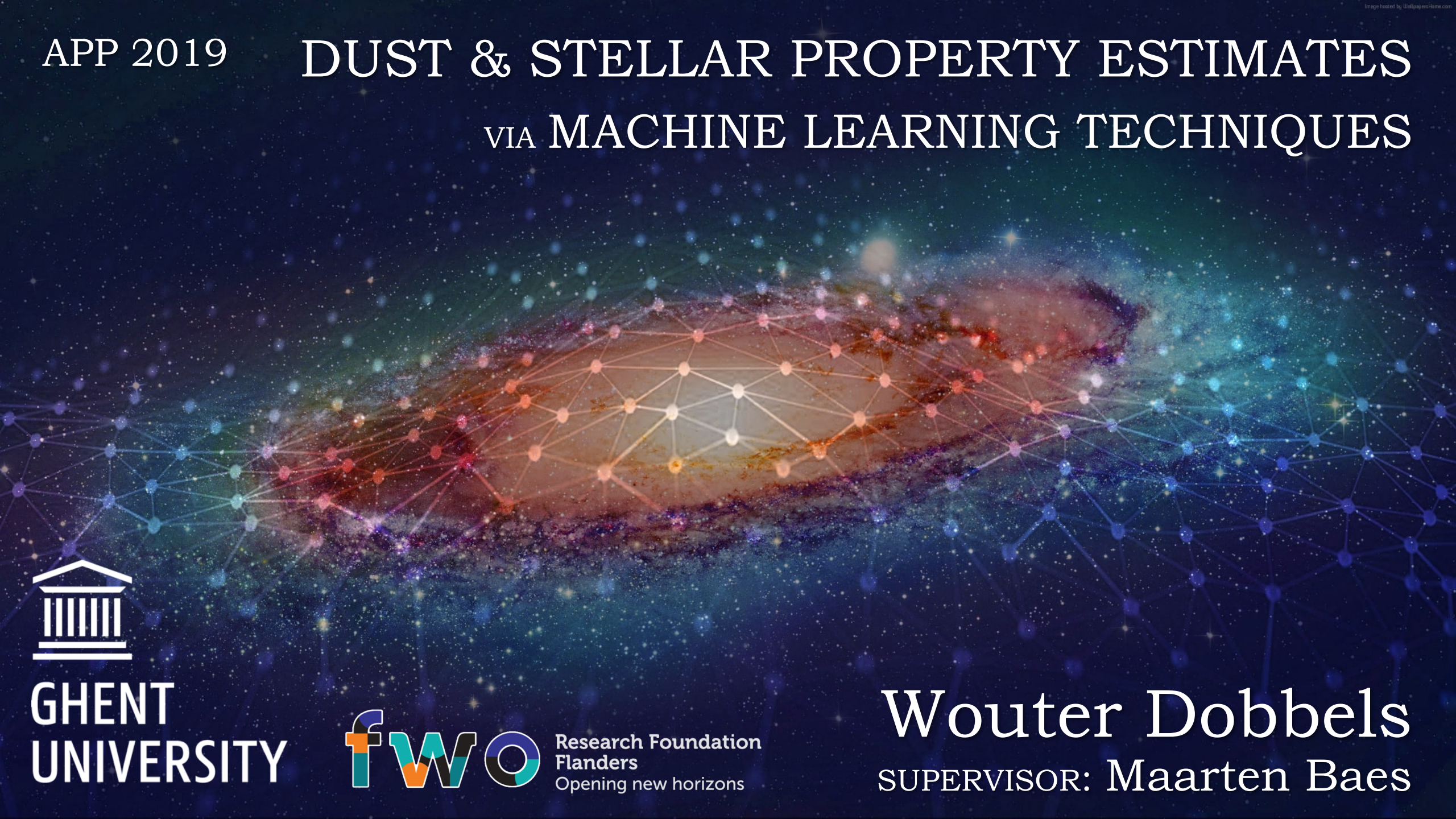
APP 2019

# DUST & STELLAR PROPERTY ESTIMATES VIA MACHINE LEARNING TECHNIQUES




GHENT UNIVERSITY

fwo Research Foundation Flanders
Opening new horizons

Wouter Dobbels

SUPERVISOR: Maarten Baes

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# Predicting the global far-infrared SED of galaxies via machine learning techniques

W. Dobbels[1], M. Baes[1], S. Viaene[1,2], S. Bianchi[3], J. I. Davies[4], V. Casasola[3,5], C. J. R. Clark[6], J. Fritz[7], M. Galametz[8], F. Galliano[8], A. Mosenkov[1,9,10], A. Nersesian[1,11,12], and A. Trčka[1]

[1] Sterrenkundig Observatorium, Universiteit Gent, Krijgslaan 281, B-9000 Gent, Belgium
e-mail: wouter.dobbels@ugent.be
[2] Centre for Astrophysics Research, University of Hertfordshire, College Lane, Hatfield AL10 9AB, UK
[3] INAF – Osservatorio Astrofisico di Arcetri, Largo E. Fermi 5, 50125 Florence, Italy
[4] School of Physics & Astronomy, Cardiff University, Queen's Buildings, The Parade, Cardiff, CF24 3AA, UK
[5] INAF – Istituto di Radioastronomia, Via P. Gobetti 101, 4019 Bologna, Italy
[6] Space Telescope Science Institute, 3700 San Martin Drive, Baltimore, Maryland 21218, USA
[7] Instituto de Radioastronomía y Astrofísica, UNAM, Campus Morelia, A.P. 3-72, C.P. 58089, Mexico
[8] AIM, CEA, CNRS, Université Paris-Saclay, Université Paris Diderot, Sorbonne Paris Cité, 91191 Gif-sur-Yvette, France
[9] Central Astronomical Observatory of RAS, Pulkovskoye Chaussee 65/1, 196140 St. Petersburg, Russia
[10] St. Petersburg State University, Universitetskij Pr. 28, 198504 St. Petersburg, Stary Peterhof, Russia
[11] National Observatory of Athens, Institute for Astronomy, Astrophysics, Space Applications and Remote Sensing, Ioannou Metaxa and Vasileos Pavlou, 15236 Athens, Greece
[12] Department of Astrophysics, Astronomy & Mechanics, Faculty of Physics, University of Athens, Panepistimiopolis, 15784 Zografos, Athens, Greece

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## ABSTRACT

*Context.* Dust plays an important role in shaping a galaxy's spectral energy distribution (SED). It absorbs ultraviolet (UV) to near-infrared (NIR) radiation and re-emits this energy in the far-infrared (FIR). The FIR is essential to understand dust in galaxies. However, deep FIR observations require a space mission, none of which are still active today.
*Aims.* We aim to infer the FIR emission across six *Herschel* bands, along with dust luminosity, mass, and effective temperature, based on the available UV to mid-infrared (MIR) observations. We also want to estimate the uncertainties of these predictions, compare our method to energy balance SED fitting, and determine possible limitations of the model.
*Methods.* We propose a machine learning framework to predict the FIR fluxes from 14 UV–MIR broadband fluxes. We used a low redshift sample by combining DustPedia and H-ATLAS, and extracted Bayesian flux posteriors through SED fitting. We trained shallow neural networks to predict the far-infrared fluxes, uncertainties, and dust properties. We evaluated them on a test set using a root mean square error (RMSE) in log-space.
*Results.* Our results (RMSE = 0.19 dex) significantly outperform UV–MIR energy balance SED fitting (RMSE = 0.38 dex), and are inherently unbiased. We can identify when the predictions are off, for example when the input has large uncertainties on WISE 22 μm, or when the input does not resemble the training set.
*Conclusions.* The galaxies for which we have UV–FIR observations can be used as a blueprint for galaxies that lack FIR data. This results in a 'virtual FIR telescope', which can be applied to large optical-MIR galaxy samples. This helps bridge the gap until the next FIR mission.

