

Sensitivity and figures of merit for dark energy supernova surveys

J.-M. Virey¹ and A. Ealet²

¹ Centre de Physique Théorique*, Case 907, 13288 Marseille Cedex 9, France
and Université de Provence, Marseille, France
e-mail: virey@cpt.univ-mrs.fr

² Centre de Physique des Particules de Marseille, Case 907, 13288 Marseille Cedex 9, France

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ABSTRACT

Tracking the origin of the accelerating expansion of the Universe remains one of the most challenging research activities today. The final answer will depend on the precision and on the consistency of data from future surveys. The sensitivity of these surveys is related to the control of the cosmological parameters errors. We focus on supernova surveys in the light of the figure of merit defined by the Dark Energy Task Force. We estimate the impact of the level of systematic errors on the optimisation of SN surveys and emphasize their importance in deriving any sensitivity estimation. We discuss the lack of information of the DETF figure of merit to discriminate among dark energy models and compare the different representations that can help to distinguish Λ CDM from other theoretical models. We conclude that all representations should be controlled through combined analysis and consistency checks to avoid biases.

Key words. cosmology: observations – cosmology: cosmological parameters

1. Introduction

The discovery of the acceleration of the Universe is one of the most intriguing questions in astrophysics today and has been the driver of many theoretical developments trying to find an explanation for this acceleration. These models introduced in general a new component called dark energy (“the DE models”) whose nature is unknown (see e.g. Peebles & Ratra 2003; Padmanabhan 2003; Copeland et al. 2006). Their comparison to observational data is complex and the experimental interpretation would benefit from a “model independent approach”. The strategy is not unique today and is linked to the definition of the cosmological parameters, in particular those that describe the properties of the dark energy component.

Many studies concentrate on the equation of state (w = pressure/density ratio) of this new component. For a cosmological constant, w is equal to -1 but it can be different and/or can vary with time in other DE models. A common way to introduce the time dependence of DE models is to use a redshift dependent parameterization such as (Linder 2003; Chevallier & Polarski 2001):

$$w(z) = w_0 + w_a z / (1 + z) = w_0 + (1 - a)w_a \quad (1)$$

a being the scale factor. The function $w(z)$ is a good observable with adequate properties (Linder 2004a; Linder & Huterer 2005).

On the theoretical side, one needs to estimate whether this parameterization is sufficient to describe DE models whatever the source of the acceleration is. This has been investigated by Linder (2006a); Barger et al. (2006); Linder (2004b) who show

that this parameterization can represent a large class of models, even those that have no real dynamical component. Nevertheless, there are still some potential biases when estimating the effective w_0 and w_a parameters from the actual theoretical phase space (Linder 2006a; Simpson & Bridle 2006).

On the experimental side, many new probes have shown their ability to constrain $w(z)$. To estimate the sensitivity of an experimental survey, named “a data model”, one needs to define figures of merit (FoM), related to the statistical error of the $w(z)$ parameters. This can be used to compare and test different experimental strategies.

The aim of this article is to compare the information provided by the various FoM calculated for Supernova (SN) surveys. In particular, we distinguish FoM needed to compare data models from FoM needed to distinguish between and separate DE models. In Sect. 2, we define the generic SN surveys used as data models in this article. In Sect. 3, we recall the definition of the FoM used by the Dark Energy Task Force (DETF 2006) and use it to compare the sensitivities of the data models. We optimize the total number of SN, N , and the redshift depth, z_{\max} , of the survey in light of the systematic errors. In Sect. 4, we compare the impact of different FoM to distinguish the source of the cosmic acceleration among the DE models.

2. Generic supernova data models

The sensitivity of future surveys depends on several experimental parameters. One concern is to well estimate their uncertainties. For this purpose, we concentrate here on Supernova surveys. We define generic SN data models that are representative of future data:

- $N = 2000$ and $z_{\max} = 1$: such a survey is close to what can be reached from the ground in the near future. Using the

* “Centre de Physique Théorique” is UMR 6207 – “Unité Mixte de Recherche” of CNRS and of the Universities “de Provence”, “de la Méditerranée” and “du Sud Toulon-Var” – Laboratory affiliated to FRUMAM (FR 2291).

DETF terminology, this will be our definition of a “stage 2” data model;

- b) $N = 15\,000$ and $z_{\max} = 1$: this is achievable from the ground with wide coverage. We call it a “stage 3” data model or a “wide” survey;
- c) $N = 2000$ and $z_{\max} = 1.7$: this needs an infrared coverage which implies a space mission. This will be possible at a later stage and we will define it as our “stage 4” or a “deep” survey;
- d) $N = 15\,000$ and $z_{\max} = 1.7$: this is postponed to the future and we will define it as a “stage 5” or a “wide and deep” survey.

