

Causal Discovery and Causal-driven Modeling in Astrophysics



2nd Annual Cosmic Horizons Conference, July 16th 2026



Zehao Jin (金泽灏)

Center for Astronomy and Astrophysics
Fudan University, Shanghai

zehaojin@fudan.edu.cn / zj448@nyu.edu

<https://zehaojin.github.io/>

Main Collaborators

復旦大學

Astro side

ML4Astro

ML side



Benjamin Davis
NYUAD → MSU



Tobias Buck
Heidelberg



Yuan-sen Ting
OSU



Yujia Zheng
CMU → UIUC



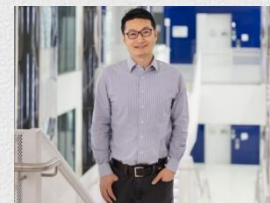
Andrea Maccio
NYUAD



Yuxi(Lucy) Lu
OSU



Mohamad Ali-Dib
NYUAD



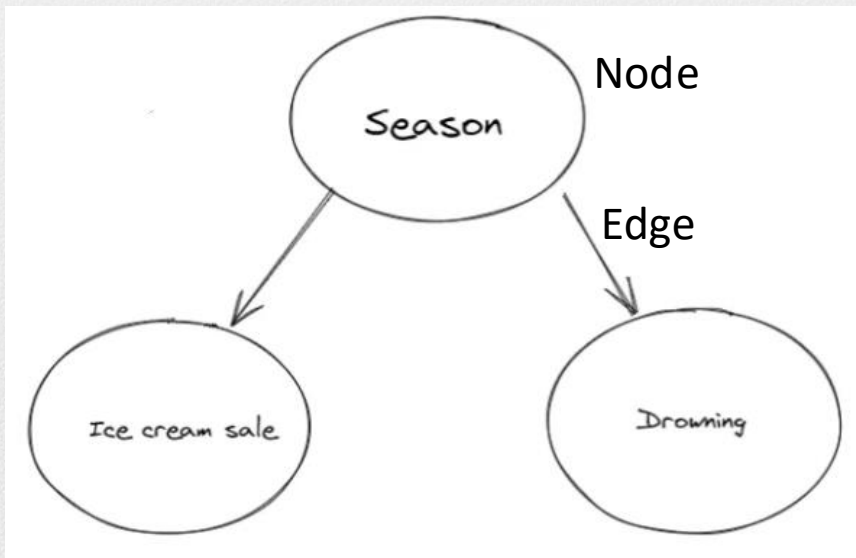
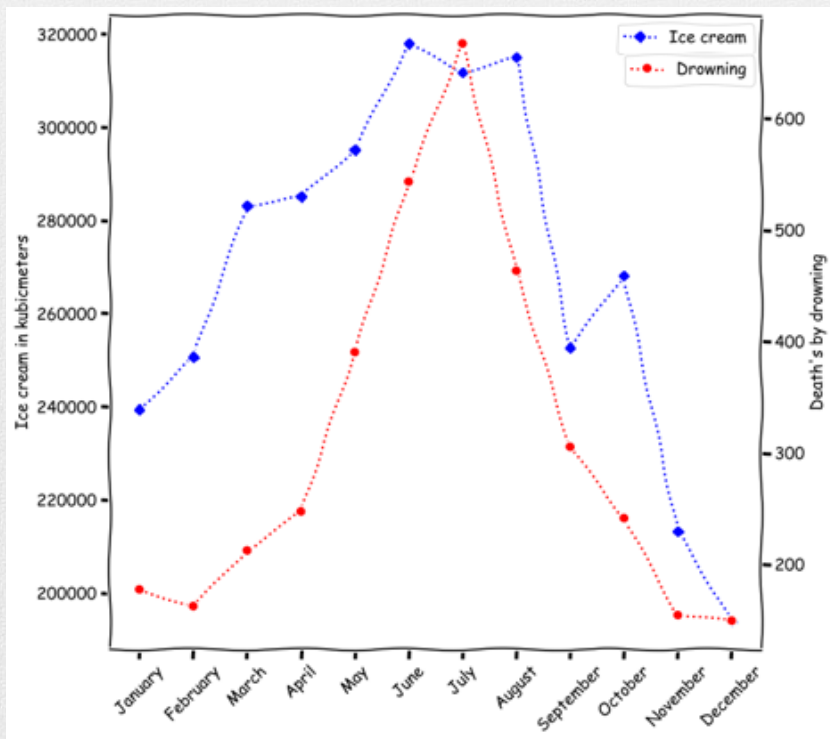
Kun Zhang
CMU & MBZUAI



Does the correlation mean that ice cream can cause drowning?



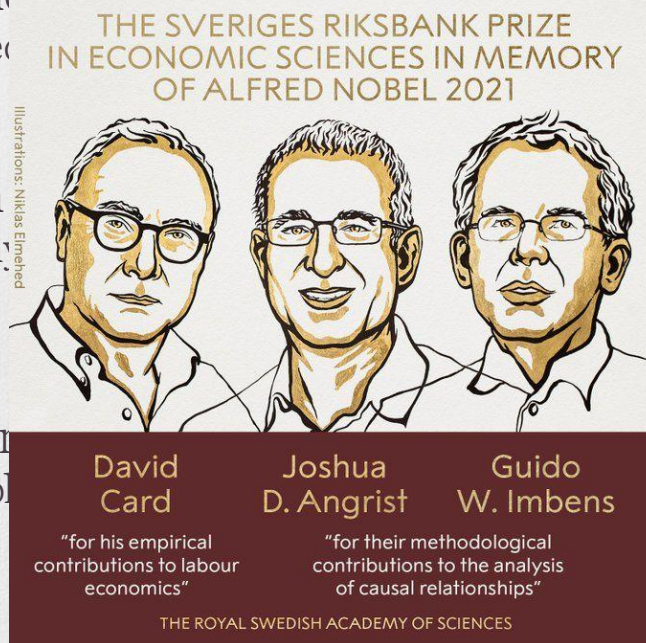
Correlation $\neq$ Causation, but why is there such a correlation?



Directed Acyclic Graph (DAG)

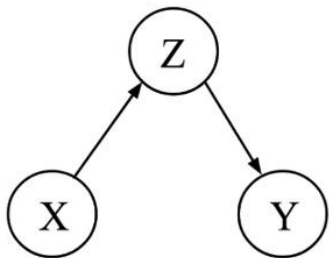
- Intervention is the gold standard to determine causation
 - randomized controlled trials

- However intervention
 - Especially in Astrophysics, we cannot intervene the universe

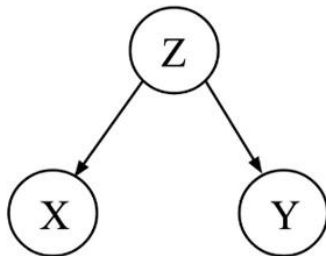


- Causal discovery: infer causation from observational data
 - Already used in Geophysics, Medicine and Economics

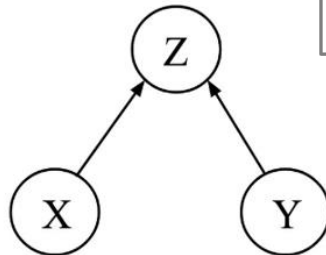
Chain


 $X \not\perp\!\!\!\perp Y$
 $X \perp\!\!\!\perp Y \mid Z$

Fork

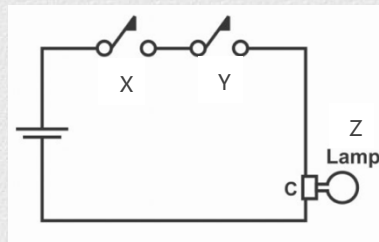

 $X \not\perp\!\!\!\perp Y$
 $X \perp\!\!\!\perp Y \mid Z$

Collider


 $X \perp\!\!\!\perp Y$
 $X \not\perp\!\!\!\perp Y \mid Z$
 $\not\perp\!\!\!\perp$: NOT independent, i.e. dependent

 $\perp\!\!\!\perp$: independent

- **Correlation $\neq$ Causation**
- **Causation = (conditional) independence**
- **Conditional independence $\rightarrow$ Causation (Causal discovery)**



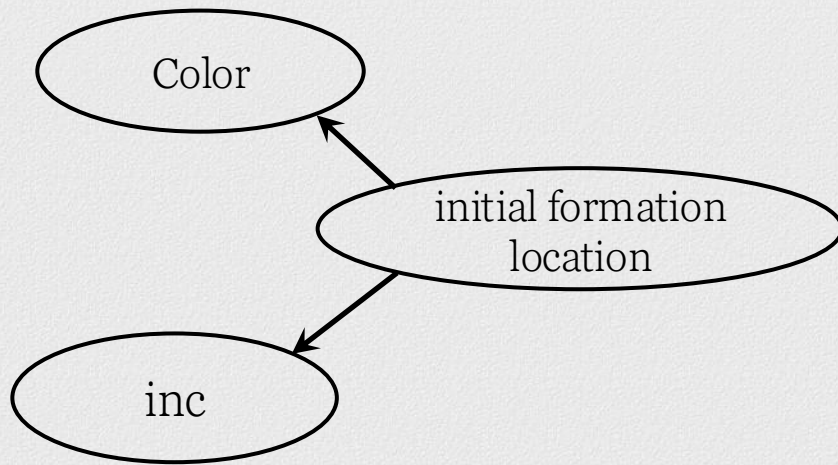
Planets: Origin of TNO colors

Causal evidence for the primordality of colours in trans-Neptunian objects,

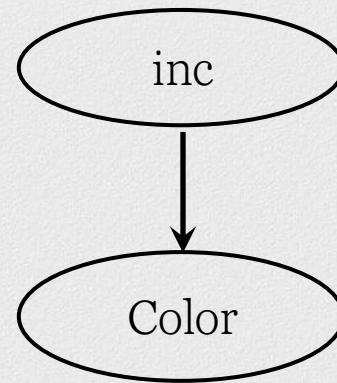
BL Davis* †, M Ali-Dib †, Y Zheng †, **Z Jin** †, K Zhang, AV Macciò, 2025, *MNRAS Letters*

Why Trans-Neptunian objects (TNOs)' s **color** and **inclination** are correlated?

