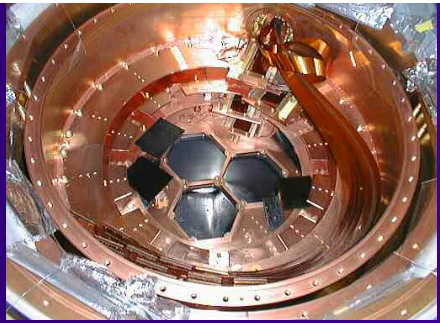

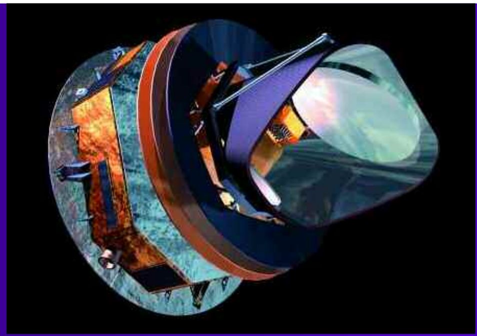

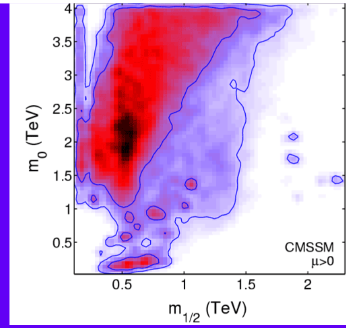

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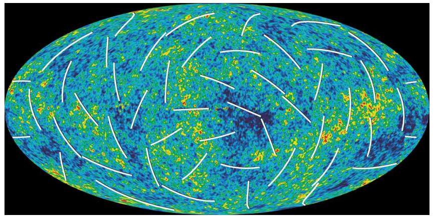
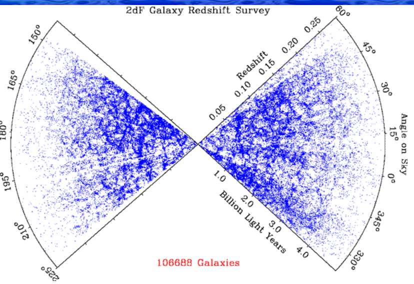
A new statistical inference tool for SUSY searches

Roberto Trotta
(collaborators: Roberto Ruiz de Austri, Leszek Roszkowski & Joe Silk)

University of Oxford, Astrophysics
St Anne's College

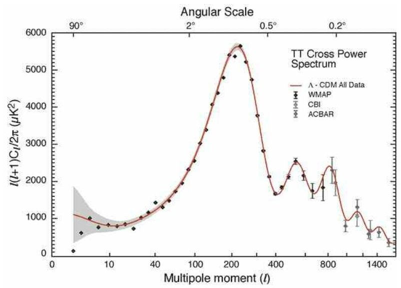
Cosmological analysis pipeline





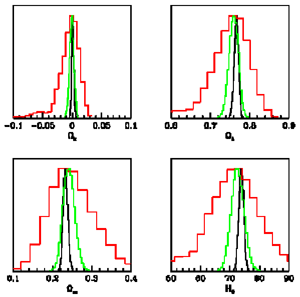
‘raw’ data » 10^6

Estimators



power spectra » 10^3

MCMC vs grid



cosmological params » 10

Purely Bayesian question

ΛCDM

model selection » 1

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The Constrained MSSM

- *General MSSM scenario: soft SUSY breaking*

105 free parameters in the Lagrangian

- *Assuming Universal boundary conditions at M_{GUT}*

Gaugino masses:

$M_1 = M_2 = M_3 = m_{1/2}$

Scalar masses:

$m_{H_d}^2 = m_{H_u}^2 = M_L^2 = M_R^2 = M_Q^2 = M_D^2 = M_U^2 = m_0^2$

Trilinear couplings

$A_u = A_d = A_l = A_0$

Higgs vev ratio

$\tan\beta = v_u/v_d$

μ^2 *from EWSB*

A 4 (5) parameters benchmark scenario
$m_{1/2}$, m_0, A_0, $\tan\beta$ (sign(μ))

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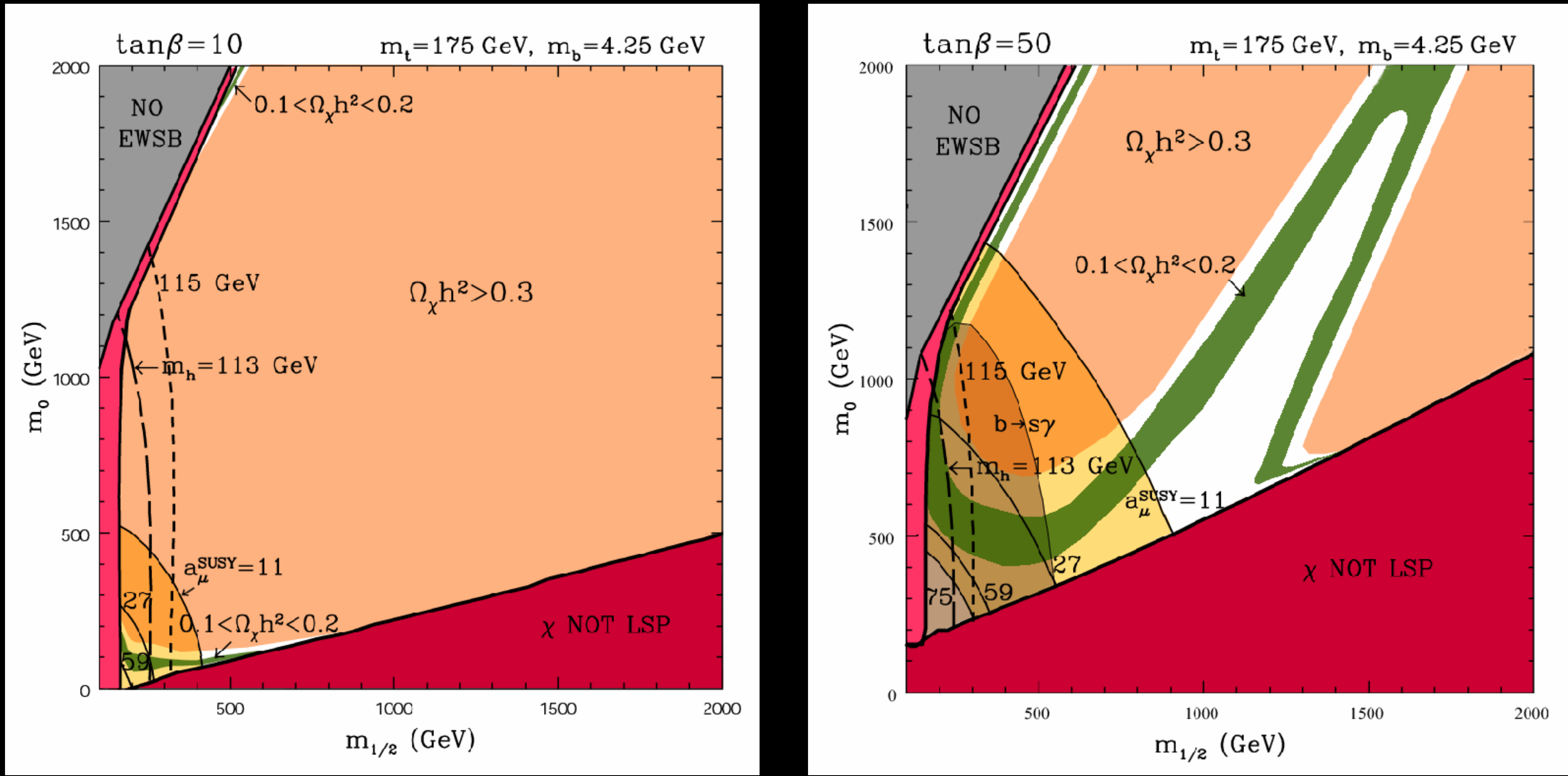
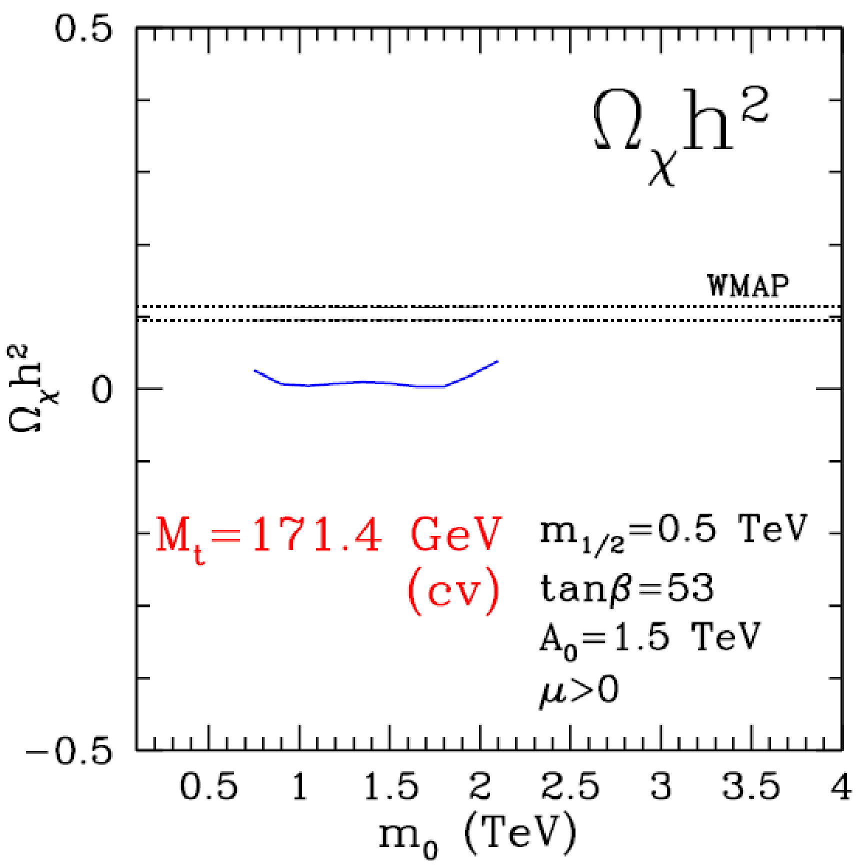
2D slices of CMSSM parameter space

