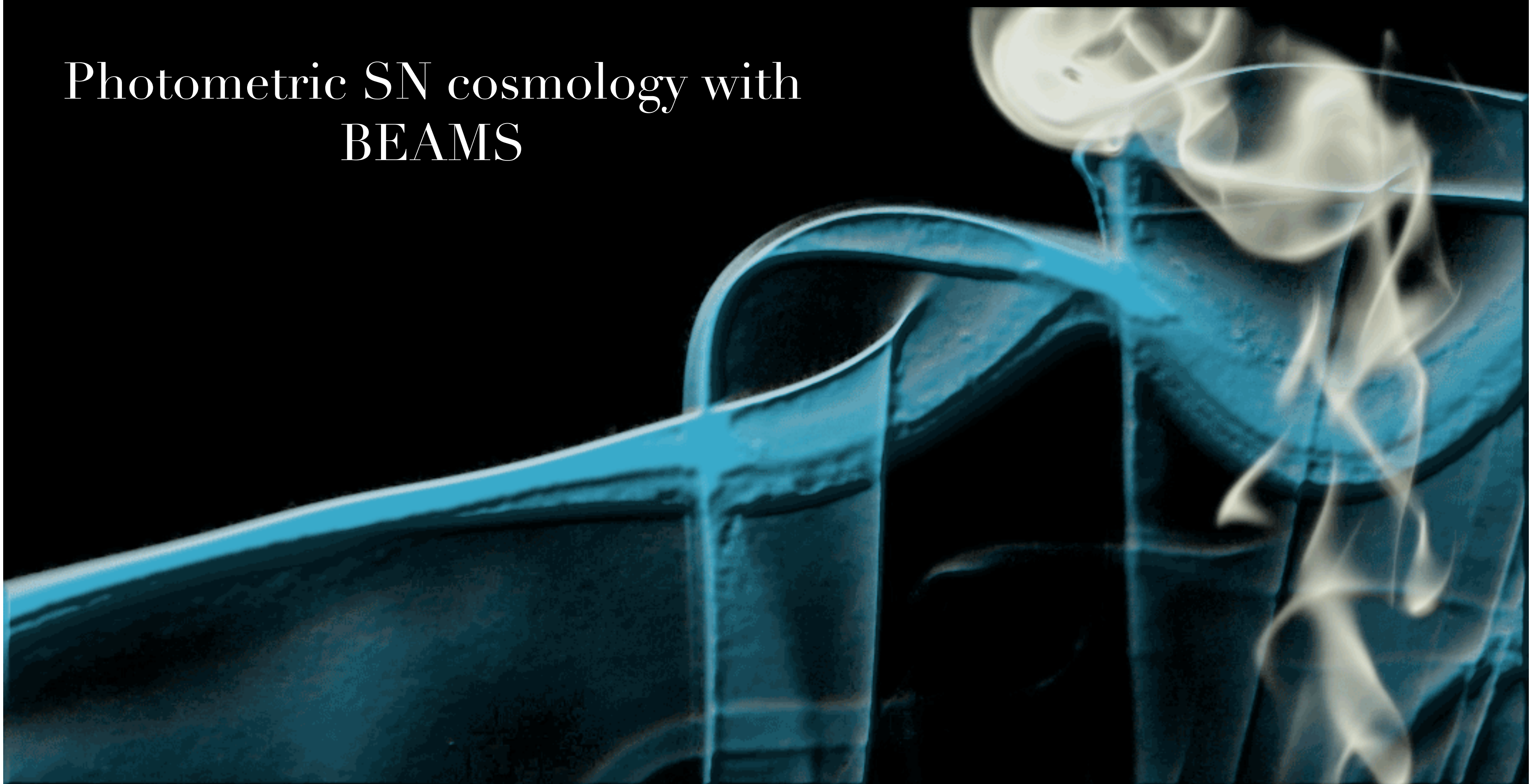
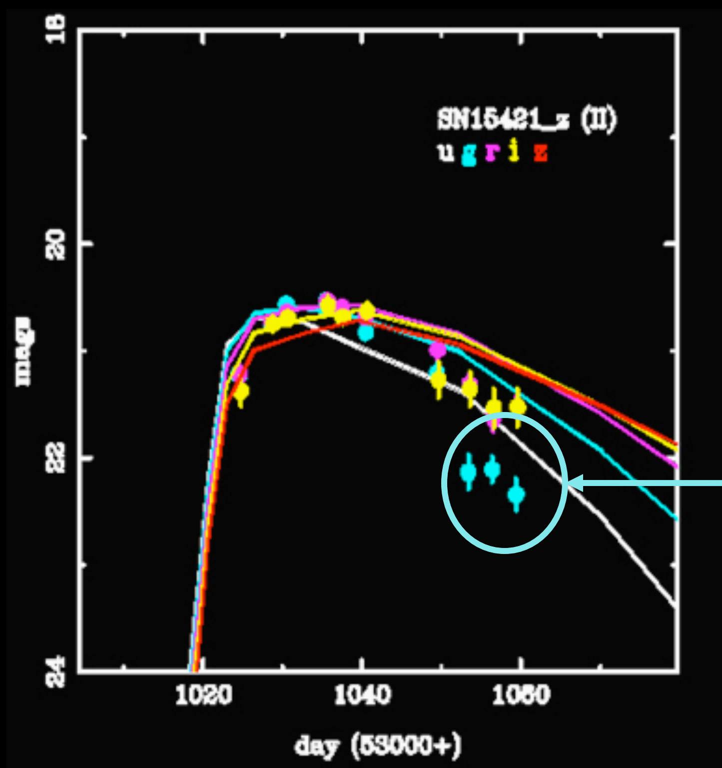
Photometric SN cosmology with BEAMS

