GAMBIT

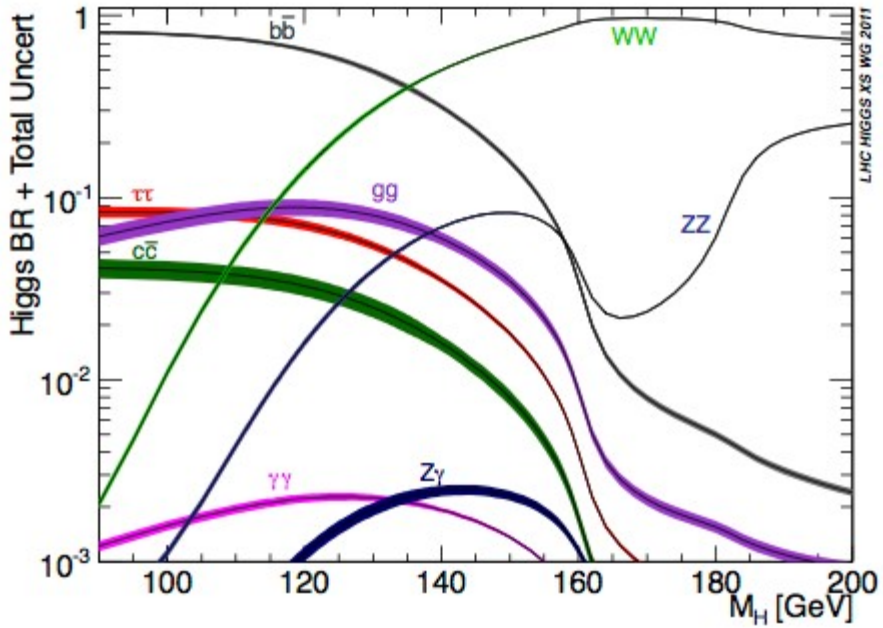
(Global and Modular BSM Inference Tool)

Martin White

Epiphany 2018

The Higgs discovery in 2012 gave us:

- The last piece of the SM
- The last occasion when we could unambiguously tell what a collider has discovered
- No definitive evidence for BSM physics so far
- Lots of intriguing hints however, plus the obvious usual suspects (dark matter, theoretical quirks...)



Places where BSM physics might appear

- low-energy accelerators
- measurements of the magnetic moment of the muon
- beam dump/fixed target
- electroweak precision tests
- dark matter direct detection experiments
- searches for antimatter in cosmic rays
- nuclear cosmic ray ratios
- radio astronomy data
- effects of dark matter on reionisation, recombination and helioseismology
- the observed dark matter cosmological abundance
- neutrino masses and mixings
- gamma ray searches (e.g. FERMI-LAT, HESS, CTA, etc)

How to validate new theories

- Correct answer is to use a global statistical fit
- Frequentist or Bayesian methods available
- Calculate a **combined likelihood**:

$$\mathcal{L} = \mathcal{L}_{\text{collider}} \mathcal{L}_{\text{DM}} \mathcal{L}_{\text{flavor}} \mathcal{L}_{\text{EWPO}} \cdots$$

Parameter estimation

Given a particular model, which set of parameters best fits the available data

(Rigorous exclusion limits and parameter measurements)

Model comparison

Given a set of models, which is the best description of the data, and how much better is it?

(Model *X* is now worse than model *Y*)

GAMBIT: The Global And Modular BSM Inference Tool

gambit.hepforge.org

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

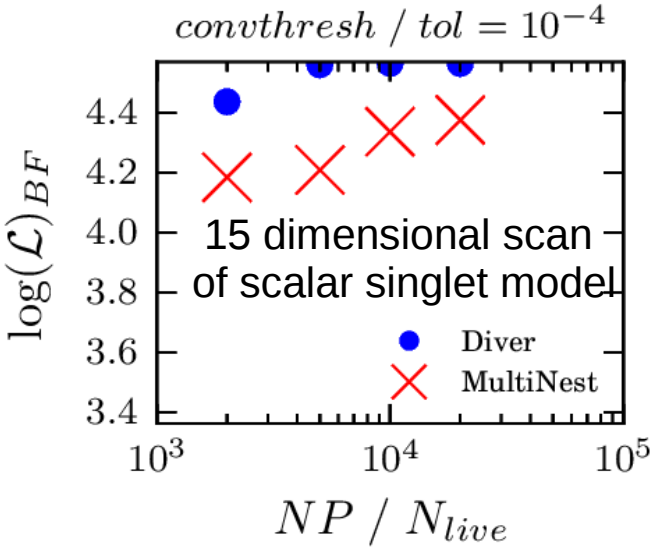
ATLAS	F. Bernlochner, A. Buckley, P. Jackson, M. White
LHCb	M. Chrząszcz, N. Serra
Belle-II	F. Bernlochner, P. Jackson
Fermi-LAT	J. Conrad, J. Edsjö, G. Martinez, P. Scott
CTA	C. Balázs, T. Bringmann, M. White
CMS	C. Rogan
IceCube	J. Edsjö, P. Scott
XENON/DARWIN	B. Farmer, R. Trotta
Theory	P. Athron, C. Balázs, S. Bloor, T. Bringmann, J. Cornell, J. Edsjö, B. Farmer, A. Fowlie, T. Gonzalo, J. Harz, S. Hoof, F. Kahlhoefer, S. Krishnamurthy, A. Kvellestad, F.N. Mahmoudi, J. McKay, A. Raklev, R. Ruiz, P. Scott, R. Trotta, A. Vincent, C. Weniger, M. White, S. Wild

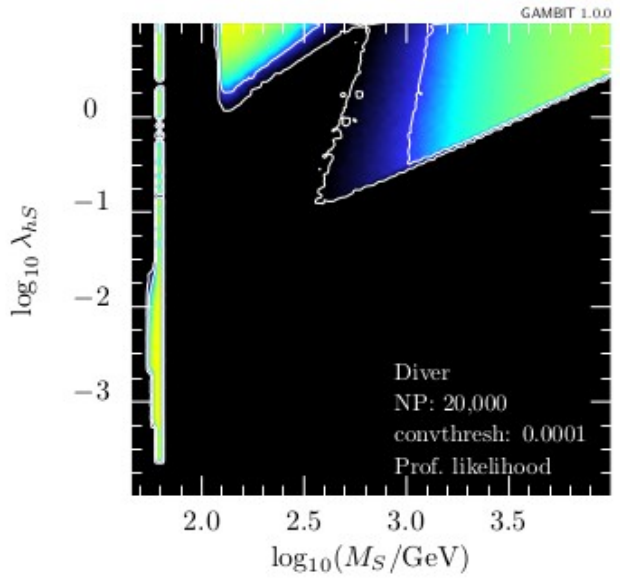
31 Members in 9 Experiments, 12 major theory codes, 11 countries

Global

- Complete global statistical fit framework
- Can be Bayesian, Frequentist or other (random, grid, etc)
- Interfaced to the best + fastest scanners available:

  Multinest, MCMC, Diver (new differential evolution scanner)

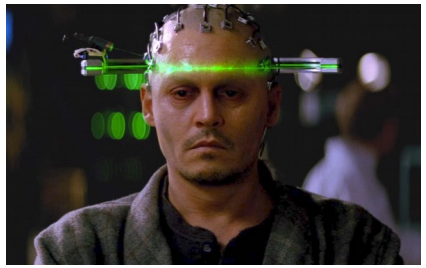




Publication ready plots available using *pippi* plotting code on the GAMBIT HDF5 output

Global and Modular

- **ColliderBit:** collider observables including Higgs + SUSY Searches from ATLAS, CMS, LEP
- **DarkBit:** dark matter observables (relic density, direct & indirect detection)
- **FlavBit:** including $g-2$, $b \to s\gamma$, B decays (new channels), angular obs., theory unc., LHCb likelihoods
- **SpecBit:** generic BSM spectrum object, providing RGE running, masses, mixings
- **DecayBit:** decay widths for all relevant SM and BSM particles
- **PrecisionBit:** precision EW tests (mostly via interface to FeynHiggs or SUSY-POPE)
- **ScannerBit:** manages stats, sampling and optimisation



What's in a module?