The Primordial origin hypothesis



The collisional evolution hypothesis

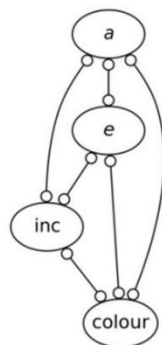


The Fast Causal Inference (FCI) algorithm

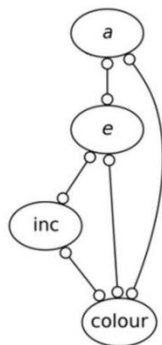
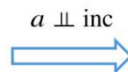
TNO data

Col-OSSOS & DES:

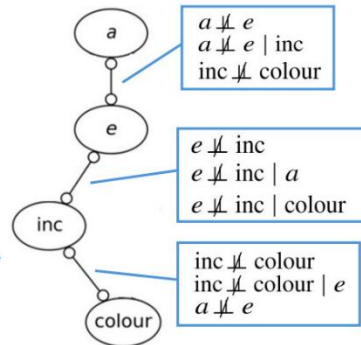
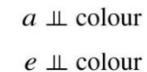
- a (semi-major axis)
- e (eccentricity)
- inc (inclination)
- $colour$



Fully-Connected Graph



Remove edges



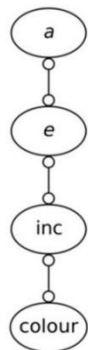
Remove more edges and verify remaining edges

PAG notations:

$$X \leftrightarrow Y \equiv X \leftarrow L \rightarrow Y$$

$$X \circ \rightarrow Y = \{X \rightarrow Y, X \leftrightarrow Y\}$$

$$X \circ \leftarrow Y = \{X \leftarrow Y, X \leftrightarrow Y\}$$



Skeleton

$a \perp inc$

excludes

$$\begin{cases} a \leftarrow \circ e \leftarrow \circ inc \\ a \leftarrow \circ e \circ \rightarrow inc \\ a \circ \rightarrow e \circ \rightarrow inc \end{cases}$$

allows

$$a \circ \rightarrow e \leftarrow \circ inc$$

$e \perp colour$

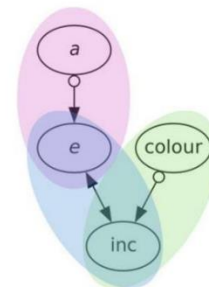
excludes

$$\begin{cases} a \leftarrow \circ inc \leftarrow \circ colour \\ e \leftarrow \circ inc \circ \rightarrow colour \\ e \circ \rightarrow inc \circ \rightarrow colour \end{cases}$$

allows

$$e \circ \rightarrow inc \leftarrow \circ colour$$

$$e \leftrightarrow inc$$

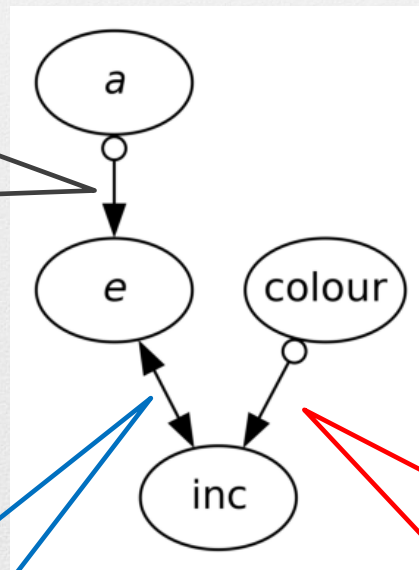


Oriented Graph

Considers possible unseen (latent) variables

through Partial Ancestral Graph (PAG)

- a determines whether gets scattered by Neptune, and this scattering alters e
- a determines whether TNOs are inside an eccentricity-raising Mean motion resonances (MMRs)



PAG notations:

$$X \leftrightarrow Y \equiv X \leftarrow L \rightarrow Y$$

$$X \circ \rightarrow Y = \{X \rightarrow Y, \\ X \leftrightarrow Y\}$$

$$X \circ \leftrightarrow Y = \{X \rightarrow Y, \\ X \leftarrow Y, \\ X \leftrightarrow Y\}$$

von Zeipel-Lidov-Kozai (vZLK) mechanism,
perturbations from a third body – Neptune

If Neptune had not already been discovered in 1846, our result here would strongly suggest the presence of an unknown perturbing body. -- “Rediscovered” Neptune!

Consistent with primordial origin hypothesis
Rules out collisional evolution hypothesis

Z Jin *†, Y Lu †, YS Ting, Y Zheng, T Buck, *ICML 2025 ML4Astro*, Journal version in prep.

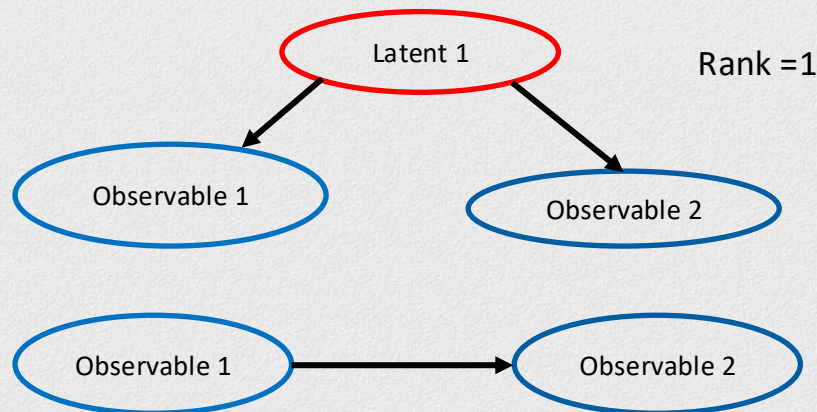
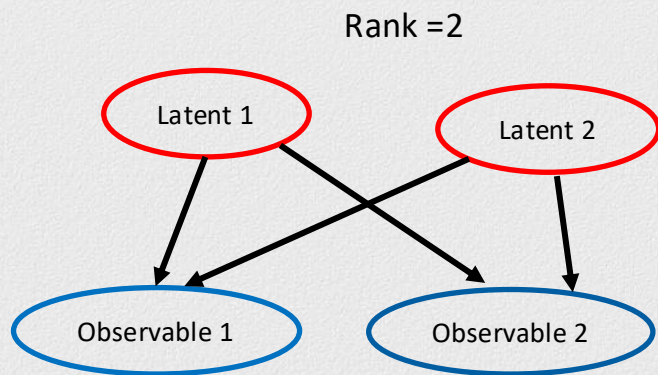
- Galactic Archaeology:
 - We only observe the snapshot of the current Milky Way.
 - How to reconstruct the stellar migration histories in Milky Way?
- Observable Clues:
 - Chemical abundances
 - Kinodynamics
- Key Unobservable: Birth radius – the initial condition

Data

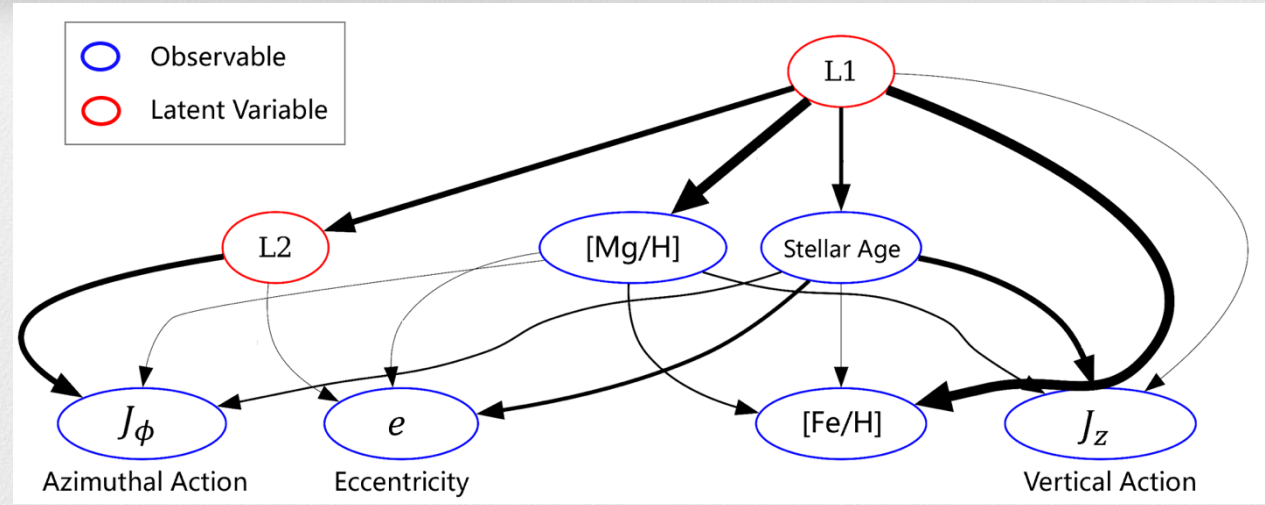
- Three “Milky Way” galaxies
 - $2 \times$ NIHAO-UHD simulation of MW-mass galaxies
 - $1 \times$ Real MW observation from APOKASC-3 sample
- Six observable properties of stars
 - $[\text{Fe}/\text{H}]$: metallicity
 - $[\text{Mg}/\text{H}]$: to trace evolution of alpha elements
 - Age
 - J_z : vertical action
 - J_ϕ : equivalent to z-component angular momentum L_z
 - e : eccentricity

Method

- Rank-based Latent Causal Discovery (RLCD)
 - Assumes linear relationship between variables.
 - Rank tests can serve as conditional independence tests ($\sim$ test of DOF)
 - latent variables leave statistical footprints in rank deficiencies in the covariance matrix of observables



