

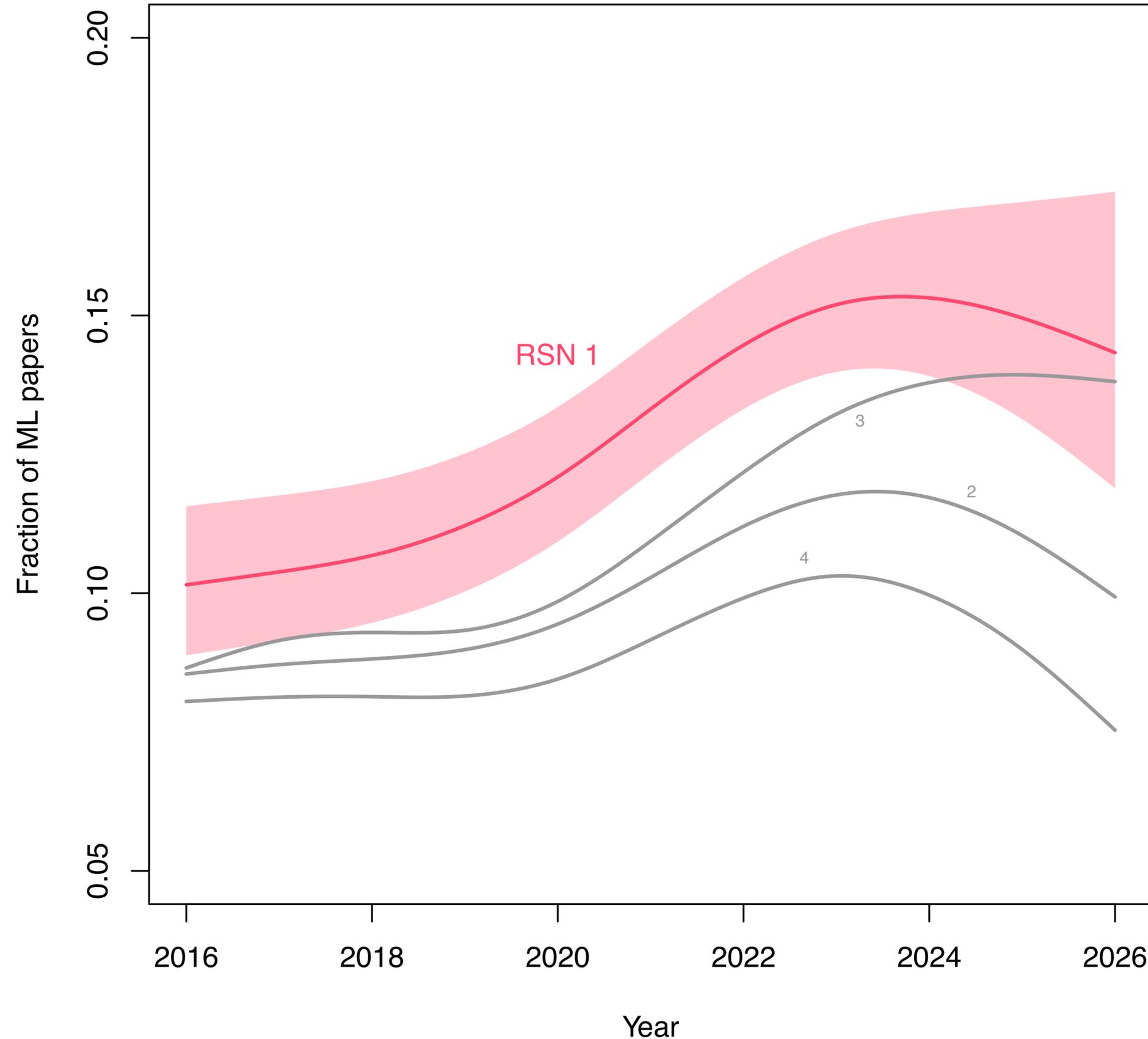
Causal discovery, a new game in town

Machine learning for RSN 1

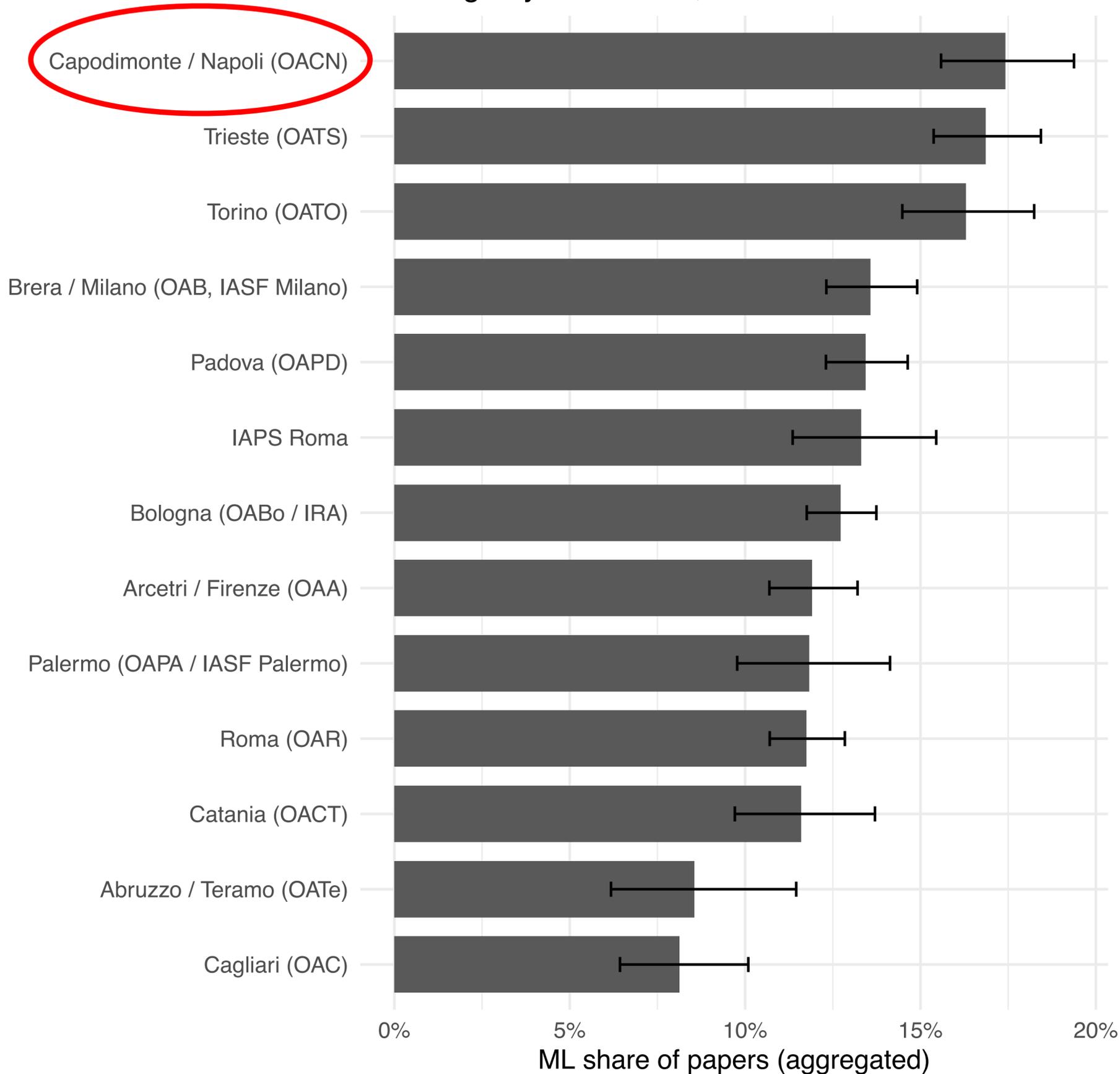
RSN 1 IS THE BEST AT ML

Methodology:

- * NASA ADS query using the API
- * INAF or Istituto Nazionale di Astrofisica affiliation, multiple count by author
- * Papers published in ApJ, A&A, MNRAS, AJ, PASP
- * Very inclusive set of ML keywords in abstract, including stuff like PCA or Gaussian processes



