HOW WE ‘KNOW’: MAKING DISCOVERIES IN MODERN PHYSICS

Lecture 4 Models

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- Bayes theorem recap - prior misspecification

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- Dark Matter

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- Models and misspecification

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- Model selection

Bayes Theorem

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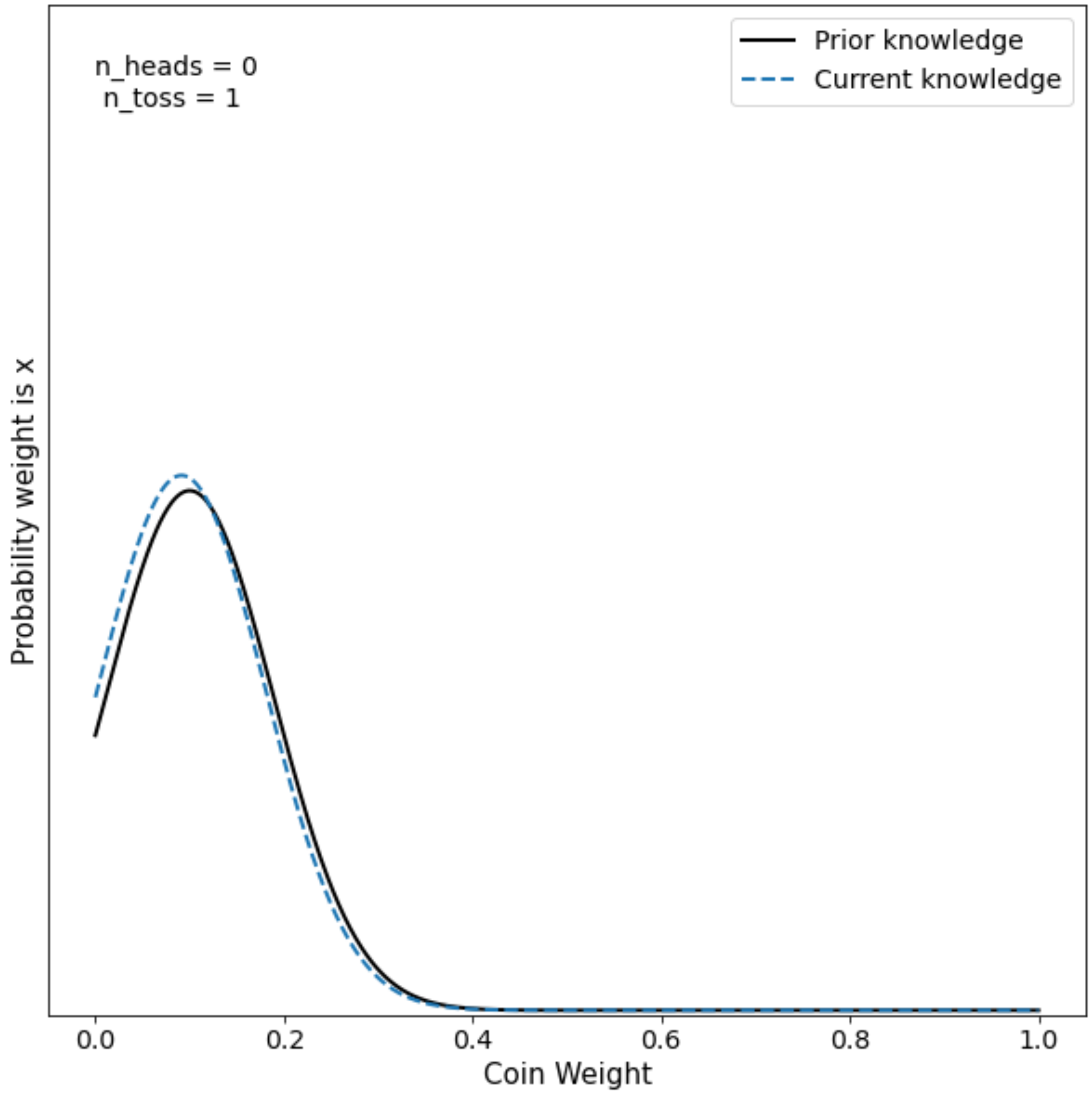
- How does this affect the outcome if our prior knowledge is wrong or heavily biased?

Weighted coin - what if our prior is wrong?



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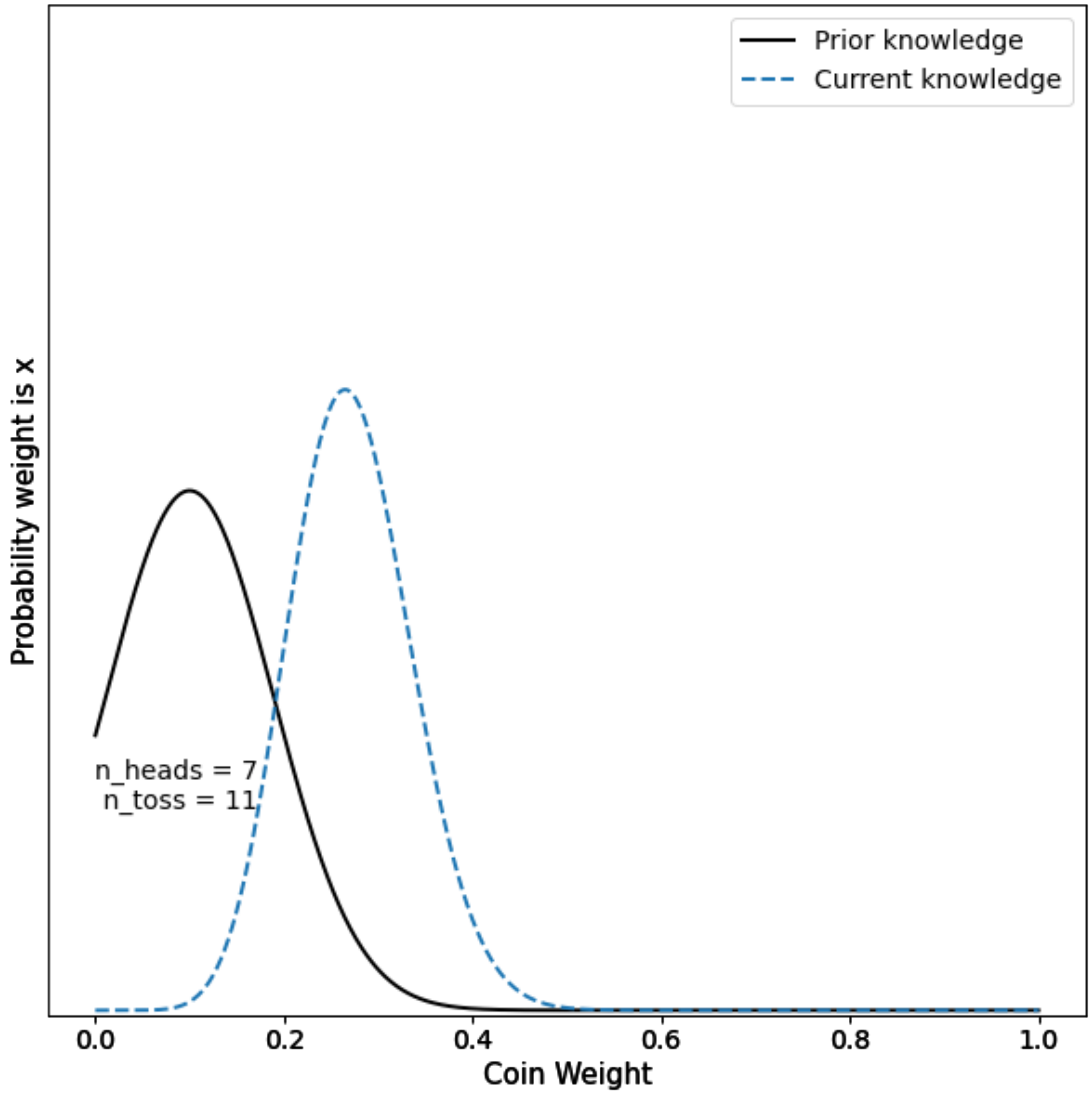

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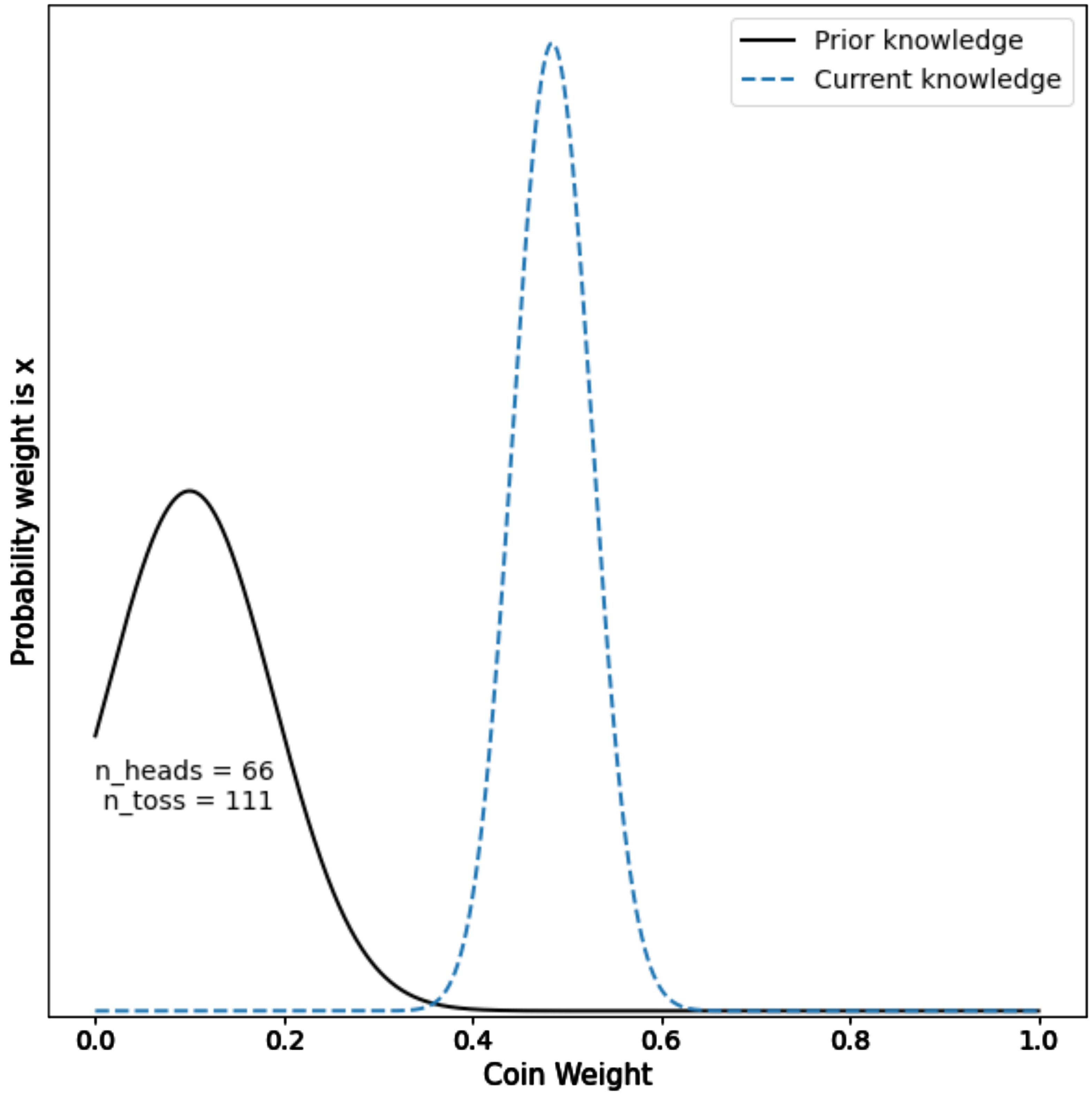

