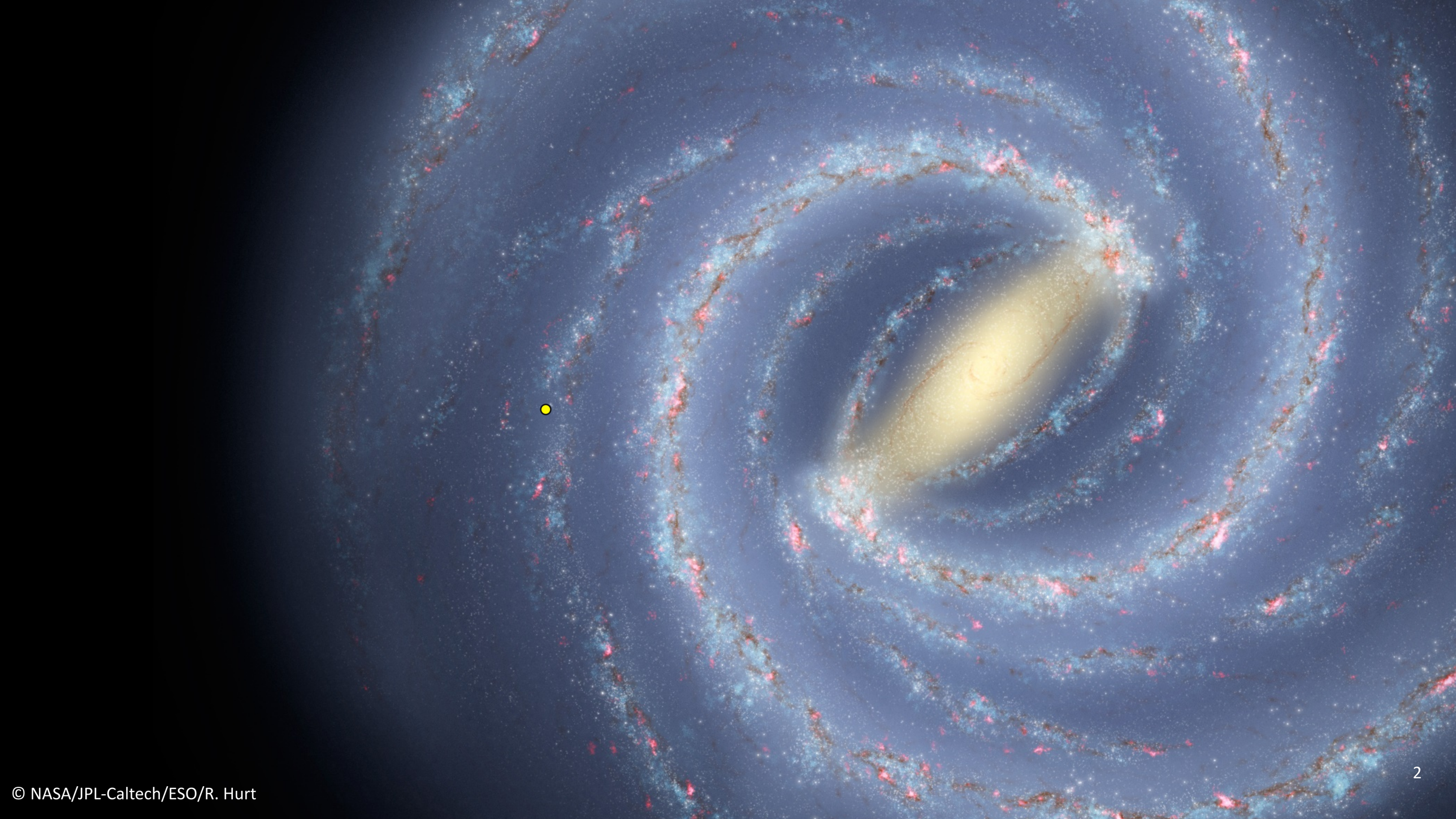
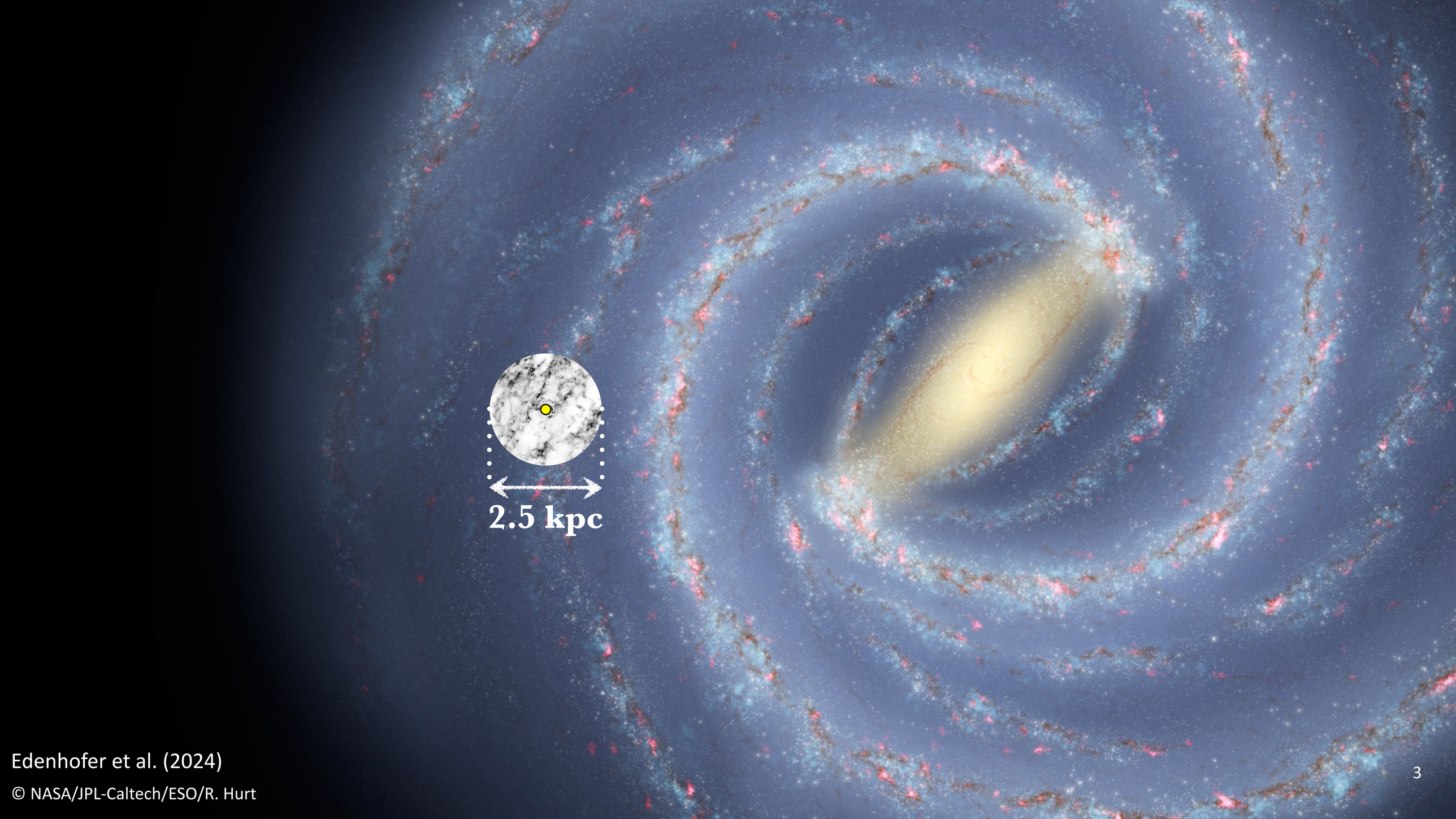
Learning with Gaps

A Domain-Adaptive SBI Framework for Mapping Young Stars from Incomplete, Multi-Survey Data

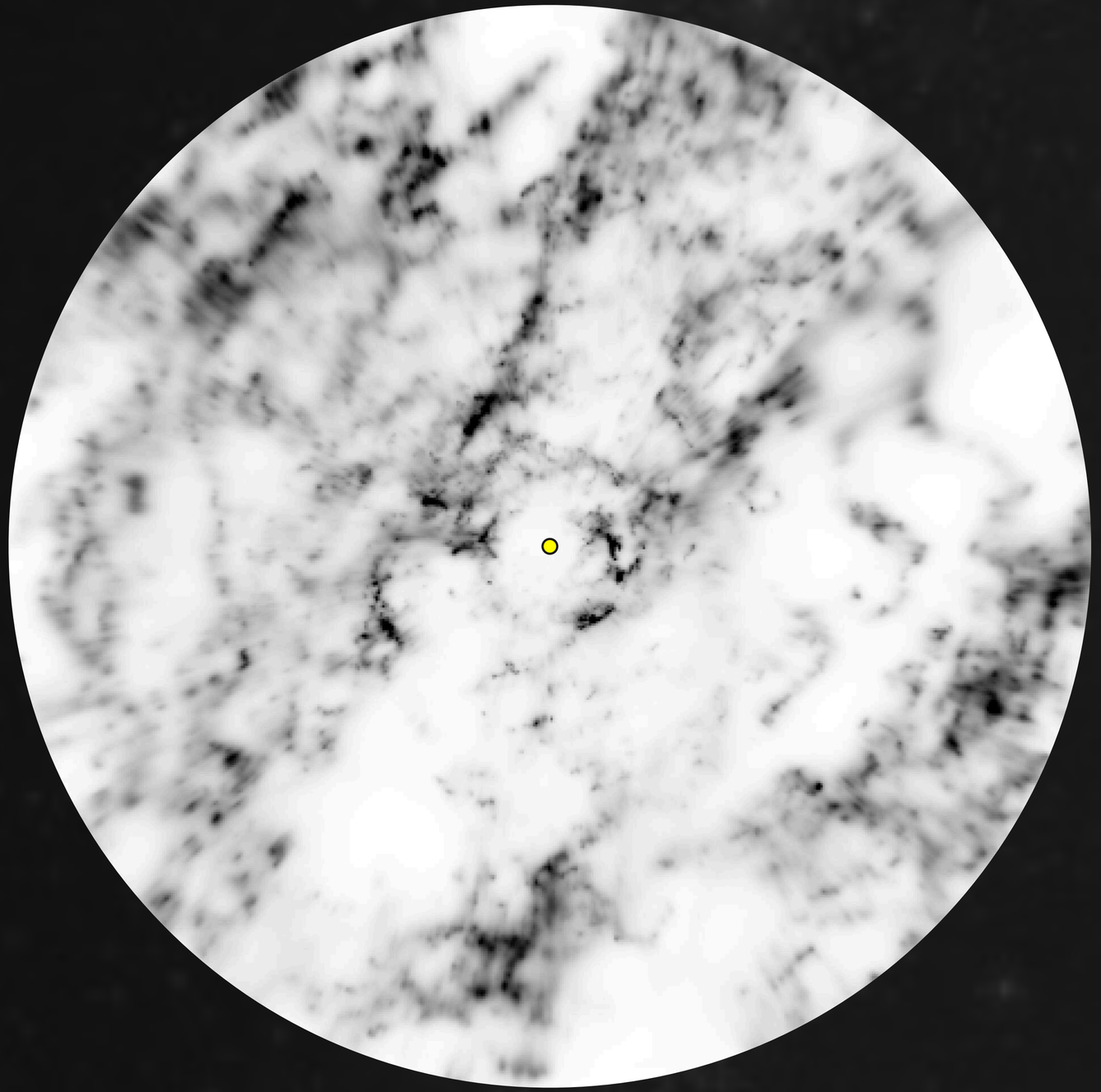
Sebastian Ratzenböck @CfA

In collaboration with
Catherine Zucker (CfA), Joshua Speagle (UToronto), Phillip Cargile (CfA), Philipp Frank (Stanford), Andrew Saydjari (Princeton)





Edenhofer et al. (2024)



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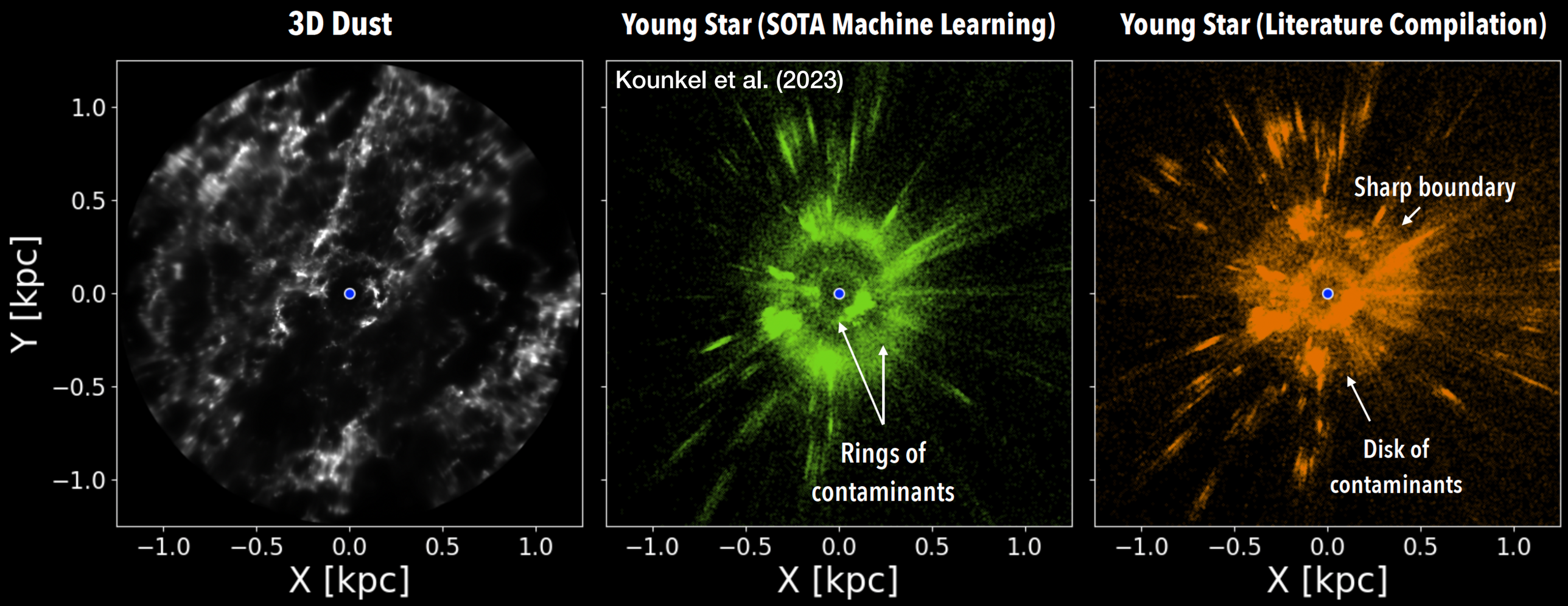
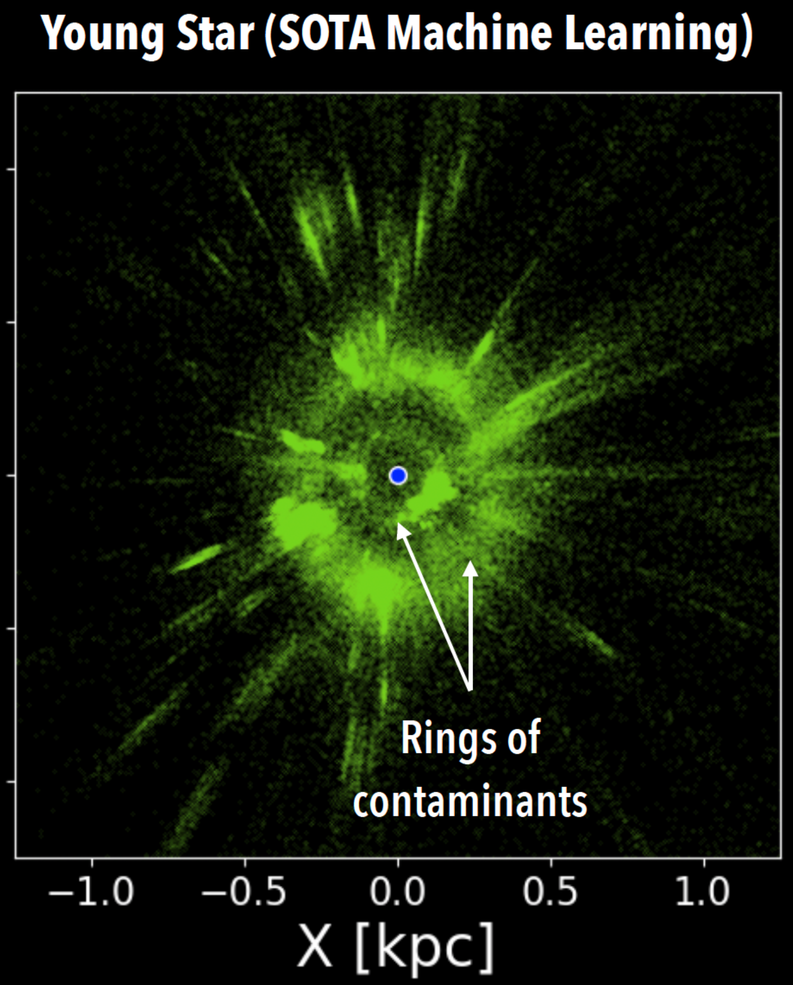

3D Dust
Young Star (SOTA Machine Learning)
Young Star (Literature Compilation)
Kounkel et al. (2023)
Rings of contaminants
Sharp boundary
Disk of contaminants
Y [kpc]
X [kpc]
X [kpc]
X [kpc]
1.0
0.5
0.0
−0.5
−1.0
−1.0
−0.5
0.0
0.5
1.0

Understanding Galactic baryon cycle

- YSOs connect *cloud* ↔ *stars* ↔ *feedback*



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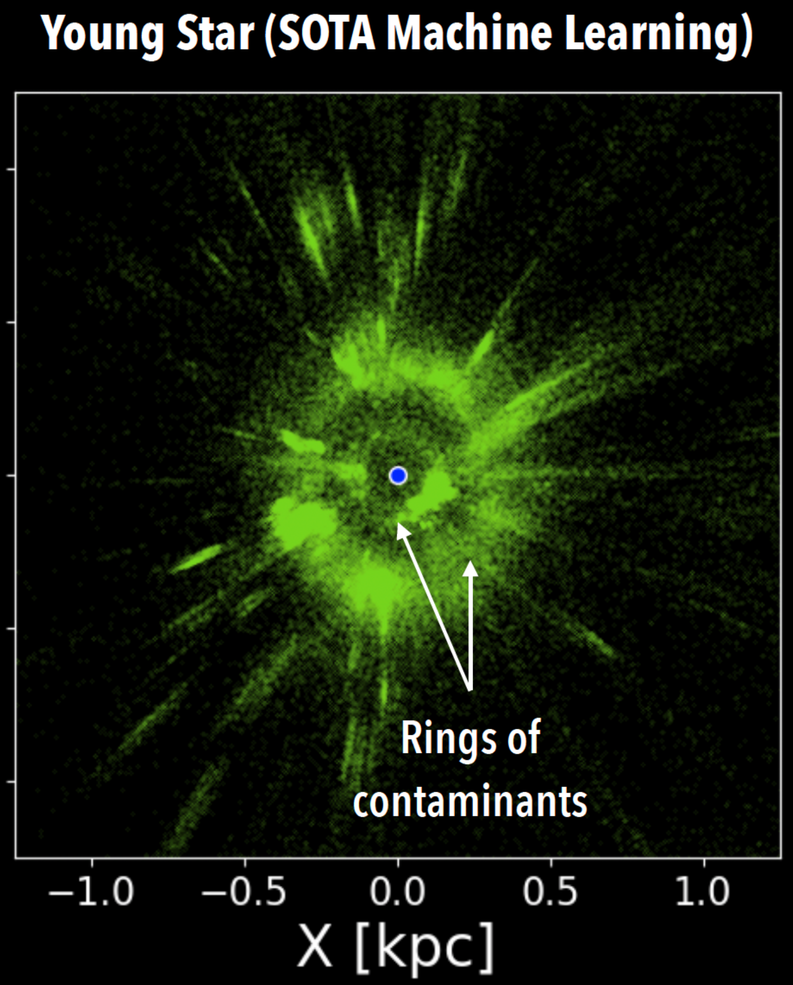

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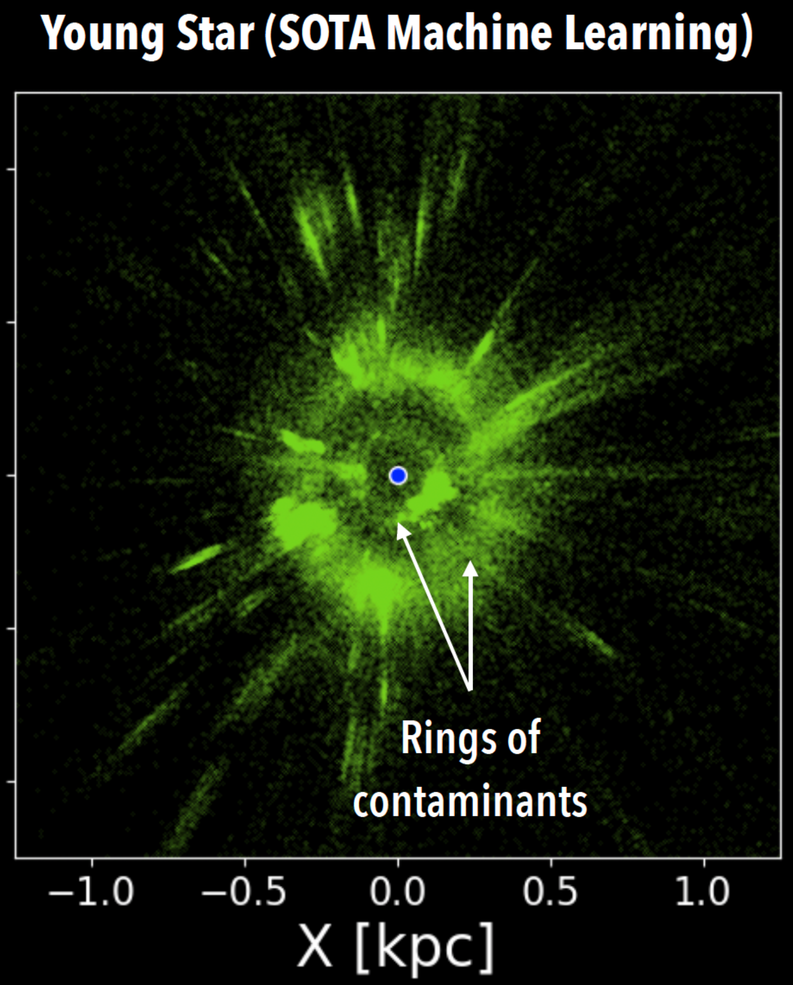

