Dust properties of nearby galaxies from the JINGLE survey

derived using a hierarchical Bayesian approach

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and the JINGLE collaboration

UCL

Dusting the Universe
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James Clerk Maxwell Telescope
East Asian Observatory

Dust properties of galaxies

QUESTIONS

> how do dust properties vary across the galaxy population?

> dust scaling relations: do dust properties correlate with other galaxy properties?

> how do dust properties in galaxies evolve across cosmic time?

In order to answer these questions we need :

SAMPLE

Large sample of galaxies with:

- consistent FIR/sub-mm photometric data
- consistent information about galaxy properties: SFR, stellar masses, gas content (atomic and molecular)

METHOD

Reliable method to measure dust properties:

- dust models suffers from degeneracy between parameters (e.g. T-beta degeneracy)

JINGLE: JCMT dust and gas In Nearby Galaxies Legacy Exploration

PIs: Saintonge (UK), Wilson (Canada), Xiang (China), Hwang (Korea), Lin (Taiwan)

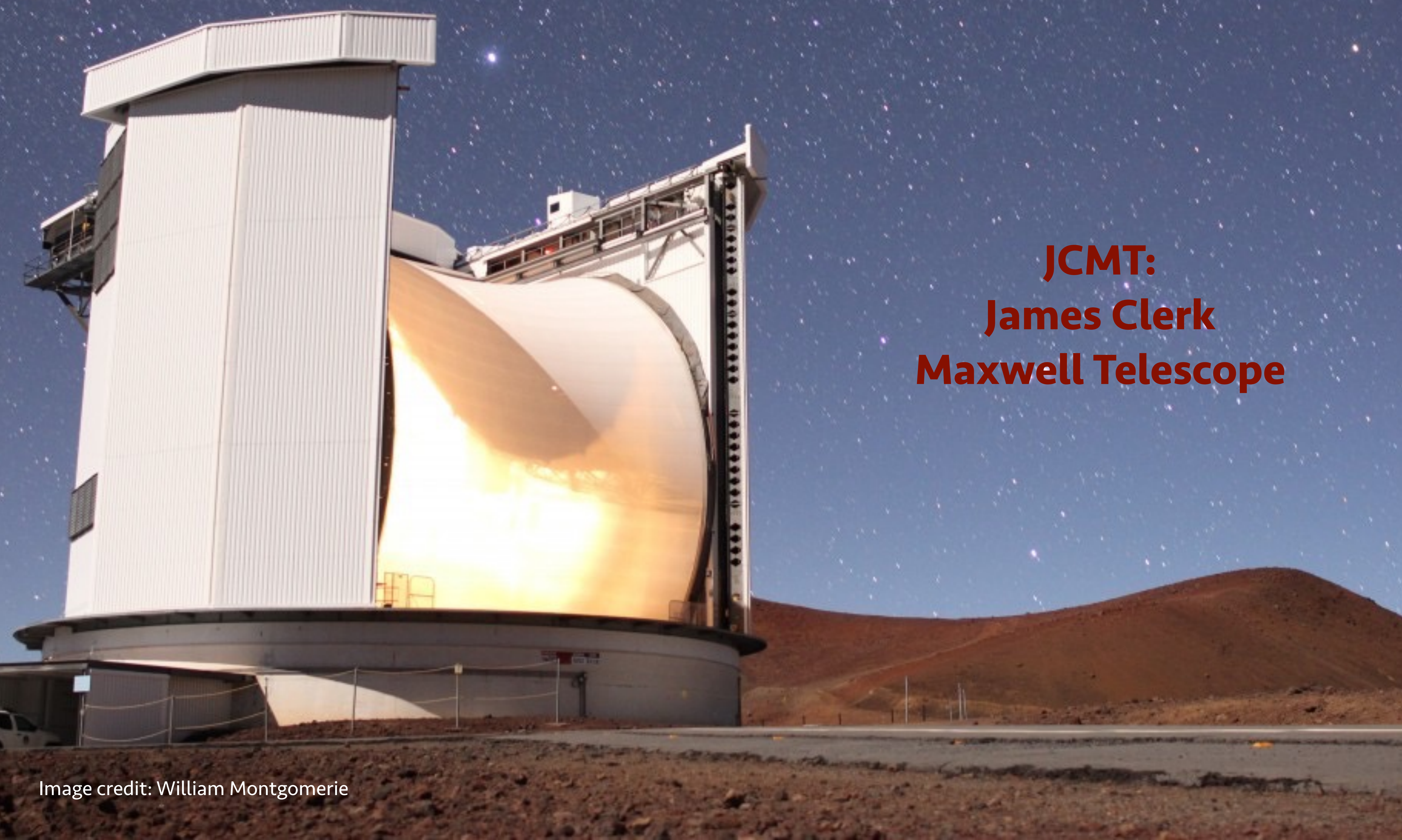


Image credit: William Montgomerie

JINGLE: JCMT dust and gas In Nearby Galaxies Legacy Exploration

Survey objectives

- study the **dust-to-gas ratio** and its variations across the galaxy population.
- derive **scaling relations** between dust properties and global galaxy observables.
- benchmark relations that can be used to infer dust and gas masses for large samples of **high-redshift** galaxies.

Image credit: William Montgomerie

JINGLE: sample overview

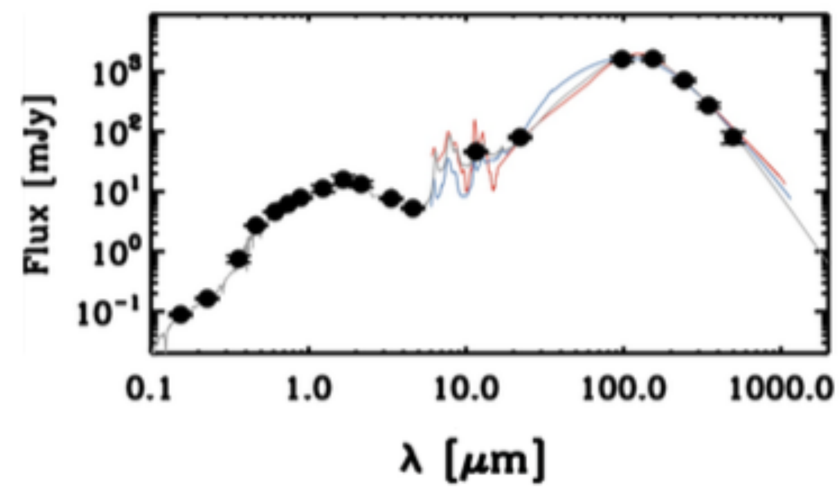
~200 nearby galaxies

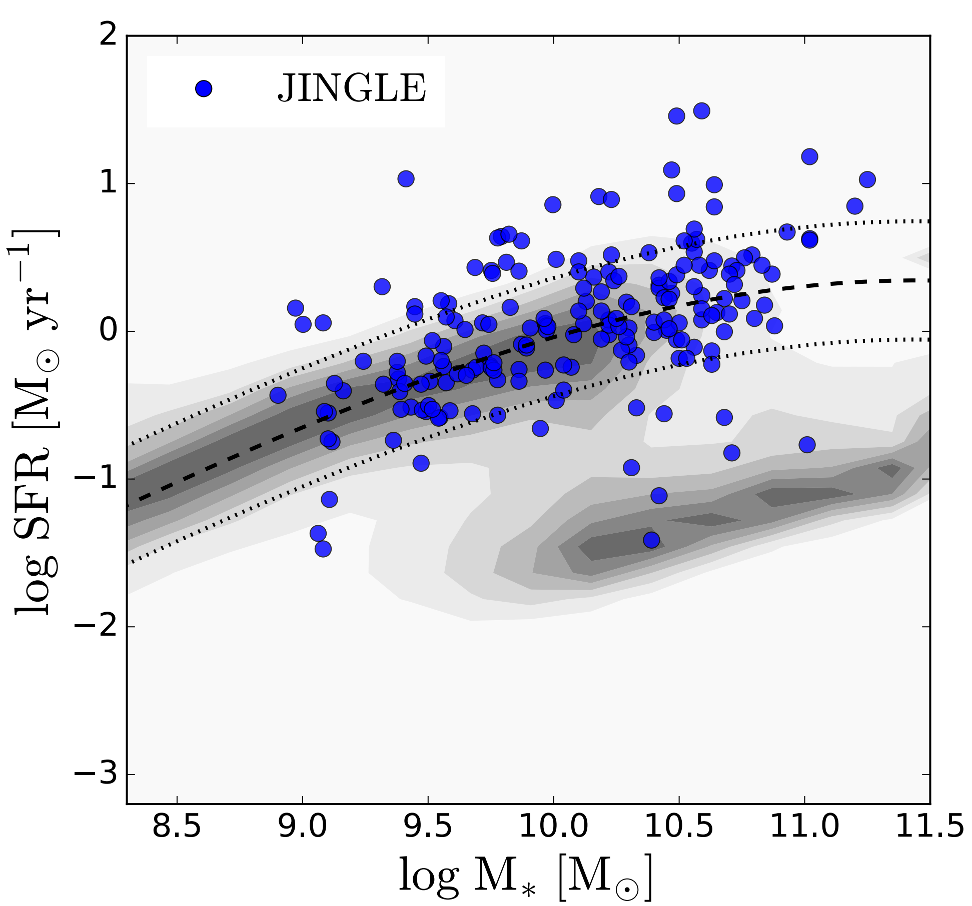
Redshift range: $0.01 < z < 0.05$

Multi-wavelength data:

- photometry: GALEX/SDSS/ WISE/Herschel (H-ATLAS)
- optical IFU maps: MANGA/SAMI
- HI maps: Apertif/ASKAP

