

Detecting Degeneracies for Simulation-based Inference

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The General Idea

- **Posterior:** $\mathcal{P}(\boldsymbol{\theta} \mid \mathbf{d}) \sim \mathcal{P}(\mathbf{d} \mid \boldsymbol{\theta})\mathcal{P}(\boldsymbol{\theta})$
- **Degeneracies:** Most posterior mass lies within an ε -neighborhood of a lower-dimensional manifold

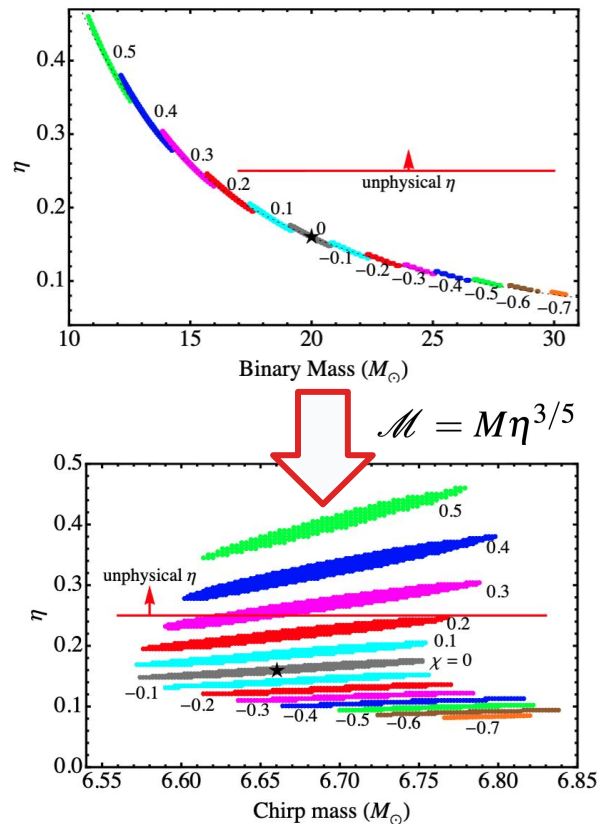
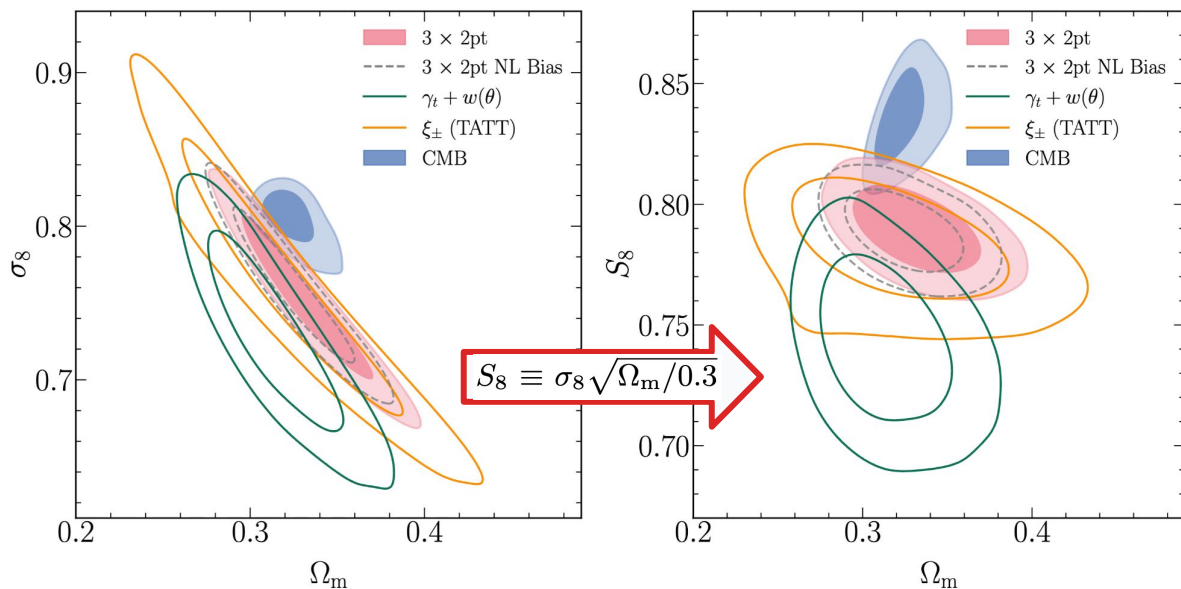
$$\mathcal{M}_c = \{ \boldsymbol{\theta} \in \mathbb{R}^M : F(\theta_{j_1}, \dots, \theta_{j_k}) = c \}$$

