Constraining the XUV Luminosity Evolution of Low Mass Stars

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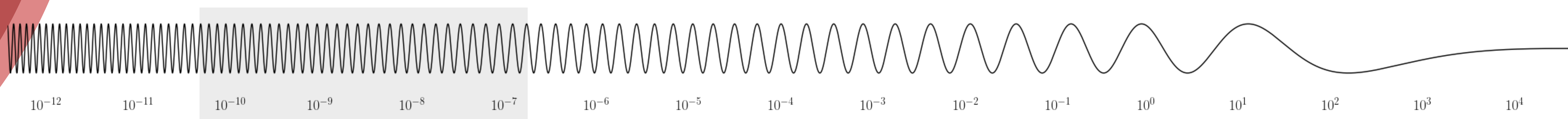
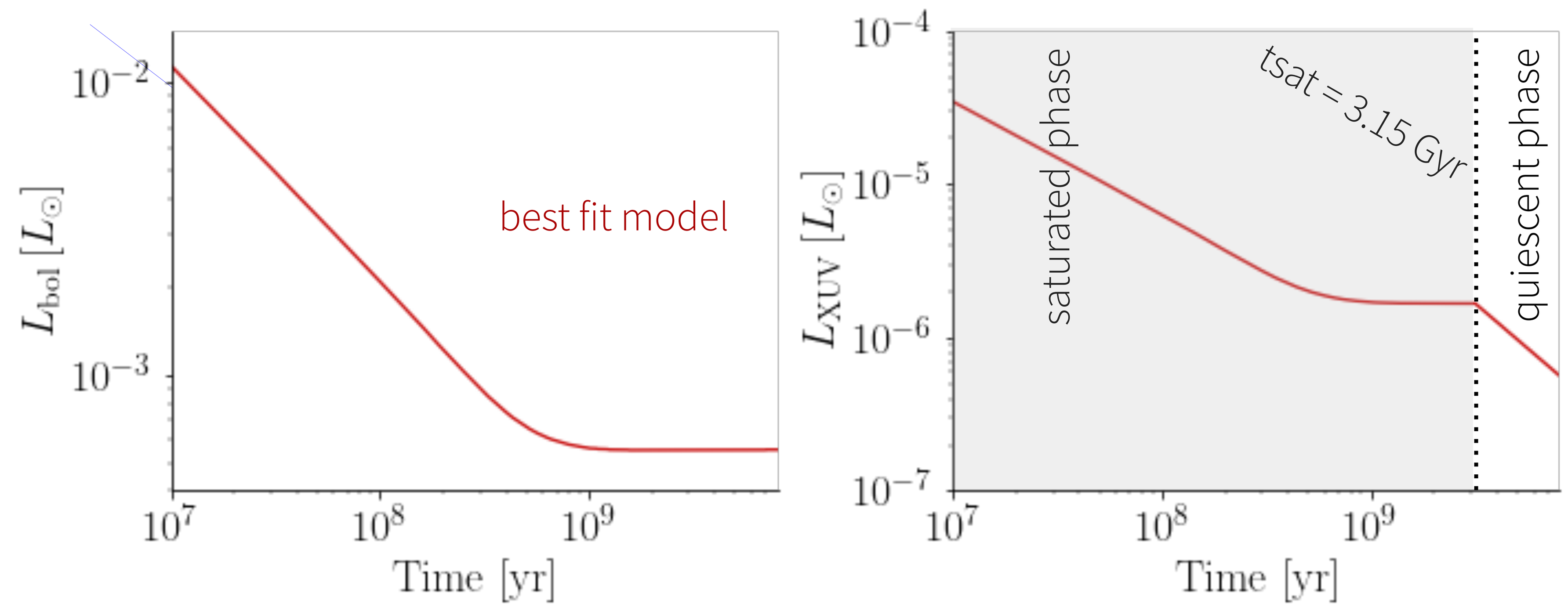
COOLSTARS 21



TRAPPIST-1

Motivation: X-ray/extreme ultraviolet (XUV; ~1–1000 A) luminosity is an informative indicator of a star's phase in magnetic activity evolution, as well as a key driver for influencing the atmospheric retention andcomposition of potentially habitable exoplanets.