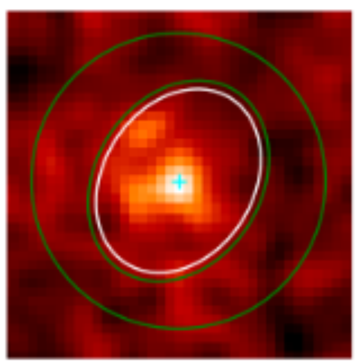
multi-wavelength





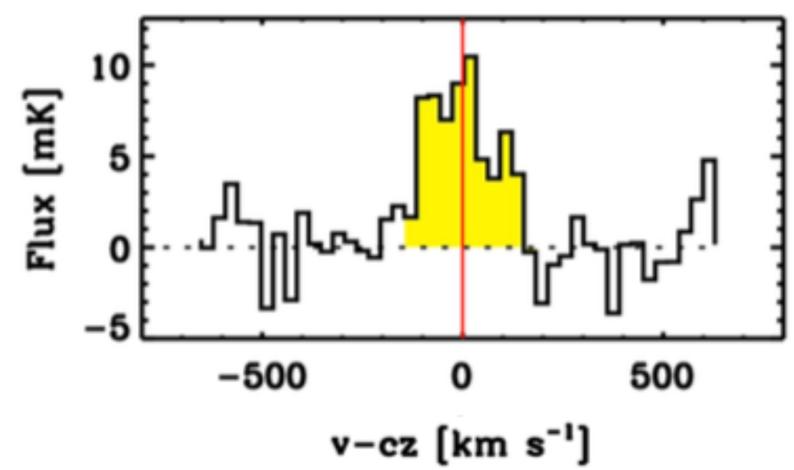
Dust

850um continuum (SCUBA-2 instrument)
193 galaxies



Molecular gas

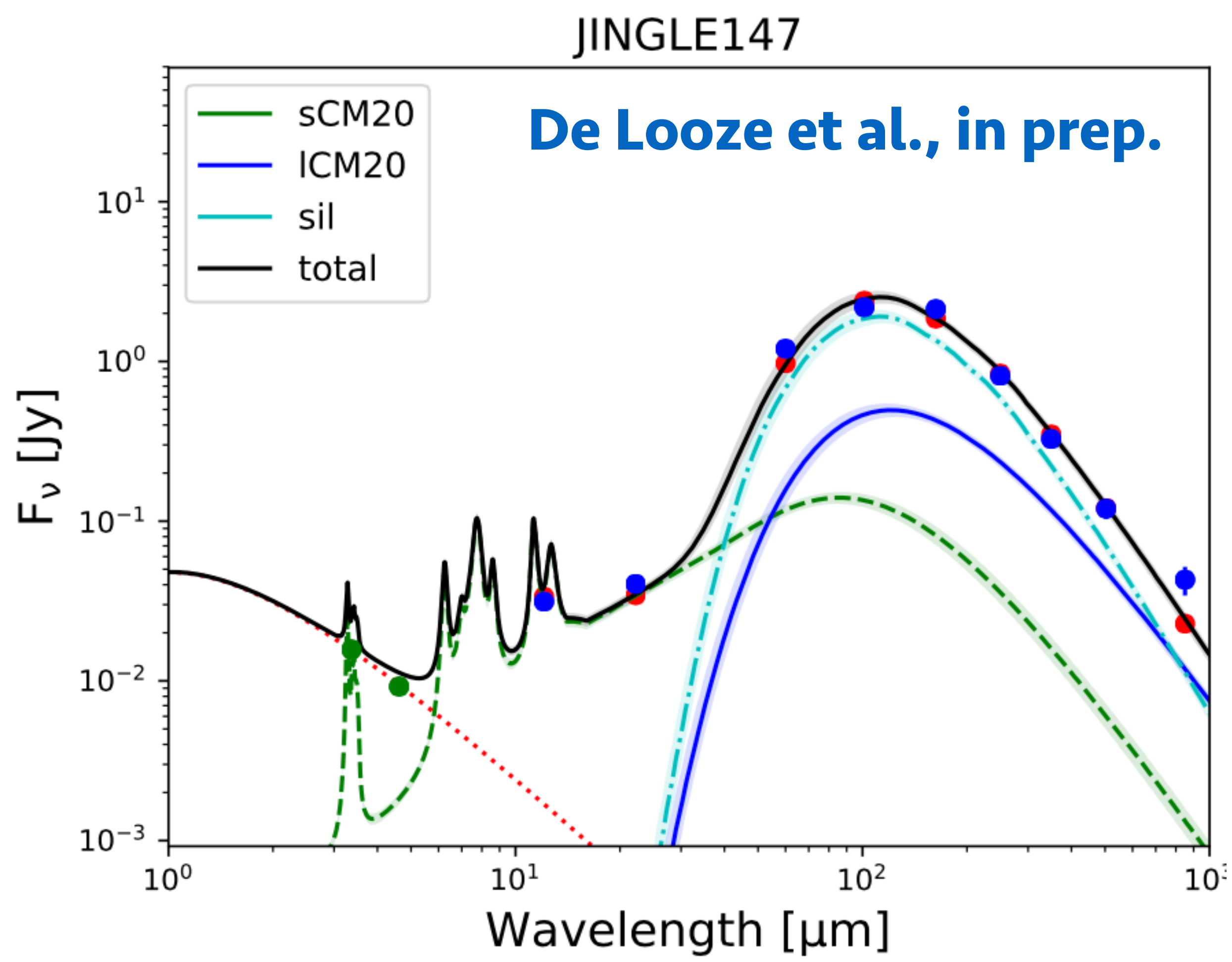
CO(2-1) line
(RxA instrument)
90 galaxies

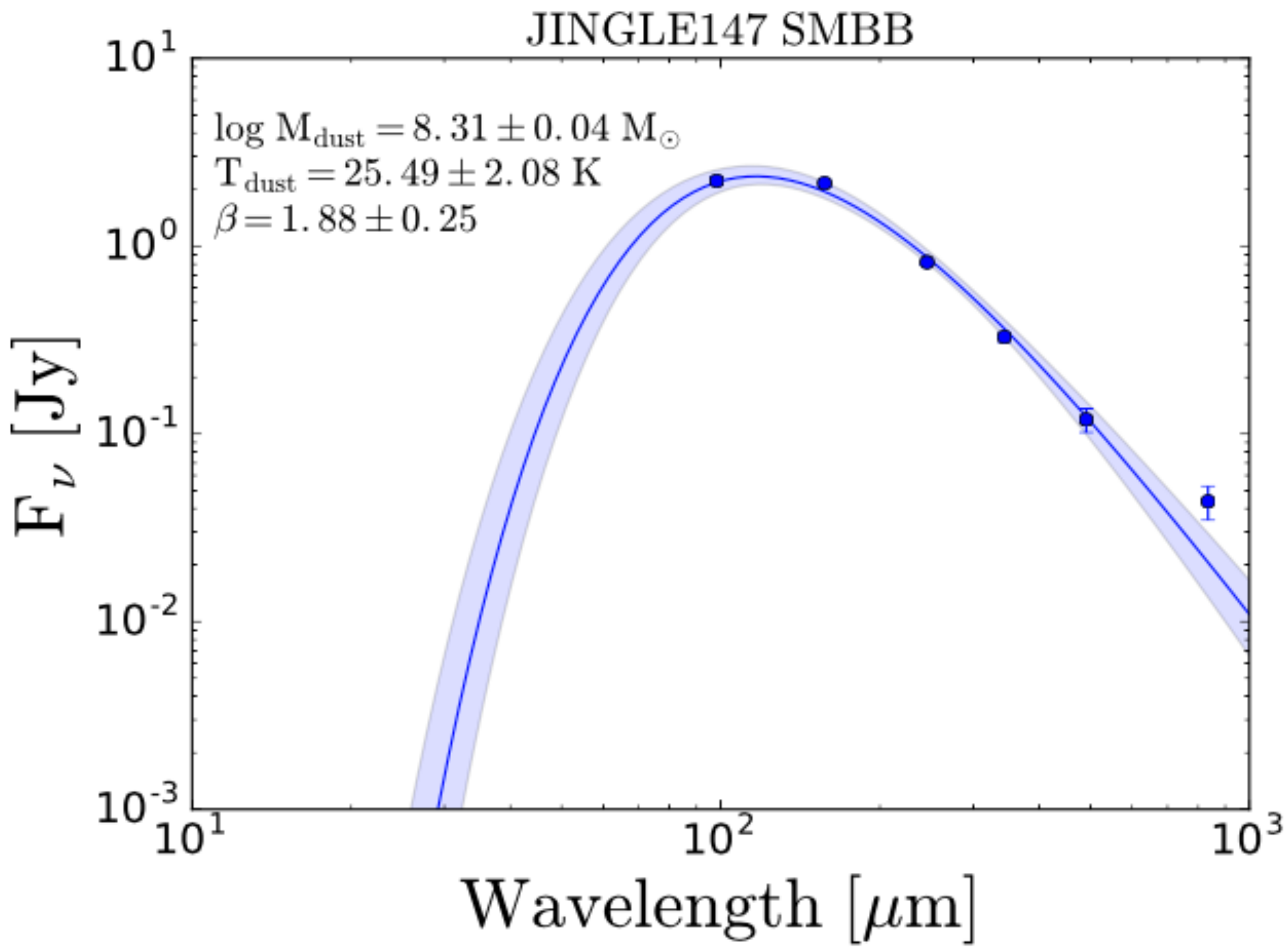


Two methods to measure the dust masses

THEMIS models
physically motivated dust models

MBB: modified black-body
analytical functions

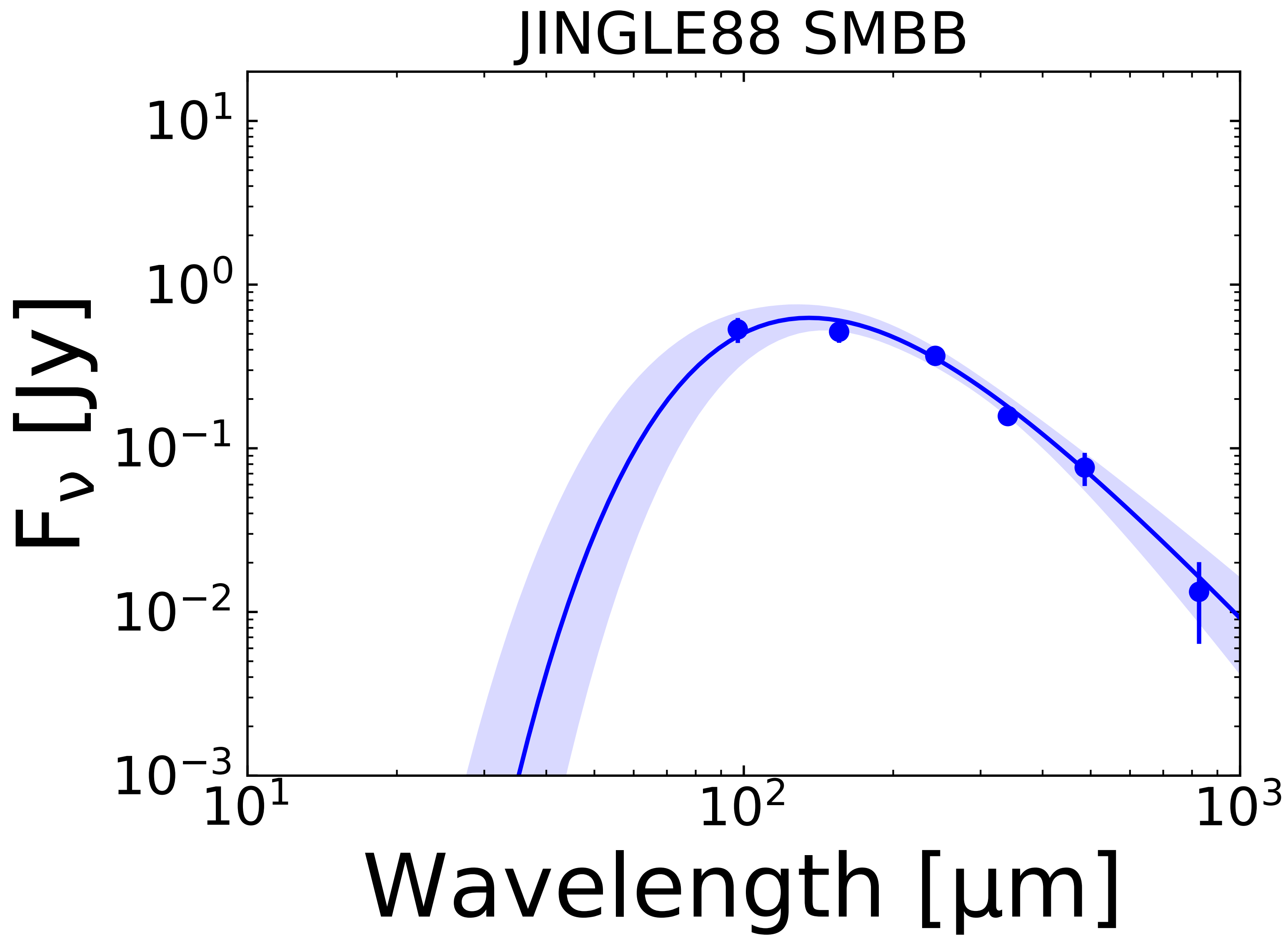




work by **Ilse De Looze**
(UGent/UCL postdoc)

Single modified black-body (SMBB) model

$$F_\lambda(M_{\mathrm{dust}}, T_{\mathrm{dust}}, \beta) = \frac{M_{\mathrm{dust}}}{D^2}\kappa_0 \left(\frac{\lambda_0}{\lambda}\right)^\beta B_\lambda(T_{\mathrm{dust}})$$



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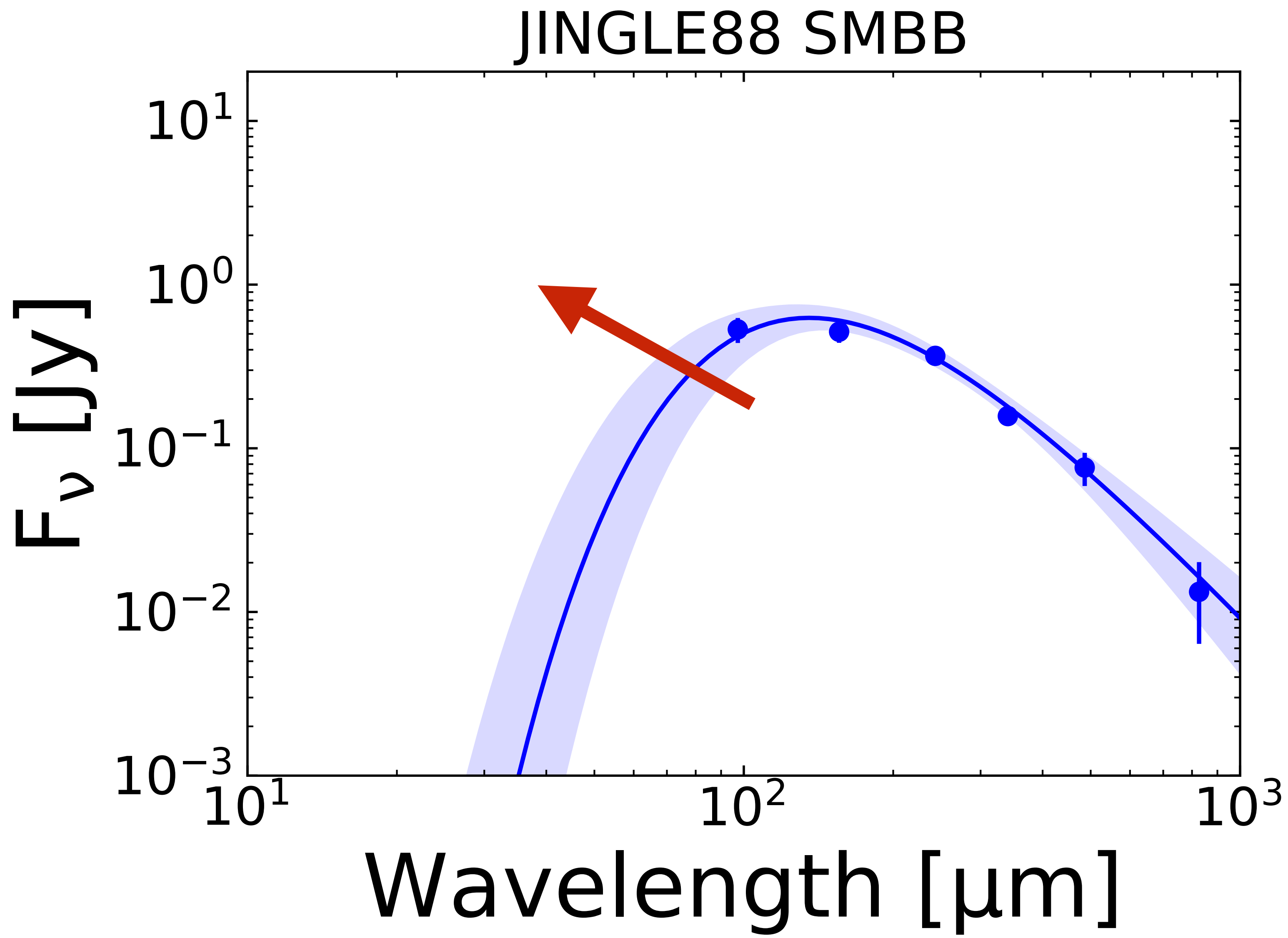

