Title: Bringing causality to astronomy

Speakers: Mario Pasquato

Series: Cosmology & Gravitation

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Abstract: Causal discovery aims at learning causal relations among variables from data. It is an emerging field at the interface of machine learning and statistics that found ample application in several disciplines. From a physicist's point of view it can be seen as an operational definition of the concept of causal relation between variables, especially in an observational context where experimental manipulation is precluded. Interestingly, causal discovery has not yet been applied to Astronomy, despite it being the observational science par excellence. Here I will present the first application of causal discovery to Astronomy with the goal of addressing a debated issue in galaxy formation: the origin of the observed scaling relations between supermassive black hole (SMBH) and host galaxy properties. I apply three causal discovery algorithms to a state-of-the-art dataset of SMBH host galaxies with dynamical mass measurements, with the goal of learning a causal structure in terms of a directed acyclic graph. The results are consistent between methods and are amenable to physical interpretation, showing that across the multiplicity of possible causal structures, in elliptical galaxies SMBH mass is predominantly an effect of galaxy properties while in spiral galaxies the reverse holds. I offer an explanation of this finding in terms of the physics of galaxy merging, and address the limitations and the theoretical implications of this new method for galaxy formation in some detail.

Zoom link TBA

Bringing causality to astronomy

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Tue 27 Feb. 2024
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Mila
Marie Curie Actions

Interdisciplinary cats

I will be talking about causality methods from machine learning applied to astrophysics.

White cat: if you know astrophysics you can sleep

Black cat: if you know statistics/machine learning you can sleep

No cat: please do not sleep

Astronomy is an observational science

- Experiments possible in the Solar System at best
- Even then, they are limited in scope

Left: on July 4, 2005 the Deep Impact space probe impactor successfully collided with the comet Tempel 1.

https://science.nasa.gov/mission/deep-impact-epoxi
https://photojournal.jpl.nasa.gov/catalog/PIA02133

Observational science means...

- Experiments are impossible
- Cosmic history is given only once
- Fixed vantage point
- We are part of the system under study

The universe is not twice given, with an Earth at rest and an earth in motion; but only once, with its relative motions alone determinable.

E. Mach, **The Science of Mechanics**,
in translation by T.J. McCormack, p. 266

The radiation rate of a star varies as $\varepsilon^{7\text{-}9}$ and for very much larger values of ε than the present value, all stars would be cold. This would preclude the existence of man to consider this problem.

R. H. Dicke, 1957, **Rev. Mod. Phys.** *29, 363*

Observational science = best science

- Experimental reach is limited in space and time
- Any science general enough in scope goes beyond these limits and becomes observational.
- E.g. we cannot re-run the Big Bang or even the Milky Way's formation
- Astronomy's status as an observational science is inevitable/fundamental

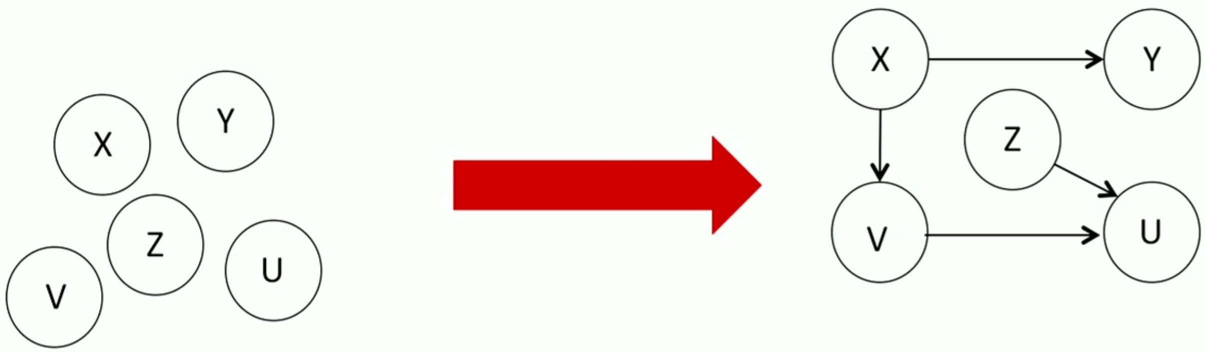
Longest running lab experiment (pitch drop experiment, University of Queensland) is just 97 yr old
thetenthwatch.com/feed

Why run experiments?

- Intervention affects one variable at a time without affecting others: do(X = x), atomic intervention
- We imagine intervention to be free, i.e. not caused by other variables; this is deliberately engineered in randomized trials
- Intervention lets us determine causal links between variables

Can we learn causal relations without running experiments?

- The goal is to learn causal links even without the ability to intervene



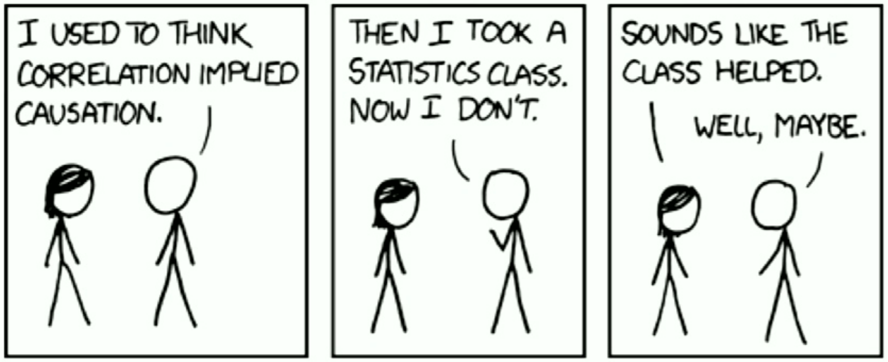
From variables

to a causal structure

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

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

But we only observe statistical associations



Three ways out (No. 3 will surprise you):

1. Make causal models, use observed correlations to validate them
2. Look for natural experiments
3. Take many correlations and rub them together (causal discovery)

