

Which probability theory for cosmology?

From Bayes theorem to the anthropic principle

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A basic inference problem

θ : parameters

Hypothesis: M or F

d : data

Pregnant: Y/N

- 1) Select a random person
- 2) Gather data (“pregnant Y/N”)
- 3) ... Don’t get confused!



$$\mathcal{P}(d = Y | \theta = F) = 0.03$$

$$\mathcal{P}(\theta = F | d = Y) \gg 0.03$$

$$\mathcal{P}(\text{data} | \text{hypothesis}) \neq \mathcal{P}(\text{hypothesis} | \text{data})$$

Bayesian parameter estimation

θ : parameters

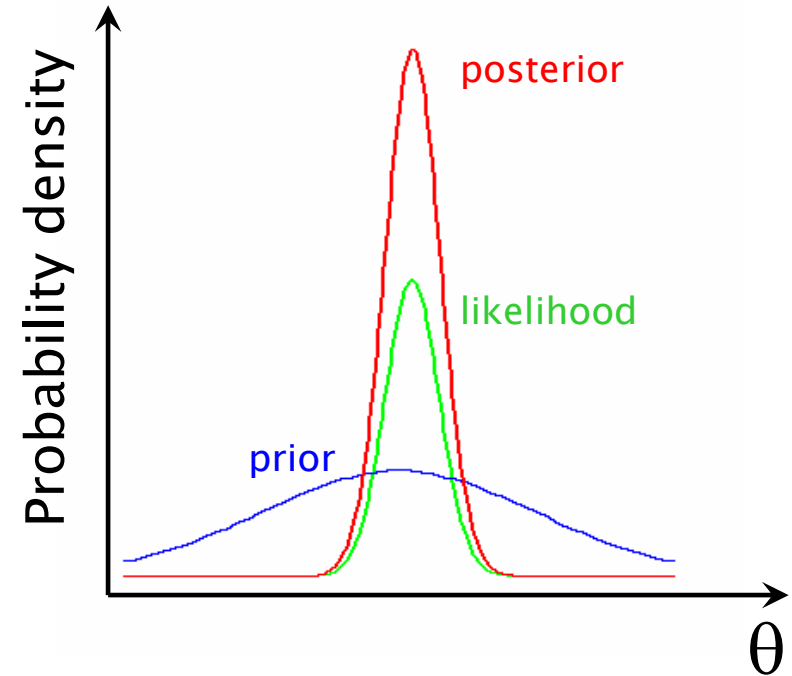
d : data

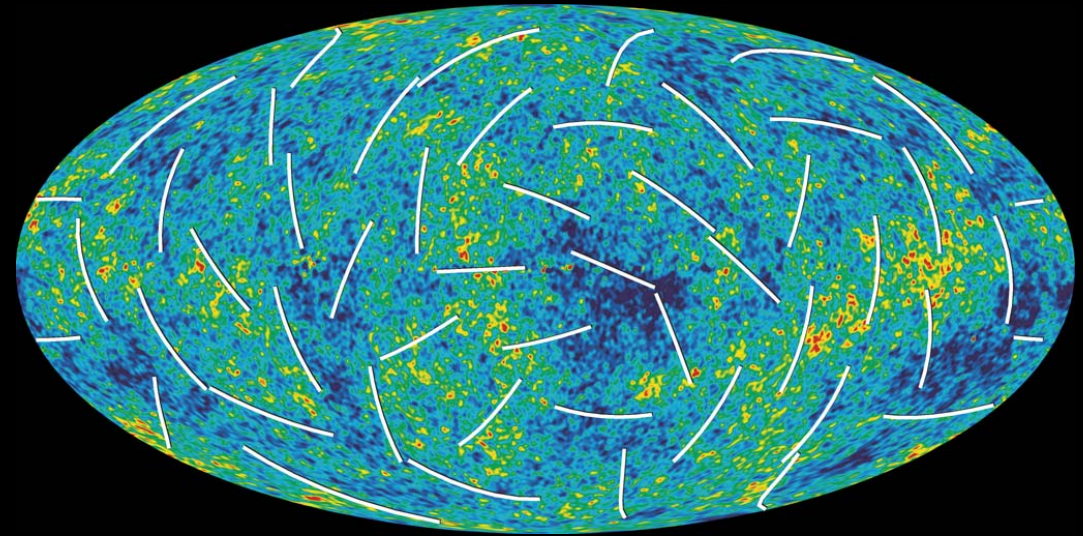
Bayes' Theorem

$$\mathcal{P}(\theta|d) = \frac{\mathbf{L}(d|\theta)\pi(\theta)}{\mathcal{P}(d)}$$

$$\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{model like}}$$

$$\mathcal{P}(\theta, d) = \underbrace{\mathbf{L}(d|\theta)}_{\text{likelihood}} \underbrace{\pi(\theta)}_{\text{prior}} = \underbrace{\mathcal{P}(\theta|d)}_{\text{inference}} \underbrace{\mathcal{P}(d)}_{\text{evidence}}$$





Probability as frequency

*Repeatable sampling
Parent distribution
Asymptotically $N \rightarrow \infty$*

Probability as state of knowledge

*Only 1 sample
“Multiverse” approach ill-defined
 N finite & limited*

Two examples: hypothesis testing & anthropic reasoning

Physics of “random” experiments



Coin tossing: is the coin fair?

Test the null hypothesis

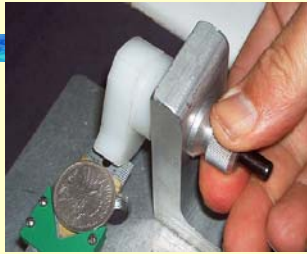
$$H_0: p = 0.5$$

“The numbers p_r [the frequency with which a certain face comes up in die tossing] should, in fact, be regarded as **physical constants** of the particular die that we are using.”

(Cramer, 1946)

Are **physical probabilities** meaningful?
What does it mean “**to throw at random**”?

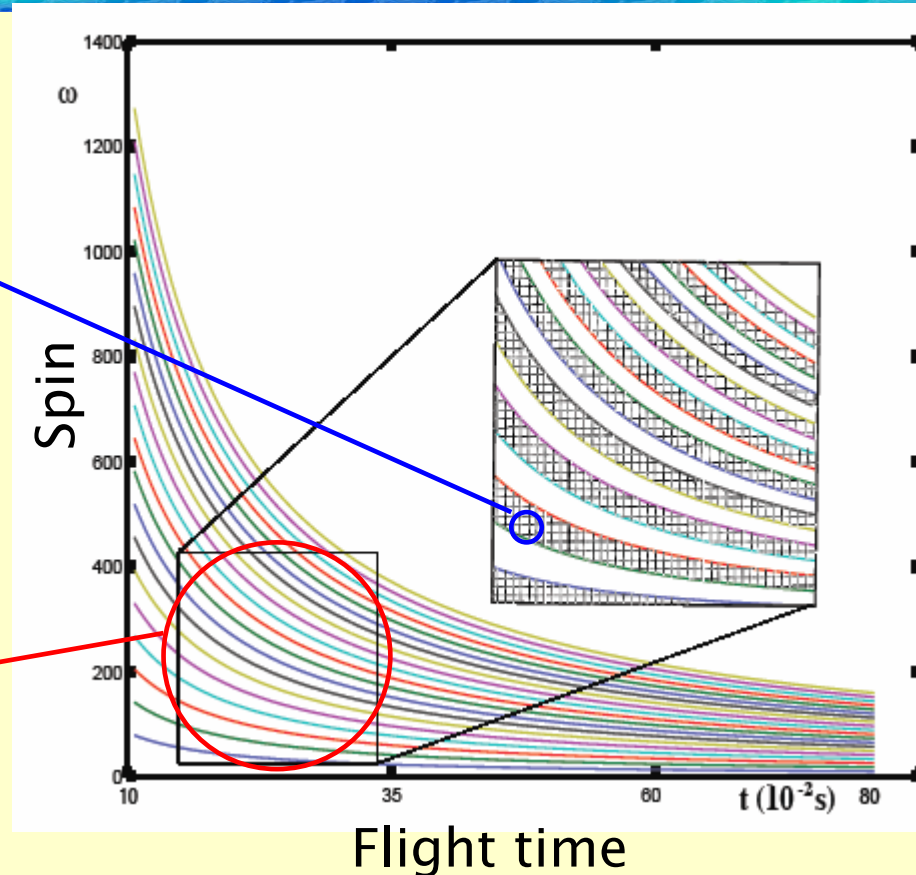
Initial conditions space



p irrelevant!



"Random" toss



With careful adjustment, the coin started heads up always lands heads up - 100% of the time. We conclude that coin-tossing is "physics" not "random".

(Diaconis et al 2004; Jaynes 1996)

Symmetric Lagrangian: $\Gamma_T = \Gamma_H$

$p \neq 0.5$: Γ_T/Γ_H is NOT independent on location!

The nature of probability

- *Probabilistic nature of physical theories due to:*

- 1) “Inherent” randomness

QUANTUM MECHANICS

(Copenhagen inter'on, collapse of the WF; consciousness?)

