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Conditional Variational Autoencoders for the analysis of the Gaia spectrophotometric data of pre-main sequence stars

This work is being carried out by the Extended Stellar Parametrizer - Cool Stars (ESP-CS) group within DPAC's Coordination Unit 8 (CU8) as part of the Gaia mission.

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T Tauri stars

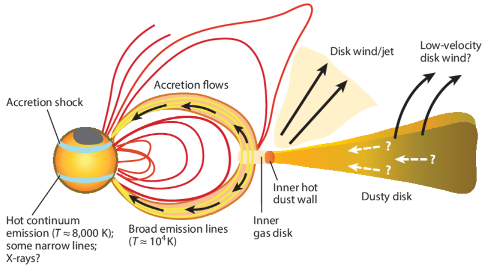

Figure 1: Magnetospheric accretion sketch for a low mass T Tauri star. From Hartmann et al. (2016).

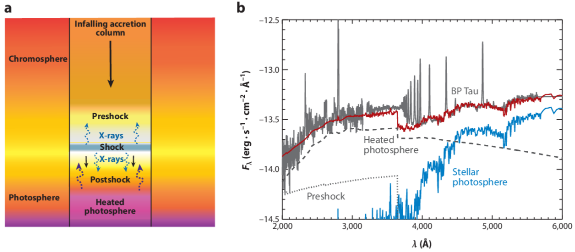

Figure 2: **a**: schematic view of an accretion column. **b**: a typical spectrum of an accreting star with the various flux contributions. From Hartmann et al. (2016)

- presence of a circumstellar disk
- magnetospheric accretion model (Hartmann 1994)
- accretion diagnostic: continuum excess

Goal: inference of stellar and accretion parameters from Gaia BP/RP spectra

Grid of $\sim$ 160 000 precomputed model BP/RP spectra parametrized by

- effective temperature, $T_{\rm eff}$: (3000, 7000) K
- surface gravity, $\log g$: (2.5, 5.0) dex
- Metallicity, $[M/H] = \log_{10}(\frac{N_{Fe}}{N_H})_{star} - \log_{10}(\frac{N_{Fe}}{N_H})_{Sun}$: (-0.5, 1.0) dex
- Mass accretion rate, $\dot{M}$: (-11, -4.52) $\log M_\odot / yr$
- filling factor, ff: (0.0, 0.3)
- Mass, M: (0.25, 1.3) $M_\odot$
- Extinction, A_0: (0.0, 10.0)

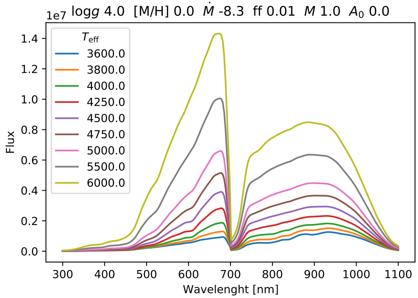

Figure 3: From Lanzafame et al. (In preparation). Gaia XP model spectra at different $T_{\rm eff}$ values.

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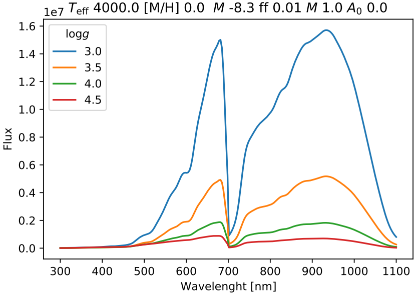

Figure 3: From Lanzafame et al. (In preparation). Gaia XP model spectra at different $\log g$ values.

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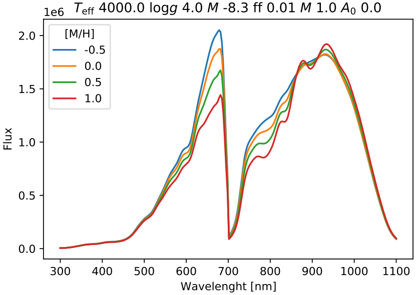

Figure 3: From Lanzafame et al. (In preparation). Gaia XP model spectra at different [M/H] values.

