Optimising Future Dark Energy Surveys for Model Selection Goals

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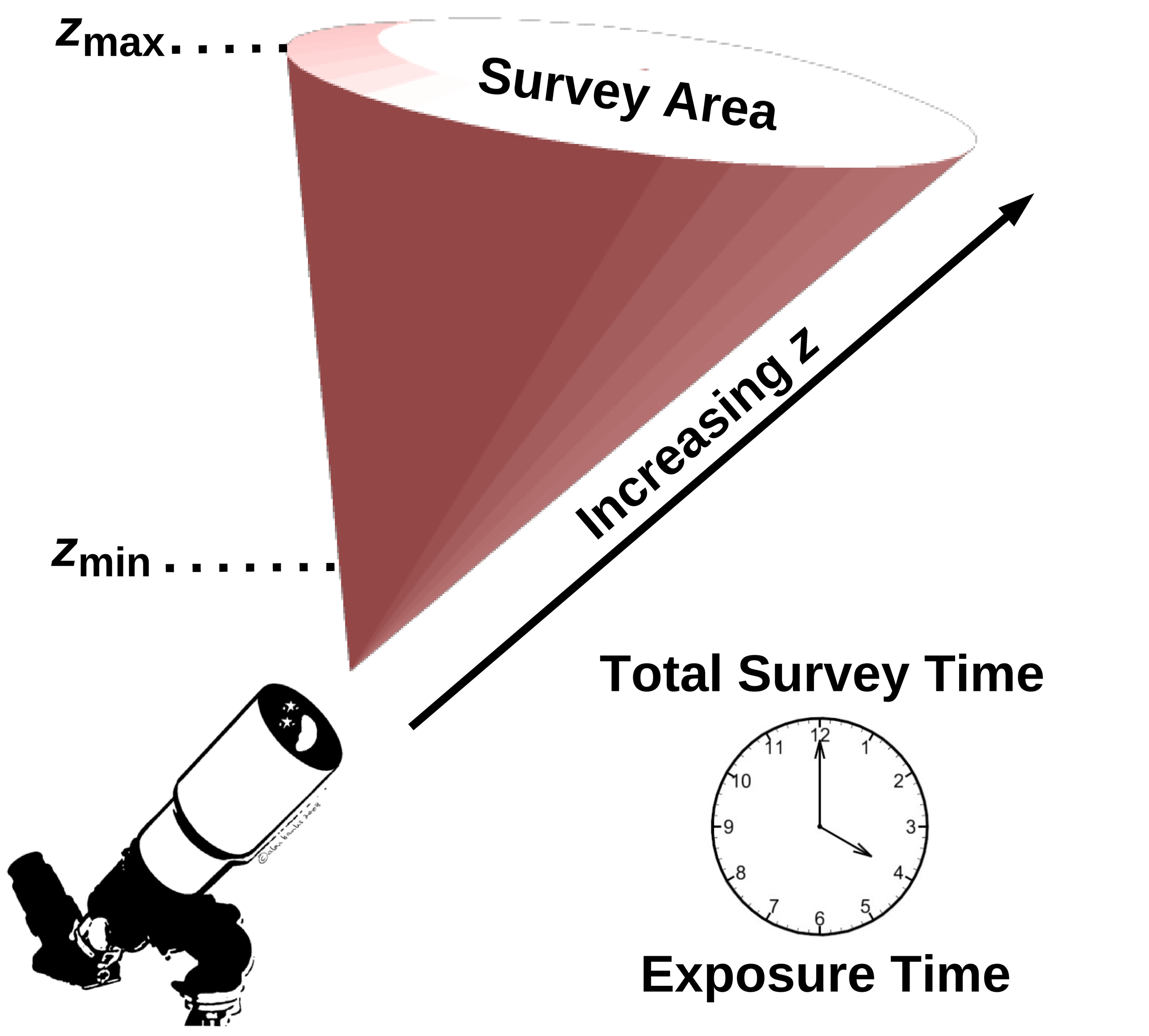


Fig 1. Overview of the typical parameters that are varied in an MCMC Optimisation.