- 2) Ignorance about initial conditions

CLASSICAL (possibly chaotic) SYSTEMS

- 3) Ignorance of our place in the cosmos

QUANTUM MECHANICS

(Many Worlds inter'on, all possible observations are made)

- 4) Ignorance of relevant bits of the theory

SCIENTIFIC PROCESS as gradual approximation to the Truth

Back to cosmology: parameters

- *Primordial fluctuations*

A, n_s, dn/dln k, features, ...

10x10 matrix M (isocurvature)

isocurvature tilts, running, ...

Planck scale (B, ω, φ, ...)

Inflation (V, V', V'', ...)

Gravity waves (r, n_T, ...)

- *Matter–energy budget*

Ω_κ, Ω_Λ, Ω_{cdm}, Ω_{wdm}, Ω_ν, Ω_b

neutrino sector (N_ν, m_ν, c²_{vis}, ...)

dark energy sector (w(z), c_s², ...)

baryons (Y_p, Ω_b)

dark matter sector (b, m_χ, σ, ...)

strings, monopoles, ...

- *Astrophysics*

Reionization (τ, x_e, history)

Cluster physics

Galaxy formation history

- *Exotica*

Branes, extra dimensions

Alignments, Bianchi VII models

Quintessence, axions, ...

Bayes + Monte Carlo Markov Chain

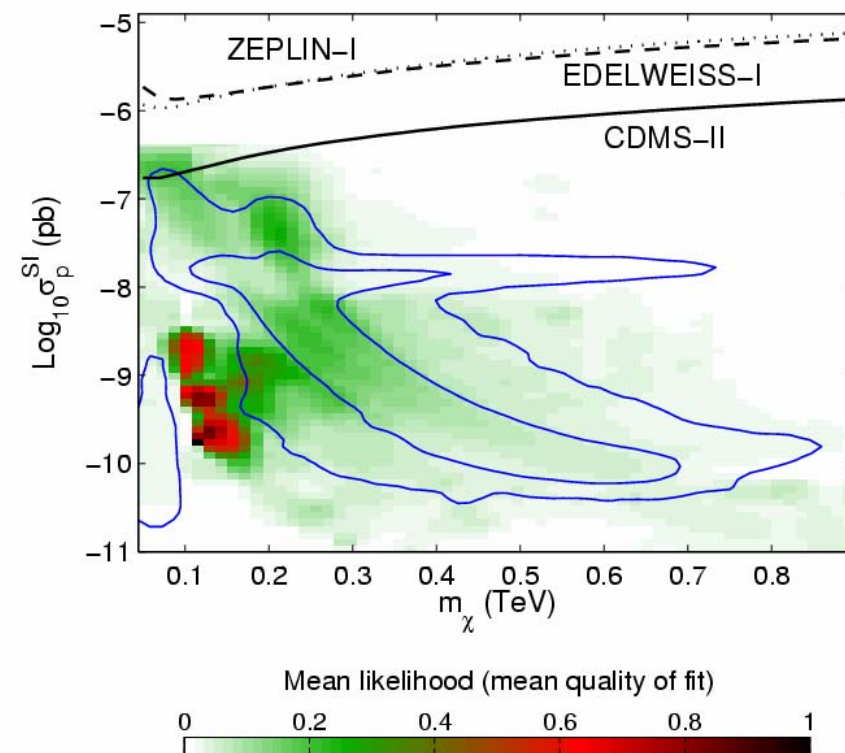
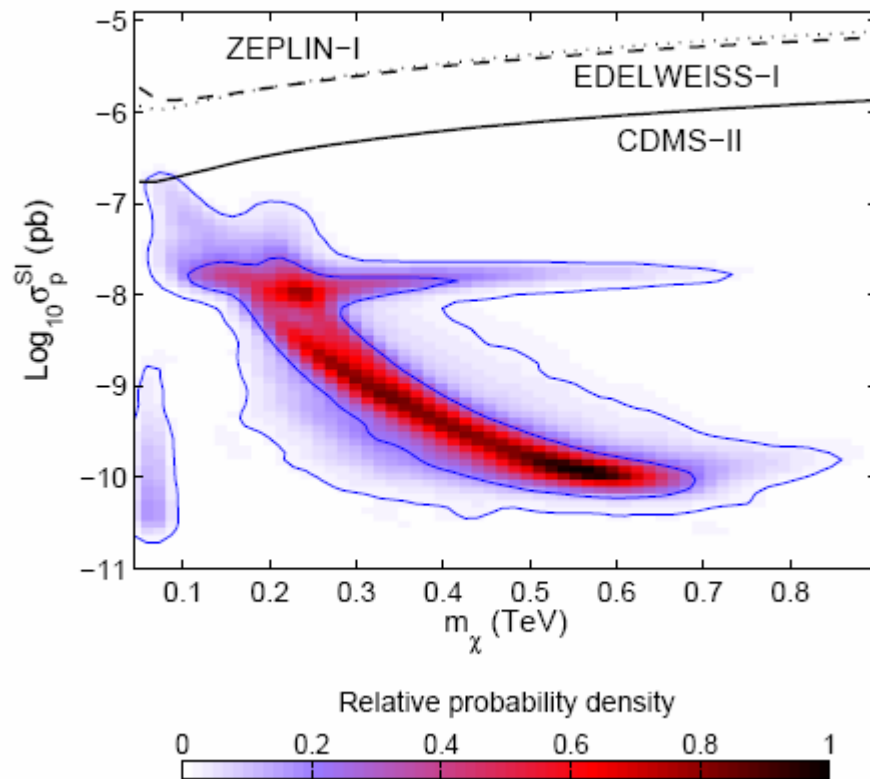
- MCMC: a procedure to draw samples from the posterior pdf*

MCMC Bayesian Frequentist

<i>Efficiency</i>	$\propto N$	$\propto k^N$
<i>Nuisance params</i>	YES	undefined
<i>Marginalization</i>	trivial	close to impossible
<i>Derived params</i>	YES	need estimator
<i>Theoretical uncertainties</i>	YES	only simplistic
<i>Prior information</i>	YES	undefined
<i>Model comparison</i>	YES	significance tests only

Bayesian vs “Frequentist”

Ruiz, Trotta, Roszkowsky (2006)



Posterior pdf
Represents “state of knowledge”
High probability regions

Akin to “chi-square” statistics
Goodness of fit test
Quality of fit regions

Bayesian model comparison

Goal: to compare the “performance” of two models against the data

the model likelihood
 (“evidence”)

$$\mathcal{P}(\mathbf{d}|\mathcal{M}) = \int_{\Omega} \mathcal{L}(\mathbf{d}|\theta, \mathcal{M})\pi(\theta, \mathcal{M})d\theta$$

the posterior prob’ty
 of the model given the data

$$\mathcal{P}(\mathcal{M}|\mathbf{d}) \propto \mathcal{P}(\mathbf{d}|\mathcal{M})\pi(\mathcal{M})$$

The Bayes factor
 (model comparison)

$$B_{01} = \frac{\mathcal{P}(\mathcal{M}_0|\mathbf{d})}{\mathcal{P}(\mathcal{M}_1|\mathbf{d})}$$

$ \ln B_{01} $	Odds	Interpretation
< 1	$< 3:1$	<i>not worth the mention</i>
< 2.5	$< 12:1$	<i>moderate</i>
< 5	$< 150:1$	<i>strong</i>
> 5	$> 150:1$	<i>decisive</i>

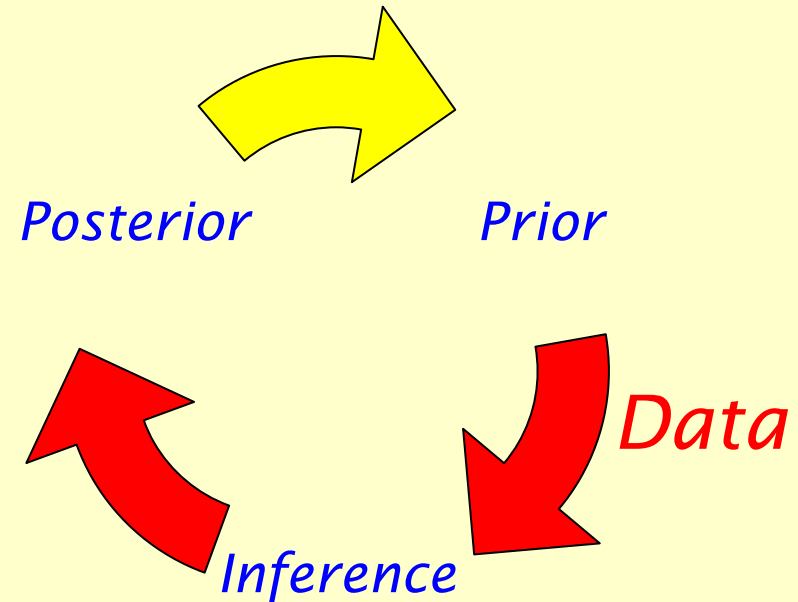
Jeffreys’ scale for the strength of evidence