Comparison of the potentialities of these data models should describe the expected improvement on the constraints of the DE equation of state with the characteristics of the survey. We focus in particular on the relative importance of increasing the total number of SN (N) collected against the redshift depth (z_{\max}). The feasibility of a deep or a wide survey is strongly correlated to the experimental strategy and is a driver of future surveys. To address this, we will keep the other parameters identical for all the data models. We use the following hypothesis for the cosmology:

- a Λ CDM model;
- a flat universe;
- a strong Ω_m prior, as expected from Planck: $\Omega_m = 0.27 \pm 0.01$. The central value has been chosen to be in agreement with the WMAP-3 year data analysis.

We add the following assumptions:

- we add a sample of nearby supernovae as expected from the SN Factory survey (Wood-Vasey et al. 2004) corresponding to 150 SN at $z = 0.03$ and 150 at 0.08. We call it the “nearby sample” in the following;
- the intrinsic magnitude dispersion is assumed to be 0.15. The corresponding “statistical error” of a redshift bin is $\delta m_{\text{stat}} = 0.15/\sqrt{N_{\text{bin}}}$. We have assumed redshift bins of width $\Delta z = 0.1$.

The level of systematic errors will appear as a fundamental ingredient in the data model comparison (it is true for any analysis as it has been emphasized by DETF 2006; and Kim et al. 2004). We define the systematic error by an extra term δm_{sys} in the magnitude. The total error on the magnitude $m(z)$ is then $\delta m^2 = \delta m_{\text{stat}}^2 + \delta m_{\text{sys}}^2$. Unless otherwise specified, we use an uncorrelated error in redshift bins. We have also estimated the effects of a redshift dependent error (i.e., correlated in redshift bins) with different amplitudes. Adding a redshift dependence does not change our conclusions on errors. It is the amplitude of the systematic errors, whatever the form, that has a strong impact on the future precision (Kim et al. 2004).

We study the two cases with and without this systematic term. Since many papers still provide analysis with statistical errors only, we start with this assumption ($\delta m_{\text{sys}} = 0$) in our study. We then choose a default value of $\delta m_{\text{sys}} = 0.02$ for the systematic case. This choice is an optimistic estimation of the experimental systematic errors. The motivation is that using 2000 SN, this systematic error value is already roughly of the same size as the statistical error and is a limiting factor of the total error.

Higher systematic error values, more realistic, provide similar conclusions when compared to the statistical case. Only the parameter error values are different.

These two “academic” scenarios illustrate the impact of a small systematic effect when statistical errors are at a percent level.

To perform the simulations we adopt a standard Fisher matrix approach which allows a rapid estimate of the parameter errors following the procedure described in Virey et al. (2004). We use the freely available tool “Kosmoshow”¹.

The redshift distribution used in this study is based on the SNAP prescription from Kim et al. (2004). The “stage 4” data model has exactly this distribution. For other data models with different N and/or z_{\max} we have scaled the distribution, truncating it at $z_{\max} = 1$ when relevant and multiplying the remaining number of SN by the adequate factor².

3. Supernova data model sensitivity

We study the potential of the previous four generic data models in term of coverage and statistics, with and without systematic errors. We examine the interpretation of the pivot redshift and of the FoM defined by the DETF. The impact of a systematic error on the sensitivity of these surveys is emphasized. Finally, we give some insights to the optimization of z_{\max} and N .

3.1. The DETF figure of merit

Recently, the DETF (DETF 2006) has proposed a FoM derived from the definition of the pivot point. The pivot parameterization is defined as:

$$w(z) = w_p + (a_p - a)w_a = w_p + \frac{w_a}{1 + z_p} - \frac{w_a}{1 + z} \quad (2)$$

and is equivalent to the parameterization given in Eq. (1). The pivot redshift z_p is defined by (Hu 2005):

$$z_p = -C_{w_0 w_a} \sigma(w_0) / (\sigma(w_a) + C_{w_0 w_a} \sigma(w_0)) \quad (3)$$

where $C_{w_0 w_a}$ is the correlation between w_0 and w_a and $\sigma(w_i)$ is the error on the parameter w_i .

It has been shown (Martin & Albrecht 2006) that the (w_0, w_a) and (w_p, w_a) contours are mathematically equivalent. In fact, w_p is directly related to w_0 and w_a through a linear transformation: $w_p = w(z_p) = w_0 + w_a z_p / (1 + z_p)$. Consequently, any volume in phase space is conserved. This change of definition is convenient to determine the mathematical redshift z_p where the function $w(z)$ has the smallest statistical error since parameters are decorrelated (this corresponds to the so-called “sweet-spot”, see e.g. Huterer & Turner 2001). Note that z_p has been shown to be analysis dependent and has then no real physical meaning (Linder 2006b; Martin & Albrecht 2006). Note also that the error on w_p is equivalent to the one obtained on w when we fix a constant w (as often done in previous work in the literature) since w_p and w_a are decorrelated.