**Key words.** Galaxies: photometry – Galaxies: ISM – Infrared: galaxies

Dobbels et al. 2019b

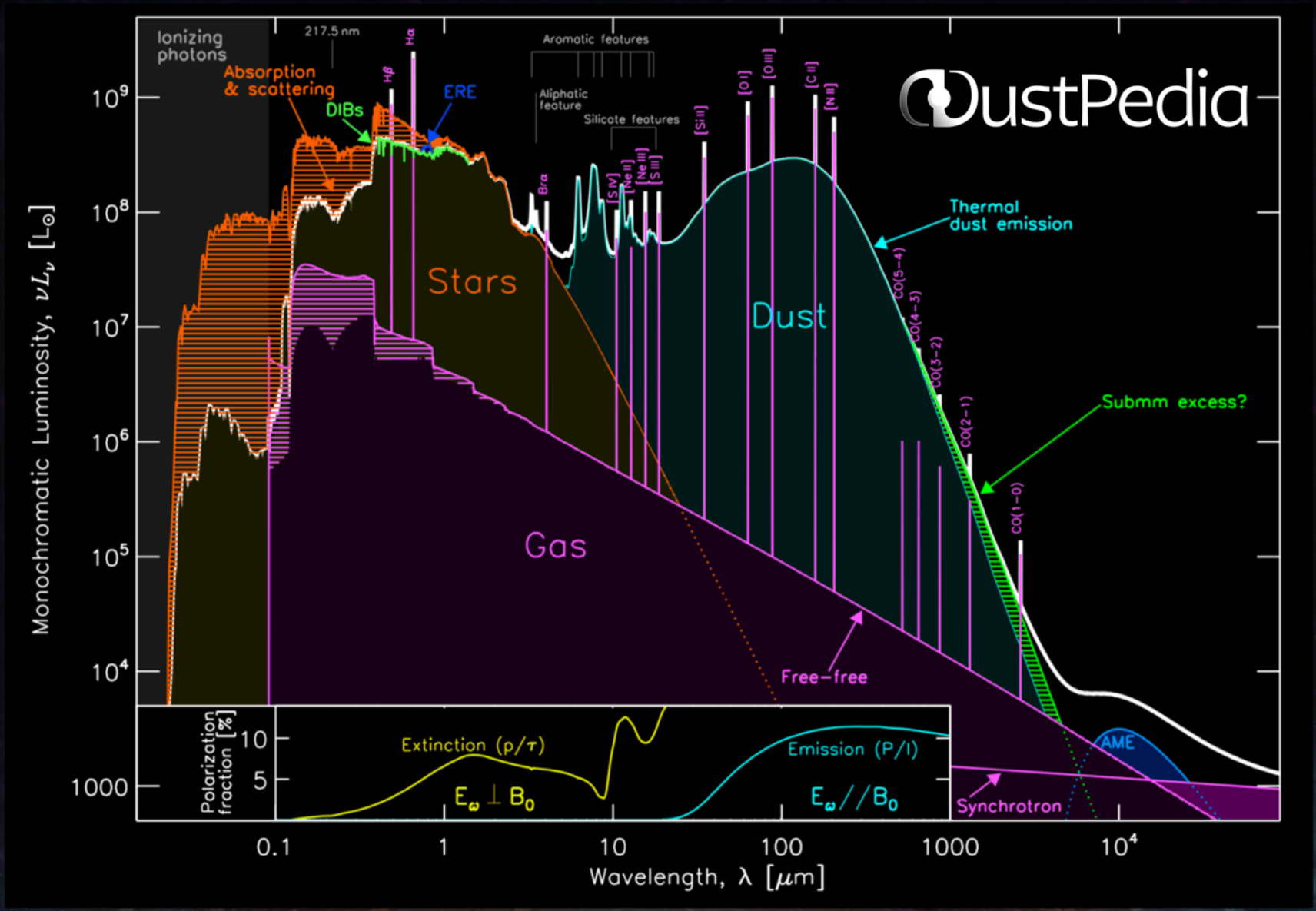
*Accepted by A&A*
arxiv:1910.06330

Code, jupyter notebooks and interactive plots on **github**

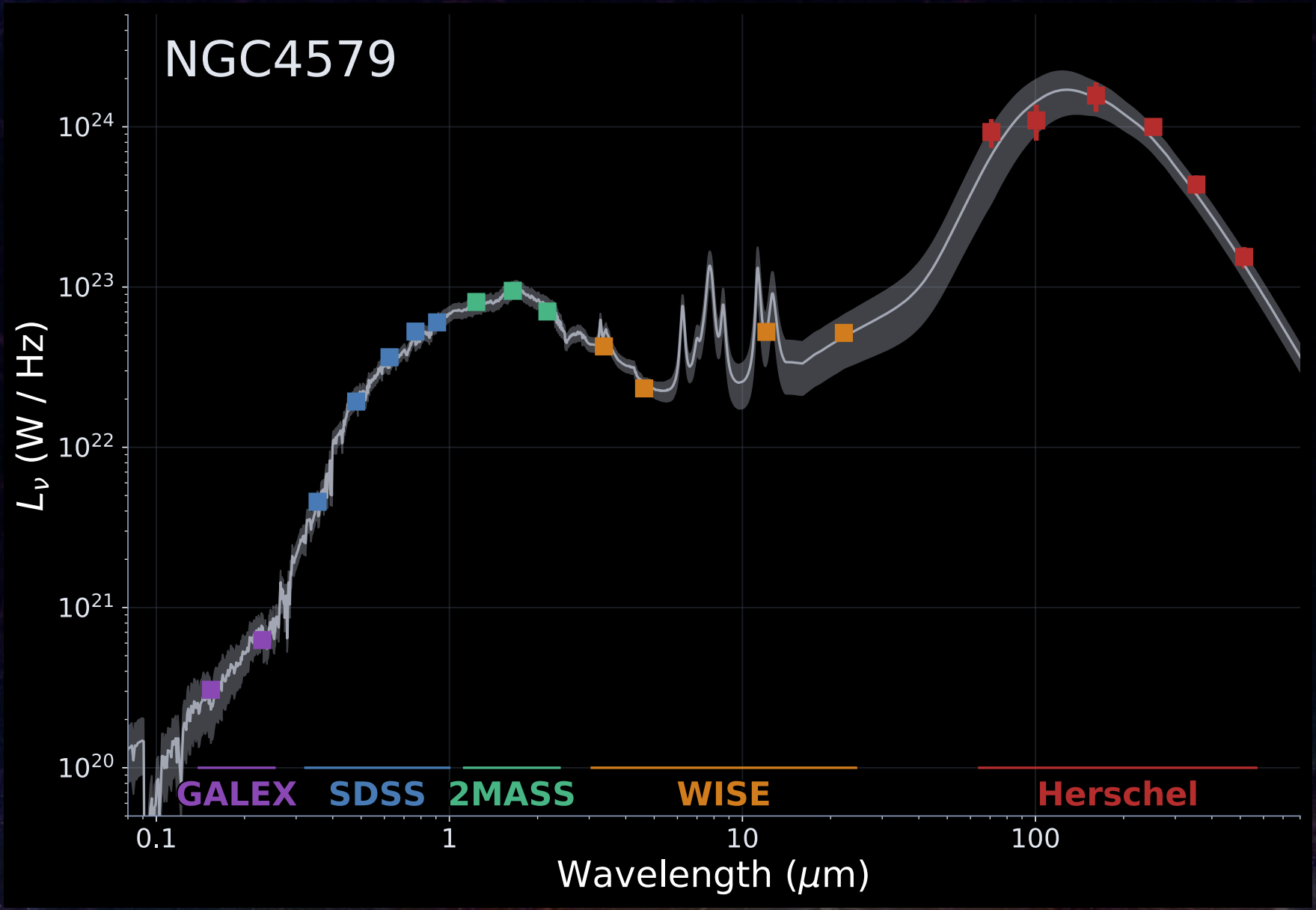
https://wdobbels.github.io/FIREnet/

https://github.com/wdobbels/FIREnet

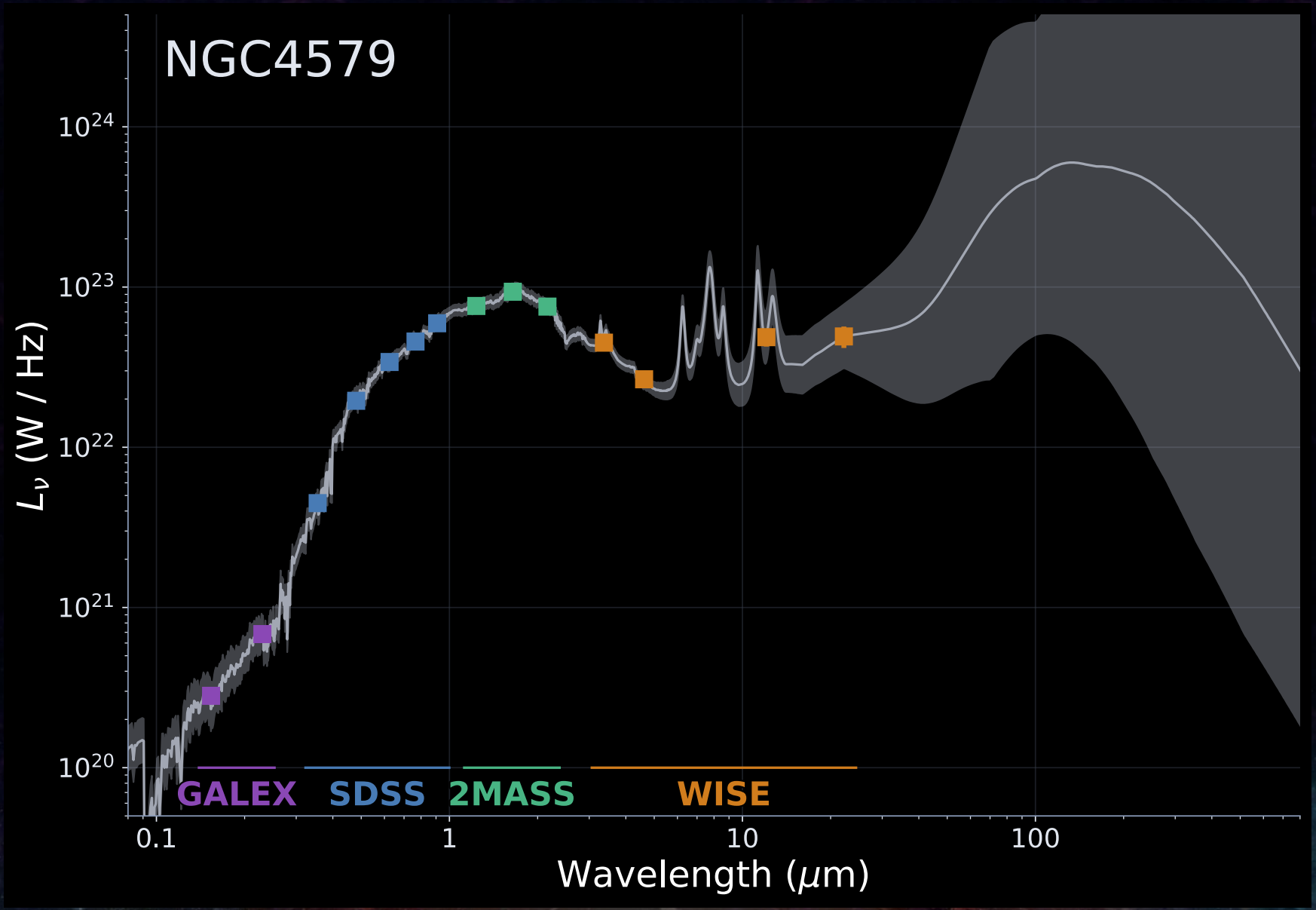
# UV-NIR + FIR ⟶ stars + dust



# Good UV-FIR sampling



# Often: only part of SED sampled



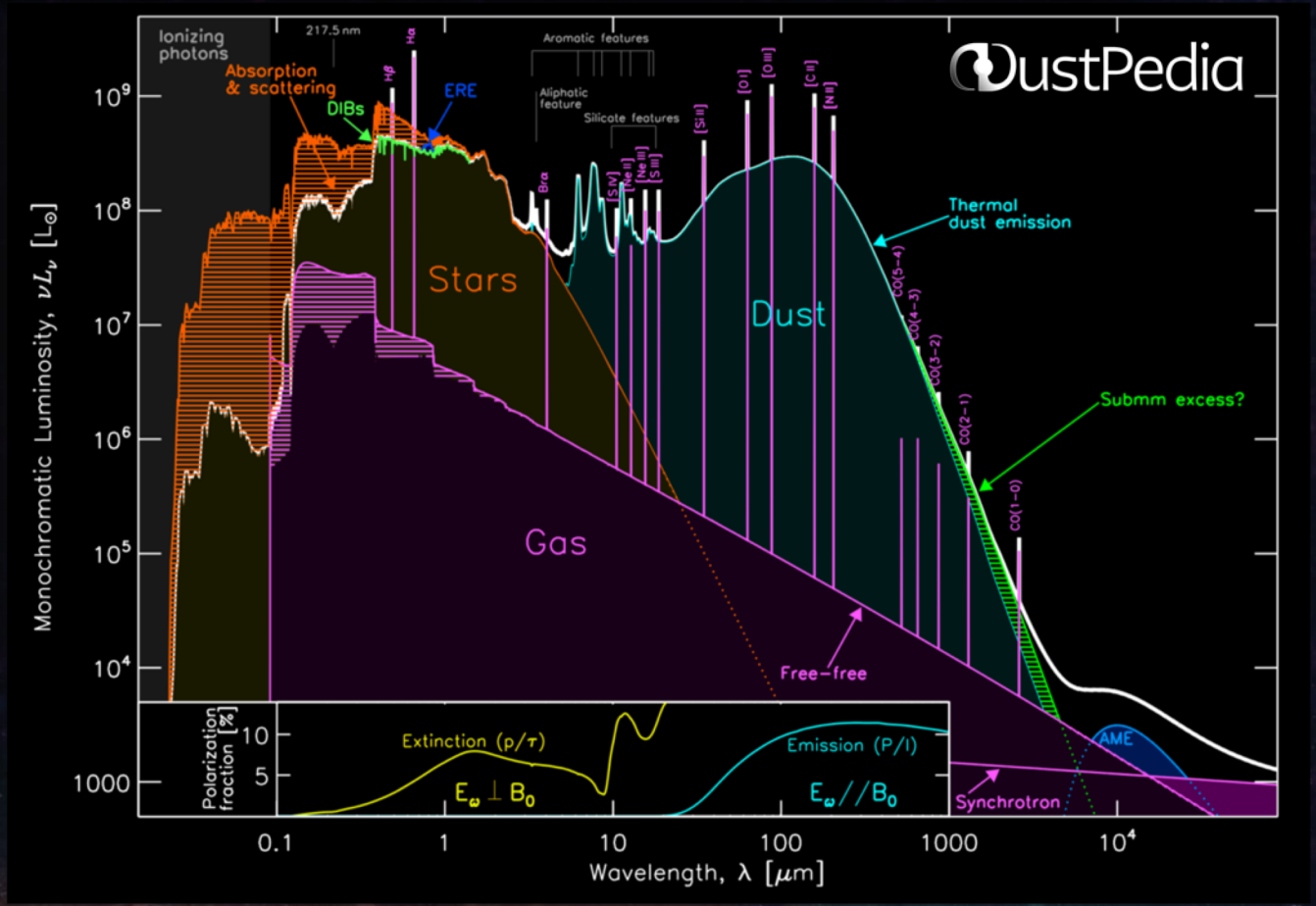
# Can we predict dust properties from UV-MIR?

SED modelling

Optical: constrain attenuation

Energy balance!