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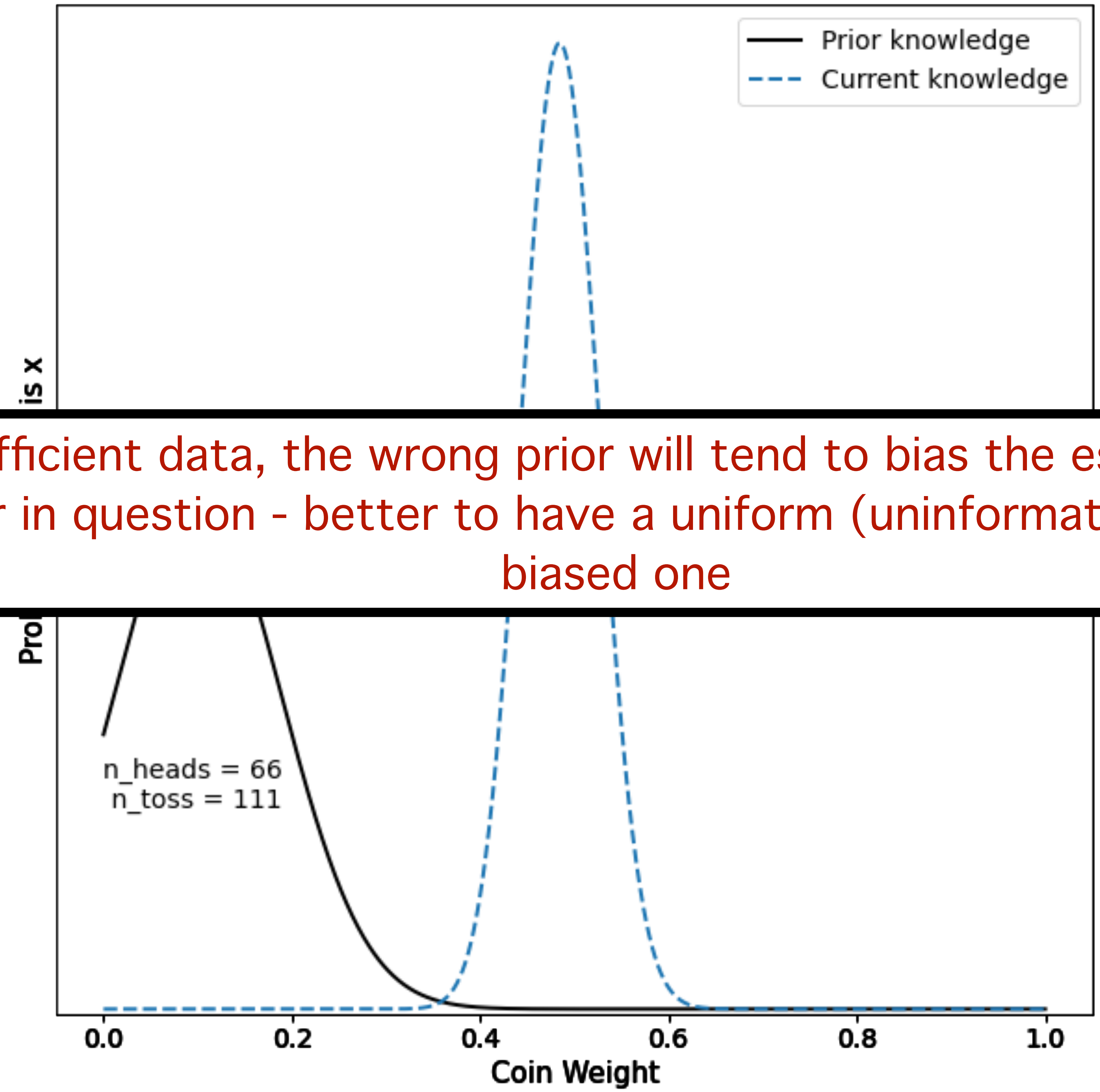

With sufficient data, the wrong prior will tend to bias the estimate of the parameter in question - better to have a uniform (uninformative) prior than a biased one

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What makes up a galaxy?

Visible matter: gas, dust and stars (plus stellar remnants)

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Rotational velocity - function of 'inertia' of the galaxy. Galaxy has most of its luminous mass in the center, and less mass at the edges.

Expect stars at the edge of the Galaxy to rotate more slowly

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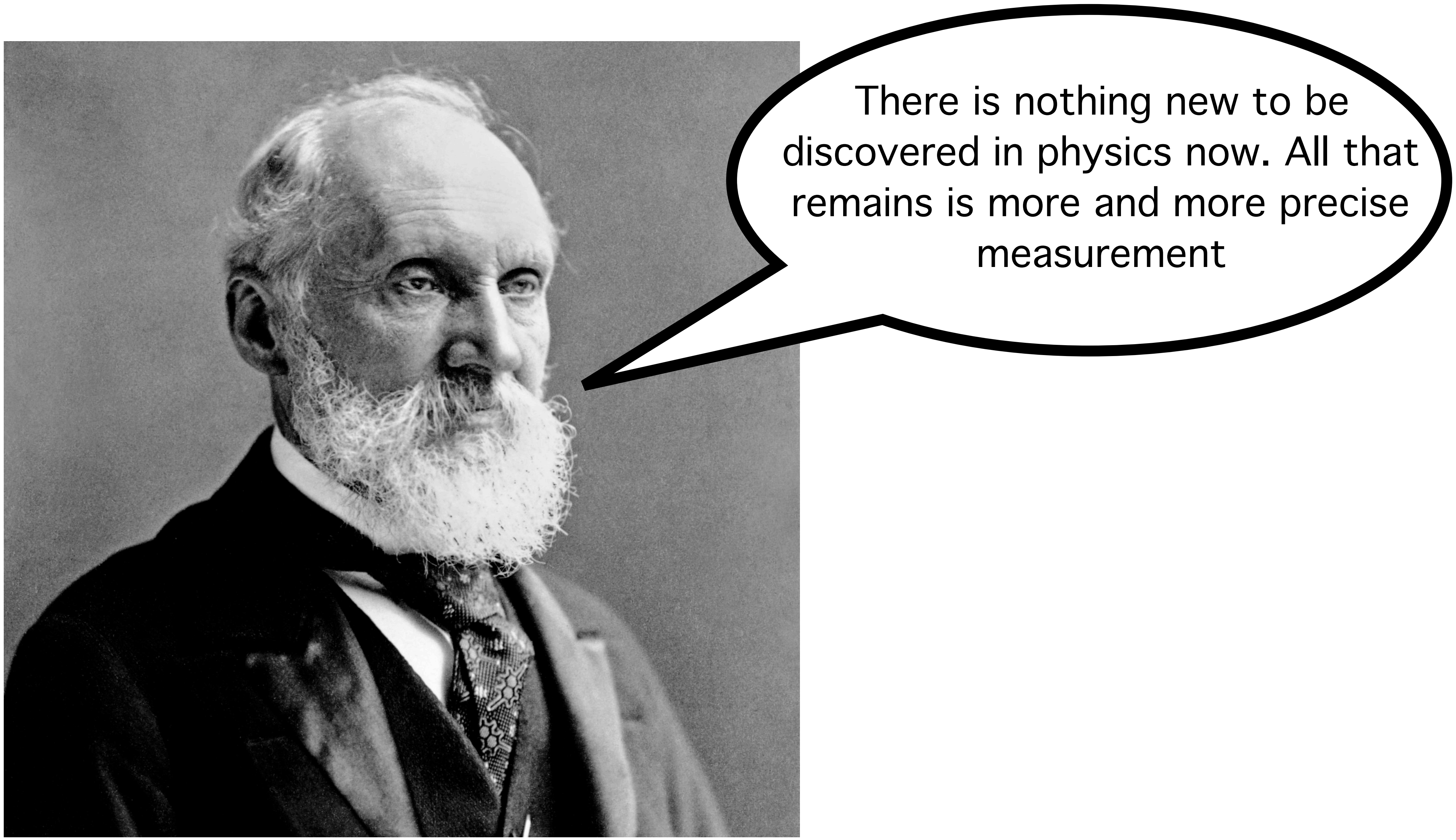

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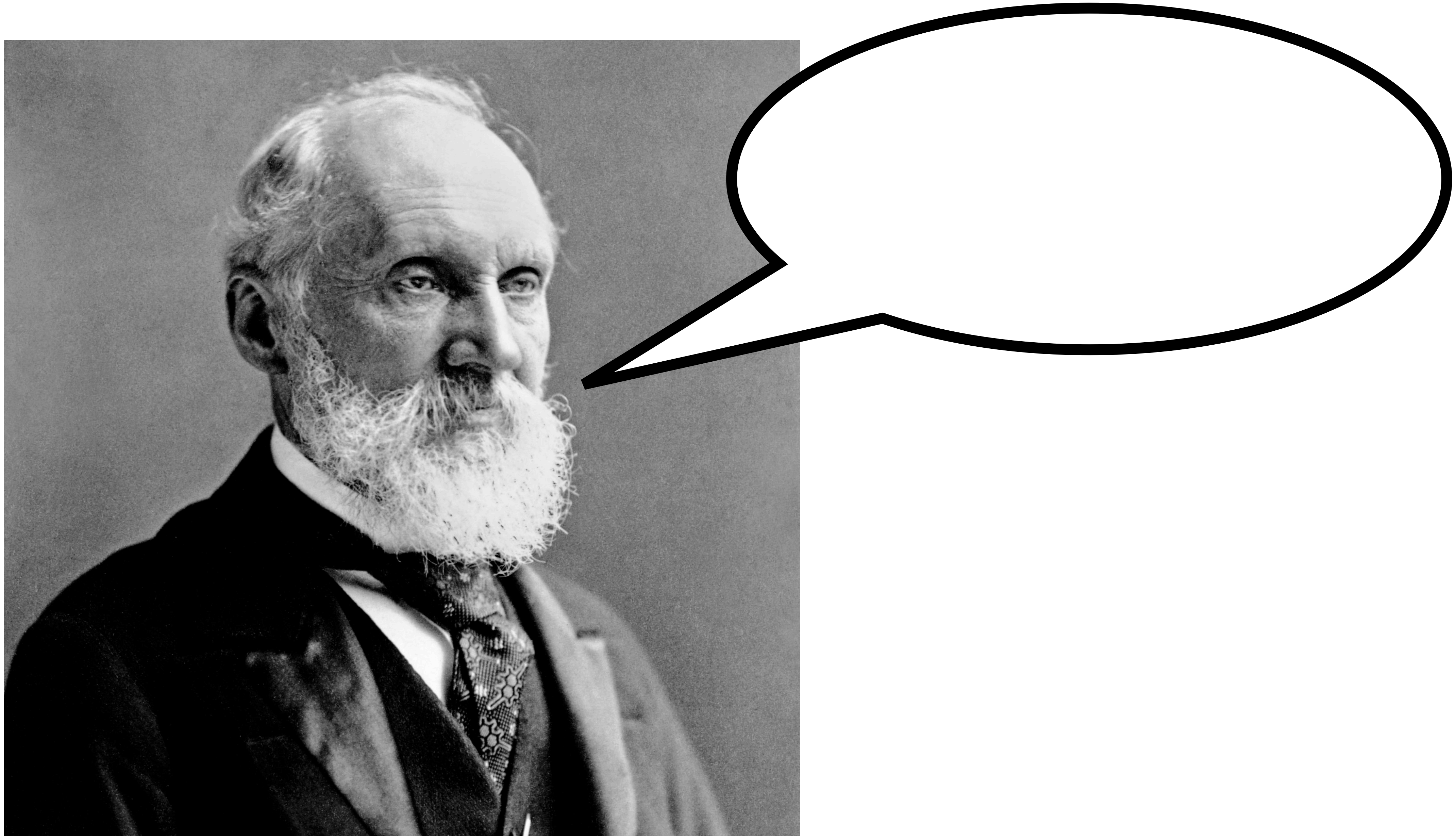