The DETF FoM is defined as $[\sigma(w_p) \times \sigma(w_a)]^{-1}$ (DETF 2006) and is proportional to the inverse of the area of the error ellipse enclosing the 95%CL in the w_0 – w_a plane. In the following, we use this DETF FoM or a ratio of it, where the normalization can change from case to case. We study and show how this FoM can compare data models. We then examine how this FoM can help to discriminate DE models (see also Linder 2006b).

¹ “Kosmoshow” is available at <http://marwww.in2p3.fr/re Noir/Kosmoshow.html>

² For example, for “stage 2”, we take the initial distribution ($N = 2000$ SN up to $z_{\max} = 1.7$) up to $z_{\max} = 1$, this selects 1171 SN then we multiply the number of SN in each redshift bin by 2000/1171 to obtain the desired $N = 2000$ total number of SN. Then, we get the stage 3(5) distribution by multiplying by 7.5 the number of SN of the stage 2(4) distribution.

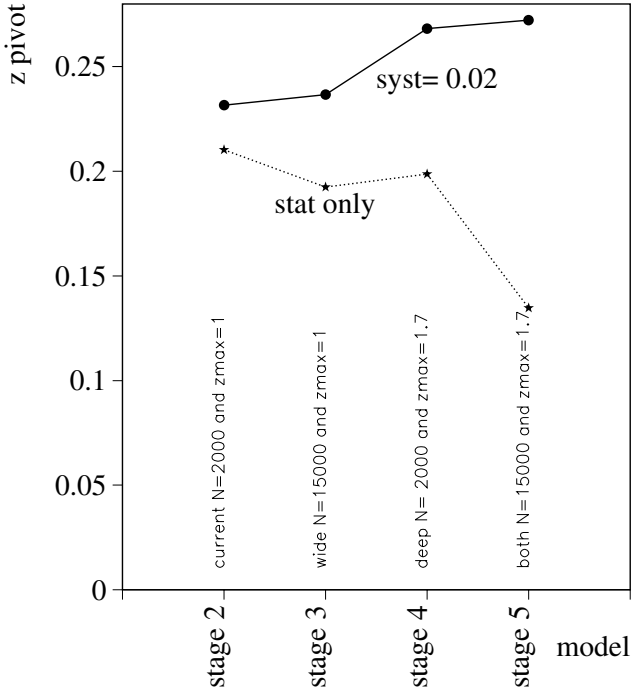


Fig. 1. Evolution of z_p for the data models with (bullets) and without (stars) systematic errors.

3.2. Evolution of z_p

Figure 1 gives the evolution of z_p for the four data models under consideration, with and without systematic errors. z_p ranges from 0.14 to 0.27 and is sensitive to the systematic errors and the data model. We have also studied the variation of z_p when changing the SN nearby sample, the Ω_m prior or the fiducial cosmology. We find, for instance, that the statistics of the SN nearby sample or the Ω_m prior have a stronger impact on the z_p value than the variation of z_{\max} . We conclude that z_p varies in the range 0 to 0.5 and the variations are neither physical nor intuitive. This study has confirmed that this parameter is not representative of any physical characteristic of a survey (or of the DE dynamics) and should not be used for any comparison.

w_p then can be ambiguous as corresponding to different redshift values for each data model. The contours in a plane where w_p is one of the two variables (e.g. the (w_p, w_a) or (Ω_m, w_p) planes) will be more difficult to interpret and should be taken with caution when comparing surveys with different characteristics. However, there is no ambiguity with the DETF FoM, as it corresponds to the area of the error ellipses which is identical in the planes (w_p, w_a) and (w_0, w_a) (DETF 2006). Similarly, w_p can be used to exclude a cosmological constant when compared to -1 (but other observables are maybe more efficient, see Sect. 4).

3.3. The DETF figure of merit for the SN data models

The DETF FoM for the four data models are shown in Fig. 2. Stars correspond to calculations with statistical errors only and bullets when a systematic error of 0.02 is included.

The strong impact of the systematic error term appears very clearly in Fig. 2. First, we observe a strong reduction of the FoM value when systematic errors are included. Secondly, we see different variations of the two cases, when increasing the size of the survey (N) or the survey depth (z_{\max}).

