

Reconstructing dark energy

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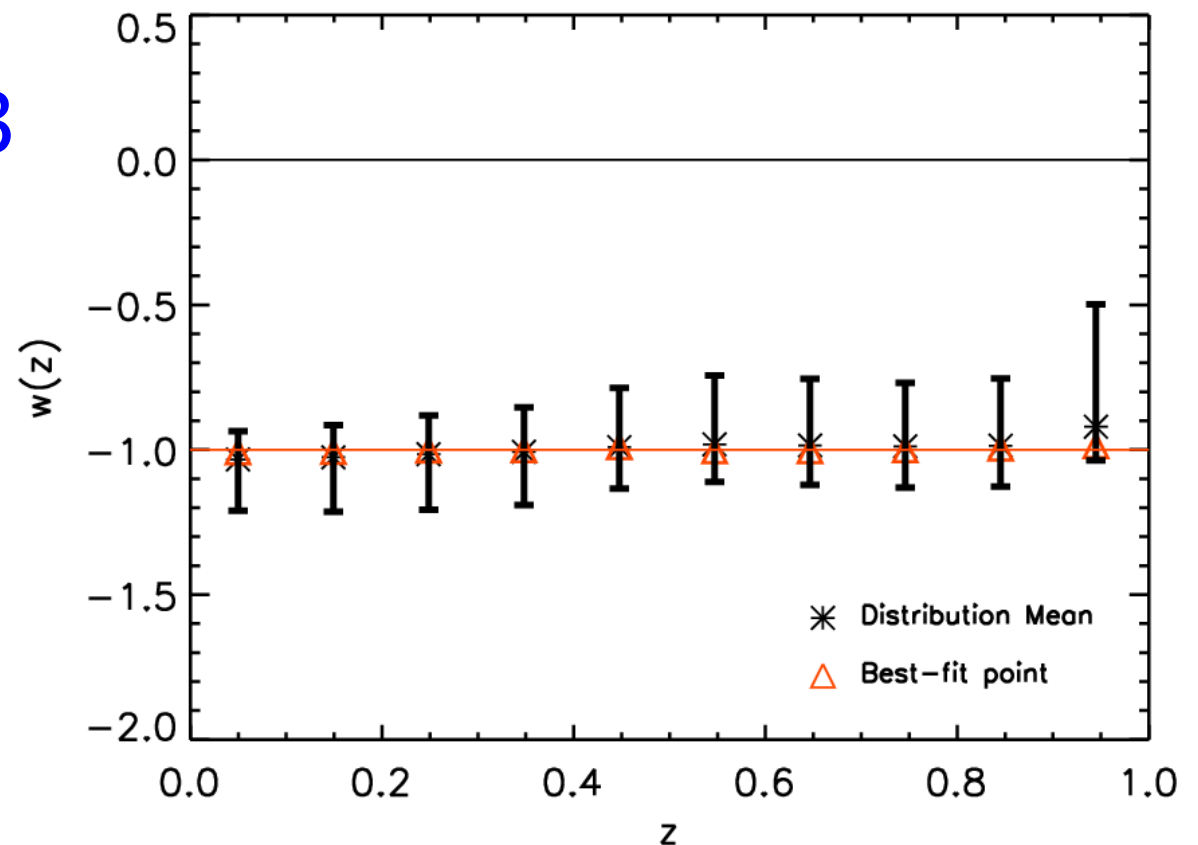
The accelerating Universe

Dark energy: a component with (possibly time dependent) negative pressure

$$\frac{d}{dt} \left(\frac{\dot{a}}{a} \right) = -\frac{4\pi G}{3} \rho(1 + 3w)$$

acceleration
for $w(z) = p/\rho < -1/3$

So far, all data
compatible with the
hypothesis of a
cosmological constant
($w = -1$)



Number of assumptions

- *Weak gravitational lensing*
Challenging control of systematics
- *Baryonic acoustic oscillations*
Less accurate, but systematics free
- *Integrated Sachs–Wolfe effect*
Limited by cosmic variance
- *SNe luminosity distance*
SNe variability, evolution
- *Cluster abundance*
Do we understand clusters? Calibration

Discriminative power

- *$w(z)$ vs Λ*
- *Dark energy vs gravity*
- *Growth of structures vs geometrical tests*

Reliability

- *Robust to systematics*
- *Based on well known physical observables*
- *Multiple, independent techniques*

Flexibility

- *Maximise discovery space*

Luminosity distance (SNIa):

$$D_L(z) = \left(\frac{L}{4\pi\ell} \right)^2 = \frac{c}{100h} (1+z) \int_0^z \frac{1}{H(x)} dx$$

Angular diameter distance (CMB, BAO \perp):

$$D_A(z) = \frac{d}{\theta} = (1+z)^{-2} D_L(z)$$

Hubble function (BAOr):

$$H^2(z) = (1 - \Omega_m - \Omega_{DE}) (1+z)^2 + \Omega_m (1+z)^3 + \Omega_{DE} \exp \left[3 \int_0^z \frac{1+w(z)}{1+z} dz \right]$$

