Applications of Astrostatistics to Dark Matter Phenomenology and Beyond the Standard Model Theories

@R_Trotta

Roberto Trotta
Astrophysics & Data Science Institute
Imperial College London

ICIC
Imperial Centre
for Inference & Cosmology

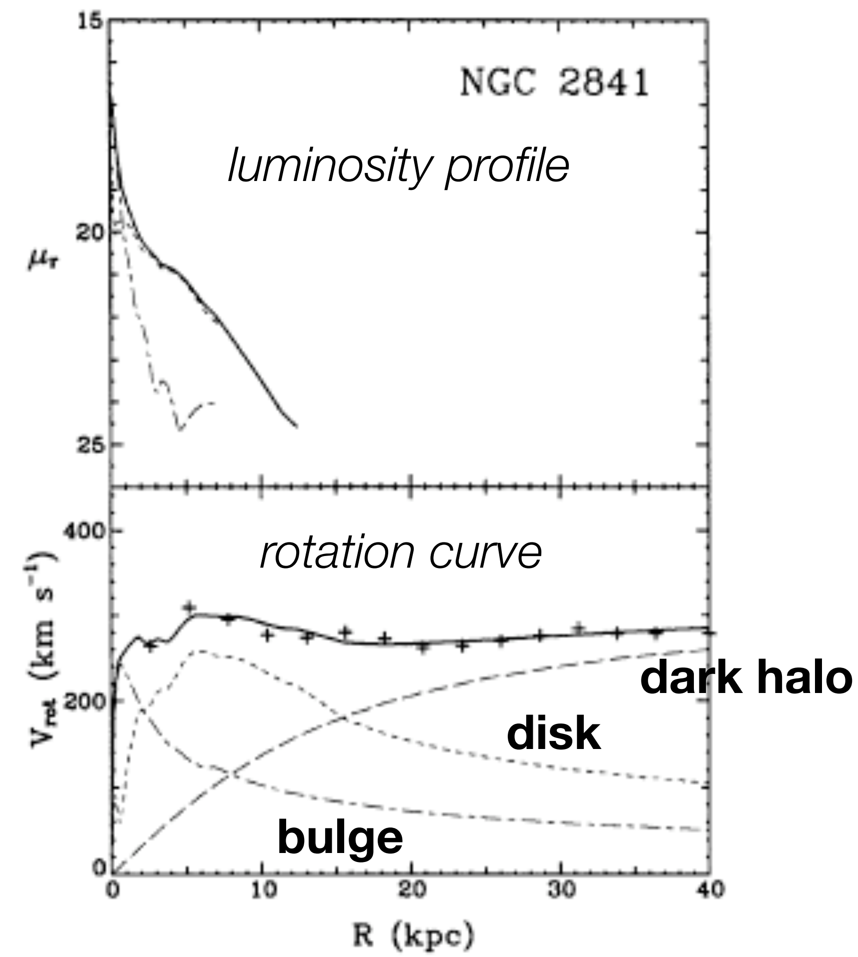
www.robertotrotta.com

Imperial College
London

Evidence for dark matter

Imperial College London

- Multiple astrophysical and cosmological probes strongly point to the existence of non-baryonic dark matter:



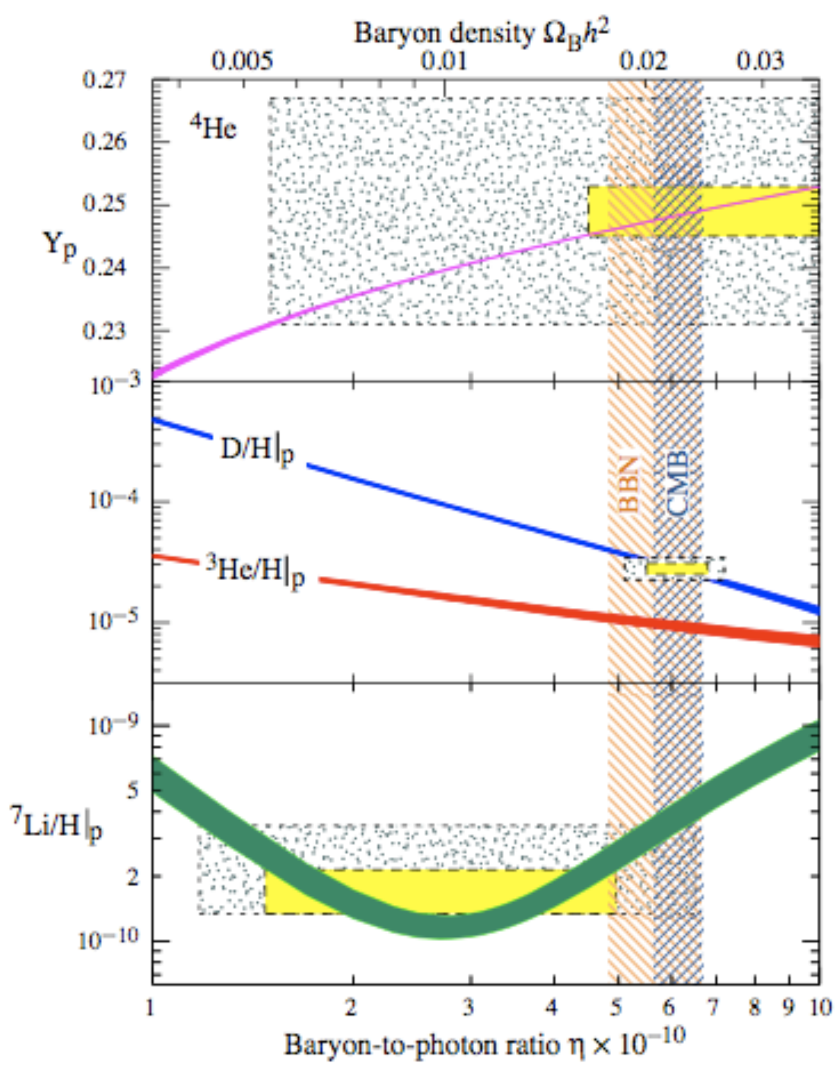
Kent 1987

Gravitational lensing
M/L >> 1

Flat rotation curves
M/L >> 1

Evidence for dark matter (cont'ed)

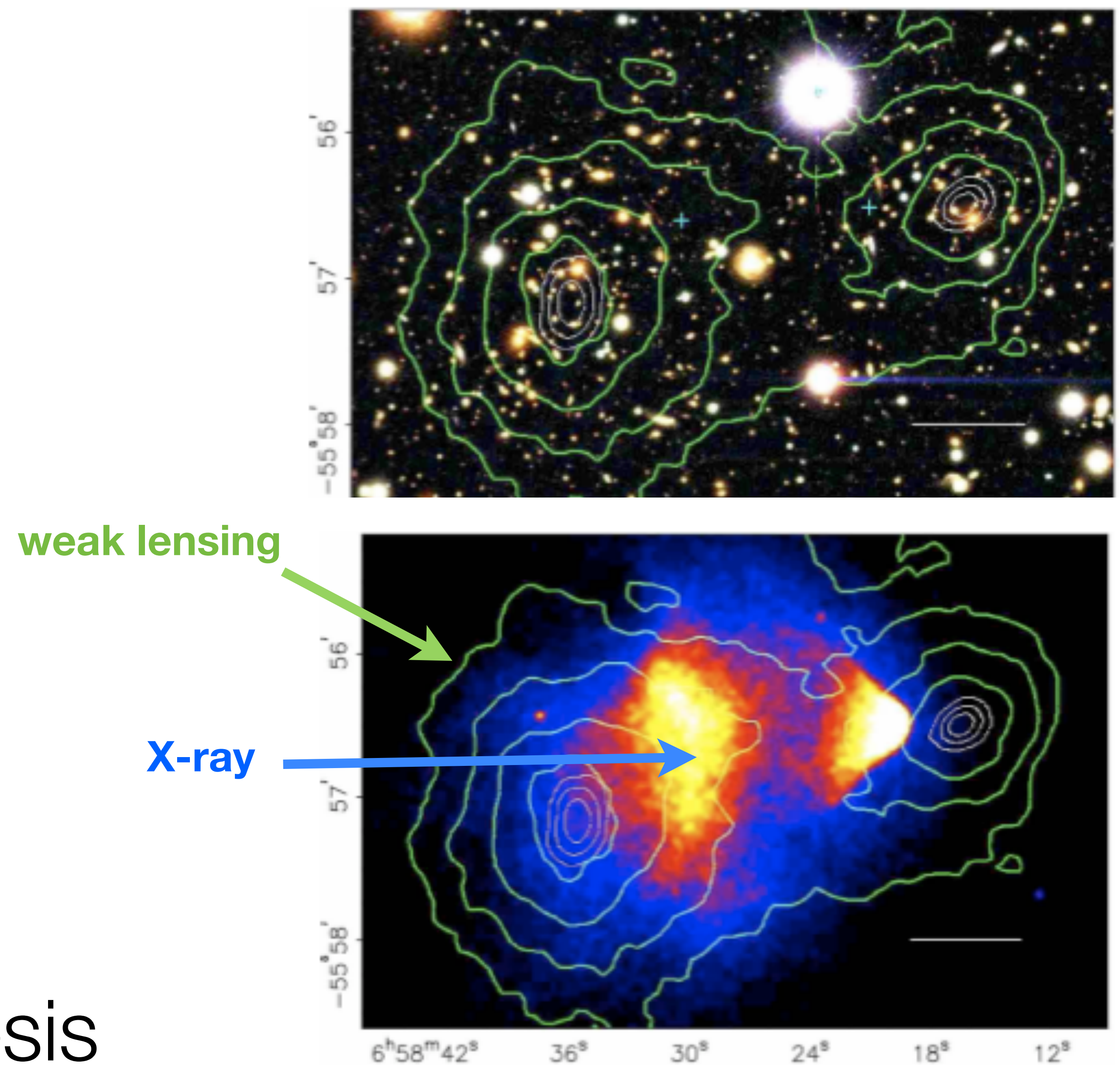
Fields & Sarkar 2006



Big Bang nucleosynthesis

$4.7 < \eta_{10} < 6.5$

$0.017 < \Omega_b h^2 < 0.024$



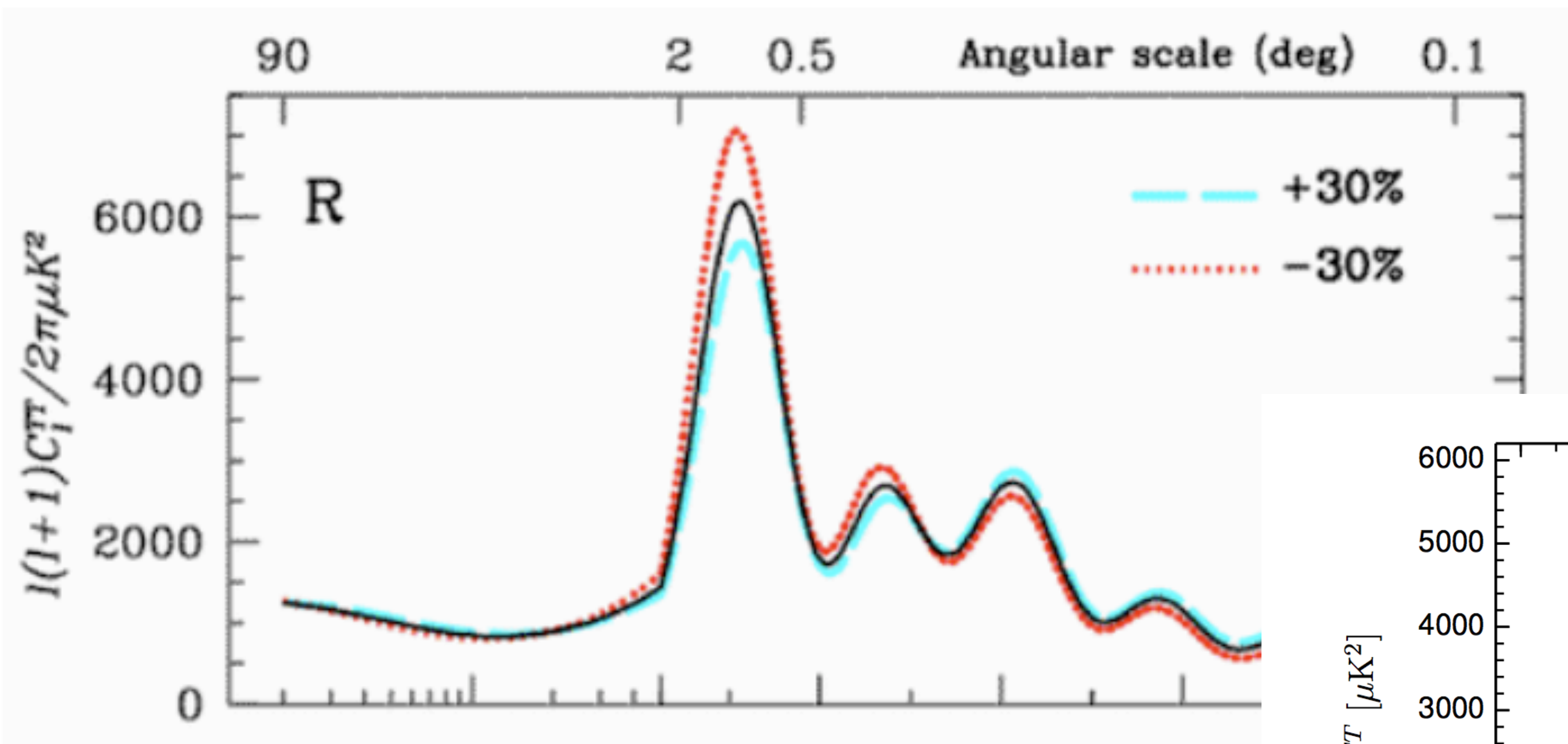
Clove et al 2006

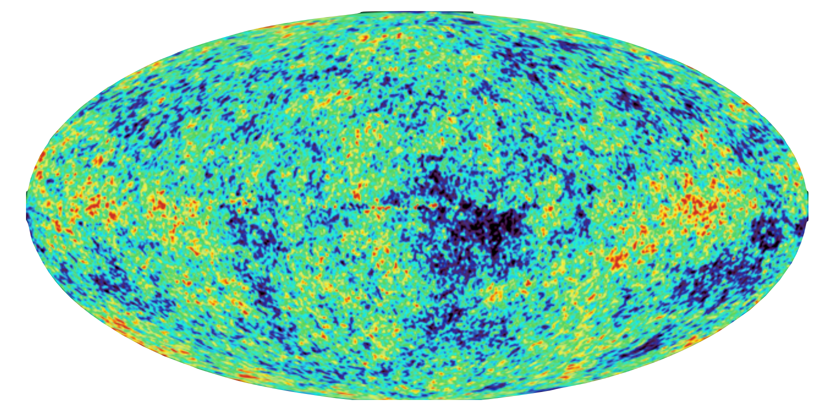
Multi-λ data + weak lensing

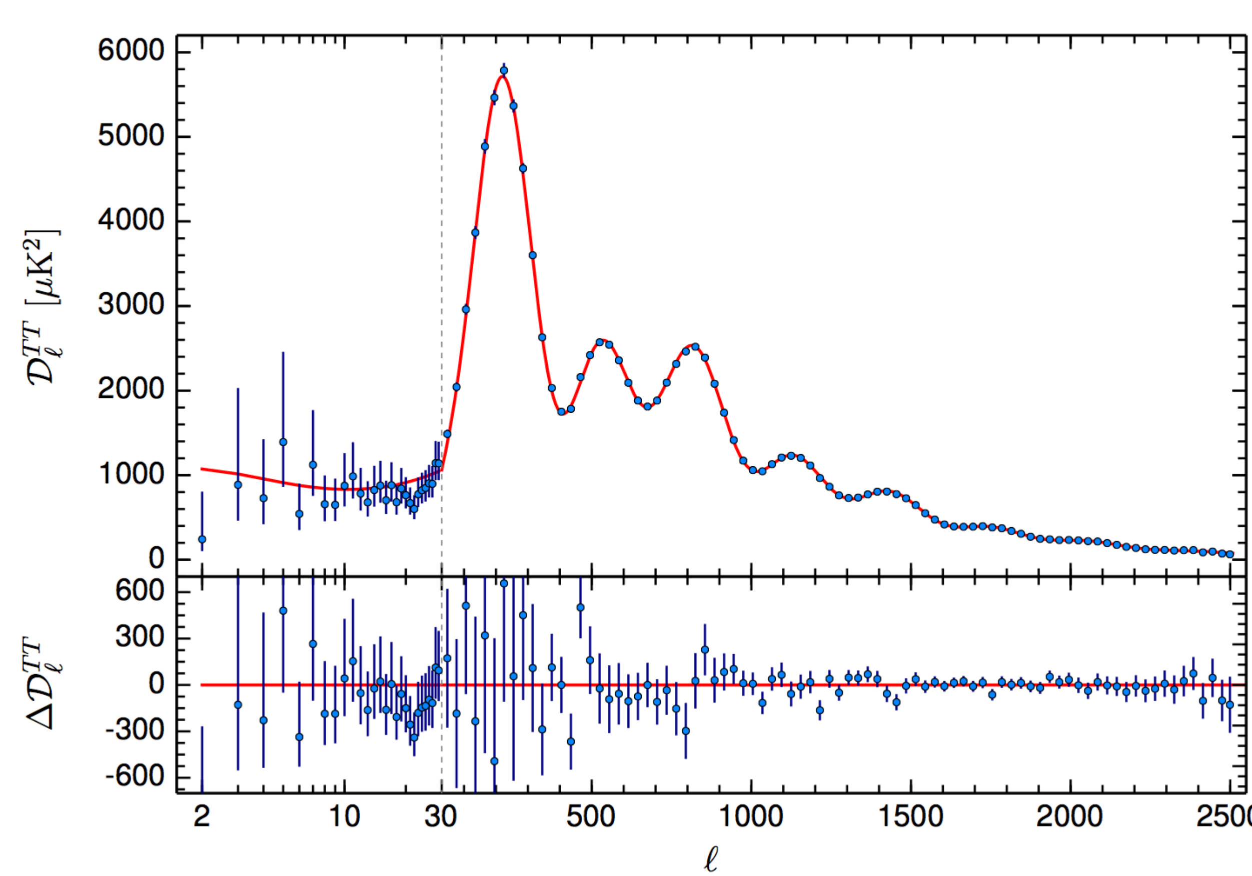
The cosmic microwave background

Imperial College London

Change in the matter/radiation energy density ratio at decoupling:





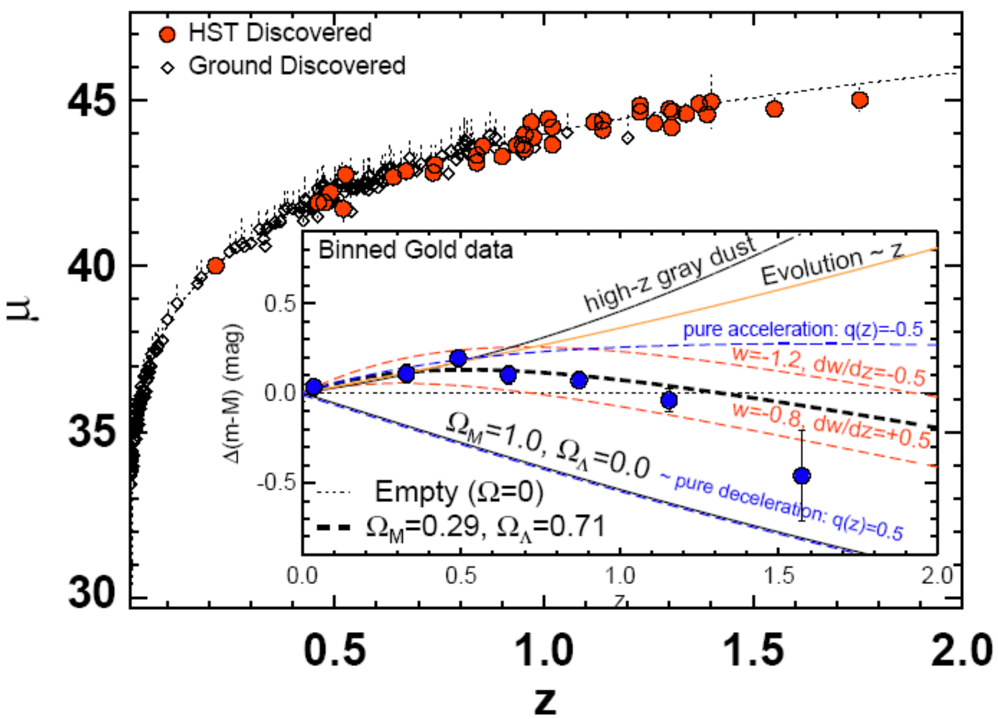


$$\Omega_{cdm}h^2 = 0.1099 \pm 0.0062$$

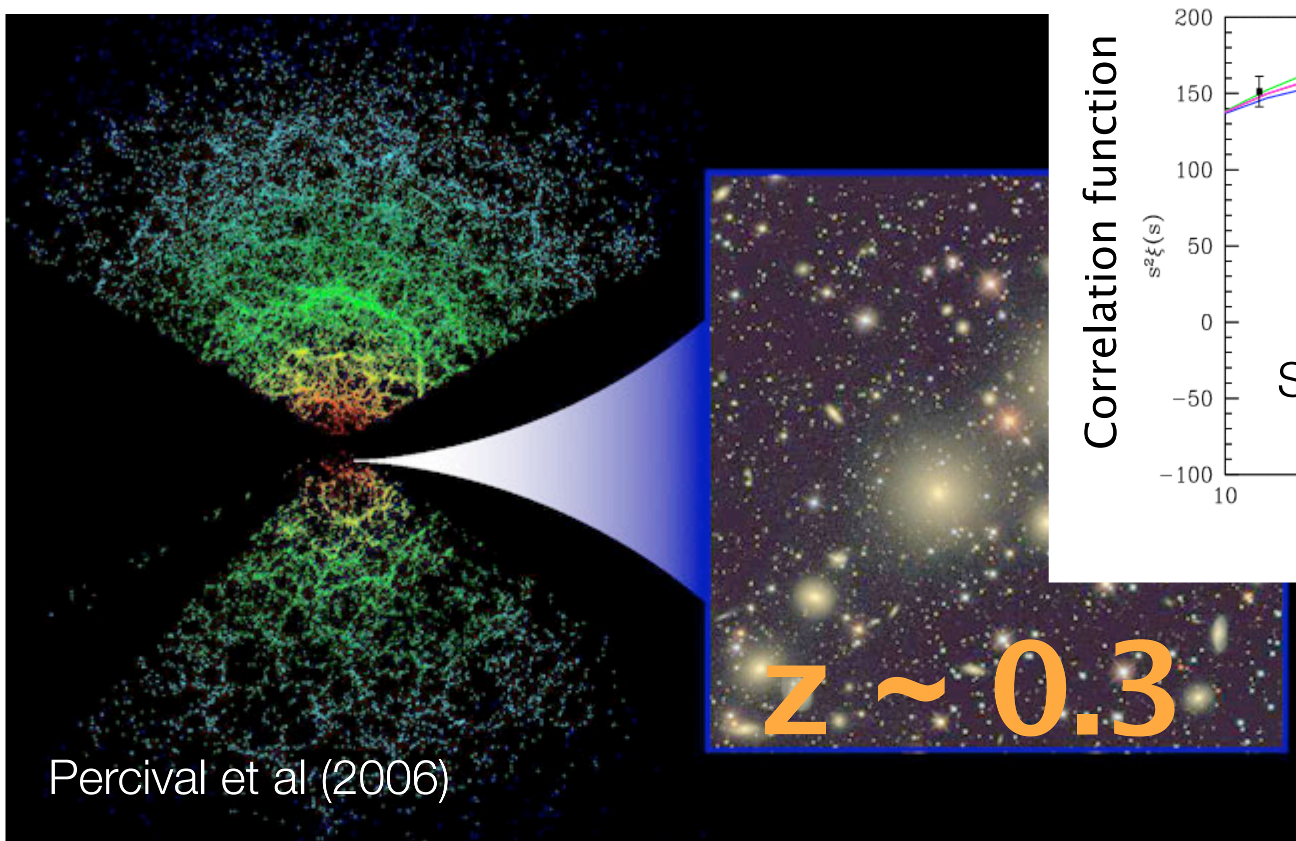
$$\Omega_m = 0.258 \pm 0.030$$

Combined cosmological probes

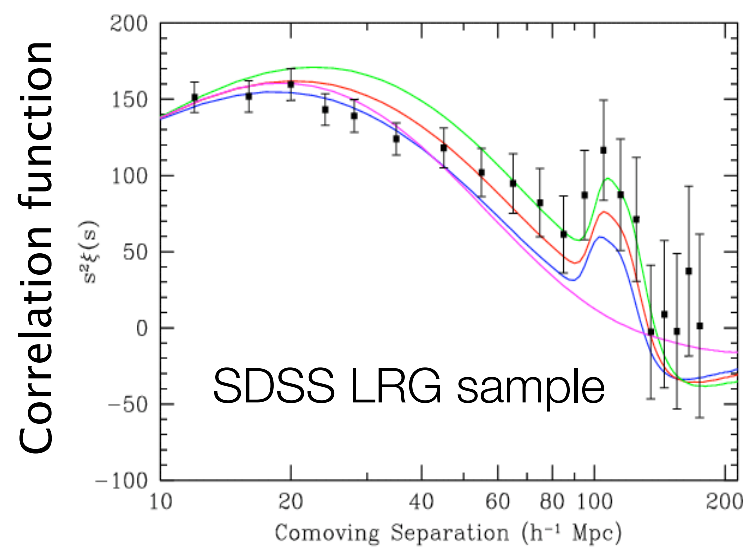
Imperial College London



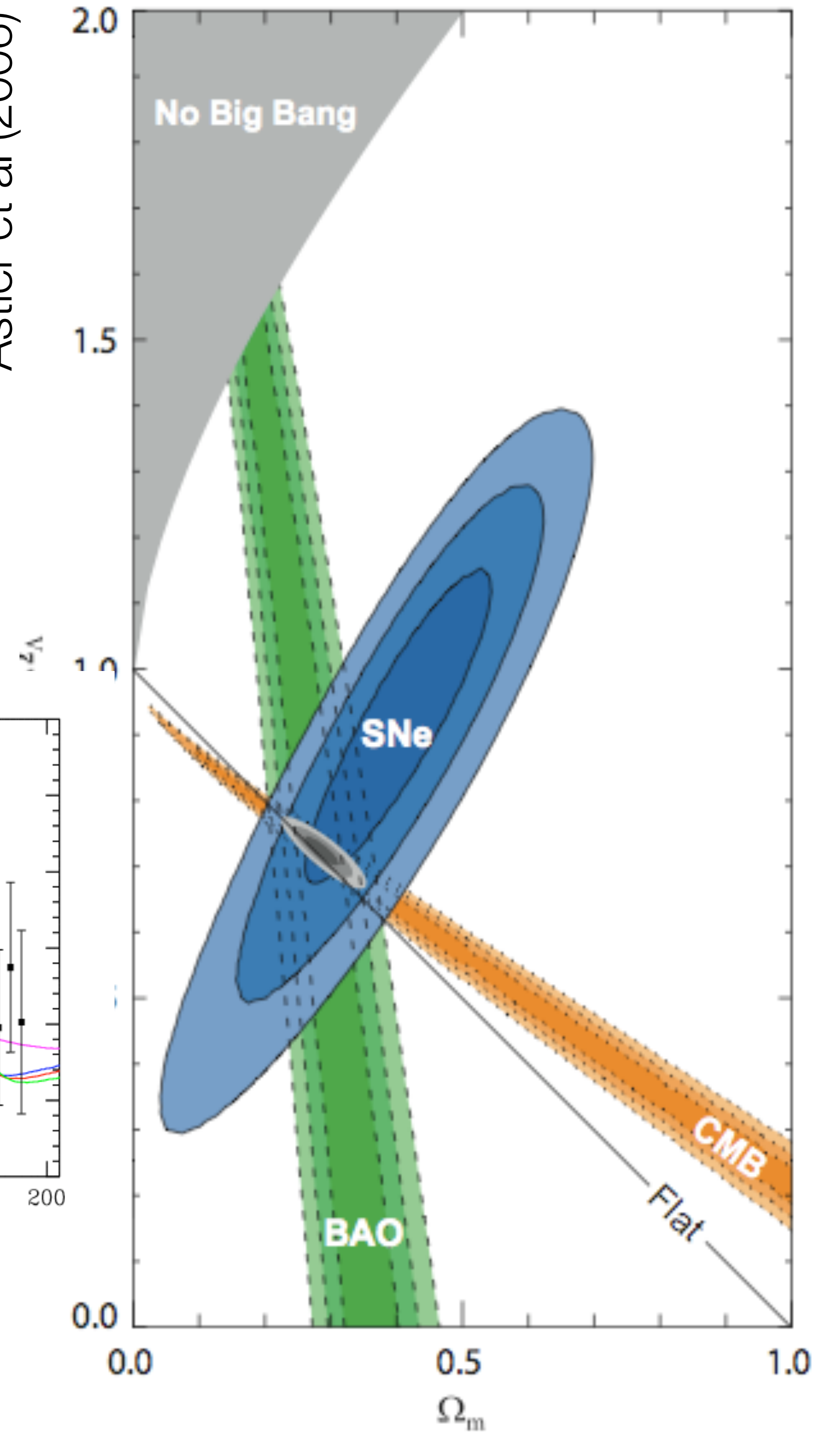
Riess et al (2006)



Percival et al (2006)



Astier et al (2006)



SUSY in a nutshell

- Every SM particle acquires a superpartner with the same quantum numbers but opposite spin statistics
- Unbroken SUSY: sparticles have the same mass as SM particles
- SUSY must be broken

Standard Model particles and fields		Supersymmetric partners			
		Interaction eigenstates		Mass eigenstates	
Symbol	Name	Symbol	Name	Symbol	Name
$q = d, c, b, u, s, t$	quark	$\tilde{q}_L, \tilde{q}_R$	squark	$\tilde{q}_1, \tilde{q}_2$	squark
$l = e, \mu, \tau$	lepton	$\tilde{l}_L, \tilde{l}_R$	slepton	$\tilde{l}_1, \tilde{l}_2$	slepton
$\nu = \nu_e, \nu_\mu, \nu_\tau$	neutrino	$\tilde{\nu}$	sneutrino	$\tilde{\nu}$	sneutrino
g	gluon	$\tilde{g}$	gluino	$\tilde{g}$	gluino
$W^\pm$	W-boson	$\tilde{W}^\pm$	wino		
H^-	Higgs boson	$\tilde{H}_1^-$	higgsino	$\tilde{\chi}_{1,2}^\pm$	chargino
H^+	Higgs boson	$\tilde{H}_2^+$	higgsino		
B	B-field	$\tilde{B}$	bino		
W^3	W^3-field	$\tilde{W}^3$	wino		
H_1^0	Higgs boson			$\boxed{\tilde{\chi}_{1,2,3,4}^0}$	$\boxed{\text{neutralino}}$
H_2^0	Higgs boson	$\tilde{H}_1^0$	higgsino		
H_3^0	Higgs boson	$\tilde{H}_2^0$	higgsino		

A natural DM candidate

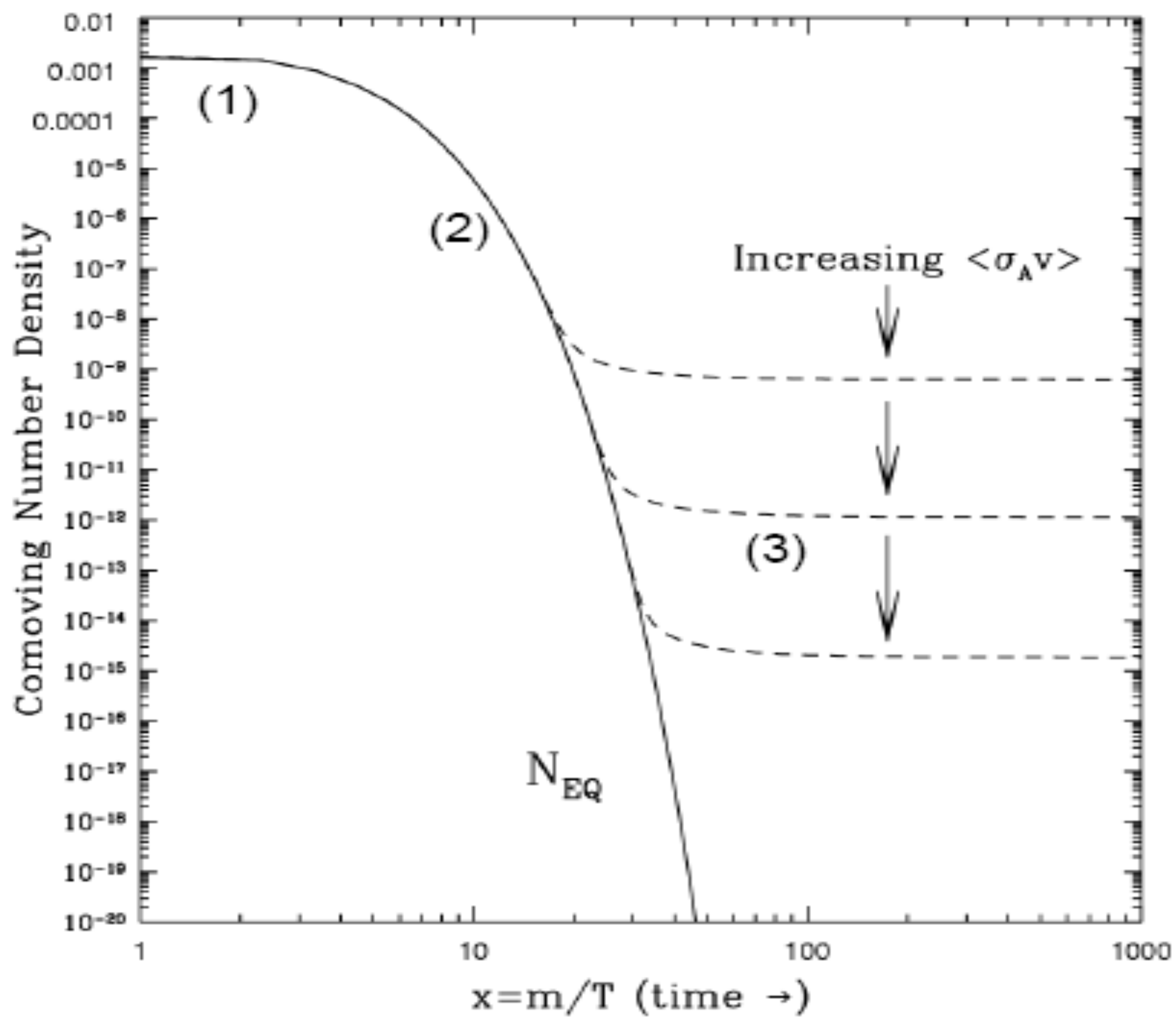
Review article: Bertone, Hooper & Silk (2005)

A solution to the DM problem

Imperial College London

- Under R-parity, the neutralino is stable
- Neutral, weakly interacting, mass in the range ~ 100 GeV to a few TeV
- Cosmological neutralino relic abundance:

$$\Omega_\chi h^2 \sim \frac{3 \times 10^{-27} \mathrm{cm}^3 \mathrm{s}^{-1}}{\langle \sigma v \rangle}$$



Courtesy Sabine Kraml

The model & data

Imperial College London

- The general Minimal Supersymmetric Standard Model (MSSM): **105 free parameters!**

- Need some (pretty strong) simplifying assumption: **the Constrained MSSM** (CMSSM) reduces the free parameters to just **4 continous variables plus a discrete one** (sign(μ)).