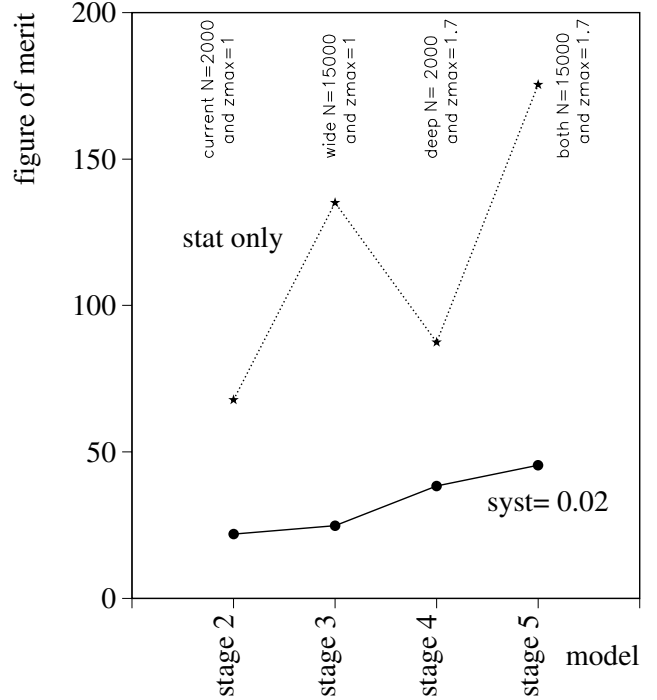


Fig. 2. DETF figure of merit with (bullets) and without (stars) systematic errors.

With statistical errors only, a large statistical sample yields a better FoM than a deep survey as can be seen in the stages 3 and 4. The relative improvement of stage 3 to stage 2 is of the order of 2.0, whereas it is only 1.3 for stage 4 relative to stage 2. In other words, a stage 3 (wide survey) provides a sensitivity 55% better than a stage 4 (deep survey). This indicates that it is better to increase N rather than z_{\max} after stage 2.

Concerning the stage 5 data model, there is also a strong improvement of the FoM. It increases by 30% (100%) compared to the stage 3 (4) data model.

With systematic errors, the conclusion is reversed and stage 4 has a far better potential than stage 3. We see in Fig. 2 an improvement of the order of 56% for stage 4 relative to stage 3.

The relative improvement of stage 3 to stage 2 is now only of the order of 1.15 compared to 1.75 for stage 4 to stage 2, showing it is now preferable to increase z_{\max} rather than N after stage 2.

Concerning stage 5, the improvement relative to stage 4 is only of 18% which is moderate compared to the technical complexity of such surveys.

For other values of systematic errors, these results are confirmed:

- with systematic errors higher than $\delta m_{\text{syst}} = 0.02$, the difference between stages 3 and 4 steepens (i.e., the FoM ratio increases) which reinforces the need for a deep survey;
- stages 3 and 4 are equivalent, if both have some systematic errors of the order of 0.006. Below this value a wide survey (stage 3) is better, and above it a deep survey (stage 4) is preferable;
- if we keep $\delta m_{\text{syst}} = 0.02$ for stage 4, then the systematic errors of stage 3 should be controlled at a better level than 0.012 to be more efficient than stage 4;
- using a redshift dependence for the error gives similar conclusions, only the various quoted values will slightly change;

- the relative merit of stage 5 compared to stage 4 or stage 3 is very dependent on the level of systematic errors assumed in the analysis.

The latest SN data from Riess et al. (2006) can be interpreted as an improvement of the FoM of the order of 5. Then a stage 2 or 3 survey with a level of systematic $\delta m_{\text{sys}} = 0.05$ will not improve the current result and may be considered as useless. Only an improvement of the systematic level can help. The limitation of stage 4 and 5 is a systematic error of 8%.

Consequently, the control of the level of systematic errors is the key parameter to discriminate between future wide and deep SN surveys. This is understandable since the statistical error soon will be dominated by these systematic errors. Our conclusions are valid to quantify the impact of systematic errors but give no estimate on the methods needed to derive such a level of control. A large sample should help in understanding systematic errors and its size will depend essentially on the SN properties. In the next section, we perform a more detailed analysis of the optimisation between N , z_{max} and the systematic errors.

3.4. Optimization of the survey depth

Linder & Hutnerer (2003) have emphasized that “the required survey depth depends on the rigor of our scientific investigation”. They show that it is mandatory to have $z > 1.5$ to reduce cosmological and DE models degeneracies when systematic error are included to avoid wrong precision and biased results.

In this section, we optimize the depth z_{max} using the figure of merit on data models that have a fixed number of SN but a different z_{max} . We move z_{max} by steps of size 0.1 equivalent to the redshift bin size of our SN distribution.

For each adjacent model, we compute the ratio of the FoM defined for the model at z_{max} to the one at an adjacent redshift bin of $z_{\text{max}} - 0.1$:

$$R = \frac{\text{FoM}^{z_{\text{max}}}}{\text{FoM}^{z_{\text{max}}-0.1}} = \frac{(\sigma(w_a)\sigma(w_p))^{z_{\text{max}}-0.1}}{(\sigma(w_a)\sigma(w_p))^{z_{\text{max}}}}. \quad (4)$$

In Fig. 3, we plot this ratio for the two statistics $N = 2000$ and $N = 15000$, with and without systematic errors. If adding a new redshift bin does not improve the errors, the ratio is close to one. The gain is defined by the difference to 1.

