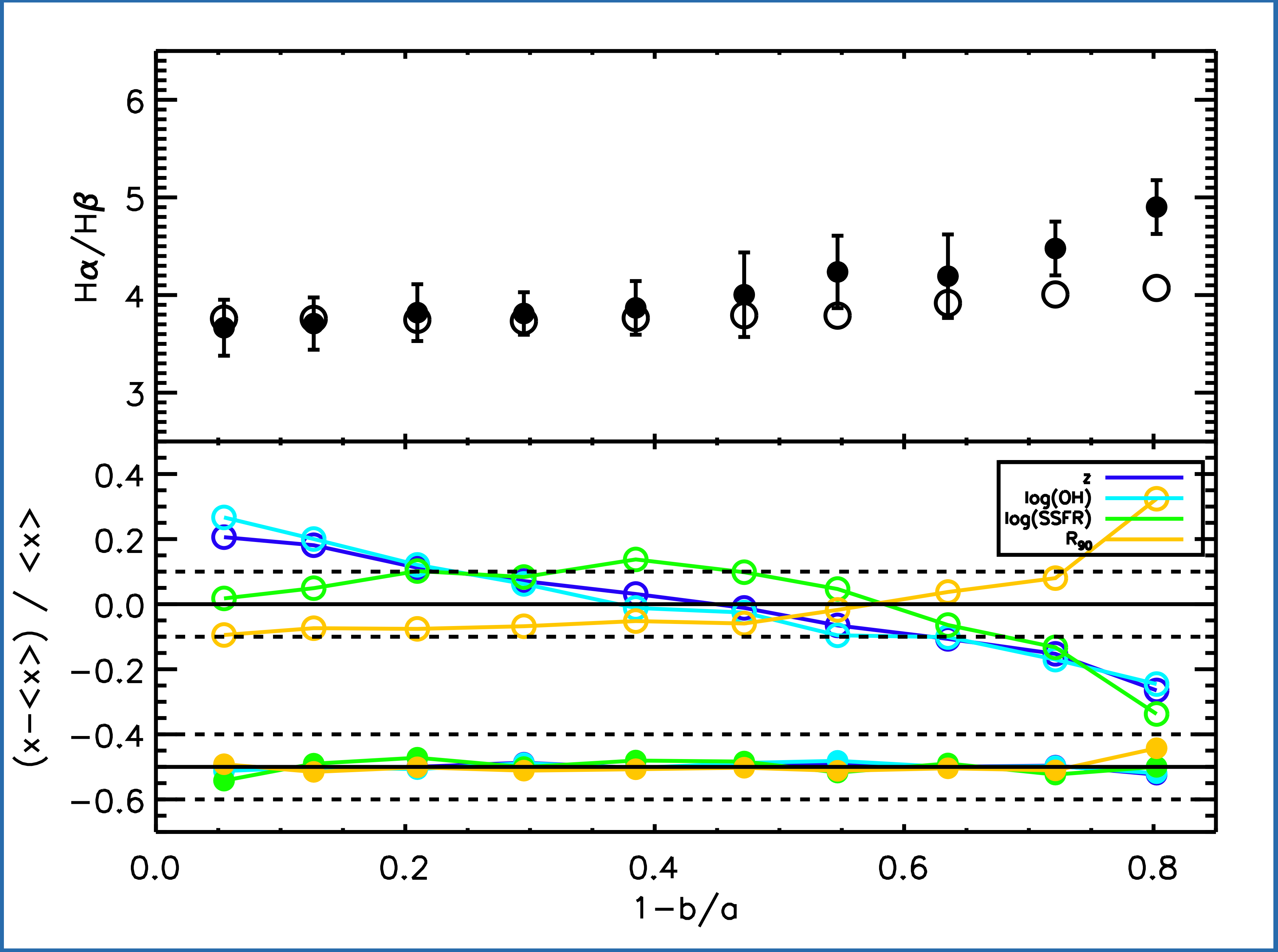

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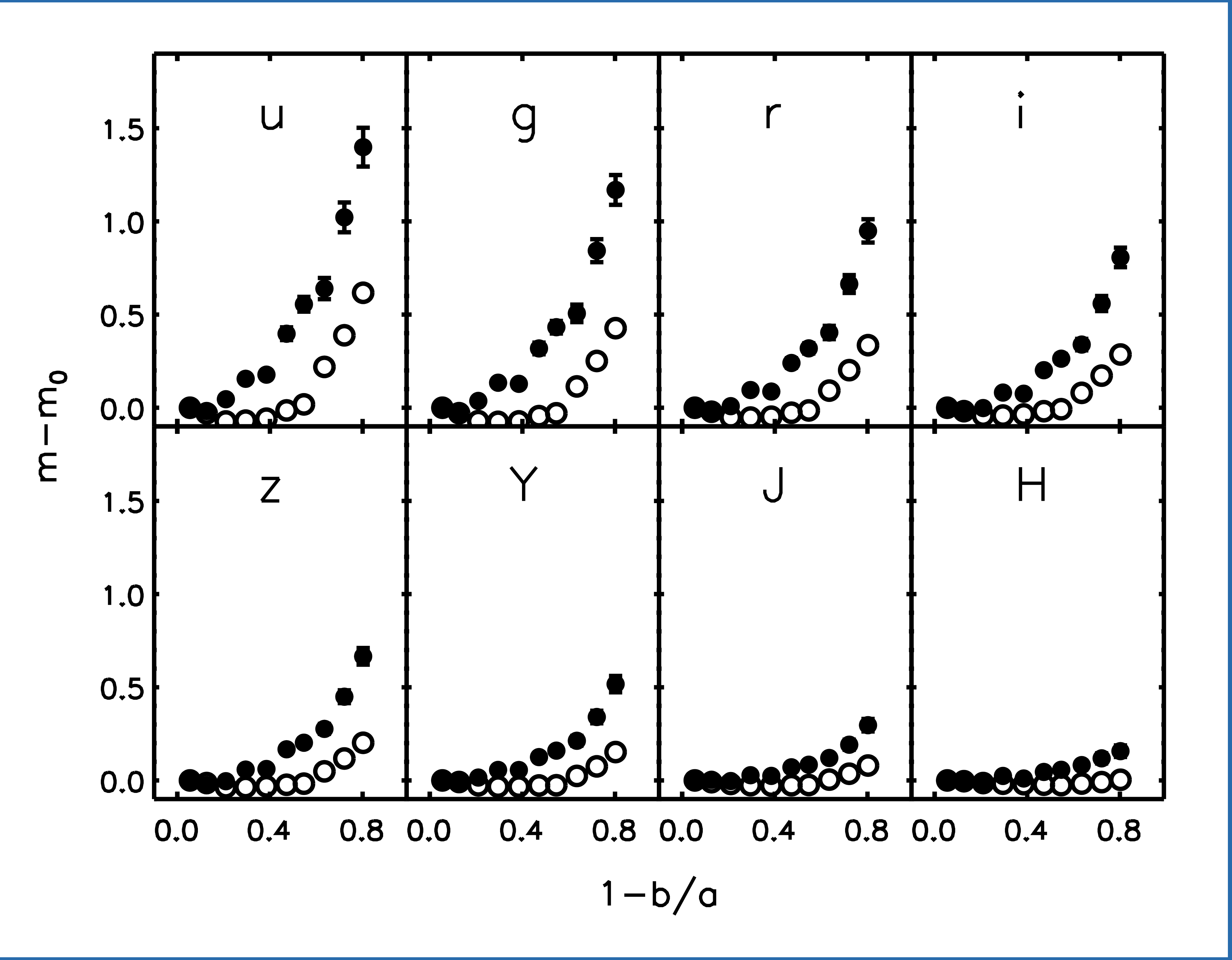

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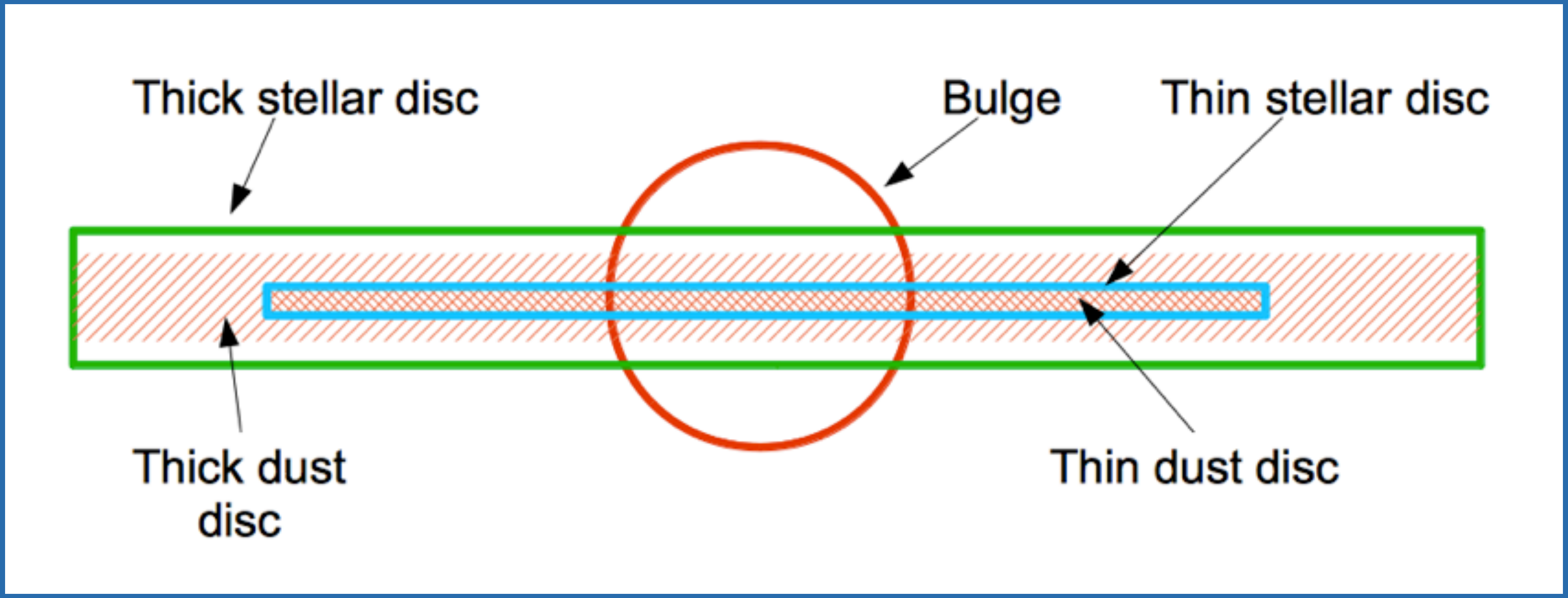

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- Adopt the Tuffs et al. model to fit the data, since they are the most flexible (composed of 3 separate geometrical components: thick, thin disc and bulge)

- 5 parameters to describe attenuation by dust:
  - $\tau_{B,\perp}$: amount of dust in the ambient (i.e. diffuse) ISM
  - $\tau_{V,BC}$: optical depth of stellar birth clouds
  - $\mathrm{t}_{\mathrm{thin}}$, $\mathrm{t}_{\mathrm{thick}}$, $\mathrm{t}_{\mathrm{bulge}}$: assign stars of different ages to the different geometrical components of the Tuffs et al. (2004) model
- Appeal to a Markov Chain Monte Carlo (MCMC) algorithm to efficiently explore the parameter space

Statistics: Gaussian Random Processes (1)

Problem:

- Tuffs et al., 2004 **thick disc and bulge** components computed for $0.45 < \lambda < 2.1\,\mu m$
- **Thin disc** component computed for $0.1 < \lambda < 2.1\,\mu m$
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(If noisy input) $\mathbf{C_{yy}}^{-1} \longrightarrow [\mathbf{C_{yy}} + \sigma^2\mathbf{I}]^{-1}$

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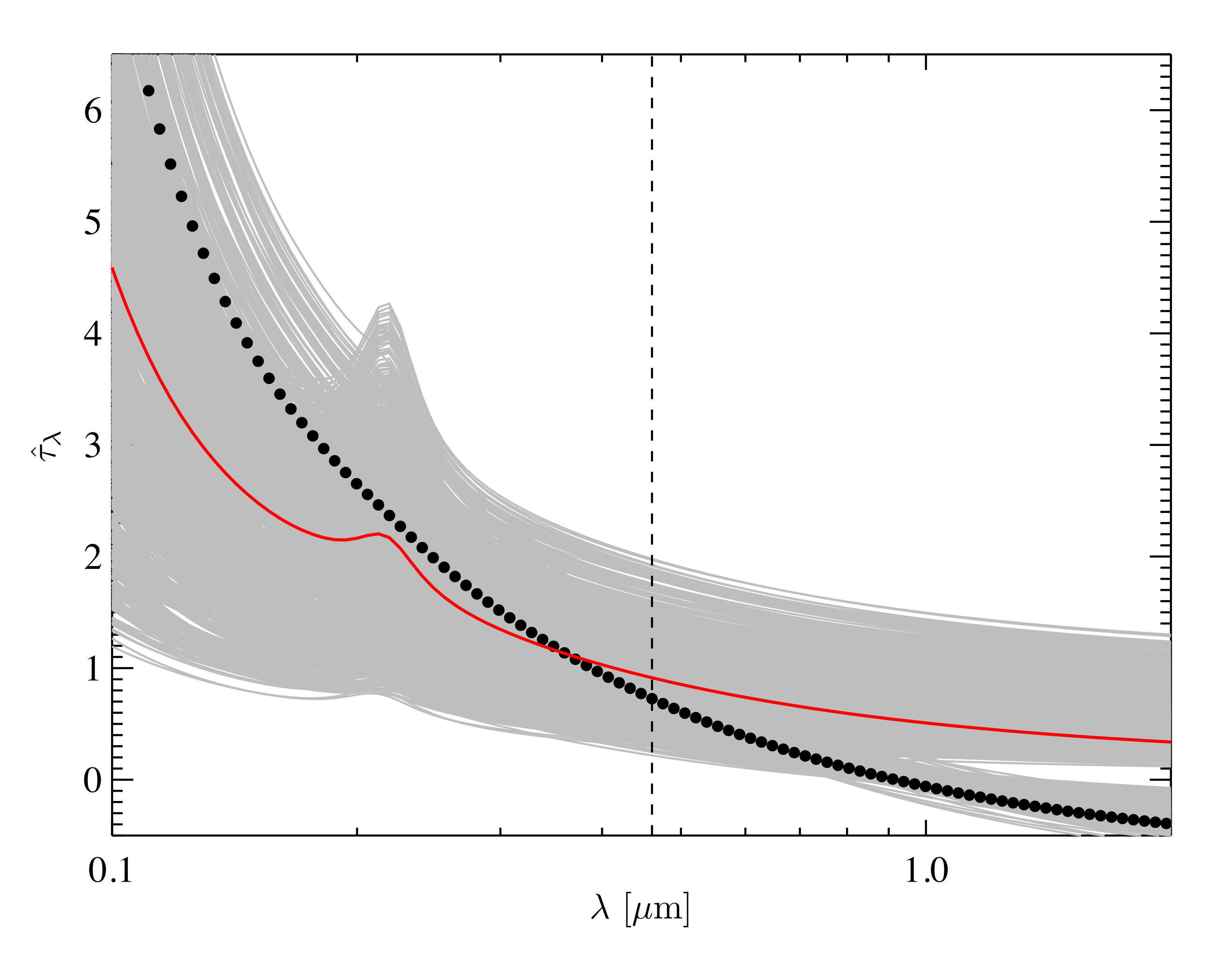

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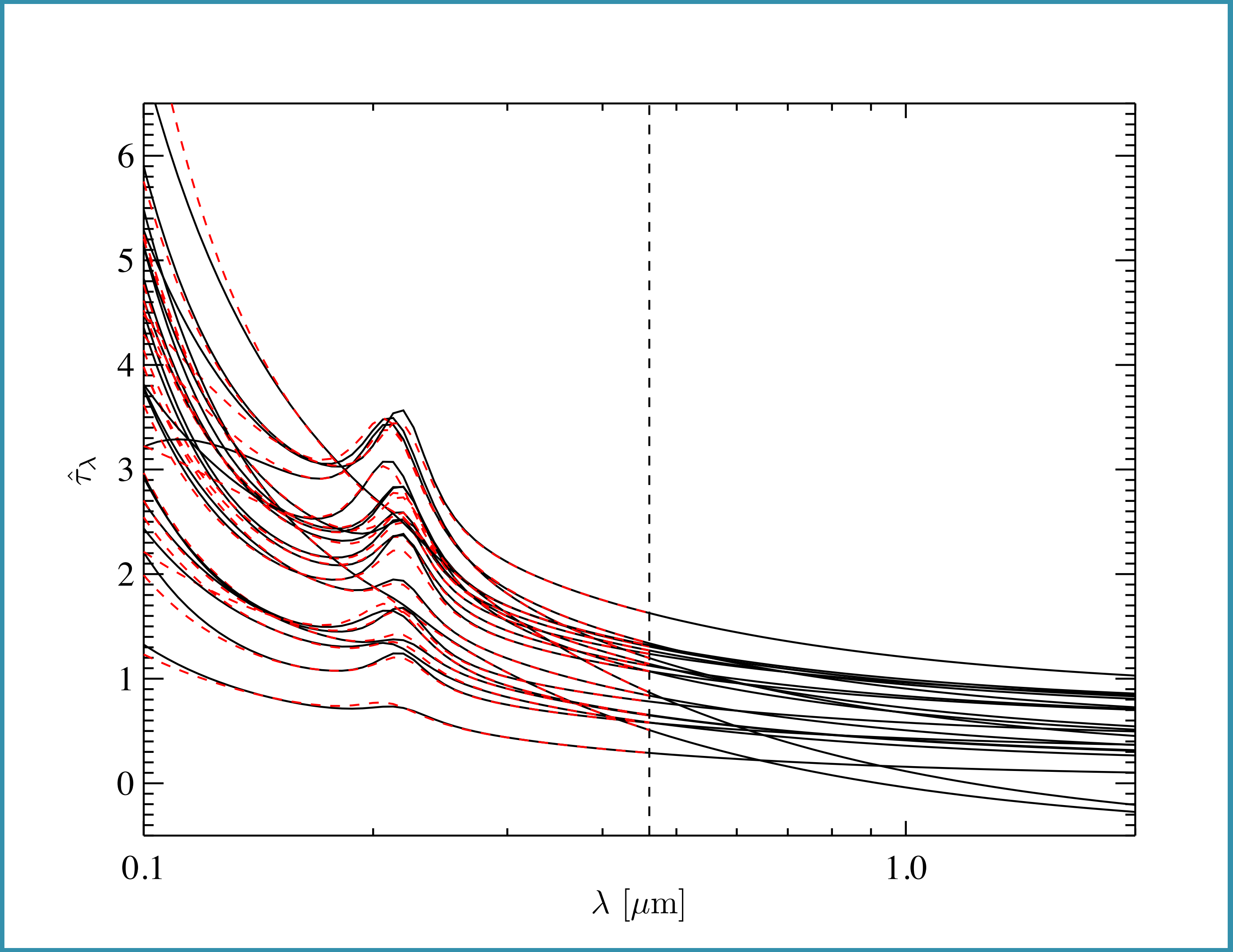
Test:

- Compute a library of 1000 attenuation curves, using parametrization of Gordon et al., 2003
- Compute 40 random curves, which are not part of previously computed library
- Try to guess curves at $\lambda < 0.45\,\mu m$, given curves at $0.45 < \lambda < 2.1\,\mu m$



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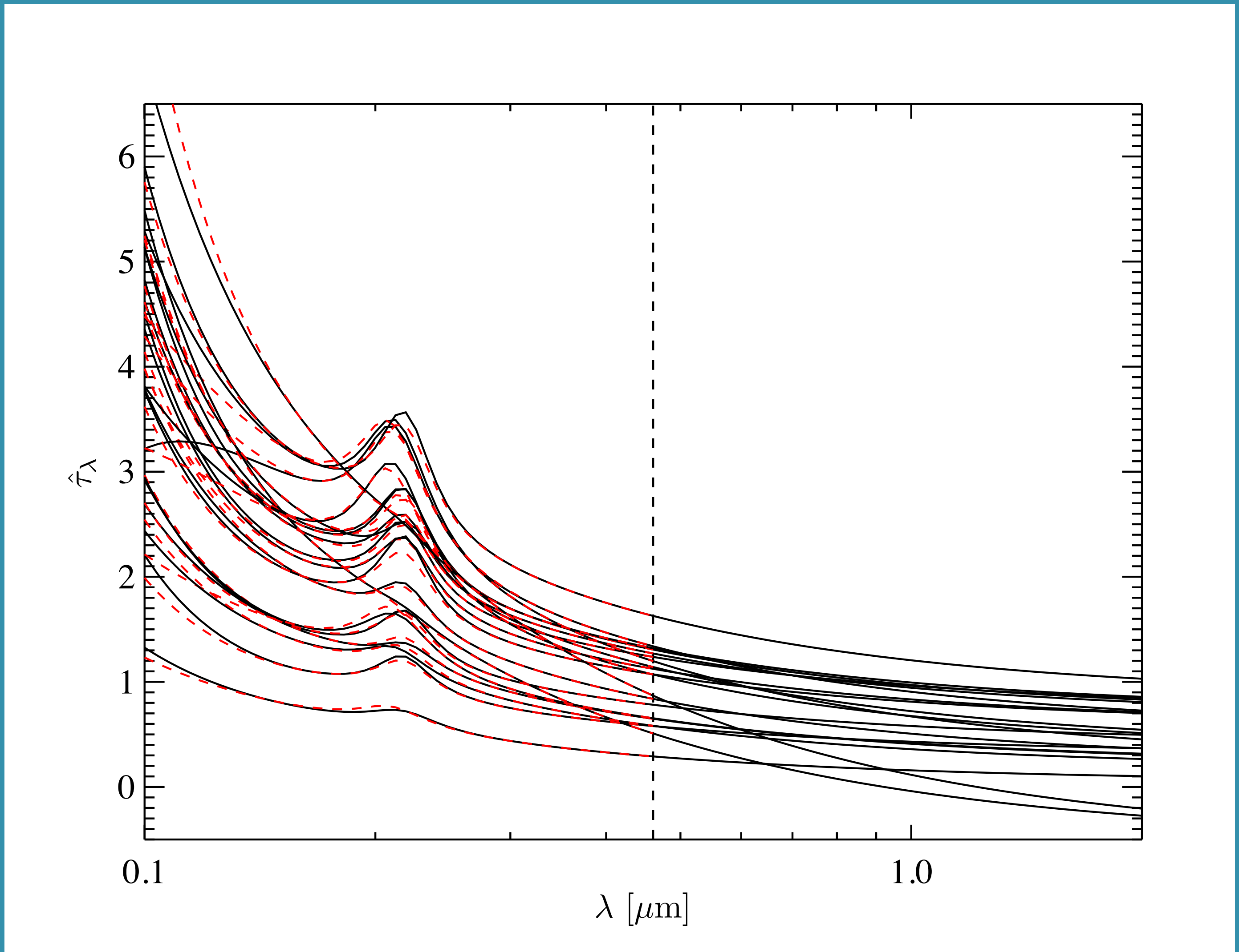

- Excellent recovery of the curves
- Apply this method to guess the T04 thick and bulge attenuation curves in the UV

Several applications:

- Multi-dimensional interpolation of sparse observations (e.g. spectral libraries)
- Tool to include interpolation uncertainties
- Planning of optimal observations
- Approximation of computationally expensive likelihood

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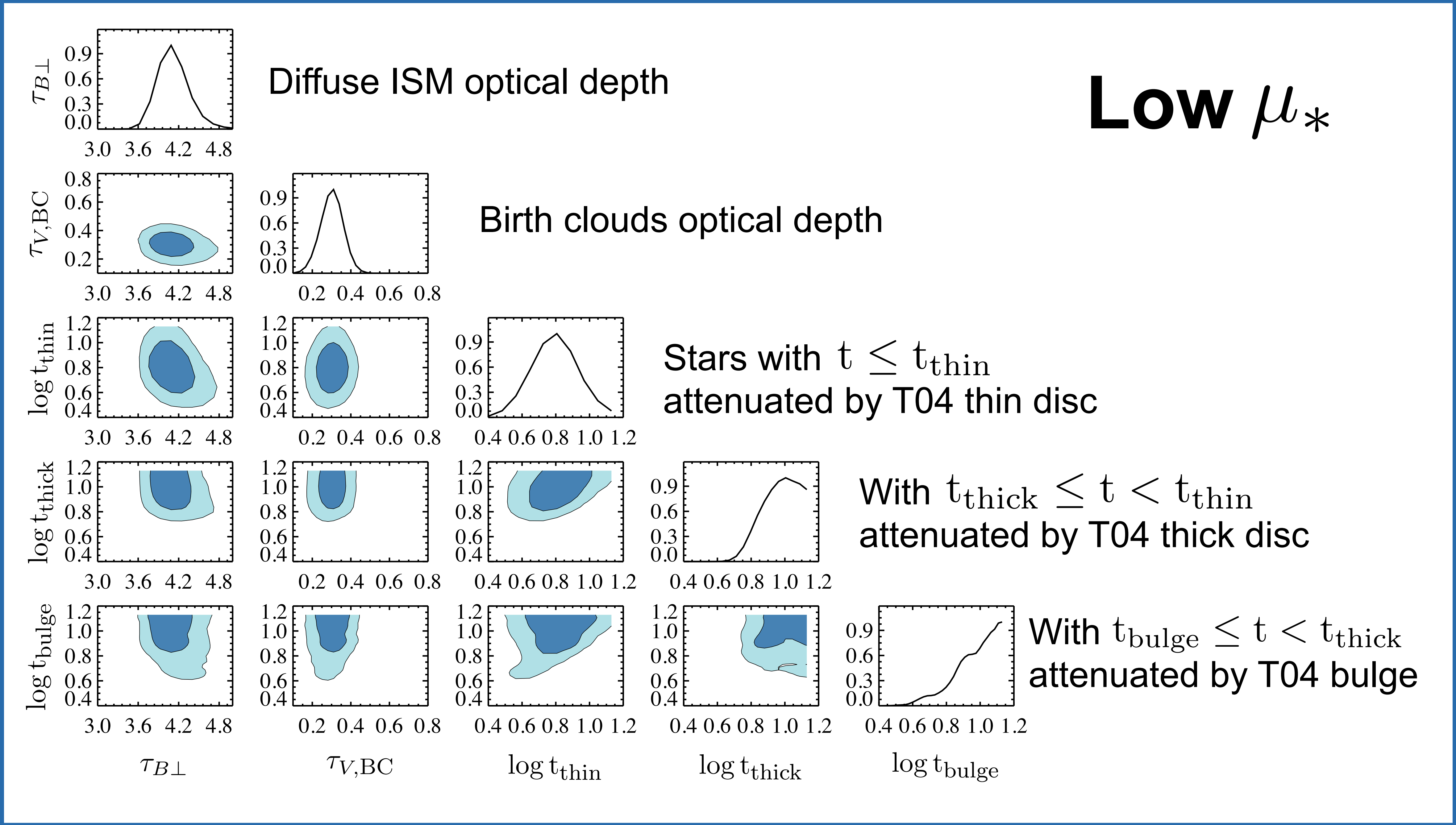

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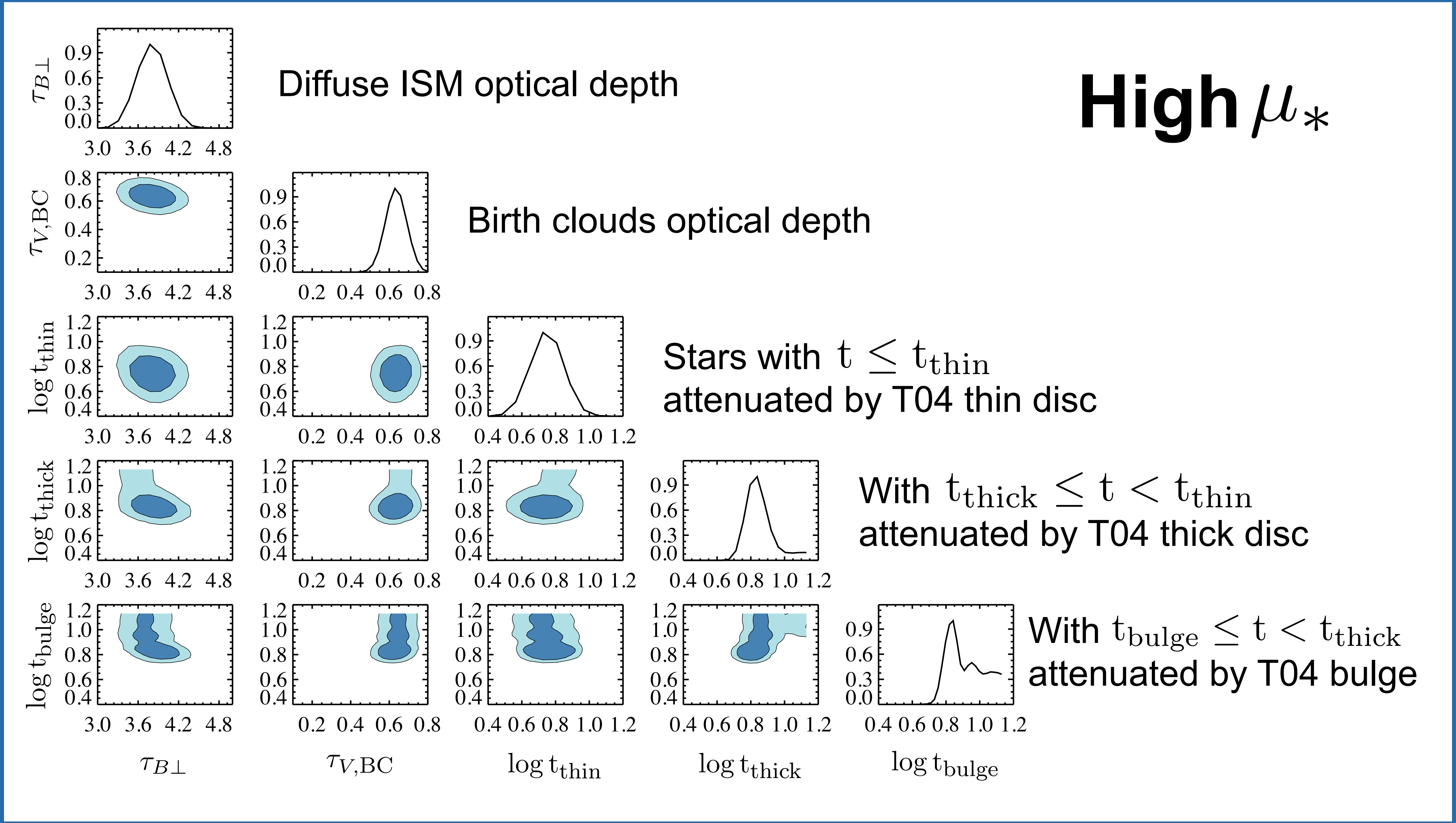

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Θ	Parameters
D	Data
P	Prior knowledge

Bayes theorem

$$\underbrace{p(\Theta|D,P)}_{\text{Posterior distribution}} \propto \underbrace{p(\Theta|P)}_{\text{Priors}}\,\underbrace{p(D|\Theta,P)}_{\text{Likelihood}}$$

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- Metropolis-Hastings (M-H) algorithm: sampling through random walk in parameter space

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In practice, computational gain from MCMC over simple grid-based methods?

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MCMC:

- ~ 30 000 likelihood evaluations
- factor of ~ 900 !!

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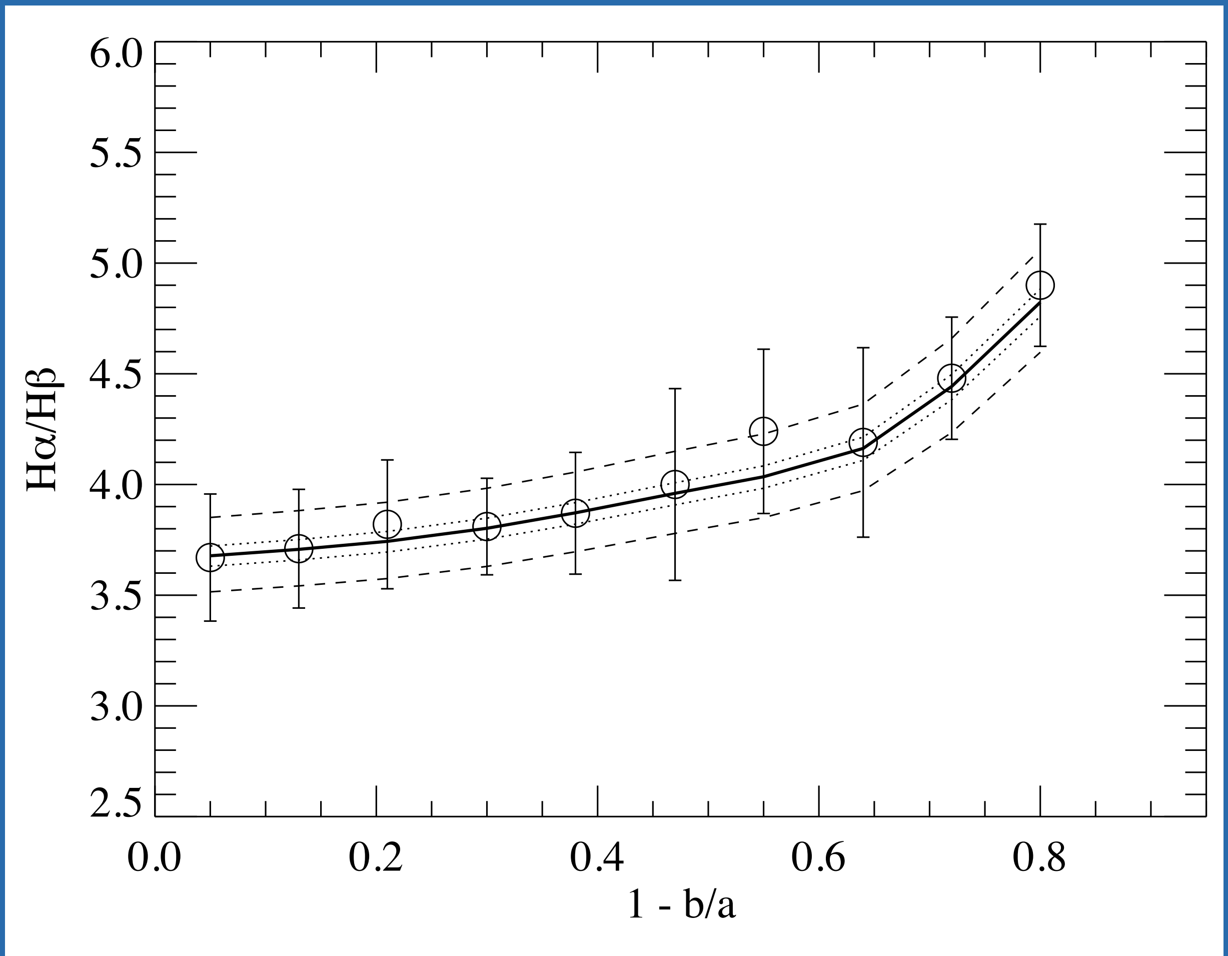
Remarkable agreement



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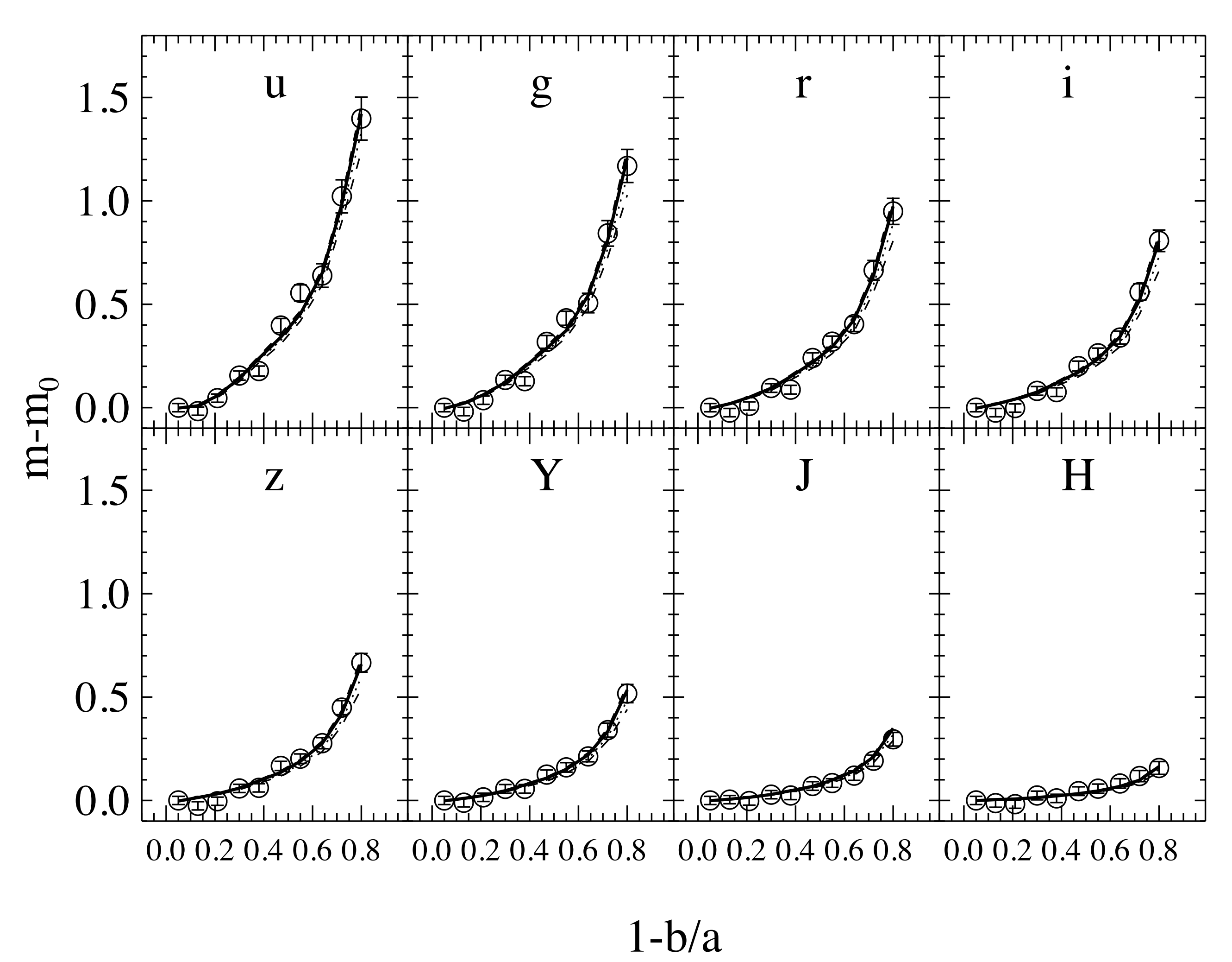