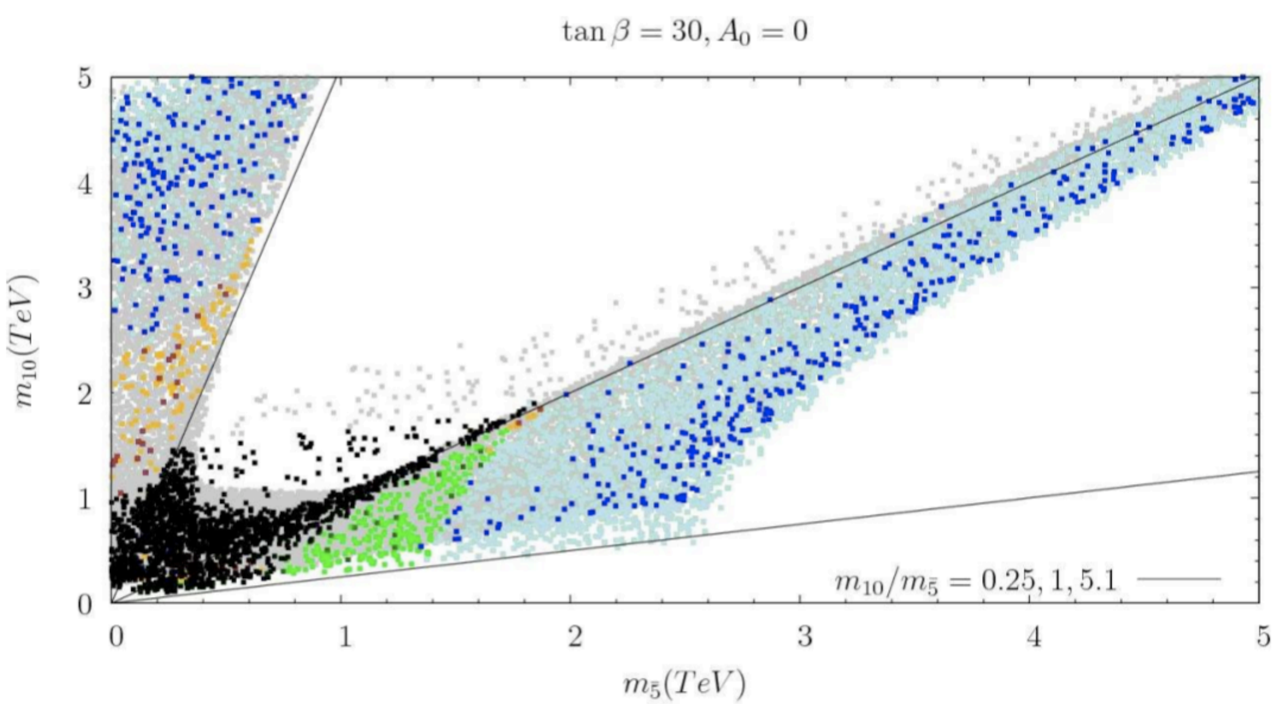
- Clearly a highly constrained model (probably not the end of the story!)

- **Present-day data:** collider measurements of rare processes, CDM abundance (Planck), sparticle masses lower limits, EW precision measurements, Higgs mass and couplings.

- **Astrophysical direct and indirect detection techniques might also be competitive:** neutrino (IceCUBE), gamma-rays (Fermi), antimatter (PAMELA), direct detection (XENON1T, LUX, PandaX,…)

Exploration with “random scans”

Imperial College London

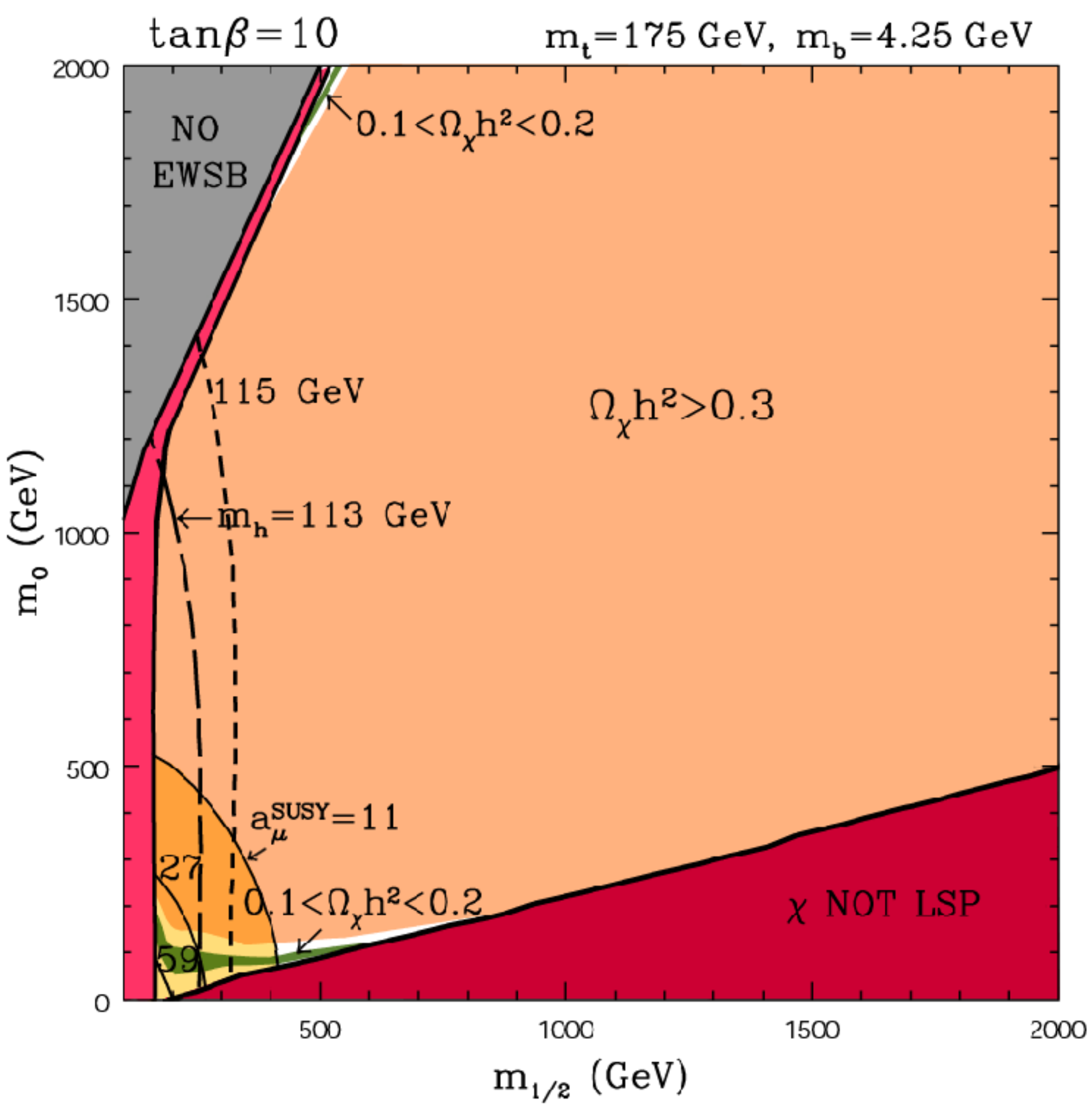


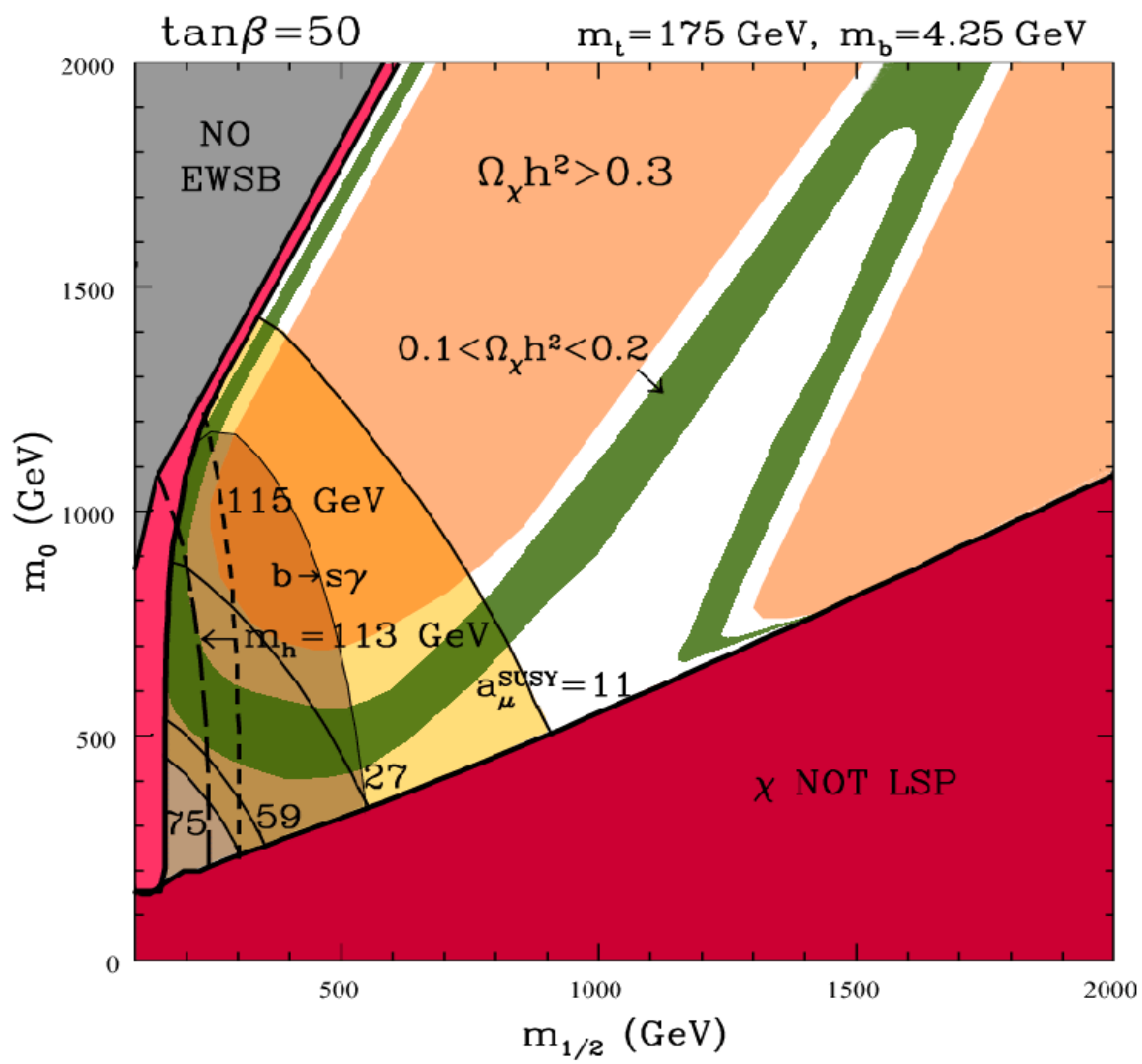
Gogoladze et al (2008)

- Points accepted/rejected in a in/out fashion (e.g., 2-sigma cuts)
- No statistical measure attached to density of points: no probabilistic interpretation of results possible
- Inefficient/Unfeasible in high dimensional parameters spaces (N>3)
- Explores only a very limited portion of the parameter space!

2 dimensional slices

Imperial College London





Roszkowski et al (2001)

Global fits for Beyond the SM physics

Imperial College London

"Global fits": multi-parameters, simultaneous likelihood-based fits to data in several observational channels (direct/indirect detection+colliders+cosmology), often including uncertainties from poorly-known nuisance parameters (e.g., astrophysical quantities)

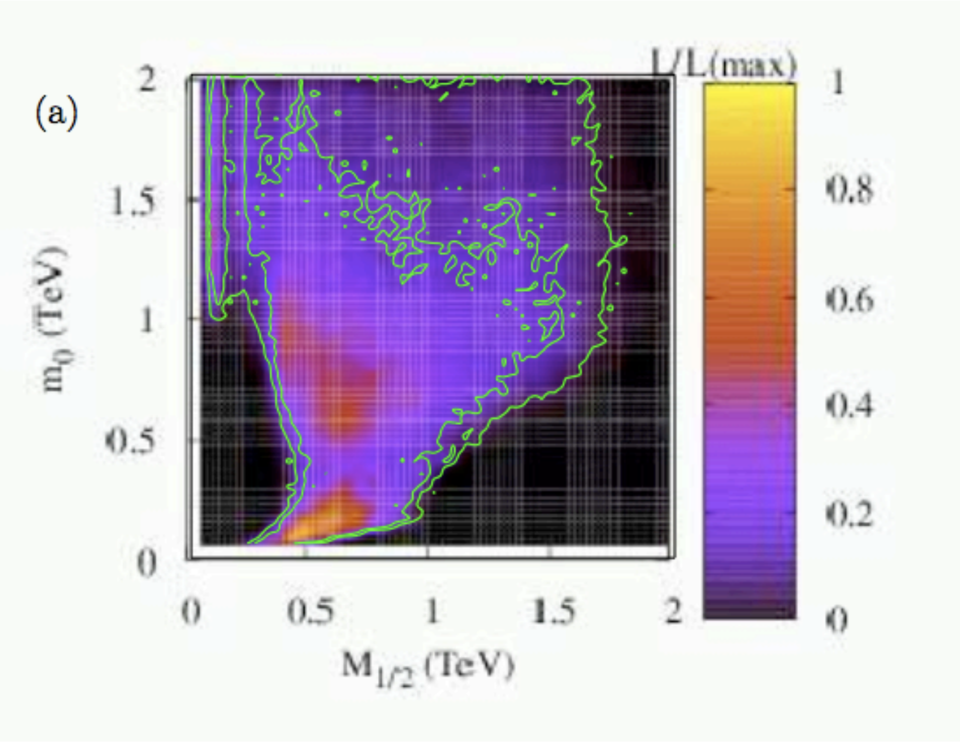
Why global fits?

- The theoretical interpretation of a Dark Matter-like signal requires fitting an underlying model (e.g., SUSY, extra dimensions, etc) to the data.
- In case of a detection, a global multi-messenger approach will allow to check the consistency of the theory across observables and to obtain more stringent constraints on the Dark Matter properties.
- Robust and believable interpretation of direct and indirect detection data requires a careful modeling of astrophysical and experimental uncertainties.

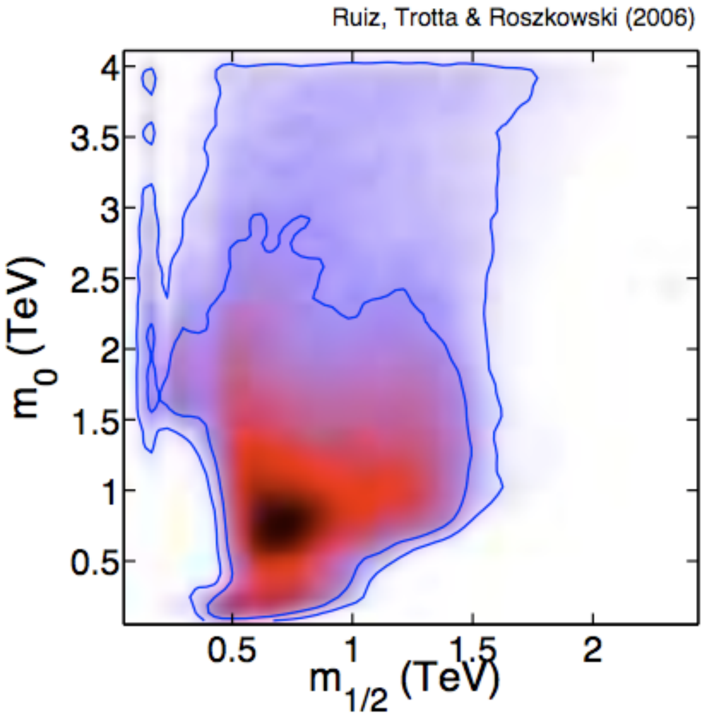
Global CMSSM scans

Imperial College London

- Bayesian approach introduced by two groups (early work by Baltz & Gondolo, 2004):
- Ben Allanach (DAMPT) and collaborators (Allanach & Lester, 2006 onwards)
- Ruiz de Austri, Roszkowski & RT (Ruiz de Austri et al, 2006 onwards)
  + Feroz & Hobson (MultiNest), + Silk (indirect detection), + Strigari (direct detection), + Martinez et al (dwarfs), + de los Heros (IceCube)



Allanach & Lester (2006)



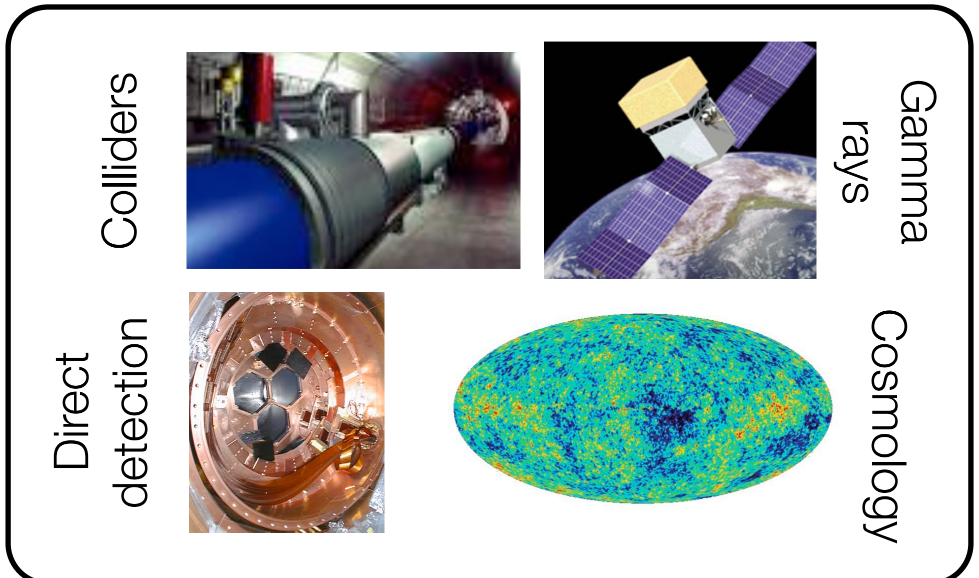
Ruiz de Austri, Roszkowski & RT (2006)

See also: Ellis et al (2004 onwards), Buchmuller et al (2008, 2009), Scott et al (2009), Akrami et al (2009)

Generic analysis pipeline for BSM physics

Imperial College London

BEYOND THE SM PHYSICS
4 to 25 parameters of interest
θ with their prior



Nuisance parameters
4 to 10
Ψ with their prior

Constrained via approximately Gaussian likelihood

Prediction
e.g., RGEs
Non-linear numerical function

Observable quantities
$f_i(\theta, \Psi)$

- Collider signatures
- Cosmological dark matter abundance
- gamma-ray, neutrino, antimatter flux
- direct detection signals

Physically acceptable?
(binary physicality conditions)

NO

Likelihood = 0

YES

Joint likelihood function from available data

Analysis pipeline for BSM physics

Imperial College London

BEYOND THE SM PHYSICS
4 to 25 parameters of interest
θ with their prior

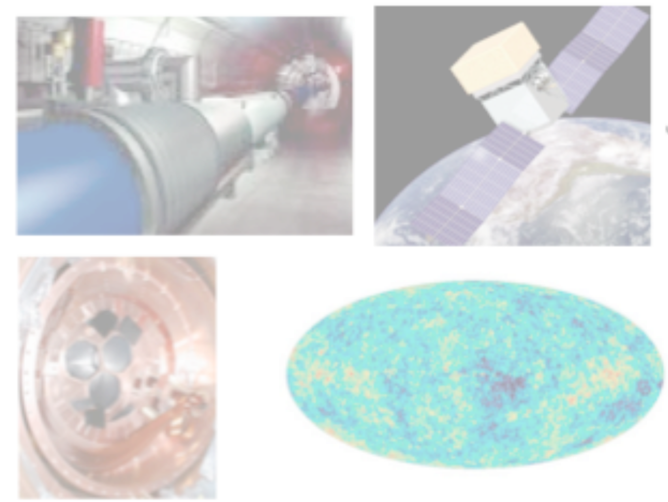
SUSY:
VCMSSM (3), CMSSM (4), NUHM1 (5), pMSSM (25)

Extra dimensions:
UED and MUED (3)

Nuisance parameters
4 to 10
Ψ with their prior

Constrained via approximately Gaussian likelihood

Prediction e.g., RGEs Non-linear numerical function



Observable quantities
$f_i(\theta, \Psi)$

- Collider signatures
- Cosmological dark matter abundance
- gamma-ray, neutrino, antimatter flux
- direct detection signals

Physically acceptable?
(binary physicality conditions)

NO

Likelihood = 0

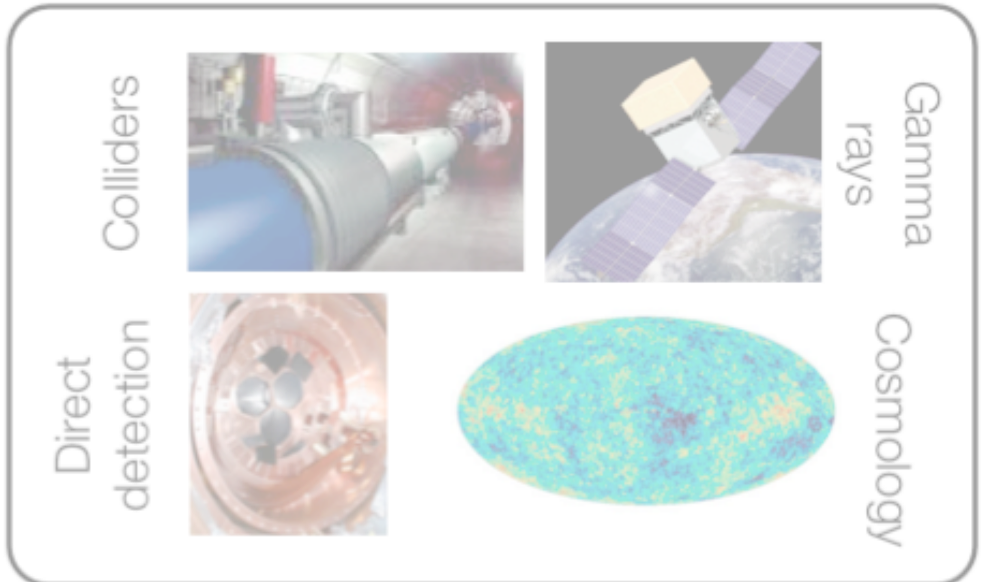
YES

Joint likelihood function from availble data

Analysis pipeline for BSM physics

Imperial College London

BEYOND THE SM PHYSICS
4 to 25 parameters of interest
θ with their prior



Likelihood = 0

NO

Physically acceptable?
(binary physicality conditions)

YES

Joint likelihood function from availble data

SM quantities (4), astrophysical parameters (~ 4-10), propagation parameters (~ 10), experimental nuisance parameters

Prediction
e.g., RGEs
Non-linear numerical function

Observable quantities
$f_i(\theta, \Psi)$

- Collider signatures
- Cosmological dark matter abundance
- gamma-ray, neutrino, antimatter flux
- direct detection signals

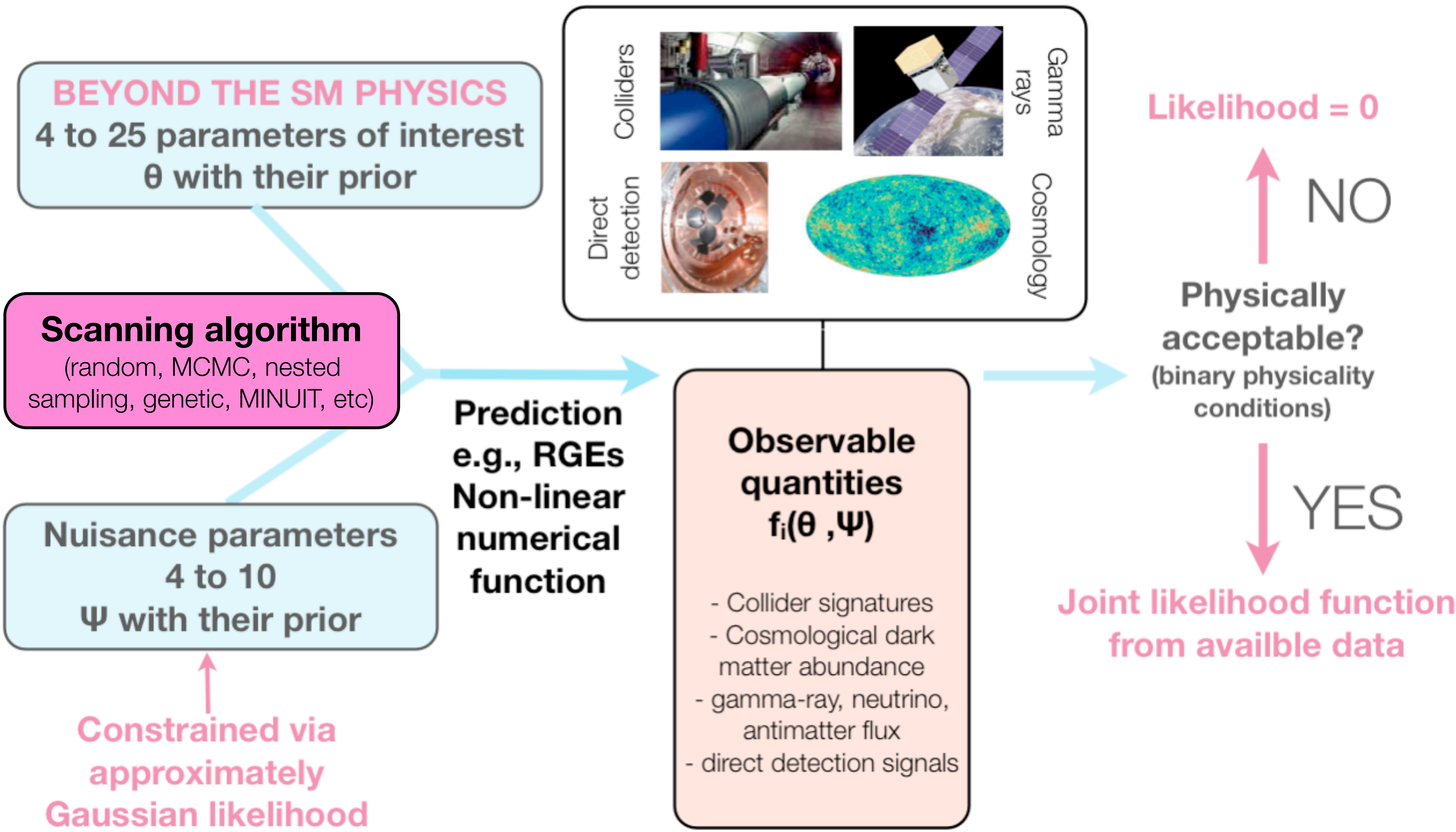
Nuisance parameters
4 to 10
Ψ with their prior

Constrained via approximately Gaussian likelihood

Likelihood:
Based on external data and/or reasonable "state of belief" (e.g., astrophysical quantities)

Analysis pipeline for BSM physics

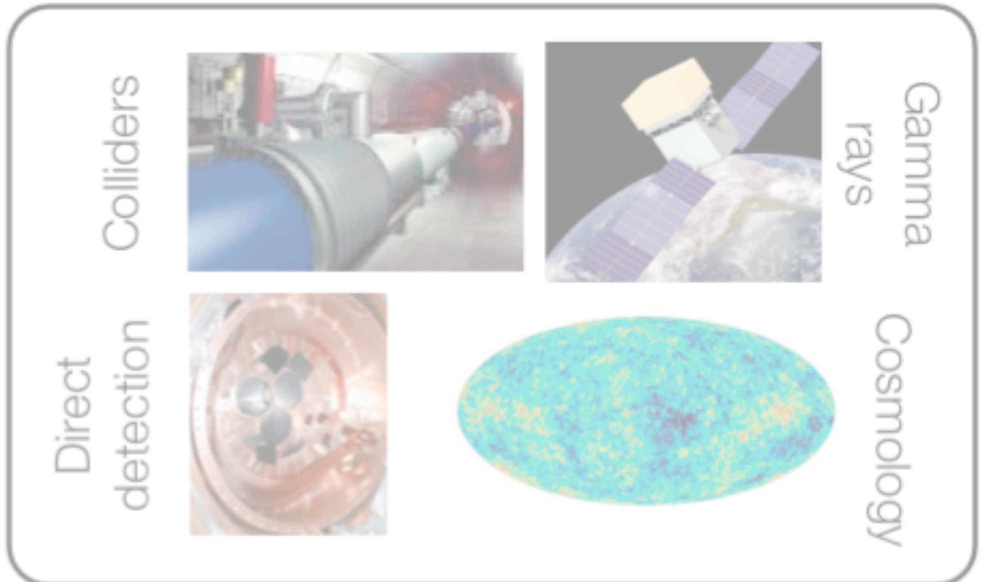
Imperial College London



Analysis pipeline for BSM physics

Imperial College London

BEYOND THE SM PHYSICS
4 to 25 parameters of interest
θ with their prior



Prediction e.g., RGEs Non-linear numerical function

Observable quantities $f_i(\theta, \Psi)$

- Collider signatures
- Cosmological dark matter abundance
- gamma-ray, neutrino, antimatter flux
- direct detection signals

Nuisance parameters
4 to 10
Ψ with their prior

Constrained via approximately Gaussian likelihood

Physically acceptable?
(binary physicality conditions)

NO

Likelihood = 0

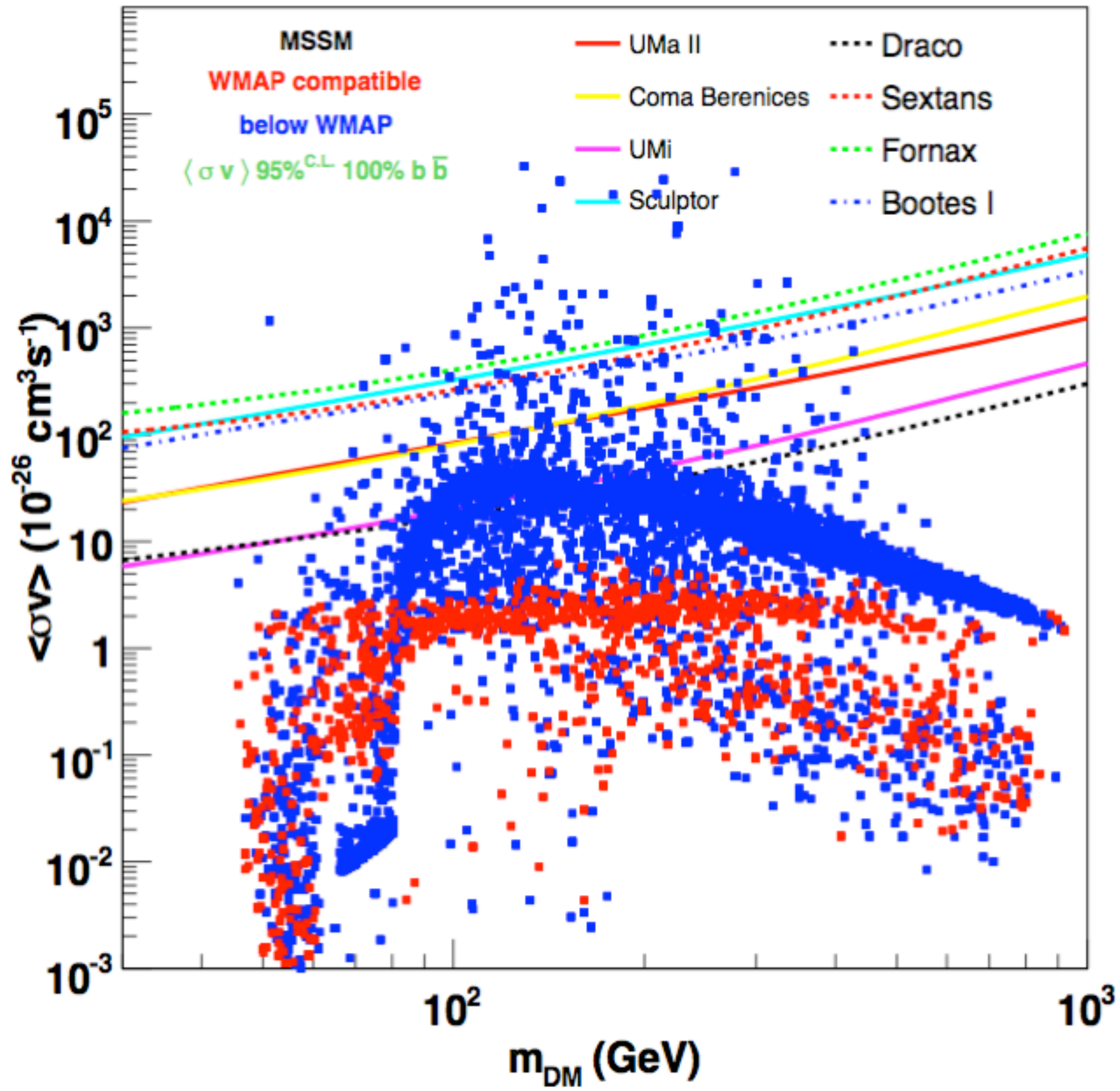
YES

Joint likelihood function from availble data

Exploration with “random scans”