The four curves of Fig. 3 show the same behaviour and a large improvement is seen when increasing z_{max} , up to a plateau where the gain start to be small. If we take a 5% gain (the horizontal line in Fig. 3) as the minimal improvement we can accept for an increase of the survey, we can estimate an optimum for z_{max} :

- with systematic errors of 0.02 and $N = 15000$ (plain curve) $z_{\text{max}} = 1.7$ (the vertical line corresponds to $z_{\text{max}} = 1.7$);
- with systematic errors of 0.02 and $N = 2000$ (dash-dotted curve) the change is small and $z_{\text{max}} \approx 1.65$;
- with statistical errors only and $N = 15000$ (dashed curve) z_{max} is strongly reduced at 1.15;
- with statistical errors only and $N = 2000$ (dotted curve) one gets $z_{\text{max}} \approx 1.25$.

Surprisingly, the statistical case has a relatively small dependence on N . This comes from cancellations in the z_{max} evolution of the w_a and w_p constraints, which exhibits strong variations with N but in opposite directions.

This can be better understood by plotting directly the FoM (not the ratio). Figure 4 shows that the FoM increases with z_{max}

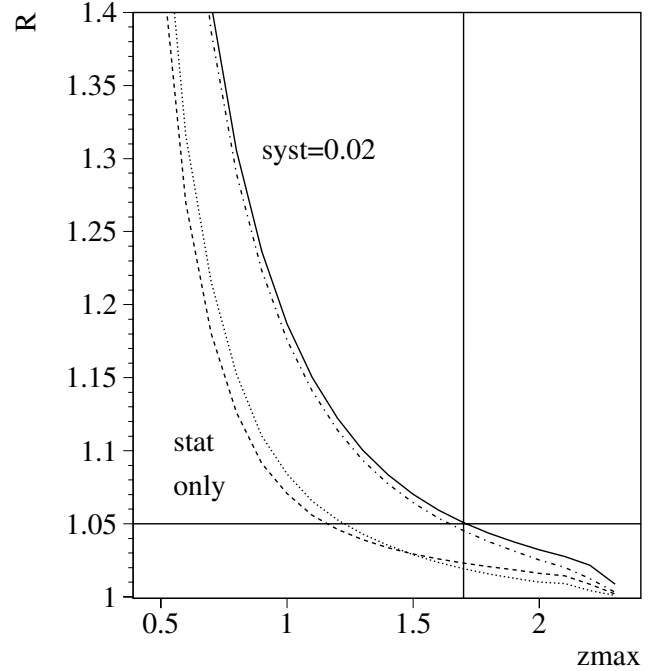


Fig. 3. Evolution with z_{max} of the DETF FoM ratio assuming either $N = 2000$ or $N = 15000$ SN and for the two cases with and without systematic errors (plain (dash-dotted) curve: systematic case with 15000 (2000) SN, dashed (dotted) curve: statistical case with 15000 (2000) SN). The FoM ratio is defined for adjacent z -bin (see text).

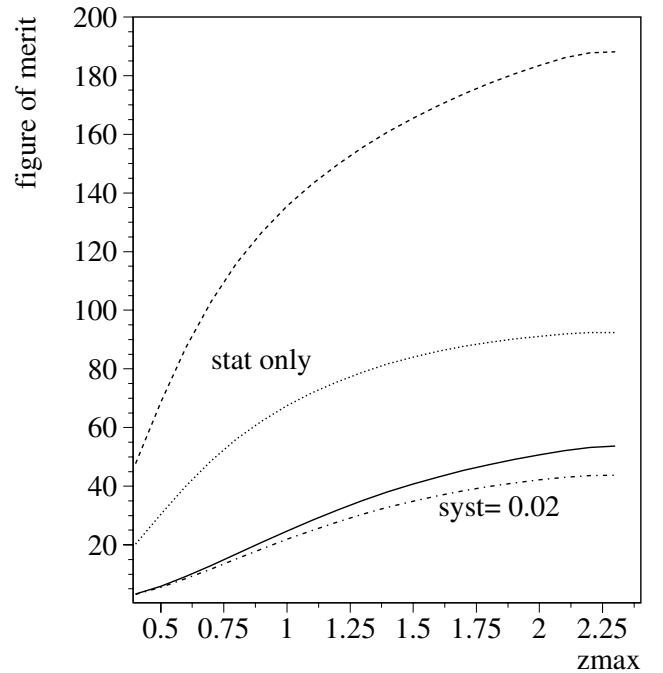


Fig. 4. The DETF figure of merit (unnormalized) as a function of z_{max} with the same labels as Fig. 3.

and also with N . With systematic errors, the FoM is not strongly dependent on N whereas with statistical errors only, the variations due to N are stronger than the ones due to z_{max} . For example, one has the same FoM (90) for $N = 2000$ with $z_{\text{max}} = 1.7$ and for $N = 15000$ with $z_{\text{max}} = 0.7$.