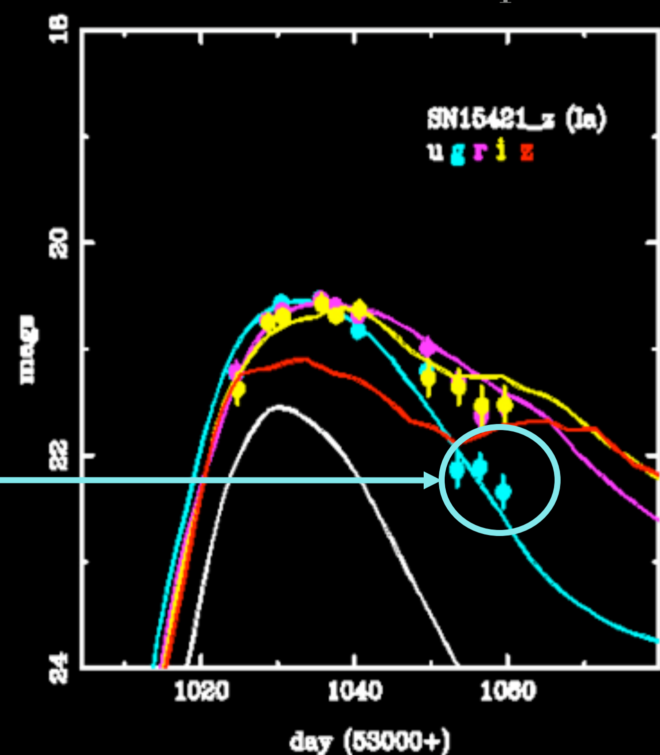


Using Photometric SNe with BEAMS

Photometric SN cosmology

Martin Kunz, BB, Renée Hlozek
arXiv:astro-ph/0611004





SDSS *ugriz* lightcurve template fits (SDSS SN Survey use g,r,i for convenience)

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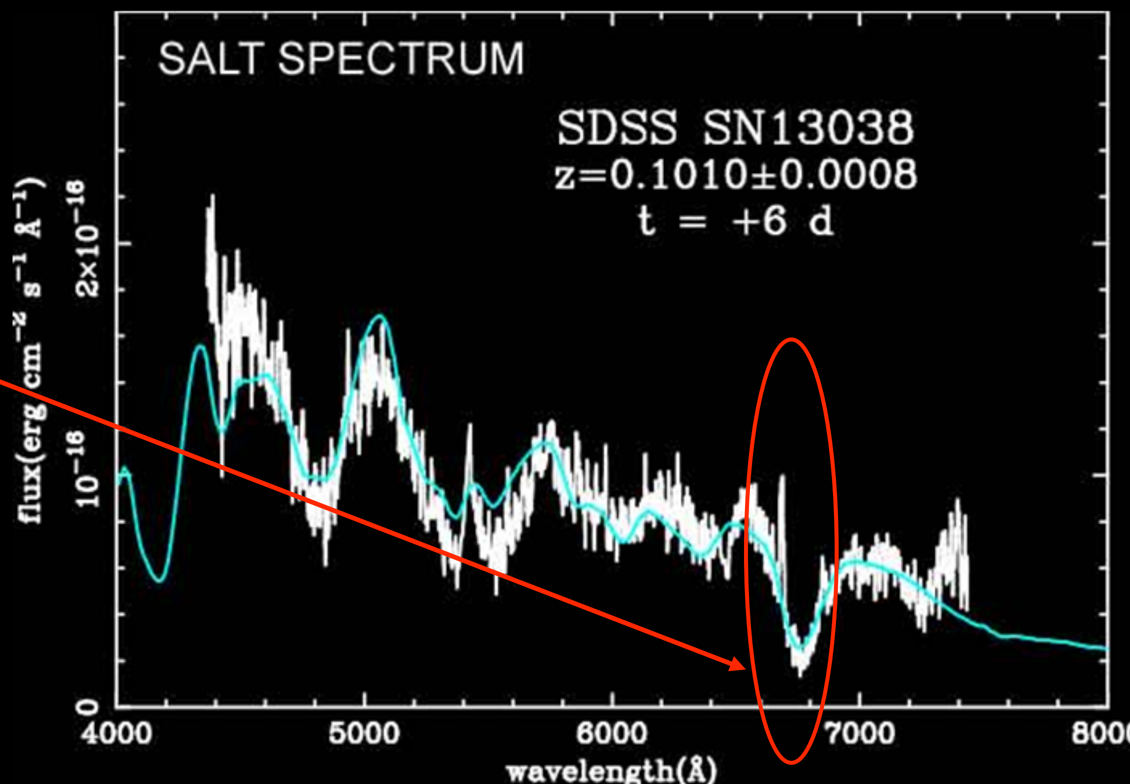
From χ^2 to a probability of being a Type Ia

$$P_i(TypeZ) \propto \exp\left(\frac{-(d_i - t_i(TypeZ)^2)}{2\sigma_i^{\,2}} \right)$$