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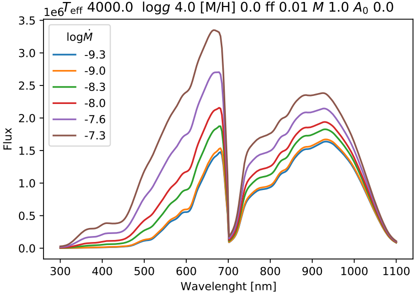

Figure 3: From Lanzafame et al. (In preparation). Gaia XP model spectra at different $\dot{M}$ values.

Goal: inference of stellar and accretion parameters from Gaia BP/RP spectra

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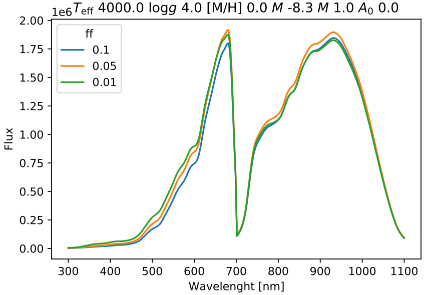

Figure 3: From Lanzafame et al. (In preparation). Gaia XP model spectra at different ff values.

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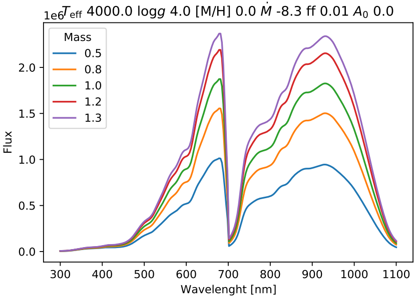

Figure 3: From Lanzafame et al. (In preparation). Gaia XP model spectra at different M values.

Goal: inference of stellar and accretion parameters from Gaia BP/RP spectra

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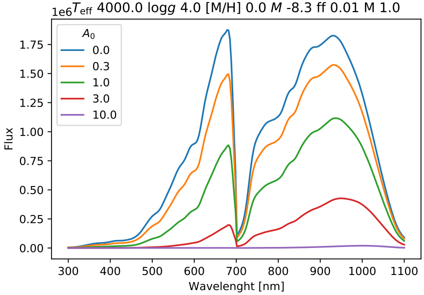


Figure 3: From Lanzafame et al. (In preparation). Gaia XP model spectra at different A_0 values.

Conditional Variational Autoencoders (CVAE)

- Autoencoders: encoder-decoder structure $\rightarrow$ compression of input data into a lower dimensional space (latent space)
- Variational: the encoder and decoder networks parametrize statistical distributions $\rightarrow$ samples from the latent space go into the decoder $\rightarrow$ range of possible reconstructed input
- Conditional: the conditional information is embedded in the encoding and decoding process

$\downarrow$

CVAE applicable to approximate the Bayesian posterior

$$p(x|y) \propto \underbrace{p(y|x)}_{likelihood}\underbrace{p(x)}_{prior}, \tag{1}$$

where

- x, stellar and accretion parameters (T_{eff}, $\log g$, [M/H], $\dot{M}$, ff, M, A_0)
- y, the BP/RP spectra

Network architecture from Gabbard et al. (2022)

Cost Function $$H(p,r) = \int dx \, \underbrace{p(x|y)}_{\text{true posterior}} \log \underbrace{r_\theta(x|y)}_{\text{parametric distribution}} \quad (2)$$

$$r_\theta(x|y) = \int dz \, \underbrace{r_{\theta_1}(z|y)}_{\text{encoder distribution}} \underbrace{r_{\theta_2}(x|y,z)}_{\text{decoder distribution}} \quad (3)$$