We model the bolometric and XUV luminosity of the star using **VPLanet** (Barnes et al. 2020)



Bolometric evolution model: Barraffe et al. 2015

XUV evolution model: Ribas et al. 2005

$$\frac{L_{XUV}}{L_{bol}} = \begin{cases} f_{sat} & t \le t_{sat} \\ f_{sat}\left(\frac{t}{t_{sat}}\right)^{-\beta_{XUV}} & t > t_{sat} \end{cases}$$

Trappist-1's planets experienced 10 – 1000× greater total XUV energy than Earth over their ~8 Gyr lifetime

b: 2.2 x 10^{32} erg

c: 1.1 x 10^{32} erg

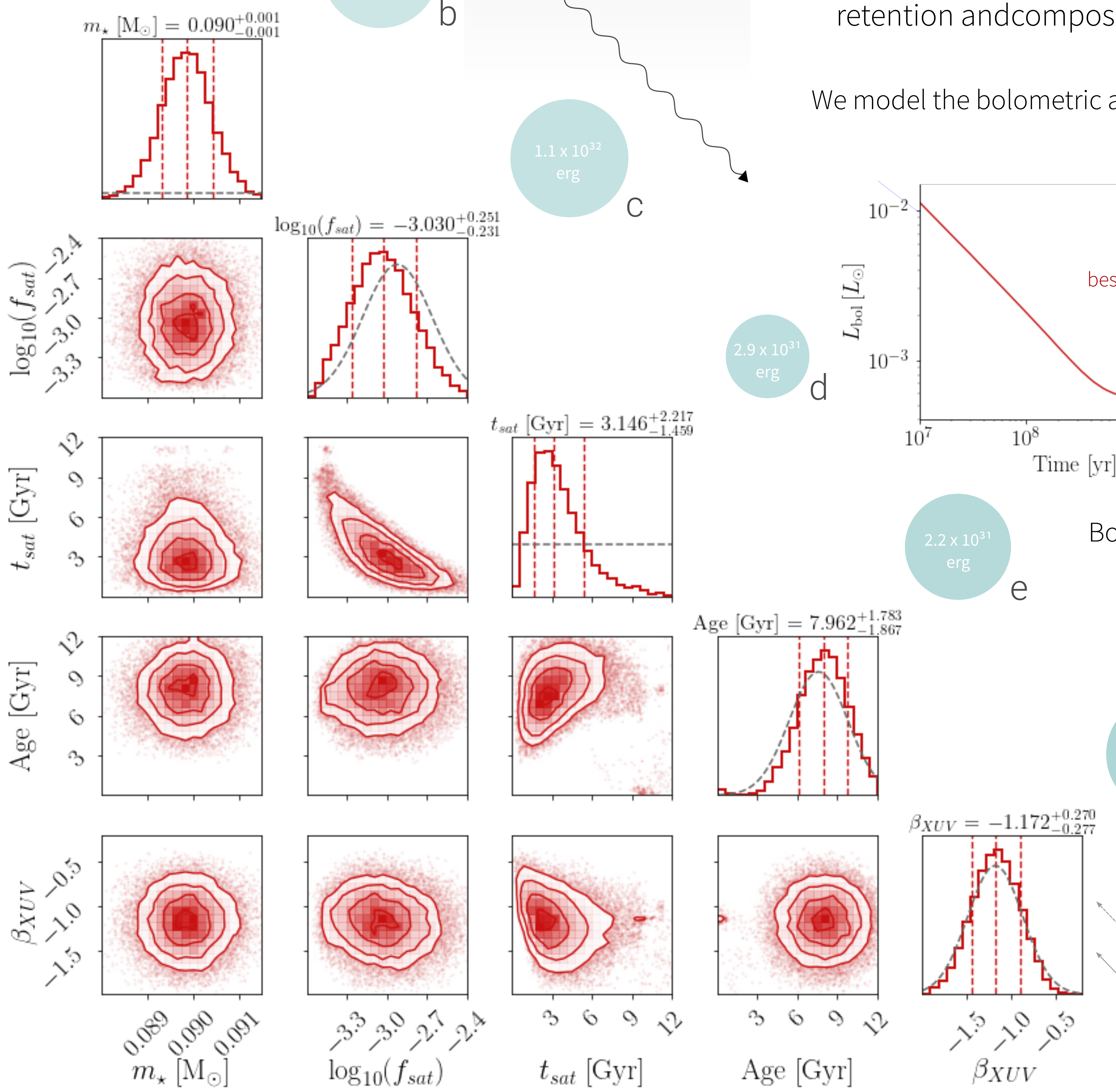
d: 2.9 x 10^{31} erg

e: 2.2 x 10^{31} erg

f: 1.7 x 10^{31} erg

g: 1.3 x 10^{31} erg

h: 3.4 x 10^{30} erg



mass of the star | early evolution saturation luminosity | duration of saturation phase | age of system | exponential decay rate of XUV from saturated to quiescent