1) Make models, test them with correlations

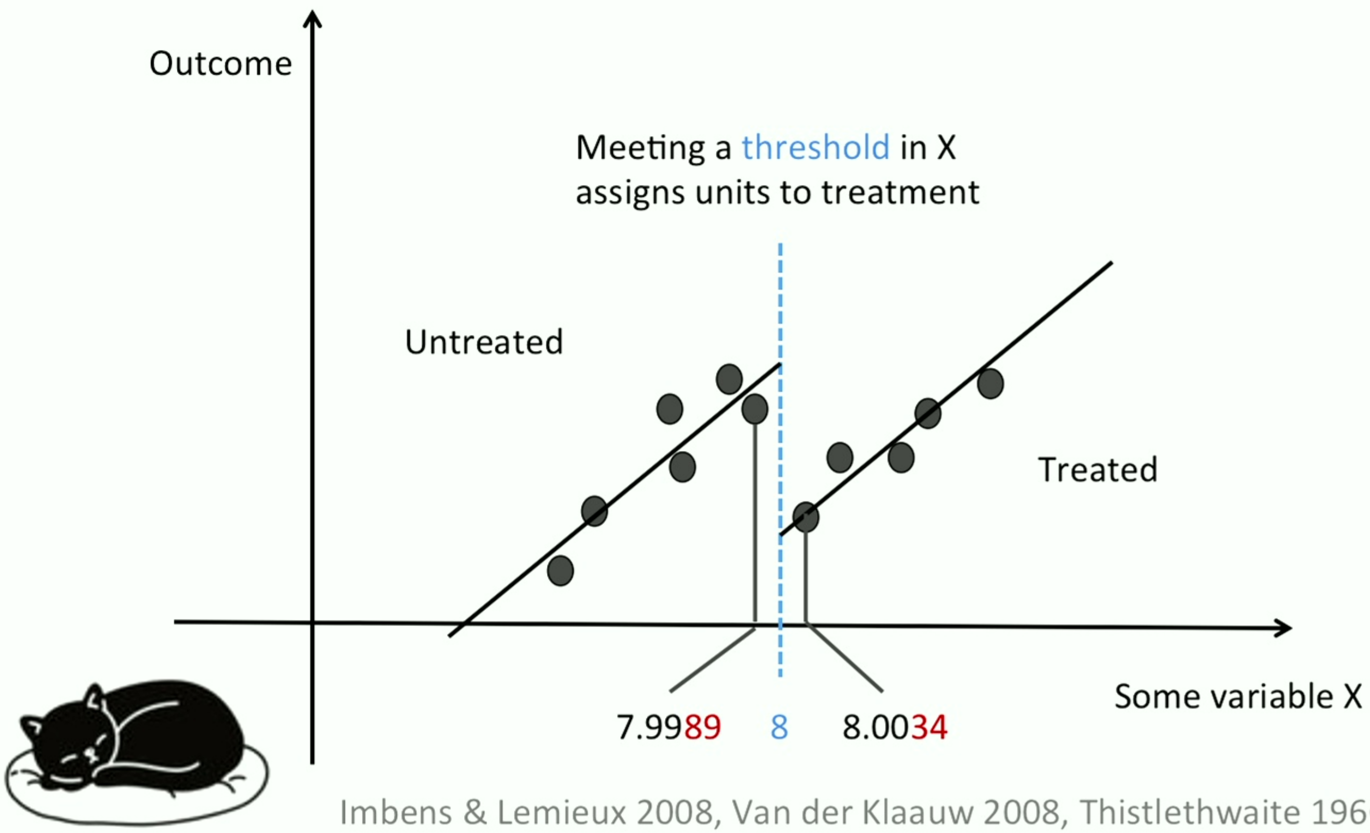
- Physicists are good at this: e.g. classical gravitation tested against Kepler's laws
- Models can be simulations a. k. a. *numerical experiments*:
  - e.g. Nihao zoom-in simulations by Andrea Macciò and his group (Benjamin Davis, Zehao Jin) at NYU Abu Dhabi
  - tested against scaling laws for galaxies

Collaborators (color coded)

2) Look for natural experiments

- Economists do this a lot
- Recipe:
  - Find random number generators in nature/society
  - Show they drive assignment to treatment
  - The treatment effect you measure is causal – like in a randomized experiment
- Problem:
  - Where are the random number generators in the sky?

Regression discontinuity *aka* least significant digits as RNG



Imbens & Lemieux 2008, Van der Klaauw 2008, Thistlethwaite 1960

Application to astronomy

- Pang, ..., Pasquato, et al. 2021 showed that stellar mass –as measured by fitting the color-magnitude diagram- is discontinuous across a supernova shell, measuring the causal effect of supernova explosion on stellar mass
- Pasquato & Matsiuk★ 2019 found that star clusters about to cross the Galactic plane are smaller than those that just crossed, measuring the causal effect of disk shocking on star cluster size
- 

★ economist

Limitations

- This only tells you if/how much treatment causes outcome
- Nature chose which variables to include in the natural experiment
- What if we care about all the relations among many variables?
- We need something else...

3) Take many correlations and rub them together: Causal Discovery!

- Represent causal structures by means of a directed acyclic graph (DAG) A -> B <- C
- Weed out the DAGs that are incompatible with the observed statistical associations between variables
- 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)

Comes in two flavors

- Constraint based: use the pattern of (conditional) independencies between variables to exclude incompatible causal structures; usually frequentist (statistical testing)
- Score based: consider all possible causal structures and rate them based on how well they represent the data; usually Bayesian

Constraint based

Needs more than two variables.

Key assumptions:

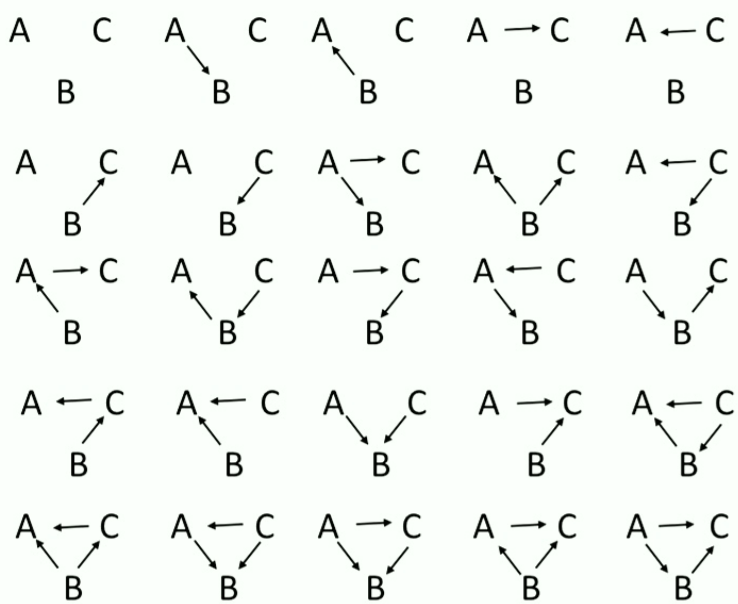
- Given its direct causes, a variable is independent of any other variable except its effects (Causal Markov Assumption)
- No other independence relation is present (Faithfulness assumption)

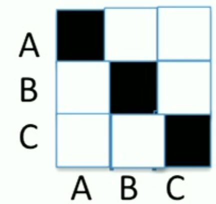
Optional assumption:

- No unobserved common causes (Causal sufficiency)

Three variable example

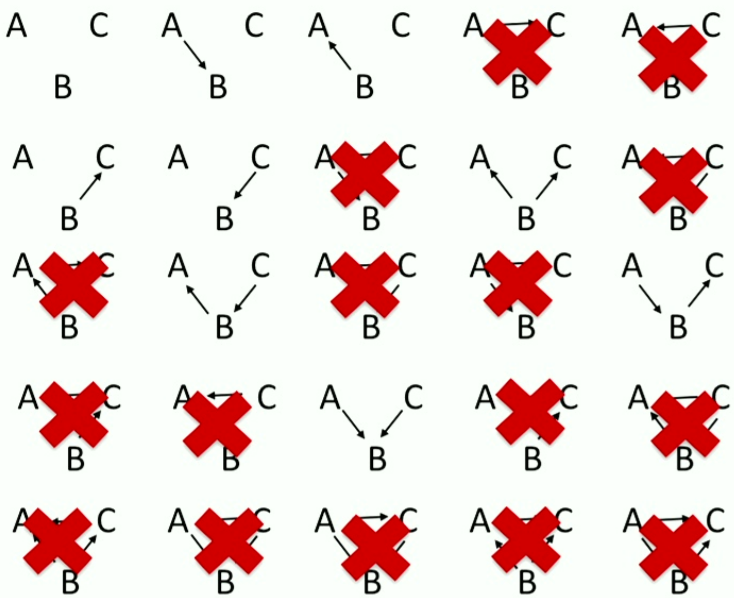
Possible DAGs (25)





Three variable example

Possible DAGs (9)