under some metric on parameter space.

- **Problem:** Param inference is very difficult along the degenerate direction.

Canonical examples

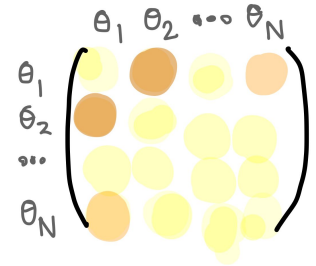
- CMB degeneracy
- weak lensing
- gravitational waves



Learn Degeneracies in 3 steps

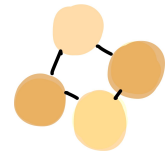
1)

Mutual Information (MI) Screening
narrow down the parameter combinations



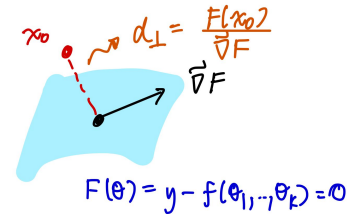
2)

Symbolic Fitting
assume separable and fit one component at a time



3)

Diagnostics
shows top symbolic equations and diagnostic visualizations



Learn Degeneracies in 3 steps

1)

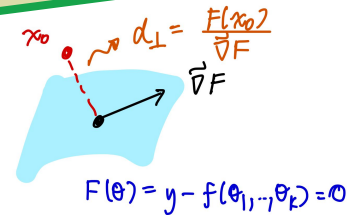
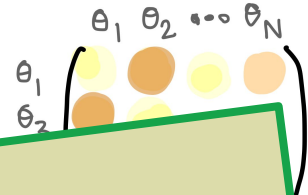
Mutual Information (MI) Screening

narrow down the parameter combinations

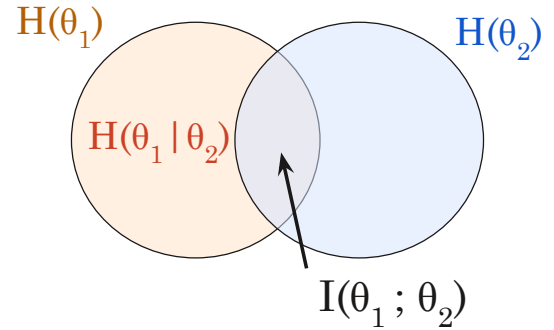
```
detector = DegenDetector(samples, param_names)
result = detector.search_couplings(coupling_depth=2, niterations=200)
```

```
runner = DiagnosticsRunner(result_dir)
runner.run()
```