Bayesian estimate



# Ingredients

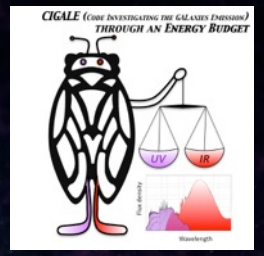
## Datasets

DustPedia + H-ATLAS

715 galaxies
$z < 0.01$

3618 galaxies
$z < 0.1$

## Code




CIGALE

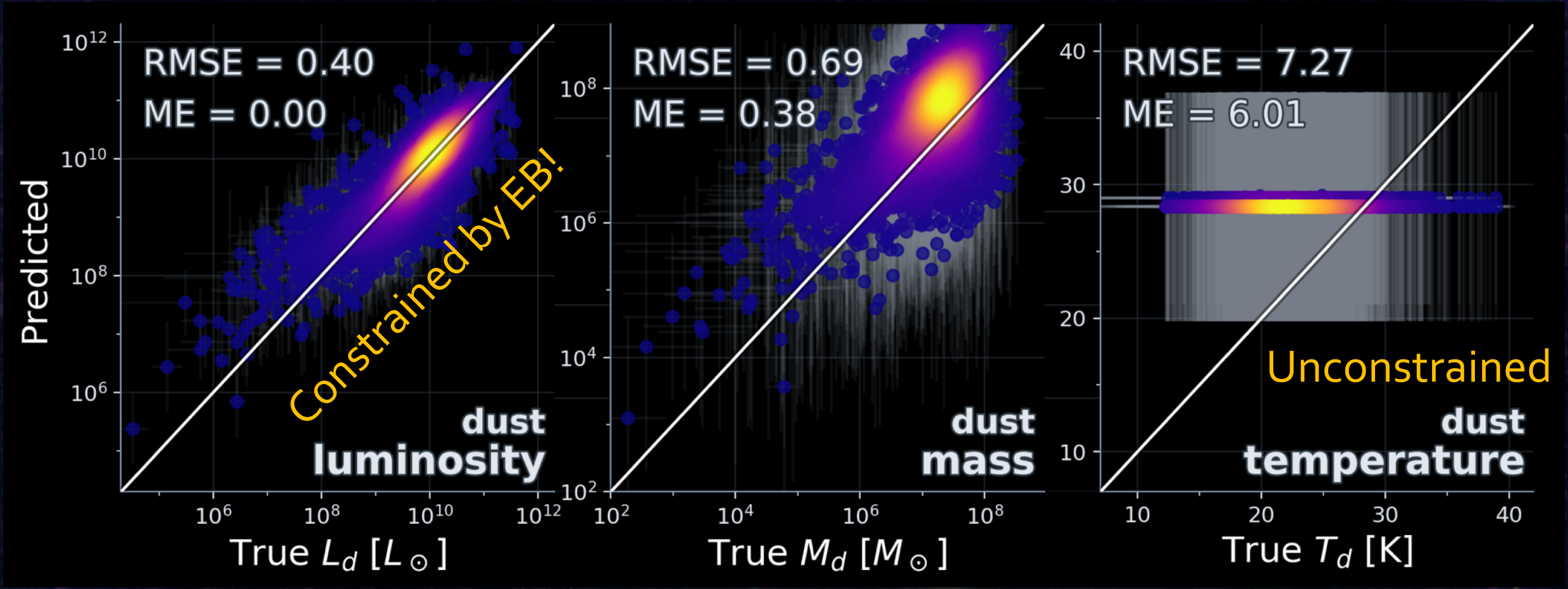
## Models

*Total*: ~80 million

*SFH*: Delayed with burst/quench

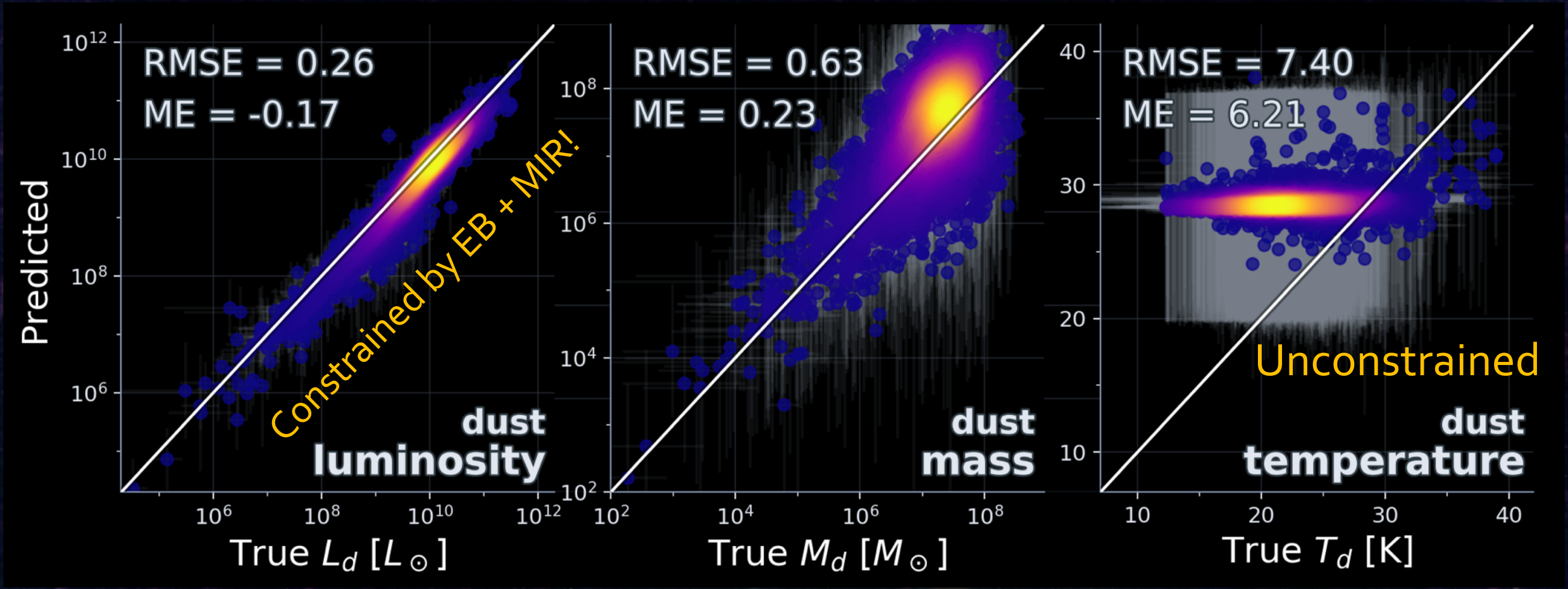
*Dust emission*: Themis

# SED modelling estimation




Using FUV – NIR (up to $K_s$)

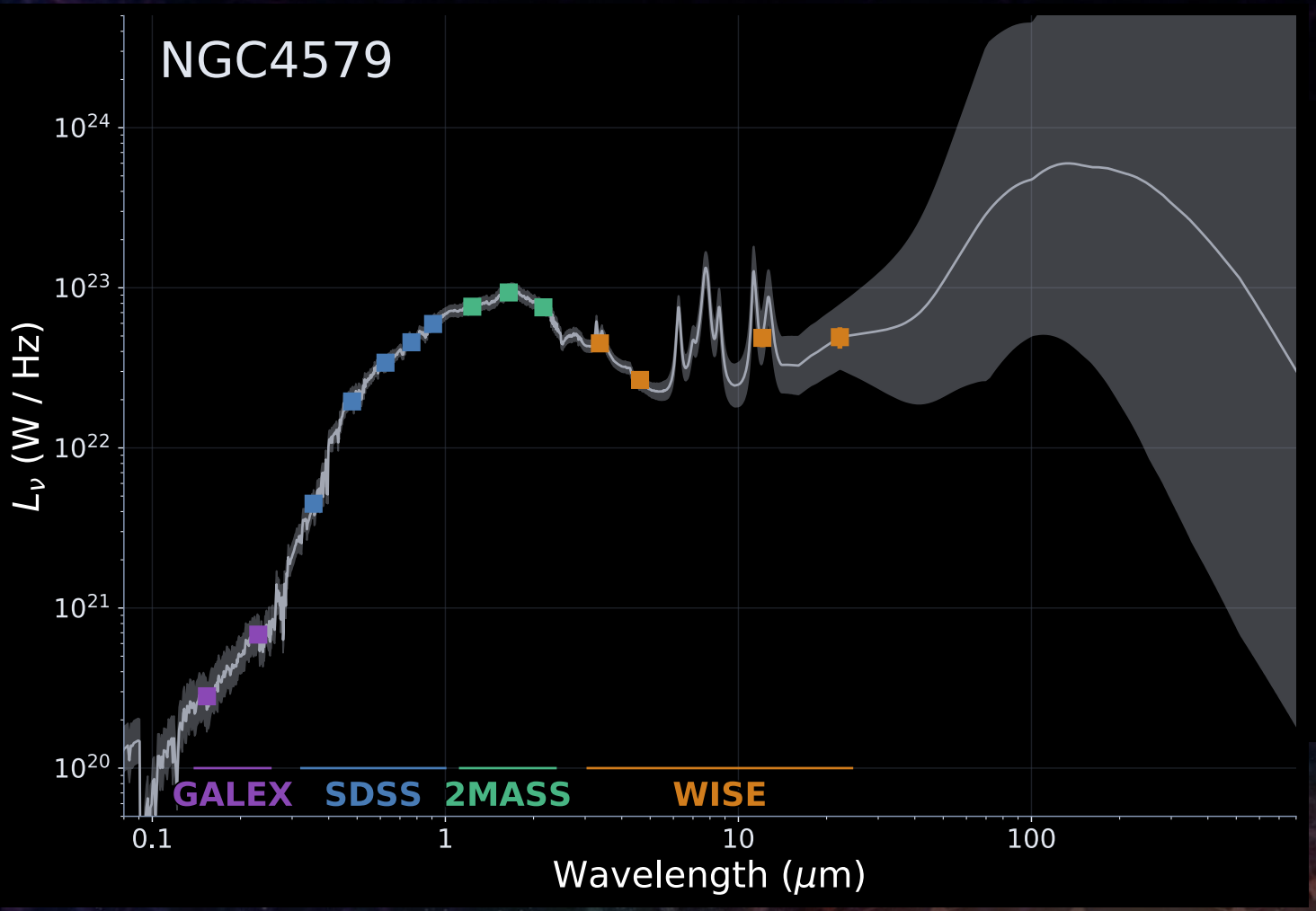
# SED modelling estimation



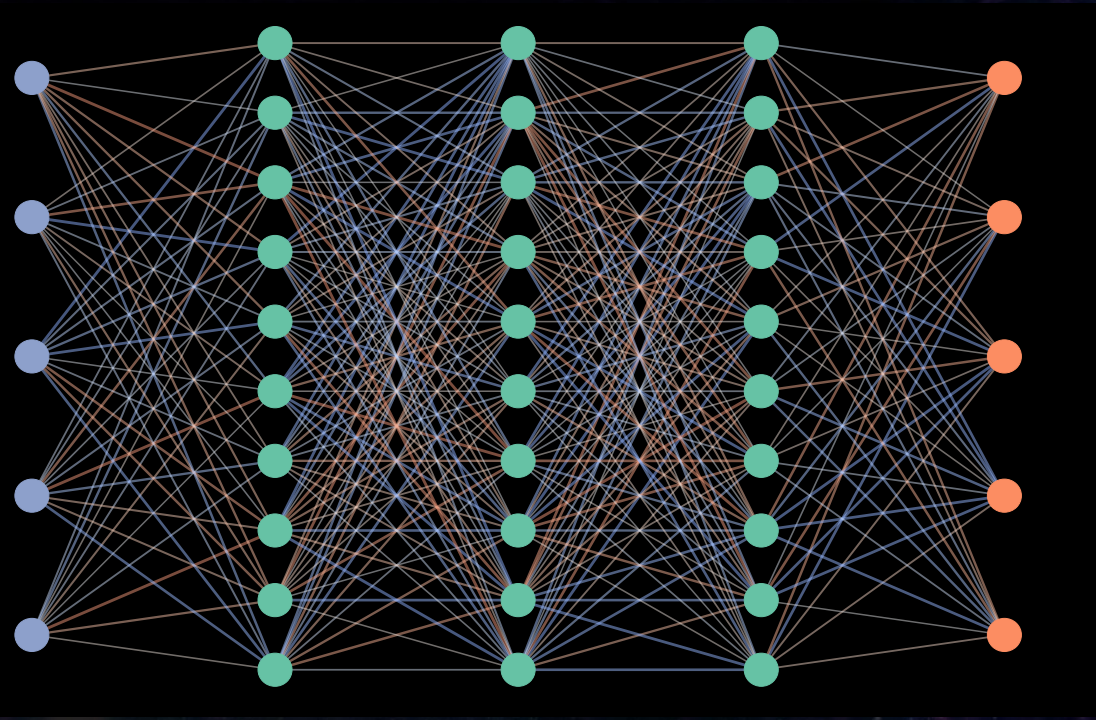

Using FUV – MIR (up to WISE 22)