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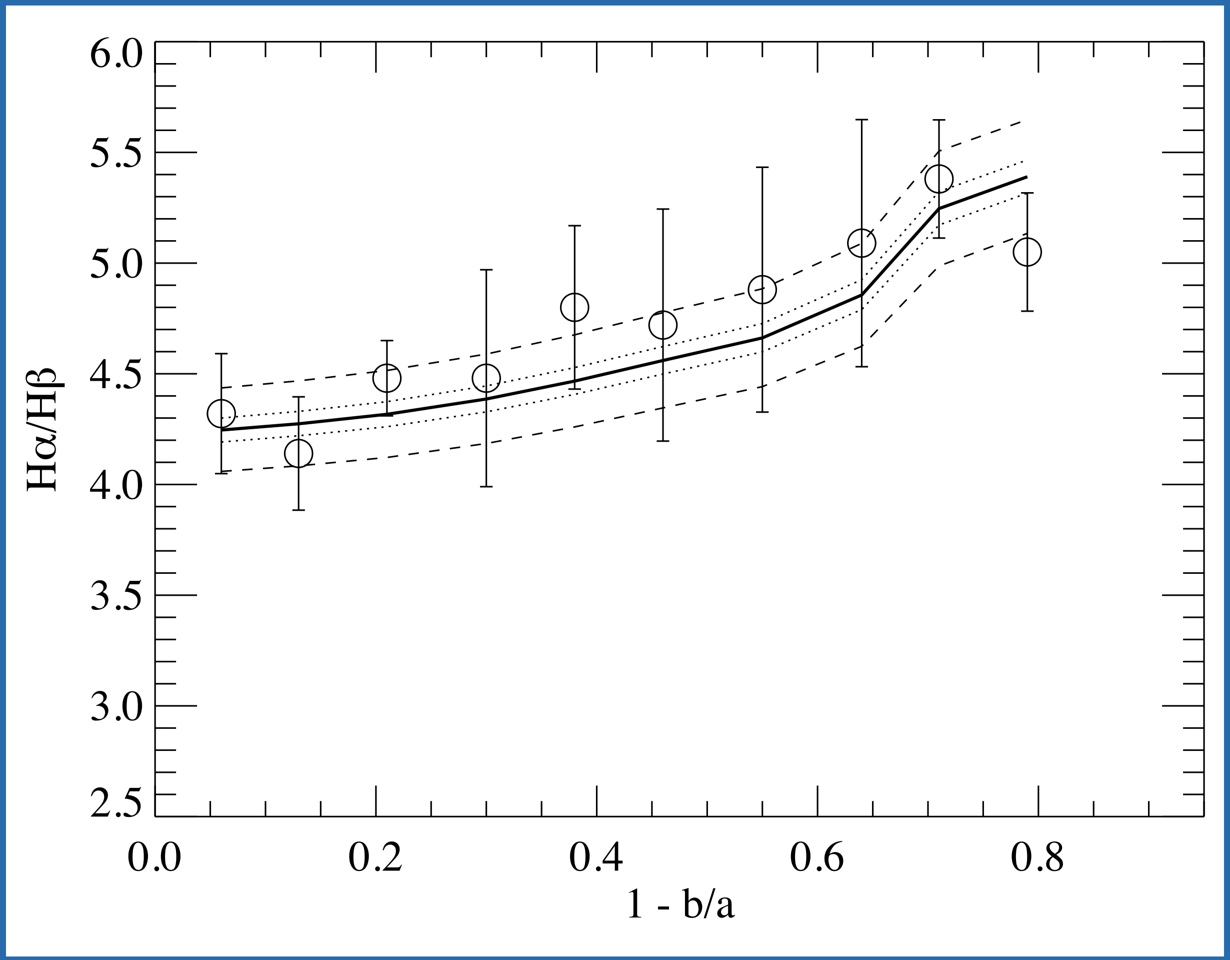

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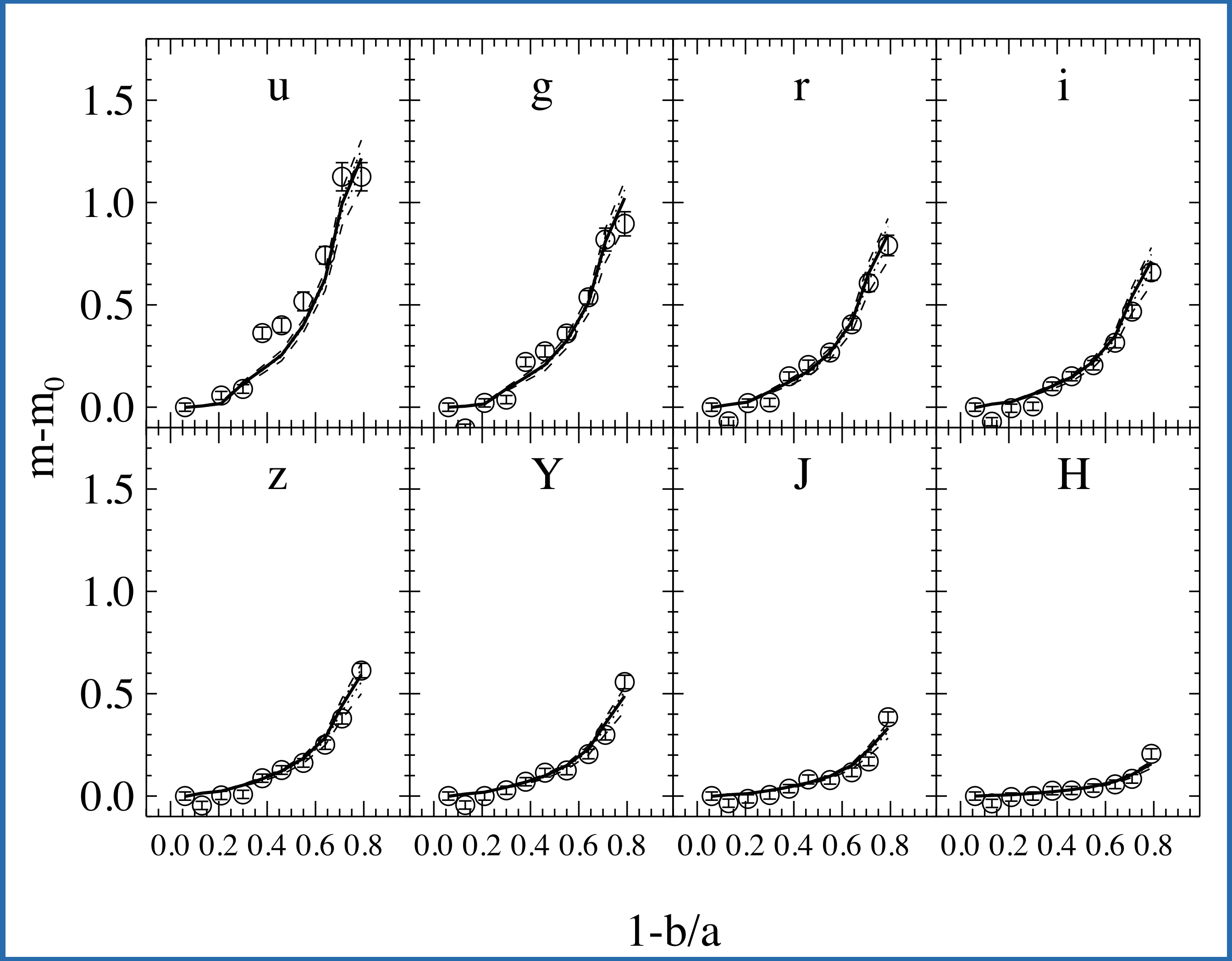

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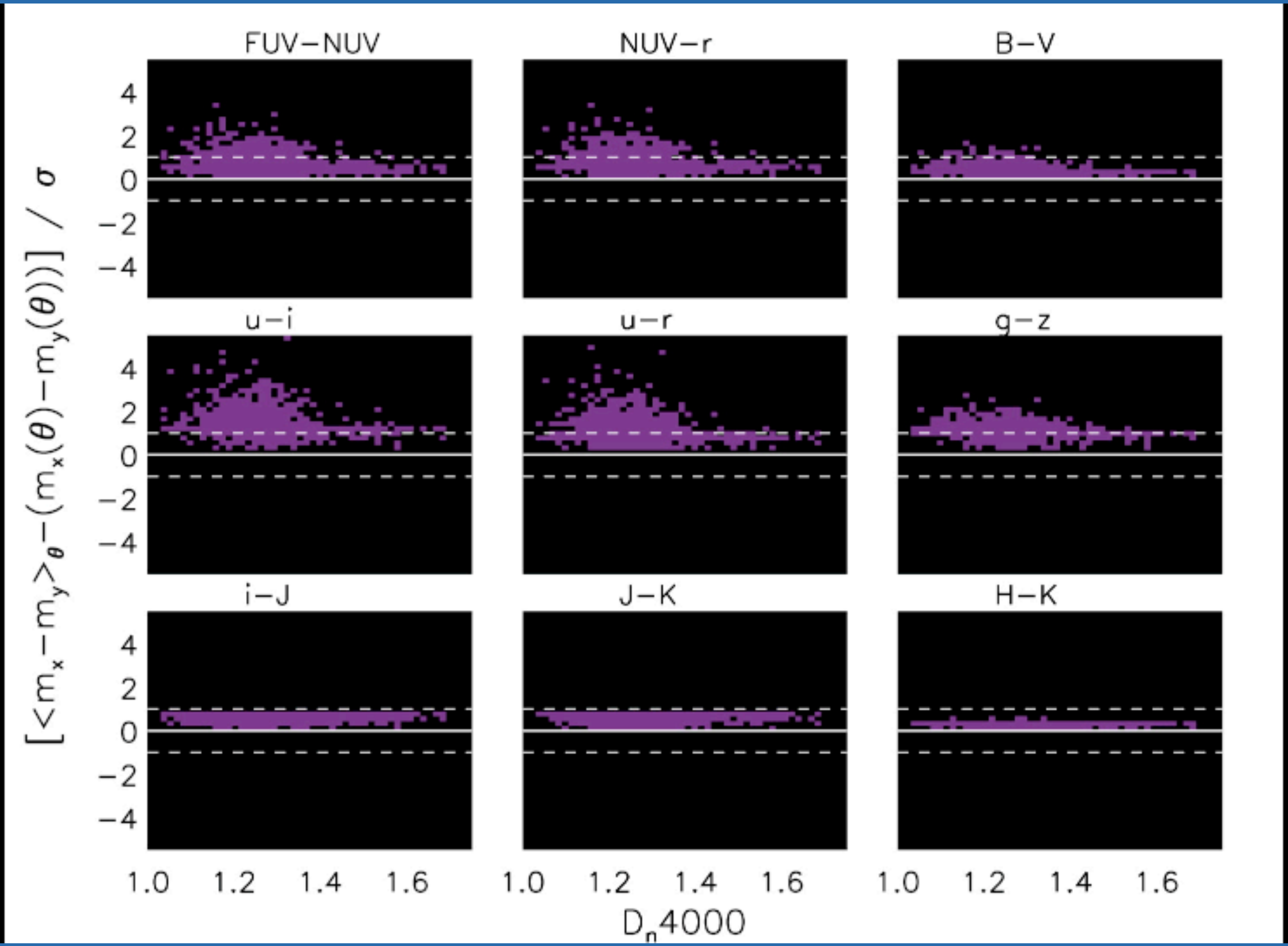
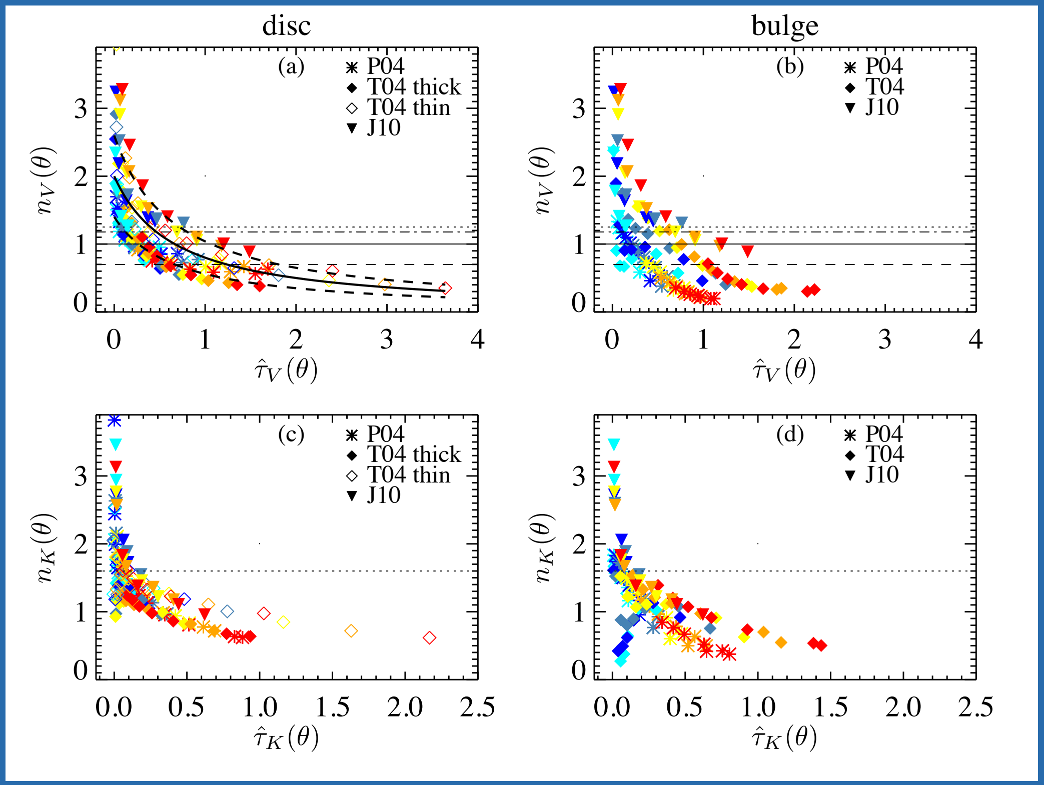


Summary of part 1...

• Popular radiative transfer models predict similar flattening of attenuation curve with increasing effective optical depth



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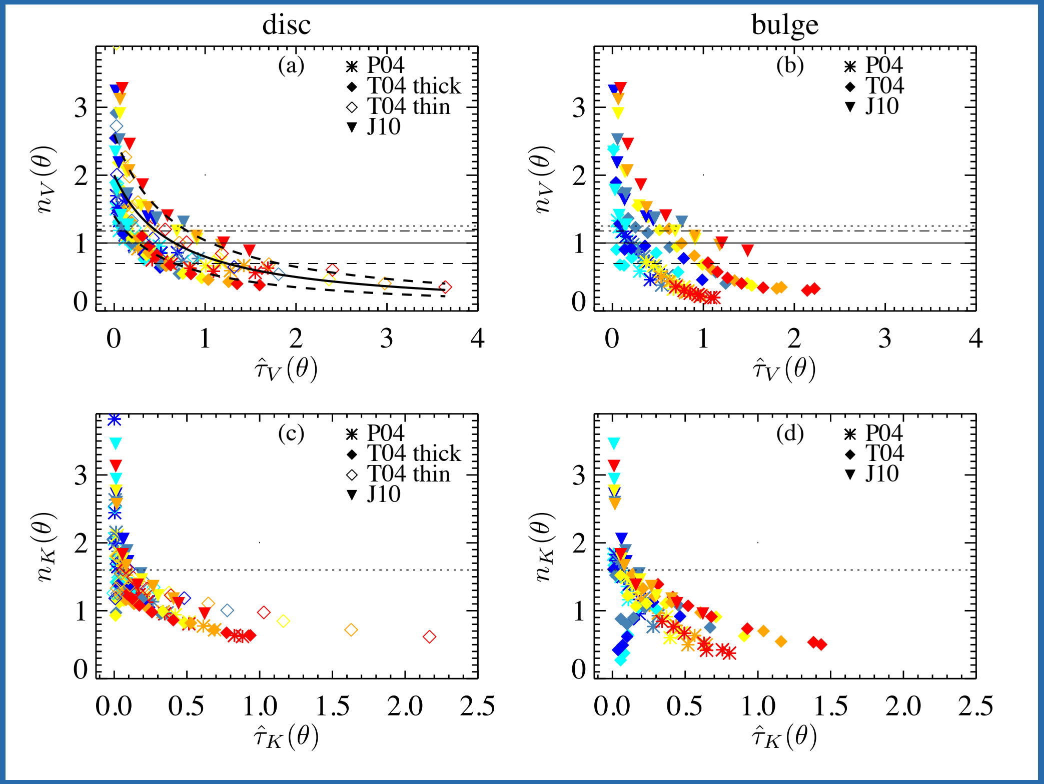

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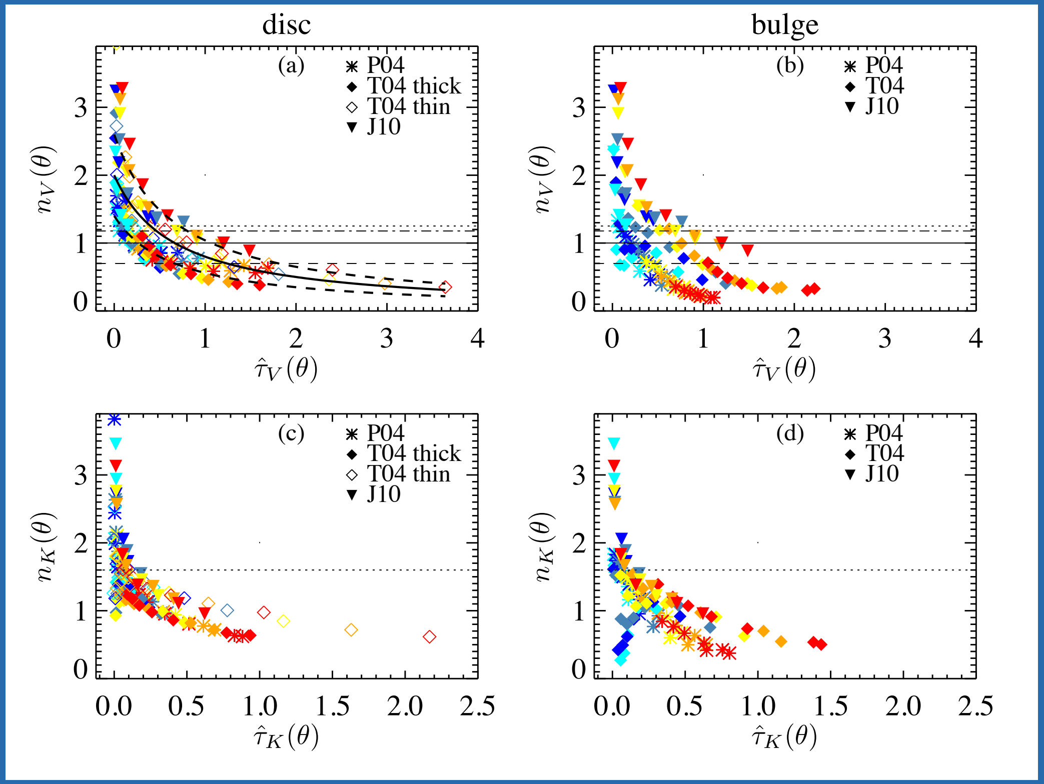