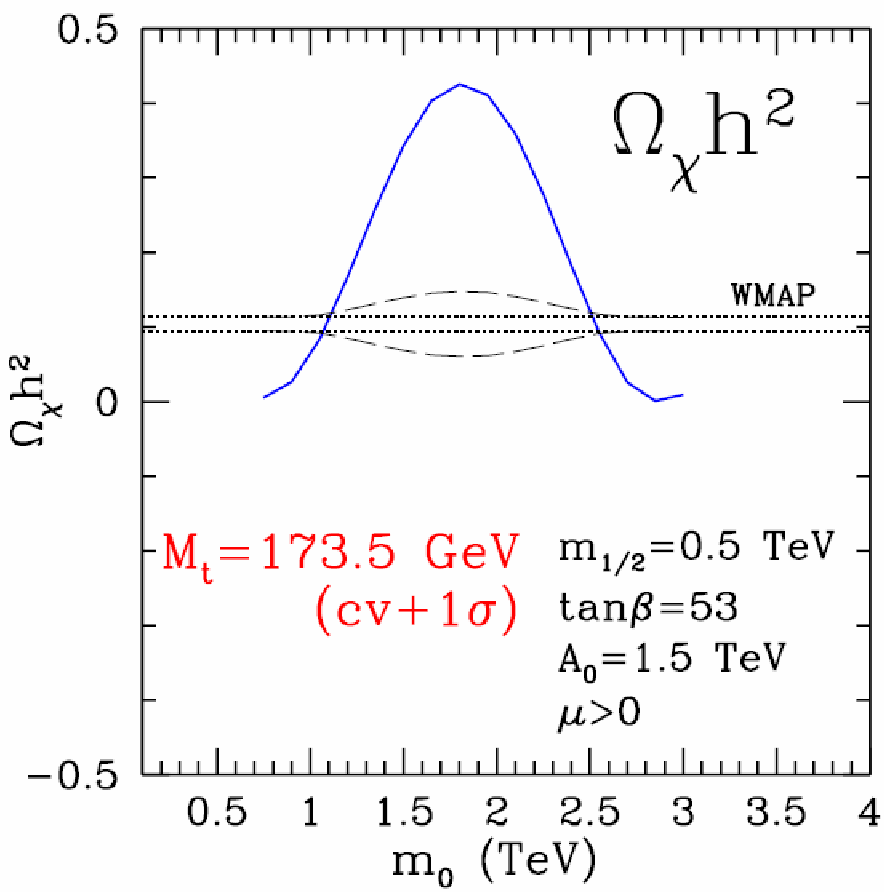


But this is only for fixed A_0, tanβ

Fixing nuisance parameters is not enough

- *Example: CDM relic abundance dependence on m_t*





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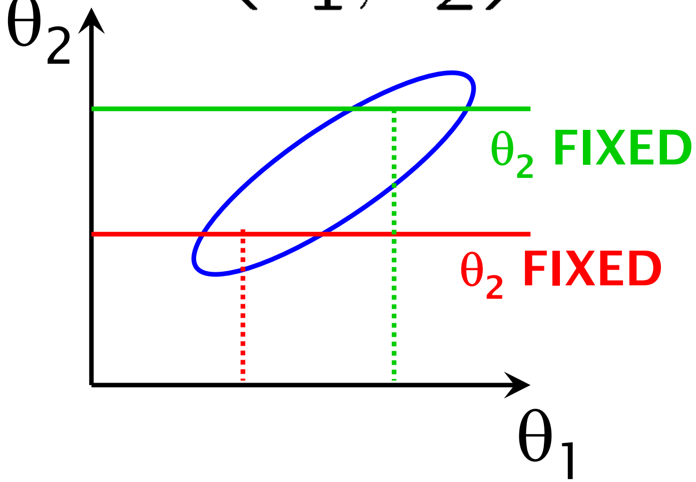
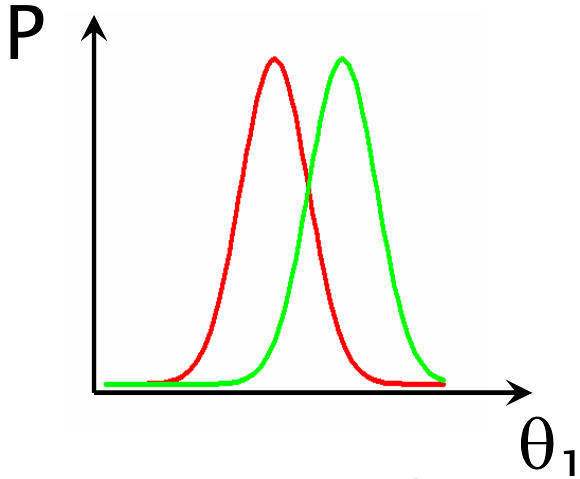
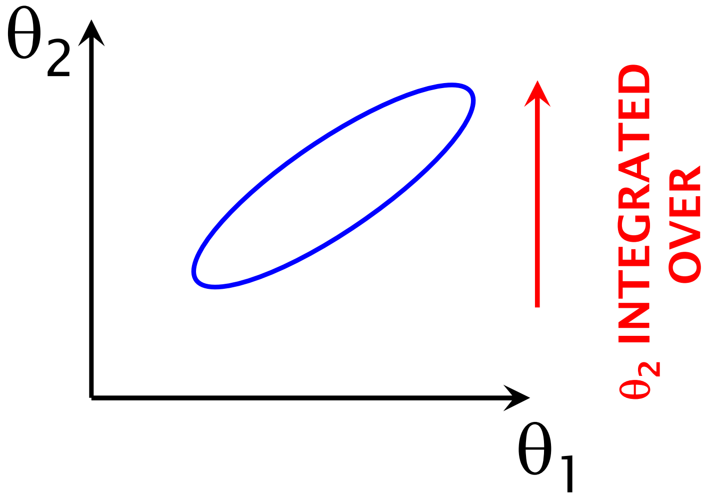
Marginalization

$$P(\theta_1, \theta_2)$$

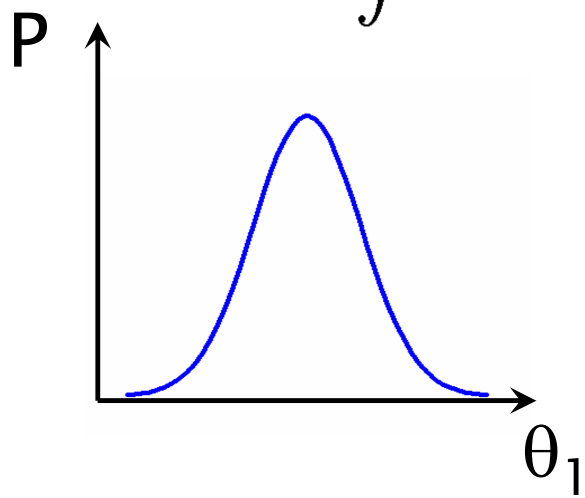


$$P(\theta_1) = P(\theta_1, \theta_2 = \theta_*)$$





$$P(\theta_1) = \int P(\theta_1, \theta_2) d\theta_2$$



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A Bayesian analysis of the CMSSM

- *CMSSM parameters*

$$m_0, m_{1/2}, A_0, \tan\beta, \mathrm{sgn}(\mu)$$

- *'Nuisance' parameters*

$$m_b(m_b)^{\overline{MS}} = 4.20 \pm 0.07 \text{ (GeV)}$$
$$m_t = 171.4 \pm 2.1 \text{ (GeV)}$$
$$1/\alpha_{\mathrm{em}}(M_Z)^{\overline{MS}} = 127.955 \pm 0.018$$
$$\alpha_s(M_Z)^{\overline{MS}} = 0.1176 \pm 0.002$$

- *Observables (with full likelihood)*

SUSY mass limits (LEPII),

Higgs limits, BR's, g-2, EW observables

cosmological CDM abundance

- *Output: probability distrib'ons for*

All observables and CMSSM parameters

Direct and indirect detection quantities (fluxes, cross sections...)

Collider cross sections and BR'os, sparticle masses, etc...

- Roszkowski, Ruiz de Austri & RT (2007)
- Roszkowski, Ruiz de Austri RT & Silk (2007)
- See also works by Baltz & Gondolo (2004), Allanach et al (2006)

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Bayesian parameter estimation

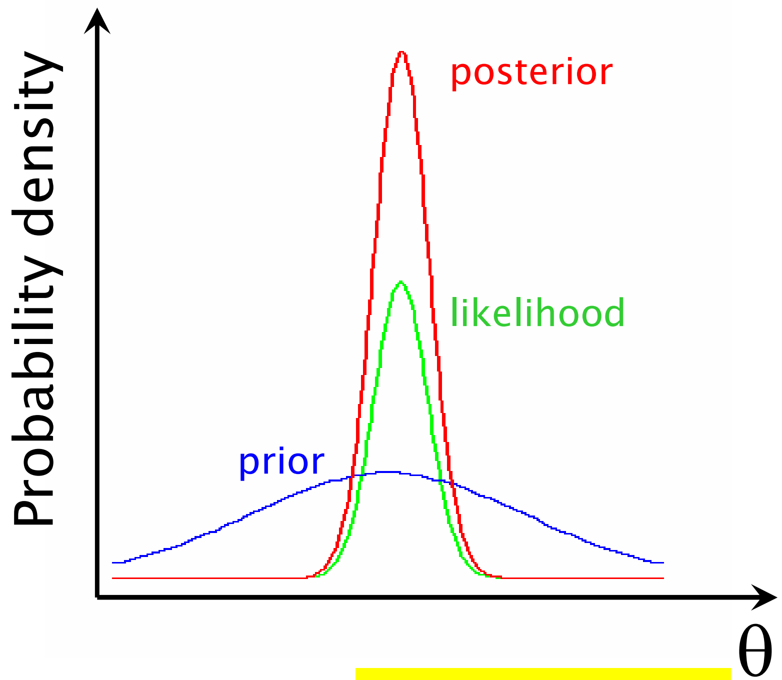
$\boldsymbol{\theta}$: parameters

$\mathbf{d}$: data

Bayes' Theorem

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

$$\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{evidence}}$$



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3 reasons to be Bayesian

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

	MCMC Bayesian	Frequentist
1) Efficiency	/ N	/ k^N
2) Marginalization	**trivial**	**close to impossible**
3) Predictivity for derived parameters	YES	**need estimator**