The role of the prior

- *Parameter inference*

Prior as “state of knowledge”

Updated to posterior through the data & Bayes Theorem



- *Model comparison*

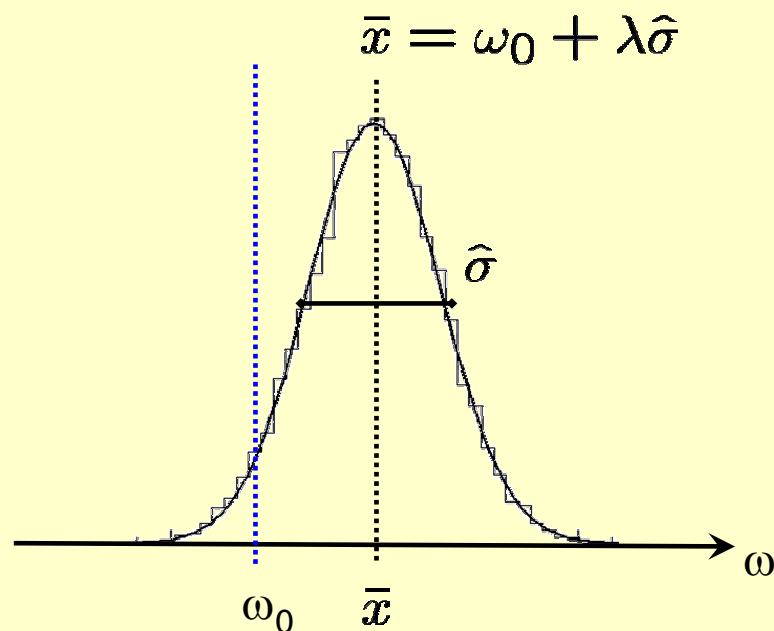
Prior inherent to model specification

Gives available model parameter space

$$\mathcal{M} \equiv \{\theta, \pi(\theta|\mathcal{M})\}$$

An automatic Occam's razor

- The Bayes factor balances quality of fit vs extra model complexity:



Model 0: $\omega = \omega_0$

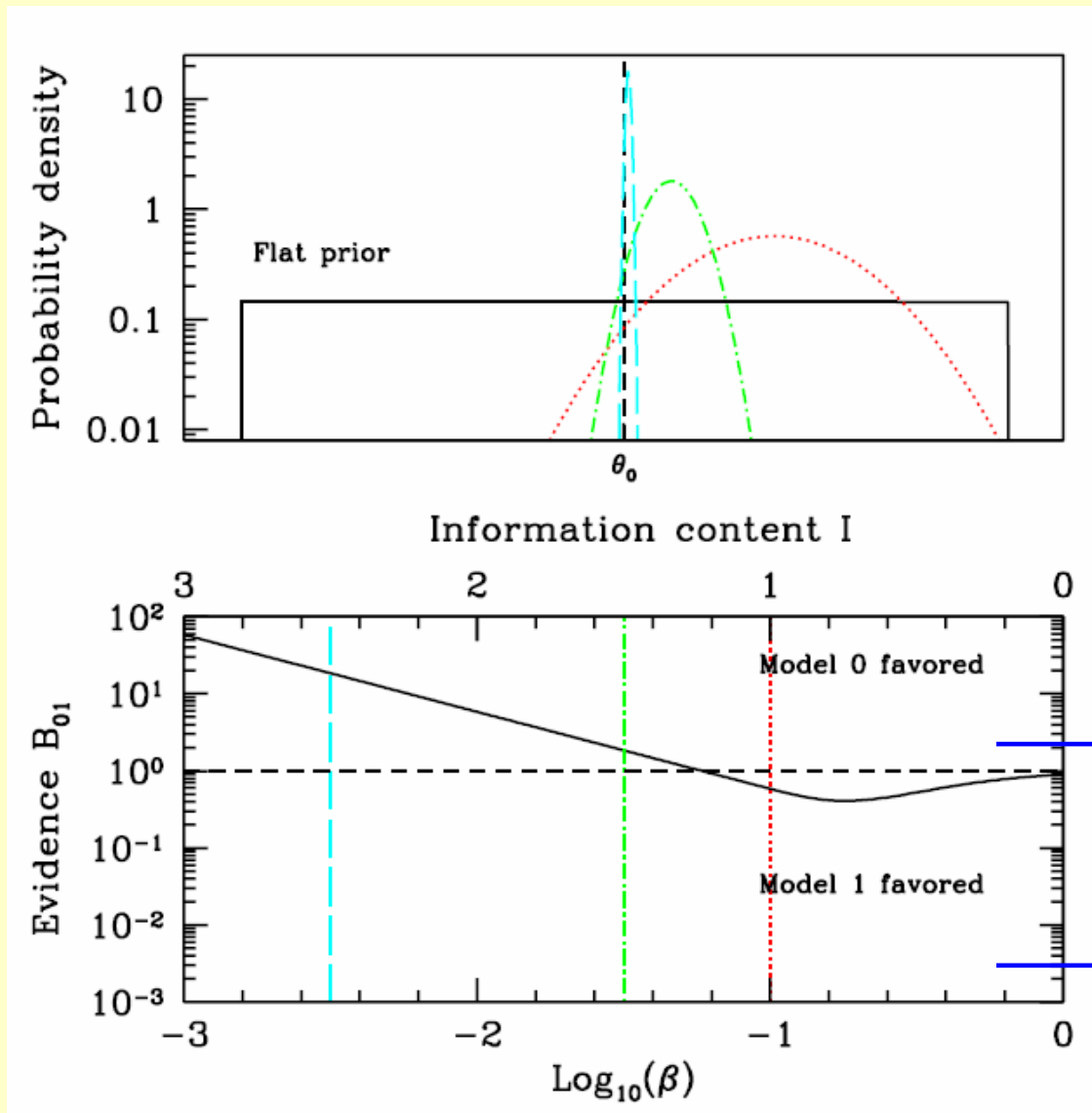
Model 1: $\omega \neq \omega_0$ with $\pi(\omega)$

For “informative” data

$$\ln B_{01} = I - \frac{\lambda^2}{2}$$

- $I = \ln(\text{prior width} / \text{likelihood width}) \geq 0$
- = “wasted” volume of parameter space
- = amount by which our knowledge has increased

Lindley's paradox



Frequentist rejection test for H_0

$\lambda = 1.96$ for all 3 cases

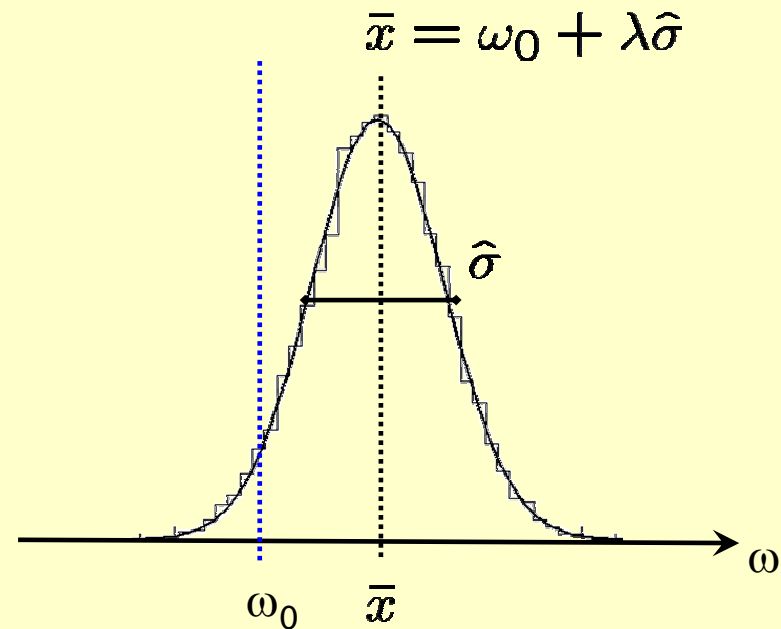
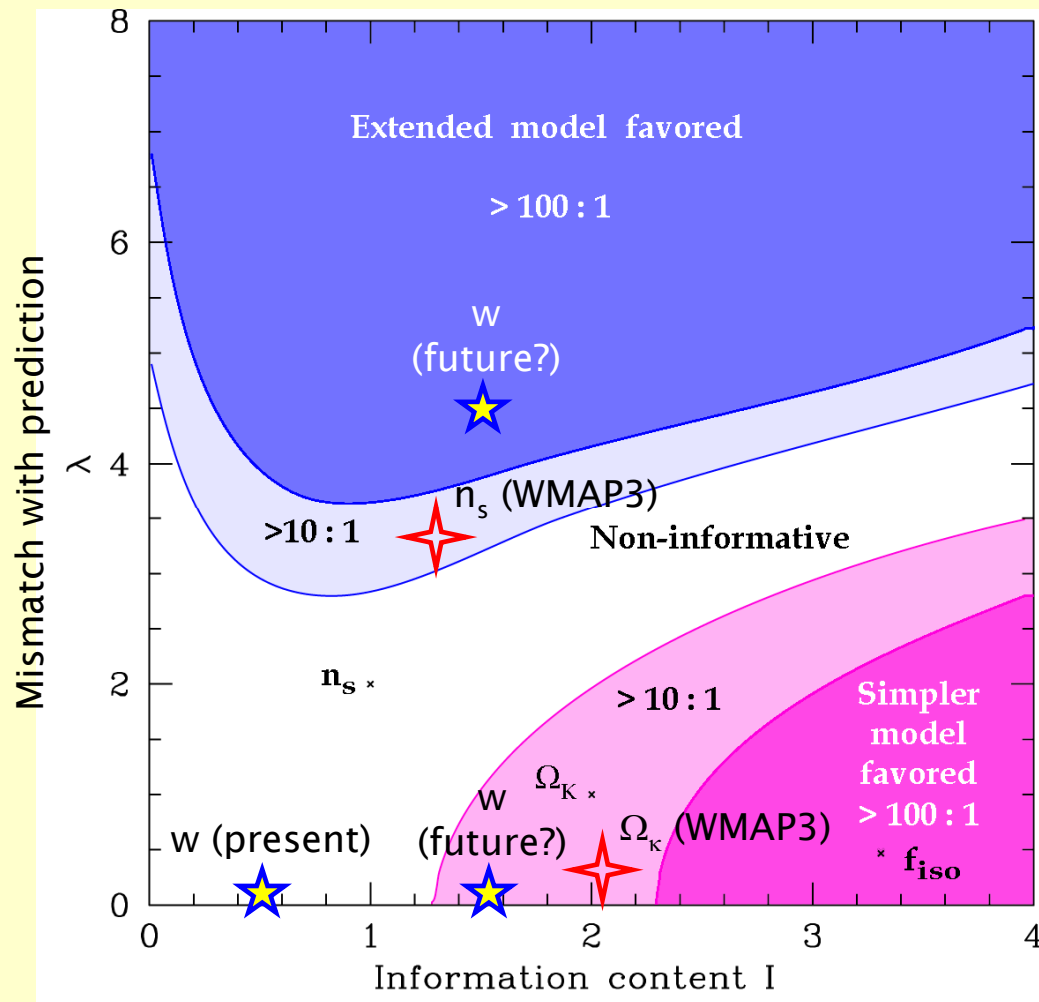
but different information content of the data