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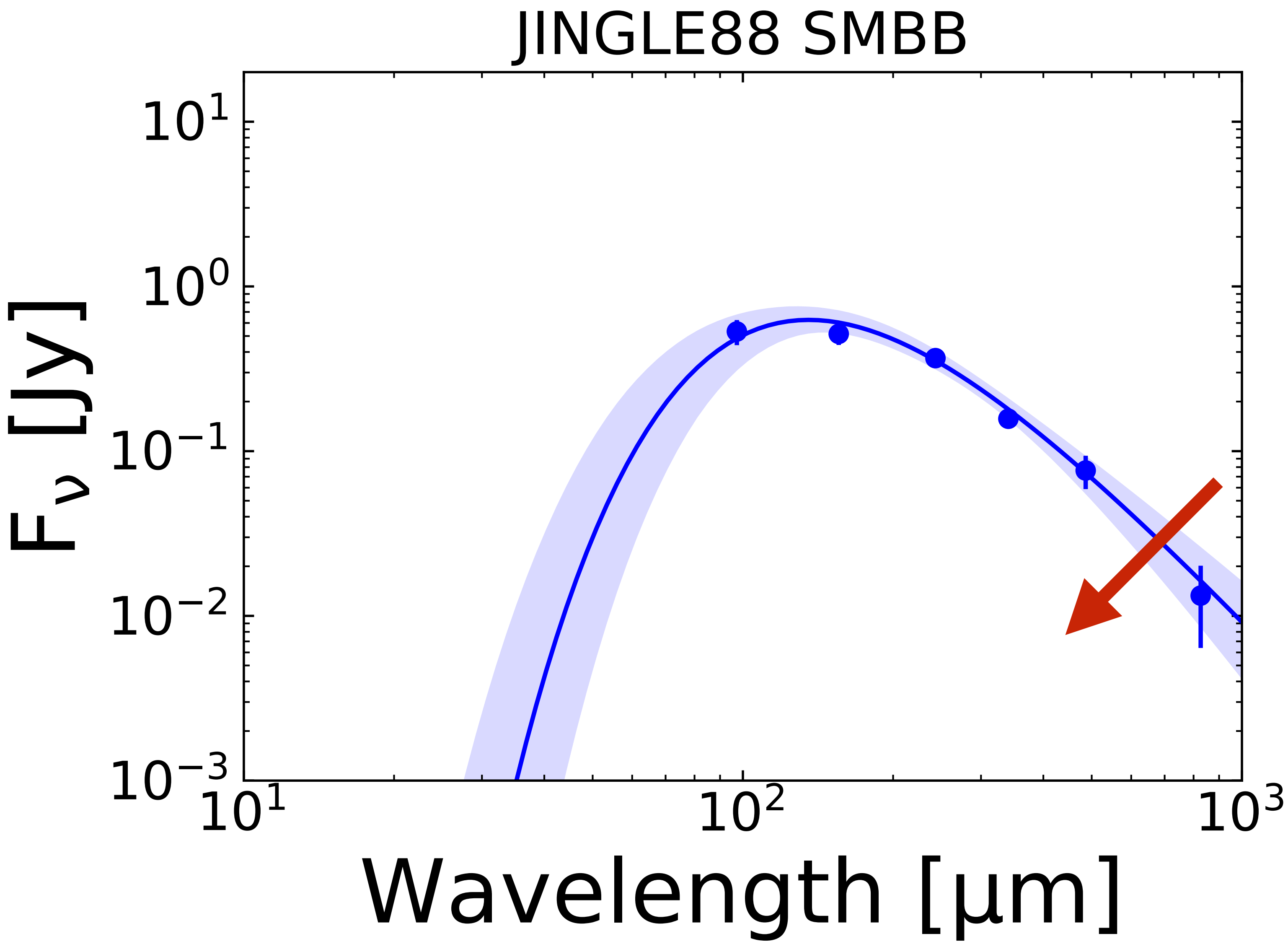
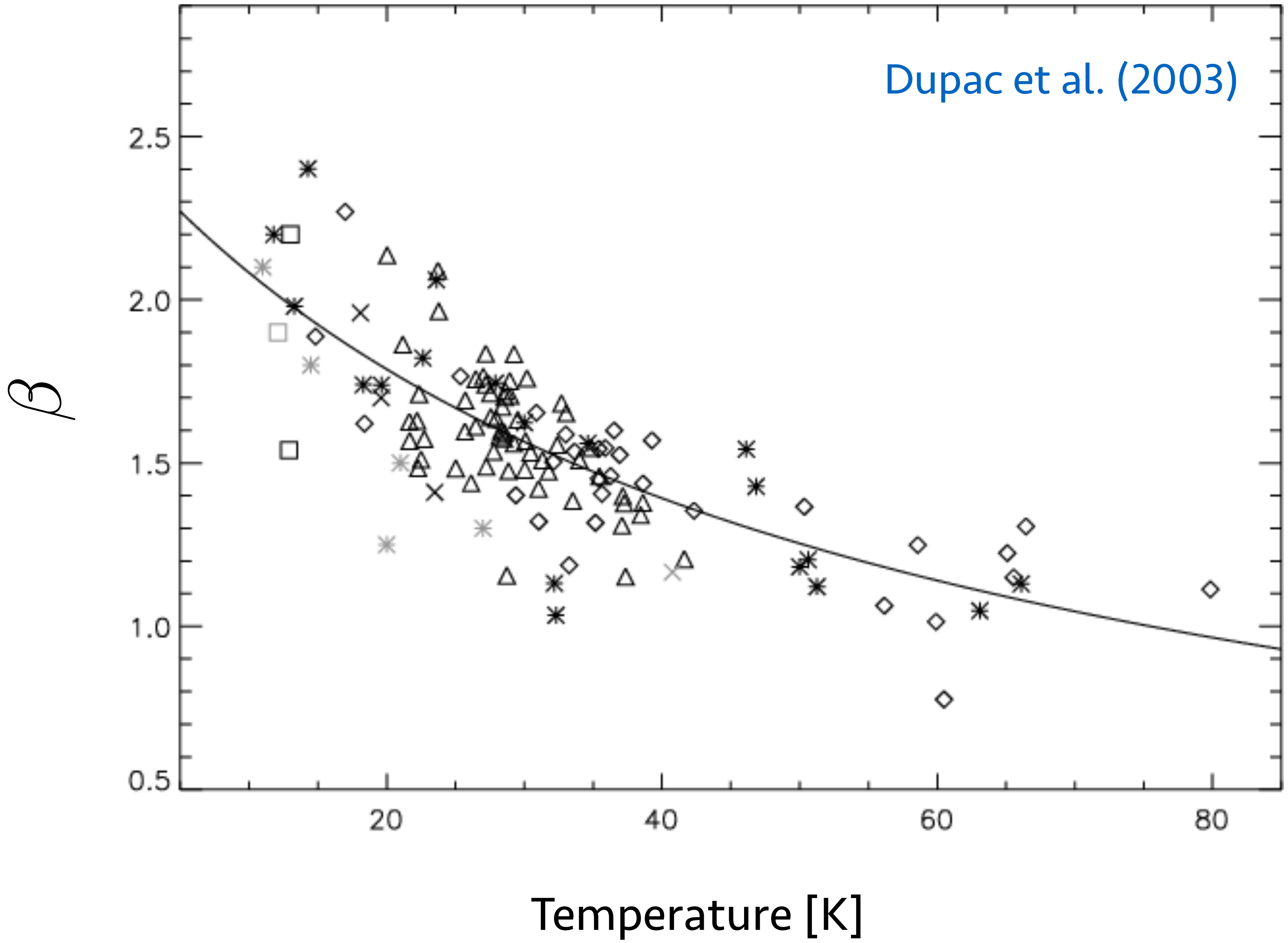
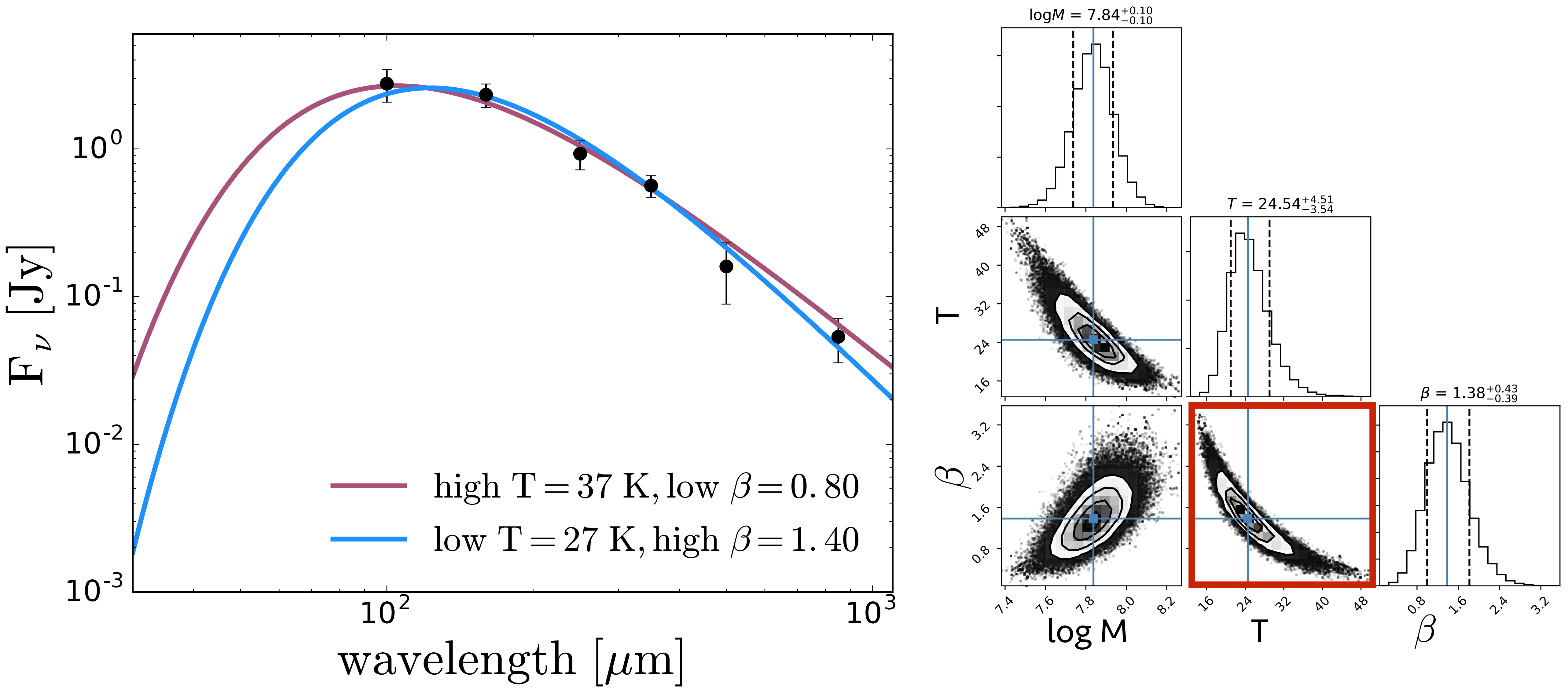