# Beyond SED fitting

# Can we predict dust properties from UV-MIR?

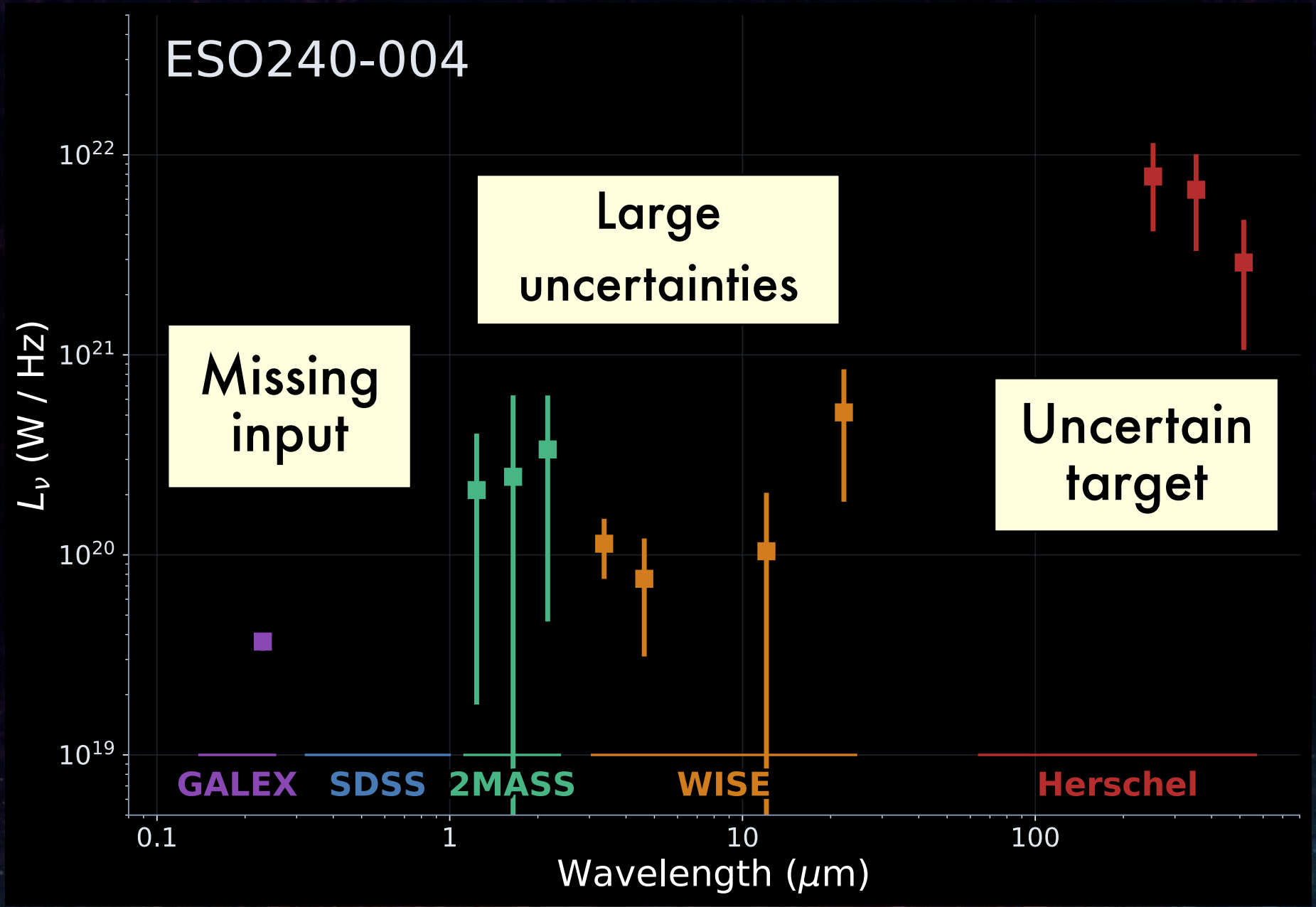



## Machine learning!



Learn optimal mapping using UV-FIR data as blueprint

# But what if the SED looks like this?



# Bayesian fits as ground truth

**input**

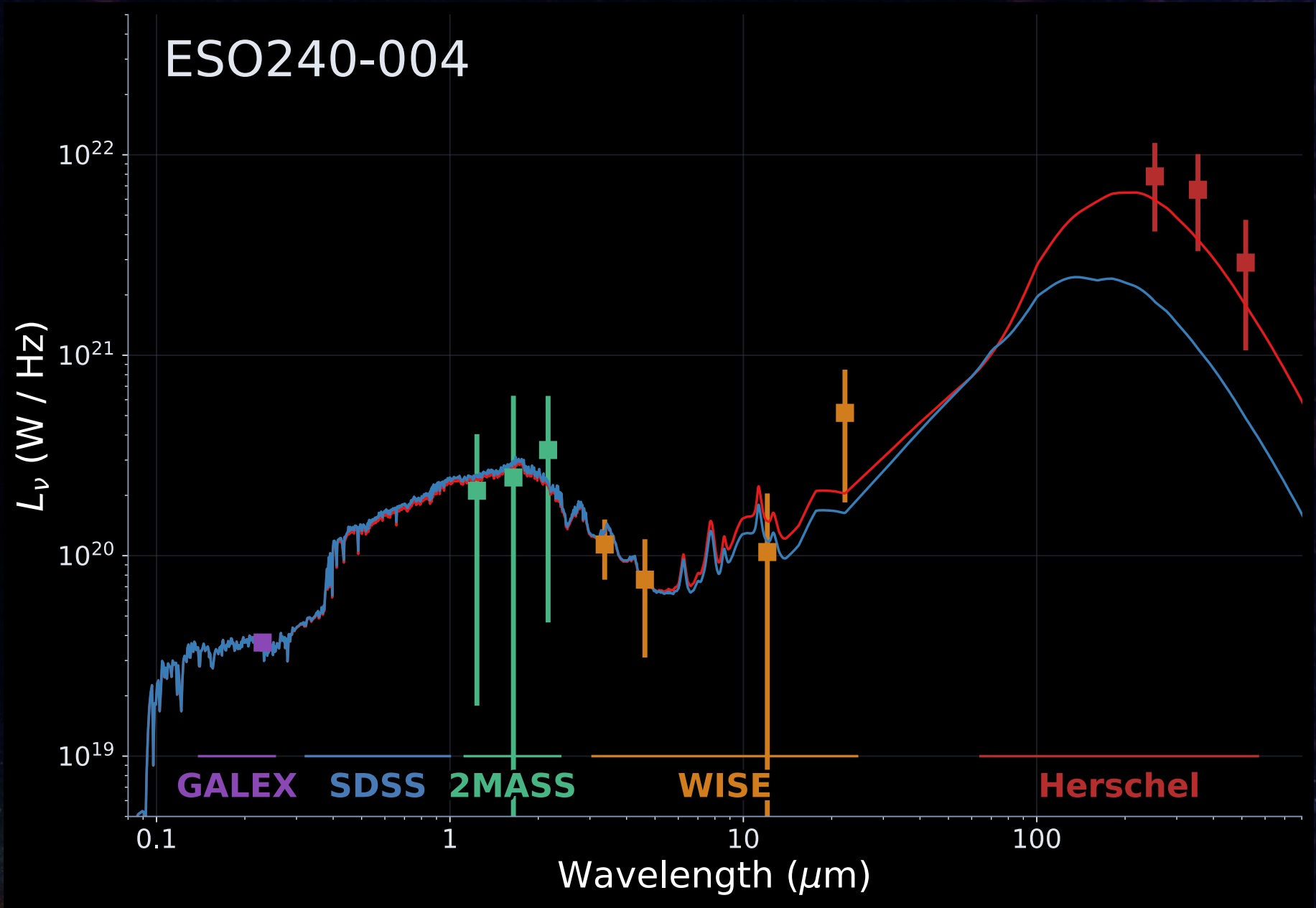
Fit UV-MIR

Extract fluxes

**target**

Fit UV-FIR

Extract properties



# Ingredients

## Datasets

DustPedia + H-ATLAS

715 galaxies
$z < 0.01$

3618 galaxies
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## Model

Shallow neural net

PyTorch

## Optimization

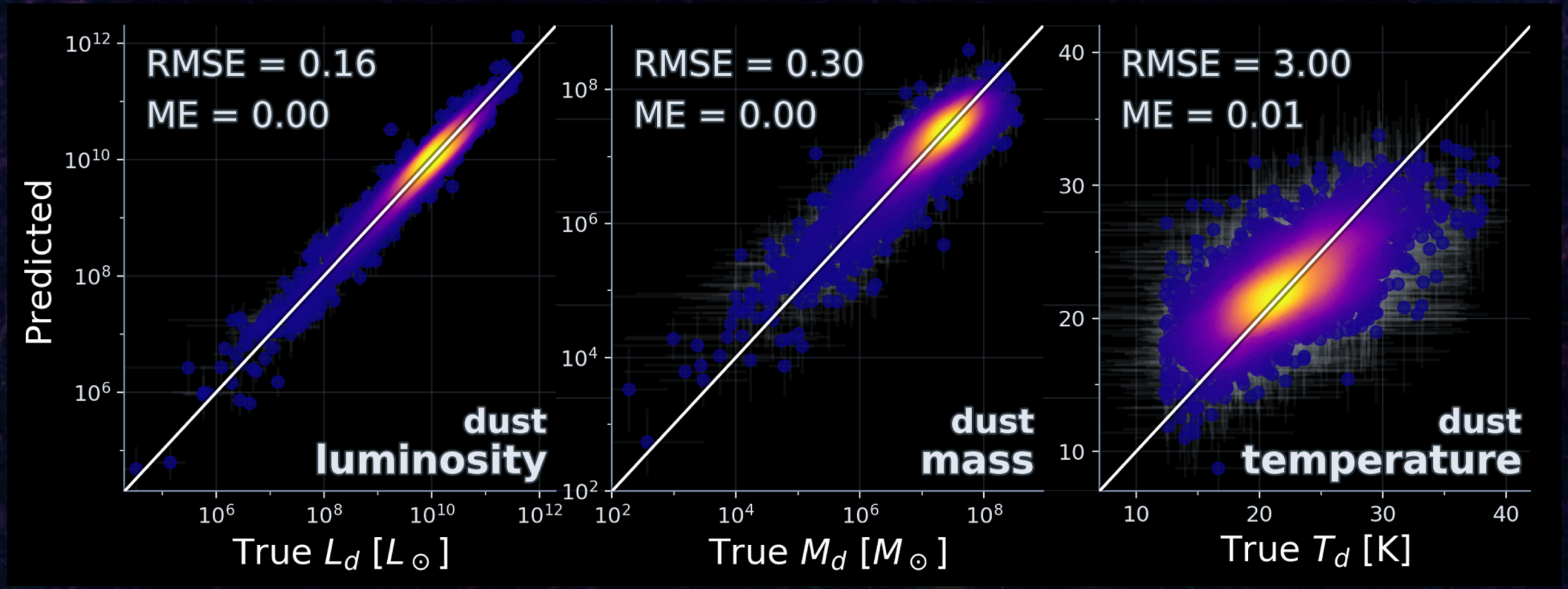
Minimize MSE

Adam with warm restarts

4-fold train-test split

Best model from cross-val set

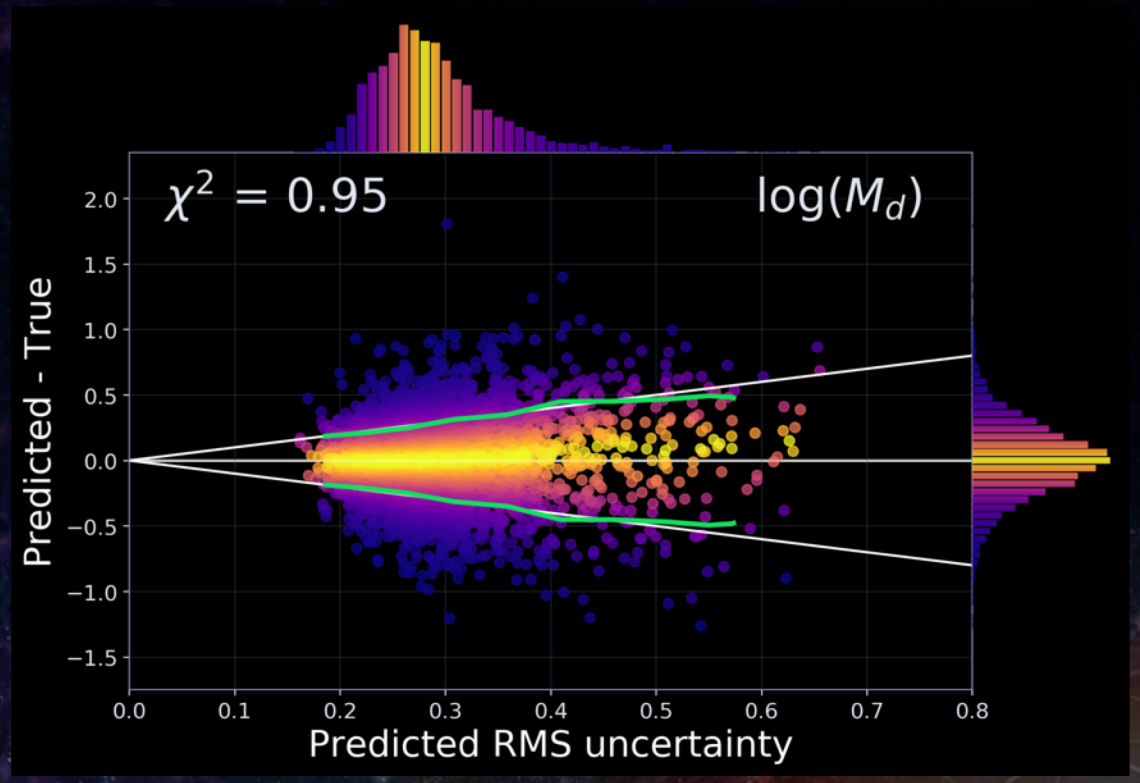
# Neural net predictions (test set)




Much better than SED modelling!

# Can we trust these predictions?

- Predict individual uncertainties

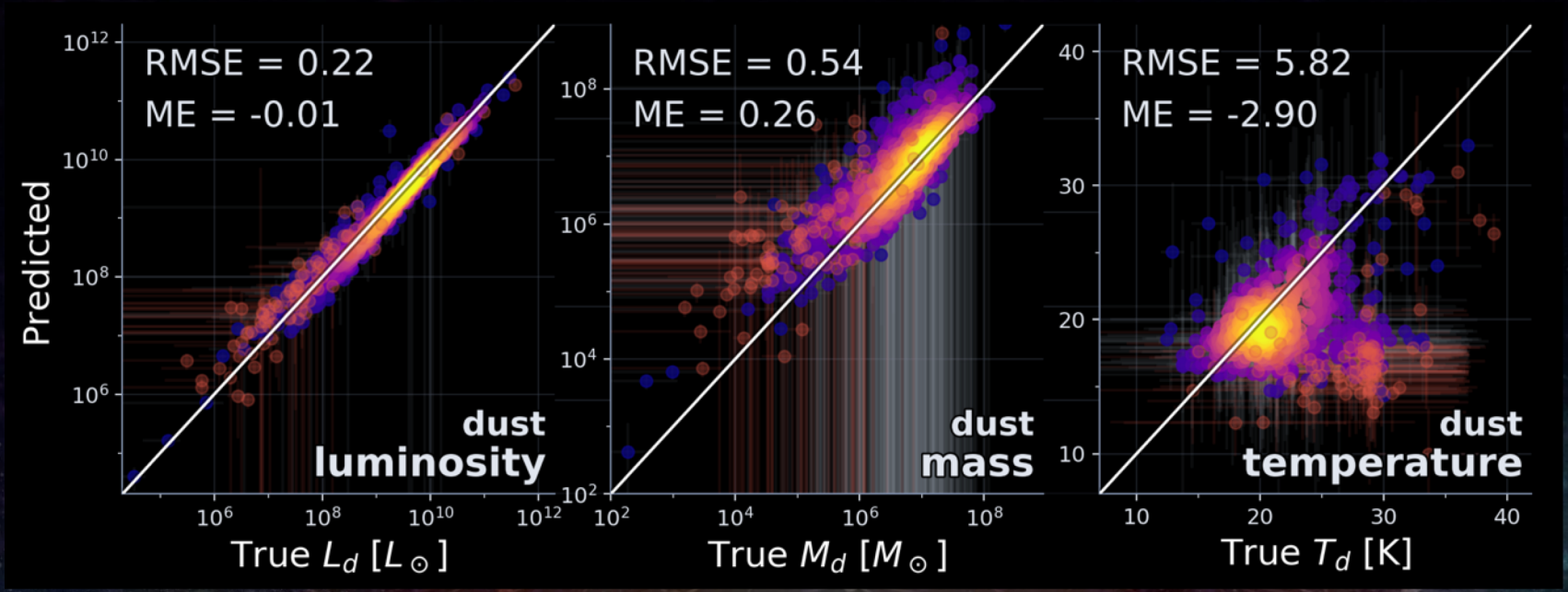



Green line: actual (binned) RMSE

White lines: predicted RMSE

# Can we trust these predictions?

- Predict individual uncertainties
- Is galaxy close to training set?