- Points accepted/rejected in a in/out fashion (e.g., 2-sigma cuts)
- No statistical measure attached to density of points: no probabilistic interpretation of results possible, although the temptation cannot be resisted...
- Inefficient in moderately large dimensional parameters spaces (even just D>5)

E.g.: Fermi constraints on DM gamma-ray flux from dwarfs compared with theory



Abdo et al, arxiv: 1001.4531

Statistical inference

Imperial College London

- Given a model *M*, with parameters of interest θ, nuisance parameters Ψ, a prior pdf P(θ, Ψ | M), and available data *d* with likelihood P(d | θ, Ψ, M) = L(θ, Ψ), we need an algorithm to compute the following statistical quantities:

1. Marginal posterior pdf:

$$P(\theta|d,M) = \int d\Psi P(\theta,\Psi|d,M) = \int d\Psi \frac{L(\theta,\Psi)P(\theta,\Psi|M)}{P(d|M)}$$

2. Profile likelihood ratio:

$$\lambda(\theta) = \frac{L(\theta,\hat{\hat{\psi}})}{L(\hat{\theta},\hat{\psi})}$$

where $\hat{\hat{\psi}}$ is the conditional MLE and $\hat{\psi}$ the unconditional MLE

3. Bayesian evidence (model likelihood):

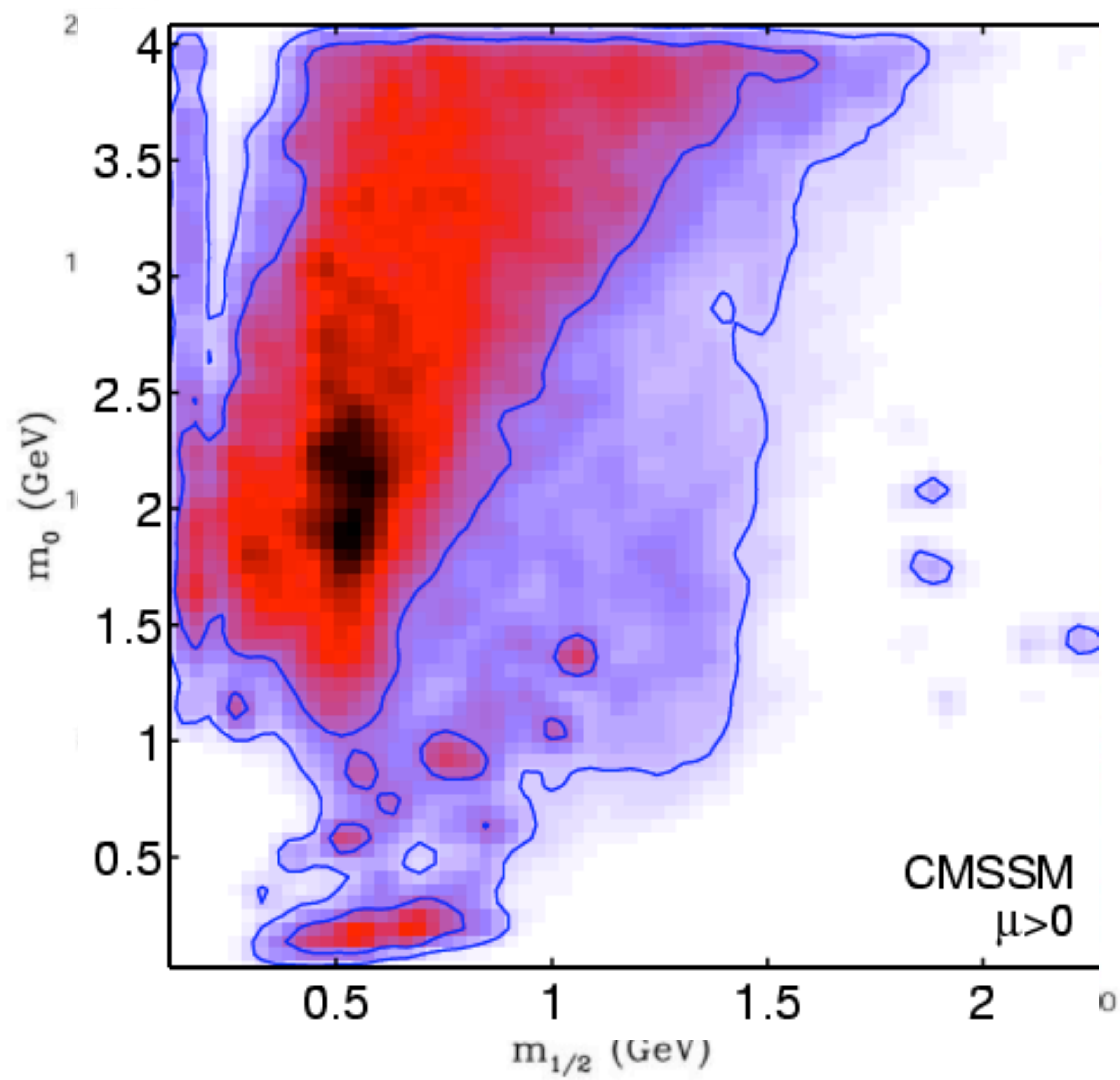
$$P(d|M) = \int d\theta d\Psi L(\theta,\Psi)P(\theta,\Psi|M)$$

Solution: global fits

Imperial College London

Carry out a **simultaneous fit** of all relevant SUSY and SM parameter to the experimental data/constraints.

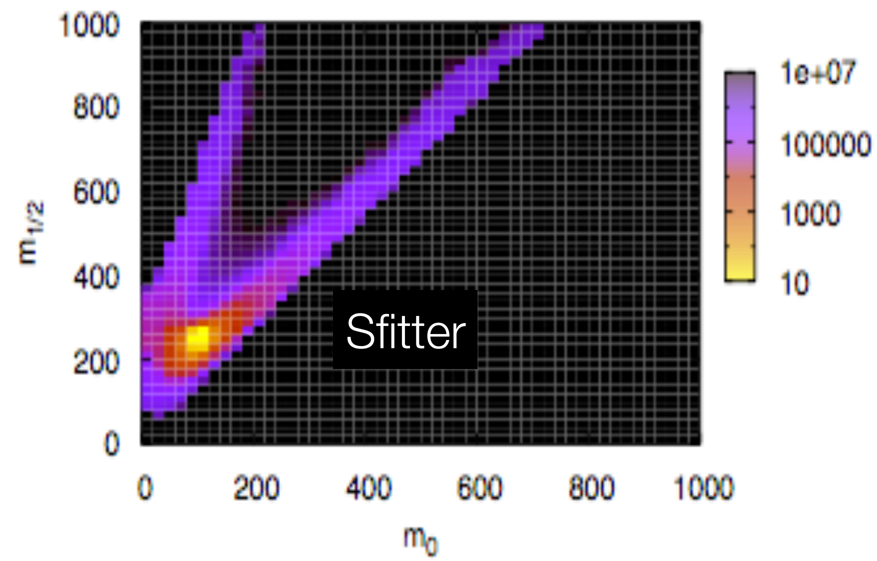
Marginalize (= integrate) or maximise along the hidden dimensions to obtain results that account for the multi-dimensional nature of the problem.



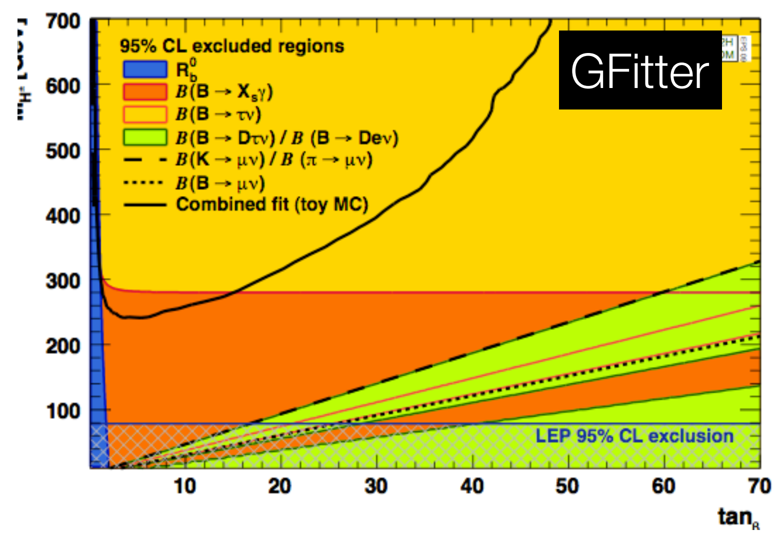
Global Fits: Some History

Imperial College London

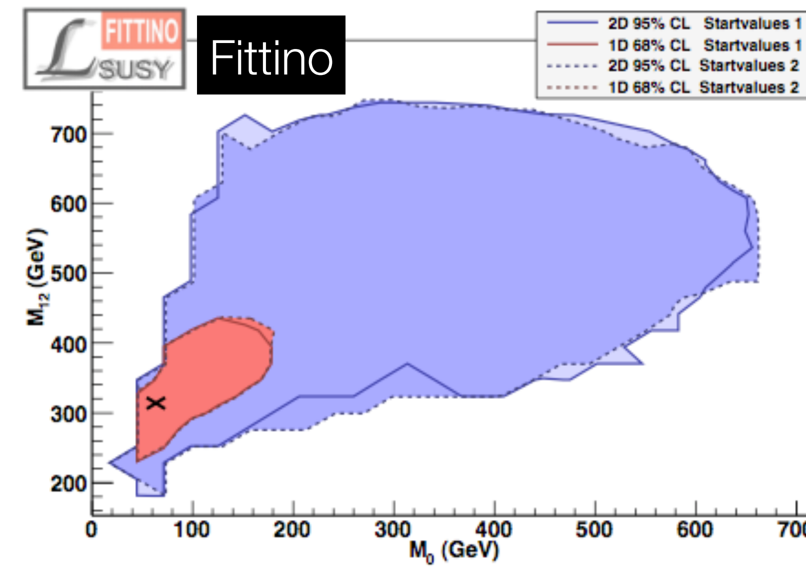
R. Lafaye , M. Rauch, T. Plehn, D. Zerwas



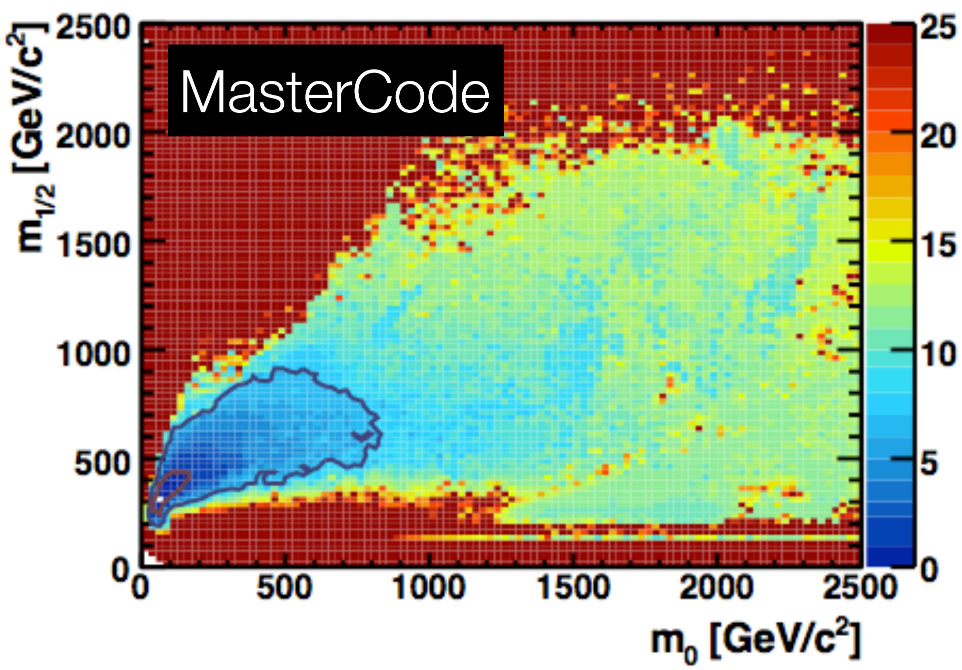
H. Flächer, M. Goebel, J. Haller,
A. Höcker, K. Mönig, J. Stelzer



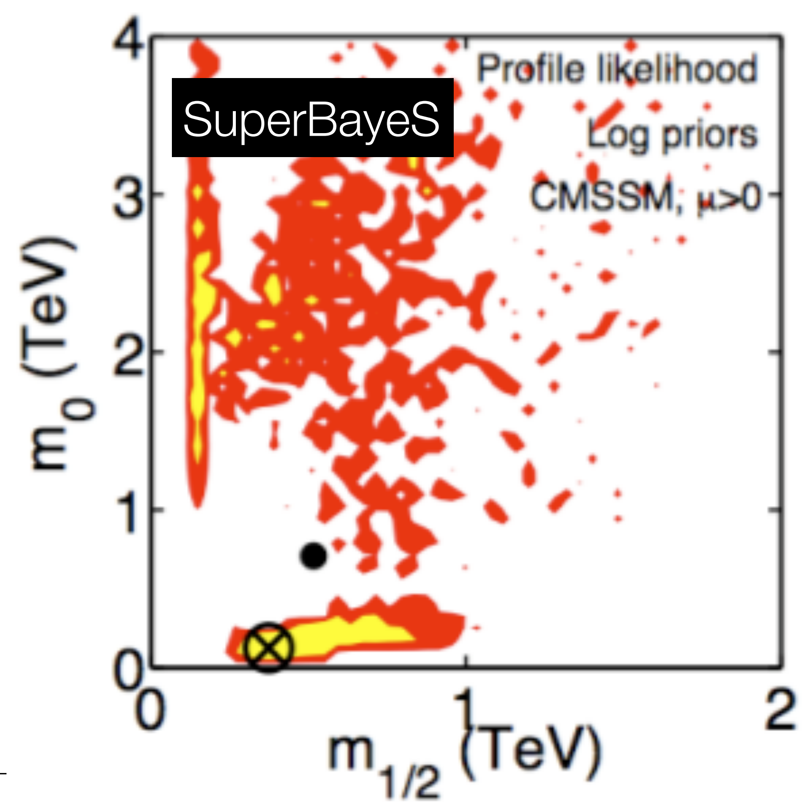
P. Bechtle, K. Desch, M. Uhlenbrock, P. Wienemann



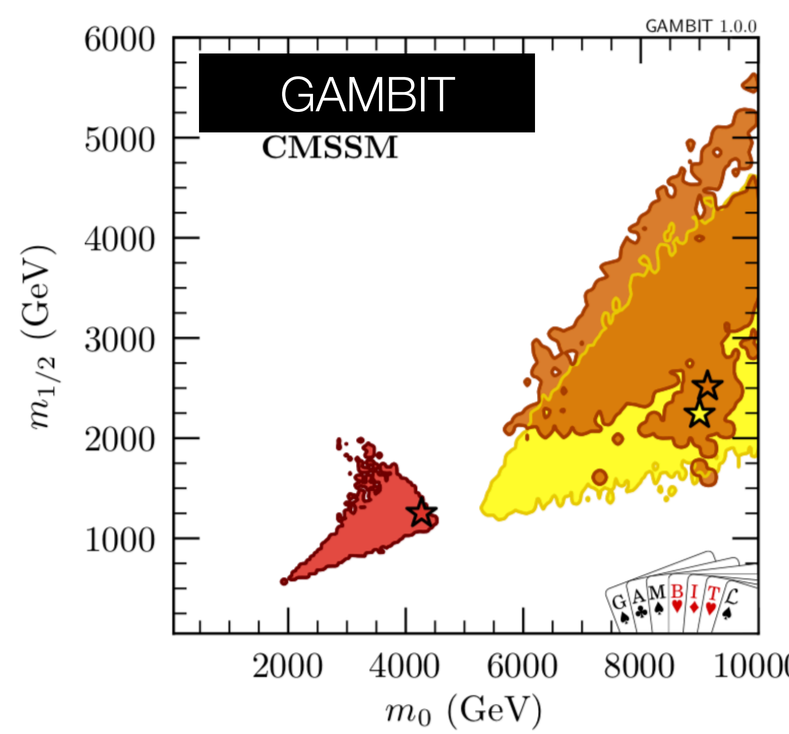
O. Buchmueller, R. Cavanaugh, A. De Roeck, J.R. Ellis,
H.Flacher, S. Heinemeyer, G. Isidori, K.A. Olive,
F.J. Ronga, G. Weiglein



F. Feroz, R. Ruiz de Austri, R. Trotta, M.P. Hobson



GAMBIT Collaboration (P. Scott, PI)



Roberto Trotta

First Generation Global Fits: SuperBayeS

SuperBayeS
Supersymmetry Parameters Extraction Routines for Bayesian Statistics

- Implements the CMSSM, but can be easily extended to the general MSSM

- **Latest release (v 1.5.1) in April 2011:** linked to SoftSusy 2.0.18, DarkSusy 5.0, MICROMEGAS 2.2, FeynHiggs 2.5.1, Hdecay 3.102. Uses MultiNest v 2.8.

- Includes up-to-date constraints from all observables, plotting routines, statistical analysis tools, posterior and profile likelihood plots. Fully parallelized, MPI-ready, user-friendly interface

- MCMC engine (Metropolis-Hastings, bank sampler), grid scan mode, multi-modal nested sampling MultiNest algorithm (Feroz & Hobson 2008)
  A full 8D scan now takes less than 2 days on 8 CPUs.

- Now discontinued

Second Generation Global Fits: GAMBIT

GAMBIT: The Global And Modular BSM Inference Tool

gambit.hepforge.org   EPJC **77** (2017) 784   arXiv:1705.07908

- Extensive model database – not just SUSY
- Extensive observable/data libraries
- Many statistical and scanning options (Bayesian & frequentist)
- *Fast* LHC likelihood calculator
- Massively parallel
- Fully open-source

- Fast definition of new datasets and theories
- Plug and play scanning, physics and likelihood packages

Members of: ATLAS, Belle-II, CMS, CTA, *Fermi*-LAT, DARWIN, IceCube, LHCb, SHiP, XENON

Authors of: DarkSUSY, DDCalc, Diver, FlexibleSUSY, gamlike, GM2Calc, IsaJet, nulike, PolyChord, Rivet, SOFTSUSY, SuperIso, SUSY-AI, WIMPSim

Collaborators:
Peter Athron, Csaba Balázs, Ankit Beniwal, Florian Bernlochner, Sanjay Bloor, Torsten Bringmann, Andy Buckley, Eliel Camargo-Molina, Marcin Chrząszc, Jan Conrad, Jonathan Cornell, Matthias Danninger, Tom Edwards, Joakim Edsjö, Ben Farmer, Andrew Fowlie, Tomás Gonzalo, Will Handley, Sebastian Hoof, Selim Hotinli, Felix Kahlhoefer, Suraj Krishnamurthy, Anders Kvellestad, Julia Harz, Paul Jackson, Tong Li, Greg Martinez, Nazilla Mahmoudi, James McKay, Are Raklev, Janina Renk, Chris Rogan, Roberto Ruiz de Austri, Patrick Stoecker, Roberto Trotta, Pat Scott, Nicola Serra, Daniel Steiner, Puwen Sun, Aaron Vincent, Christoph Weniger, Sebastian Wild, Martin White, Yang Zhang

40+ participants in 10 Experiments & 14 major theory codes

Slide: Sebastian Hoof

The Global And Modular BSM Inference Tool

- A new framework for BSM **global fits**
- Fully **open source**
- **Modular design:** easily extended with
  — new models
  — new likelihoods
  — new theory calculators
  — new scanning algorithms
- Use external codes (**backends**) as **runtime plugins**
  — Currently supported:
  C, C++, Fortran, Mathematica
  — Coming soon: Python
- **Two-level parallellization** with MPI and OpenMP
- **Hierarchical** model database
- **Flexible output streams** (ASCII, HDF5, …)
- Many **scanners** and **backends** already included

gambit.hepforge.org

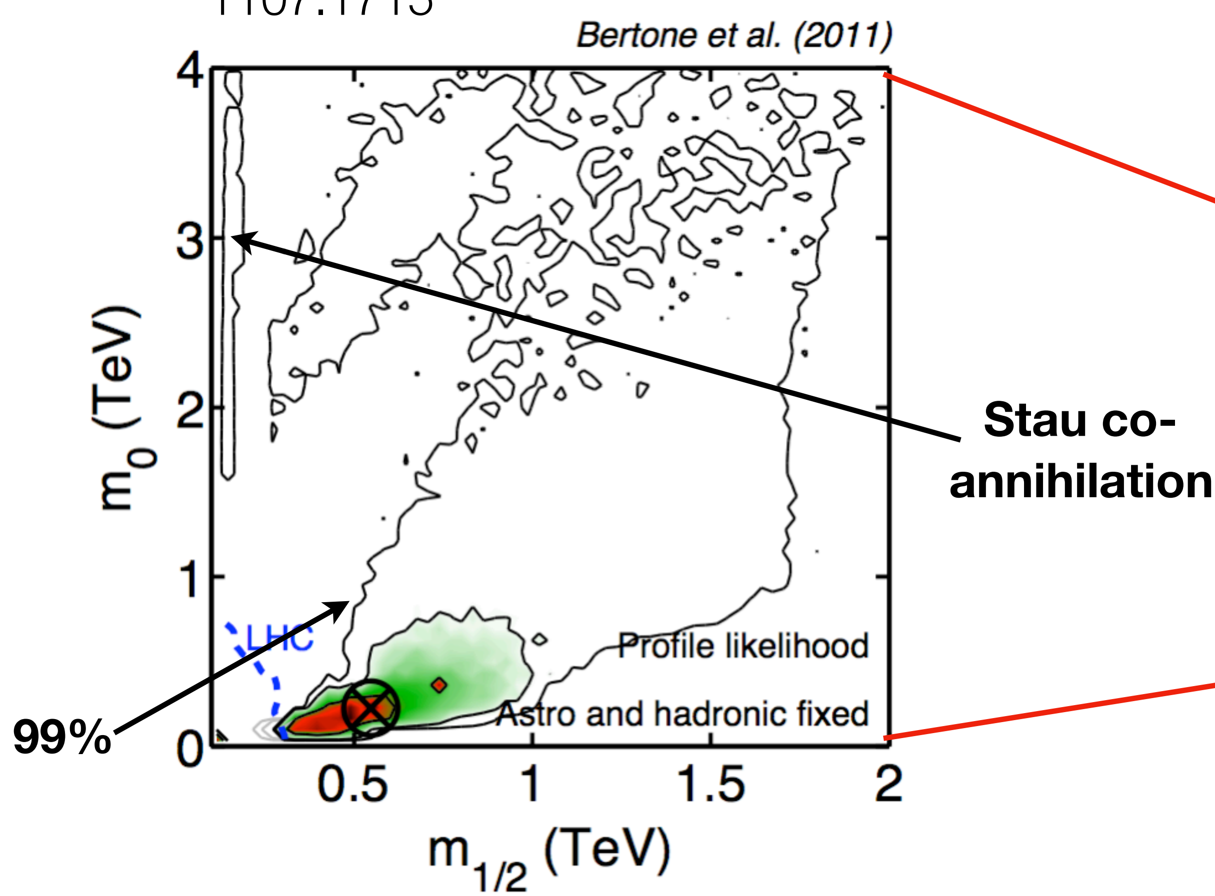
Slide: Anders Kvellestad

CMSSM: Frequentist Fits

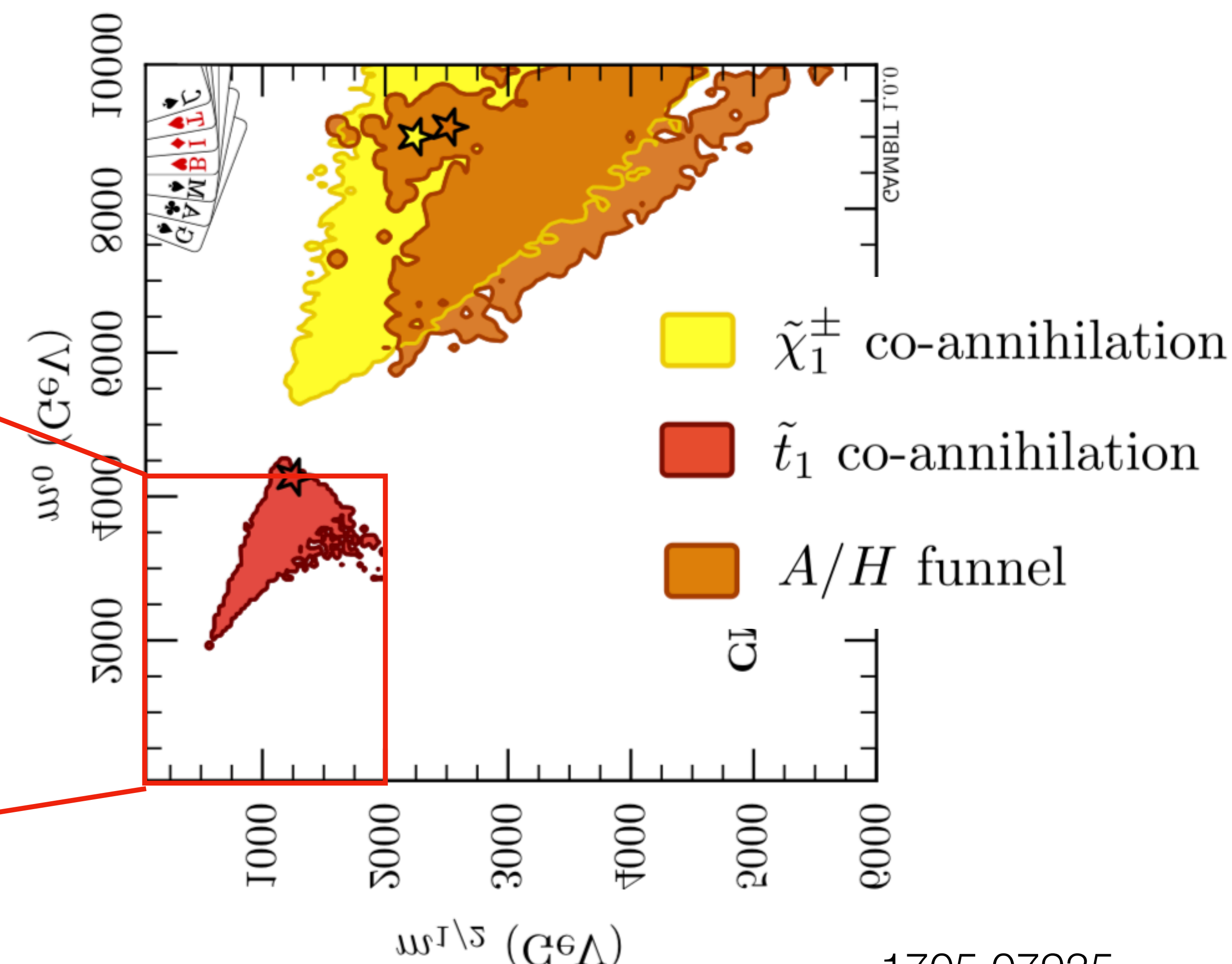
Imperial College London

SuperBayeS: profile likelihood
2011, 41M samples (~1 week on 8 CPUs)
incl. ATLAS 35 fb^{-1} Run I and WMAP-7

1107.1715



GAMBIT: profile likelihood (95% CL)
2018, 71M samples (3 days on 2400 CPUs)
incl. ATLAS/CMS Run I + II, Planck 2018



1705.07935

Stau co-annihilation region now ruled out at > 95% CL in the CMSSM.