step symbolic equations and diagnostic visualizations



1) MI Screening



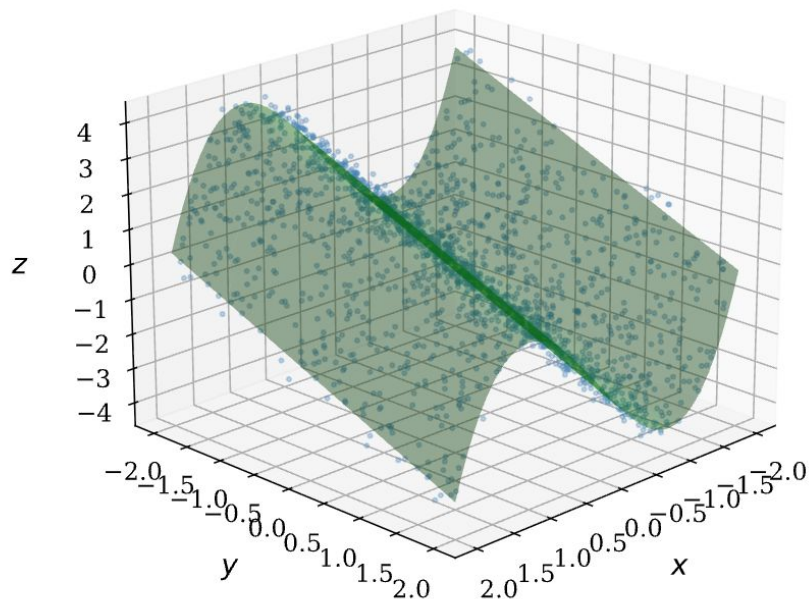
- MI measures the reduction in uncertainty about θ_1 given knowledge of θ_2 .

Intuition:

- Entropy as a proxy for “surprise”:
$$H(\theta) = - \sum_{\theta \in \Theta} \mathcal{P}(\theta) \log(\mathcal{P}(\theta))$$
- Conditional entropy:
$$H(\theta_1 | \theta_2) = - \sum_{\theta_2} \mathcal{P}(\theta_2) \sum_{\theta_1} \mathcal{P}(\theta_1 | \theta_2) \log(\mathcal{P}(\theta_1 | \theta_2))$$
- Mutual information:
$$I(\theta_1; \theta_2) = H(\theta_1) - H(\theta_1 | \theta_2)$$

MI matrix effectively isolates the degeneracy.

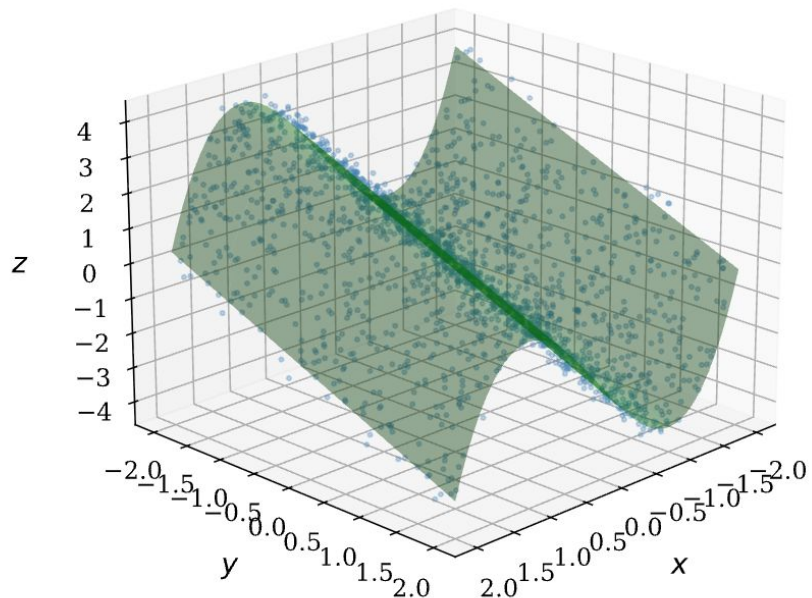
$$x^3 - 3x + y + z = 0$$



	x	y	z	a	b	c	d
x	0.00	0.00	0.48	0.02	0.00	0.00	0.00
y	0.00	0.00	0.47	0.02	0.01	0.00	0.00
z	0.48	0.47	0.00	0.00	0.00	0.00	0.00
a	0.02	0.02	0.00	0.00	0.04	0.00	0.02
b	0.00	0.01	0.00	0.04	0.00	0.01	0.01
c	0.00	0.00	0.00	0.00	0.01	0.00	0.00
d	0.00	0.00	0.00	0.02	0.01	0.00	0.00