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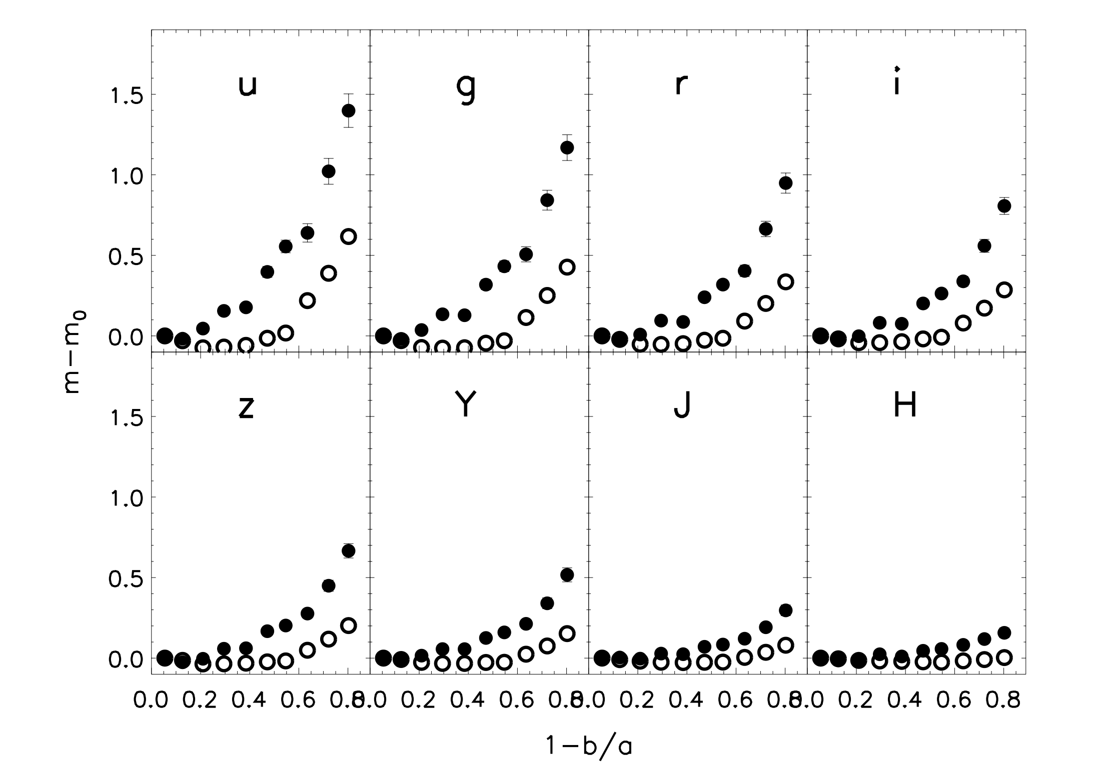

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• RT models are computationally expensive, hence limited use for large sample of galaxies

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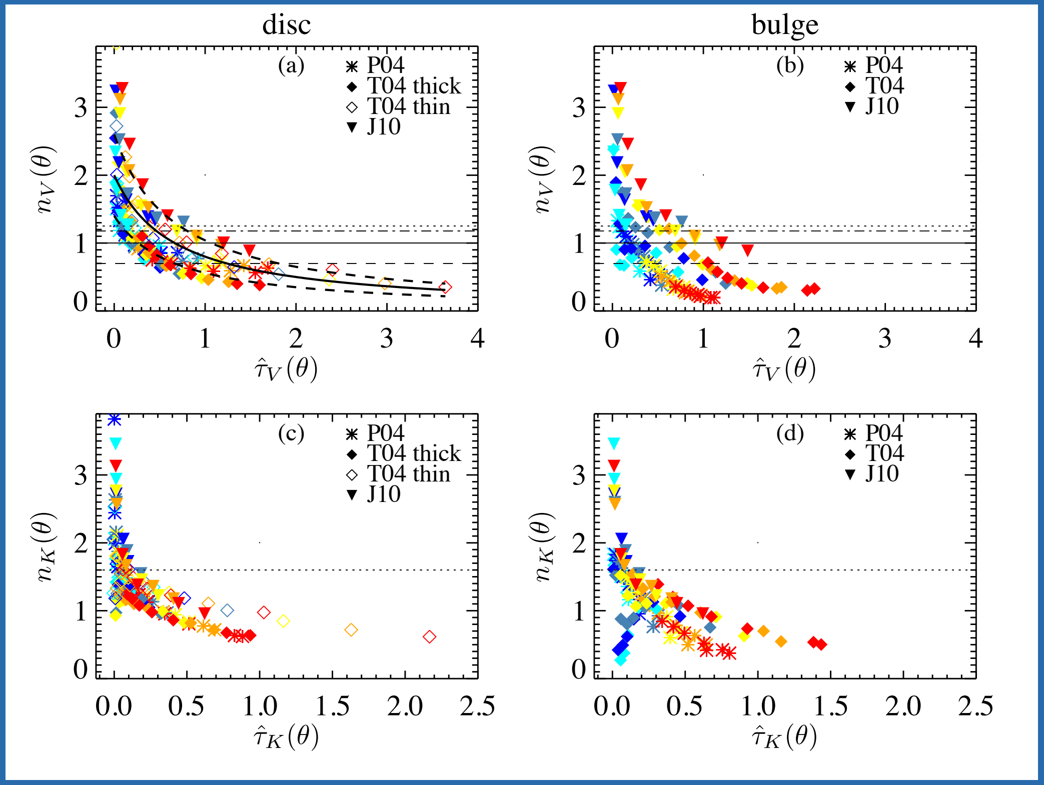

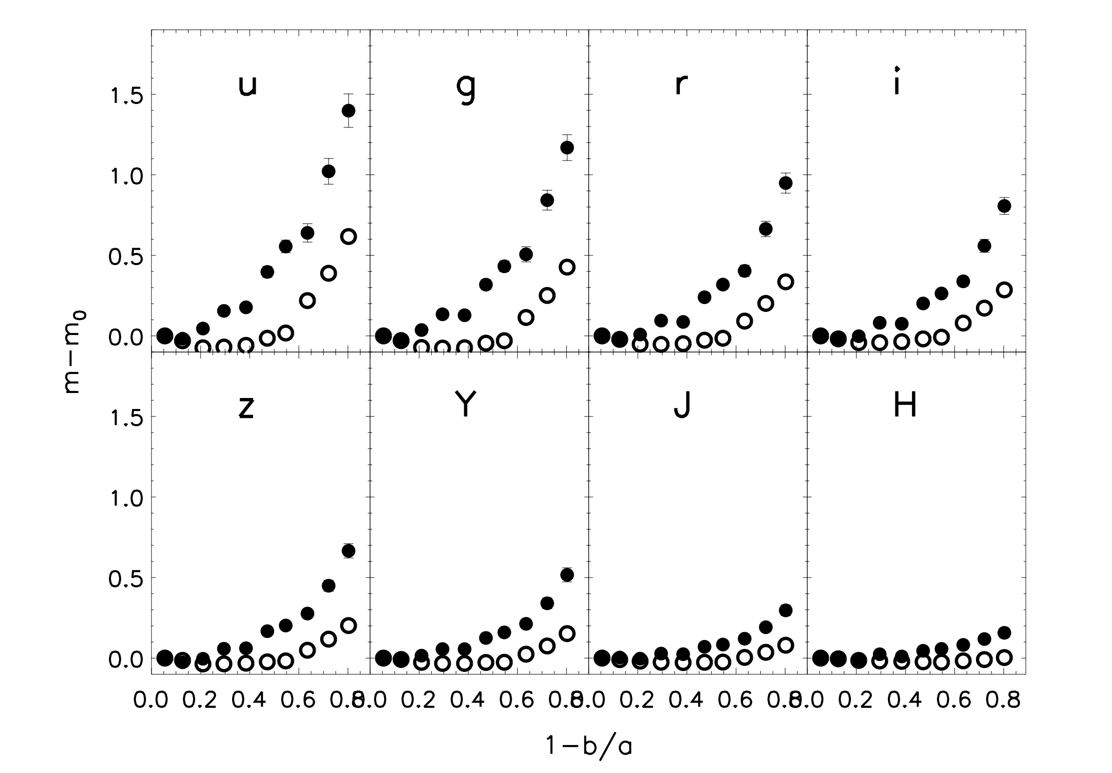

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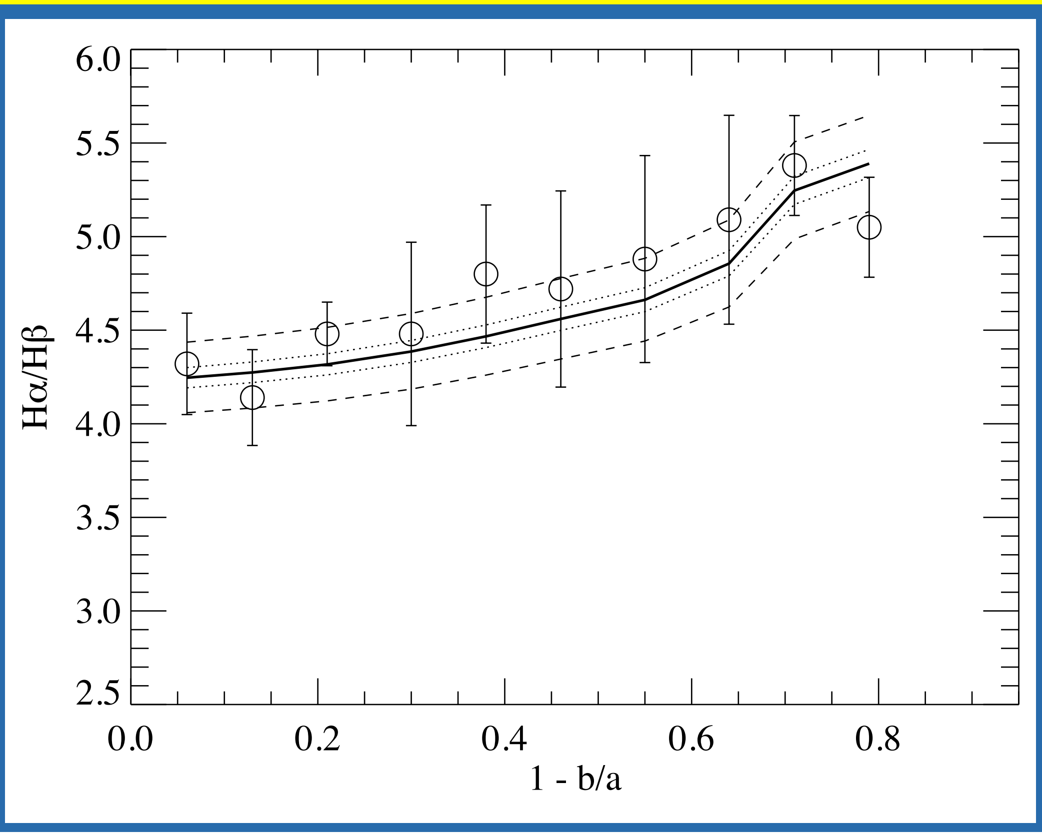

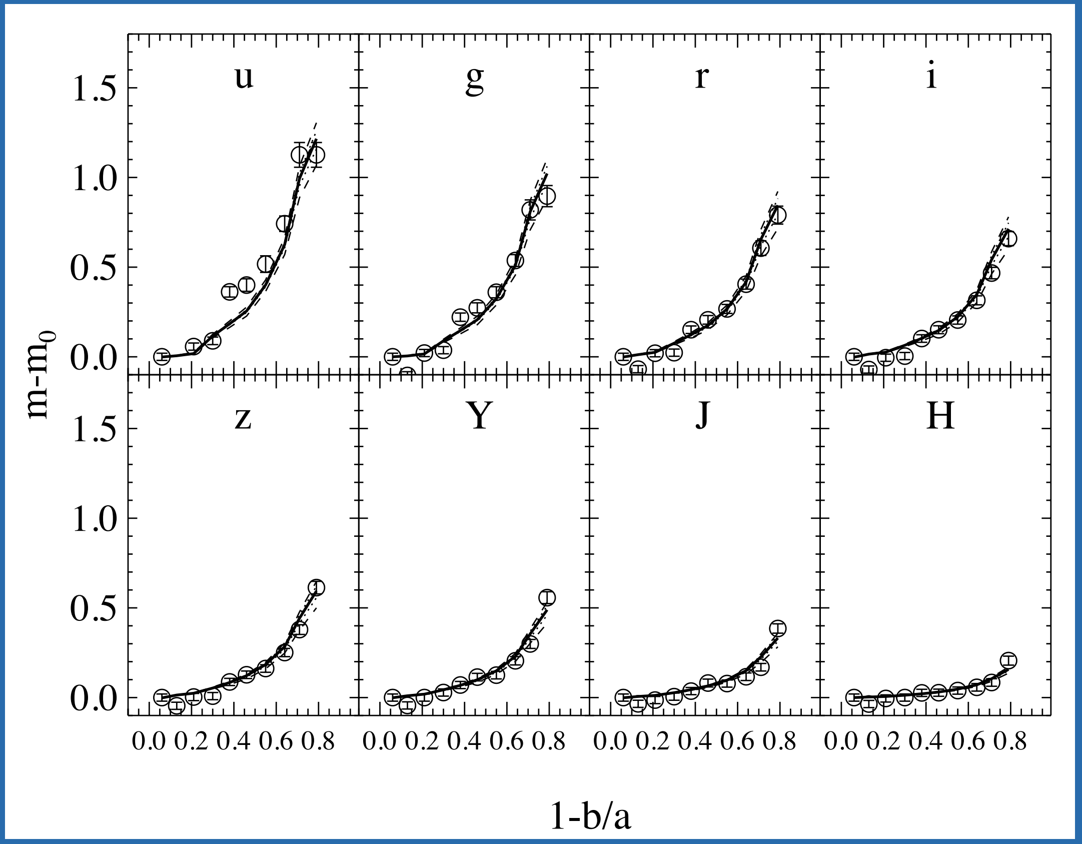

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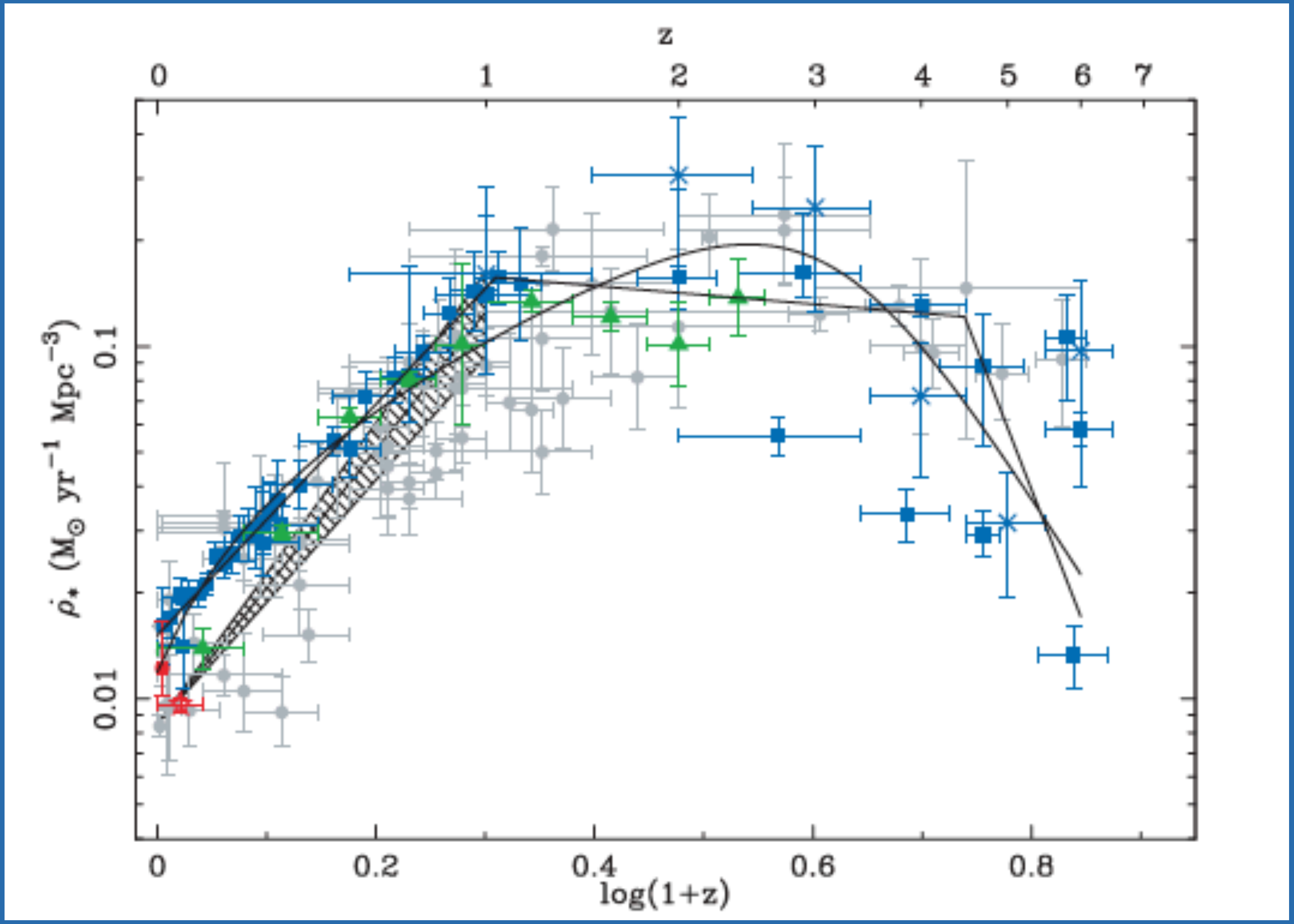
- Linked to merging history of galaxies, gas inflows and outflows, AGN and SNe feedback