Understanding Galactic baryon cycle

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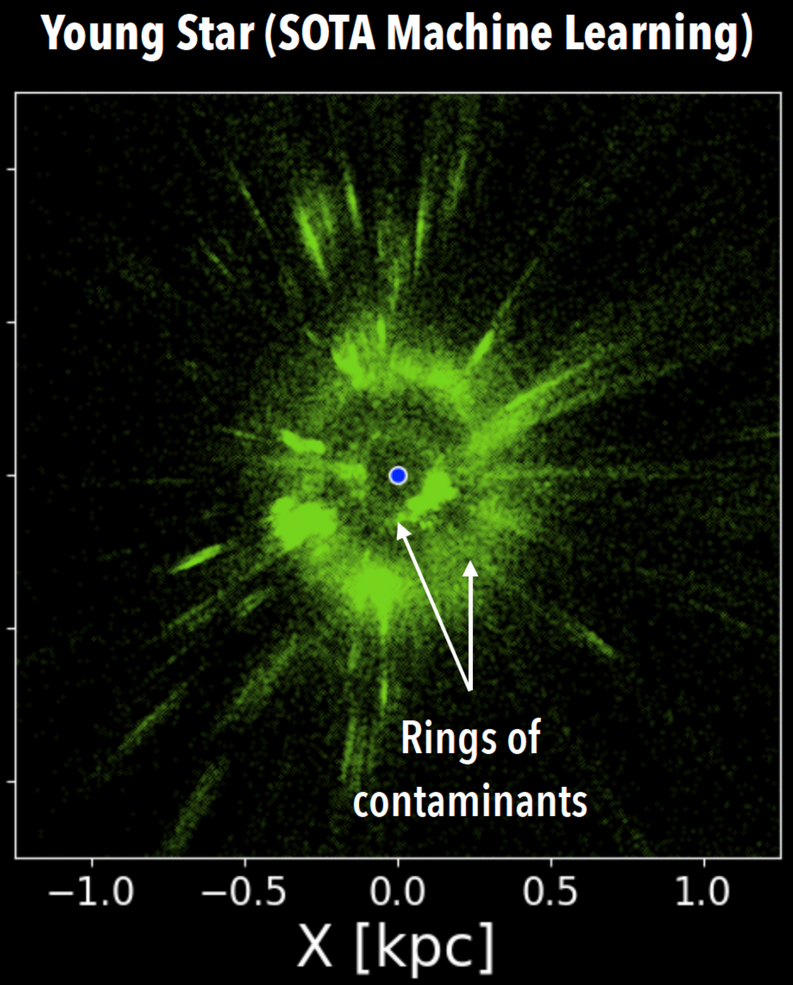
- How does the Milky Way convert gas into stars?
- How do stars leave their birth clouds and shape the ISM?
- How do supernovae regulate, trigger, or suppress new generations of stars?



Aim to improve YSO catalog

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Aim to improve YSO catalog

- Employ dedicated YSO models
- Data fusion: use as many informative data sets as possible
- Produce well-calibrated posteriors over stellar parameters given spectra & photometric observations
- Scale inference to > 1M - 1B stars

Challenges with “1 model does it all” approach

- Fusing surveys is hard due to different
  - resolutions & depths
  - coverage
  - instrument response
  - noise model
  - …

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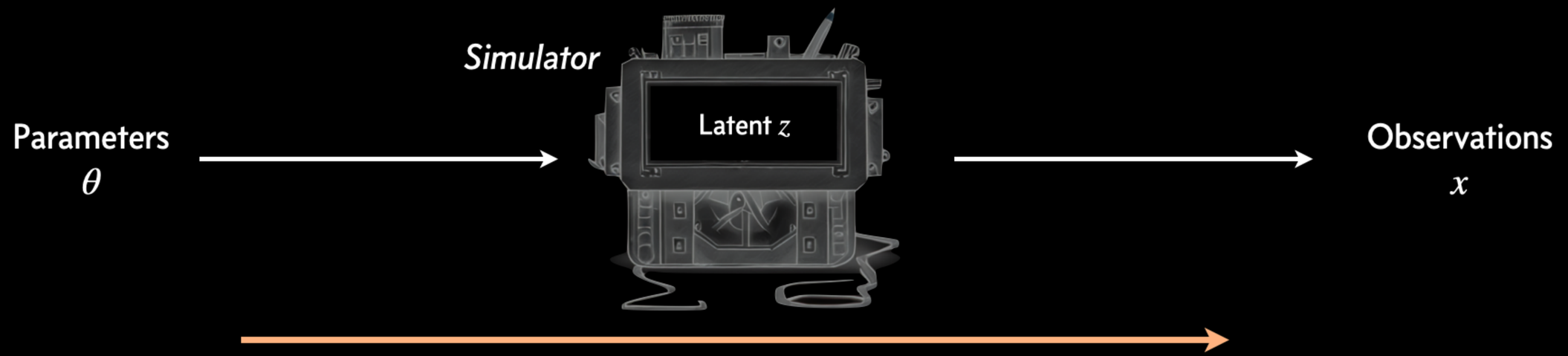
→ ***Domain-Adaptive*** *SBI w/* ***incomplete, multi-survey*** *data*

Model implementation

I. SBI model

Simulation based inference setup



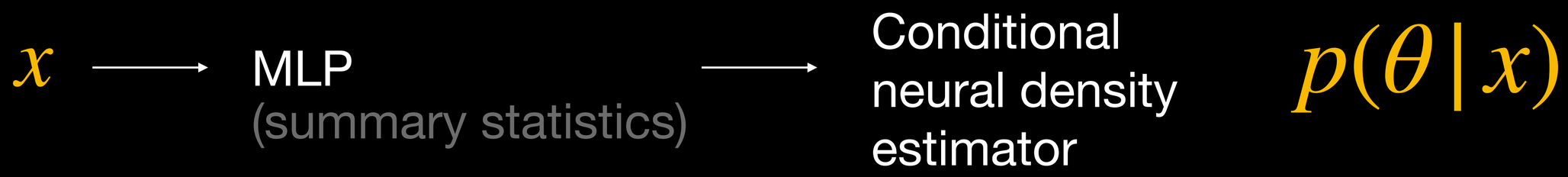
Prediction:

- Mechanistic forward model
- We can generate samples from a simulator $x \sim p(x \mid \theta)$

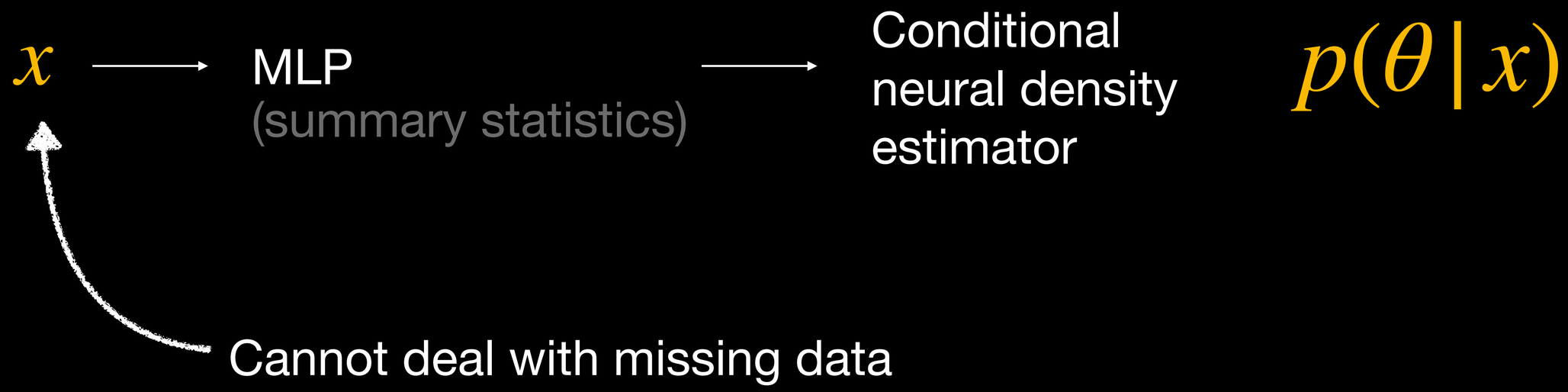
Inference:

- Likelihood $p(x \mid \theta) = \int \mathrm{d}z\, p(x, z \mid \theta)$ is intractable
- *Inference is challenging*

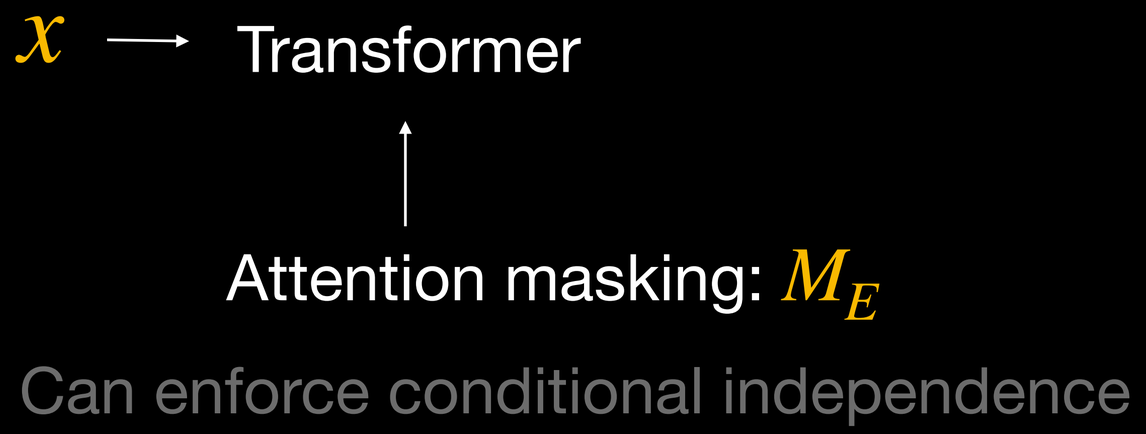
Neural posterior estimation



Neural posterior estimation



Simformer: learning with incomplete data



Can enforce conditional independence

Gloeckler et al. (2024)

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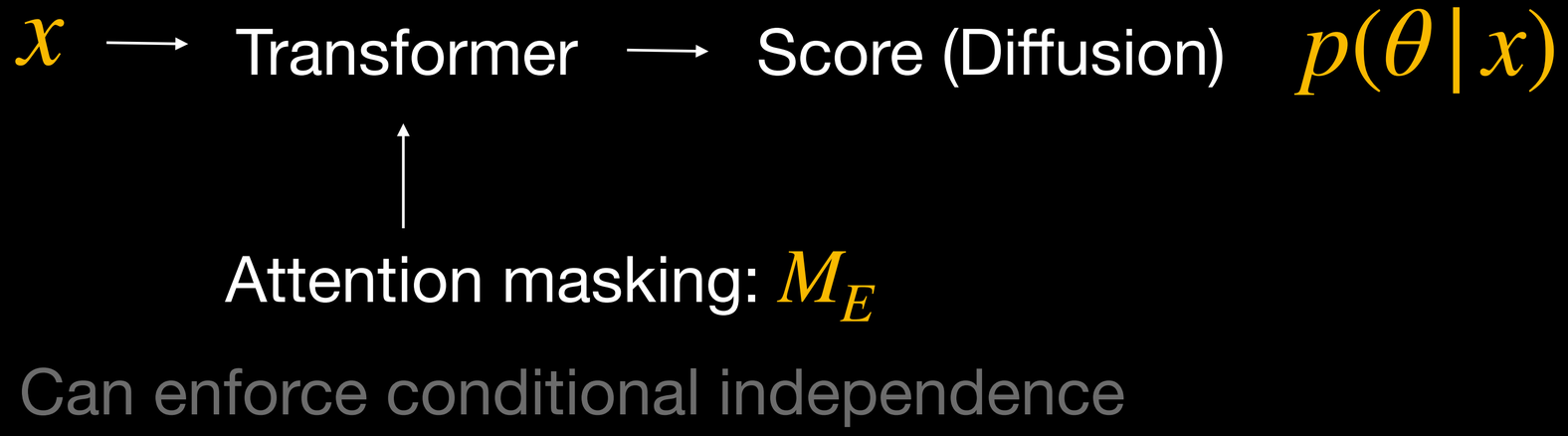

Can enforce conditional independence

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Model implementation

II. Domain adaption

Architecture

$(X, \theta) \longrightarrow$ Transformer $\longrightarrow$ Score (Diffusion)

Input split into *simulated*, *real* & *paired* data

$$\theta$$

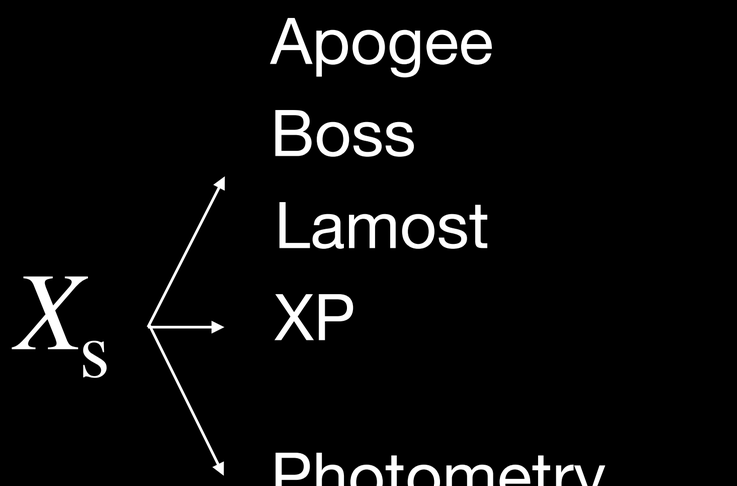
$$X \rightarrow \begin{matrix} X_{\text{sim}} \\ X_{\text{real}} \\ X_{\text{sim-real-pairs}} \end{matrix}$$

→ Transformer → Diffusion

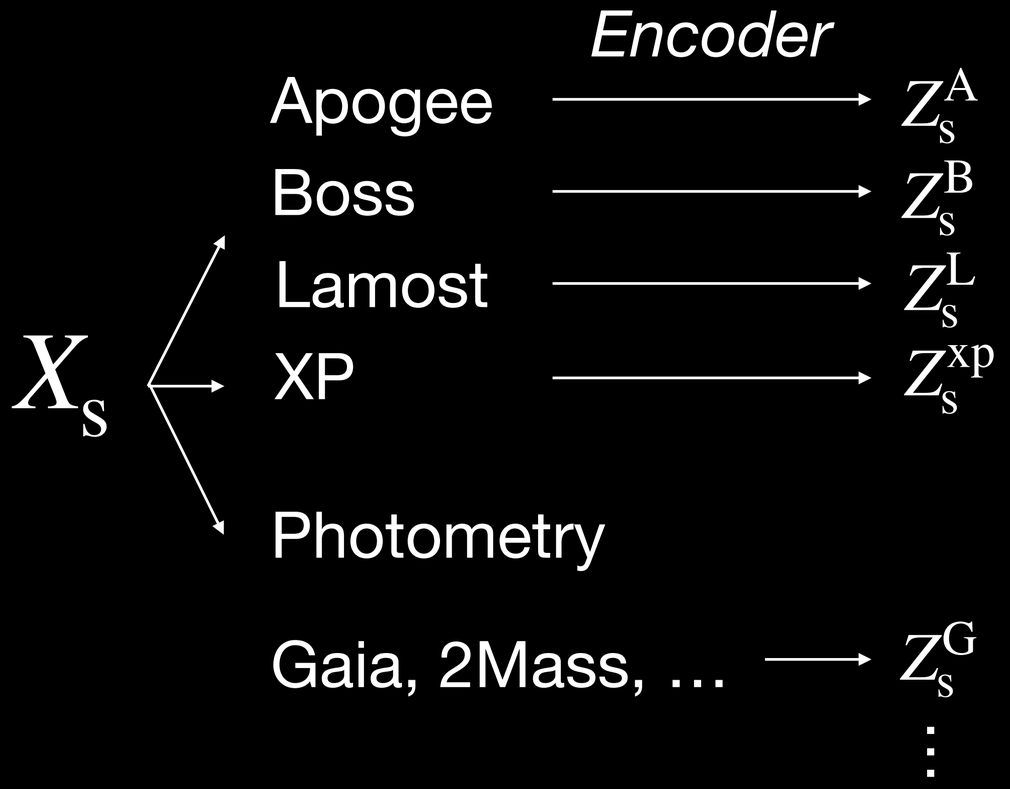
Modality encoders

$$X \rightarrow \begin{matrix} X_{\mathrm{s}} \\ X_{\mathrm{r}} \\ X_{\mathrm{s-r}} \end{matrix}$$

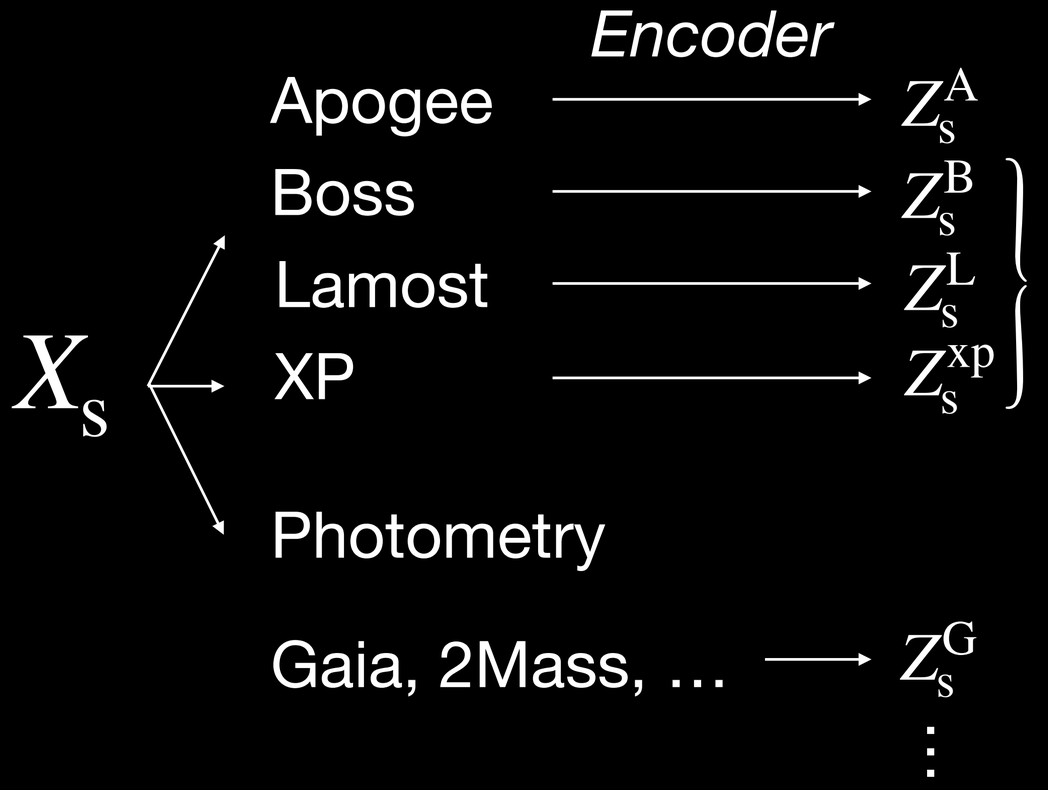
Modality encoders: split into indiv. spectra



Modality encoders: encode



Modality encoders: contrastive loss

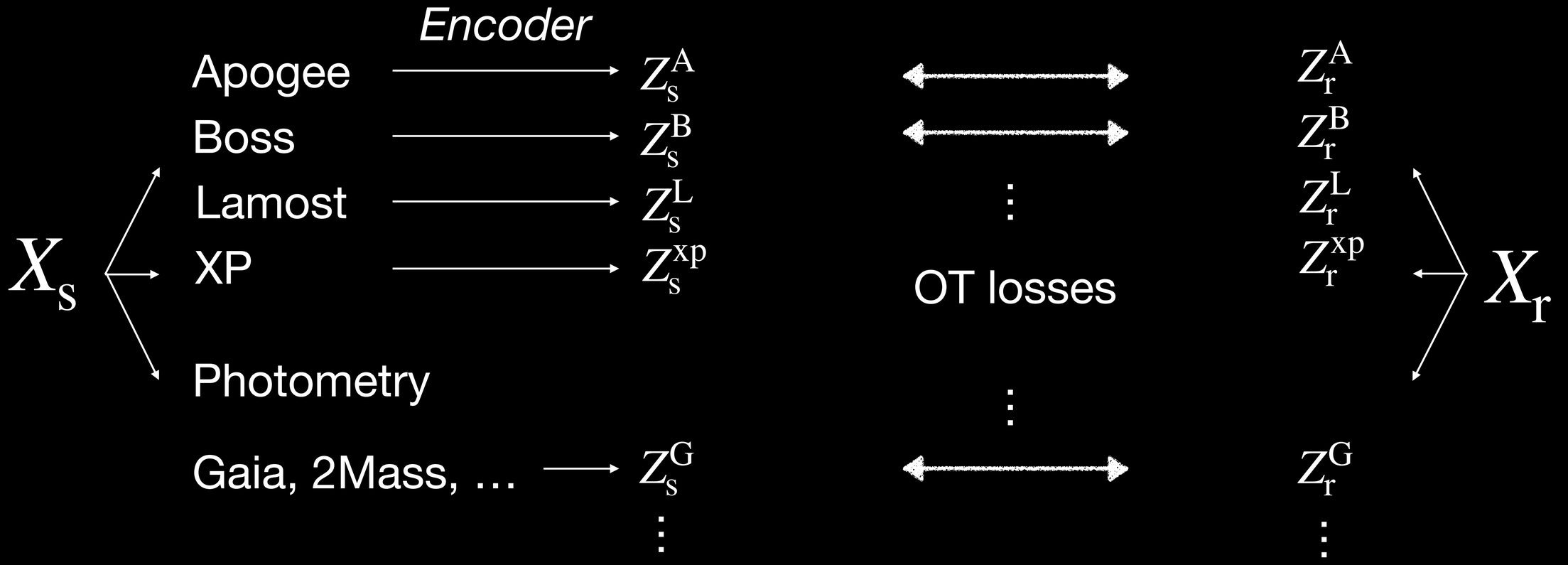


Pool embedding (mean)