Reconstructing dark energy

- *Parametric methods might lead us astray, especially if they are purely phenomenological*
- *Popular methods:*

$$w(z) = w_{\text{eff}}$$

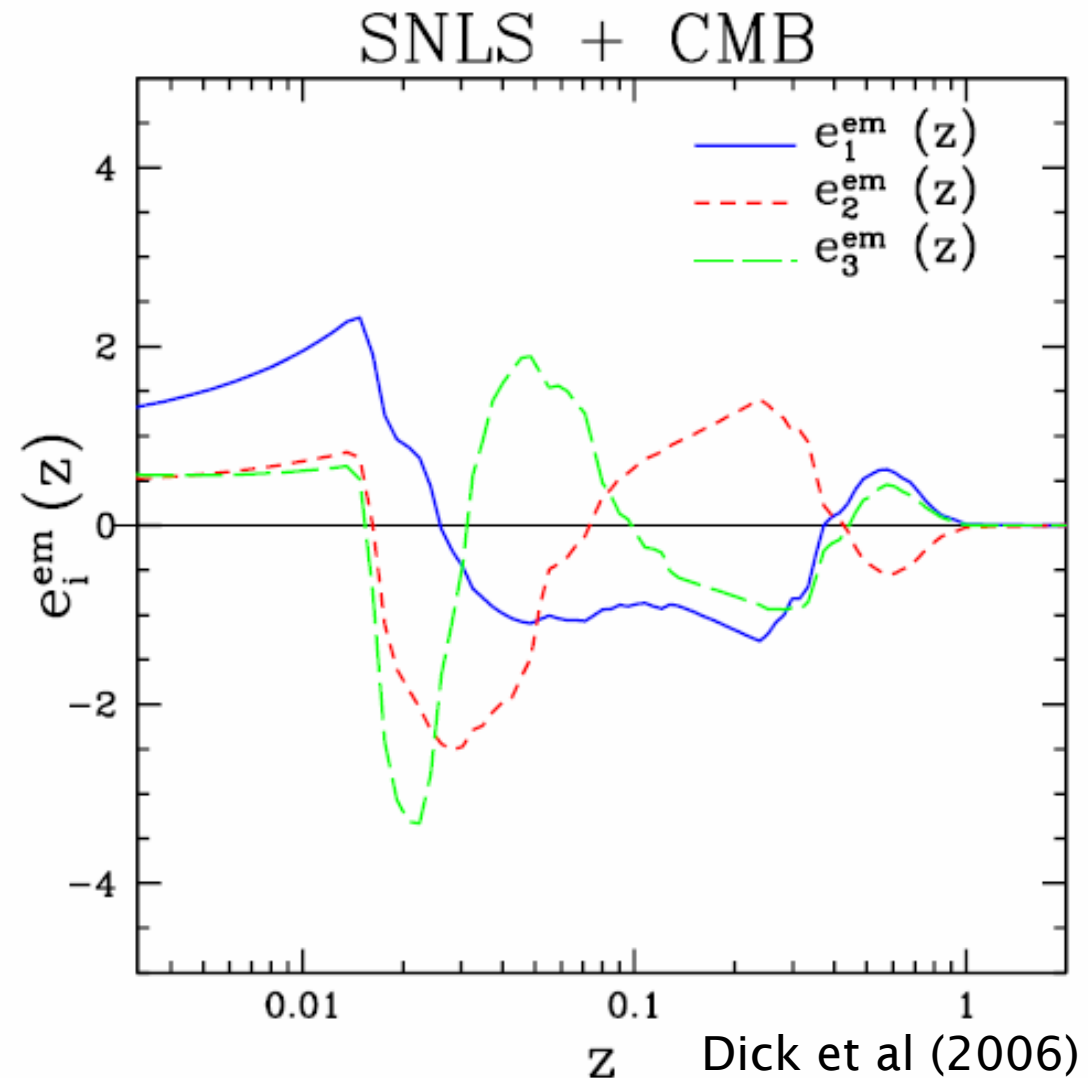
$$w(z) = w_0 + (1-a)w_a$$

eigenmodes or
PCA analysis

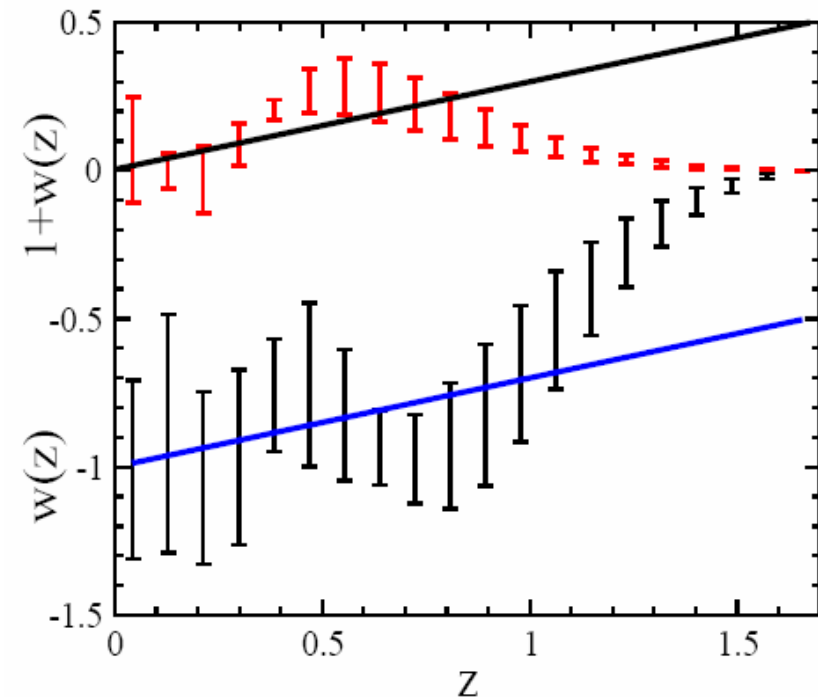
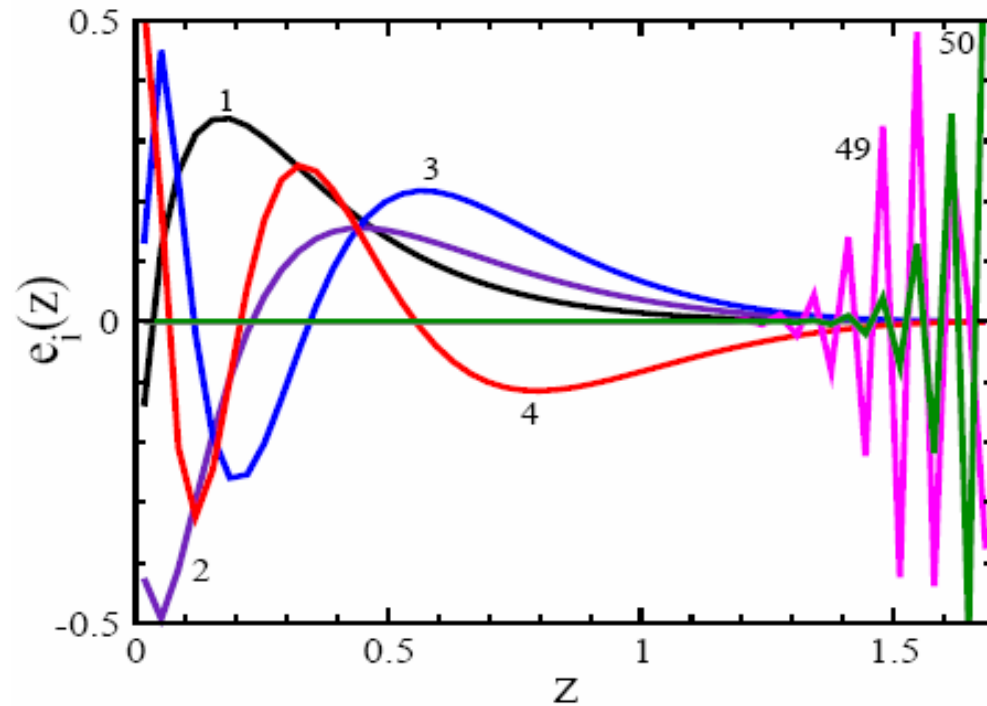
Huterer & Starkman, 2003

Simpson & Bridle, 2006

Dick et al., 2006



- *Principal Component Analysis aims at reducing the noise of the reconstruction. The price you pay is **bias***



Huterer & Starkmann (2003)

*There is no inference
without assumptions*

*State your
assumptions!*

- *Maximum freedom in $w(z)$*
- *Unbiased reconstruction with suitably large errors*
- *Optimal efficiency in extracting info on $w(z)$ from noisy data*
- *Robust wrt to noise, does not overfit*
- *Adjust itself to structure in the data*
- *Analogy: deconvolution in spectral analysis (due to the integral relating observables and $w(z)$)*

A possible (Bayesian) solution:

Maximum Entropy Bayesian Reconstruction

Zunckel and Trotta (2007)

“Reconstructing the history of dark energy using maximum entropy”, MNRAS, 380, 3, 865

astro-ph/0702695

A new reconstruction technique

- Goal: maximum freedom in $w(z)$ while avoiding overfitting

Bayes' Theorem:
$$P(\mathbf{w}|\mathbf{D}) = \frac{\overset{\text{likelihood}}{P(\mathbf{D}|\mathbf{w})} \overset{\text{Prior}}{\pi(\mathbf{w})}}{P(\mathbf{D})}$$