Prior information

BE CAREFUL

THIS MACHINE HAS NO BRAIN USE YOUR OWN

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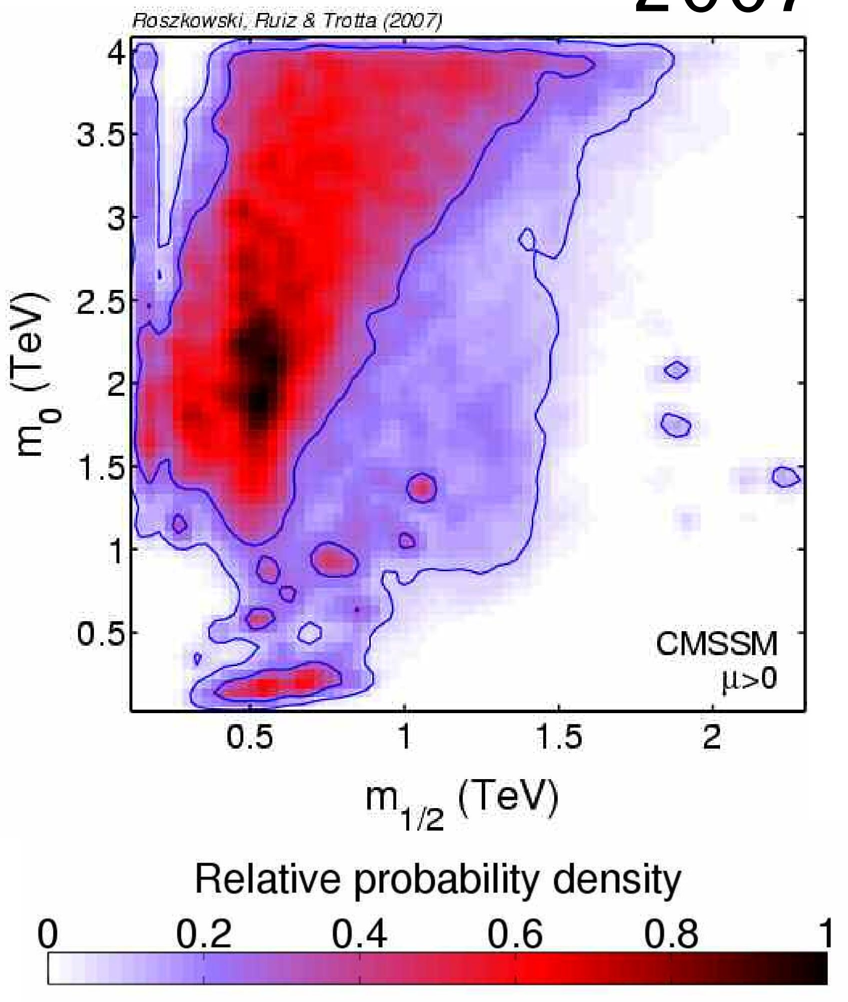
An 8-dimensional Bayesian scan

Experimental b->sγ: (3.55 § 0.26) £ 10^{-4}

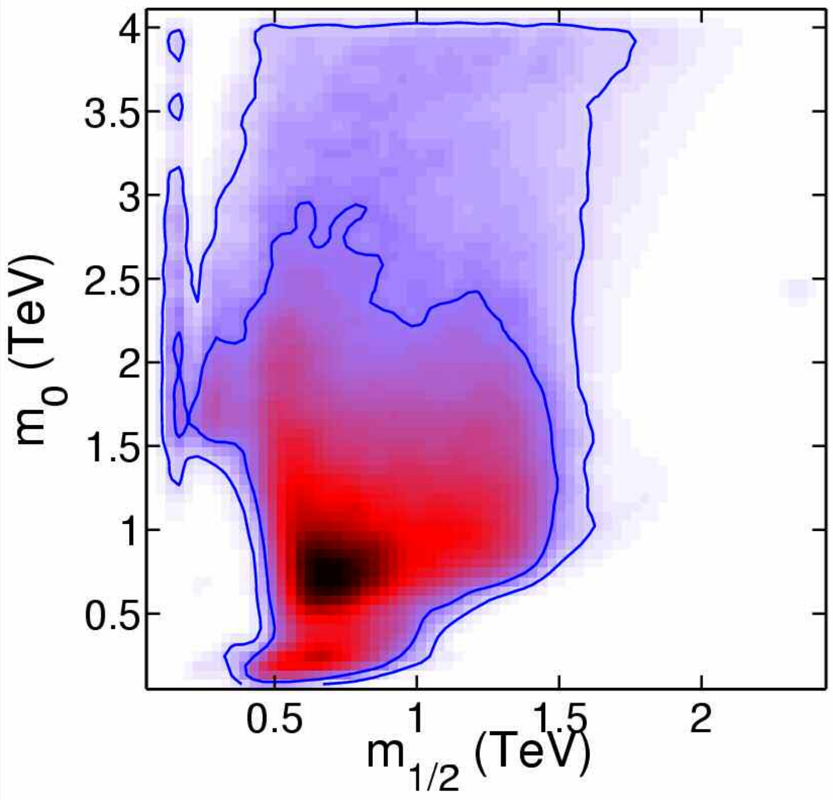
Theory SM: (3.15 § 0.23) £ 10^{-4} (Misiak et al 07)

Old value: (3.60 § 0.30) £ 10^{-4}

2007



2006 Ruiz, Trotta & Roszkowski (2006)



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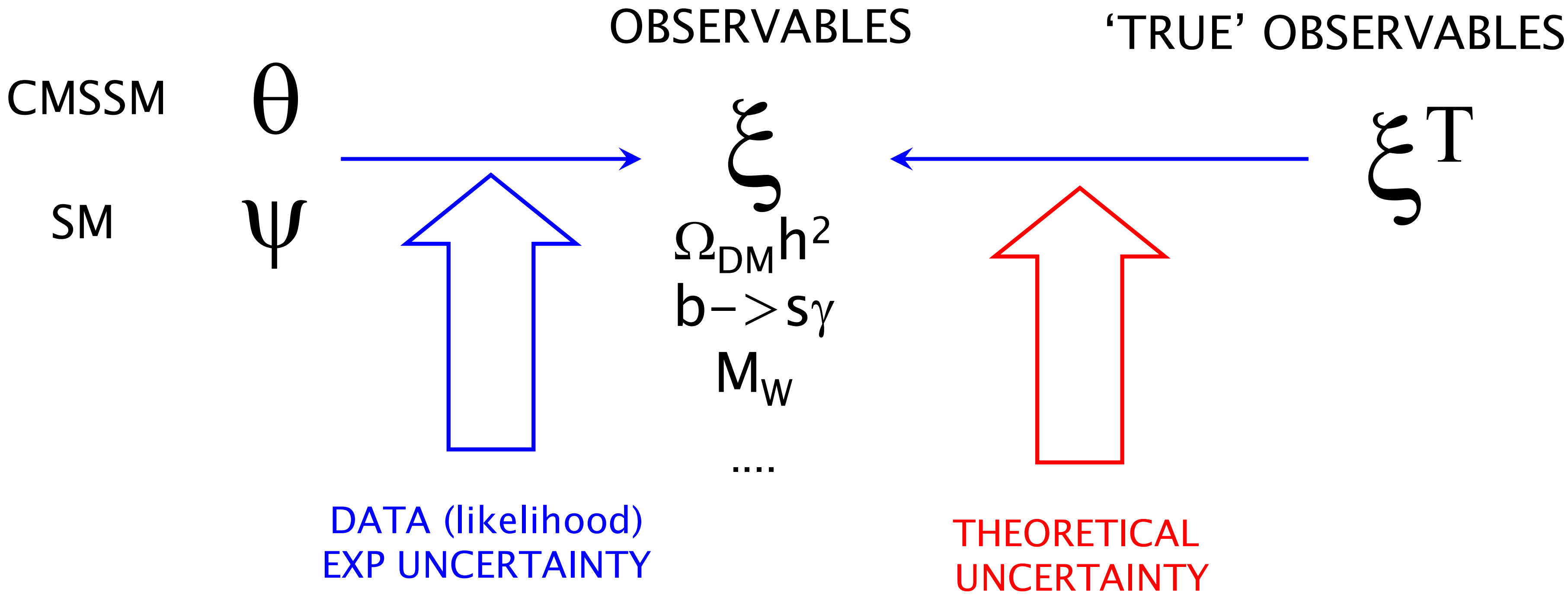
Theoretical uncertainties

- *The Bayesian framwork allows effortless incorporation of theoretical uncertainties:*



likelihood: $p(d\,|\theta,\psi) = s\ p(d|\xi^t)p(\xi^t|\xi)d\xi$

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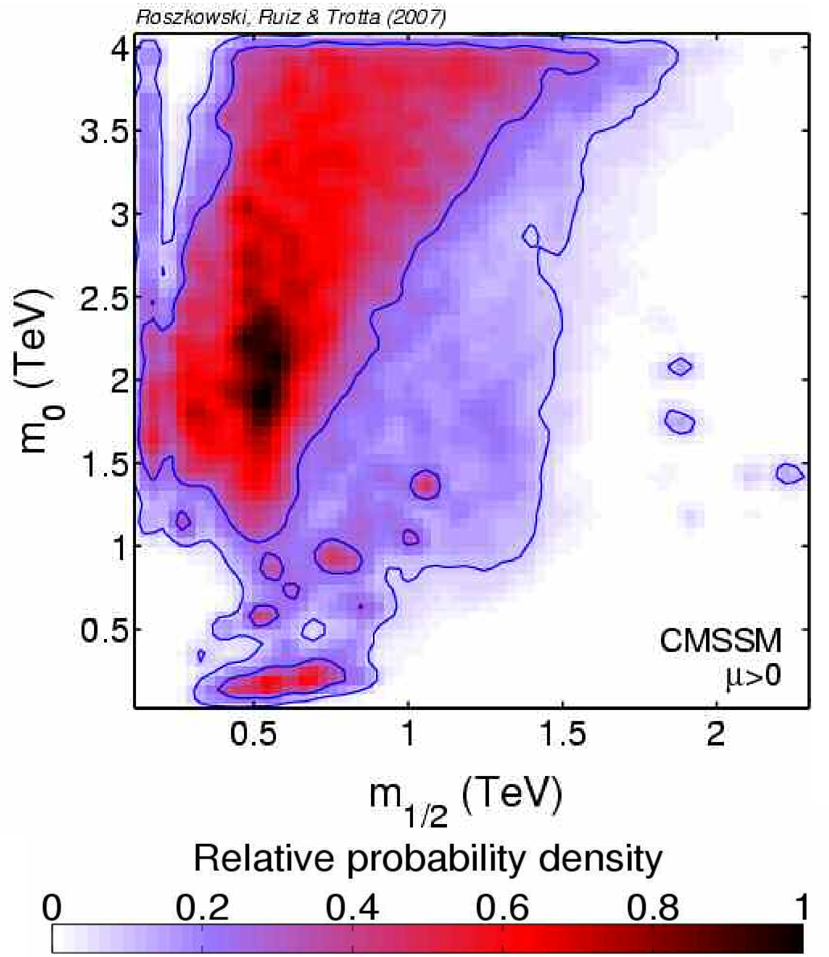
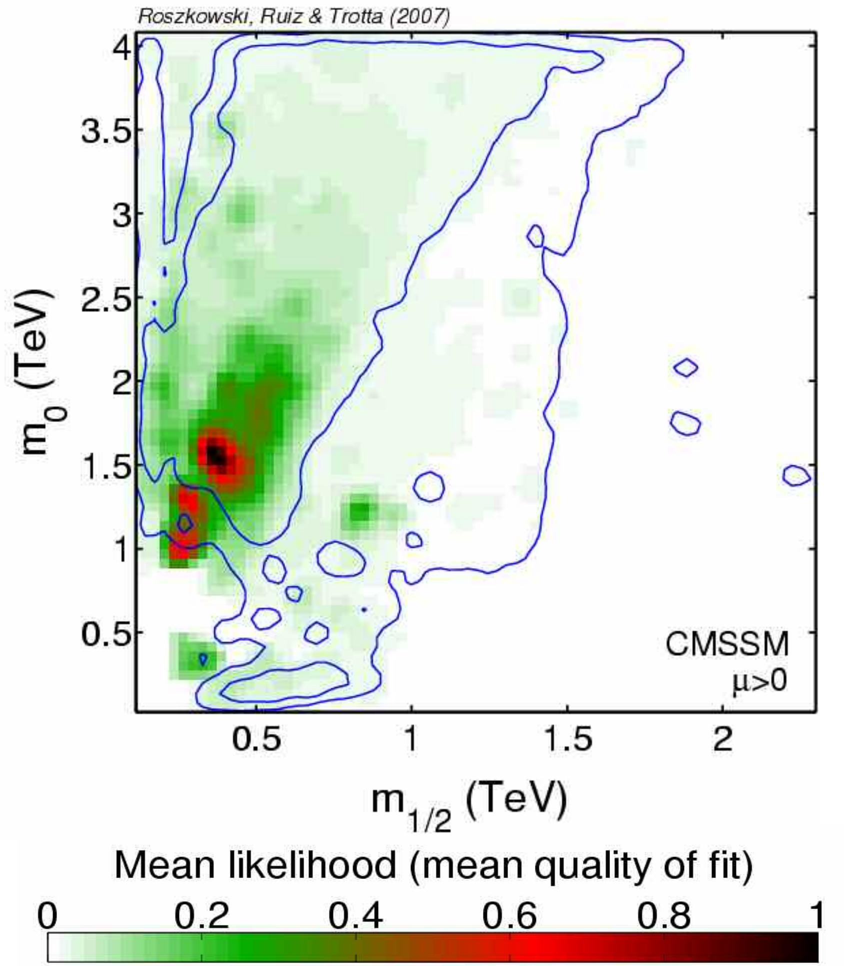
Bayesian vs "quality-of-fit"