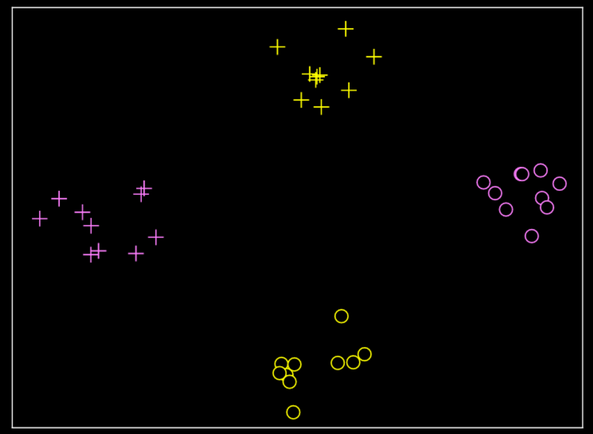
Contrastive loss: $Z^{\{xp,L,B\}}$ & Z^{pool}

Goal: learn shared information across spectra, that's (hopefully) invariant of detector systems

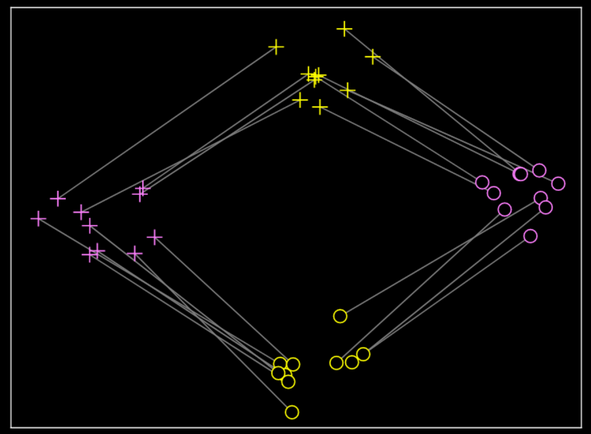
Modality encoders: alignment loss



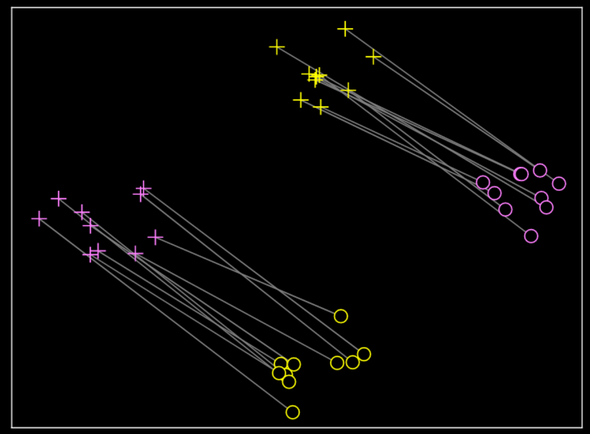
Alignment via optimal transport



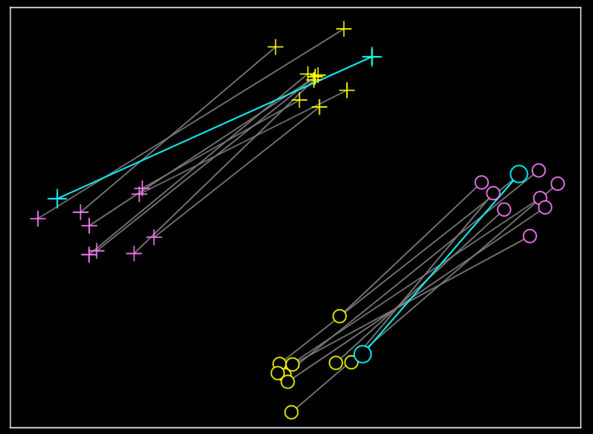
(a) Samples



(b) Exact



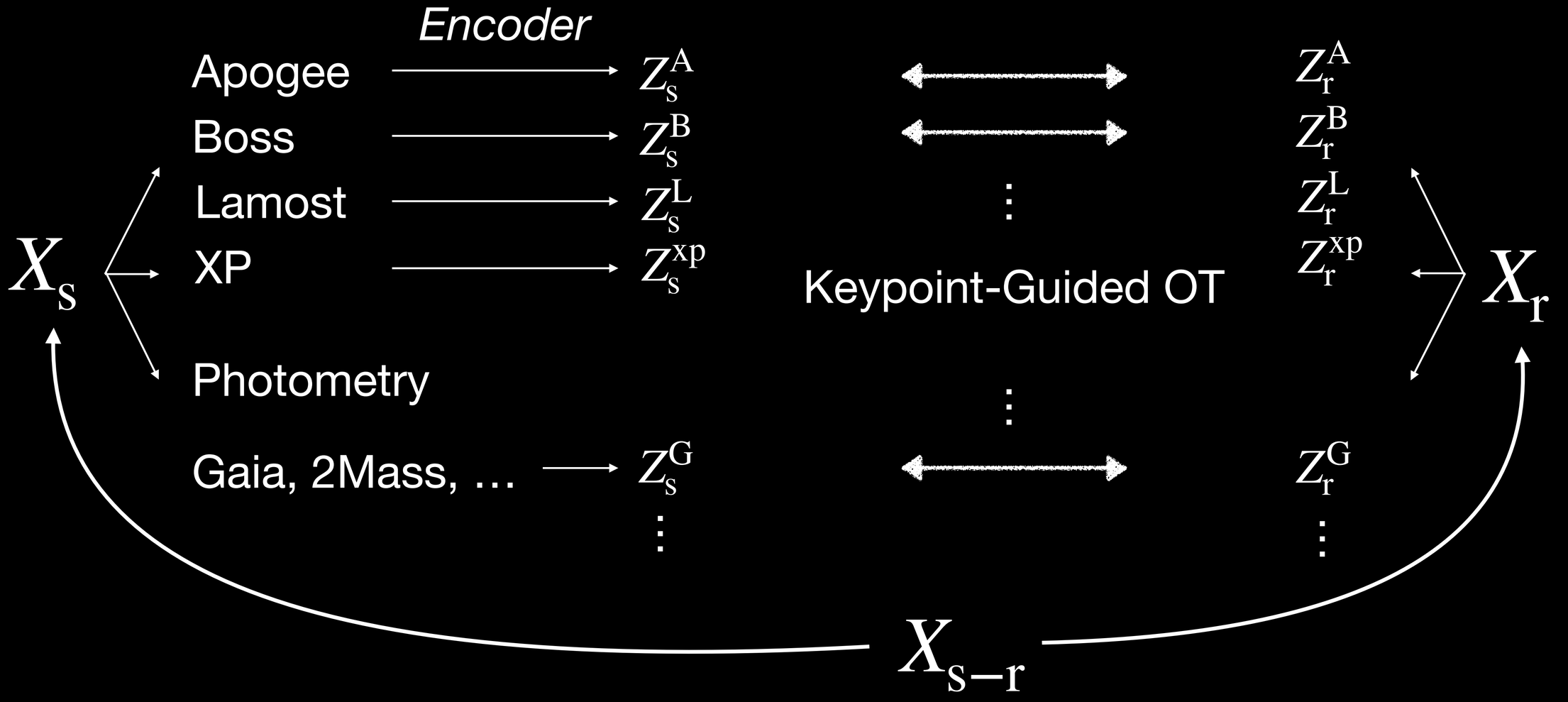
(c) Gromov-Wasserstein



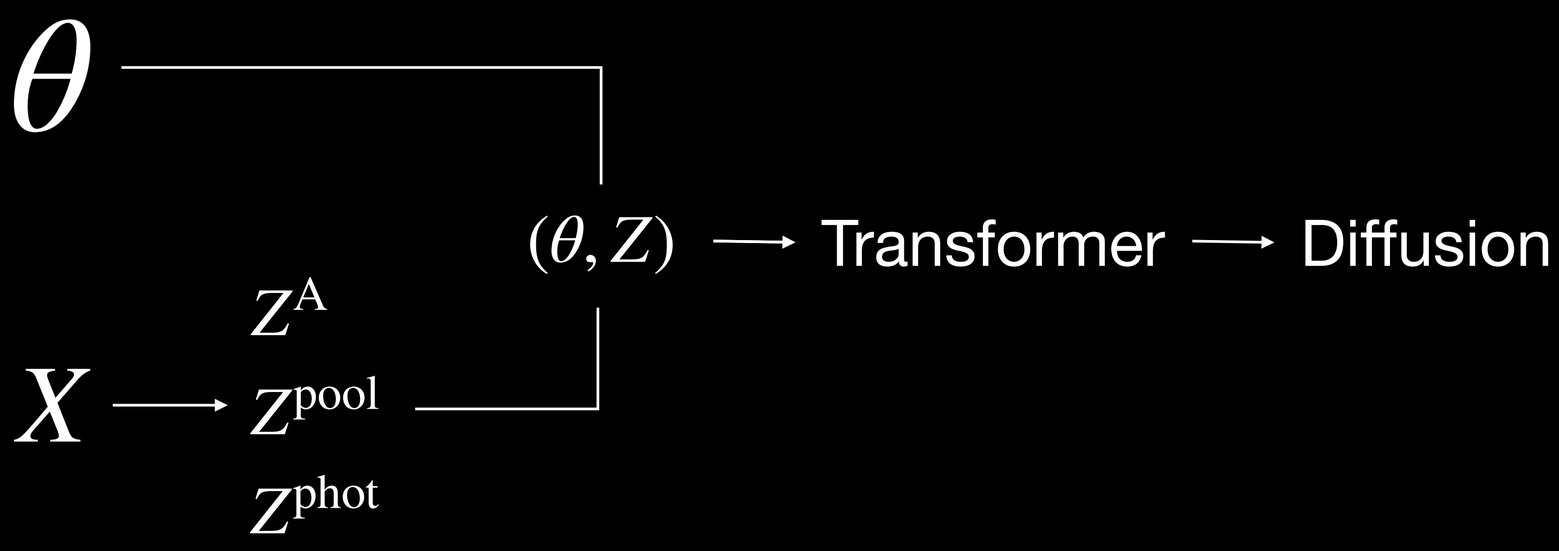
Gu et al. (2022)

Gu et al. (2022)

Additional pair constraint



Final model

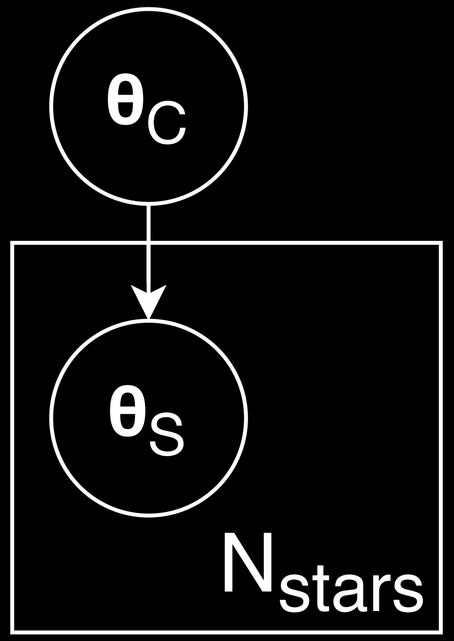


Loss

$$\ell(\phi, M_C, t, \hat{\mathbf{x}}_0, \hat{\mathbf{x}}_t) + \mathscr{L}_C + \mathscr{L}_{OT} + \mathscr{L}_{R-S}$$

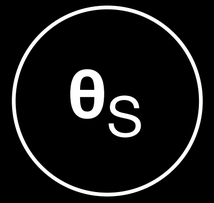
Forward model

Clusters/young stars

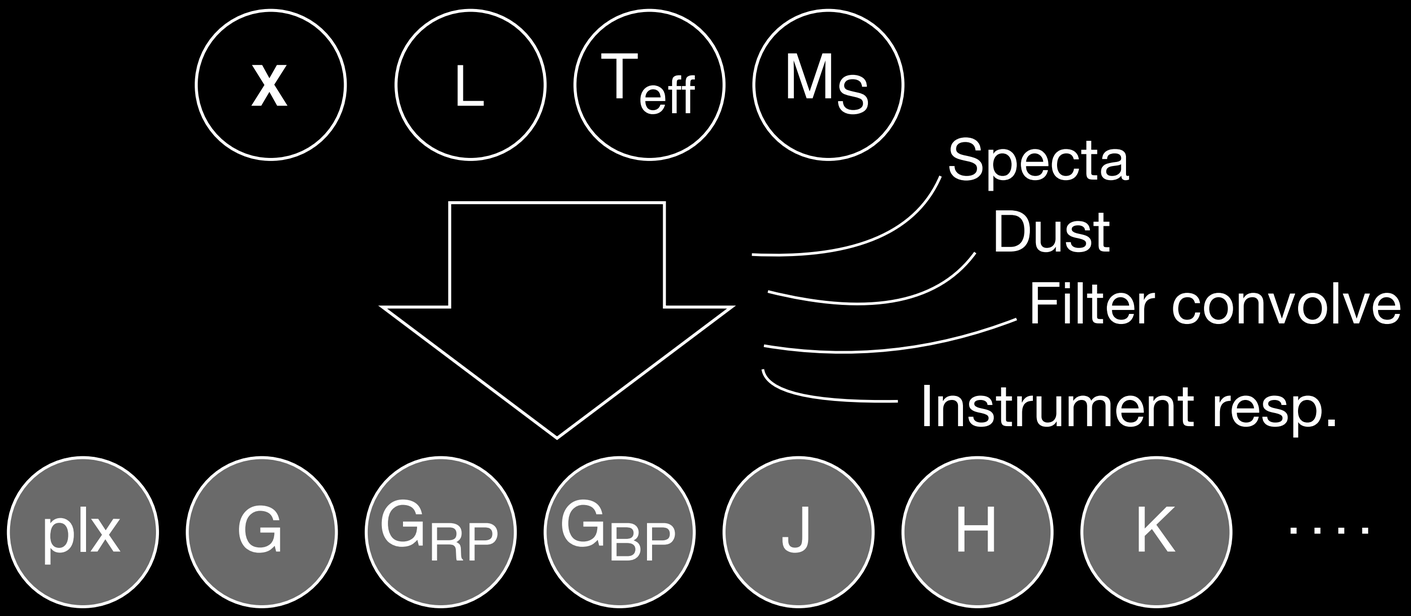


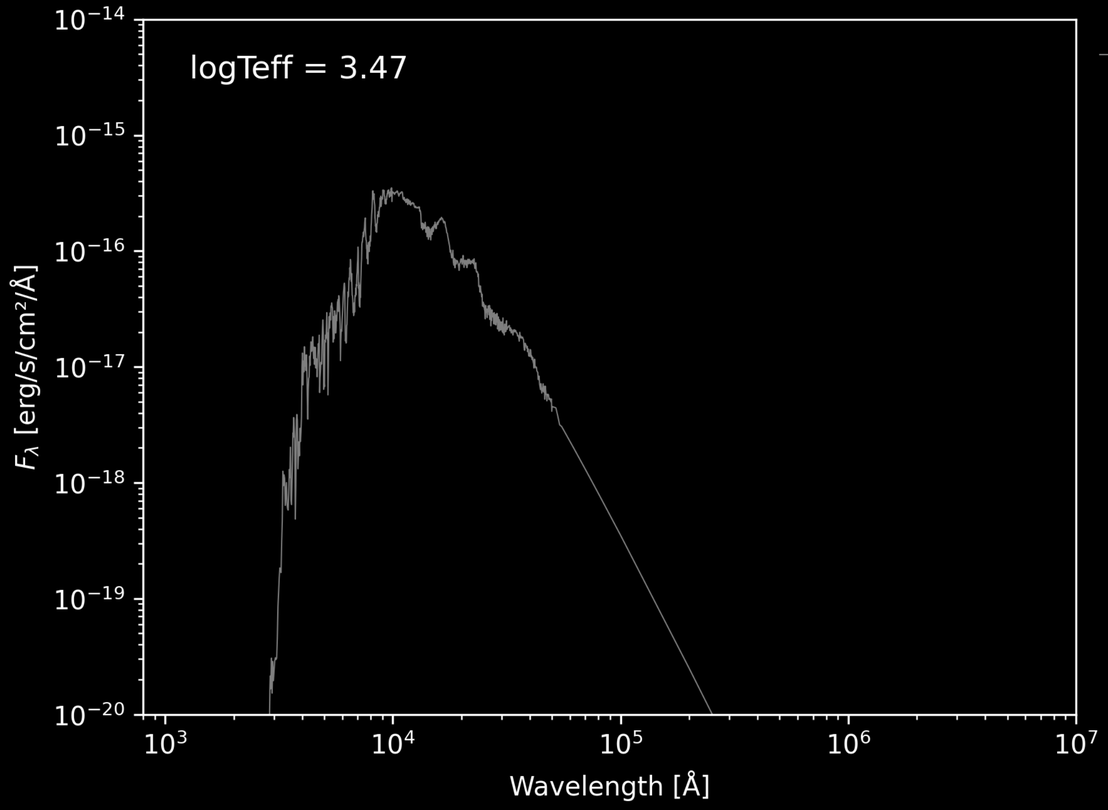
Milky Way model

- Rybizki et al. (2018)
- *galaxia* code
- thin+thick+halo+bulge

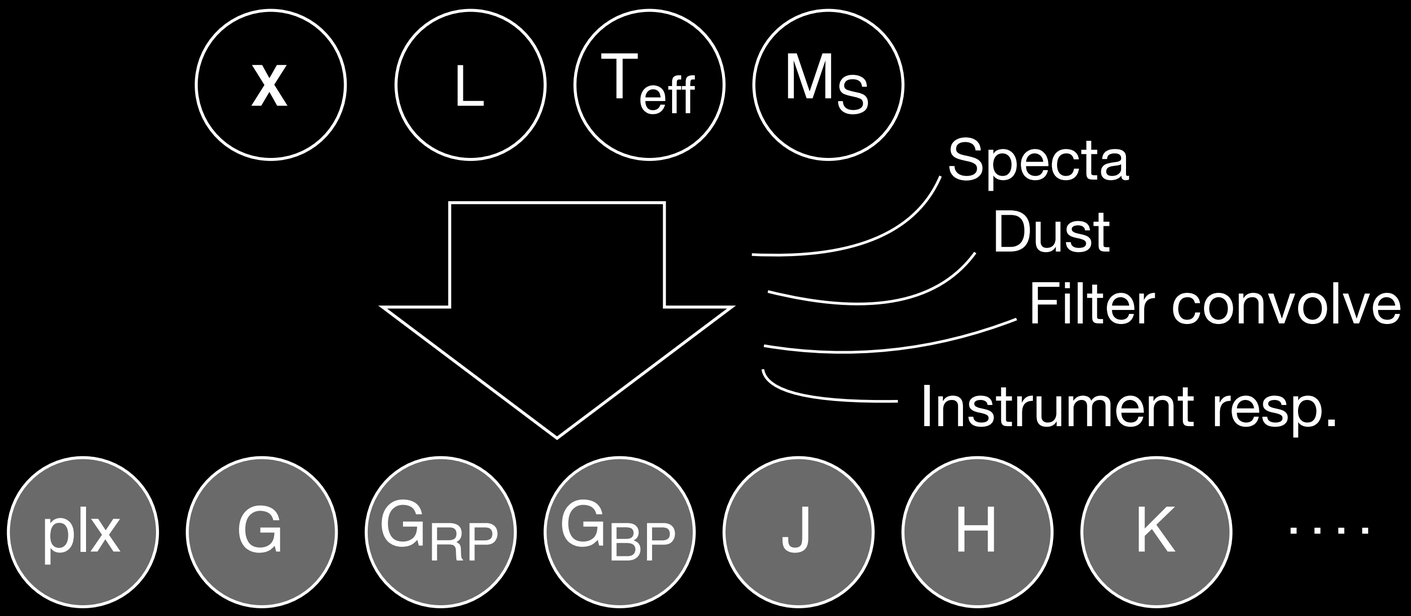


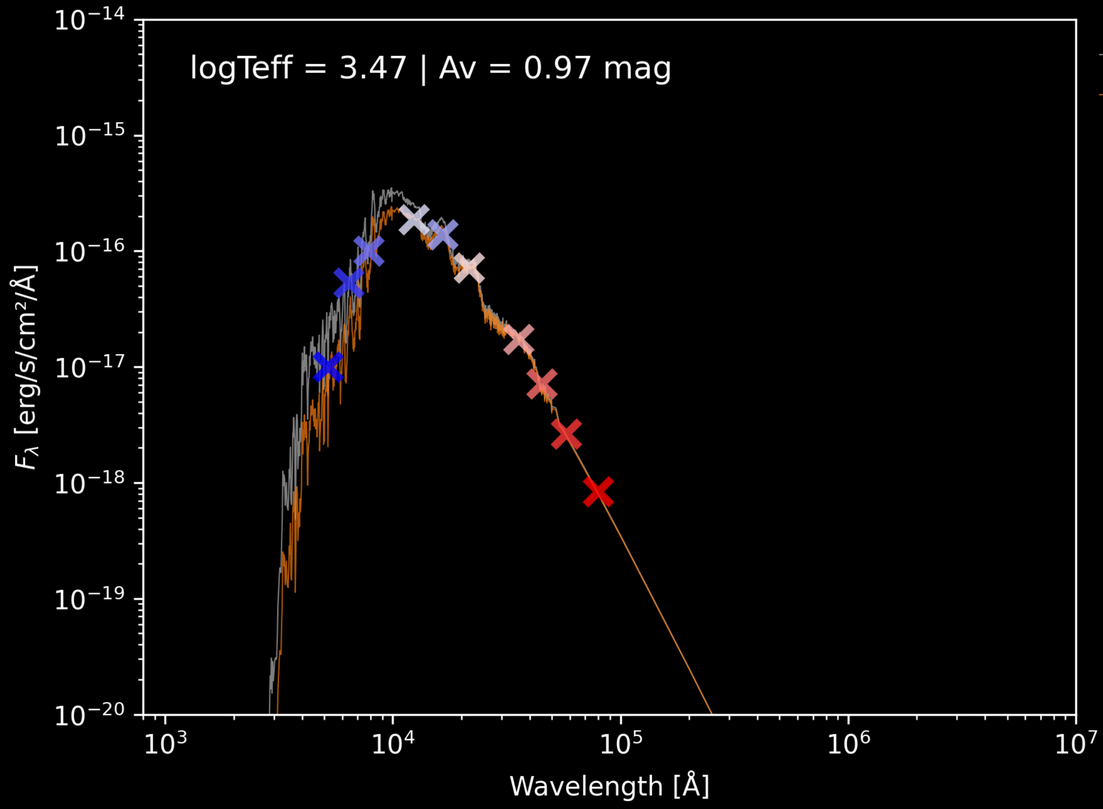
Fwd model


x
L
T_{eff}
M_S
Specta
Dust
Filter convolve
Instrument resp.
plx
G
G_{RP}
G_{BP}
J
H
K
....