Pairwise MI matrix (nats)

$$x^3 - 3x + y + z = 0$$




	x	y	z	a	b	c	d
x	0.00	0.00	0.48	0.02	0.00	0.00	0.00
y	0.00	0.00	0.47	0.02	0.01	0.00	0.00
z	0.48	0.47	0.00	0.00	0.00	0.00	0.00
a	0.02	0.02	0.00	0.00	0.04	0.00	0.02
b	0.00	0.01	0.00	0.04	0.00	0.01	0.01
c	0.00	0.00	0.00	0.00	0.01	0.00	0.00
d	0.00	0.00	0.00	0.02	0.01	0.00	0.00

Pairwise MI matrix (nats)

2) Symbolic Fit

- **But...it's still a k-dimensional fitting problem.**
 - The search space of potential formulas grows combinatorially as $\mathcal{O}(k^k)$ with input features.

Solution: We *split* into k independent one-dimensional symbolic regression problems by modeling the degeneracy as the level set of a *separable* function.

$$g_1(\theta_{j_1}) + g_2(\theta_{j_2}) + \cdots + g_k(\theta_{j_k}) = c$$


univariate functions to be fitted

Q: How do we fit these component functions?

(1) normalize using the z-score $\tilde{\theta}_\ell = \frac{\theta_\ell - \mu_\ell}{\sigma_\ell}$ and initialize $\left[\begin{array}{l} g_\ell(\tilde{\theta}_\ell) = \tilde{\theta}_\ell \\ c = \text{mean}(\sum_\ell \tilde{\theta}_\ell) \end{array} \right.$

(2) Repeat for $l = 1, \dots, k$ until convergence

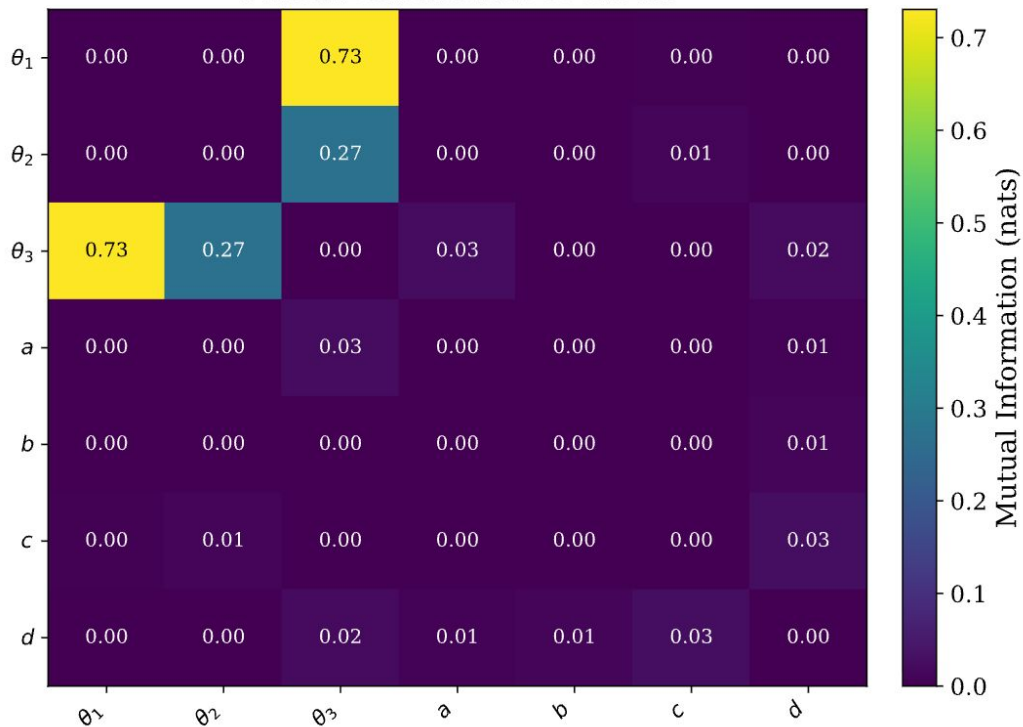
➤ Do symbolic regression for the pairs $(g_\ell(\tilde{\theta}_\ell), c - \sum_{m \neq \ell} g_m(\tilde{\theta}_m))$

regression target!