We deduce from this study:

- when the systematic errors are neglected, N is the fundamental parameter and z_{\max} around 1 is sufficient to derive strong constraints on the dark energy equation of state;
- if systematic errors are of the order of $\delta m_{\text{sys}} = 0.02$, a SN sample at $z > 1$ is mandatory to increase the constraints that can be reached from the ground (e.g. stages 2 and 3) whatever the statistical size;
- beyond $z > 1.7$, the improvement is marginal (less than 5% by redshift bin of size 0.1). This result is weakly dependent on N but dependent on δm_{sys} ;
- a survey with a higher level of systematic errors requires a higher z_{\max} and has a reduced dependency on N ;
- if we introduce systematic errors with a redshift dependency (a correlation between bins), the conclusion is identical to the constant case and the optimal z_{\max} depend on the larger systematic error value.

Thus, we see that for any realistic surveys, it will be more important to have a coverage beyond $z = 1$ to be able to control the precision than to increase the statistics. This is an important driver for any future SN survey.

4. Comparing dark energy models

We want to address not only the statistical sensitivity of the SN surveys but also their capability to separate Dark Energy models. More precisely, we would like to know if a particular DE model is in agreement with the standard Λ CDM model. Then we need to test the compatibility of the two models. The DETF FoM is only one number and does not allow us to answer this question. For example, Linder has shown (Linder 2006b) that the key discriminant for thawing (freezing) models (see Caldwell & Linder 2005, for model definitions) is the long (short) axis of the (w_0, w_a) ellipse.

Consequently, contour plots should provide more information than the DETF FoM and/or the pivot point to interpret data. We have looked in more detail at the different information to estimate the most useful FoM when we compare DE models.

The information is contained in the following FoM: $\sigma(w_0)$, $\sigma(w_a)$, $\sigma(w_p)$, $\sigma(w_0) \times \sigma(w_a)$, $\sigma(w_p) \times \sigma(w_a)$, the two-dimensional (w_0, w_a) contours and the redshift function $w(z)$ with its error shape $\sigma(w(z))$. We do not consider contours with w_p since they are mathematically equivalent to the contours with w_0 instead (Martin & Albrecht 2006), and multiple w_p contours are difficult to interpret (see Sect. 3.2).

The study of the variations of the different errors, as we have done in the previous section for the DETF FoM, is particularly interesting in comparing data models. The individual variations of w_0 , w_a and w_p do not provide any supplementary information to that given by the DETF FoM. The behaviours of $\sigma(w_0)$, $\sigma(w_a)$ and the DETF FoM are very similar. Only $\sigma(w_p)$ behaves very differently as it has a very weak dependence on data models, in particular it has almost no dependence on z_{\max} (see Fig. 3 of Linder & Huterer 2003).

To compare DE models, in addition to the errors we also need the central values of the cosmological parameters. We focus now on two different FoM: contour plots in the (w_0, w_a) plane and some representation of $w(z)$ with error shape variations with the redshift.

Figure 5 gives the 95% CL contours in the (w_0, w_a) plane for the four data models with systematic errors. We see two sets of contours, the larger ones with the data models with $z_{\max} < 1$ and

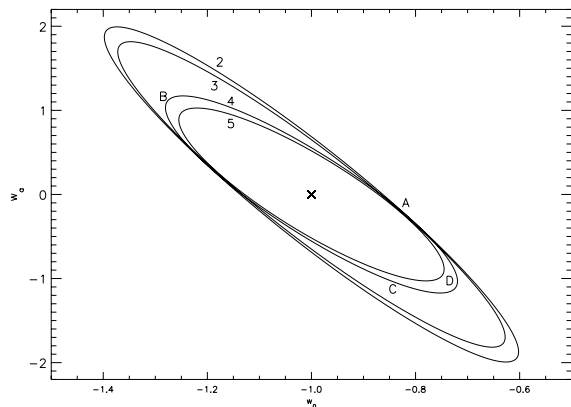


Fig. 5. 95% CL contours in the (w_0, w_a) plane for the four data models with systematic errors. The labels of the DE models are given on the plot (with a small shift of model D for clarity). Stage number for the data models are given on each contour.

Table 1. Definition and properties of the DE models taken for illustration. The “parameters” (“z-region”) column gives the cosmological parameters (the redshift region) which are the most efficient to distinguish the DE model from a cosmological constant.

