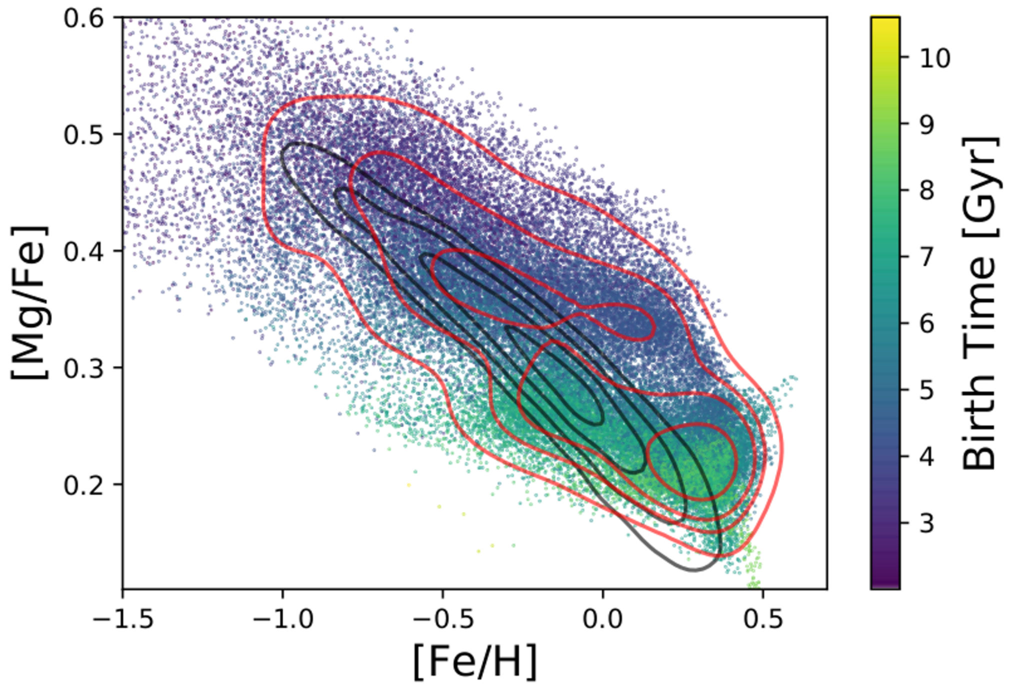
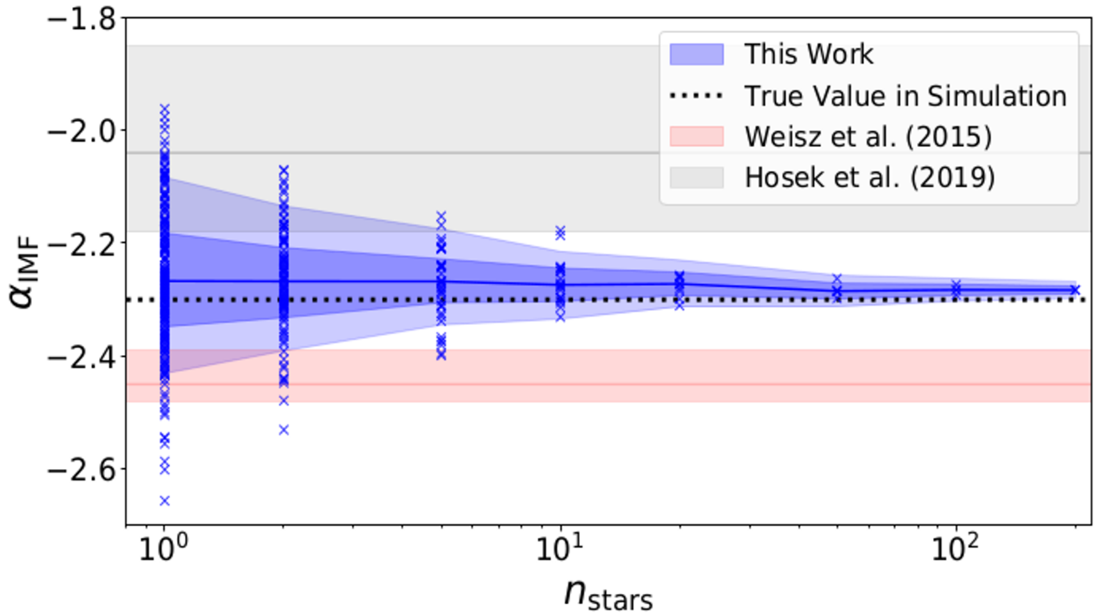
CHEMISTRY



PHYSICS



Inferring Galactic Parameters from Chemical Abundances

Oliver Philcox (Princeton)

with:

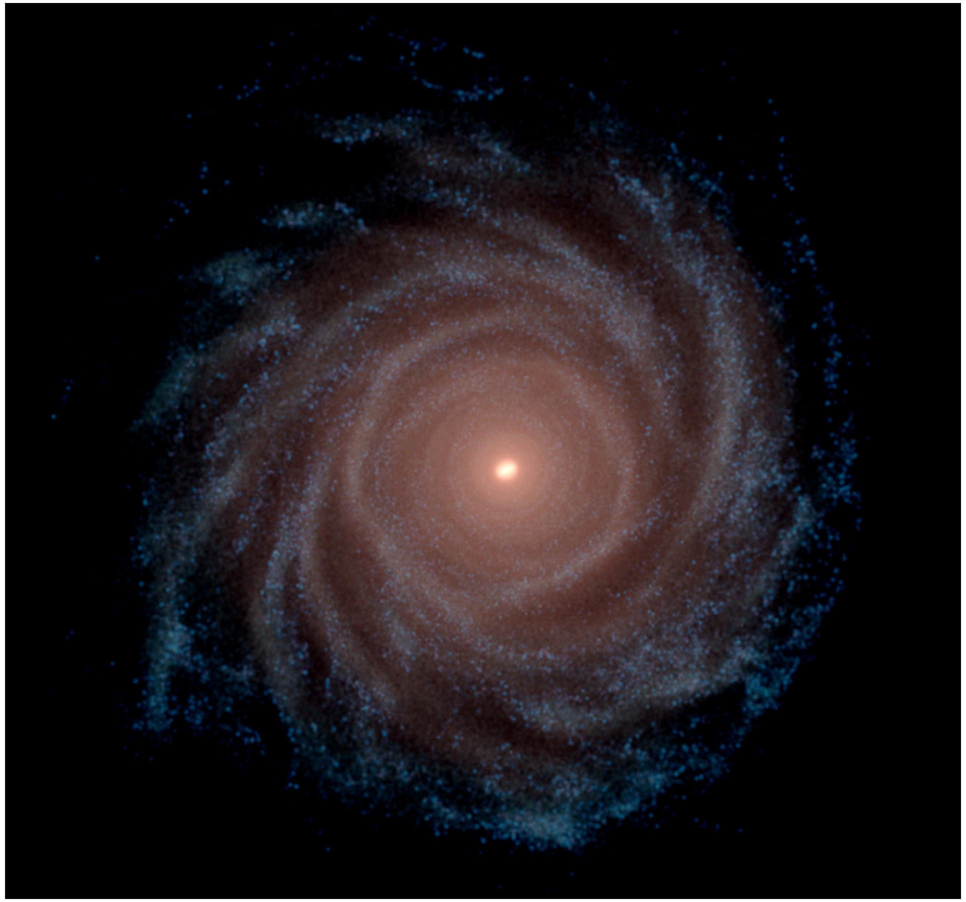
Jan Rybizki (MPIA, Heidelberg)

Joint Statistical Meeting

Aug 5th 2020

arXiv: 1909.00812

Simulating Galaxies



Mock Galaxy

(Auriga Simulations)

Are these consistent?

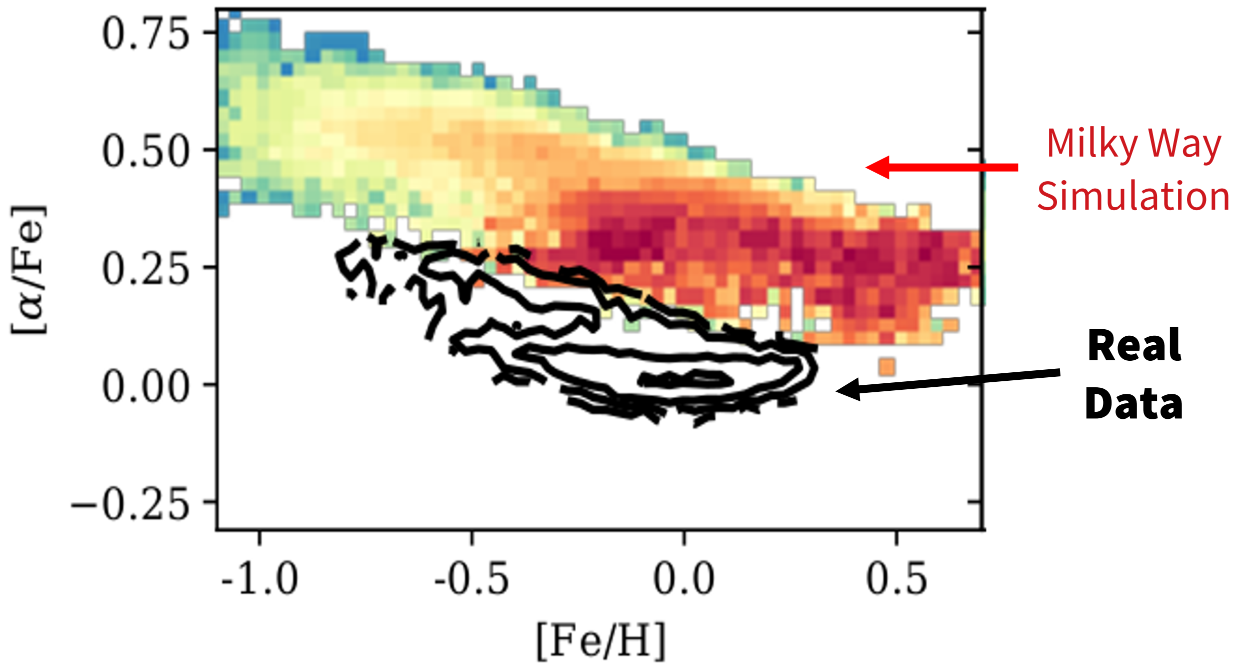
Real Galaxy

(M101)

Grand+16

Are our Simulations Accurate?