Optimisation is essential for maximising the science return of a survey

Surveys require a huge investment time and money; a given survey will also often be the only shot at a certain dataset for a long period of time.

Optimisation systematically varies the parameters of a survey to maximise a Figure of Merit (FoM). This is usually done via Monte-Carlo Markov Chain (MCMC) methods.

The design of a survey is almost always motivated by model selection. Therefore to assume a single model is correct when optimising is misguided

We consider Bayesian model selection, specifically the *Bayes factor B*, to formulate new FoM.

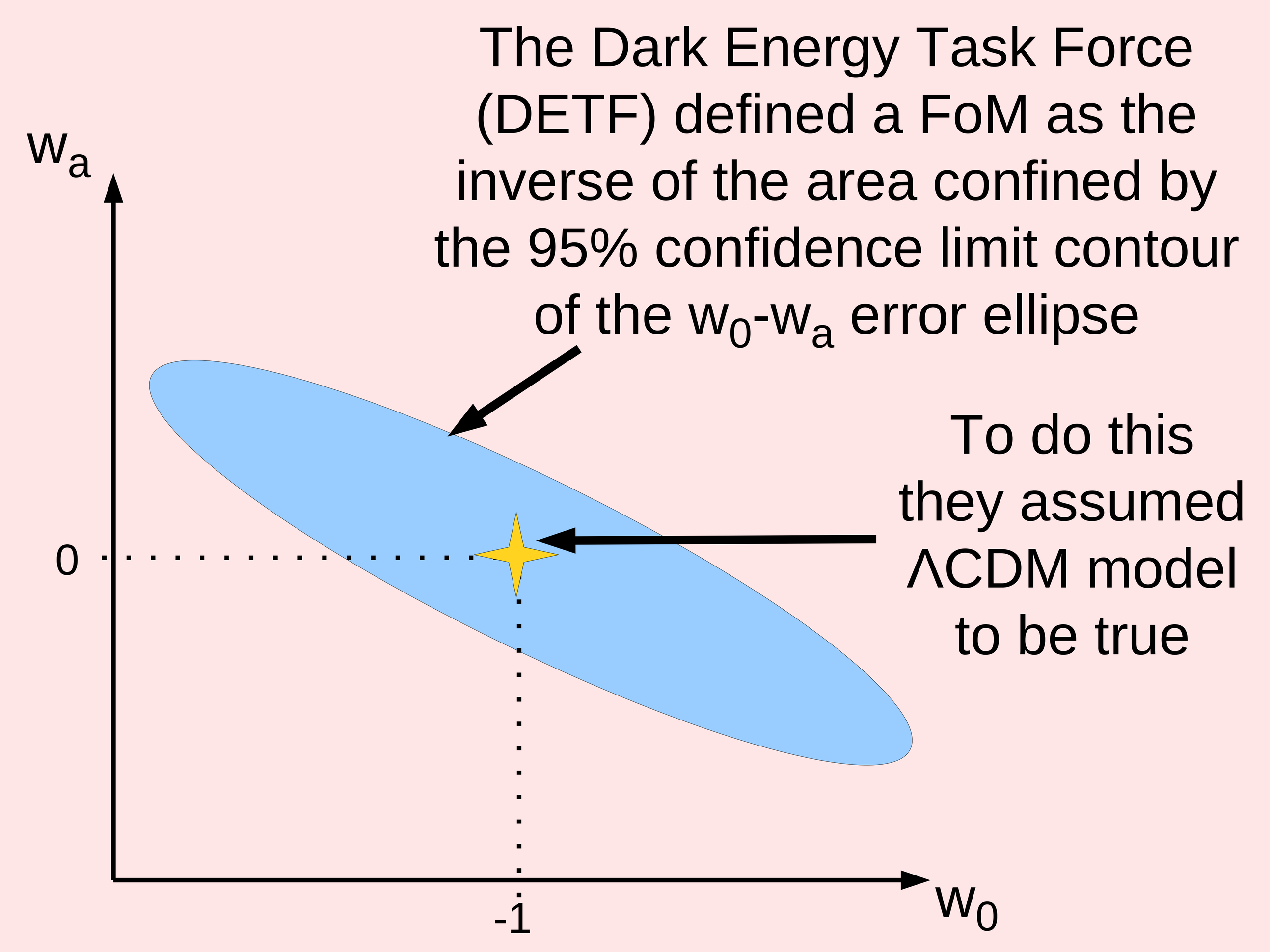


Fig 2. Depiction of the 95% dark energy error ellipse, this uses the CPL parametrisation of the dark energy equation of state w_{DE}.

We identify methods for calculating the Bayes factor that can be effectively implemented in optimisation

The Bayes factor B gives the ratio of the probability, i.e. the change in odds, of two models given a new dataset. In our case we chose M_0 to be ΛCDM and M_1 to be a general evolving dark energy model, the parameter space of which is covered in fig.3.

$$B_{01}=\frac{P(M_0|D)}{P(M_1|D)}=\frac{P(D|M_0)P(M_0)}{P(D|M_1)P(M_1)}$$

| ln(B) | > 2.5 is strong support for M_0 (+ve) or M_1 (-ve).

Calculating P(D|M) involves a complex integral

We use nested sampling to accurately calculate this, then to improve calculation time we instead utilise a Gaussian approximation to the Savage-Dickey Density Ratio (SDDR).

We define two model selection FoM

ln B(-1,0) Bayes factor assuming ΛCDM model, i.e. w_0 =-1 and w_a =0.

Area^{-1} Inverse of the area in which ΛCDM is not discounted despite it not being the assumed model.

