Getting serious about including astroparticle data in global fits to new physics scenarios

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Outline

1. The Problem
   - Beyond the SM with astroparticle probes
   - Global fits
2. Progress
   - Gamma-rays
   - Neutrinos
   - CMB constraints
3. Future Challenges
   - Respectable LHC likelihoods
   - Coverage & optimisation vs contour mapping
   - Parameter space $\longrightarrow$ Theory space

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- Direct detection – nuclear collisions and recoils – CDMS, XENON, DAMA, CRESST, CoGeNT, etc

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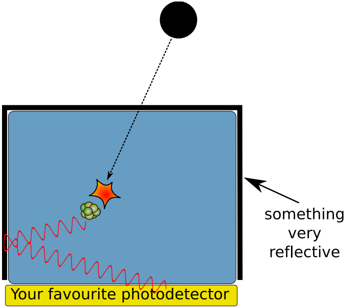

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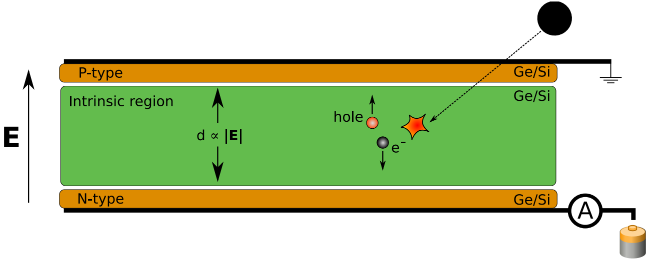

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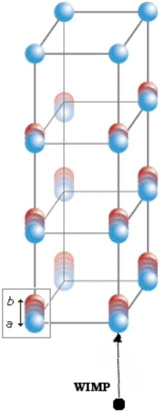

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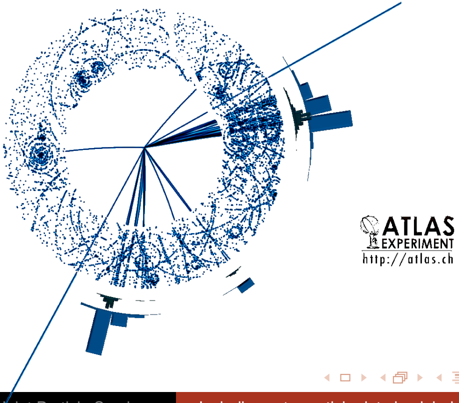

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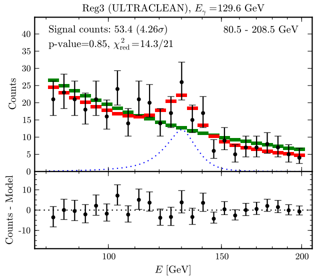
(Weniger *JCAP*, 1204.2797)



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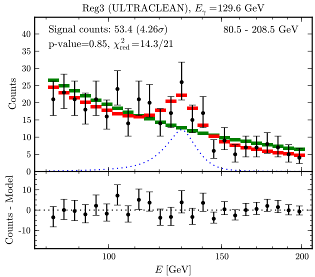

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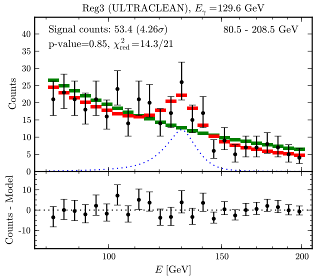

"The rest"

In order of (my own completely biased opinion of) usefulness for probing BSM physics:

1. Neutrino physics (cosmological, solar, atmospheric)
   Masses, mixings, additional sterile neutrinos
   Mass-generation models often require RH ν, extra symmetry groups
2. BBN
   Extra particles can change elemental yields (decays, resonances, etc)
3. Baryogenesis / Leptogenesis
   Baryon asymmetry may be generated by some new CP violation
   May even be linked to dark matter production ('asymmetric DM')
4. Inflation
   Eventually the inflaton needs to actually come from somewhere. . .

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Goals:

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Why simple IN/OUT analyses are not enough. . .