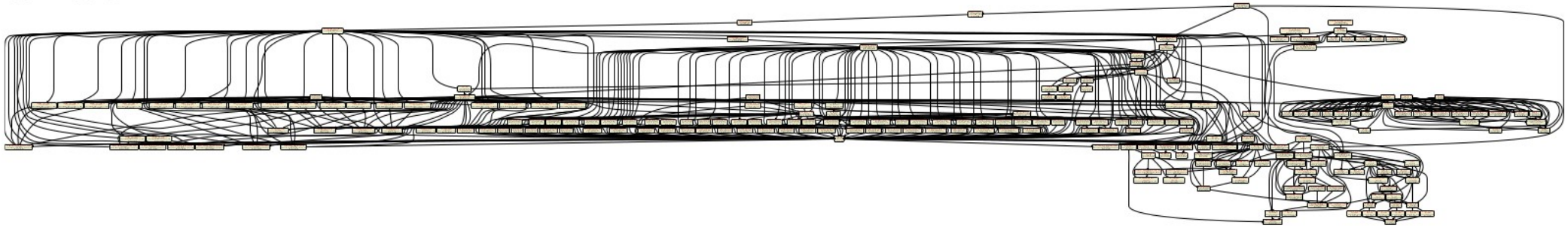
- Module functions (actual bits of GAMBIT C++ code)
- These can depend on other module functions
- Or can they can depend on *backends*(external codes)
- Adding new things is ***easy*** (detailed manual)
- Hooking up new backends or swapping them is ***easy***
- Module functions are **tagged** according to what they can calculate → plug and play!

How does GAMBIT work?

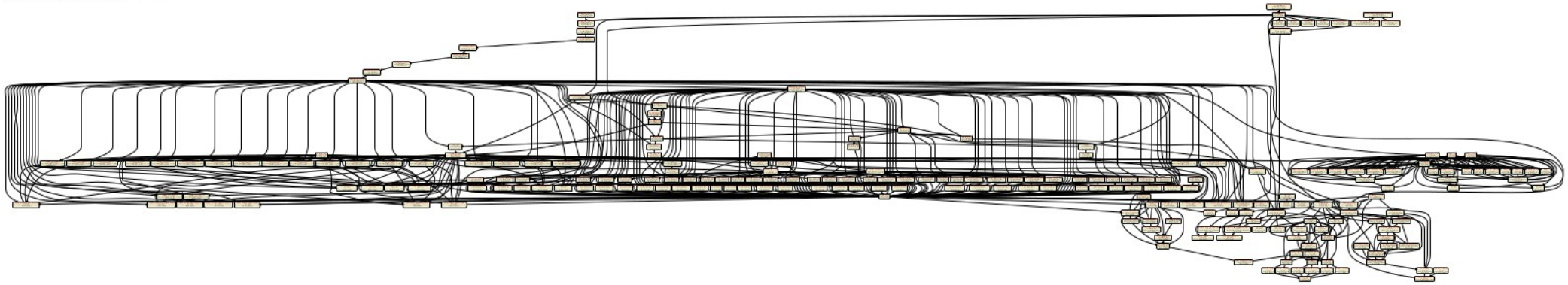
- You specify what to calculate and how (yaml input file)
- GAMBIT checks to see which functions can do it
- A dependency resolver stitches things together in the right order, and calculations are also ordered by speed
- GAMBIT performs the scan and writes output
- Pippi makes the plots
- You(r student) write(s) the paper

Dependency resolution in action

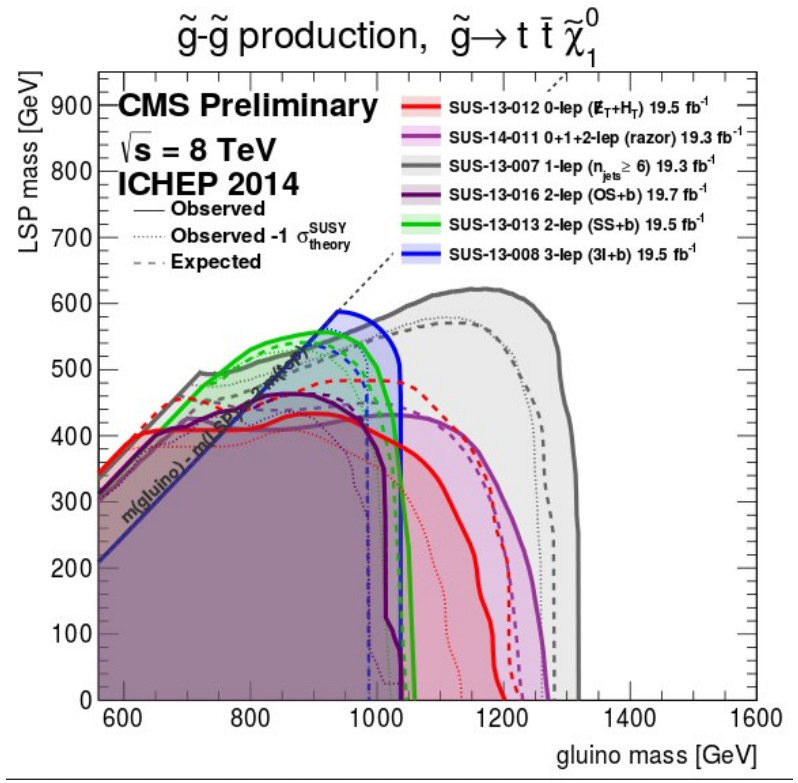
CMSSM:



MSSM7:



LHC limits: the problem



ColliderBit

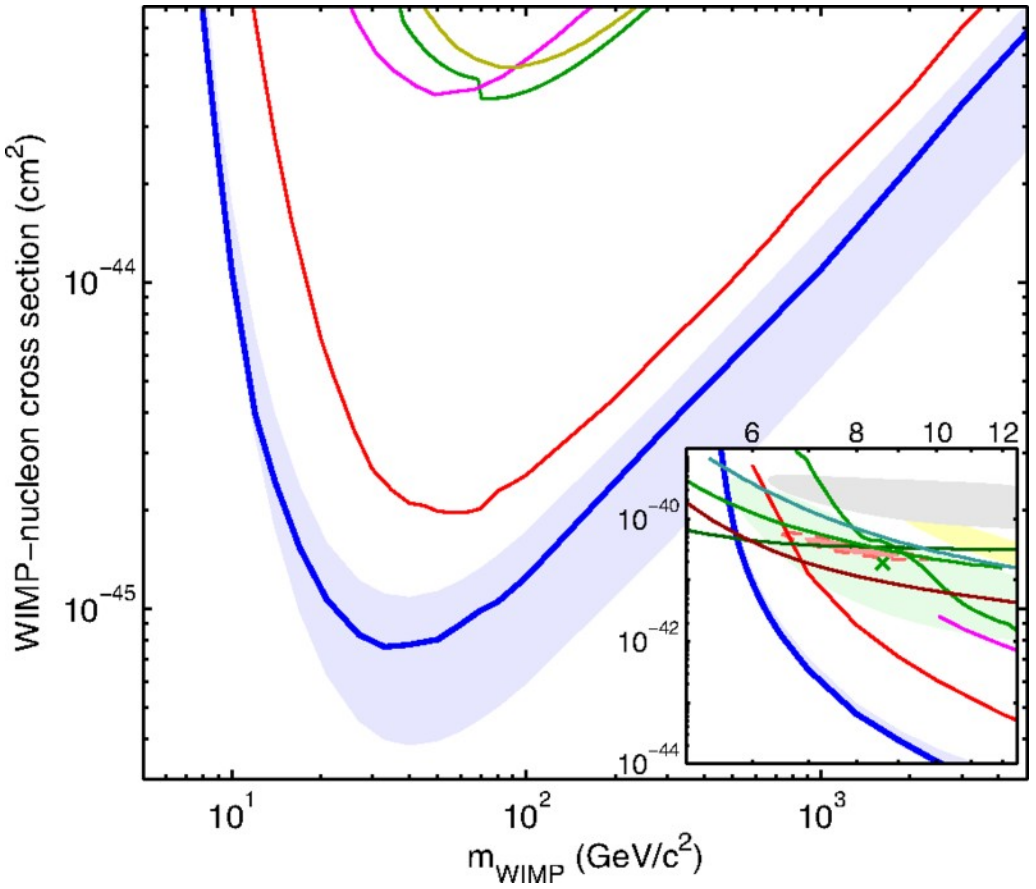
- Handles LHC and LEP limits
- LEP: complete recast of sparticle xsec limits
- SUSY & Exotic LHC search limits from real-time MC simulation
- LHC resonance search limits from HiggsBounds+HiggsSignals
- Future: new resonance limits (beyond NW?)
- Future: interface to Rivet for LHC analyses

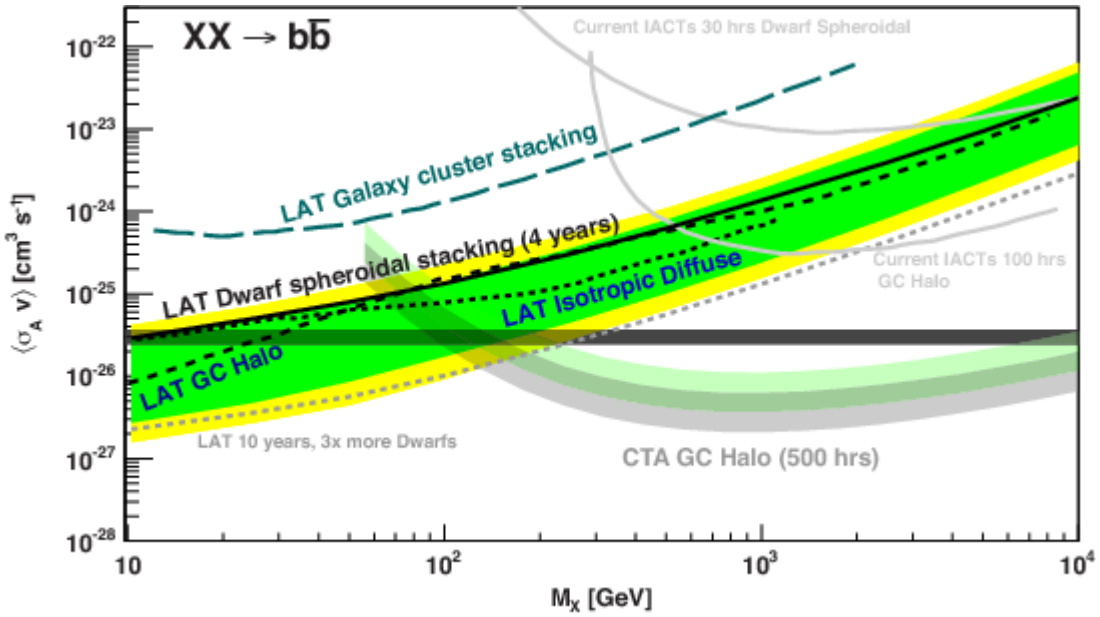
Model independent LHC limits

- Custom parallelised Pythia MC + custom detector sim
- Can generate 20,000 events on 12 cores in < 5 s
- Then apply Poisson likelihood with nuisance parameters for systematics
- Combine analyses using best expected exclusion
- The best you can do without extra public info from the experiments. CMS are getting better at this:

  https://cds.cern.ch/record/2242860/files/NOTE2017_001.pdf

Astro limits: the problem

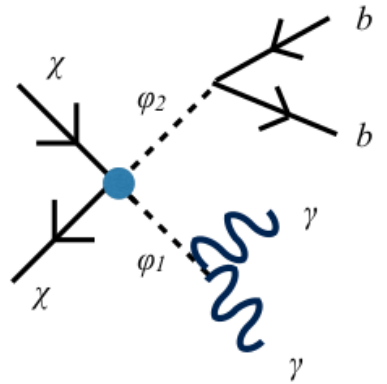


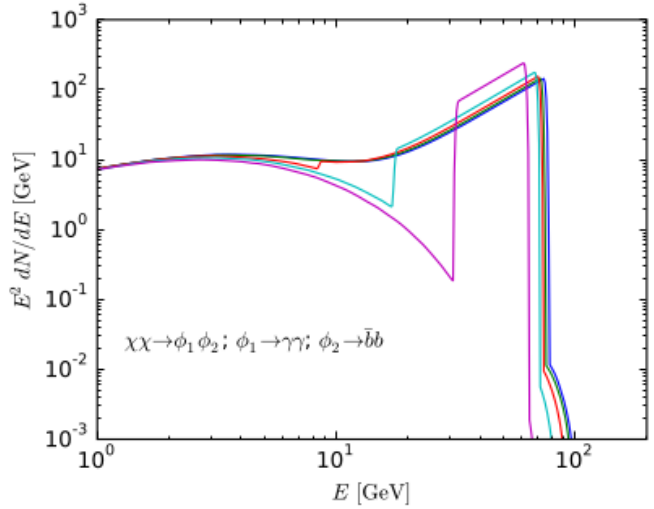


DarkBit: indirect detection

Gamma rays:

- Theoretical spectra calculated using branching fractions and tabulated gamma-ray yields
- Non-SM final state particles and Higgs are decayed on the fly with cascade Monte Carlo
- gamLike (gamlike.hepforge.org): New standalone code with likelihoods for DM searches from Fermi-LAT (dwarf spheroidals, galactic centre) and H.E.S.S. (galactic halo)



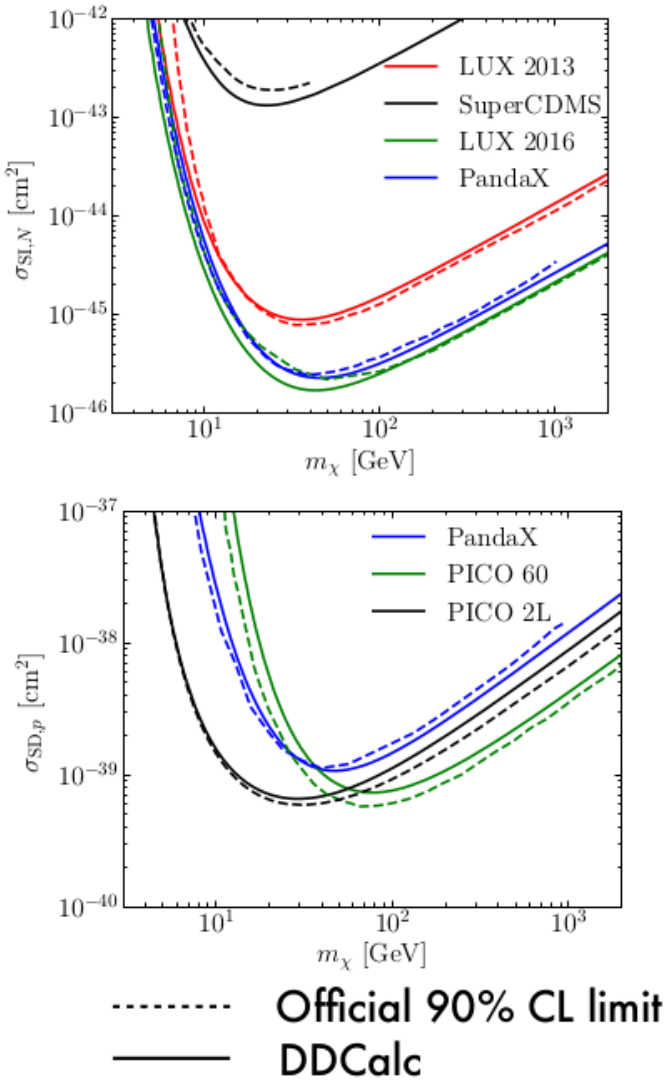


Solar neutrinos:

- Yields from DM annihilation in sun calculated by DarkSUSY. IceCube likelihoods contained in nulike (nulike.hepforge.org) standalone code.

DarkBit: direct detection

- In parallel with GAMBIT, we introduce *DDCalc* (ddcalc.hepforge.org), a tool to calculate event rates and complete likelihood functions for direct detection experiments taking into account:
  - A mix of both spin-independent and dependent contributions to the scattering rate.
  - Halo parameters (local density, DM velocity dispersion, etc.) chosen by the user.
- We currently have implemented likelihoods for Xenon(1T, 100), LUX, PandaX, SuperCDMS, PICO(60, 2L), and SIMPLE



FlavBit

- Models a series of experimental flavour anomalies
- Theoretical predictions currently based on SuperIso
- Theoretical and experimental uncertainties are carefully considered for each observable (including correlations)

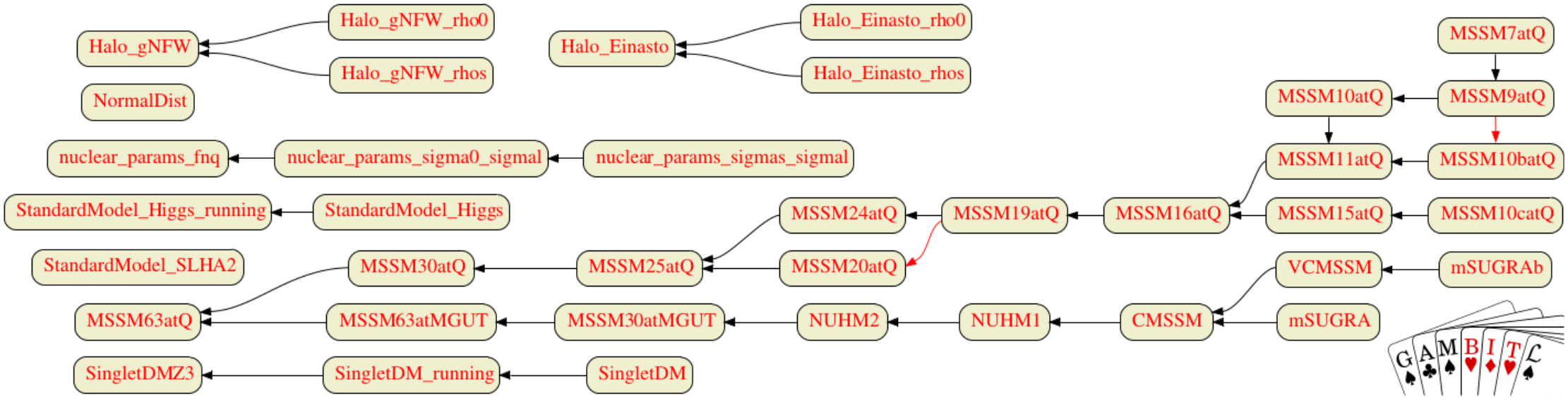
FlavBit likelihoods (more to come...)

- $B \to D^{(*)}\mu\nu$ (PDG, take correlated theoretical uncertainties from SuperIso study)
- $R_{D^{(*)}} \equiv \mathcal{B}(B \to D^{(*)}\tau\nu_\tau)/\mathcal{B}(B \to D^{(*)}\ell\nu_\ell)$ (HFAG, take correlated experimental uncertainties)
- $B^\pm \to \ell\nu_\ell$ (PDG value)
- $D^\pm \to \mu\nu_\mu$, $D_s^\pm \to \tau\nu_\tau$, $D_s^\pm \to \mu\nu_\mu$ (PDG values, theoretical correlations considered)
- Angular observables of $B^0 \to K^{*0}\mu^+\mu^-$ in q^2 bins (LHCb) (experimental correlations within each bin + theory correlations)
- $B_s^0 \to \mu^+\mu^-$ (latest LHCb result)
- $B^0 \to \mu^+\mu^-$ (combined LHCb and CMS)
- $B \to X_s\gamma$ for $E_\gamma > 1.6$ GeV (BaBar and Belle average by Misiak et al)
- ΔM_s: (average of CDF and LHCb, theory error is an order of magnitude greater than experimental uncertainty)

$$\begin{aligned}\frac{1}{\Gamma}\frac{\mathrm{d}^3(\Gamma+\bar{\Gamma})}{\mathrm{d}\cos\theta_\ell\,\mathrm{d}\cos\theta_K\,\mathrm{d}\phi} = \frac{9}{32\pi}\Big[&\frac{3}{4}(1-F_\mathrm{L})\sin^2\theta_K \\ &+ F_\mathrm{L}\cos^2\theta_K + \frac{1}{4}(1-F_\mathrm{L})\sin^2\theta_K\cos 2\theta_\ell \\ &- F_\mathrm{L}\cos^2\theta_K\cos 2\theta_\ell + S_3\sin^2\theta_K\sin^2\theta_\ell\cos 2\phi \\ &+ S_4\sin 2\theta_K\sin 2\theta_\ell\cos\phi + S_5\sin 2\theta_K\sin\theta_\ell\cos\phi \\ &+ \frac{4}{3}A_\mathrm{FB}\sin^2\theta_K\cos\theta_\ell + S_7\sin 2\theta_K\sin\theta_\ell\sin\phi \\ &+ S_8\sin 2\theta_K\sin 2\theta_\ell\sin\phi + S_9\sin^2\theta_K\sin^2\theta_\ell\sin 2\phi\Big]\end{aligned}$$