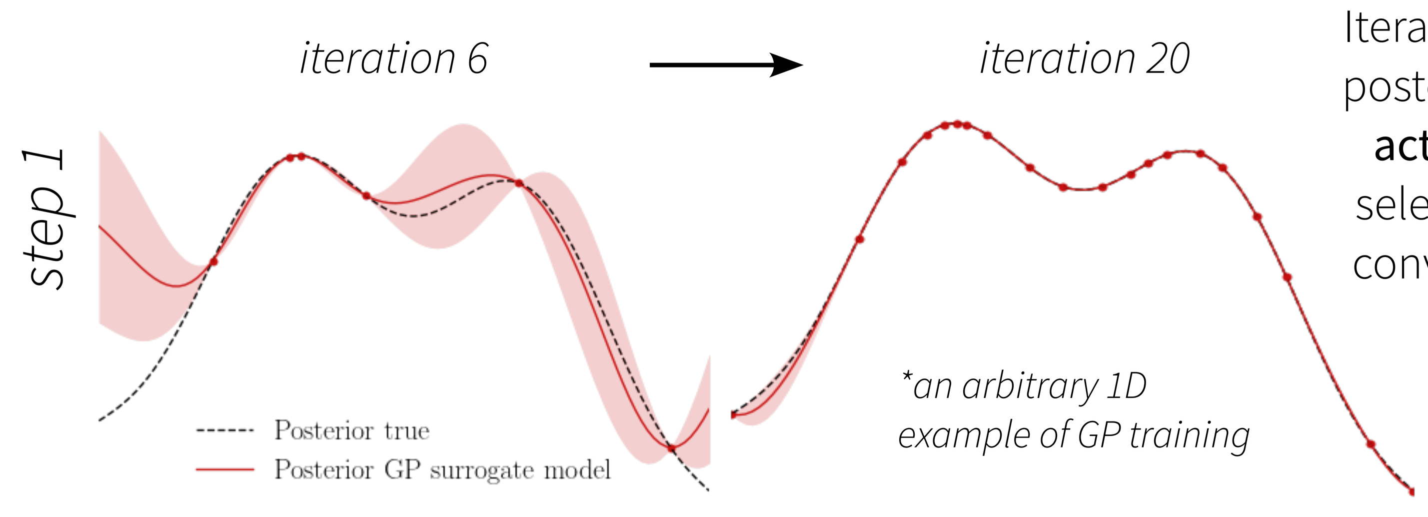
Take-away

We employ the machine learning code ALABI to infer the XUV history of the star TRAPPIST-1 and find it has **only a ~4% chance of being in the saturated phase today**. Despite its present quiescent state, T1's planets likely received an extreme amount of XUV energy (integrated XUV energy of ~10^{30} – 10^{32} erg), potentially **driving significant atmospheric loss over their lifetime**.

How did we infer TRAPPIST-1's evolutionary history?

		P(x)	
Prior	mass [msun]	U(0.7, 0.11)	
	log(fsat)	N(-2.92, 0.26)	Wright et al. (2011)
	tsat [Gyr]	U(0, 12)	
	age [Gyr]	N(7.6, 2.2)	Burgasser et al. (2017)
	beta	N(-1.18, 0.31)	Jackson et al. (2012)
		P(D/x)	
Likelihood	Lbol [Lsun]	N(5.53, 0.19) × 10^{-4}	Ducrot et al. (2020)
	Lxuv [Lsun]	N(1.77, 0.22) × 10^{-7}	Becker et al. (2020)

Posterior $\ln P(x|D) \propto \ln P(D|x) + \ln P(x)$



Iteratively train a GP model on posterior function P(x|D) using **active learning** to efficiently select training samples which converge to the true posterior (Kandasamy 2017, Fleming 2018)

Sample the GP model using Markov Chain Monte Carlo (MCMC) with samplers like **emcee** (Foreman Mackey 2012)

Paper & References:

Active Learning for Accelerated Bayesian Inference (**ALABI**) trains a **Gaussian Process (GP) surrogate model** to enable fast analysis of stellar XUV evolution (1000x less CPU hours than only **emcee**) and has broad applicability for performing Bayesian inference with computationally expensive models: **https://github.com/jbirky/alabi**