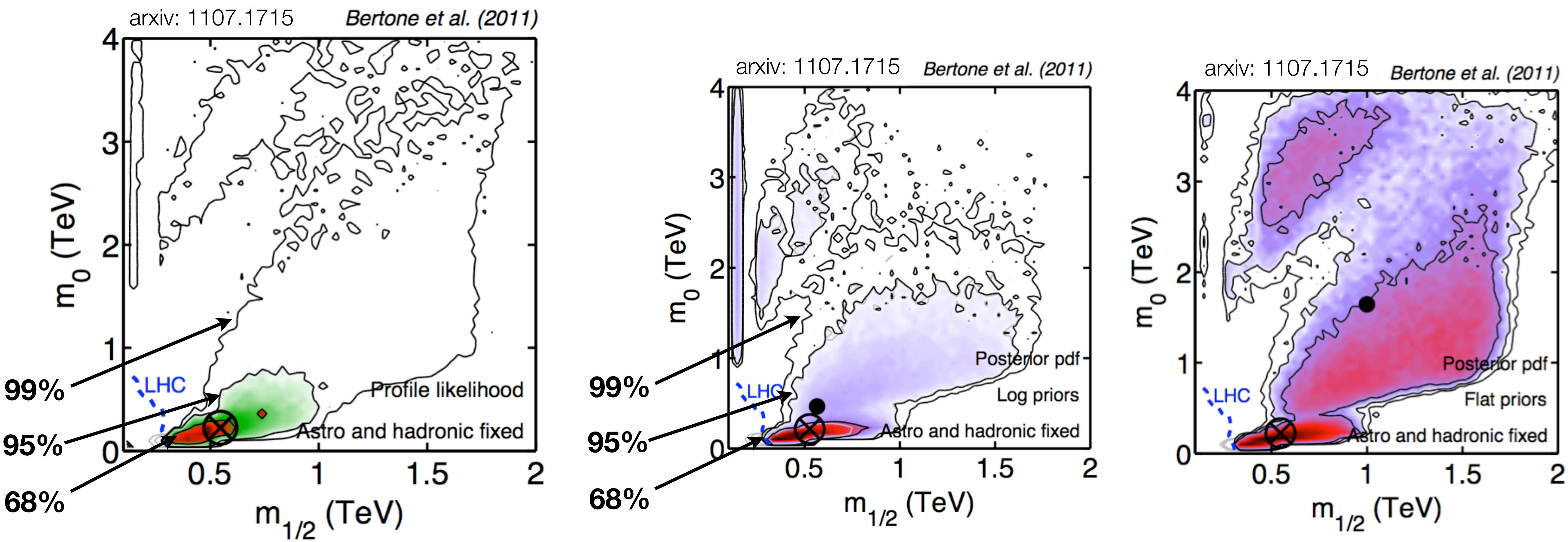
CMSSM: Bayesian posteriors (2011)

Imperial College London

SuperBayeS: profile likelihood

SuperBayeS: Bayesian pdf

“log” priors **“flat” priors**



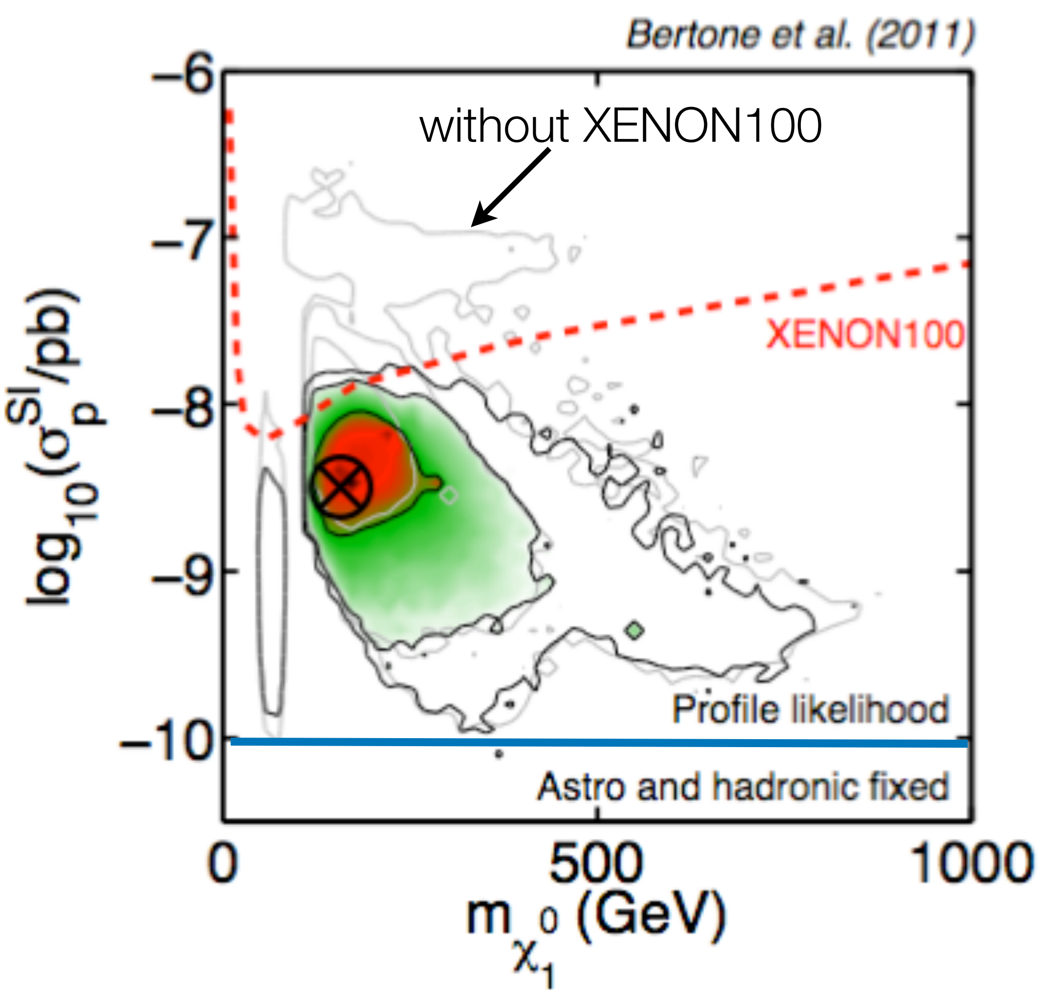
Tentative convergence between Frequentist and Bayesian scans has not improved despite 7 years of additional data (and stronger LHC lower limits).
The relative viability of the Focus Point region cannot be robustly established

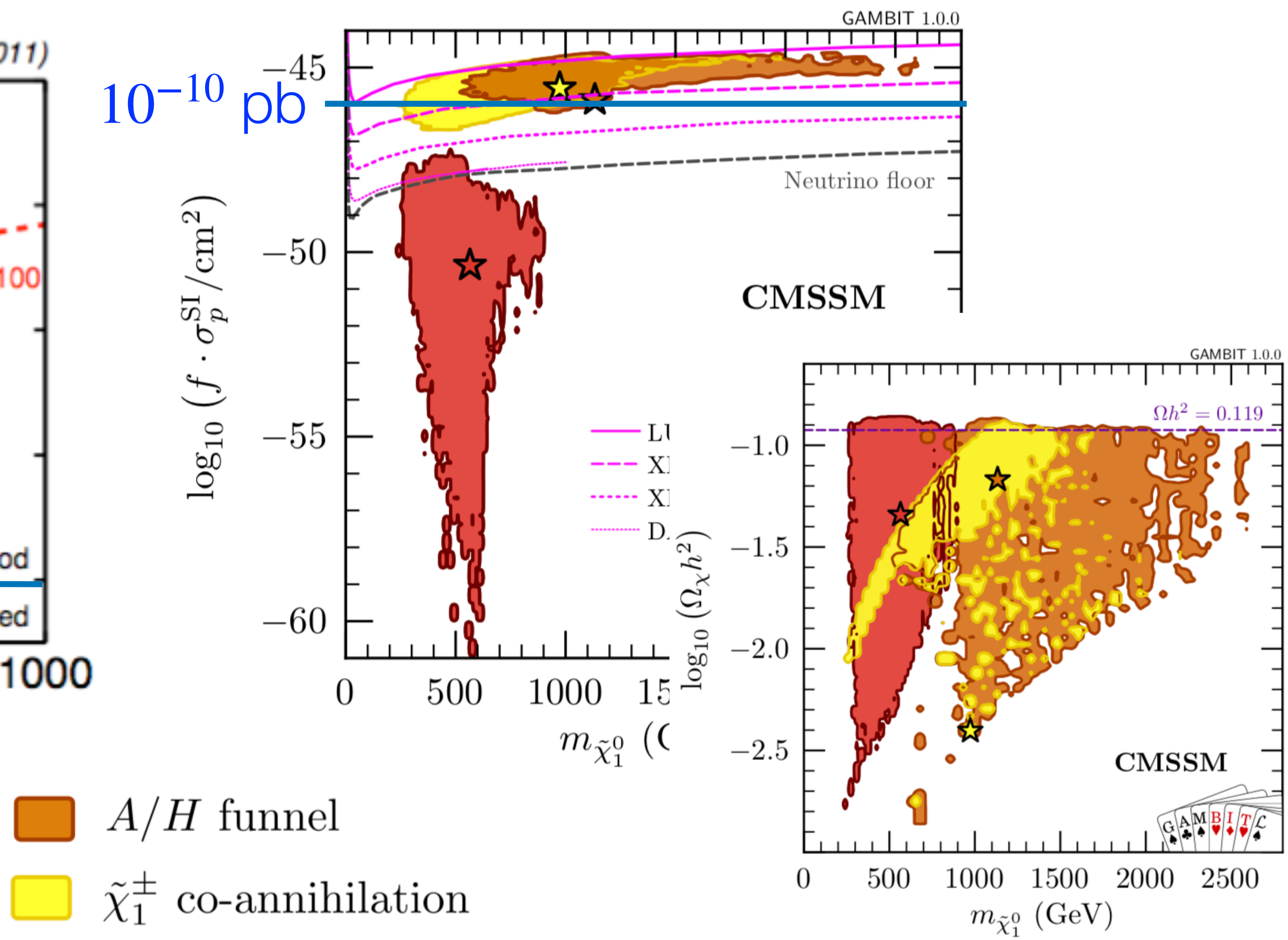
Direct Detection Prospects

Imperial College London

Profile likelihood, 2011
Astrophysical parameters fixed
Relic density constraint imposed

Profile likelihood, 2018
Astrophysical parameters varied
Relic density as upper limit only





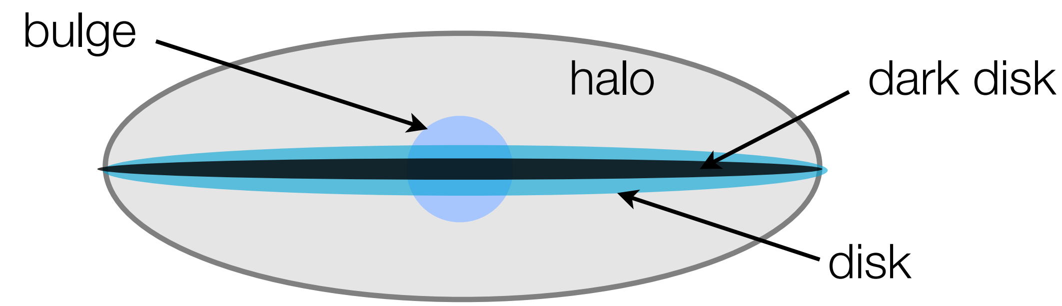
The importance of modeling the Milky Way

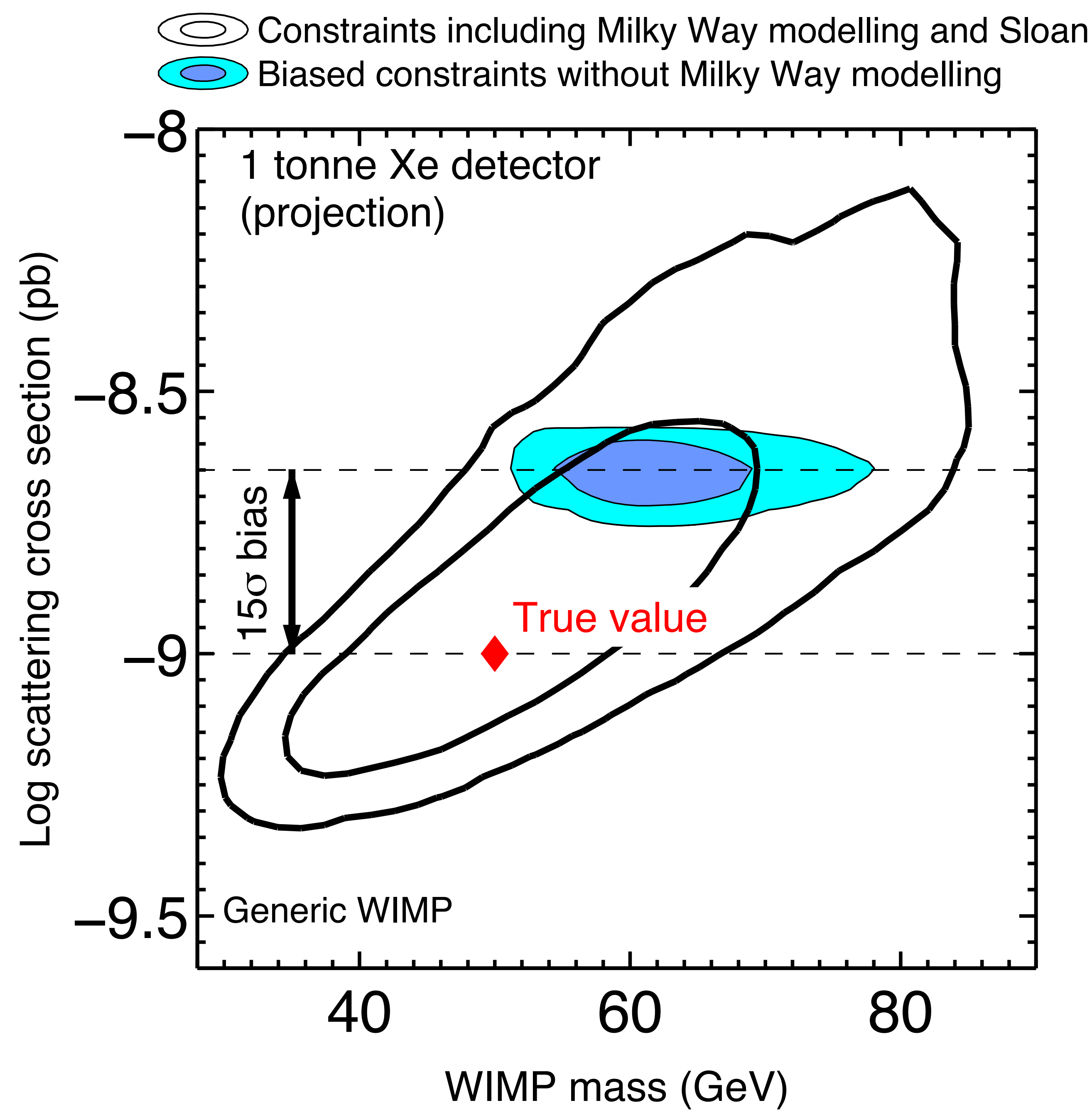
- Assuming an incorrect local density (by a factor of 2) can lead to **a 15 sigma bias** in the reconstructed cross section

- Milky Way modeled as a parameterized bulge+halo+disk spherical, isotropic superposition. Sloan-like data used to constrain the model's parameters

- **Marginalization over Milky Way halo model parameters converts catastrophic direct detection systematic errors into more manageable statistical errors**

Parameterized Milky Way model (7 parameters)



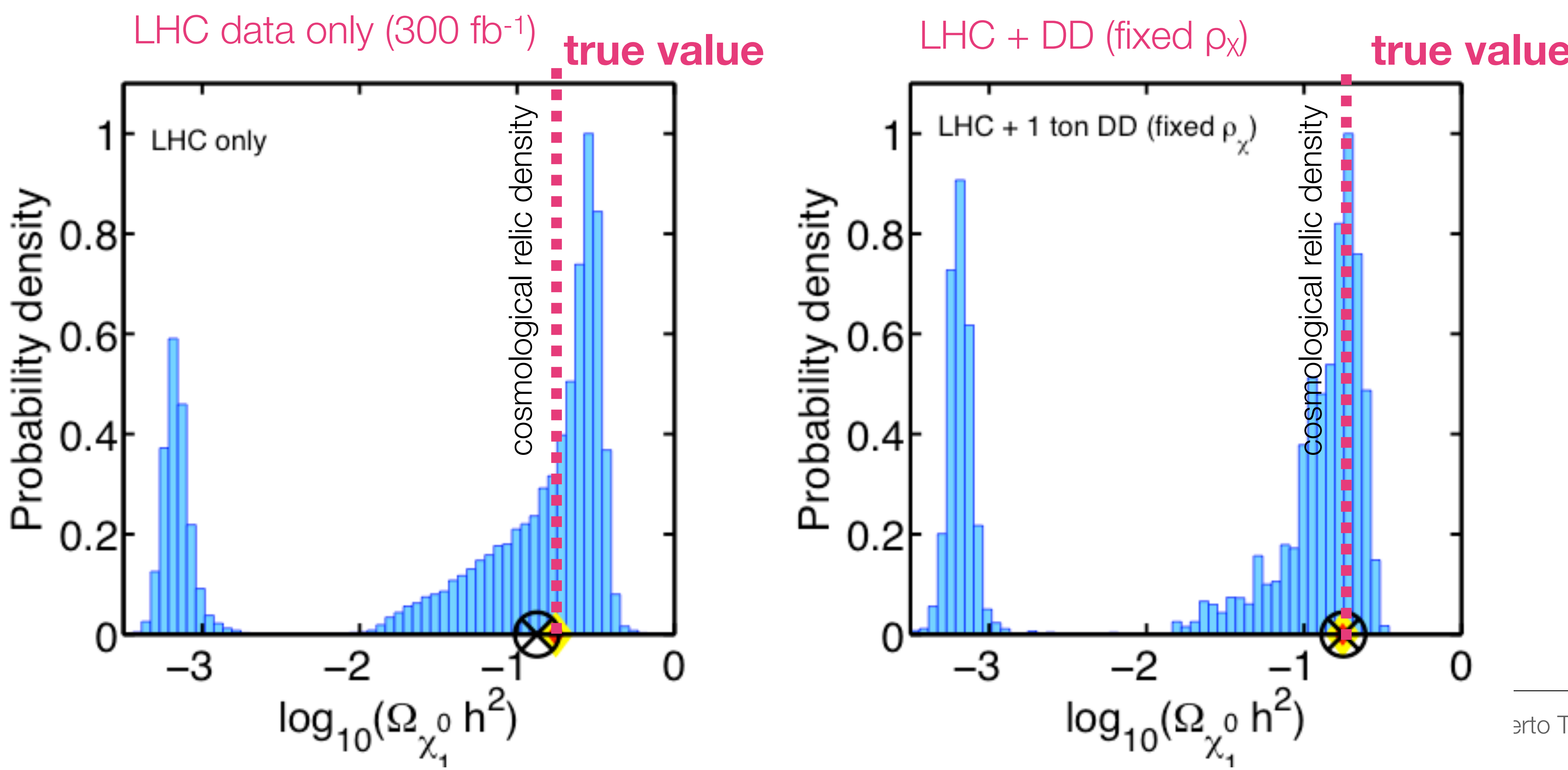


Strigari & Trotta (0906.5361)

Identification of Cosmological DM

If a signal is seen both at the LHC and in direct detection detectors, how can we check that this WIMP makes up the bulk of the cosmological relic density?

- Fit low-energy SUSY parameters and try to predict Ωh^2 from LHC data alone.
- **Problem**: LHC data alone are unable to constrain the relic abundance. Even DD data cannot break the degeneracy (if ρ_χ assumed fixed):

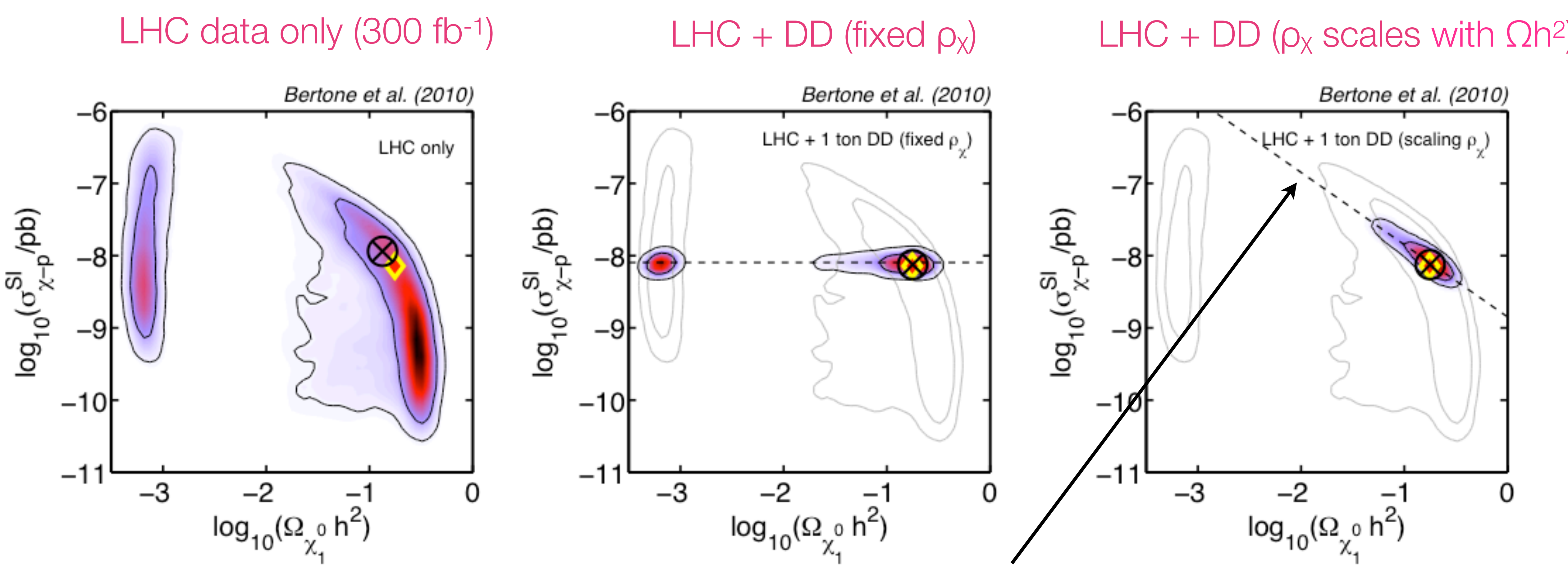


Complementarity of direct detection and LHC data

Imperial College London

- **Strategy**: assume that the local density scales with the cosmological relic abundance (“*scaling Ansatz*”):

$$\rho_\chi \propto \Omega h^2_\chi$$



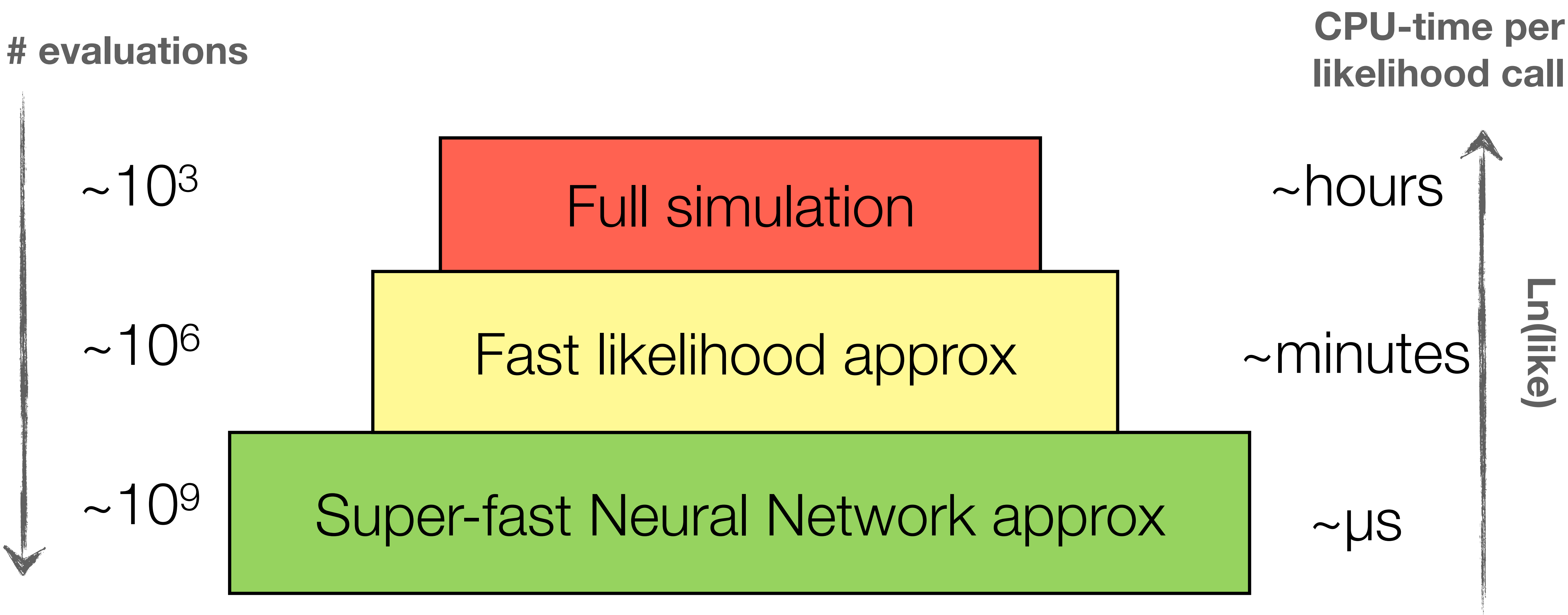
Bertone, RT et al, 1005.4280

Our scaling Ansatz breaks degeneracy in parameter space
Cosmological solution identified!

Wedding-cake approach

Imperial College London

- A full MSSM-15 profile likelihood scan might require $O(10^9)$ ATLAS likelihood evaluations
- Not feasible with full (expensive simulations). Wedding-cage strategy:



Coverage properties of intervals

Imperial College London

- Coverage of intervals is a frequentist property.
- Guaranteed when using e.g. Feldman-Cousins procedure to build intervals.
- Approximate confidence intervals are obtained via the Neyman construction with profile likelihood ratio as a test statistic.
- From a Bayesian perspective, coverage properties of credible intervals (if desired) can be used to calibrate priors.
- **Coverage studies are computationally expensive:**
  (a) choose fiducial point in parameter space
  (b) generate pseudo-data
  (c) reconstruct credible/confidence interval
  (d) check whether fiducial point within/without interval.

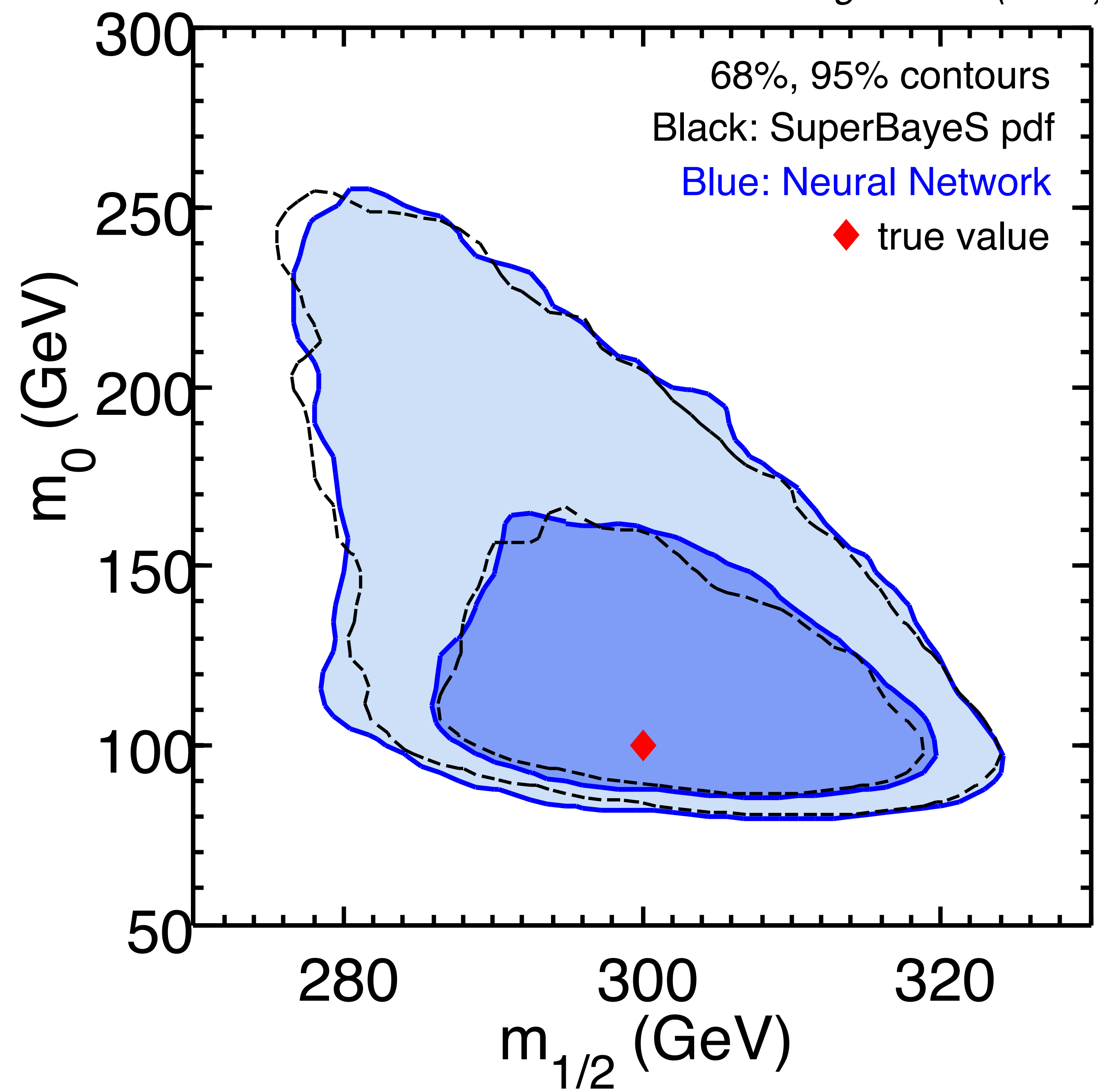
“Instantaneous” inference with neural networks

Imperial College London

- **Standard MCMC**
  (SuperBayeS v1.23, 2006 release)
  720 CPU days
- **MultiNest**
  (SuperBayeS v1.5, 2010 release)
  16 CPU days
  speed-up factor: ~ 50
- **SuperBayeS+Neural Networks**
  (Bridges, Cranmer, Feroz, Hobson, Ruiz & RT, 1011.4306)
  less than 1 CPU minute
  speed-up factor: 30’000

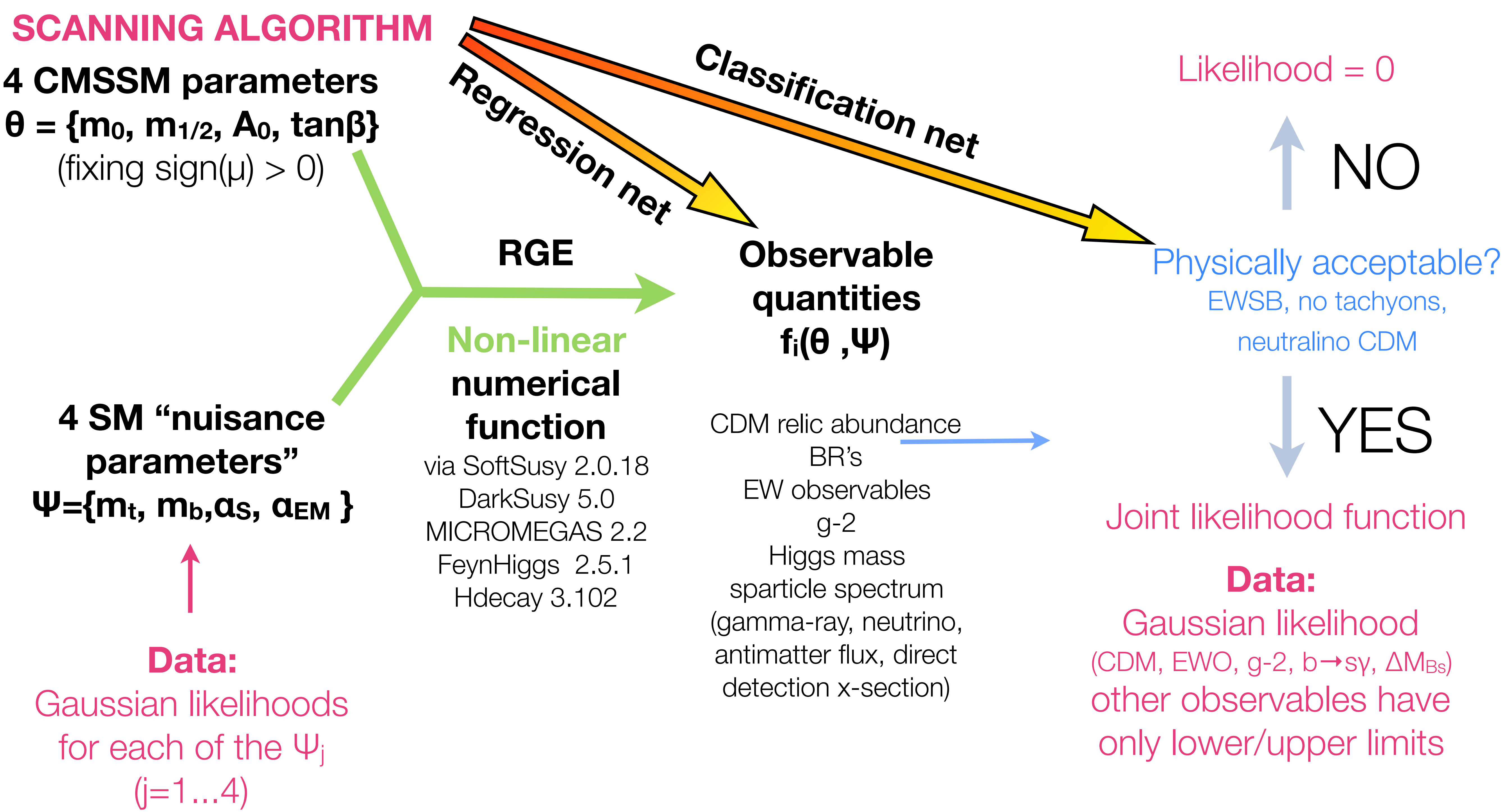
Simulated ATLAS data

Bridges et al (2010)