# Can we trust these predictions?

- Predict individual uncertainties
- Is galaxy close to training set?
- Which part of UV-MIR drives predictions?

# General framework

## Use sample with many observations as blueprint for galaxies with fewer observations

More ground truth constraints:

- (optical) spectra
- X-ray, radio

More input:

- Morphology (*Dobbels et al. 2019a*)
- Environment

More ground truth targets:

- stellar properties
- gas properties (*Acquaviva 2015*)
- SMBH properties

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| Input | Target | Target constraints |
|---|---|---|
| Morphology + g | $M_*$ | UV-MIR broadbands |

# General framework

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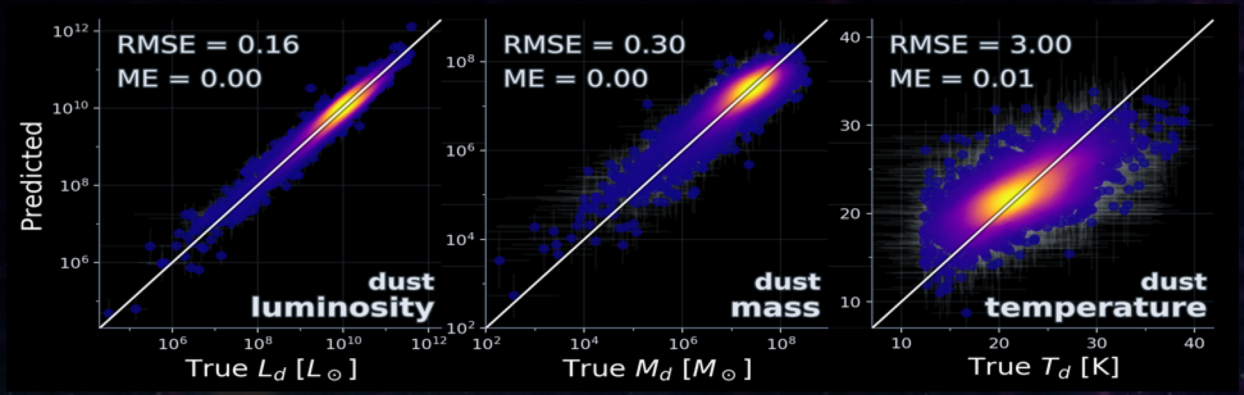
| Input | Target | Target constraints |
|---|---|---|
| SDSS ugriz | Metallicity | SDSS spectrum |

# Conclusion

## Machine learning can make up for lack of data

- Improvement over Bayesian SED modelling
- Estimate individual uncertainties
- Can extend to higher redshift and different sample
- Needed with excellent upcoming optical-NIR telescopes, but no confirmed FIR telescope