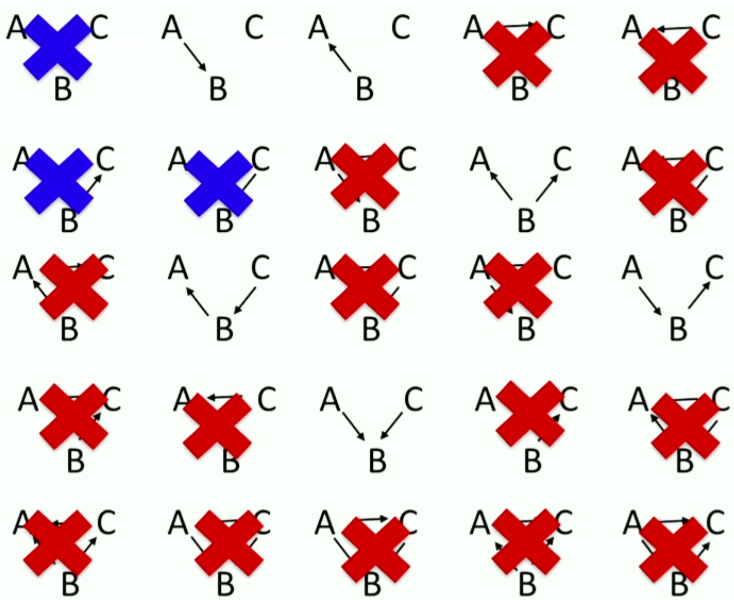


A and C unconditionally independent

Faithfulness rules out causal relations between A and C

Three variable example

Possible DAGs (6)

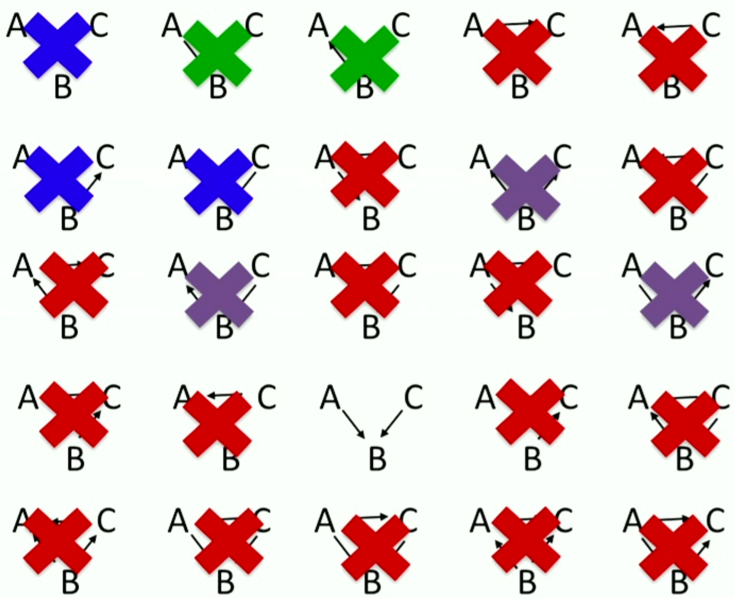


A and C unconditionally independent

A and B unconditionally dependent
Causal Markov Assumption rules out absence of causal relation (or common cause) between A and B

Three variable example

Possible DAGs (1)



A and C unconditionally independent

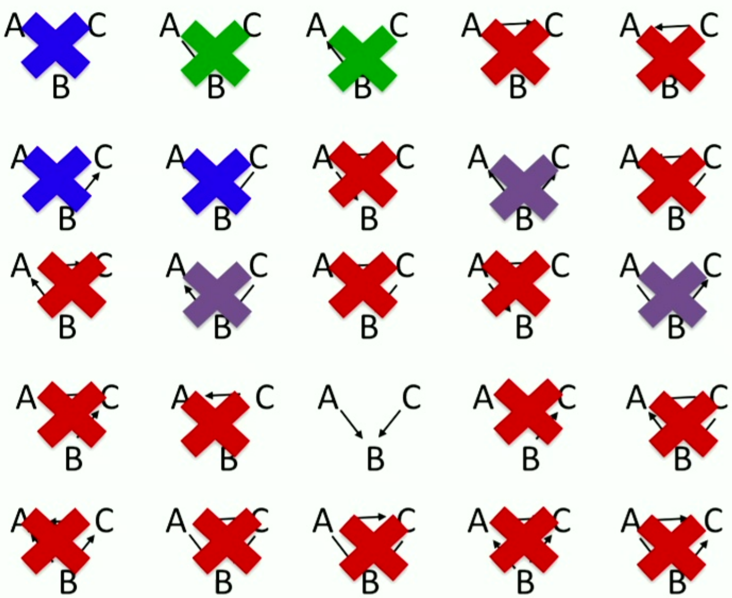
A and B unconditionally dependent

B and C unconditionally dependent

A and C dependent conditional on B
Causal Markov Assumption rules out B -> A because then given B (direct cause) A should be independent on C, similarly rules out B -> C

Three variable example

Possible DAGs (1)



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A and B unconditionally dependent

B and C unconditionally dependent

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Score based

- Given a DAG and assumptions on P(B|A) when A -> B, write the implied joint distribution $P(X_i)$
- Compute the likelihood of your data under the joint distribution
- Given a prior on DAGs, get a posterior
- Problem: the space of DAGs is enormous

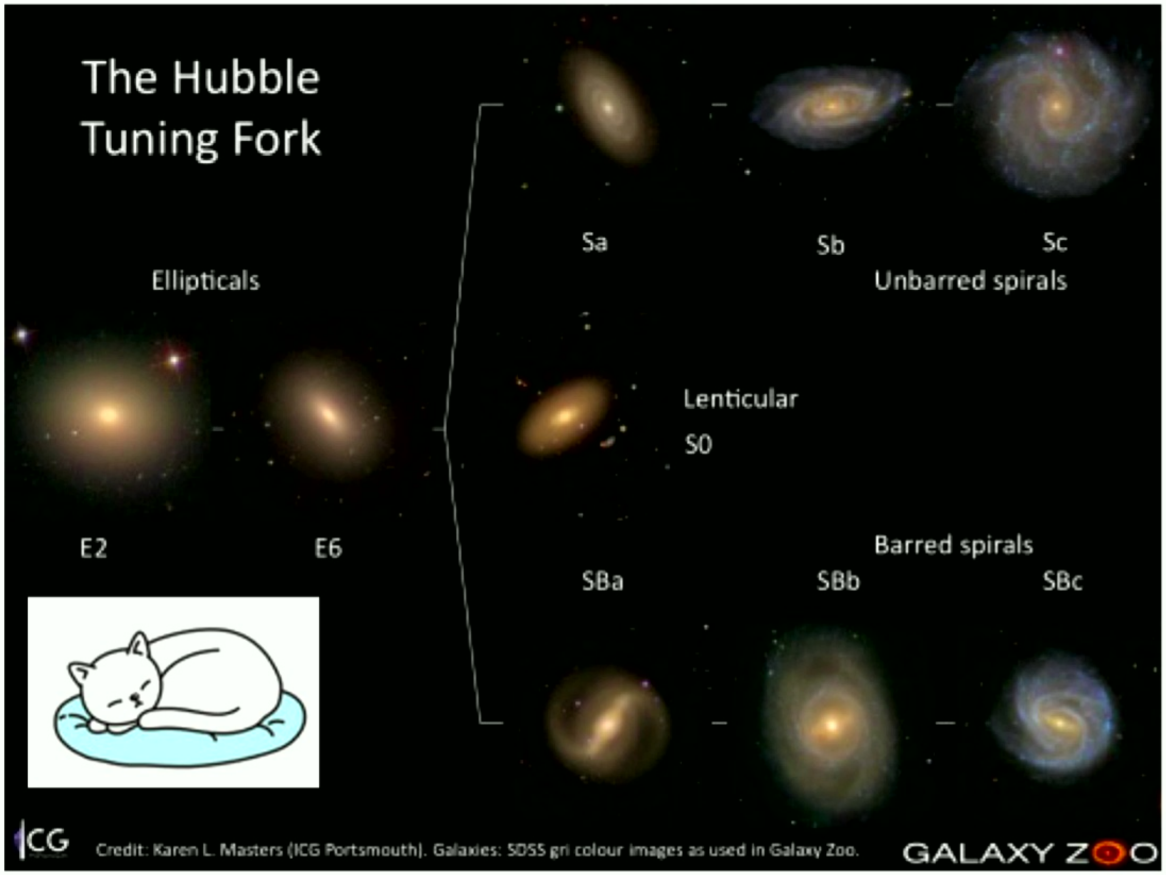
Our problem

- How does this machinery fare on real astrophysical problems? For instance:
  - Supermassive black holes (SMBHs) co-evolve with their host galaxies. Do galaxy properties cause SMBH mass or does SMBH mass cause galaxy properties?
  - Elliptical galaxies obey the 'fundamental plane' relation. In which direction is this relation causal?

