DIANE MALINDA SALIM

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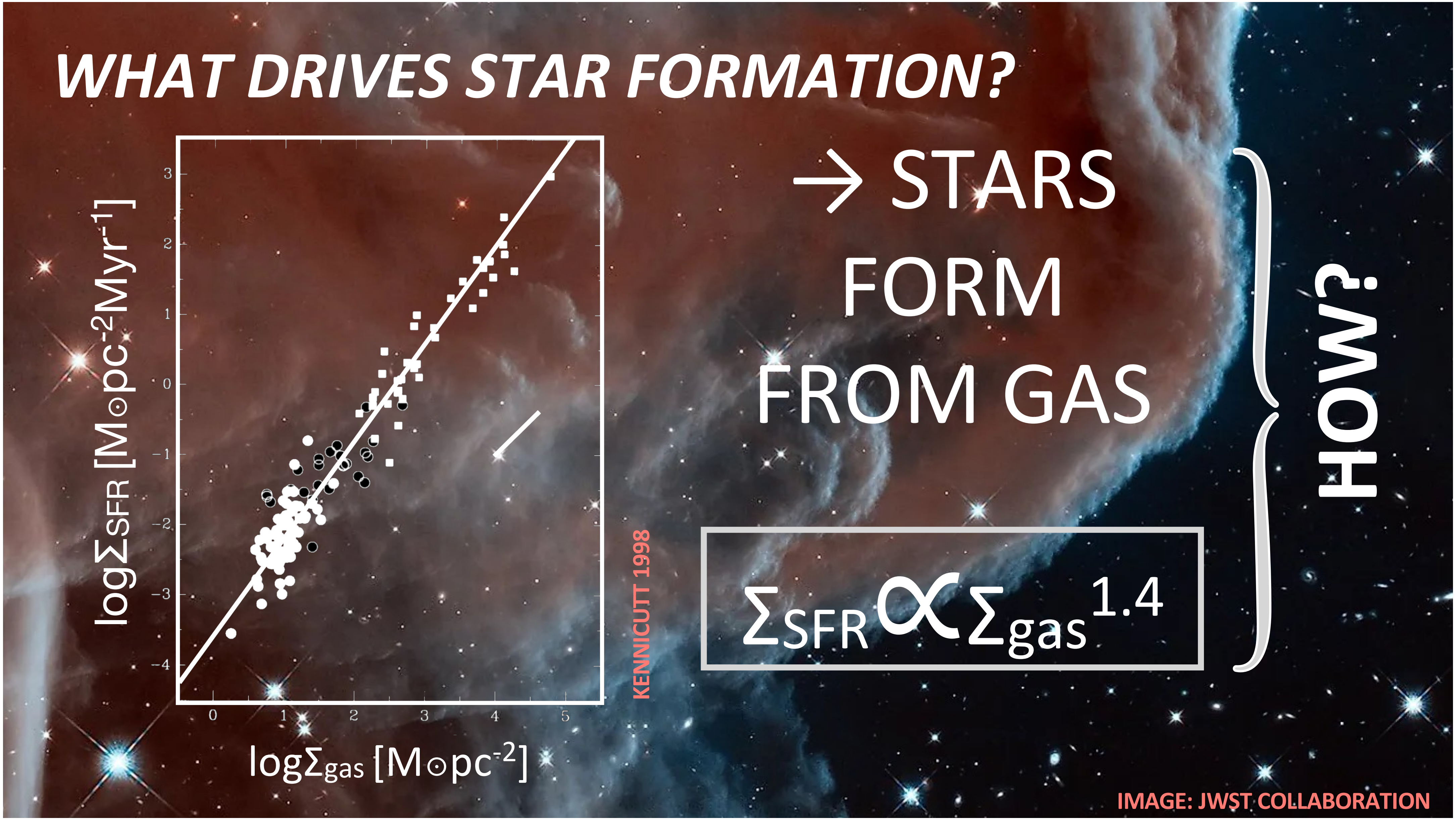
a data-driven approach for star formation parameterisation

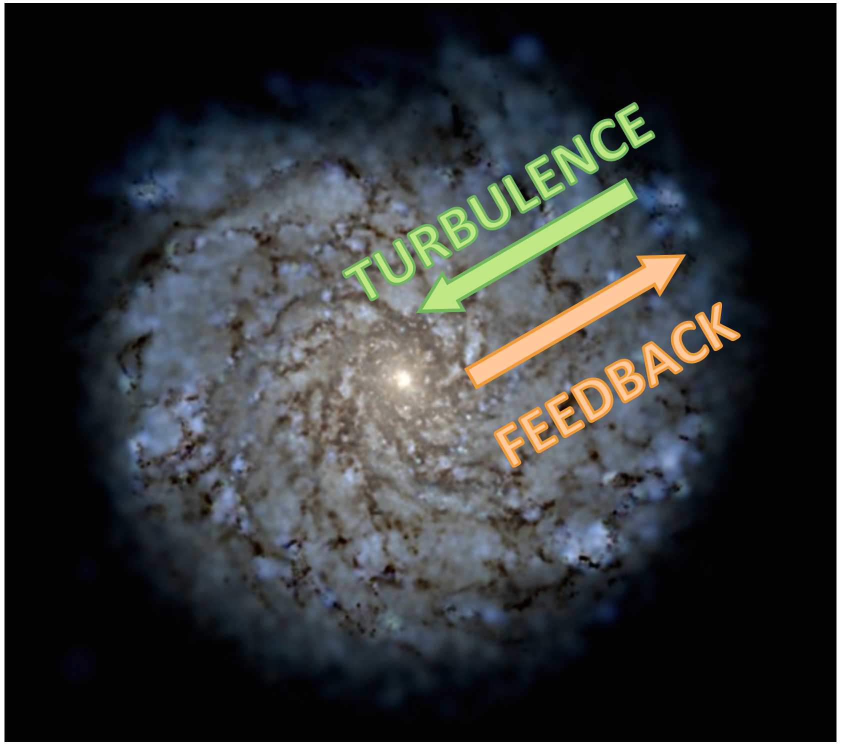
Machine Learning for Astrophysics, 2nd Edition

Thursday, 9th July 2024


WHAT DRIVES STAR FORMATION?
$\log\Sigma_{SFR}\,[M_\odot pc^{-2} Myr^{-1}]$
$\log\Sigma_{gas}\,[M_\odot pc^{-2}]$
KENNICUTT 1998
→ STARS
FORM
FROM GAS
$\Sigma_{SFR} \propto \Sigma_{gas}^{1.4}$
HOW?
IMAGE: JWST COLLABORATION

WHAT DRIVES STAR FORMATION?

TOP-DOWN MODELS



FIRE COLLABORATION

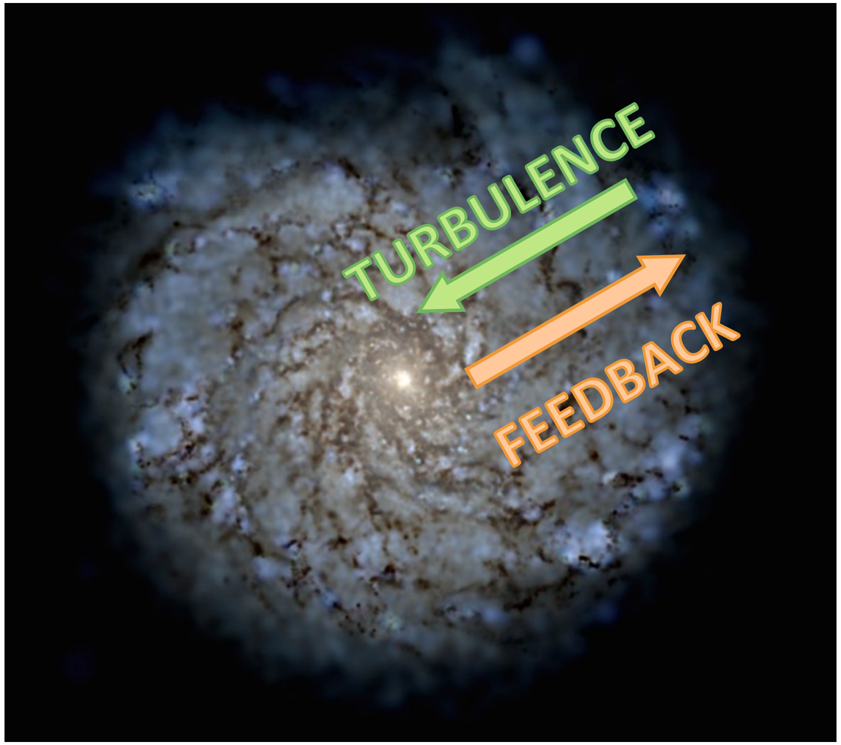
TURBULENCE MOMENTUM DECAY = **FEEDBACK INJECTION RATE**

$$\frac{dP_{\rm turb}}{dt} = -\frac{\Omega_{\rm dyn}}{2} P_{\rm turb} = -\frac{\Sigma_{\rm gas}\sigma_{\rm gas}\Omega_{\rm dyn}}{2}$$

$$\frac{dP_{\rm inj}}{dt} = \left(\frac{P_*}{m_*}\right)\frac{d\Sigma_*}{dt} = \left(\frac{P_*}{m_*}\right)\Sigma_{\rm SFR}$$

WHAT DRIVES STAR FORMATION?