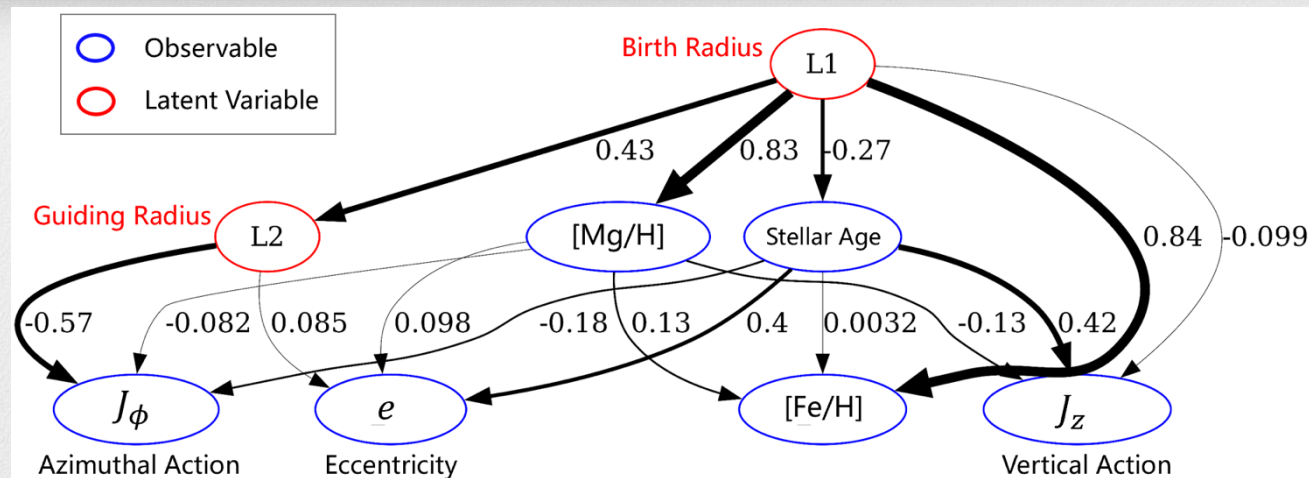
Result on first simulated galaxy



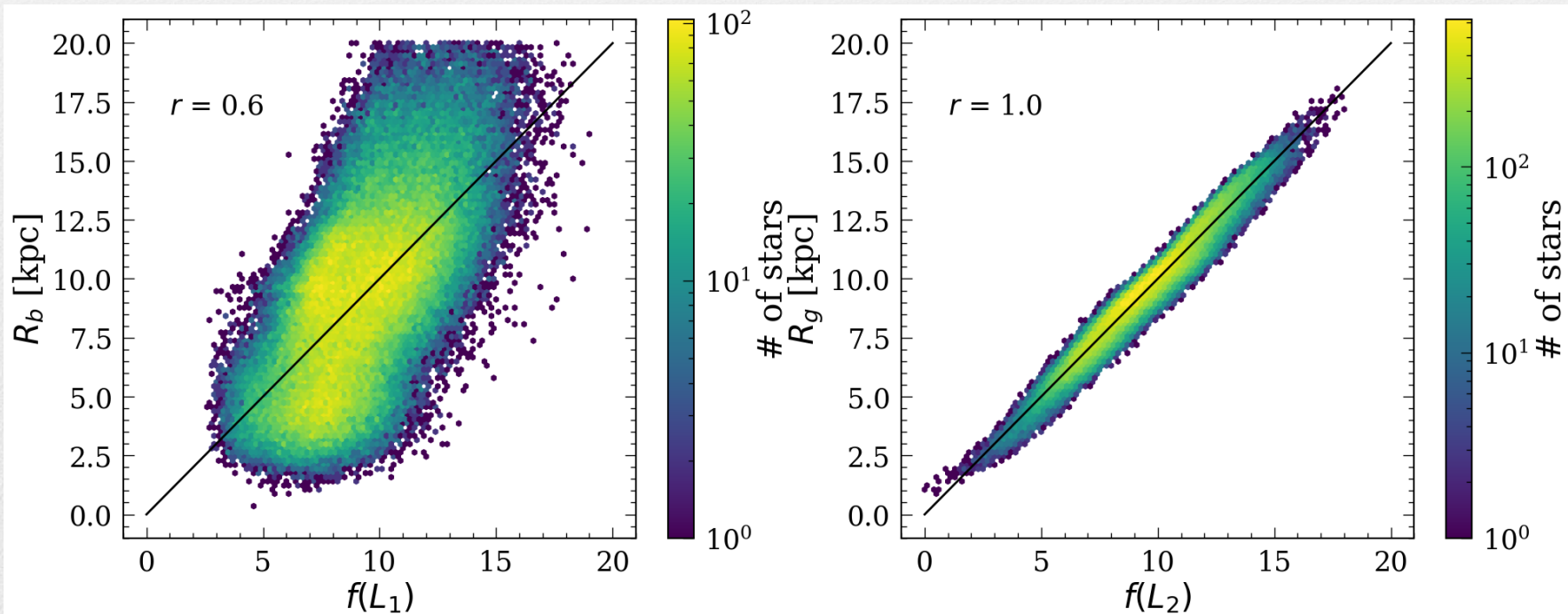
2 latent variables are found: **L1 & L2**

- L1 governs all other variables -- we hypothesize that L1 encodes info about stellar birth conditions (radial abundance, inside-out formation, vertical motions, gravitational potential). -- **L1 = birth radius?**
- L2 influences J_ϕ and e -- Stars orbits can heat up radially (increase in e) through gravitational scattering ("blurring") -- **L2 = guiding radius?**

Result on first simulated galaxy



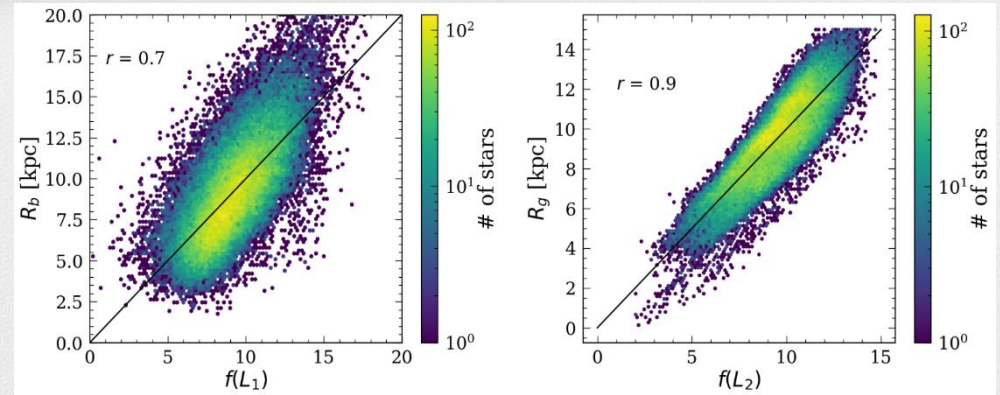
- To check our hypothesis, we calculate the coefficients on edges, and the value of **L1** and **L2** for each star
- Since in a simulated galaxy, we can compare **L1** and **L2** to the ground truth **birth radius** (R_b) and **guiding radius** (R_g)



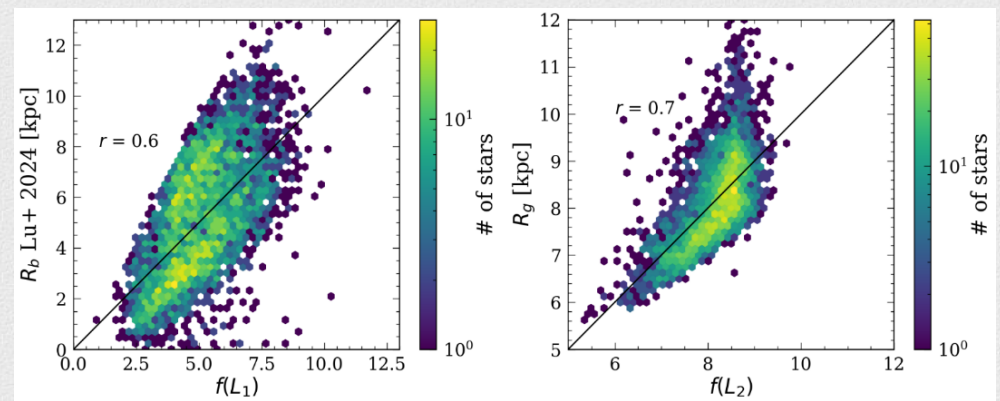
Extrapolation and Generalization

- If the model really learns the underlying physics, the same causal graph should generalize to the stellar dynamics of other galaxies, whether simulated or observationally inferred.
- The numerical values of the causal coefficients, may differ from galaxy to galaxy, as each has distinct global properties (total mass, size, etc)
- Extrapolate to another simulated galaxy and real MW observation
 - Keep the same causal model: the nodes, the number of edges, direction of edges are kept the same
 - The coefficients are re-estimated respectively

Causal model extrapolated to
a new simulated galaxy



Causal model extrapolated to
the real Milky Way



- Without any prior astro knowledge, the “AI scientist” draws a causal graph that consistent to our standing of stellar chemodynamics, with two physically meaningful latent nodes.
- Completely ignorant of birth radius, predicts the birth radius with a causal-driven model.
- The causal model demonstrates excellent generalizability across different simulations as well as real observation.

- Causal discovery in:
 - Planets: original of TNO colors
 - *Distinguish different causation that shares similar correlation*
 - Stars: Galactic Archaeology
 - *Causal discovery in the latent world, and highly generalizable causal model*
- Causal ML in Astronomy
 - Complementary to traditional approach
 - Causal ML x Deep learning
 - Inductive bias to NN architecture
 - Causal discovery to higher dimensional data:
Causal representation learning
- Still a blue sea in Astro

Thank you!

List of papers



Open Source code
for every project

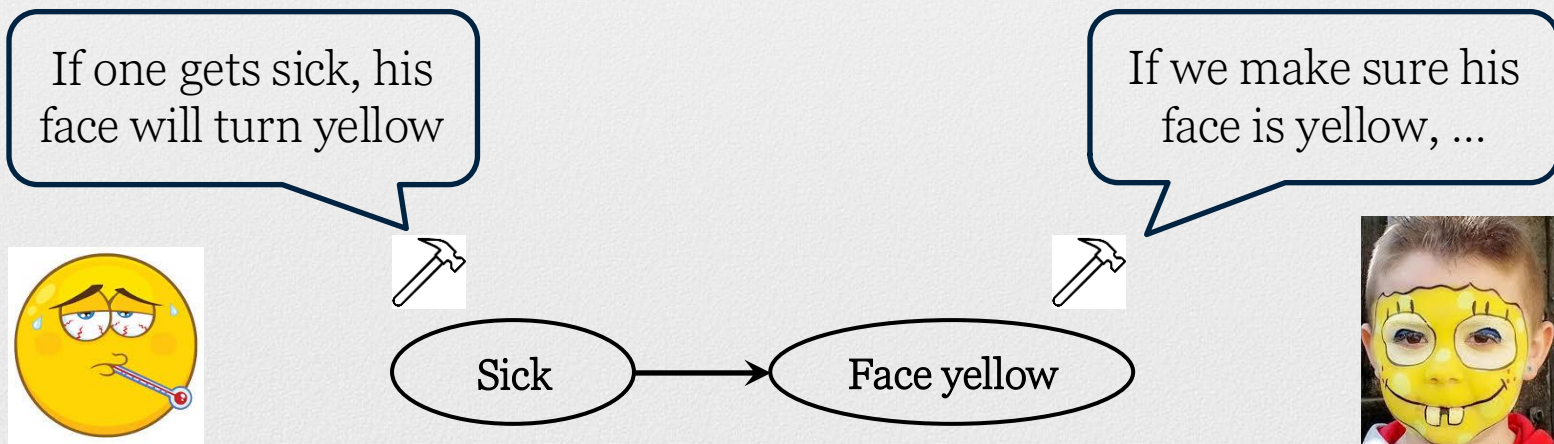


Intro to Causality
hosted on my website

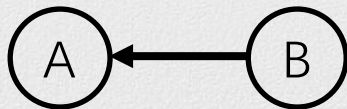
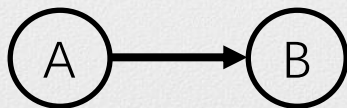
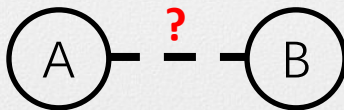


Zehao Jin
zehaojin@fudan.edu.cn
zj448@nyu.edu
July 16th 2026

A side note: What exactly is causality? / How to understand $X \rightarrow Y$?
-- Intervention is the key



What is the **causation** behind a correlation?