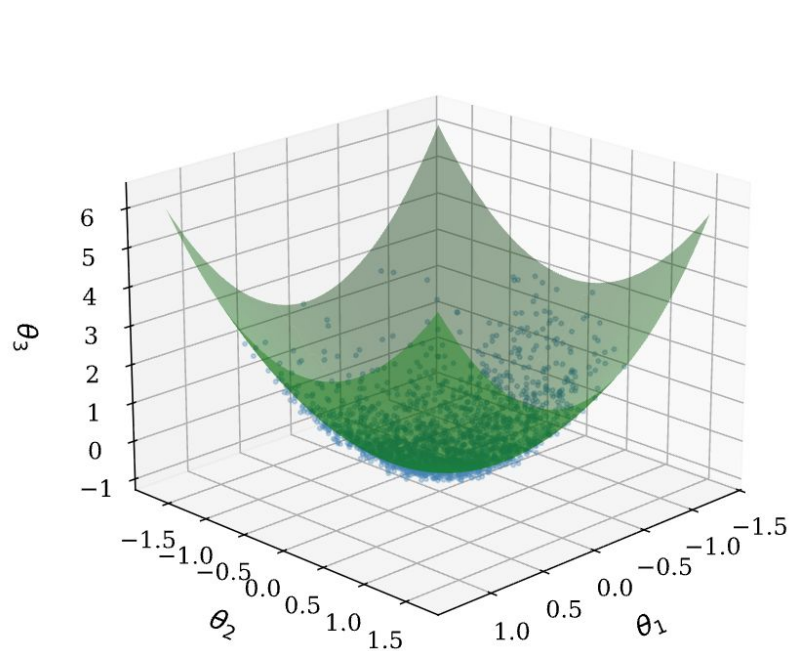
➤ **Goal:** want to minimize MSE for all the N pairs of the dataset

Benchmark Results

Mutual Information Matrix



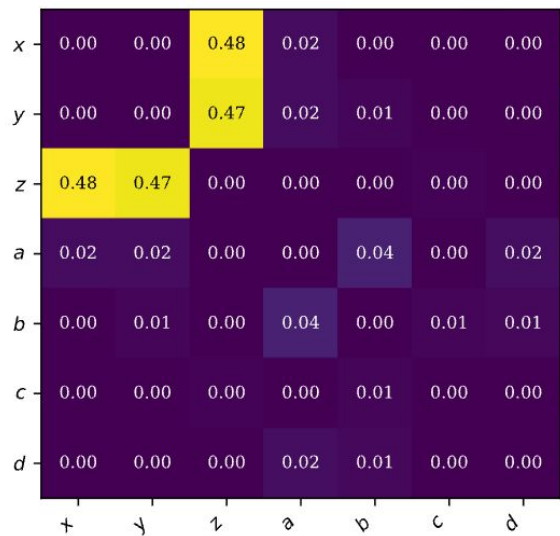
Fitted Surface ($R^2_{\perp} = 0.9957$)



Benchmark Results

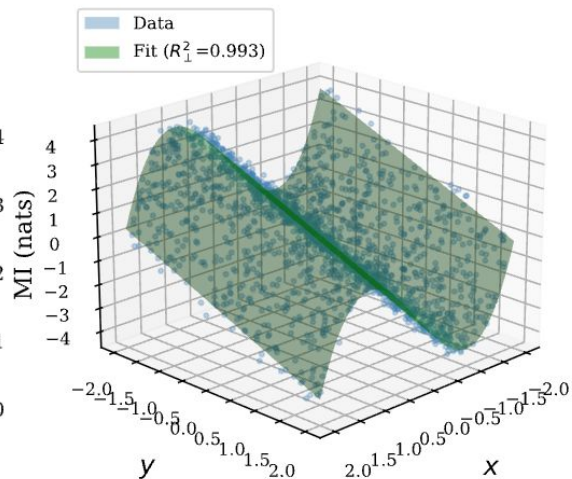
(a)