- Simulations of galaxies do **not** match the Milky Way
- **Chemical evolution** is wrong
- They depend on **poorly constrained** parameters

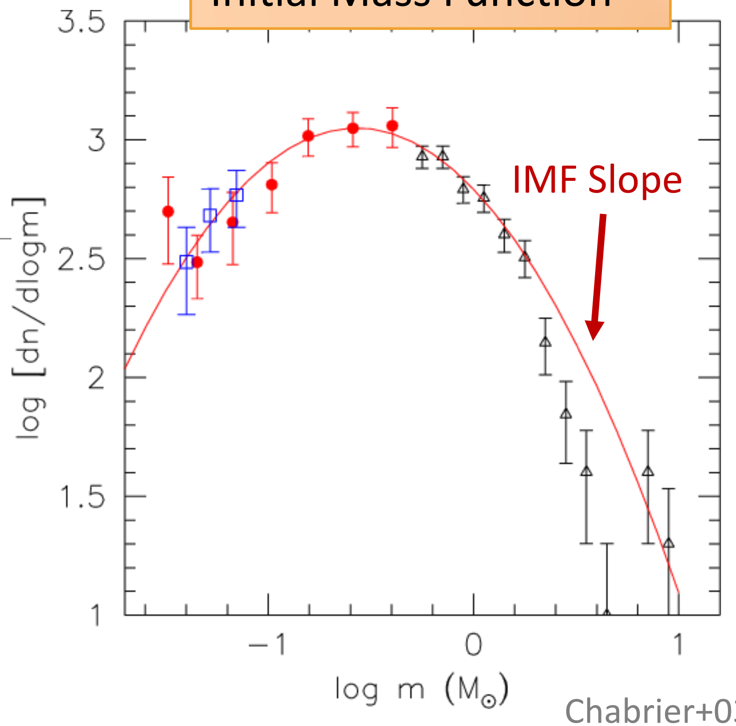


Philcox+18

Parametrizing the Galaxy

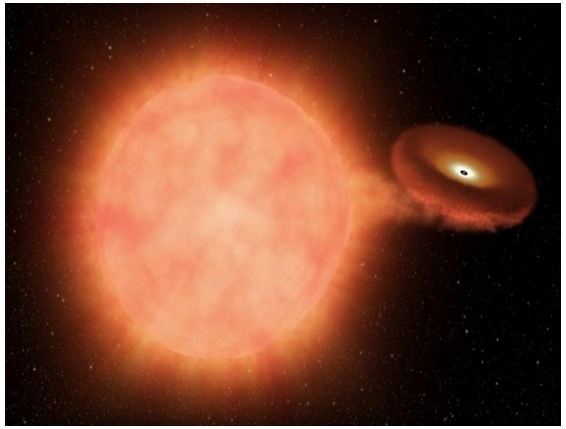
- What are these parameters?
  - The slope of the **Initial Mass Function (IMF)**
    - Controls stellar **mass distribution**
  - The number of **Type Ia Supernovae**
    - Removes **gas** from galaxies and spreads metals
  - And many more…

Initial Mass Function



Chabrier+03

Type Ia Supernovae

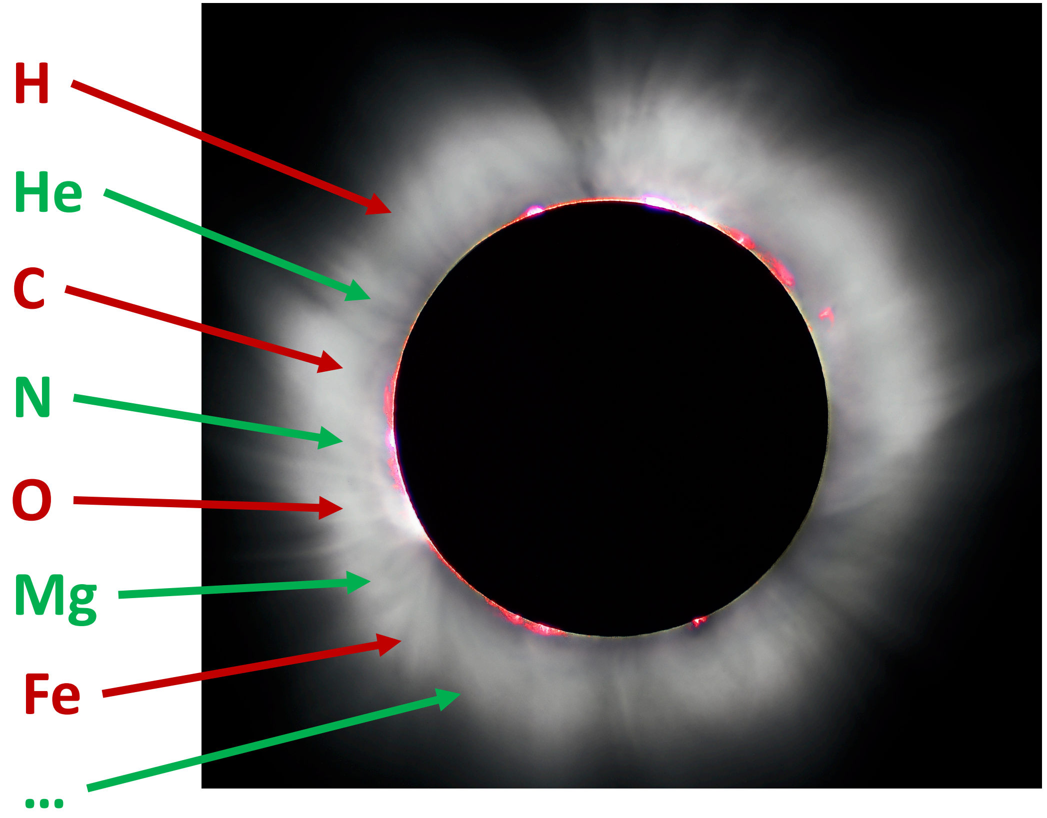


Chemistry from Stellar Atmospheres

- Stars **explode** and enrich the **interstellar medium**
- Stellar atmospheres encode chemical **abundances** of the interstellar medium
- These depend on **galactic parameters**, e.g.,

More massive stars → More He, C, O fusion → More He, C, O in atmospheres

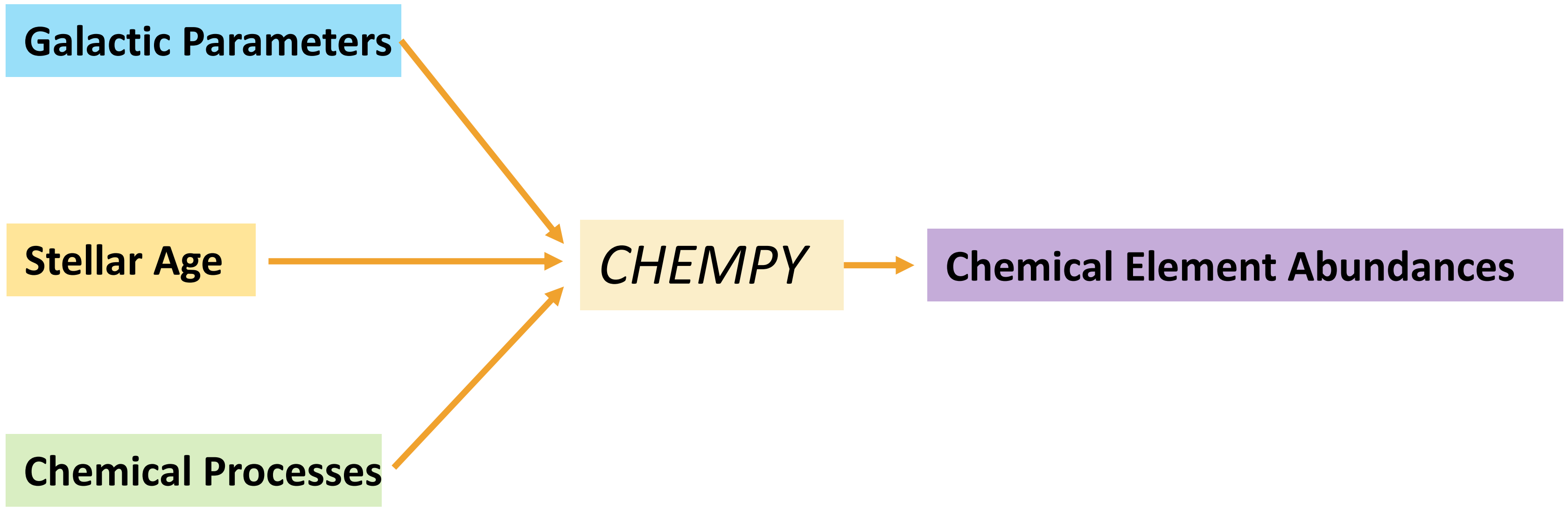
More Type Ia SNe → More Fe Produced → More Fe in atmospheres



github.com/oliverphilcox/ChempyMulti

Modeling Chemical Evolution

- Given **galactic parameters** we can model the **element abundances** in stellar atmospheres
- We need a **fast** and **flexible** model: *Chempy*



Rybizki+17

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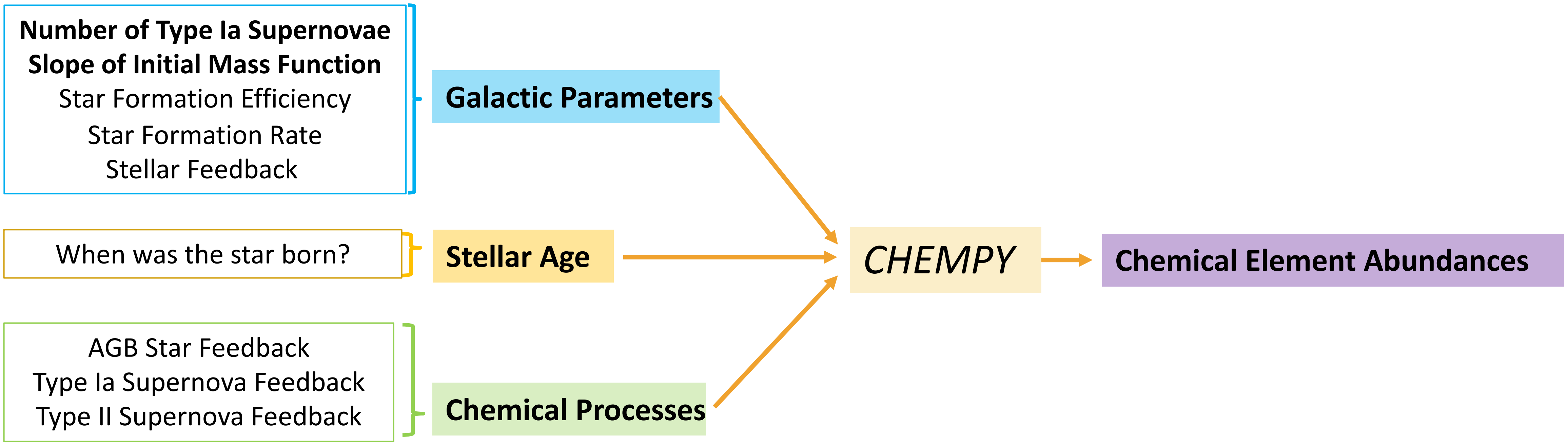

Rybizki+17

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Modeling Chemical Evolution

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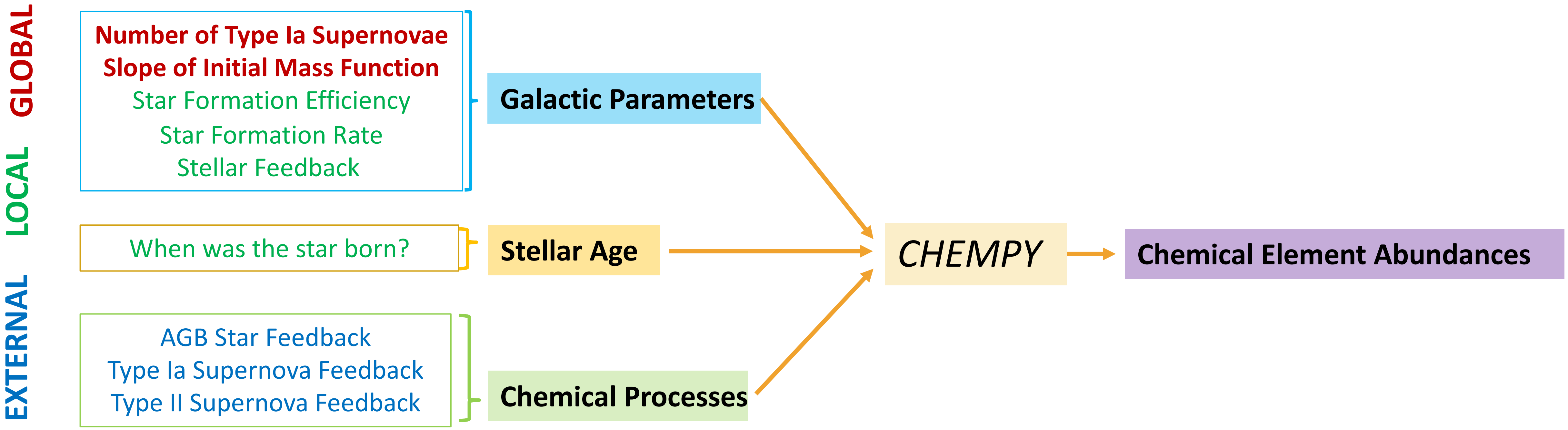


Rybizki+17

A Bayesian Framework

- From a set of **stellar chemical abundances** we can infer **galactic parameters**, Λ

- Via Bayes' theorem:

$$P(\boldsymbol{\Lambda}|\mathrm{Data}) \sim \int d\boldsymbol{\Theta}\, dT\; \underbrace{P(\mathrm{Data}|\boldsymbol{\Lambda},\boldsymbol{\Theta},T)}_{\textit{Likelihood}}\,\underbrace{p(\boldsymbol{\Lambda})p(\boldsymbol{\Theta})p(T)}_{\textit{Priors}}$$

integrating over local parameters Θ and the age of the star, T with priors p.

