



A Bayesian model selection framework to probe the structure of Langmuir-Blodgett monolayers from neutron reflectometry

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🐦 [an_drewmcc](#)

♂ (he/him)

let's break that title down

A Bayesian model selection framework to probe the structure
of Langmuir-Blodgett monolayers from neutron reflectometry

Langmuir-Blodgett monolayers

Langmuir/Blodgett



Irving Langmuir



Katharine Blodgett

amphiphiles

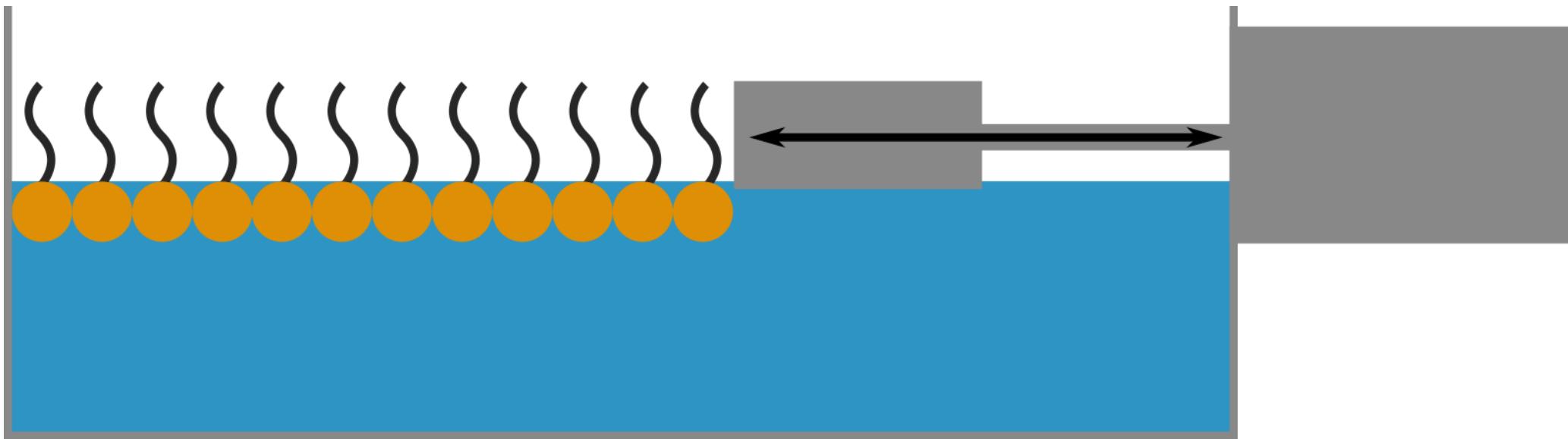


important biologically and technologically

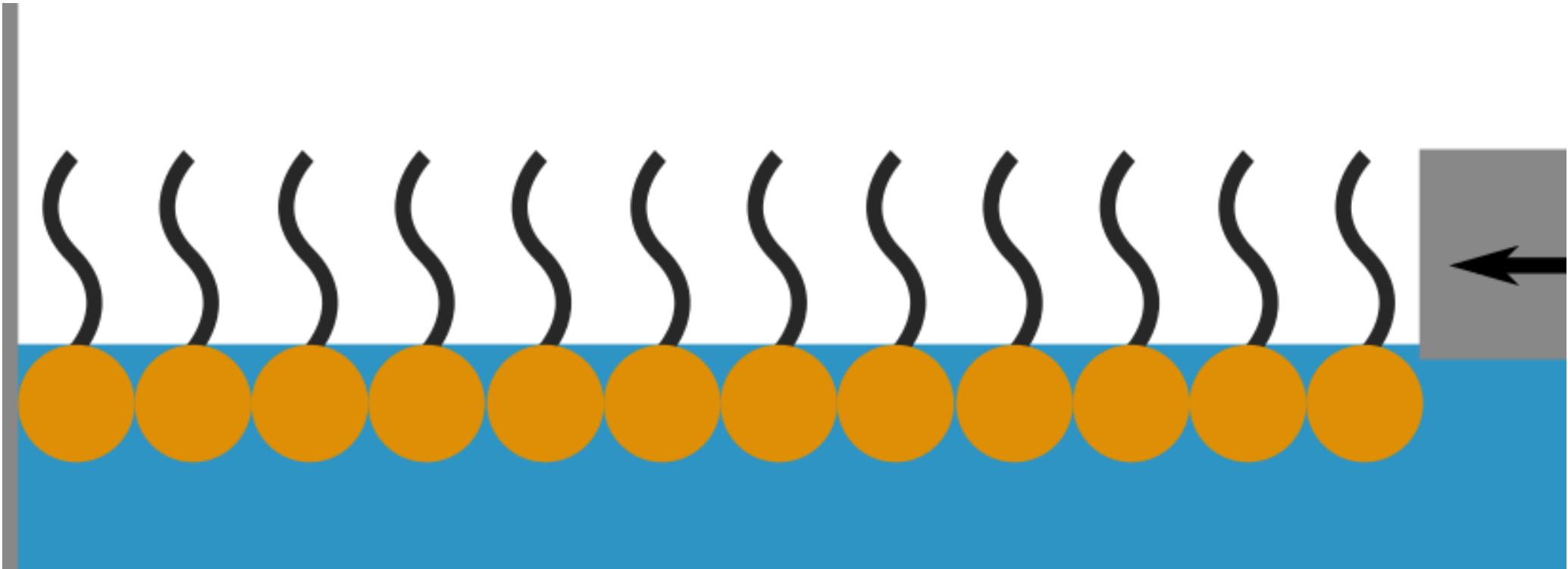
- lipids: make up cell membranes
- surfactants: present in many consumer products