DE model	w_0	w_a	Parameters	z-region
A	-0.82	-0.2	w_p	z_p
B	-1.27	1.15	w_0, w_a	low- z & high- z
C	-0.85	-1	w_a	high- z
D	-0.75	-0.95	w_0	low- z

the smaller ones with $z_{\max} > 1$, a result already obtained from the DETF FoM. (Adding in this figure the curves corresponding to the pure statistical cases for the four data models allows us to recover the results of Sect. 3.3, however the resulting figure is not easily readable.)

The advantage of the (w_0, w_a) contour representation is the possibility to “directly” define some classes of DE models in this plane. Several recent works have been devoted to this subject (Barger et al. 2006; Linder 2006a; see also Caldwell & Linder 2005; Scherrer 2006; Chiba 2006, for DE model trajectories/locations in the $(w, w' = dw/d \ln a)$ plane). Consequently, in Fig. 5 we can represent the different classes of models and study their compatibility with Λ CDM in each data model. In this way, Linder has shown (Linder 2006b) that to increase the constraints on “thawing” (“freezing”) models we need to reduce the long (short) axis of the ellipse. However, to optimize such constraints we need to know which parameters control the long and short axis (and their directions) of the contour. To understand what is important in a survey to improve the discrimination among DE models, we introduce four phenomenological models defined by their (w_0, w_a) pair of values (see Table 1) and which are at the boundary of the 95% CL of the stage 4 data model. We study the variation of the constraints for these DE models for the four data models.

Model A is close to the border of the thawing region and, from Fig. 5, we see it will be difficult to exclude this model even at stage 5. On the other hand, the exclusion of models B, C and D is improved with better surveys.

It appears that the sensitivity to the data models is higher along the larger axis. Consequently, the optimization of future SN surveys are able to reduce the degeneracy among w_0 and w_a which is represented by a reduction of the long axis, whereas it has almost no impact on the short axis. This conclusion should

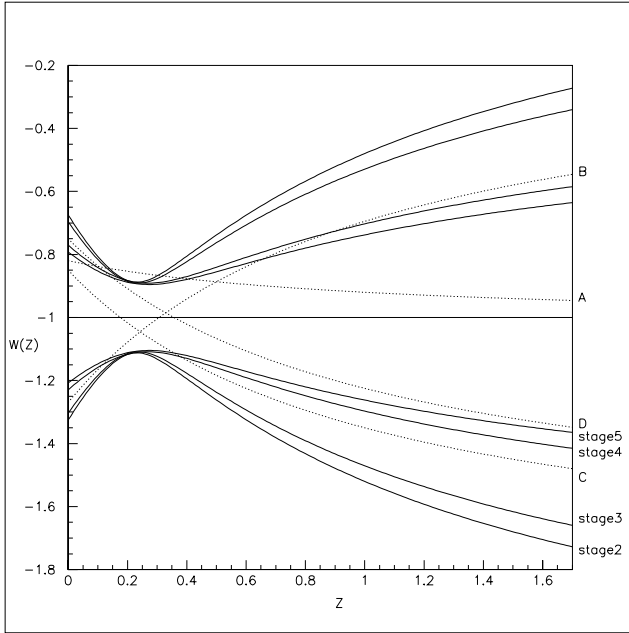


Fig. 6. Reconstructed $w(z)$ and the associated errors for the four data models with systematic errors. The errors correspond in increasing order to stage 5, 4, 3 and 2. The dotted curves give the equation of state for the models A–D and are labelled on the plot.

be tempered. Indeed, if all the ellipses for the data models meet in two points (model A being one of them) this is mainly due to two assumptions: we have taken the same SN distributions (including the same nearby sample) and the same systematic errors ($\delta m_{\text{sys}} = 0.02$). An important effect of these assumptions concerns the orientation of the ellipses but realistic survey characteristics allow only small rotations of the contours. The strongest effect, as mentioned in the previous section, comes from the assumed level of systematic errors which is the fundamental limitation of the size of the constraints. Then to go beyond, a better understanding of the systematic errors is mandatory.

It is possible to represent the result in a different way which can be easier for theoreticians. The error on $w(z)$, within the Fisher matrix approximation, is given by:

$$\sigma^2(w(z)) = \sigma^2(w_0) + \sigma^2(w_a) \frac{z^2}{(1+z)^2} + 2C_{w_0 w_a} \sigma(w_0) \sigma(w_a) \frac{z}{(1+z)}. \quad (5)$$

Figure 6 represents the equation of state $w(z)$ for the different DE models with the error shapes obtained for the various data models.