TOP-DOWN MODELS

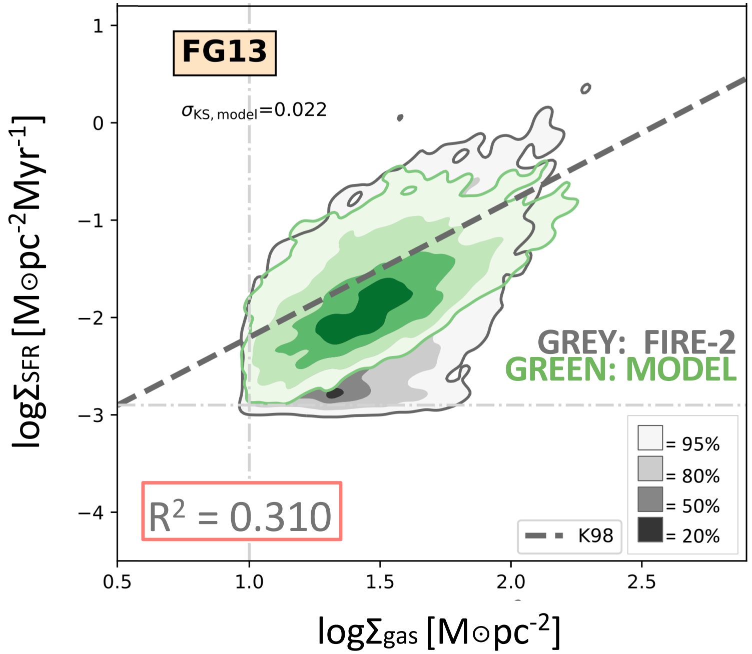


FIRE COLLABORATION

STAR FORMATION RATE (SFR)

$$\Sigma_{\rm SFR} = \frac{\sqrt{3}}{2}\frac{\Sigma_{\rm gas}\Omega_{\rm dyn}\sigma_{\rm gas,z}}{(P_*/m_*)}$$

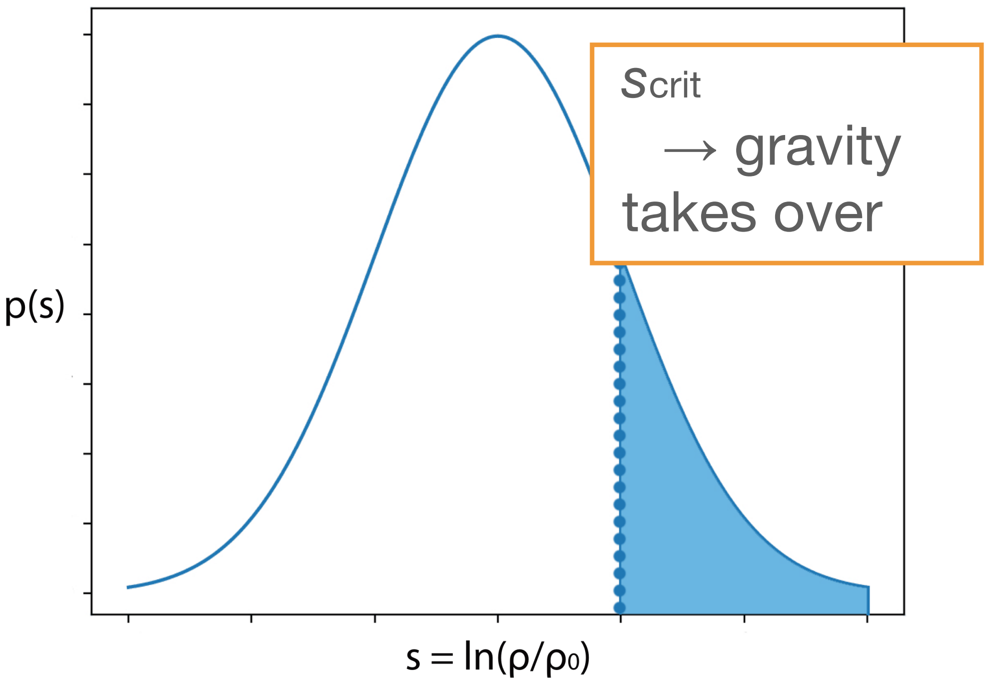
FAUCHE-GIUGÉRE (2013) (FG13)



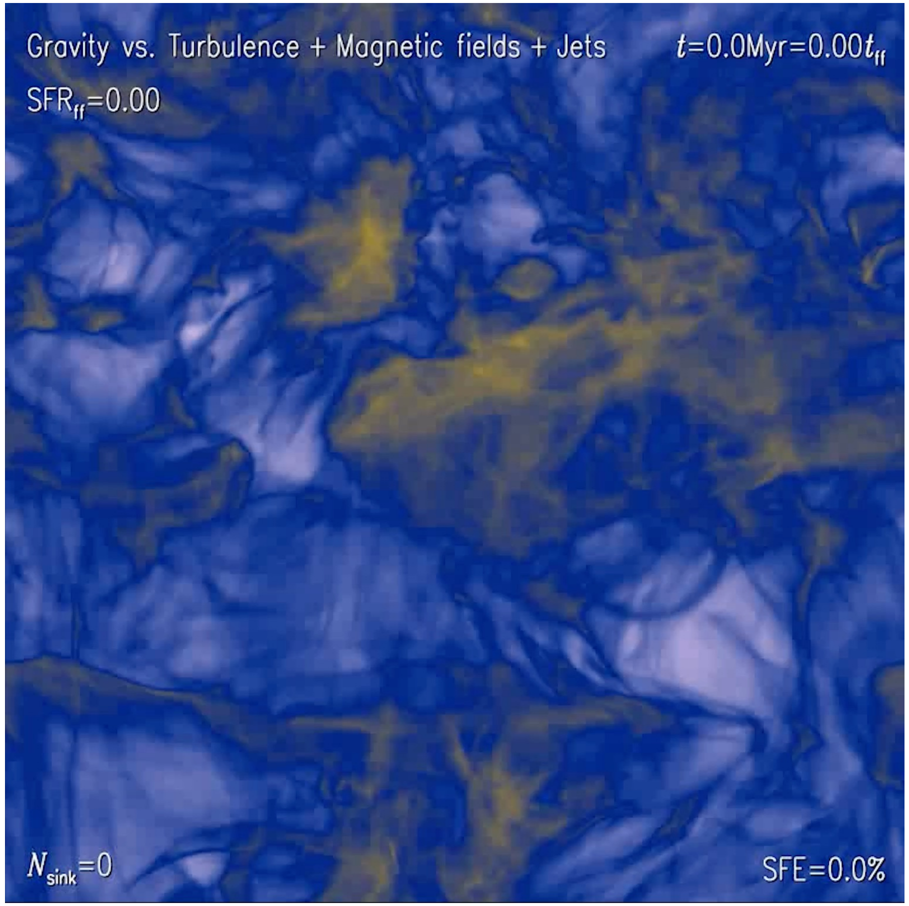
THIS WORK (IN PREP.)

WHAT DRIVES STAR FORMATION?