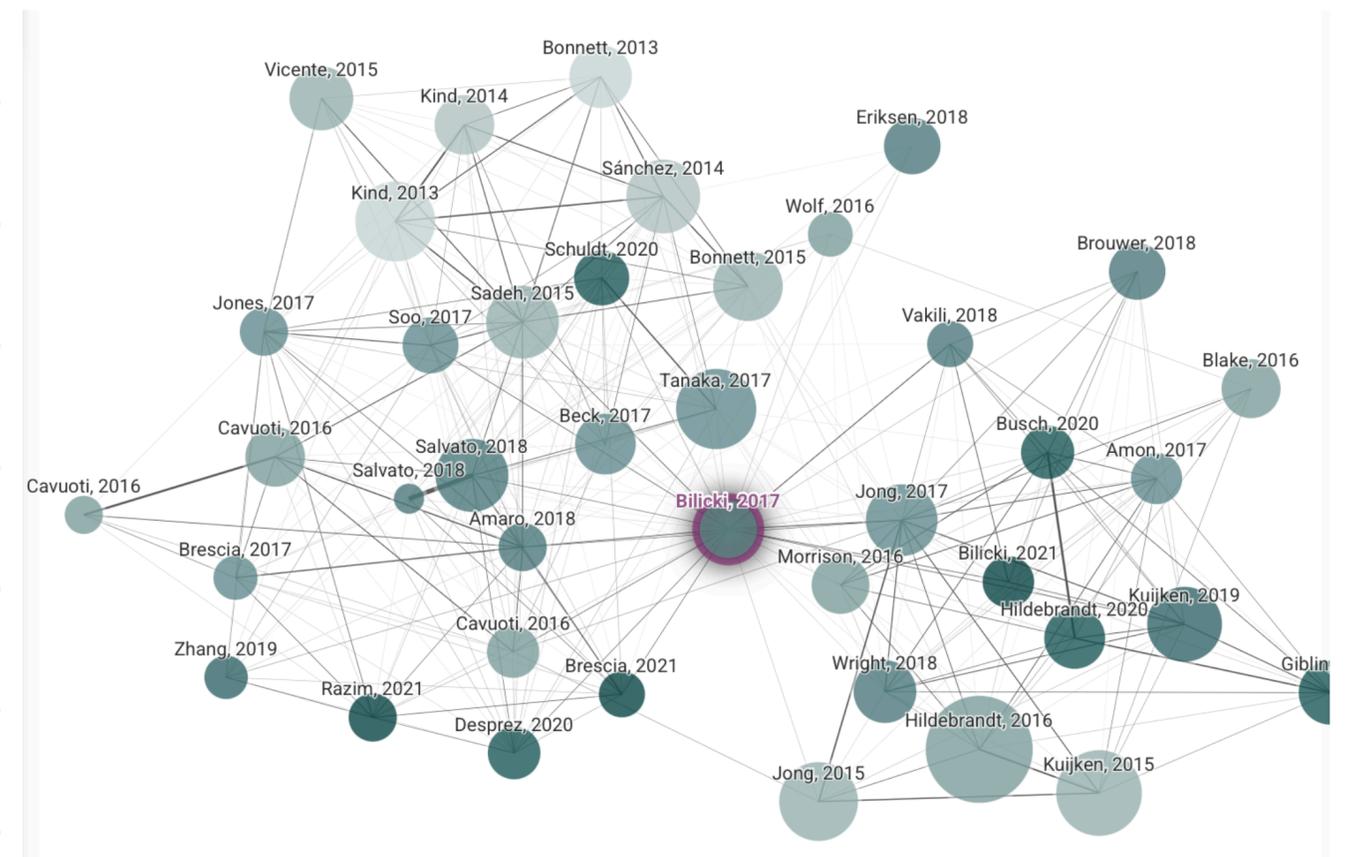
ML usage by INAF sede, binomial 95% CI



INAF-wide trends

Papers using ML / total

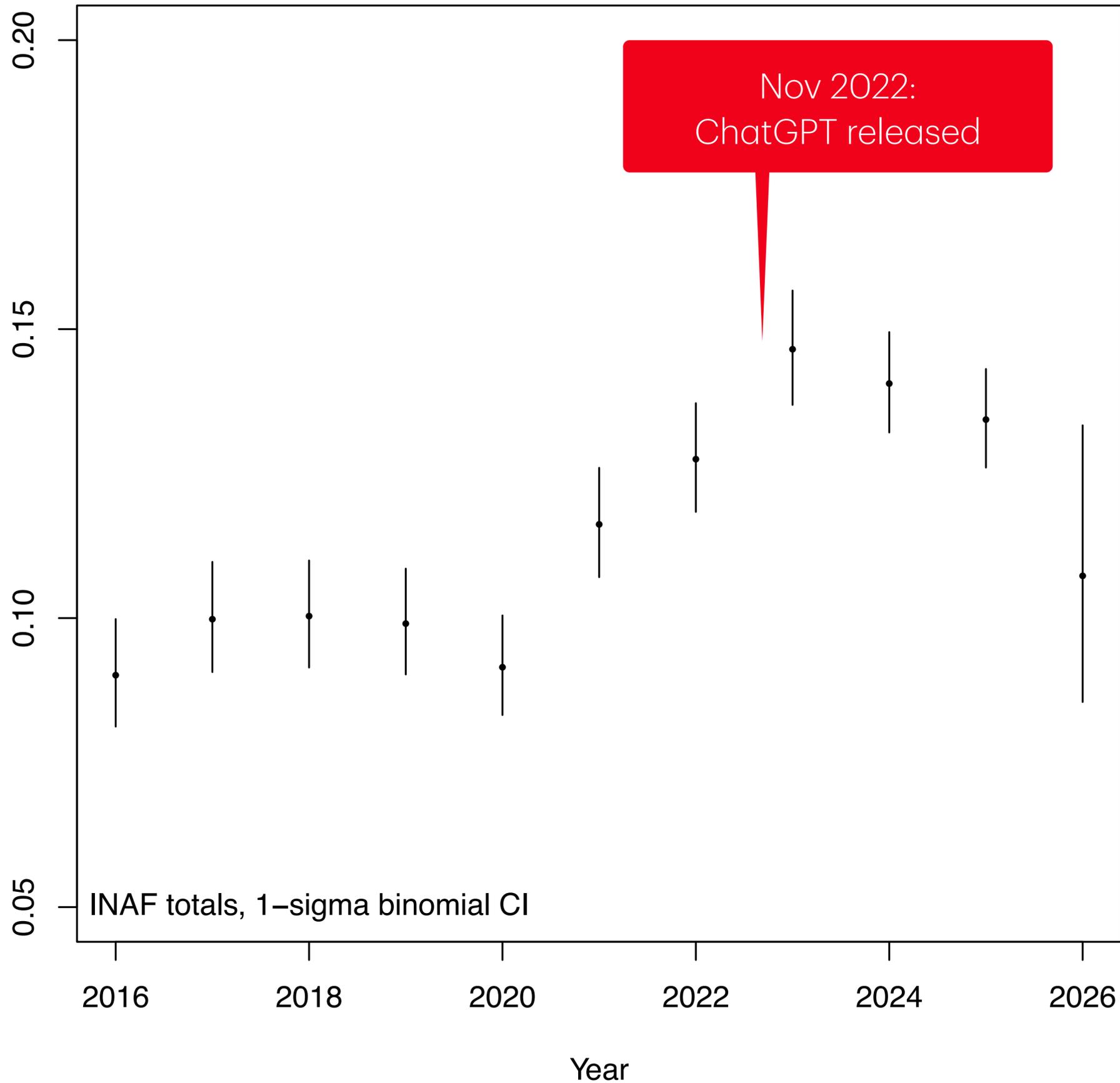
CAPODIMONTE IS THE BEST AT ML



Bilicki et al. 2017 and related papers

But I have bad news

Fraction of machine learning papers



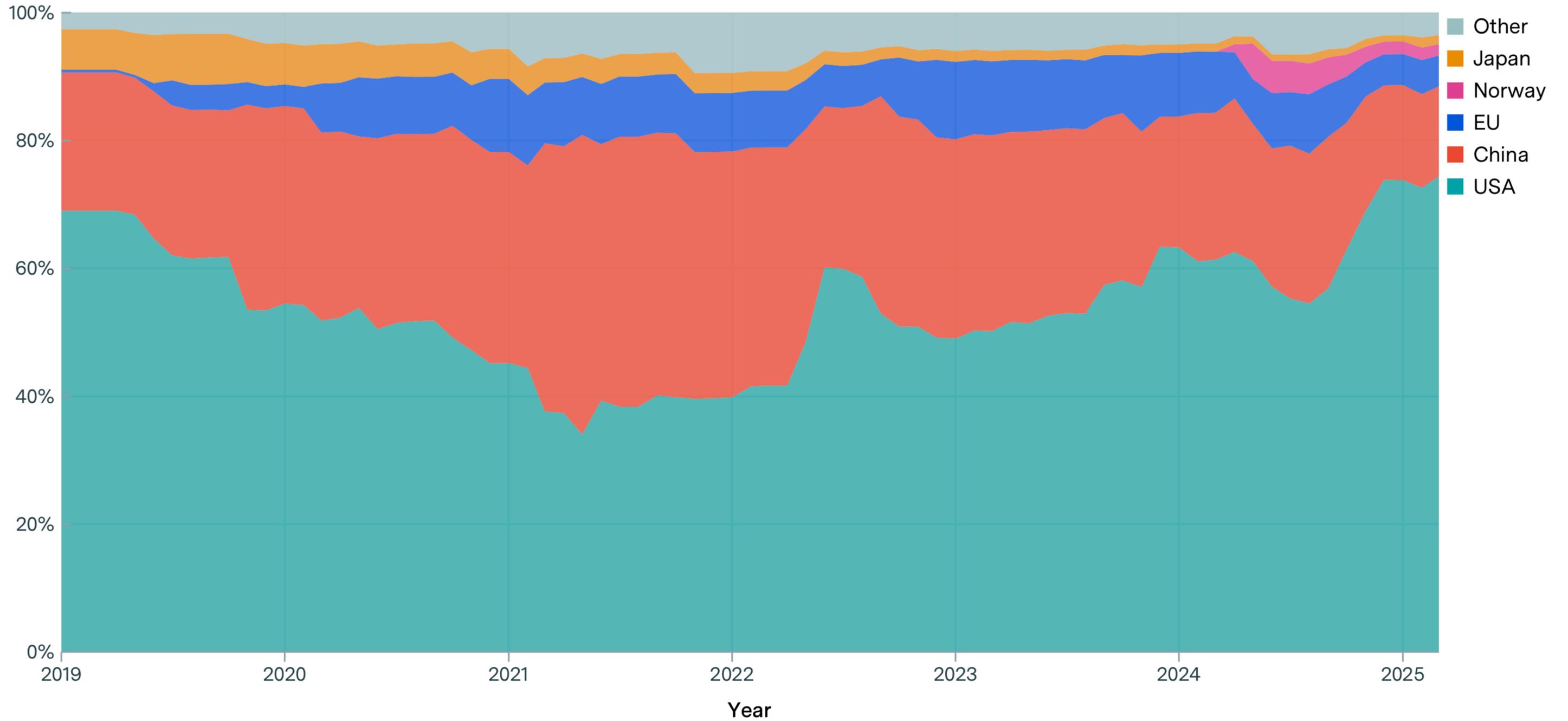
**MACHINE
LEARNING IS
NOT COOL
ANYMORE**