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

Galaxy morphology refresher



See e.g. Buta 2011 for reference https://arxiv.org/abs/1102.0550

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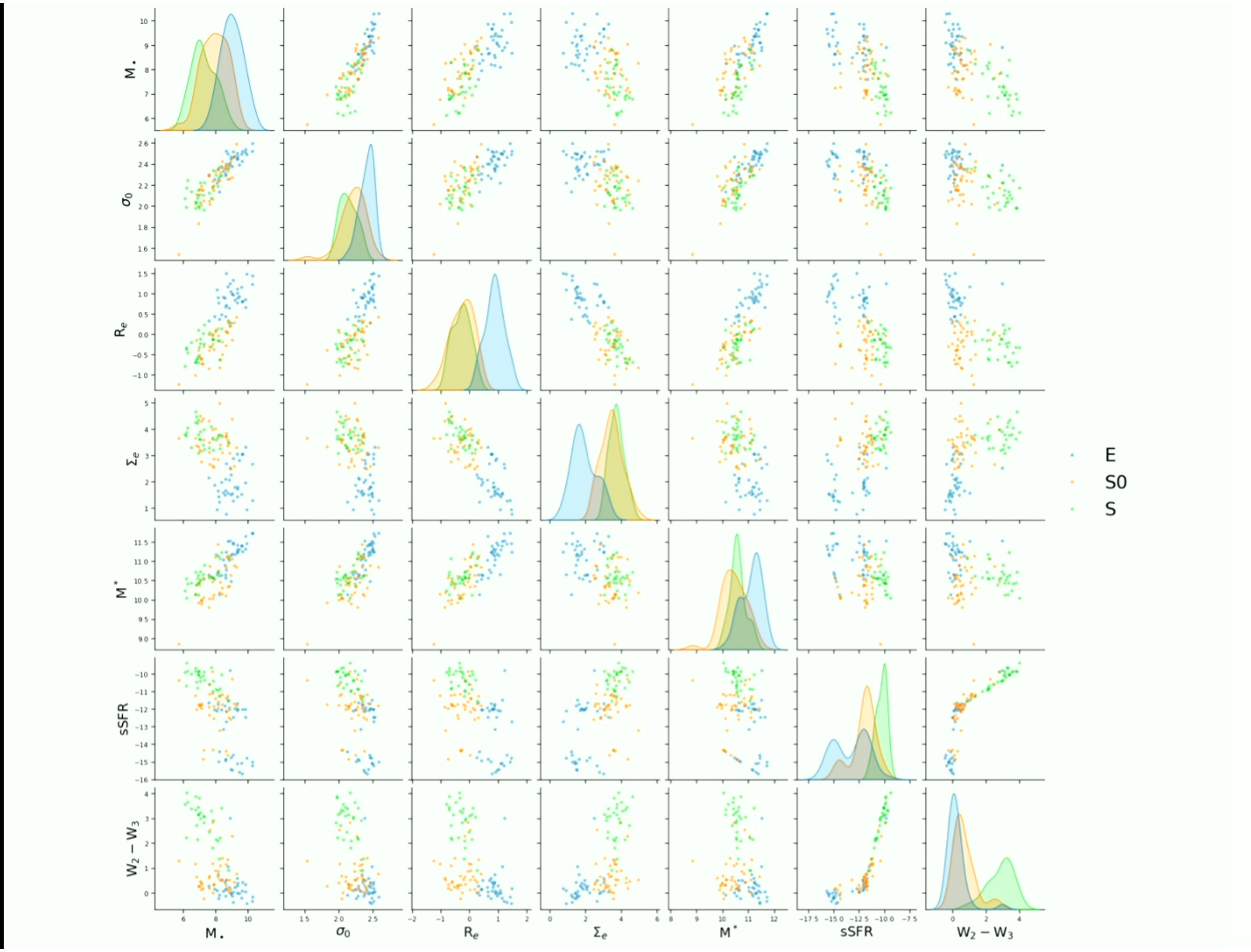
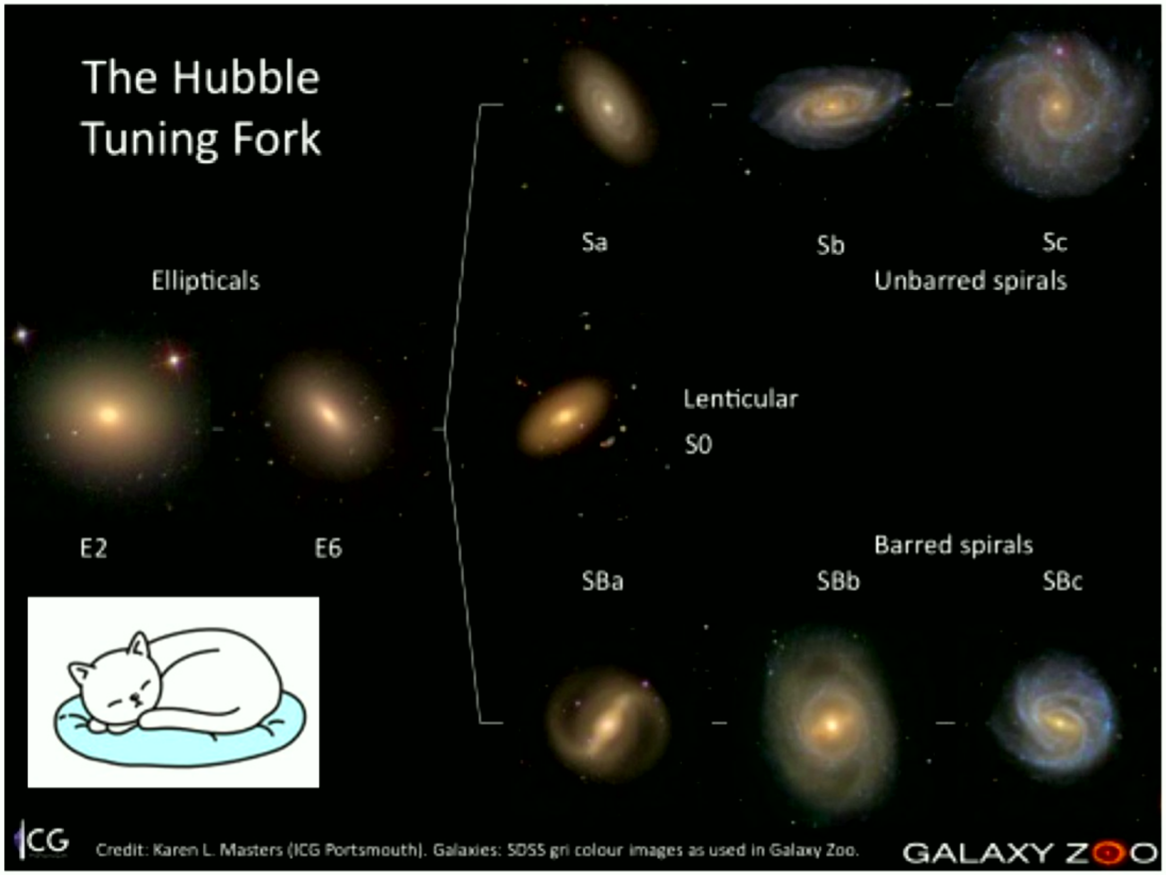