Liley, *et al.*, Langmuir, **33**, 4301 (2017);
Fisher, *et al.*, in *Neutron Scattering - Applications in Biology, Chemistry, and Materials Science* (Academic Press, 2017) pp. 1-75

self-assemble



structure is important

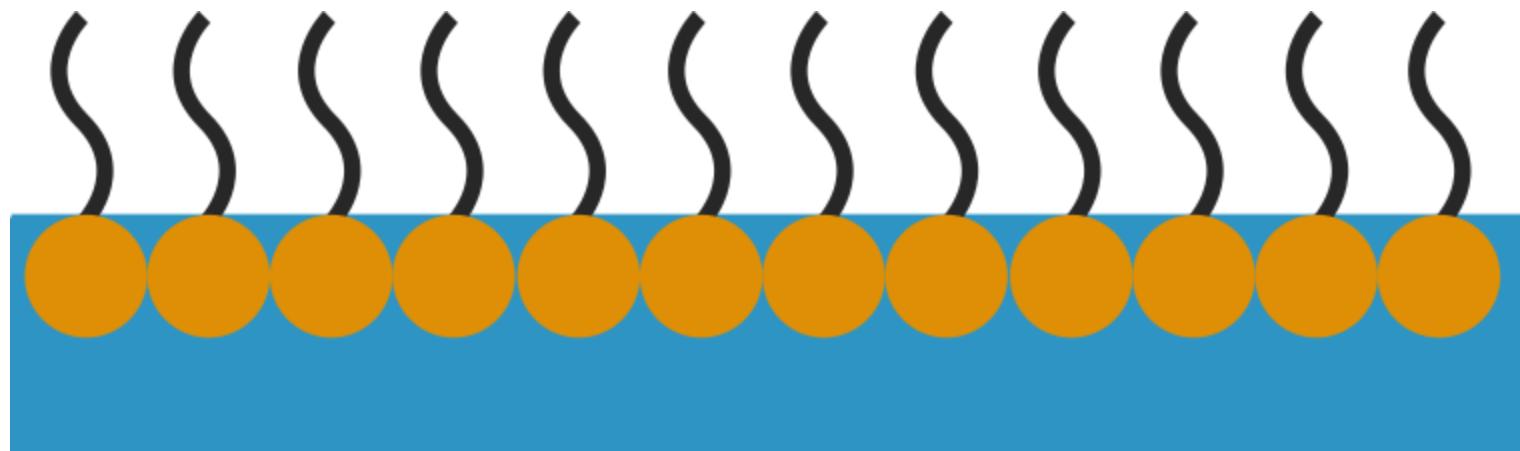


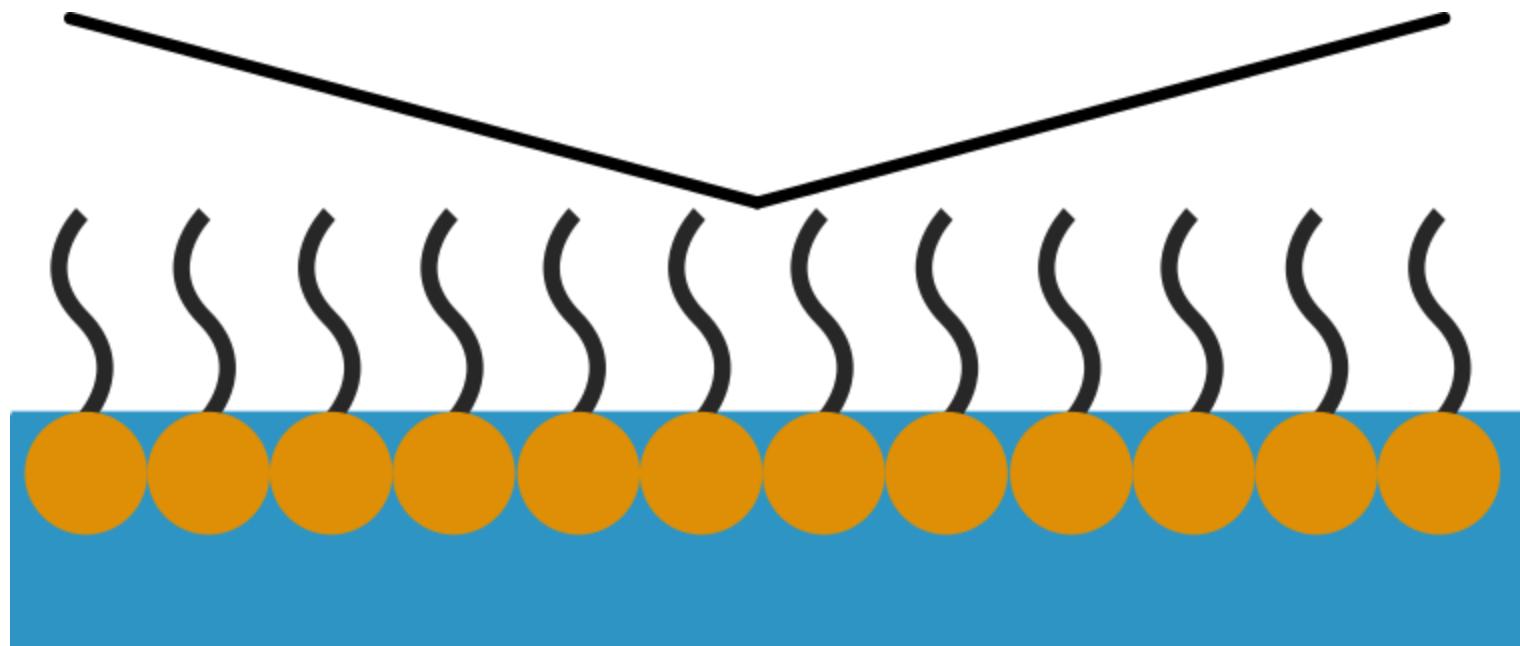
neutron reflectometry