simpler model

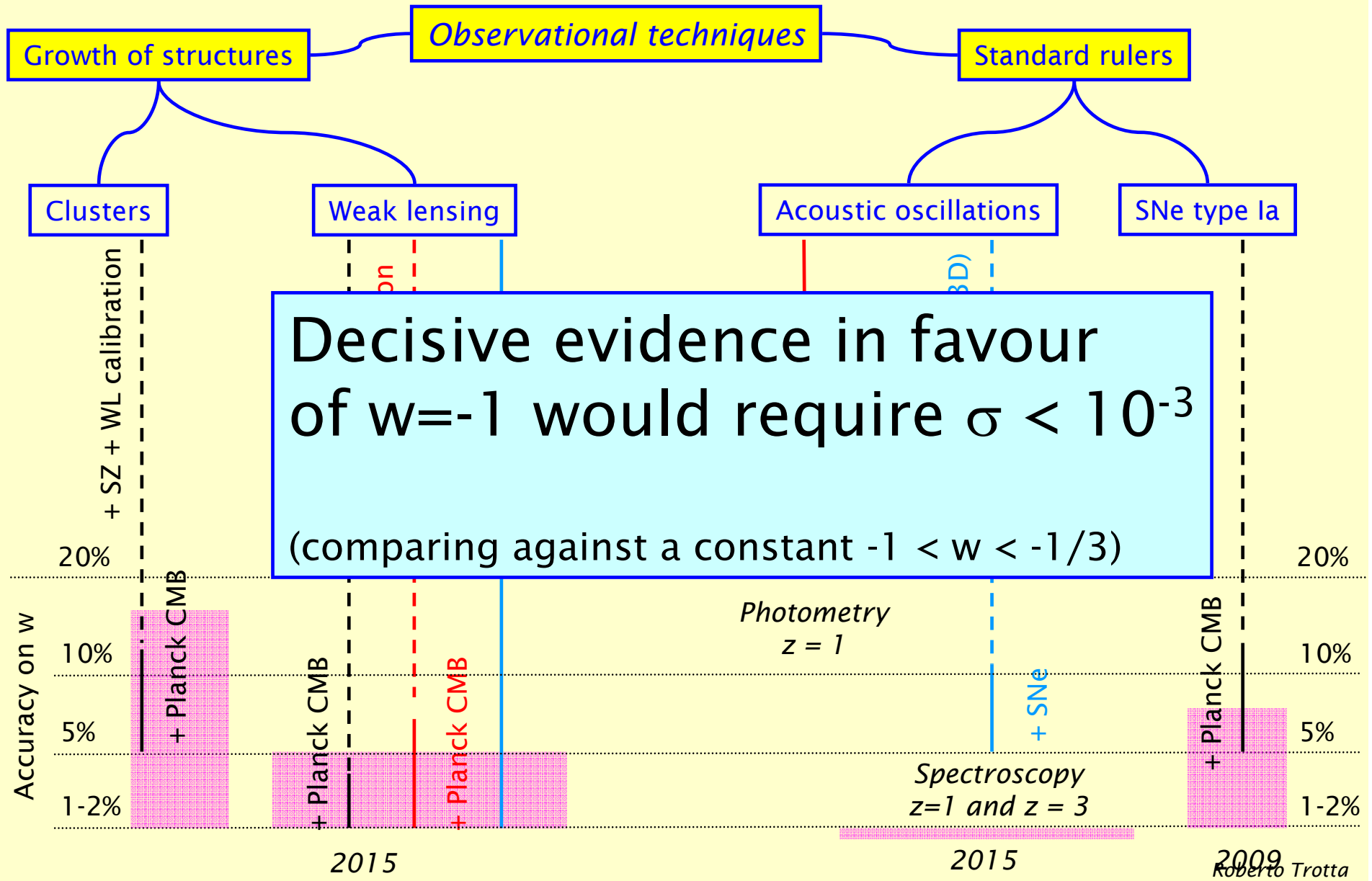
model with 1 extra parameter

“Trust me, I’m a Bayesian!”

(Trotta 2005, 2006 in prep)



Dark energy discovery space



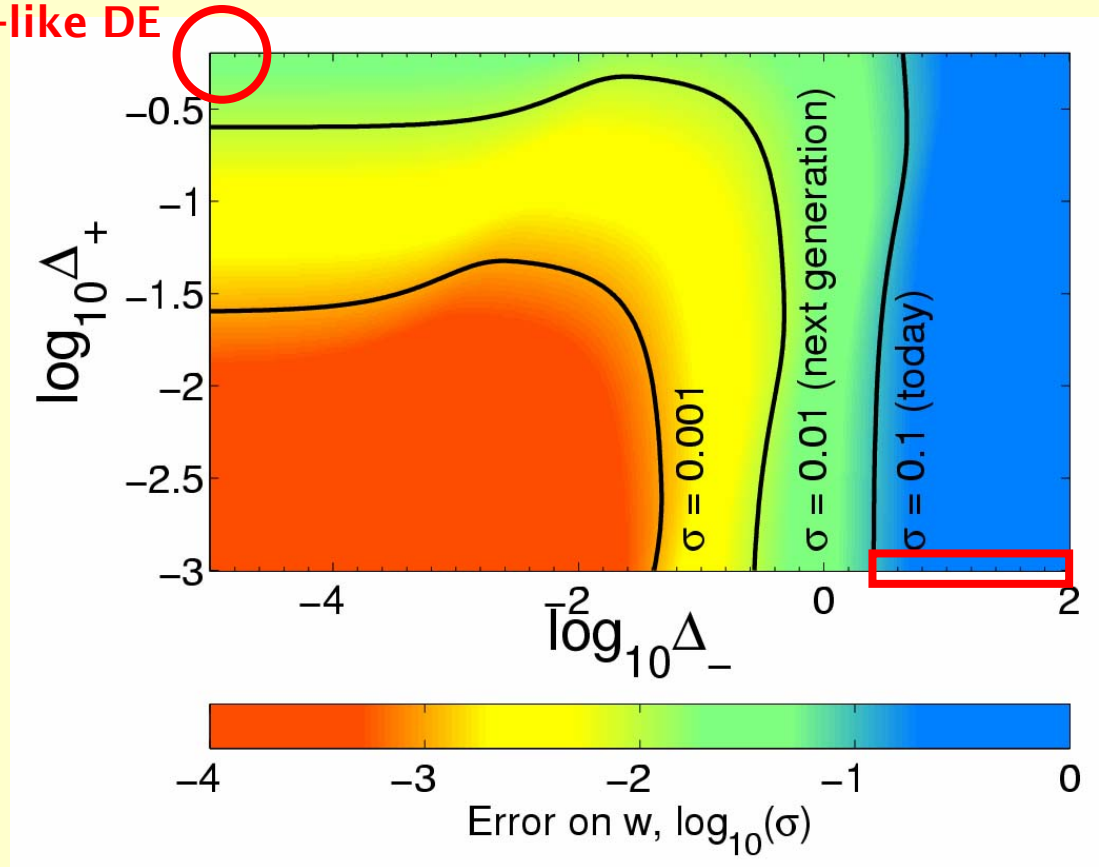
Ruling in Λ

Trotta (2006)