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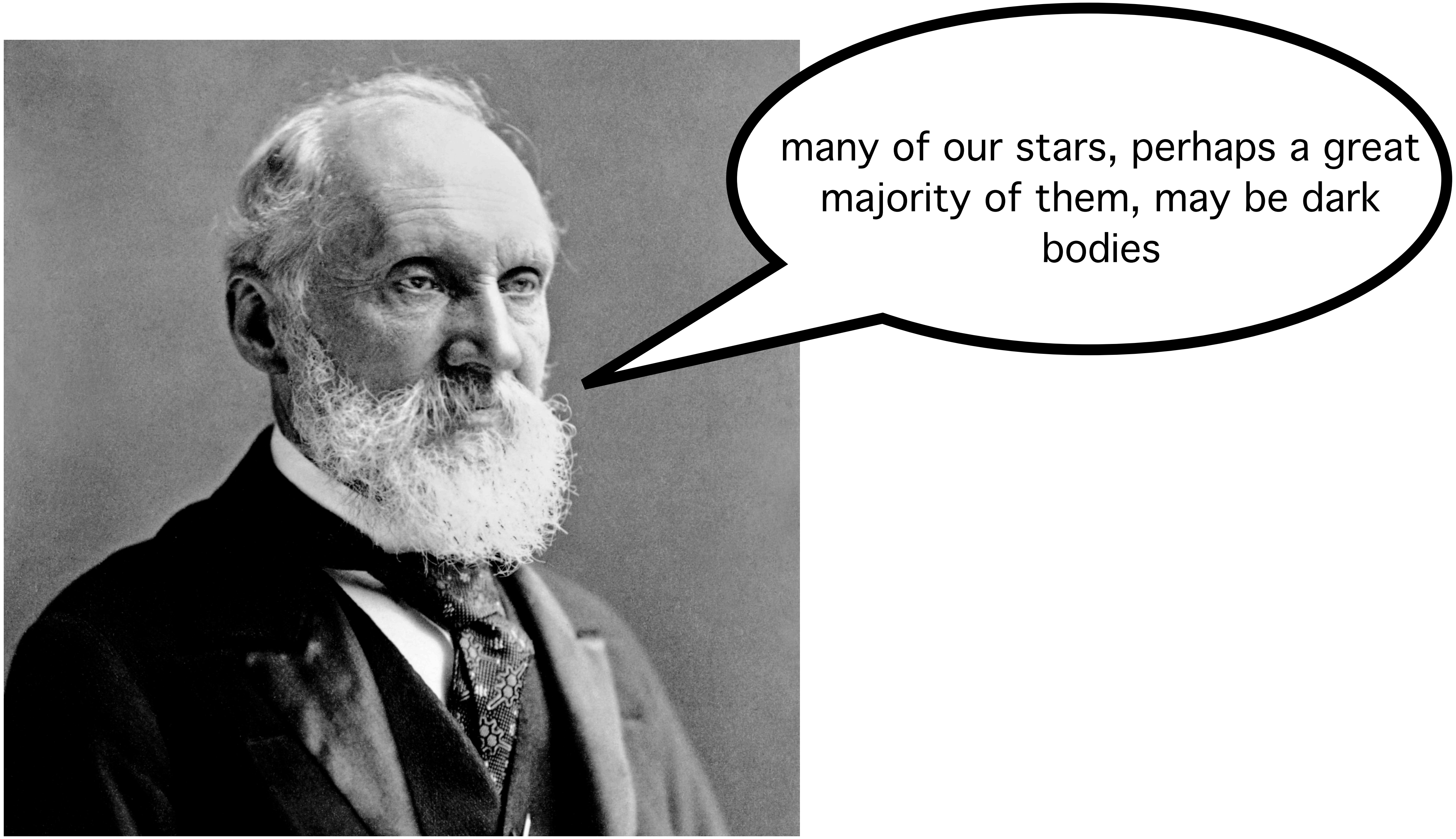

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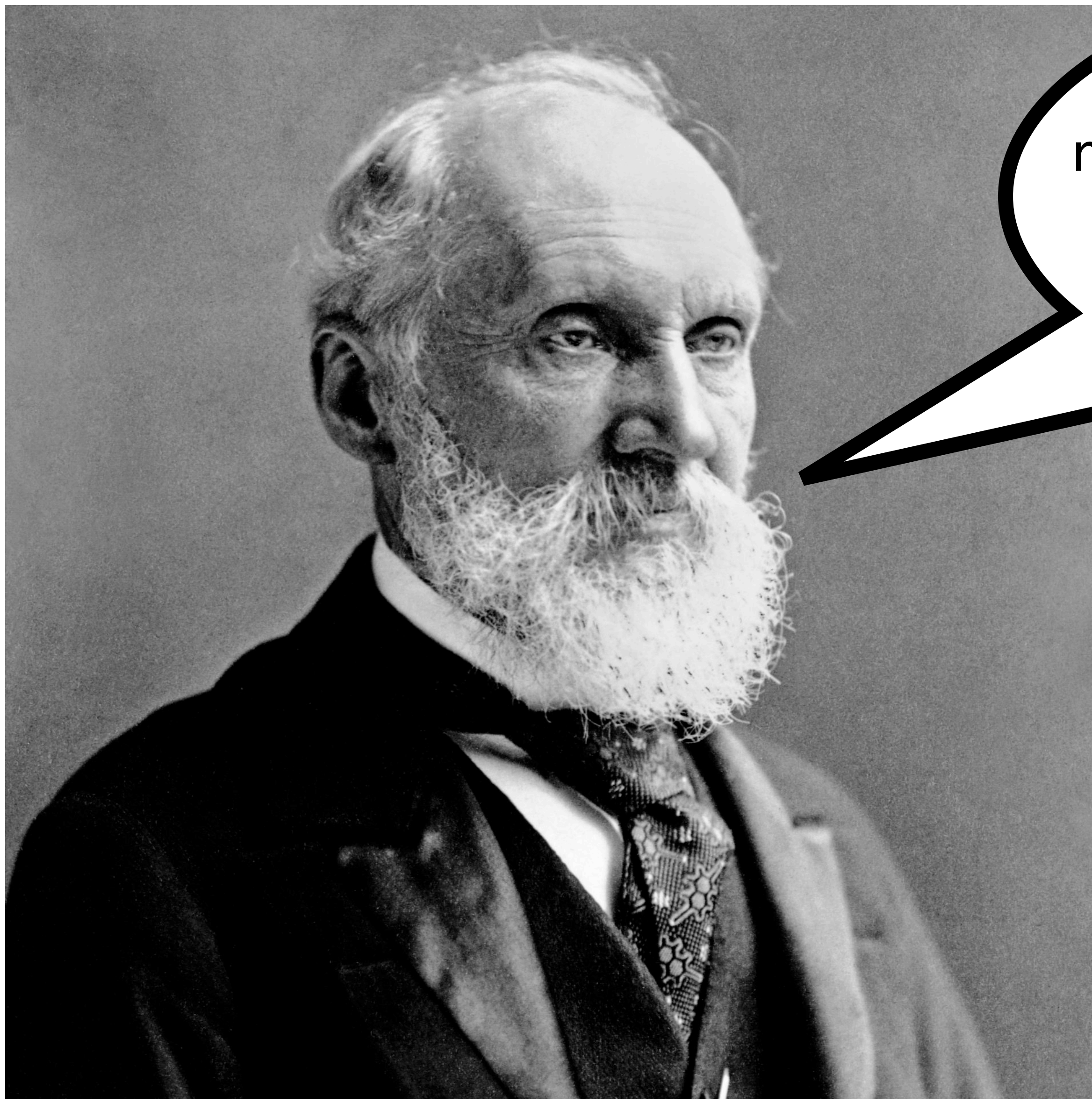


many of our stars, perhaps a great majority of them, may be dark bodies

Fritz Zwicky: motion of galaxies in the Coma cluster suggests there is additional ‘hidden’ or ‘invisible’ mass

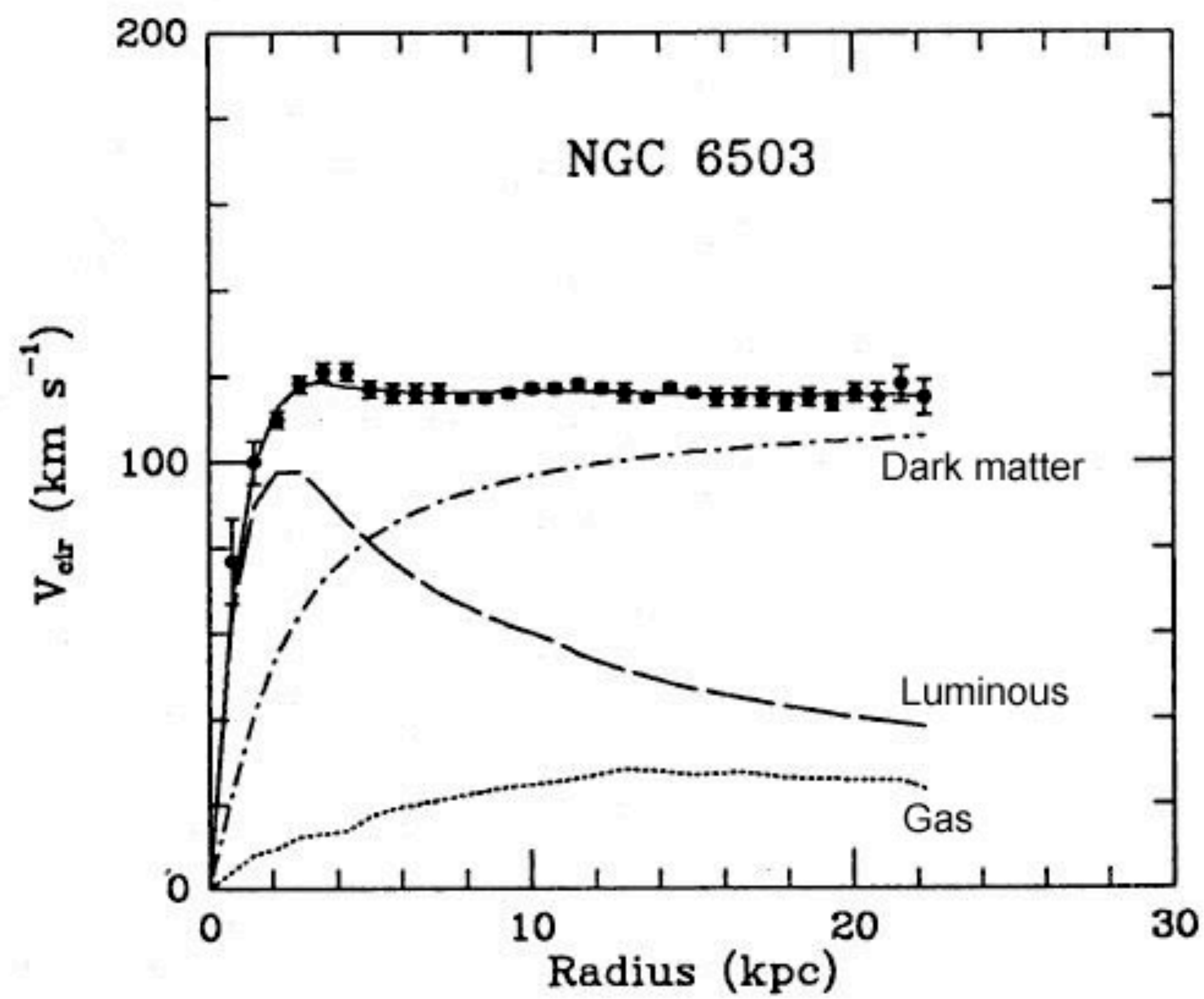
Dark Matter - Discovery

Vera Rubin, Kent Ford and Ken Freeman: Observed the velocity of stars orbiting the centre of spiral galaxies

Even when combining the velocity you expect to observe from gas + stars + dust, some mass is missing

Model is misspecified: easy to see comparing observations and our models

Missing mass = 'Dark Matter'