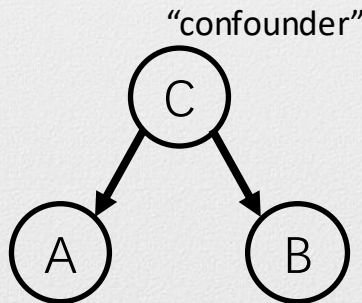


How we know it is one causes another without having time-series data?

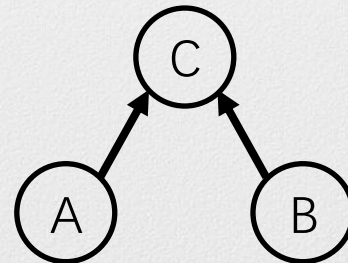
Age of the Universe: 1.38×10^{10} years

First human in Africa: 3×10^5 years

-- Can't observe a galaxy to evolve during a grad student's lifetime



- Does A still cause B although there is a confounder?
- What is the confounder?
- What if we can't observe the confounder?



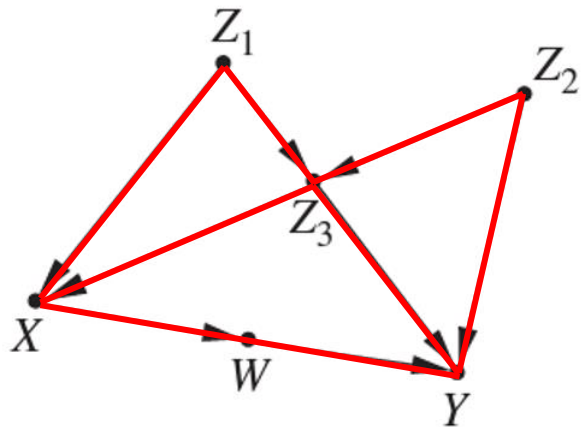
Biased dataset

Our dataset is always biased towards luminous and nearby objects.

i.e. Luminosity $\rightarrow$ visibility $\leftarrow$ distance

More complicated DAGs

Two variables are *independent* (*d-separated*) if every path between them is blocked.



	uncondition	condition
Chain	unblock	block
Fork	unblock	block
Collider	block	unblock

$$Z_2 \not\perp\!\!\!\perp X$$

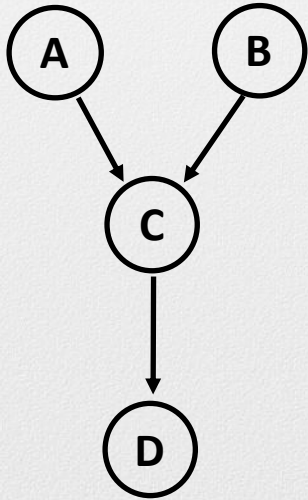
$$Z_2 \perp\!\!\!\perp X \mid (Z_3, Z_1)$$

$$Z_2 \not\perp\!\!\!\perp X \mid (Z_3, Z_1, Y)$$

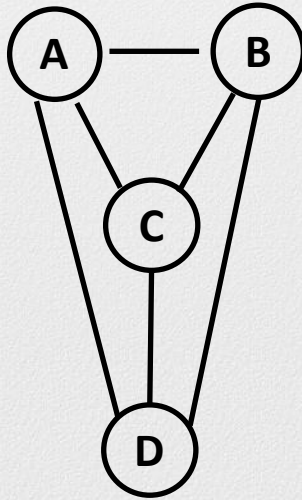
⋮

Peter-Clark (PC) Algorithm

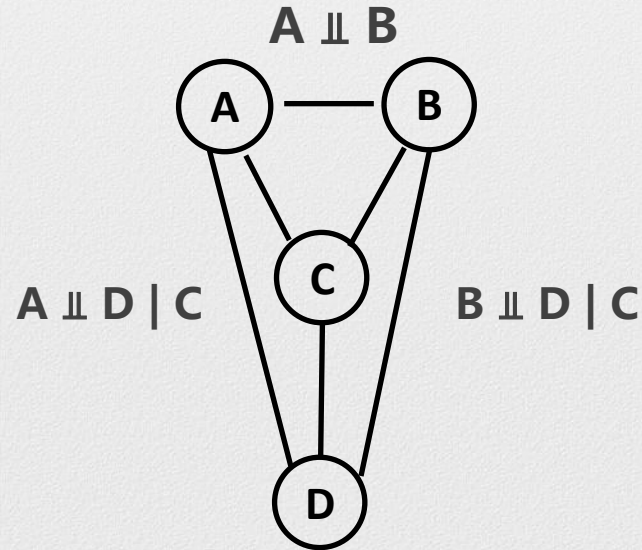
Stage 1: Skeleton discovery



Ground Truth



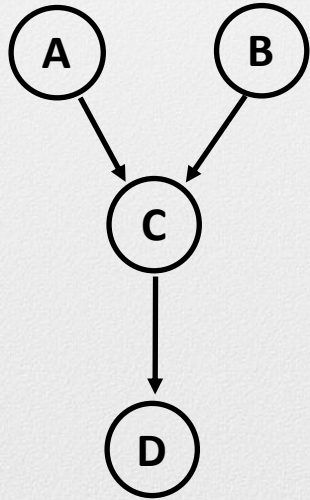
Fully connected graph



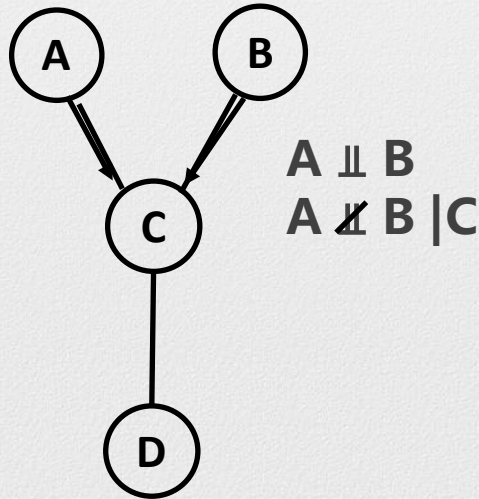
Skeleton

Peter-Clark (PC) Algorithm

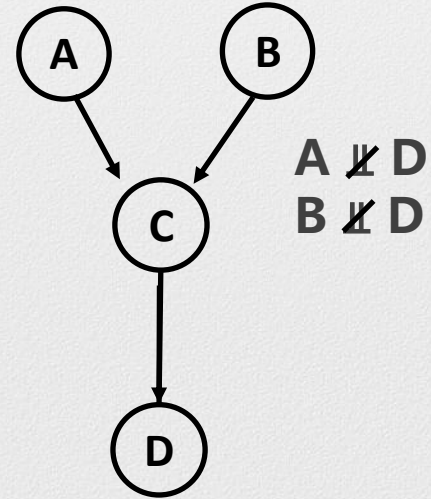
Stage 2: Orientation



Ground Truth



Orientation



Orientation

Conditional independence tests

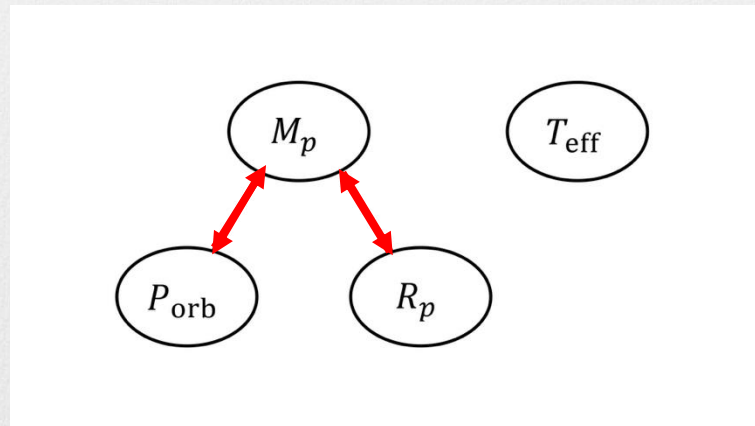
Conditional independencies	Conditional independence test p -value			
	Col-OSSOS		DES	
	Fisher-Z	KCI	Fisher-Z	KCI
$a \not\perp e$	0.000	0.000	0.000	0.000
$a \perp\!\!\!\perp \text{inc}$	0.144	0.421	0.006	0.568
$a \perp\!\!\!\perp \text{colour}$	0.918	0.488	0.677	0.250
$e \not\perp \text{inc}$	0.005	0.085	0.000	0.001
$e \perp\!\!\!\perp \text{colour}$	0.211	0.135	0.181	0.010
$\text{inc} \not\perp \text{colour}$	0.001	0.009	0.000	0.000
$a \not\perp e \mid \text{inc}$	0.000	0.068	0.000	0.001
$e \not\perp \text{inc} \mid a$	0.018	0.070	0.000	0.002
$e \not\perp \text{inc} \mid \text{colour}$	0.010	0.041	0.000	0.003
$\text{inc} \not\perp \text{colour} \mid e$	0.003	0.004	0.000	0.000

- Hot Jupiters often have radii larger than predicted by standard cooling–contraction models, but it remains unclear which process supplies or preserves the extra internal heat.
- Some source of external heat is needed
 - radiation from the star: thermal tides, kinetic/mechanical heating, ohmic dissipation
 - Planet radius (R_p), or fraction radius excess $\Delta_i \equiv \frac{R_p - R_0}{R_0}$
is likely linked to $F \propto T_{\text{eff}}^4 P_{\text{orb}}^{-4/3}$
 - Gravity from the star: gravitational tides
 - R_p or Δ_i is likely linked to P_{orb}
 - Heat is locked inside the planet: delayed cooling, Layered convection, Potential-temperature advection
 - Weaker link to T_{eff} and P_{orb}

Causal discovery to infer causal structure among R_p , M_p , T_{eff} , P_{orb} in observation data