- Only partial goodness of fit, no measure of convergence, no idea how to generalise to regions or whole space.
- Frequency/density of models in IN/OUT scans means essentially nothing.
- More information comes from a **global statistical fit.**

Putting it all together: global fits

Issue 1: Combining fits to different experiments
Relatively easy – composite likelihood ($\mathcal{L}_1 \times \mathcal{L}_2 \equiv \chi_1^2 + \chi_2^2$ for simplest $\mathcal{L}$)

- dark matter relic density from WMAP
- precision electroweak tests at LEP
- LEP limits on sparticle masses
- B-factory data (rare decays, $b \to s\gamma$)
- muon anomalous magnetic moment
- LHC searches, direct detection (only roughly implemented for now)

Putting it all together: global fits

Issue 2: Including the effects of uncertainties in input data
Easy – treat them as *nuisance parameters*

Issue 3: Finding the points with the best likelihoods
Tough – MCMCs, nested sampling, genetic algorithms, etc

Issue 4: Comparing theories
Depends – Bayesian model comparison, p values
(TS distribution? $\longrightarrow$ coverage???)

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Two different approaches to including astro data in BSM scans

1. Just use the published limits on $\langle \sigma v \rangle$ (or $\sigma_{\mathrm{SI,SD}}$)
   - Fast – can cover large parameter spaces
   - Not so accurate – experimental limits are invariably based on theoretical assumptions, e.g. $b\bar{b}$ spectrum
   - Full likelihood function almost never available
2. Use the data points directly in BSM scans
   - Slow – requires full treatment of instrument profile for each point
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3. (indirect only: use just flux upper limits)

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Gamma-rays

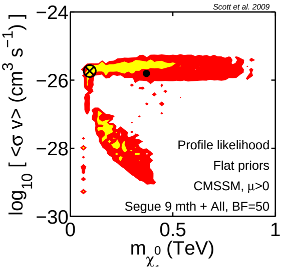
Gammay-ray annihilation searches have been added to the global fits:

Fermi-LAT

Satellite pair conversion telescope

Dwarf galaxy Segue 1

(PS, Conrad et al *JCAP*, 0909.3300)



- Full binned Poissonian likelihood (no χ^2 approximation)
- Full treatment of PSF *and* energy dispersion (with fast convolution library FLATlib)
- Marginalisation over systematic error on effective area
- Diffuse BG from Fermi-LAT Galprop fits
- Isotropic BG best-fit isotropic power law
- *J*-factor from Martinez et al (*JCAP*, 0902.4715; best at the time)

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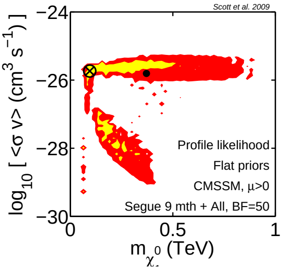

The other notable effort in this vein: combined dwarf pMSSM random scan by Cotta et al *JCAP*, 1111.2604

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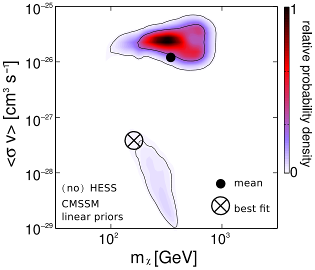

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Milky Way+Carina+Sculptor+Sag dwarf

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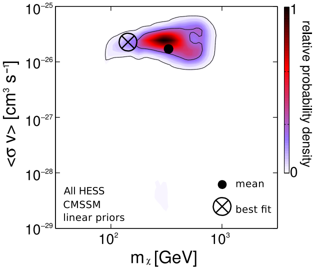

- χ^2-based analysis using public flux limits
- 'Milky Way' = halo just beyond GC (45–150 pc)
- Virtual internal bremsstrahlung from co-annihilation strip models caught at high-*E* by HESS
- but: *J*-factors for Sag dwarf rather uncertain

Outline

Example: Advanced IceCube Likelihood (Part 1)

Simplest way to do anything is to make it a counting problem...

Compare observed number of events n and predicted number θ for each model, taking into account error σ_ϵ on acceptance:

$$\mathcal{L}_{\rm num}(n|\theta_{\rm BG}+\theta_{\rm sig}) = \frac{1}{\sqrt{2\pi}\sigma_\epsilon}\int_0^\infty \frac{(\theta_{\rm BG}+\epsilon\theta_{\rm sig})^n e^{-(\theta_{\rm BG}+\epsilon\theta_{\rm sig})}}{n!}\frac{1}{\epsilon}\exp\left[-\frac{1}{2}\left(\frac{\ln\epsilon}{\sigma_\epsilon}\right)^2\right]\mathrm{d}\epsilon\,. \tag{1}$$

Nuisance parameter ϵ takes into account systematic errors on effective area, from theory, etc. $\sigma_\epsilon \sim 20\%$ for IceCube.