Many studies have observed an anti-correlation between temperature and beta



See also Désert et al. (2008), Paradis et al. (2010), Baracco et al. (2011), Smith et al. (2012)

Intrinsic degeneracy between temperature and beta



- Reference: Shetty et al. 2009a,b

How to overcome this problem?
Kelly et al. (2012): use the Hierarchical Bayesian approach

see also Galliano (2018)

Non-hierarchical Bayesian method

Bayes' theorem:

$$\boxed{p(\vec{\theta}_i|\vec{F}_i) \propto p(\vec{F}_i|\vec{\theta}_i) \cdot p(\vec{\theta}_i)}$$

posterior distribution

likelihood

prior

Non-hierarchical

Bayes' theorem:

$$\boxed{p(\vec{\theta}_i|\vec{F}_i) \propto p(\vec{F}_i|\vec{\theta}_i) \cdot p(\vec{\theta}_i)}$$

posterior distribution   likelihood   prior

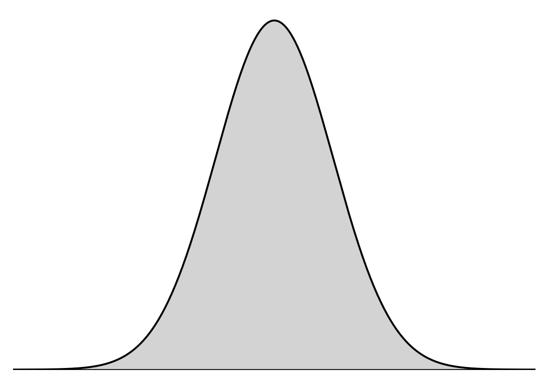
$$p(\vec{\theta}_i)$$

prior

uniform prior

$$p(\vec{F}_i|\vec{\theta}_i)$$

likelihood



Gaussian noise:

$$p(F|\theta, F_{err}) \propto \exp\left(-\frac{1}{2}\left(\frac{F - F_{model}(\theta)}{F_{err}}\right)^2\right)$$

Non-hierarchical

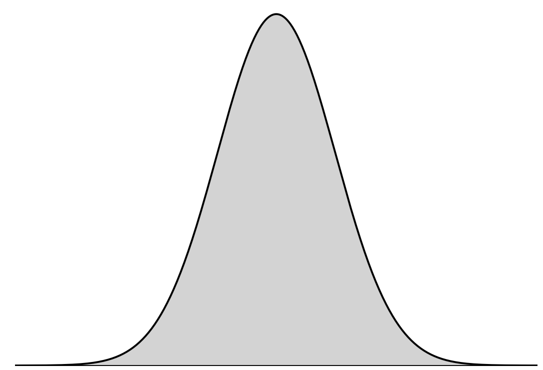
$$\boxed{p(\vec{\theta}_i|\vec{F}_i) \propto p(\vec{F}_i|\vec{\theta}_i) \cdot p(\vec{\theta}_i)}$$

mean

standard deviation

$$p(\vec{\theta}_i|\vec{\mu}, \Sigma)$$

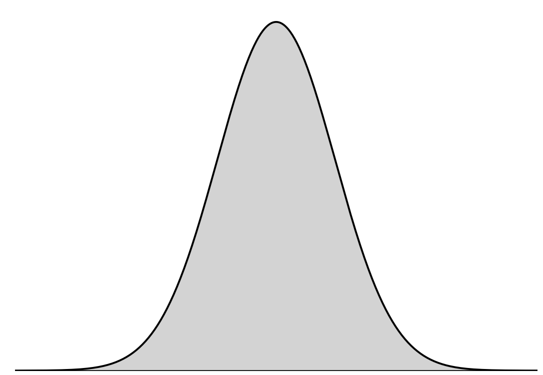
prior



Gaussian prior

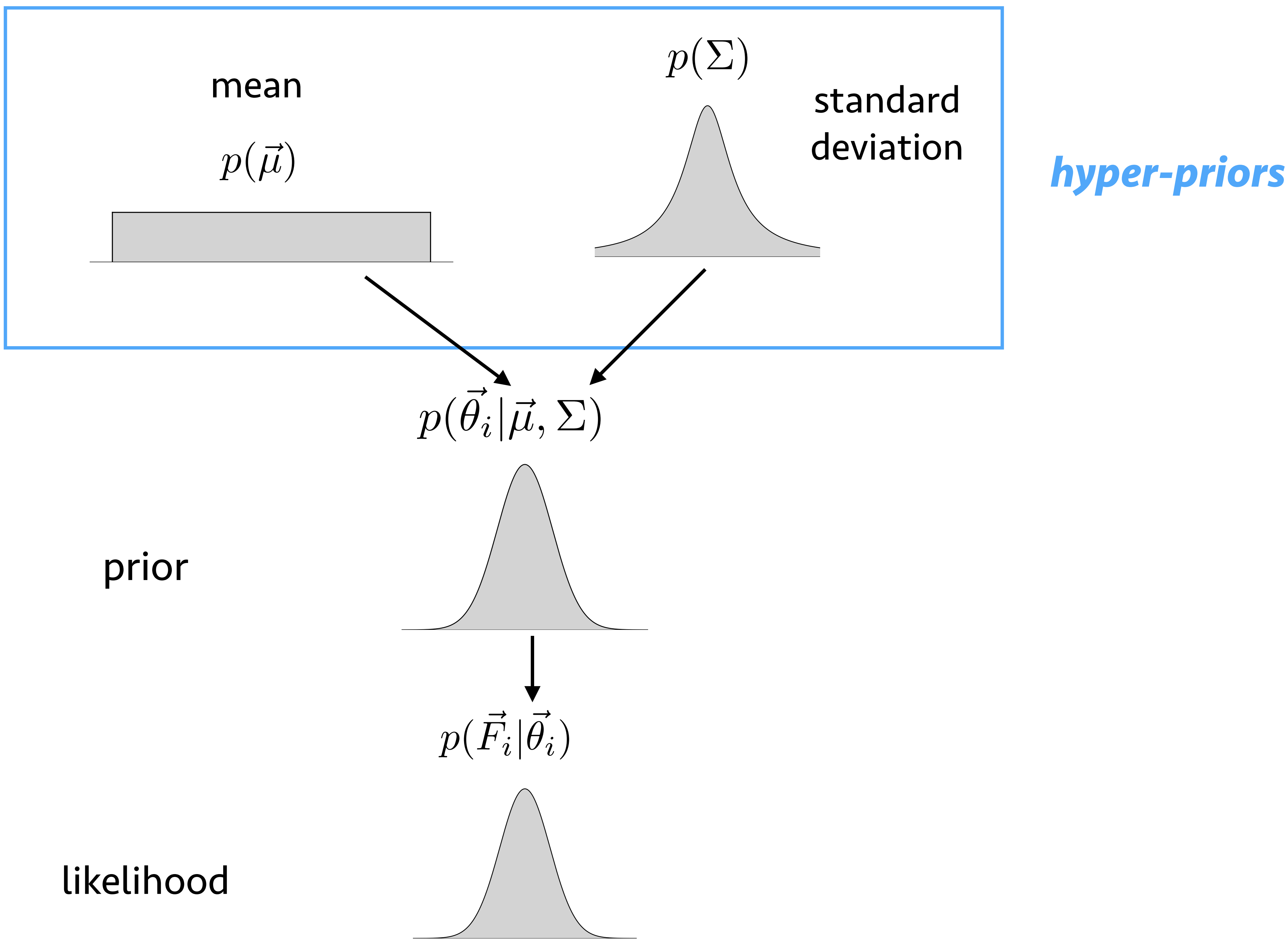
$$p(\vec{F}_i|\vec{\theta}_i)$$

likelihood



Hierarchical

$$p(\vec{\theta}_1, ..., \vec{\theta}_n, \vec{\mu}, \Sigma | \vec{F}) \propto \prod_{i=1}^{n} p(\vec{F}_i | \vec{\theta}_i) \cdot p(\vec{\theta}_i | \vec{\mu}, \Sigma) \cdot p(\vec{\mu}) \cdot p(\Sigma)$$



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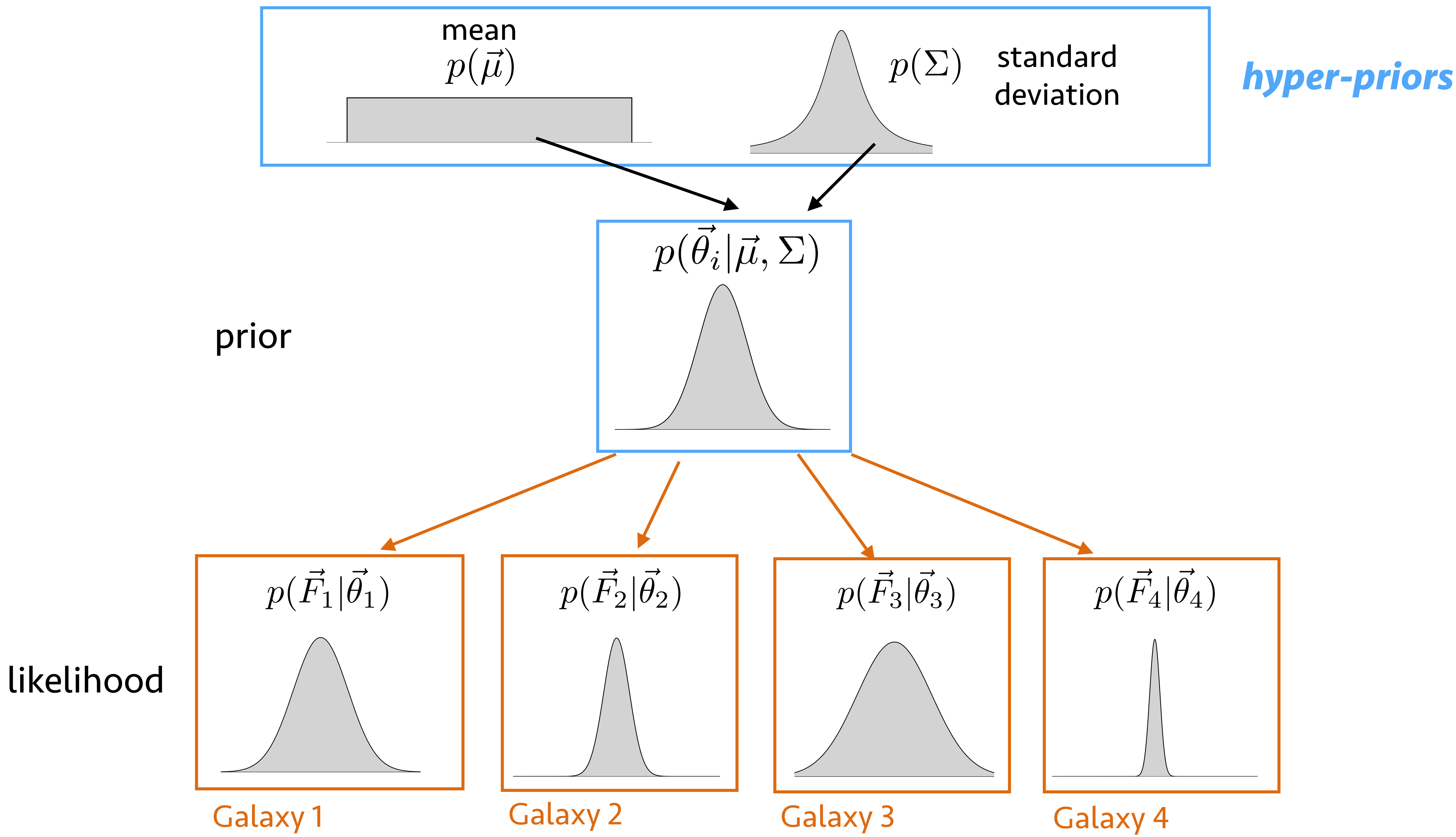
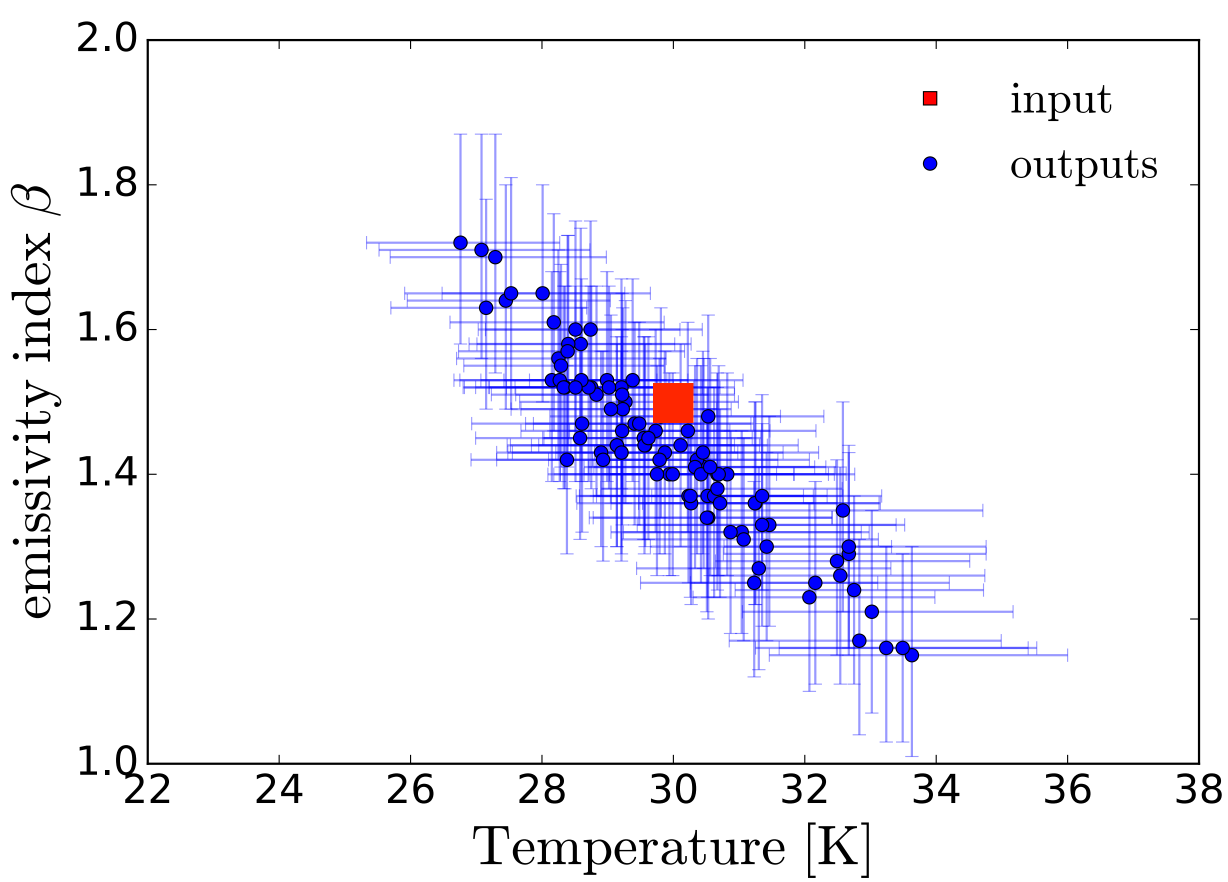