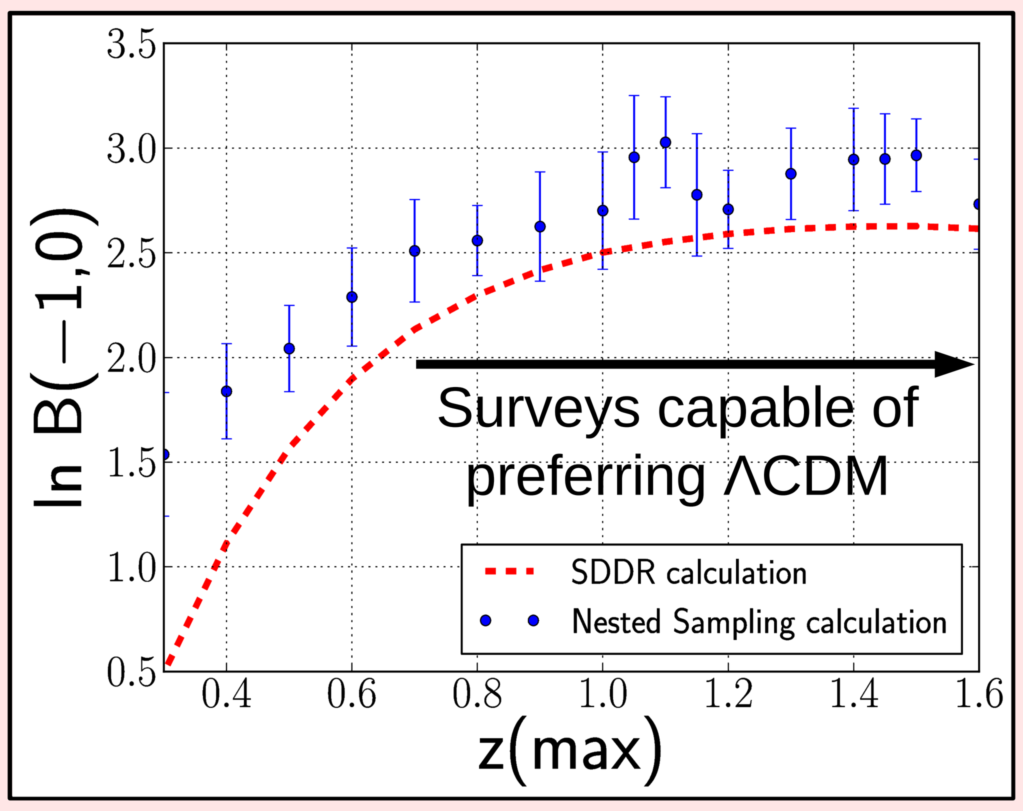


Fig 4. Comparison of nested to SDDR calculations of ln B(-1,0) FoM

Model selection FoM are found to be easier to interpret and add a greater degree of flexibility. Most essentially it is explicit when a survey is good enough.

With nested calculations, z_{max} can be as low as 0.8 for this survey to be effective, much less than z=1.6 as preferred by a DETF optimisation.

Fig. 5 underlines how the model selection FoM can accept a survey when it performs as badly as 50% of optimal according to the DETF FoM.

Fig 3. Scatter plot of Bayes factor calculations involved in calculating our model selection FoMs.