...not in and of
itself, at least

How can INAF

(and specifically RSN 1)

stay ahead of the curve?



Probably **not** by out-computing
the US or China

Focus on selected strategical topics:

Causal learning

Topological data analysis

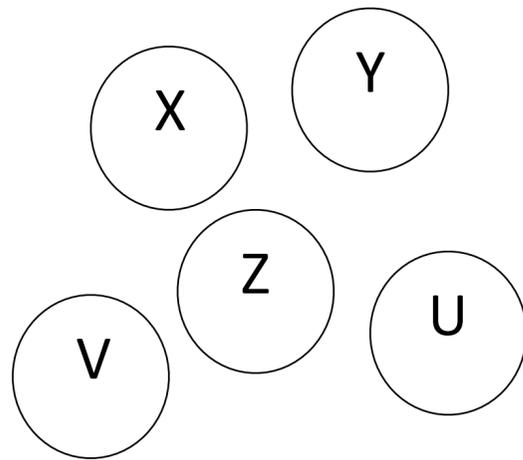
Interpretability, explainability, fairness*

Human-in-the-loop

*yes fairness tools apply to astronomy! think "bias"

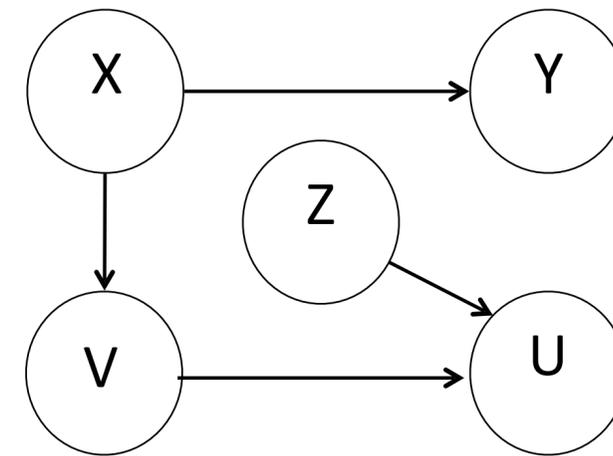
Develop a clear, realistic vision for
AI co-scientists, agents, new
workflows enabled by AI

Can we learn causal relations **without** **running experiments?**



From observed variables

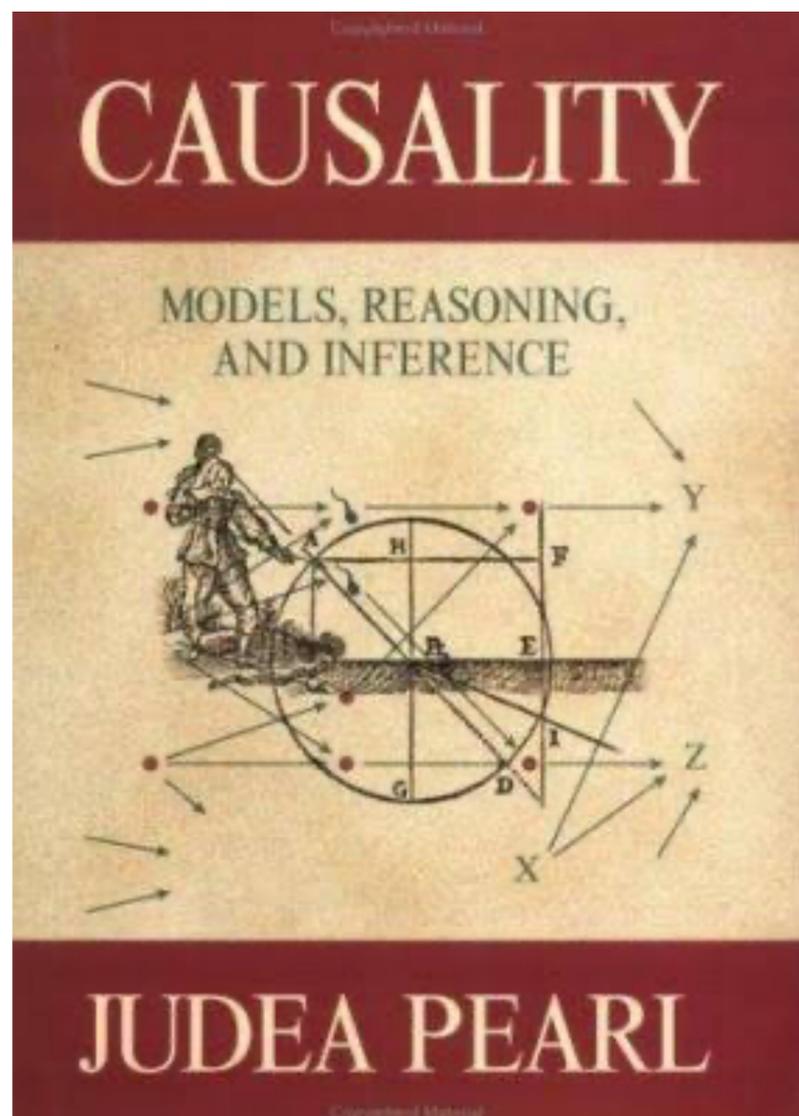
$$P(U, V, X, Y, Z)$$



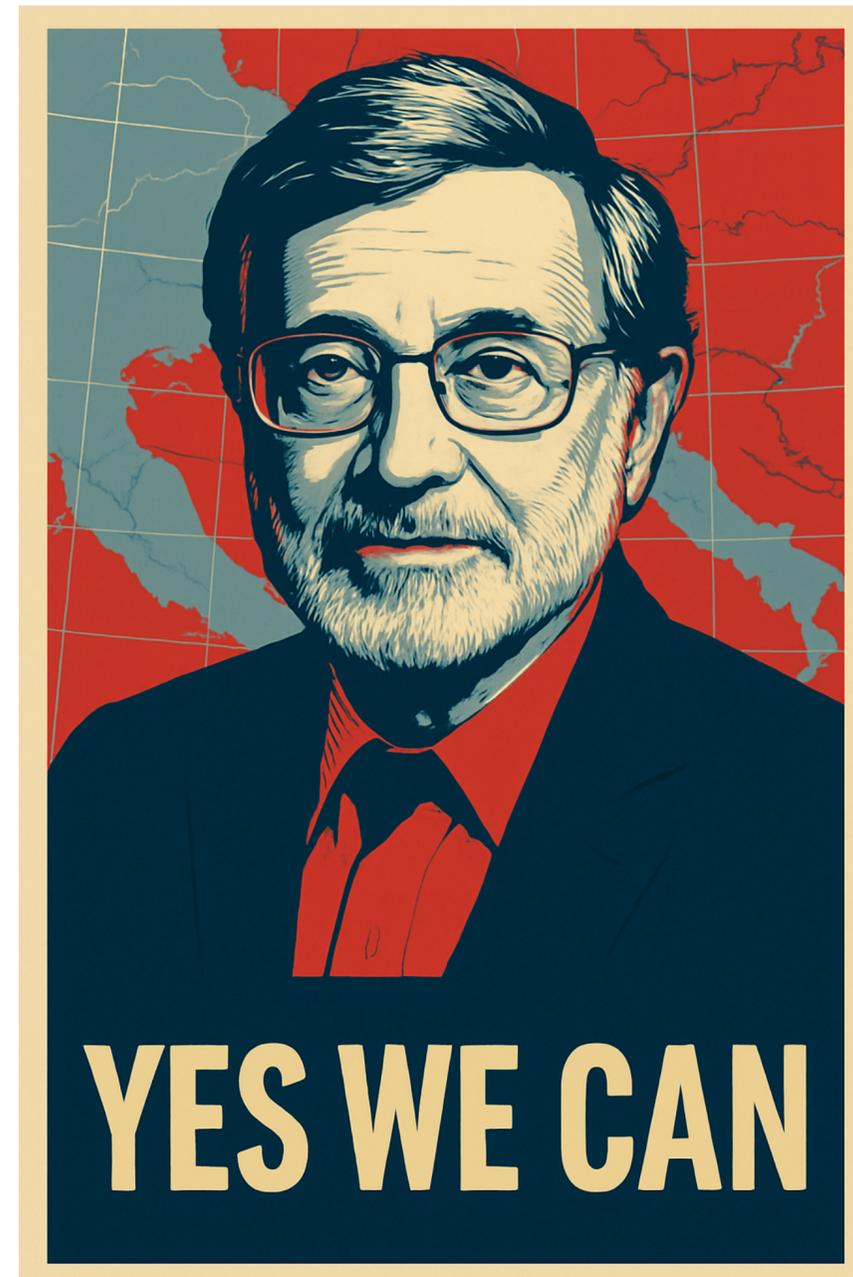
to a causal structure

$$P(U|V, Z)P(Z)P(V|X)P(Y|X)P(X)$$

Can we learn causal relations without running experiments?