- The “maximum entropy” prior: a carefully chosen regularizing prior

$$\pi(\mathbf{w}|\alpha, \mathbf{m}) \propto \exp(\alpha S(\mathbf{w}, \mathbf{m}))$$

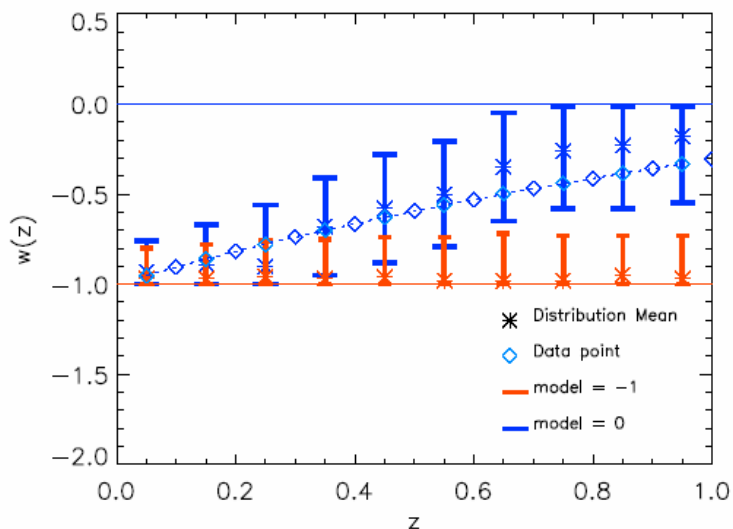
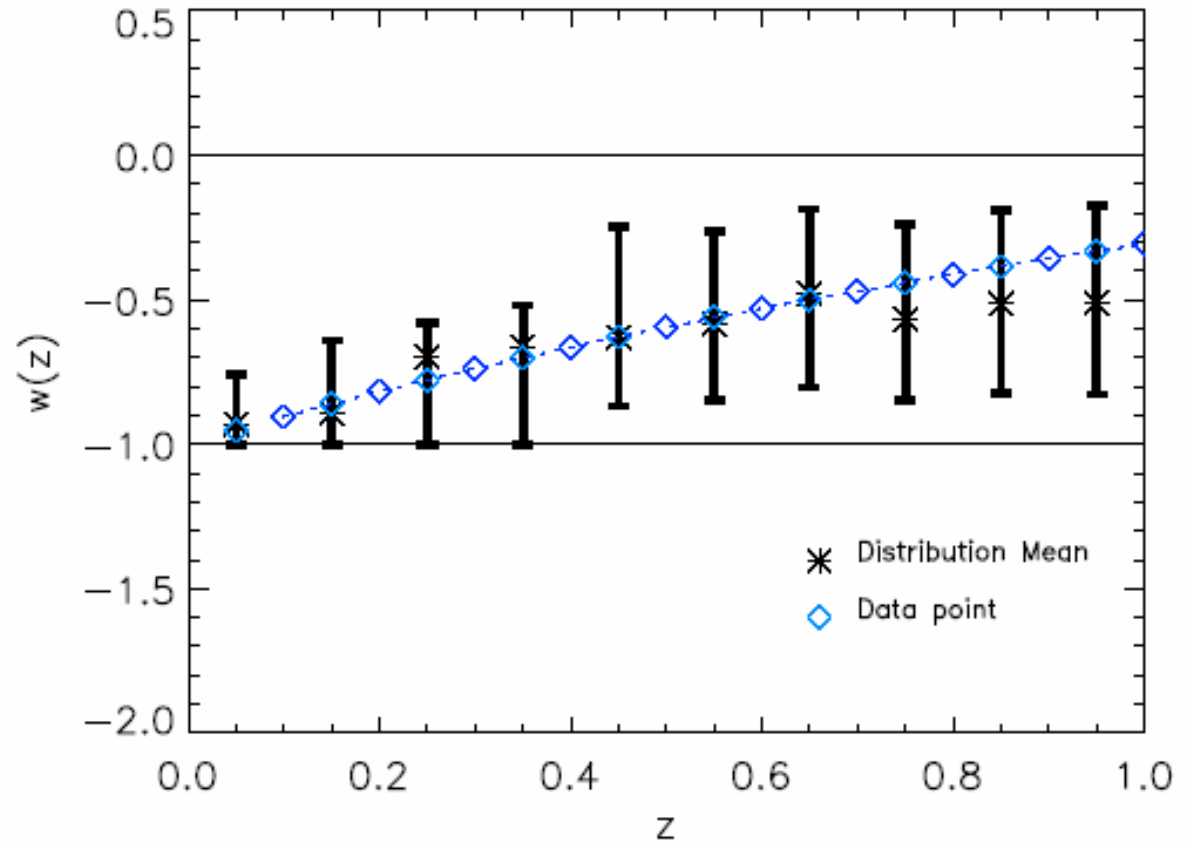
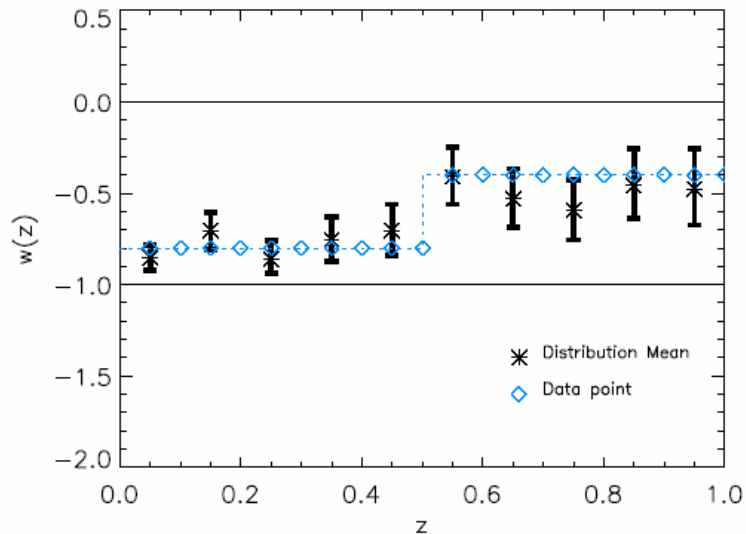
Regularization parameter