S-curve: MI Matrix



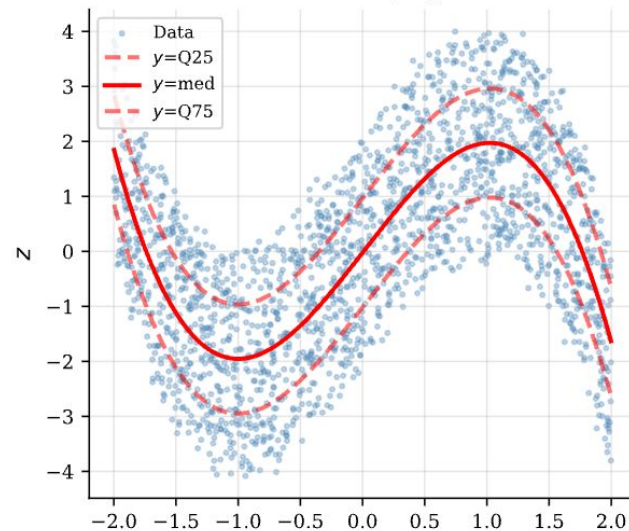
(b)

S-curve: $(x^3 - 3x) + y + z = 0$

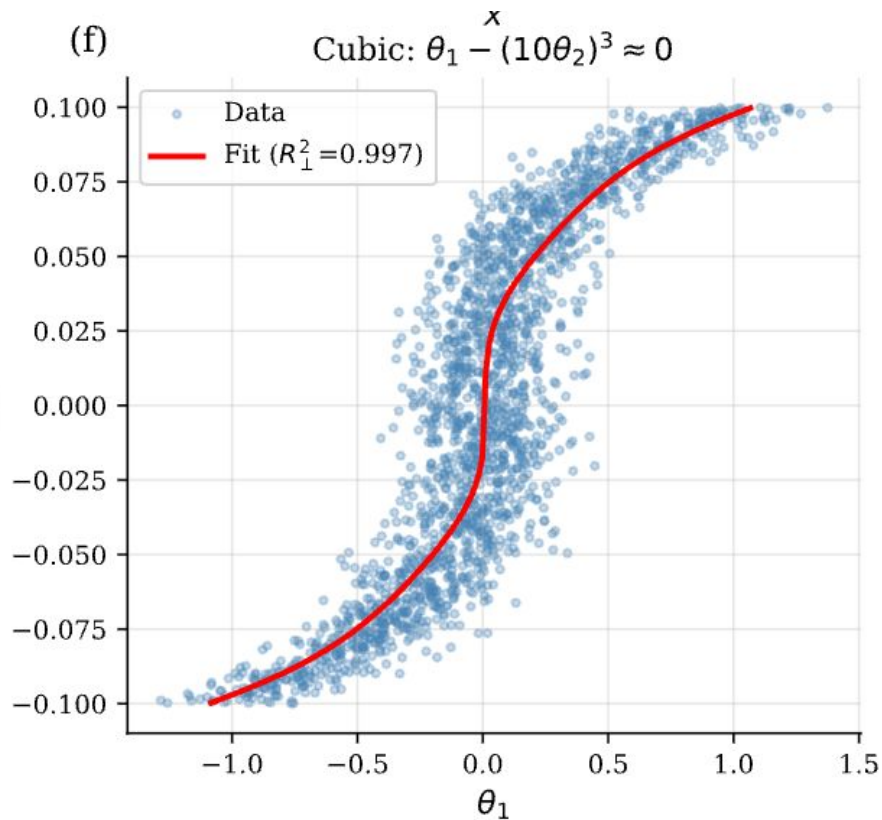
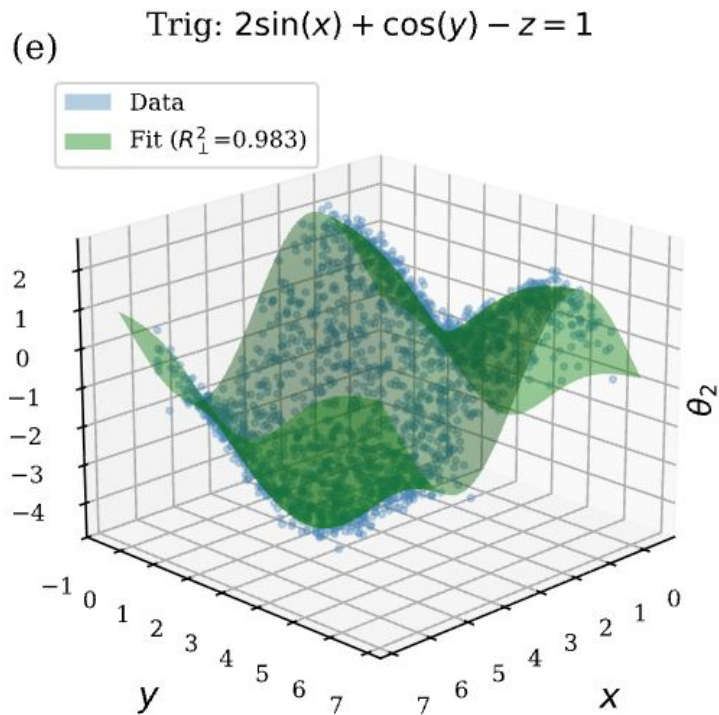