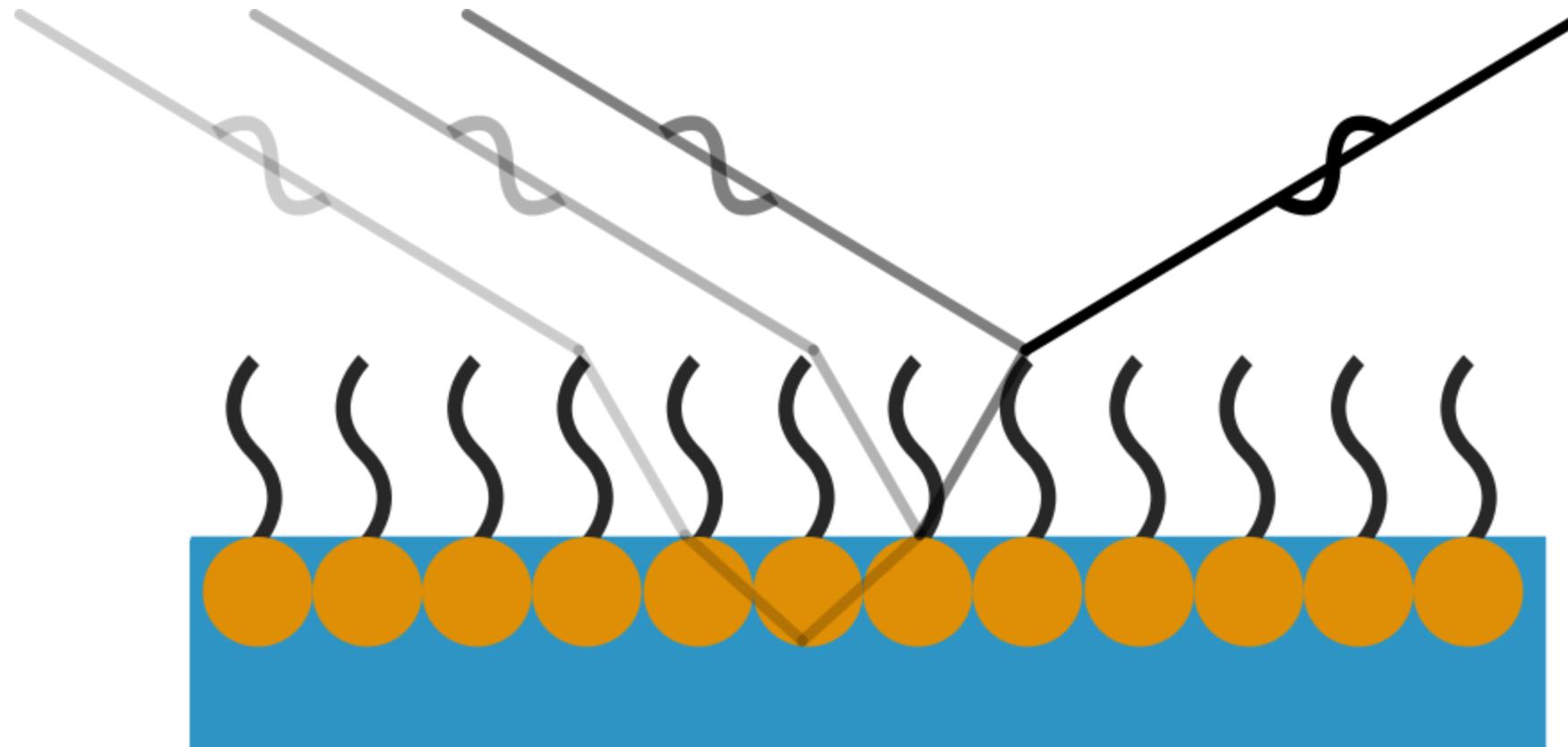
neutron reflectometry

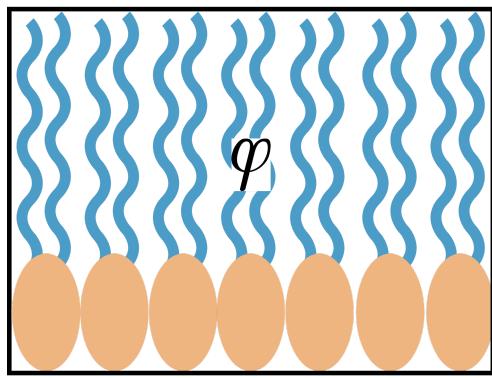
- Non-invasive measurement of structure at an interface
- Application to Langmuir-Blodgett monolayers only developed in the past thirty years
 - Popularised through the work of Penfold, Thomas and others