“Entropy” between w and a “default” model m

$$S(\mathbf{w}, \mathbf{m}) = \sum_{j=1}^N w_j - m_j - w_j \log\left(\frac{w_j}{m_j}\right)$$

Performance on synthetic data

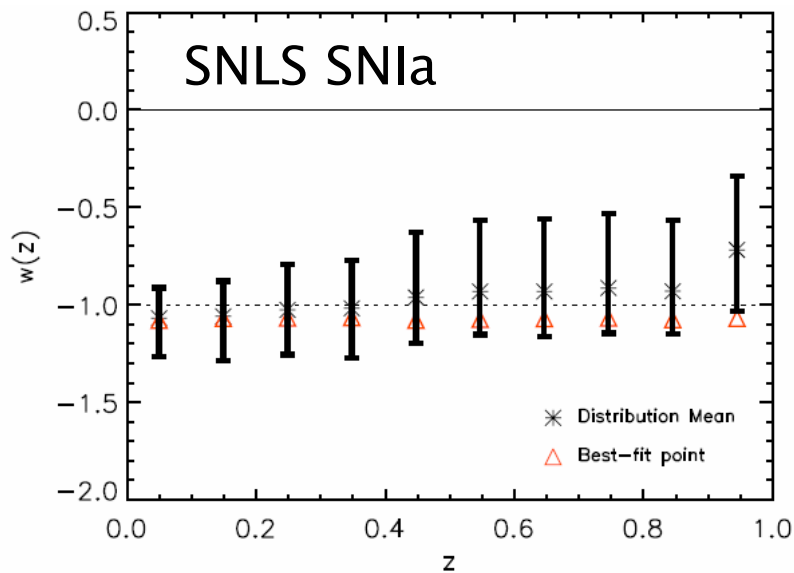
- The parameter α is adjusted through the data themselves. The model can also be included in the parameter space



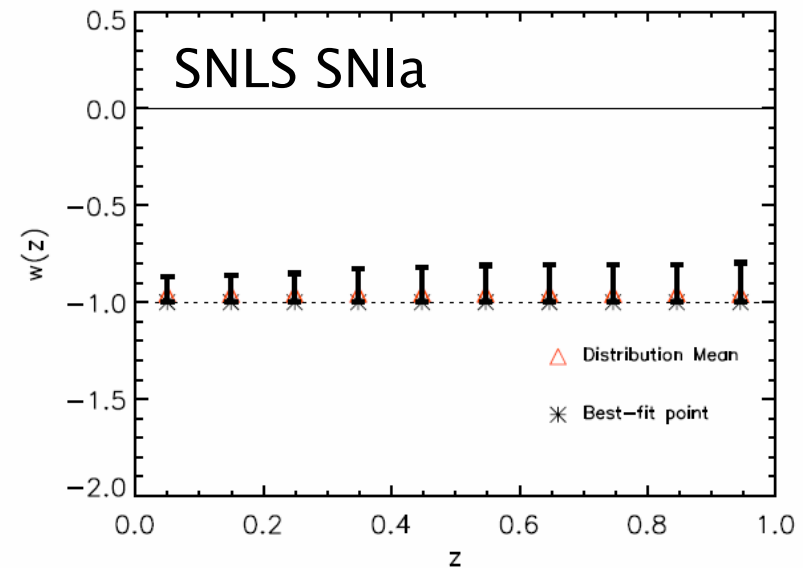
After marginalization on prior model

Data used: supernovae type Ia, acoustic oscillations and CMB

CONSERVATIVE
(model marginalized, $-2 < w < 0$)



AGGRESSIVE
(model = -1, $-1 < w < 0$)