BOTTOM-UP MODELS



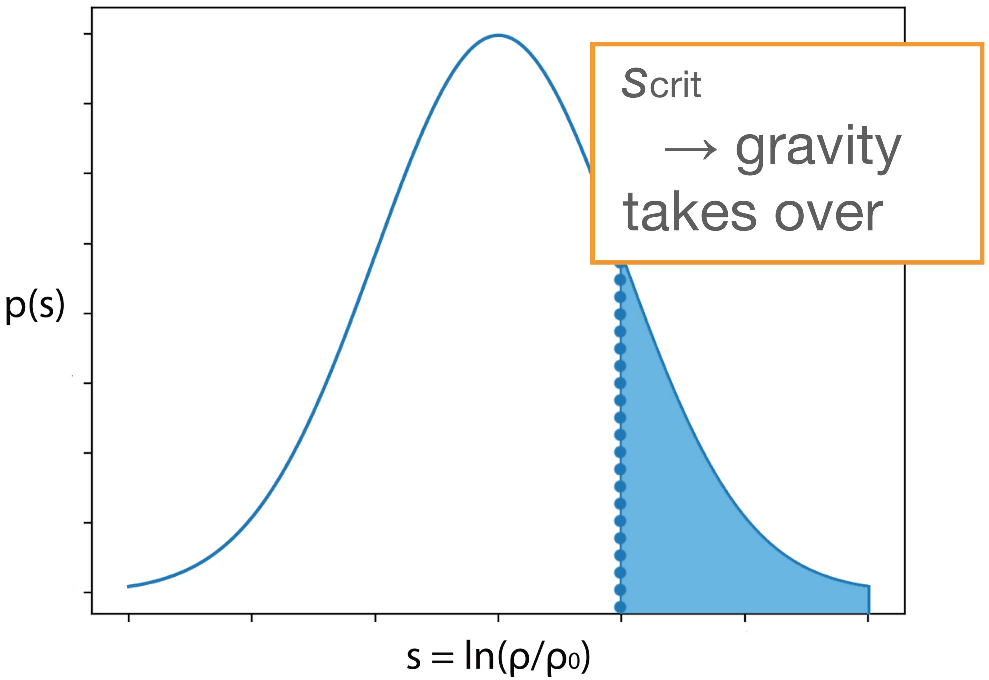
$$\Sigma_{\rm SFR} = \epsilon_{\rm ff} \cdot \int_{s_{\rm crit}}^{\infty} \frac{\Sigma_{\rm gas}}{t_{\rm ff}} \exp\left(\frac{3}{2}s\right) p(s)\, ds \quad = \epsilon_{\rm ff} \cdot \frac{\Sigma_{\rm gas}}{t_{\rm ff}} \exp\left(\frac{3}{8}\,\sigma_s^2\right) \frac{1}{2}\left[1 + \mathrm{erf}\left(\frac{\sigma_s^2 - s_{\rm crit}}{\sqrt{2\sigma_s^2}}\right)\right]$$



FEDERRATH 2015

WHAT DRIVES STAR FORMATION?

BOTTOM-UP MODELS



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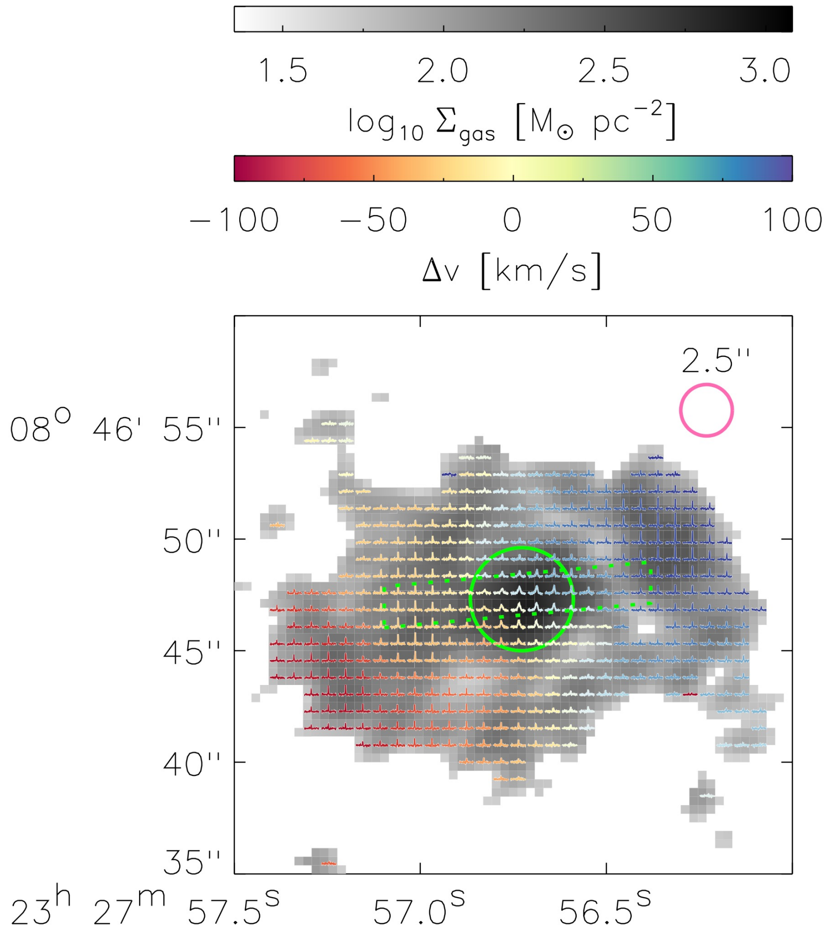
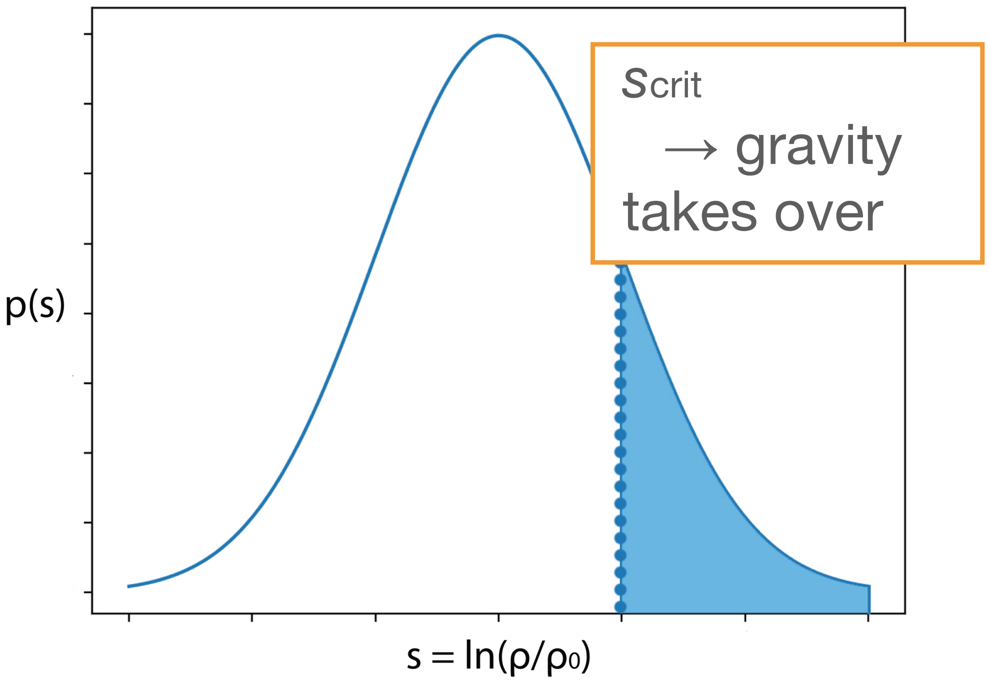
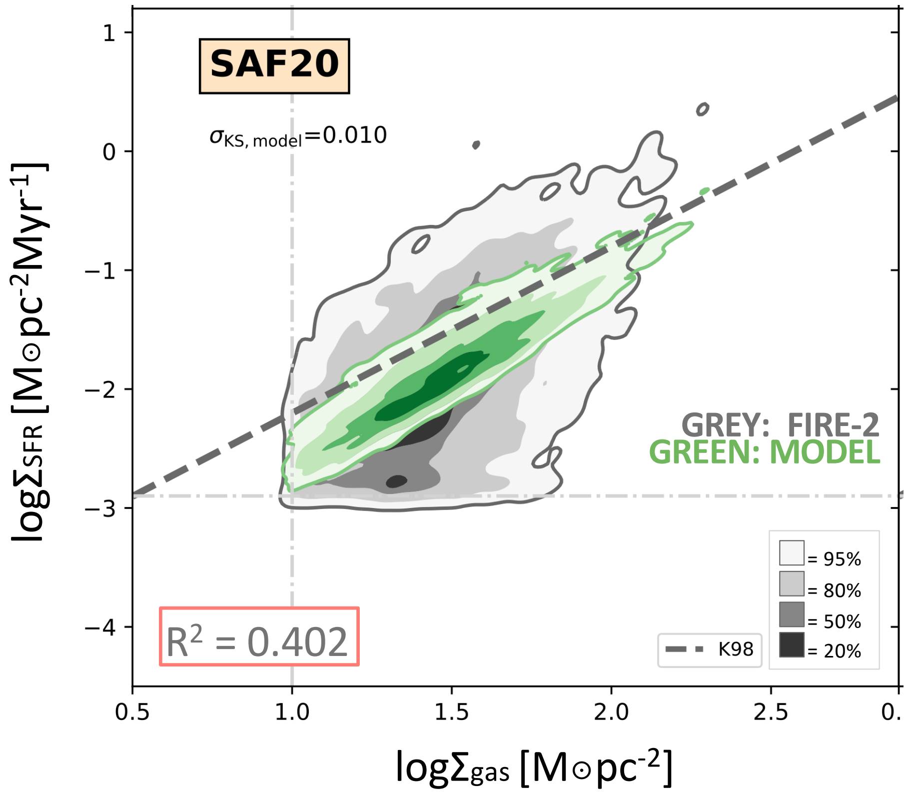