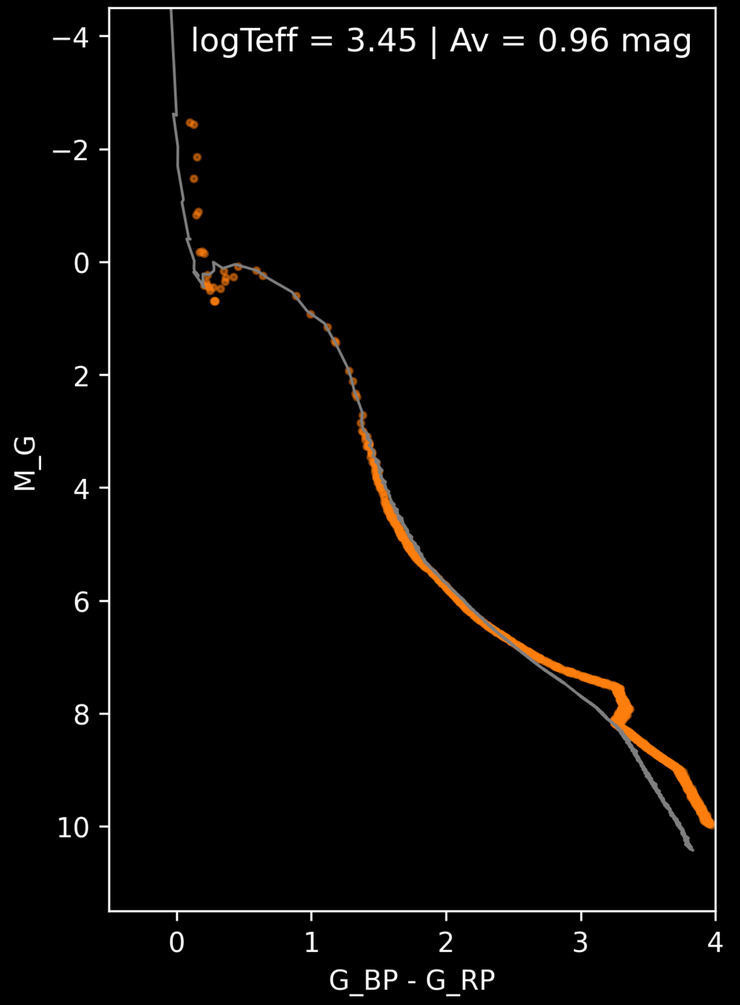

logTeff = 3.47
10^{-14}
10^{-15}
10^{-16}
10^{-17}
10^{-18}
10^{-19}
10^{-20}
F_λ [erg/s/cm²/Å]
10^3
10^4
10^5
10^6
10^7
Wavelength [Å]

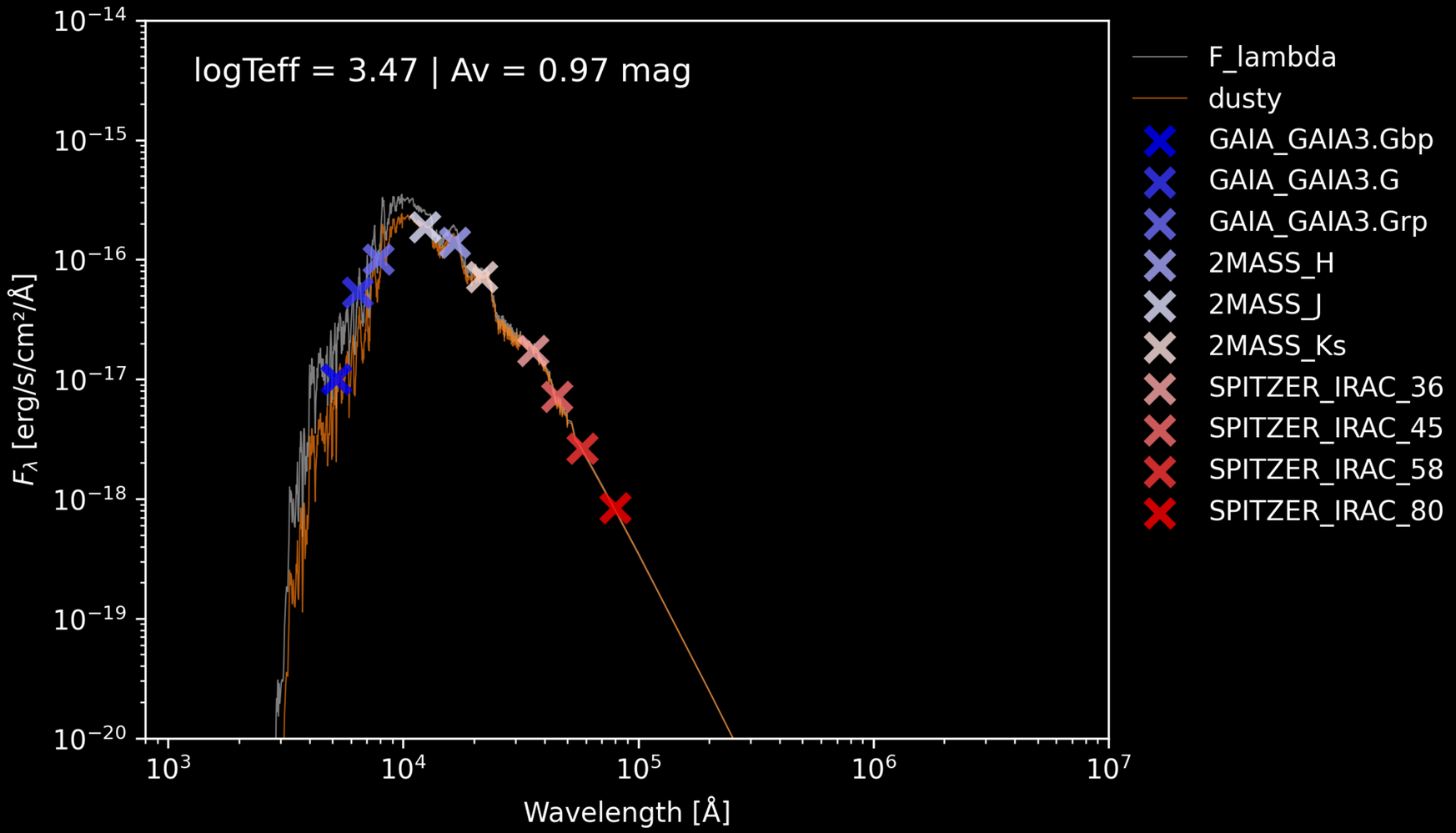
Fwd model


x
L
T_{eff}
M_S
Specta
Dust
Filter convolve
Instrument resp.
plx
G
G_{RP}
G_{BP}
J
H
K
....

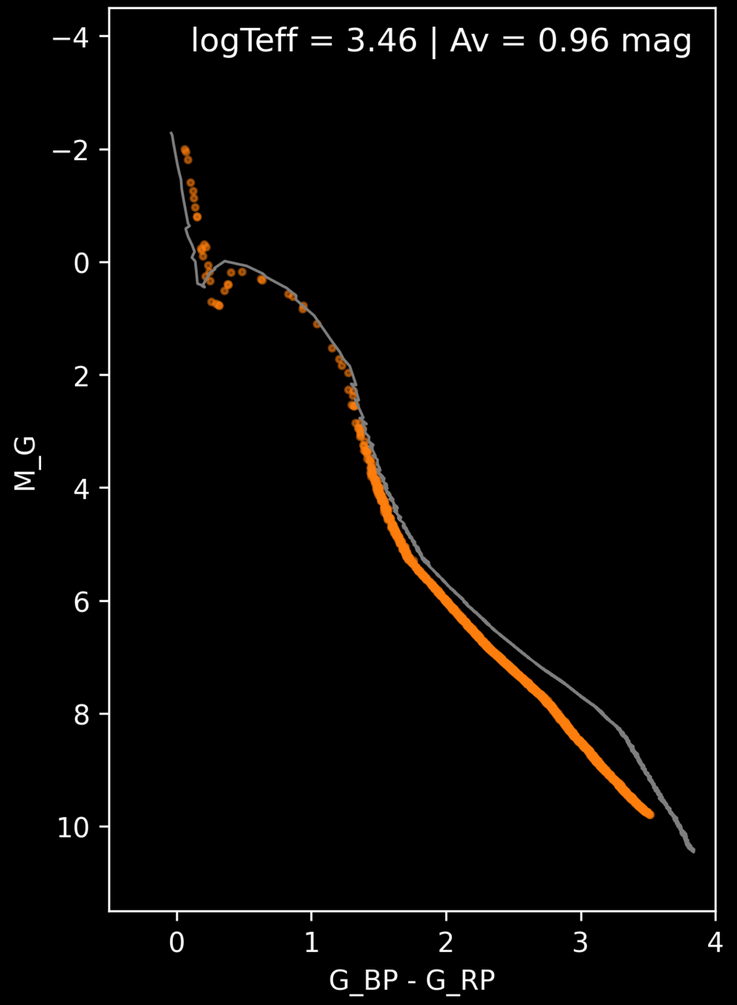

logTeff = 3.47 | Av = 0.97 mag
F_λ [erg/s/cm²/Å]
Wavelength [Å]
10^{-14}
10^{-15}
10^{-16}
10^{-17}
10^{-18}
10^{-19}
10^{-20}
10^3
10^4
10^5
10^6
10^7

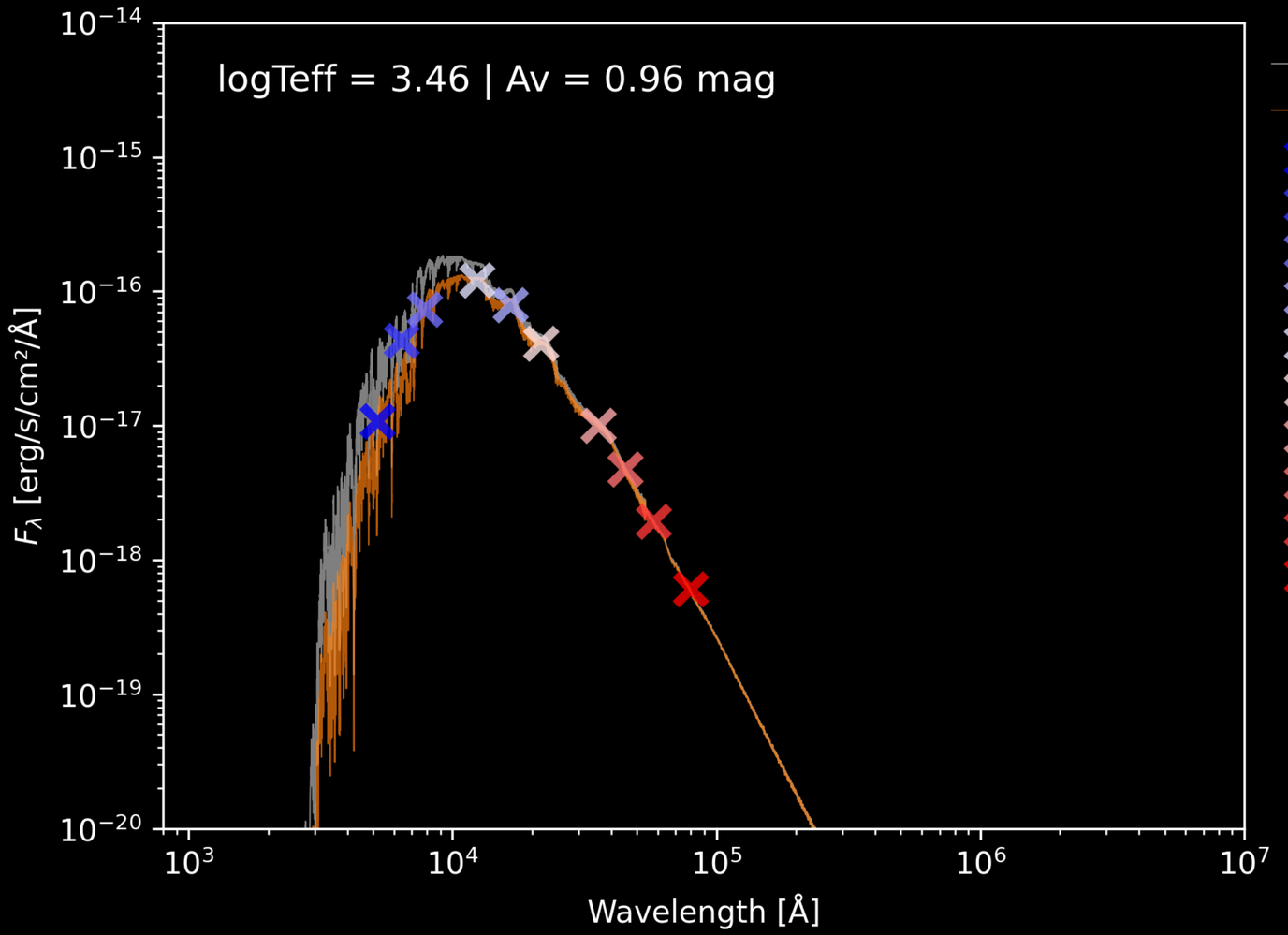
Model differences (BaSeL)



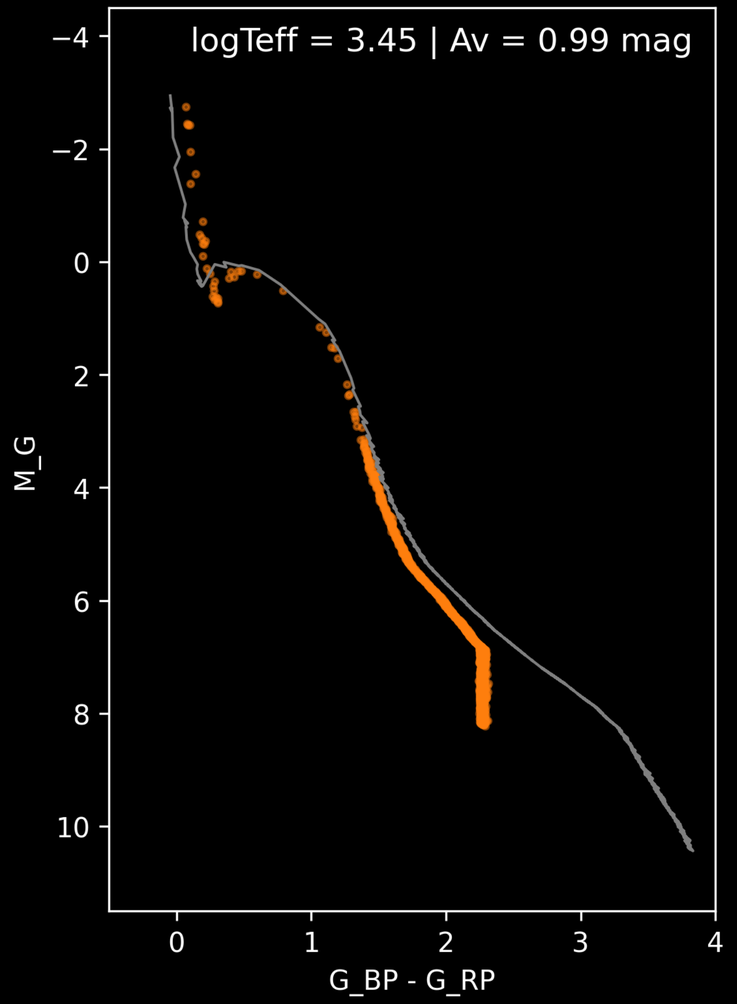


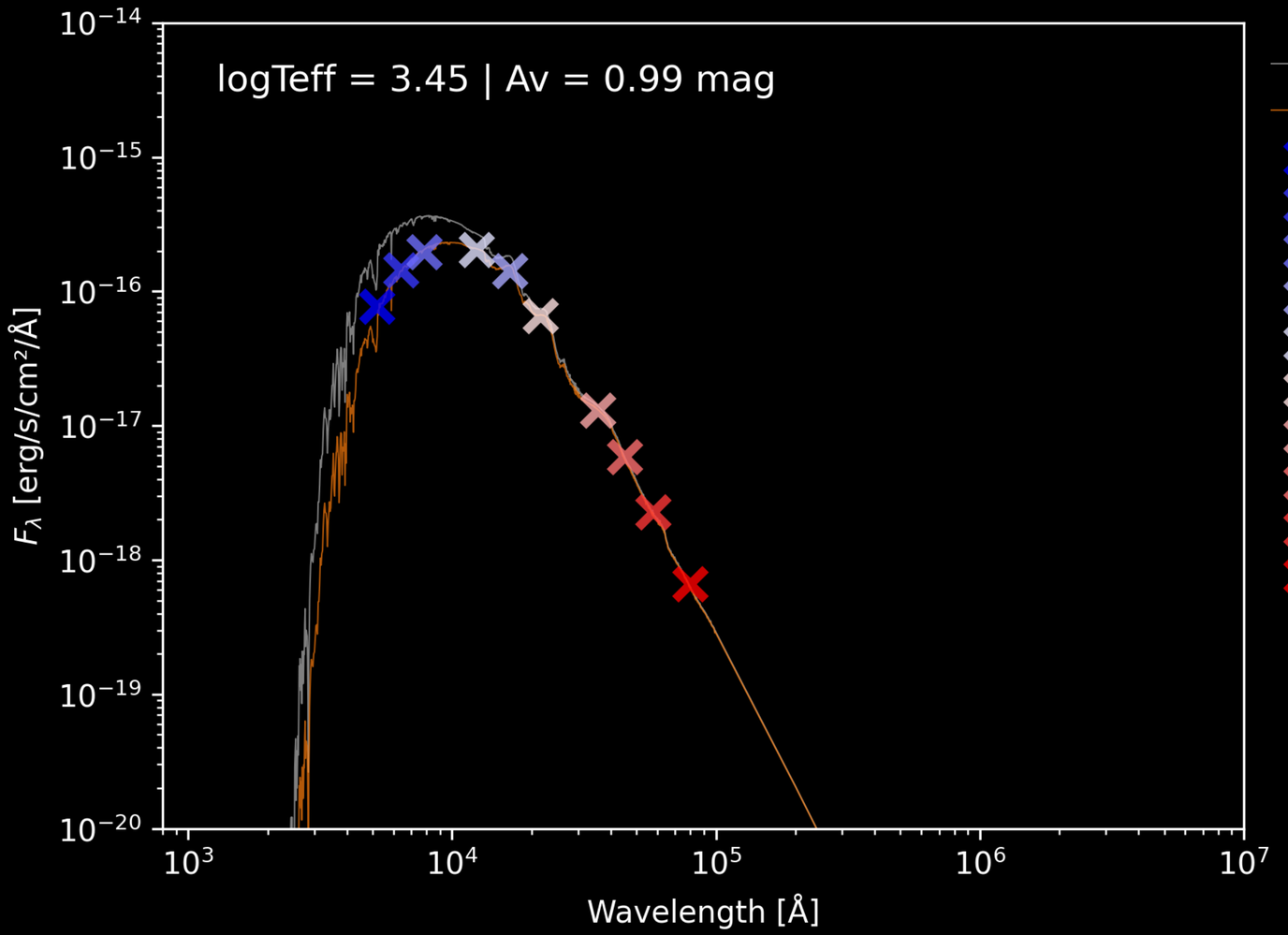
Model differences (BTSettl)





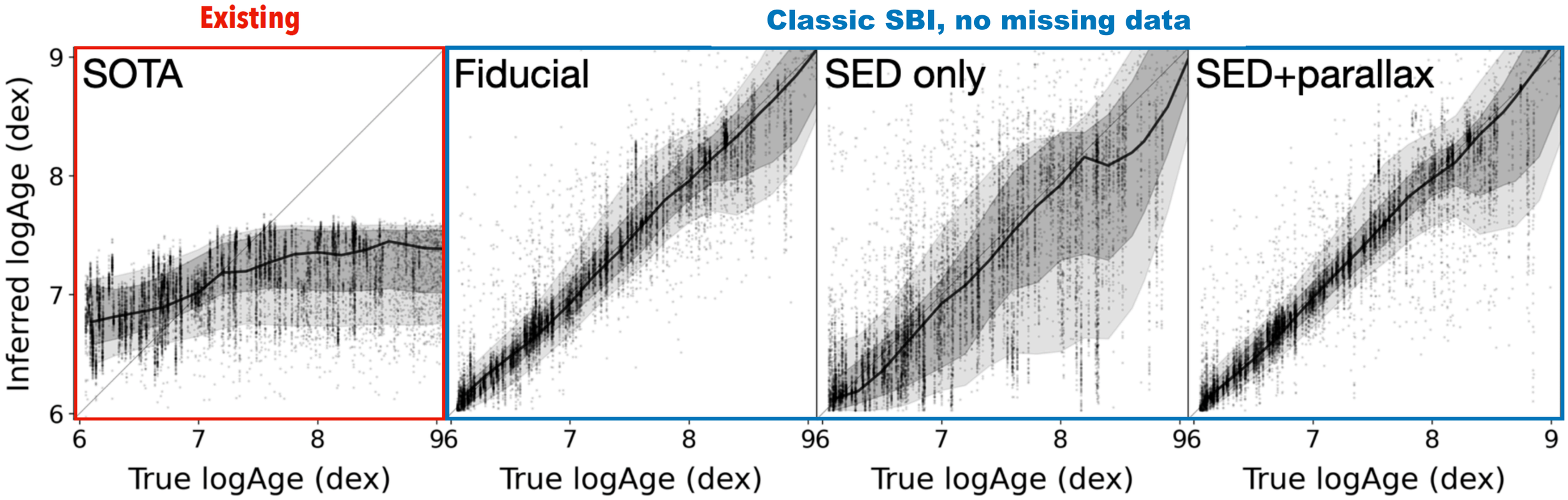
Model differences (Kurucz)