Grundy, *et al.*, Thin Solid Films, **159**, 43 (1988); Penfold and Thomas, J. Phys. Condens. Matter, **2**, 1369 (1990); Penfold and Thomas, Curr. Opin. Colloid Interface Sci., **19**, 198 (2014)

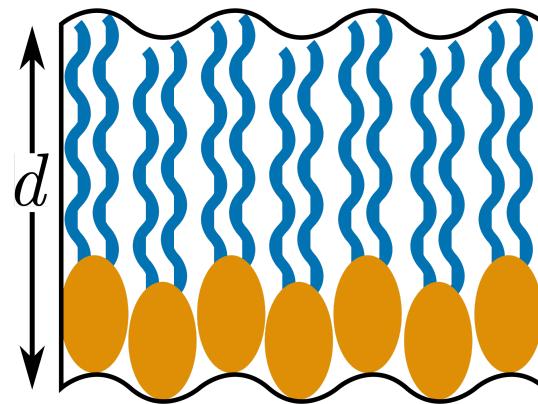




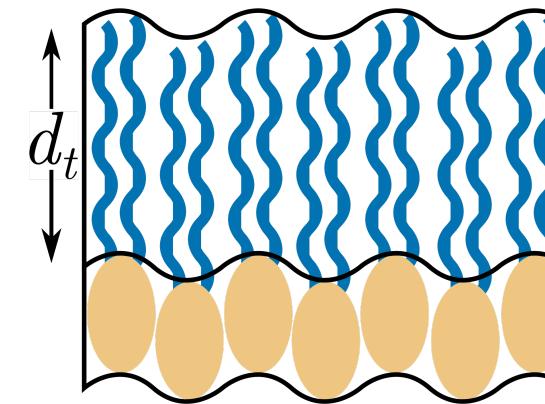




Model 1



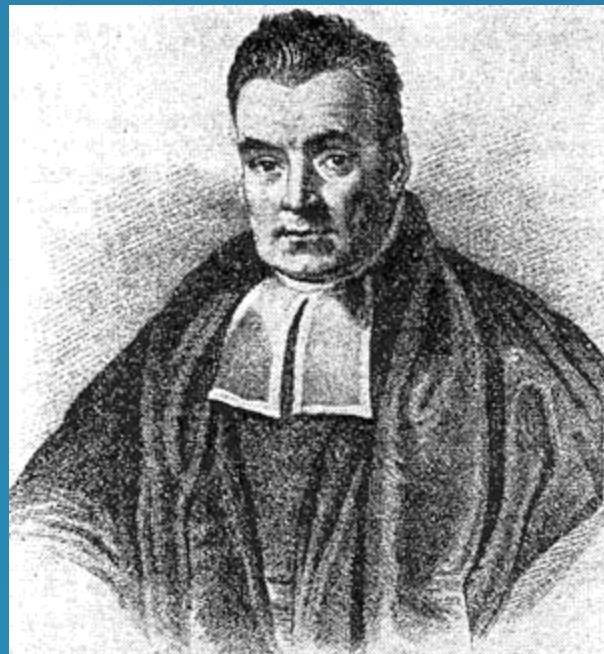
Model 2



Model 3

Campbell, *et al.*, J. Colloid Interface Sci., 531, 98 (2018)

Bayesian model selection



❤️ Thomas Ba(e)yes ❤️
English statistician; 1701-1761

Bayes theorem

$$p(H|D, I) = \frac{p(D|H, I)p(H|I)}{p(D|I)}$$

Bayes, Phil. Trans. Roy. Soc., 53, 370 (1763)

model comparison

$$\frac{p(H_x | \mathbf{D}, \mathbf{I})}{p(H_y | \mathbf{D}, \mathbf{I})} = \frac{p(\mathbf{D} | H_x, \mathbf{I})}{p(\mathbf{D} | H_y, \mathbf{I})} \times \frac{p(H_x | \mathbf{I})}{p(H_y | \mathbf{I})}$$

Pullen and Morris, PLOS ONE 9, e88419 (2014)

parity between the hypotheses

$$\frac{p(H_x | \mathbf{D}, \mathbf{I})}{p(H_y | \mathbf{D}, \mathbf{I})} = \frac{p(\mathbf{D} | H_x, \mathbf{I})}{p(\mathbf{D} | H_y, \mathbf{I})}$$

possibly multi-dimensional

$$p(\mathbf{D}|H, \mathbf{I}) = \iint_{\mathbf{R}} \mathcal{L}(\mathbf{X}) p(\mathbf{X}|H, \mathbf{I}) d^M \mathbf{X}$$



Sivia and Skilling, *Data Analysis: A Bayesian Tutorial*, Oxford University Press, Oxford (2006)



Dynamic nested sampling using dynesty

Higson *et al.*, arXiv: 1704.03459; Speagle, arXiv: 1904.02180

nested sampling

- Draw K "live points" from the prior
- Get natural logarithm of likelihood at each live point
 - Kill the live point with the lowest likelihood
- Draw new live point from prior subject to the constraint
$$\mathcal{L}_{i+1} \geq \mathcal{L}_i$$
 - Continue until stopping criteria is reached

evidence evaluation

$$p(\mathbf{D}|H, \mathbf{I}) \approx \sum_{i=1}^N \frac{\mathcal{L}_{i-1} + \mathcal{L}_i}{2} (X_{i-1} - X_i)$$

$$\ln X_i \approx -\frac{i \pm \sqrt{i}}{K}$$

dynamic nested sampling

- The number of live points is dynamically allocated
- This allows the algorithm to adapt to the shape of the evidence distribution in real time
 - Leading to improved accuracy and efficiency