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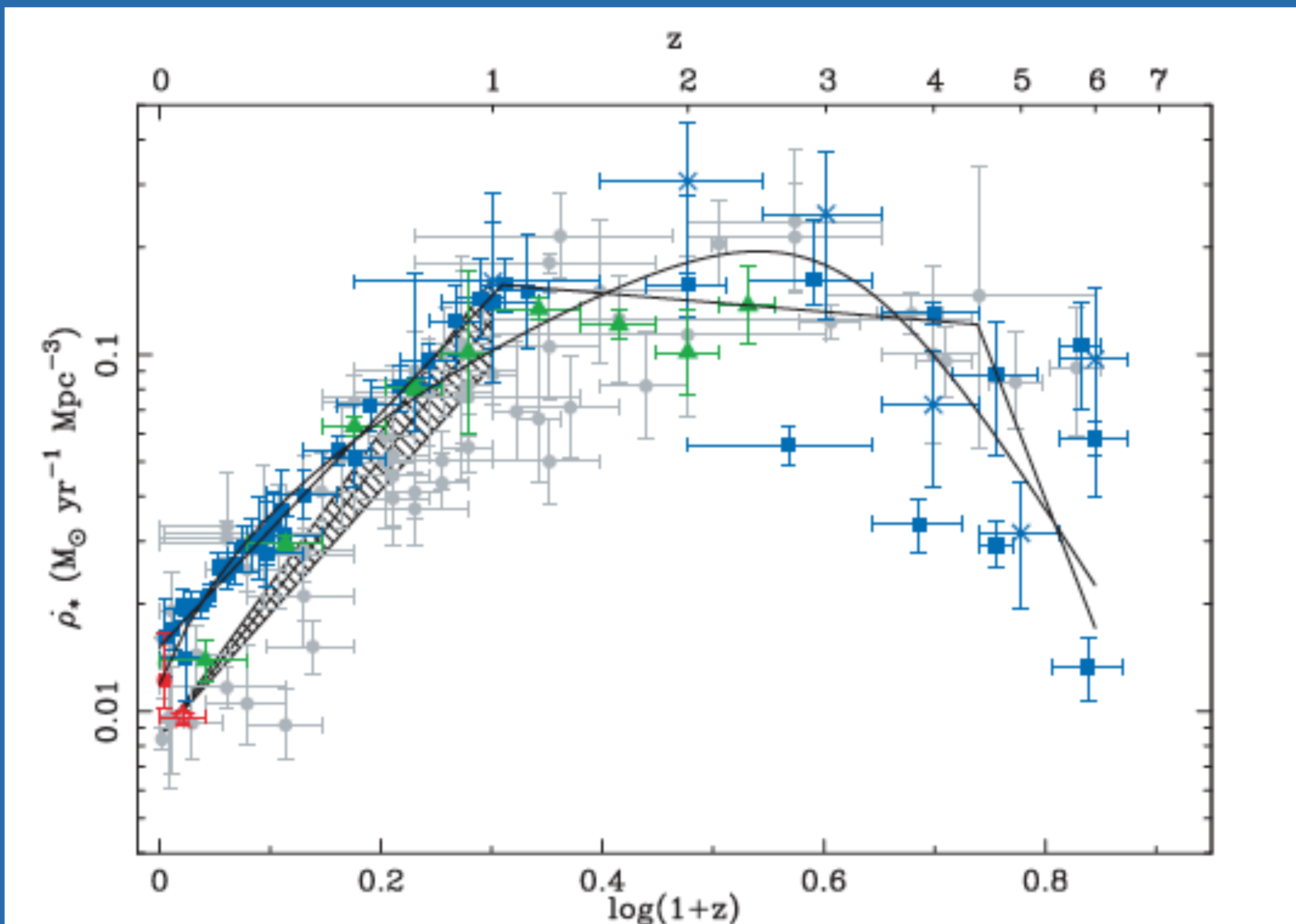

Hopkins & Beacom (2006)

- But...challenging to get SFR estimate at intermediate-to-high z
- Difficult to use emission lines
- FIR also difficult to observe (at least right now...)
- UV is the most accessible SFR proxy, but suffers severe dust attenuation

SFR and dust attenuation: data

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- 31 passbands
- Spectroscopic redshift (zCOSMOS) where available, otherwise photo-z
- Maximum redshift $z_{max} = 1.3$
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$$SFR^{tot}[M_\odot/yr] = 8.6\ 10^{-11}(L_{IR} + 1.9\ \mathcal{L}_{NUV})$$

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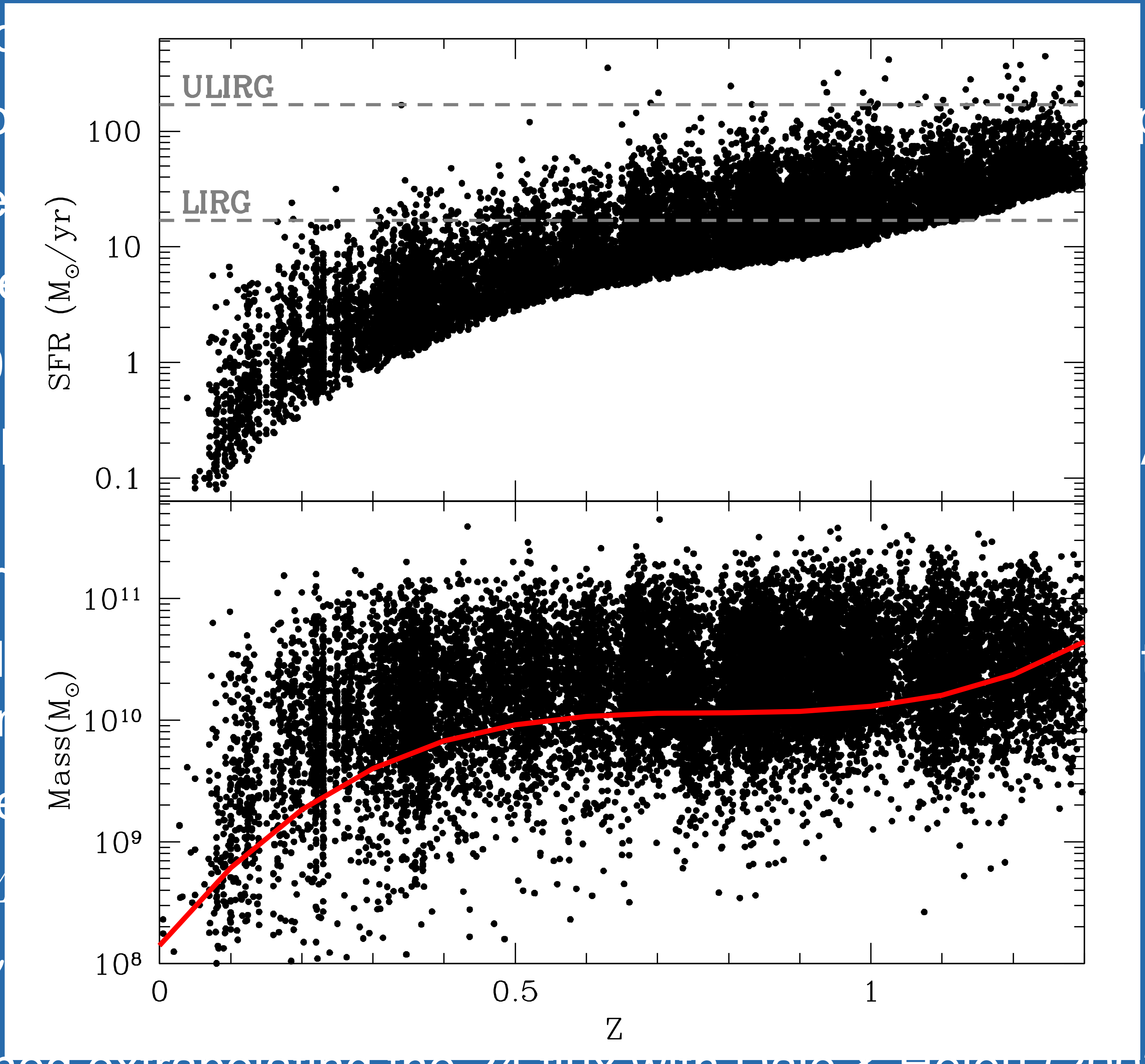

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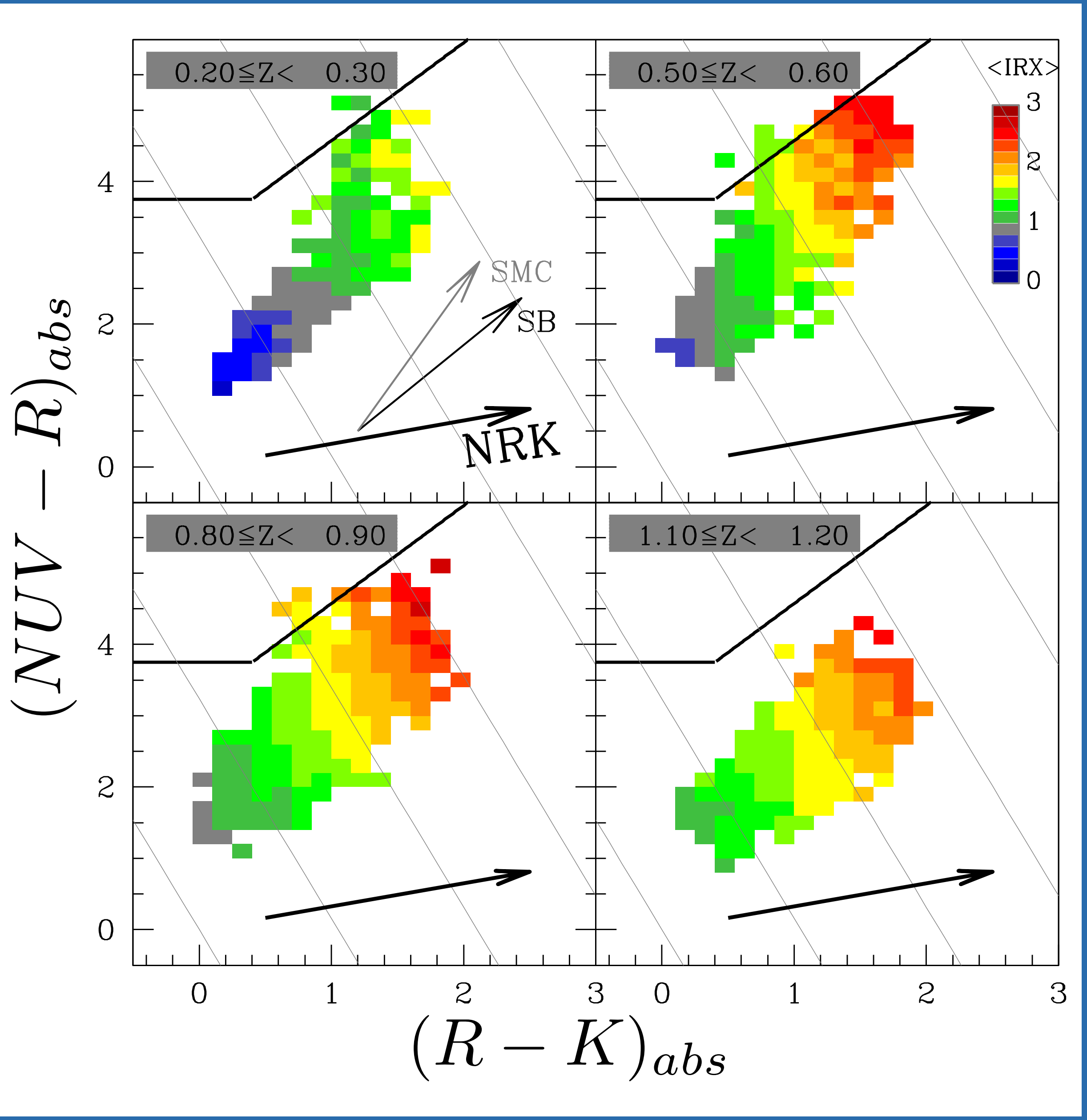

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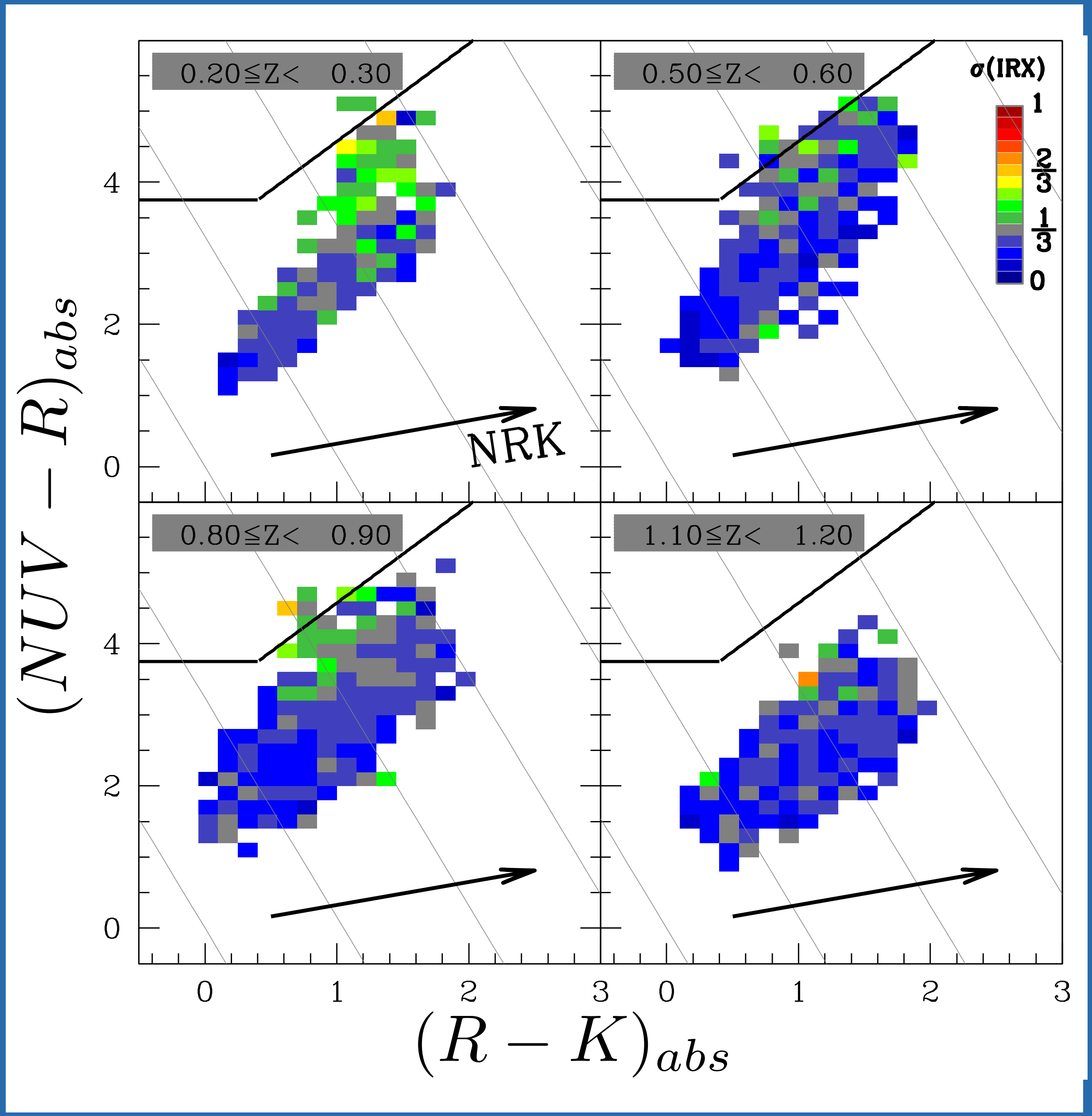

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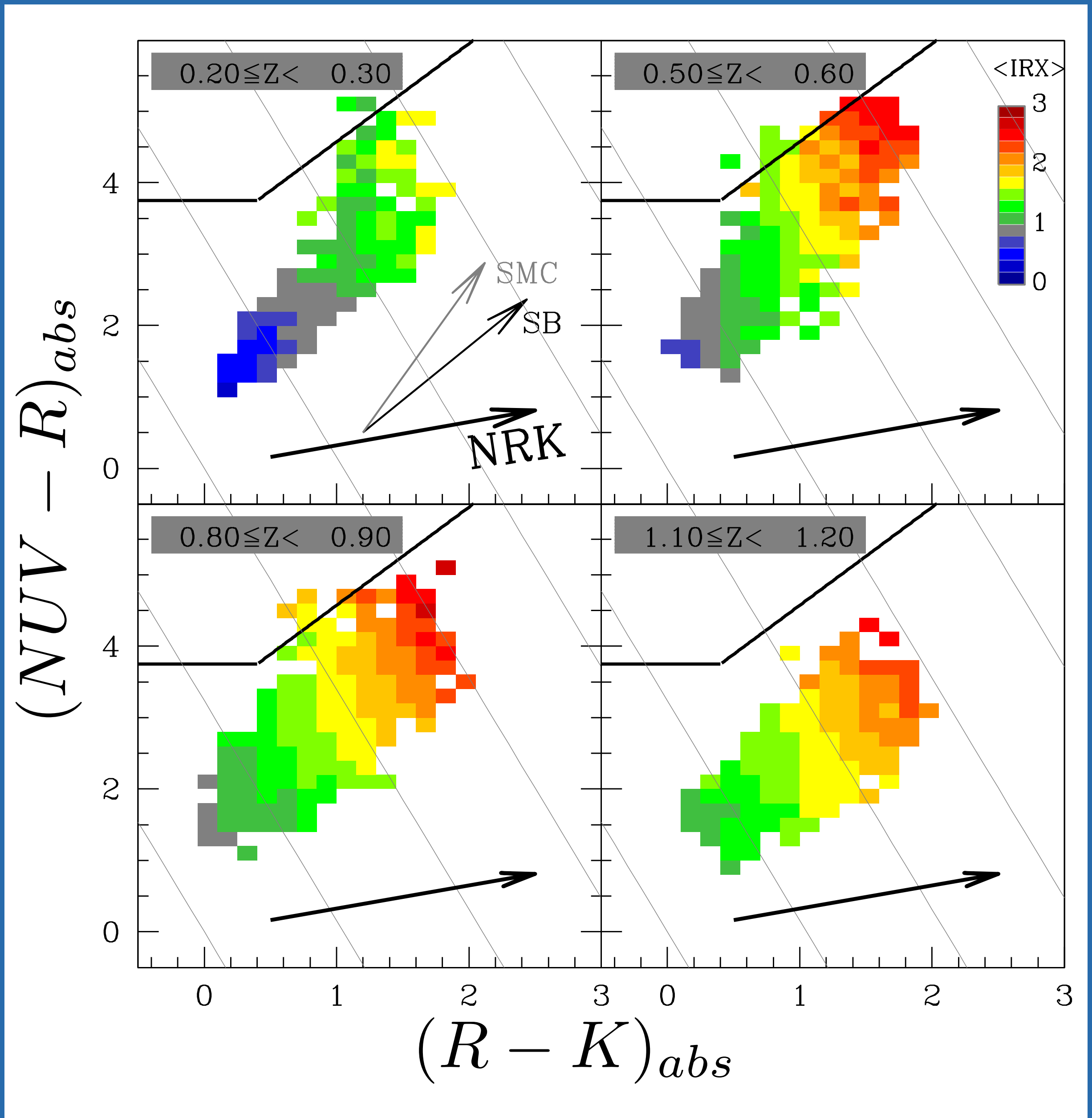