Example: Advanced IceCube Likelihood (Part 2)

Full unbinned likelihood with number ($\mathcal{L}_{\rm num}$), spectral ($\mathcal{L}_{\rm spec}$) and angular ($\mathcal{L}_{\rm ang}$) parts

$$\mathcal{L} = \mathcal{L}_{\rm num}(n|\theta_{\rm signal+BG}) \prod_{i=1}^{n} \mathcal{L}_{{\rm spec},i}\, \mathcal{L}_{{\rm ang},i} \tag{2}$$

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Observed BG distribution

Instrument response function

$$\mathcal{L}_{{\rm ang},i}(\cos\phi_i) = \frac{\theta_{\rm BG}}{\theta_{\rm signal+BG}} \frac{dP_{\rm BG}}{d\cos\phi_i}(\cos\phi_i) + \frac{\theta_{\rm signal}}{\theta_{\rm signal+BG}} PSF(\cos\phi_i|1) \tag{4}$$

Predicted signal direction (δ function at Sun)

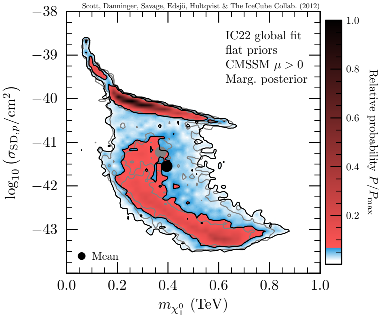
Global fits with IceCube event data

New likelihood analysis including IceCube Neutrino Telescope WIMP-search neutrino events

IceCube 22-string data

Not expected to be very constraining

(PS, Savage, Edsjö & IceCube *JCAP*, 1207.0810)



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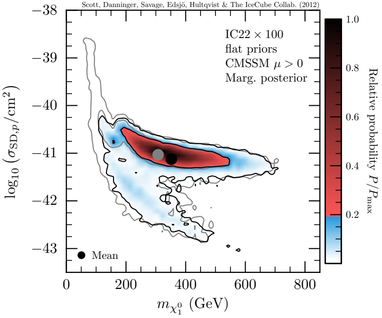

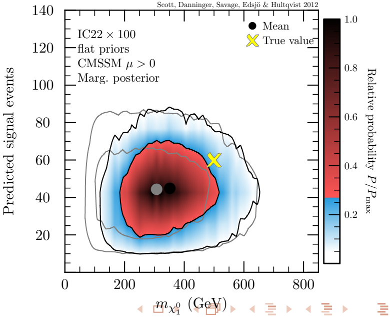

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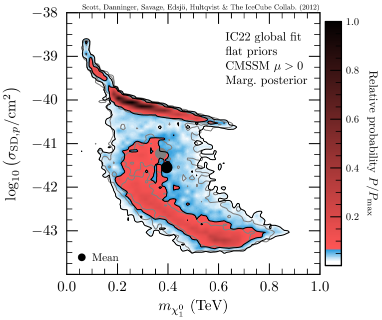
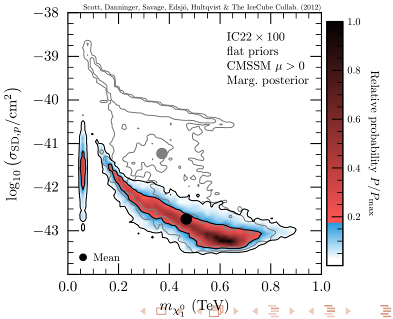


IceCube-DeepCore (86-string)

Very constraining (projection)