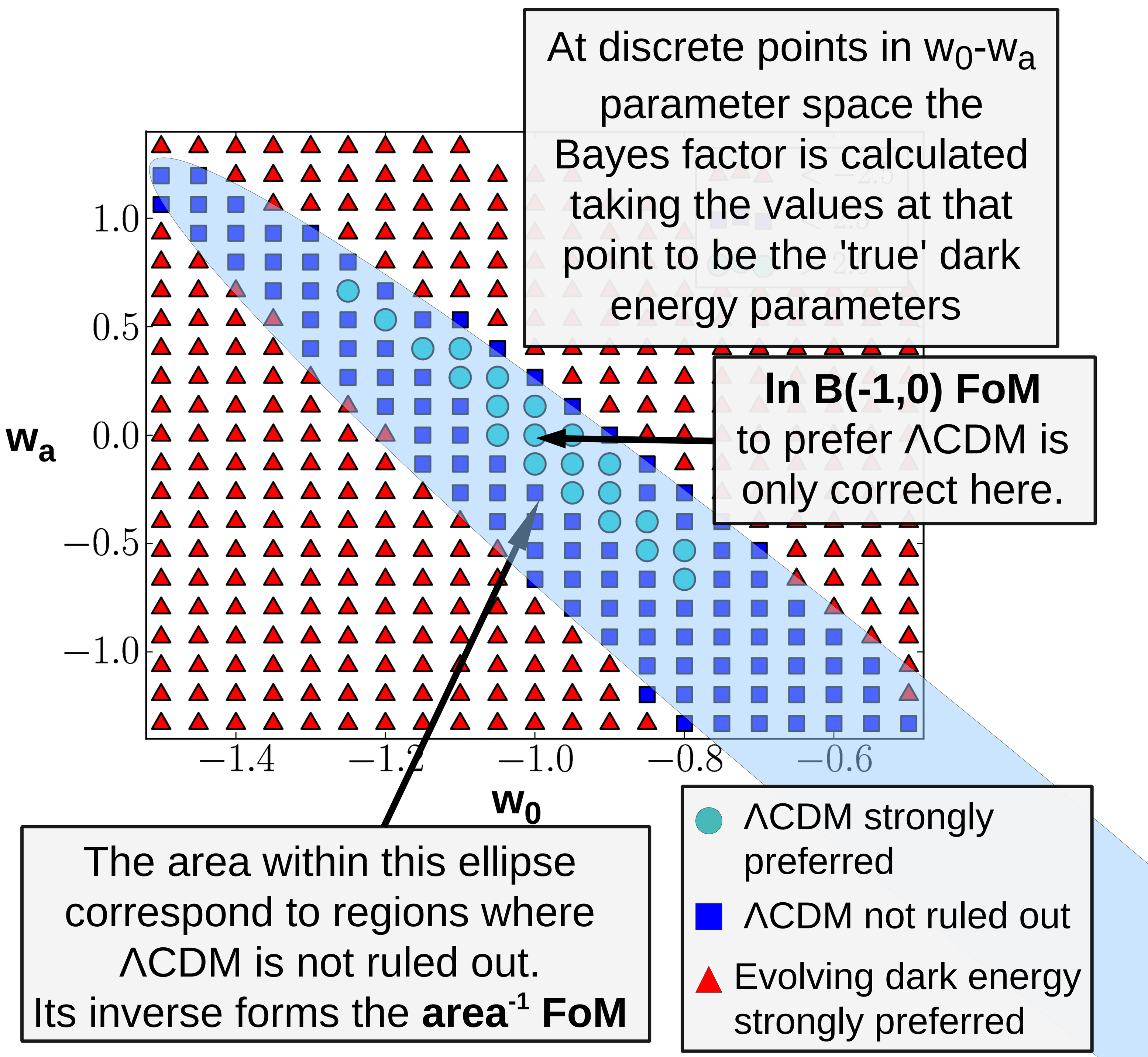