Global and Modular BSM

- Models are defined by their parameters and relations to each other
- Models can inherit from parent models, easy translation between relations
- We have so far scanned SUSY + Higgs portal + axion + two Higgs doublet models



Global and Modular BSM Inference

- **Scalar singlet** – m_S, λ_{hS} + 13 nuisances

[EPJC 77 (2017) 568, 1705.07931]

$$\mathcal{L}_S = \frac{1}{2}\partial_\mu S \partial^\mu S + \frac{1}{2}\mu_S^2 S^2 + \frac{1}{2}\lambda_{hS} S^2 |H|^2 + \frac{1}{4}\lambda_S S^4$$

- **GUT-motivated** MSSM-models [EPJC 77 (2017) 824, 1705.07935]

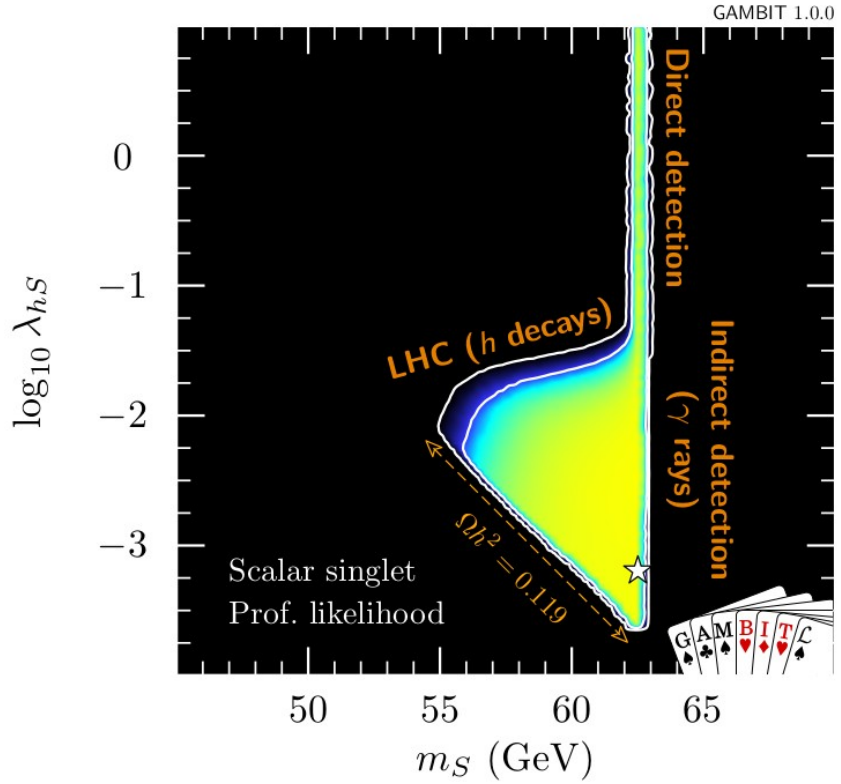
  - **CMSSM** – m_0, $m_{1/2}$, A_0, tan β, sgn μ
  - **NUHM1** – m_0, m_H, $m_{1/2}$, A_0, tan β, sgn μ
  - **NUHM2** – m_0, m_{Hu}, m_{Hd}, $m_{1/2}$, A_0, tan β, sgn μ

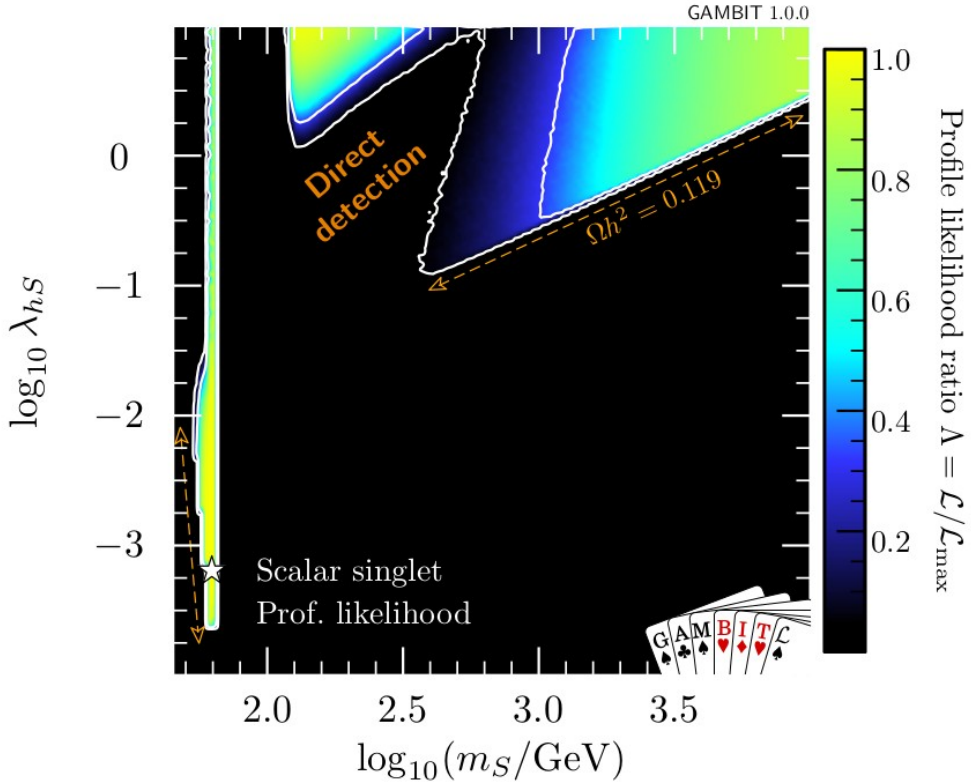
  + 5 nuisances (α_s, m_t, ρ_0, σ_l, σ_s)

- **MSSM-7** – $m_{\tilde{f}}$, m_{Hu}, m_{Hd}, M_2, A_u, A_d, tan β + 5 nuisances

[EPJC 77 (2017) 879, 1705.07917]