From (2) $\rightarrow$ Evidence Lower Bound optimization

$$\downarrow$$

$$H \lesssim \frac{1}{N} \sum_{n=1}^{N_b} \left(\underbrace{-\log r_{\theta_2}(x_n|z_n|y_n)}_{\text{reconstruction loss L}} \right) + \underbrace{KL\left(q_\phi(z|x_n, y_n)||r_{\theta_1}(z|y_n)\right)}_{\text{Kullback-Leibler (KL) divergence}} \quad (4)$$

where $q_\phi(z|x_n, y_n)$, 'recognition' encoder network

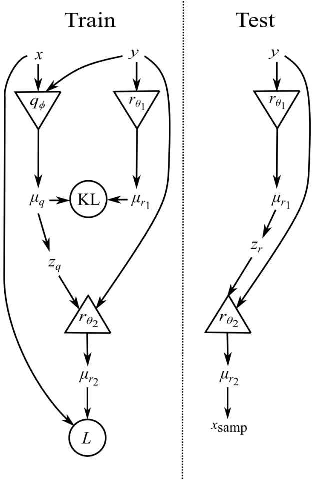
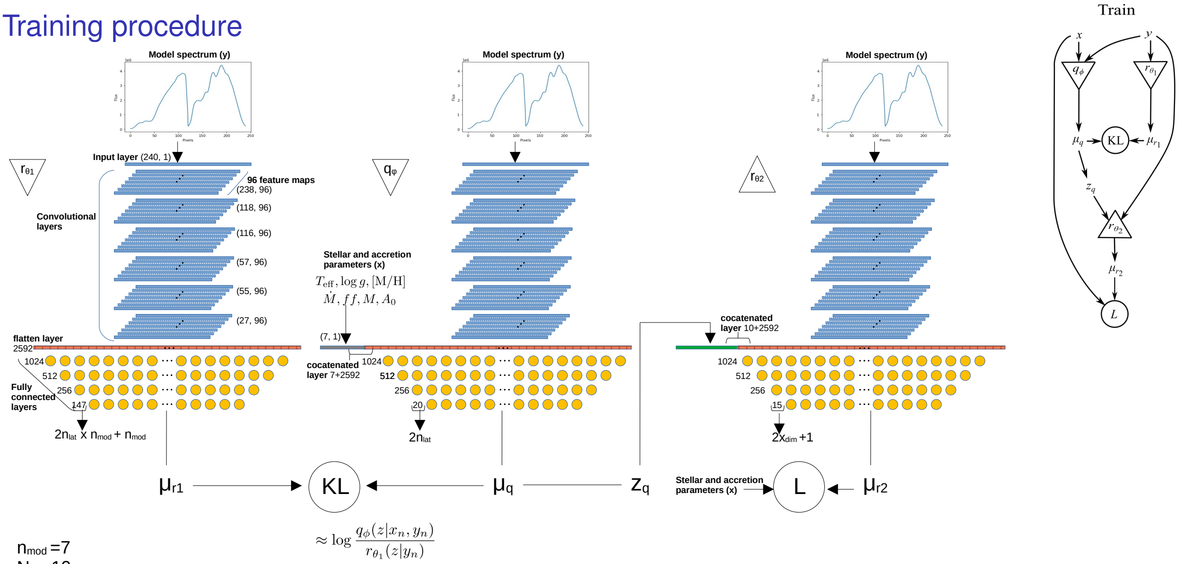


Figure 4: Network architecture. From Gabbard et al. (2022).