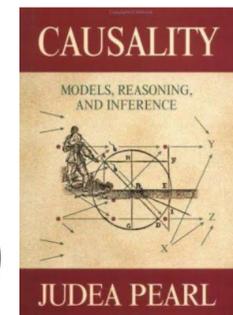


<- read this book or get a PhD student or a postdoc to read it for you



Causal Discovery!

- Represent causal structures by means of a **directed acyclic graph (DAG)**: $A \rightarrow B \leftarrow C$
- Score DAGs based on the likelihood of their implied joint distribution on actual data
- Reference material:
 - <https://www.bradyneal.com/causal-inference-course> (very good lectures, also on youtube)
 - *Causality* (Pearl, 2000)
 - *Causation, prediction, and search* (Spirtes et al. 2001)



A galactic test problem

How does this machinery fare on real astrophysical problems?

E.g. Supermassive black holes (SMBHs) co-evolve with their host galaxies. Do galaxy properties cause SMBH mass or does SMBH mass cause galaxy properties?



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

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Changhyun Cho^{1,2} , Pablo Lemos^{3,4,5} , Laurence Perreault-Levasseur^{3,4,5,11} , Yoshua Bengio^{4,8,15,16} , Xi Kang
(康熙)^{10,12} , Andrea Valerio Macciò^{1,2,13} , and Yashar Hezaveh^{3,4,5,11} 

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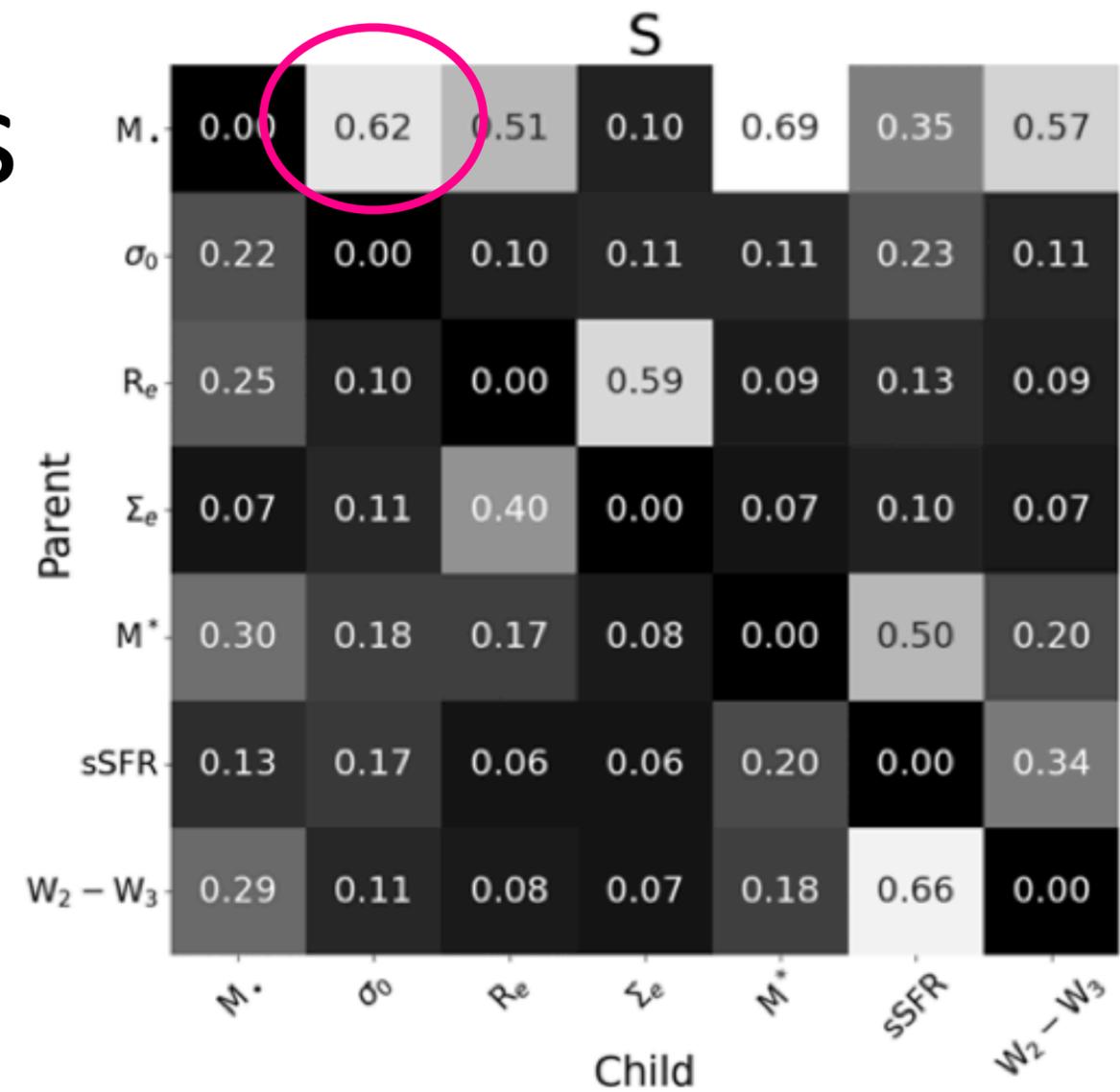
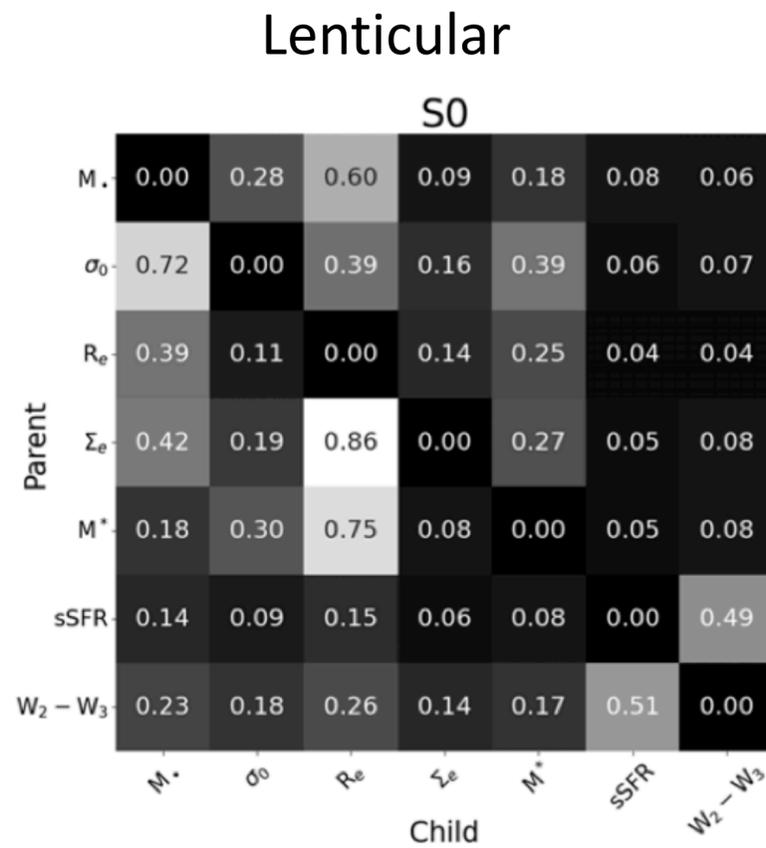
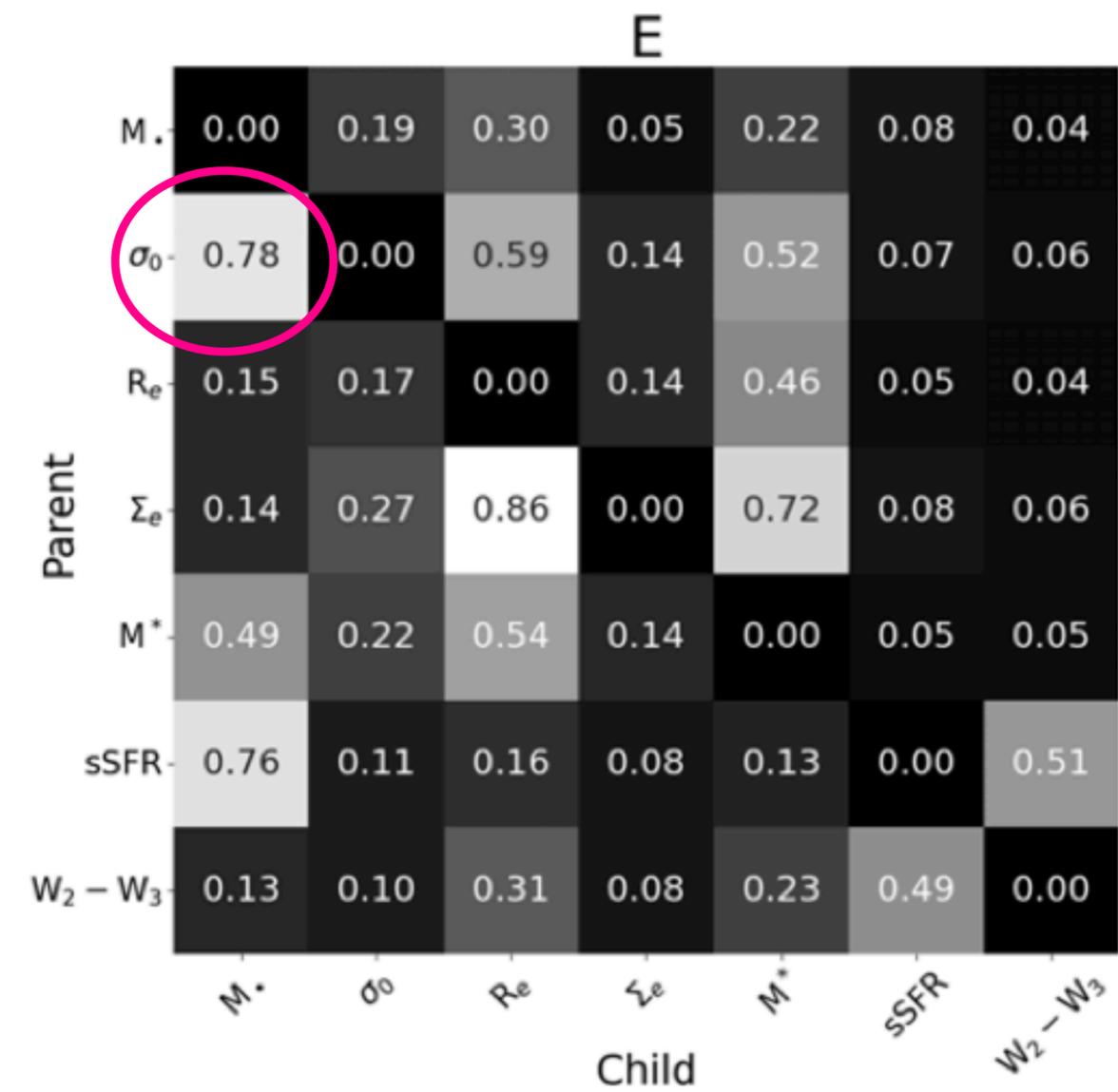
Abstract