Posterior pdf
Represents "state of knowledge"
Volume effect of parameter space

Akin to "chi-square" statistics
Goodness of fit test

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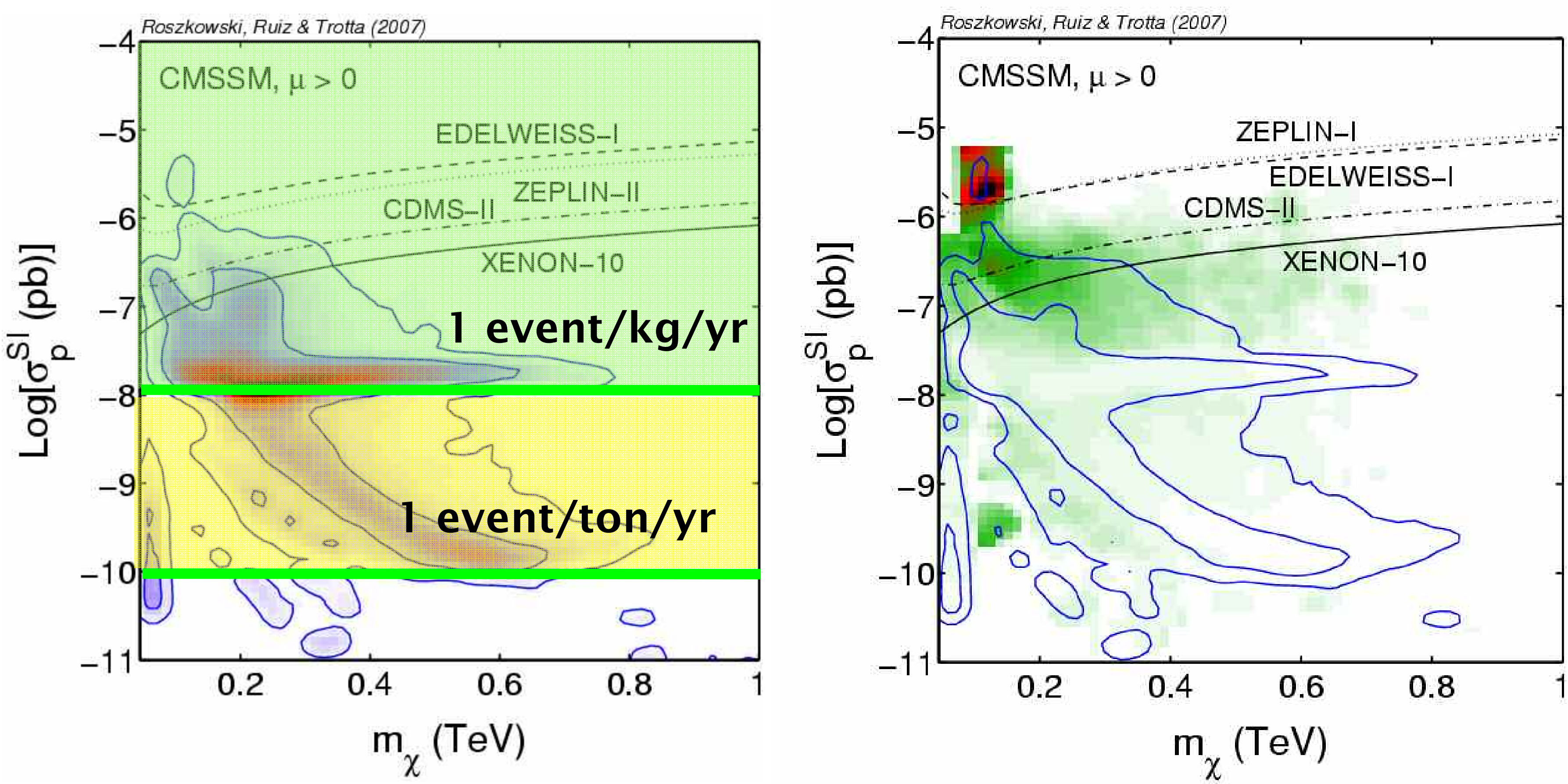
DM direct detection in the CMSSM

New b-> sγ value (2007)
BR(B_s -> sγ) = 3.11§ 0.21 (TH)



The new generation of detectors will probe most of the favoured region in the CMSSM

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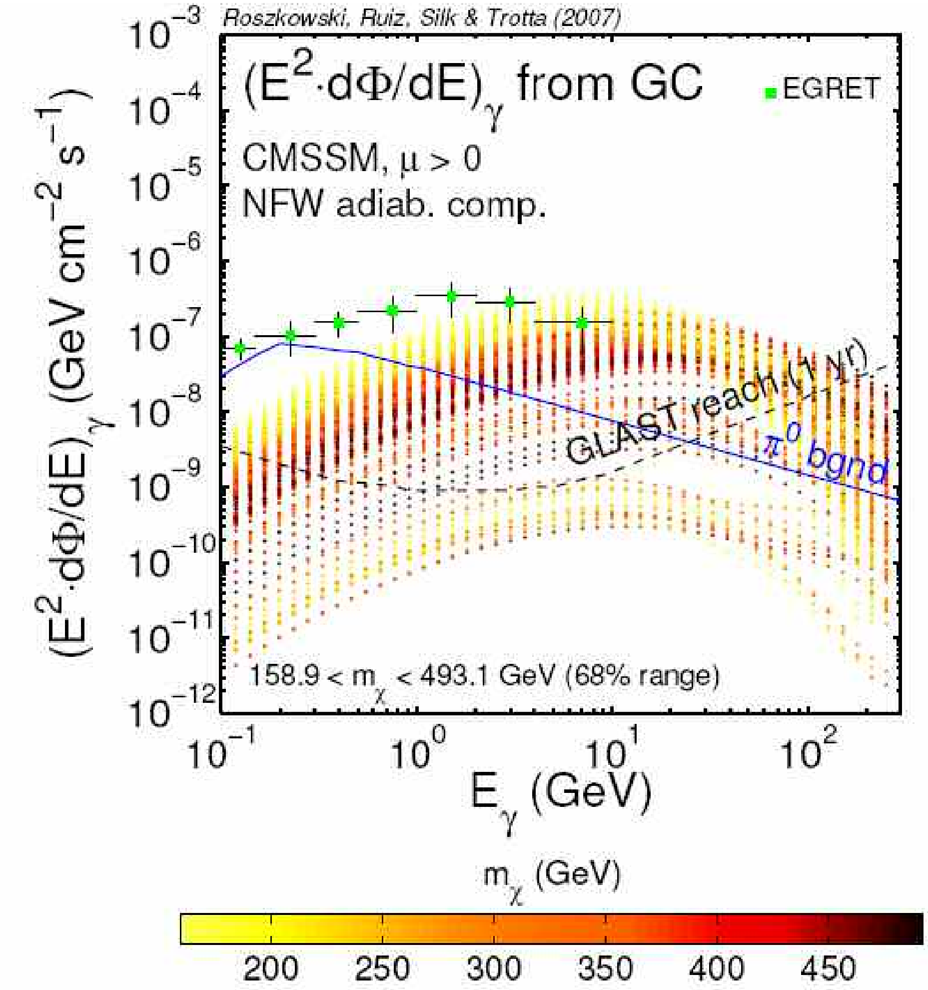
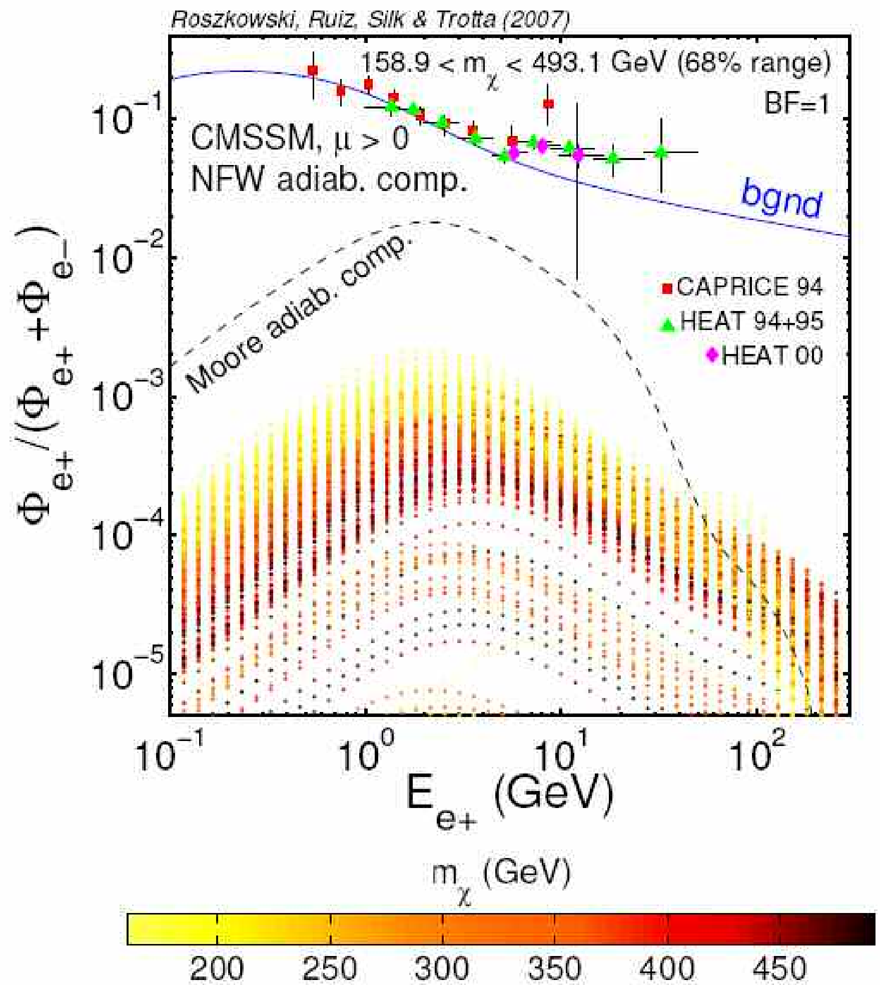
Indirect detection *(Roszkowski et al 2007)*