M•
σ0
Re
Σe
M*
sSFR
W2 − W3
E
S0
S

Galaxy morphology refresher



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Two scaling relations

- Fundamental plane of elliptical galaxies
  - relatively clear physical origin
  - causal direction open to interpretation
- M_{BH}-σ relation
  - dirtier physics
  - causal direction debated

Fundamental plane

galactic mass

Potential energy $$U \propto -\frac{GM^2}{R_e}$$

effective radius

Kinetic energy $$T \propto M\sigma_0^2$$

central velocity dispersion

Virial equilibrium $$2T + U = 0$$

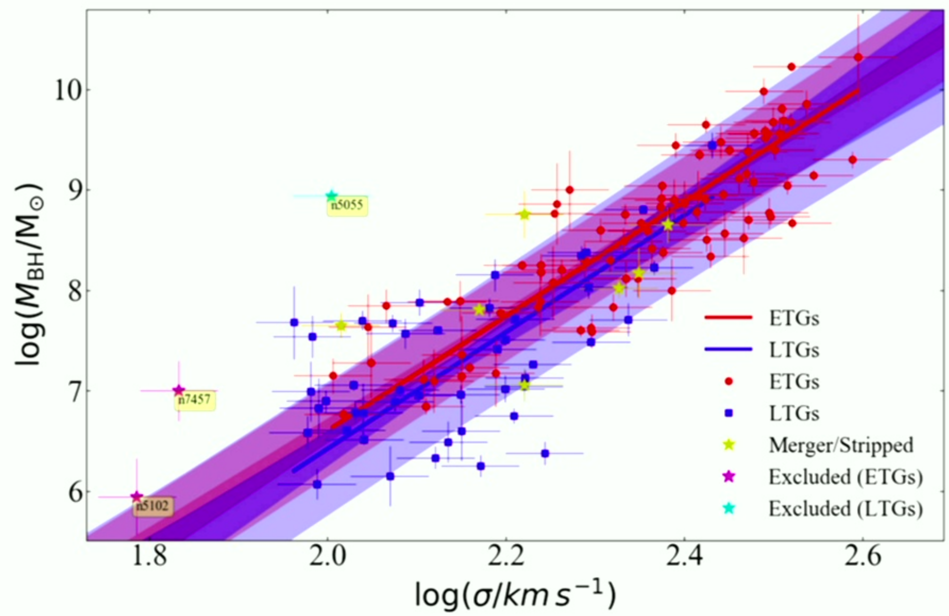
Hence $$\sigma_0^2 \propto \frac{M}{R_e}$$

Surface density definition $$\Sigma_e \propto -\log \frac{M}{R_e^2}$$

Fundamental Plane $$\log \sigma_0 \propto a\Sigma_e + b \log R_e$$

M_{BH}-σ_0 relation

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



Sahu et al. 2019

M_{BH}-σ_0 relation

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

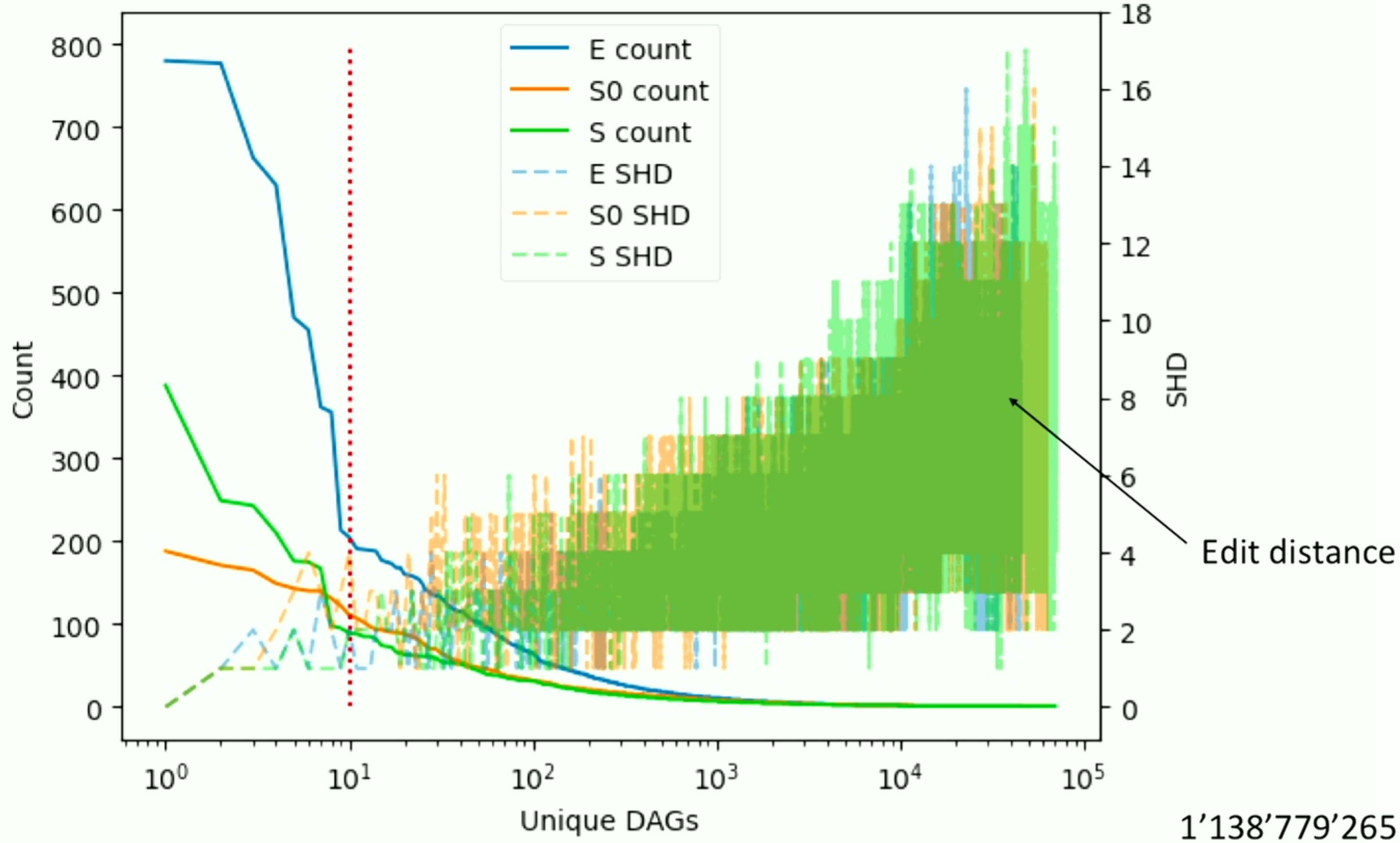
So, what did we do?