- We can extend this to **multiple stars**

$$P(\boldsymbol{\Lambda}|\mathrm{Data}) \sim p(\boldsymbol{\Lambda}) \prod_{i=1}^{n_{\mathrm{stars}}} \int d\boldsymbol{\Theta}_i\, dT_i\; \underbrace{P(\mathrm{Data}_i|\boldsymbol{\Lambda},\boldsymbol{\Theta}_i,T_i)}_{i^{th}\textit{ star likelihood}}\,\underbrace{p(\boldsymbol{\Theta}_i)p_i(T_i)}_{\textit{Priors}}$$

Philcox & Rybizki 2019

A Bayesian Framework

- We can extend this to **multiple stars**

$$P(\boldsymbol{\Lambda}|\mathrm{Data}) \sim p(\boldsymbol{\Lambda}) \prod_{i=1}^{n_{\mathrm{stars}}} \int d\boldsymbol{\Theta}_i \, dT_i \; P(\mathrm{Data}_i|\boldsymbol{\Lambda}, \boldsymbol{\Theta}_i, T_i) p(\boldsymbol{\Theta}_i) p_i(T_i)$$

i^{th} star likelihood *Priors*

- What about inadequacies in our model?
  - Add free **model error** parameters, σ_{model} (one per chemical element)
  - These will **downweight** constraints from poorly modeled elements

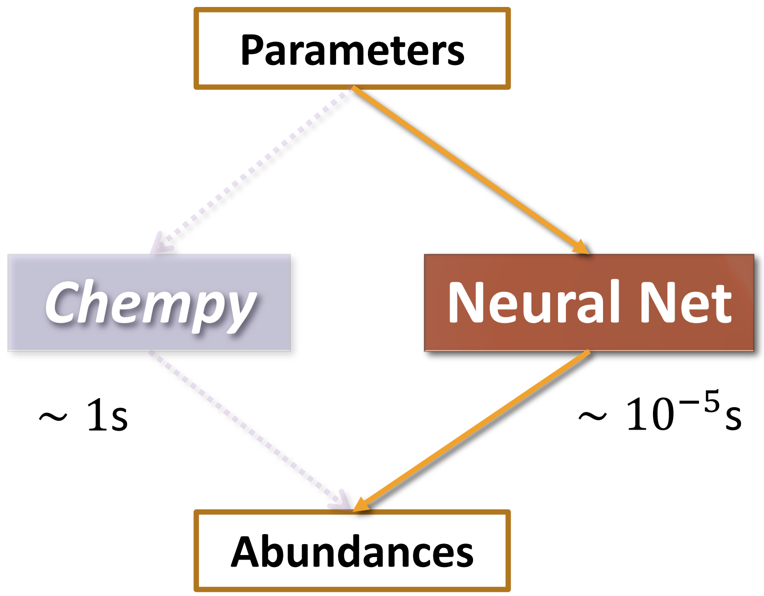
$$P(\boldsymbol{\Lambda}|\mathrm{Data}) \sim p(\boldsymbol{\Lambda}) \int d\sigma_{\mathrm{model}} \, p(\sigma_{\mathrm{model}}) \prod_{i=1}^{n_{\mathrm{stars}}} \int d\boldsymbol{\Theta}_i \, dT_i \; P(\mathrm{Data}_i|\boldsymbol{\Lambda}, \boldsymbol{\Theta}_i, T_i, \sigma_{\mathrm{model}}) p(\boldsymbol{\Theta}_i) p_i(T_i)$$

Philcox & Rybizki 2019

21^{st} Century Statistics

- Our model for the two **global** galactic parameters depends on:
  - 3 local **star formation** parameters per star
  - 1 **age** parameter per star
  - 1 **error** parameter per element.

For 100 stars with 8 elements, this gives **408** free parameters!



- We need **modern methods** for efficient sampling:
  - 1. Replace the **slow** *Chempy* model with a (differentiable) trained **neural network**
  - 2. Use **Hamiltonian Monte Carlo** with **No U-Turn Sampling** (NUTS)

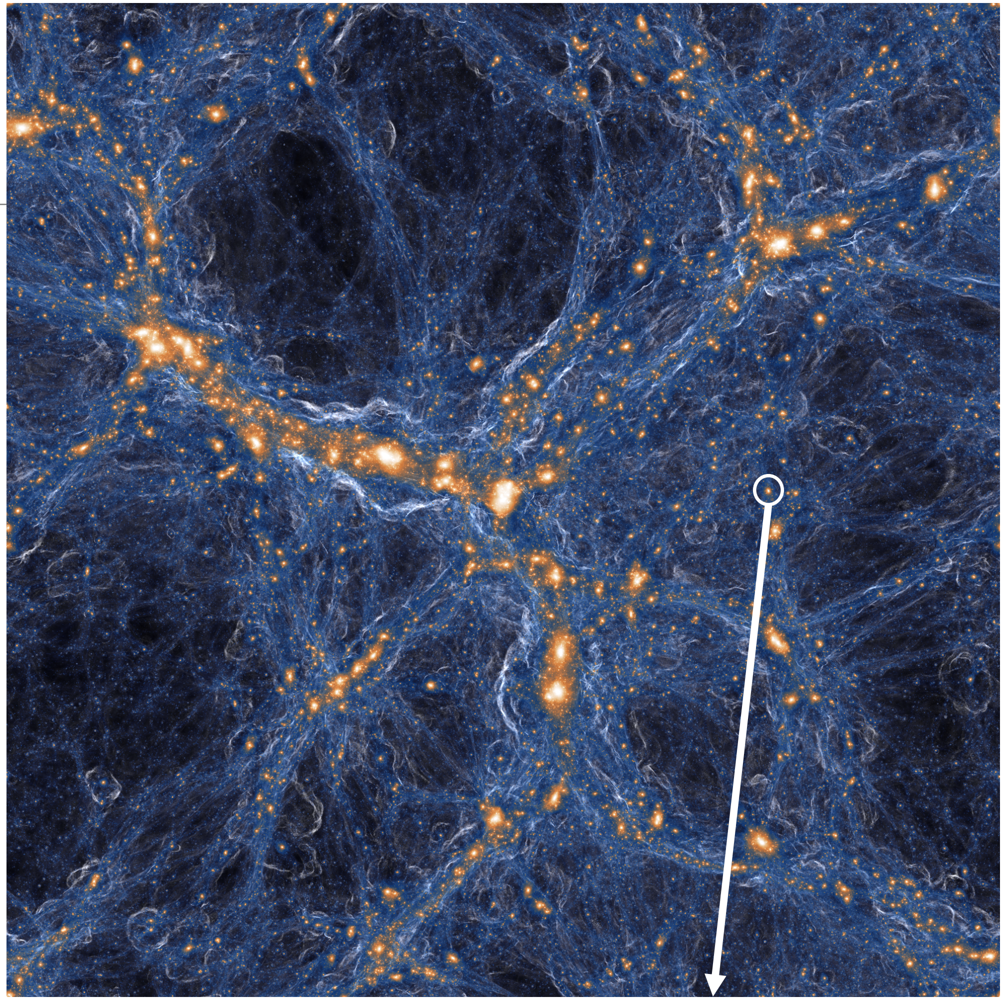
Philcox & Rybizki 2019

Mock Data

- Use the **IllustrisTNG-100** simulation
  - Has **much** more complex physics than *Chempy!*

- Extract ~200 **'stellar particles'** from a **Milky Way**-like galaxy each with:
  - **Stellar ages**
  - **Abundances** of H, He, C, N, O, Mg, Si, Ne, Fe

- Supplement these with realistic observational **errors**

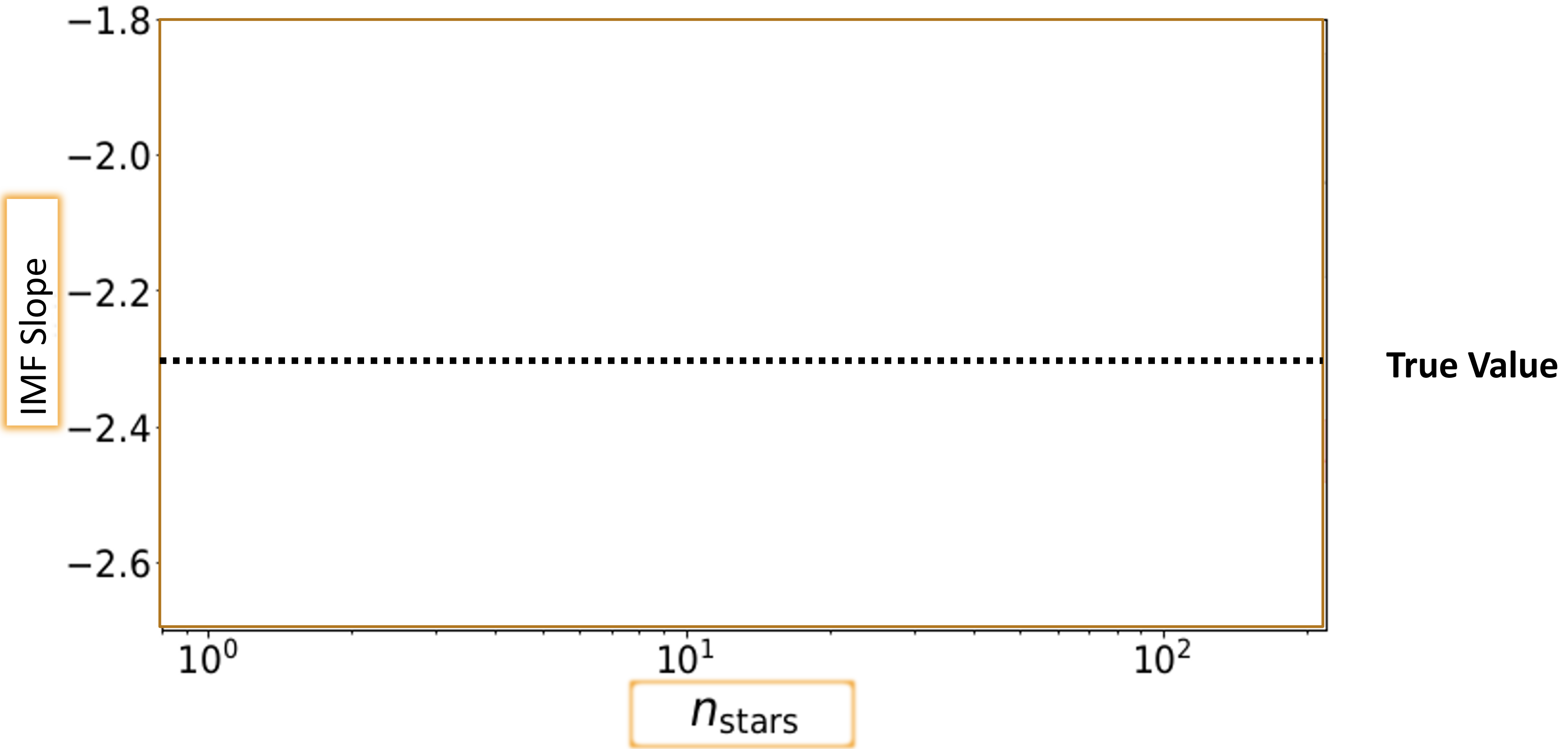


Milky Way v2.0

Springel+18

How well do we do?

- Compare our parameter inference with the true values in the simulation



Philcox & Rybizki 2019

How well do we do?