Predicted
γ rays flux



Predicted
positron flux



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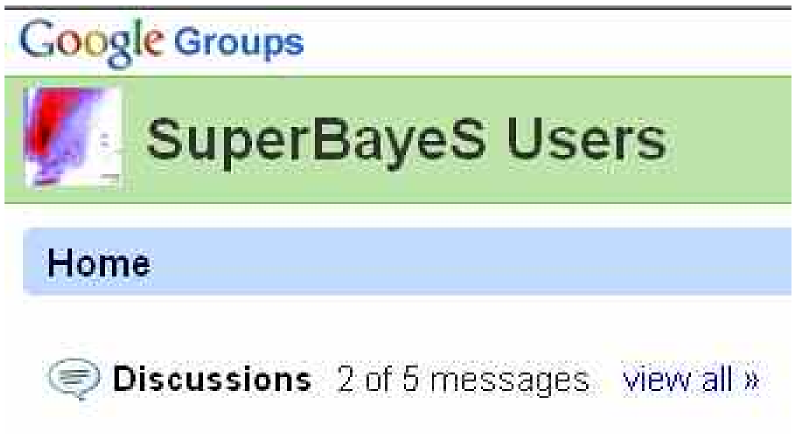
Code released in July 2007, v 1.0:

- *Implements the CMSSM, but can be easily extended to the general MSSM*
- *Includes up-to-date constraints from all observables*
- *Fully parallelized, MPI-ready, user-friendly interface*
- *Bayesian MCMC or grid scan mode, plotting routines*
- *Produces probability and quality of fit plots for all observables, CMSSM parameters, derived quantities, ...*



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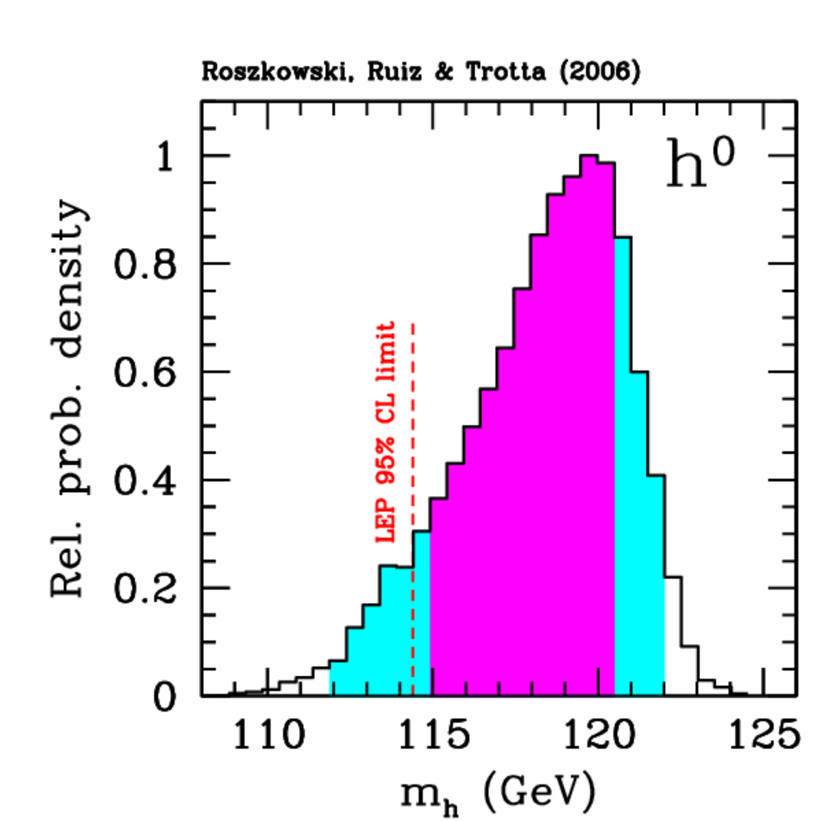
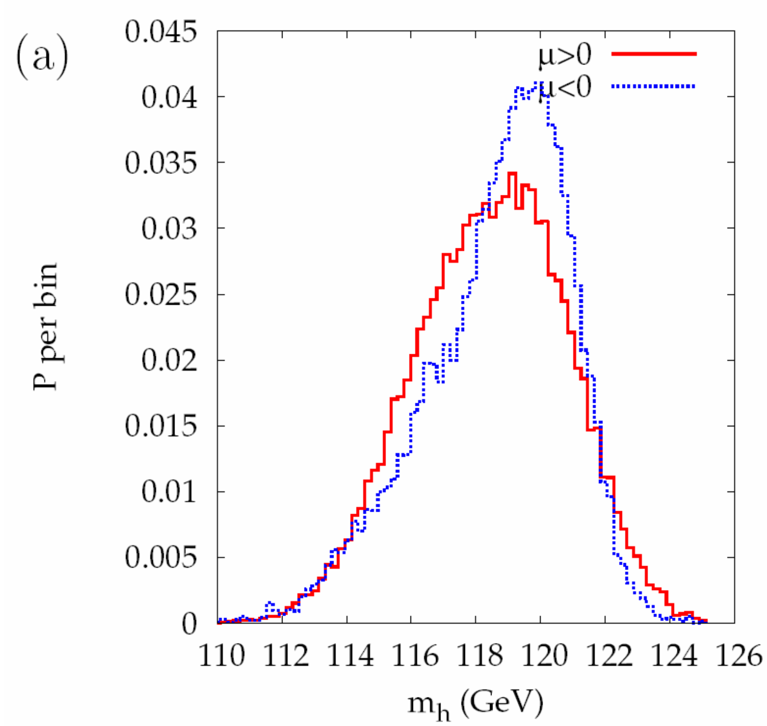
Thanks!

Light Higgs mass distribution

- *Detailed analysis in:* Roszkowski, Ruiz de Austri & RT (2006), *hep-ph/0611173, m_0 < 4 TeV prior.*
  Recently updated with new value
  $BR(B_s$ -> $s\gamma)$ £ 10^4 = 3.55§0.26 (EXP) , 3.11§ 0.21 (TH) *(Misiak et al 2006)*





m_h range will be covered by Tevatron

Allanach (2006); Allanach et al (2006)

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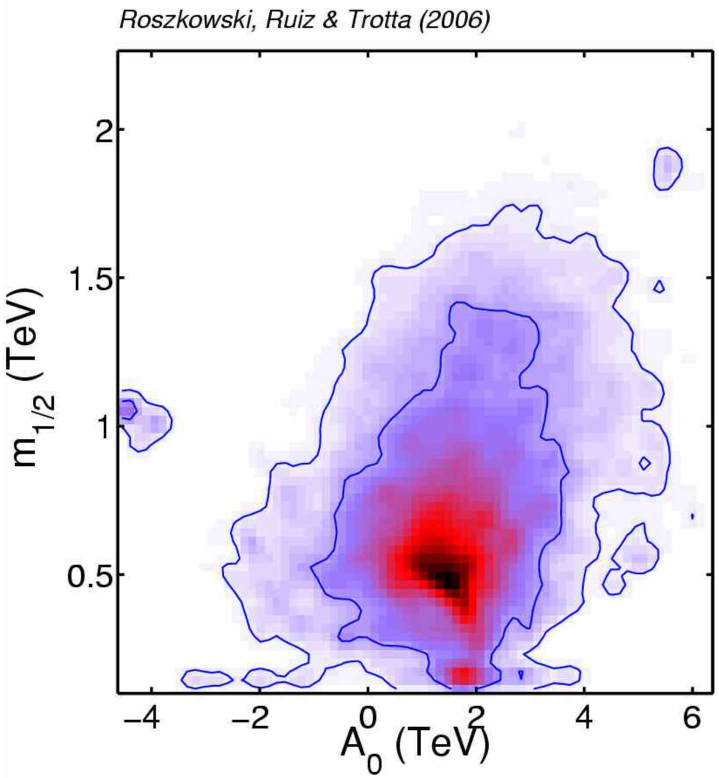
Telling the truth with statistics

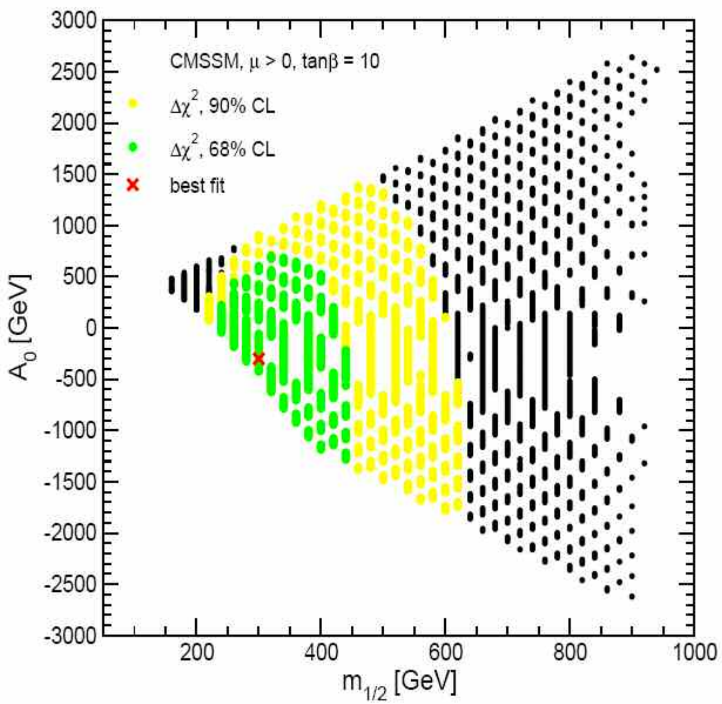
- *Fully marginalised constraints vs chi-sq fits*

m_t, m_b, α_S, α_{EM},
$\tan\beta$, m_0 constrained through data
and integrated over

m_t fixed
$\tan\beta = 10$ fixed
m_0 fitted to WMAP



Ruiz de Austri et al (2006)
Roszkowski et al (2007, in prep)