Training procedure



$n_{mod}=7$
$N_{lat}=10$
$x_{dim}=7$

The cost function as a function of the training epochs

- annealing procdure: KL contribution ignored for the first 50 epochs, then logarithmically increased from 0 to 1 between epoch 50 and 150.
- Adam optimizer, learning rate 10^{-5}
- Total elapsed time $\sim$ 5.5 days (HPC resources: Pleiadi Cluster, OACT)

No overfitting to the training data

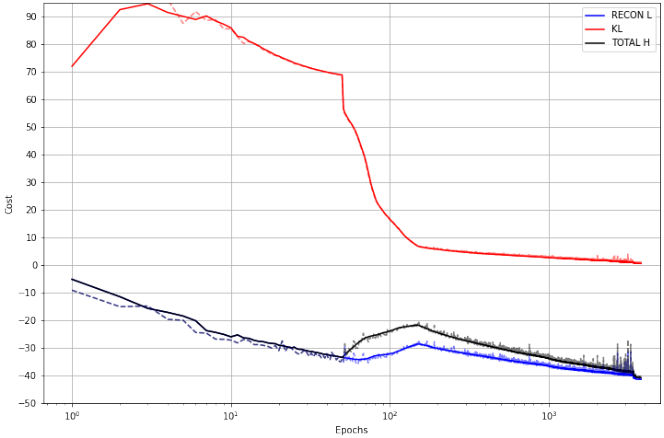
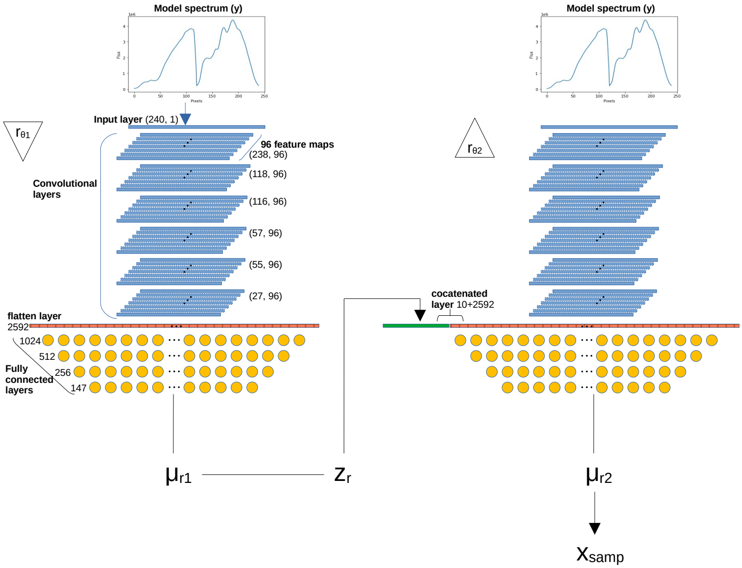
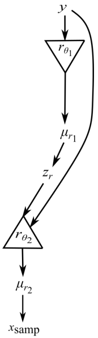


Figure 6: The total cost function H, the KL-divergence contribution and the reconstruction component L as the training proceeds.