Si II line

6150 Å

rest frame

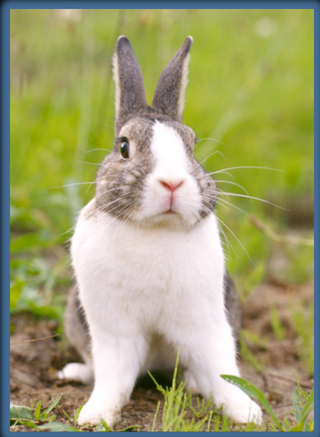


SALT spectrum (Bassett, Chen, van der Heyden, Vaisanen)

Only spectroscopically confirmed candidates used in cosmology

Why do we need BEAMS?

Current SN surveys find around 1000 SNIa. *Only* those with spectra are used for cosmology.



LSST will find ~250K SNIa per year for 10 years. Probably only 0.1% will have spectra.

WE NEED TO BE ABLE TO DO PHOTOMETRIC SUPERNOVA COSMOLOGY → BEAMS

What is BEAMS?

- For a cosmological model θ and data set d:

- Imagine you knew all SN types: then τ is a logical vector with entries 1 if a SNIa, 0 if not.
- $\rightarrow P(\theta|d, \tau = [1101...]) = L_{ia} * L_{Ia} * L_{nonIa} * L_{Ia} * \ldots$

- Marginalising over vector τ and assuming uncorrelated data:

- $P(\theta|d) = \Pi_j [P(\theta|d_j, Ia) P_j(Ia) + P(\theta|d_j, nIa)(1 - P_j(Ia))]$

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Posterior: $$P(\theta \mid D)$$

$\tau_i = \begin{cases} 1 \text{ if SN Ia} \\ 0 \text{ if non-Ia} \end{cases}$

Marginalisation

$$P(\theta \mid D) = \sum_{\tau} P(\theta, \tau \mid D)$$

D, τ have N entries

Bayes

$$P(\theta, \tau \mid D) = P(D \mid \theta, \tau) \frac{P(\theta, \tau)}{P(D)}$$

Independent Priors on q,θ

$$P(\theta, \tau) = P(\theta) P(\tau) = P(\theta) \prod_{\tau_i = 1} P_i \prod_{\tau_j = 0} 1 - P_j$$

$P_i = P(\tau_i = 1)$

Uncorrelated data : P(D|θ,t) separates into independent factors for Ia and non-Ia distributions

$$P(D|\theta,\tau) = \prod_{\tau_i=1} P(D|\theta,\tau_i=1) \prod_{\tau_j=0} P(D|\theta,\tau_j=0)$$

Combining the two

$$P(\theta|D) \propto \sum_{\tau} \prod_{\tau_i} P(D|\theta,\tau_i=1) P_i \prod_{\tau_j} P(D|\theta,\tau_j=0)(1-P_j)$$

Combinatorial simplification (Press)

$$\sum_{\tau} \prod_{\tau_i=1} X_i \prod_{\tau_j=0} Y_j = \prod_{\tau_k} (X_k + Y_k)$$

Ia distribution

Non-Ia distribution

$$P(\theta|D) \propto \prod_{k=1}^{N} \left[P(D|\theta,\tau_k=1) P_i + P(D|\theta,\tau_k=0)(1-P_i) \right]$$

Bayesian Estimation Applied to Multiple Species

$$P(\theta \mid D) \propto \prod_{k=1}^{N} \left[L_{Ia} P_k + L_{NonIa} (1 - P_k) \right]$$