Bayes' factor

$$\ln(B_{x,y}) = \ln \left[\frac{p(\mathbf{D}|H_x, \mathbf{I})}{p(\mathbf{D}|H_y, \mathbf{I})} \right] = \begin{cases} > 0, & \text{prefer model } x \\ \approx 0, & \text{no preference} \\ < 0, & \text{prefer model } y \end{cases}$$

Sivia *et al.*, Physica D, **66**, 234 (1993)

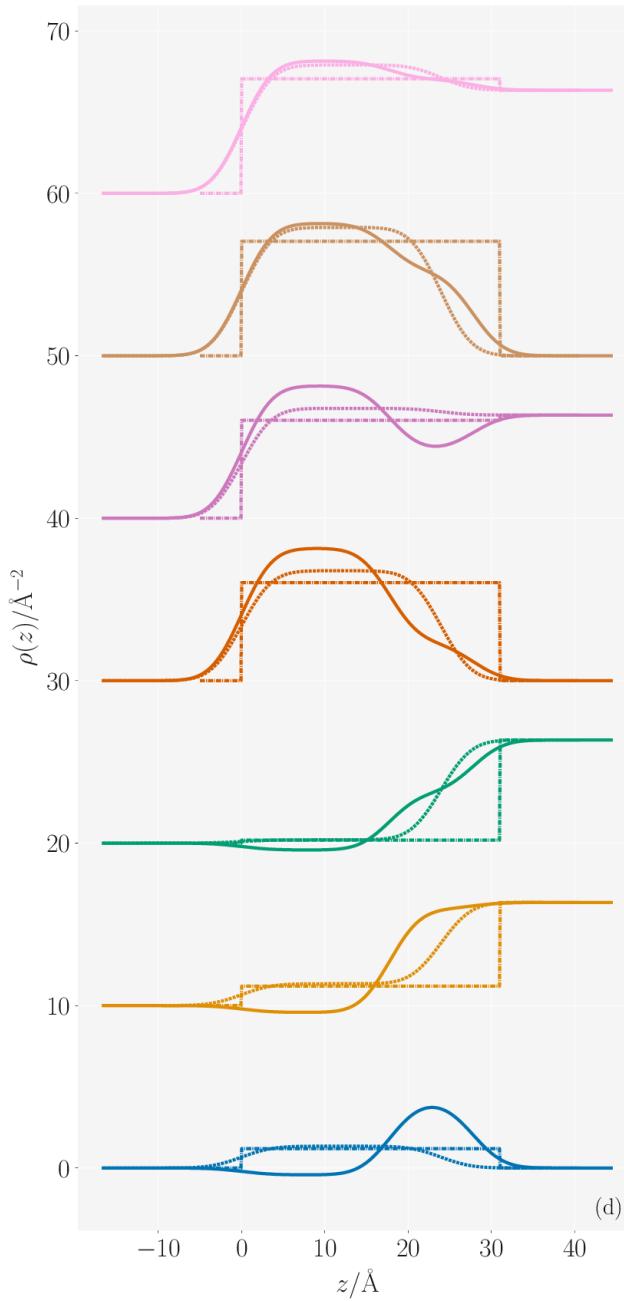
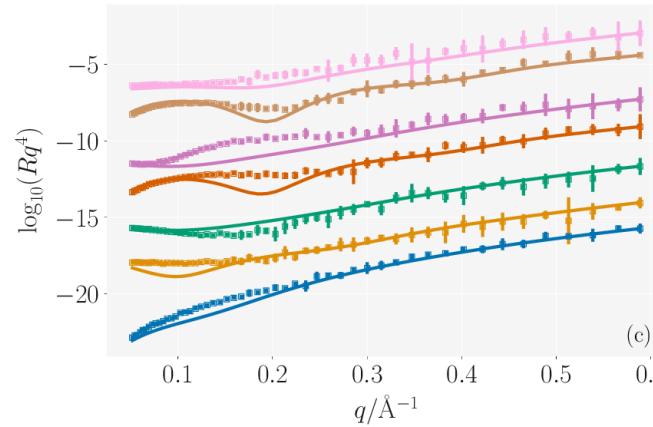
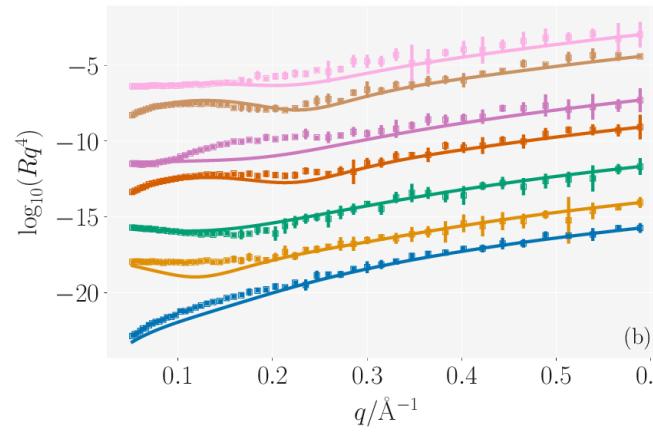
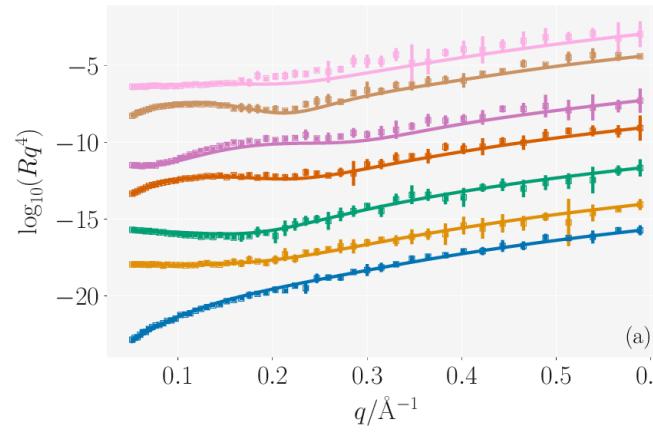
Bayesian model comparison