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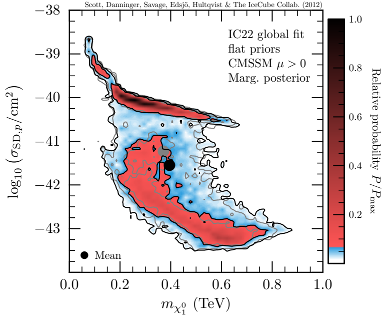
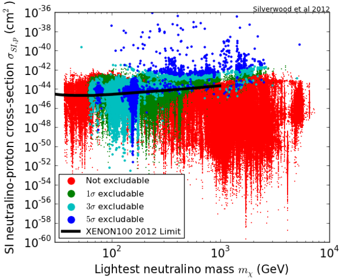


IceCube-DeepCore (86-string)

Very constraining (projection) $\Longrightarrow$ unique access to pts in more general MSSM

(Silverwood, PS, Danninger et al *JCAP*, 1210.0844)



Global fits with IceCube event data

New likelihood analysis including IceCube Neutrino Telescope WIMP-search neutrino events

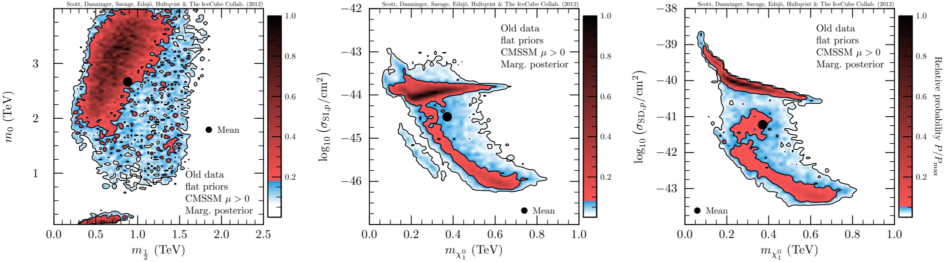
The examples here are CMSSM & MSSM-25 – but this about a framework, applicable to any model.

All the methods discussed here are available in DarkSUSY v5.0.6 and later: www.darksusy.org

All IceCube data used are available at http://icecube.wisc.edu/science/data/ic22-solar-wimp (and in DarkSUSY, for convenience)

Example of Combined Direct + Indirect + LHC constraints

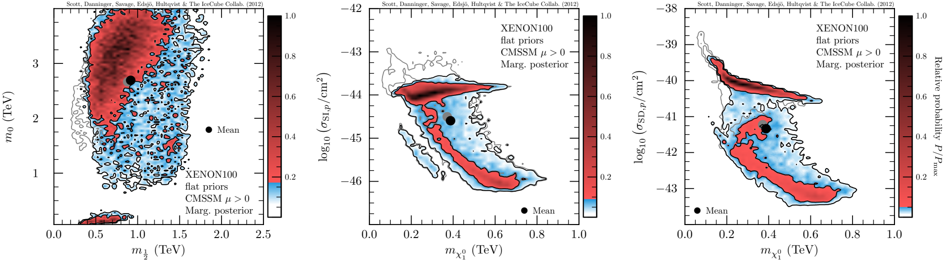
Base Observables



Example of Combined Direct + Indirect + LHC constraints

Base Observables + XENON-100 (2011)

Grey contours correspond to Base Observables *only*



Example of Combined Direct + Indirect + LHC constraints

Base Observables + XENON-100 + CMS 5 fb^{-1}

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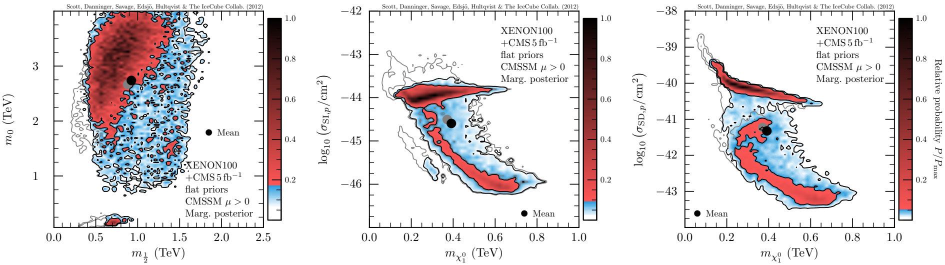
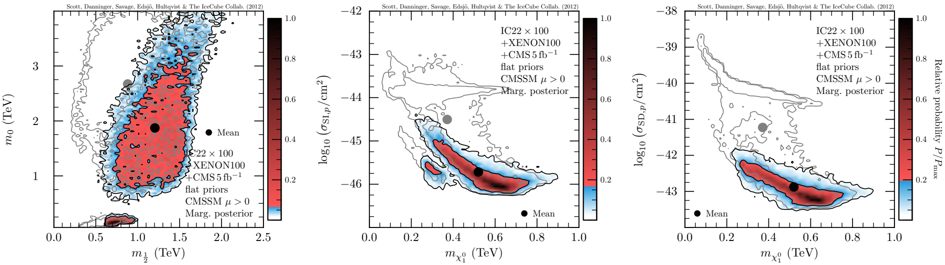