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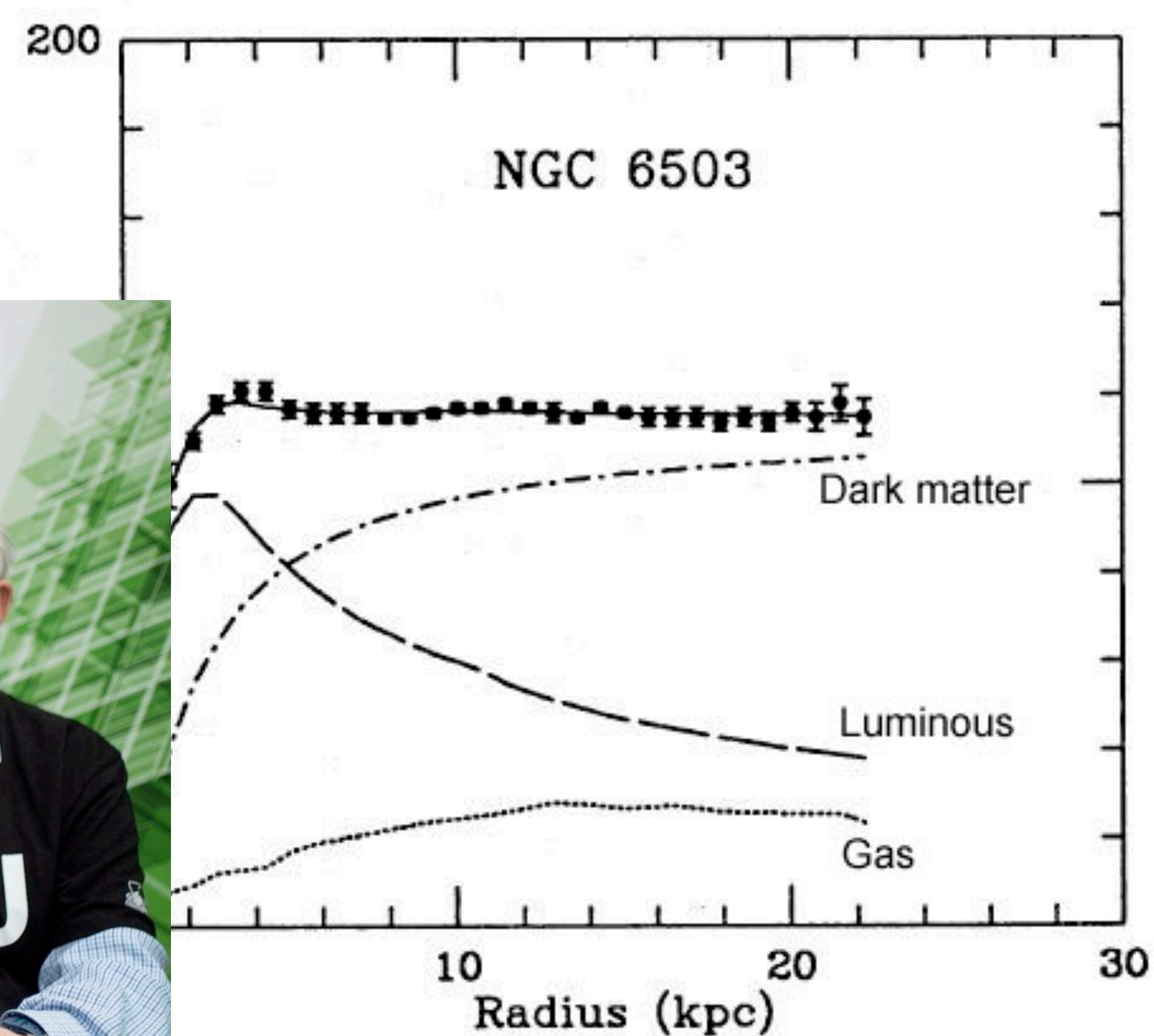

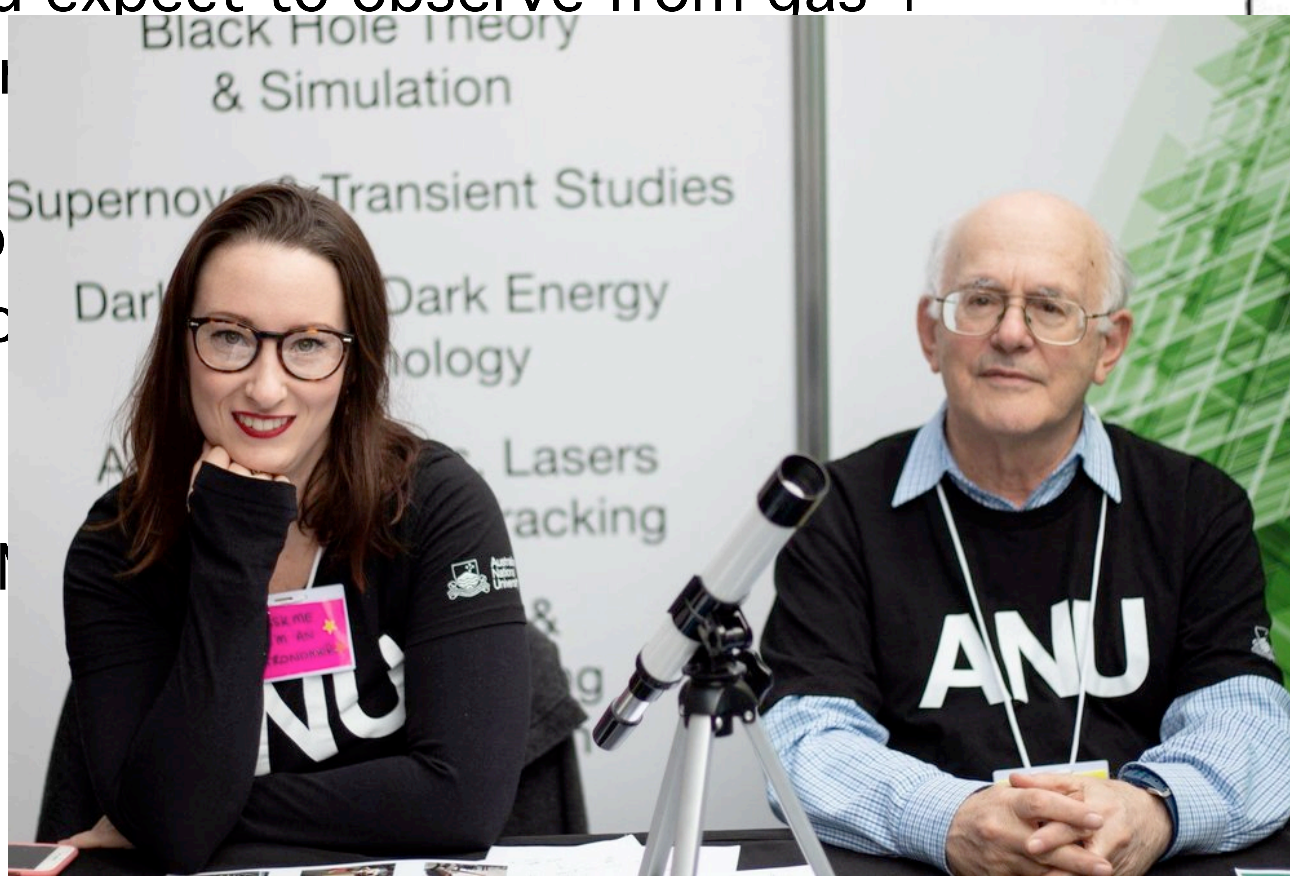

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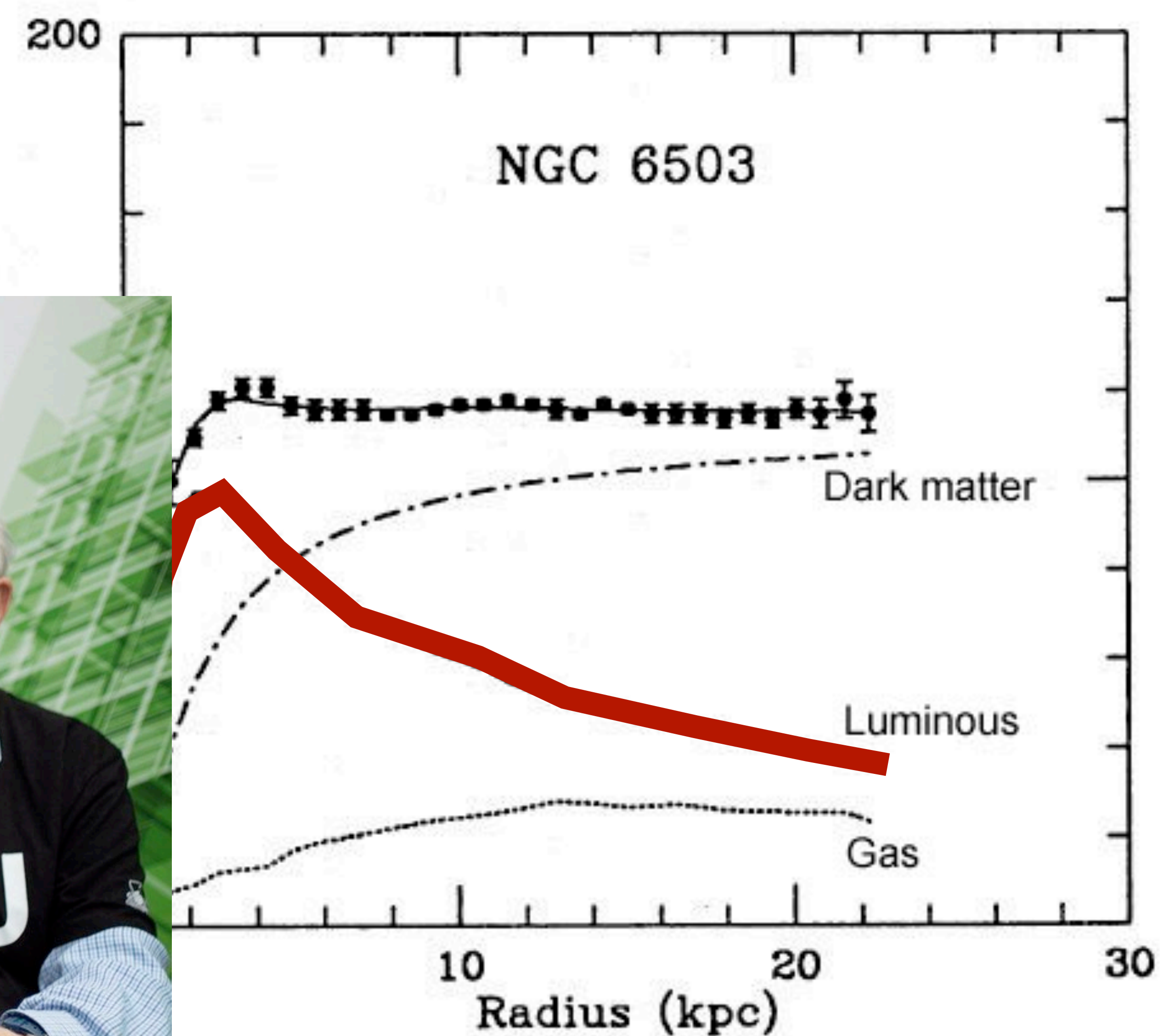