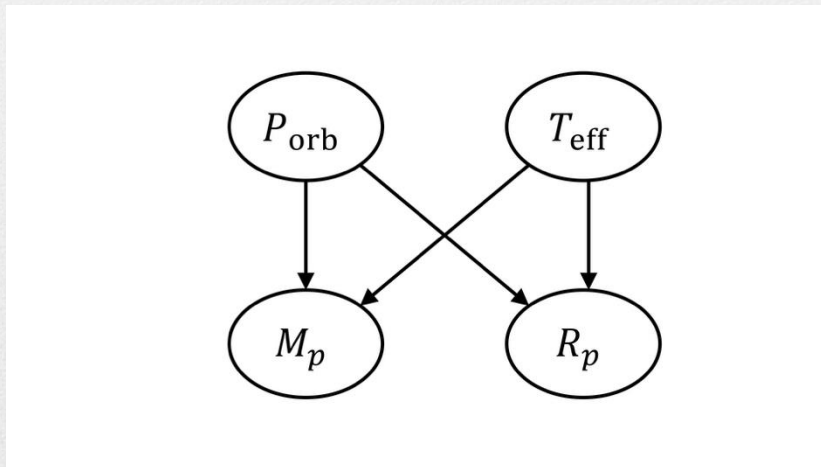
- Data: Encyclopedia of exoplanetary systems (J. Schneider et al. 2011)
 - 328 hot Jupiters
 - 179 super-Earths for sanity check
 - 4 nodes: R_p , M_p , T_{eff} , P_{orb}
- Causal discovery Method:
 - Go over possible causal graphs, checking the likelihood that the observed data is compatible with the conditional independence relationships implied by the causal graph, until arriving at a causal graph with the highest likelihood.
 - Specifically, a search strategy called Best Order Score Search (BOSS; B. Andrews et al. 2023)
 - A likelihood defined by the Fourier Feature Marginal Likelihood (FFML) score (J. D. Ramsey 2026)

Sanity Check on Super Earth



- R_p governed by M_p
- $M_p - P_{\text{orb}}$ reflects formation and migration in setting which planet masses are delivered to close-in orbits and survive there
- Isolated T_{eff} node since super-Earths have already lost their primordial envelope

Hot Jupiters



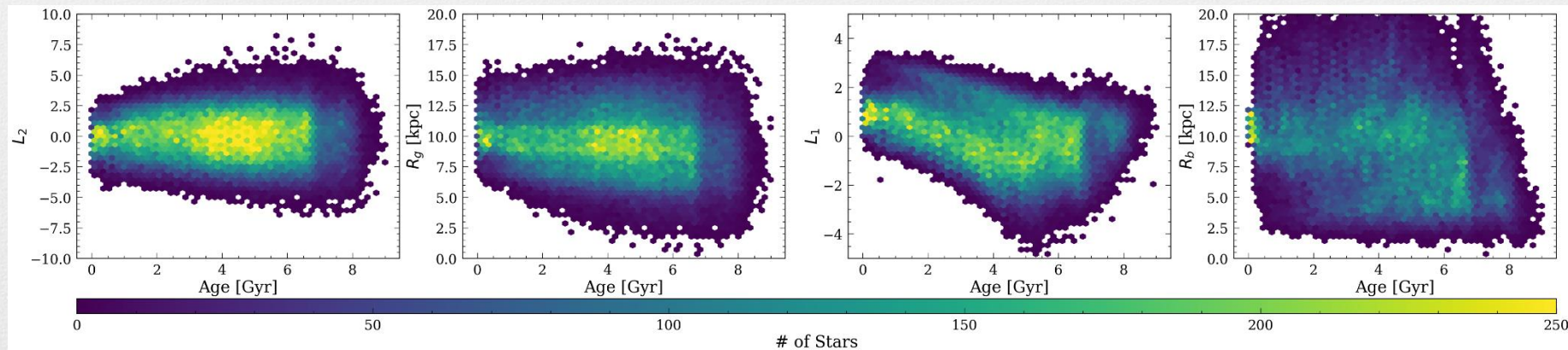
- R_p driven by T_{eff} and P_{orb} $\rightarrow$ irradiation-regulated inflation.
- The arrows into M_p : interpreted as population-level formation, migration, tidal-survival, photoevaporation/Roche-limit, and detection/selection effect.
- Purely period-controlled gravitational tides are disfavored.

Table 1. Numerical Local Theoretical Scalings for the Radius-excess Law $\Delta_i \propto M_p^{\alpha_M} P_{\text{orb}}^{\alpha_P} T_{\text{eff}}^{\alpha_T}$.

Scenario	α_M	α_P	α_T	Dominant Causal Implication	Comparison to Data-driven Causal Graph
Ohmic dissipation, pre-turnover	-0.62	-0.33	+1.00	$M_p \rightarrow R_p, T_{\text{eff}} \rightarrow R_p$	Dominant $M_p \rightarrow R_p$ not identified in observation
Ohmic dissipation, near efficiency peak	-0.62	-0.27	+0.80	$M_p \rightarrow R_p, T_{\text{eff}} \rightarrow R_p$	Dominant $M_p \rightarrow R_p$ not identified in observation
Thermal tides, Gold-Soter	-0.42	-0.60	+0.60	$P_{\text{orb}} \rightarrow R_p, T_{\text{eff}} \rightarrow R_p$	Cleanest match
Thermal tides, dynamical	-0.44	-0.80	0.00	$M_p \rightarrow R_p, P_{\text{orb}} \rightarrow R_p$	Missing $T_{\text{eff}} \rightarrow R_p$
Kinetic / mechanical heating	-0.40	-0.27	+0.80	$M_p \rightarrow R_p, T_{\text{eff}} \rightarrow R_p$	Dominant $M_p \rightarrow R_p$ not identified in observation
Eccentricity / obliquity tides	-0.44	-1.00	0.00	$M_p \rightarrow R_p, P_{\text{orb}} \rightarrow R_p$	Missing $T_{\text{eff}} \rightarrow R_p$
Radiative opacity / delayed cooling	-0.78	-0.08	+0.25	$M_p \rightarrow R_p, T_{\text{eff}} \rightarrow R_p$	Missing $P_{\text{orb}} \rightarrow R_p$
Layered convection, fixed layer strength	-1.06	0.00	0.00	$M_p \rightarrow R_p$	Missing $P_{\text{orb}} \rightarrow R_p, T_{\text{eff}} \rightarrow R_p$
Potential-temperature advection	-1.06	-0.33	+1.00	$M_p \rightarrow R_p, T_{\text{eff}} \rightarrow R_p$	Dominant $M_p \rightarrow R_p$ not identified in observation

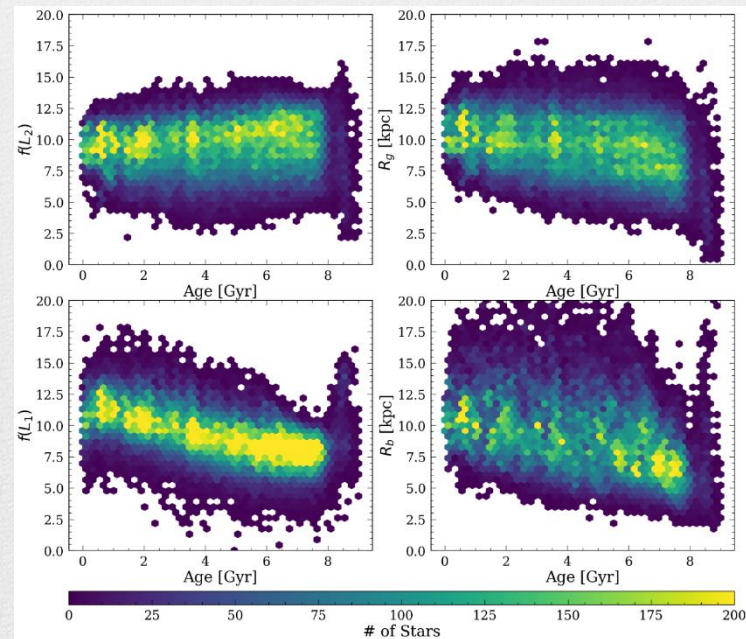
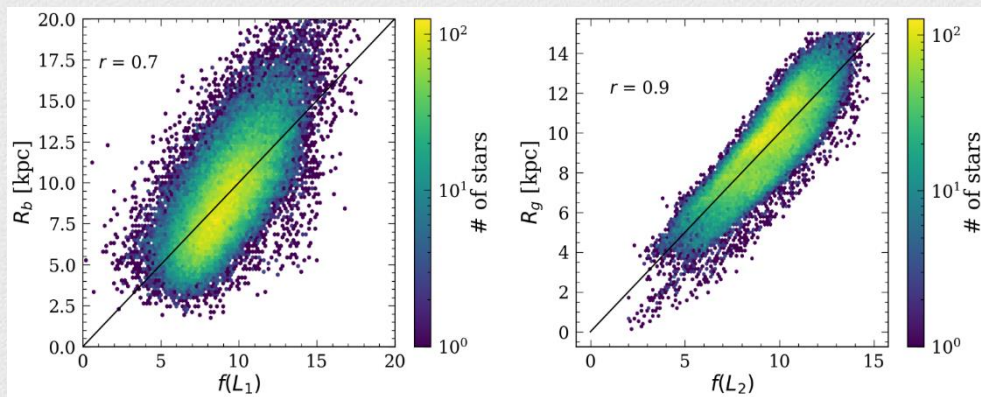
NOTE— The entries are the exponents in Eq. (1): α_M exponentiates M_p , α_P exponentiates P_{orb} , and α_T exponentiates stellar T_{eff} . The values assume $R_0 \propto M_p^{-0.06}$, $T_{\text{int}} \propto M_p^{0.50}$ at fixed age for active-heating channels, $\chi = 0.20$ for active deep heating, fixed stellar mass and radius, fixed age and composition, fixed B , fixed e or obliquity, and fixed tidal Q'_p . The first ohmic row applies on the rising, pre-turnover branch; the second applies near the empirical heating-efficiency maximum. The dominant causal implication is the qualitative expected parent set; the mapping from exponent magnitude to graph edge is heuristic because causal discovery explores conditional dependence, not the local power-law slope.

- Gold–Soter thermal tides provide the closest single-mechanism match
- kinetic/mechanical heating and ohmic dissipation remain viable contributors
- Purely period-controlled gravitational tides and purely delayed cooling/layer convention are disfavored.