Global and Modular BSM Inference: Scalar singlet DM



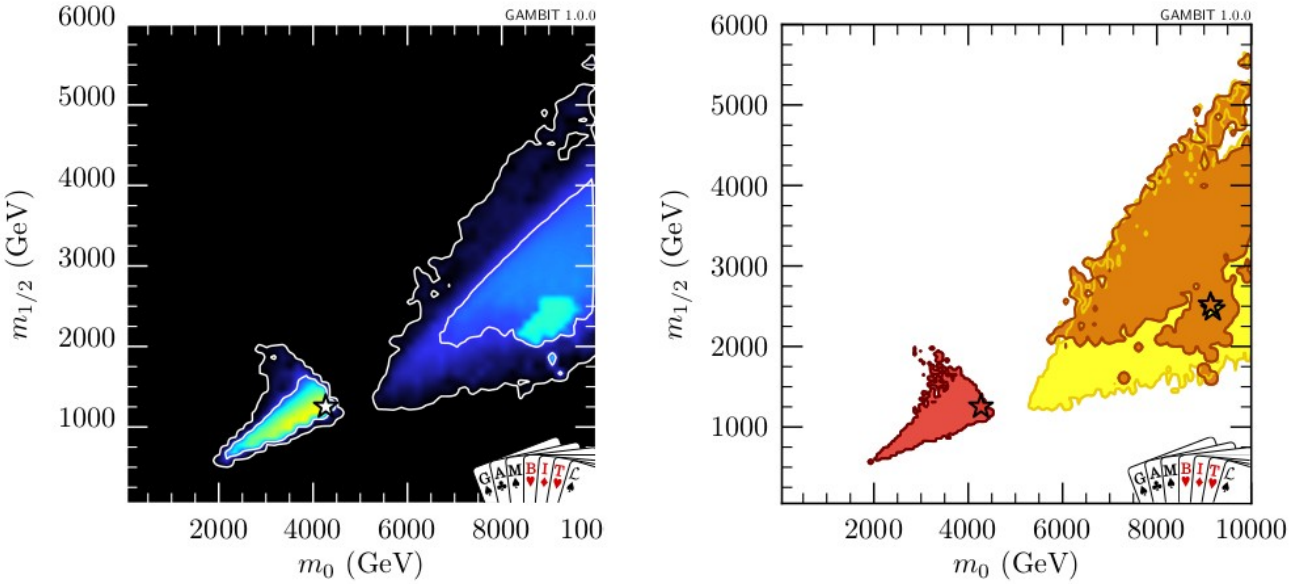


$$\mathcal{L} = \frac{1}{2}\mu_S^2 S^2 + \frac{1}{2}\lambda_{hS} S^2 |H|^2 + \frac{1}{4}\lambda_S S^4 + \frac{1}{2}\partial_\mu S \partial^\mu S$$

(m_s, λ_{hS} + 13 nuisances)

White lines: 68% and 95% CL contours
Star: best fit point

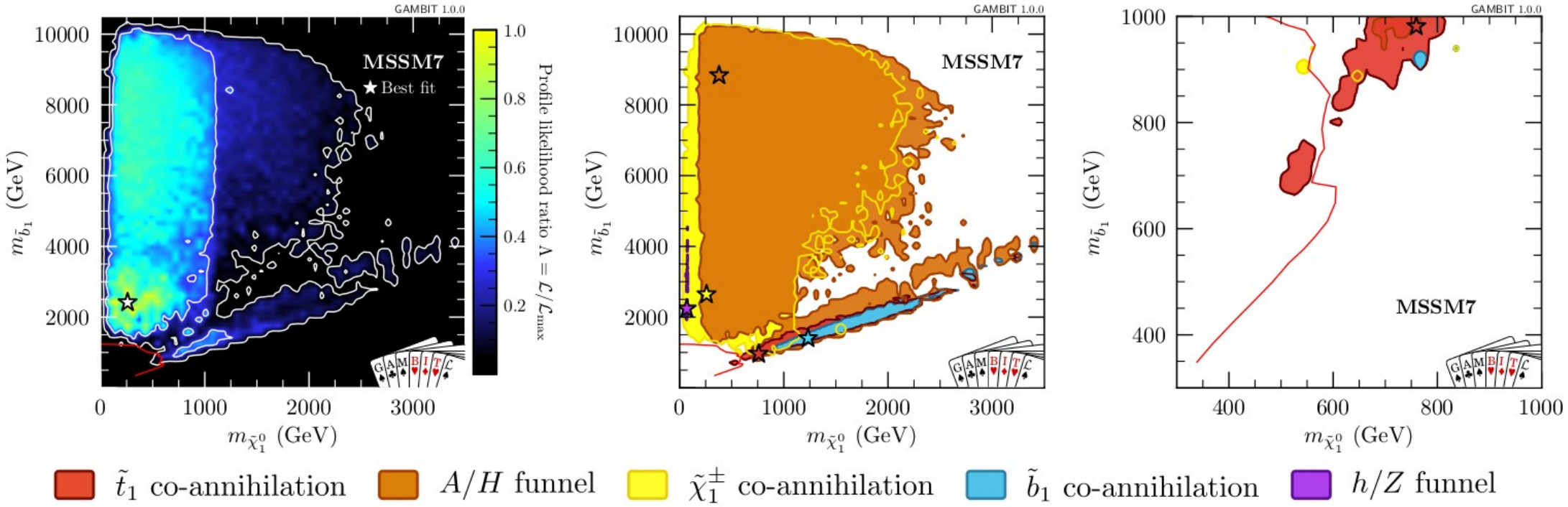
Global and Modular BSM Inference: CMSSM



- m_0, $m_{\frac{1}{2}}$, A_0, $\tan\beta$ + 5 nuisances
- H/A^0 funnel, $\chi^{\pm}$ co-annihilation, $\tilde{t}$ co-annihilation
- $\tilde{\tau}$ **co-annihilation now ruled out**
- Includes LUX 2016, Panda-X + direct simulation of LHC Run 1 & Run 2 limits.

(also have NUHM1 and NUHM2 results)

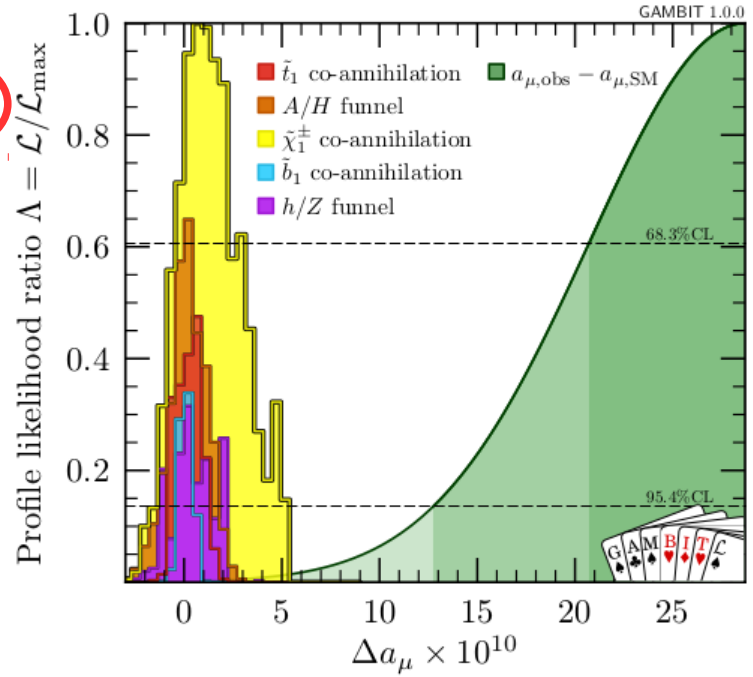
Global and Modular BSM Inference: MSSM7



- $m_{\tilde{f}}$, M_2, A_u, A_d, m_{Hu}, m_{Hd}, $\tan\beta$ + 5 nuisances
- H/A^0 funnel, h/Z funnel, $\chi^\pm$ co-annihilation, $\tilde{t}/\tilde{b}$ co-annihilation
- Includes LUX 2016, Panda-X + direct simulation of LHC Run 1 & Run 2 limits.