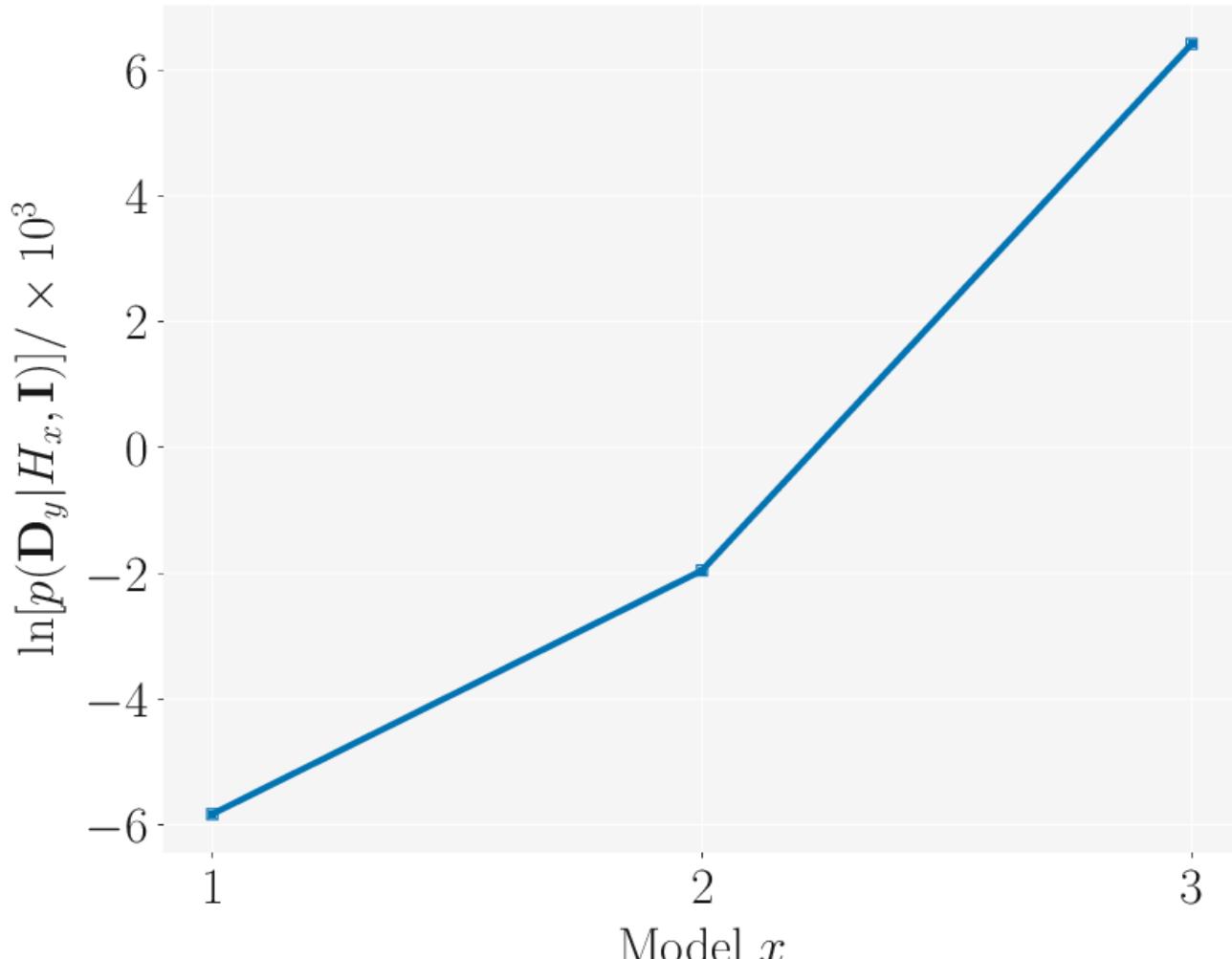
- This offers a clear, robust, and scalable method for comparison of reflectometry models
 - The evidence is *data-dependent*, so can compare different data quantities
 - Not the first to apply Bayesian model comparison to neutron reflectometry

Sivia *et al.*, Physica B, **173**, 121 (1991); Geoghegan *et al.*, Thin Solid Films, **53**, 825 (1996); Sivia and Webster, Physica B, **248**, 327 (1998)

what did we do?