- Which dark energy models are strongly disfavoured against Λ for a given accuracy σ around $w = -1$?

$$-1 - \Delta_- \leq w_{\text{eff}} \leq -1 + \Delta_+$$

fluid-like DE



phantom DE

Computing the Bayes factor

$$\mathcal{P}(\mathbf{d}|\mathcal{M}) = \int_{\Omega} \mathbf{L}(\mathbf{d}|\boldsymbol{\theta}, \mathcal{M})\pi(\boldsymbol{\theta}, \mathcal{M})\mathrm{d}\boldsymbol{\theta}$$

*Multi-dimensional integral
for the model likelihood*

- *Thermodynamic integration: brute force, computationally intensive*
- *Laplace approximation (possibly + 3rd order corrections): inaccurate for non-Gaussian posteriors*
- *Nested sampling (Skilling, implemented by Mukherjee et al): neat algorithm, more efficient than TDI, needs to be rerun if priors changed*
- *Savage-Dickey density ratio (RT 2005): fast & economical for nested model, clarifies the role of prior*

The Savage-Dickey formula

How can we compute Bayes factors efficiently ?

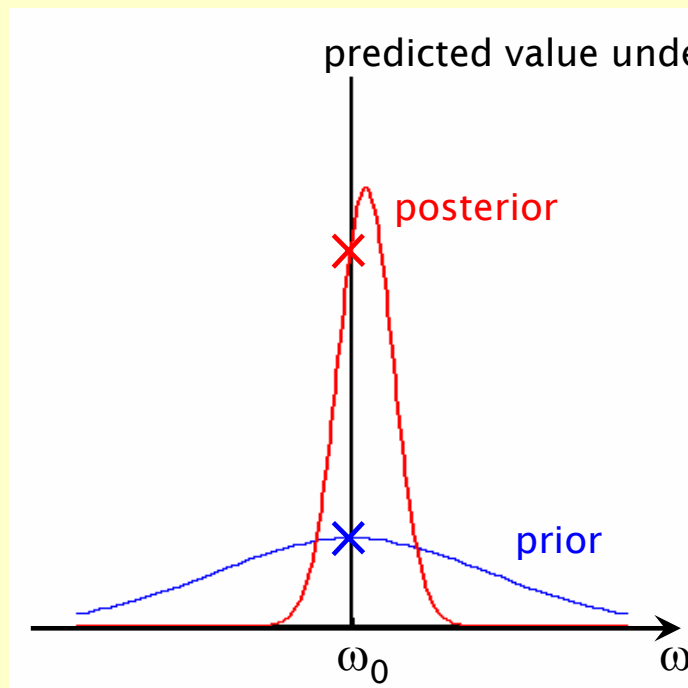
$$\mathcal{P}(\mathbf{d}|\mathcal{M}) = \int_{\Omega} \mathbf{L}(\mathbf{d}|\boldsymbol{\theta}, \mathcal{M})\pi(\boldsymbol{\theta}, \mathcal{M})d\boldsymbol{\theta}$$

For **nested models** and **separable priors**: use the **Savage-Dickey density ratio**

Model 1 has
one extra param
than Model 0

no correlations
between priors

$$B_{01} = \frac{\mathcal{P}(\omega_0|\mathbf{d})}{\pi(\omega_0)}$$

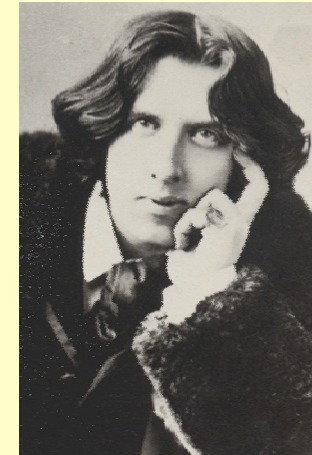


- *Economical*
at no extra cost than MCMC
- *Exact*
no approximations (apart from sampling accuracy)
- *Intuitively easy*
clarifies role of prior

Introducing complexity

“For every complex problem, there is a solution that is simple, neat, and wrong”

Oscar Wilde



How many parameters can the data support, regardless of whether they have been measured or not?

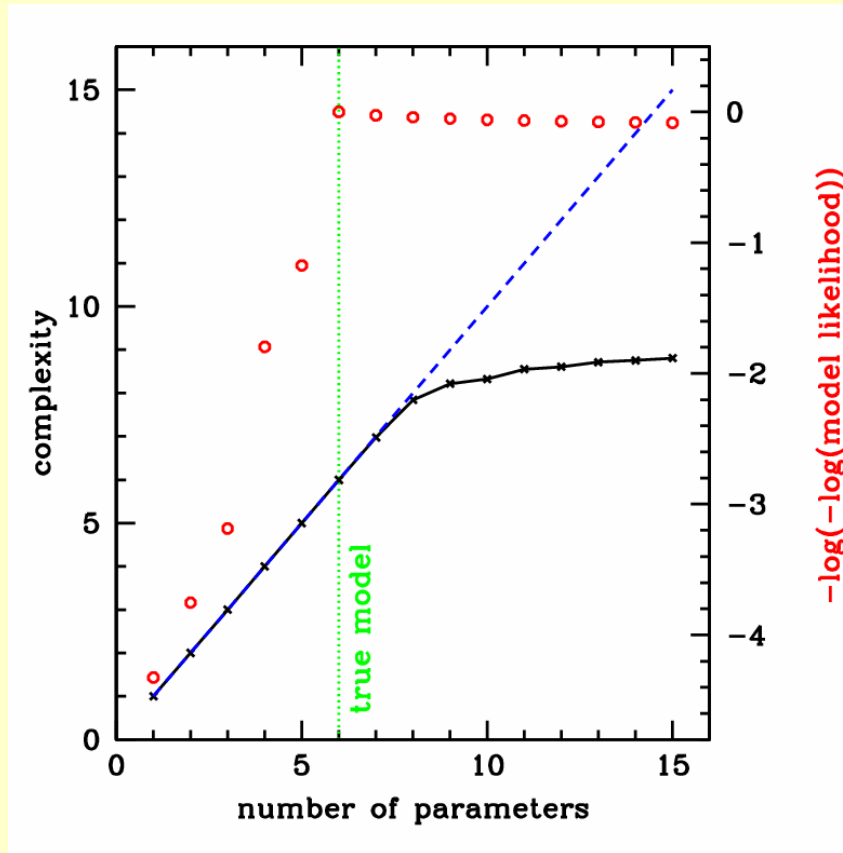
Bayesian complexity

$$\begin{aligned} C_b &= -2 \left(D_{KL}(p, \pi) - \widehat{D}_{KL}(p, \pi) \right) \\ &= \overline{\chi^2(\theta)} - \chi^2(\hat{\theta}) \end{aligned}$$

(Kunz, RT & Parkinson, astro-ph/0602378, PRD accepted)