Mock data set: noise in the data can introduce an anti-correlation between the dust temperature and beta

- Simulation of MBB with the same input T = 30 K and beta = 1.5, but with some Gaussian noise added to the flux points

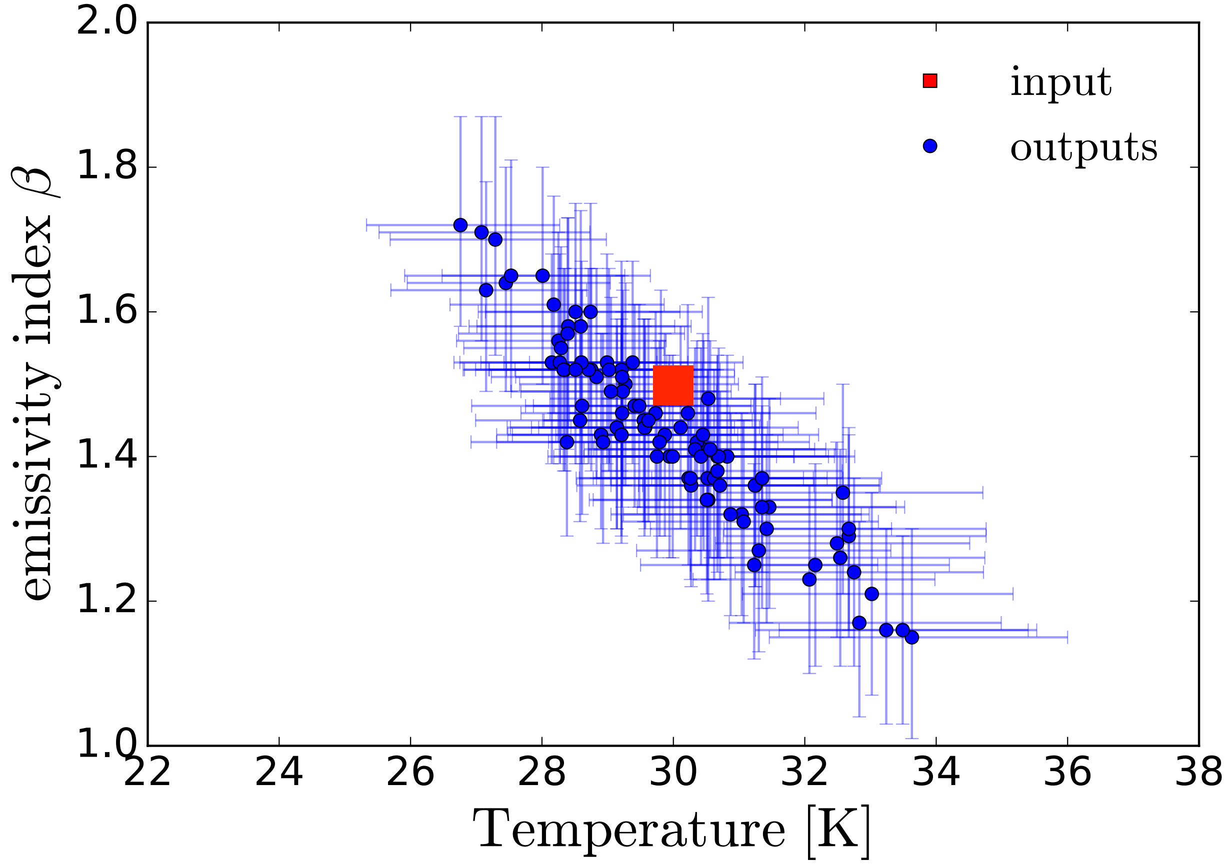
non-hierarchical



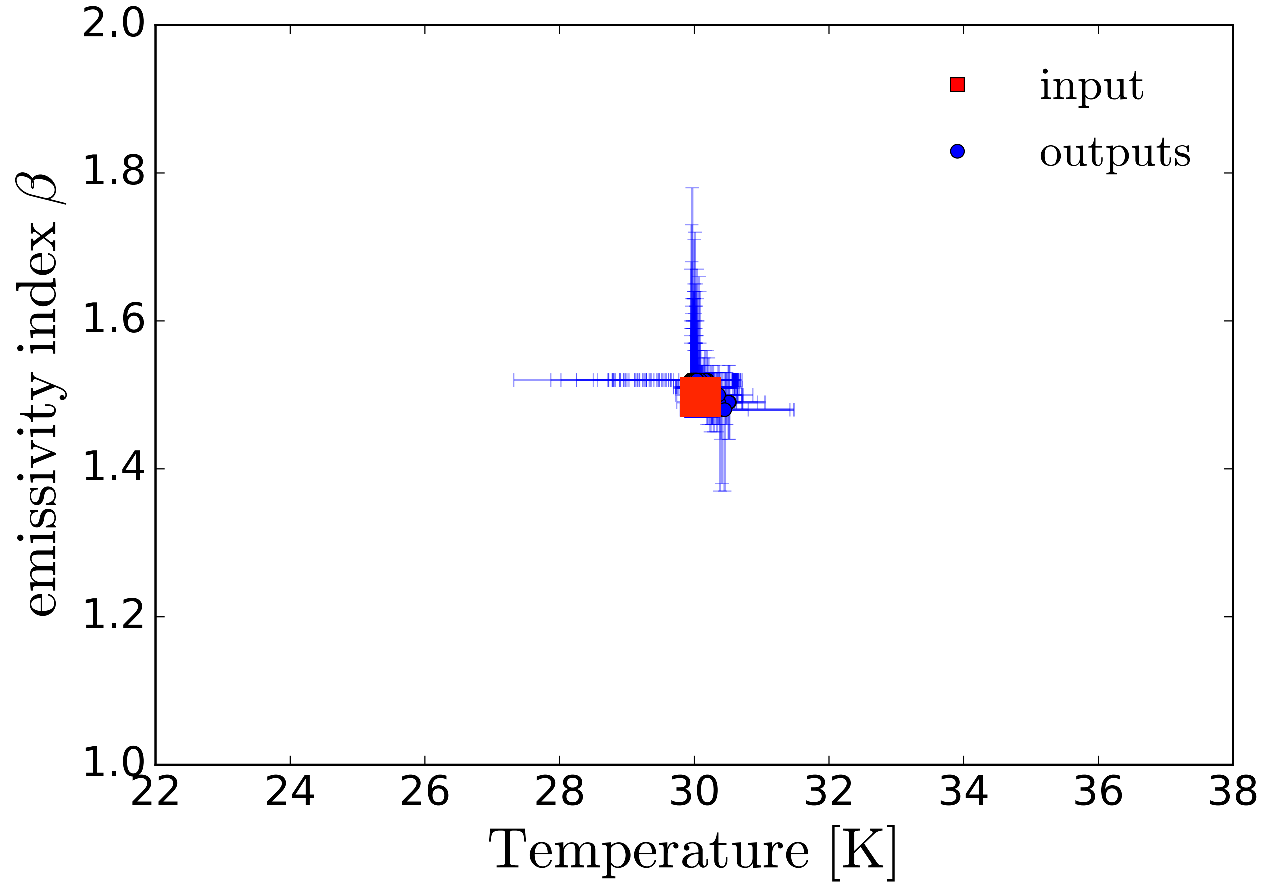
Mock data set: hierarchical approach can recover better the input temperature and beta

- Simulation of MBB with the same input T = 30 K and beta = 1.5, but with some Gaussian noise added to the flux points