Dobbels et al. 2019b
arxiv:1910.06330

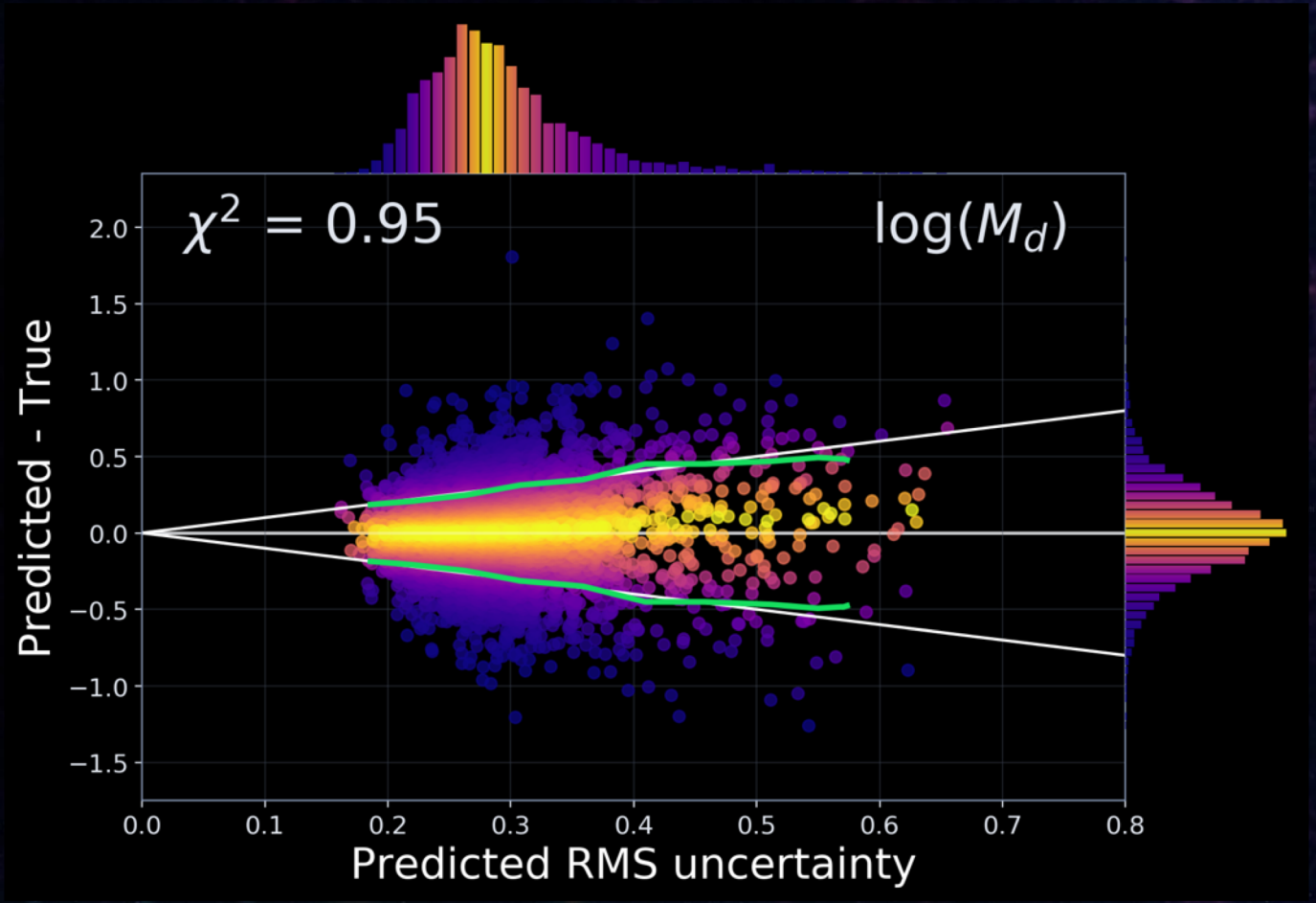
# Extra Slides

# Predicting uncertainties

Use a second neural net:
*uncertainty quantifier*

Estimates RMSE for each sample
(using a joint loss)

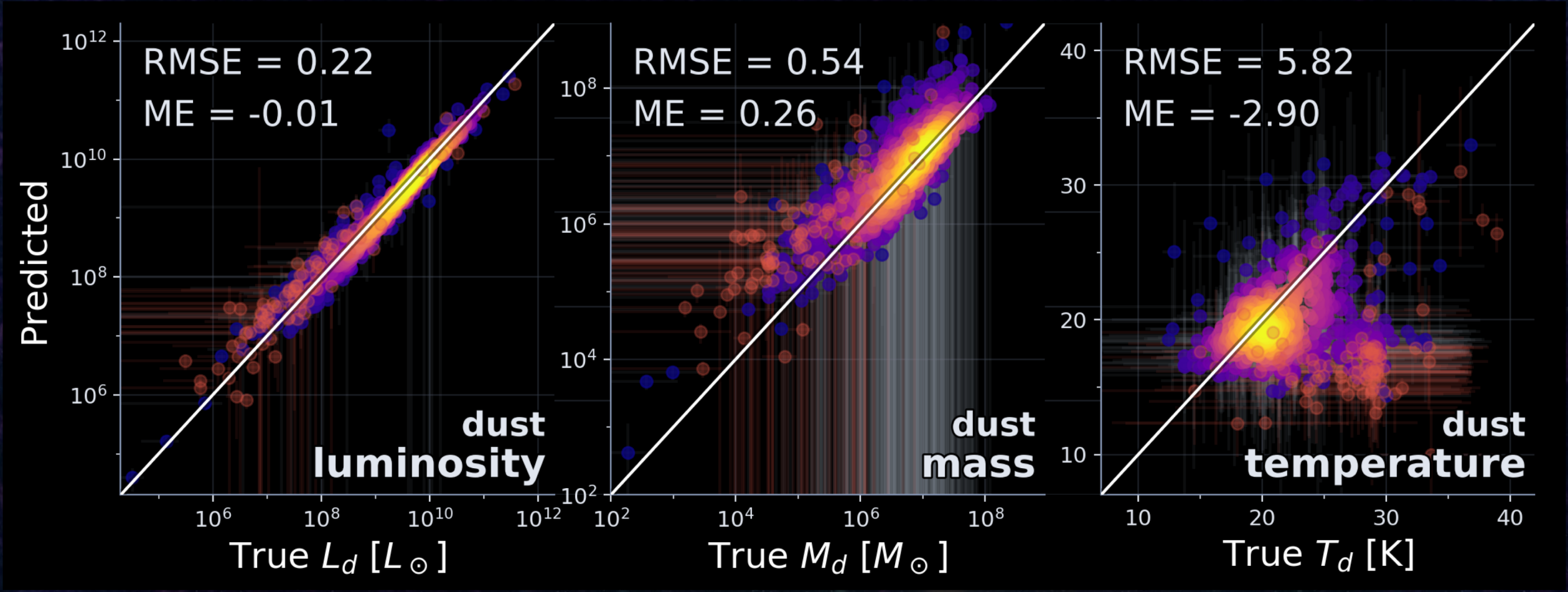
Captures aleatoric uncertainty
(irreducible with more data)