Neural nets shortcuts

Imperial College London



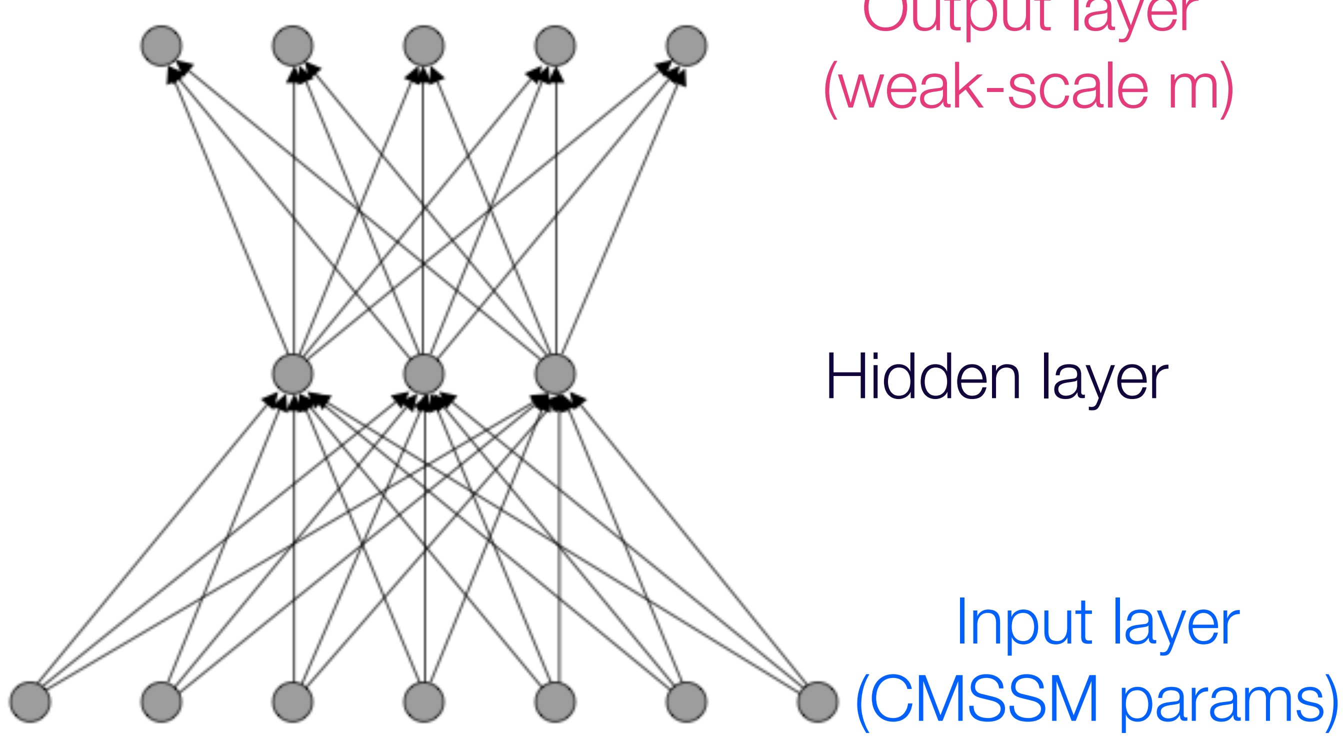
Neural networks technology

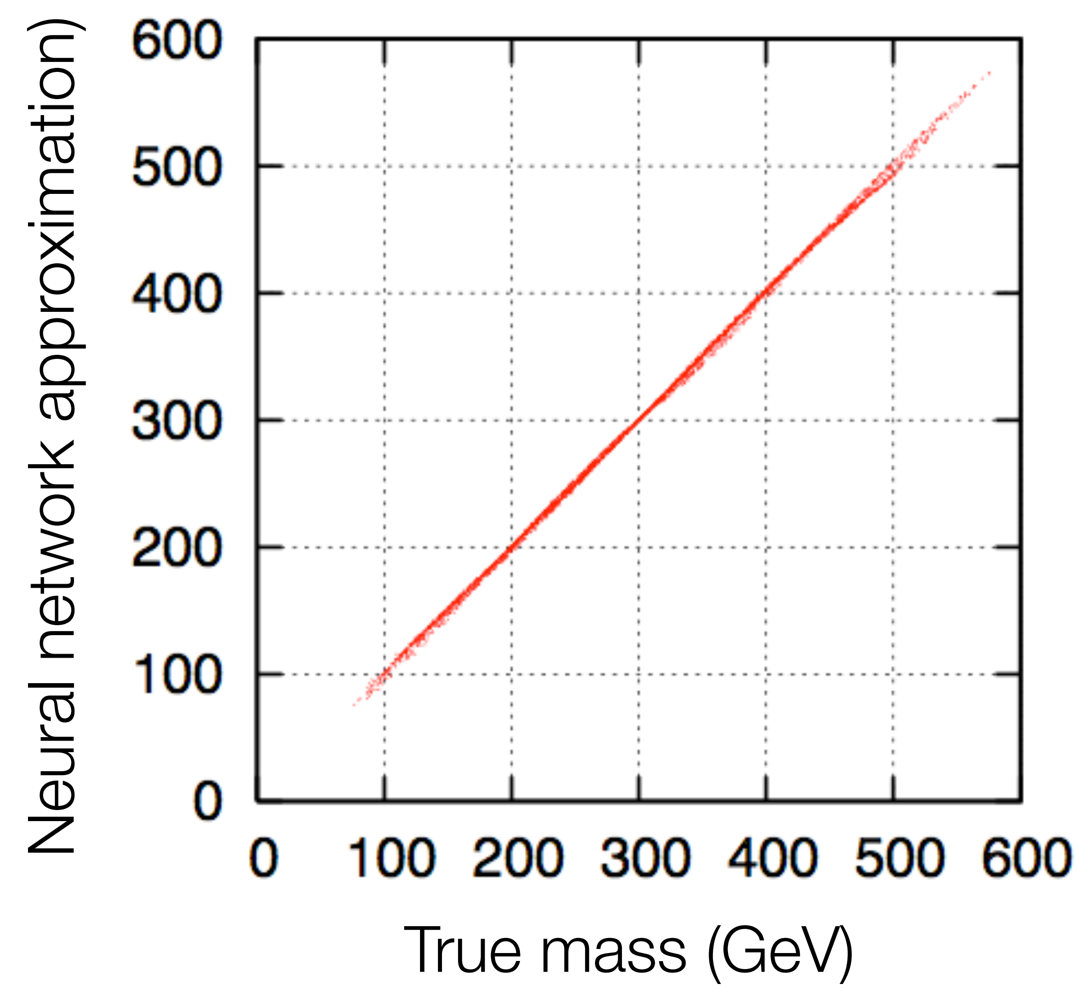
Bridges, KC,
RT et al (1011.4306)

Imperial College
London

- We used a feed-forward multi-layer perceptron to “replace” SoftSusy in predicting the weak-scale masses from the CMSSM input parameters

- After training with a few 1000’s samples, the neural net achieved a correlation > 99.99%



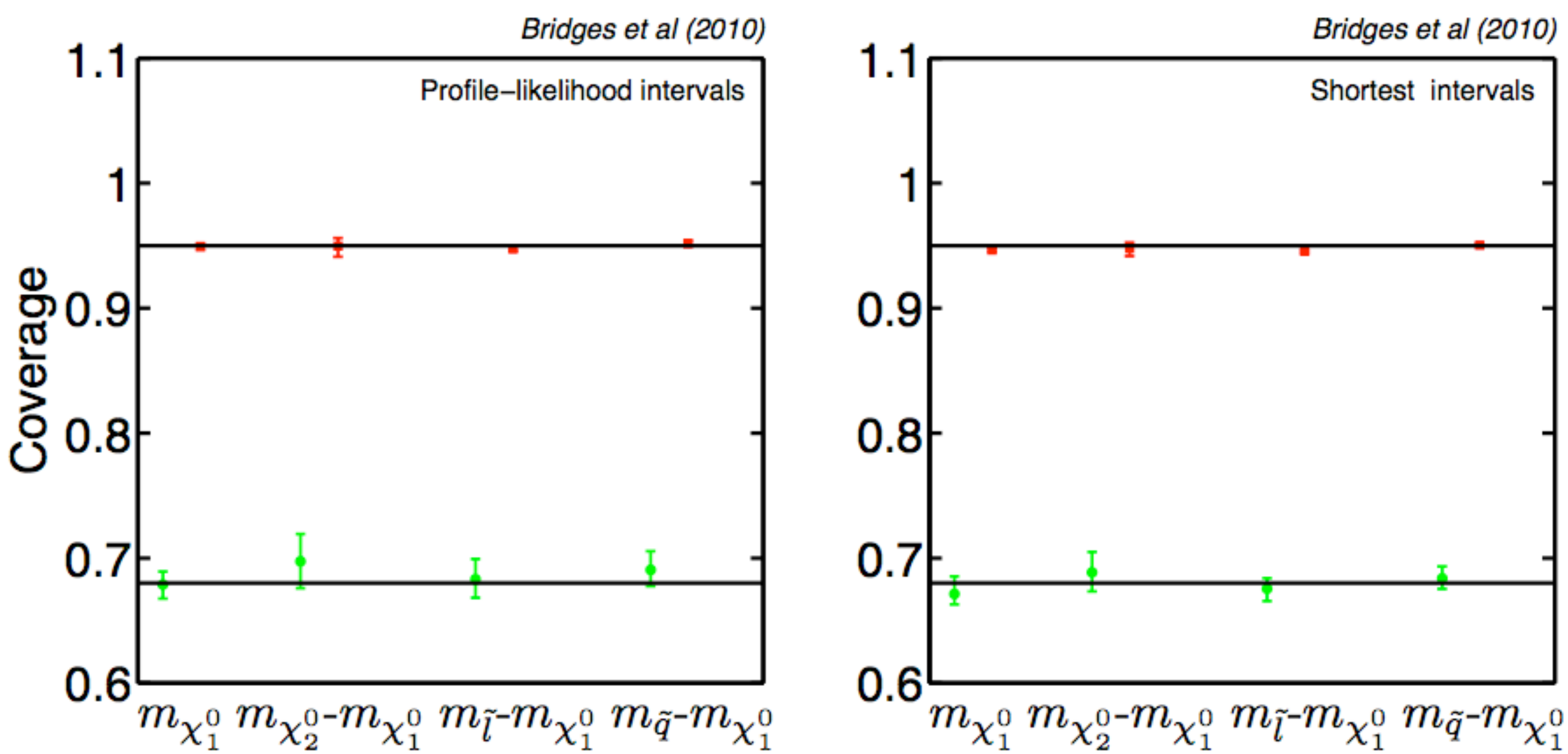


Coverage: are intervals what they say?

Imperial College London

- We did 10,000 reconstructions, each with 1 million samples. This would have taken 1,100 CPU yrs using standard methods. **Neural network speed-up is dramatic, of order 10^4.**

- Test case: use weak-scale masses as input, with Gaussian likelihood. Coverage is exact (within noise), as expected:



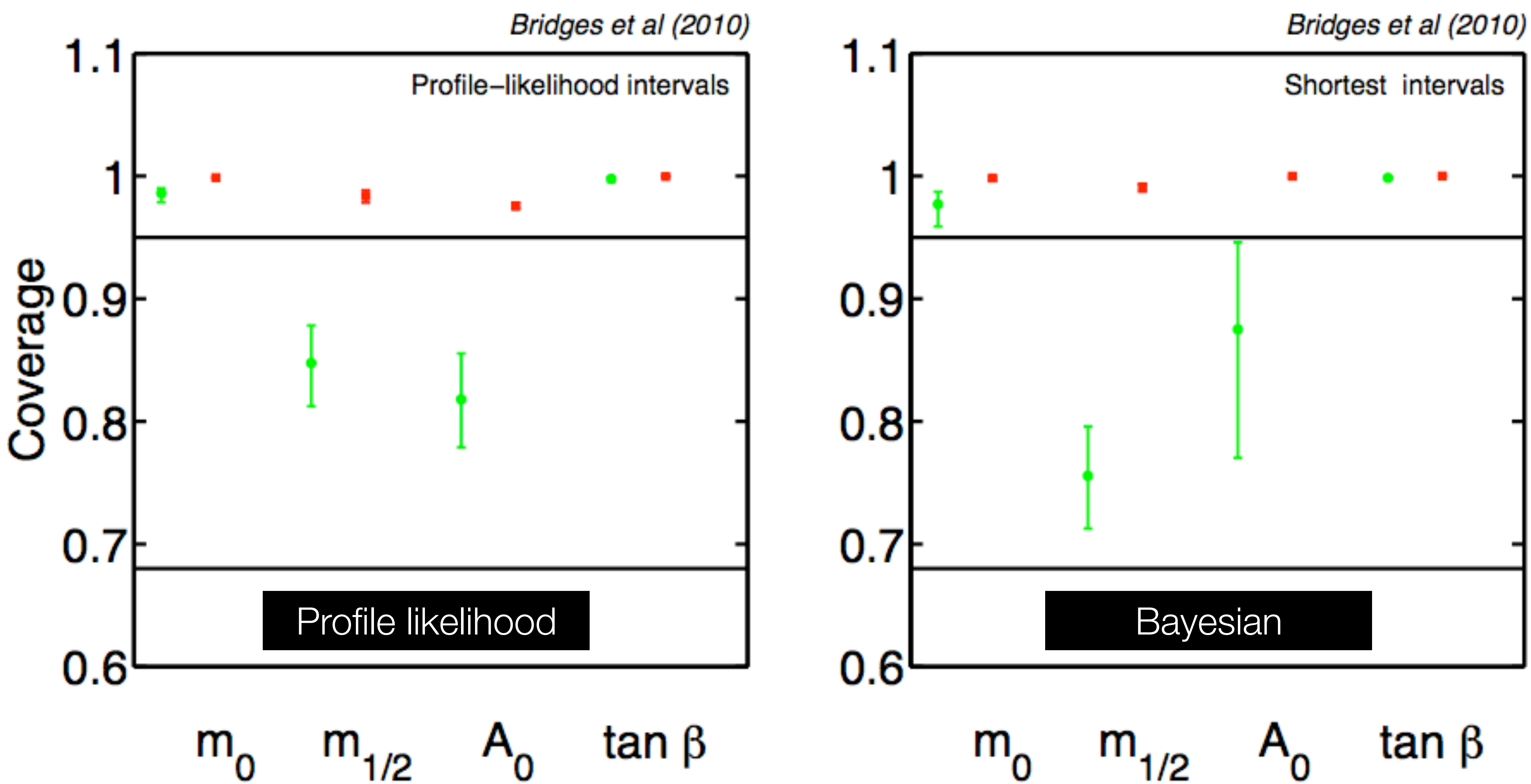
Profile likelihood

Bayesian

Coverage: are intervals what they say?

Imperial College London

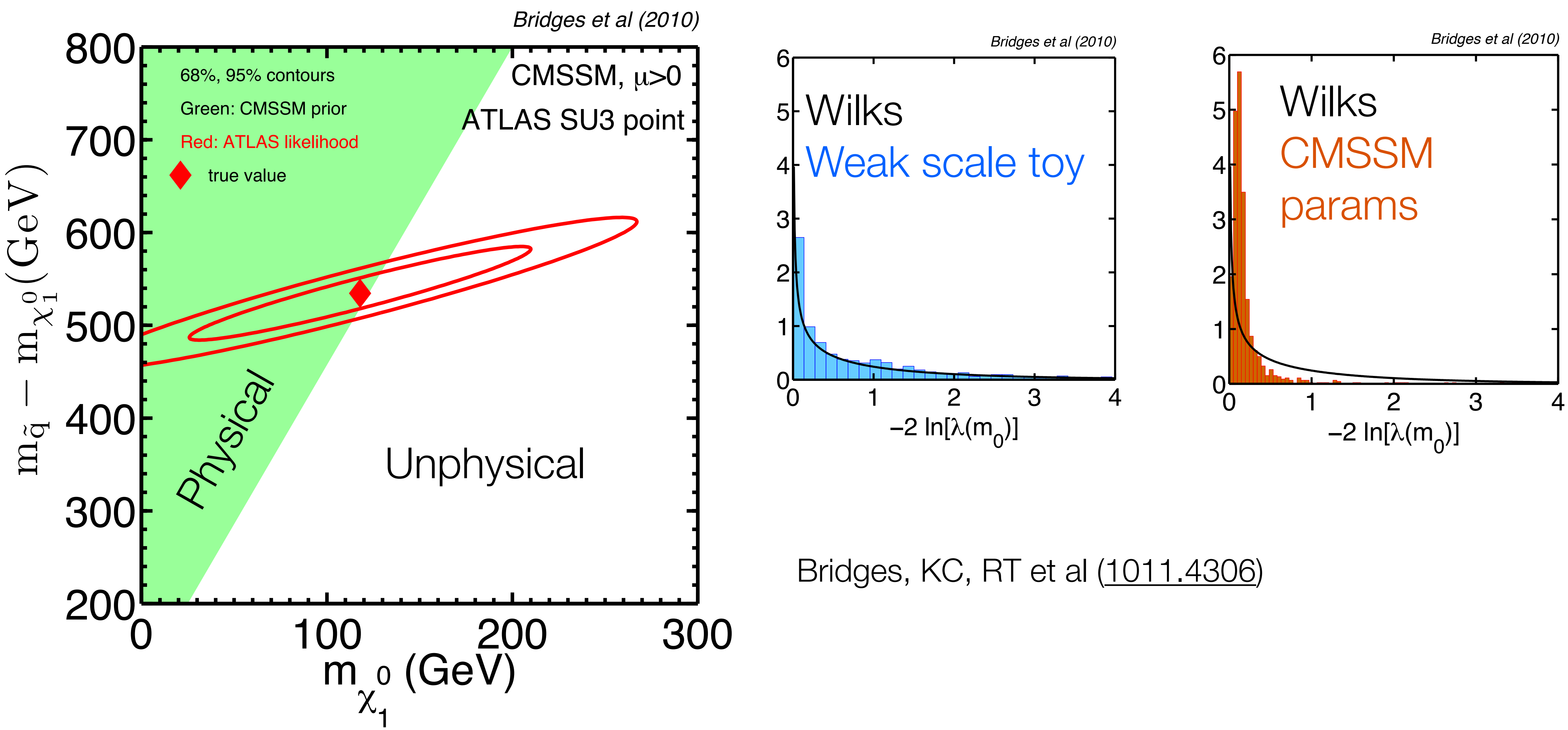
- Mapping back constraints to the CMSSM parameters, we find substantial over-coverage for both Bayesian and profile likelihood intervals:



Origin of over-coverage in the CMSSM

Imperial College London

- The CMSSM prior introduces “physicality” boundaries in the weak-scale masses space. As a consequence, the distribution of -2 ln(λ) is not well approximated by χ^2 and Wilks’ theorem does not apply.



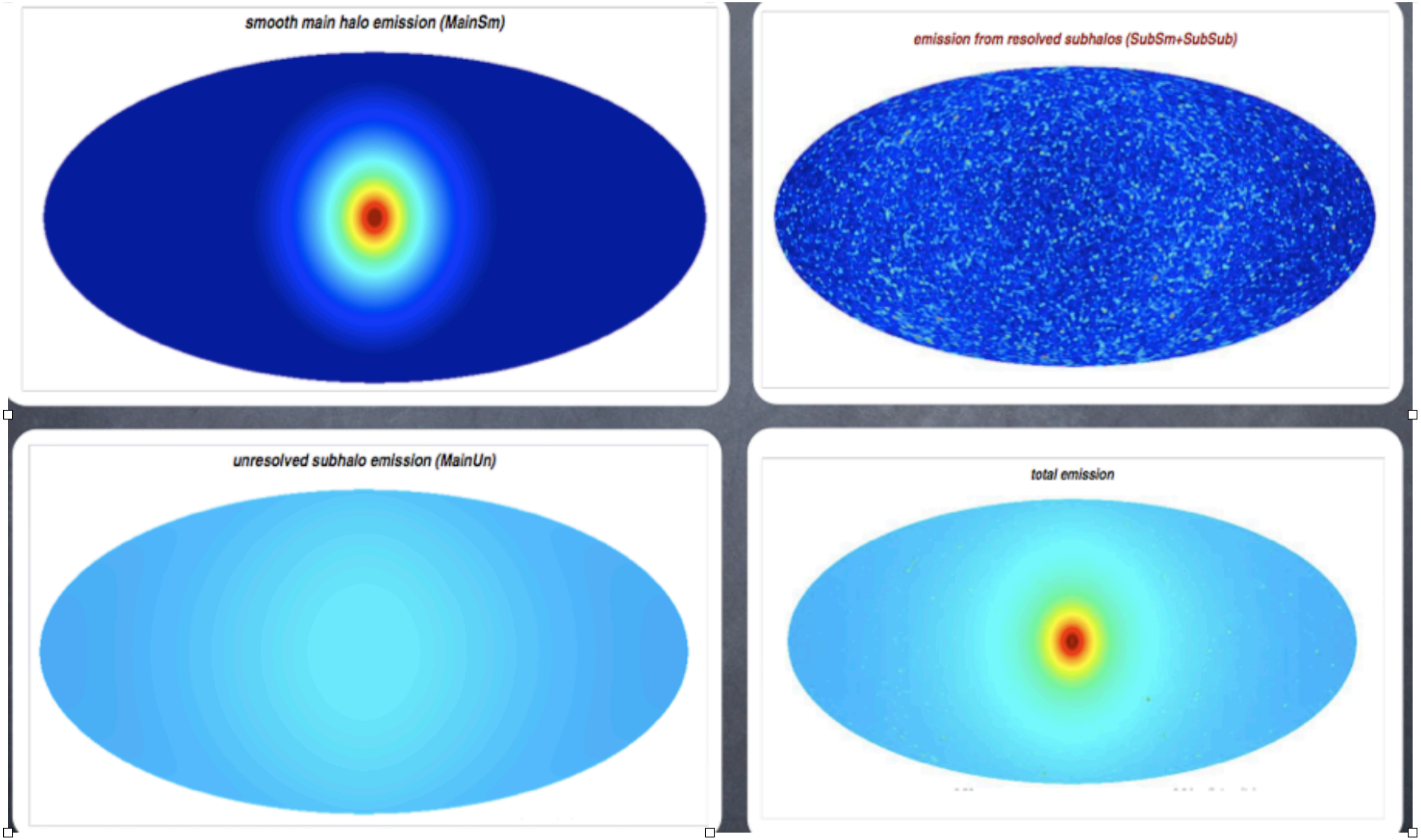
Bridges, KC, RT et al (1011.4306)

Conclusions - BSM Global Fits

Imperial College London

- Global scans of Beyond the Standard Model theories are now a mature field
- Ensuing predictions for direct/indirect detection experiments have to be interpreted with care due to weakness of current constraints
- BUT, quantitative, accurate inference tools will be required to pursue a robust and believable multi-messenger identification of DM
- Current tools have the ability to include statistical and systematic uncertainties in a statistically principled way
- Further work will focus on the careful assessment of their performance on simulated data sets under a variety of conditions

Gamma-ray from WIMP annihilation



Diemand et al (2008)

Predicting the gamma ray flux

Differential flux: $$\frac{d\Phi_\gamma}{dE_\gamma} \propto \sum_i \frac{\langle \sigma_i v \rangle}{m_\chi^2} \frac{dN_\gamma^i}{dE_\gamma} \int \rho_\chi^2 dl$$

particle physics

astrophysics

DM density profile: $$\rho_\chi(r) = \rho_0 \frac{(r/r_0)^{-\gamma}}{[1+(r/a)^\alpha]^{\frac{\beta-\gamma}{\alpha}}} [1+(r_0/a)^\alpha]^{\frac{\beta-\gamma}{\alpha}}$$

Halo model	a (kpc)	α	β	γ
isothermal cored	3.5	2	2	0
NFW	20.0	1	3	1
NFW+ac	20.0	0.8	2.7	1.45
Moore	28.0	1.5	3	1.5
Moore+ac	28.0	0.8	2.7	1.65

Predicting the GC gamma ray signal

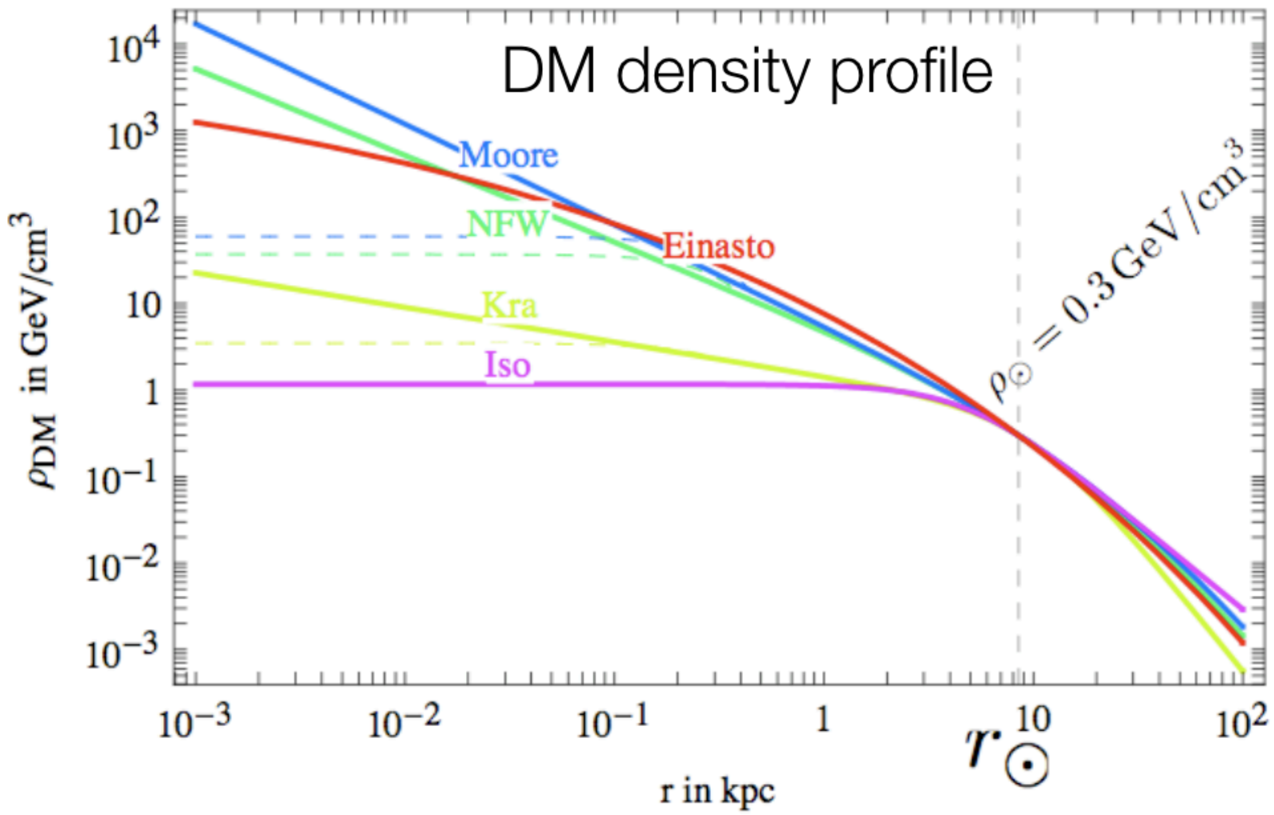
Einasto profile:

$$\rho_\chi(r) = \rho_0 \exp\left[-\frac{2}{\alpha}\left(\left(\frac{r}{r_s}\right)^\alpha - 1\right)\right]$$

$$J(\Psi) = \int_{\rm los} dl \rho_\chi^2(r(l,\Psi))$$

$$\bar{J} = \frac{1}{\Delta\Omega}\int_{\Delta\Omega} J(\Psi) d\Omega$$

DM density profile



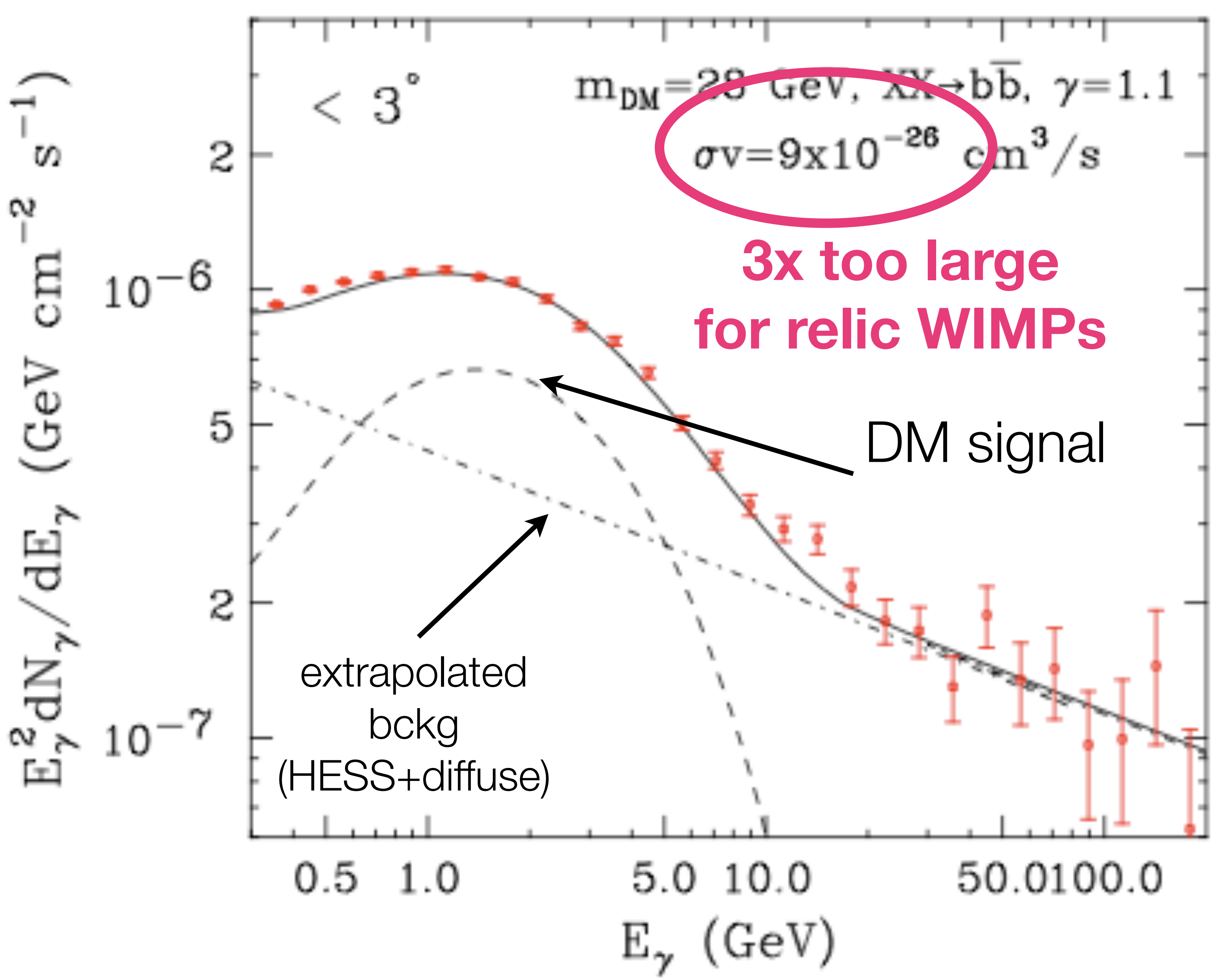
Cirelli (2009)

Halo model	a (kpc)	α	β	γ	$\bar{J}(10^{-3}\mathrm{sr})$	$\bar{J}(10^{-5}\mathrm{sr})$
isothermal cored	3.5	2	2	0	30.35	30.40
NFW	20.0	1	3	1	1.21×10^3	1.26×10^4
NFW+ac	20.0	0.8	2.7	1.45	1.25×10^5	1.02×10^7
Moore	28.0	1.5	3	1.5	1.05×10^5	9.68×10^6
Moore+ac	28.0	0.8	2.7	1.65	1.59×10^6	3.12×10^8

A GC Excess?

Imperial College London

Goodenough & Hooper (2009)



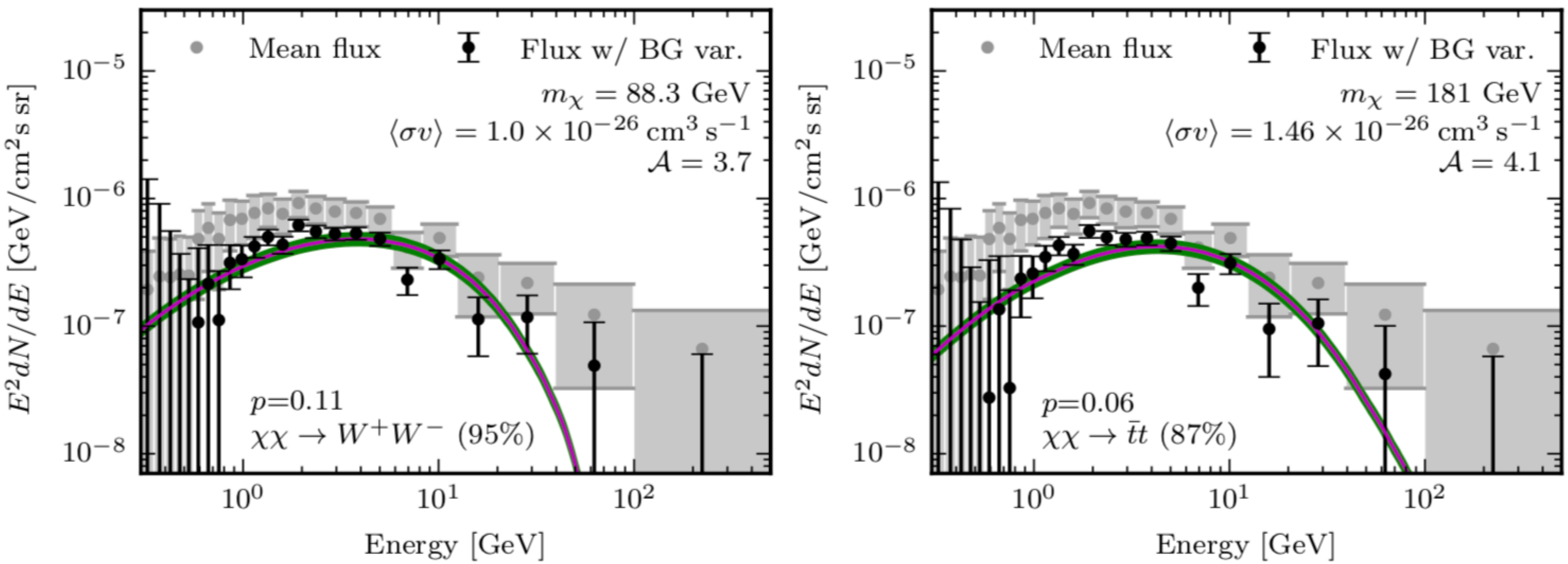
- Initial hints of a DM signal from the galactic center (Goodenough & Hooper 2009)
- Caveats:
  - GC very complex region: point sources, diffuse emission, etc
  - Strong bounds from PAMELA antiproton data and radio data constraining synchroton emission
  - The Hooper & Goodenough model is effectively ruled out.

GC Excess from the pMSSM

Imperial College London

- Astrophysical explanations most plausible for the “excess” (unresolved population of millisecond pulsars, inverse Compton from cosmic rays).