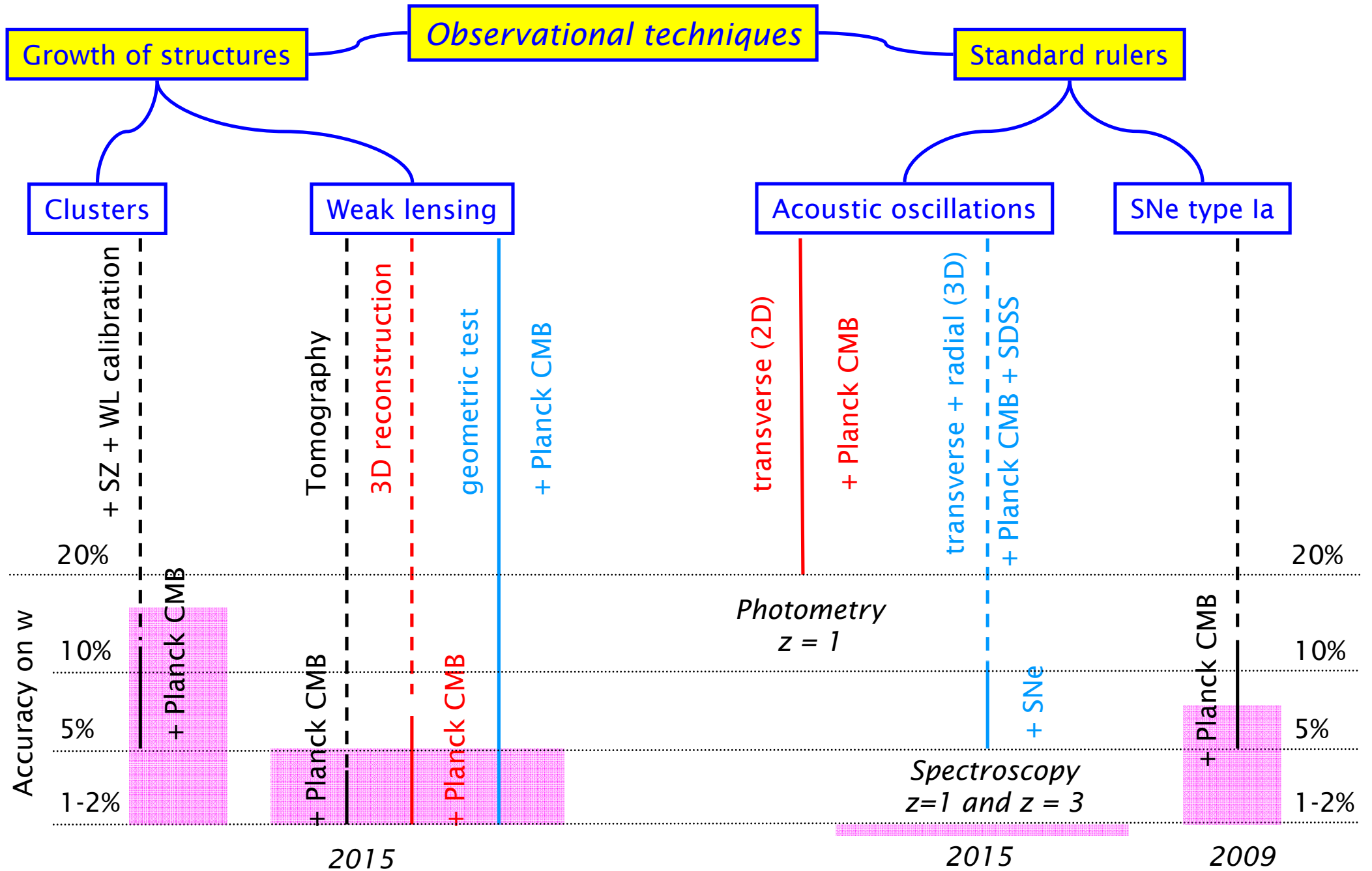
Conclusion:

the cosmological constant, $w = -1$, remains the best description

Zunckel & Trota (2007)

Dark energy discovery space

 systematics impact



Bayesian model comparison

Goal: to compare the “performance” of two models against the data. Do we need $w(z)$?

the model likelihood
 (“evidence”)

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

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)