Example of Combined Direct + Indirect + LHC constraints

Base Observables + XENON-100 + CMS 5 fb^{-1} + IC22$\times$100

Grey contours correspond to Base Observables *only*



CMSSM, IceCube-22 with 100$\times$ boosted effective area
(kinda like IceCube-DeepCore)

Outline

Generalised DM CMB likelihood functions

Simple CMB likelihood function, for

- Any combination of annihilation or decay channels
- Any dark matter mass
- Any decay lifetime/annihilation cross-section

$\rightarrow$ just requires interpolating one number in a table.

Cline & PS, 1301.5908, using

- CMB energy deposition from Slatyer, 1211.0283 and Finkbeiner et al, 1109.6322
- PYTHIA annihilation/decay spectra of Cirelli et al, 1012.4515.

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$f_{\rm eff}$ for annihilation:

$$\ln \mathcal{L}(\langle\sigma v\rangle | m_\chi, r_i) = -\frac{1}{2} f_{\rm eff}^2(m_\chi, r_i)\lambda_1 c_1^2 \left(\frac{\langle\sigma v\rangle}{2\times 10^{-27}\mathrm{cm}^3\mathrm{s}^{-1}}\right)^2 \left(\frac{\mathrm{GeV}}{m_\chi}\right)^2 \quad (5)$$

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η for decay:

$$\ln \mathcal{L}(\tau|m_\chi, r_i) = -\frac{1}{2}\left(\frac{\delta\Omega}{\Omega_{\rm DM}\tau}\right)^2 \eta^2(\tau, m_\chi, r_i) \quad (6)$$

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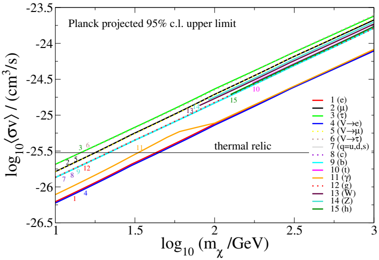

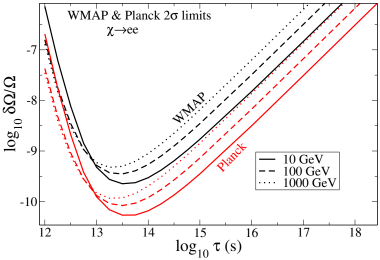

Outline

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The LHC likelihood monster

Time per point:

$\mathcal{O}(minute)$ in best cases

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Time per point for global fits to converge:

$\mathcal{O}(\textit{seconds})$ in worst cases

The LHC likelihood monster

Time per point:

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Time per point for global fits to converge:

$\mathcal{O}(seconds)$ in worst cases

Challenge:

About 2 orders of magnitude too slow to actually include LHC data in global fits properly

Taming the LHC monster

Zeroth Order Response:

“Stuff it, just use the published limits and ignore the dependence on other parameters”

Taming the LHC monster

Zeroth Order Response:

"Stuff it, just use the published limits and ignore the dependence on other parameters"

Obviously naughty – plotted limits assume CMSSM, and fix two of the parameters

- Don't really know dependence on other parameters
- Don't have a likelihood function, just a line
- Can't use this at all for non-CMSSM global fits – e.g. MSSM-25

Taming the LHC monster

First Order Response:

"Test if things depend on the other parameters (hope not), re-simulate published exclusion curve"

Taming the LHC monster

First Order Response:

"Test if things depend on the other parameters (hope not), re-simulate published exclusion curve"

Not that great, but OK in some cases

- At least have some sort of likelihood this time
- Still a bit screwed if things do depend a lot on other parameters, but
- allows (potentially shaky) extrapolation, also to non-CMSSM models

Fittino, Mastercode

Taming the LHC monster

Second Order Response:

"That's ridiculous. I've never met a calculation I can't speed up. There must be some way to have my cake and eat it too"

Taming the LHC monster

Second Order Response:

"That's ridiculous. I've never met a calculation I can't speed up. There must be some way to have my cake and eat it too"

Maybe – this is the challenge.