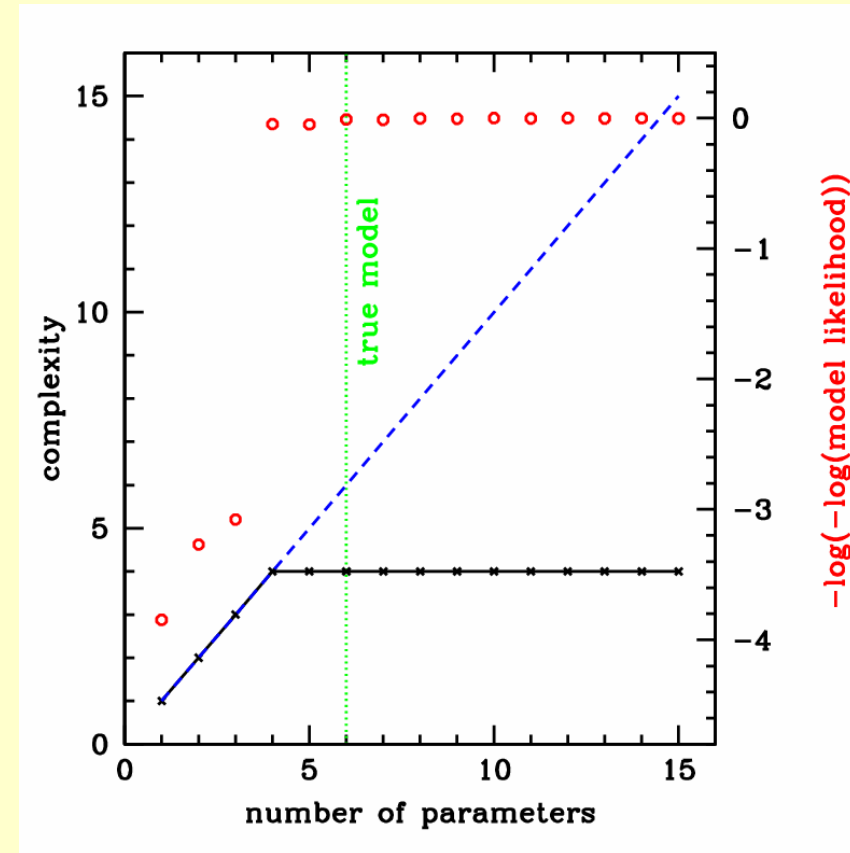
Example: polynomial fitting

Data generated from a model with $N = 6$



GOOD DATA

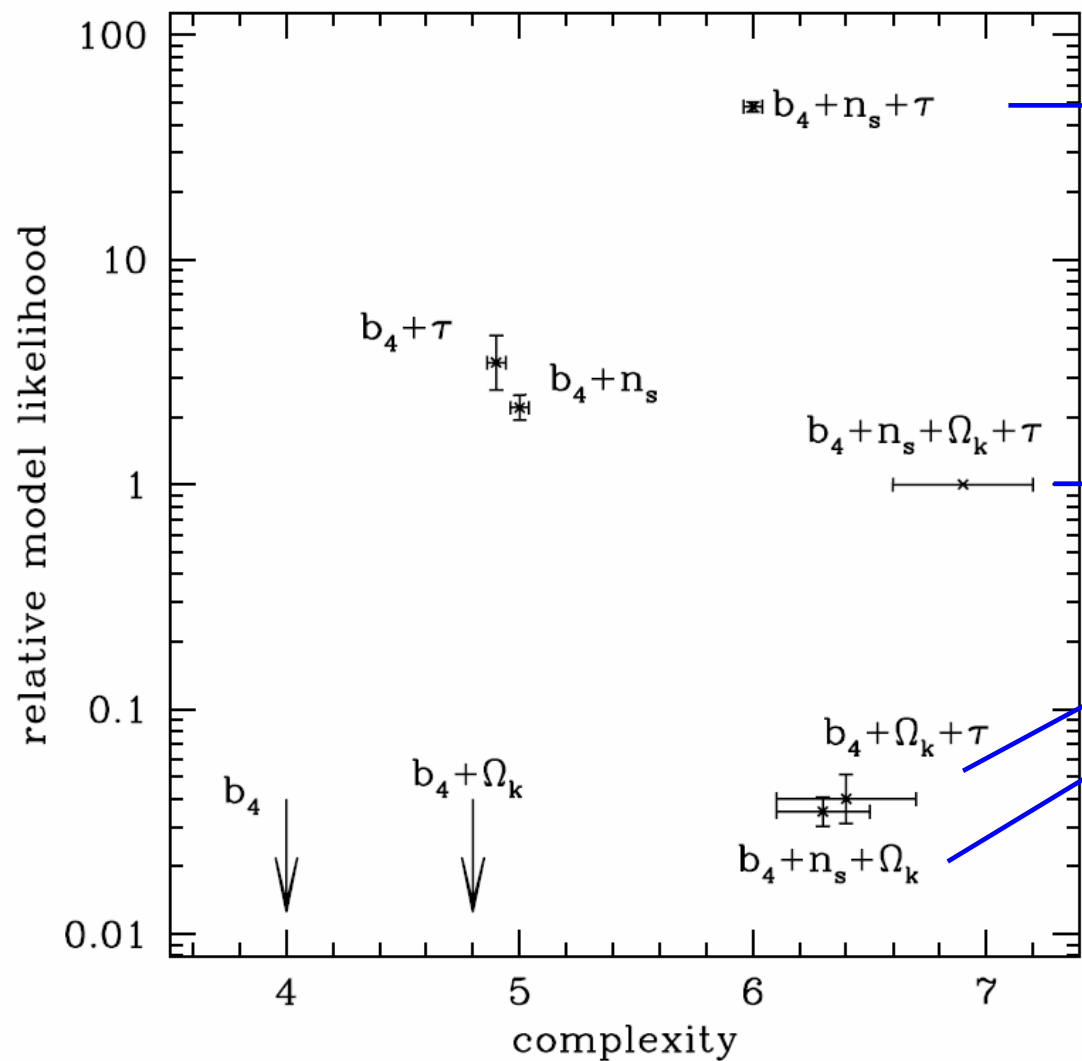
Max supported complexity ≈ 9



INSUFFICIENT DATA

Max supported complexity ≈ 4

How many parameters does the CMB need?



$b_4 + n_s + \tau$
measured &
favoured

Ω_k
measured &
unnecessary

7 params measured
only 6 sufficient

(Kunz, RT & Parkinson
astro-ph/0602378)

The many uses of model comparison

Bayesian model comparison tools provide a framework for new questions & approaches:

- *Model building: phenomenologically work out how many parameters we need. Needs model insight (prior).*
- *Experiment design: what is the best strategy to discriminate among models?*
- *Performance forecast: how well must we do to reach a certain level of evidence?*
- *Science return optimization: use present-day knowledge to optimize future searches (eg DES, WFMOS, SKA)*

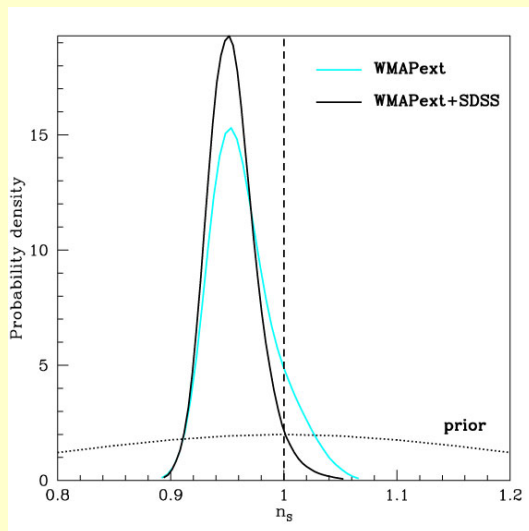
Predictive Posterior Odds Distribution

PPOD: a new hybrid technique

(RT, astro-ph/0504022; see also Pahud et al, Parkinson et al (2006))

- Gives the probability distribution for the model comparison result of a future measurement
- Conditional on our present knowledge
- Useful for experiment design & model building:

Current data posterior



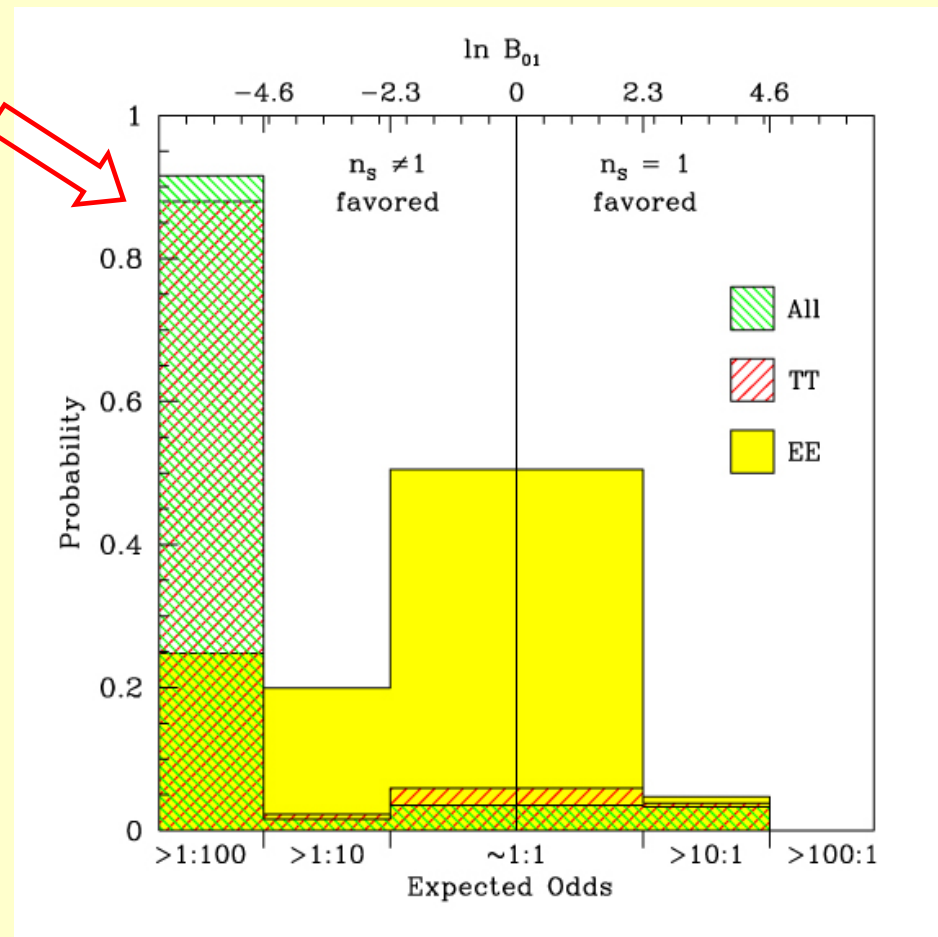
PPOD procedure

- Start from the posterior PDF from current data
- Fisher Matrix forecast at each sample
- Combine Laplace approximation & Savage-Dickey formula
- Compute Bayes factor probability distribution

PPOD in action

Scale invariant vs $n_s \neq 1$:
PPOD for the Planck satellite (2008)
(Based on WMAP1 + SDDS data)

About 90%
probability
that Planck will
disfavor $n_s = 1$
with odds of
1:100 or higher



Anthropic coincidences?