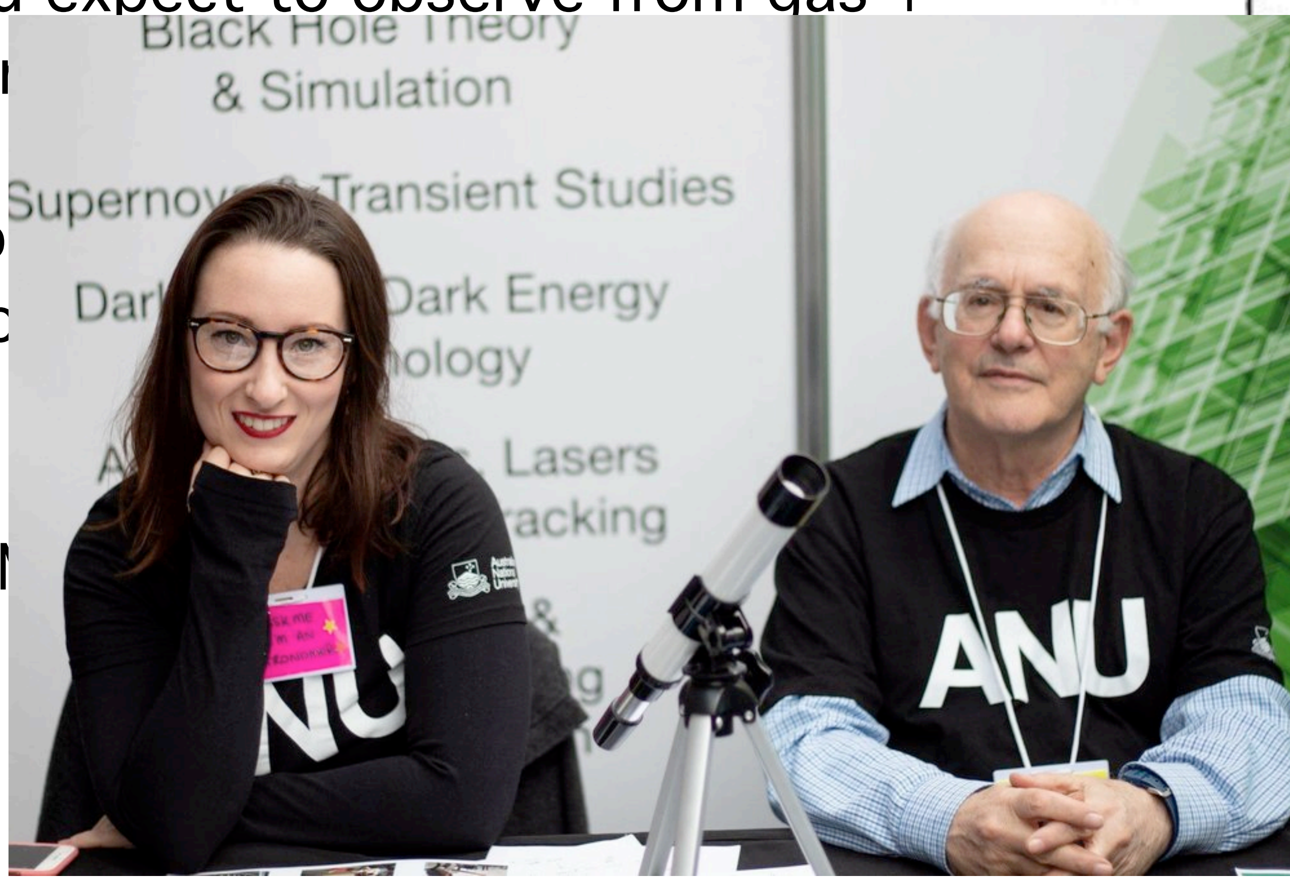

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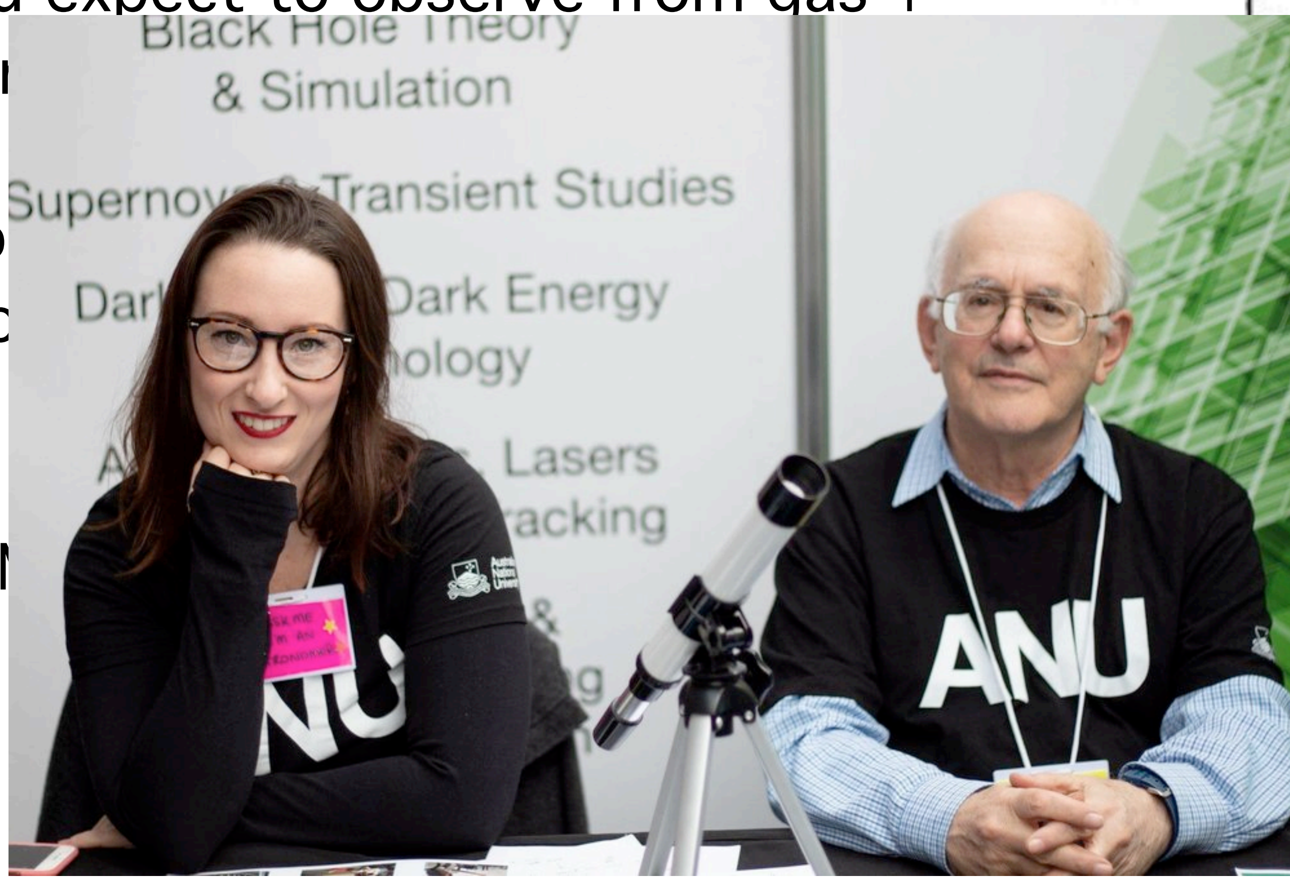
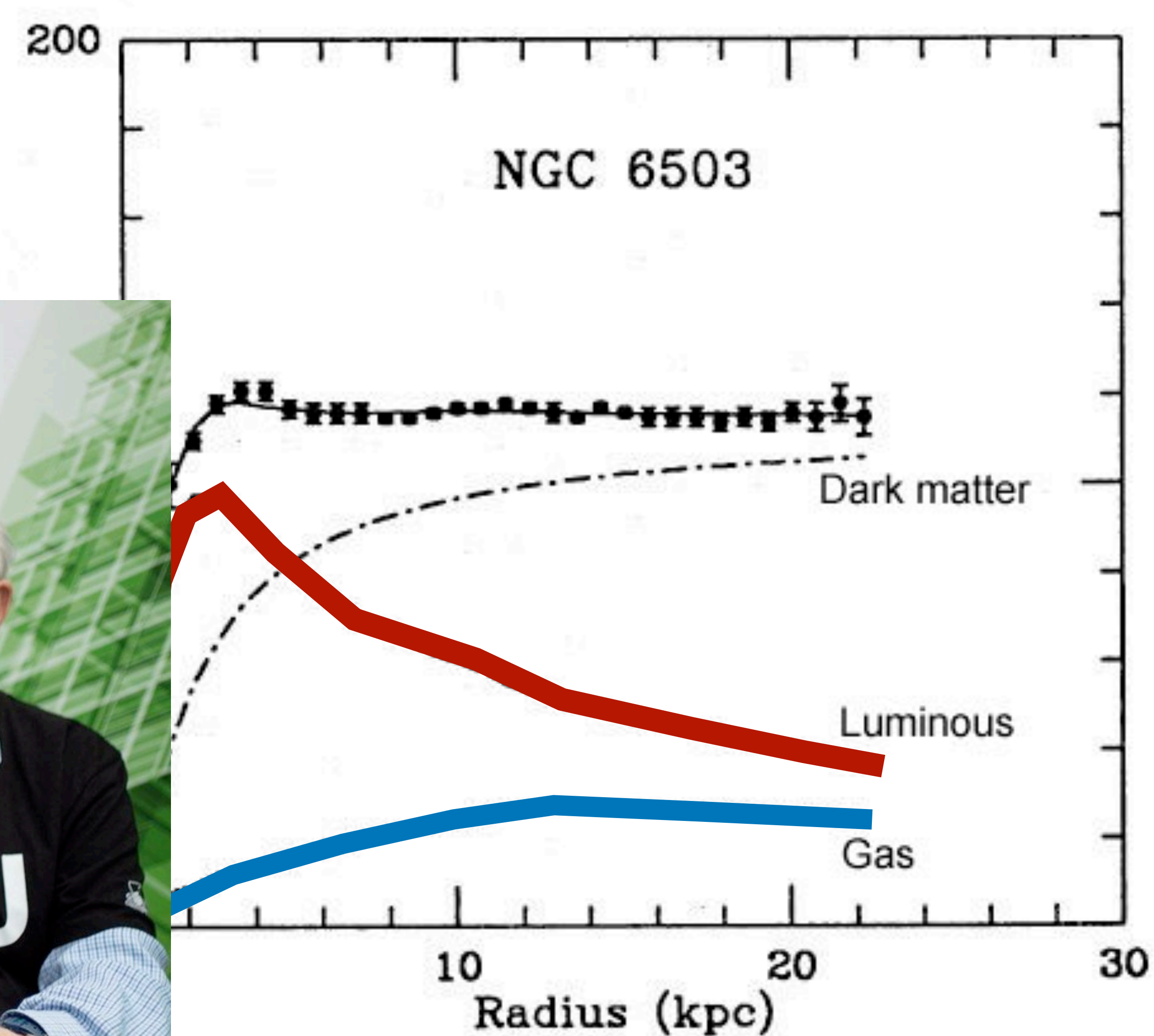
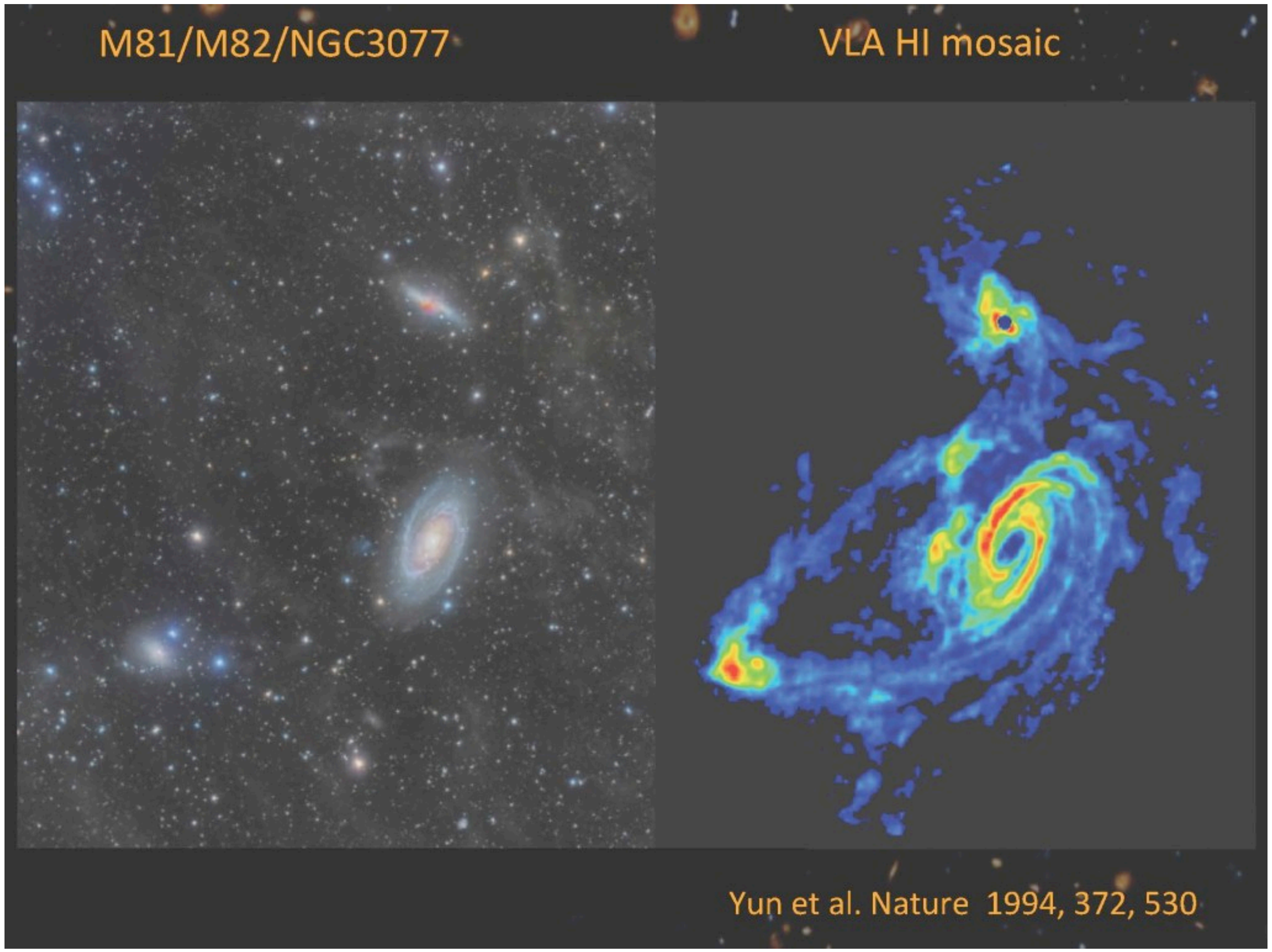