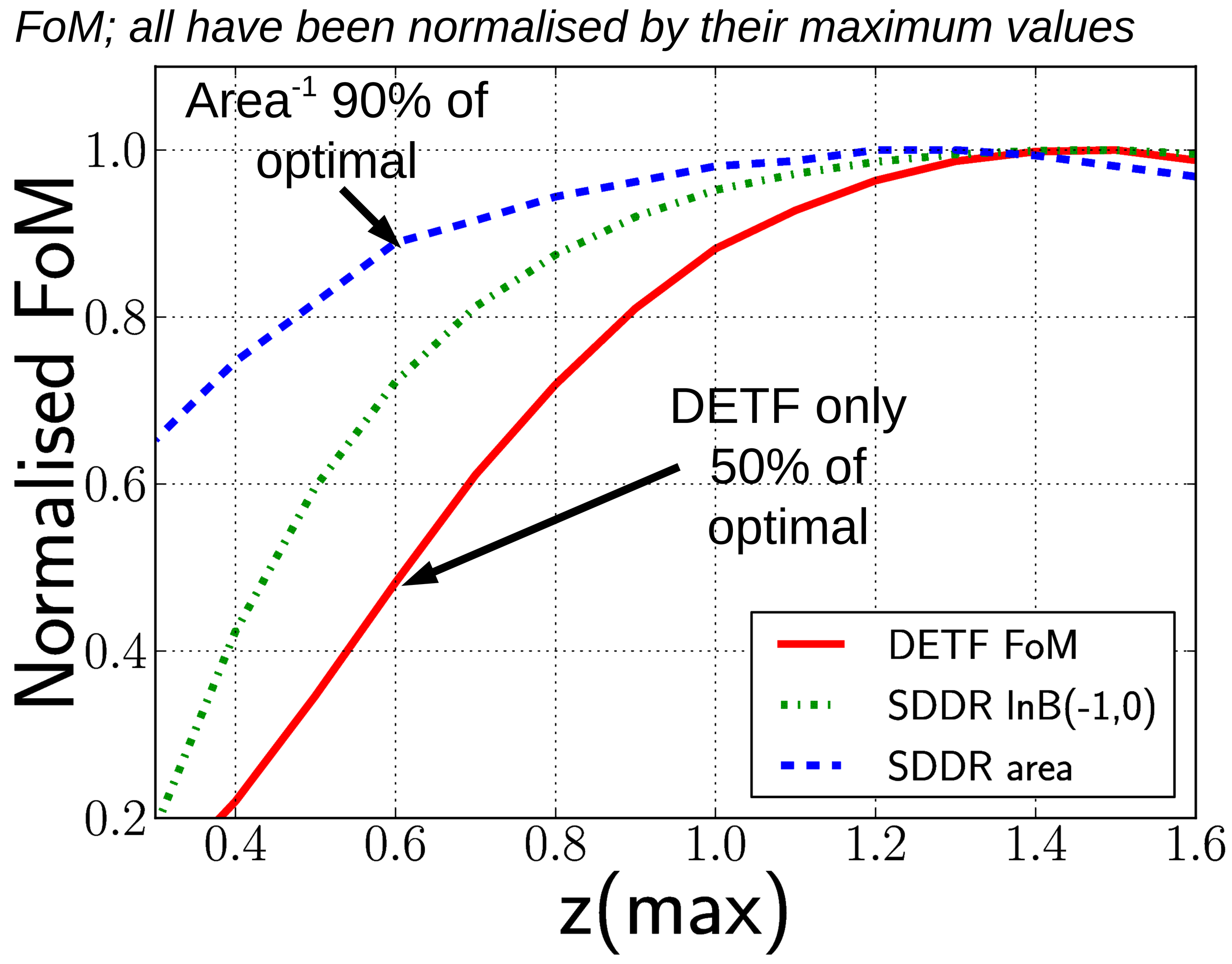