Are physical constants tuned for life?

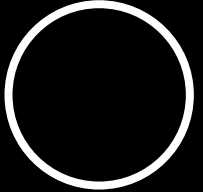
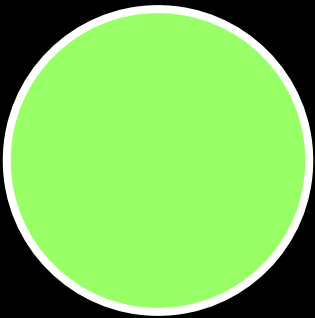
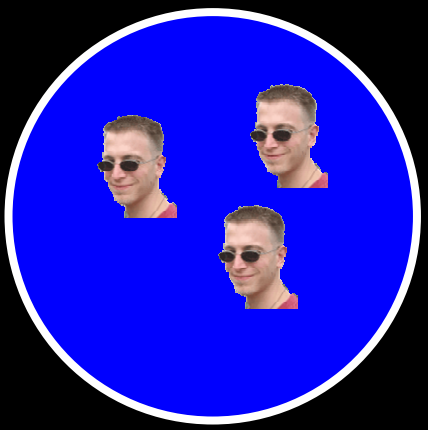
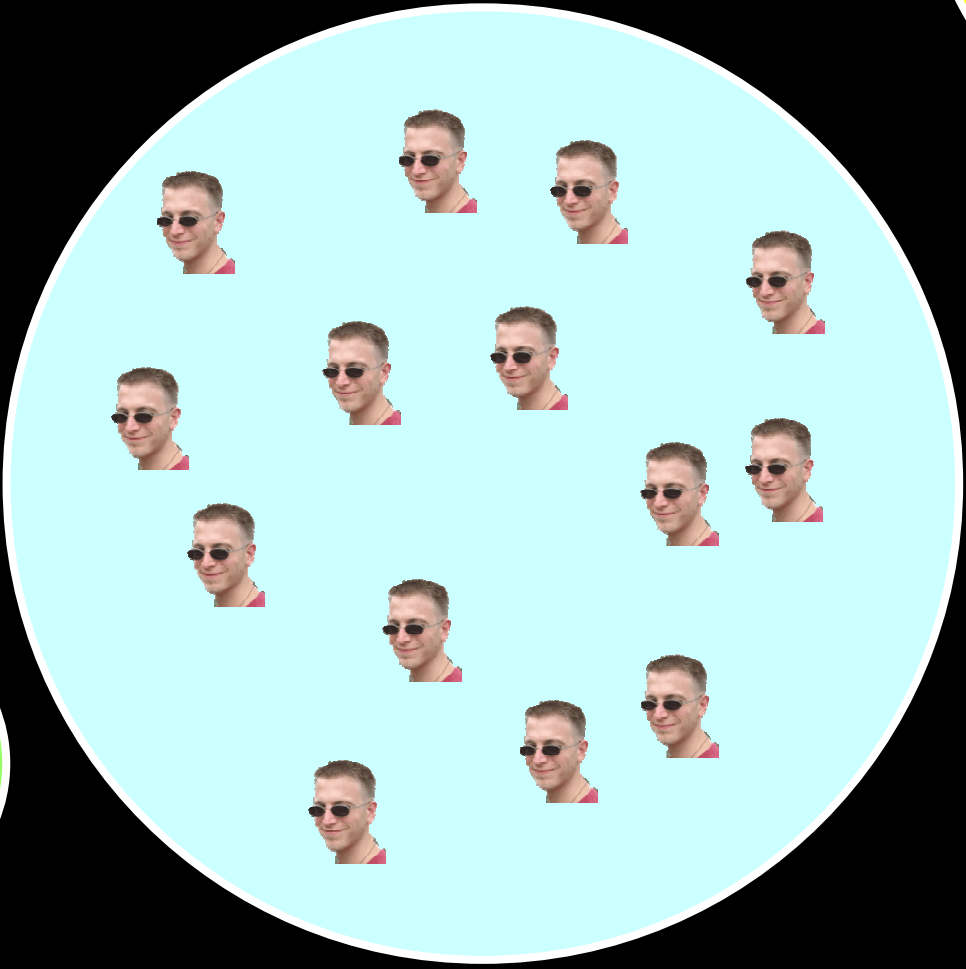
- *Primordial fluctuations amplitude Q*
- *α_{EM}/G and α_s*
- *Cosmological constant Λ , ...*

(Aguirre 2001, 2005;
Weinberg, 2000;
Tegmark et al 2005;
Rees 1998,)

Possible viewpoints:

- *Deeper symmetry / laws of Nature*
(but what determined THAT particular symmetry in the first place?)
- *Design or necessity*
(outside the scope of scientific investigation)
- *Any parameters will do (no explanatory power)*
- *Multiverse: we must live in one “realization” favourable for life*

Life in a multiverse



Anthropic reasoning and Λ

The cosmological constant problem:

why is $\Lambda/M_{\text{pl}} \approx 10^{-121}$?

The anthropic “solution”:

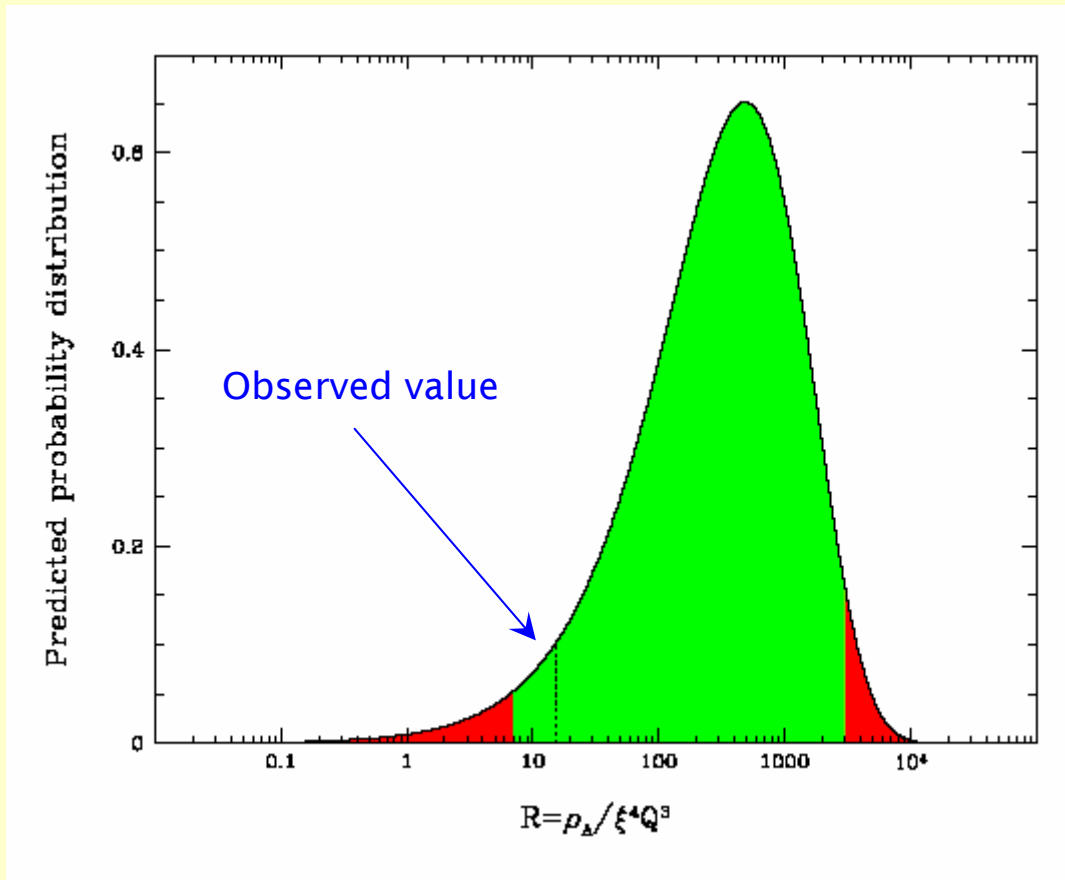
if $\Lambda \gg 1$ galaxies cannot form
hence no observers

(Weinberg, 1987)

Shortcuts & difficulties:

- What counts as observers?
- Which parameters are allowed to vary?
- Is the multiverse a scientific (ie testable) theory?

Which parameters should we vary?



(Tegmark et al 2005)

“Prediction” only successful
conditional on ξ , $Q = \text{fixed}$
(AND that $T_{\text{CMB}} = 2.73 \text{ K}$)

if Λ , Q and ξ varied:

$\Lambda = 10^{17} \Lambda_0$
perfectly “viable” !