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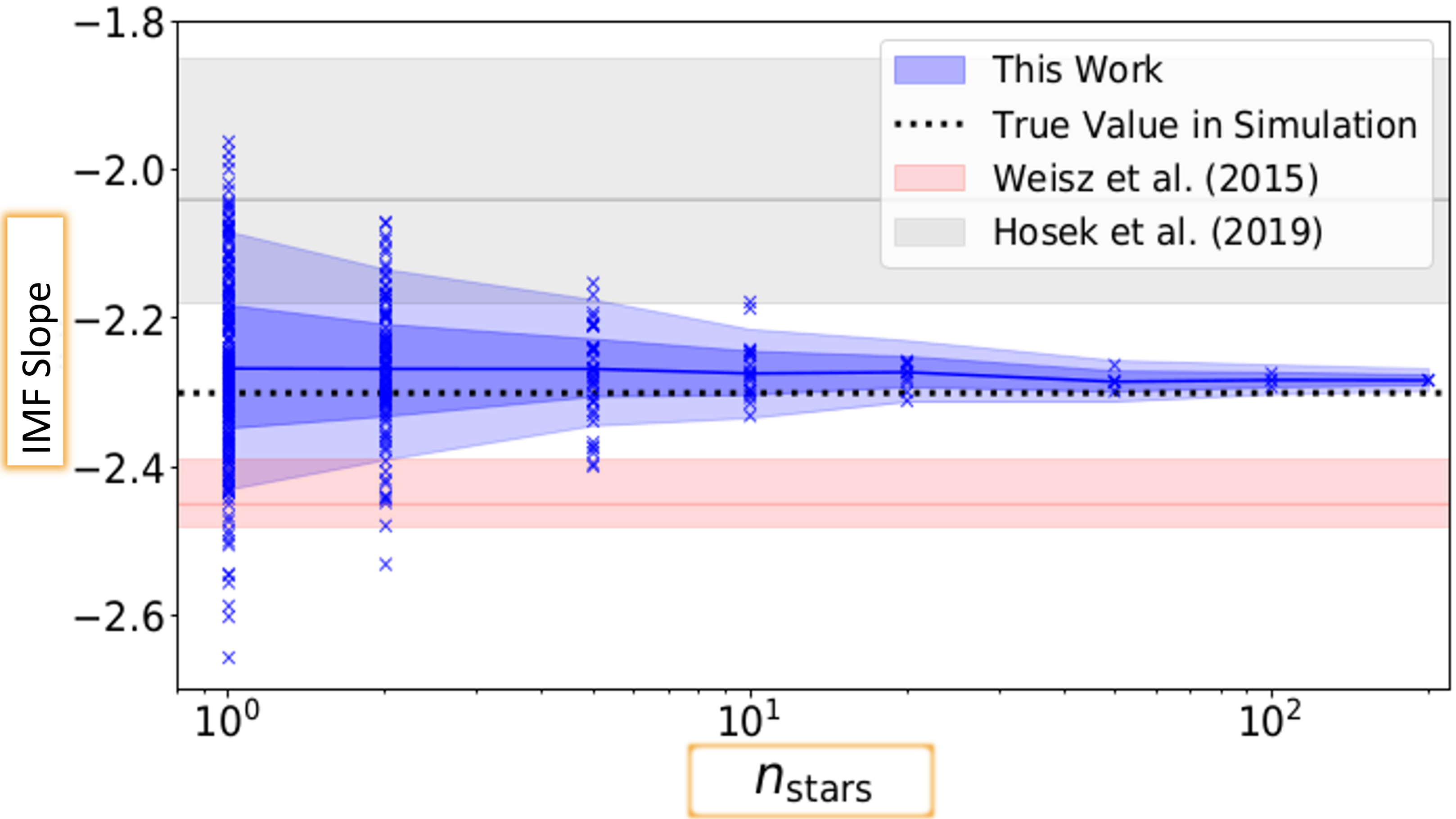
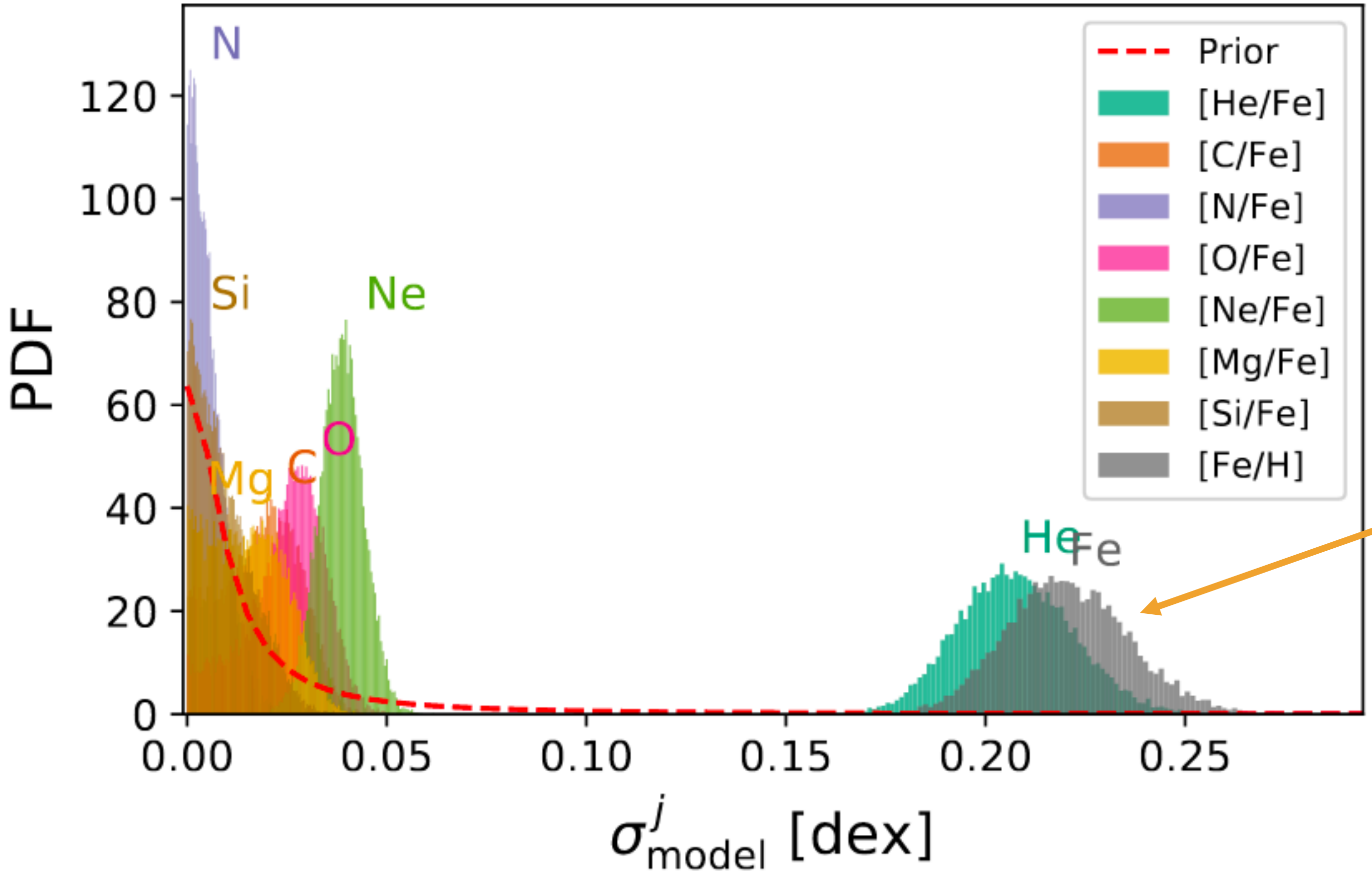


- A strong measurement of galactic parameters
- Tightens with more stars

Philcox & Rybizki 2019

How well do we do?

Model error posteriors



Absolute metallicity is **poorly predicted** but **metal line ratios** are useful

Philcox & Rybizki 2019

Summary

- We can use measure **galactic evolution** parameters from **stellar atmospheres** using:
  - A **simple** chemical evolution model (*Chempy*)
  - **Modern** statistical methods
- This has other applications e.g.;
  - **Application** to real data
  - **Optimizing** hydrodynamical simulation parameters
  - **Constraining** stellar nucleosynthesis

github.com/oliverphilcox/ChempyMulti

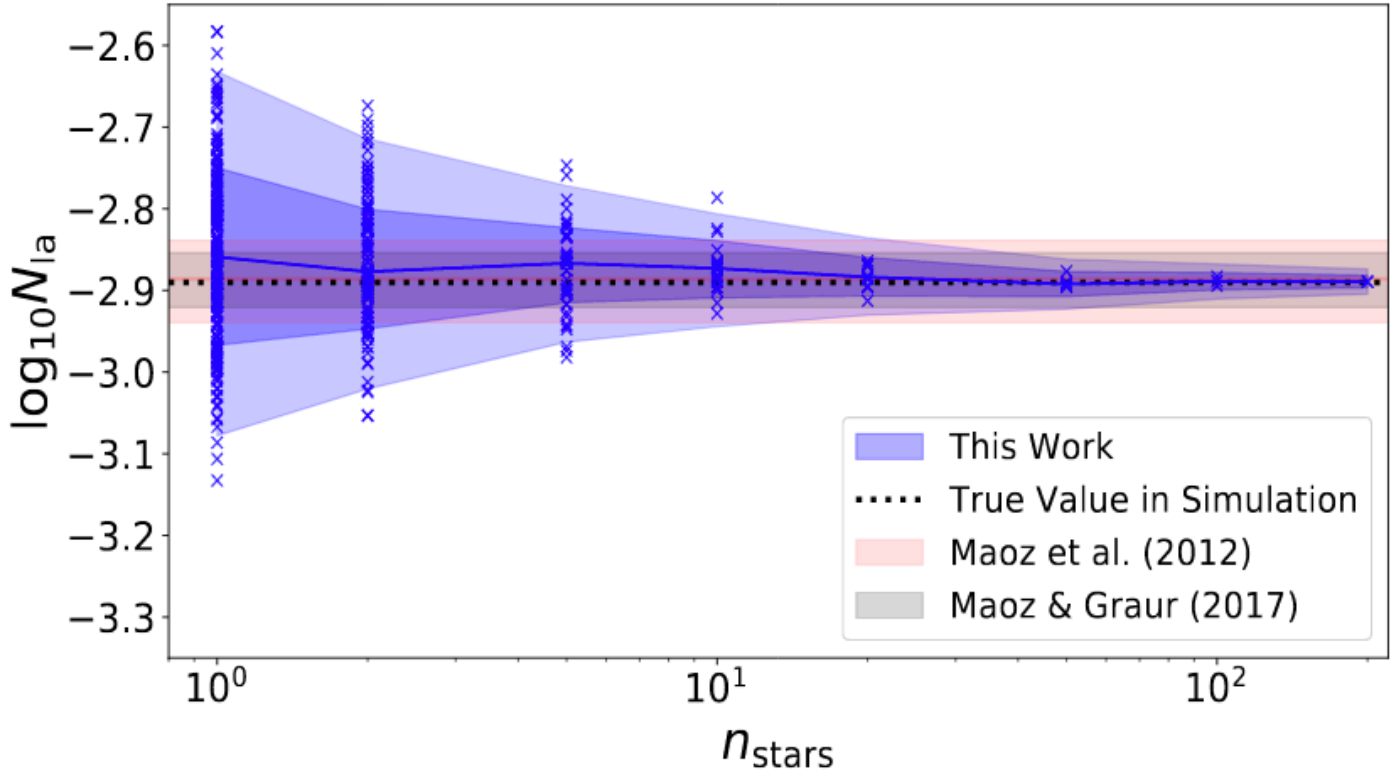
Further Questions?

ophilcox@princeton.edu

arXiv: 1909.00812

Type Ia Supernova Constraints

- Compare our parameter inference with the true values in the simulation



Philcox & Rybizki 2019

Neural Networks

- ❑ Evaluation of the *Chempy* function is slow ($\sim$ 1s)
- ❑ Use neural networks to **predict** output chemical elements from input parameters.
- ❑ This acts as a **fast**, **non-linear** interpolator, which is **differentiable**.