- We applied two constraint based methods, Peter-Clark (PC) and Fast Causal Inference (FCI) and a score-based method DAG-GFN
- DAG-GFN Deleu et al. 2022 samples DAGs efficiently using a GFlowNet Bengio et al. 2021

More collaborators
(color coded)

Sampled DAG frequency

We sample 10^5 DAGs with frequency proportional to their likelihood (flat prior)



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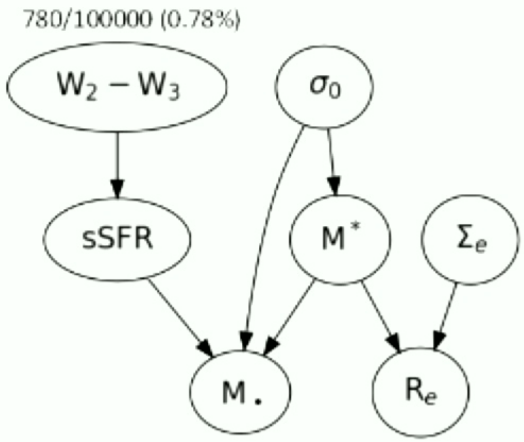
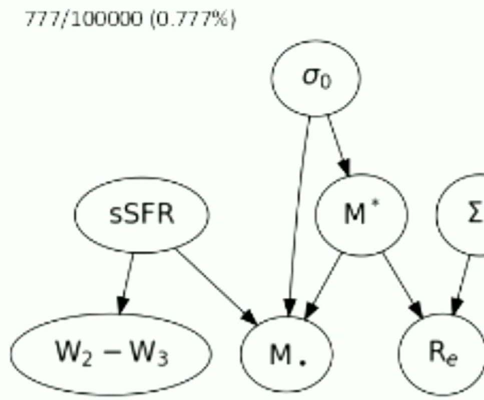
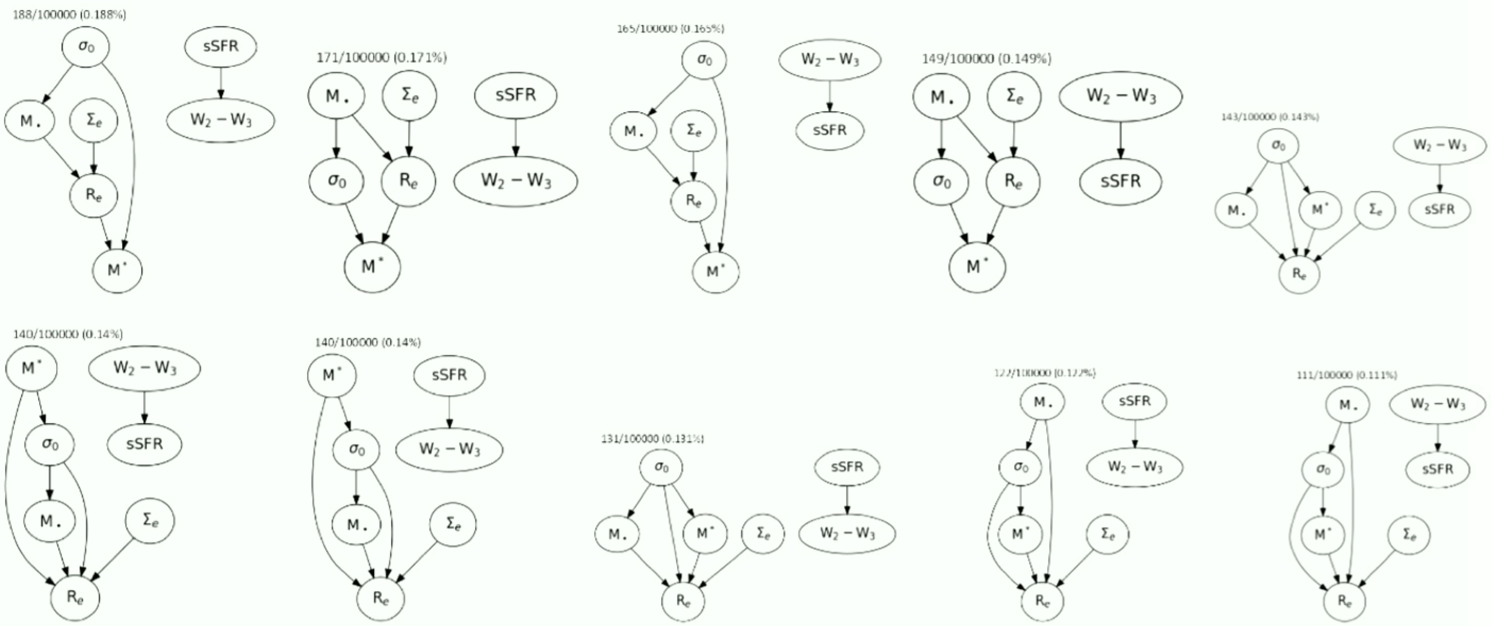
Most frequent DAGs: ellipticals