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

Interpretation: Jeffreys’ scale for the strength of evidence

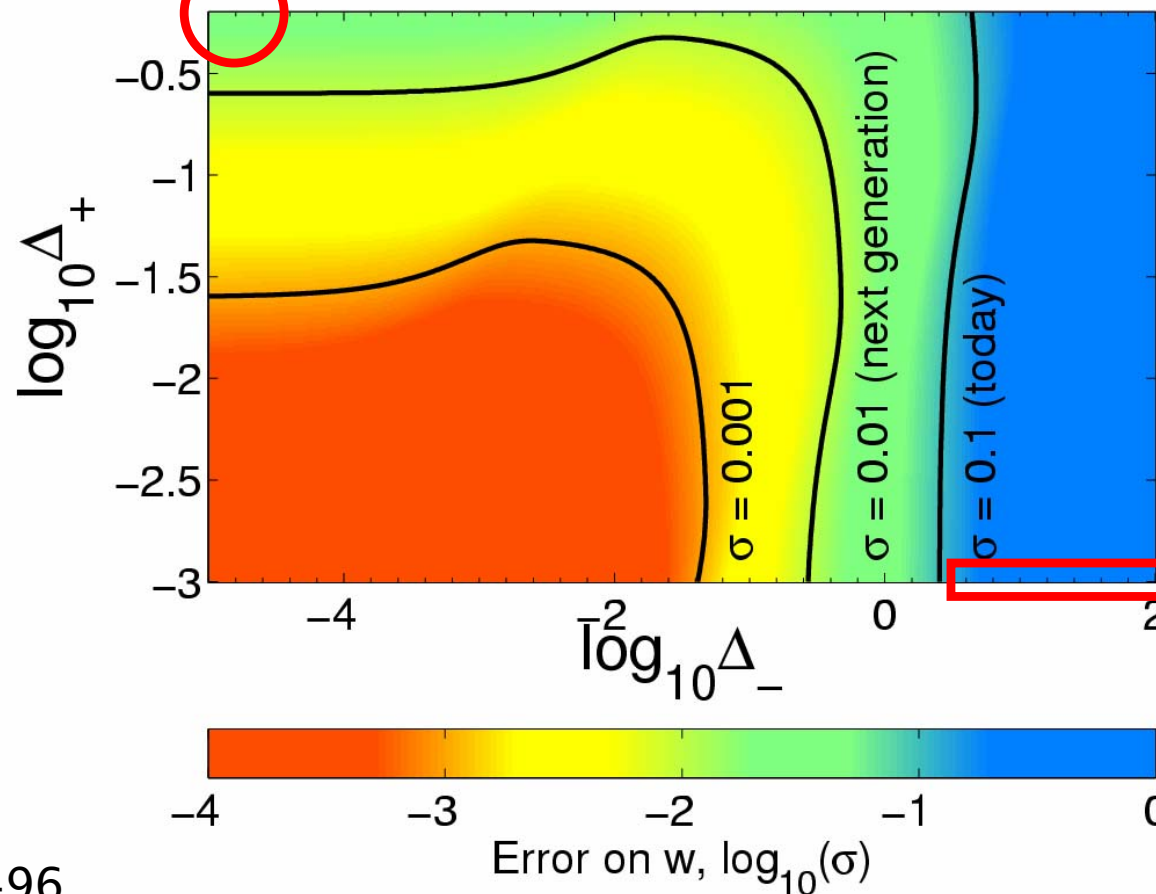
$ \ln B_{01} $	Odds	Probability	Equiv σ	(My) Interpretation
< 1.0	$< 3:1$	< 0.750	1.15	<i>not worth the mention</i>
< 2.5	$< 12:1$	0.923	1.77	<i>positive</i>
< 5.0	$< 150:1$	0.993	2.70	<i>moderate</i>
> 5.0	$> 150:1$	> 0.993	> 2.70	<i>strong</i>

Ruling in Λ : A Bayesian perspective

- Which dark energy models can be ruled out with moderate evidence ($\ln B > 3$) compared to Λ for a given accuracy σ ?