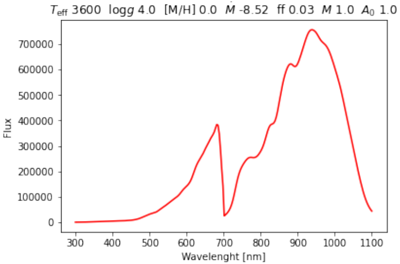
Test procedure

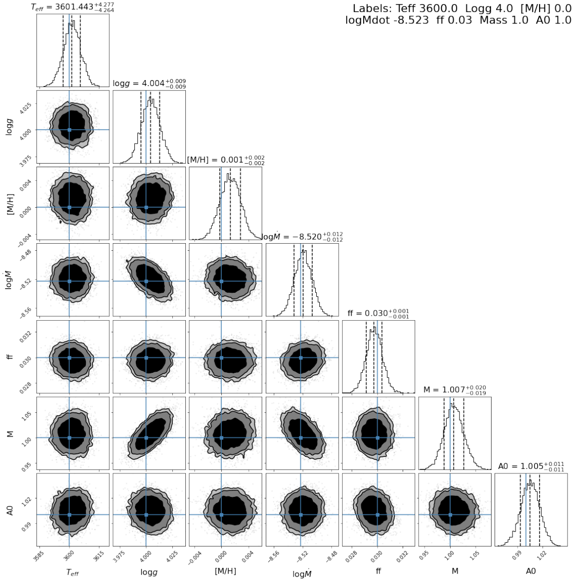


Test



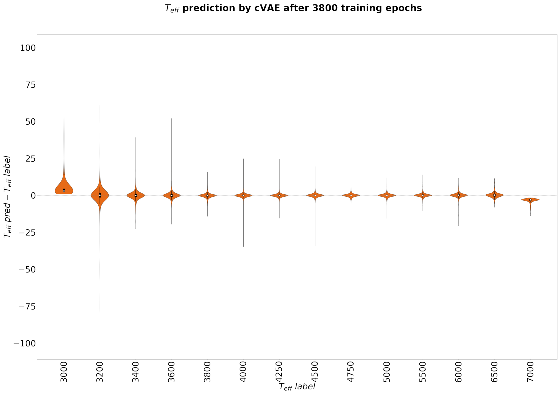
Recovering stellar and accretion parameters of a model spectrum from the test dataset

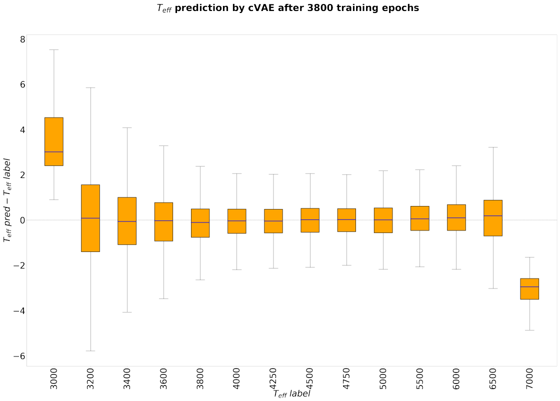




- x, stellar and accretion parameters ($T_{\rm eff}$, $\log g$, [M/H], $\dot{M}$, ff, M, A_0)
- y, the BP/RP spectra

Accuracy at recovering stellar and accretion parameters of the whole test dataset





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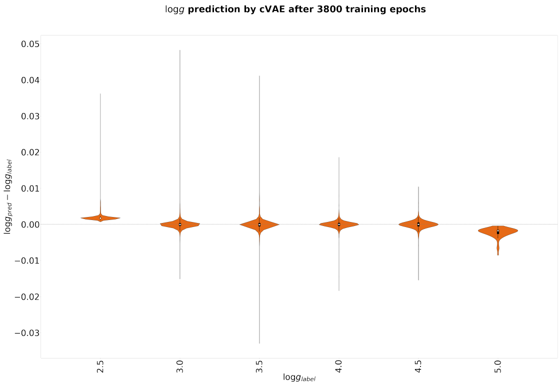

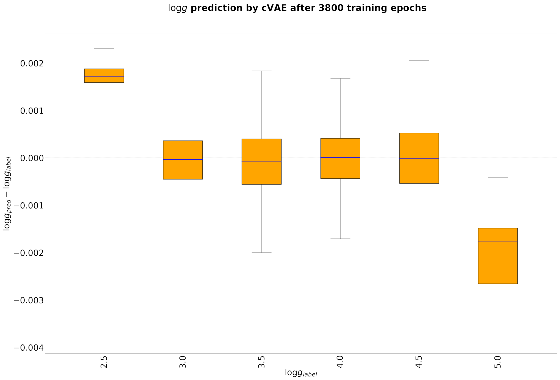

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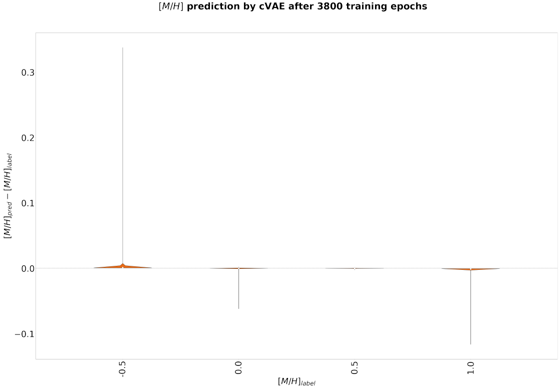