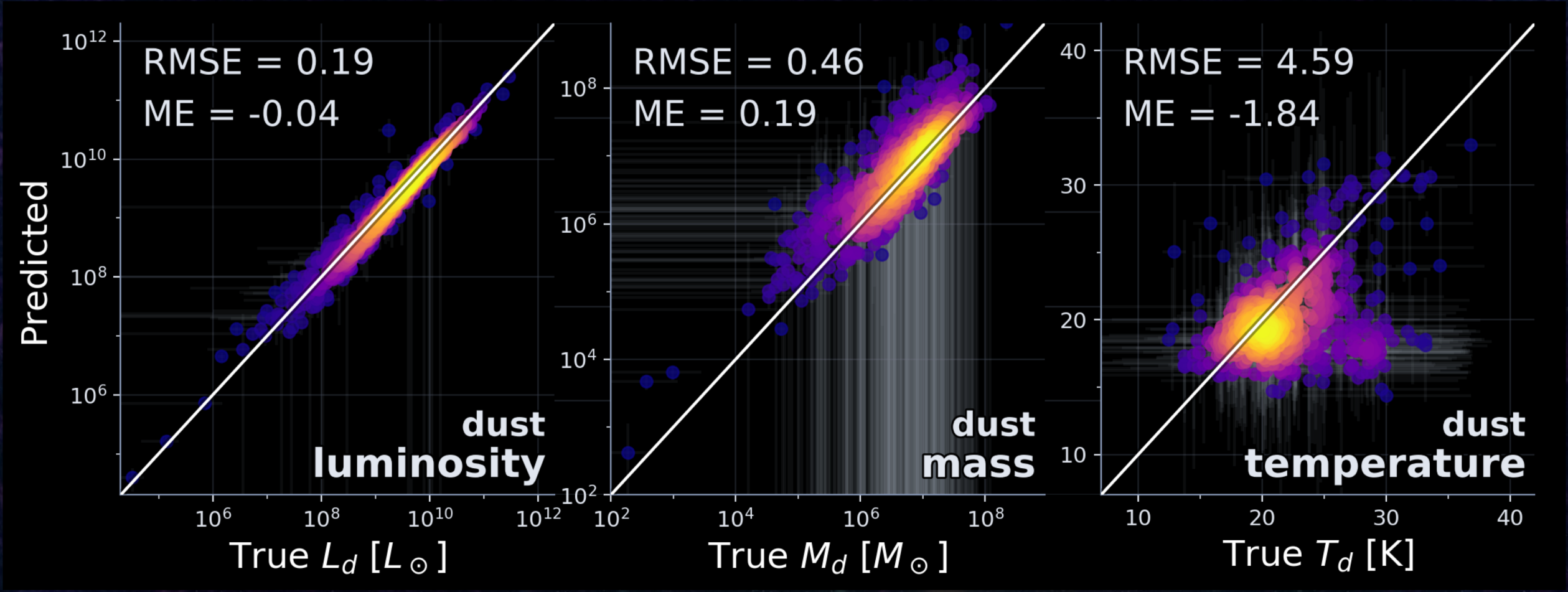

Green line: actual (binned) RMSE

White lines: predicted RMSE

# Train on H-ATLAS, test on DustPedia



# Train on H-ATLAS, test on DustPedia



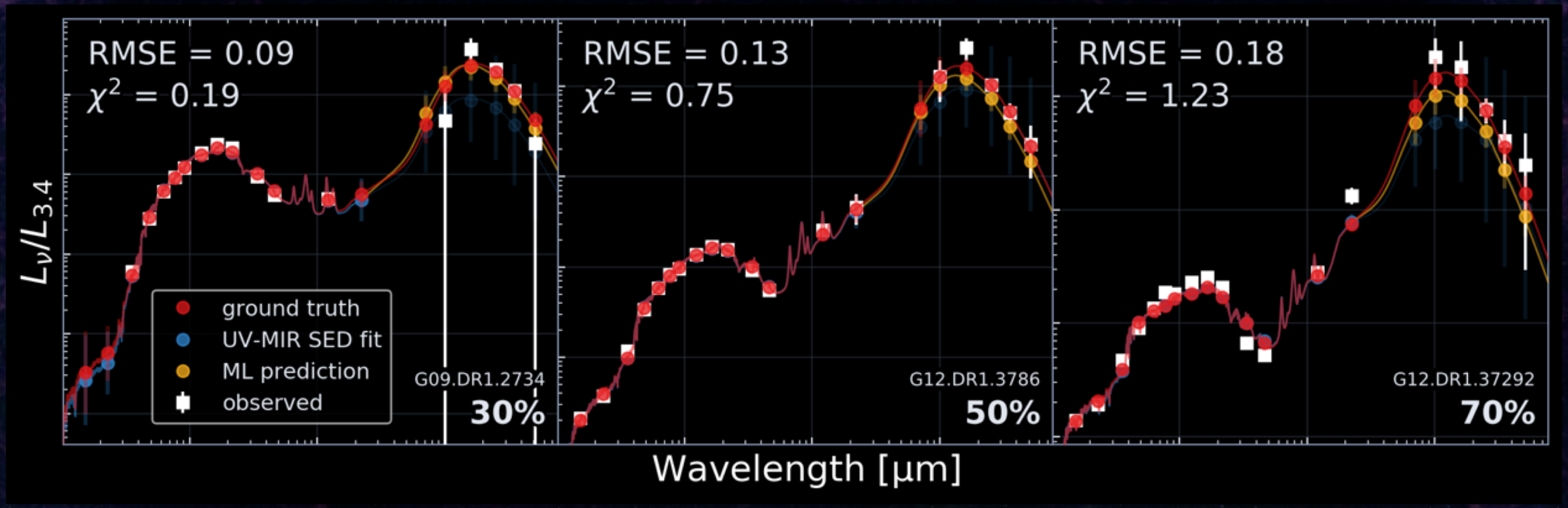

Exclude 100 galaxies that least resemble training set

# Predicting FIR broadbands

Dobbels et al. 2019b

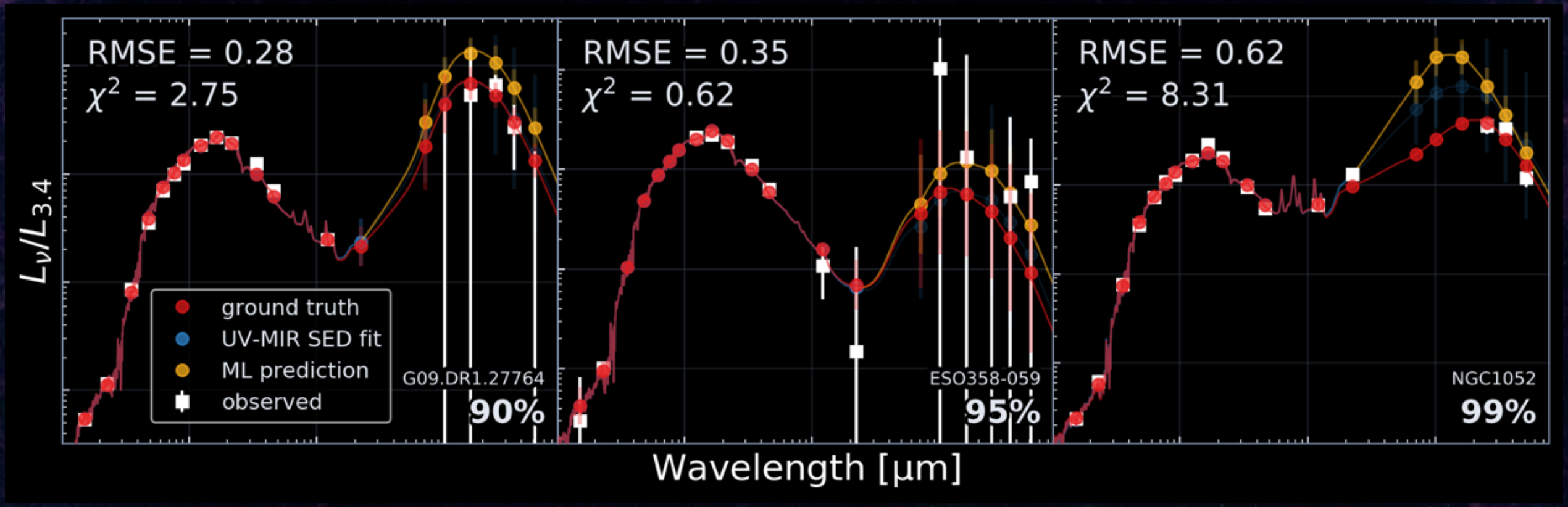
*Accepted by A&A*

# Predicting FIR broadbands




Order by RMSE (of 6 Herschel bands)

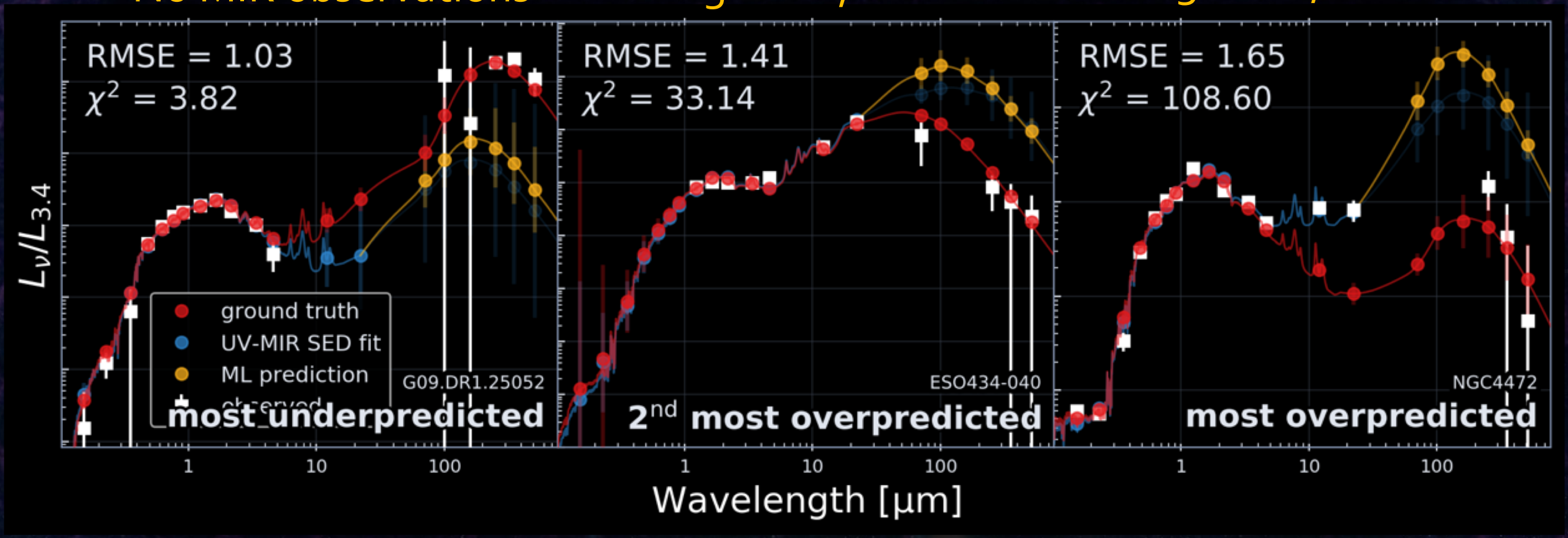
# Predicting FIR broadbands




10% worst

# Predicting FIR broadbands

No MIR observations | High MIR, low FIR | High MIR, low FIR




3 worst

# SED modelling flux estimation

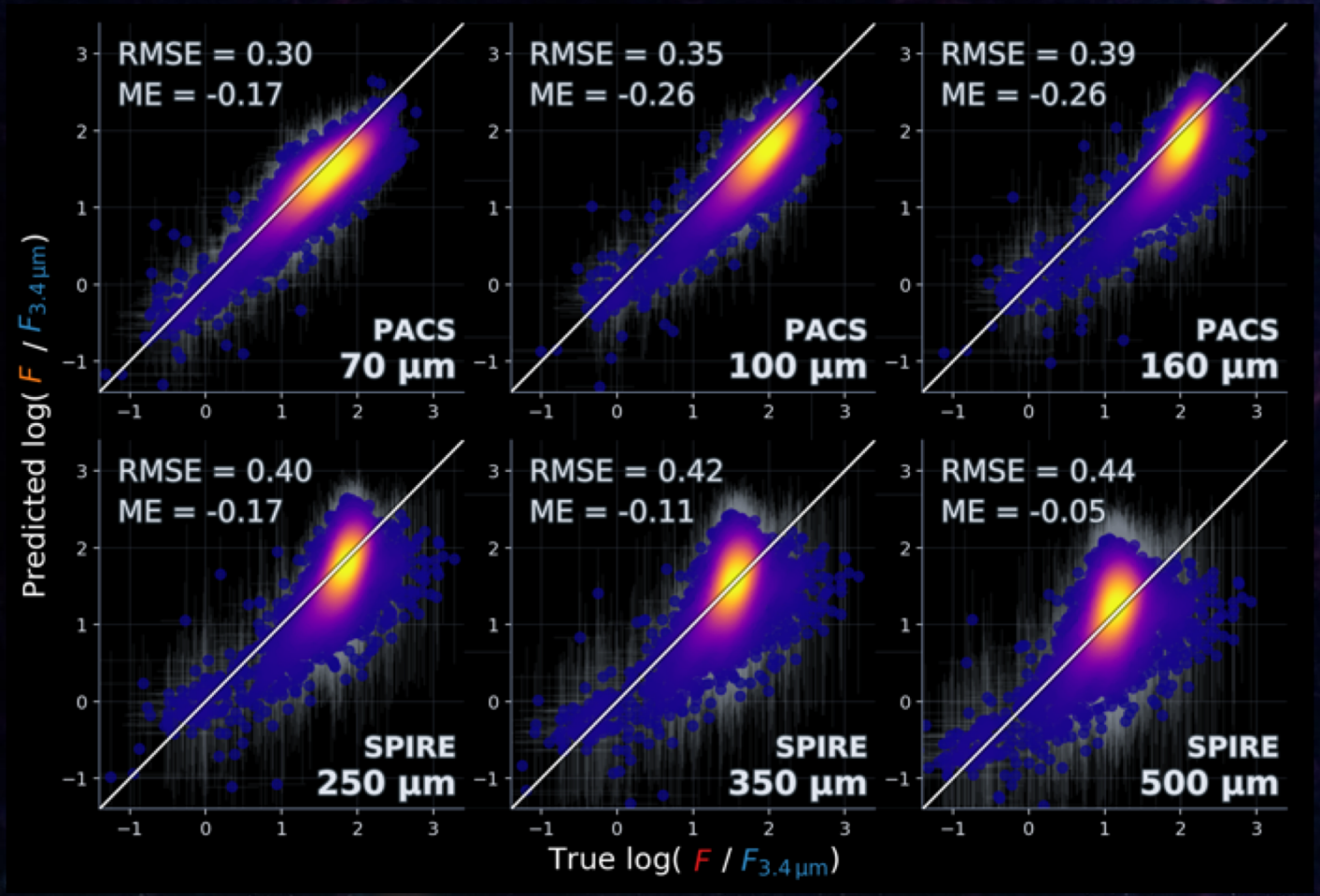
## Target

$$y_i = \log\left(\frac{F_i}{F_{3.4}}\right)$$

Not bad, but some biases

Depends on chosen models

- Energy balance is not enough
- Attenuation and emission properties not independent