SALIM ET. AL. 2020 (SAF20)

WHAT DRIVES STAR FORMATION?

BOTTOM-UP MODELS





THIS WORK (IN PREP.)

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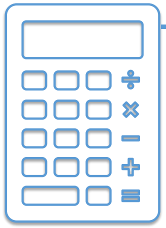
→ SALIM ET. AL. 2020 (SAF20)

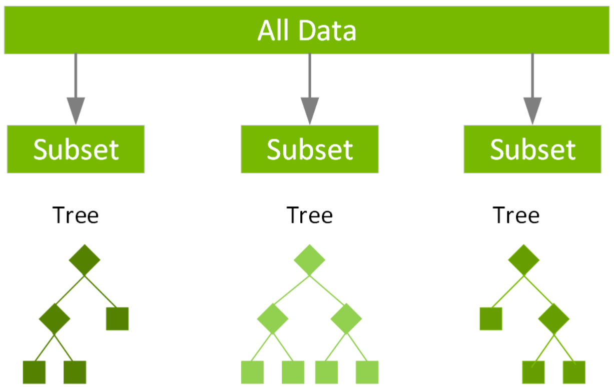
CAN MACHINE LEARNING HELP?

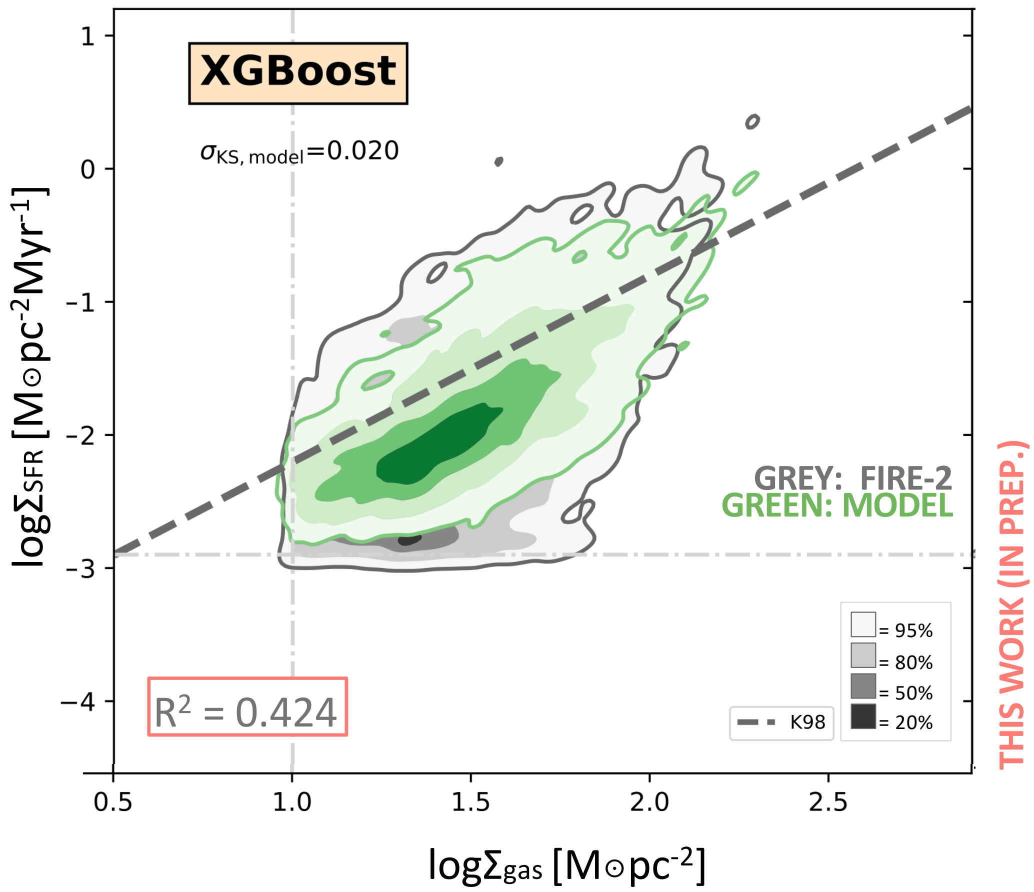
REGRESSION MODEL: XGBoost

INPUT: pixel-scale properties
eg. Σ_{gas}, σ_{gas}, Ω_{dyn}



OUTPUT: pixel-scale values for Σ_{SFR}





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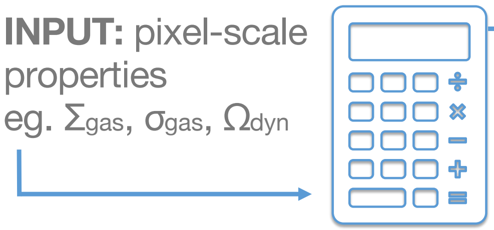


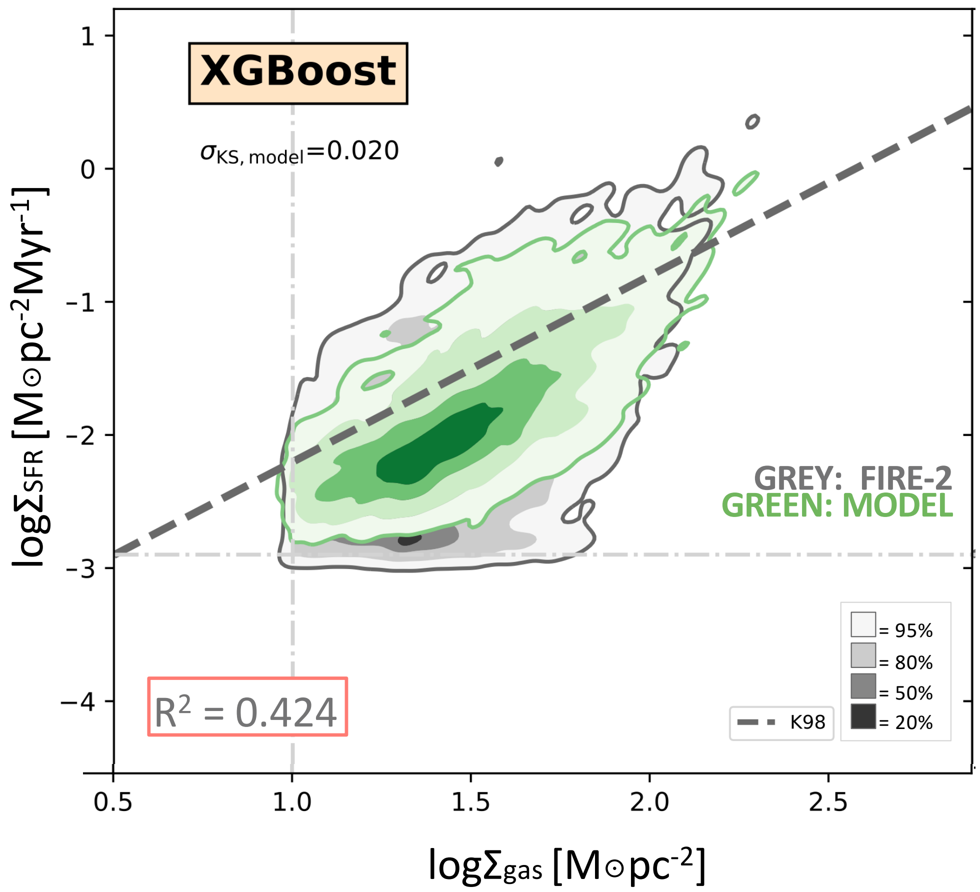
OUTPUT: pixel-scale values for Σ_{SFR}

PROS

- Highly optimised to be accurate on a point-by-point basis
- Places limits on **how good** any equation-based model *can* be