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

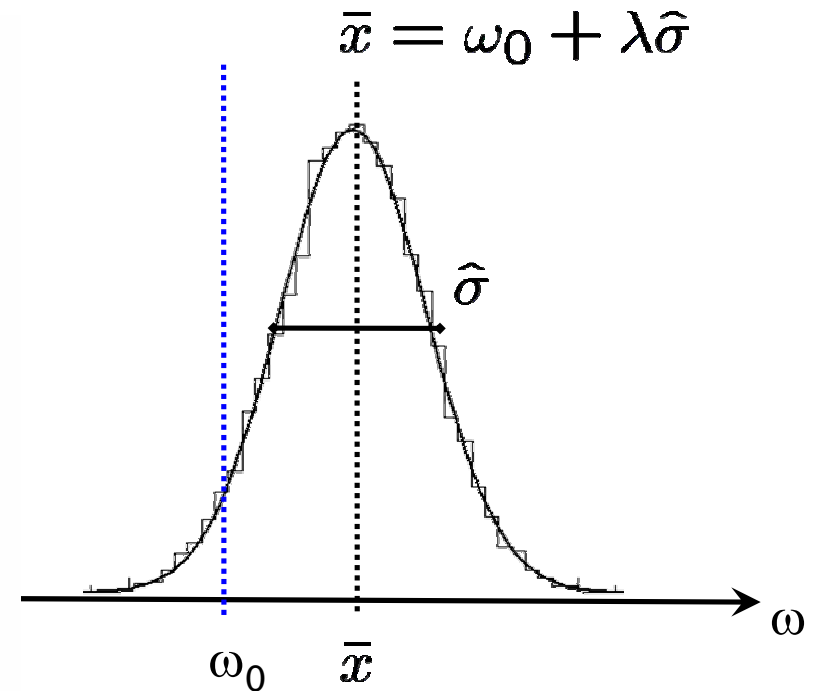
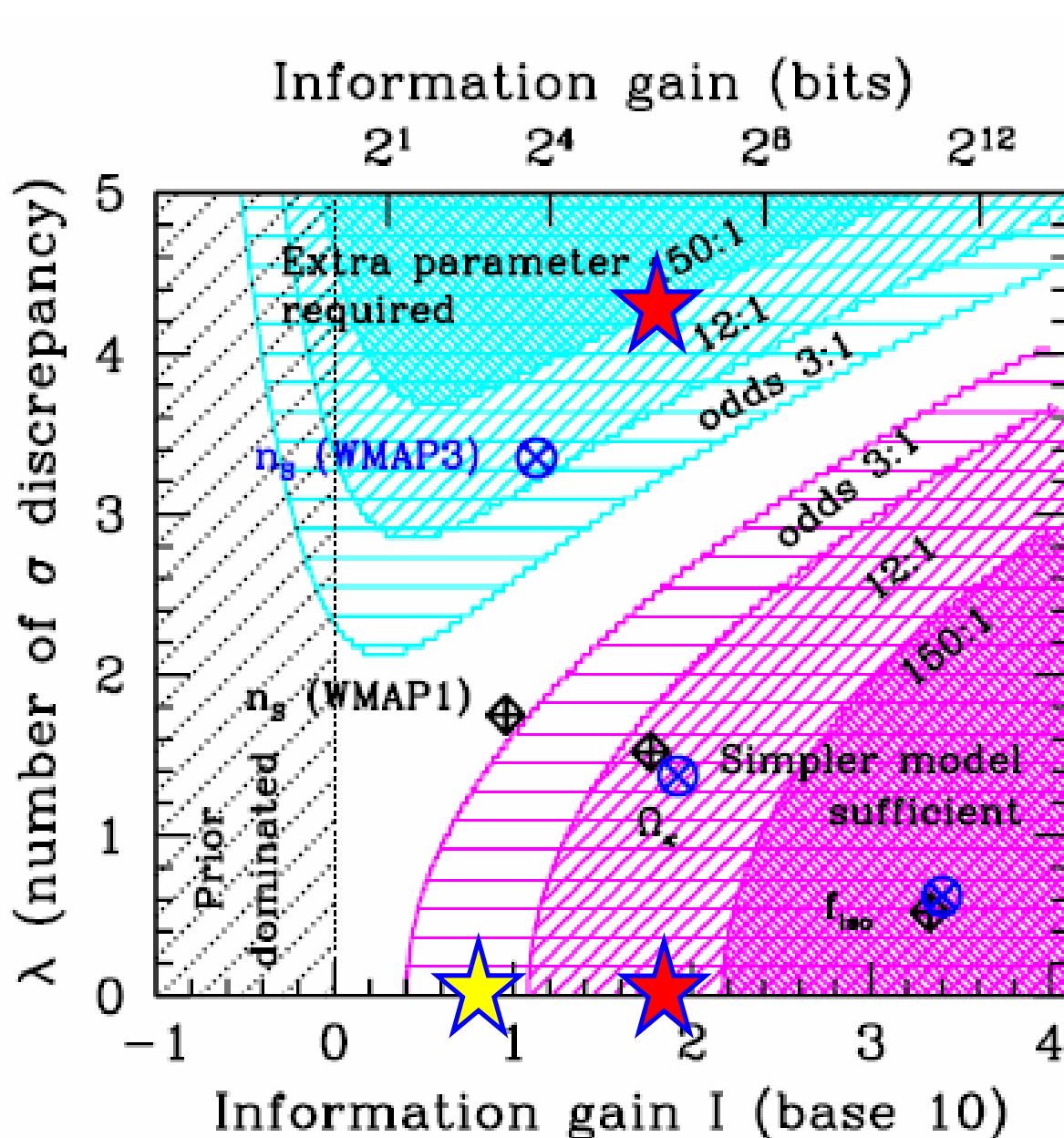
fluid-like DE



phantom DE

Bayesian model selection

Trotta 2005, astro-ph/0504022
Trotta 2007, astro-ph/0703063



Strength of evidence (Bayes factor) in favour of $w=-1$ compared to $-1/3 < w < -1$

- *Preparing for the unexpected*
 - What will be the most interesting questions in 2010?
 - Dark energy could surprise us again: maximise the discovery potential
- *Developping know-how*
 - Indispensable tools on the road to even larger surveys
- *Making the most of the data*
 - Statistical tools for optimal parameter inference: eg, MaxEnt method
 - Model selection approach, surveys optimization
- *Plenty of other science!*
 - Next generation of surveys will provide extremely high quality data for numerous astronomical and astrophysical studies