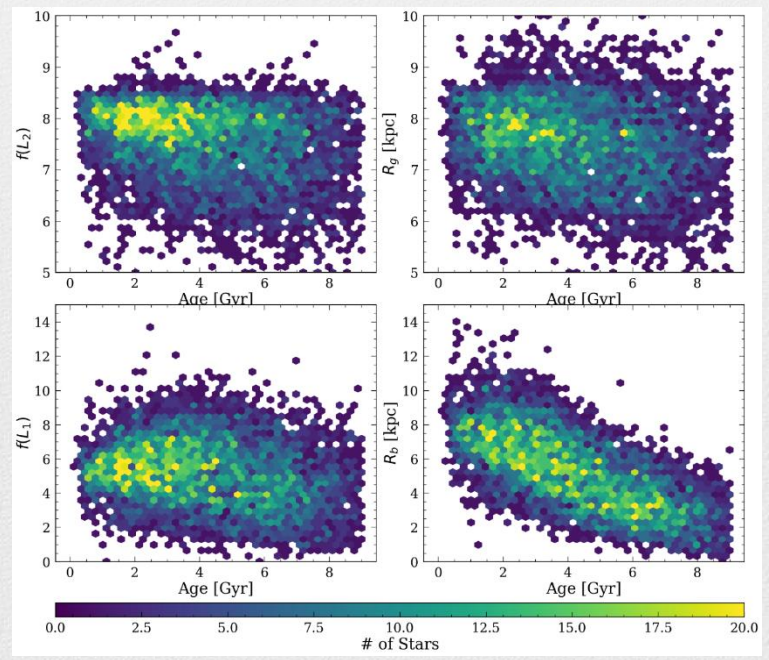
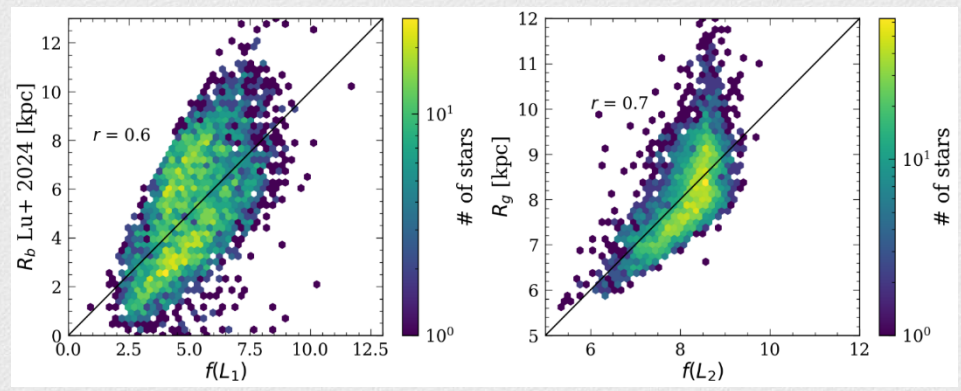


Notably, L₁ (third plot) clearly captures the two star-forming sequences seen in R_b (fourth plot), which are produced by infalling gas from the merging satellite.

Causal model extrapolated to
a new simulated galaxy



Causal model
extrapolated to
the real Milky Way



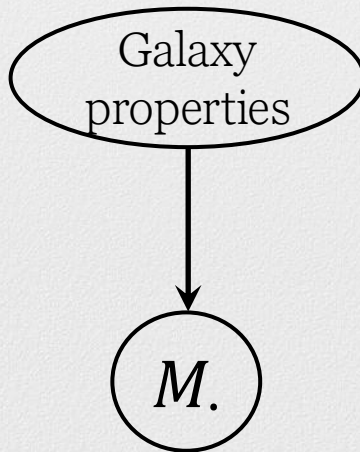
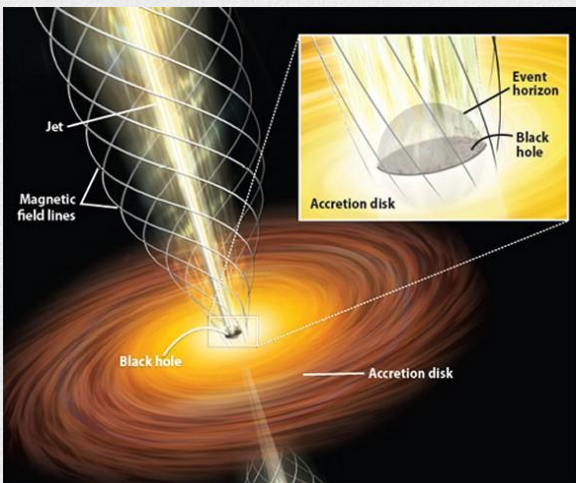
Galaxies: Galaxy – SMBH coevolution

Causal Discovery in Astrophysics: Unraveling Supermassive Black Hole and Galaxy Coevolution

Z Jin*, M Pasquato [†], BL Davis [†], T Deleu,..., Y Bengio, X Kang, AV Maccio, Y Hezaveh, 2025, *ApJ*

Causal Reversal in the $M_{\bullet}$ - σ_0 Relation: Implications for High-redshift Supermassive Black Hole

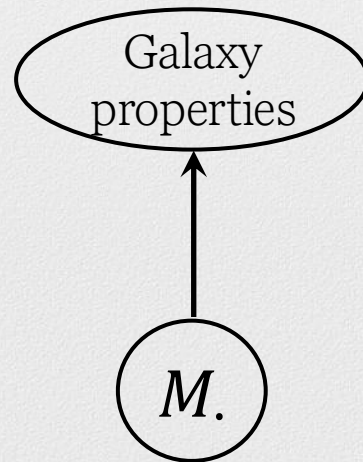
Mass Estimates, BL Davis, S More, **Z Jin***, M Pasquato, AV Macciò, F Yuan, 2026, *ApJ*



星系性质

黑洞质量

black hole accretion, Mergers
黑洞吸积, (星系/黑洞)并和



black hole feedback
黑洞反馈

- Calculate $P(\text{Graph} | \text{Data})$ for all possible DAGs (1,138,779,265 in total)
- $P(\text{Data} | \text{Graph})$ = Bayesian Gaussian Equivalent (BGe) score, by comparing the conditional independence found in the data vs. in the hypothetical graph

Real Data of 7 nodes:

M_* = 101 local, dynamical black hole mass

σ_0 = velocity dispersion

R_e = half-light radius

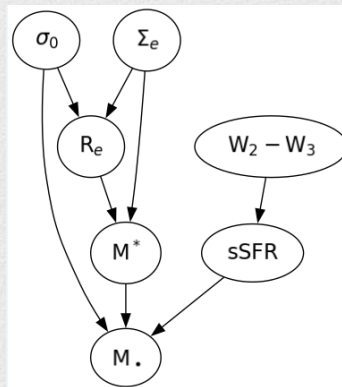
$\langle \Sigma_e \rangle$ = average surface density within R_e

M^* = stellar mass

$W_2 - W_3$ = WISE color

$sSFR$ = specific star-formation rate

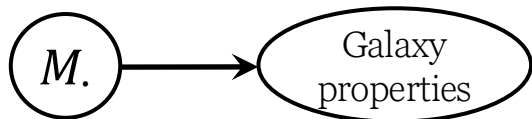
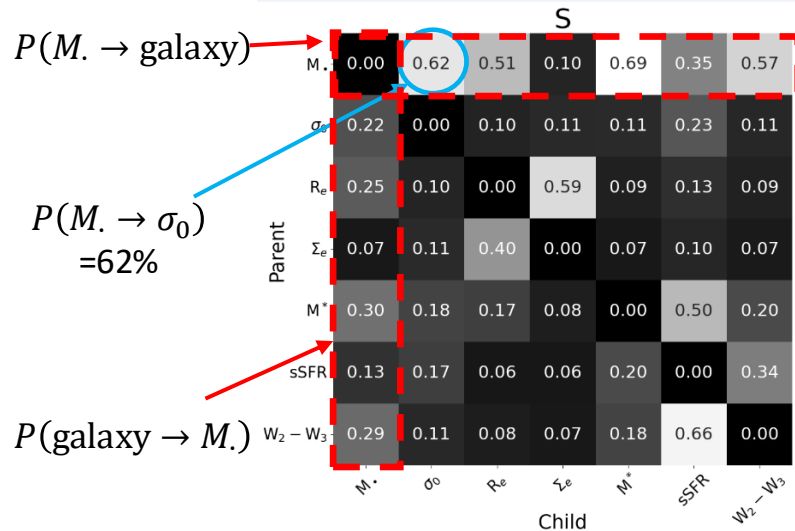
One example out of
1,138,779,265 DAGs



- GPU parallelization with JAX,
- GFlowNet estimation version also available for more nodes

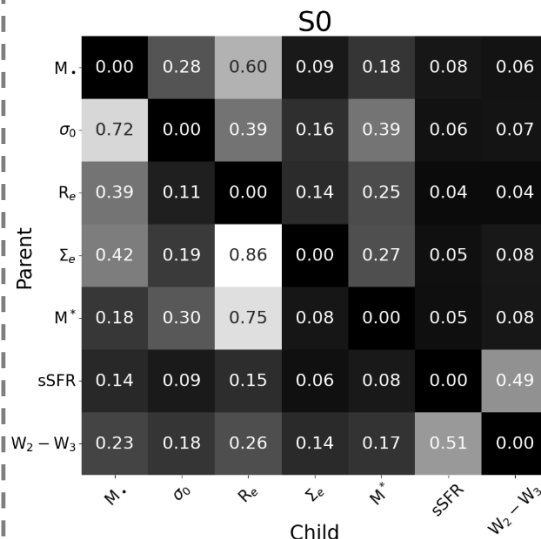


Spirals / Star forming galaxies



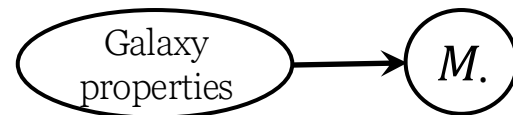
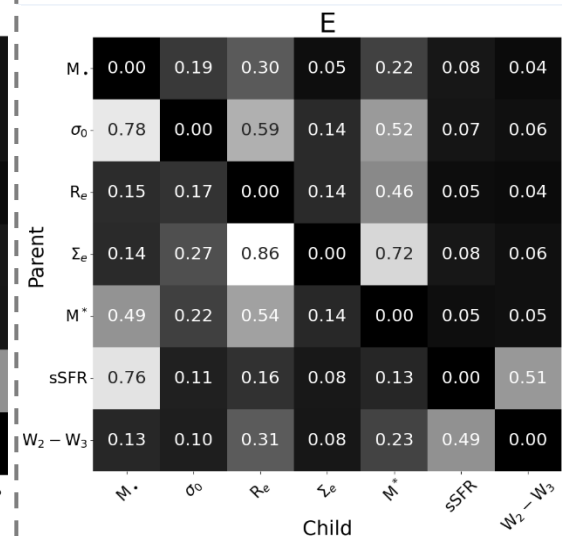
- Gas-rich
- BH feedback pushes gas out and progressively quench star formation.