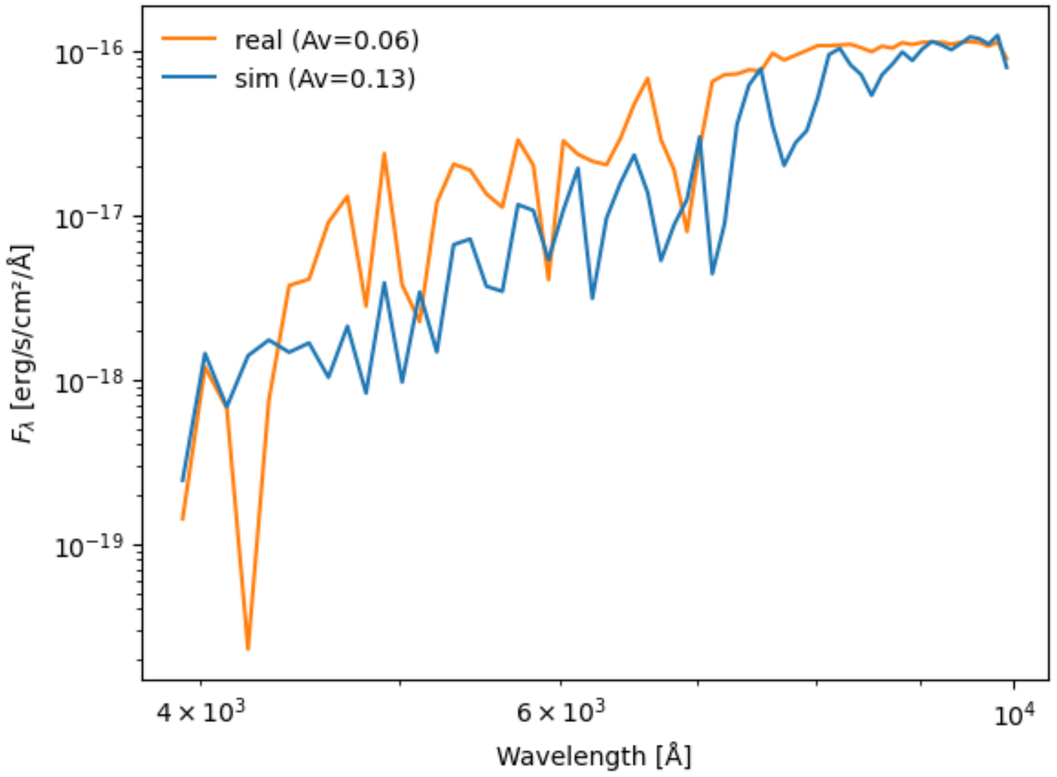


Results

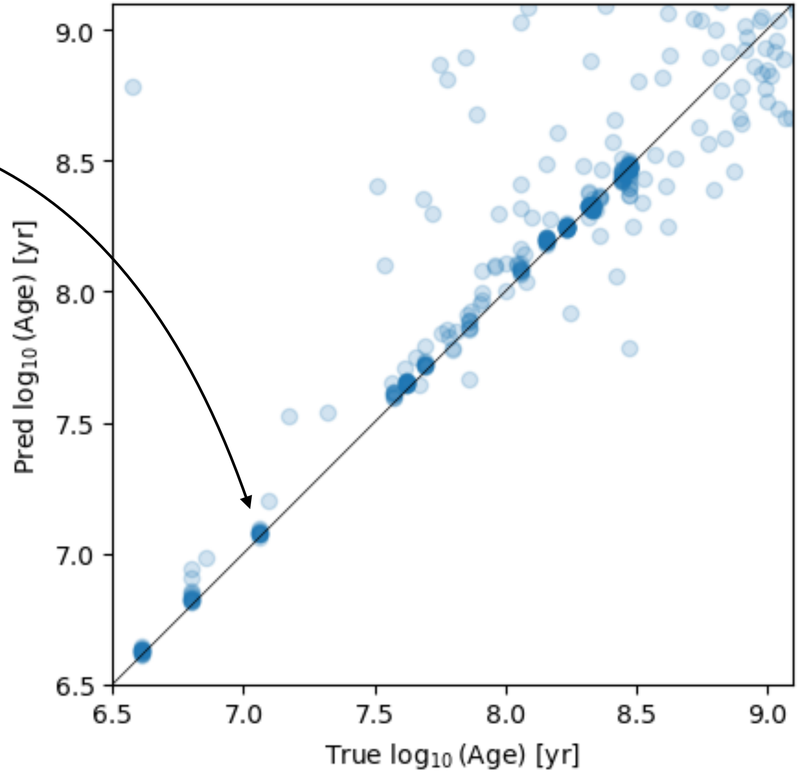
Pilot study: Gaia+2MASS+WISE



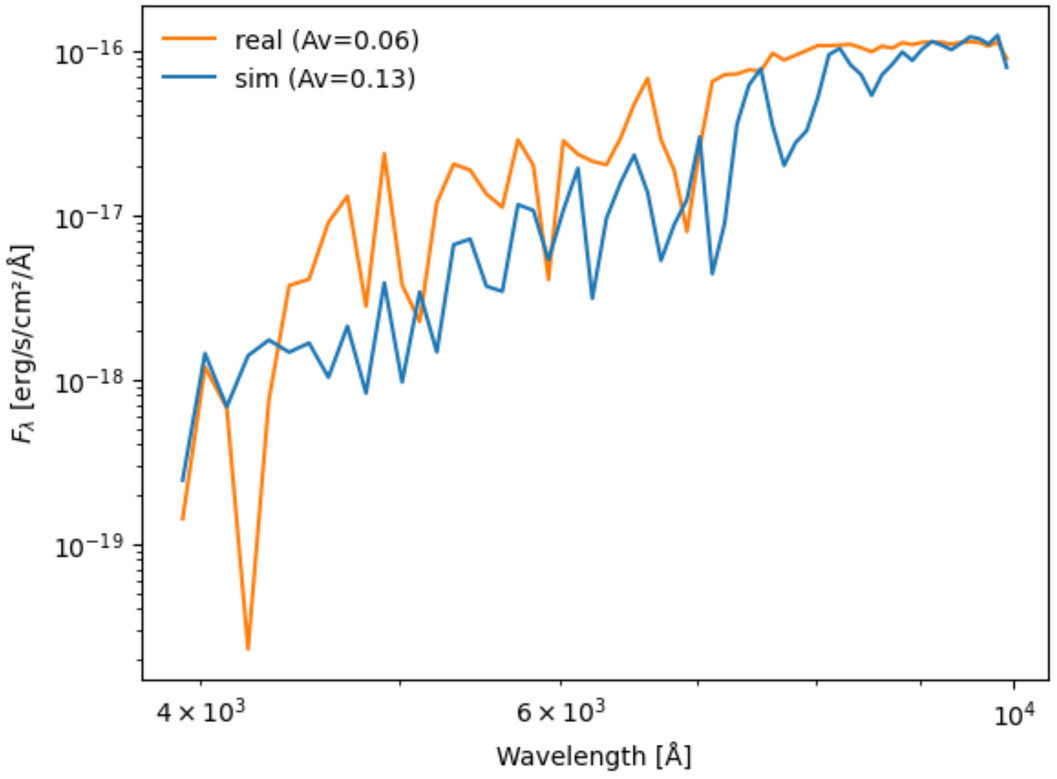
Updated pipeline + 50% missing + XP spectra

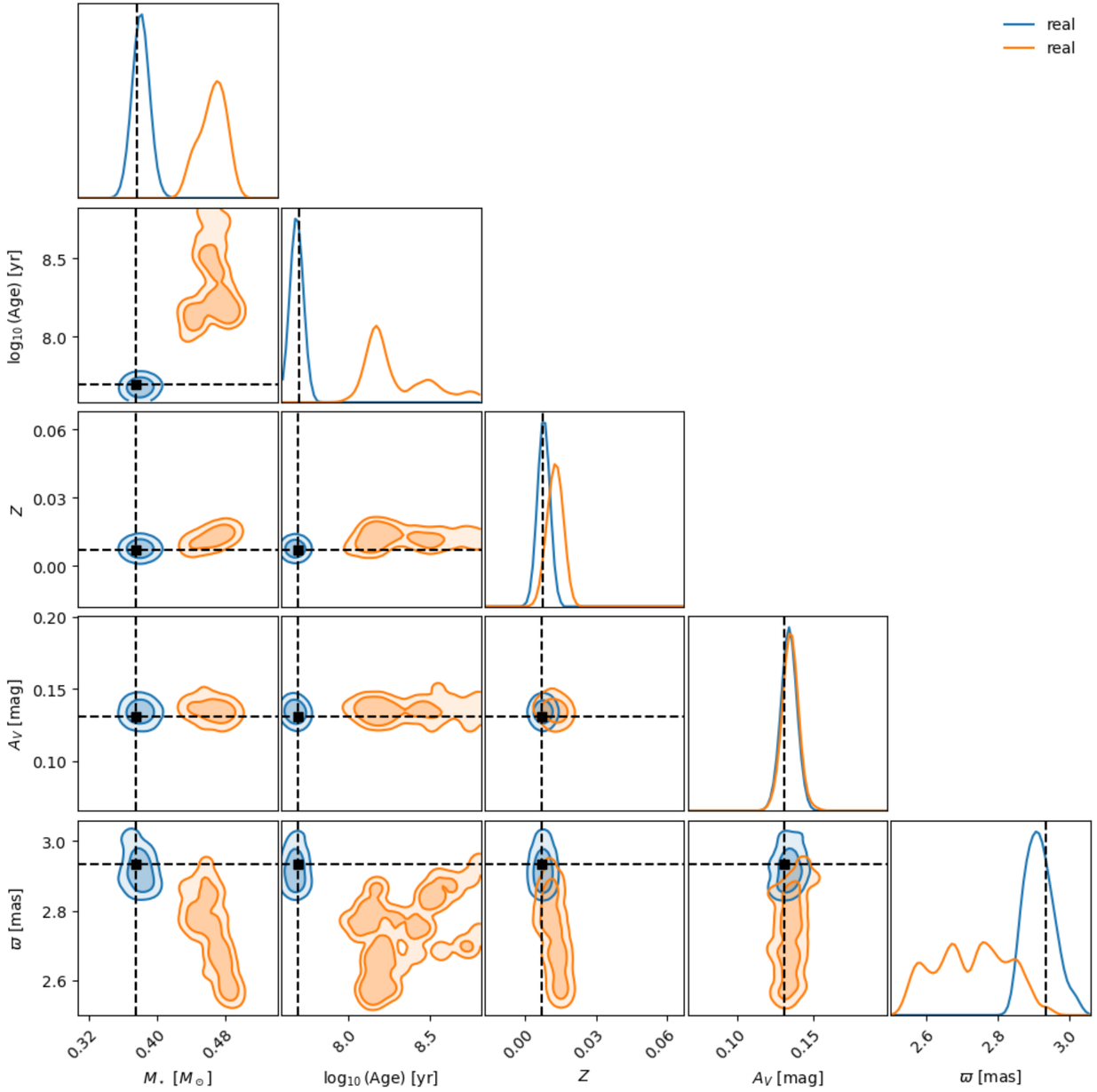


Posterior mean **sim**

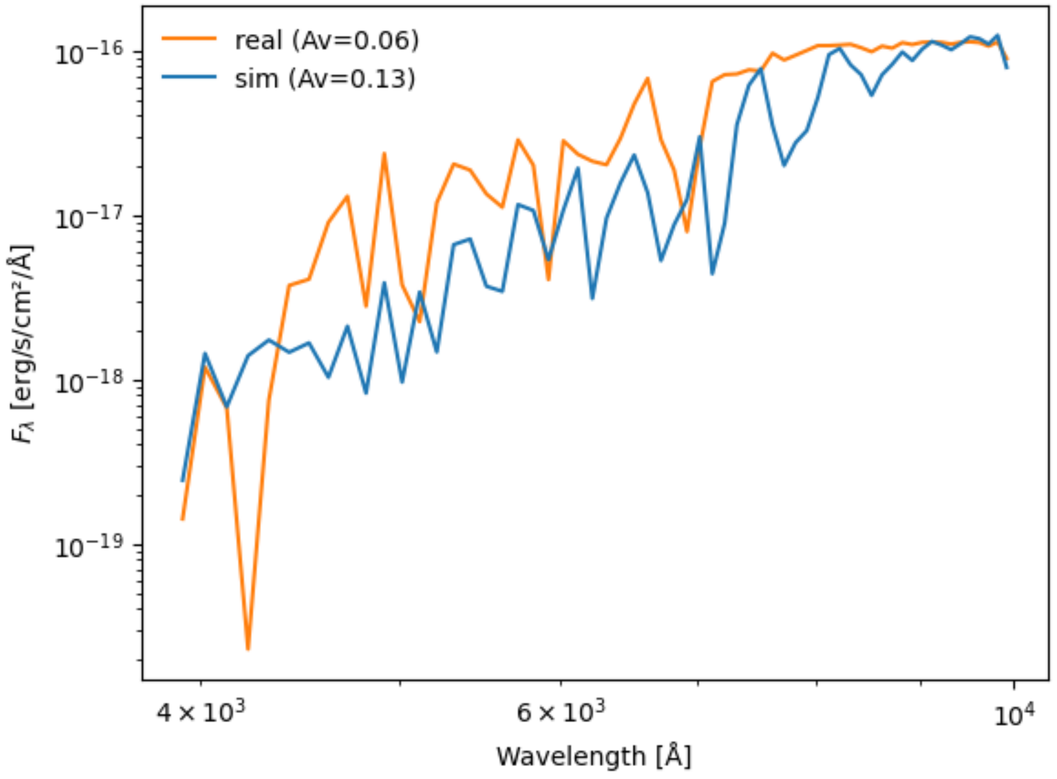


Without DA


real (Av=0.06)
sim (Av=0.13)
10^{-16}
10^{-17}
10^{-18}
10^{-19}
F_λ [erg/s/cm²/Å]
4×10^3
6×10^3
10^4
Wavelength [Å]


real
real
$\log_{10}$(Age) [yr]
8.5
8.0
Z
0.06
0.03
0.00
A_V [mag]
0.20
0.15
0.10
ϖ [mas]
3.0
2.8
2.6
0.32
0.40
0.48
$M_\star$ [$M_\odot$]
8.0
8.5
$\log_{10}$(Age) [yr]
0.00
0.03
0.06
Z
0.10
0.15
A_V [mag]
2.6
2.8
3.0
ϖ [mas]

With DA


real (Av=0.06)
sim (Av=0.13)
10^{-16}
10^{-17}
10^{-18}
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F_λ [erg/s/cm²/Å]
4×10^3
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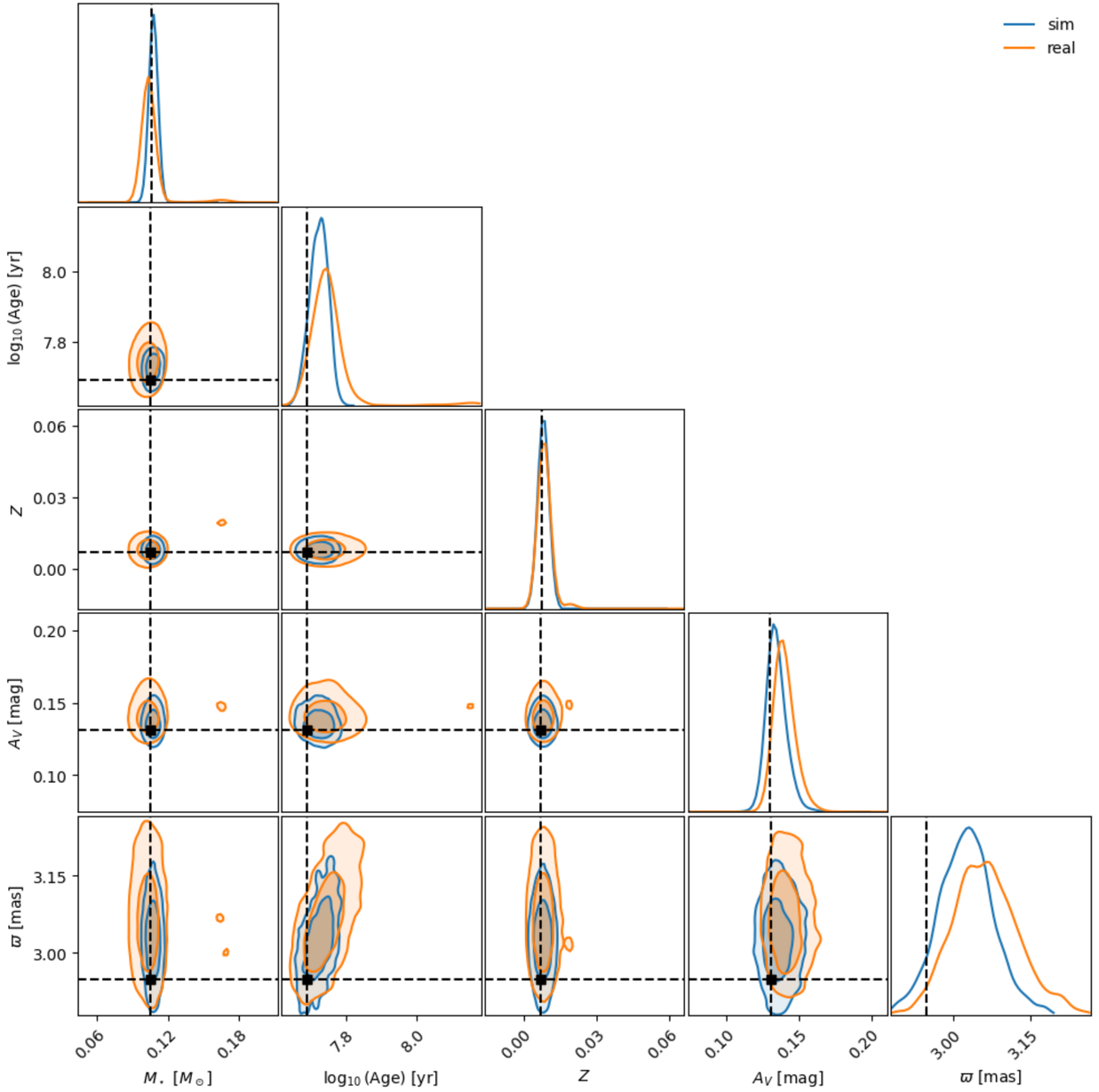
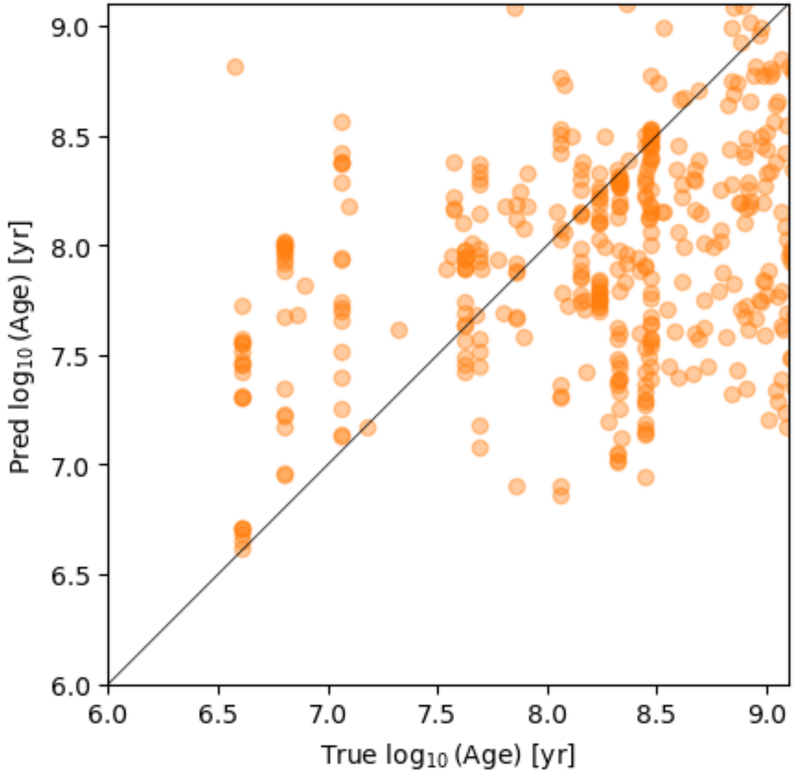
10^4
Wavelength [Å]


sim
real
$\log_{10}$(Age) [yr]
8.0
7.8
Z
0.06
0.03
0.00
A_V [mag]
0.20
0.15
0.10
ϖ [mas]
3.15
3.00
0.06
0.12
0.18
$M_\star$ [$M_\odot$]
7.8
8.0
$\log_{10}$(Age) [yr]
0.00
0.03
0.06
Z
0.10
0.15
0.20
A_V [mag]
3.00
3.15
ϖ [mas]