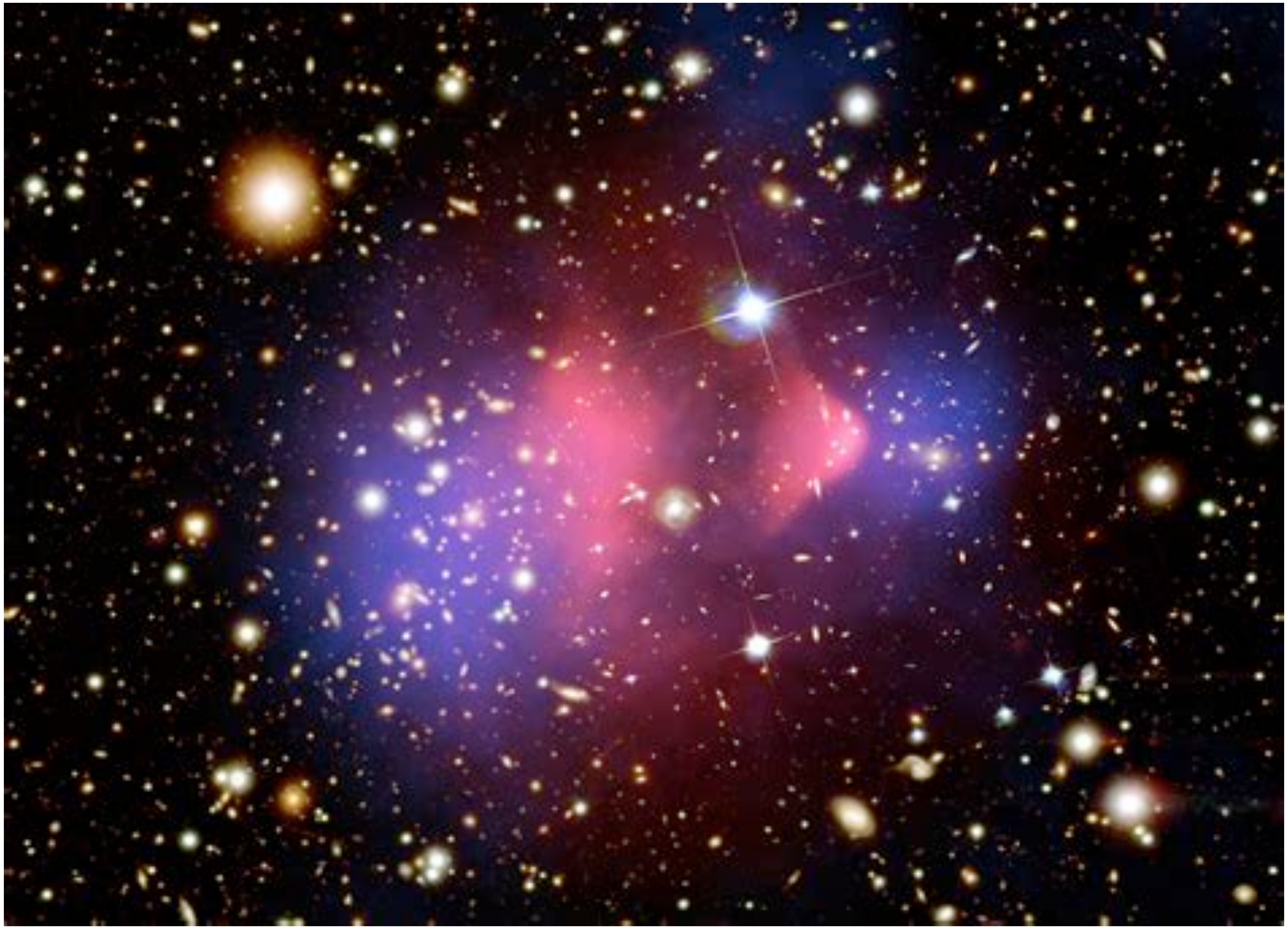


Missing Physics



- Previous explanations for the discrepancy had suggested that the ‘missing’ dark matter could be unseen gas (e.g. neutral hydrogen) that does not glow with visible light
- disfavoured when radio observations reveal distribution of neutral hydrogen in galaxies
- Some sort of object or substance that interacts only via gravitational force

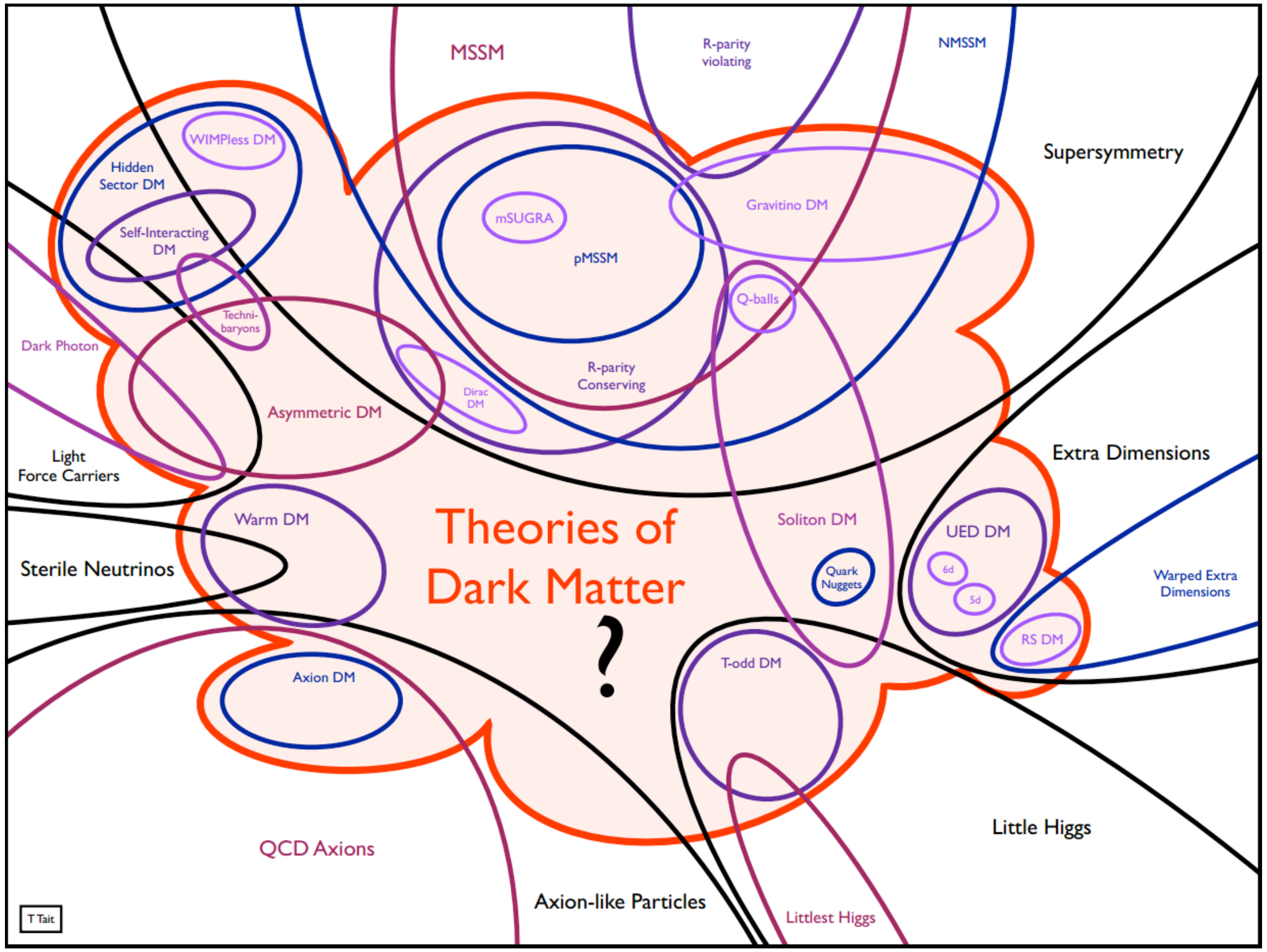
Bullet Cluster



Pink: gas Blue: calculated model of where the mass (Dark Matter + visible) is

Dark Matter models

- There are now hundreds, if not thousands, of models that propose to explain what dark matter is made of
- Famous: MACHOs vs. WIMPS
- Tiny black holes from the beginning of the universe?
- Mysterious particles?
- Build a model, see if it ‘fits’ well with all the observations, and use the observations to ‘fine tune’ your model