- Can the putative excess be explained with a SUSY model? YES



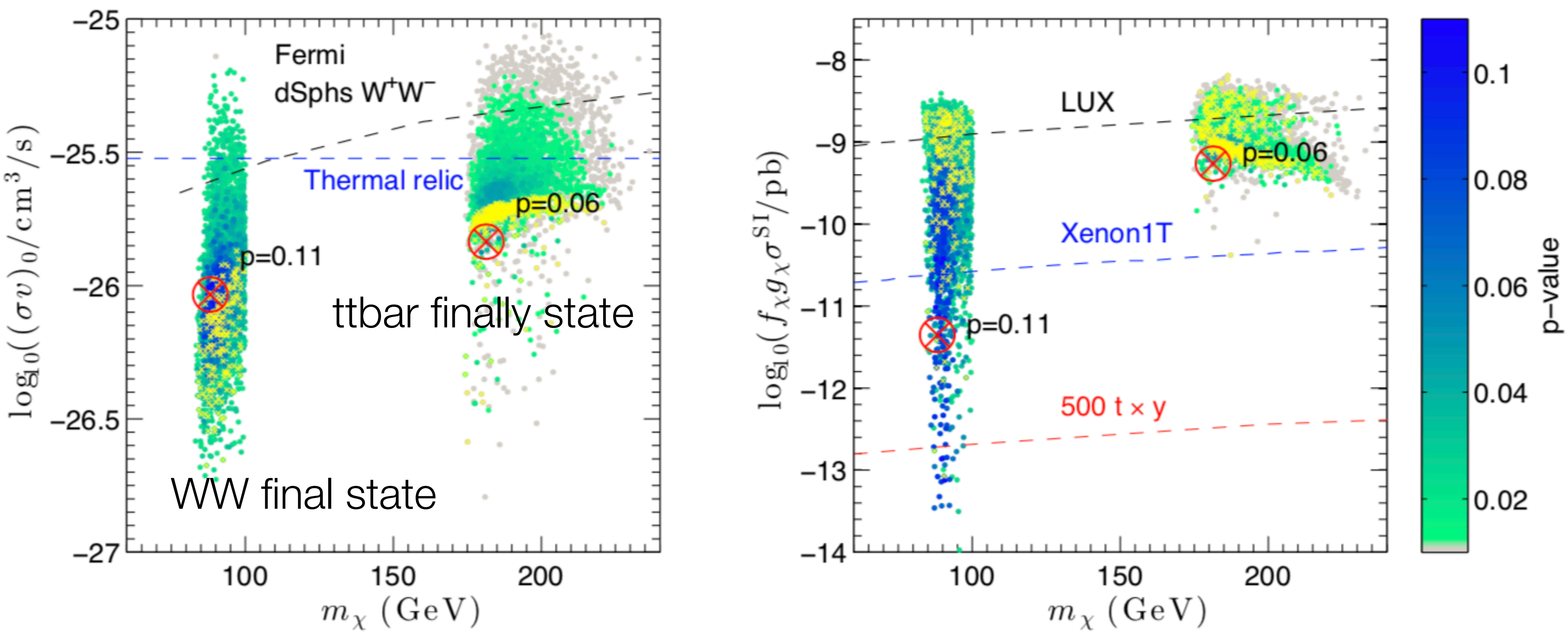
Bertone, RT et al 2016

GC Excess from the pMSSM

Imperial College London

- There exist points in the 19-dimensional pMSSM that can explain the GC excess while satisfying all other constraints

- Since this study was done, direct detection constraints have further improved, largely ruling out the ttbar island.



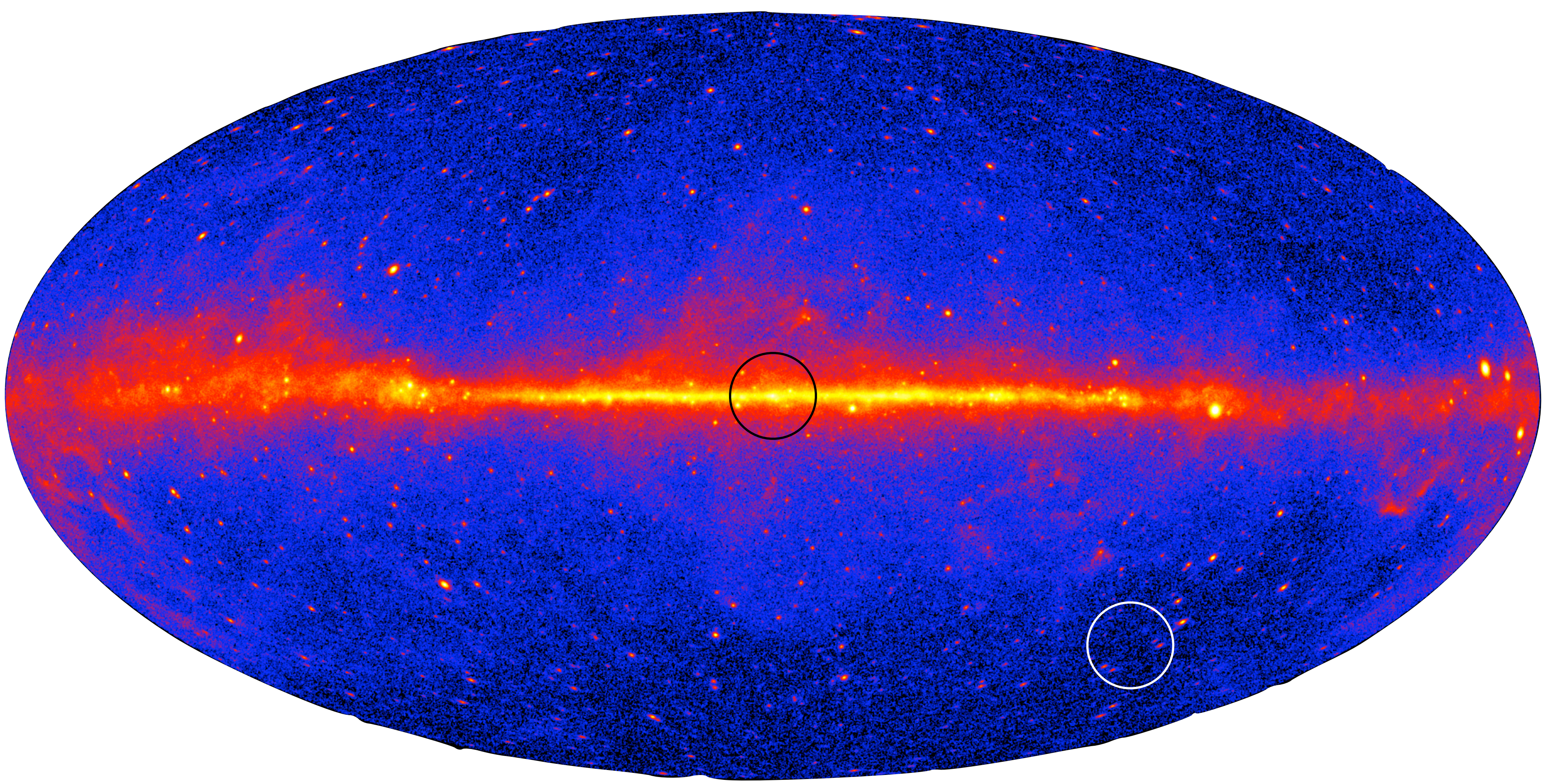
Bertone, RT et al 2016

Milky Way dwarf galaxies

Nearby, lots of dark matter ($\log_{10} J \sim 18 - 20$)

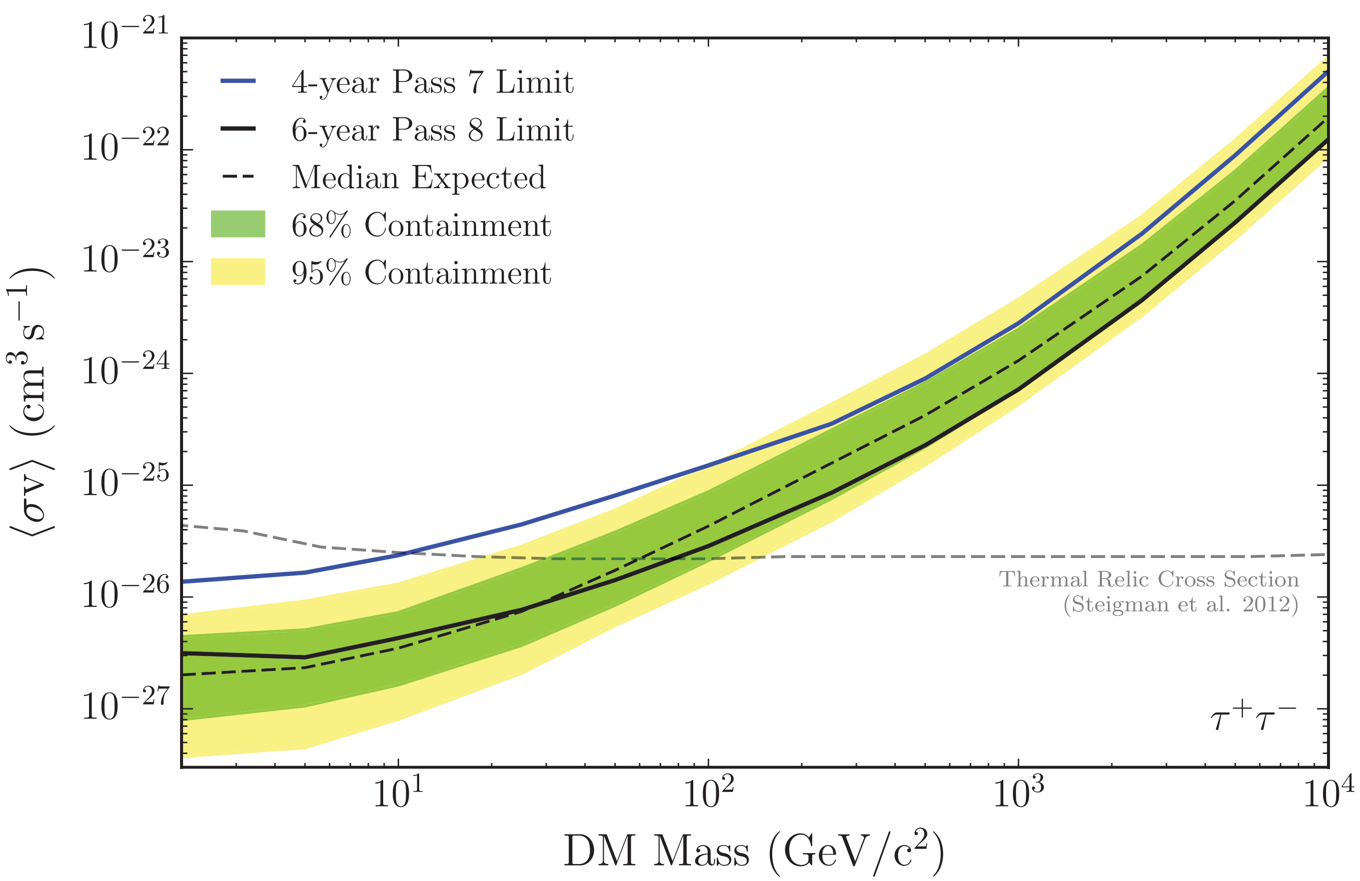
Not much else: no astrophysical background*

compare to Galactic center



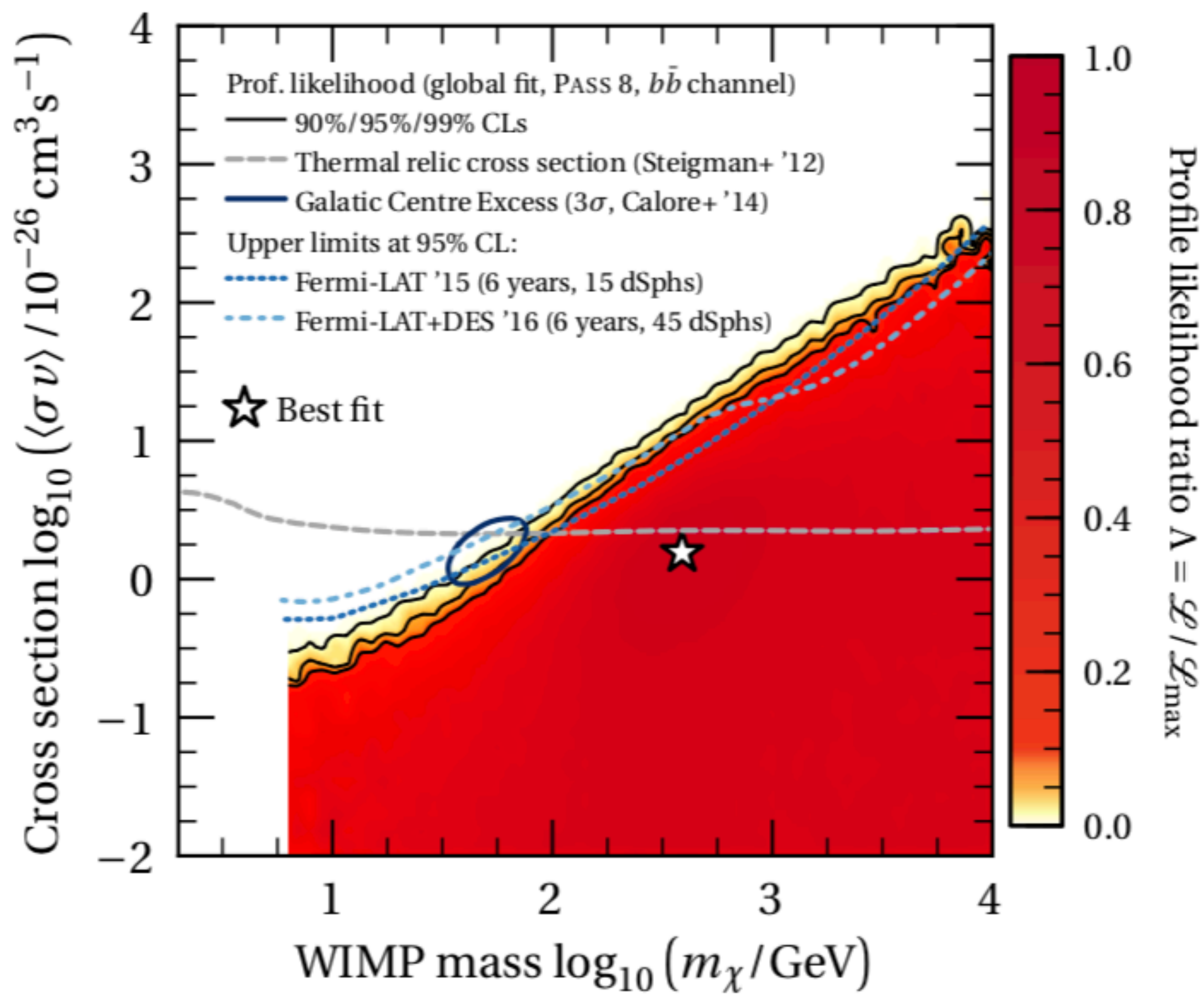
Dwarf searches reach the relic cross section

Cross section limits



Fermi collaboration 1503.02641 (PRL)

27 dwarfs, 10 yrs of data



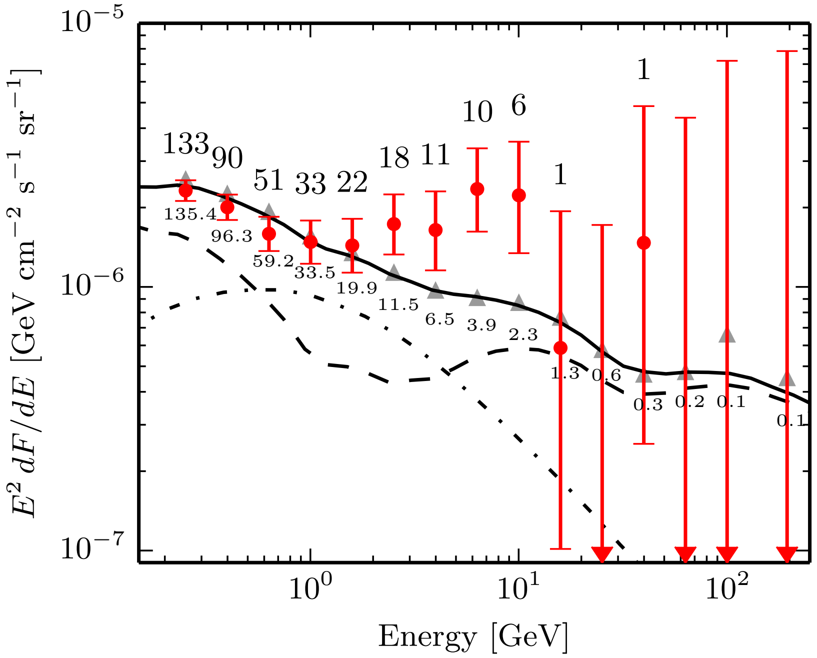
Hoof, Geringer-Sameth & RT (in prep)

Case study: Reticulum II

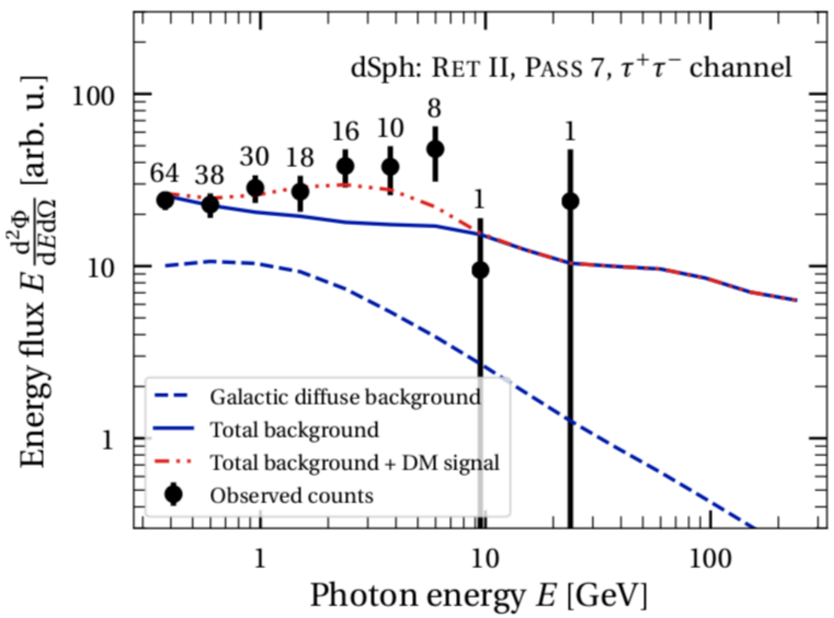
Imperial College London

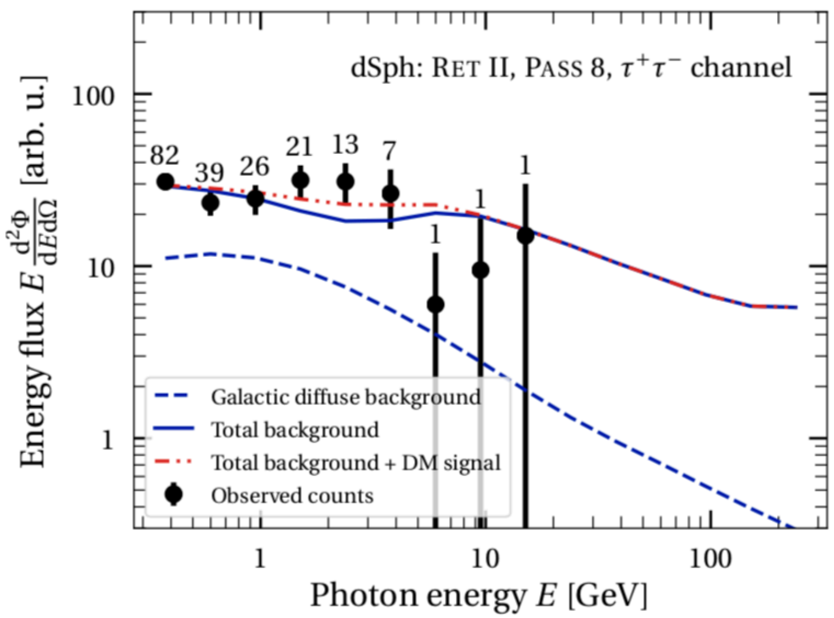
6.5 yr Pass 7 Fermi LAT data

6.5 yr Pass 8 Fermi LAT data

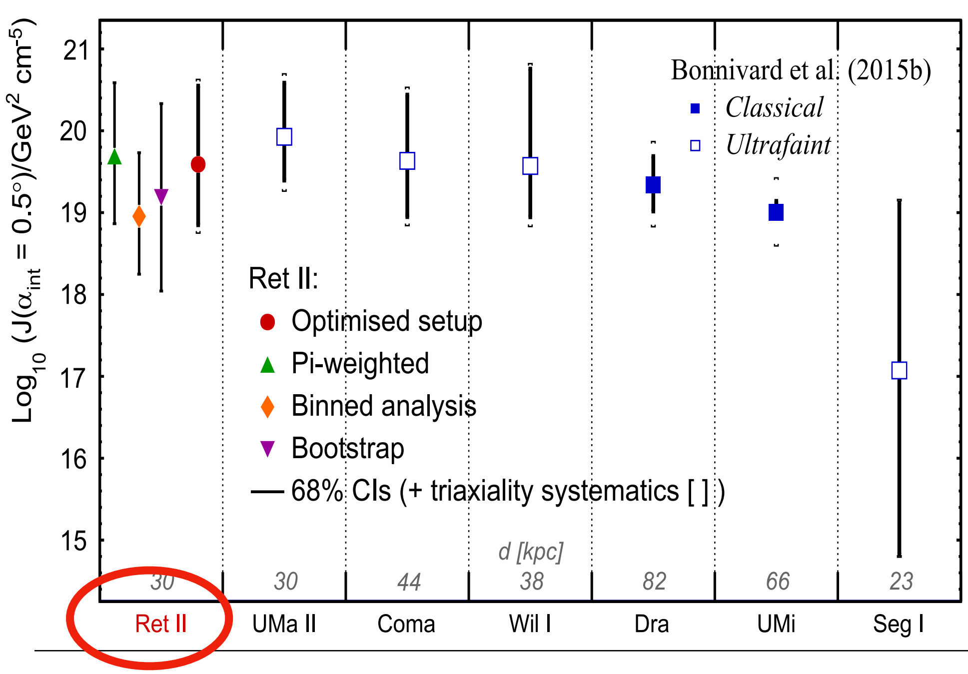


Geringer-Sameth+1503.02320 (PRL)





Hoof, Geringer-Sameth & RT (in prep)



Bonnivard+ 1504.03309 (ApJL)

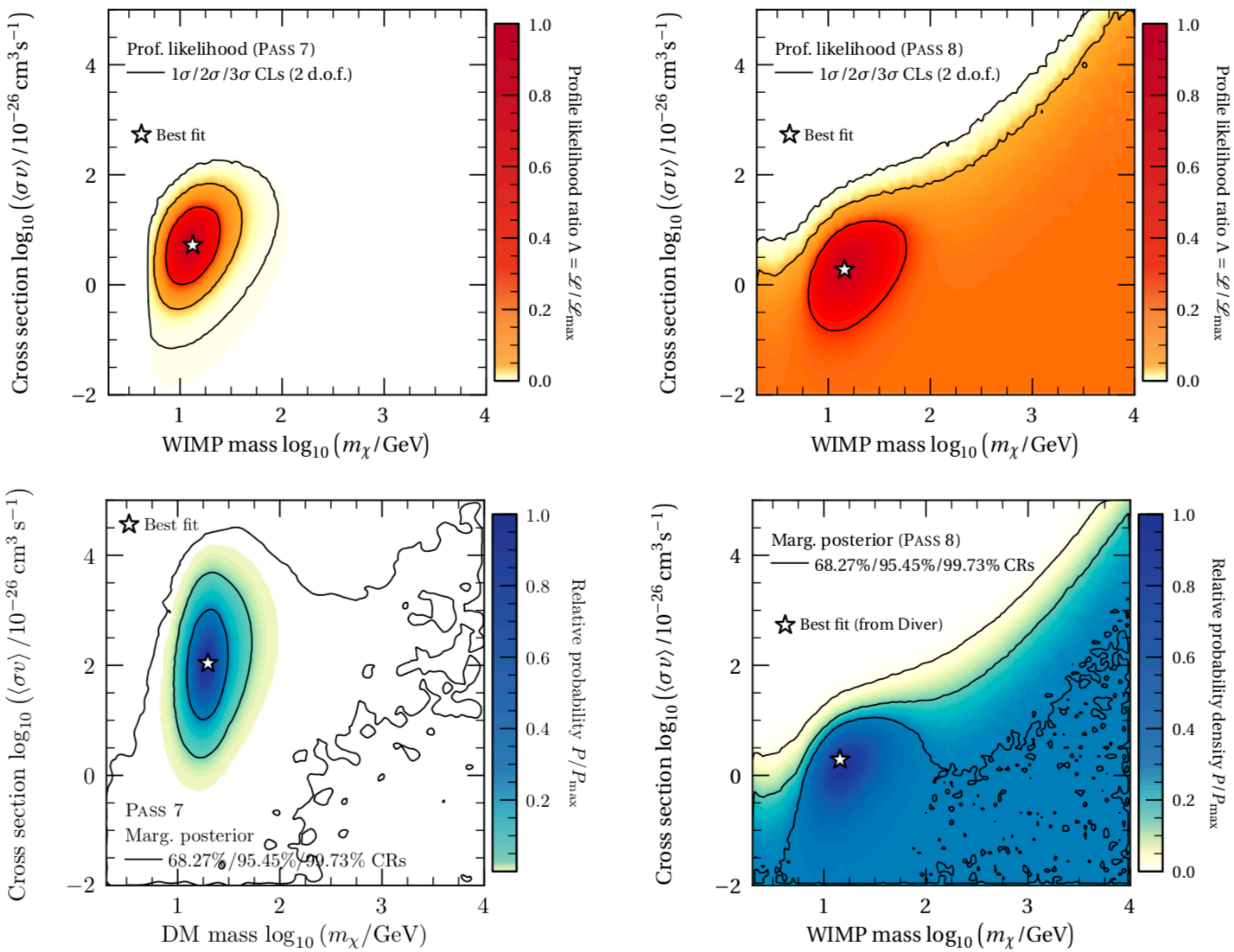
Case study: Reticulum II

Imperial College London

6.5 yr Pass 7 Fermi LAT data | **6.5 yr Pass 8 Fermi LAT data**

Profile likelihood

Posterior pdf



Hoof, Geringer-Sameth & RT (in prep)

To discover dark matter annihilation using dwarfs:

1. Gamma-ray data is inconsistent with background

2. Inconsistent with any other possible source
   (e.g. non-DM astrophysics, incorrect diffuse bg models)

3. Consistent with dark matter annihilation
   (compare with other dwarfs, other experiments)

Slide: Alex Geringer-Sameth

Two ways to model background give two different significances. Beware of the Look Elsewhere Effect, too!

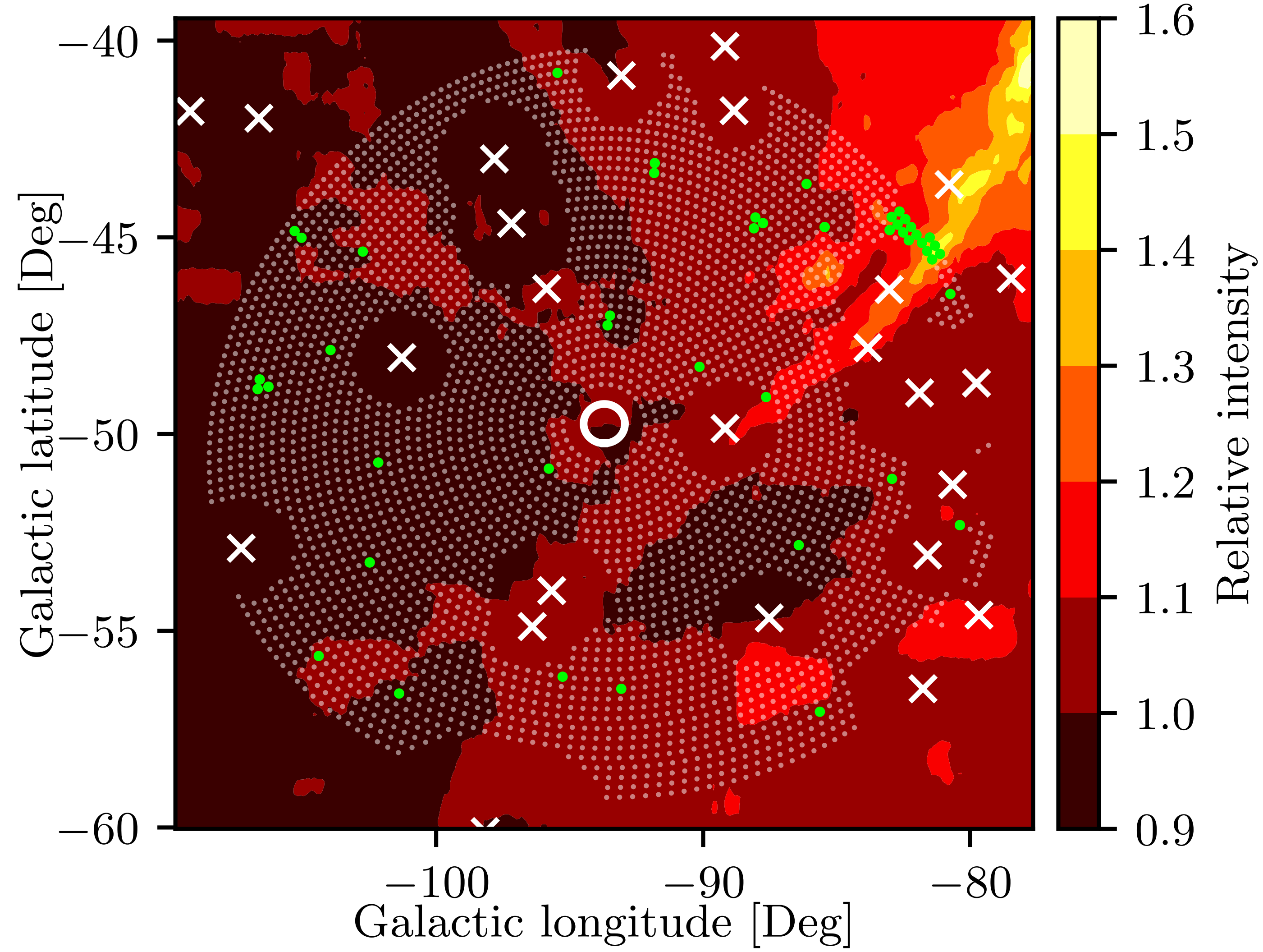
Diffuse background *model*

- Poisson with given spectrum:
  - “physical” model — cosmic ray interactions in Milky Way, extragalactic isotropic emission, charged particle misidentification
  - No additional non-DM sources along line of sight towards dwarf

H_0: No additional source

p-value = 0.0001

Empirical background from sampling



H_0: No dark matter annihilation

p-value = 0.01

Slide: Alex Geringer-Sameth

Geringer-Sameth & Koushiappas 1108.2914 (PRL), Geringer-Sameth+ 1410.2242 (PRD), Geringer-Sameth+ 1503.02320 (PRL)

To discover dark matter annihilation using dwarfs:

1. Gamma-ray data is inconsistent with background

2. Inconsistent with any other possible source
   (e.g. non-DM astrophysics, incorrect diffuse bg models)

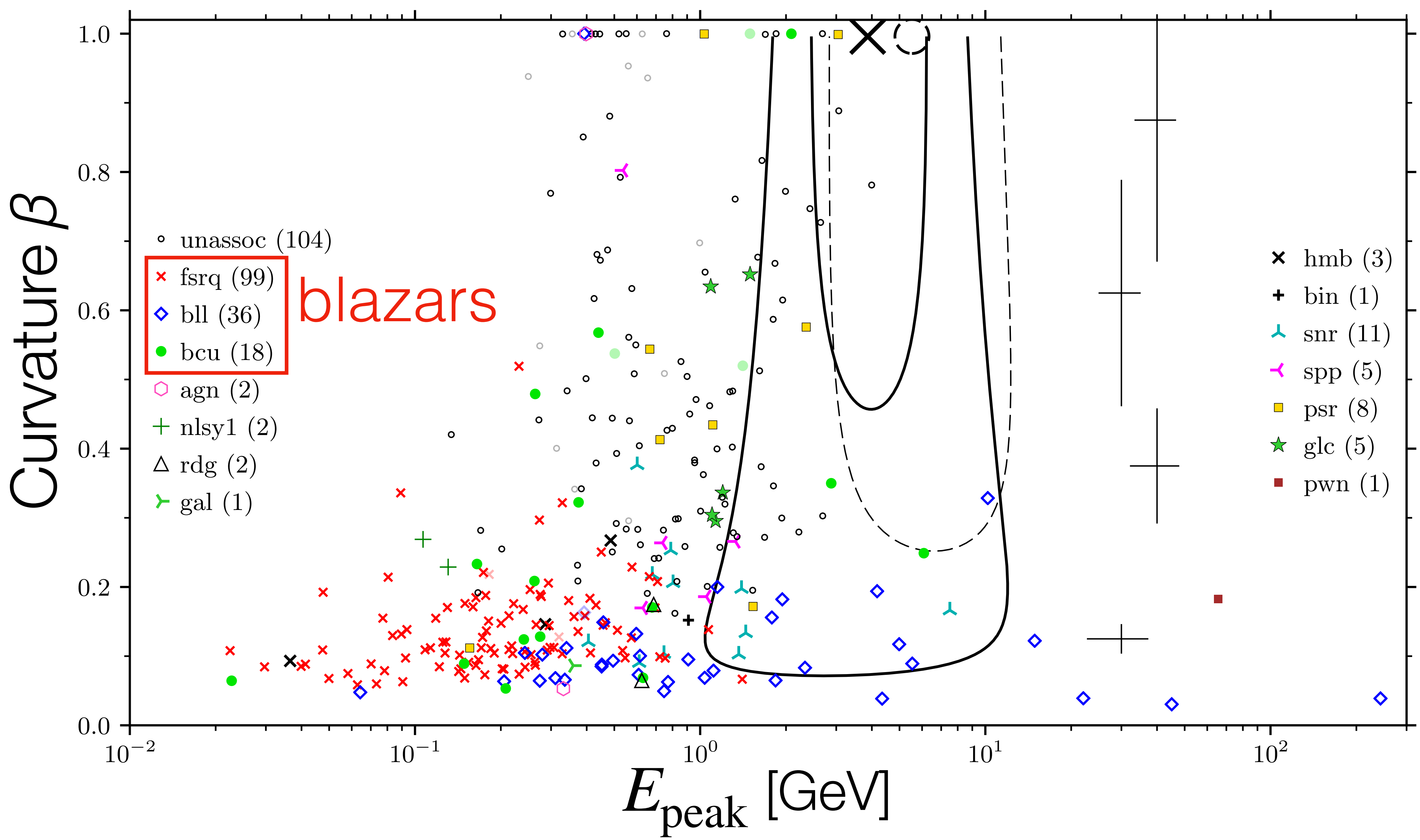
3. Consistent with dark matter annihilation
   (compare with other dwarfs, other experiments)