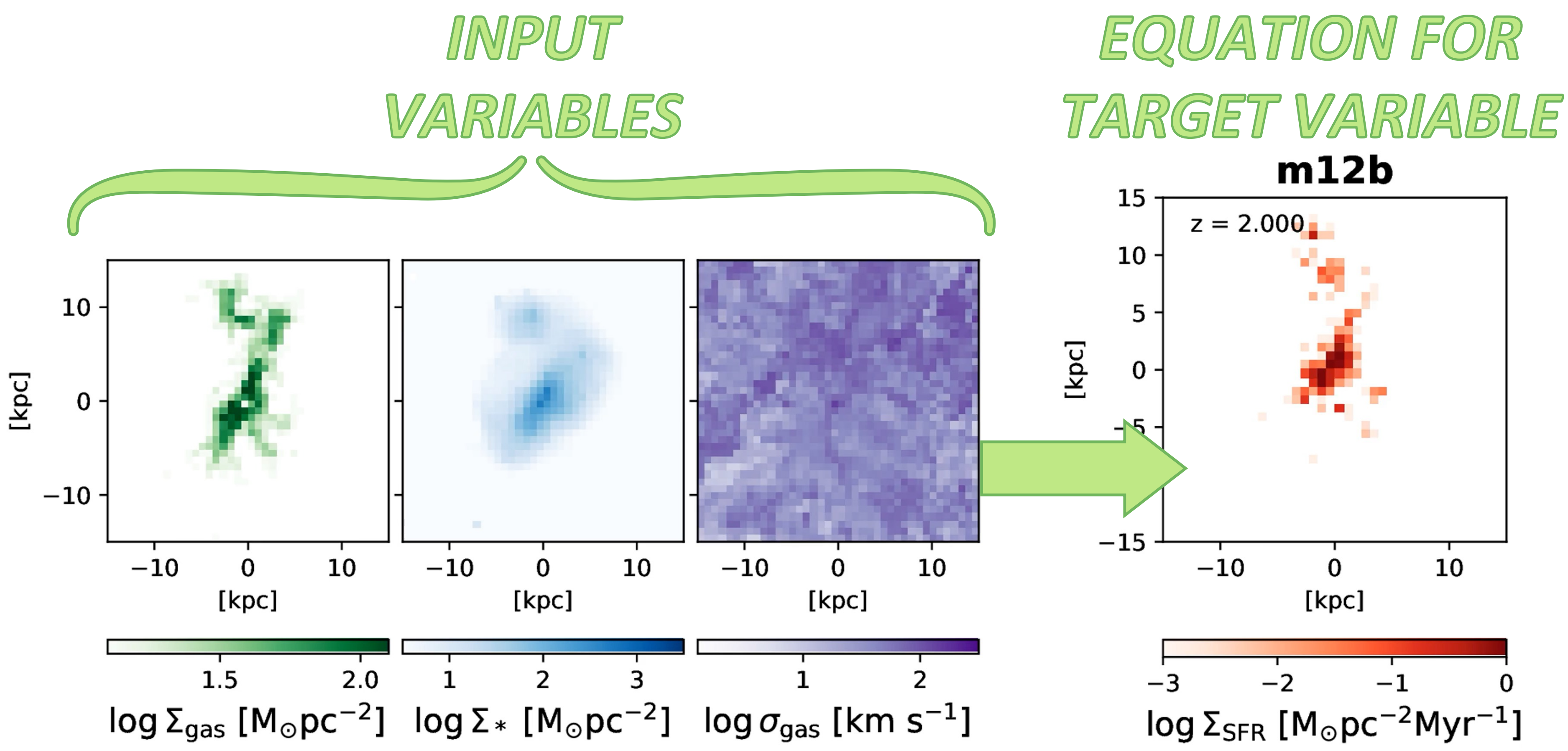
CONS

- Not easily interpretable
- Not physically meaningful



THIS WORK (IN PREP.)

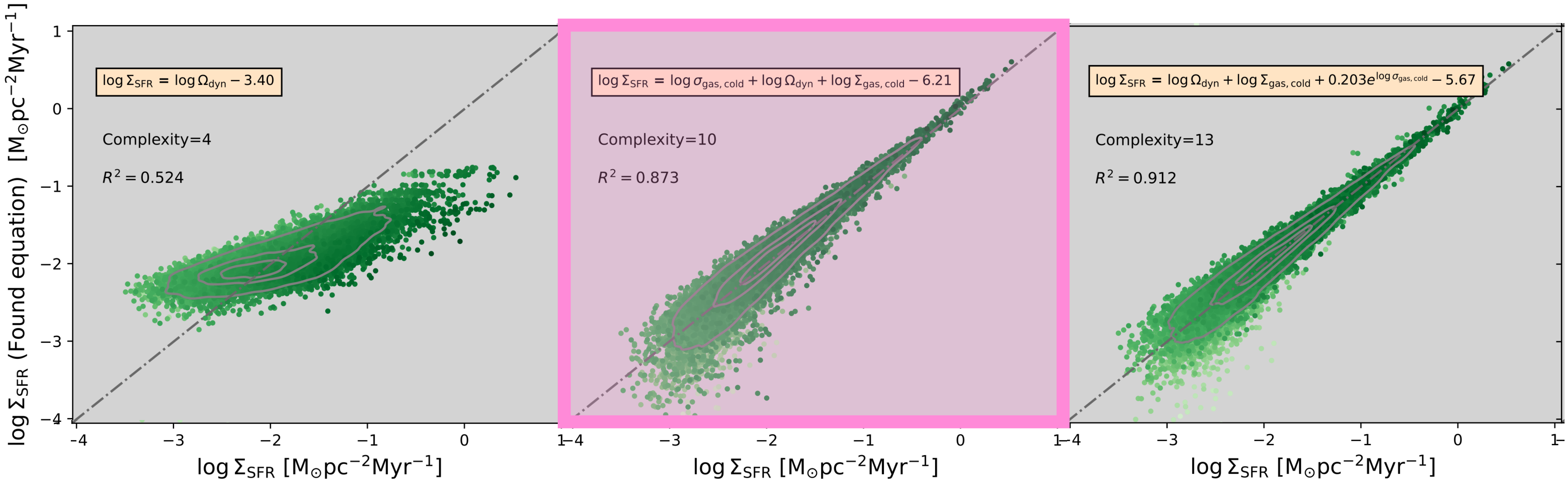
STUDY GOAL: INTERPRETABLE ML



SYMBOLIC REGRESSION (PySR)

MOVIE CREDIT: MILES CRANMER 2023

TOY DEMO: "SYNTHETIC FG13 DATASET"