non-hierarchical

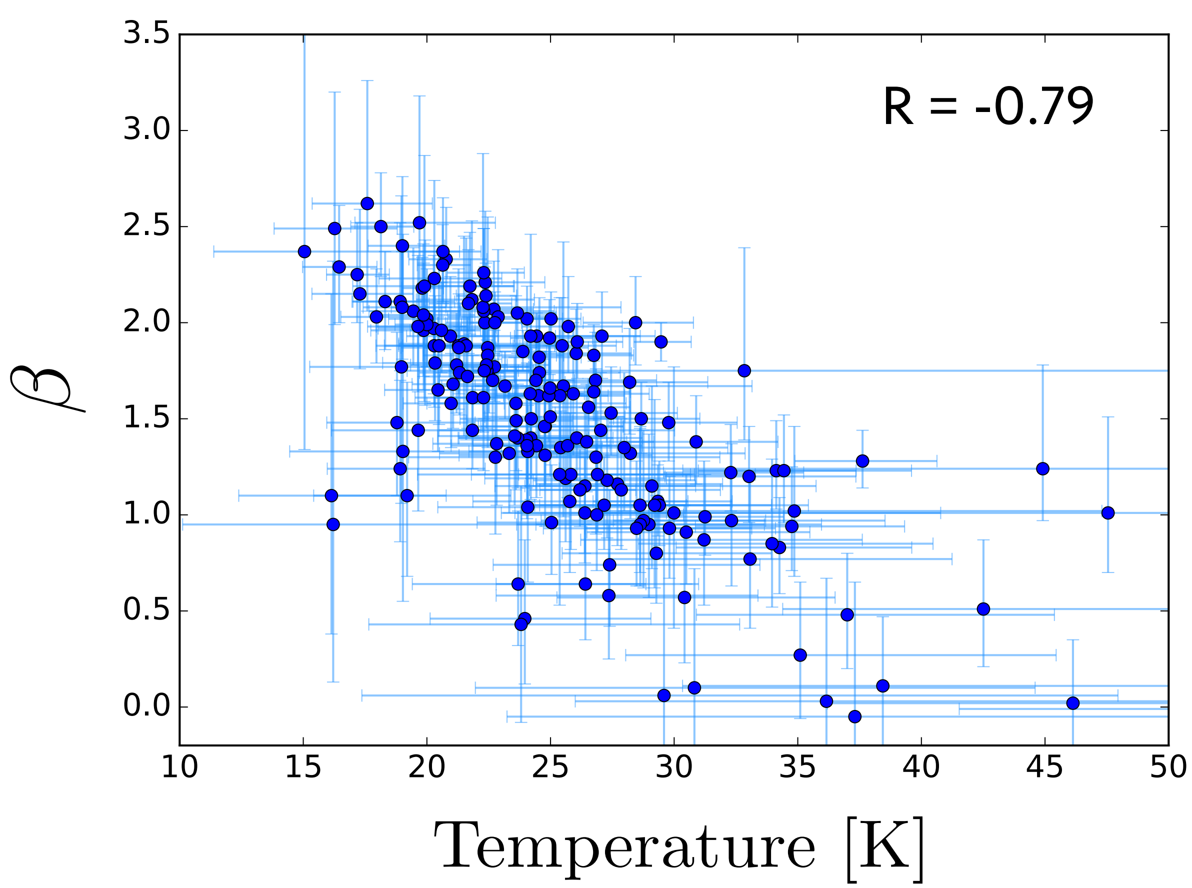


hierarchical

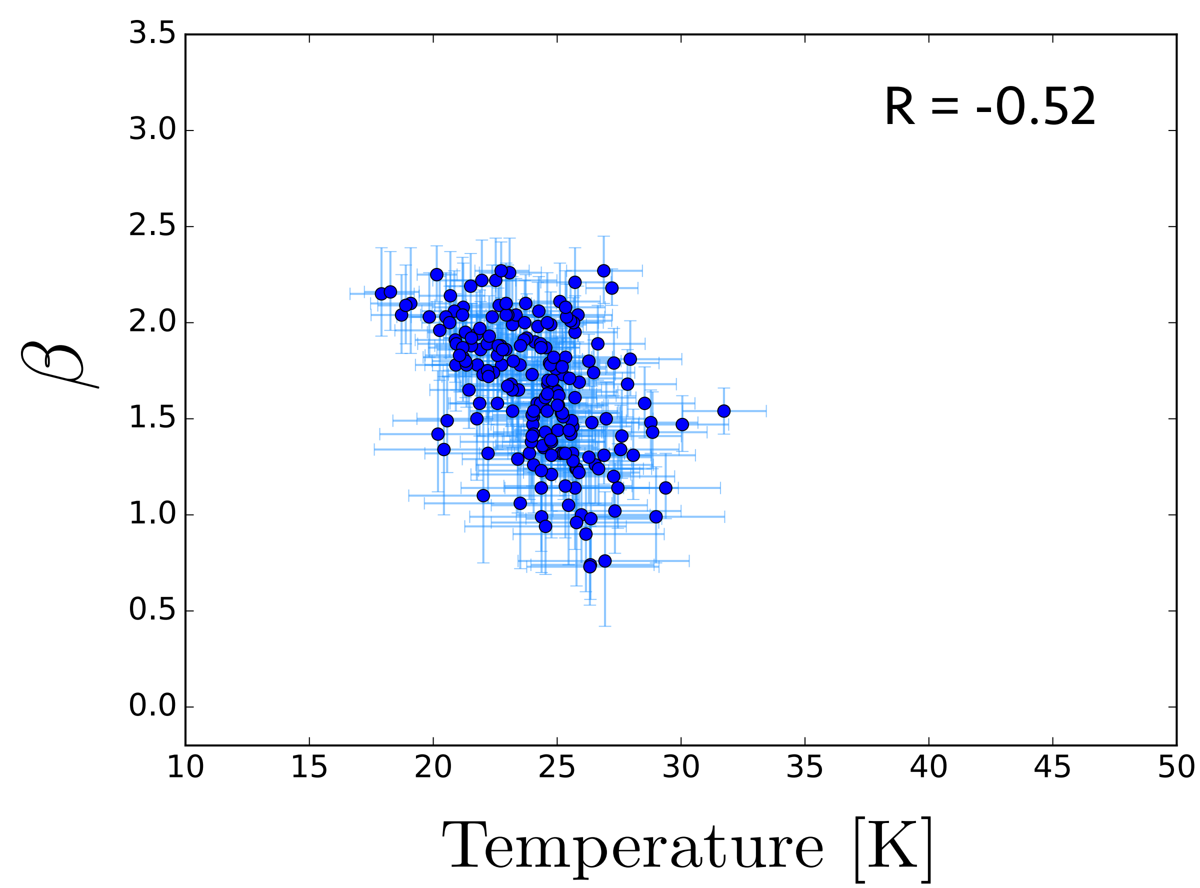


The hierarchical method reduces the T-beta anti-correlation in the JINGLE sample

non-hierarchical



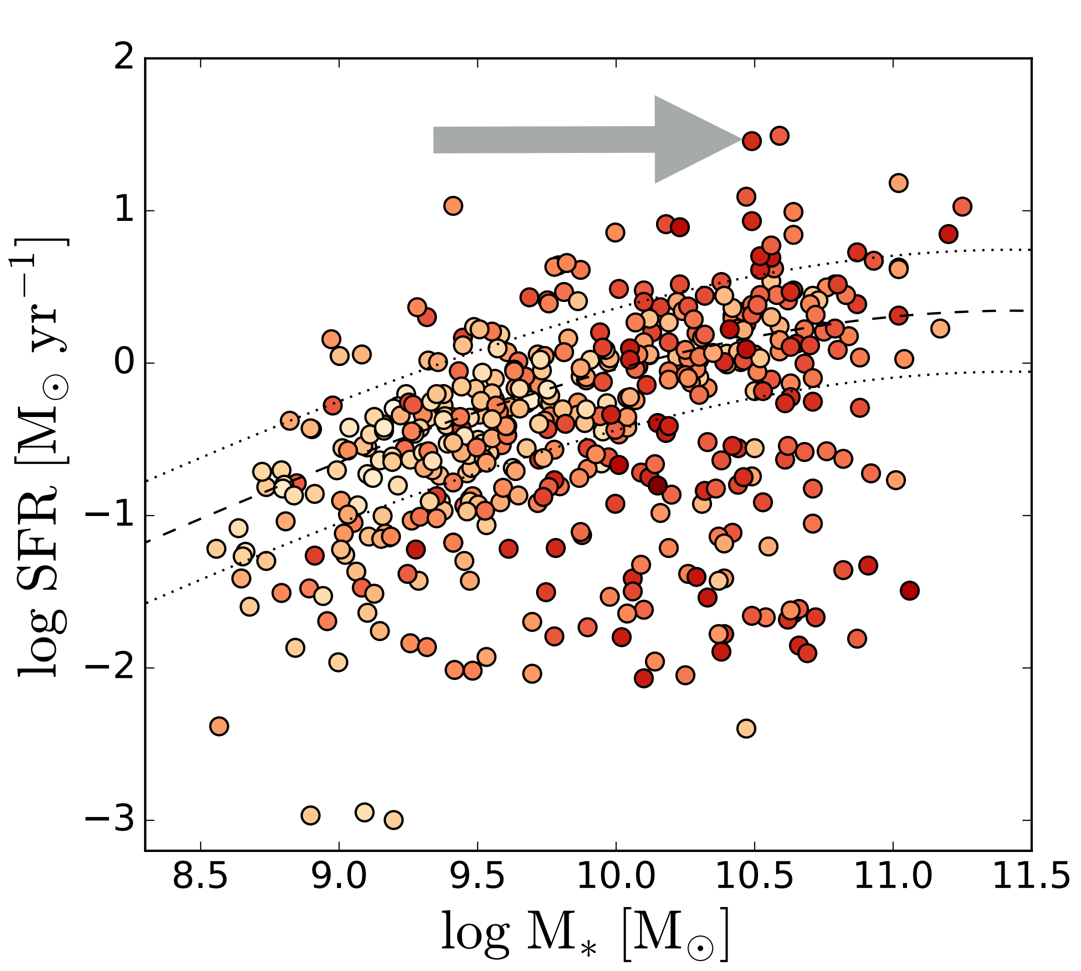
hierarchical



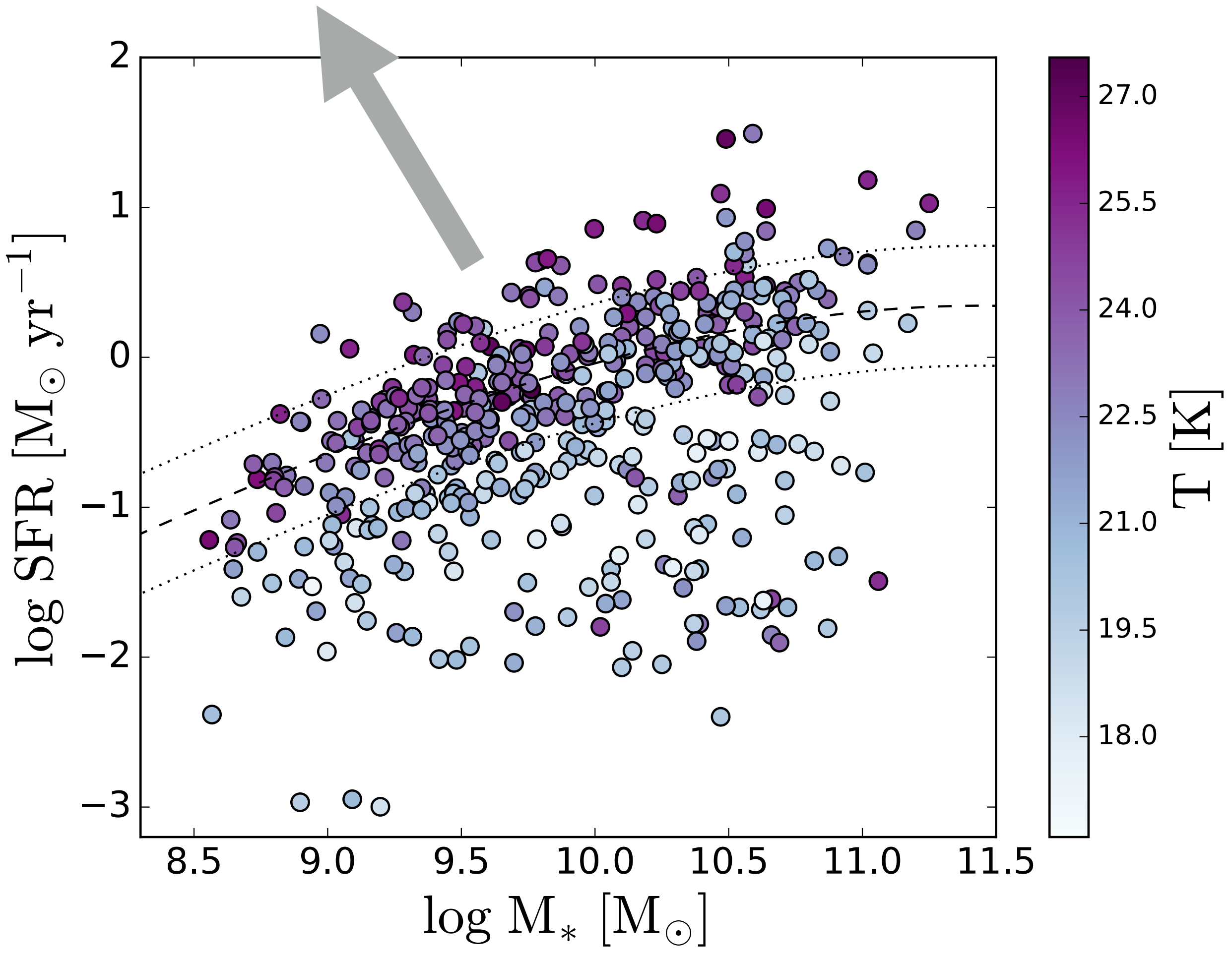
Lamperti et al., in prep.