Lenticulars



Transition phase

Ellipticals / Quiescent galaxies



- Quenching is complete
- AGN feedback is still there but gas is depleted
- Galaxy influence SMBH by mergers

Sanity Check with Semi-Analytical Models (SAMs)

Manually shut down BH feedback in SAM, such that SMBH $\rightarrow$ Galaxy is not possible

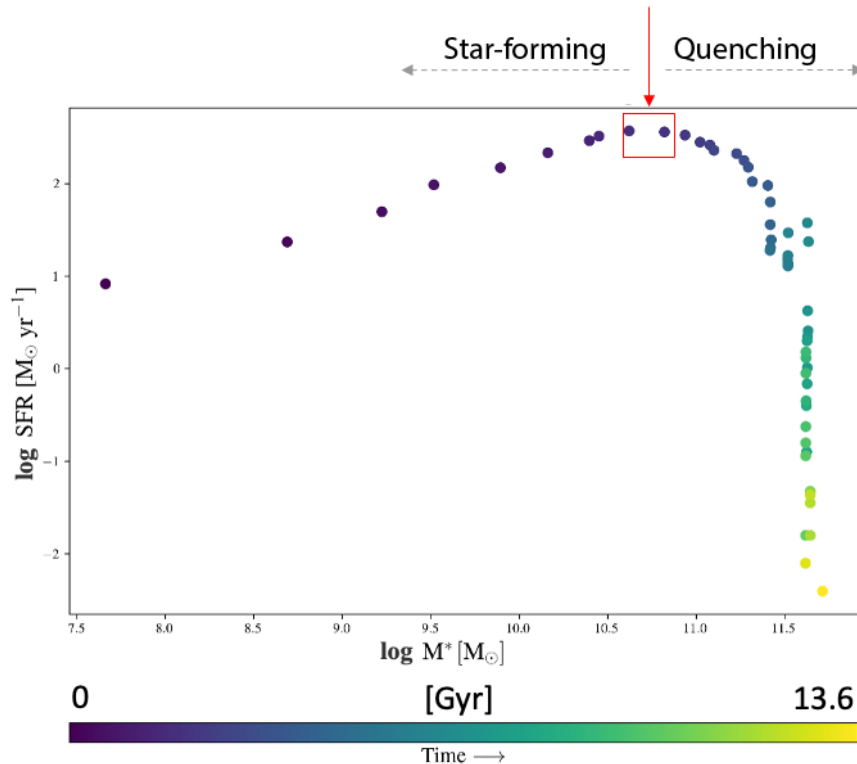
**Should Only find
Galaxy $\rightarrow$ SMBH**

SAM no feedback

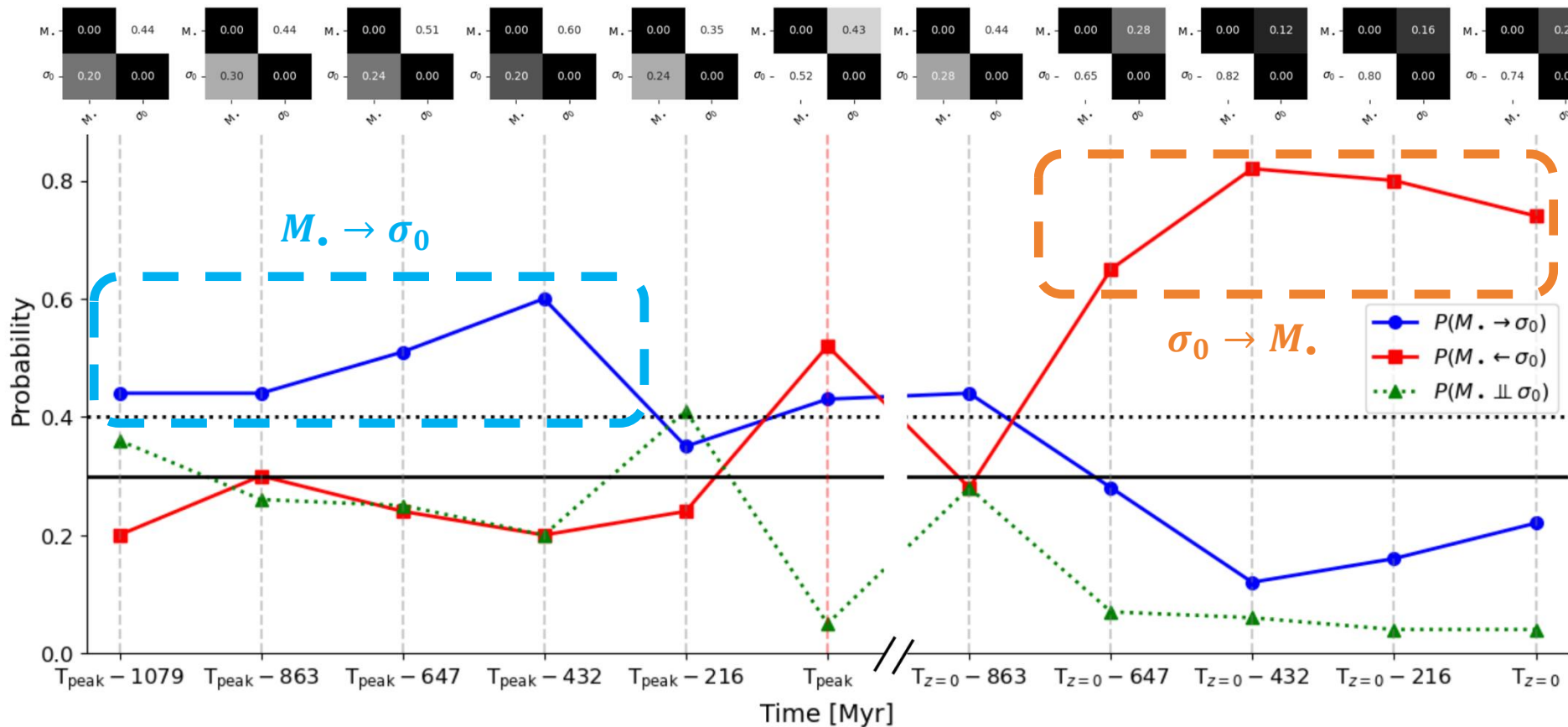
Parent		Child			
		$M_{\bullet}$	M_{bulge}^*	R_e	SSFR
$M_{\bullet}$	$M_{\bullet}$	0.00	0.06	0.01	0.01
	M_{bulge}^*	0.94	0.00	0.47	0.05
	R_e	0.99	0.53	0.00	0.01
	SSFR	0.99	0.11	0.02	0.00

Causality as a function of time

- Data: NIHAO cosmological zoom-in hydrodynamical simulations
- 27 galaxies that quench by $z = 0$
- Each 64 snapshots
 - 216 Myr between each
- Align snapshots at SFR_{peak}
- Causal discovery on five snapshots before SFR_{peak} , and five last snapshots



The $M_{\bullet}-\sigma_0$ Causation as a Function of Time



Causally-informed $M-\sigma$ Relations

Different Causal direction



Different Physical mechanism



Different M_* – σ_0 relation

Spirals/star-forming:

SMBH $\rightarrow$ Galaxy

“ $\sigma_0 - M_*$ relation”

i.e. $\sigma_0 = \alpha M_* + \beta$,

Fit with star forming galaxies only

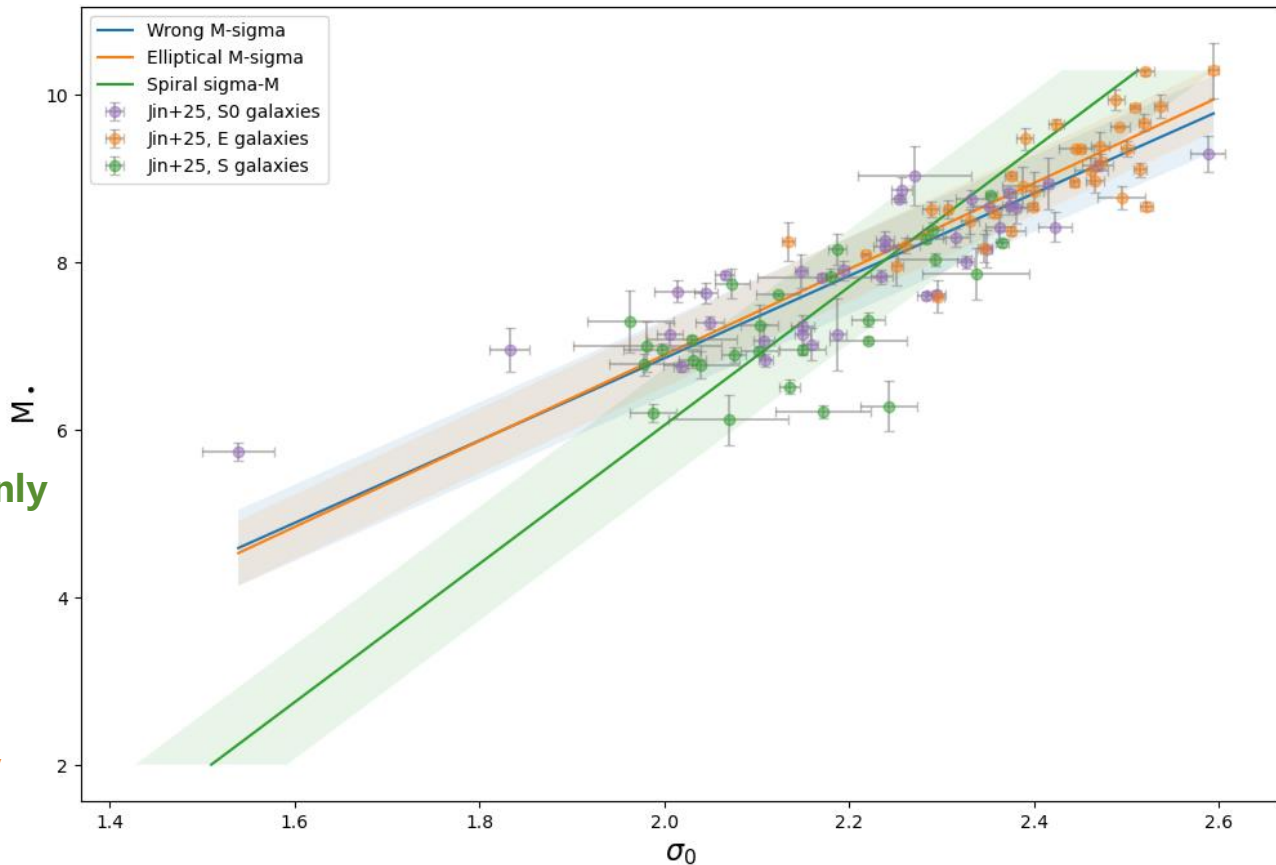
Ellipticals/Quiescent:

Galaxy $\rightarrow$ SMBH

“ $M_* - \sigma_0$ relation”

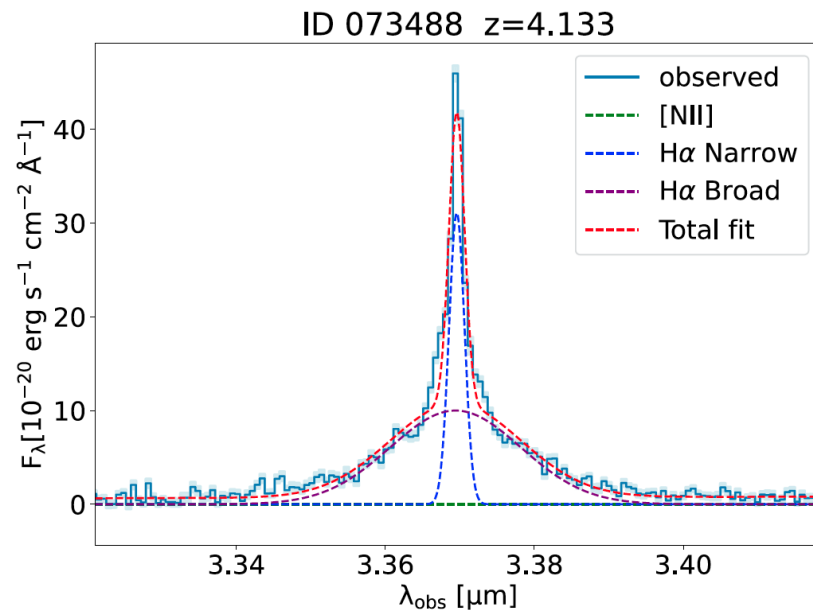
i.e. $M_* = \alpha \sigma_0 + \beta$,

Fit with Quiescent galaxies only



Estimation of High- z BH Masses

- Fit $M_{\bullet} - \sigma_0$ relation with dynamical BH masses at $z = 0$
- Reverberation Mapping (RM):
 - $GM_{\bullet} = f R_{BLR} (\Delta V)^2$
 - "virial factor" f is calibrated from local $M_{\bullet} - \sigma_0$
- Single-epoch spectroscopic SMBH masses are correlated with RM
 - via the broad-line region (BLR) radius-luminosity relation.