(c)

S-curve: x vs z projection



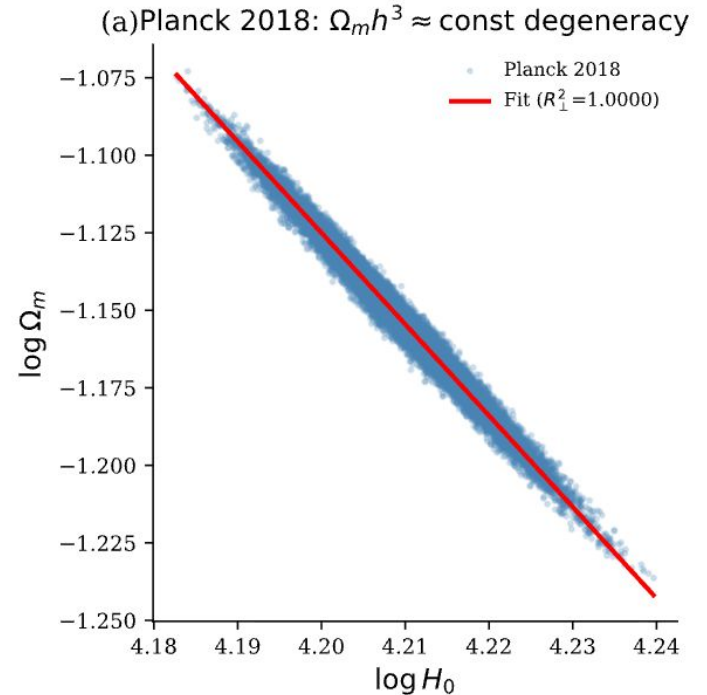
Benchmark Results



Science Experiment

- **DegenLogMode:** Although the power law degeneracy is non-separable in the original space, it can be recovered as the level set in log space.

$$\Omega_m h^3 \approx \text{const} \rightarrow \log \Omega_m + 3 \log h \approx \text{const}$$



$$123.97 \log H_0 + 42.07 \log \Omega_m = \text{const}$$

Conclusion

- We developed **DegenDetector**, a new degeneracy detection framework that combines mutual information ranking and alternating symbolic regression to find coupled parameters and express that degeneracy as an interpretable equation.
- On synthetic benchmarks and Planck 2018 posteriors, we recover the true functional form of degeneracies with orthogonal $R^2 > 0.98$ across all cases without domain-specific input.
- The main limitation of our method is the assumption of separability, which could be extended in future works to non-separable functional forms using multivariate symbolic regression or reparameterizations.

Questions?

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