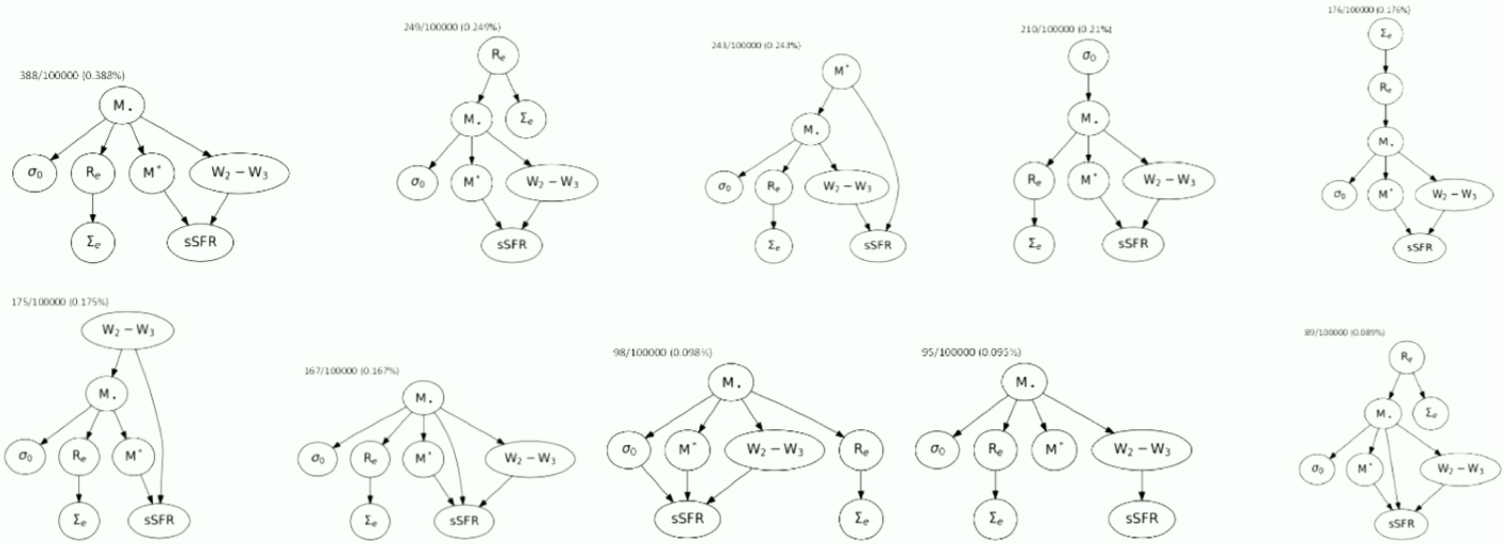




Most frequent DAGs: lenticulars

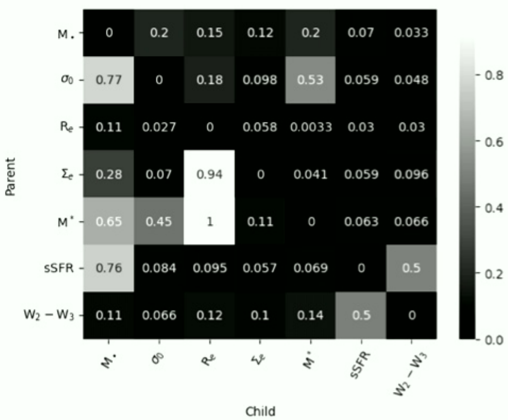


Most frequent DAGs: spirals

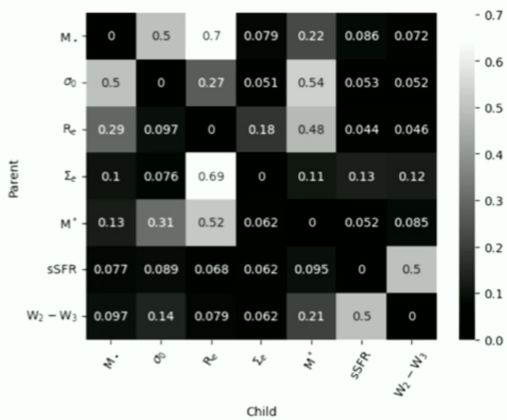


Edge marginals

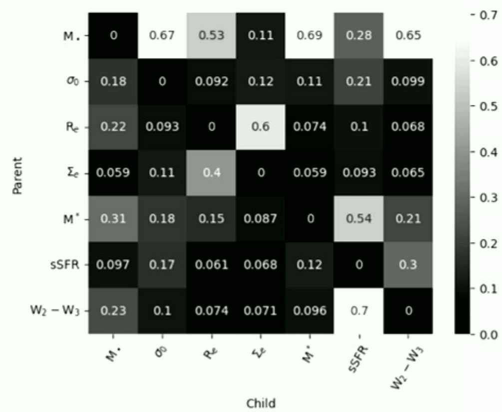
Elliptical



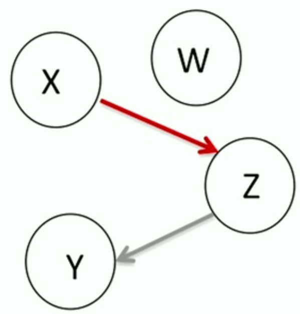
Lenticular



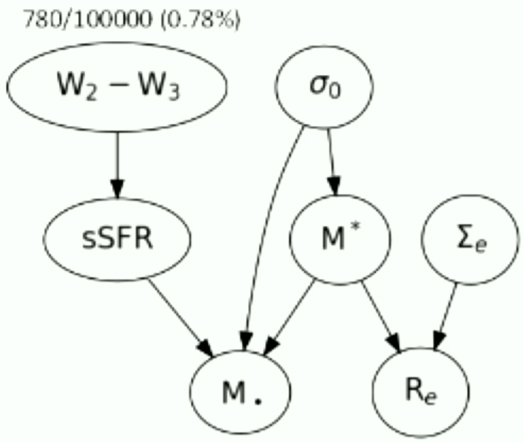
Spiral

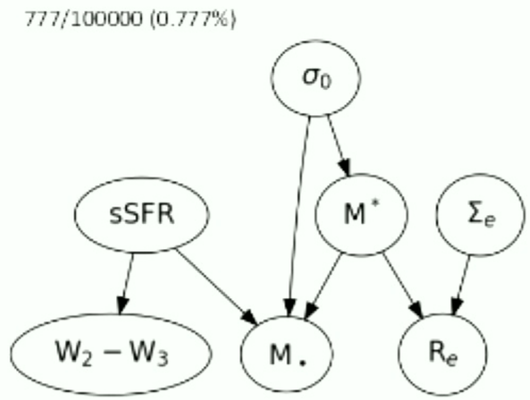


$$
\begin{array}{c|cccc|}
X & 0 & 0 & 1 & 0 \\
Y & 0 & 0 & 0 & 0 \\
Z & 0 & 1 & 0 & 0 \\
W & 0 & 0 & 0 & 0 \\
 & X & Y & Z & W
\end{array}
$$



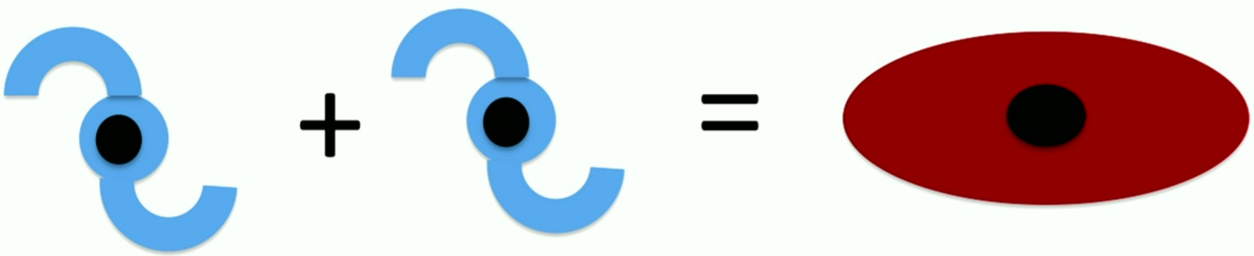
Most frequent DAGs: ellipticals



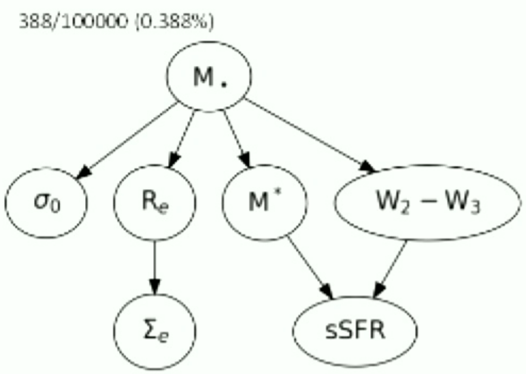


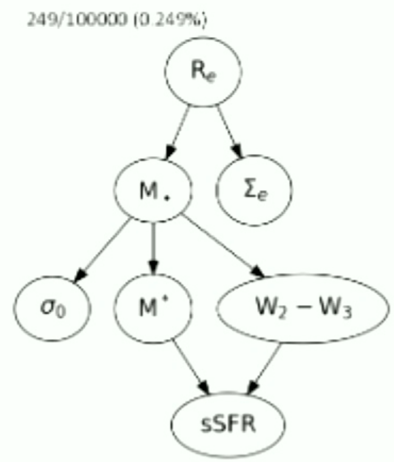
Role of gas and mergers

- In spirals the SMBH affects the galaxy by acting on the gas
- In ellipticals there is no gas; galaxy properties determine SMBH mass by driving mergers
- Both paths are active in lenticulars