- Apply this Bayesian method to the three Campbell models
 - Investigate the effect of different isotopic contrasts
 - Show (mathematically) what everyone already knew



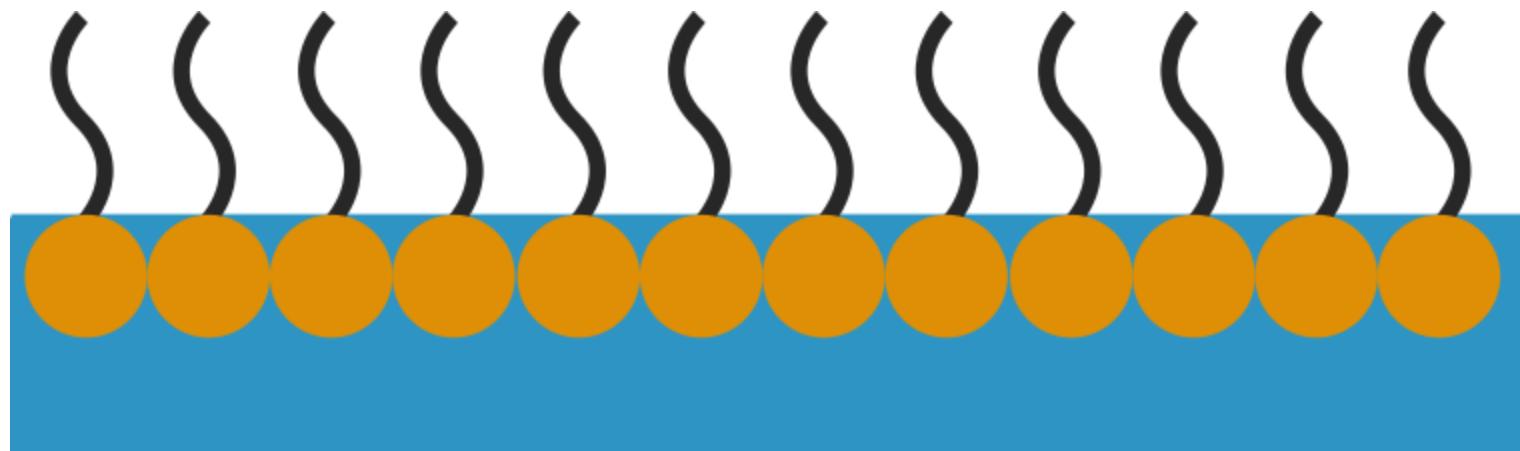


Agrees well with the Campbell *et al.* result

but getting seven contrasts of neutron data isn't easy

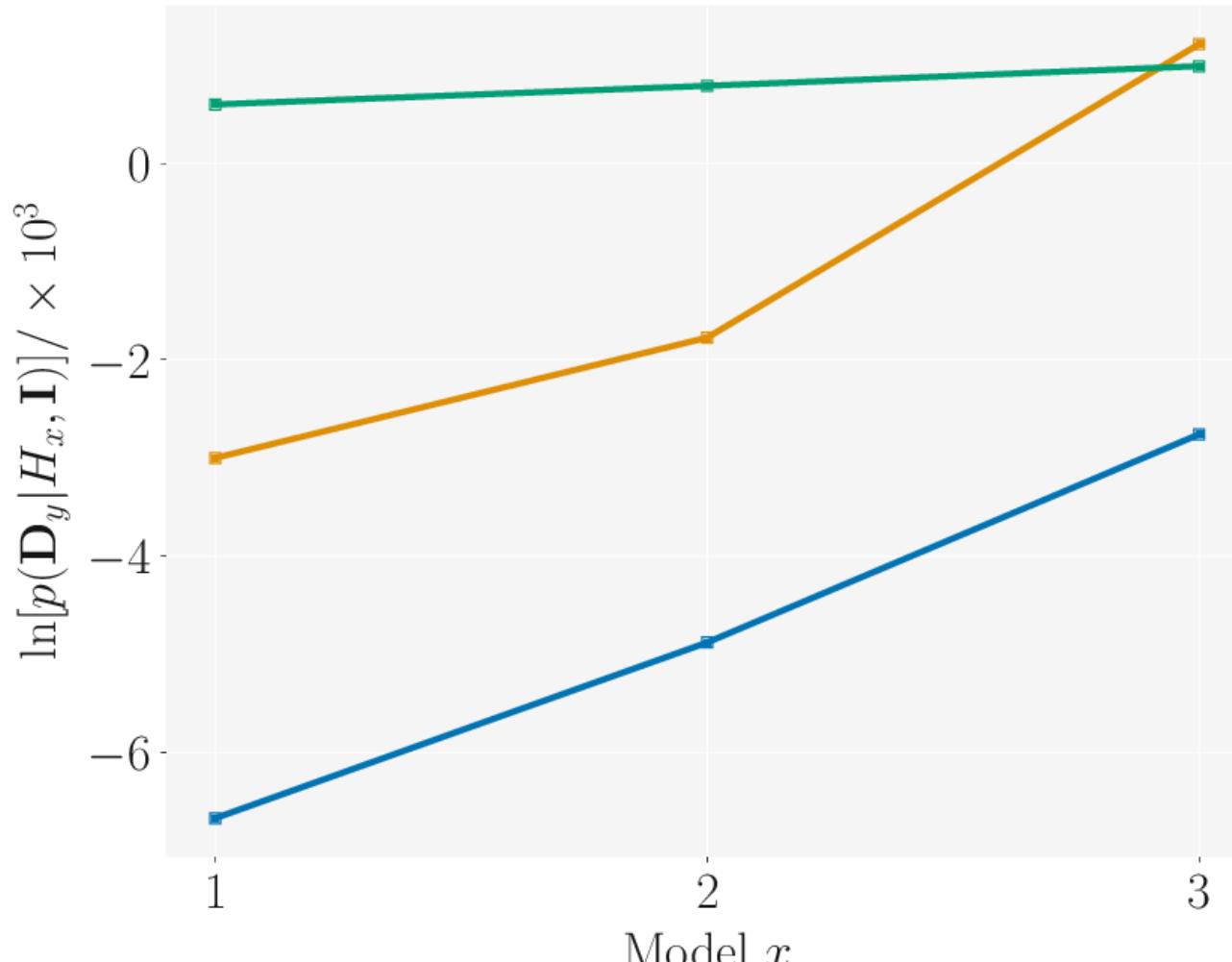
- usually expensive and synthetically difficult
- most of the time only a few contrasts are used