Input

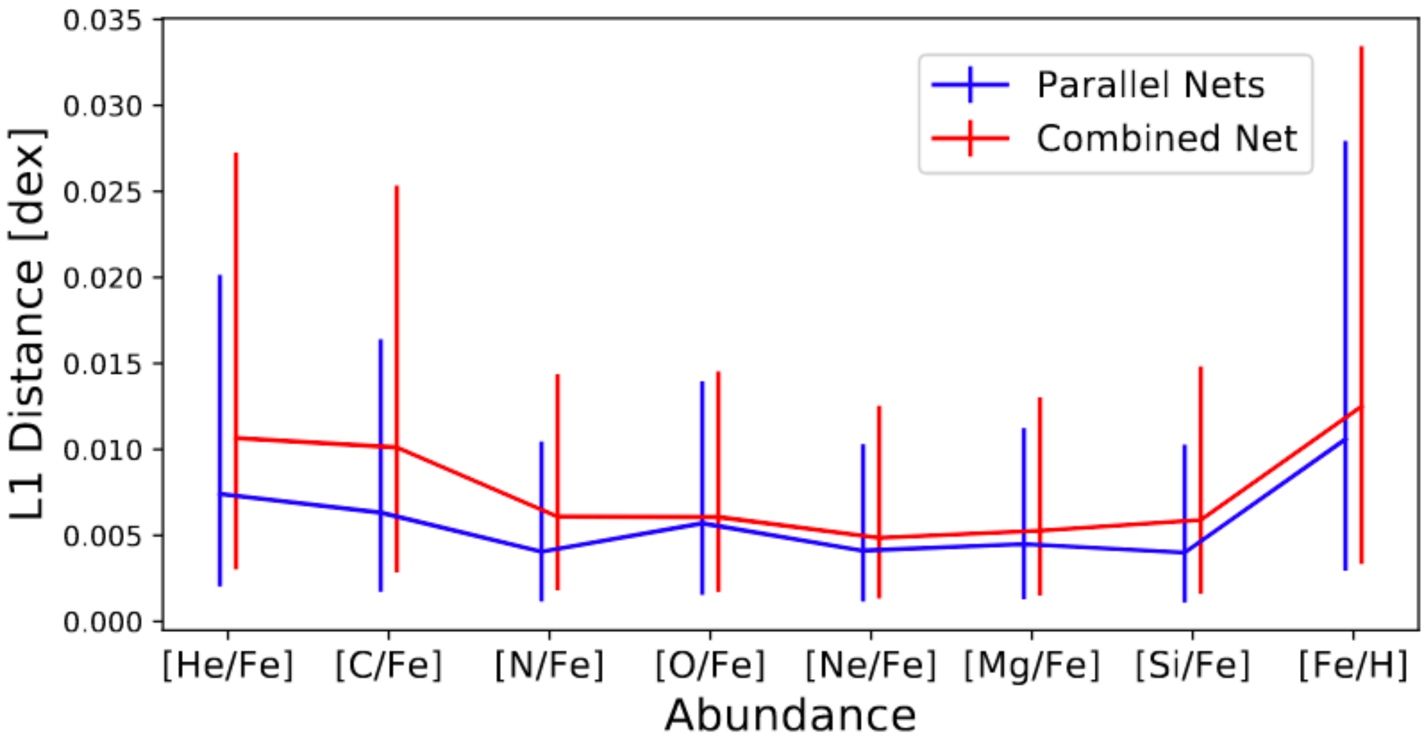
Hidden Layer → $\mathbf{h} = \mathbf{W}_0 \cdot \mathbf{x} + \mathbf{b}_0$

Output → $\mathbf{y} = \mathbf{W}_1 \cdot f(\mathbf{h}) + \mathbf{b}_1$

Non-Linearity

Neural Networks

- This is trained by running *Chempy* on $\sim 10^4$ points in parameter space.



Errors are much below observational error ~ 0.05 dex

Philcox & Rybizki (2019)

Hamiltonian Monte Carlo (HMC)

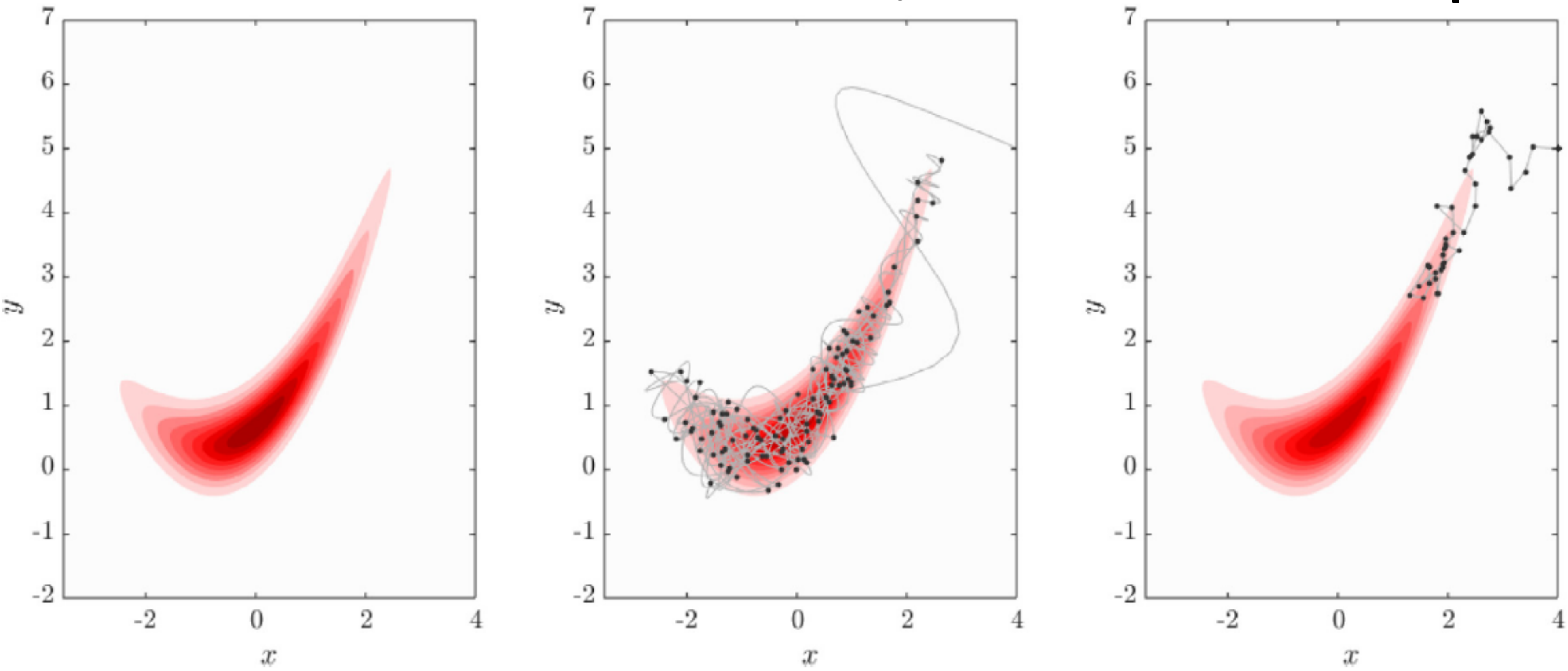
- Markov Chain Monte Carlo (MCMC) is **slow** and **unsuitable** for high-dimensional problems.
- MCMC works by jumping between points in parameter space at random.
- HMC preferentially samples where the posterior is **large.**
- It’s **much more efficient** but requires a **differentiable** model.

Betancourt (2017)

Hamiltonian Monte Carlo (HMC)

- HMC preferentially samples where the posterior is **large.**

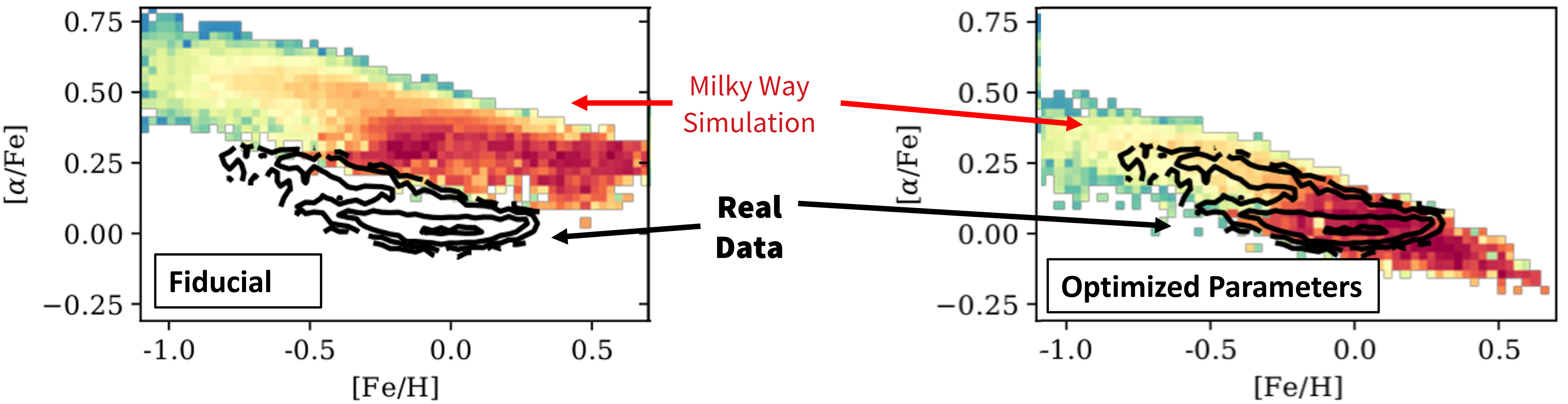
Posterior **HMC Samples** **MCMC Samples**



Wang+ (2019)

Optimizing Simulations

- *Chempy* can be combined with **solar abundances** to measure parameters.
- This is done via **MCMC** or more advanced methods
- To test, we can put our **best-fit parameters** into a cosmological simulation
  - **Do we get a more realistic galaxy simulation?**

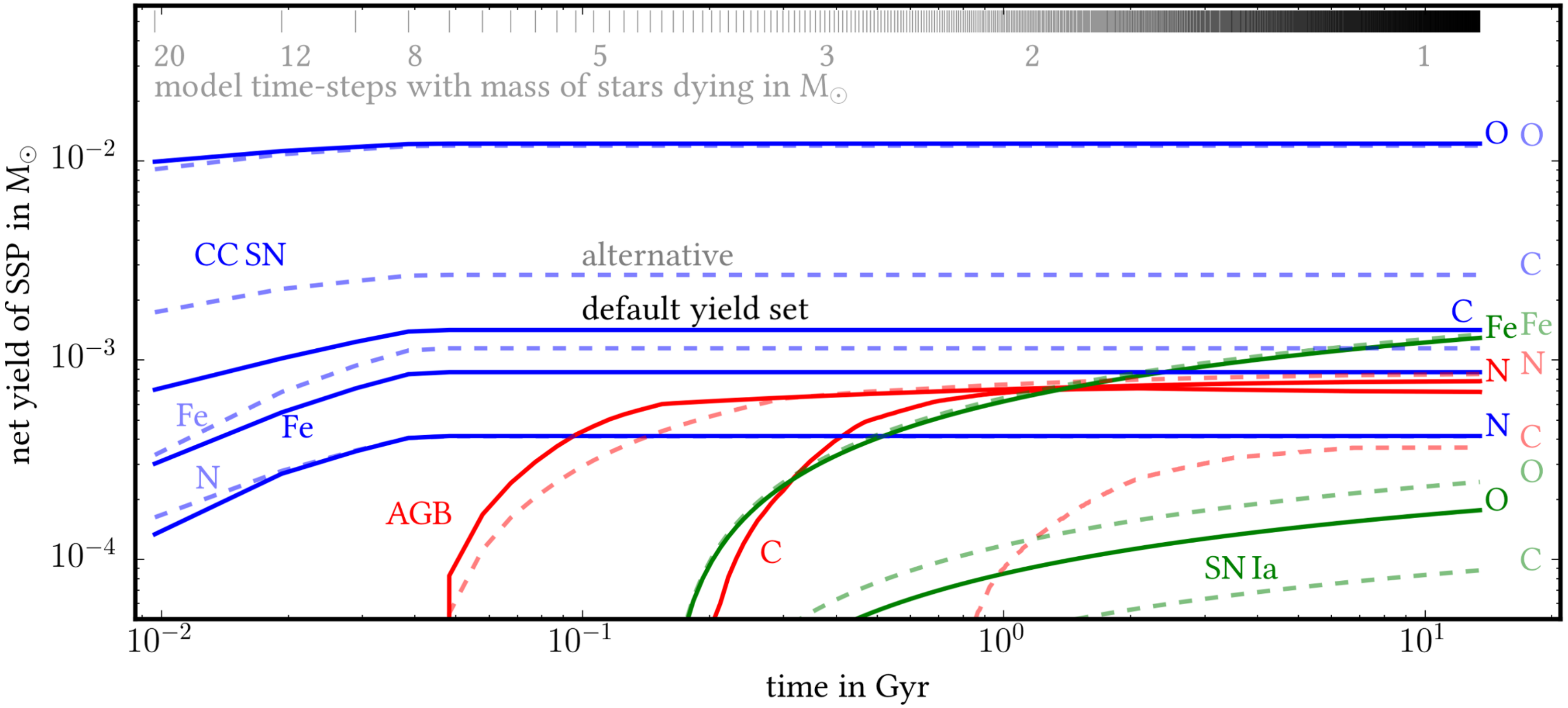


Philcox, Rybizki & Gutcke 2018

github.com/jan-rybizki/Chempy

Building a Fast and Flexible GCE: *Chempy*

- ❑ *Chempy* (including **chemical yields**, and **SSP** parameters):
  - ❑ **IMF** integrated, metallicity-dependent yield over time