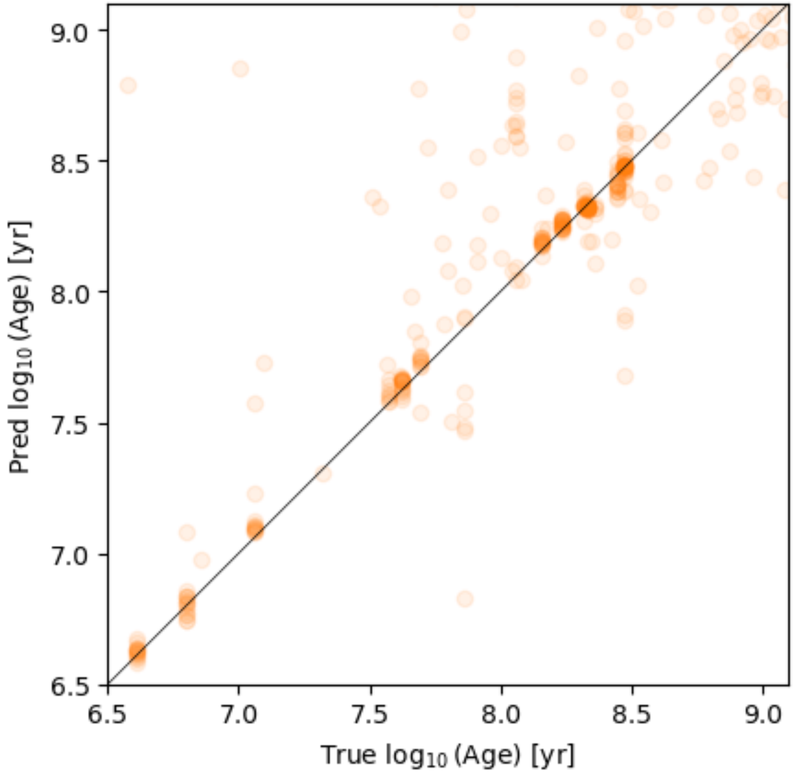
Predictions

Posterior mean **real**



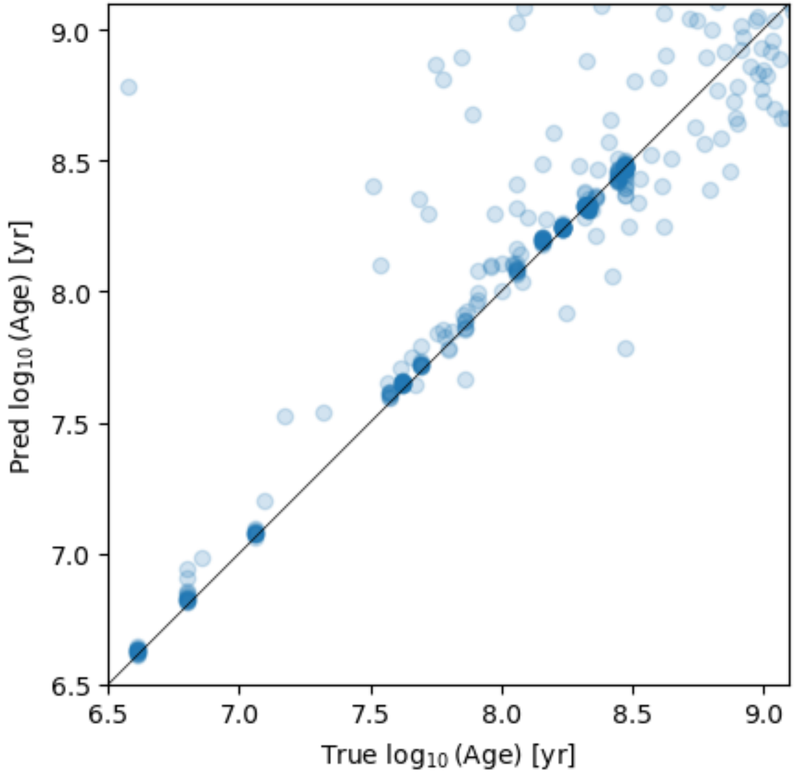
no domain adaption

Posterior mean **real**



with domain adaption

Posterior mean **sim**



Summary

- Combine **diffusion models** + **transformer model** to learn arbitrary **conditionals** and **marginals**
- Add OT + pair + contrastive loss to close domain gap
- Obtain promising results on simulations

Thank you!

Backup

Quick recap

Score based diffusion models

Langevin dynamics

Rossky, Doll & Friedman (1978)

Besag (1994)

Roberts & Tweedie (1996)

$$\mathbf{x}_{t+1} = \mathbf{x}_t + \epsilon \nabla_{\mathbf{x}} \log p(\mathbf{x}) + \sqrt{2\epsilon}\, \mathcal{N}(0, I_d)$$

…MCMC method that samples from $p(\mathbf{x})$

Langevin dynamics

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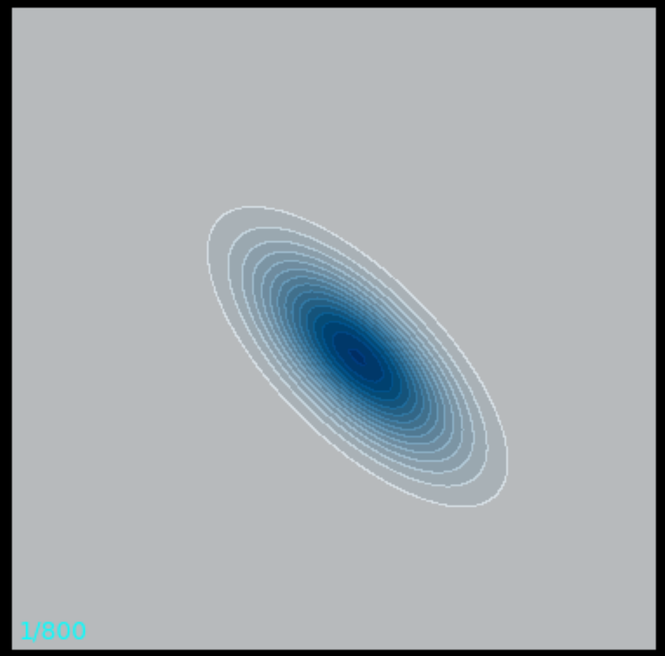

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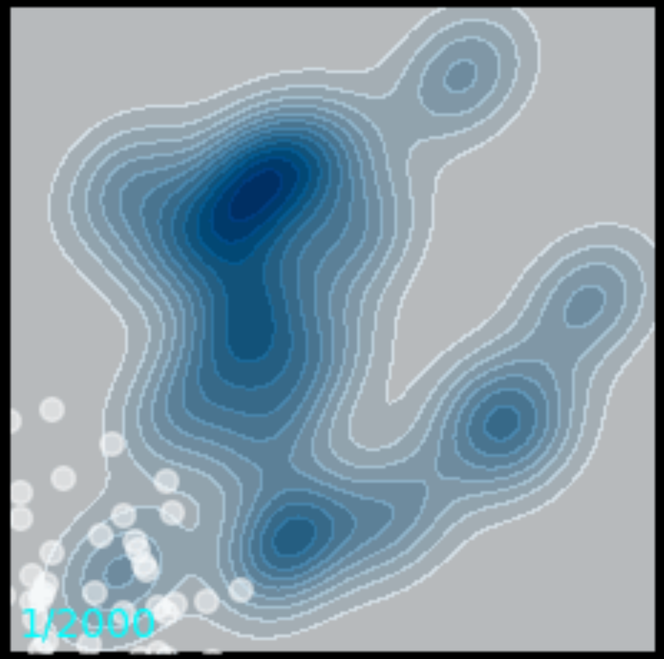

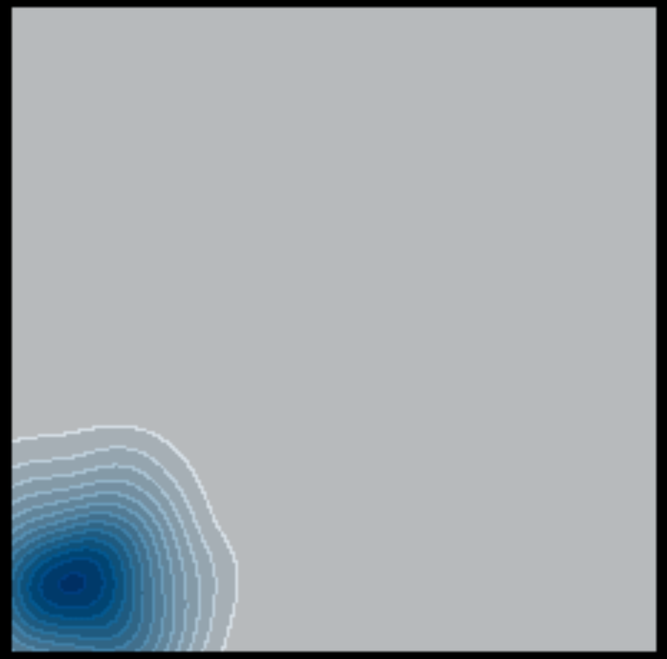

Langevin dynamics requires score

$$\mathbf{x}_{t+1} = \mathbf{x}_t + \epsilon \nabla_{\mathbf{x}} \log p(\mathbf{x}) + \sqrt{2\epsilon}\, \mathcal{N}(0, I_d)$$

…MCMC method that samples from $p(\mathbf{x})$

Would like to learn this

$$\mathcal{L} = \mathbb{E}_{p(\mathbf{x})}[\,||\, s_\phi(\mathbf{x}) - \nabla \log p(\mathbf{x}) \,||_2^2]$$

Problem 1: don't have access to $p(\mathbf{x})$

Estimating the score

$$\mathscr{L} = \mathbb{E}_{p(\mathbf{x})}[\,||\,s_\phi(\mathbf{x}) - \nabla \log p(\mathbf{x})\,||_2^2]$$

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Vincent (2010) "*A Connection Between Score Matching and Denoising Autoencoders*"

$$\mathscr{L} = \mathbb{E}_{\mathbf{x}\sim p(\mathbf{x}),\, \tilde{\mathbf{x}}\sim p_\sigma(\tilde{\mathbf{x}}|\mathbf{x})}[\,||\,s_\phi(\tilde{\mathbf{x}}) - \nabla_{\tilde{x}} \log p_\sigma(\tilde{\mathbf{x}}\,|\,\mathbf{x})\,||_2^2]$$

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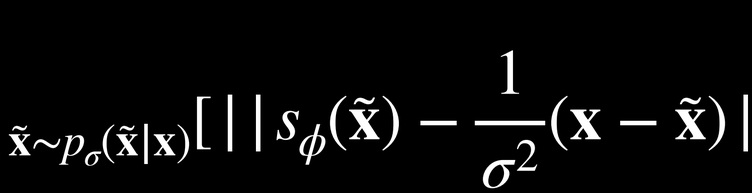

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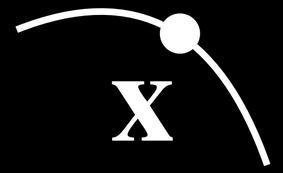

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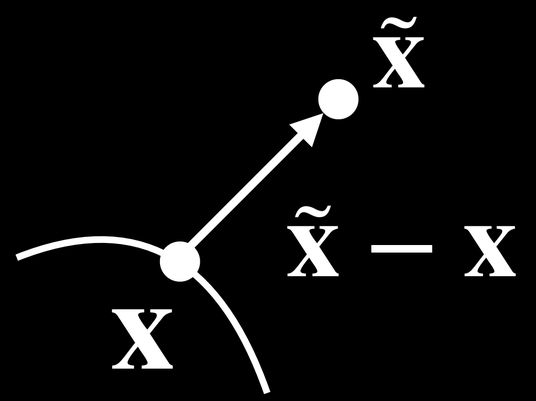

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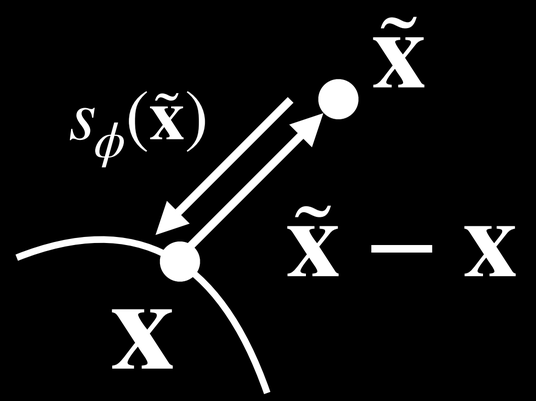

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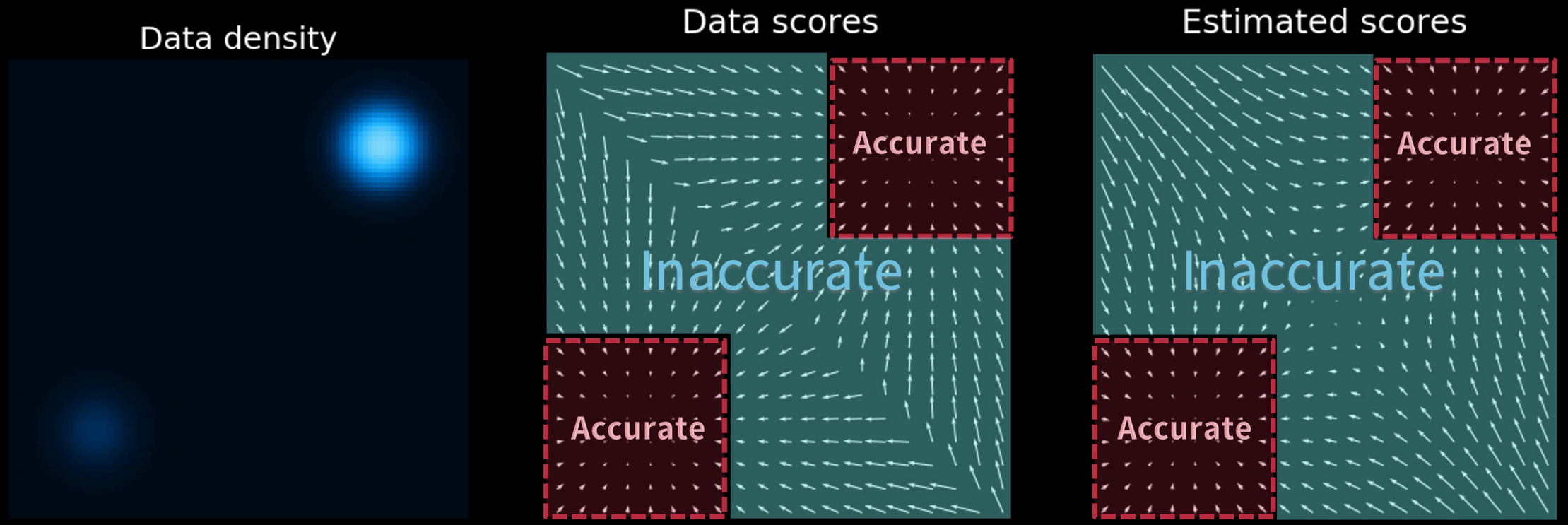
Training score models

Problem 2: low coverage of data space → inaccurate score



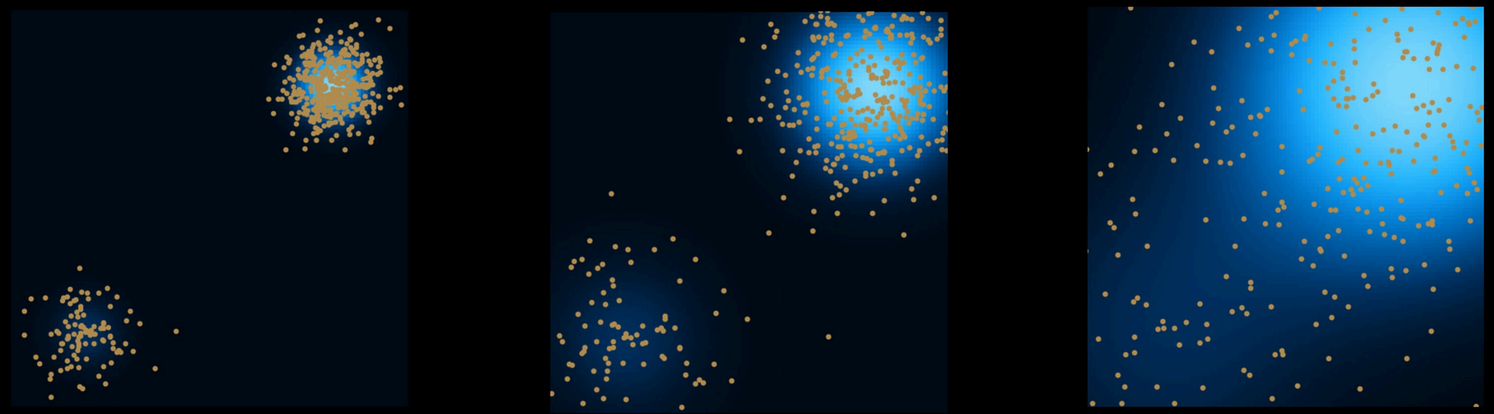
Training score models: multiple noise levels

Fix: add gradual noise

$$p_t(\tilde{\mathbf{x}} \mid \mathbf{x}) = \mathcal{N}(\tilde{x} \mid \mu_t(x), \sigma_t(x))$$

$$\mathscr{L} = \mathbb{E}_{\mathbf{x}\sim p(\mathbf{x}),\, \tilde{\mathbf{x}}\sim p_t(\tilde{\mathbf{x}}|\mathbf{x}),t\sim\mathcal{U}(0,1)}[\,||\, s_\phi(\tilde{\mathbf{x}}, t) - \nabla_{\tilde{x}} \log p_t(\tilde{\mathbf{x}} \mid \mathbf{x})\,||_2^2]$$

$\sigma_1 < \sigma_2 < \sigma_3$



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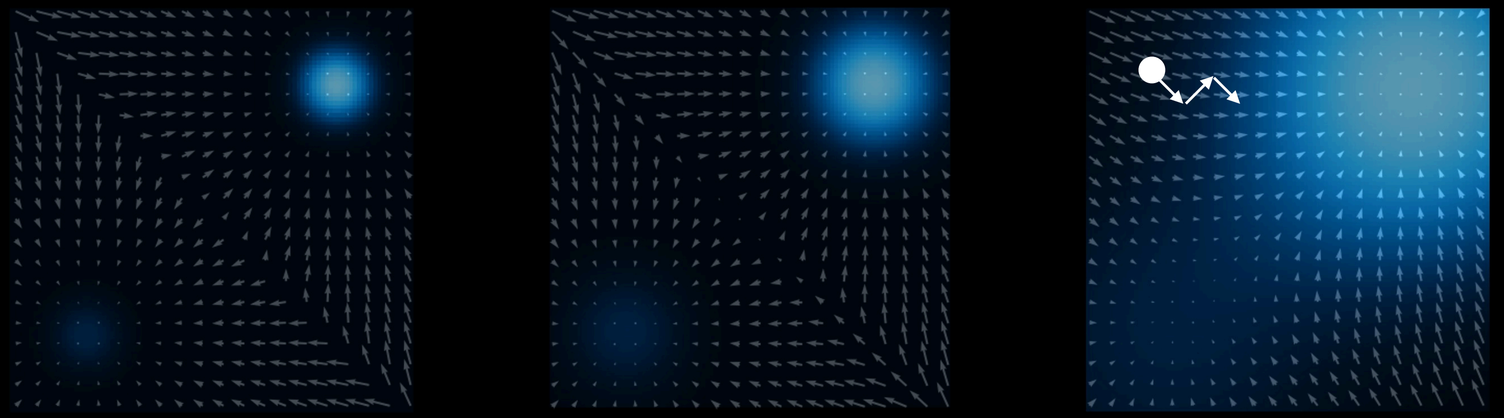

Sampling via **annealed** Langevin dynamics

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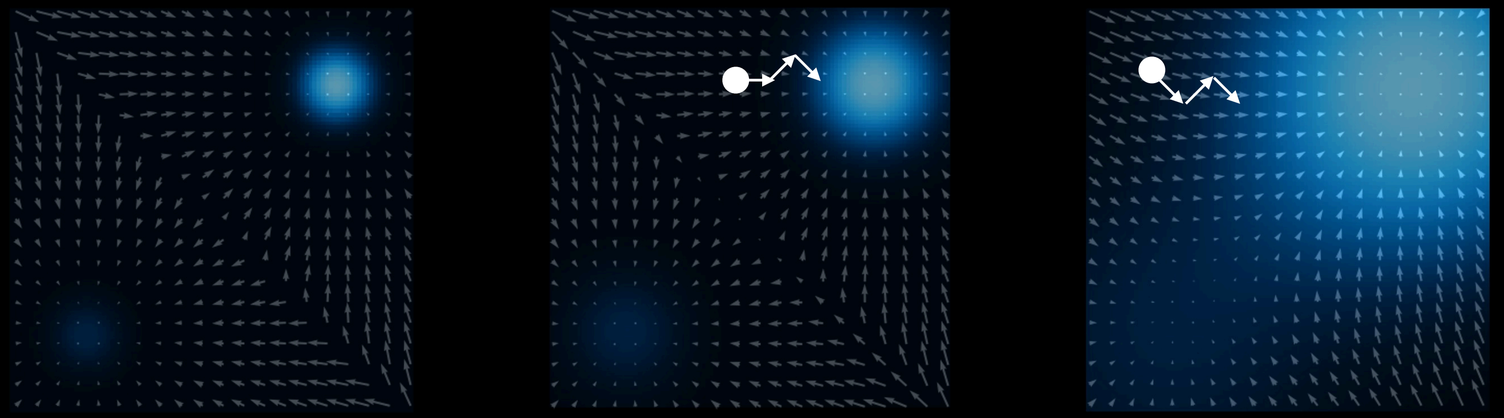

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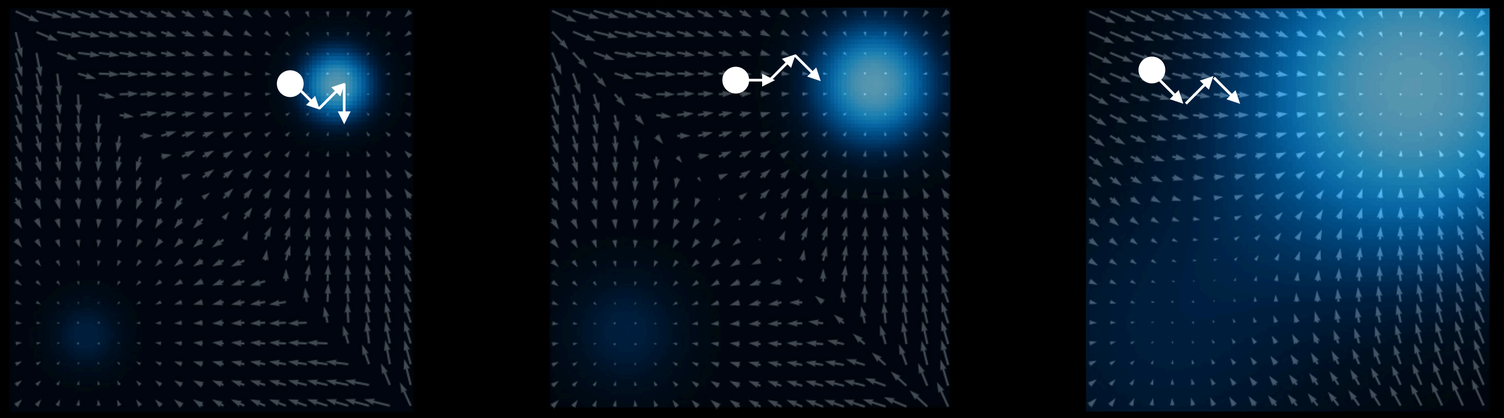