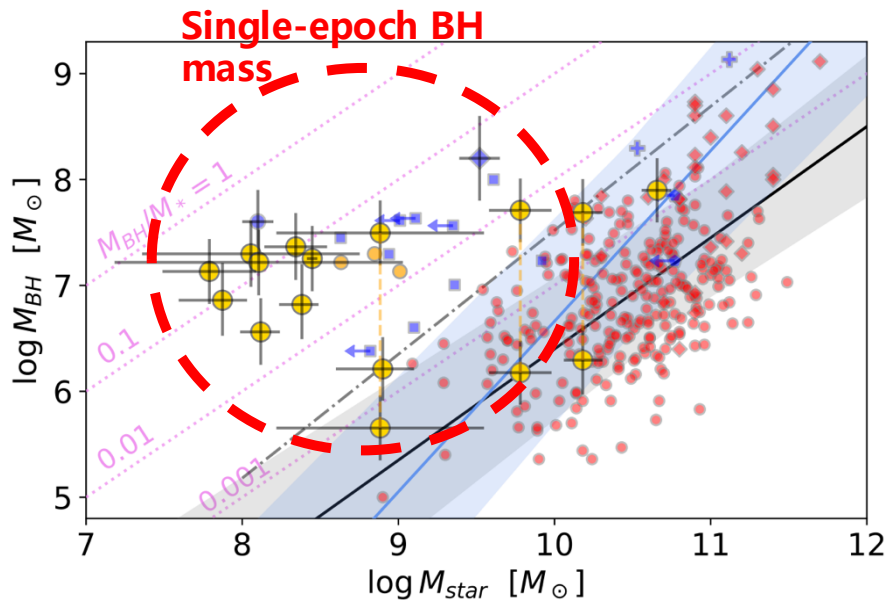


Maiolino et al. (2024)

$$\log \left(\frac{M_{\text{BH}}}{M_{\odot}} \right) = 6.60$$
$$+ 0.47 \log \left(\frac{L_{\text{H}\alpha}}{10^{42} \text{ erg/s}} \right) + 2.06 \log \left(\frac{\text{FWHM}_{\text{H}\alpha}}{10^3 \text{ km/s}} \right)$$

Reines & Volonteri (2015)

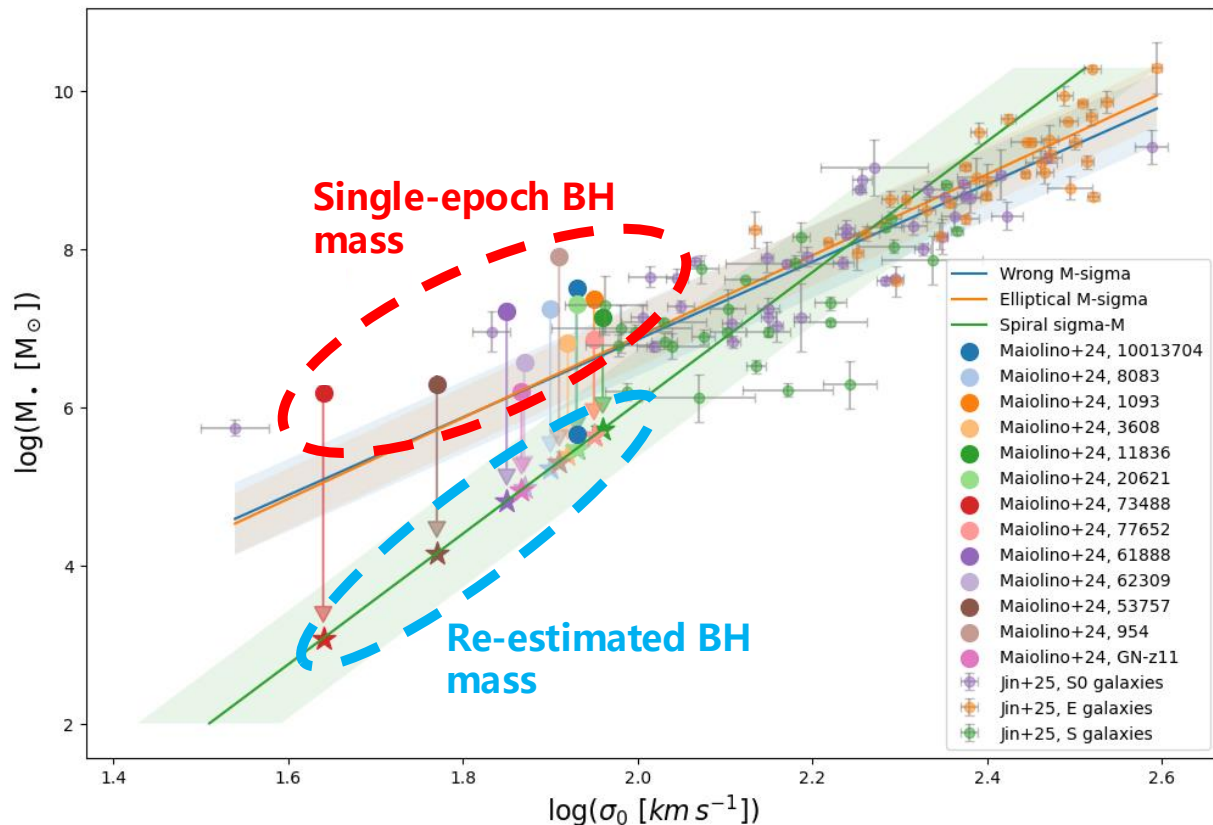
Revising black holes masses in 13 star-forming, late-type systems at $4.1 < z < 10.6$ from Maiolino et al. (2024)



- | High redshift | Local |
|-----------------------------------|------------------------------|
| ● JADES Maiolino+23, $4 < z < 11$ | ● Reines+Volonteri 15 |
| --- JADES cand. merging BH | ◆ Greene+20 |
| ● JADES max M_* | ▲ Bennert+21 |
| ■ JADES rot-corr | ■ Kormendy+Ho 13 |
| ■ Harikane+23, $4 < z < 7$ | — Reines+Volonteri 15 |
| ◆ Kocevski+23, $z \sim 5$ | — Greene+20 |
| ◆ Übler+23, $z = 5.5$ | ⋯ const. M_{BH}/M_* ratios |
| ◆ Ding+22, $z \sim 6.4$ | --- Bennert+21 |
| ● Bogdan/Goulding+23, $z = 10.1$ | --- Kormendy+Ho 13 |
| ▲ Izumi+19, $z \sim 6.5$ | |

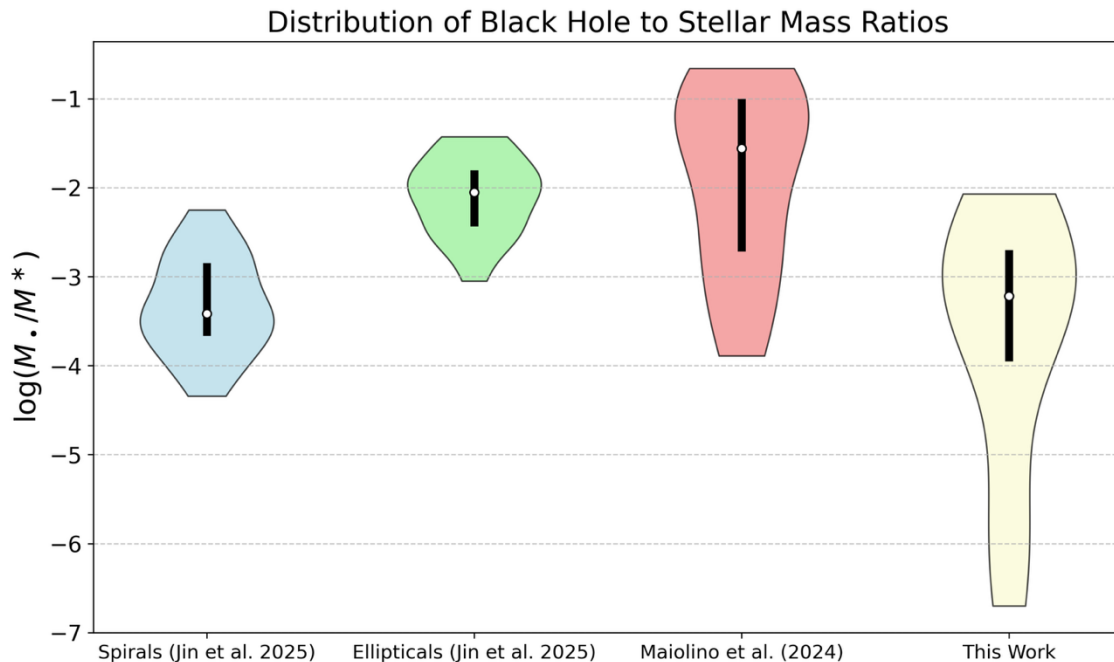
Maiolino et al. (2024)

Revising black holes masses in 13 star-forming, late-type systems at $4.1 < z < 10.6$ from Maiolino et al. (2024)



$M_{\bullet}$ might be overestimated, especially on the lower end

Revising black holes masses in 13 star-forming, late-type systems at $4.1 < z < 10.6$ from Maiolino et al. (2024)



median reduction of $\log(M_{\bullet}/M^{*}) = 1.93 \pm 0.51$ dex

- Spirals/star-forming: SMBH $\rightarrow$ Galaxy,
 - AGN feedback regulates
 - Fit $\sigma_0 - M_*$ relation with spirals
- Ellipticals/Quiescent: Galaxy $\rightarrow$ SMBH
 - Gas poor, hierarchical assembly governs
 - Fit $M_* - \sigma_0$ relation with ellipticals
- High- z BH Masses might be overestimated