(Aguirre 2001)

$$f_{\text{obs}}(\Lambda) = f(\Lambda) f_{\text{sel}}(\Lambda)$$

*prob of observing = sampling distribution * selection function*

“random sample”

“typical observer”

The sampling distribution $f(\Lambda)$

As a frequency of outcomes? (untestable in cosmology)

Flat distribution (the “Weinberg conjecture”) ? (assumed)

Ergodic arguments? (unclear in an infinite Universe)

*No operational def'n of “random” sample: probabilities are
NOT physical properties!*

$$f_{\text{obs}}(\Lambda) = f(\Lambda) f_{\text{sel}}(\Lambda)$$

The selection function $f_{\text{sel}}(\Lambda)$

What counts as “observers”? (it’s the total number that counts!)

What if the Universe is infinite? (number density/Hubble volume?)

Do observers outside your causal horizon count?

Certainly important to integrate over time: we might not be “typical” in that we are early arrivals...

*An explicit counter-example: **MANO** weighting
Maximum **N**umber of **A**llowed **O**bservations*

MANO weighting of Universes

- *Integrate over lifetime of the Universe to obtain the total number of observations that can POTENTIALLY be carried out*
- *Universes that allow for more observations should weight more*
- *Gauge invariant, time independent quantity*
- *Maximum number of thermodynamic processes in a $\Lambda > 0$ Universe:*

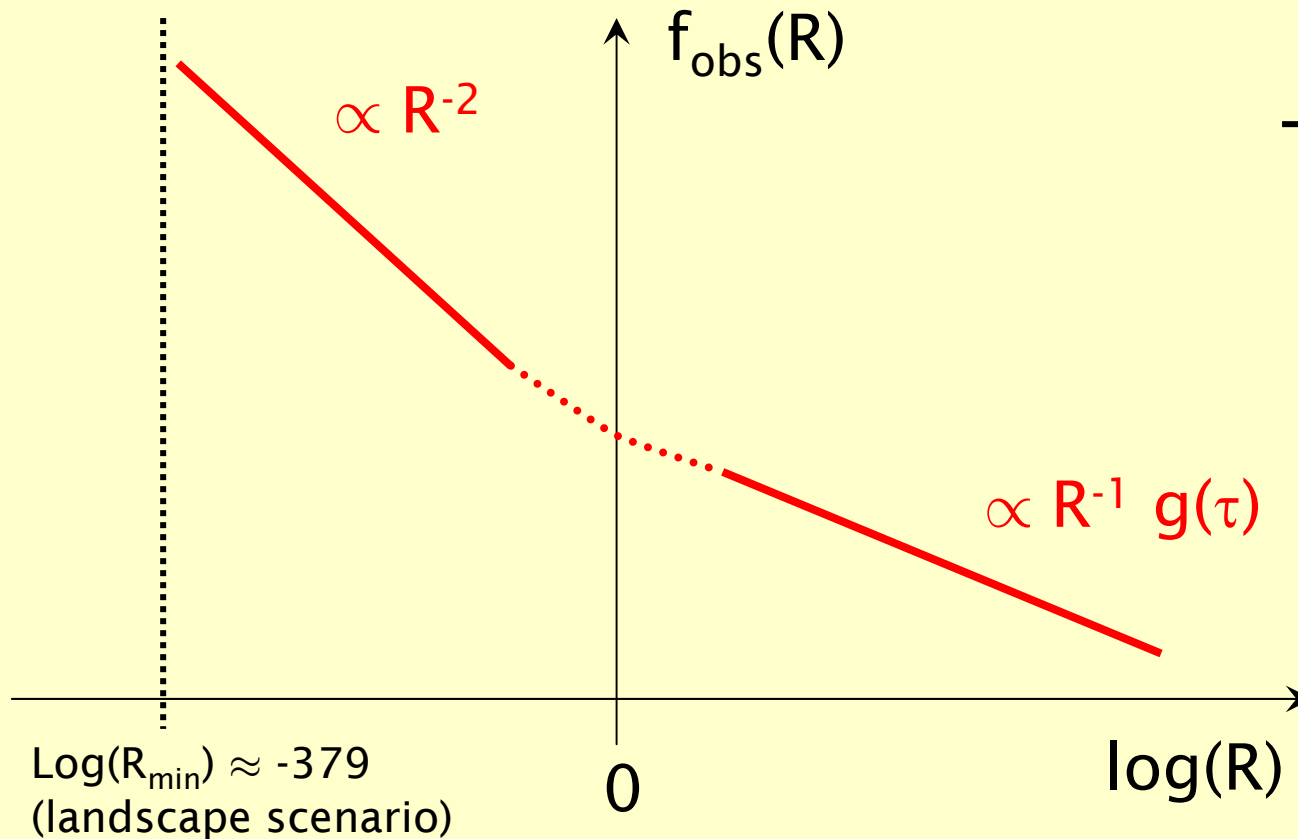
$$N_{max} < E_{coll}/k_B T_{ds}$$

- *This assumes “rare observers”, otherwise density of observers sets the limit*
- *Still suffers from dependence of micro-physics + details of how civilizations arise & evolve*

Probability of observing Λ

- 2 parameters model:

$$R = \Omega_\Lambda / \Omega_\Lambda^0 \quad \tau = t_{obs} / t_0$$



τ	$f_{obs}(R > 1)$
.1	8×10^{-3}
1	3×10^{-5}
3	5×10^{-8}
10	2×10^{-16}

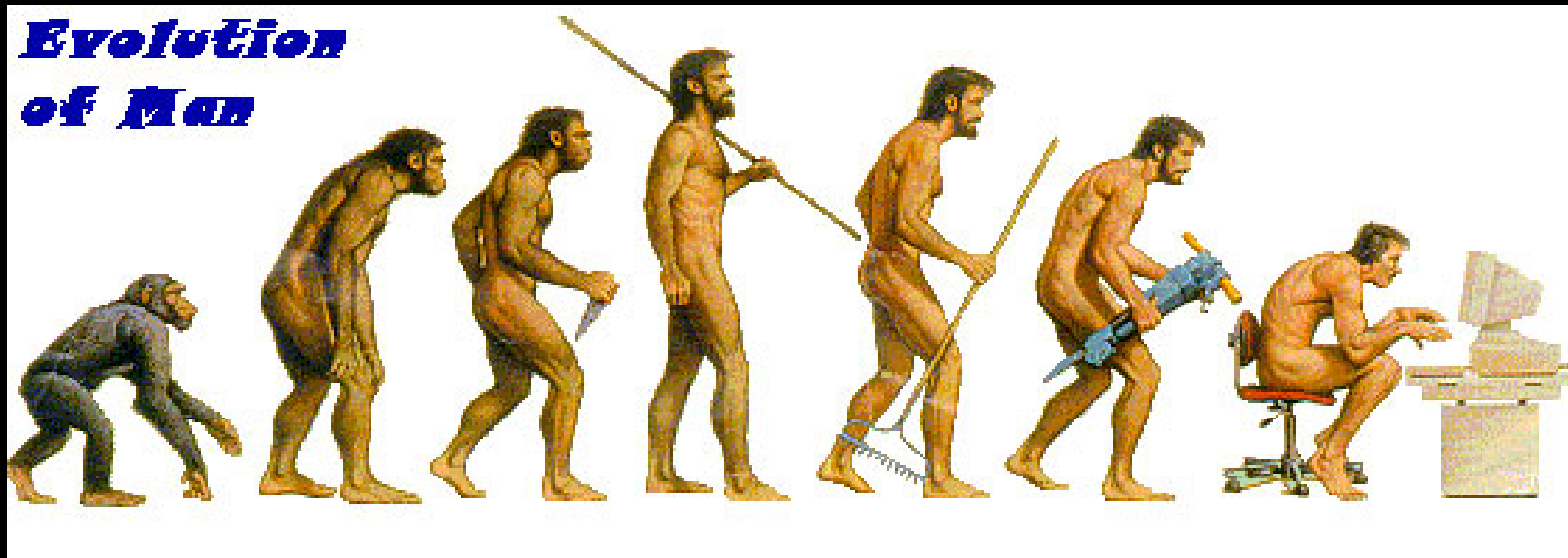
PROBABILITY THEORY AND COSMOLOGY

- *Probabilities are not physical properties but states of knowledge*
- *Uniqueness of the Universe calls for a fully Bayesian approach*

ANTHROPIC REASONING AND SELECTION EFFECTS

- *Outcome depends on selection function*
- *Probability theory as logic at odds with multiverse approach*
- *Within “traditional” anthropic arguments: you should at least integrate over time*
- *MANO counterexample: $P(\Lambda > 0.7) \sim 10^{-5}$*
- *Anthropic “predictions” completely dependent on (many) assumptions*

*Evolution
of Man*



Homo
a prioris

Homo
frequentistus

Homo
Bayesianus

$$\pi(\theta)$$



$$L(d|\theta)$$

$$\mathcal{P}(\theta|d)$$