Sampling via **annealed** Langevin dynamics

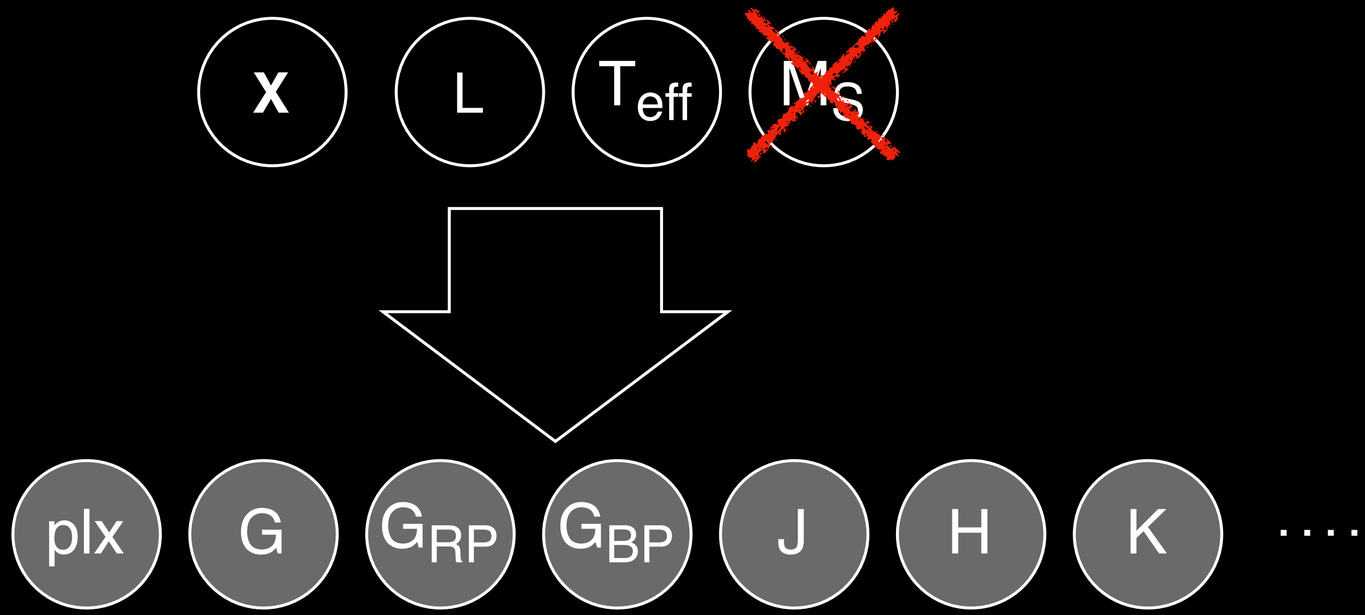
YSO models

Fwd model: YSO (Robitaille17+Richardson+24)

- Mass not input parameter
  - Unlink to evo. tracks

  ➡ logg = 4

  ➡ Small impact for $T_{\rm eff} \in [3,20]$ kK
- Low resolution (R~15)



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➡ Small impact for $T_{\rm eff} \in [3,20]$ kK

- Low resolution (R~15)
- Introduces many additional parameters

Parameter	Symbol	Minimum	Maximum	Sampling
Stellar radius	$R_\star$	$0.1\,R_\odot$	$100\,R_\odot$	Log
Stellar temperature	$T_\star$	2000 K	30 000 K	Log
Disk mass [dust]	$M_{\rm disk}$	$10^{-8}\,M_\odot$	$0.1\,M_\odot$	Log
Disk inner radius	$R_{\rm min}^{\rm disk}$	$R_{\rm sub}$	$1000\,R_{\rm sub}$	Log
Disk outer radius	$R_{\rm max}^{\rm disk}$	50 AU	5000 AU	Log
Disk flaring power	β	1	1.3	Linear
Disk surface density power	p	−2	0	Linear
Disk scaleheight	$h_{100\rm AU}$	1 AU	20 AU	Log
Envelope density [dust]	$\rho_0^{\rm env}$	10^{-24} g/cm^3	10^{-16} g/cm^3	Log
Envelope density power	γ	−2	−1	Linear
Envelope centrifugal radius	$R_{\rm c}$	50 AU	5000 AU	Log
Cavity density [dust]	$\rho_0^{\rm cav}$	10^{-23} g/cm^3	10^{-20} g/cm^3	Log
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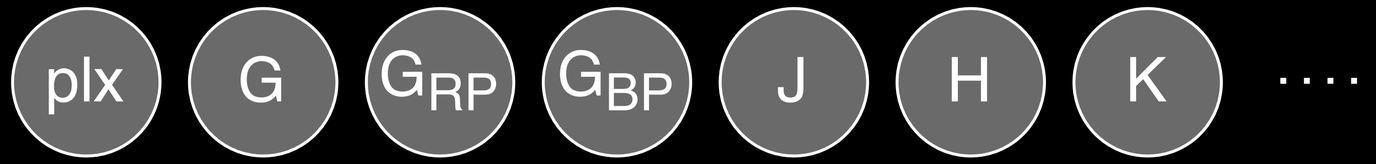

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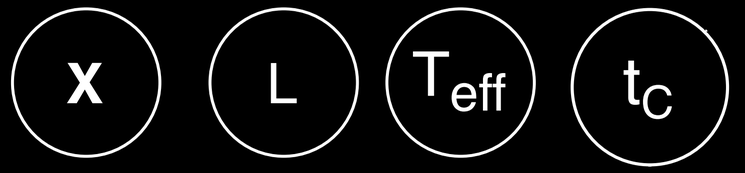

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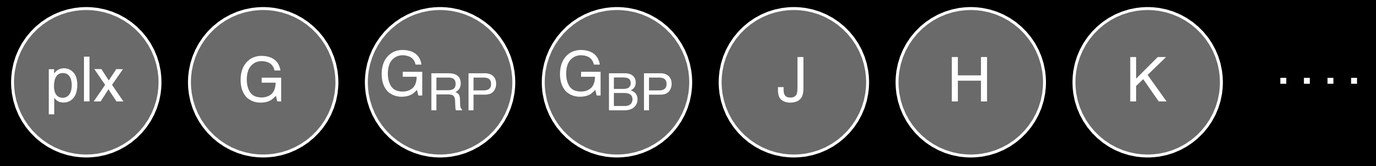

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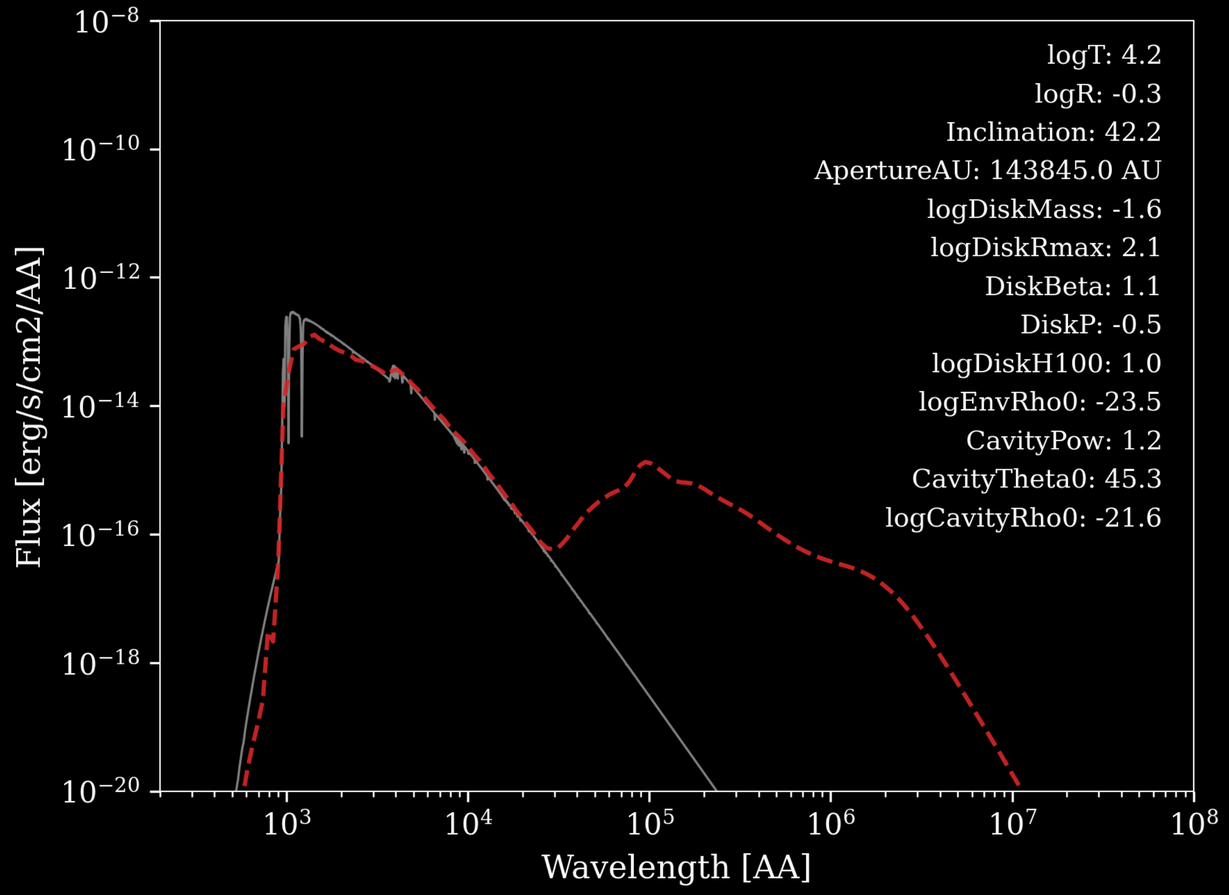

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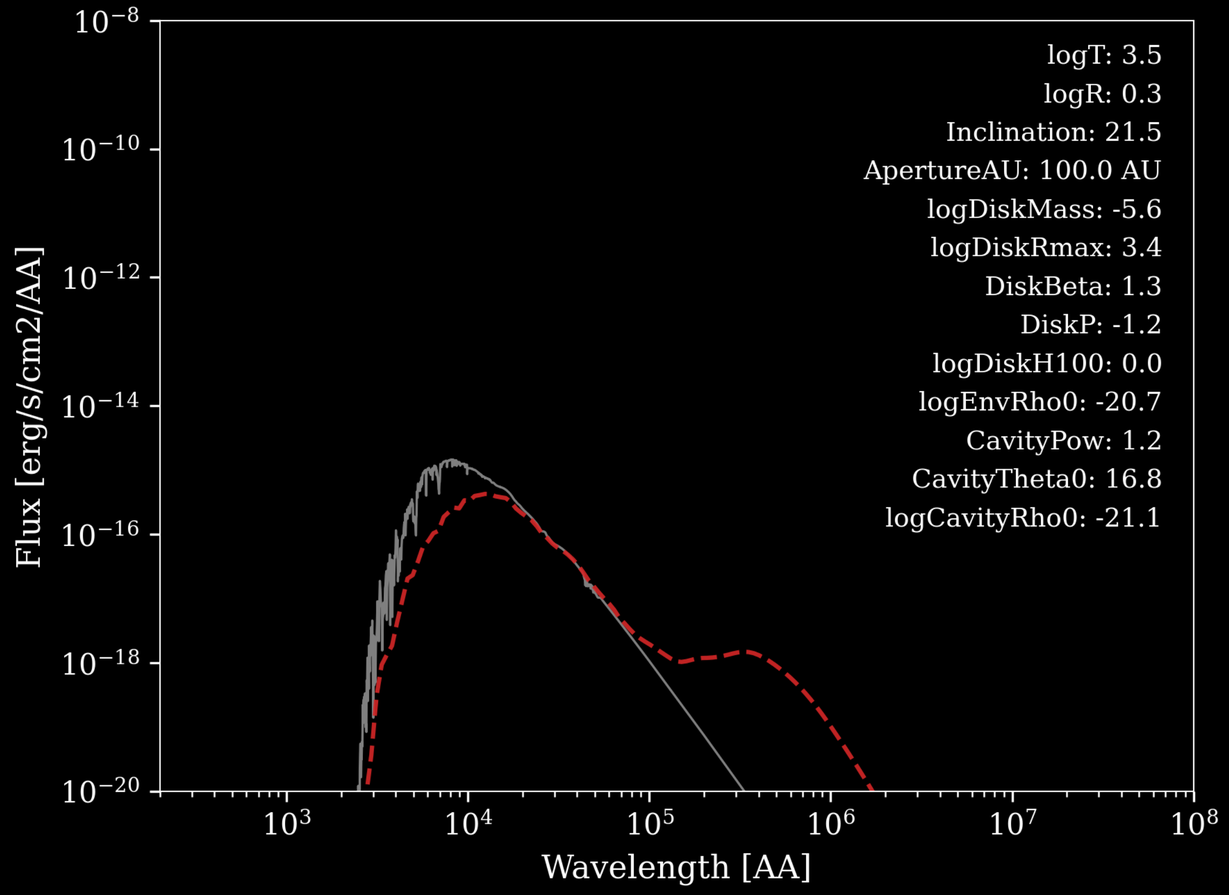

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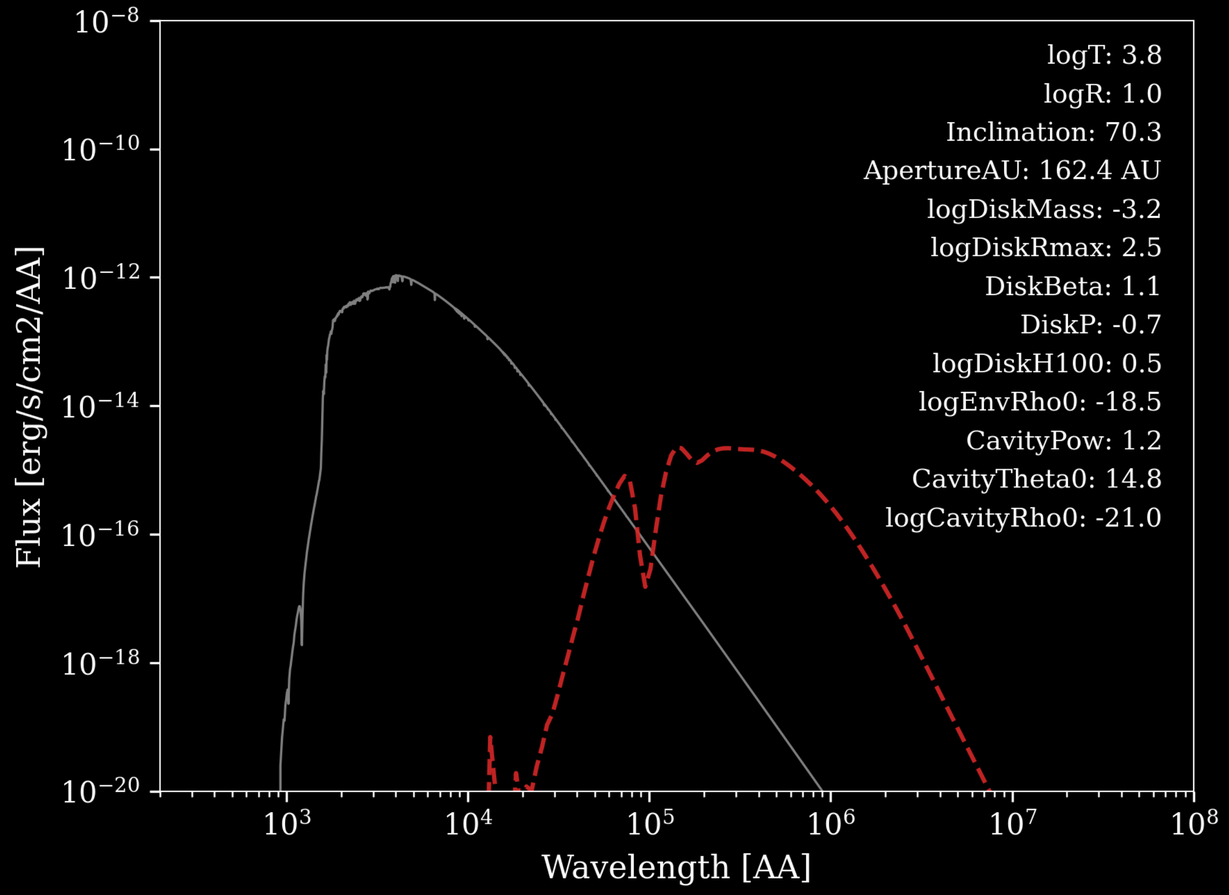

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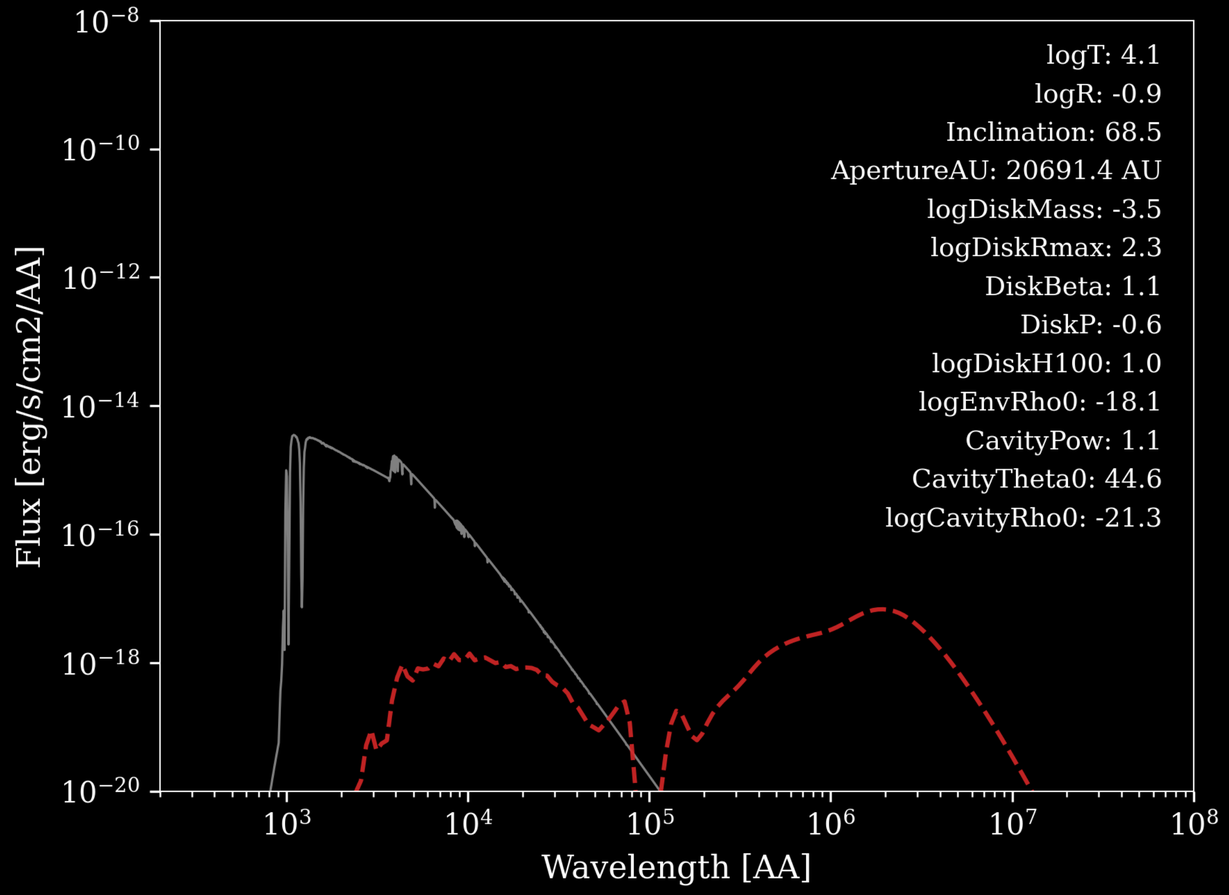
Disk scaleheight	$h_{100\rm AU}$	1 AU	20 AU	Log
Envelope density [dust]	$\rho_0^{\rm env}$	10^{-24} g/cm^3	10^{-16} g/cm^3	Log
Envelope density power	γ	-2	-1	Linear
Envelope centrifugal radius	$R_{\rm c}$	50 AU	5000 AU	Log
Cavity density [dust]	$\rho_0^{\rm cav}$	10^{-23} g/cm^3	10^{-20} g/cm^3	Log
Cavity opening angle	θ_0	0°	60°	Linear
Cavity power	c	1	2	Linear

Fwd model: YSO (Robitaille17+Richardson+24)