- Volume-weighted IRX increases by 1.5-2 dex from blue- to red-side
- Stripes of constant IRX
- Can combine (NUV-r) and (r-K) in a single vector perpendicular to IRX stripes

$$NRK(\theta) = \sin\theta(NUV - r) + \cos\theta(r - K)$$

- IRX depends on redshift and vector NRK

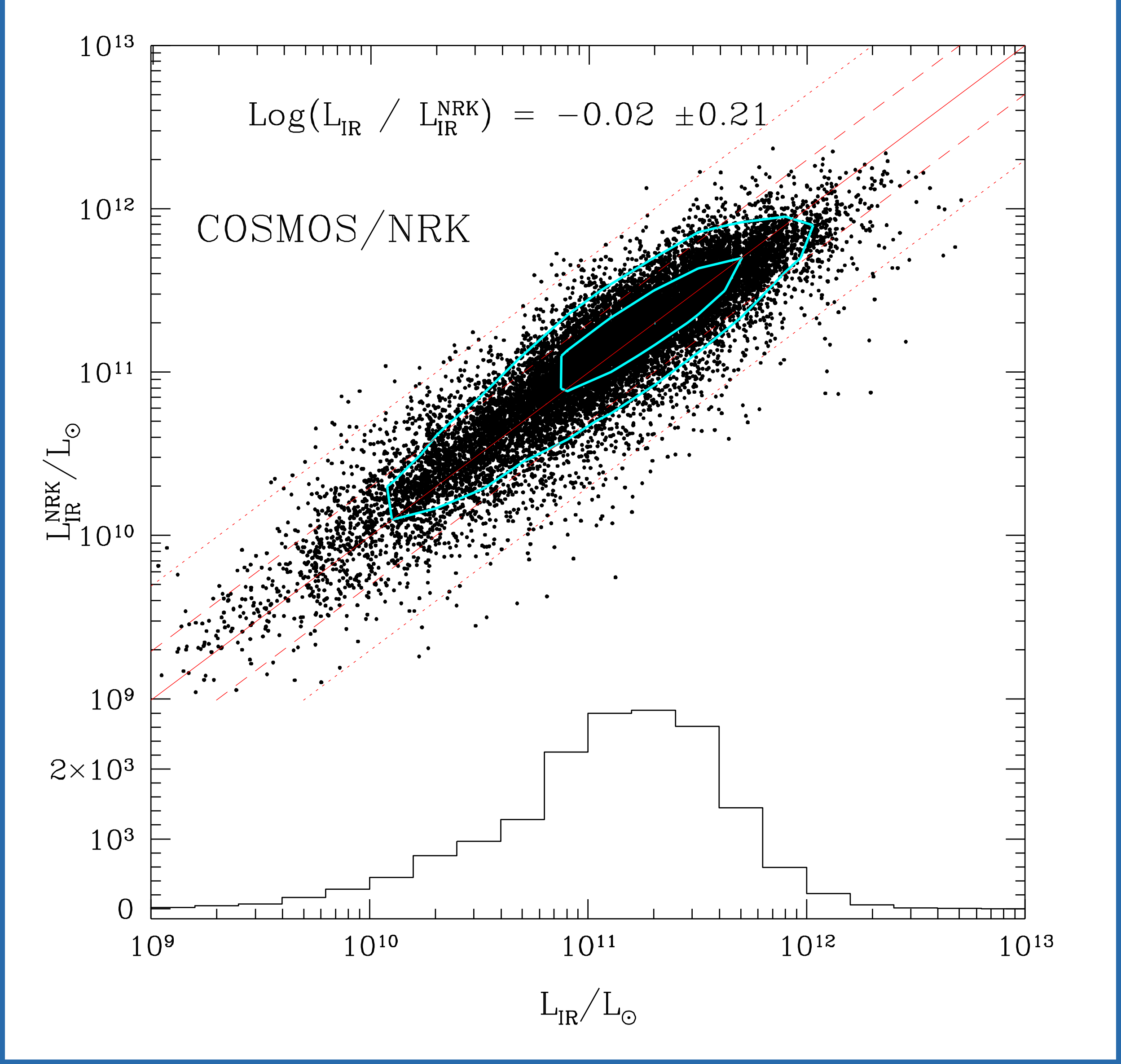
$$IRX(z, NRK) = f(z) + a \cdot NRK$$

- Redshift shifts relation to larger IRX (slope of relation does not depend on z)

The infrared excess IRX

- Previous relations can be used to estimate the total IR luminosity from UV + NIR

$$L_{IR}^{NRK} = \mathcal{L}_{NUV} \cdot IRX(z, NRK)$$



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- Almost no bias, and small rms (0.2 dex)
- Shows that IRX, hence total IR luminosity, is encoded in NUV-to-NIR broadband colors

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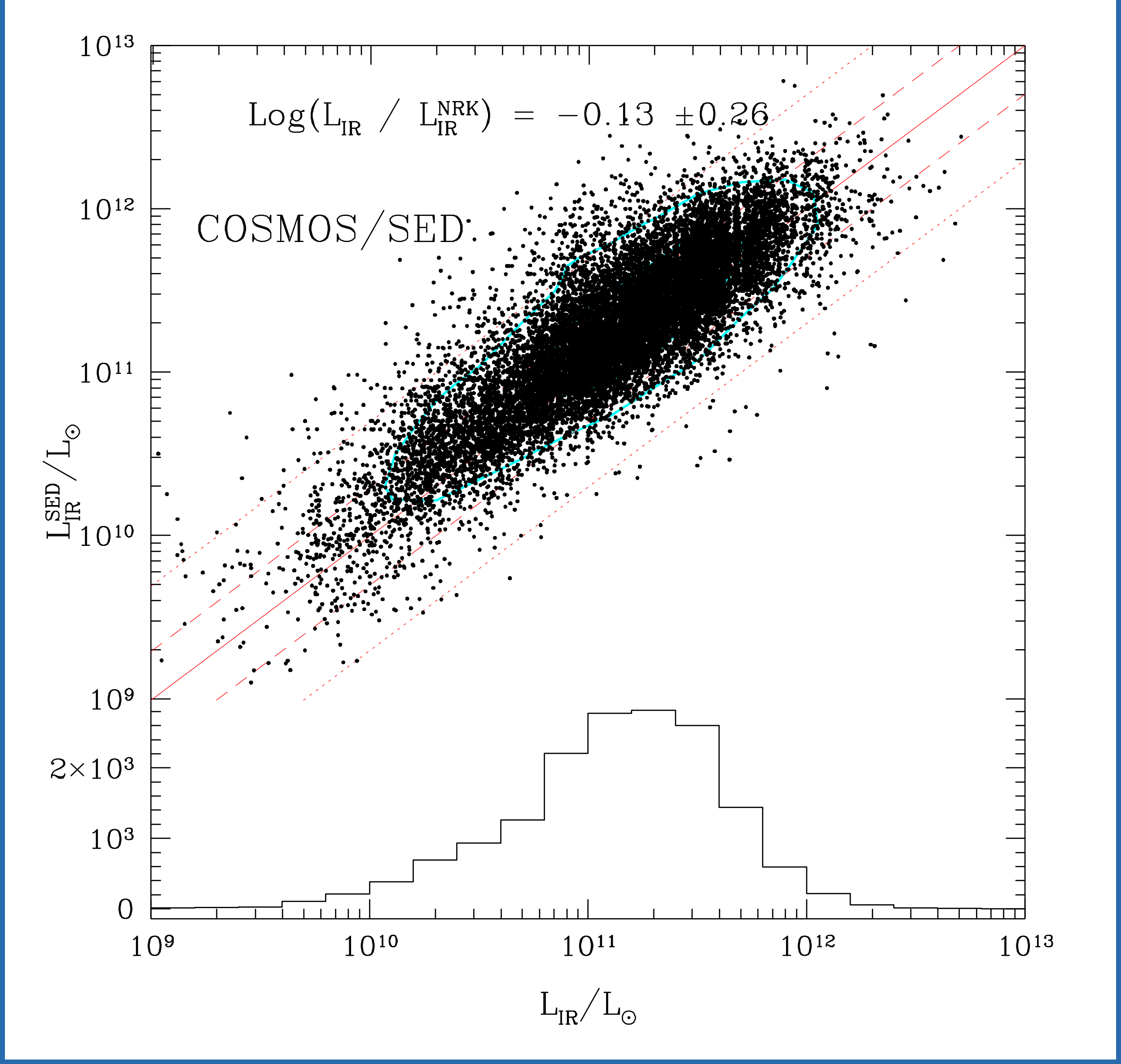

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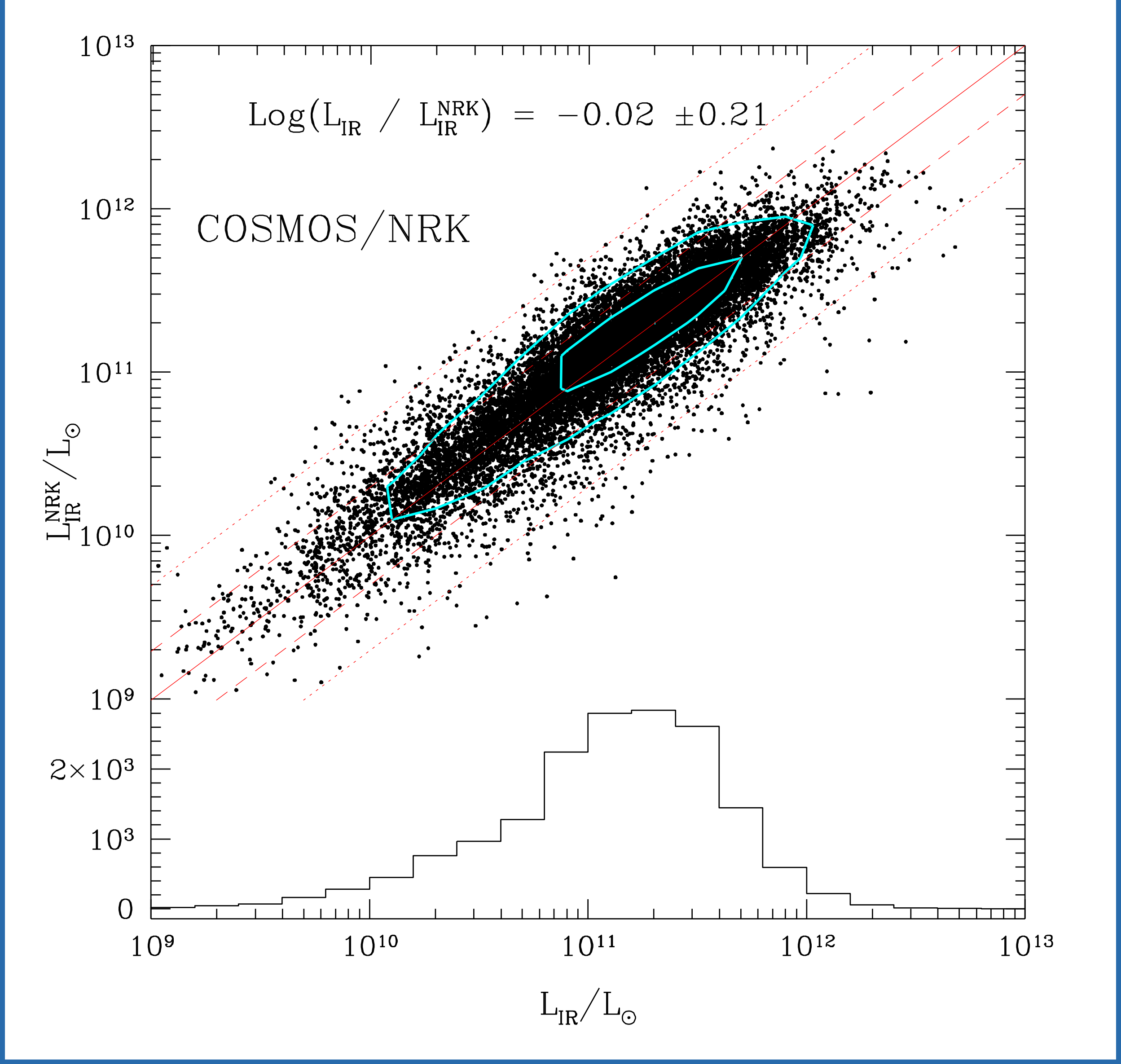

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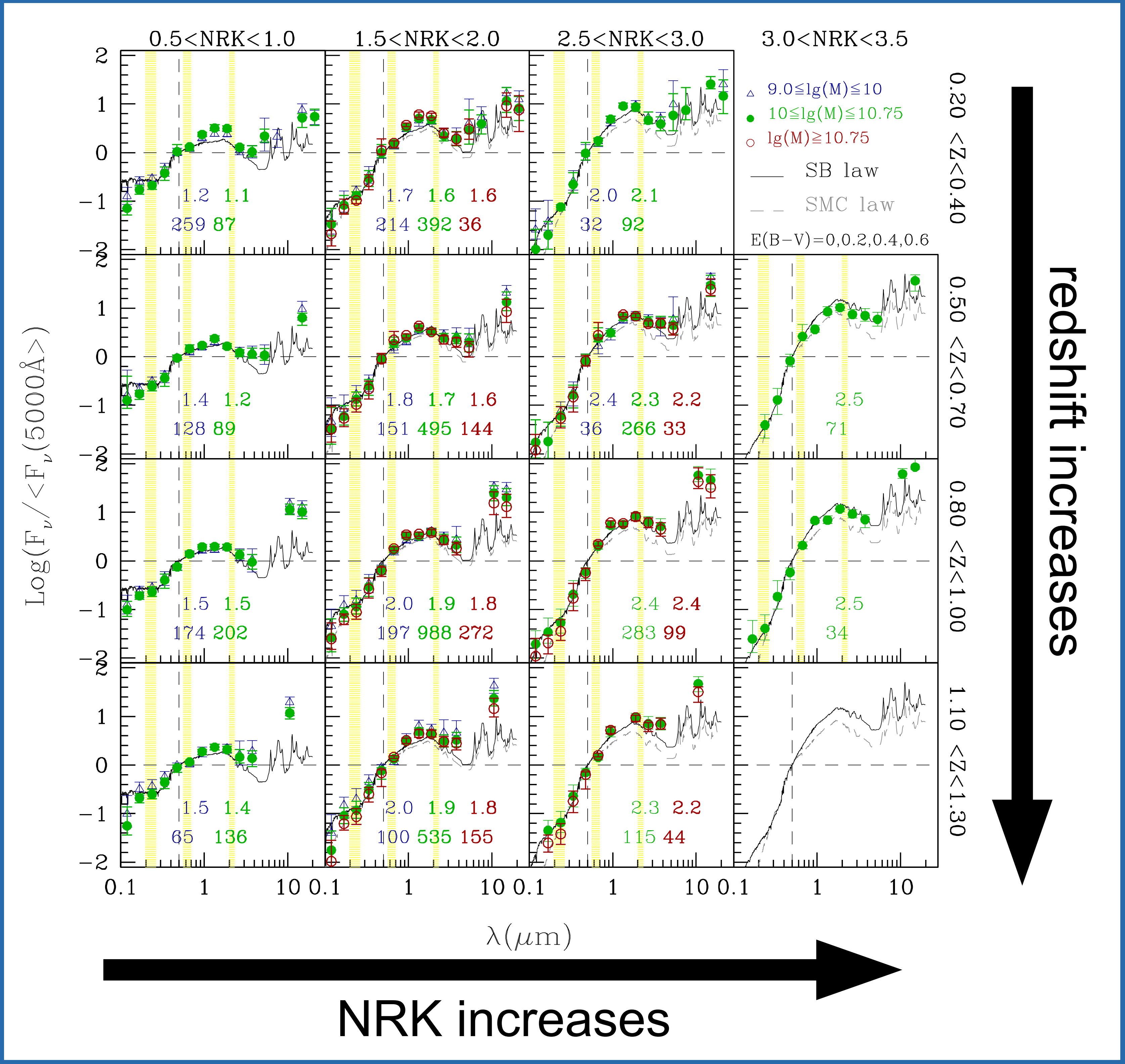
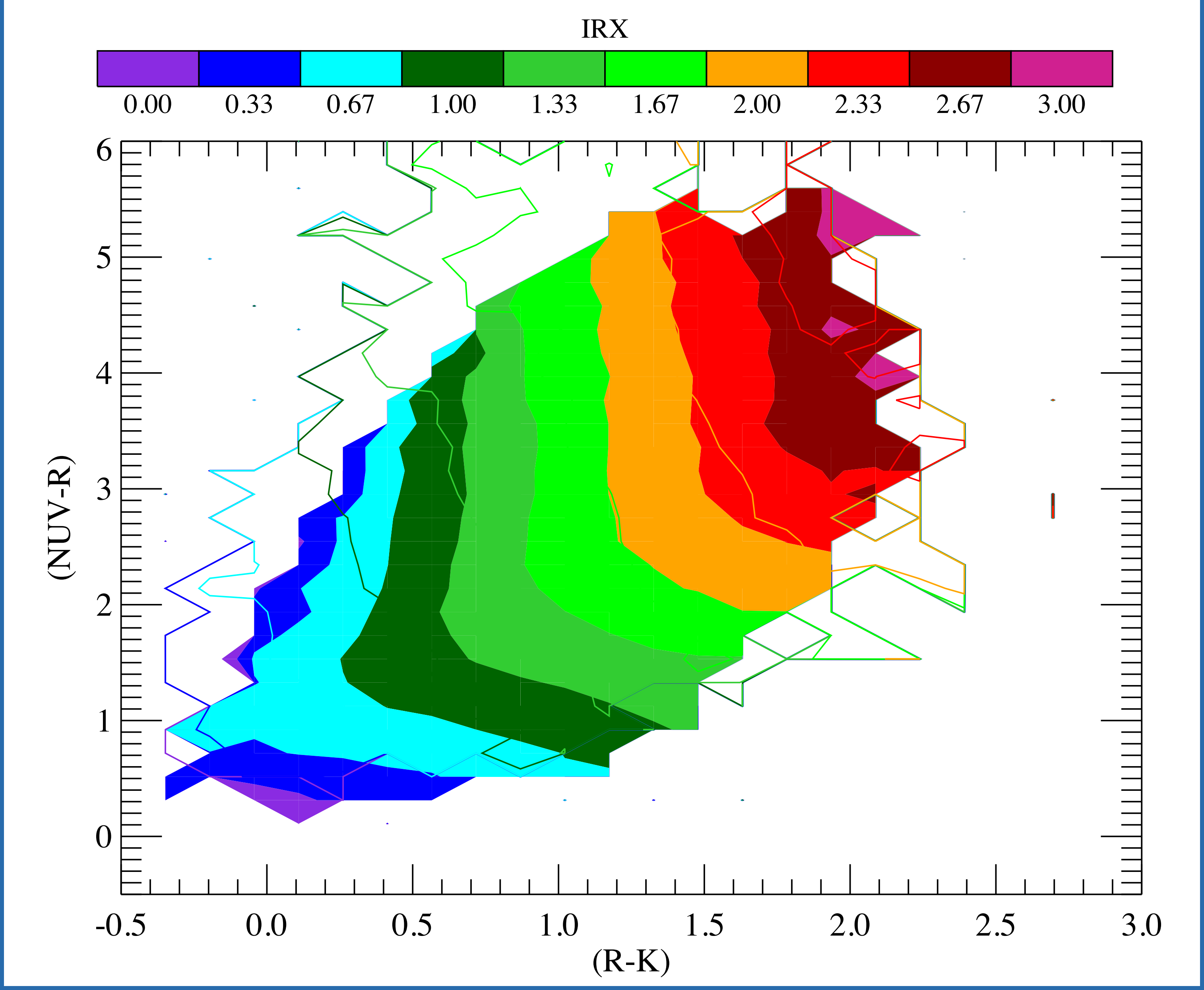
How well does NRK vector trace SED evolution?