Slide: Alex Geringer-Sameth

Compare with known classes of gamma-ray sources

$$\frac{dF(E \mid \theta)}{dE} = F_0 \left(\frac{E}{E_0}\right)^{-\alpha-\beta \log(E/E_0)}$$

$E_{\rm peak}$ = energy at peak of SED E^2dF/dE



Geringer-Sameth+ 1807.08740

Slide: Alex Geringer-Sameth

Combine all three tests into a single search using a Bayesian approach

Gamma-ray data is inconsistent with background

+

Inconsistent with any other possible source
(e.g. non-DM astrophysics, incorrect diffuse bg models)

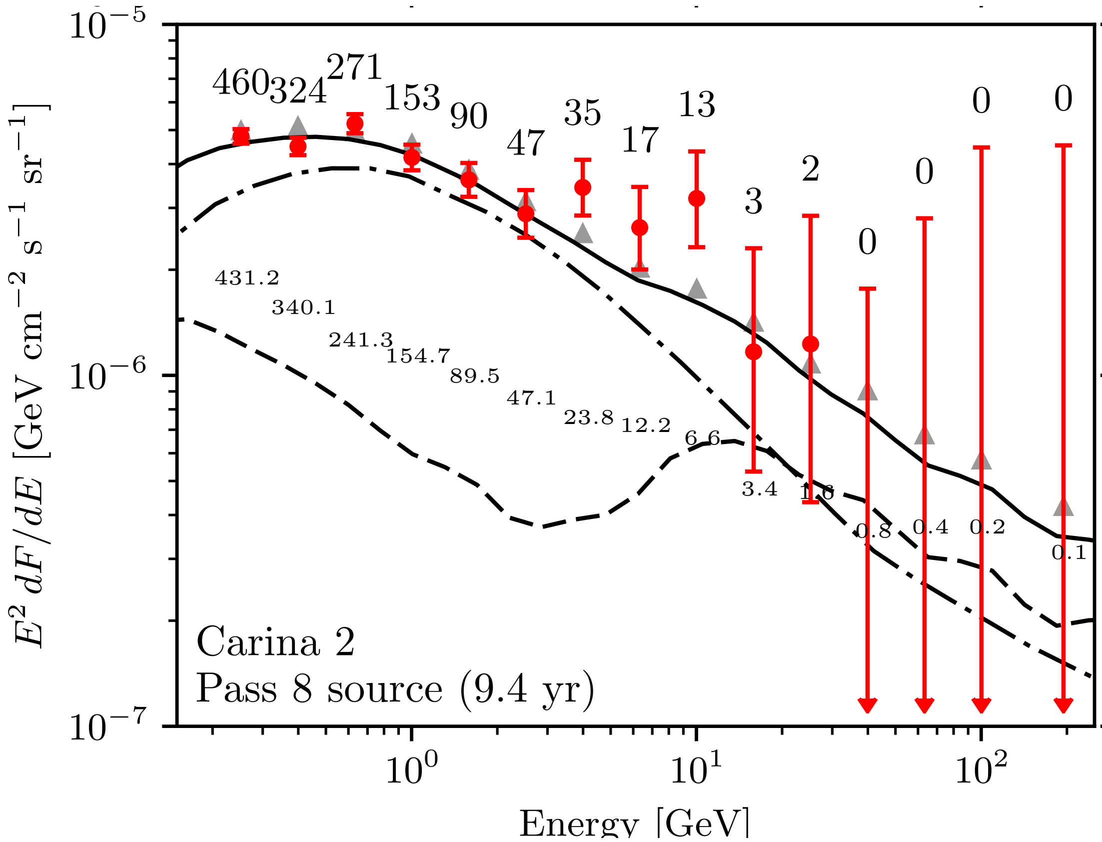
+

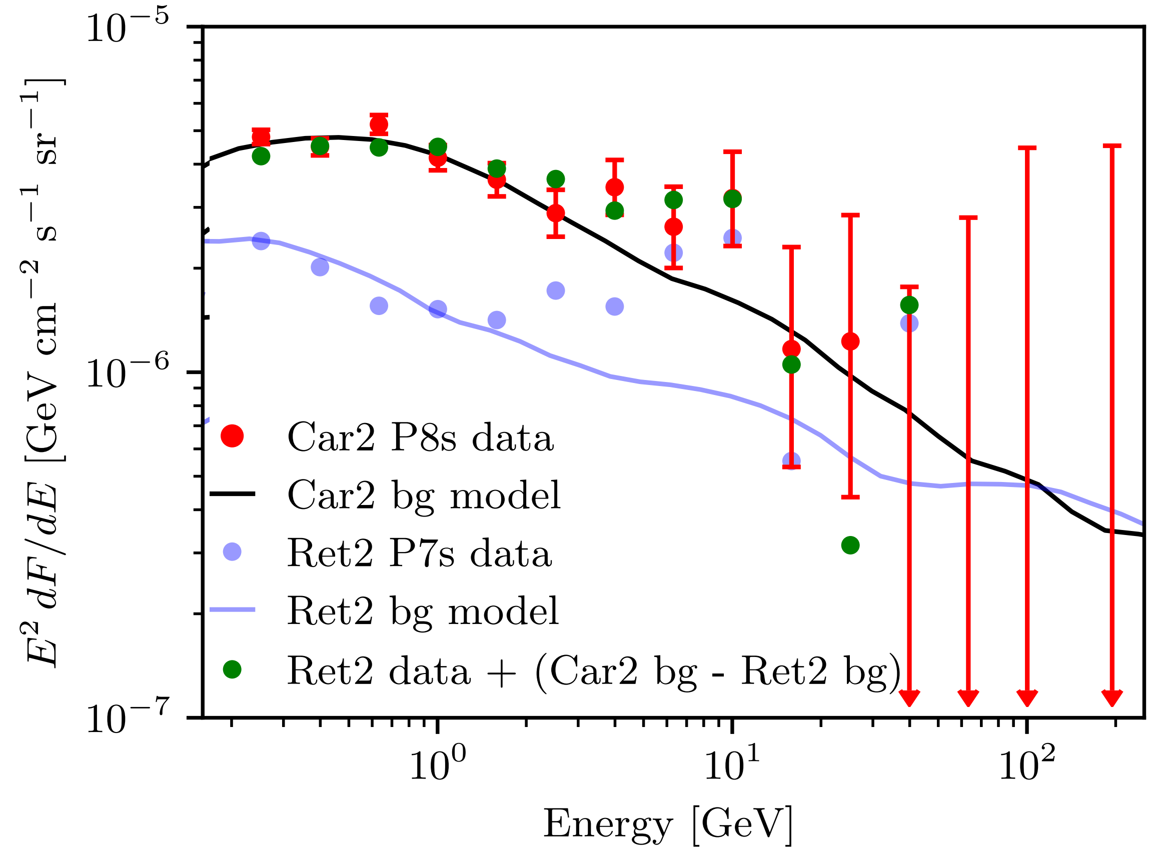
Consistent with dark matter annihilation

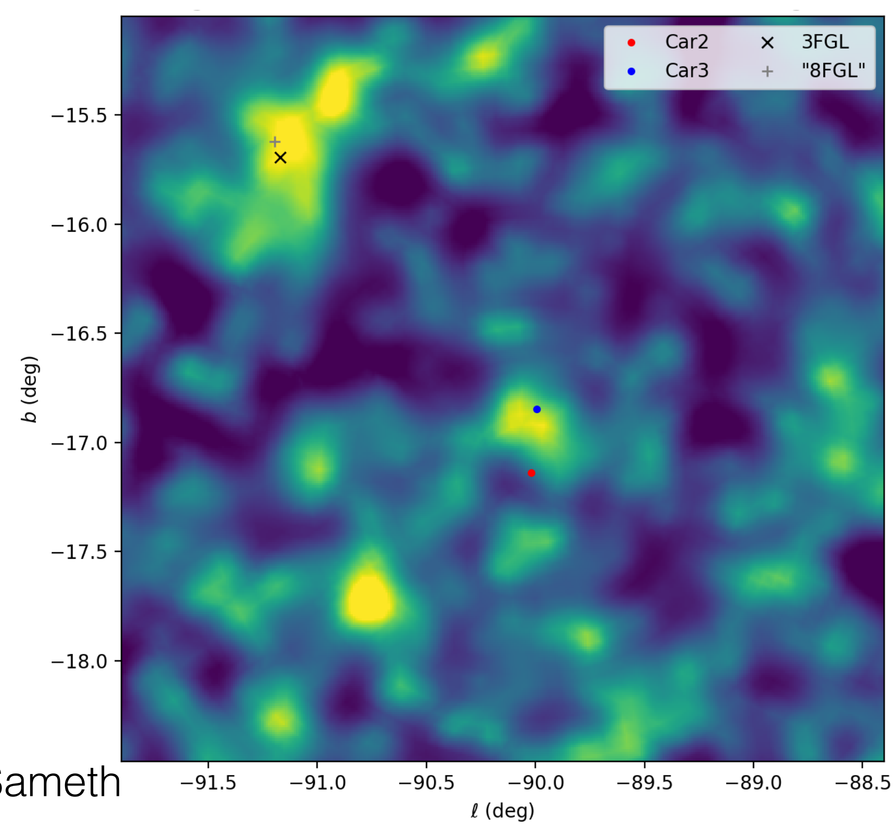
Slide: Alex Geringer-Sameth

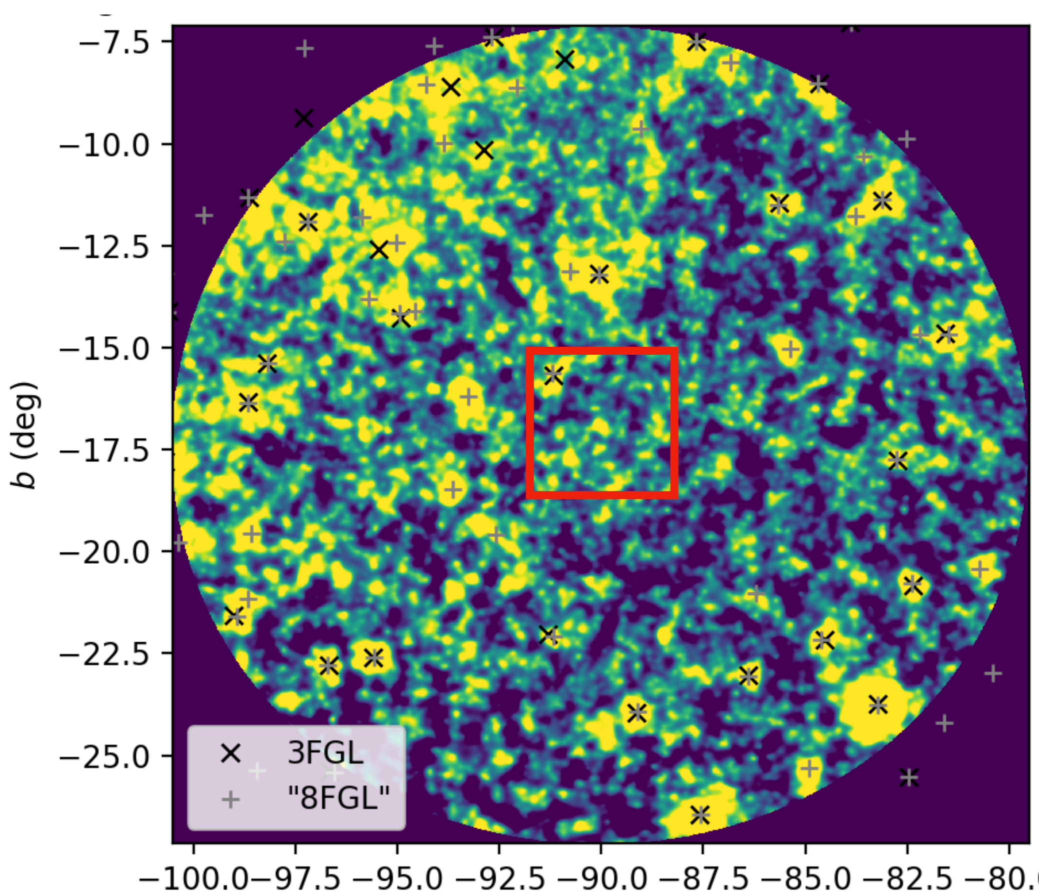
Carina 2 and 3

Discovered by Torrealba+ 1801.07279 (MNRAS)



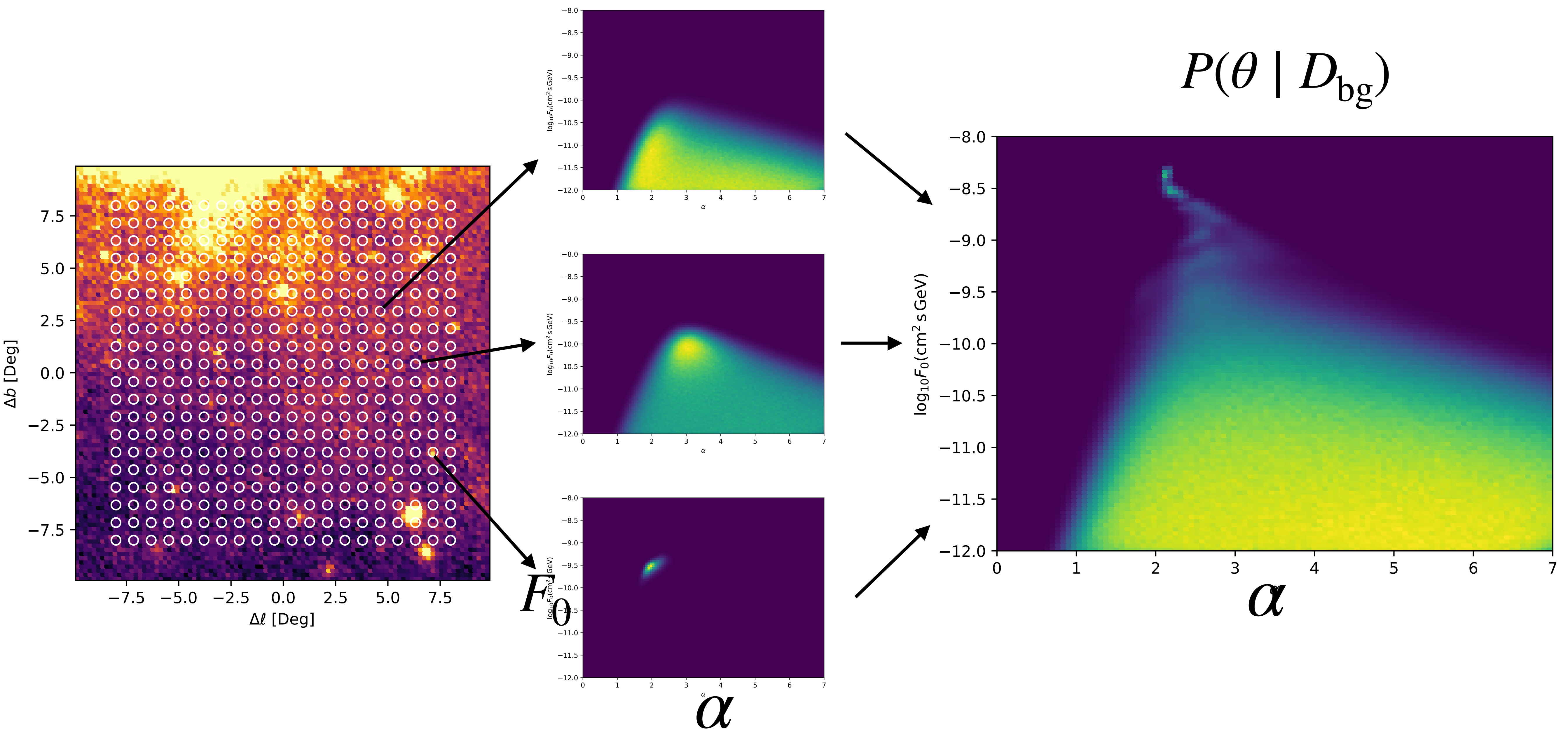






Slide: Alex Geringer-Sameth

Idea: empirical prior distribution of background sources leads to empirical prior on non-DM point-like sources around the target



fit each bg region with diffuse + point source $\dfrac{dF(E)}{dE} = F_0 \left(\dfrac{E}{E_0}\right)^{-\alpha}$

Slide: Alex Geringer-Sameth

Conclusions - Constraints on DM from dwarfs

- Ruling out diffuse bg model is not enough
- Want to distinguish DM annihilation from non-DM source populations without sacrificing sensitivity
- Methods apply to any dwarf which is a promising DM target and shows evidence for gamma-ray emission along line of sight
- Should be simple to extend to any dark matter target where you expect localized emission (e.g. galaxy clusters, groups, dark subhalos)

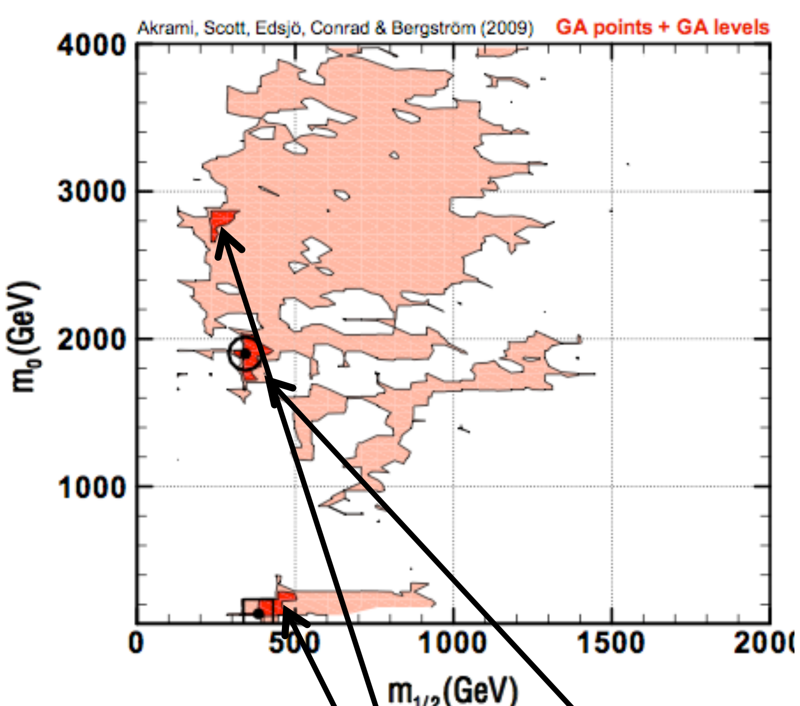
SUPPLEMENTARY MATERIAL

Profile likelihood results: comparison

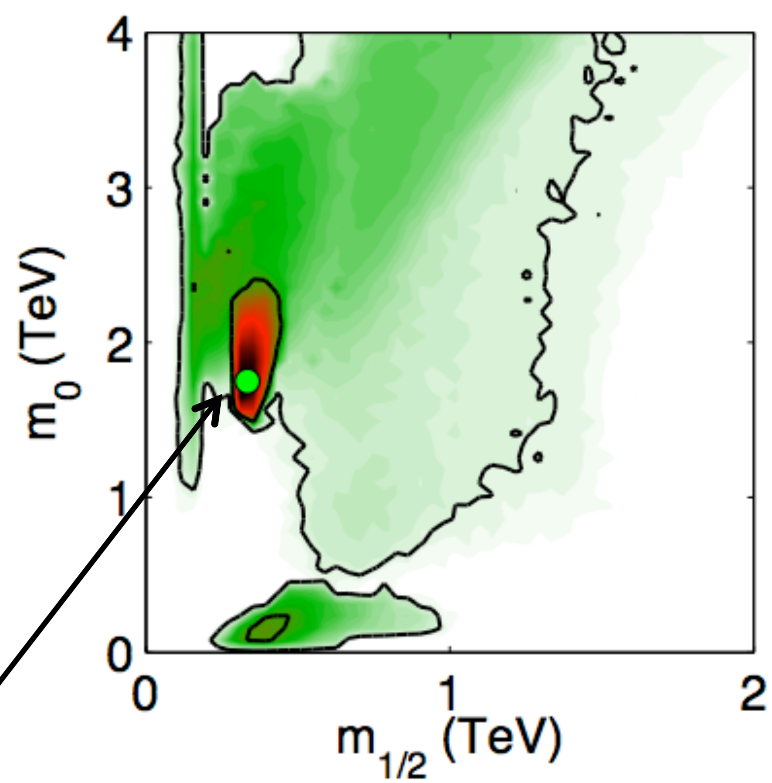
- Akrami et al (0910.3950) adopted a genetic algorithm (GA) to map out the profile likelihood.

- This allows to find isolated spikes in the likelihood in the focus point region:
  is this something other frequentist fits might have missed?

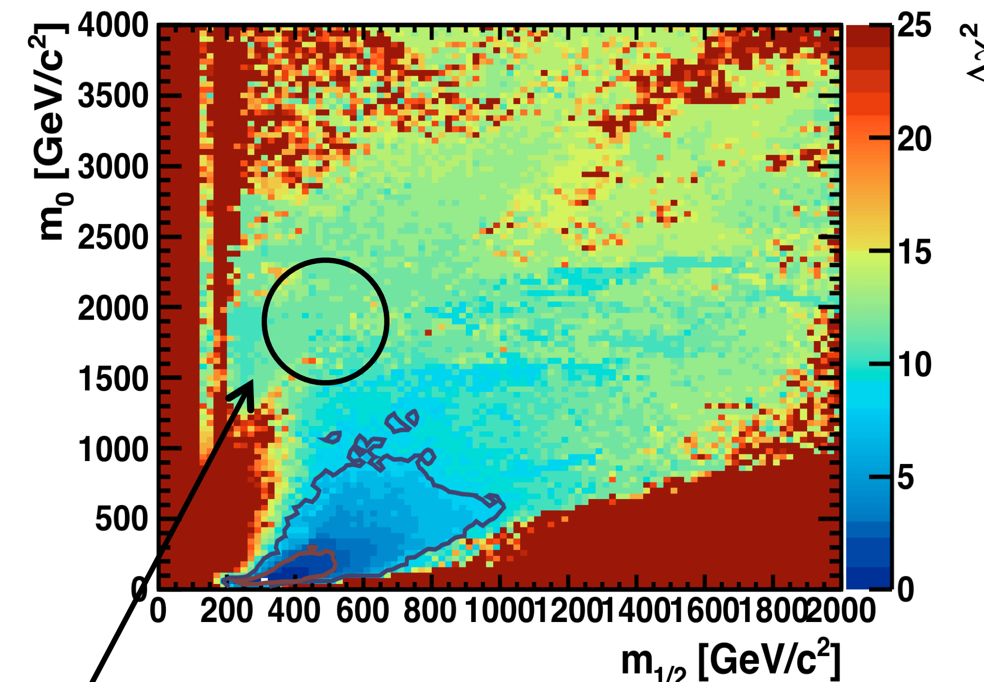
Genetic Algorithm profile likelihood



MultiNest profile likelihood



MasterCode profile likelihood



isolated local maxima

overall best-fit

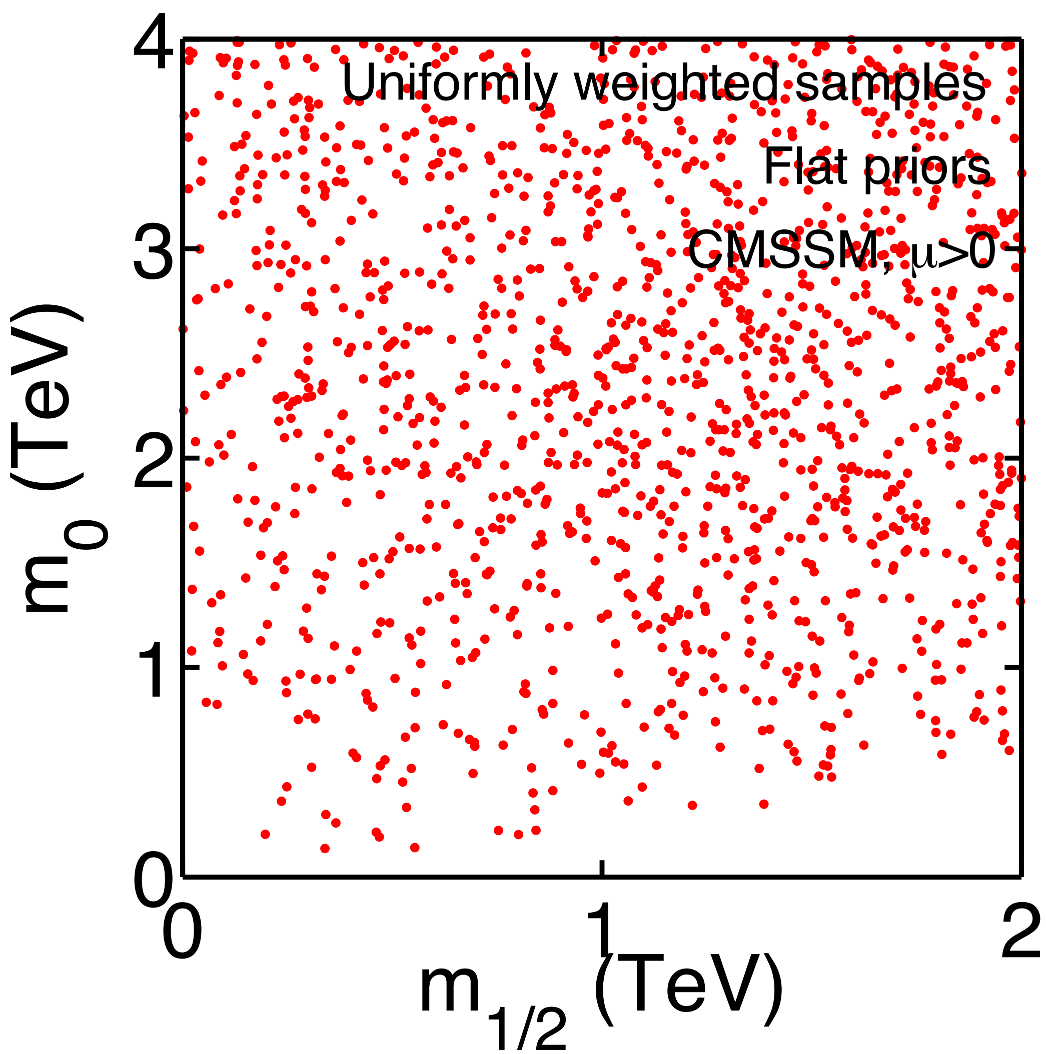
excluded at ~ 3σ

Samples from priors only

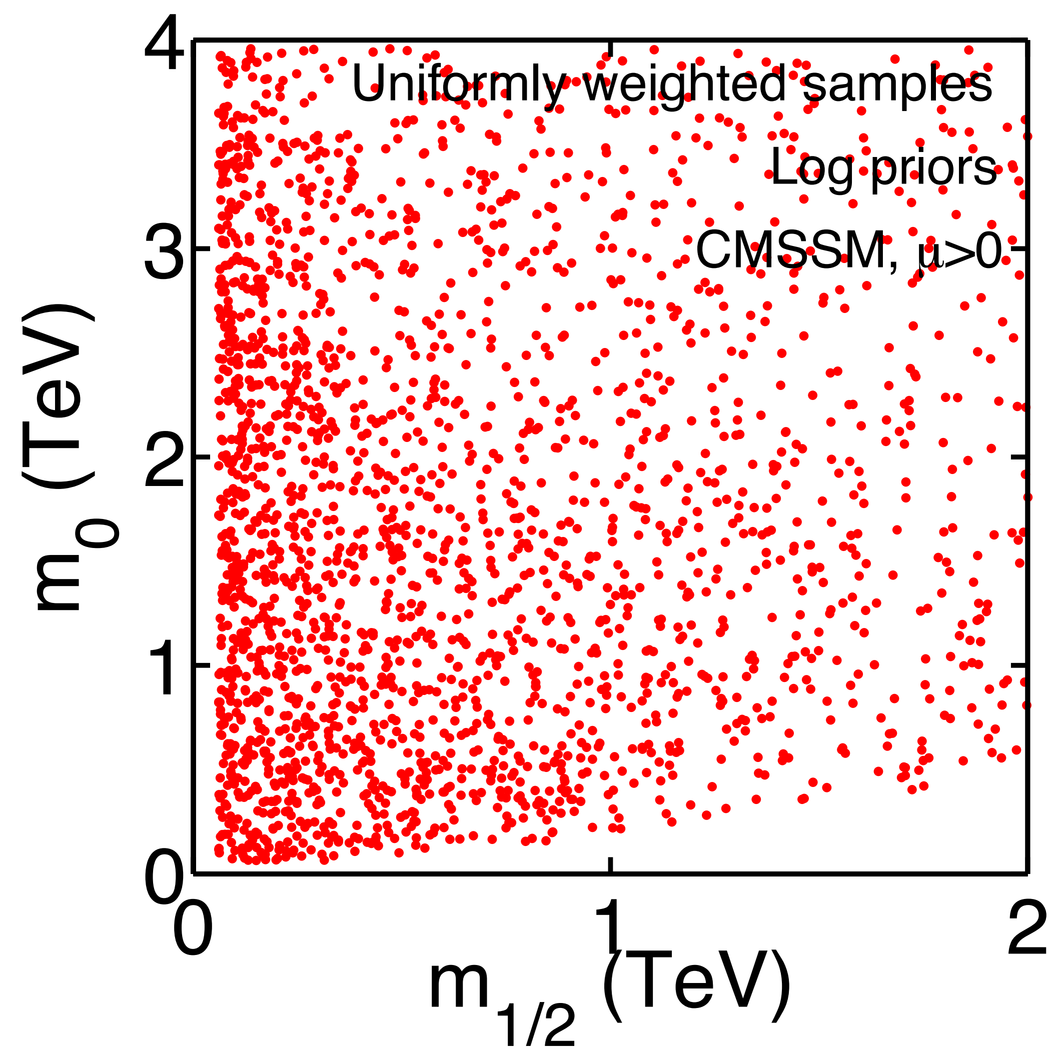
Imperial College London

- No data in the likelihood, non-physical points discarded

Flat priors
uniform in m_0, $m_{1/2}$



Log priors
uniform in $\log(m_0)$, $\log(m_{1/2})$



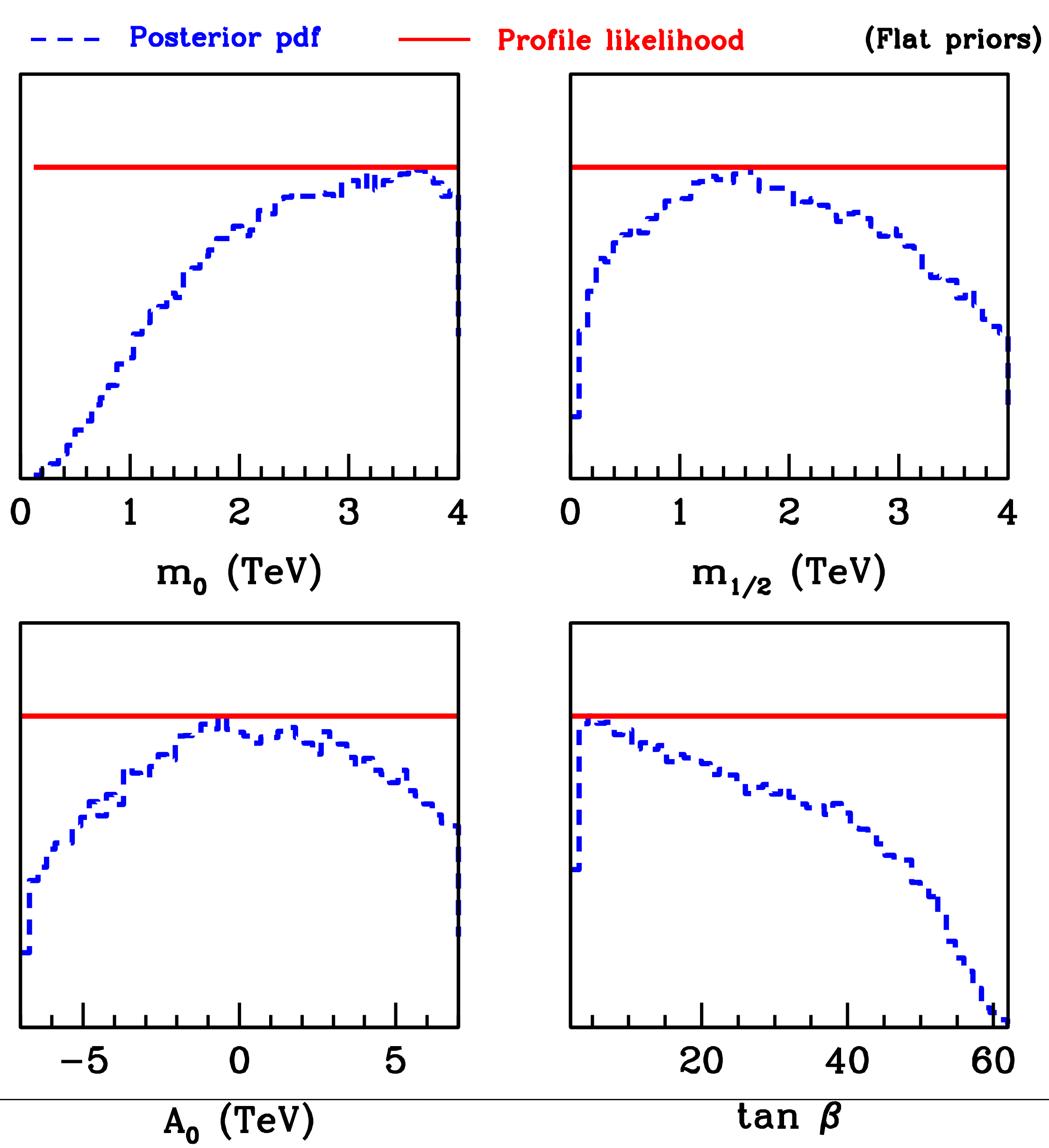
Trotta et al (2008)