the most common contrasts



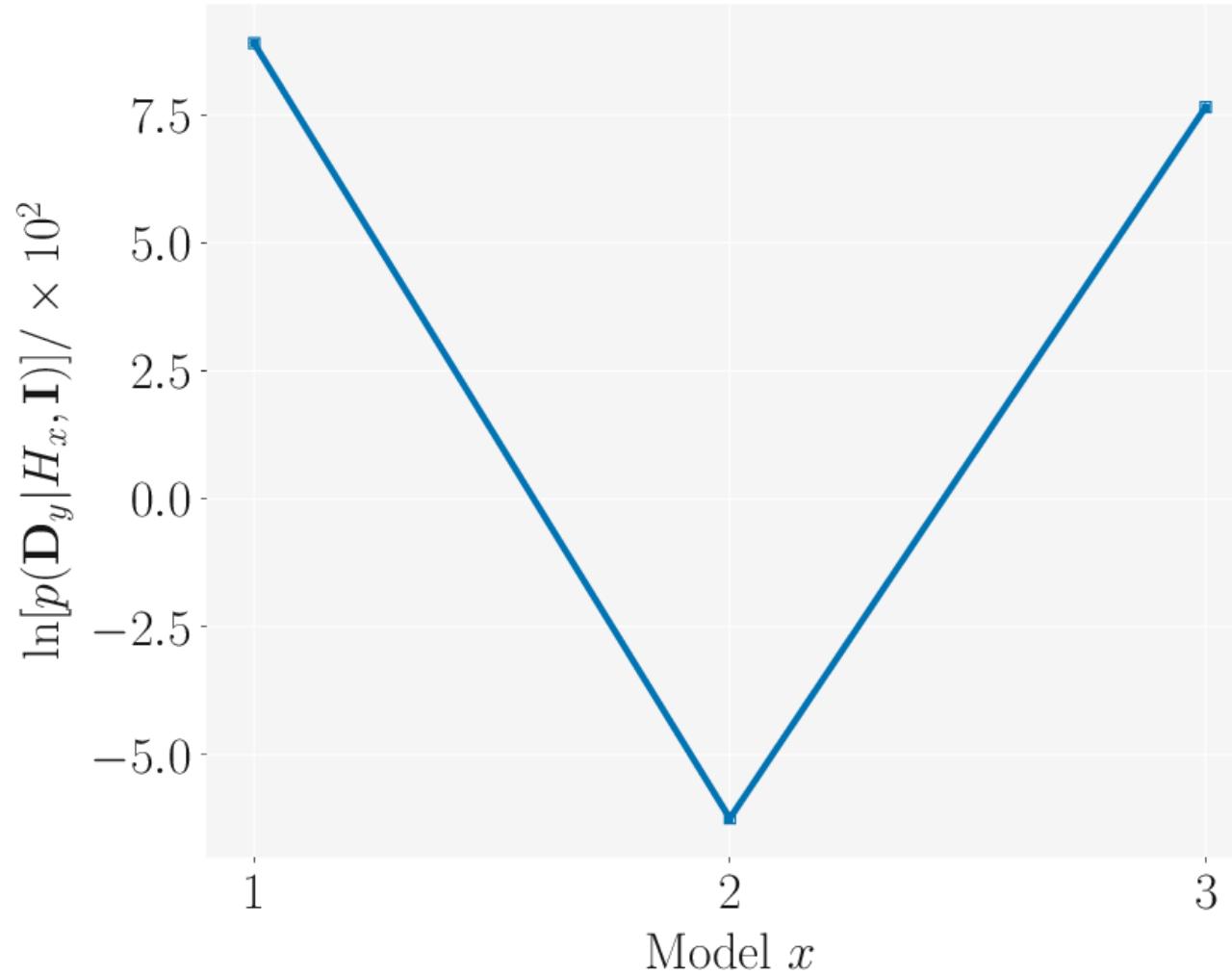
- tail-deuterated with D₂O and ACMW and fully-hydrogenated with D₂O

Pabois *et al.*, J. Colloid Interface Sci., **556**, 266 (2019); Ortiz-Collazos *et al.*, BBA - Biomembranes, **1861**, 182994 (2019)



Fewer contrasts, less relative evidence

is there a combination where model 3
doesn't have the most evidence?



Fully-deuterated molecules on D₂O and ACMW and fully hydrogenated molecules on D₂O

consider the evidence for different models

- If an experimentalist wants to use a model of lesser evidence, important to accept that this is based on a qualitative understanding of the system

conclusions

- Statistically rigorous method for the comparison of relative model evidence
 - *Known knowledge* is usually true
 - Fewer contrasts, less confidence
 - Lots of nice work on this possible in the future

acknowledgements

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thanks for listening



Penny and Sadie, good dogs