- SED evolution primary driven by NRK
- Redshift and mass play secondary role at fixed NRK

Modeling of IRX stripes

Can spectral evolution models reproduce observed IRX stripes?



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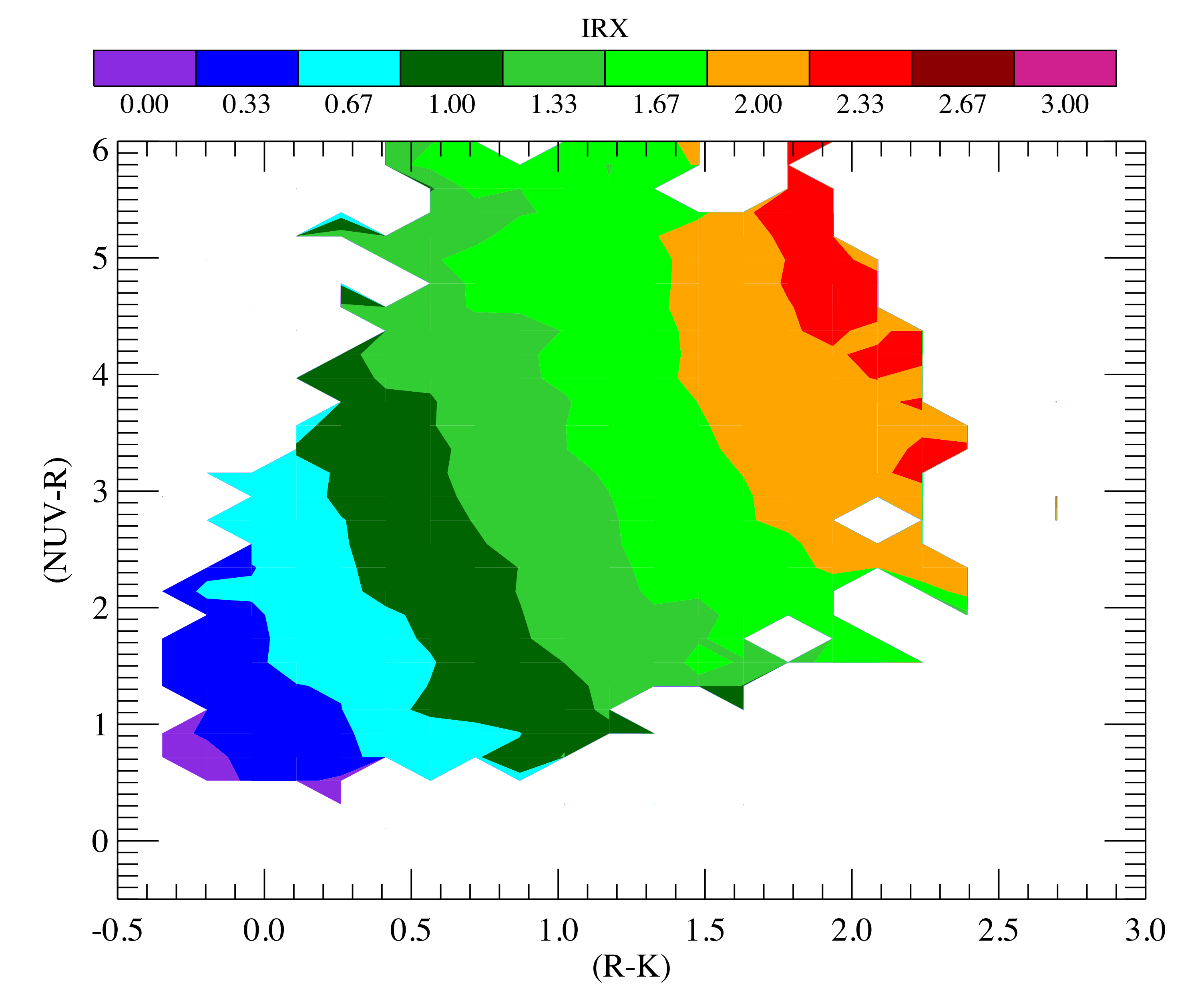

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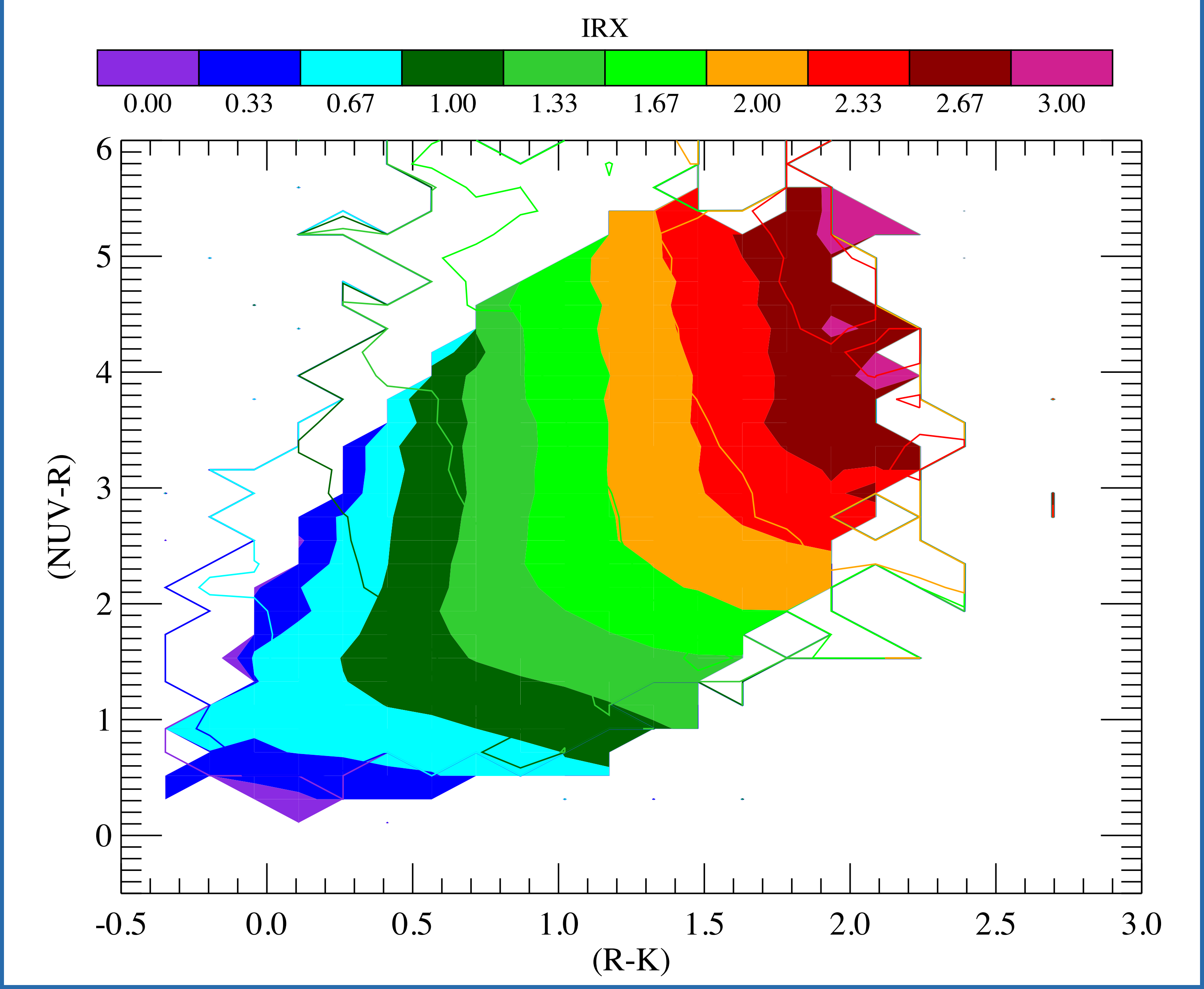

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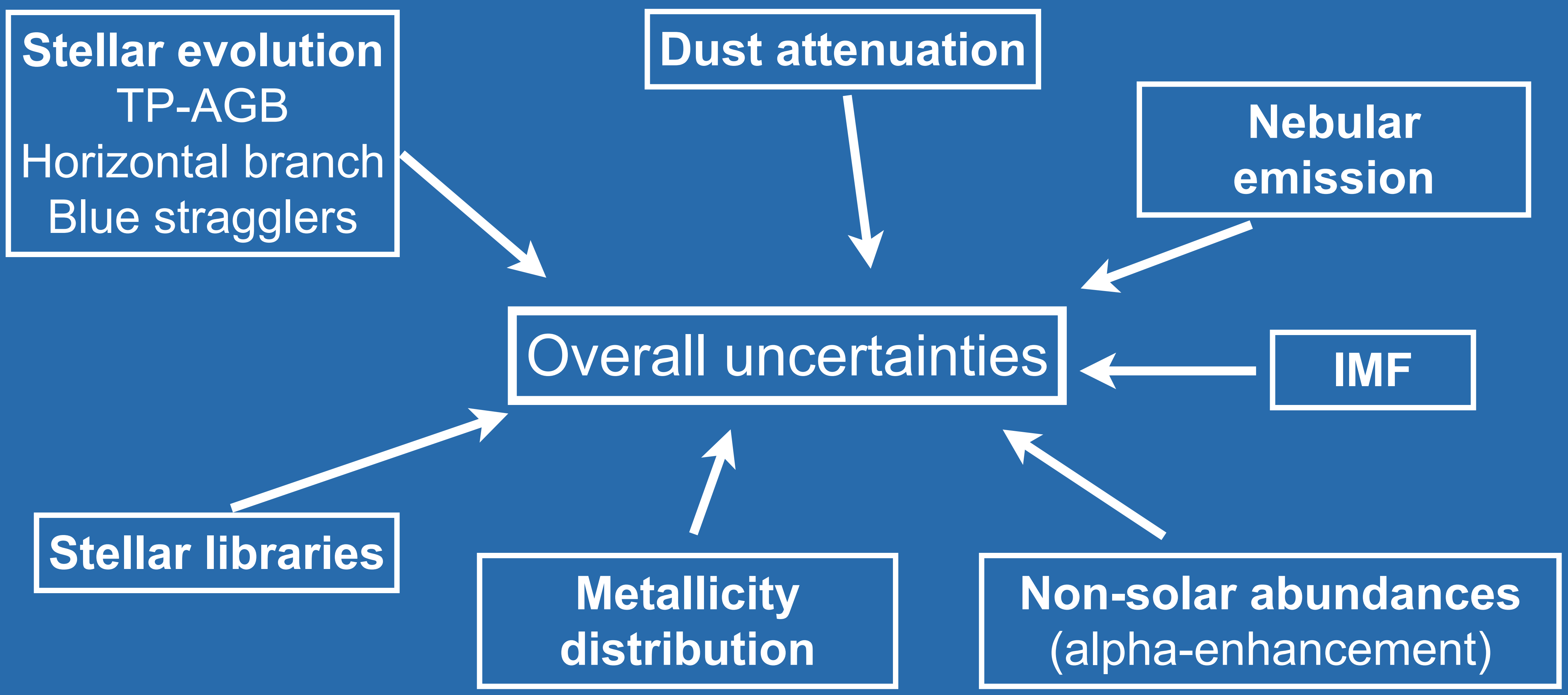
Future developments (1)

General motivation:

Uncertainties in the spectral modeling of galaxies



Future developments (2)

- Work motivated by fact that **systematics uncertainties of spectral evolution models are main current limitation in interpretation of galaxies SEDs**
- Limitation becoming more crucial as both observation accuracy and data flow increase with new generation of instruments (e.g. **LSST and EUCLID)**
- Need different statistical approach, incorporating tools already used by cosmo-statisticians (e.g. full Bayesian approach, MCMC, Gaussian Random Process)

Future developments (3)

- Several projects in progress:
  - Spectral libraries interpolation / extrapolation based on Gaussian Random Processes
  - IMF, constraints from integrated colors and spectra
  - Non-solar abundances, alpha-elements and CN
- Finally, in collaboration with Stephane Charlot and Ben Wandelt we are searching for the best Bayesian tool (Fisher matrix? Monte Carlo?) to incorporate all the above-cited uncertainties into the new generation of Charlot & Bruzual spectral models


Thanks!!

Statistics: Reverse Importance Sampling (1)

Problem:

- Want to study variation of $H\alpha/H\beta$ ratio and $ugrizYJH$ attenuation curve with galaxy inclination
- Selection function of SDSS and of Wild et al., 2011 make other properties (gas-phase metallicity, specific star formation rate, redshift, radius), correlated with attenuation, to vary with inclination
- Difficult to model all correlation existing in data (they are both physical, and selection effects)
- “Erase” effect of correlations playing with the data

Statistics: Reverse Importance Sampling (2)

Firstly, a few words about importance sampling:

- Common situation in physics: computing expectations = solving integrals

$$\mathbb{E}[h(\boldsymbol{X})] = \int_{\mathcal{X}} dx \, h(x) \, f(x)$$

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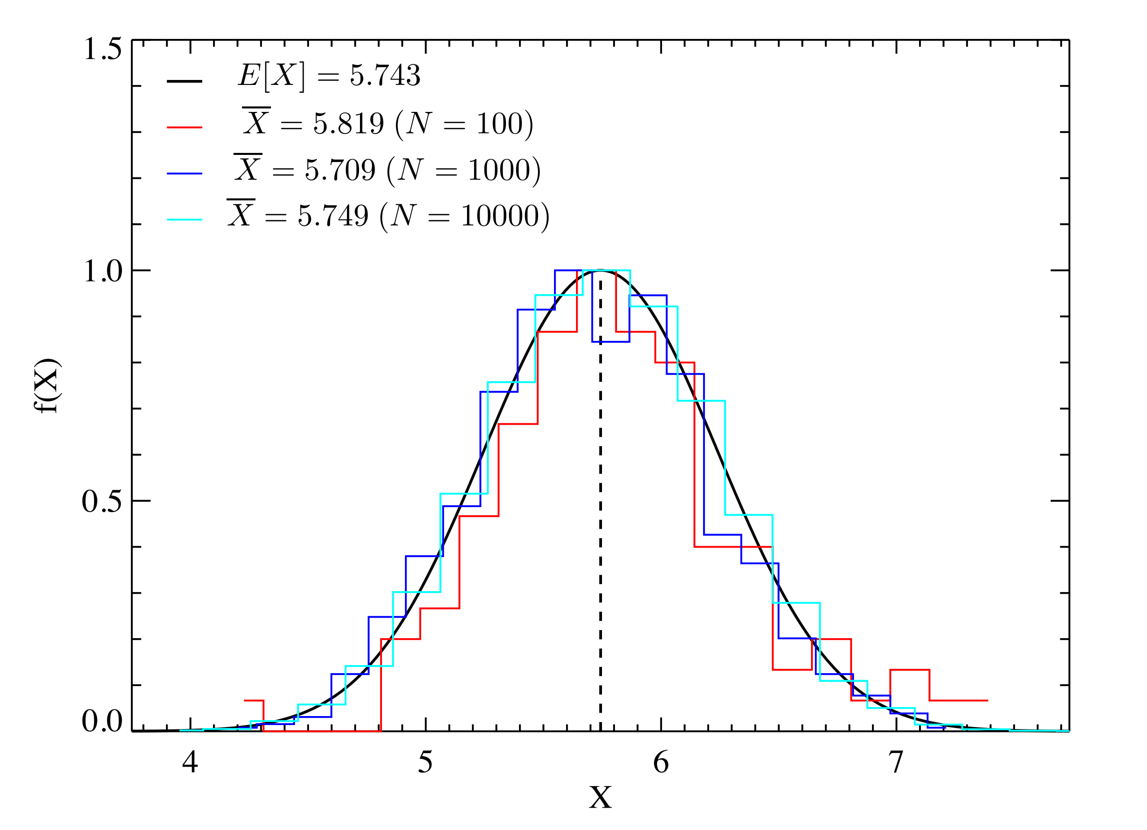

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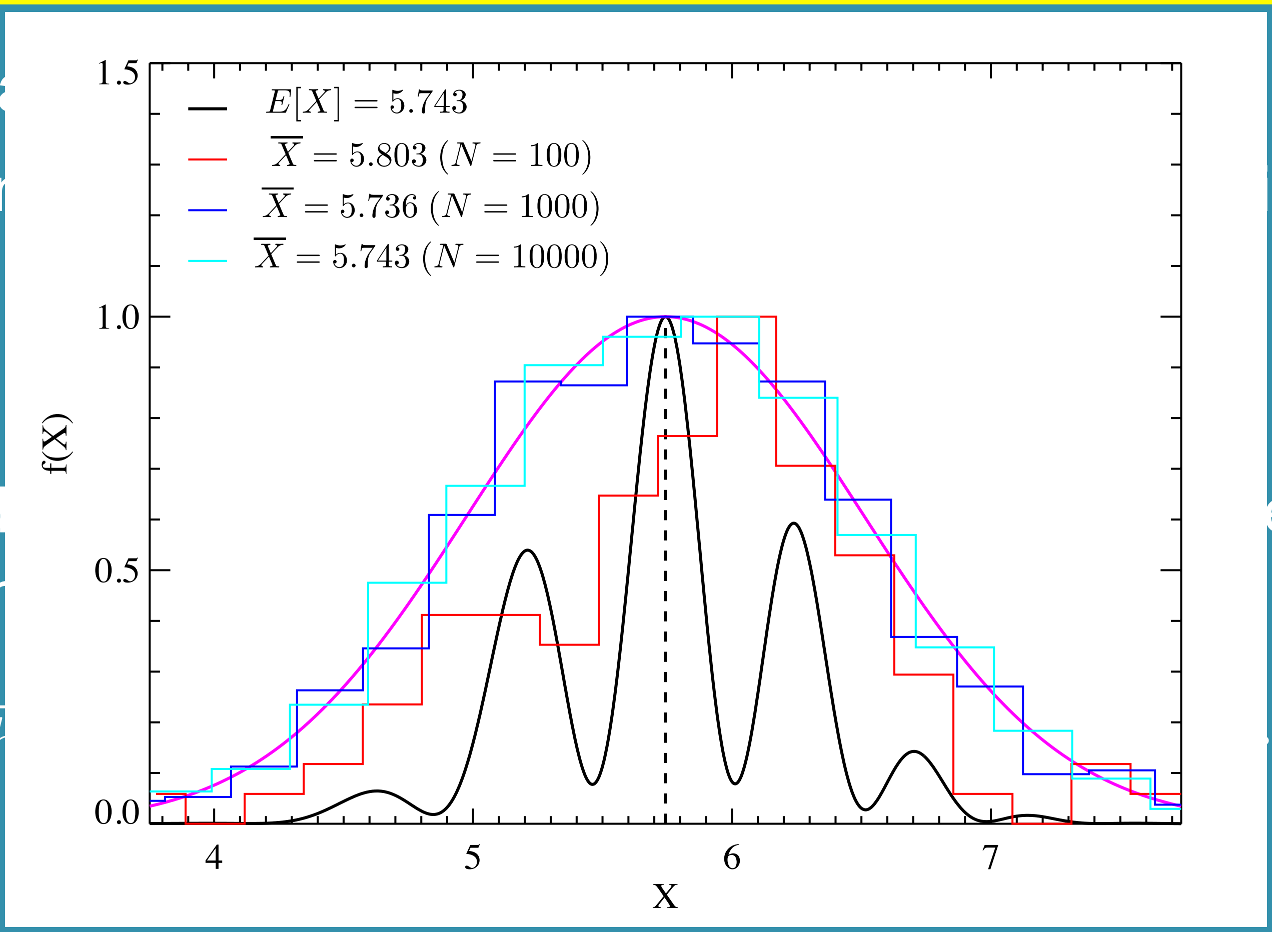