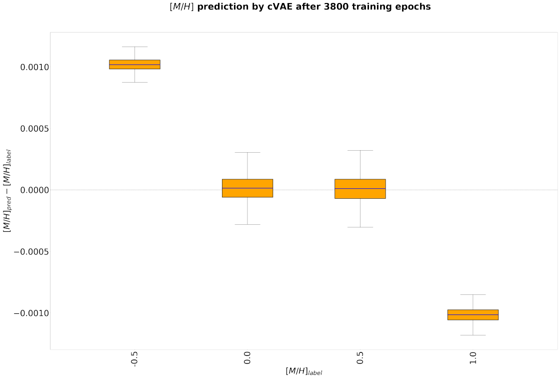

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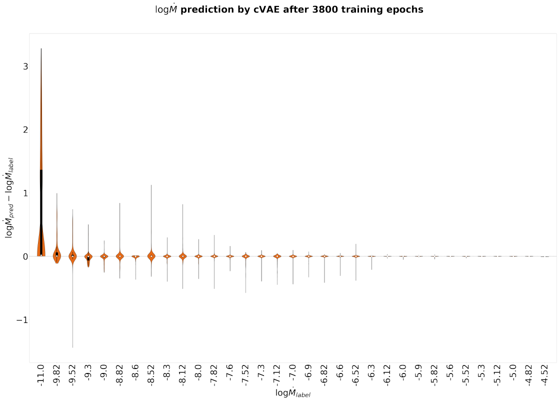

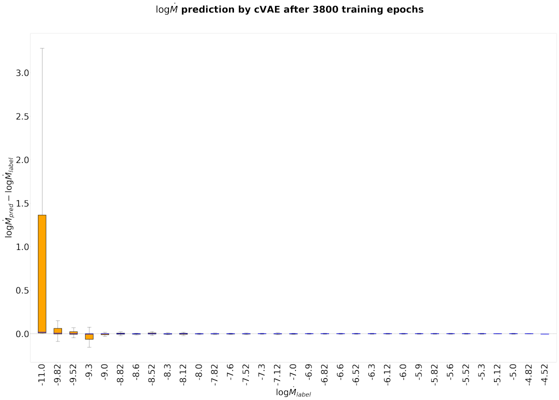

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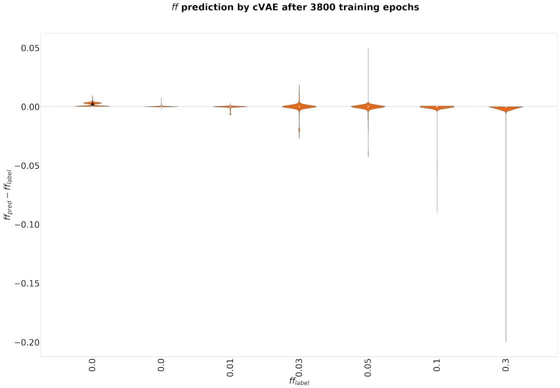