SSP = Simple Stellar Population
(A group of stars born at the same time in the same environment)

IMF = Initial Mass Function
(Contribution of stars born in a certain mass range to total mass)

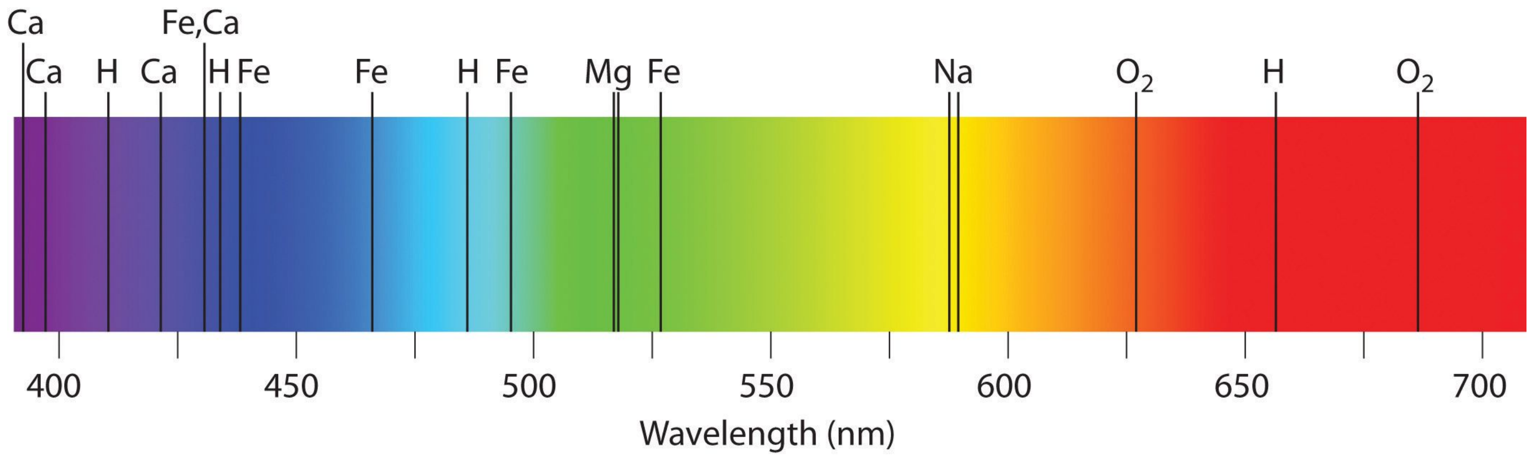
Rybizki, Just & Rix (2017)

How do we measure ISM Abundances?

- **Option 1:** Spectroscopy of the ISM
  - Difficult
  - Depends on the ISM temperature and density

- **Option 2:** Stellar Atmospheres
  - Can observe stellar chemistry in **absorption lines**
  - Many data catalogs exist, e.g. APOGEE
  - Metal lines have little contamination

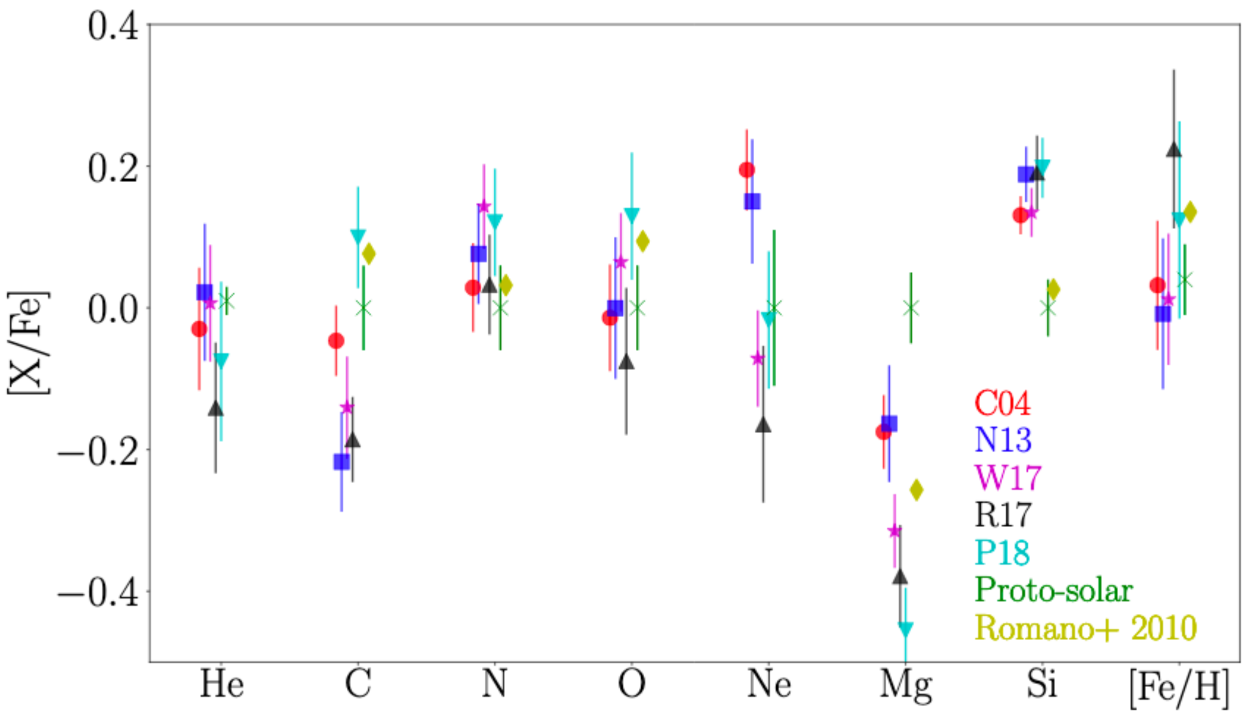
To Begin: Use a *single* star – the **Sun** with 28 elements



github.com/oliverphilcox/ChempyMulti

Yield Table Scoring

- ❑ Different Yield Tables predict **very different** proto-Solar abundances



Philcox, Rybizki & Gutcke (2018)

github.com/oliverphilcox/ChempyMulti

Yield Table Scoring

- **Method:**
  - Compare *Chempy* observations to **proto-Solar** abundances
  - **Marginalize** over SSP and ISM parameters
  - Include **model error** to account for modeling inaccuracies

- **Model Comparison Statistics:**
  - Bayes Factor
    - $B \sim \int d\Theta \ \mathrm{Posterior}(\Theta \mid Data)$
  - Cross-Validation
    - Use $n-1$ elements to predict n-th element

Philcox, Rybizki & Gutcke (2018)

github.com/oliverphilcox/ChempyMulti

Yield Table Scoring

Comparing Core-Collapse Supernovae Yield Tables using 28 Elements

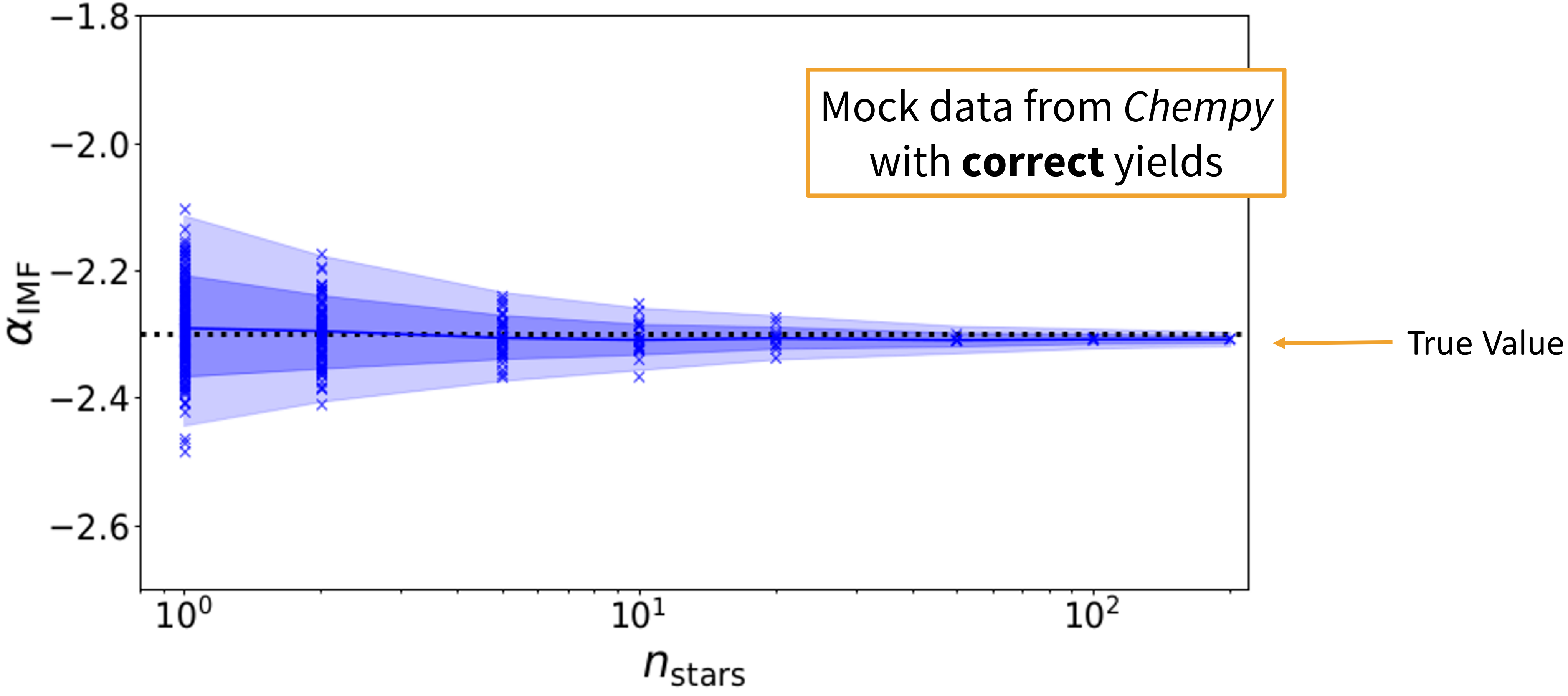
Yield Set	Bayes Score
C04	-1.21
N13	-5.69
W17	-0.78
R17	-6.11
P18	0.86

Nikos Prantzos' yields perform best here!