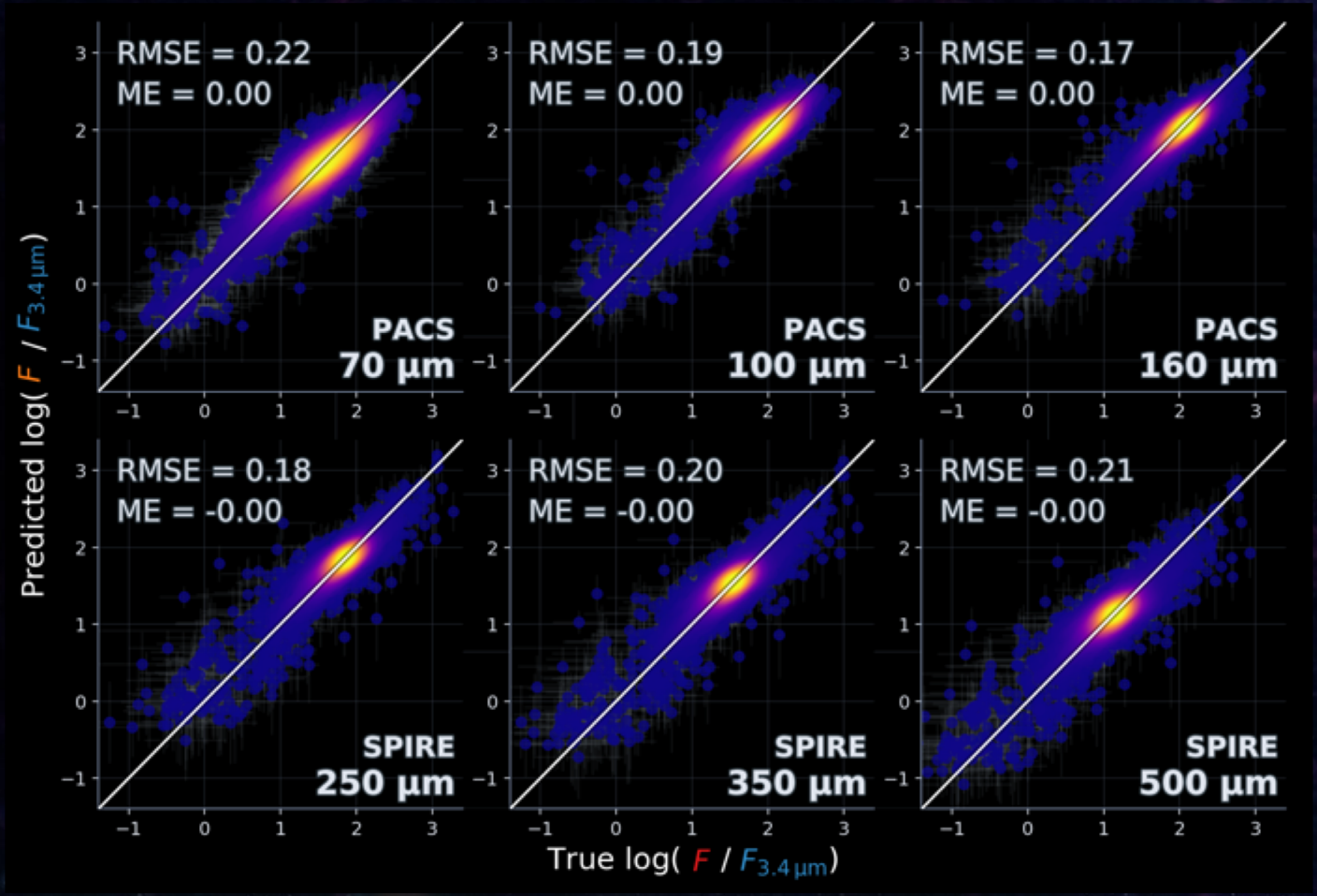



Total RMSE = 0.39 dex

# Machine learning flux estimation

## Target

$$y_i = \log\left(\frac{F_i}{F_{3.4}}\right)$$



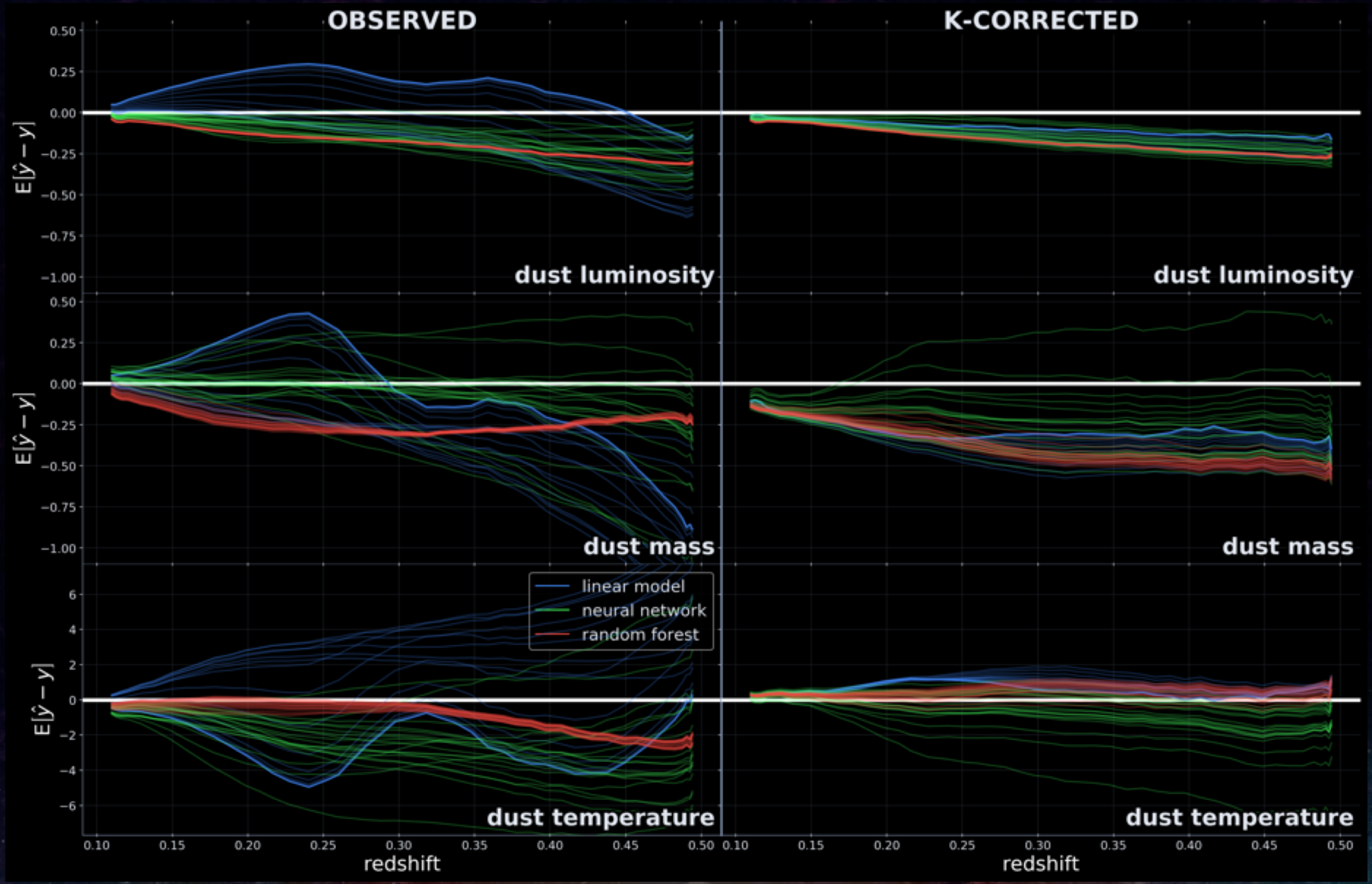

No biases

PACS mostly relies on MIR

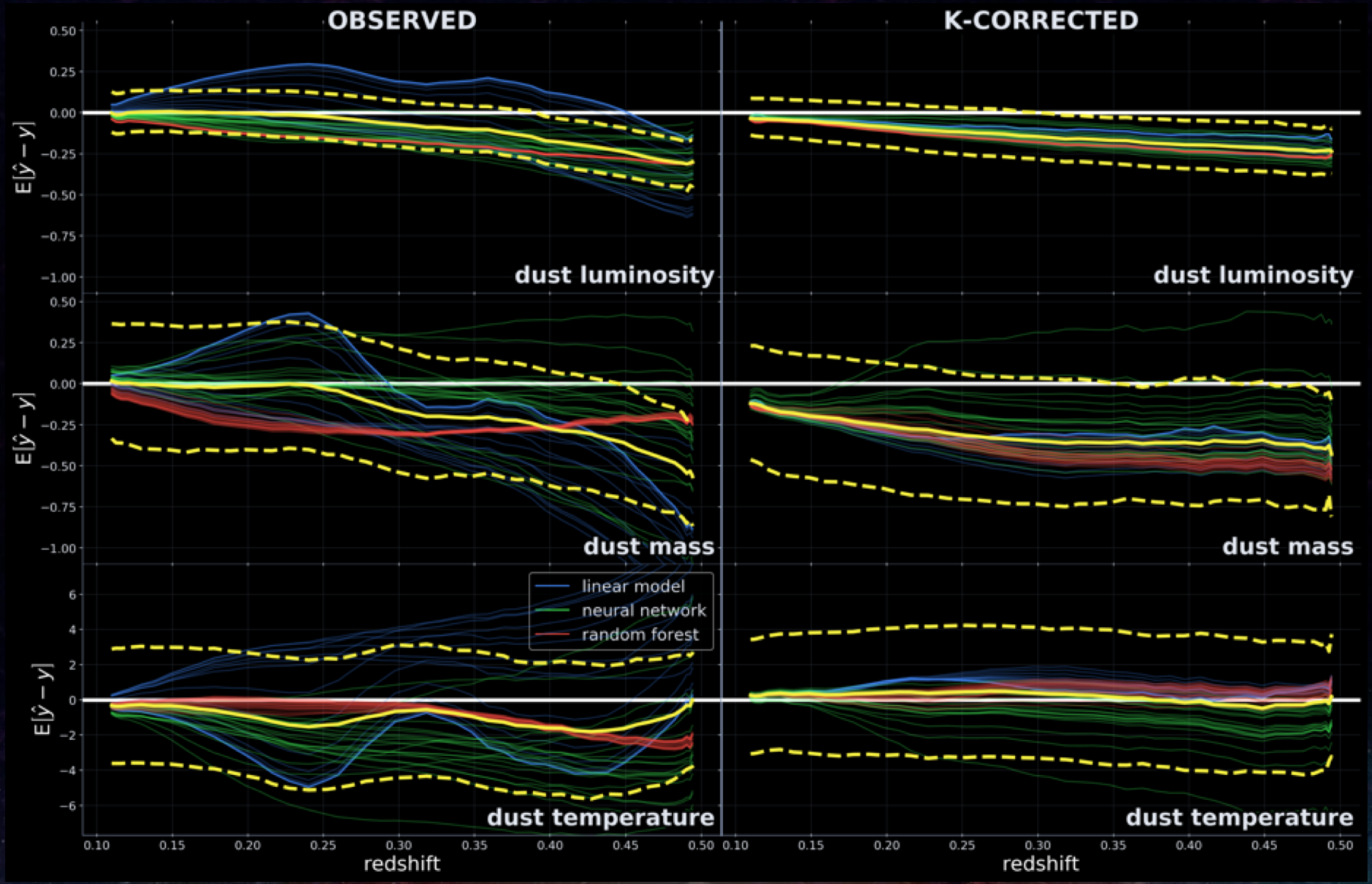
SPIRE mostly relies on NIR

Total RMSE = 0.19 dex

# Train on z < 0.1, test on z > 0.1



# Train on z < 0.1, test on z > 0.1



# Predicting uncertainties?

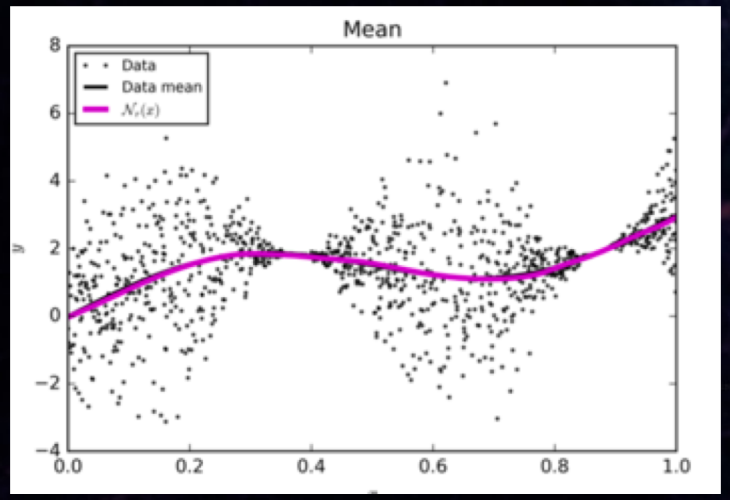
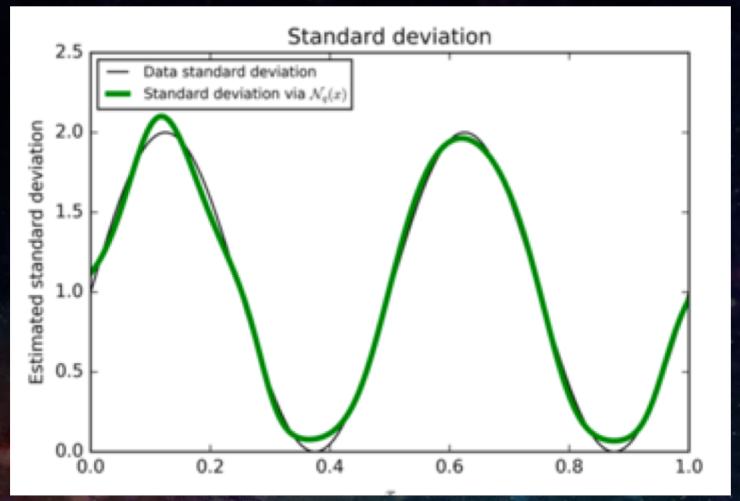
Use a second neural net: *uncertainty quantifier*

Minimize

$$\mathcal{L}_{\text{joint}} = \mathcal{L}_r(\aleph_r) f(\aleph_q) + \lambda g(\aleph_q)$$

joint loss — large uncertainty for large regressor loss — punish too large uncertainties

P. Gurevich, H. Stuke 2018

Estimates MSE for each sample

Other approaches are possible