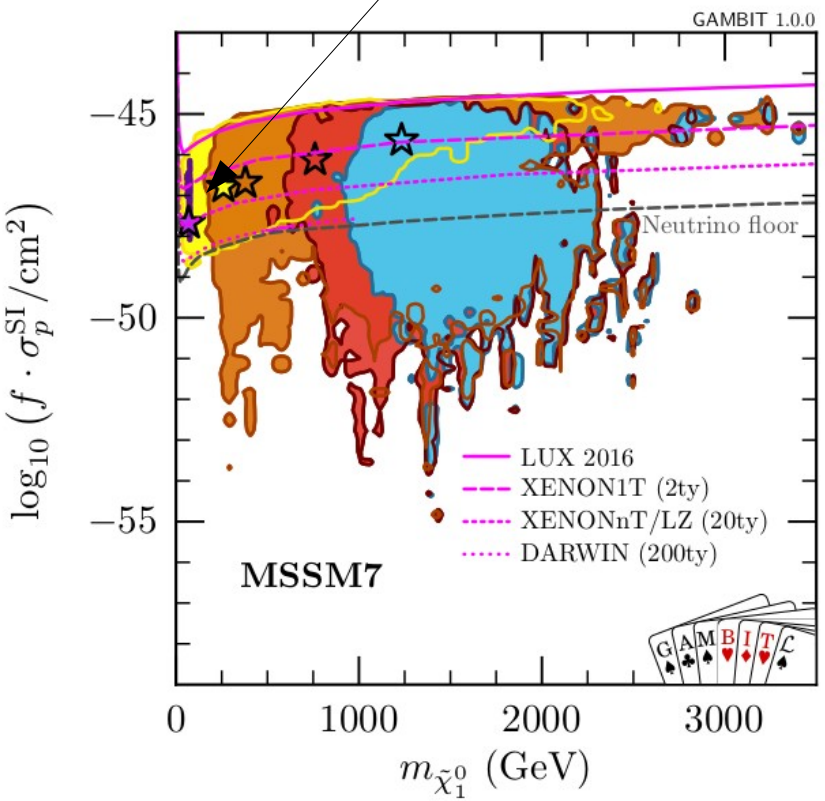
Likelihood term	Ideal	A/H-funnel	$\tilde{b}$ co-ann.	$\tilde{t}$ co-ann.	$\tilde{\chi}_1^\pm$ co-ann.	Z/h-funnel	$\Delta \ln \mathcal{L}_{\rm BF}$
LHC sparticle searches	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LHC Higgs	−37.734	−38.657	−38.647	−39.050	−38.347	−38.593	0.613
LEP Higgs	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ALEPH selectron	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ALEPH smuon	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ALEPH stau	0.000	0.000	0.000	0.000	0.000	0.000	0.000
L3 selectron	0.000	0.000	0.000	0.000	0.000	0.000	0.000
L3 smuon	0.000	0.000	0.000	0.000	0.000	0.000	0.000
L3 stau	0.000	0.000	0.000	0.000	0.000	0.000	0.000
L3 neutralino leptonic	0.000	0.000	0.000	0.000	0.000	0.000	0.000
L3 chargino leptonic	0.000	0.000	0.000	0.000	0.000	0.000	0.000
OPAL chargino hadronic	0.000	0.000	0.000	0.000	0.000	0.000	0.000
OPAL chargino semi-leptonic	0.000	0.000	0.000	0.000	0.000	0.000	0.000
OPAL chargino leptonic	0.000	0.000	0.000	0.000	0.000	0.000	0.000
OPAL neutralino hadronic	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$B_{(s)} \to \mu^+\mu^-$	0.000	−2.033	−2.024	−2.021	−1.998	−1.997	1.998
Tree-level B and D decays	0.000	−15.318	−15.284	−15.287	−15.315	−15.333	15.315
$B^0 \to K^{*0}\mu^+\mu^-$	−184.260	−194.316	−195.283	−193.103	−194.734	−195.551	10.474
$B \to X_s\gamma$	9.799	8.030	8.710	6.978	8.334	8.795	1.465
a_μ	20.266	14.027	14.114	14.299	14.269	14.090	5.997
W mass	3.281	3.081	2.813	2.778	3.096	2.643	0.185
Relic density	5.989	5.989	5.989	5.989	5.989	5.989	0.000
PICO-2L	−1.000	−1.000	−1.000	−1.000	−1.000	−1.000	0.000
PICO-60 F	0.000	0.000	0.000	0.000	0.000	−0.001	0.000
SIMPLE 2014	−2.972	−2.972	−2.972	−2.972	−2.972	−2.972	0.000
LUX 2015	−0.640	−0.657	−0.693	−0.670	−0.660	−0.650	0.020
LUX 2016	−1.467	−1.501	−1.574	−1.527	−1.506	−1.487	0.039
PandaX 2016	−1.886	−1.909	−1.960	−1.927	−1.912	−1.899	0.026
SuperCDMS 2014	−2.248	−2.248	−2.248	−2.248	−2.248	−2.248	0.000
XENON100 2012	−1.693	−1.684	−1.667	−1.678	−1.683	−1.688	0.010
IceCube 79-string	0.000	−0.032	0.000	0.000	−0.069	0.000	0.069
γ rays (Fermi-LAT dwarfs)	−33.244	−33.374	−33.367	−33.363	−33.371	−33.255	0.127
ρ_0	1.142	1.139	1.115	1.138	1.142	1.141	0.000
σ_s and σ_l	−6.115	−6.115	−6.117	−6.115	−6.128	−6.116	0.013
$\alpha_s(m_Z)(\overline{MS})$	6.500	6.493	6.427	6.409	6.496	6.457	0.004
Top quark mass	−0.645	−0.647	−0.687	−0.645	−0.654	−0.751	0.009
Total	−226.927	−263.704	−264.354	−264.016	−263.272	−264.426	36.345