Philcox, Rybizki & Gutcke (2018)

github.com/oliverphilcox/ChempyMulti

Multi-Star Inference with *Chempy*



Philcox & Rybizki (2019)

github.com/oliverphilcox/ChempyMulti

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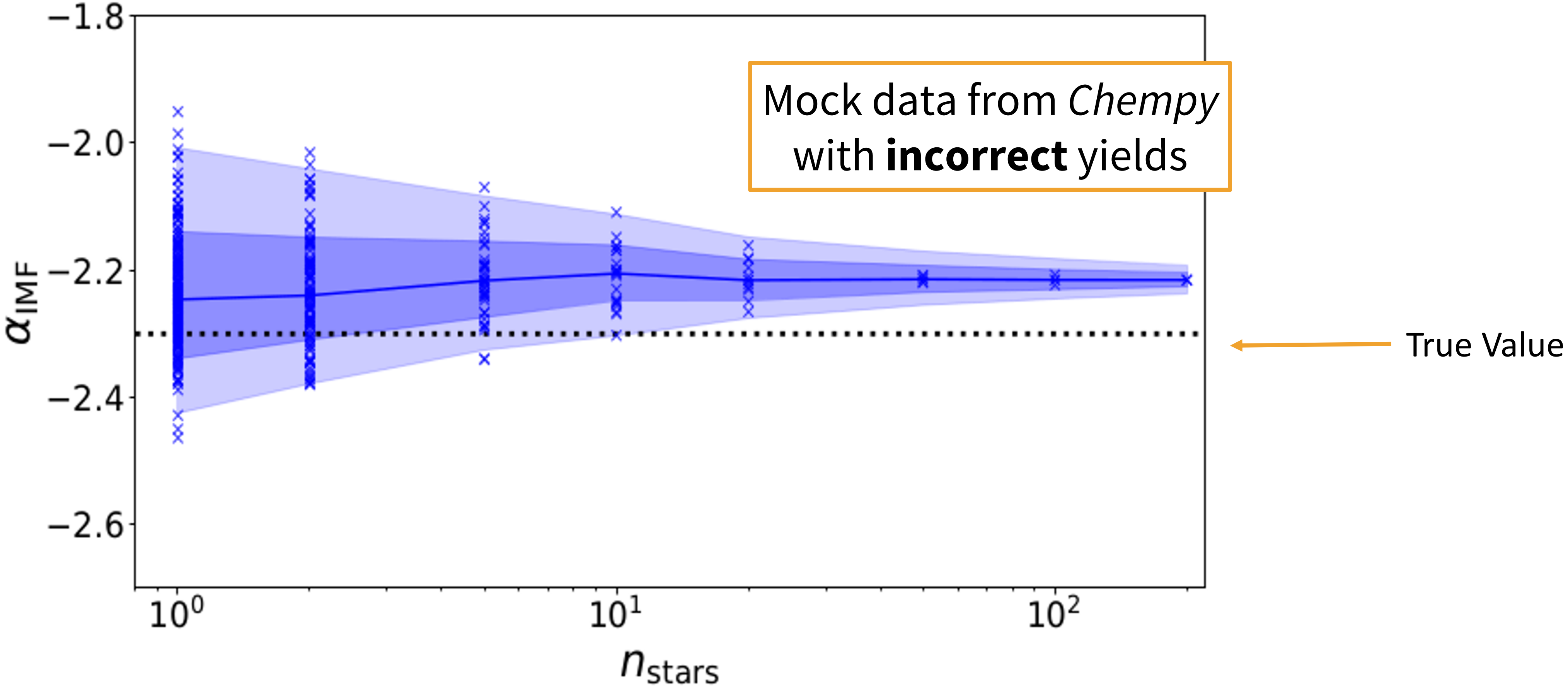

Philcox & Rybizki (2019)

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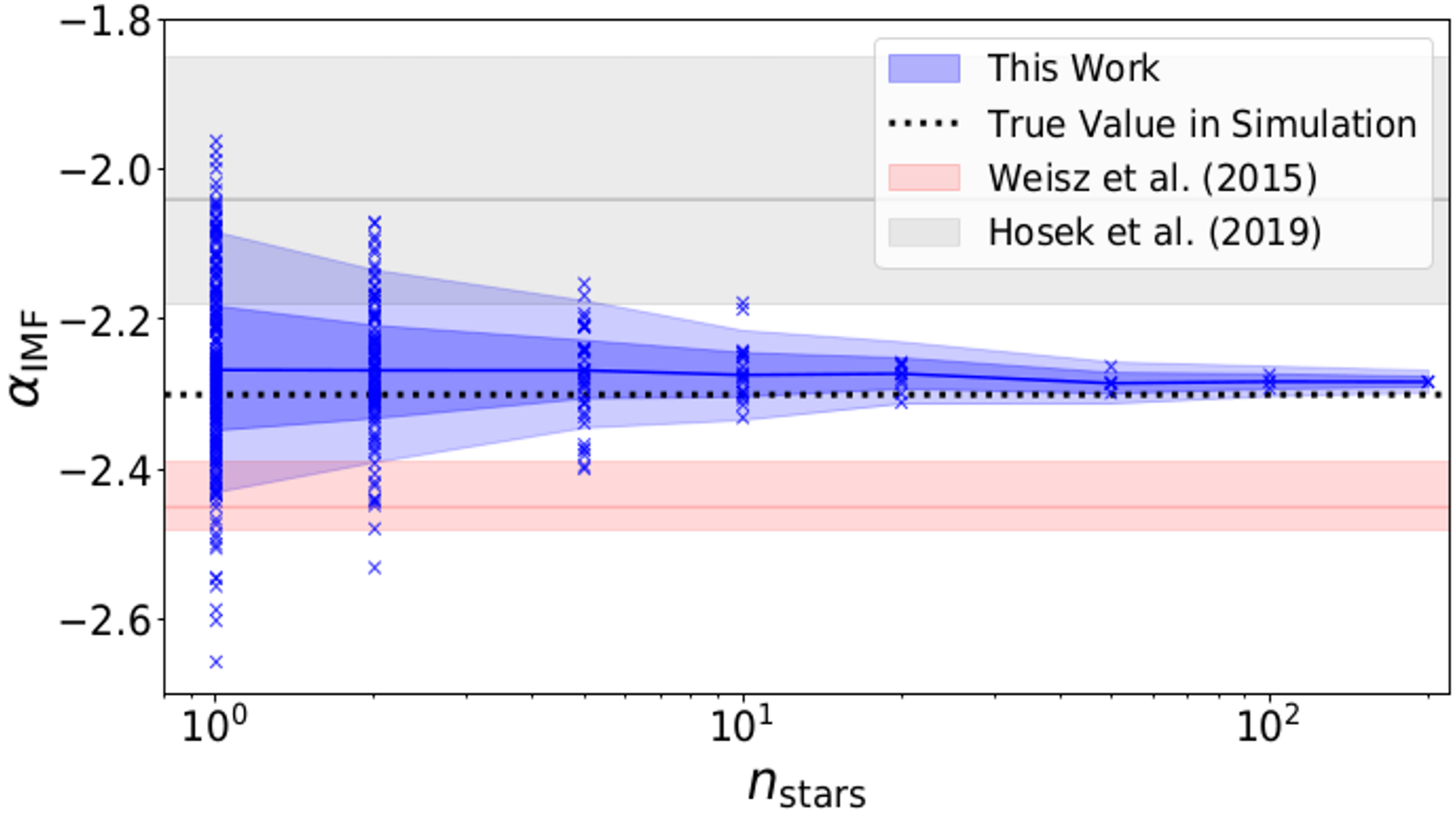


Mock data from **IllustrisTNG** with **correct** yields

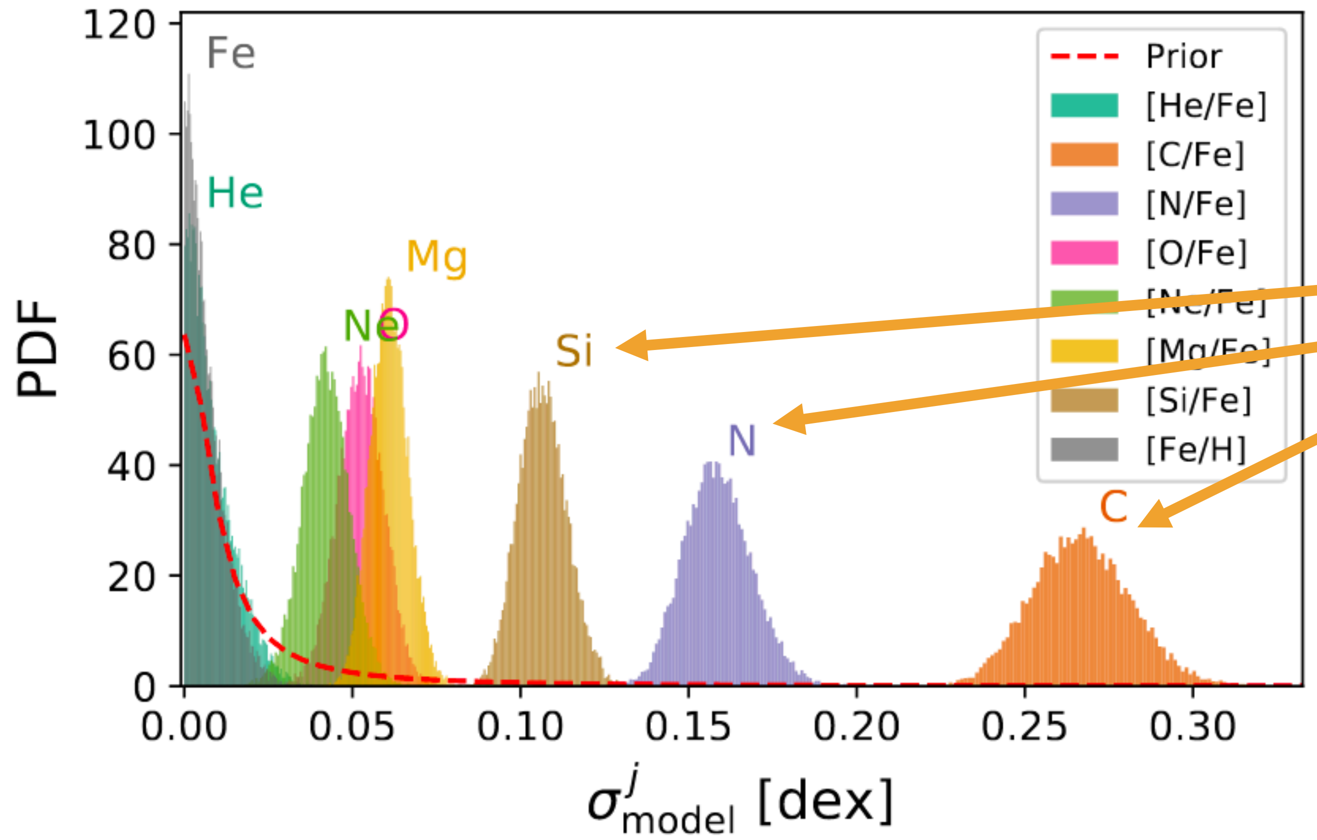
Philcox & Rybizki (2019)

github.com/oliverphilcox/ChempyMulti

Multi-Star Inference with *Chempy*

- **Model errors** indicate errors in our yield tables.