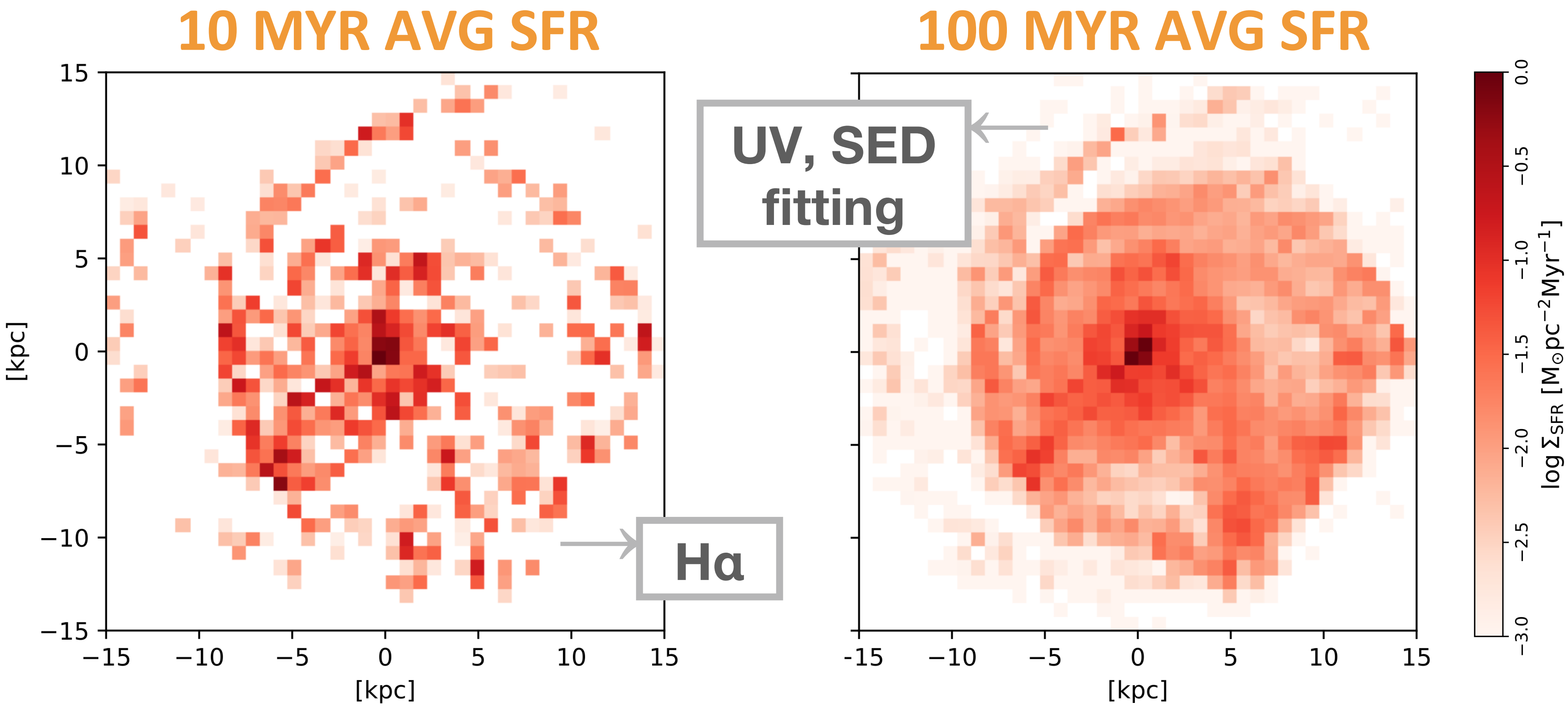
SFR FG13:

$$\Sigma_{\rm SFR} = \frac{\sqrt{3}}{2}\frac{\Sigma_{\rm gas}\Omega_{\rm dyn}\sigma_{\rm gas,z}}{(P_*/m_*)}$$

FG13 model functional form found!

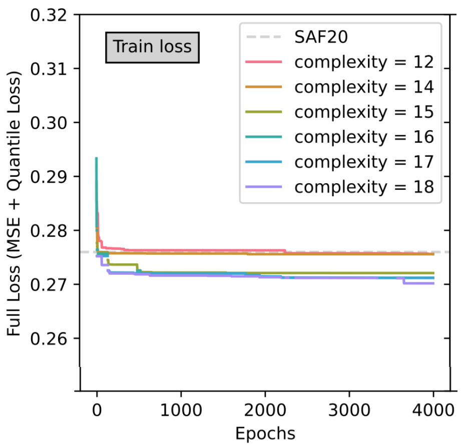
$\log\Sigma_{\rm SFR} = \log\sigma_{\rm gas,\,z} + \log\Omega_{\rm dyn} + \log\Sigma_{\rm gas} + C$

TWO TIMESCALES, TWO EXPERIMENTS

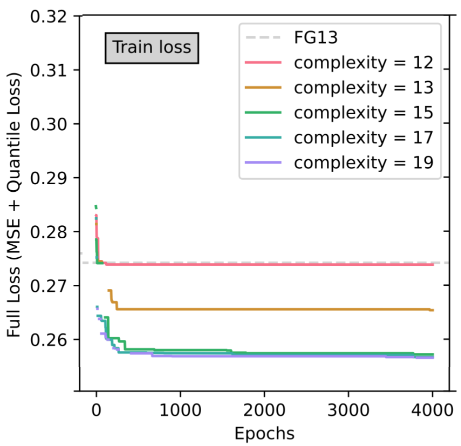


MACHINE LEARNING TRAINING

10 MYR AVG SFR



100 MYR AVG SFR



$$\mathcal{L}_{TOT} = \mathcal{L}_{MSE} + \mathcal{L}_{Q}$$

$$\mathcal{L}_{Q} = \text{Quantile Loss}$$

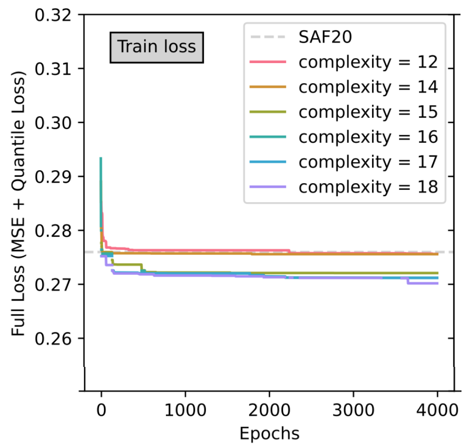
$Q = [0.1, 0.25, 0.5, 0.75, 0.9]$

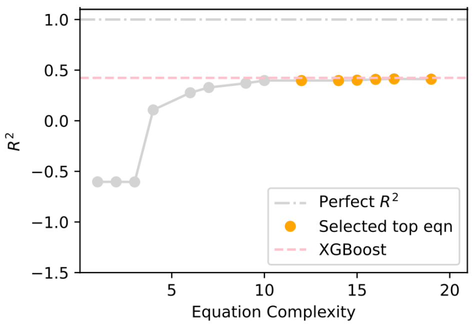
CHOOSING TOP EQUATIONS

$\mathcal{L}_{PYSR}$ MODEL $<$ $\mathcal{L}_{BEST}$ ANALYTIC MODEL

MACHINE LEARNING TRAINING

10 MYR AVG SFR





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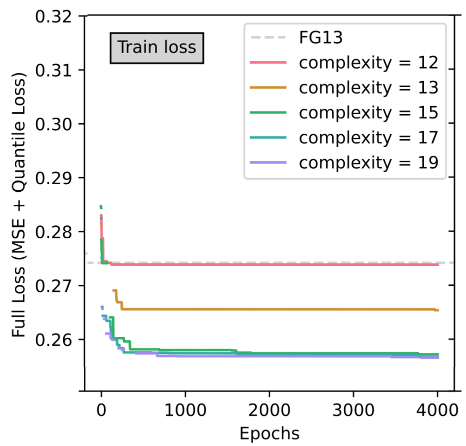