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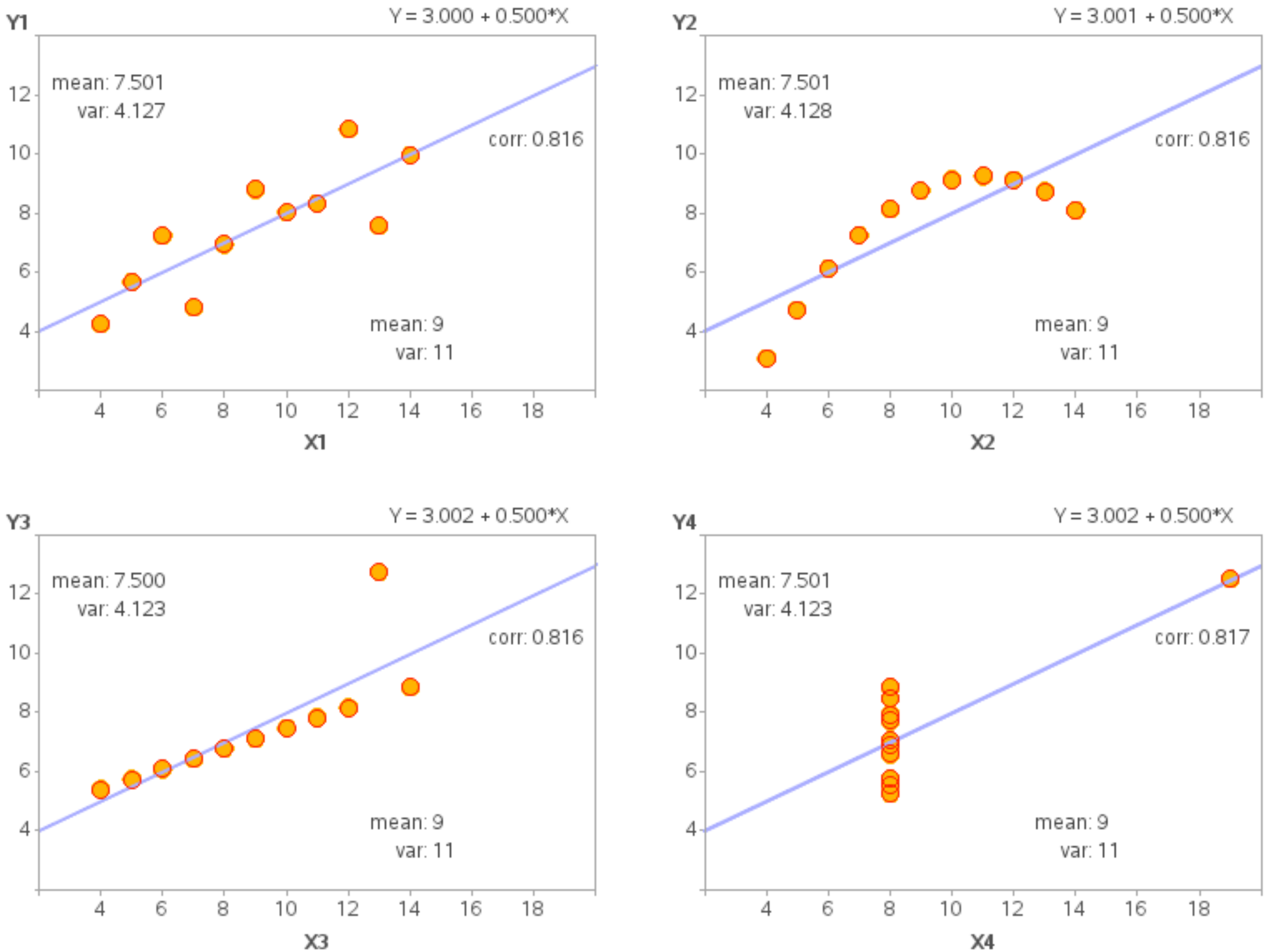
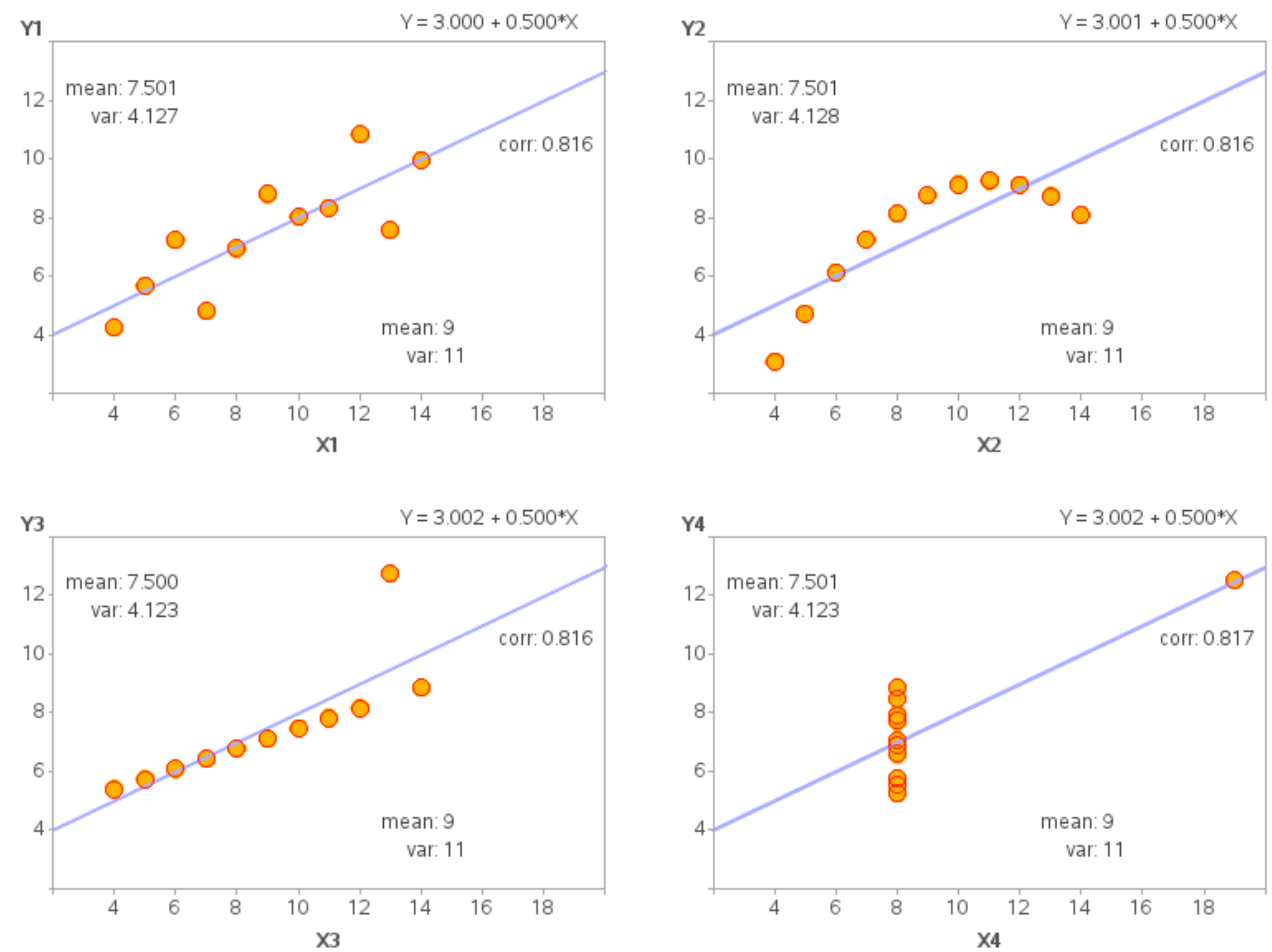
Data vs. Model - Anscombe's Quartet



Data vs. Model - Anscombe's Quartet

- All data has the same mean and variance
- All fitted with the same model (a straight line)
- All have the same correlation coefficient
- How do we decide if the line is a good representation of the data?

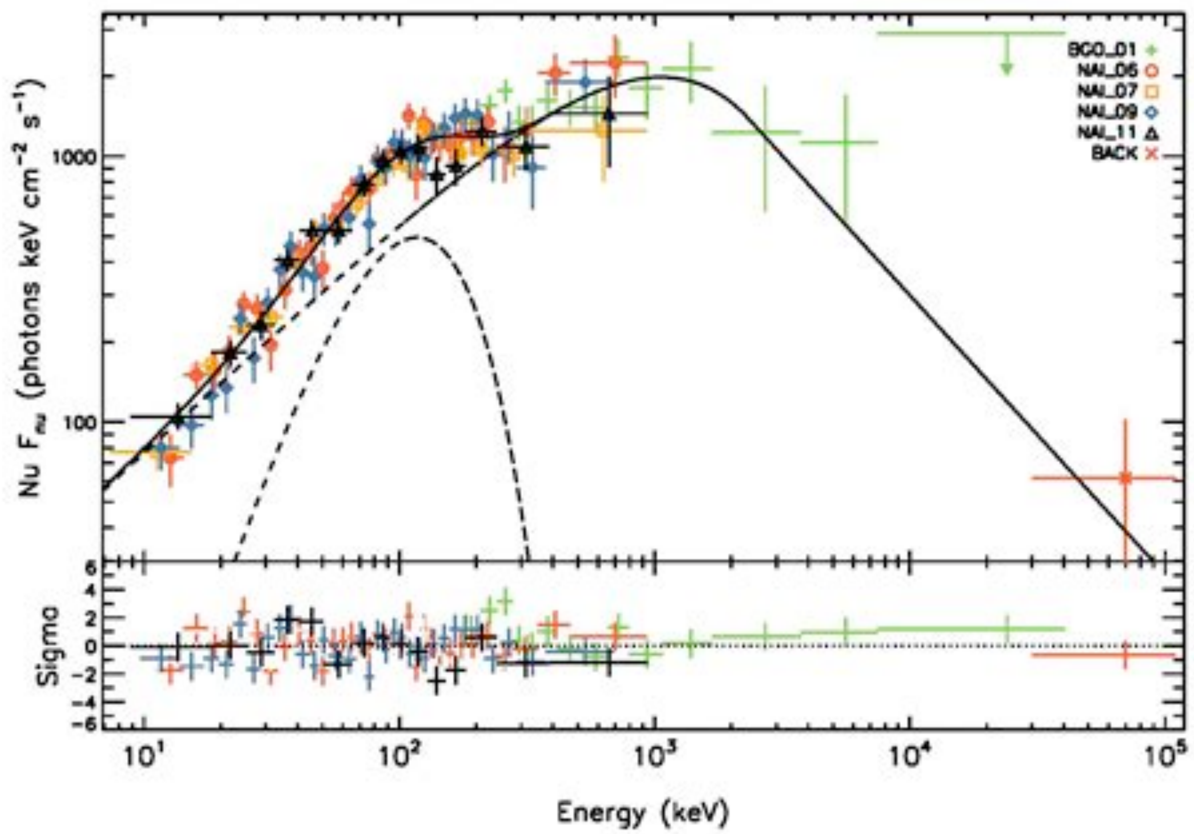


Physical or Empirical

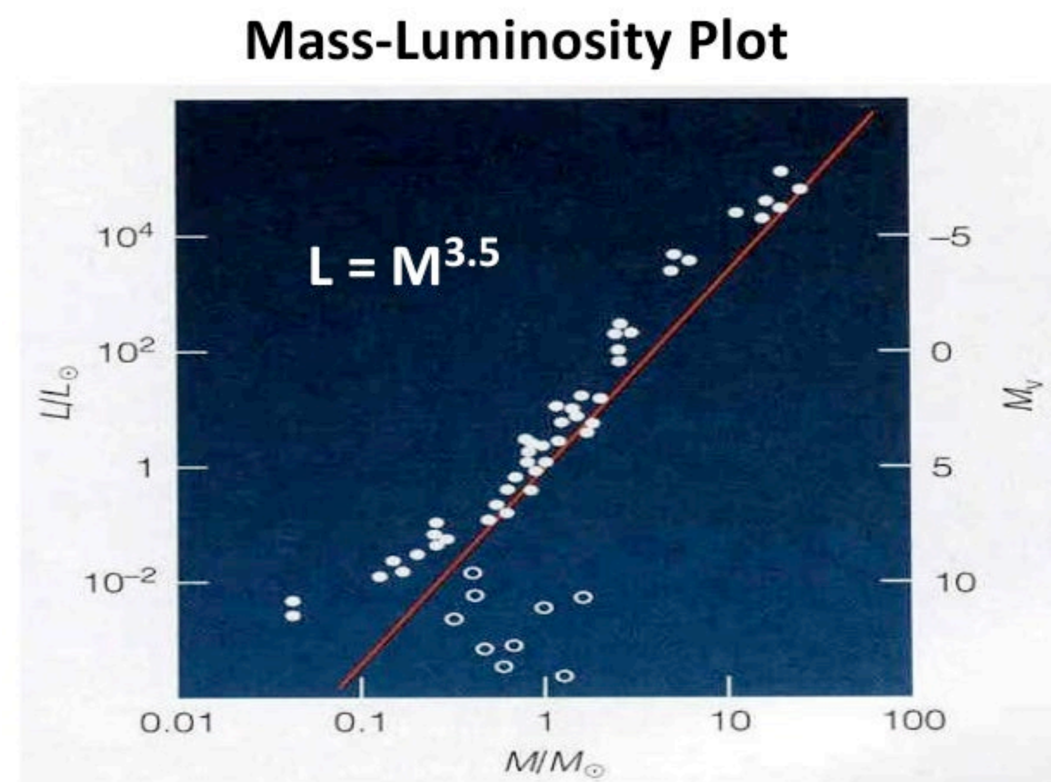
- To estimate a parameter that tells us something about the universe (e.g. from last time, the mass of each black hole in a black hole binary) we need a model that we can fit to our data
- When the parameter is 'just right', it will reproduce our observed data well
- Physical models: parameters estimated are directly linked to a physical quantity
- Empirical: parameters estimated are assumed to be a proxy for a physical quantity

Physical or Empirical

Sometimes an empirical or simplified model is preferable when our physical understanding is not very good, or the process we are modelling is exceptionally complex



Bad empirical model: We know the physics of what is happening, and empirical formula does not accurately explain physics/get wrong answer



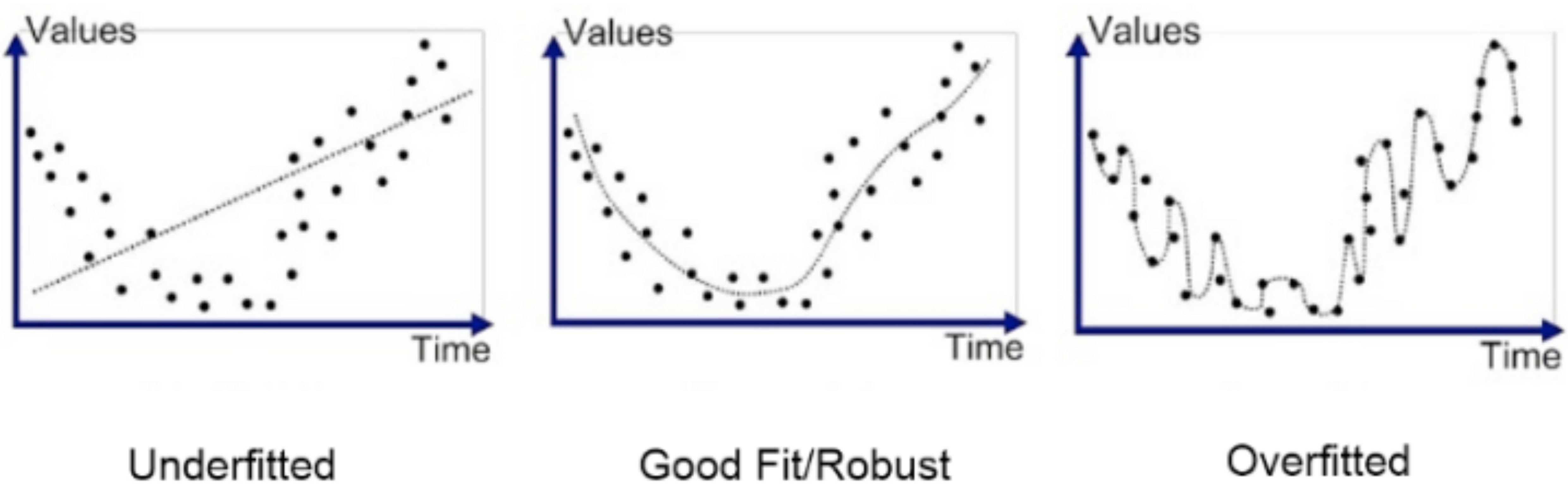
Less bad model: lots of complicated things happening, and we can't account for them, but still tells us something physically useful/get right answer

Physical or Empirical

All models are wrong, but some models are useful - Cox

Goodness of Fit

When we have a model, we usually want to know how well it represents our data (remember Anscombe's quartet!)