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Statistics: Reverse Importance Sampling (3)

- Biases of $\boldsymbol{\Theta} = [12 + \log(\mathrm{O/H}), \psi_S, z, R]$ = their expectations (or mean values) vary with galaxy inclination

1) Compute the densities (joint probability distributions) of the parameters $\boldsymbol{\Theta}$ in each axis ratio bin

   $\ast$ Cannot use multi-dimensional histograms (non-continuous densities, choice of bin width)

   $\ast$ Use of adaptive kernel density estimators (LIBAGF), to obtain the densities $\Delta_i(\boldsymbol{\Theta})$, $i = 1, n_{\text{axis ratio bins}}$

2) Suppose that the densities $\Delta_i(\boldsymbol{\Theta})$ are the importance functions, and we search for a suitable function $f(x)$

3) Condition on $f(x)$:

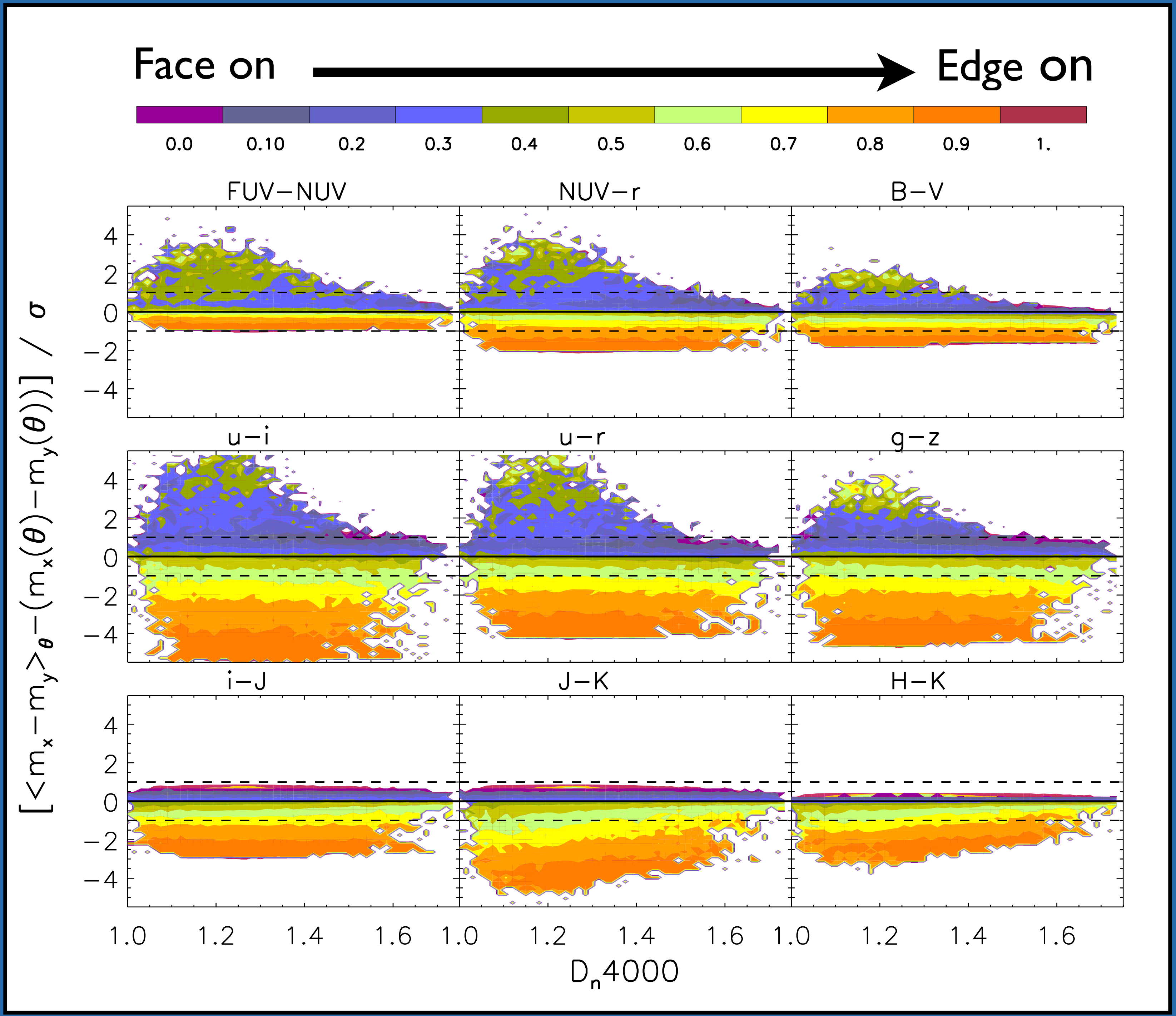
   $\ast$ $g(x) = 0 \implies f(x) = 0$

   $\ast$ for $M > 0$ and $\forall x, \dfrac{f(x)}{g(x)} < M \implies var(\bar{h}_N) < \infty$

$$f(x) = \prod_i \Delta_i \, , \text{ with } \Delta_i \in [0, 1]$$

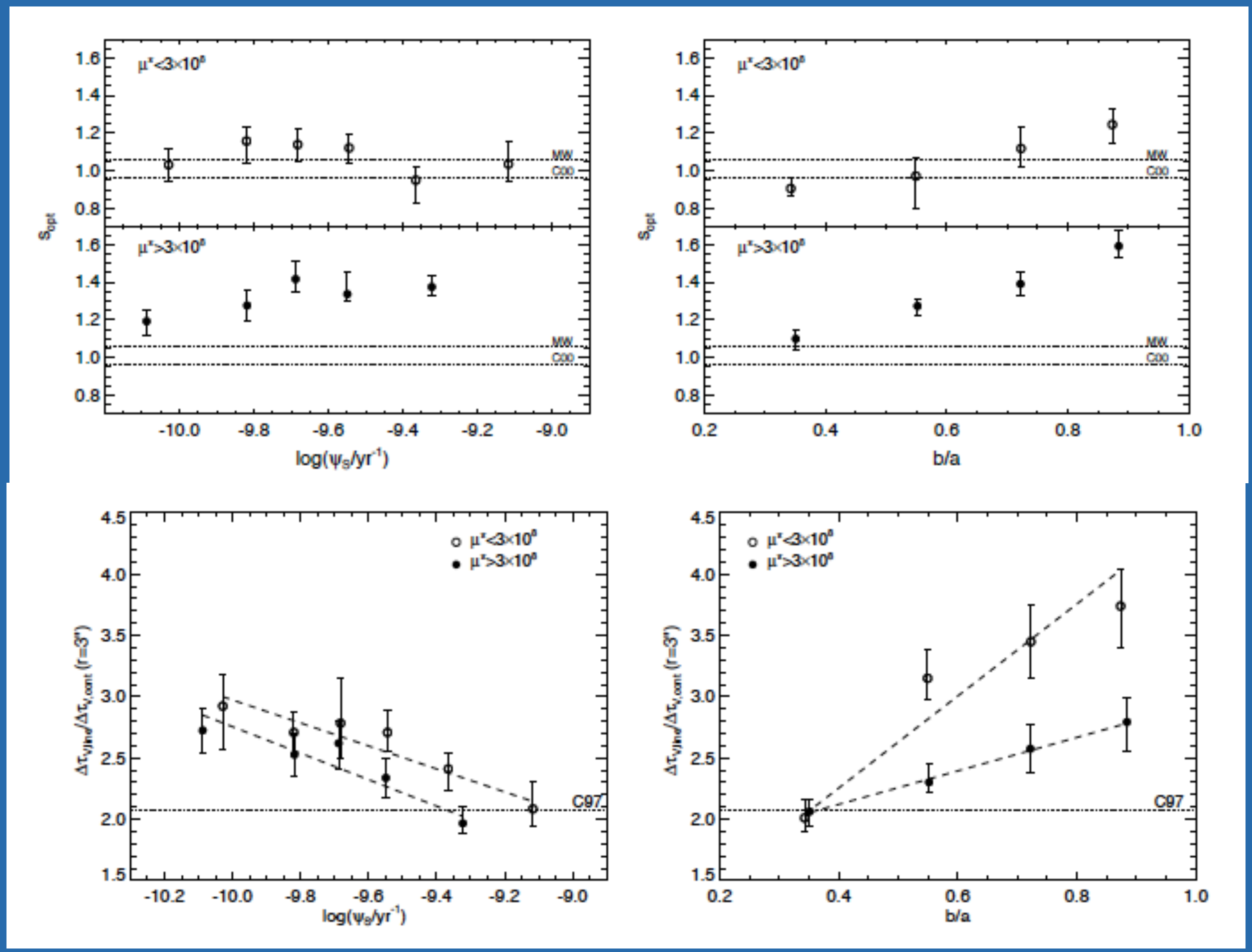
Dust attenuation: modeling

Which is the effect of such dust prescriptions on galaxy colors?
Use the already built model library!



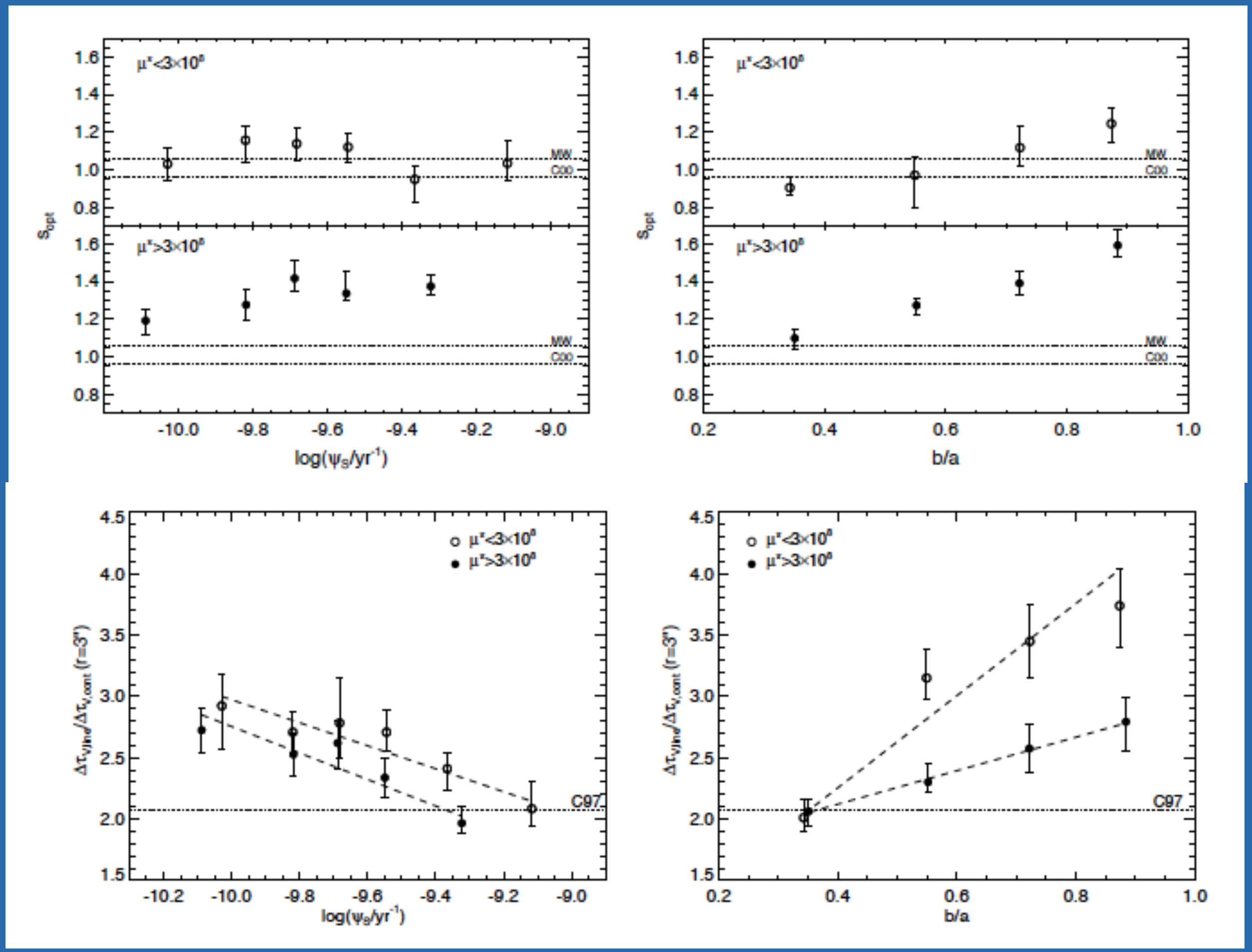
Color	Error [mag]
FUV - NUV	0,20
NUV - r	0,20
B - V	0,05
u - i	0,05
u - r	0,05
g - z	0,05
i - J	0,08
J - K	0,10
H - K	0,10

Data



Wild et al., MNRAS 2011

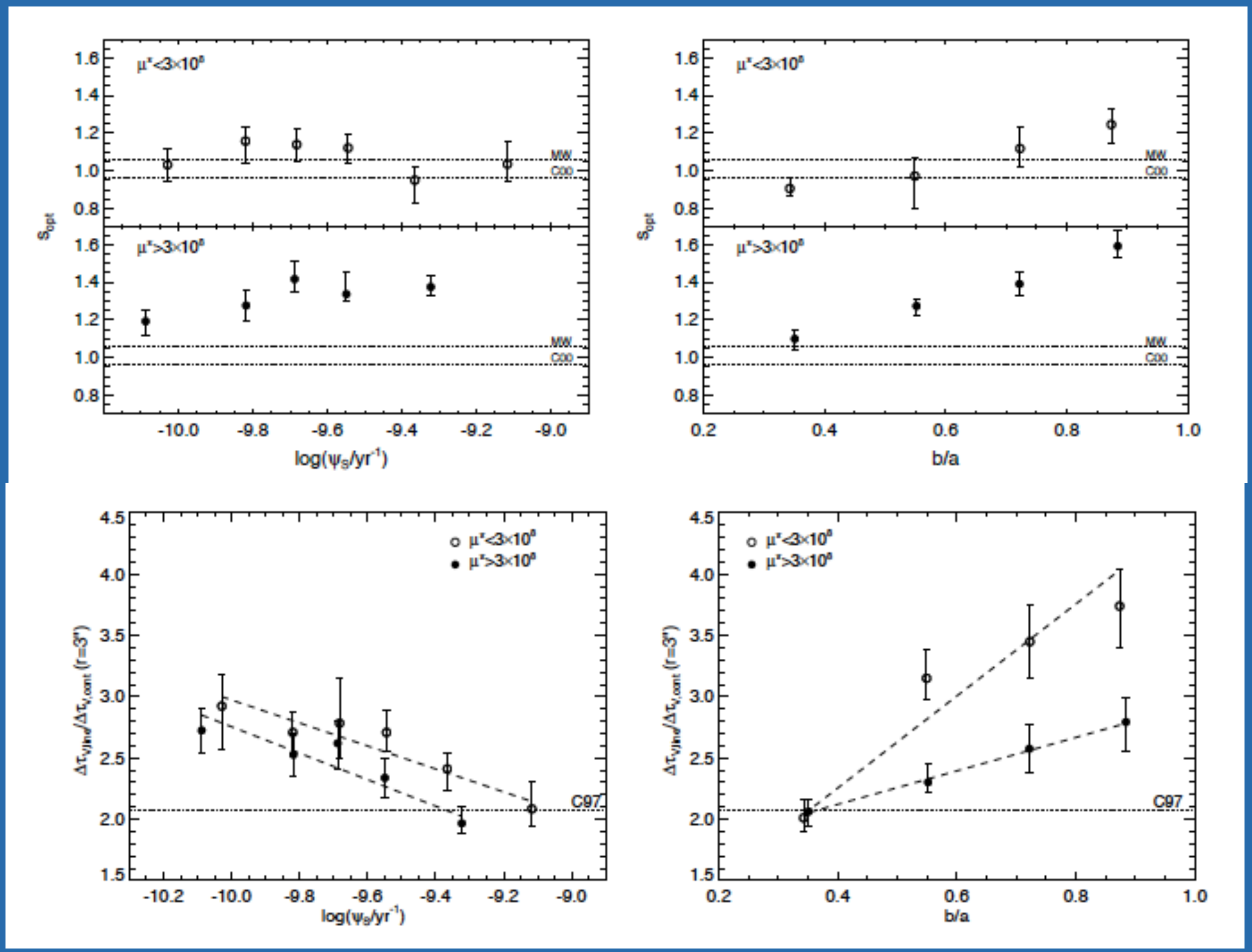
Data



Wild et al., MNRAS 2011

- 23 000 star forming galaxies
- Optical-to-NIR photometry and optical spectra (SDSS + UKIDSS)
- High and low μ_* sub-samples to separate galaxy with/without bulge
- Wild et al. used pair matching of galaxies with different Balmer ratios to obtain attenuation curves
- Find trends between attenuation slopes and SSFR / axis ratio
- Valid only if attenuation curves are independent on τ_V
- RT models show that this is not the case

Data



Wild et al., MNRAS 2011

Need of a different approach to get attenuation curves from galaxies SEDs

- 23 000 star forming galaxies
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Results from fit of ugrizYJH + Ha/Hb ratio

Results from fit of ugrizYJH + Ha/Hb ratio

- RT models predictions of the variation of dust attenuation with inclination agree with data from local galaxies
- Important to consider attenuation curves with different shapes to reproduce observations
- Fixed curves (Calzetti or Milky Way) unable to catch the variety of curves arising from the effect of inclination