Parameter	Symbol	Minimum	Maximum	Sampling
Stellar radius	$R_\star$	$0.1\,R_\odot$	$100\,R_\odot$	Log
Stellar temperature	$T_\star$	2000 K	30 000 K	Log
Disk mass [dust]	$M_{\rm disk}$	$10^{-8}\,M_\odot$	$0.1\,M_\odot$	Log
Disk inner radius	$R_{\rm min}^{\rm disk}$	$R_{\rm sub}$	$1000\,R_{\rm sub}$	Log
Disk outer radius	$R_{\rm max}^{\rm disk}$	50 AU	5000 AU	Log
Disk flaring power	β	1	1.3	Linear
Disk surface density power	p	-2	0	Linear
Disk scaleheight	$h_{100\rm AU}$	1 AU	20 AU	Log
Envelope density [dust]	$\rho_0^{\rm env}$	10^{-24} g/cm^3	10^{-16} g/cm^3	Log
Envelope density power	γ	-2	-1	Linear
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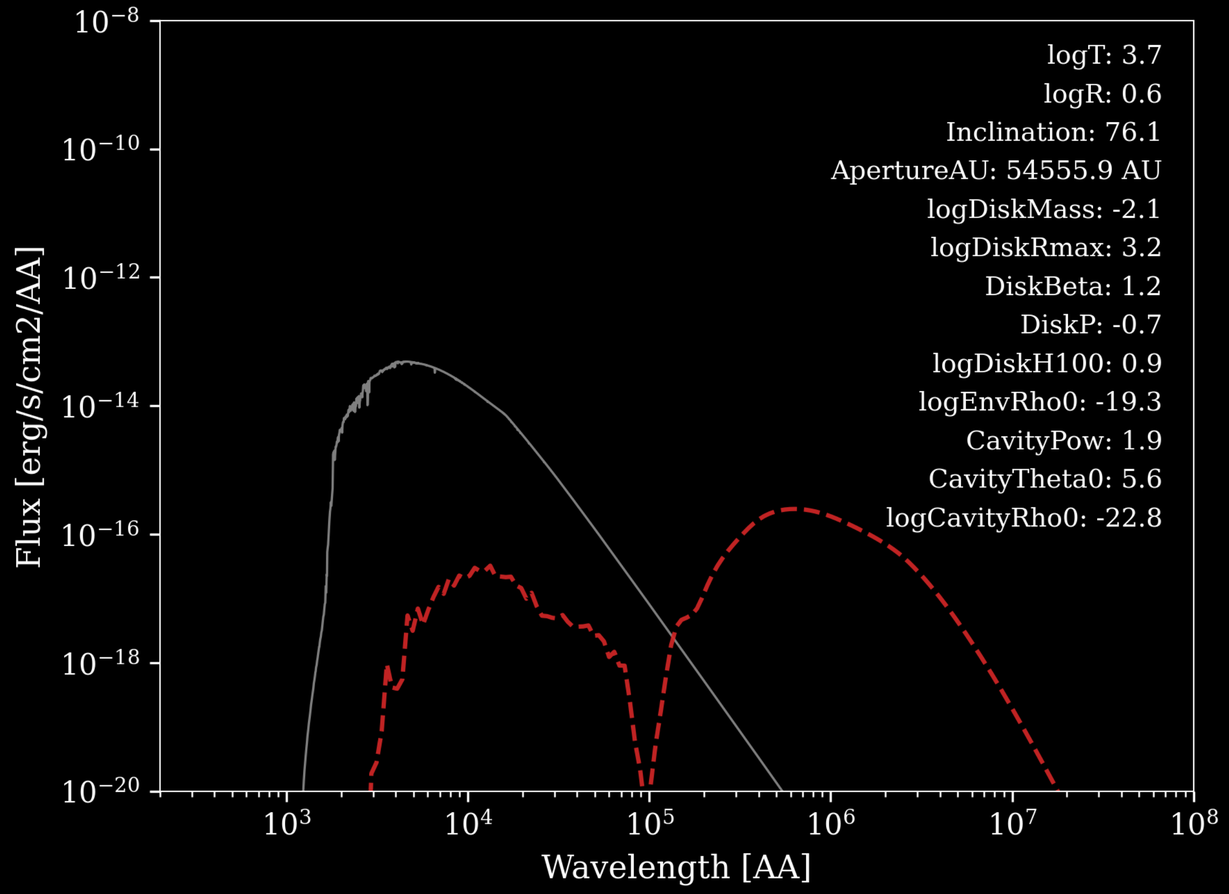
Fwd model: YSO (Robitaille17+Richardson+24)



Parameter	Symbol	Minimum	Maximum	Sampling
Stellar radius	$R_\star$	$0.1\,R_\odot$	$100\,R_\odot$	Log
Stellar temperature	$T_\star$	2000 K	30 000 K	Log
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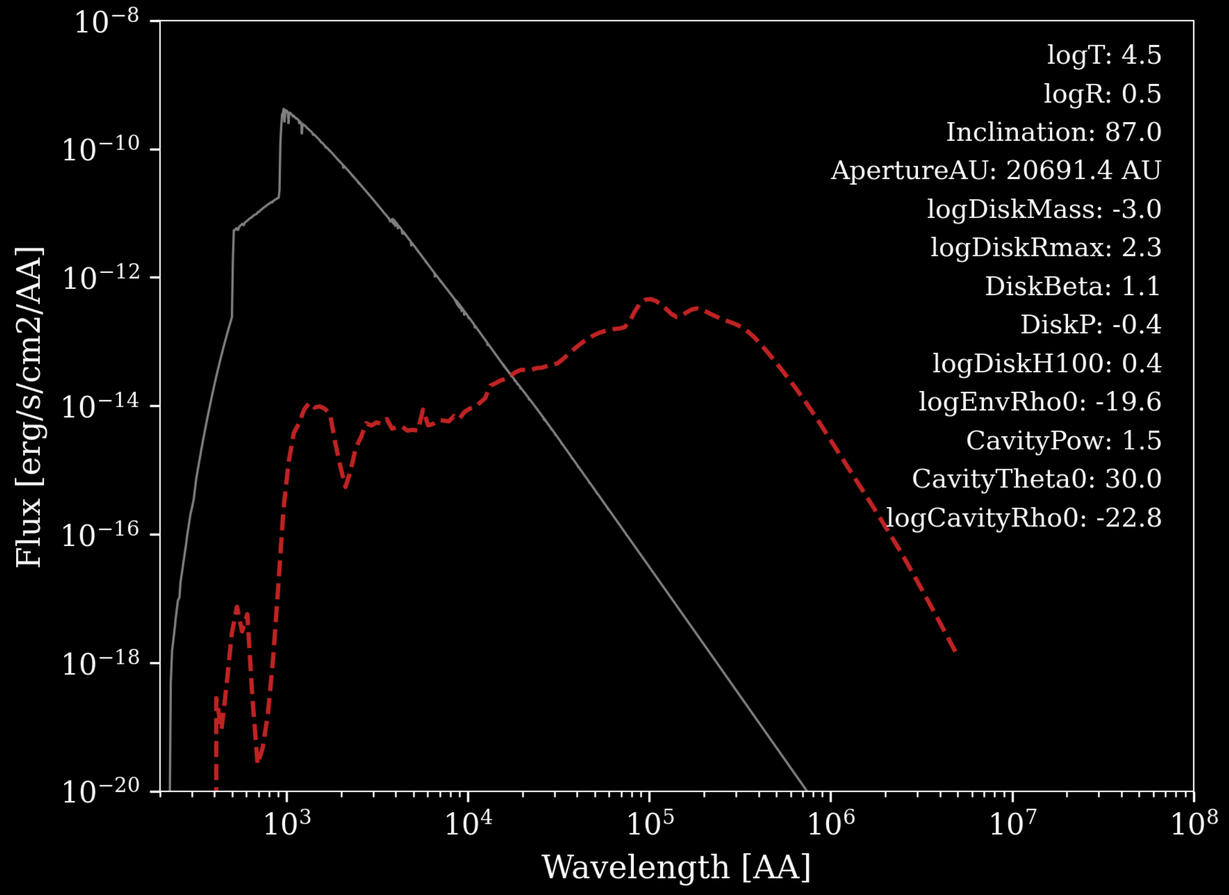
Fwd model: YSO (Robitaille17+Richardson+24)



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Stellar temperature	$T_\star$	2000 K	30 000 K	Log
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Disk outer radius	$R_{\rm max}^{\rm disk}$	50 AU	5000 AU	Log
Disk flaring power	β	1	1.3	Linear
Disk surface density power	p	-2	0	Linear
Disk scaleheight	$h_{\rm 100AU}$	1 AU	20 AU	Log
Envelope density [dust]	$\rho_0^{\rm env}$	10^{-24} g/cm^3	10^{-16} g/cm^3	Log
Envelope density power	γ	-2	-1	Linear
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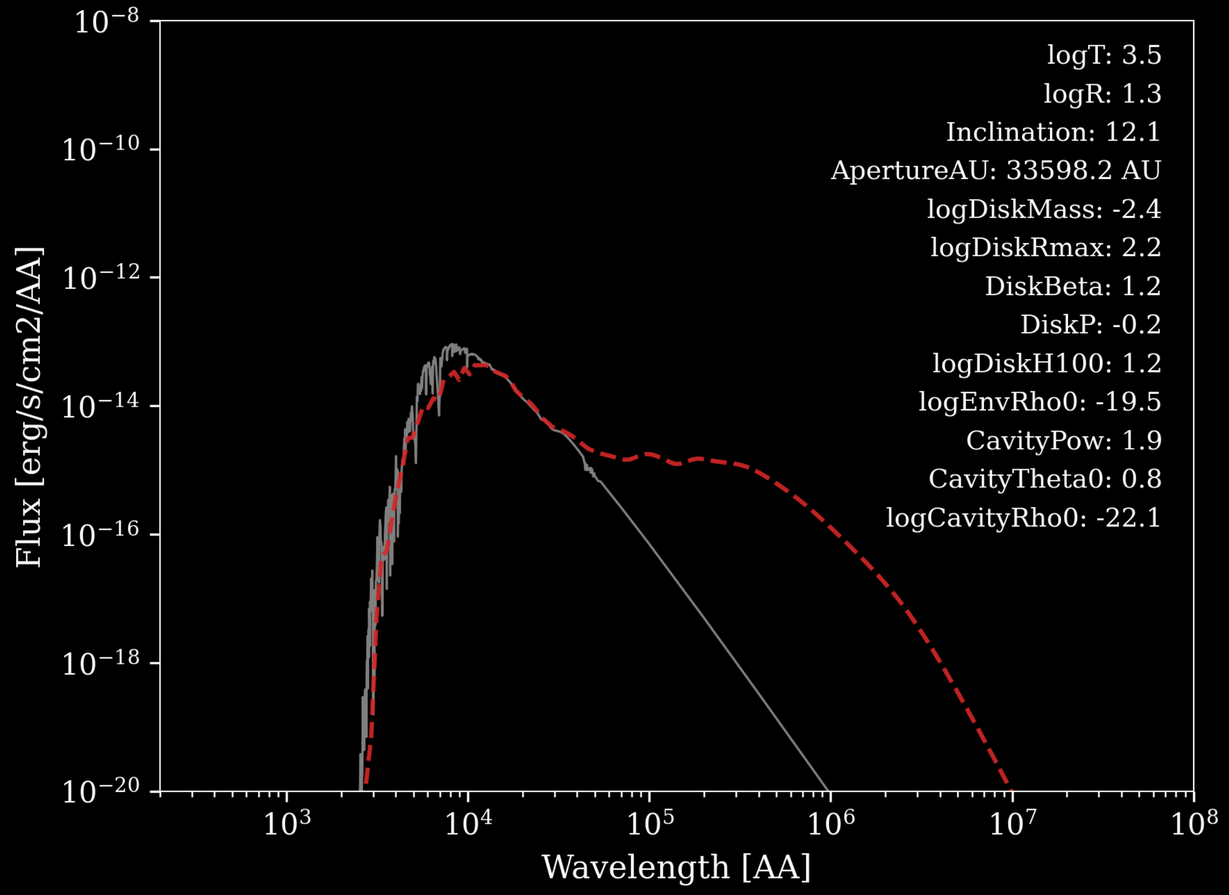
Cavity opening angle	θ_0	0°	60°	Linear
Cavity power	c	1	2	Linear

Fwd model: YSO (Robitaille17+Richardson+24)



Parameter	Symbol	Minimum	Maximum	Sampling
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Stellar temperature	$T_\star$	2000 K	30 000 K	Log
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Cavity opening angle	θ_0	0°	60°	Linear
Cavity power	c	1	2	Linear

YSO (Robitaille17+Richardson+24)

Model set	Icon	Star	Disk	Envelope	Cavity	Ambient	Inner radius	Variables	Models
`s-s-i`		yes	…	…	…	…	…	2	10 000
`sp-s-i`		yes	passive	…	…	…	$R_{\rm sub}$	7	10 000
`sp-h-i`		yes	passive	…	…	…	variable	8	10 000
`s-smi`		yes	…	…	…	yes	$R_{\rm sub}$	2	10 000
`sp-smi`		yes	passive	…	…	yes	$R_{\rm sub}$	7	10 000
`sp-hmi`		yes	passive	…	…	yes	variable	8	10 000

sp-smi		yes	passive	…	…	yes	R_{sub}	7	10 000
sp-hmi		yes	passive	…	…	yes	variable	8	10 000
s-p-smi		yes	…	power-law	…	yes	R_{sub}	4	10 000
s-p-hmi		yes	…	power-law	…	yes	variable	5	10 000
s-pbsmi		yes	…	power-law	yes	yes	R_{sub}	7	10 000
s-pbhmi		yes	…	power-law	yes	yes	variable	8	10 000
s-u-smi		yes	…	Ulrich	…	yes	R_{sub}	4	10 000
s-u-hmi		yes	…	Ulrich	…	yes	variable	5	10 000
s-ubsmi		yes	…	Ulrich	yes	yes	R_{sub}	7	10 000
s-ubhmi		yes	…	Ulrich	yes	yes	variable	8	10 000

s-pbhmi		yes	…	power-law	yes	yes	variable	8	10 000
s-u-smi		yes	…	Ulrich	…	yes	R_{sub}	4	10 000
s-u-hmi		yes	…	Ulrich	…	yes	variable	5	10 000
s-ubsmi		yes	…	Ulrich	yes	yes	R_{sub}	7	10 000
s-ubhmi		yes	…	Ulrich	yes	yes	variable	8	10 000
spu-smi		yes	passive	Ulrich	…	yes	R_{sub}	8	10 000
spu-hmi		yes	passive	Ulrich	…	yes	variable	9	10 000
spubsmi		yes	passive	Ulrich	yes	yes	R_{sub}	11	40 000
spubhmi		yes	passive	Ulrich	yes	yes	variable	12	80 000

YSO (Robitaille17+Richardson+24)

`sp-h-i`		yes	passive	…	…	…	variable	8	10 000
`s-smi`		yes	…	…	…	yes	$R_{\rm sub}$	2	10 000
`sp-hmi`		yes	passive	…	…	yes	variable	8	10 000
`spubhmi`		yes	passive	Ulrich	yes	yes	variable	12	80 000

Model implementation

II. Learning to condition and marginalize

Conditional properties: 3D example

$\ell(\phi, M_C, \mathbf{x}) = (1 - M_C) \times (s_\phi(\mathbf{x}) - \nabla \log p(\mathbf{x}))$ $\mathbf{x} = (x, y, z)$ $M_C = (0,0,1)$

Conditional properties: 3D example

$$\ell(\phi, M_C, \mathbf{x}) = (1 - M_C) \times (s_\phi(\mathbf{x}) - \nabla \log p(\mathbf{x}))$$

$\mathbf{x} = (x, y, z)$ $M_C = (0,0,1)$

$$\log p(x, y, z) = \log p(x, y \mid z) + \log p(z)$$

Conditional properties: 3D example

$$\ell(\phi, M_C, \mathbf{x}) = (1 - M_C) \times (s_\phi(\mathbf{x}) - \nabla \log p(\mathbf{x}))$$

$\mathbf{x} = (x, y, z)$ $M_C = (0,0,1)$

$$\log p(x, y, z) = \log p(x, y \mid z) + \log p(z)$$

$$\nabla \log p(x, y, z) = \nabla \log p(x, y \mid z) + \nabla \log p(z)$$

Conditional properties: 3D example

$$\ell(\phi, M_C, \mathbf{x}) = (1 - M_C) \times (s_\phi(\mathbf{x}) - \nabla \log p(\mathbf{x}))$$

$\mathbf{x} = (x, y, z)$ $M_C = (0,0,1)$

$$\log p(x, y, z) = \log p(x, y \mid z) + \log p(z)$$

$$\nabla \log p(x, y, z) = \nabla \log p(x, y \mid z) + \nabla \log p(z)$$

$$\nabla_{x,y} \log p(x, y \mid z) + \nabla_{x,y} \log p(z) = \nabla_{x,y} \log p(x, y \mid z)$$

Conditional properties: 3D example

$\ell(\phi, M_C, \mathbf{x}) = (1 - M_C) \times (s_\phi(\mathbf{x}) - \nabla \log p(\mathbf{x}))$ $\quad \mathbf{x} = (x, y, z) \quad M_C = (0,0,1)$

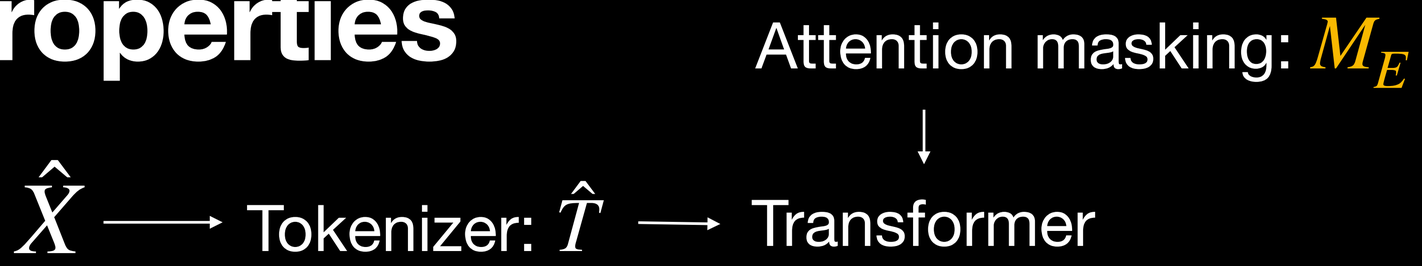
$\log p(x, y, z) = \log p(x, y \mid z) + \log p(z)$

$\nabla \log p(x, y, z) = \nabla \log p(x, y \mid z) + \nabla \log p(z)$

$\nabla_{x,y} \log p(x, y \mid z) + \nabla_{x,y} \log p(z) = \nabla_{x,y} \log p(x, y \mid z)$

$\nabla_z \log p(x, y \mid z) + \nabla_z \log p(z) \leftarrow$ Is set to 0 due to $(1 - M_C)$ in ℓ

Marginalization properties



Marginalization properties

Attention masking: M_E

$\downarrow$

$\hat{X} \longrightarrow$ Tokenizer: $\hat{T} \longrightarrow$ Transformer

$$\hat{T} \in (N, D_{\hat{X}}, E) \rightarrow S \propto QK^T \in (N, D_{\hat{X}}, D_{\hat{X}})$$

$$\text{softmax}(S + M_E)\, V\, P \in (N, D_{\hat{X}})$$

$$M_E = \begin{pmatrix} 0 & 0 & -\infty \\ 0 & 0 & -\infty \\ -\infty & -\infty & 0 \end{pmatrix} \longrightarrow s_\phi^{M_E}(\hat{x}^{M_C}) = \begin{pmatrix} f(x,y) \\ f(x,y) \\ f(z) \end{pmatrix}$$

Marginalization properties

Attention masking: M_E

$\downarrow$

$\hat{X} \longrightarrow$ Tokenizer: $\hat{T} \longrightarrow$ Transformer

$$\hat{T} \in (N, D_{\hat{X}}, E) \rightarrow S \propto QK^T \in (N, D_{\hat{X}}, D_{\hat{X}})$$

$$\text{softmax}(S + M_E)\, VP \in (N, D_{\hat{X}})$$

$$M_E = \begin{pmatrix} 0 & 0 & -\infty \\ 0 & 0 & -\infty \\ -\infty & -\infty & 0 \end{pmatrix} \longrightarrow s_\phi^{M_E}(\hat{x}^{M_C}) = \begin{pmatrix} f(x,y) \\ f(x,y) \\ f(z) \end{pmatrix}$$

$$\ell(\phi, M_C, t, \hat{\mathbf{x}}_0, \hat{\mathbf{x}}_t) = (1 - M_C) \cdot \left(s_\phi^{M_E}(\hat{\mathbf{x}}_t^{M_C}, t) - \nabla_{\hat{\mathbf{x}}_t} \log p_t(\hat{\mathbf{x}}_t | \hat{\mathbf{x}}_0) \right) \propto \begin{pmatrix} f(x,y) - \Delta x \\ f(x,y) - \Delta y \\ f(z) - \Delta z \end{pmatrix}$$

$$\propto \hat{x}_0 - \hat{x}_t$$

$$\hat{x}_t \sim p_t(\hat{x}_t \,|\, \hat{x}_0) = \mathcal{N}(\mu_t(\hat{x}_0), \sigma_t(\hat{x}_0))$$

Marginalization properties

$$\ell(\phi, M_C, t, \hat{\mathbf{x}}_0, \hat{\mathbf{x}}_t) = (1 - M_C) \cdot \left(s_\phi^{M_E}(\hat{\mathbf{x}}_t^{M_C}, t) - \nabla_{\hat{\mathbf{x}}_t} \log p_t(\hat{\mathbf{x}}_t | \hat{\mathbf{x}}_0) \right) \propto \begin{pmatrix} f(x,y) - \Delta x \\ f(x,y) - \Delta y \\ f(z) - \Delta z \end{pmatrix}$$

$$\propto \hat{x}_0 - \hat{x}_t$$

$$\mathscr{L} \propto (f(x,y) - \Delta x)^2 + (f(x,y) - \Delta y)^2 + (f(z) - \Delta z)^2$$

Marginalization properties

$$\ell(\phi, M_C, t, \hat{\mathbf{x}}_0, \hat{\mathbf{x}}_t) = (1 - M_C) \cdot \left(s_\phi^{M_E}(\hat{\mathbf{x}}_t^{M_C}, t) - \nabla_{\hat{\mathbf{x}}_t} \log p_t(\hat{\mathbf{x}}_t | \hat{\mathbf{x}}_0) \right) \propto \begin{pmatrix} f(x,y) - \Delta x \\ f(x,y) - \Delta y \\ f(z) - \Delta z \end{pmatrix}$$

$$\propto \hat{x}_0 - \hat{x}_t$$

$$\mathscr{L} \propto (f(x,y) - \Delta x)^2 + (f(x,y) - \Delta y)^2 + (f(z) - \Delta z)^2 =$$

$$= \nabla \log p(x,y) + \nabla \log p(z) = \nabla \log p(x,y)p(z)$$