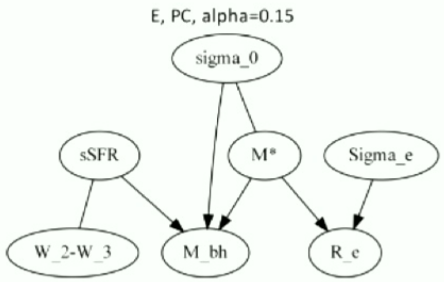


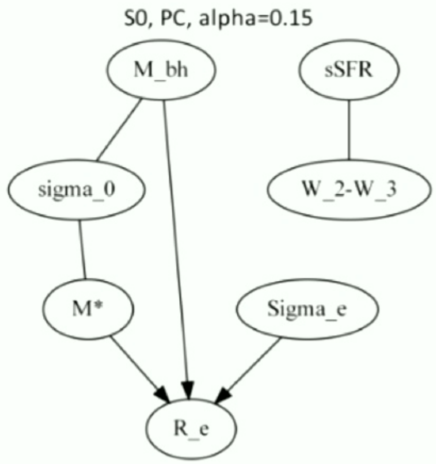
Most frequent DAGs: spirals





PC


E, PC, alpha=0.15
sigma_0
sSFR
M*
Sigma_e
W_2-W_3
M_bh
R_e


S0, PC, alpha=0.15
M_bh
sSFR
sigma_0
W_2-W_3
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Sigma_e
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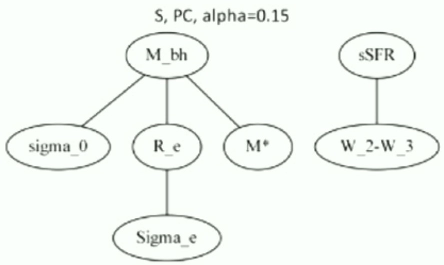
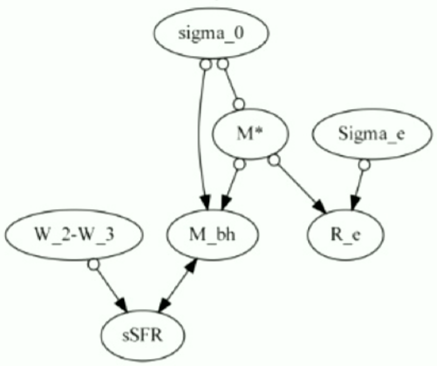
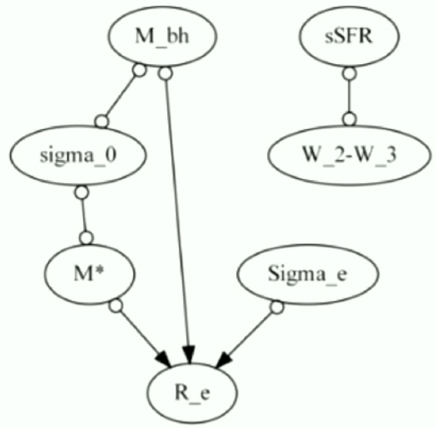

S, PC, alpha=0.15
M_bh
sSFR
sigma_0
R_e
M*
W_2-W_3
Sigma_e

FCI

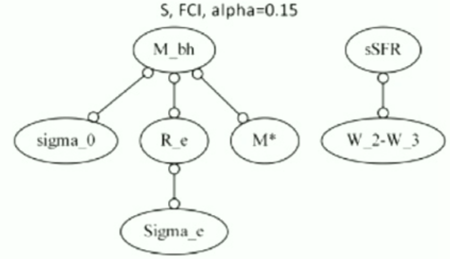
E, FCI, alpha=0.15



S0, FCI, alpha=0.15

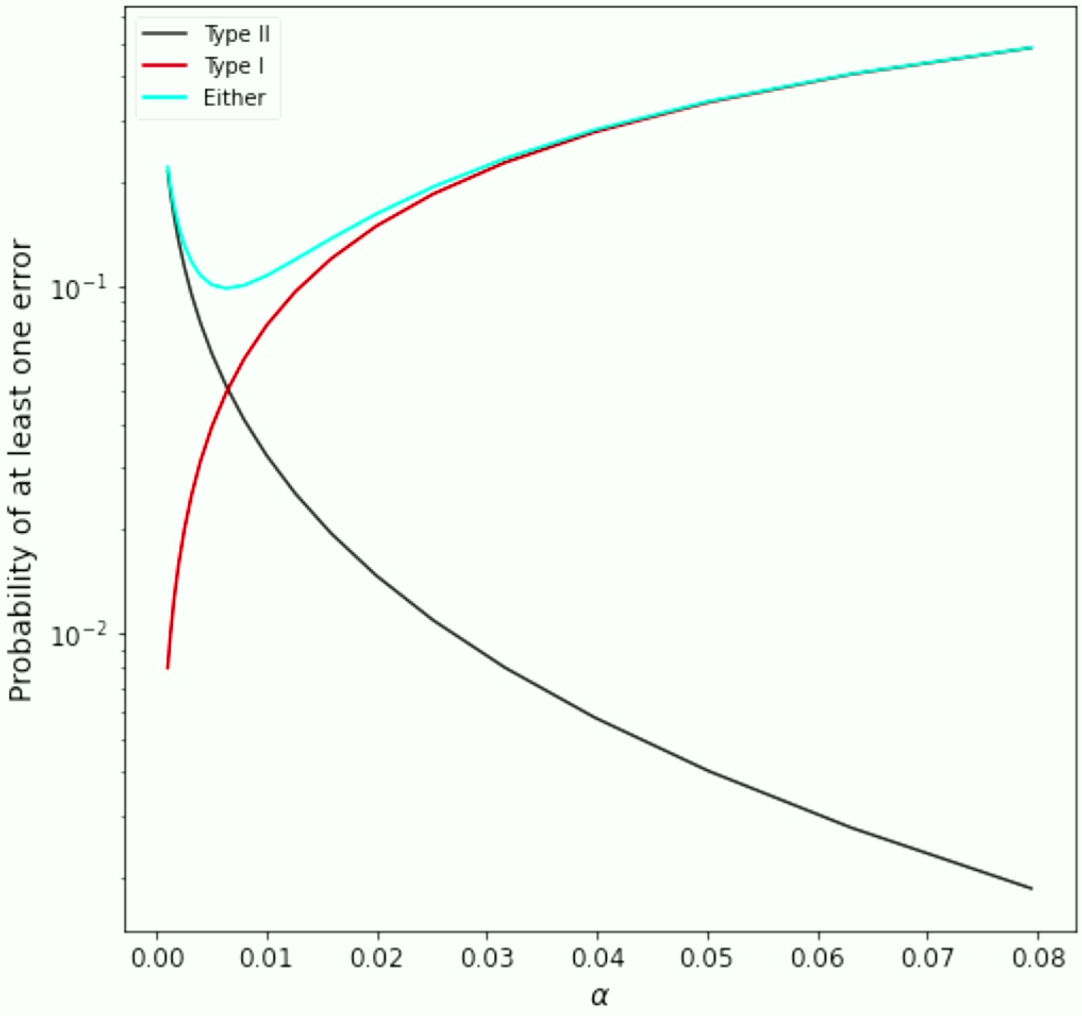


S, FCI, alpha=0.15



<-> confounded relation (unobserved shared cause)

o-> either confounded relation <-> or causal ->


Type II
Type I
Either
Probability of at least one error
10^{-1}
10^{-2}
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
α

M_{BH}-σ_0 relation

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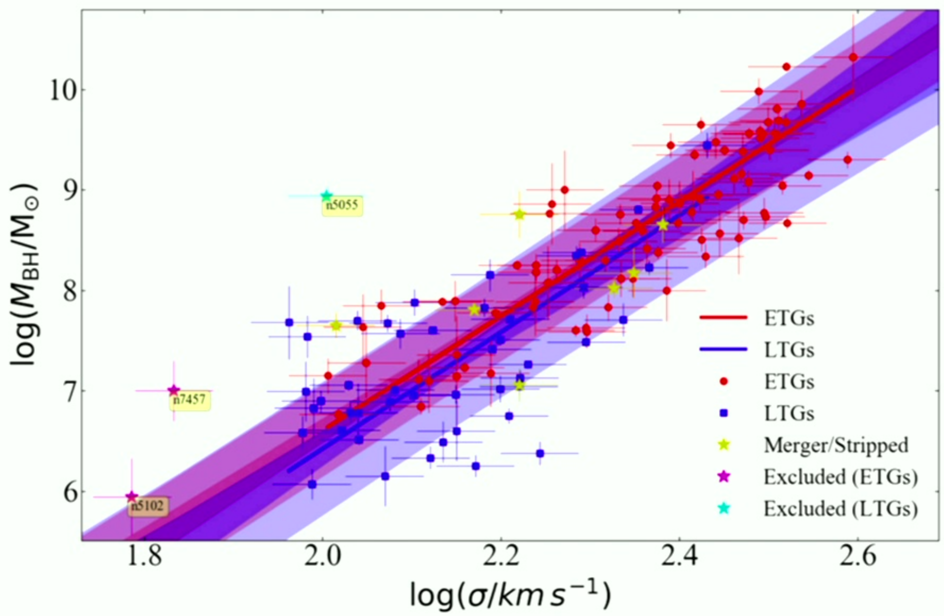

Sahu et al. 2019

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 σ_0 <- M_{BH} in spirals
- Ask me about the limitations, philosophical qualms, etc... I love that.