Fig 5. Comparison of the DETF FoM, and our two model selection FoM; all have been normalised by their maximum values



Application: SuMIRe PFS Baryon Acoustic Oscillation Survey

This future BAO survey is planned for the Subaru telescope in Japan.

By the time it is operational BOSS and WiggleZ will be complete. This survey will add very little to their datasets, as is clear from the time allocation performance of the survey.

SuMIRe PFS would not even take us near the next region of relevance for model selection, which is |ln(B)| > 5 corresponding to decisive model preference.

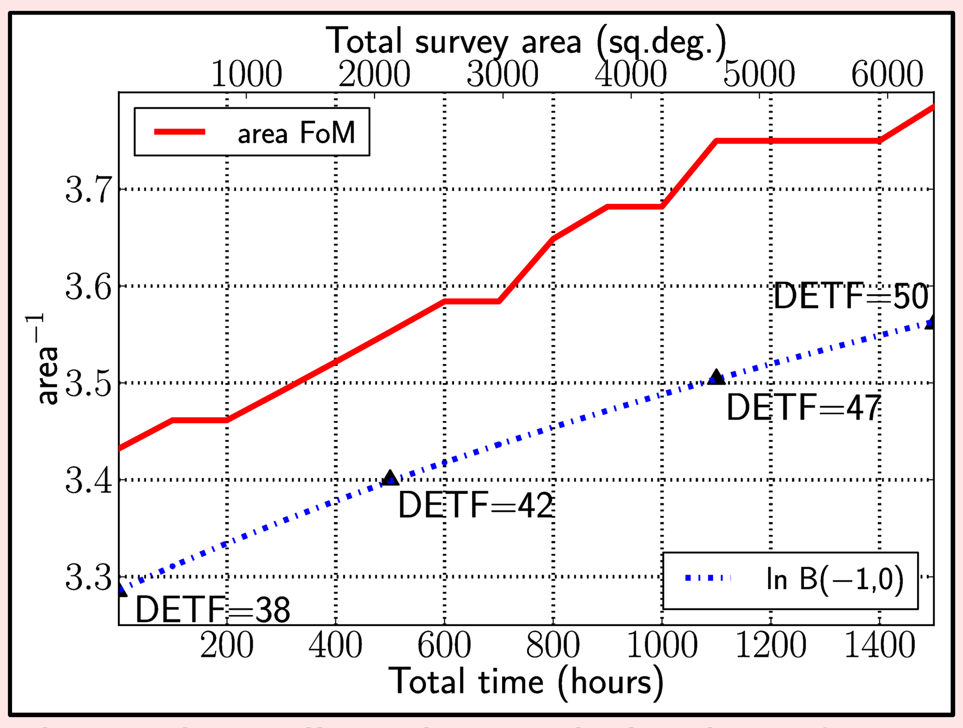


Fig 6. Time allocation optimisation of SuMIRe

Acknowledgements

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Further reading

Watkinson et al. ArXiv: 1111.1870 (or QR Code)
Mukherjee et al. ArXiv: 0512484
Parkinson et al. ArXiv: 0905.3410