Correlation does not imply causation, but patterns of statistical association between variables can be exploited to infer a causal structure (even with purely observational data) with the burgeoning field of causal discovery. As a purely observational science, astrophysics has much to gain by exploiting these new methods. The supermassive black hole (SMBH)–galaxy interaction has long been constrained by observed scaling relations, which is low-scatter correlations between variables such as SMBH mass and the central velocity dispersion of stars in a host galaxy's bulge. This study, using advanced causal discovery techniques and an up-to-date data set, reveals a causal link between galaxy properties and dynamically measured SMBH masses. We apply a score-based Bayesian framework to compute the exact conditional probabilities of every causal structure that could possibly describe our galaxy sample. With the exact posterior distribution, we determine the most likely causal structures and notice a probable causal reversal when separating galaxies by morphology. In elliptical galaxies, bulge properties (built from major mergers) tend to influence SMBH growth, while, in spiral galaxies, SMBHs are seen to affect host galaxy properties, potentially through feedback in gas-rich environments. For spiral galaxies, SMBHs progressively quench star formation, whereas, in elliptical galaxies, quenching is complete, and the causal connection has reversed. Our findings support theoretical models of hierarchical assembly of galaxies and active galactic nuclei feedback regulating galaxy evolution. Our study suggests the potentiality for further exploration of causal links in astrophysical and cosmological scaling relations, as well as any other observational science.

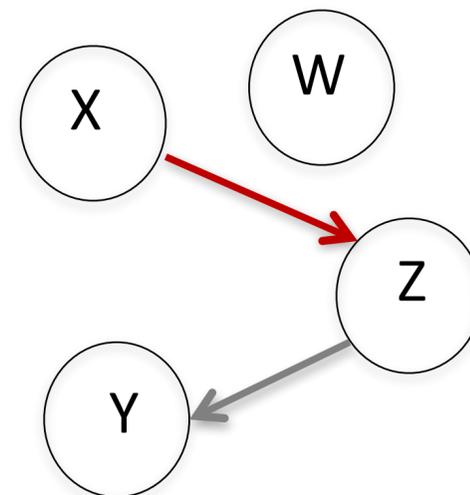
Unified Astronomy Thesaurus concepts: [Astrostatistics \(1882\)](#); [Black hole physics \(159\)](#); [Galaxies \(573\)](#); [Galaxy evolution \(594\)](#); [Galaxy formation \(595\)](#); [Galaxy physics \(612\)](#); [Galaxy properties \(615\)](#); [Scaling relations \(2031\)](#); [Supermassive black holes \(1663\)](#)



Edge marginals



$$\begin{matrix} X \\ Y \\ Z \\ W \end{matrix} \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \begin{matrix} X \\ Y \\ Z \\ W \end{matrix}$$



In short

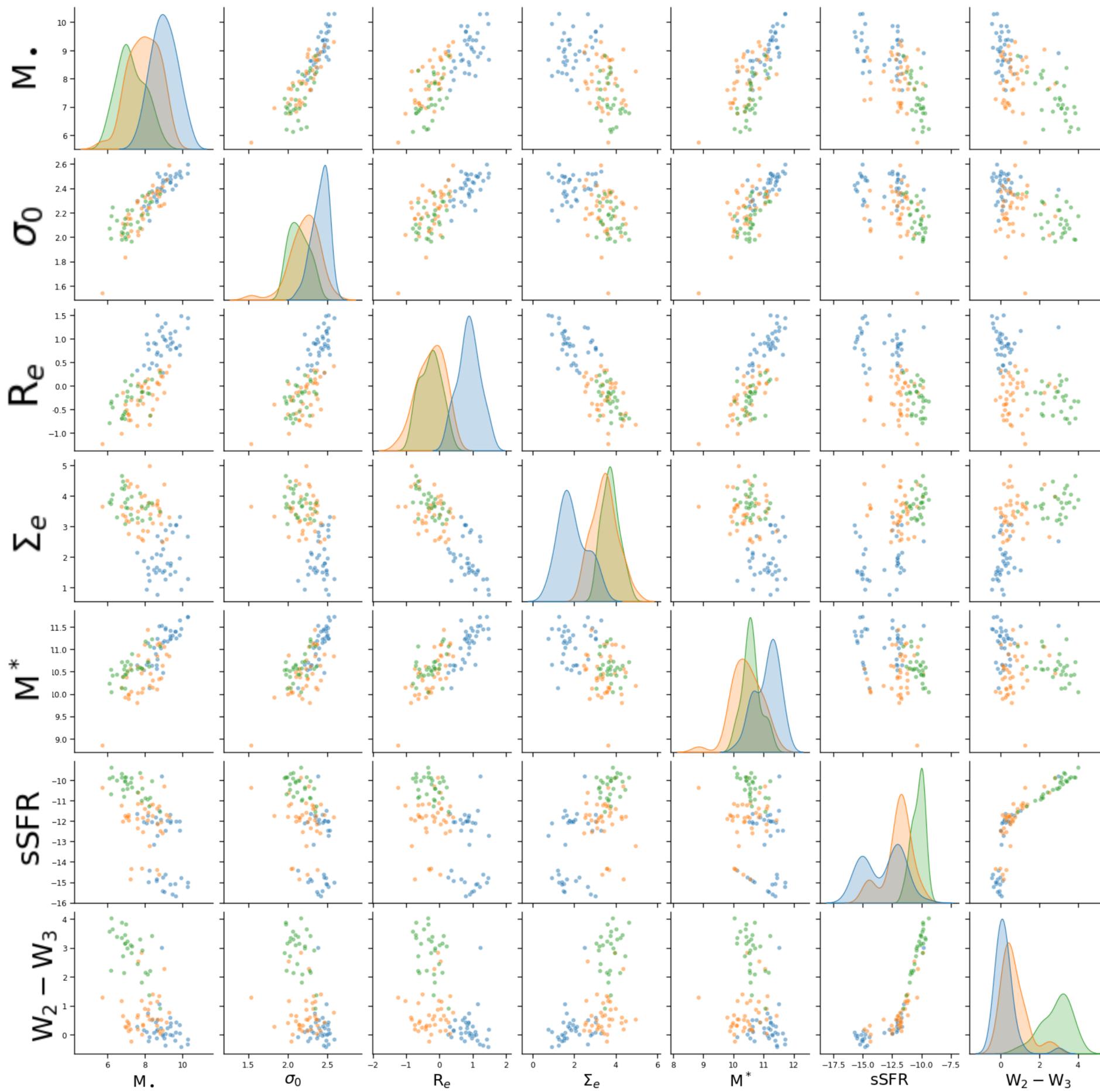
- 25 year old question on SMBH-galaxy coevolution: SMBH causes galaxy properties or vice versa?
- **Causal learning** finds that in spiral galaxies SMBH \rightarrow sigma, in ellipticals sigma \rightarrow SMBH
- Debatable, but a clear cut result
- Lots of low-hanging fruit to pick, would you like to pick it with me?