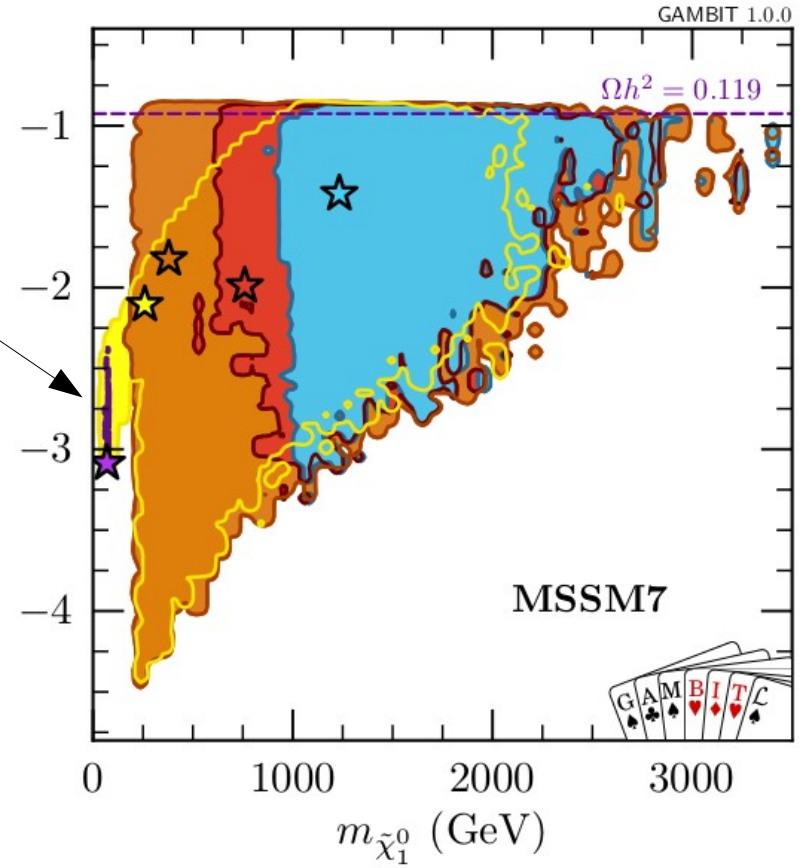
- $\Delta \ln L$ dominated by failure of MSSM7 (and SM) to explain R_D and R_{D^*}, plus the measured magnetic moment of the muon and the electroweak penguin decay angular observables



Global and Modular BSM Inference: MSSM7

- Light Higgs funnel region that evades LEP constraints
- Completely testable with DARWIN





Global and Modular BSM Inference Tool

- GAMBIT has been released as an ***open source public tool***
- 9 papers published in EPJC (design, manual + first physics results)
- Sampling results available online for studies
- Feature article in *Physics World* March 2017 issue if you want a gentler introduction
- See **gambit.hepforge.org** for more info

Eur. Phys. J. C manuscript No.
(will be inserted by the editor)

CERN-TH-2017-166, CoEPP-MN-17-6, NORDITA 2017-074

GAMBIT: The Global and Modular Beyond-the-Standard-Model Inference Tool

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Coding and computing: Dark-matter searches

When supercomputers go over to the dark side

Despite oodles of data and plenty of theories, we still don't know what dark matter is. **Martin White** and **Pat Scott** describe how a new software tool called GAMBIT will test how novel theories stack up when confronted with real data

The most memorable thrillers are those where you get part-way through and then suddenly realize that nothing is as you imagined. Unexpected scientific paradigm shifts, where reality turns out not to be as we believed, can be just as exciting and perplexing. One such dramatic change in perspective has been the dawning realization over the last few decades that "ordinary" matter accounts for just a fifth of the matter in the universe, with the rest made of a mysterious "dark" matter. Physicists love unsolved problems, and they don't come much bigger than working out the nature of this dark stuff.

If a blockbuster movie is ever made about the discovery of dark matter, the next decade may well be the climax. New data from experiments such as CERN's Large Hadron Collider (LHC) are telling us more about what dark matter can and cannot be, while the recent discovery of gravitational waves reminds us that even century-old theories (general relativity in this case) can be spectacularly confirmed in the blink of an eye (or the chirp of a coalescing black hole). Meanwhile, searches for dark matter here on Earth are entering a crucial phase. Detectors weighing over a tonne are being placed deep underground to try to catch dark matter passing through the Earth itself, while construction is now starting on the Cherenkov Telescope Array – one of the finest facilities for hunting the annihilation of dark matter in outer space. These probes are so sensitive that they will be able to test – and potentially discover – many leading models of dark matter over the next 10 years.

What is less clear is how to make sense of these disparate datasets. Imagine being shown a 10-acre field and told a tiny new insect is hiding somewhere in the grass. You are also given, every few days, a new photo of a cow with a distinctive bite mark, and three distorted recordings of a strange chirrup (one of which is from a dying grasshopper). After 30 years – having seen a lot of cows and heard a lot of chirrups – your job is to determine the properties of the insect. Unfortunately, you have never seen it, and have only a vague hunch about its size given that it has never killed any of the cows.

Replace the insect by dark matter and the photo and chirrups by astrophysical data (which may or may not be related to the insect) and you'll see why studying dark matter is so hard. Still, dark-matter hunters perhaps have an easier job than our hypothetical entomologist, as they have much more data, plus decades of accurate astronomical observations (see box on p XX).

These include measurements of the orbital speed of stars as a function of their radial distance from the galaxy's centre, so-called "galactic rotation curves", which deviate from the form expected based on visible matter. There are gravitational-lensing observations – in which massive objects bend light as predicted by general relativity – that let us measure a system's mass independently of the visible matter. Finally, we have very precise measurements of the temperature fluctuations in the cosmic microwave background (CMB), which are highly sensitive to the assumed matter content of the early universe.

But despite so much information, all we have is decades of null results – we only know that the insect is neither bee nor beetle, not what it is. Any one experiment we carry out has a huge range of possible outcomes, depending on what the dark-matter particle might be. In fact, the only way of learning the true nature of dark matter is to piece together clues from many different experiments, and seek distinct patterns in observations from totally different sources, such as evidence of a single property emerging in different ways in different datasets.

This quest puts us firmly in the realm of data science, which is booming thanks to the abundance of data provided by everything from social-media applications to government spies and mobbish spatric grasshoppers. The cross-pollination of techniques from a variety of disciplines is transforming how we look at and model the world, with research into dark matter benefiting from, and contributing to, this expertise. Machine-learning techniques, including neural networks, for example, are being used to improve algorithms for identifying particles at the LHC.

Genesis of GAMBIT

The GAMBIT (Global and Modular Beyond-the-Standard-Model Inference Tool) Collaboration can trace its origins back to the 2012 International Conference on High Energy Physics in Melbourne, Australia, where the discovery of the Higgs boson was announced via a live video link to CERN in Geneva. Celebrating in the bars on the south bank of the Yarra river, a group of us began a series of spirited discussions about how to find new physics and solve the dark-matter problem with software.

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What's next for GAMBIT?

- More models (2HDM, axion models, more Higgs portal models, RH neutrinos, MSSM9 + 4D EW MSSM)
- Better LHC Higgs likelihoods
- Direct link to CalcHEP and MadGraph
- Implementation of more complex LHC likelihoods (e.g. CMS simplified likelihood analyses for monojet and 0 lepton searches) plus Run II LHC searches
- A new cosmology module