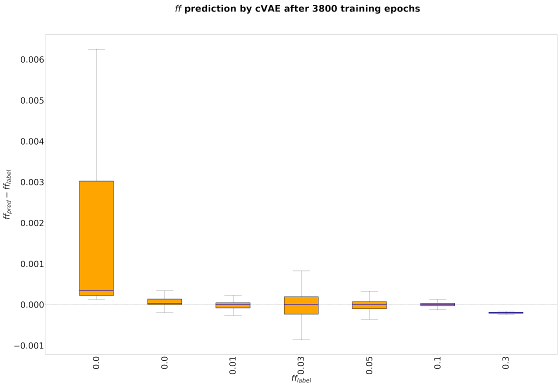

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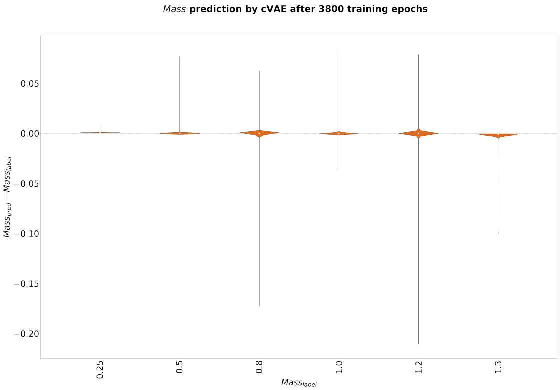

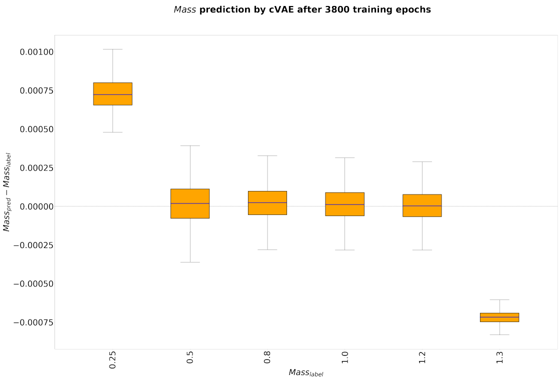

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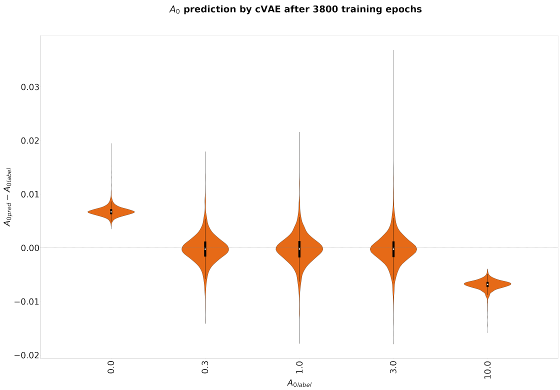
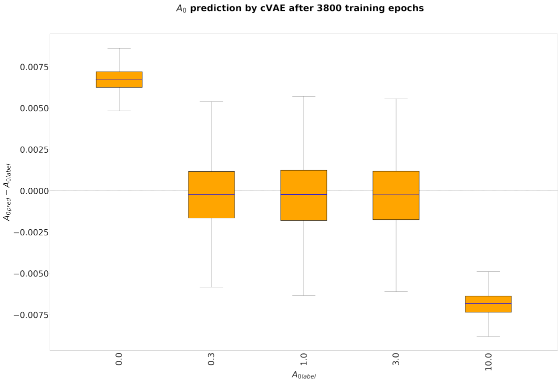
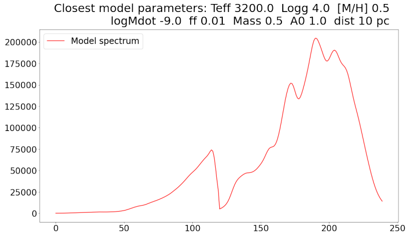
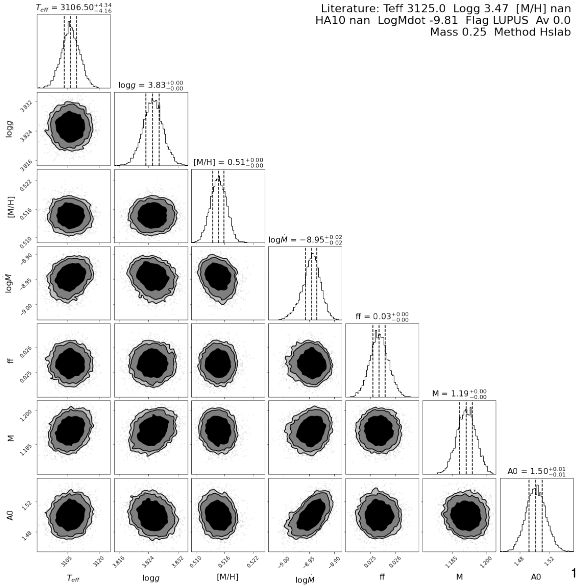