Dust properties on the SFR-M* plane

dust emissivity index β

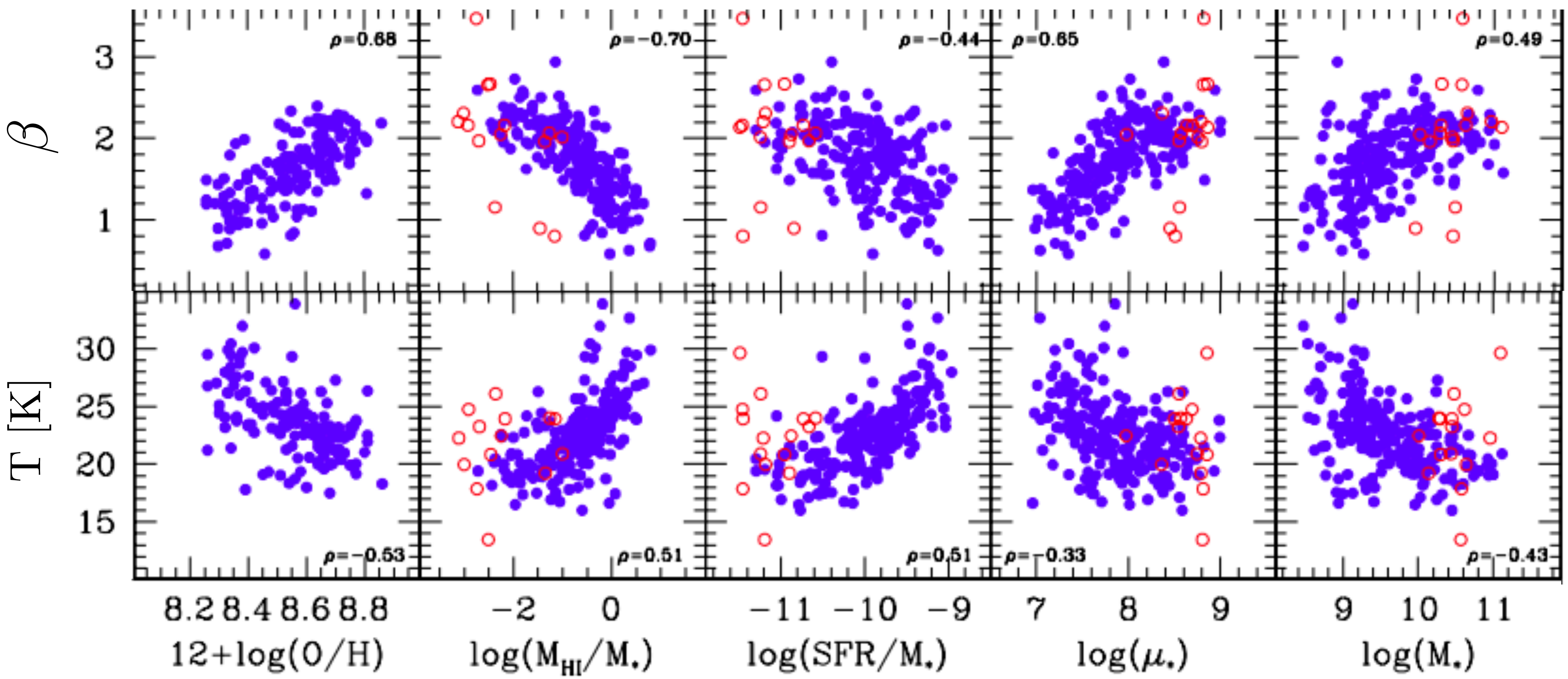


dust temperature



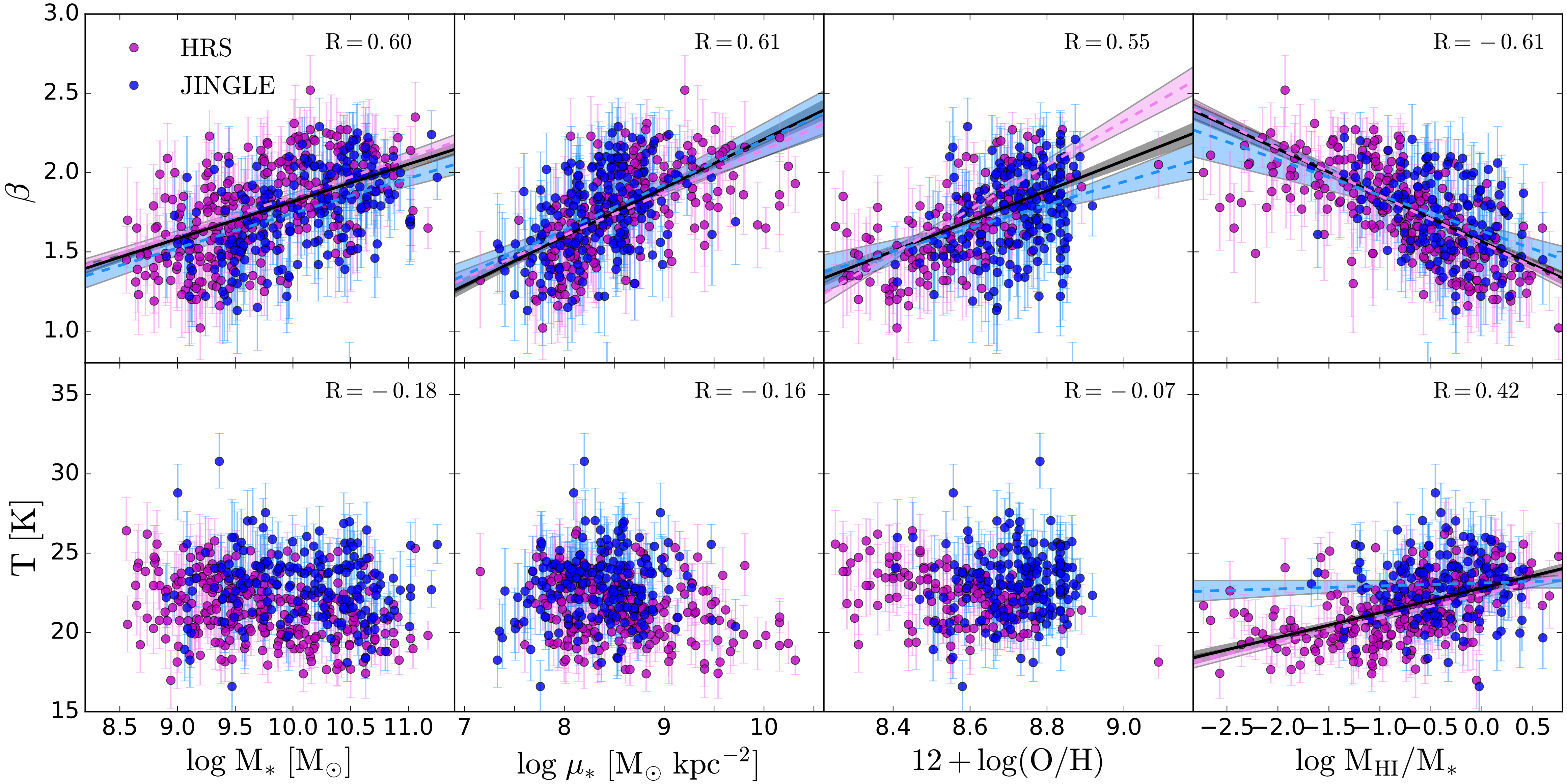
Lamperti et al., in prep

Dust scaling relations:
with the non-hierarchical method it is difficult to distinguish whether T or beta is the fundamental parameter driving the correlation



Cortese et al. (2014): data from the Herschel Reference Survey

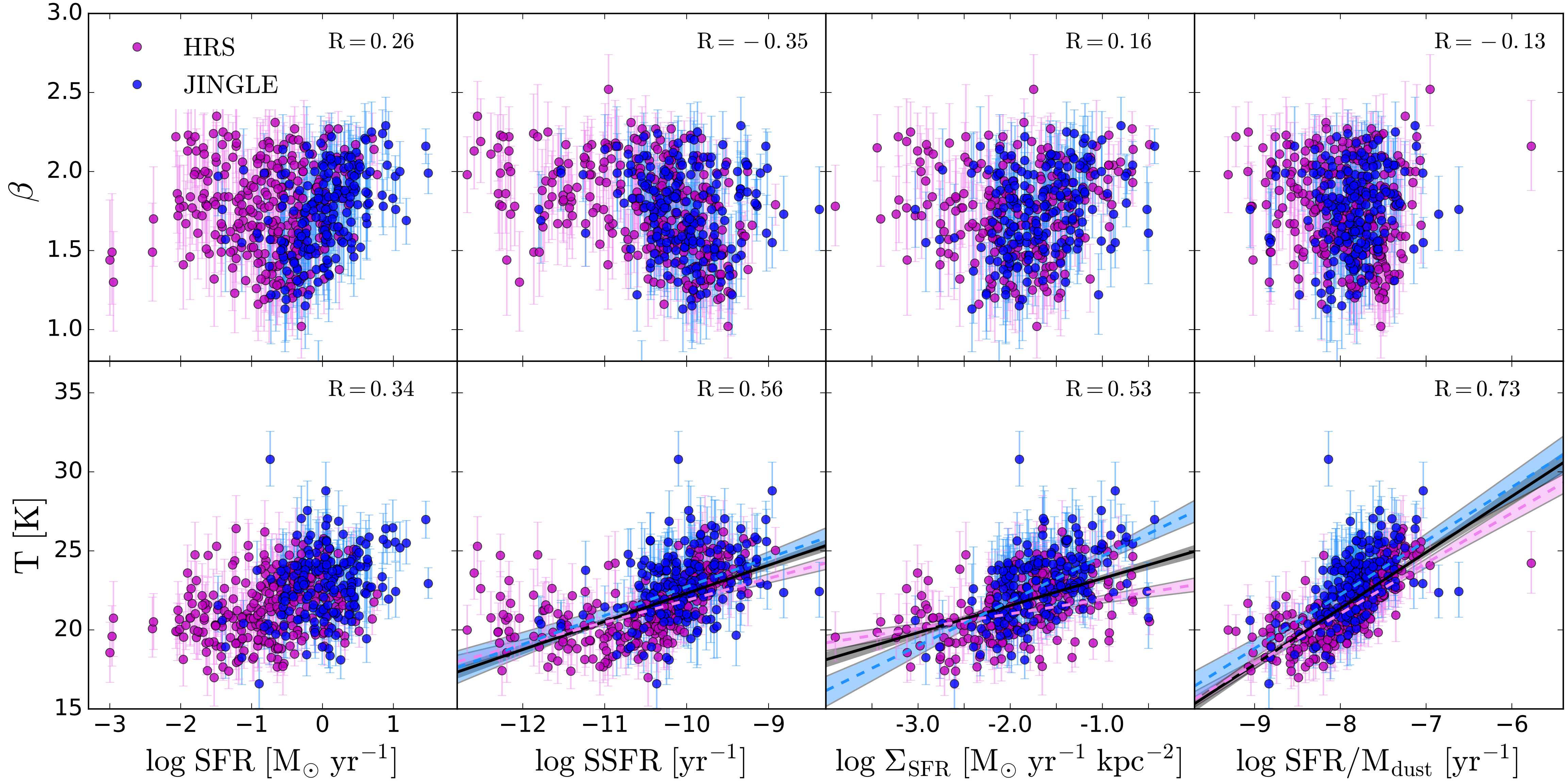
Hierarchical method helps to disentangle the relation with beta and with temperature



- Emissivity index beta correlates with the stellar mass, metallicity, stellar mass surface density, HI mass fraction

Lamperti et al., in prep

Hierarchical method helps to disentangle the relation with beta and with temperature



- Dust temperature correlates with SFR over dust mass

Lamperti et al., in prep

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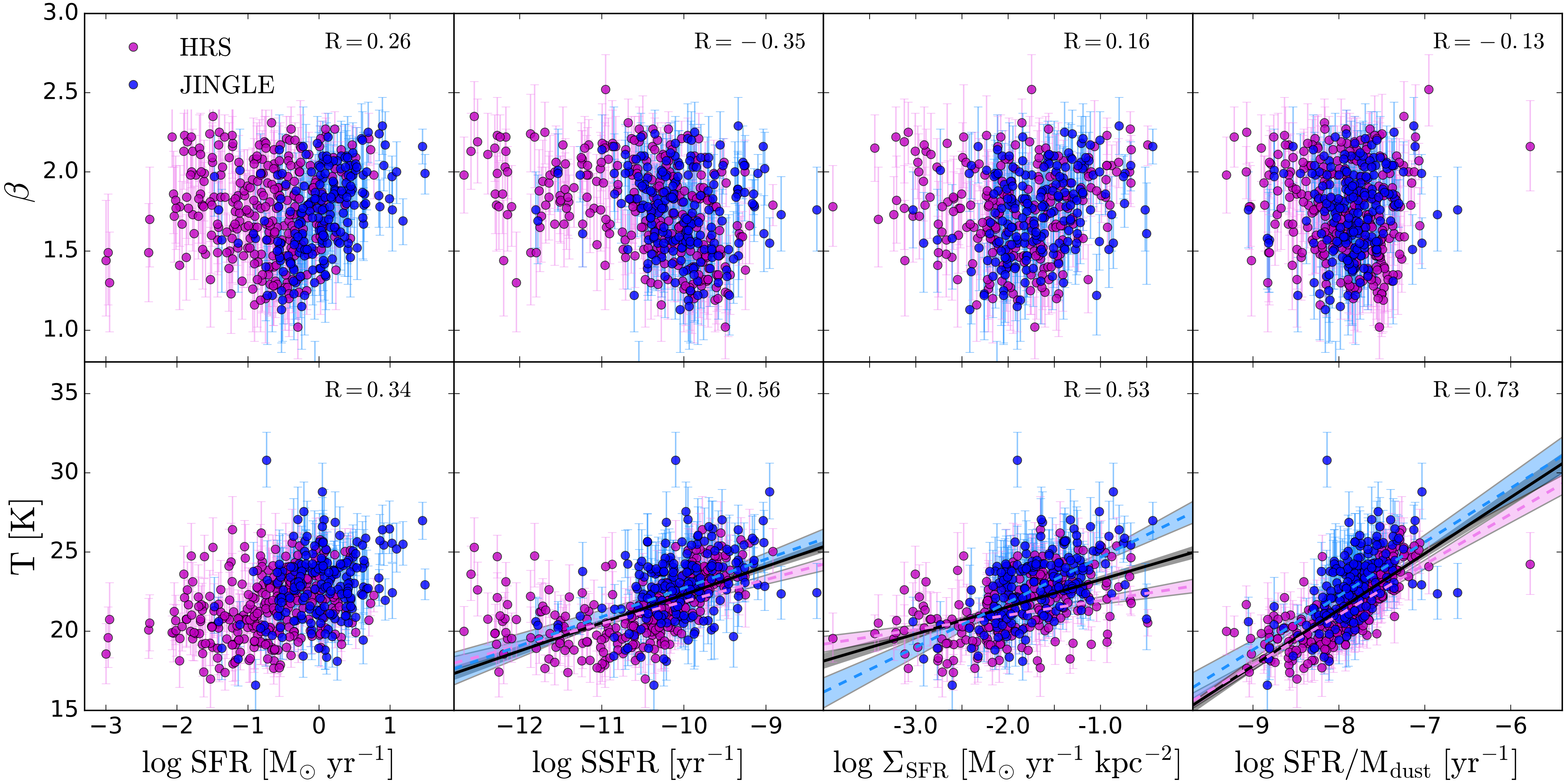