...

The data

- Sample of 101 nearby (i.e., a median luminosity distance of 21.5 Mpc) galaxies that possesses SMBHs that are close enough and/or large enough to directly resolve the dynamics of their spheres of influence
- 35 ellipticals (E), 38 lenticular (S0), 28 spiral (S)
- Seven measured variables:
 - SMBH mass M_{BH}
 - central stellar velocity dispersion σ_0
 - effective (half-light) radius of the spheroid R_e
 - average projected density within it Σ_e
 - color WISE $W_2 - W_3$
 - total stellar mass M_*
 - star formation rate SFR

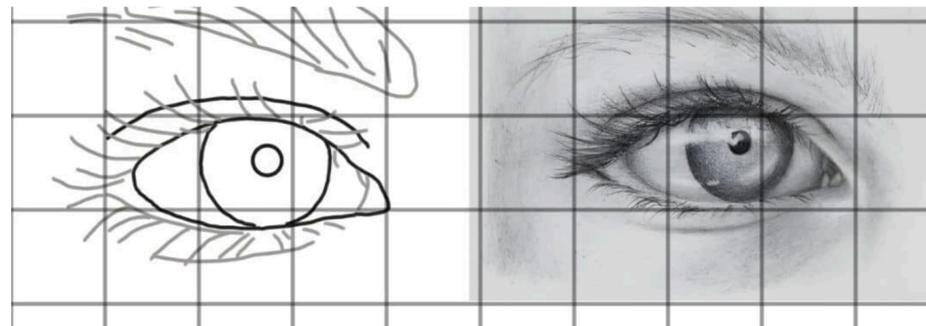
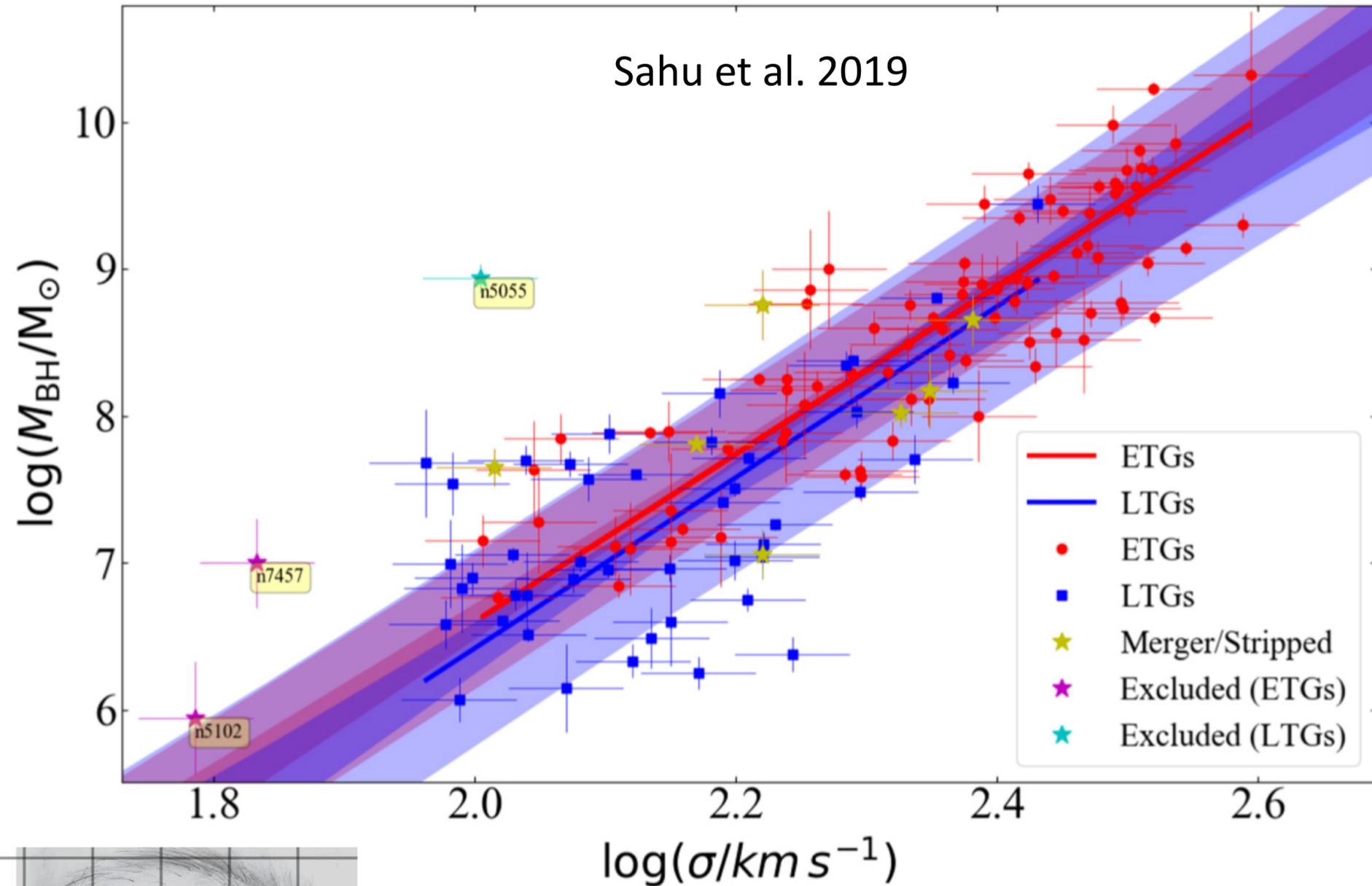


• E
 • SO
 • S

$M_{\text{BH}}-\sigma_0$ relation

- $M_{\text{BH}} \sim \sigma_0^\alpha$ with $\alpha = 4.8 \pm 0.5$ Ferrarese & Merritt 2000
- $M_{\text{BH}} \sim \sigma_0^\alpha$ with $\alpha = 3.8 \pm 0.3$ Gebhardt et al. 2000