In this figure, we represent the expected error at 2σ of each survey for a Λ CDM fiducial model compared with the true $w(z)$ of each DE models (A–D). This representation is complete and explicitly gives the z dependence of the constraints. The four DE models are described with the same parameterization and show behaviours outside the 2σ limit of the error shape of the Λ CDM model for stages 4 and 5. They are excluded for different reasons:

- model A is excluded by the best constraints at the pivot redshift, i.e., the best observable to exclude A is w_p ;
- model B is excluded by the low z and high z constraints;
- model C is excluded by the high z (i.e., w_a) behaviour;
- model D is excluded by the low z (i.e., w_0) behaviour.

The $w(z)$ vs. z representation has the advantage to visualise the existence of the sweet-spot at the pivot point and its impact on the result. Anyway, it shows also that it is not possible to use w_p only. For example, model A is excluded by the w_p constraints at $z = z_p$ and not thanks to the SN discovered at this redshift. This is an example of the difficulty of using this information as physical. Then, even if this representation is convenient it should be taken with some caution. The error shapes given by Eq. (4) are strongly parameterization dependent. Consequently, some bias may be present if the chosen parameterization ($w(z) = w_0 + w_a z / (1+z)$ in this study) is far from reality. In addition, there are strong correlations among the cosmological parameters and among the redshift bins, and the error shapes of $w(z)$ may have some artefacts if not used in a realistic redshift range (i.e., the range probed by data).

Nevertheless, beside the above difficulties this representation may be useful for consistency checks. This representation is also sensitive to the systematic errors and whatever the parameterization is, one can express the constraints and make some data model comparisons. We emphasize that it is also possible to provide some results in this plane that are independent of any choice of parameterization to describe the DE dynamics, like the so-called “kinematical” approach (see e.g. Daly & Djorgovski 2003, 2004). This kind of analysis has also some problems of interpretation: errors are in general difficult to estimate and more noisy, and it does not avoid the correlation in redshift bins of the results. However, these various approaches are complementary and may be confronted in this plane.

Thus, excluding particular DE models from a cosmological constant, require the use of the (w_0, w_a) plane and/or of the $w(z)$ vs. z representation. This is far better than simply comparing w_p with -1 . In order to obtain more subtle details, like the connection to a particular class of DE models or the z dependence of the constraints, both representations are useful. For instance, the expression of the redshift dependence has some advantages in breaking the degeneracy line present in the (w_0, w_a) plane. Models along this line may be discriminated from a cosmological constant by the measurement of the low and high redshift behaviour of the equation of state, as encoded in the w_0 and w_a parameters. But DE models that are orthogonal to the degeneracy line may be excluded by the constraints at the pivot redshift, whose expected precision depends weakly on the SN survey configuration but more on the control of systematic errors.

The expected interpretation is then very dependent on all the details of the design of the SN surveys, and in particular very dependent on the level of systematic errors. This strategy is also dependent on the chosen parameterization, whose effect should also be carefully estimated.

5. Conclusions

We have studied, using the DETF figure of merit, the optimisation and interpretation of future supernova surveys compared to the forthcoming ground precision.

We find that the DETF figure of merit is a good approach for testing the optimisation of a survey.

We test this approach by looking at the sensitivity of the surveys in term of the number of SN and on the depth of the survey with particular attention to the effects of systematic errors. The DETF figure of merit is very powerful to show the difference in sensitivities of surveys with large statistics compared to deep surveys with smaller statistics. We show, for example, that adding 1 or 2% of systematic errors changes drastically the optimisation and push to increase the depth rather than the number

of objects. This conclusion is very strong when not only statistical errors are considered, and is not dependant on the kind of systematic errors we can consider (e.g. correlated in redshift or not).

More precisely, for 2% of uncorrelated systematic errors, we show that there will be no extra information for the cosmology with more than 2000 SN and that the gain will mainly come from an increase of the depth of the survey up to a redshift of 1.7.

The drawback of the DETF method is the lack of information to estimate the discriminating power among DE models, as the central values of the parameters are not used.

Contour plots in the (w_0, w_a) plane give a better understanding and a good discrimination since classes of DE models can be placed in this plane. Comparing data models we find that some degeneracies among cosmological models remain even for the most ambitious project. Complementary information is contained in a representation of $w(z)$ with its error shape. This allows us to understand the compatibility of the model with the different observables, and in particular, to represent the redshift dependence of the error. However, the results remain in general parameterization dependent and the interpretation is challenging. This redshift plane may be useful for consistency checks and data model compatibility and comparison.

A solution to improve the sensitivity of the SN analysis is to combine SN data with other probe information. This is certainly powerful as emphasized by the DETF but this should be manipulated with some caution as systematic errors will dominate the future analyses and will introduce even stronger bias in a combination. The best test will be to check the compatibility between probes when dominated by systematic errors, in a coherent way (same theoretical assumptions, same framework, same treatment of systematic errors). Combination of probes two by two will

then help to control systematic effects. This will be also a good cross check of the internal hypothesis and a control of results.

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