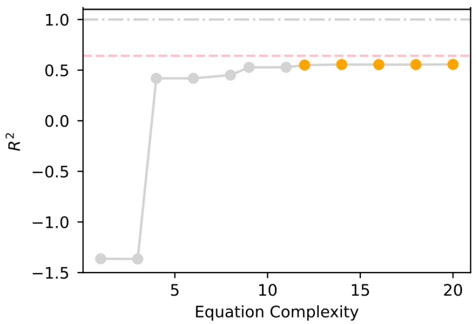

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CHOOSING TOP EQUATIONS

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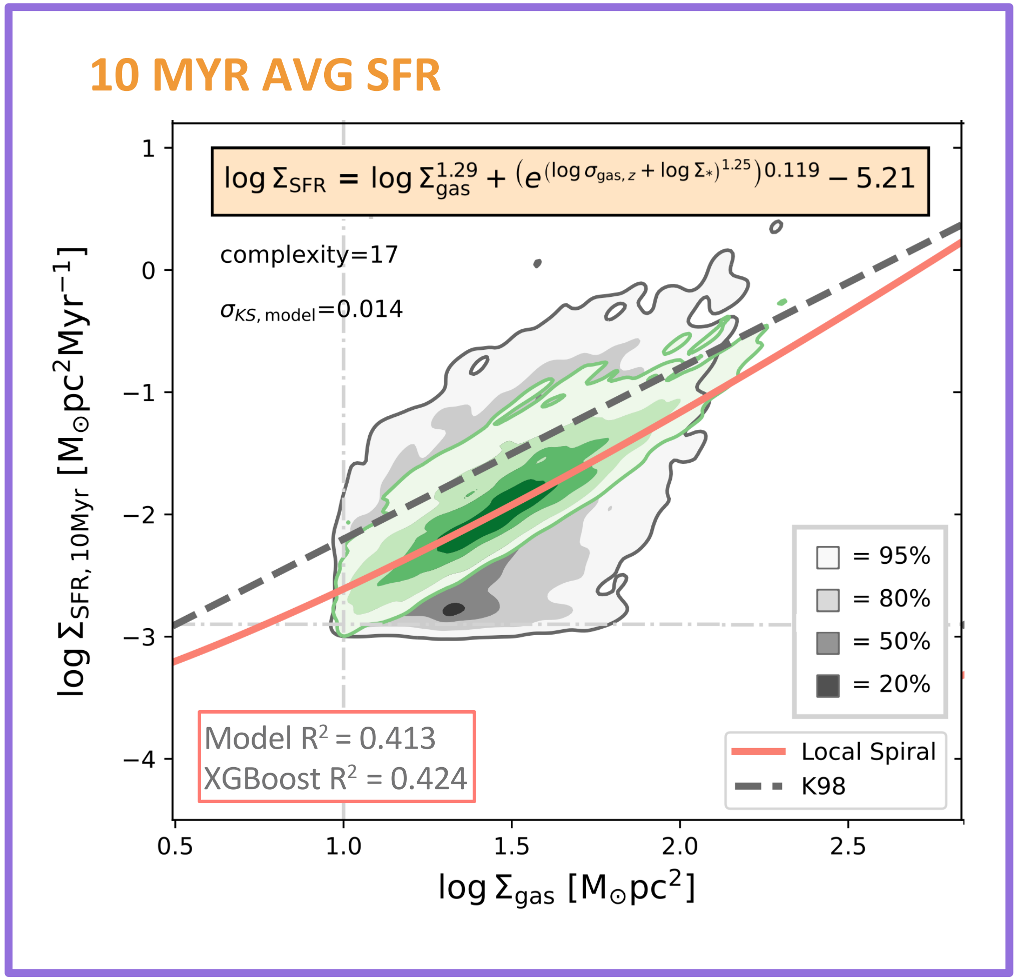
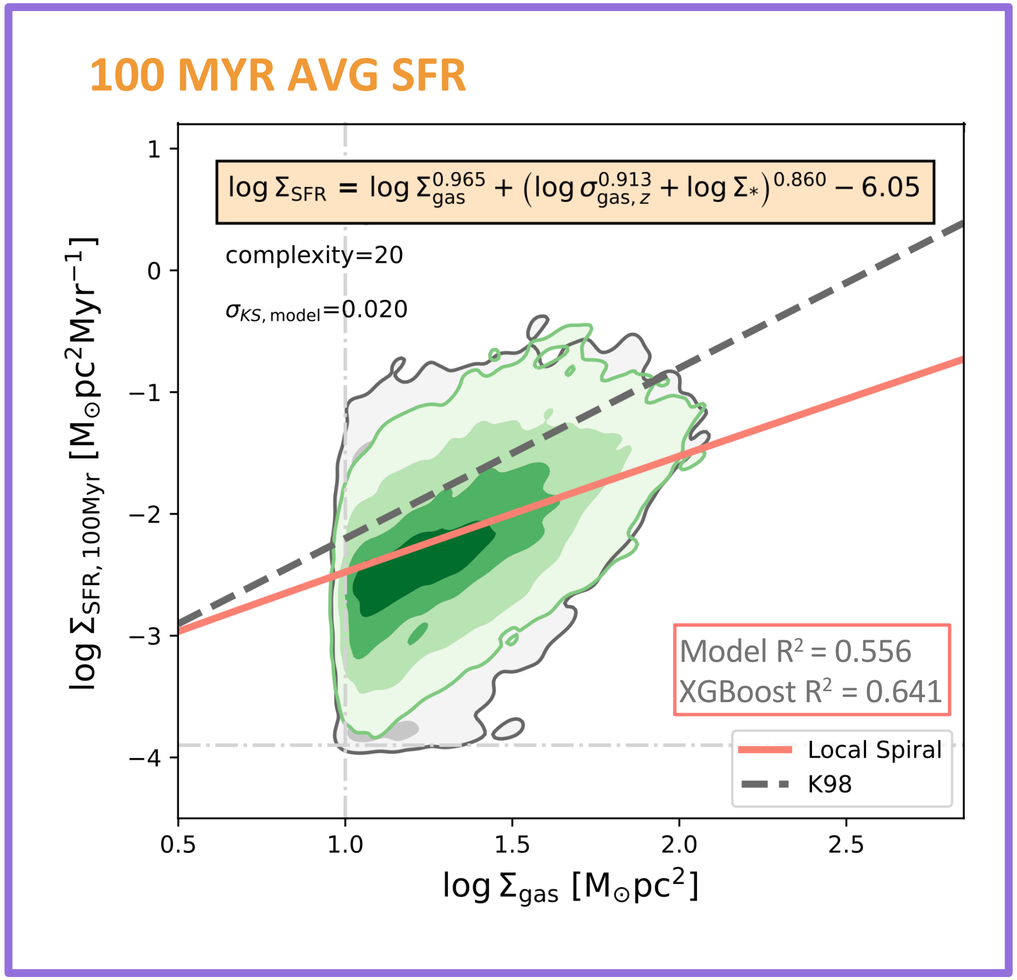
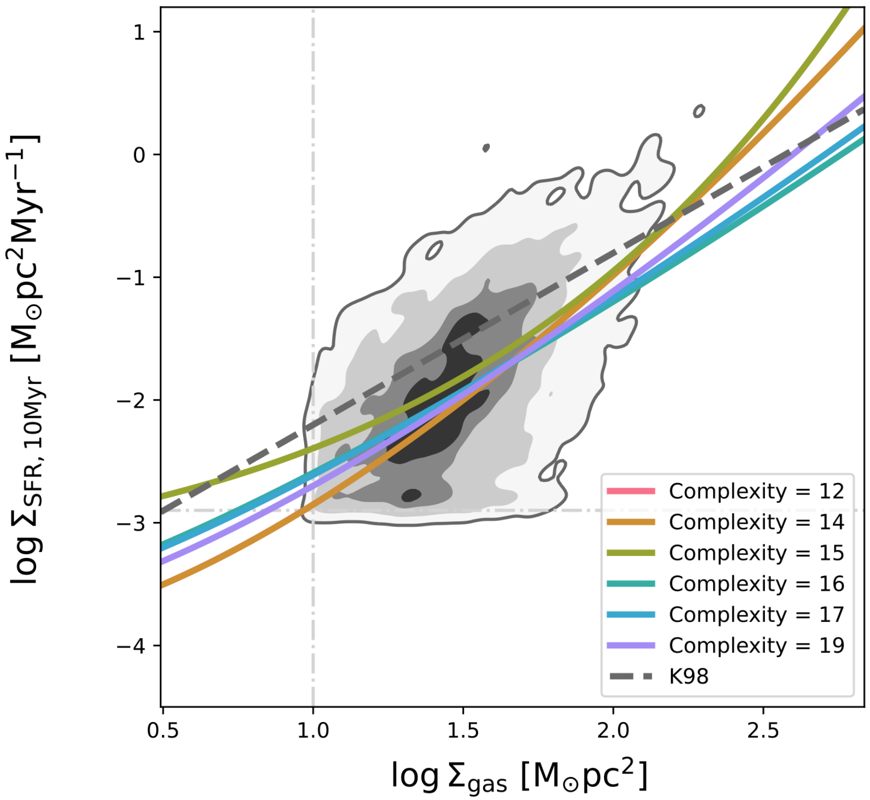
FIRE-2 FOUND EQUATION EXAMPLES