Samples from priors only

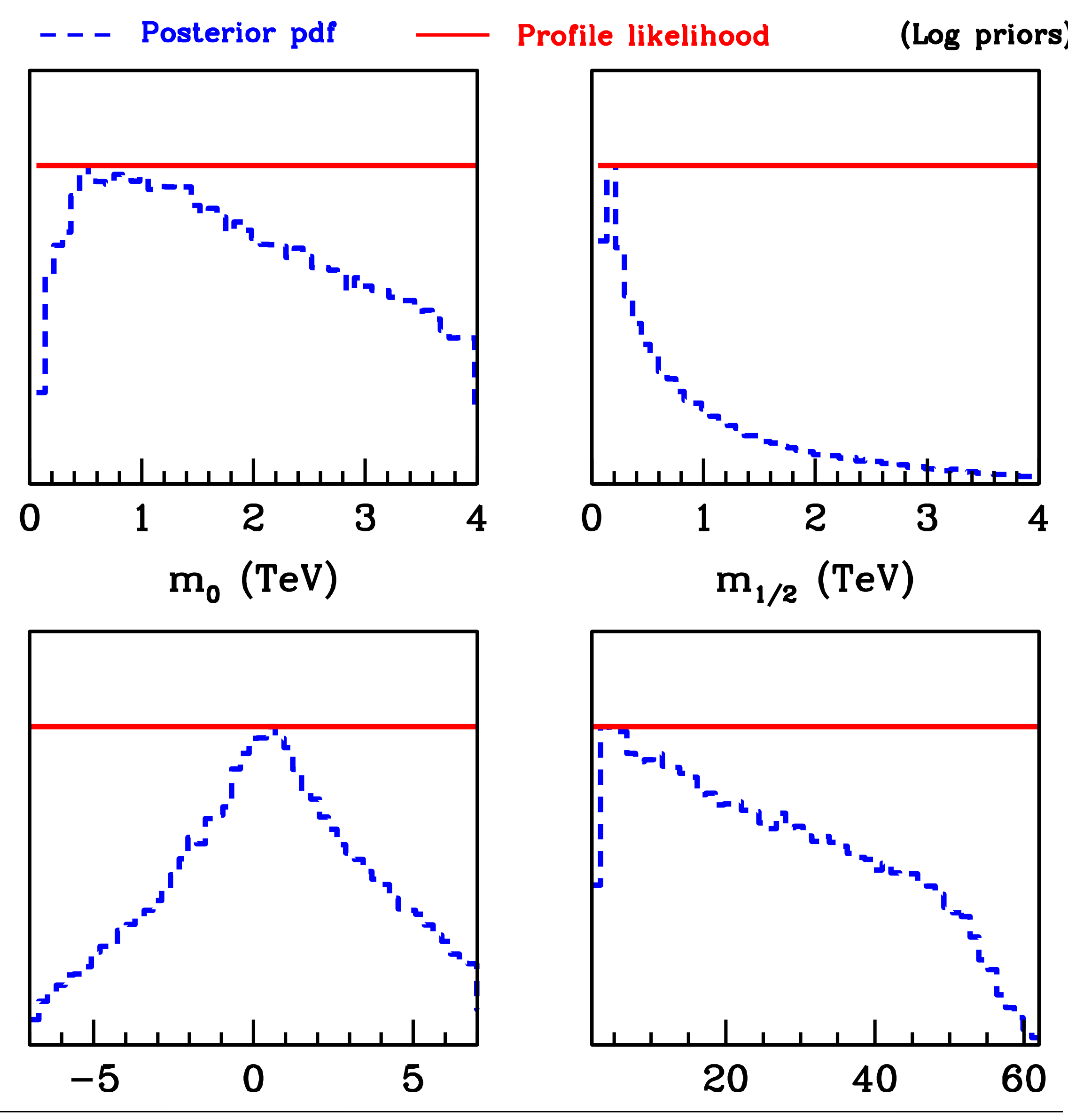
Imperial College London

- Volume effect from the non-physical regions

Flat priors

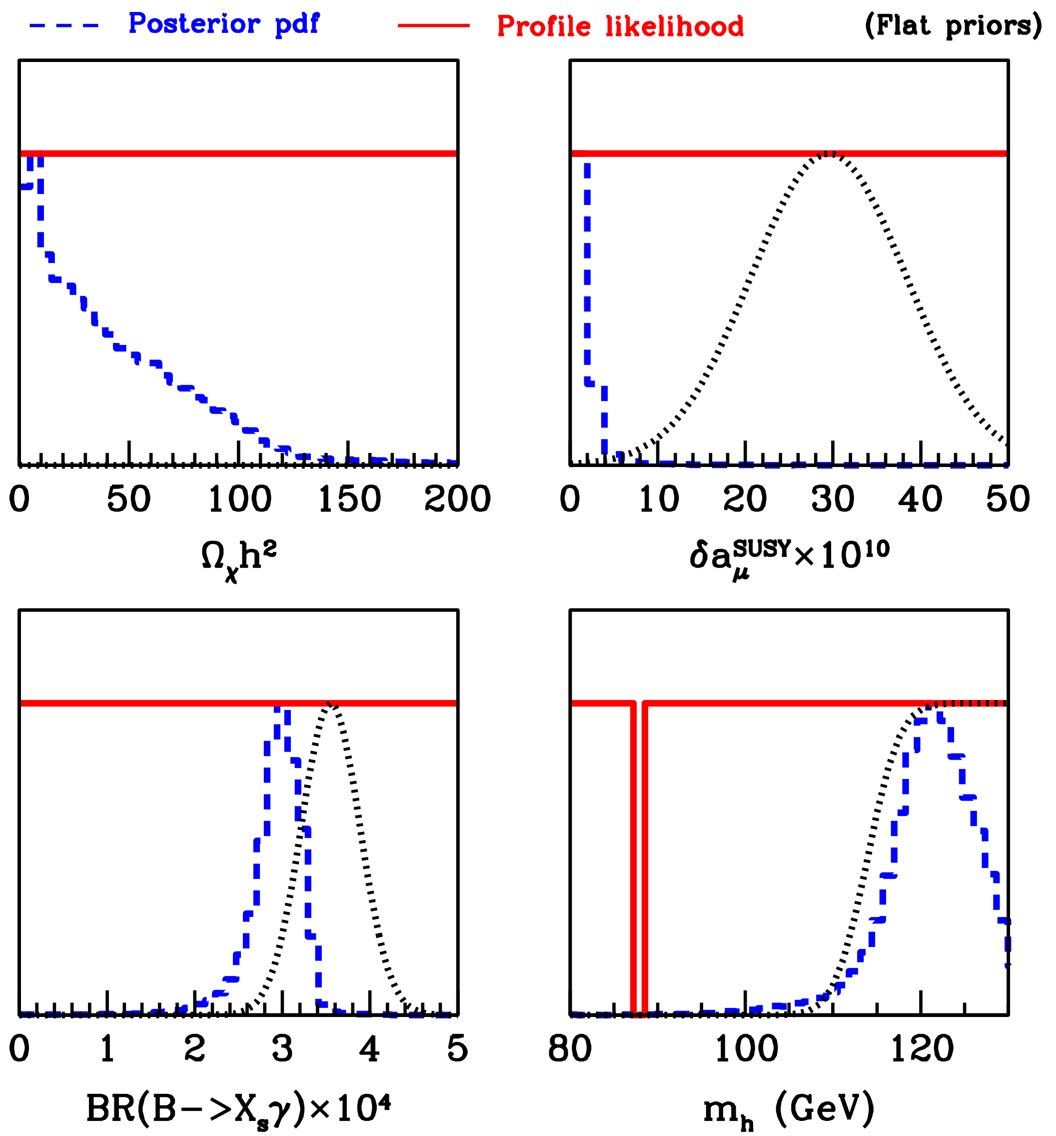


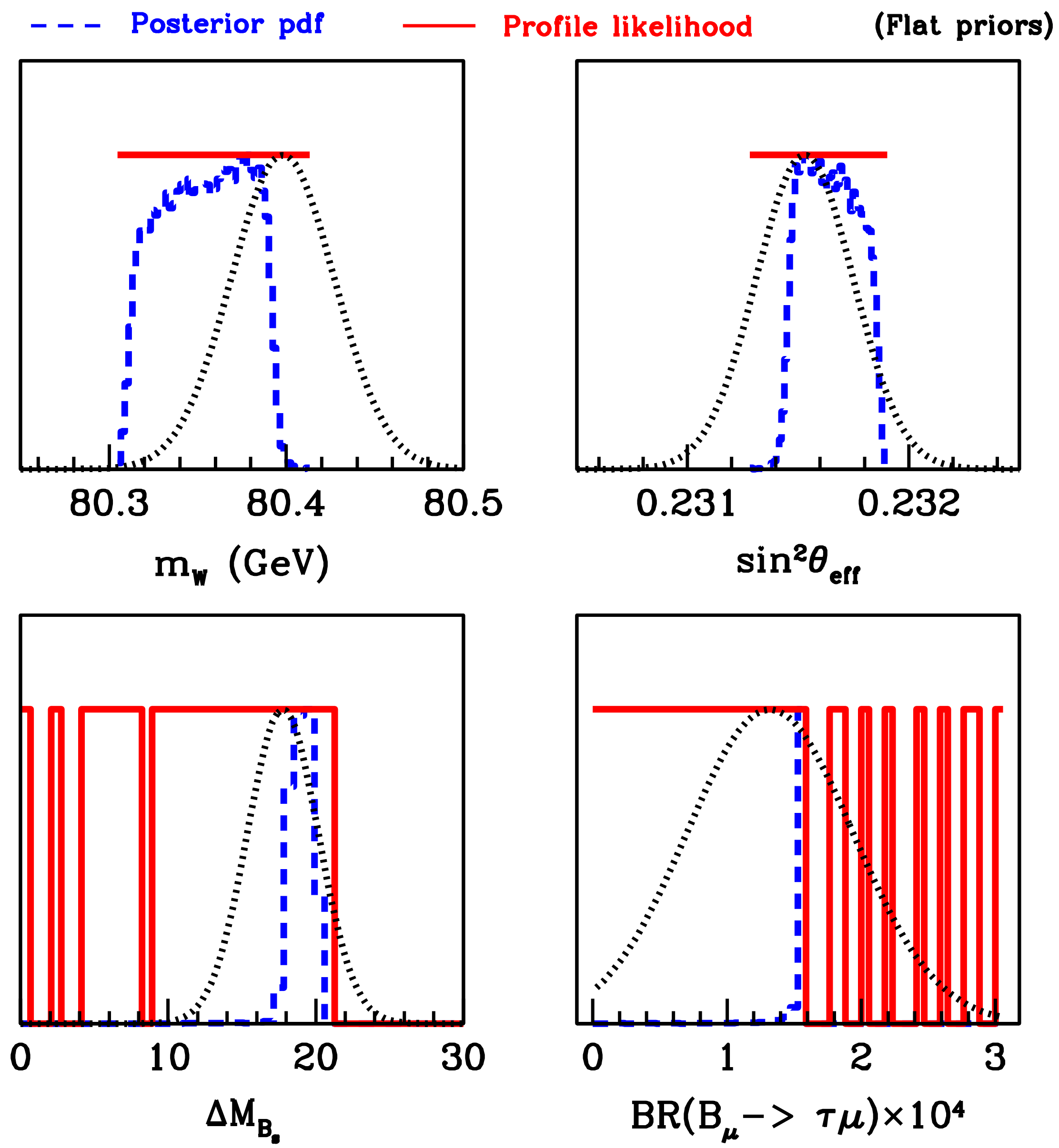
Log priors



Prior distribution for observables

Imperial College London





Priors are highly informative regarding the quantities being constrained!

Current constraints

Imperial College London

Indirect observables

Observable	Mean value μ	Uncertainties σ (exper.)	τ (theor.)	ref.
M_W	80.398 GeV	25 MeV	15 MeV	[30]
$\sin^2\theta_{\rm eff}$	0.23153	16×10^{-5}	15×10^{-5}	[30]
$\delta a_\mu^{\rm SUSY}\times10^{10}$	29.5	8.8	1.0	[31]
$BR(\overline{B}\to X_s\gamma)\times10^4$	3.55	0.26	0.21	[32]
ΔM_{B_s}	17.77 ps^{-1}	0.12 ps^{-1}	2.4 ps^{-1}	[33]
$BR(\overline{B}_u\to\tau\nu)\times10^4$	1.32	0.49	0.38	[32]
$\Omega_\chi h^2$	0.1099	0.0062	$0.1\,\Omega_\chi h^2$	[34]
	Limit (95% CL)		τ (theor.)	ref.
$BR(\overline{B}_s\to\mu^+\mu^-)$	$<5.8\times10^{-8}$		14%	[35]
m_h	>114.4 GeV (SM-like Higgs)		3 GeV	[36]
ζ_h^2	$f(m_h)$ (see text)		negligible	[36]
$m_{\tilde q}$	>375 GeV		5%	[25]
$m_{\tilde g}$	>289 GeV		5%	[25]
other sparticle masses	As in table 4 of ref. [6].			

SM parameters

SM (nuisance) parameter	Mean value μ	Uncertainty σ (exper.)	Ref.
M_t	172.6 GeV	1.4 GeV	[24]
$m_b(m_b)^{\overline{MS}}$	4.20 GeV	0.07 GeV	[25]
$\alpha_s(M_Z)^{\overline{MS}}$	0.1176	0.002	[25]
$1/\alpha_{\rm em}(M_Z)^{\overline{MS}}$	127.955	0.03	[26]

Plus consistency with astrophysical probes

Challenges of profile likelihood evaluation

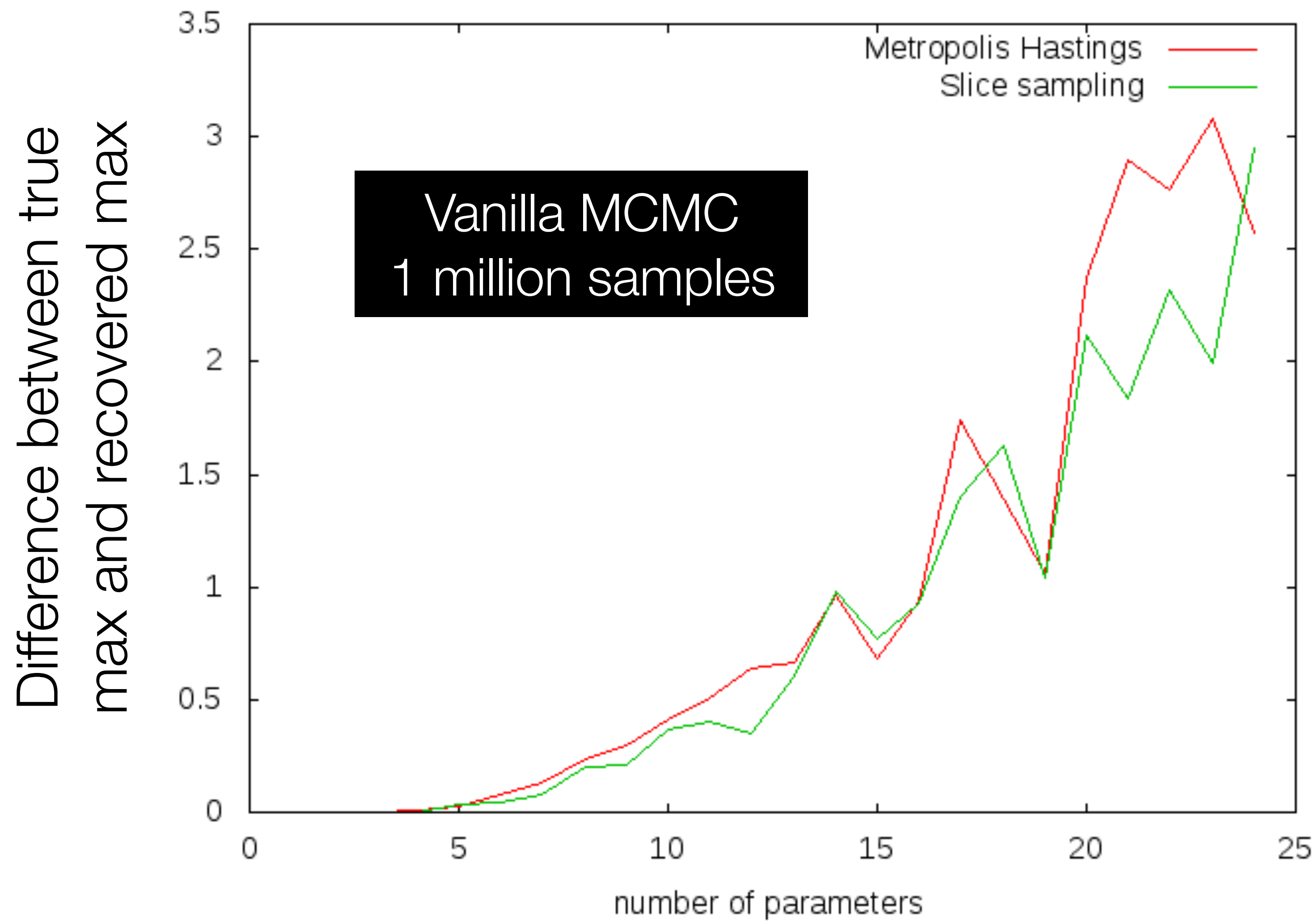
Imperial College London

- MCMC/MultiNest are not designed to find the best-fit point. Bayesian algorithms are designed to map out regions of significant posterior probability mass

- Even for a simple Gaussian toy model, this becomes difficult to do as the number of dimensions of the parameter space increases

- **Profiling with vanilla MCMC or MultiNest scans has to be done with caution!**

Toy multinormal likelihood



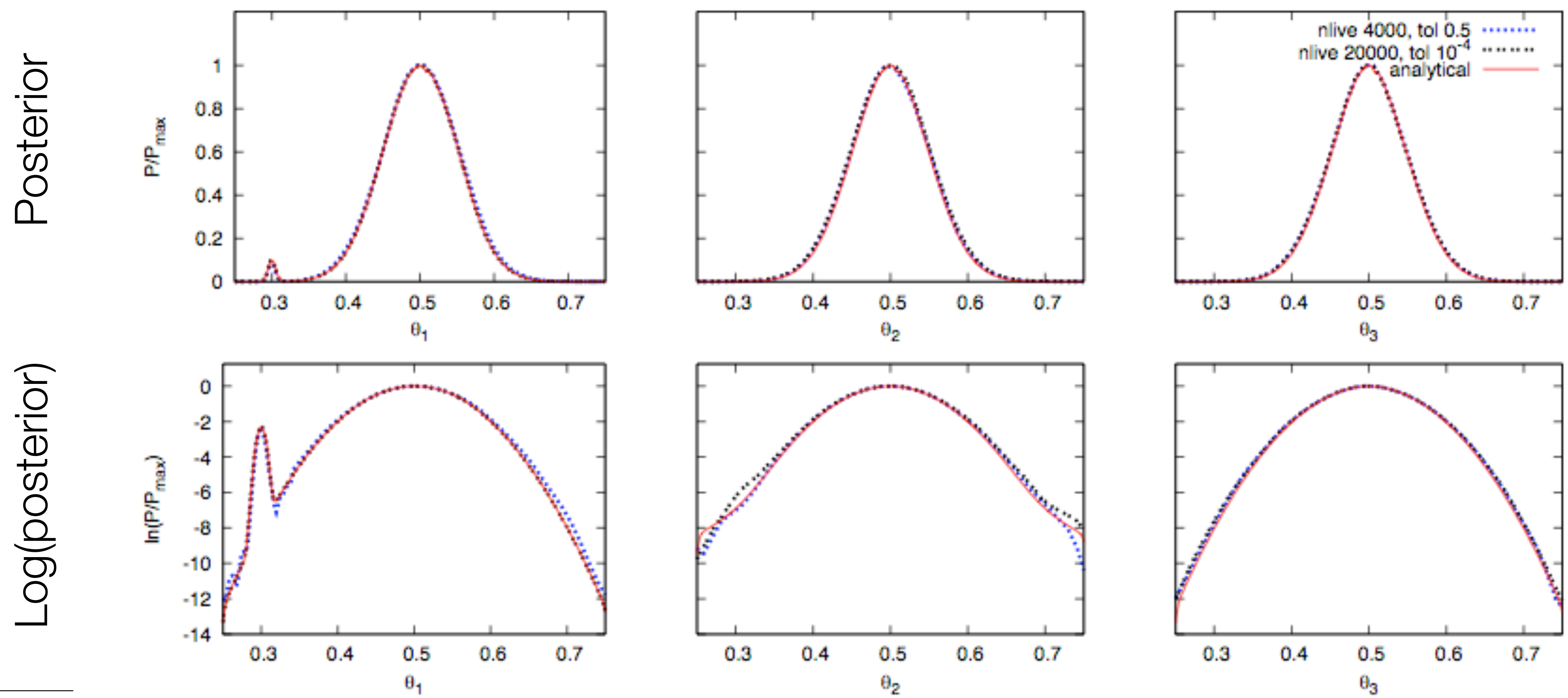
Posterior pdf from MultiNest scans

Imperial College London

- MultiNest is primarily aimed at evaluation of the posterior pdf. It does an excellent job even for multi-modal problems. 8D toy case (Feroz, KC, RT et al, in prep)

- The tolerance parameter (**tol**) determines the stopping criterium (based on the incremental change of the value of the local evidence). Lower tol gives a finer exploration around the peak, important for profile likelihood evaluation

red: analytical **blue: MN, tol=0.5** **black: MN, tol=0.0001**

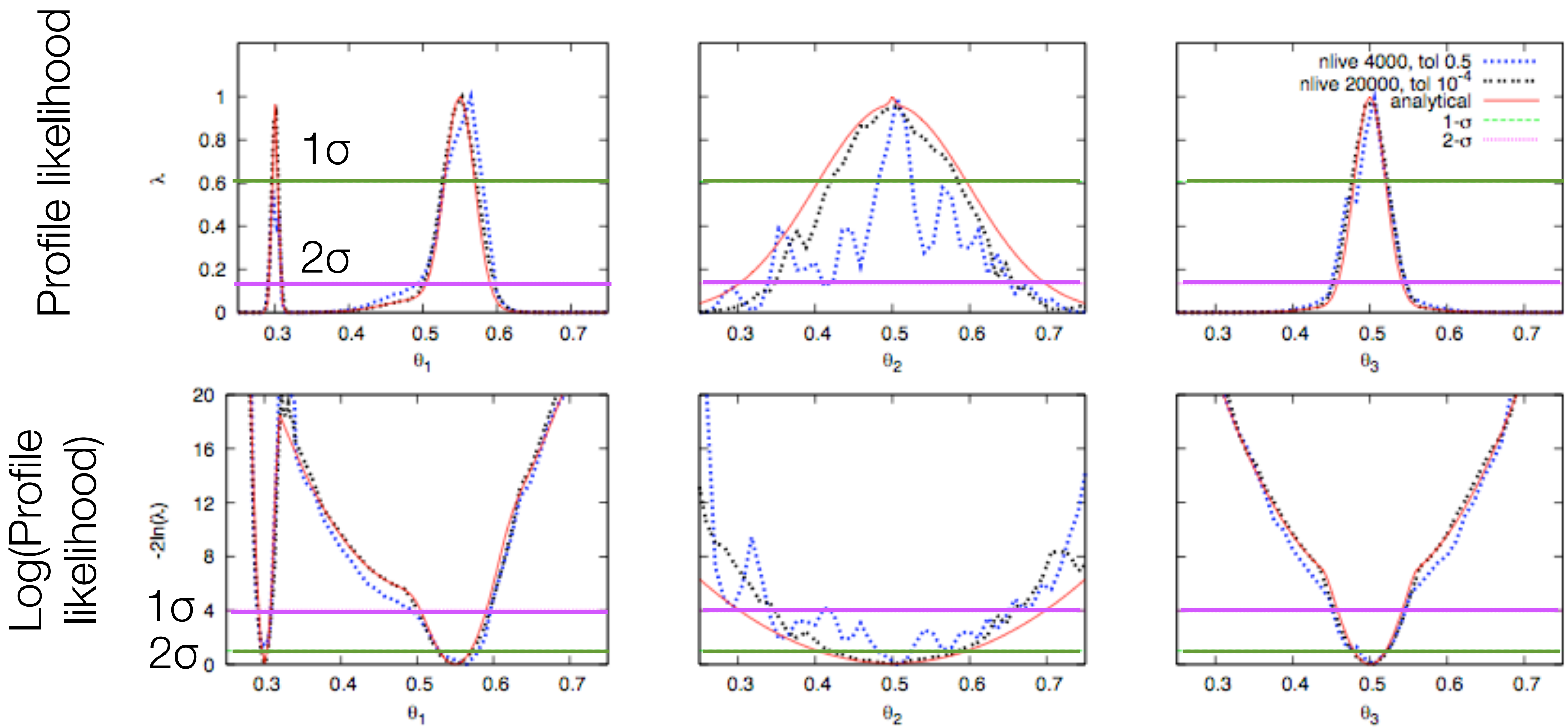


Profile likelihood from MultiNest scans

Imperial College London

- A fairly accurate the profile likelihood can be obtained with MultiNest by tuning the tolerance (lower, **tol=0.0001**) and the number of live points (higher, **n_{live}=20,000**) (Feroz, KC, RT et al, in prep), even for highly multi-modal distributions. 8D toy:

red: analytical **blue: MN, tol=0.5** **black: MN, tol=0.0001**

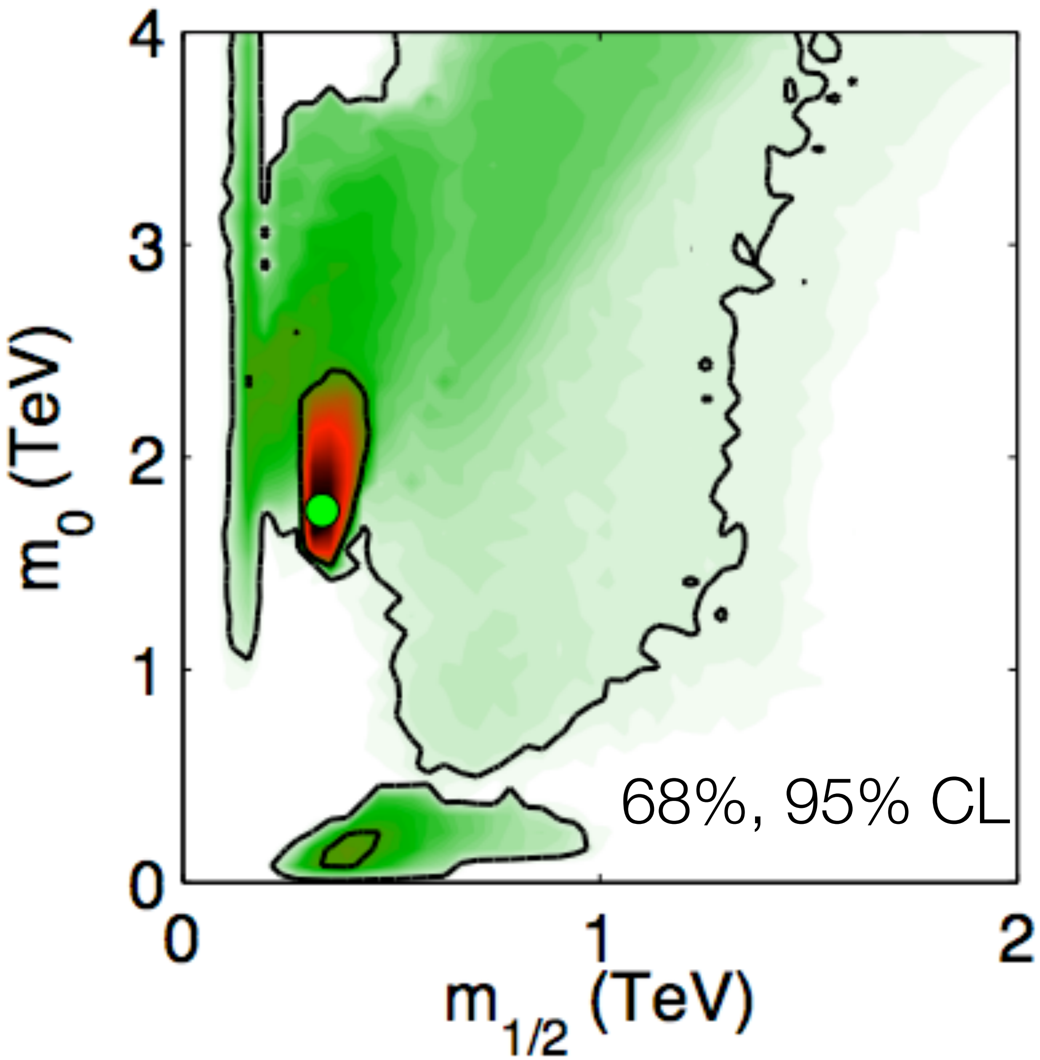


Profile likelihood from MultiNest

Imperial College London

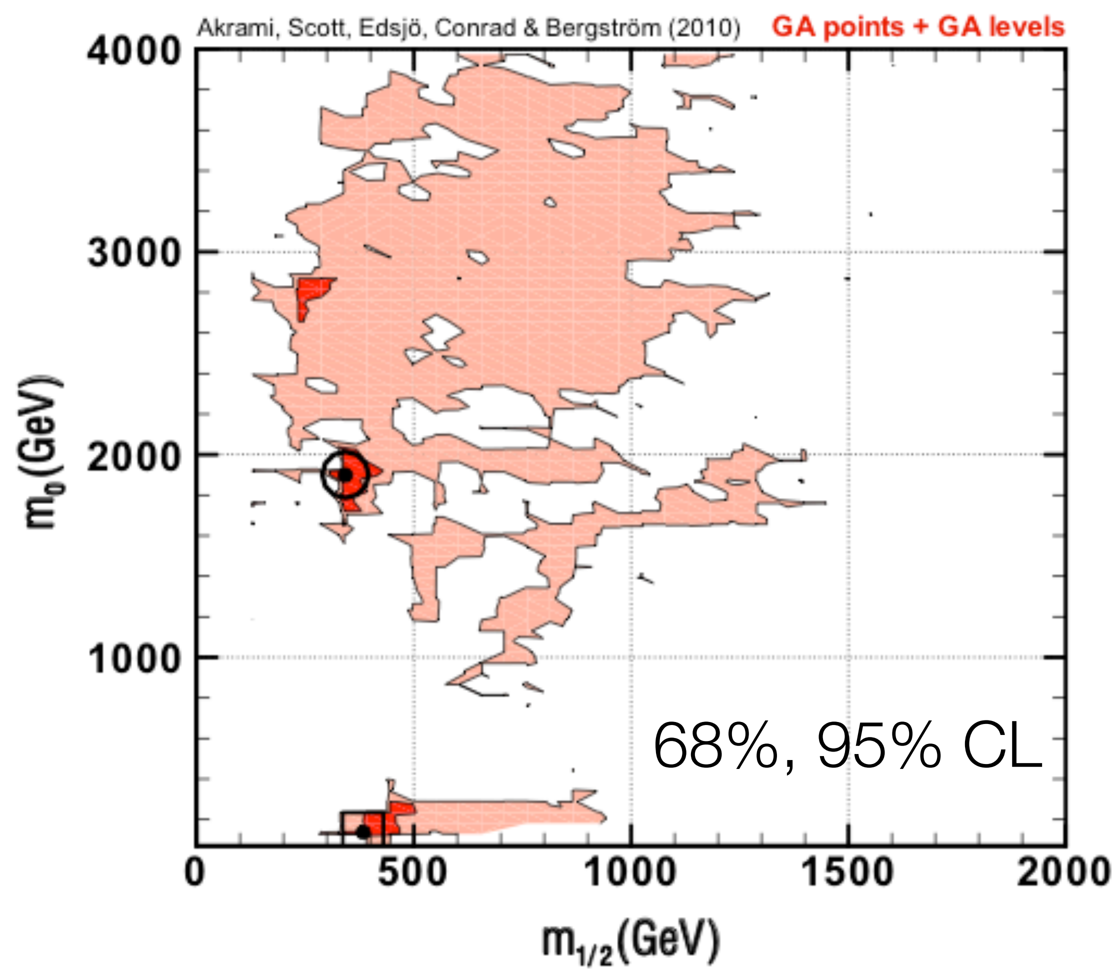
- MultiNest scan with 20,000 live points (usually: 4,000) and tolerance 0.0001 (usually: 0.5) results in 5.5 million likelihood evaluations (Akrami et al, GA: 3 million), and best-fit chi-square = 9.26 (Akrami et al, GA: 9.35).
  MultiNest finds a better best-fit + smoother contours than GA.

Profile likelihood MultiNest, tol=10^{-4}
Merged log and flat priors scans



Feroz, KC, RT et al (2011)

Profile likelihood
Genetic algorithm



Akrami et al (2010)