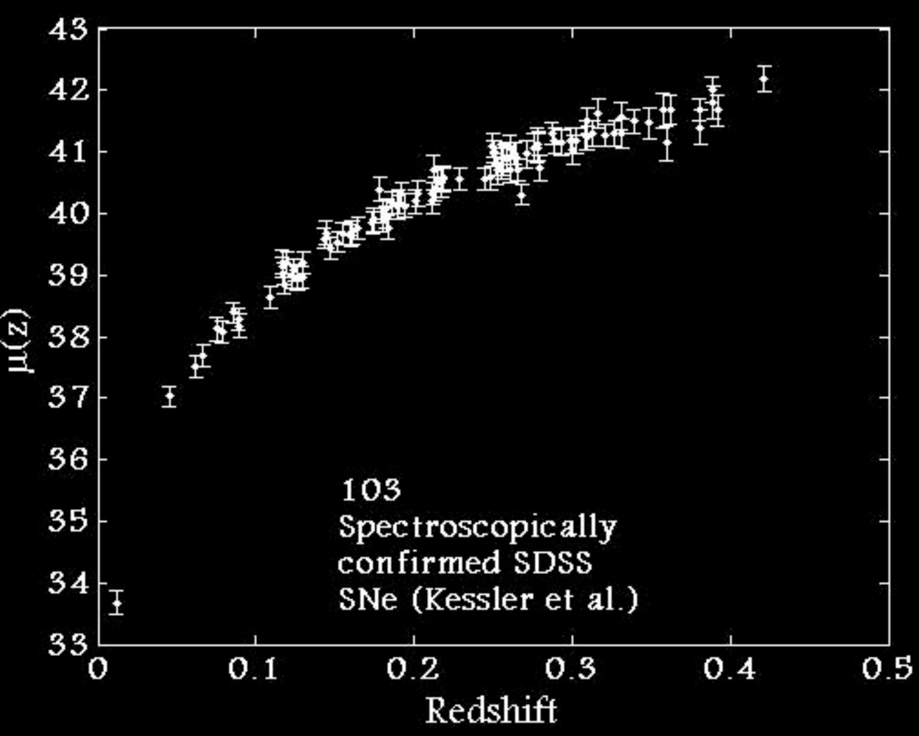
$P_k \rightarrow P_{IA}$

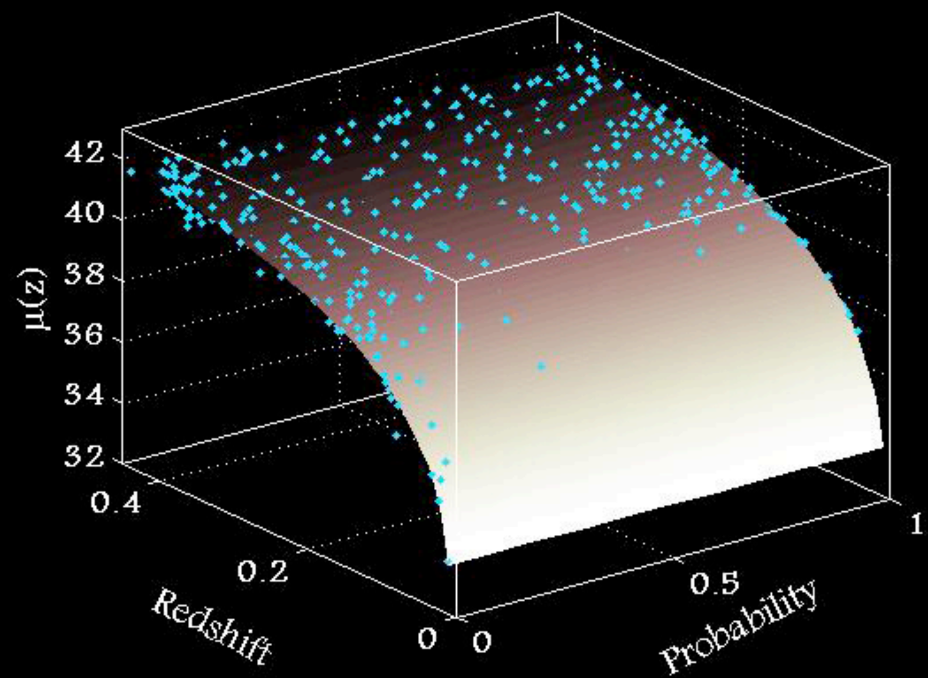
BEAMS Posterior :