- Interpolated likelihoods (how to choose nodes?)
- Neural network functional approximation (how to train accurately?)
- Some sort of smart reduction based on event topology?
- Something else?

Outline

We don't *really* know the distribution of our test statistic in BSM global fits, as it is too expensive to Monte Carlo

- coverage is rarely spot-on unless mapping from parameters to data-space is linear

  (Akrami, Savage, PS et al *JCAP*, 1011.4297, Bridges et al *JHEP*, 1011.4306, Strege et al *PRD*, 1201.3631)

- *p*-value assessments of goodness of fit should be viewed with scepticism ($\rightarrow$MasterCode)

Convergence remains an issue, especially for profile likelihood

Messy likelihood $\implies$ best-fit point can be (and often is) easily missed (Akrami, PS et al *JHEP*, 0910.3950, Feroz et al *JHEP*, 1101.3296)

- frequentist CLs are often off, as isolikelihood levels are chosen incorrectly
- can impact coverage (overcoverage, or masking of undercoverage due to non-χ^2 *TS* distribution)
- need to use multiple priors and scanning algorithms (one optimised for profile likelihoods?)

Outline

CMSSM, SMS $\neq$ BSM

(SMS = Simplified Model Spectrum)

Want to do model comparison to actually work out which theory is right. . .

Challenge:

How do I easily adapt a global fit to different BSM theories?

CMSSM, SMS $\neq$ BSM

(SMS = Simplified Model Spectrum)

Want to do model comparison to actually work out which theory is right...

Challenge:

How do I easily adapt a global fit to different BSM theories?

Somehow, we must recast things quickly to a new theory

- data
- likelihood functions
- scanning code 'housekeeping'
- even predictions

$\Longrightarrow$ a new, very abstract global fitting framework

Hitting the wall

Issues with current global fit codes:

- Strongly wedded to a few theories (e.g. constrained MSSM / mSUGRA)
- Strongly wedded to a few theory calculators
- All datasets and observables basically hardcoded
- Rough or non-existent treatment of most experiments (astroparticle + collider especially)
- Sub-optimal statistical methods / search algorithms
- $\Longrightarrow$ *already hitting the wall on theories, data & computational methods*

GAMBIT: a *second-generation* global fit code

GAMBIT: Global And Modular BSM Inference Tool

Overriding principles of GAMBIT: flexibility and modularity

- General enough to allow fast definition of new datasets and theoretical models
- Plug and play scanning, physics and likelihood packages
- Extensive model database – not just small modifications to constrained MSSM (NUHM, etc), and not just SUSY!
- Extensive observable/data libraries (likelihood modules)
- Many statistical options – Bayesian/frequentist, likelihood definitions, scanning algorithms
- A smart and *fast* LHC likelihood calculator
- Massively parallel
- Full open-source code release

The GAMBIT Collaboration

23 Members, 12 Institutes
8 Experiments, 3 major theory codes

Fermi-LAT	J. Conrad, J. Edsjö, G. Martinez, P. Scott (Coordinator)
IceCube	J. Edsjö, C. Savage, P. Scott
ATLAS	A. Buckley, C. Clement, P. Jackson, A. Saavedra, M. White
CMS	C. Rogan
HESS	J. Conrad, H. Dickinson
AMS-02	A. Putze
CTA	T. Bringmann, J. Conrad, H. Dickinson
DARWIN	J. Conrad
Theory	C. Balázs, T. Bringmann, L.-A. Dal, J. Edsjö, B. Farmer, A. Krislock, A. Kvellestad, N. Mahmoudi, A. Raklev, C. Savage, P. Scott, C. Weniger

Closing remarks

- Robust analysis of dark matter and BSM physics requires multi-messenger global fits
- Lots of interesting astroparticle observables to include in global fits
- Quite a bit of technical (statistical/computational) detail to worry about
- GAMBIT is coming