Ellis et al (2005), hep-ph/0508169

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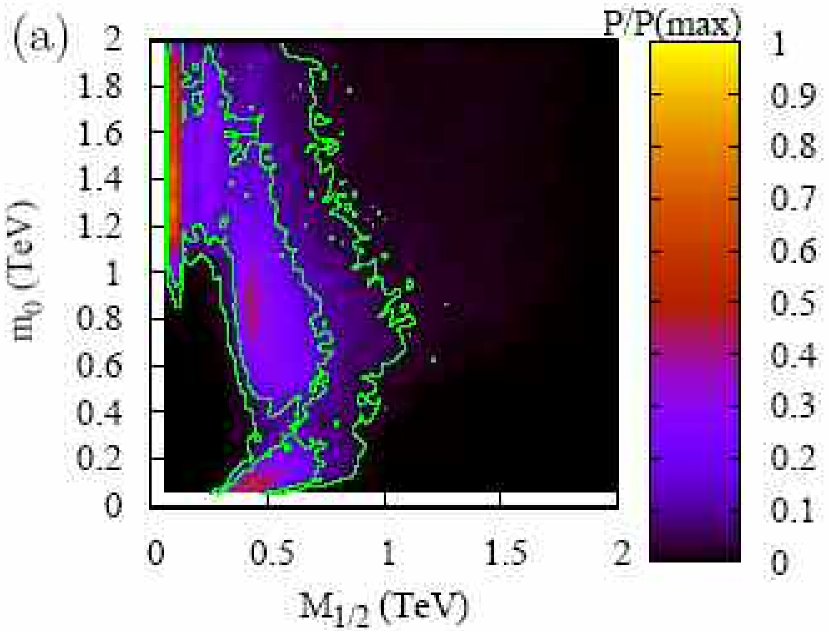
Change in priors I

- *The fine tuning problem:*

$$\frac{M_Z^2}{2} = \frac{m_{H_1}^2 - m_{H_2}^2 \tan^2\beta}{\tan^2\beta - 1} - \mu^2$$

- *Amount of fine tuning:*

$$c_i \equiv \left| \frac{\partial \ln M_Z}{\partial \ln p_i} \right|, \qquad c \equiv \max\{c_i\}.$$



Naturalness prior

Flat prior

Allanach (2006)

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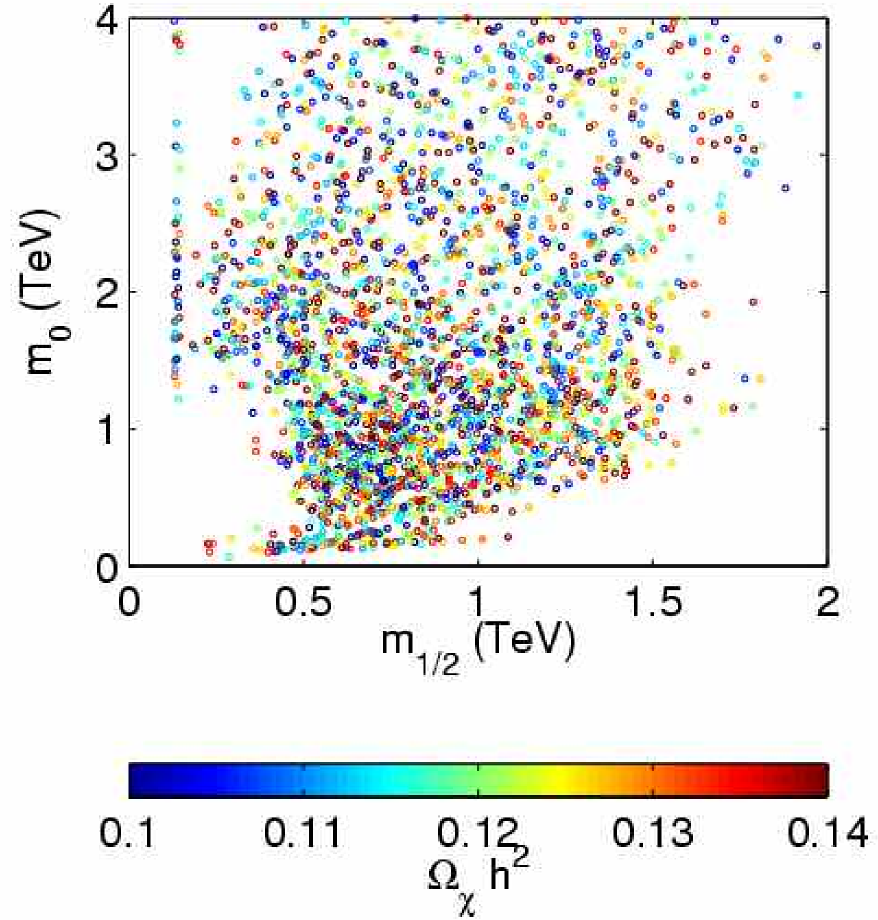
Just how constraining is $\Omega_m h^2$?

Not very much
apart from setting an upper limit to $m_{1/2}$!



(WMAP1 data)

Ruiz de Austri, Trotta, Roszkowski (2006)

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MCMC Metropolis-Hastings algorithm

Oxford Physics

MCMC = Markov Chain Monte Carlo

(1) *Select a random point in parameter space, θ_0*
*Compute $P(\theta_0)$ = Like*Prior*

(2) *Propose a new point, θ_1*
with transition probability T, satisfying

$$T(\theta_0, \theta_1) = T(\theta_1, \theta_0)$$

(3) *Evaluate $P(\theta_1)$ = Like*Prior*

(4) *If* *$P(\theta_1) > P(\theta_0)$ move to θ_1*
else
move to θ_1 with probability = $P(\theta_1)/P(\theta_0)$

Obtain a Markov Chain: θ_i, i = 1, ..., N
The density of points is proportional to the target distribution, $P(\theta)$

Statistical inference eg: $< f(\theta) > / 1/N \sum_i f(\theta_i)$

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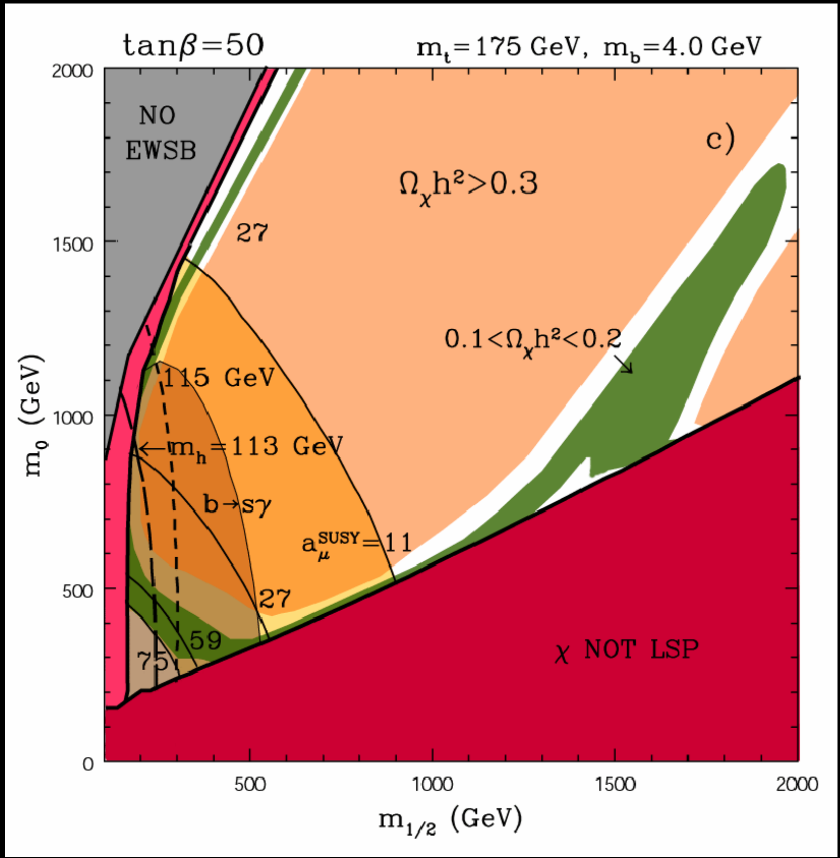
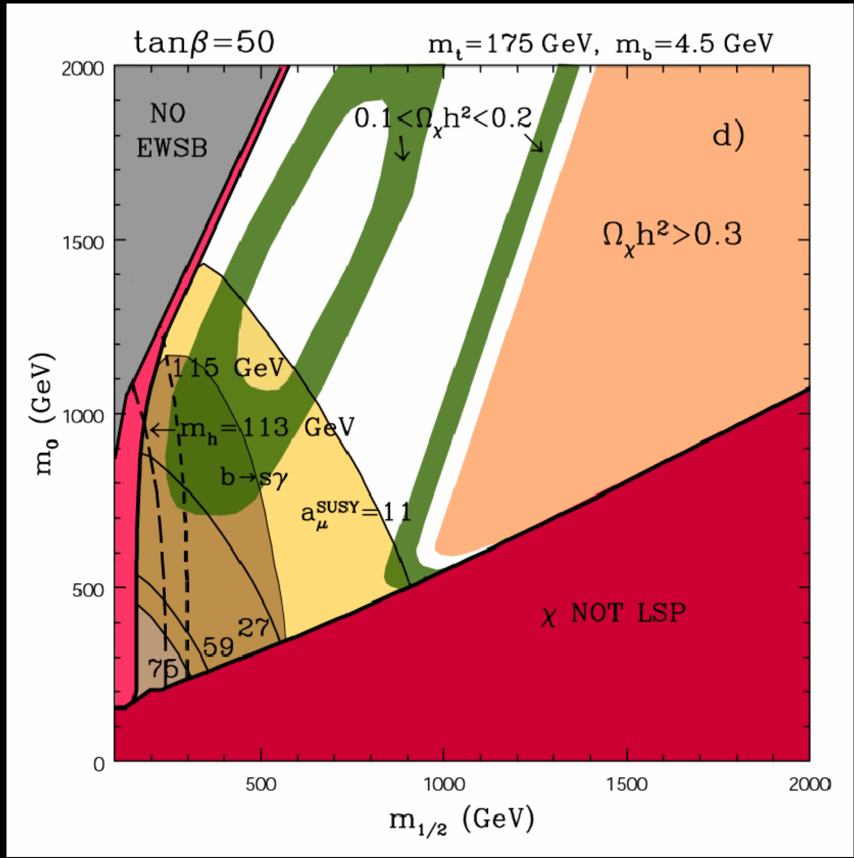
$m_b = 4.0$ GeV $m_b = 4.5$ GeV