weight likelihood assuming it is of type Ia by P_{Ia}, probability it is type Ia

Martin Kunz, Bruce Bassett , RH
arXiv:astro-ph/0611004

Using Light-curve Candidates…

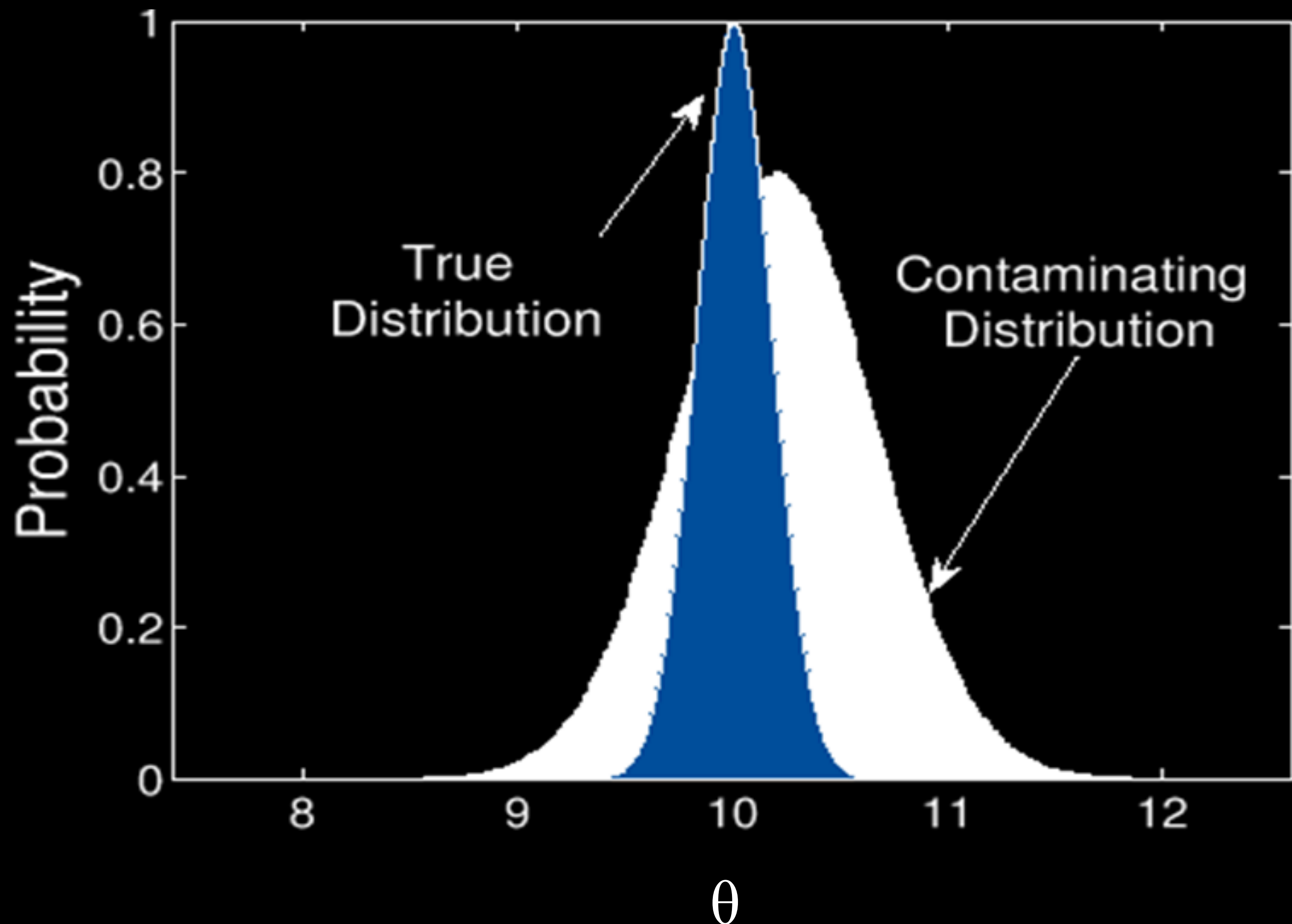




Probabilities from χ^2 from light-curve

$0 < P(Ia) < 1$

Dealing with Contamination



Testing with a Toy Distribution

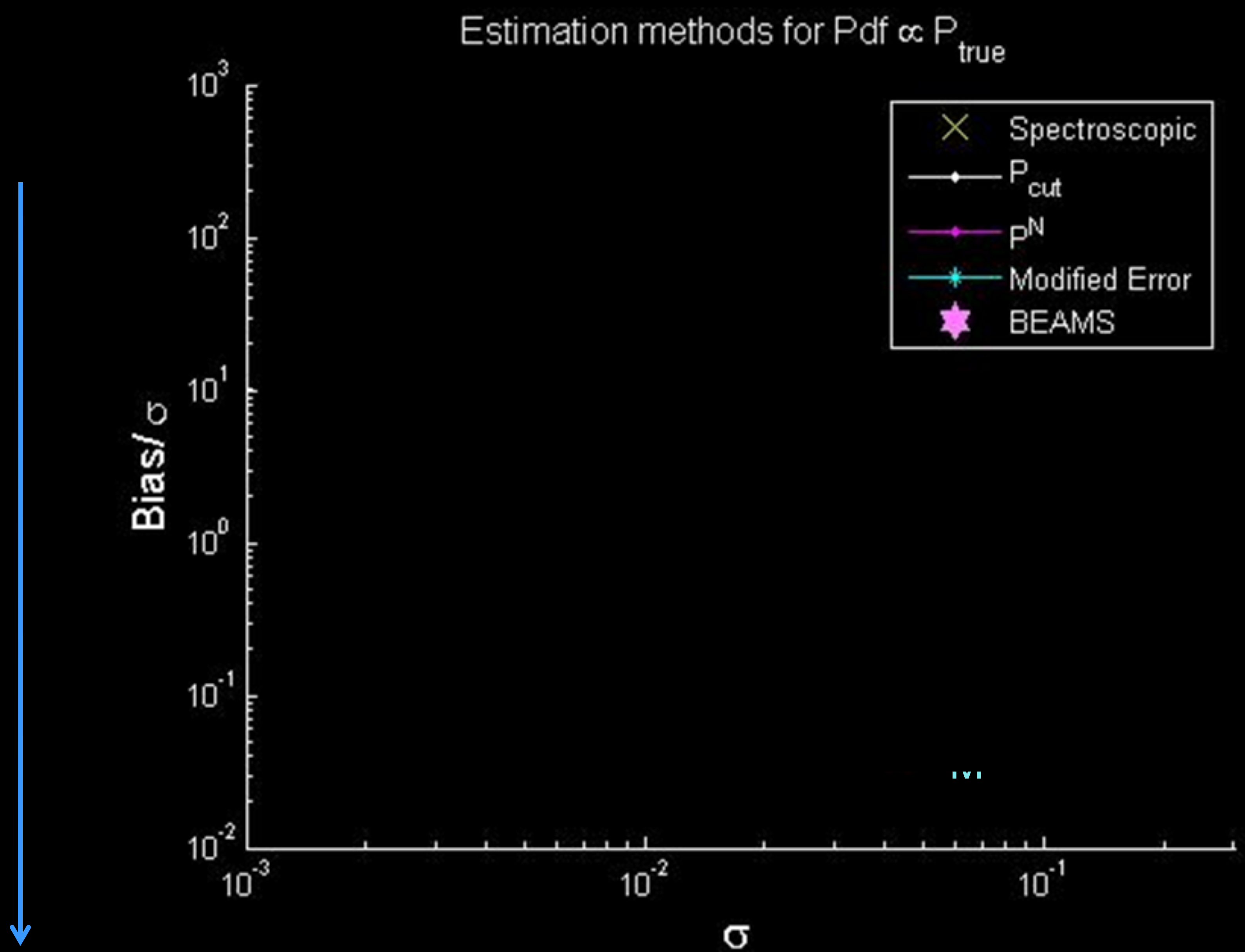
Compare with other methods

1. Including only those candidates with

   $P_i > P_{cut}$ in standard χ^2 analysis

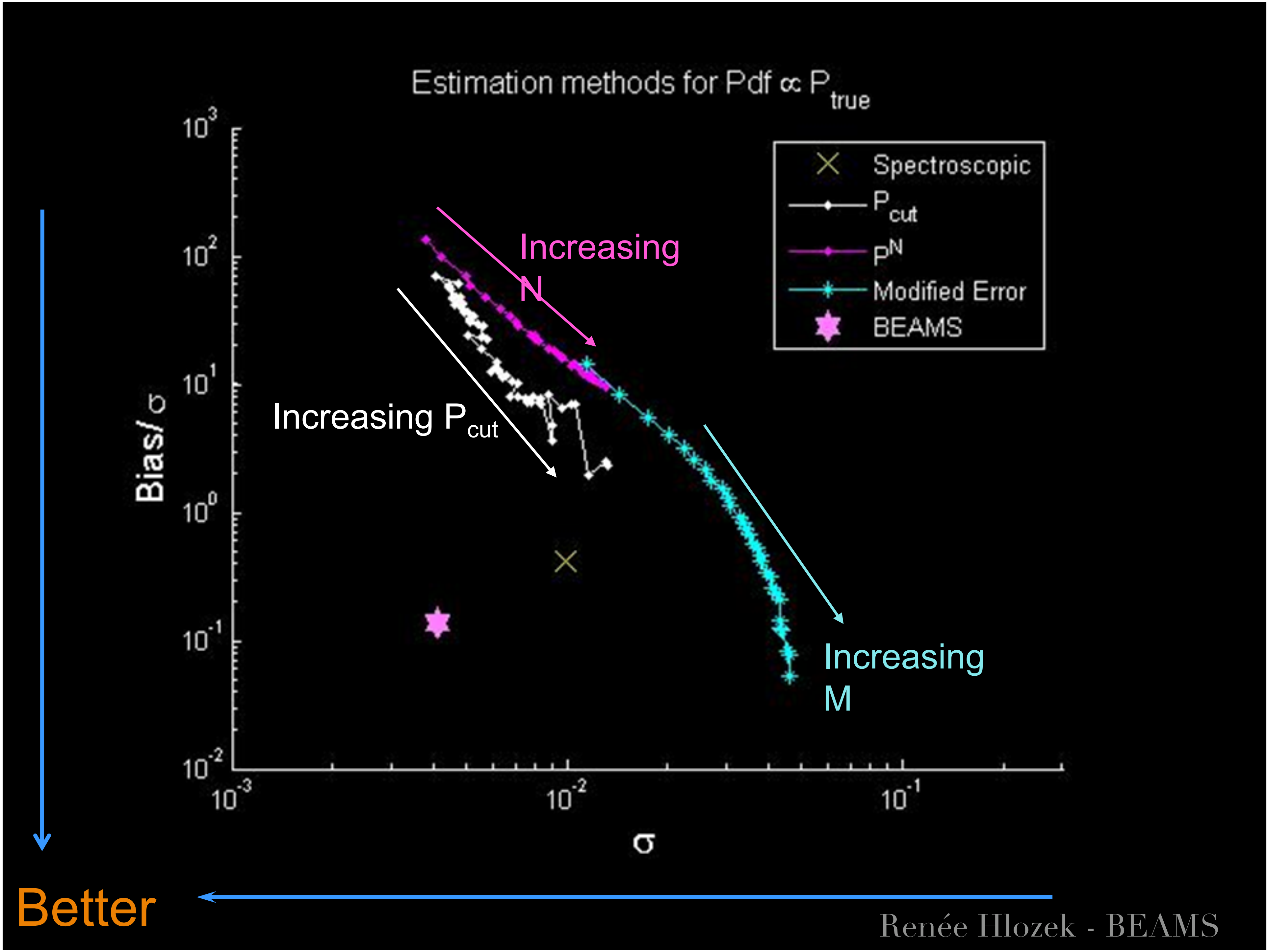
2. Weighting the data from each candidate by P_i^N

3. Modify the error: $\sigma_i^2 \rightarrow \sigma_i^2 + 1/P_i^N - 1$



Estimation methods for Pdf ∝ P_true
Spectroscopic
P_cut
P^N
Modified Error
BEAMS
Bias/ σ
10^3
10^2
10^1
10^0
10^-1
10^-2
10^-3
10^-2
10^-1
σ

Better



Estimation methods for Pdf ∝ P true
Spectroscopic
P cut
P N
Modified Error
BEAMS
Increasing N
Increasing P cut
Increasing M
Bias/ σ
σ
10^3
10^2
10^1
10^0
10^-1
10^-2
10^-3
10^-2
10^-1
Better
Renée Hlozek - BEAMS