Goodness of fit alone CANNOT tell us which model we prefer (regardless of what may be taught) - possible to overfit when optimising goodness of fit

Model Selection - return to Occam's Razor

General problem: we have two models to represent a phenomenon. Which is the best representation?

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$$y = ax + b$$

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Frequentist

- For each model, determine the best fitting parameters (or region of parameter space)
- Calculate the goodness of fit (e.g. maximum likelihood methods, chi-square)
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- Calculate the ratio

$$\frac{\text{P(observe this data given model 1)}}{\text{P(observe this data given model 2)}}$$

Requires computing the posterior (see last lecture), and having a prior expectation the model is true

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Occam's Razor free with this product!

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- Dark matter detection in lab: design experiment to find one particular type of Dark Matter
- Either DM exists or doesn't - frequentist question!
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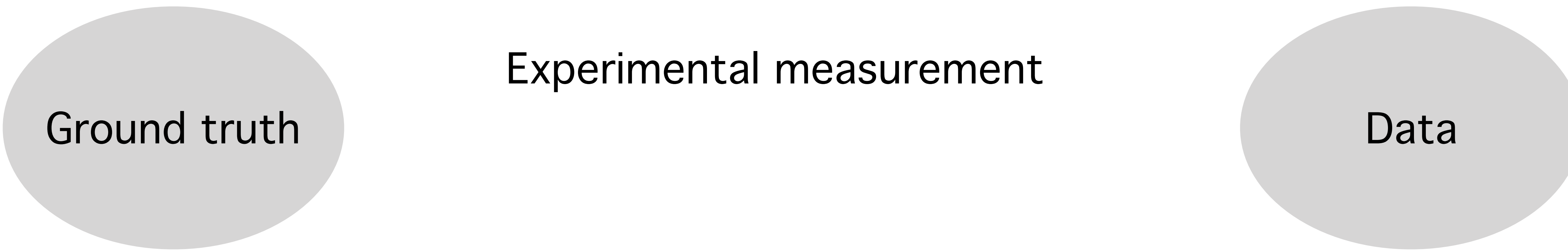

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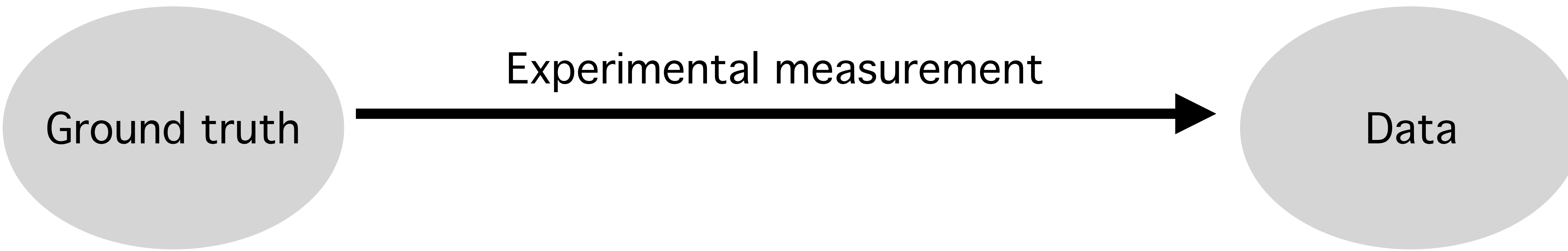

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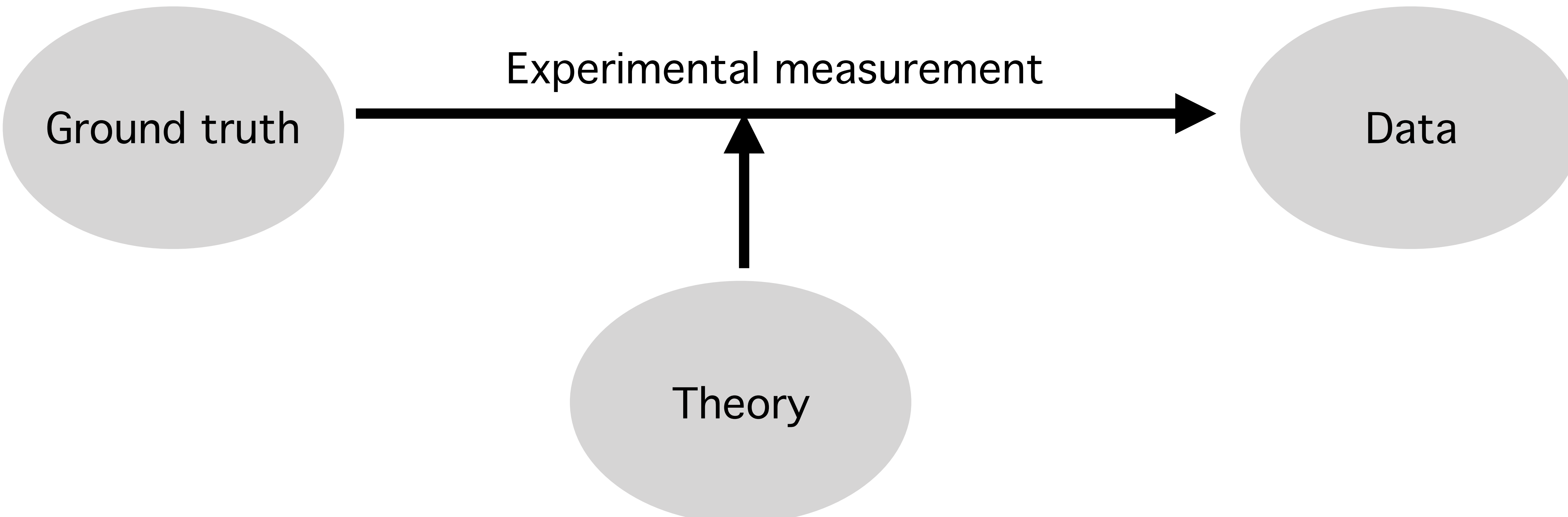

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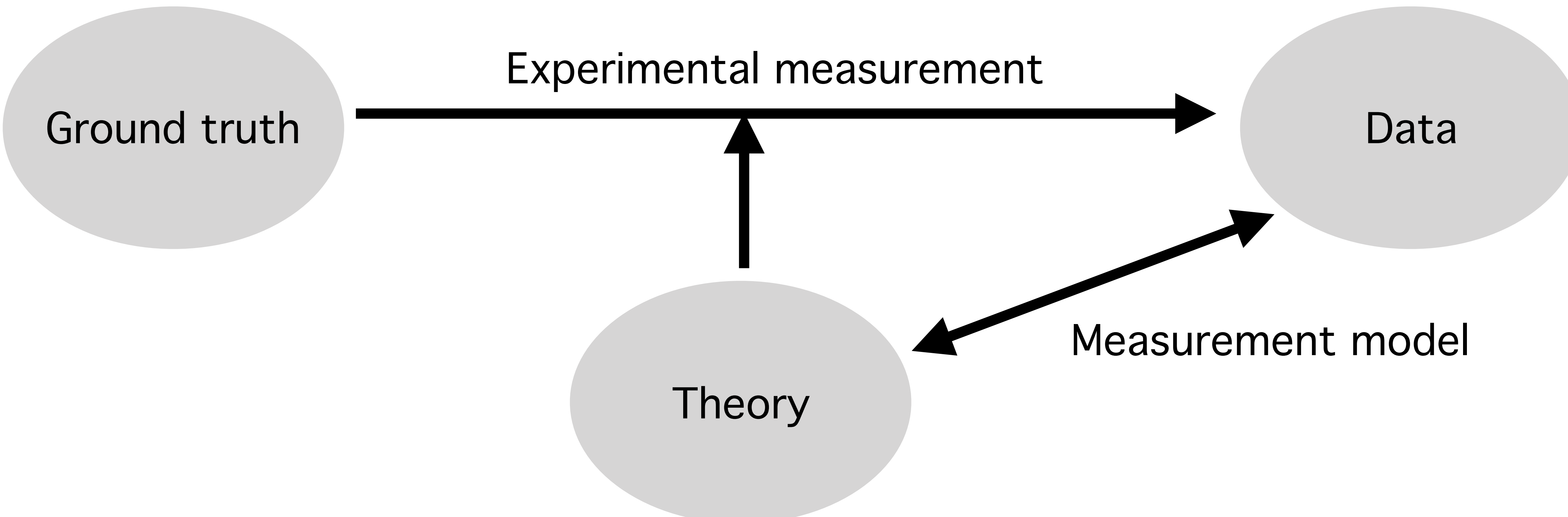

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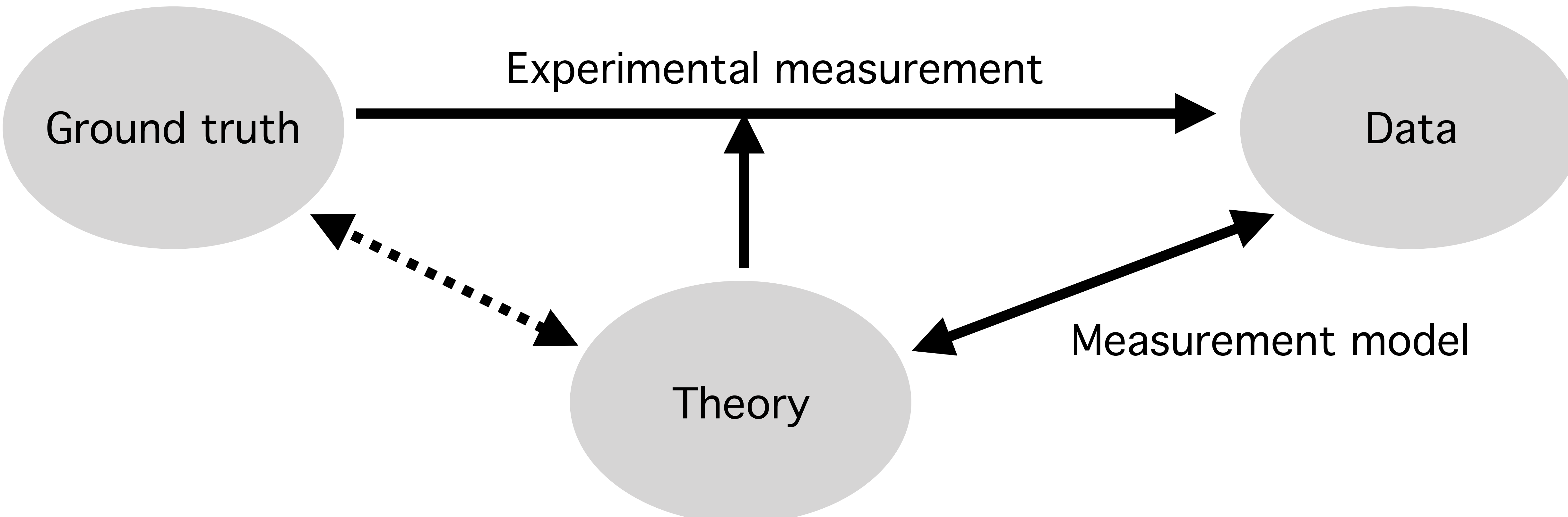

Cautionary tales and a view of the future

There are lots of egregious examples of model misspecification in science, but subtle model misspecification is hard to find.

Trouble with Bayes theorem and frequentist methods: no inbuilt way to prevent model misspecification, both depend on domain expertise

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- Next time - more real examples of the challenges and triumphs
- How will we ‘know’ in the future - what is machine learning and can we trust it