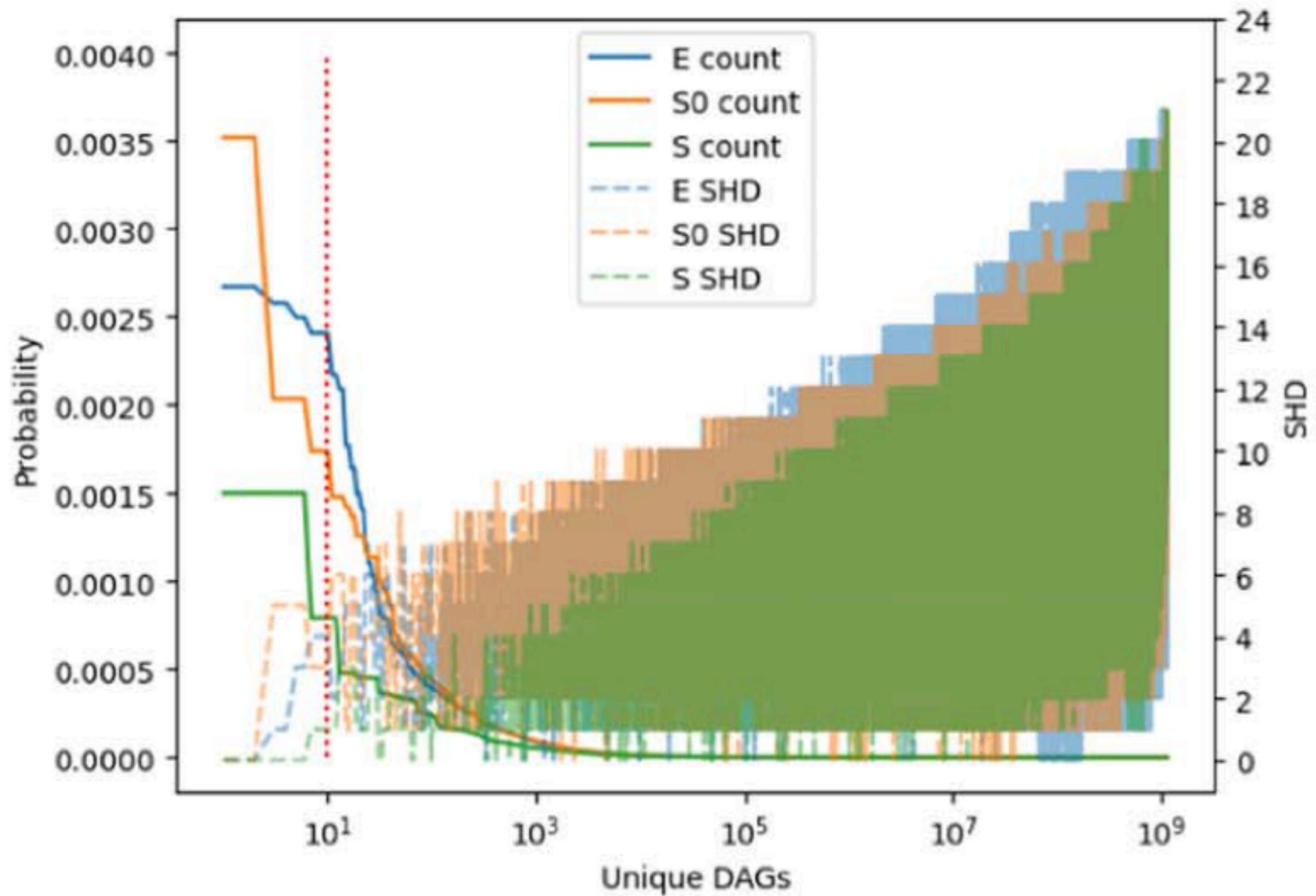
- Accreting SMBH outflows heat gas and affect star formation rate (e.g. Cresci & Maiolino 2018)
- Gas accretion feeds SMBHs
- This is **sub grid physics** in cosmological simulations and even in zoom simulations!



Methods

- We applied two constraint based methods, Peter-Clark (PC) and Fast Causal Inference (FCI) and a score-based method based on the Bayesian Gaussian Equivalent (BGe) score
- DAG-GFN [Deleu et al. 2022](#) samples DAGs efficiently using a GFlowNet [Bengio et al. 2021](#)
- Exact posterior also feasible with few (up to 8, we had 7) variables