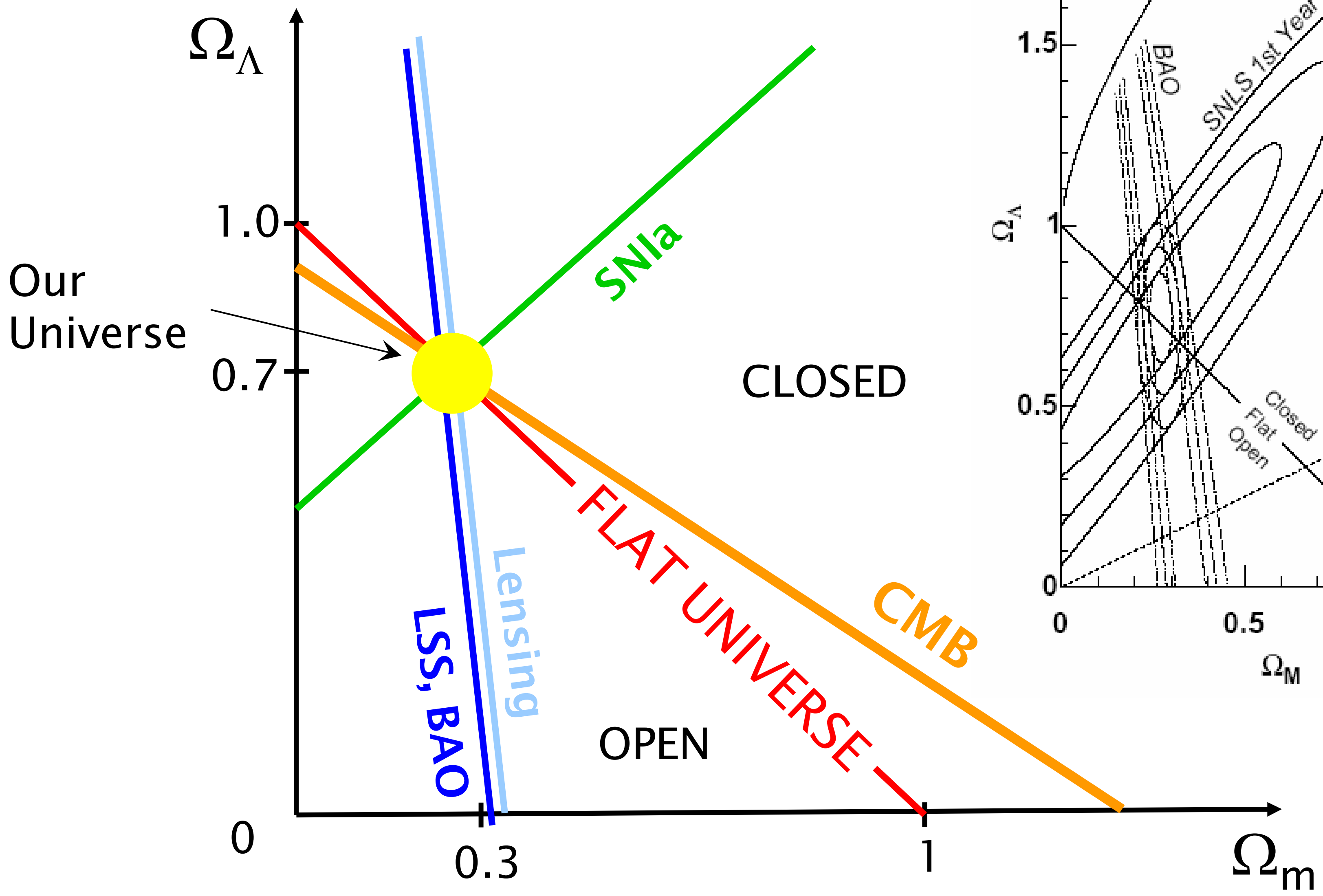


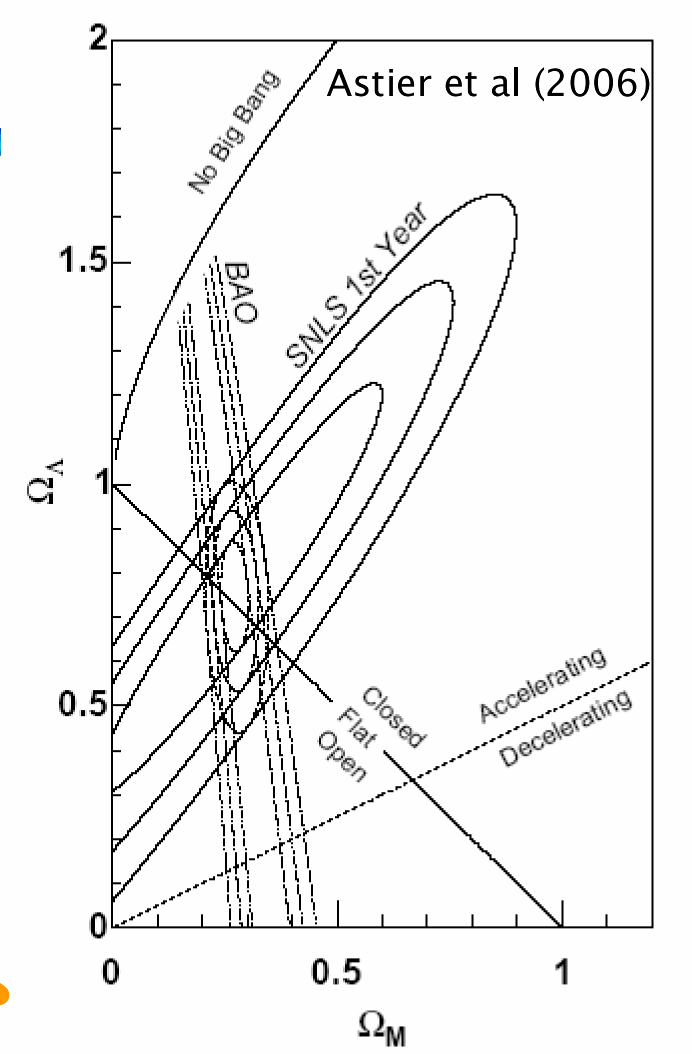


Uncertainty in SM parameters
cannot be neglected

(Roszkowski, Ruiz de Austri, Nihei 2001)

Accumulating evidence





Ω_m = 0.271 § 0.020, Ω_Λ = 0.751 § 0.082

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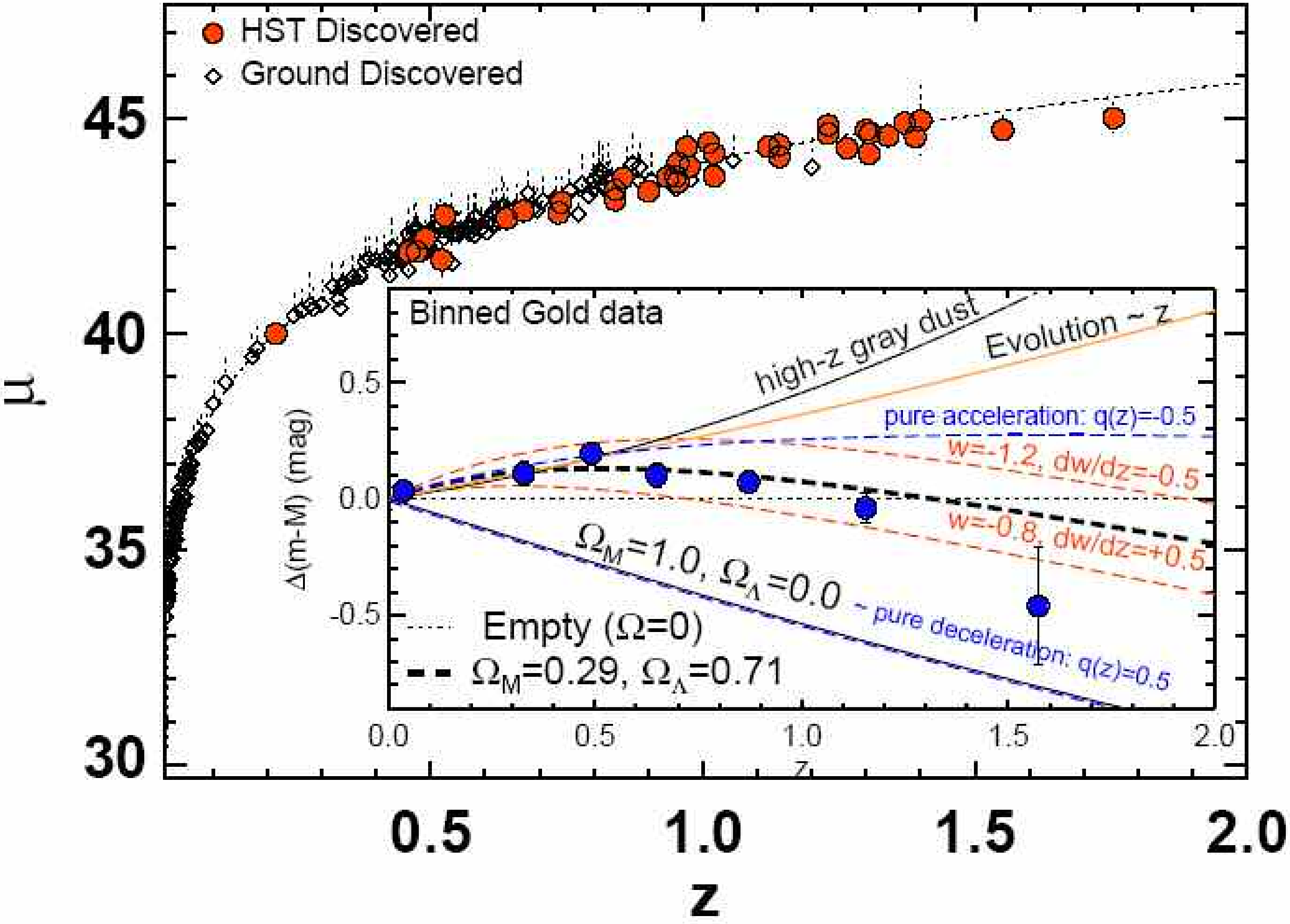
Luminosity distance measurements

- *Supernovae type Ia as (almost) standard candles*



Riess et al (2006)

$D_L(z)$ (a function of Ω_m, Ω_Λ, Ω_κ, H_0)