Inferring the posterior of stellar parameters of an anonymous source





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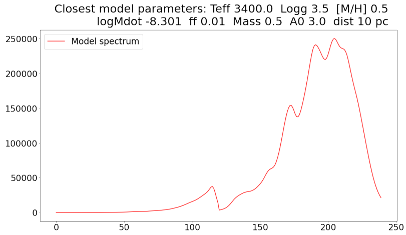
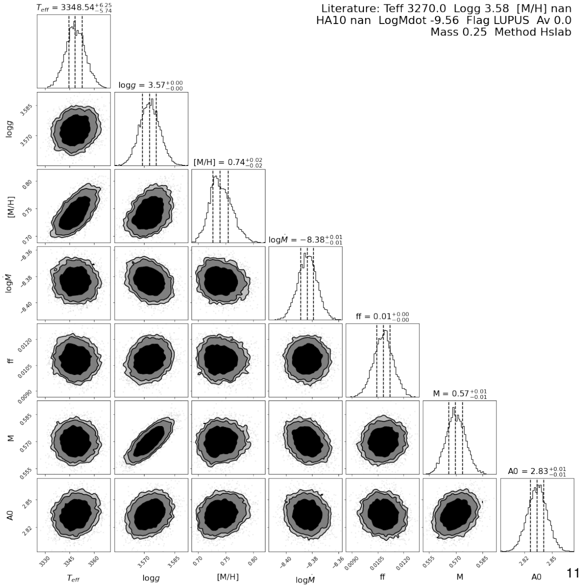
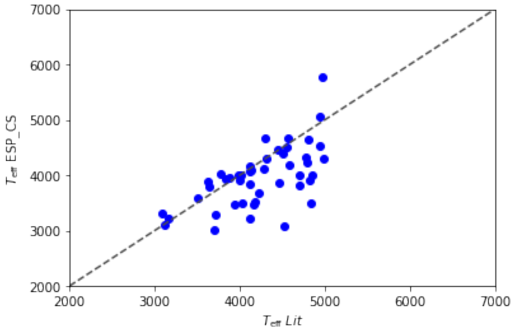
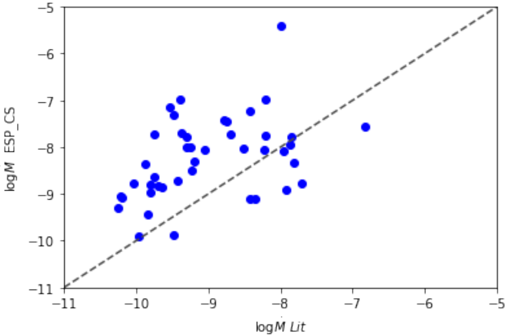




Comparison with the literature for 40 anonymous sources





Conclusions

- CVAE allow to approximate a multidimensional bayesian posterior $\rightarrow$ uncertainties on the parameters of interest
- Inference with CVAE is faster than by traditional sampling methods (0.5 s per source with Java)
- Our CVAE are not data-driven: they are conditioned on BP/RP model spectra generated by taking the magnetospheric accretion model into account. The CVAE model is good as our training set.

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Hartmann, L. 1994, in Theory of Accretion Disks — 2, ed. W. J. Duschl, J. Frank, F. Meyer, E. Meyer-Hofmeister, & W. M. Tscharnuter (Dordrecht: Springer Netherlands), 19–33

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