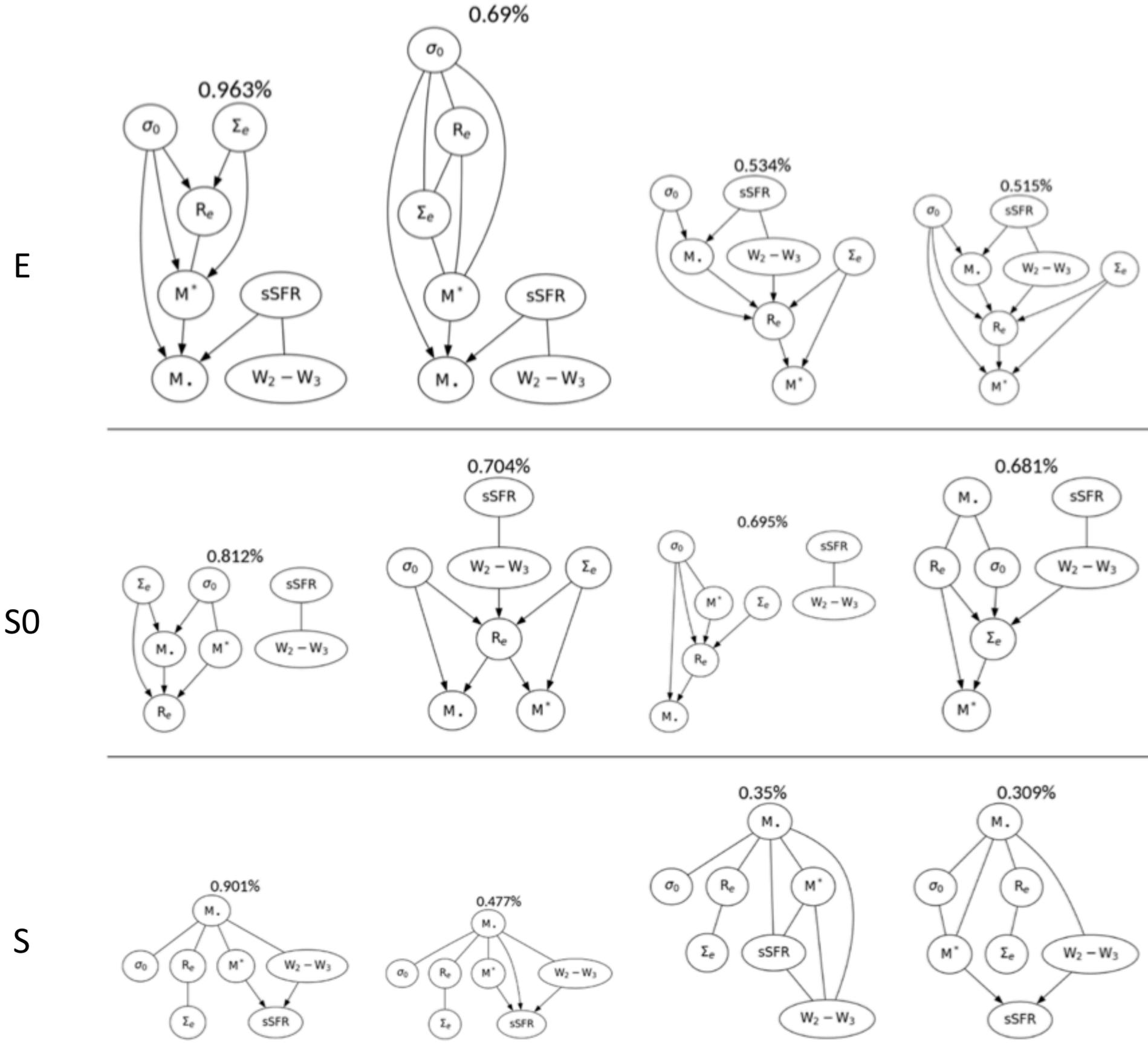
DAG posterior



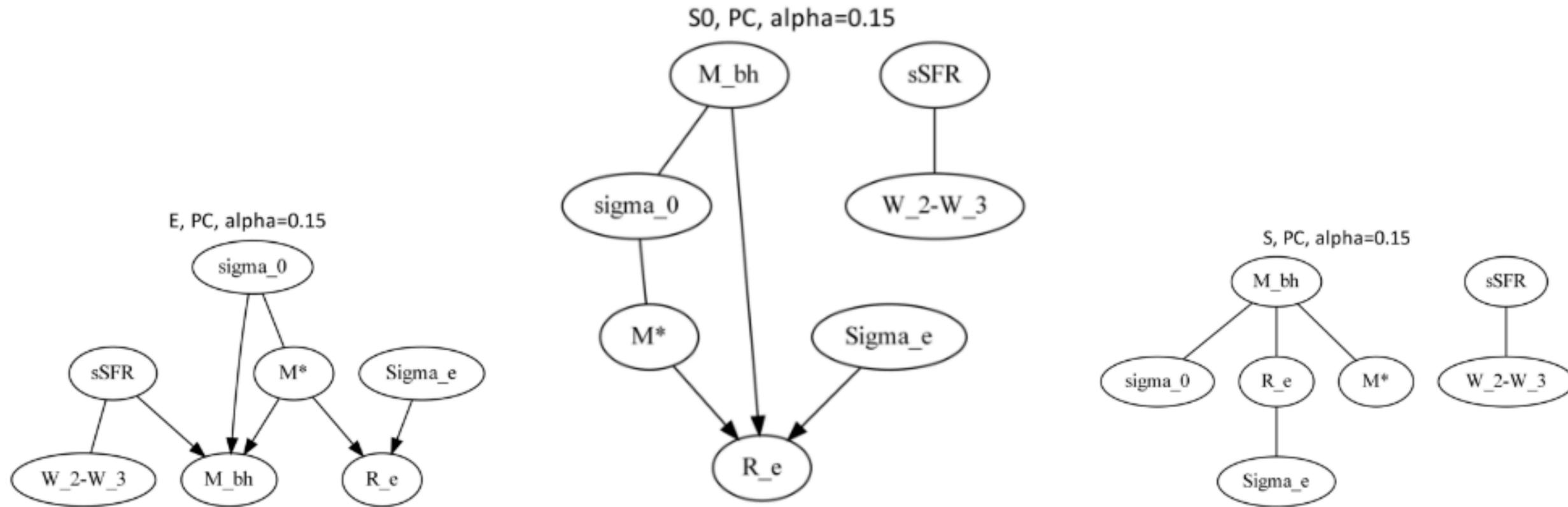
Edit distance

1'138'779'265

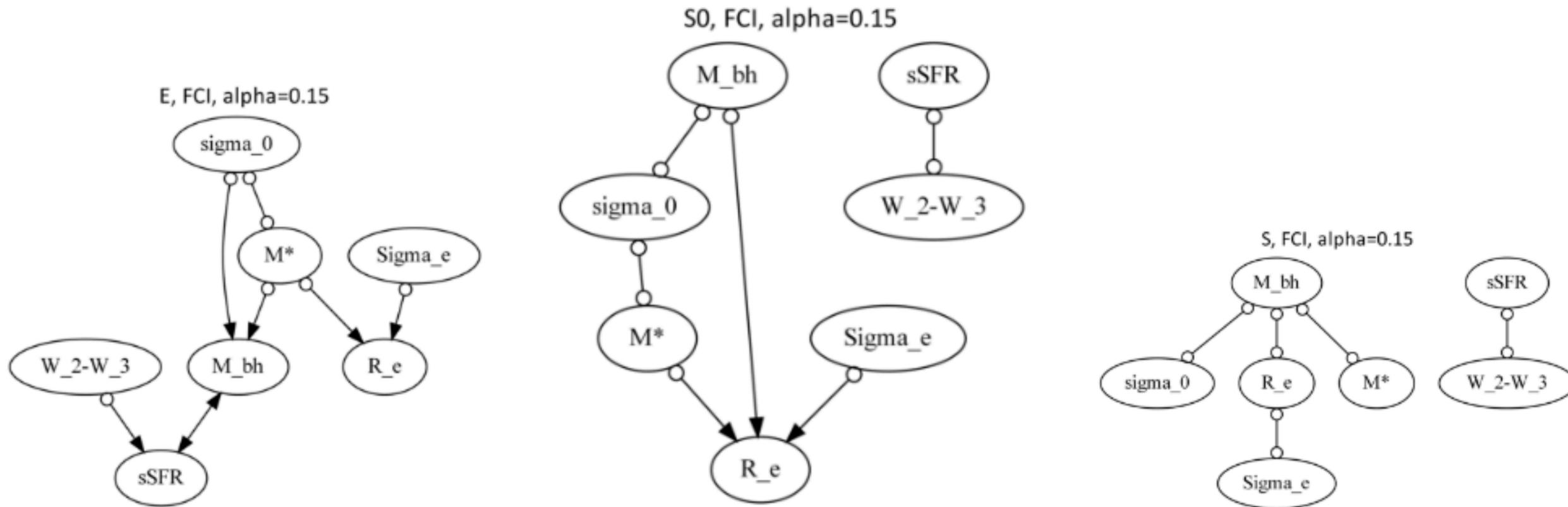
Most frequent DAG equivalence classes



Constraint based: PC



Constraint based: FCI

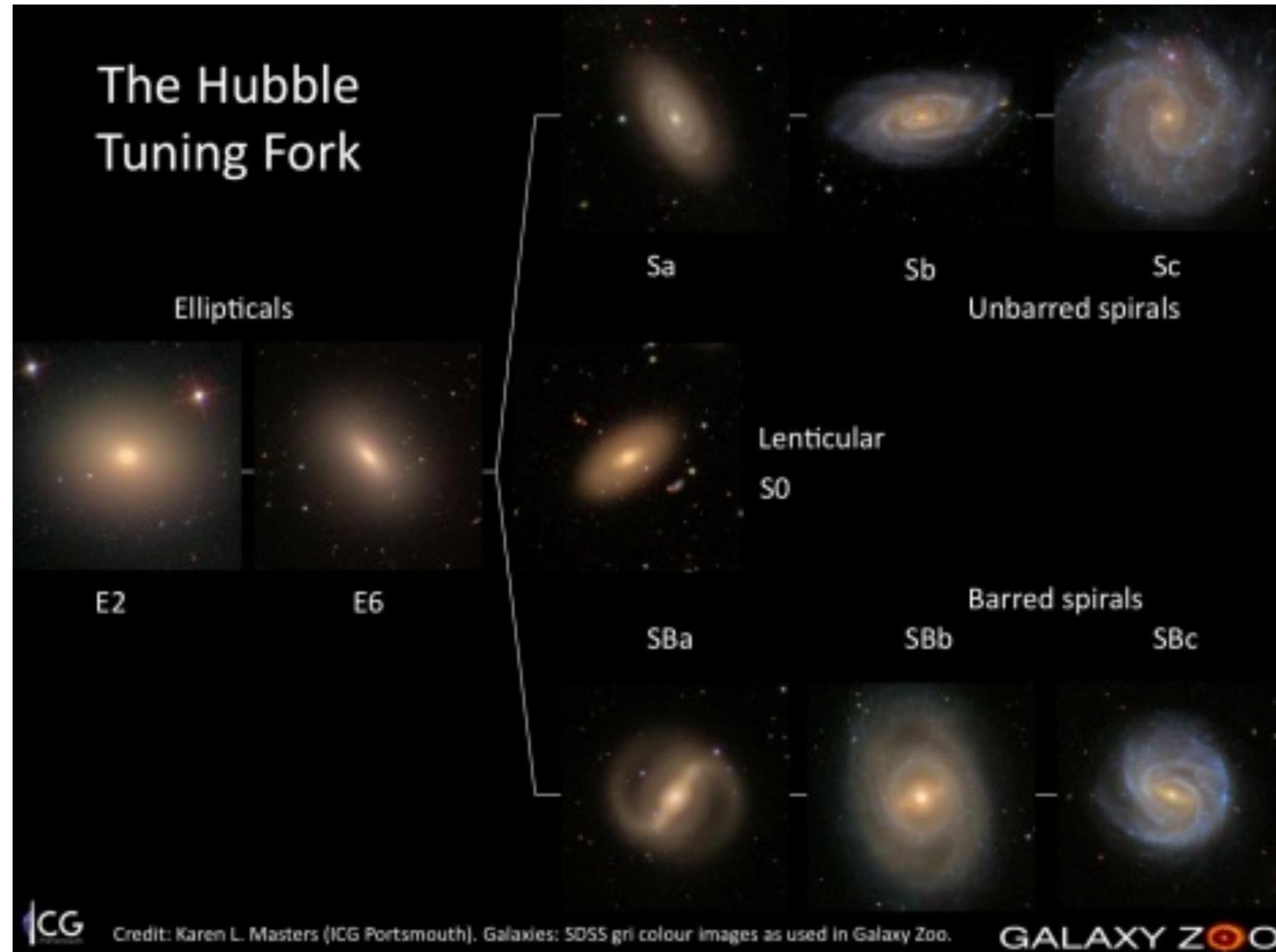


$\leftarrow\rightarrow$ confounded relation (unobserved shared cause)

$o\rightarrow$ either confounded relation $\leftarrow\rightarrow$ or causal \rightarrow

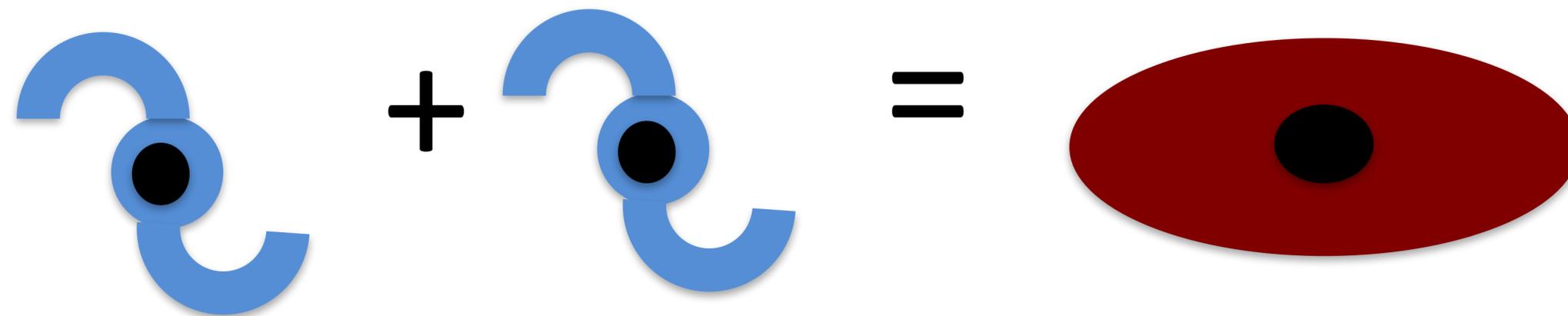
Physical interpretation

- Velocity dispersion causes SMBH mass in ellipticals
- The opposite holds for spirals
- Lenticulars are in-between but more similar to ellipticals



Gas and mergers as mediators

- Spirals: SMBH \rightarrow gas \rightarrow galaxy properties
- Ellipticals: galaxy properties \rightarrow mergers \rightarrow SMBH



Summary

- First application of causal discovery to astronomical data
- Causal interpretation of scaling relations in galaxies, in particular σ_0
-> M_{BH} in elliptical galaxies and $\sigma_0 \leftarrow M_{\text{BH}}$ in spirals
- **What next? A whole new field is taking off...**