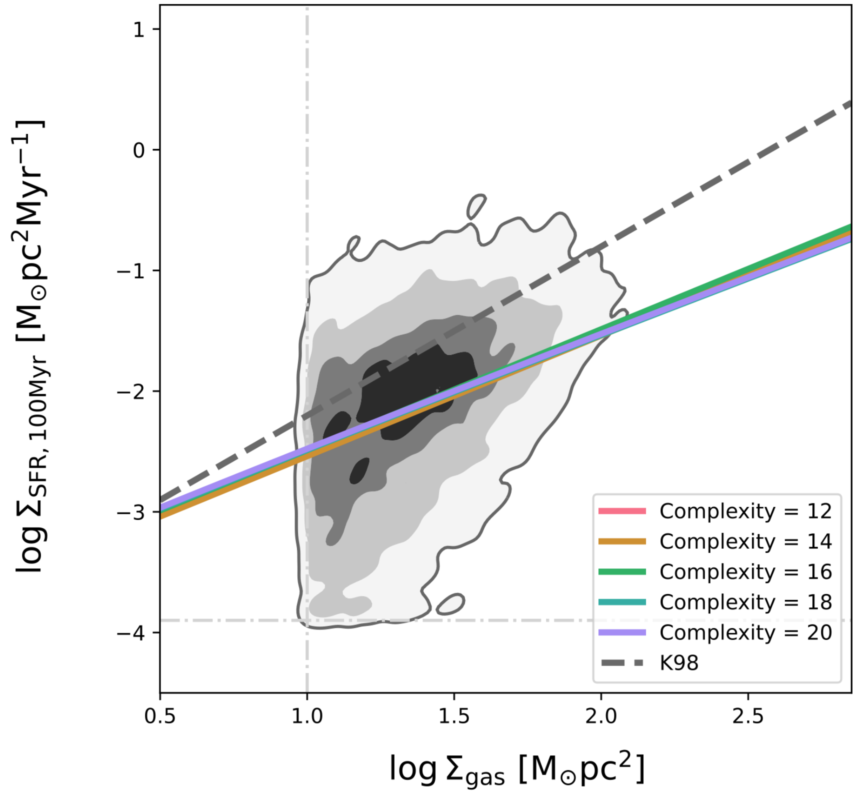


ALL FOUND EQUATIONS AT FIDUCIAL VALUES

10 MYR AVG SFR



100 MYR AVG SFR

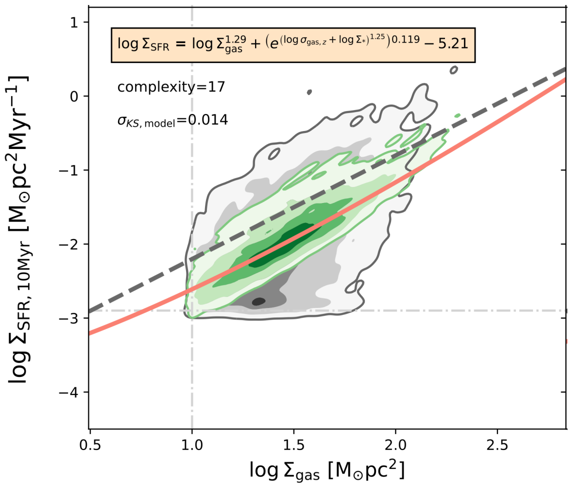


SUMMARY & POTENTIAL FUTURE ENDEAVOURS

STUDY ACHIEVEMENTS

- SR to understand observational & empirical SF scaling relations
- Applied to cosmological zoom-in simulations (FIRE-2)
- Found equations!

10 MYR AVG SFR



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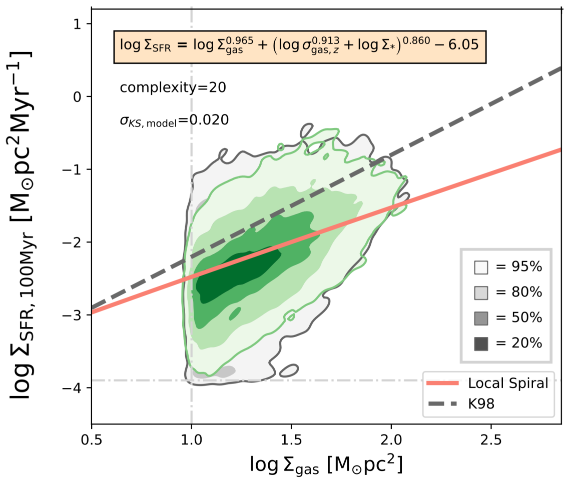
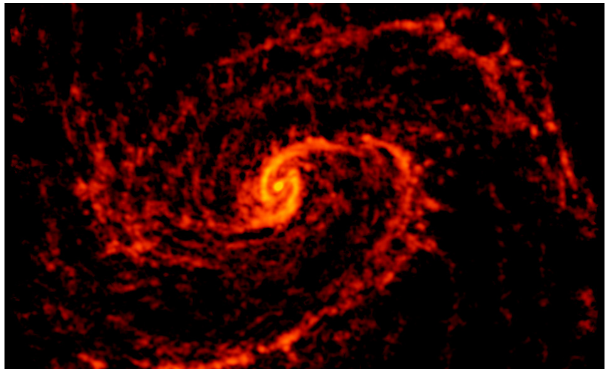


FUTURE WORKS

- Apply to observational data eg. PHANGS
  → consideration of errors during training

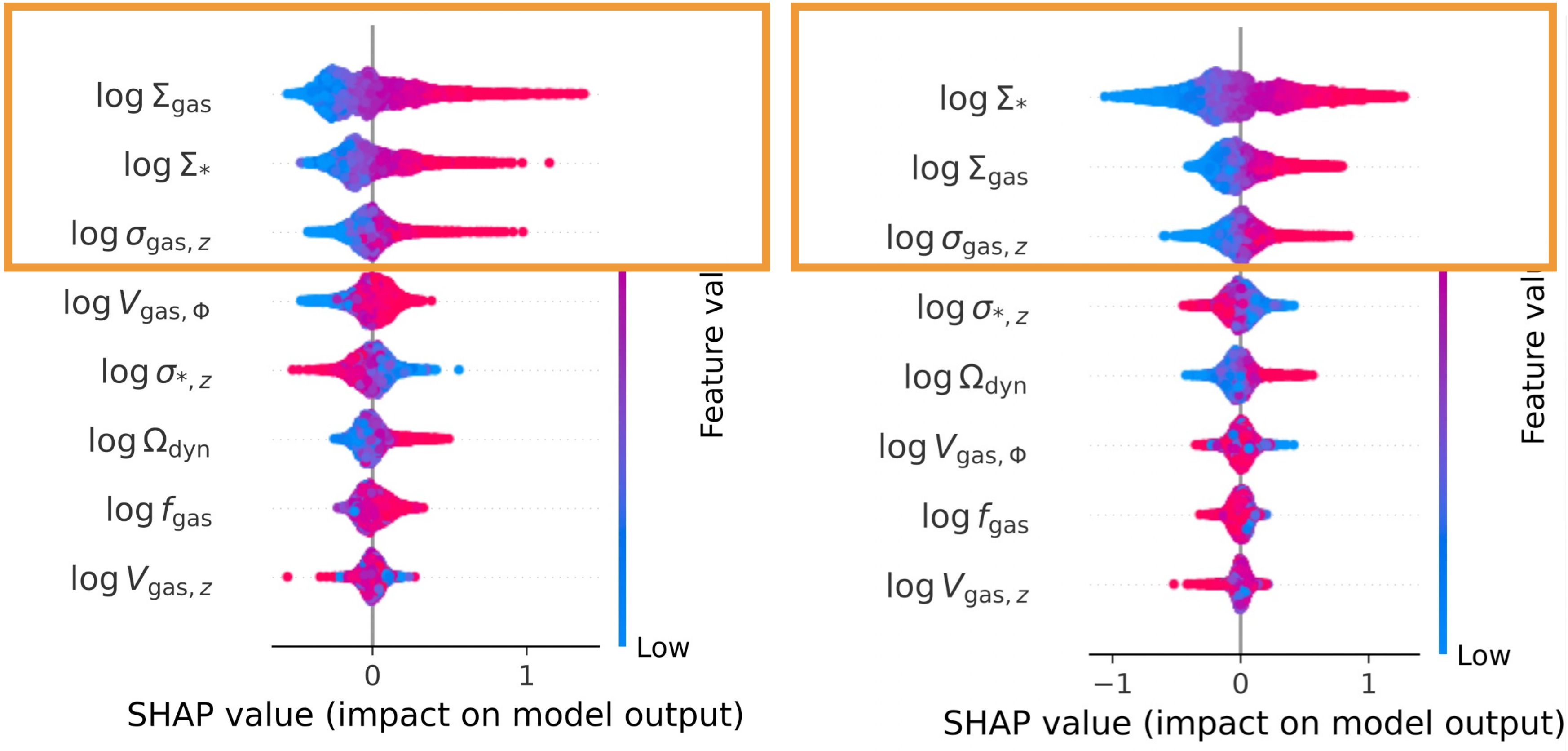


- Input into SAMs
- Architectural features to recover dispersion in feature space

TWO TIMESCALES, TWO EXPERIMENTS: SHAP

10 MYR AVG SFR

100 MYR AVG SFR



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2
3