SDSS-II SN Survey

~ 500 SNe Ia

1st year cosmology results based on spectroscopic data

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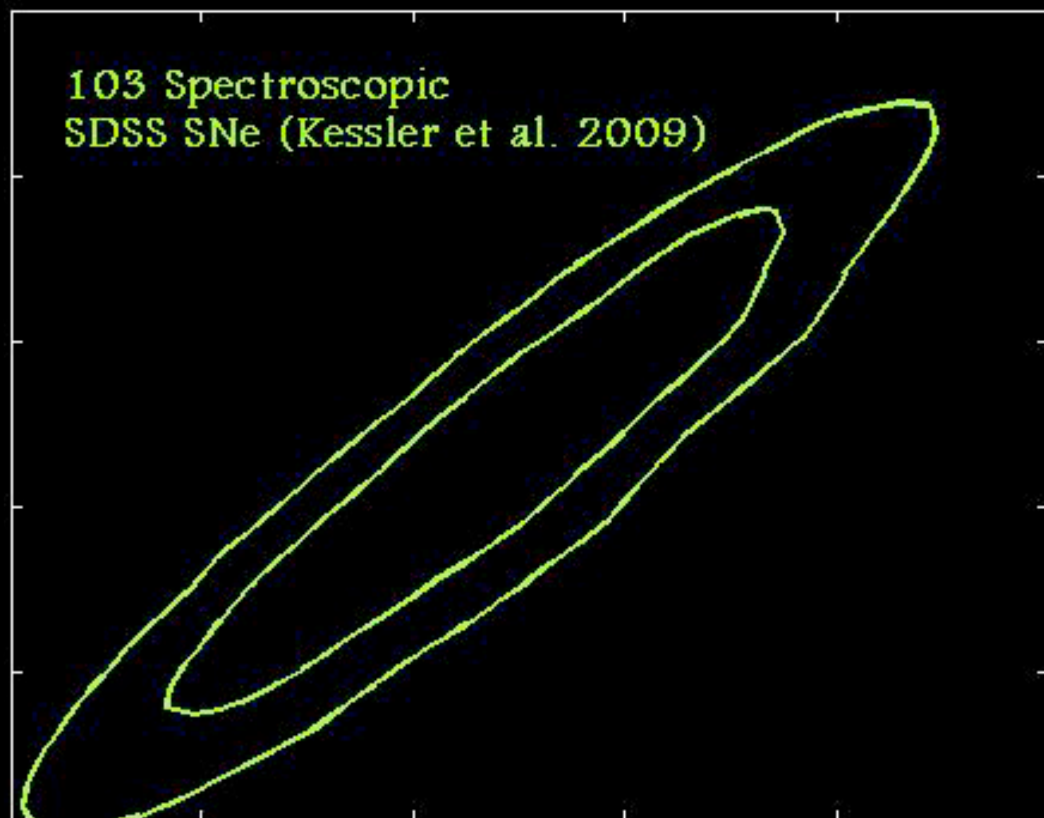
SDSS-II: 1st year Spectroscopic Data