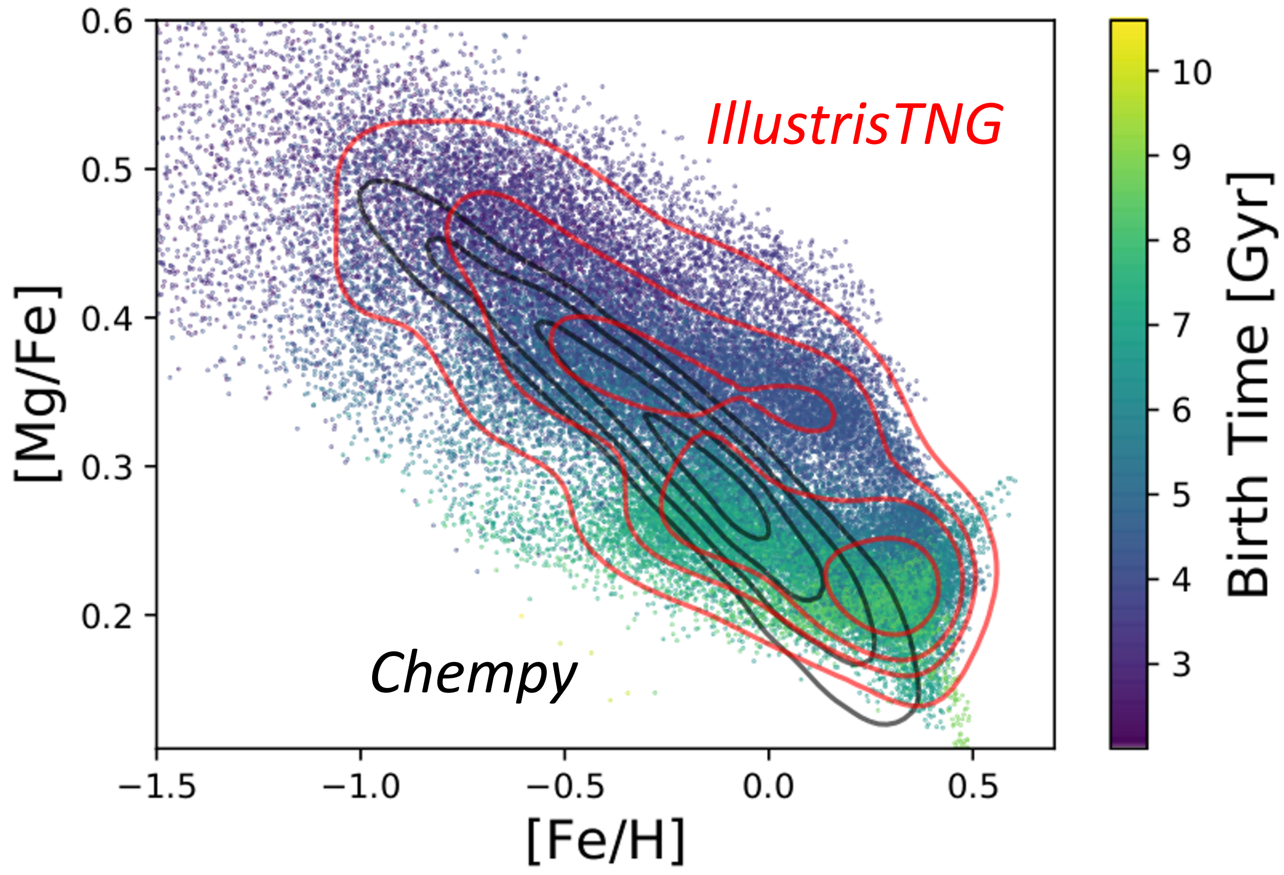
Model Error Distributions for analysis with **incorrect** yield set



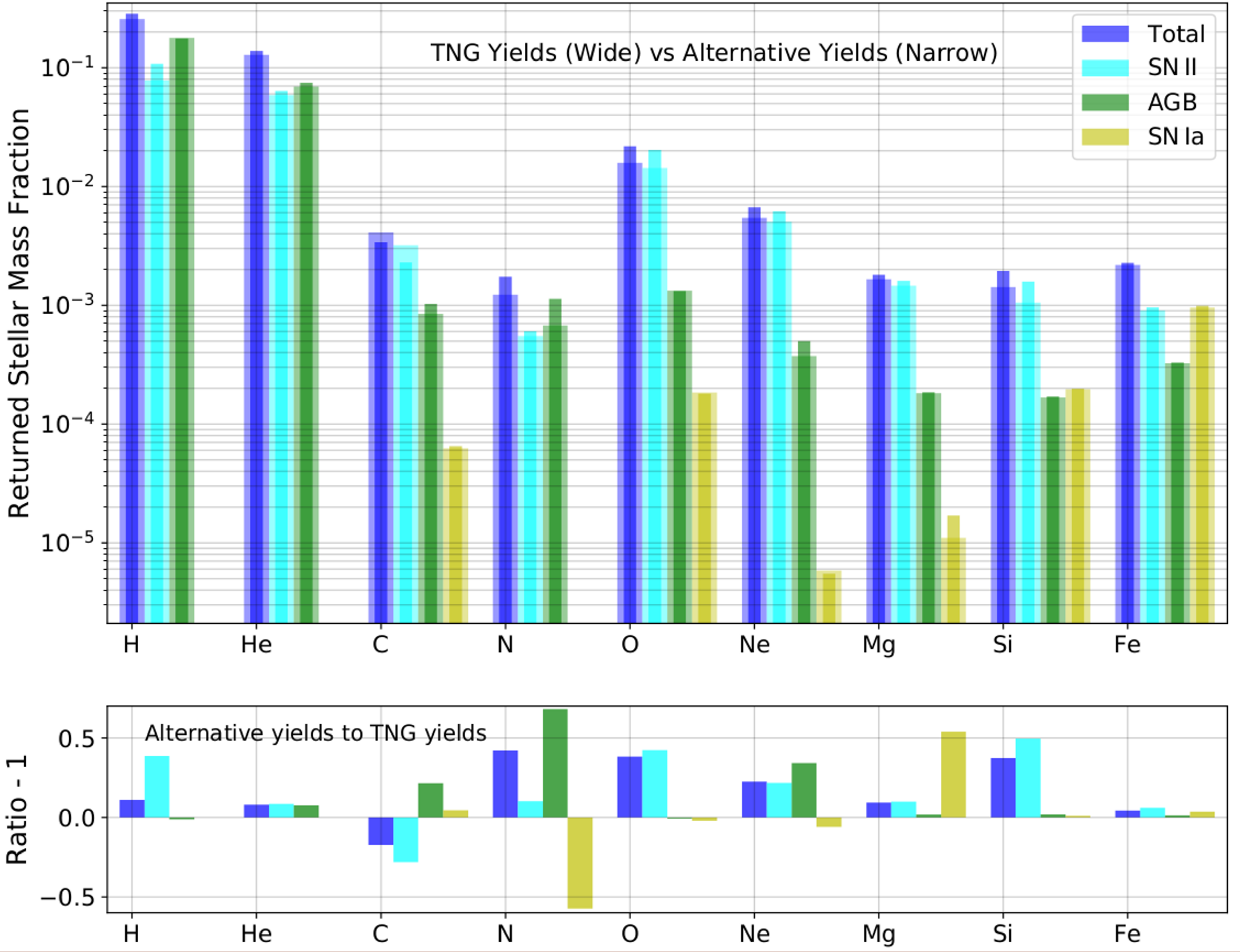
Si, N and C ***are*** *the most discrepant elements between our yield sets!*

Philcox & Rybizki (2019)

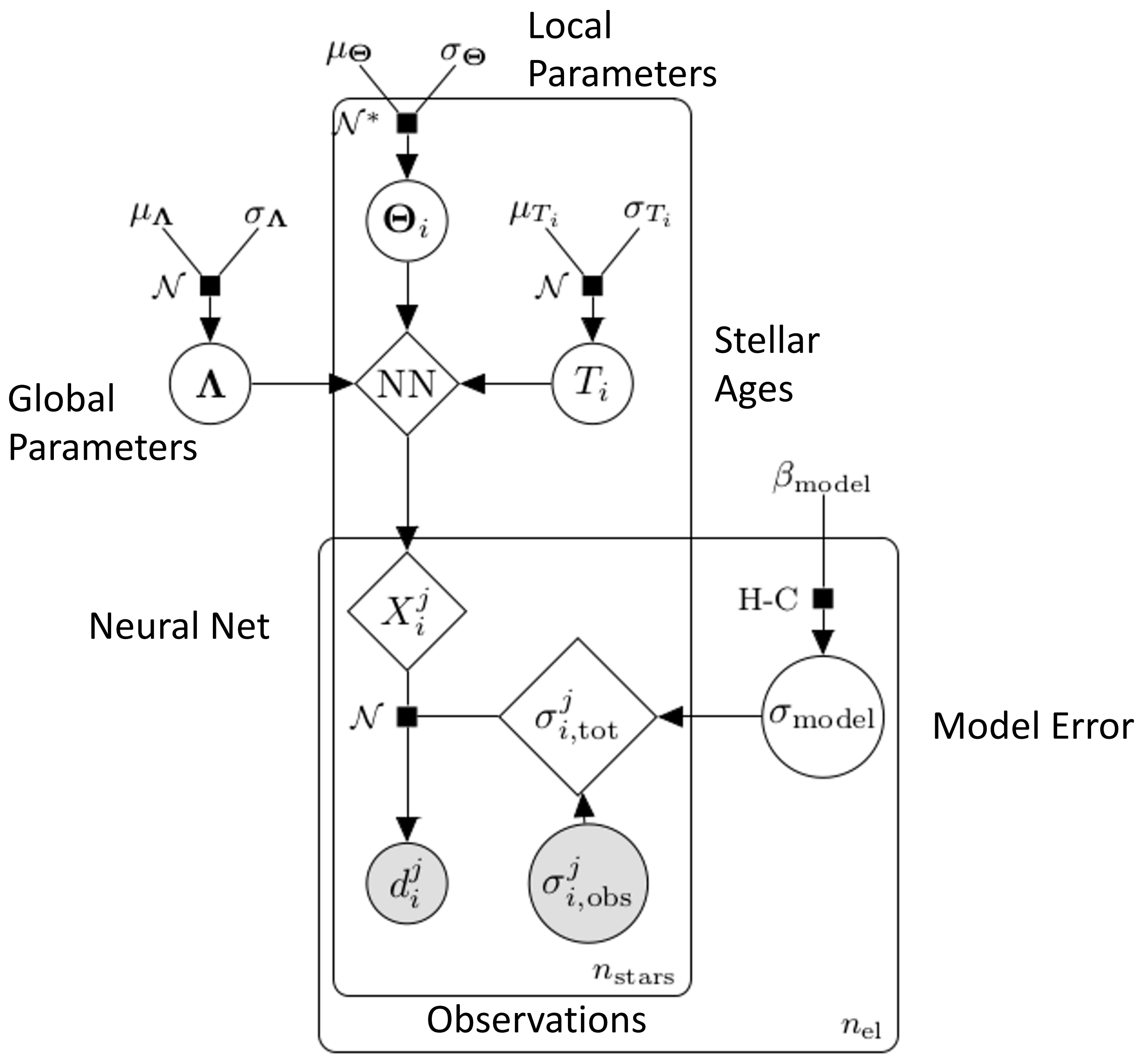
Abundance Diagrams



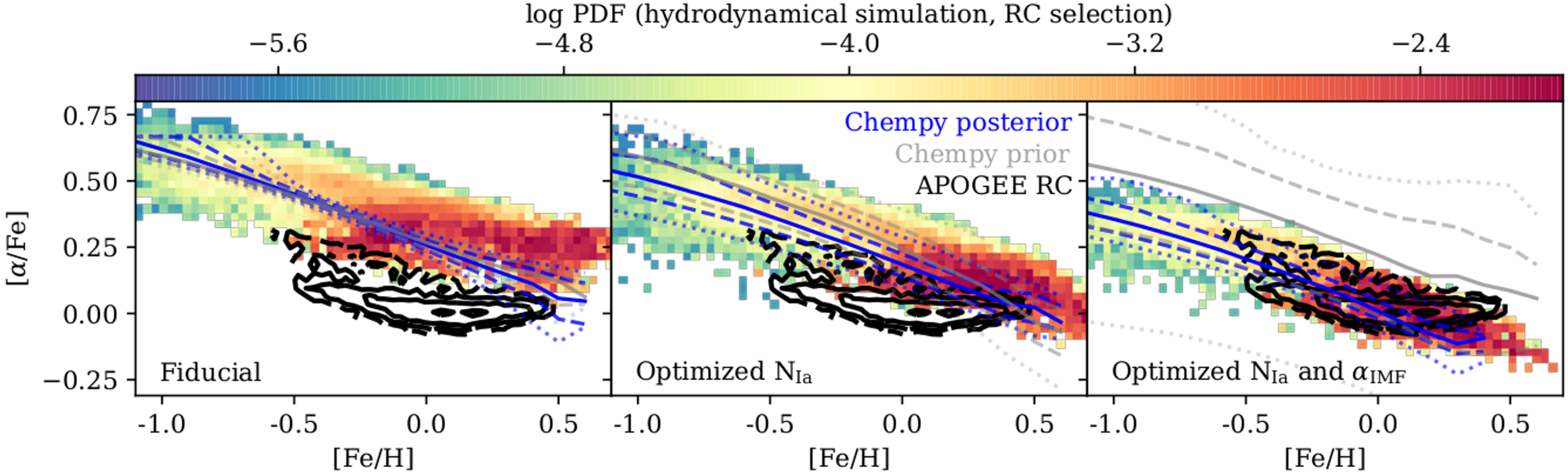
Default and Alternative Yields



ChempyMulti Architecture



Full Hydrodynamical Simulation Optimization



Full Corner Plot