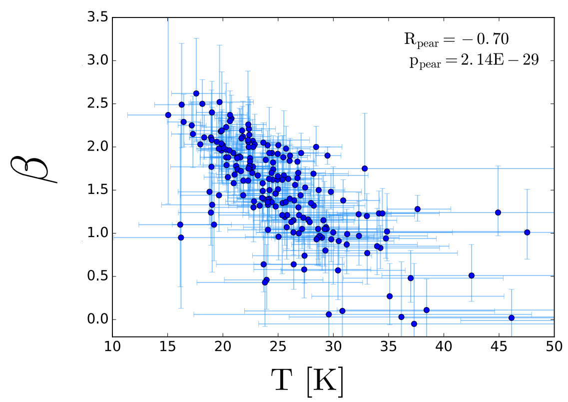
- Dust temperature correlates with SFR over dust mass

Scaling relations can be used to predict T or beta for samples were fewer photometric data are available (e.g. high redshift galaxies, faint galaxies, ...)

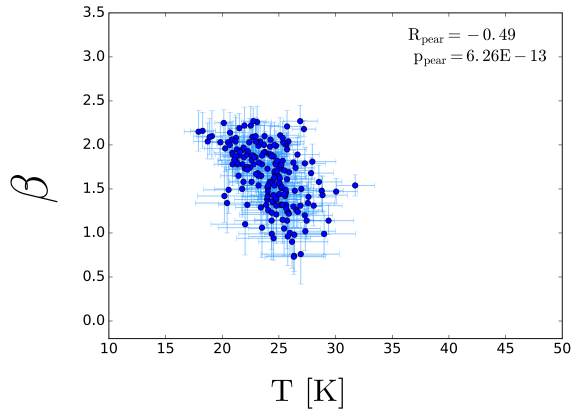
Conclusions

The hierarchical Bayesian approach reduces the **T-beta degeneracy**

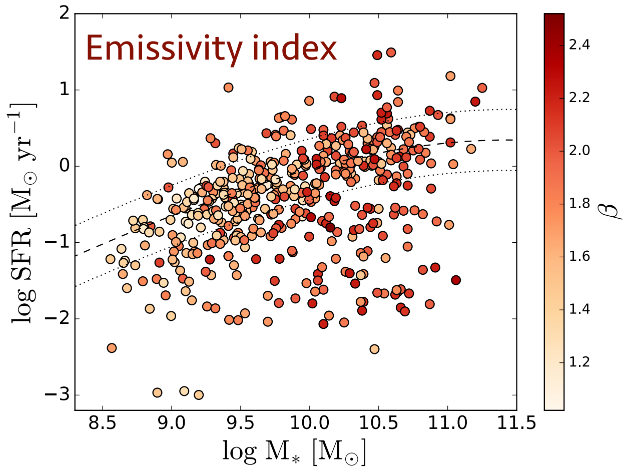
non-hierarchical

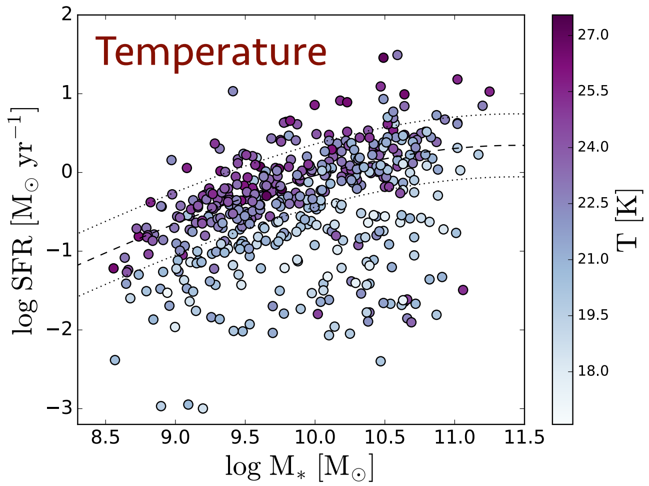


hierarchical

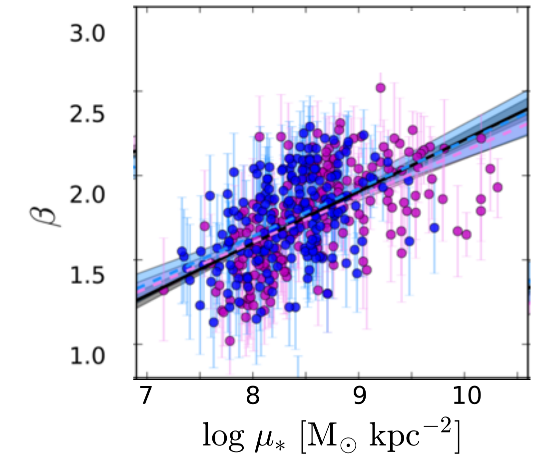


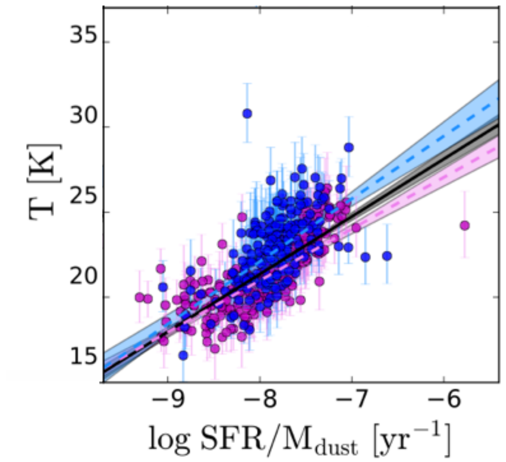
Dust properties vary across the SFR-M* plane





Dust scaling relations can be used to estimate dust temperature and beta from other galaxy properties





Conclusions

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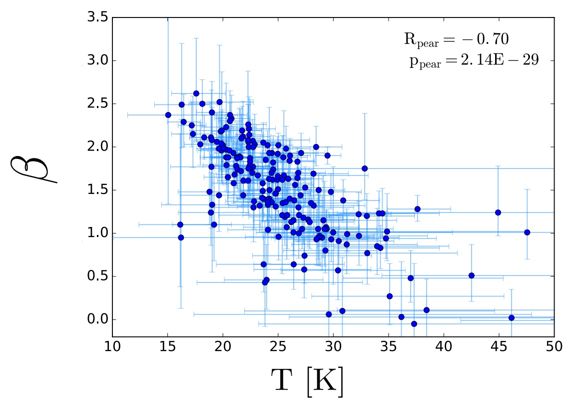
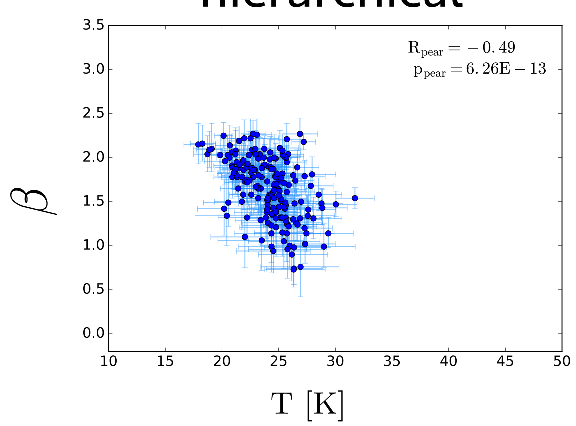
non-hierarchical



hierarchical



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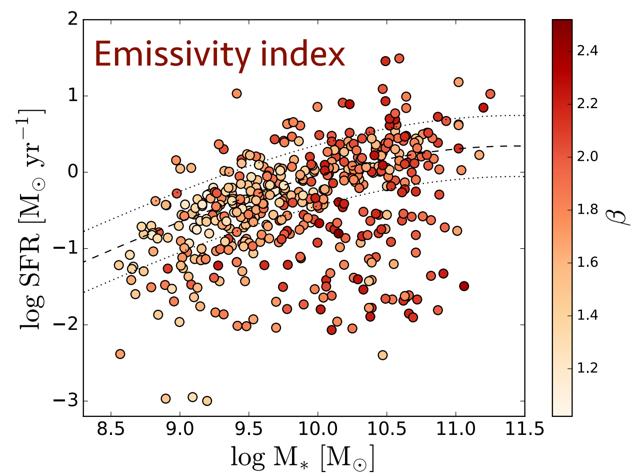

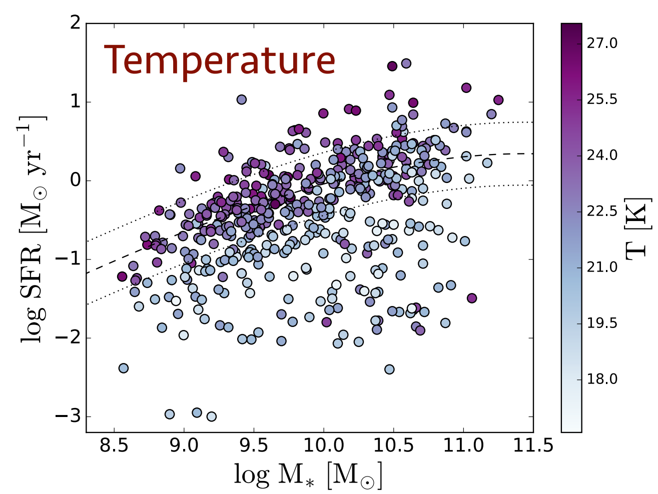

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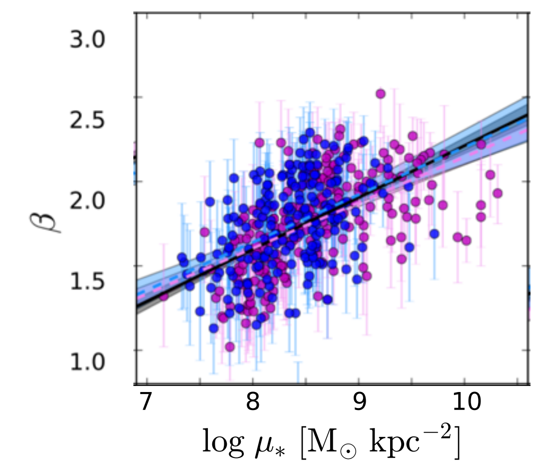

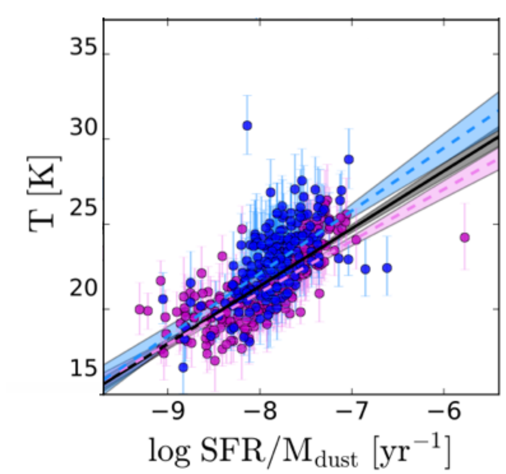

Dust scaling relations can be applied to derive dust properties for samples were fewer photometric data are available, for example at higher redshift.