Ω_Λ

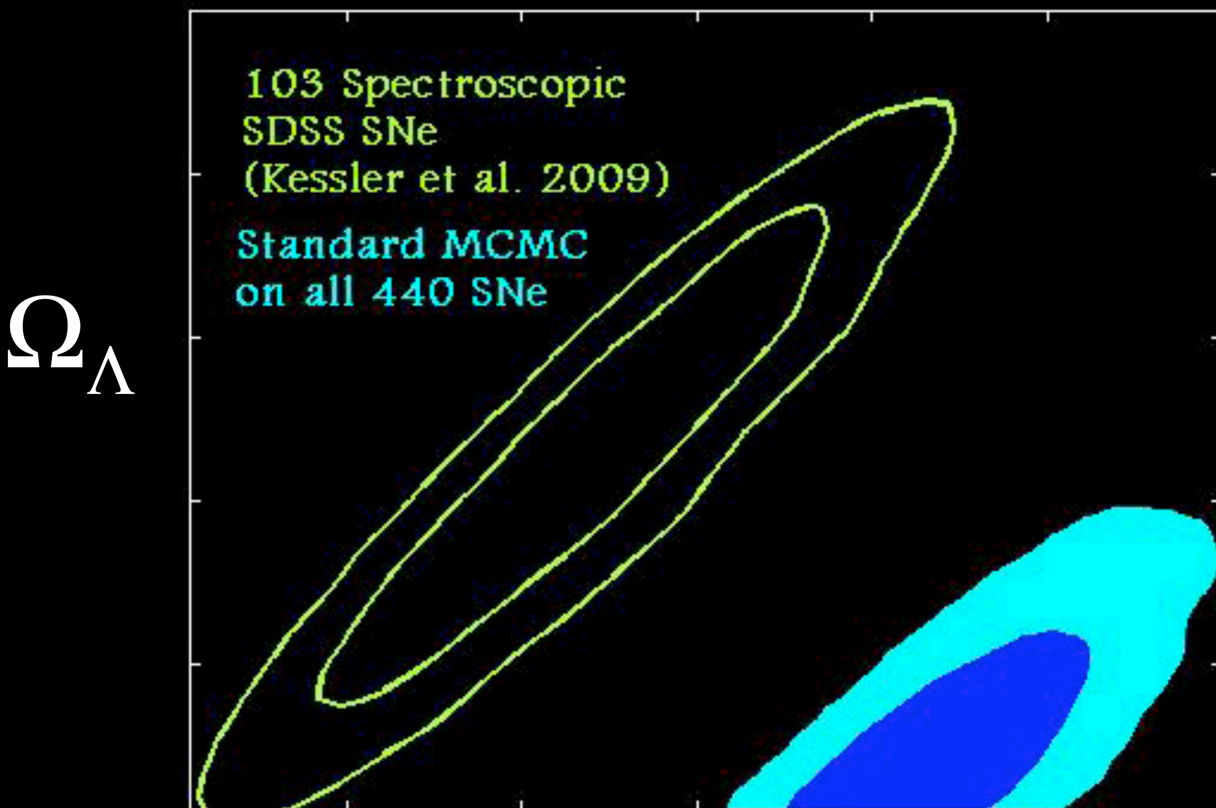


Ω_m

Preliminary Results

How BEAMS tightens constraints..

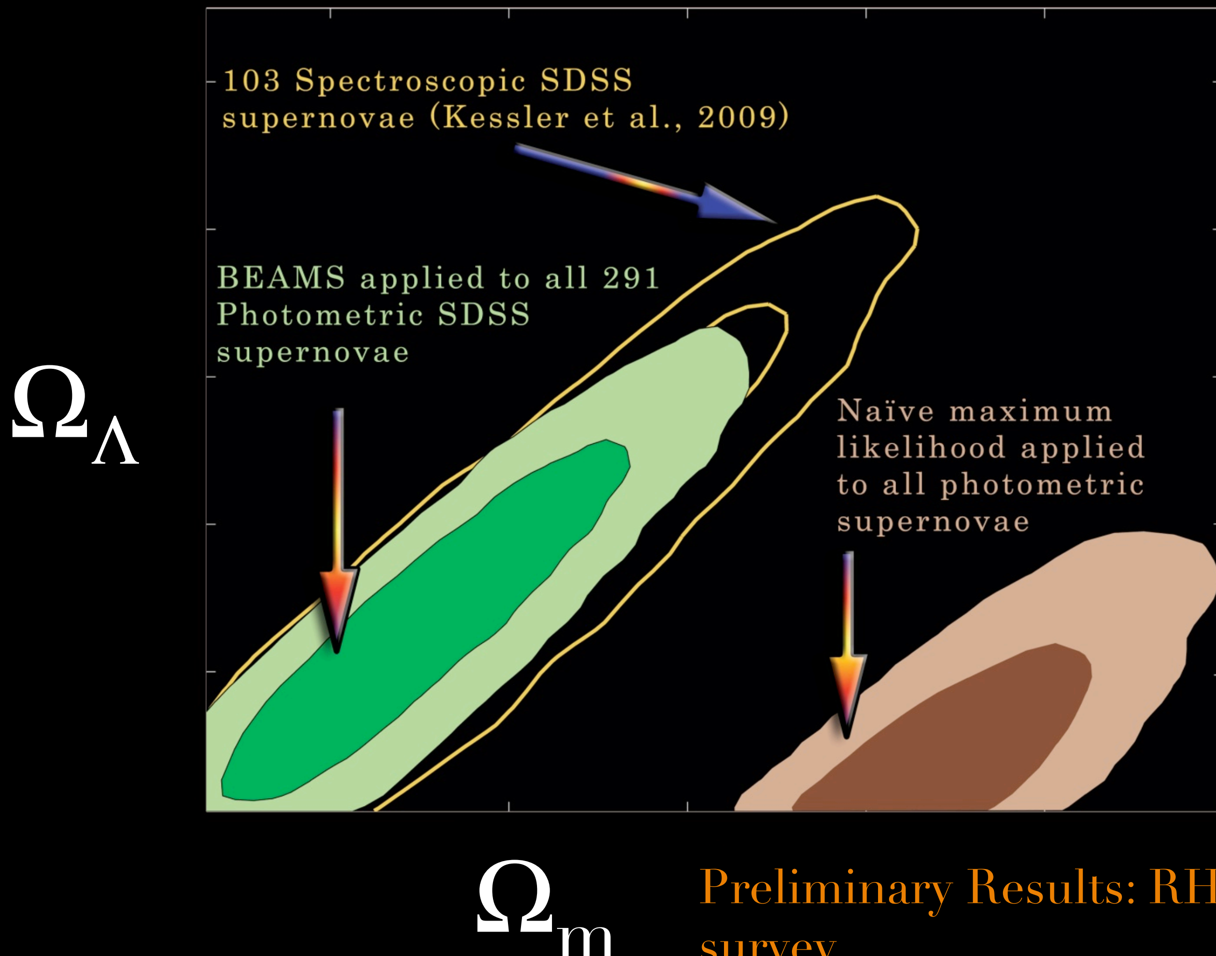
Just doing the Usual



Ω_m

Preliminary Results: RH and SDSS-II SN survey

Quality Cuts and Nuisance Parameters



Preliminary Results: RH and SDSS-II SN survey

Renée Hlozek - BEAMS

BEAMS 'washes whiter'

- BEAMS: no discarded data, no bias if you can parametrise all the errors

- Optimally reduces errors on parameters

$$\sigma \rightarrow \sigma / \sqrt{N_{eff}}$$

$$N_{eff} = N_{spectro} + \langle P \rangle N_{photo}$$

Crucial for next-generation SNIa surveys (e.g. DES, PanSTARRS, LSST)