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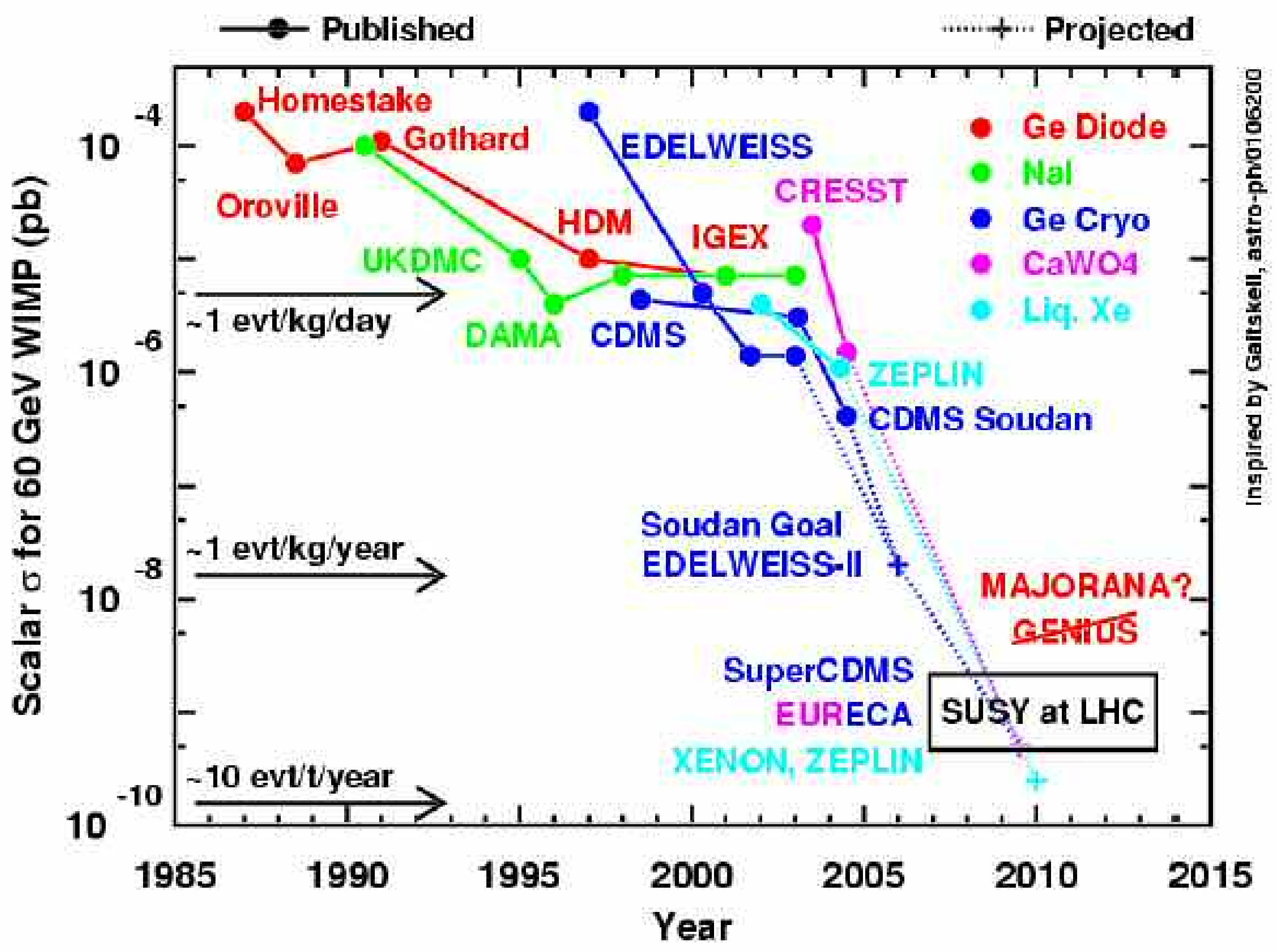
Direct searches: present & future



Courtesy Hans Kraus

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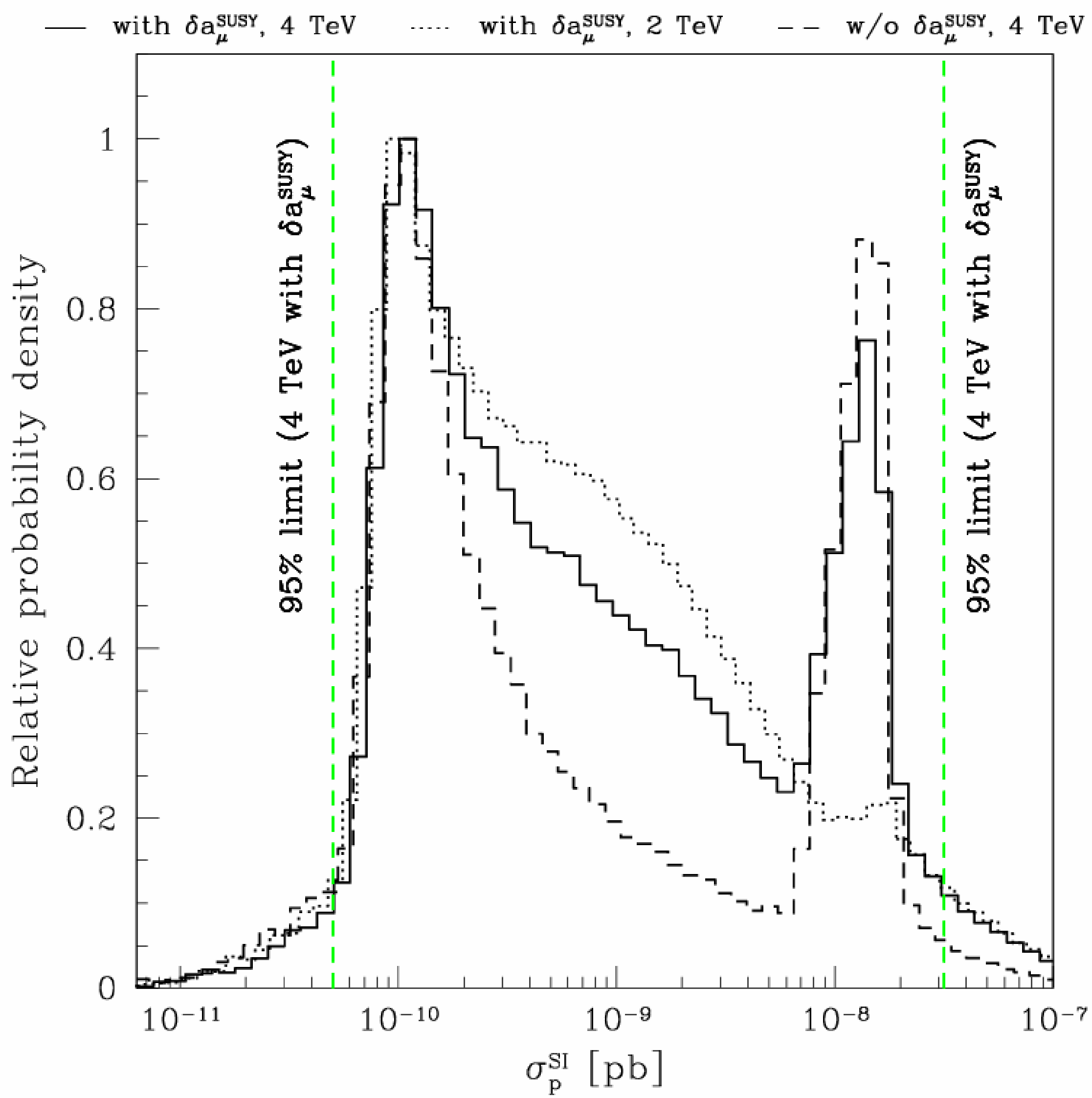
Sensitivity to assumptions

1D probability distribution fairly robust with respect to a change in prior ranges or inclusion of g-2 data



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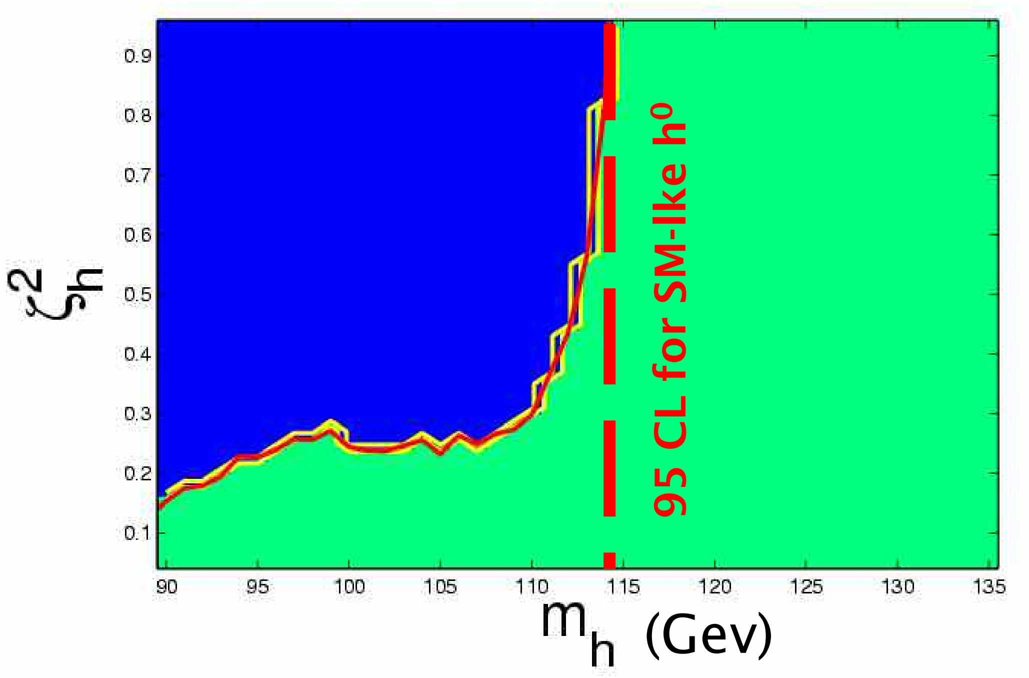
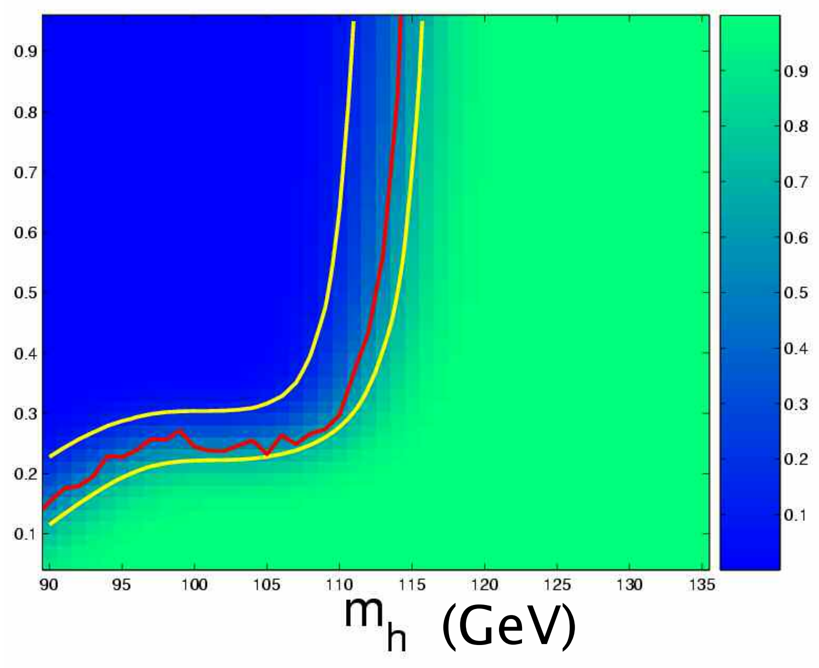
An example: Higgs mass LEP bounds

- *Need to consider likelihood in the (m_h, ζ_h^2) plane. Cannot simply assume that h^0 is SM-like*



NO THEORETICAL ERRORS



THEORETICAL ERRORS
in m_h (3 GeV) and ξ_h^2 (10%)

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