# Global fits and Bayesian inference in beyond-Standard Model physics

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ISNET-9 - May 23, 2023





# The Standard Model is incomplete!

(c)(g) 6 S 8 A X: Yis Xsp +h  $+ \left| \sum_{\alpha} \varphi \right|^2 - \sqrt{(\phi)}$  $\bigcirc$ Z.

- Why is the Higgs particle so light?
- Why are the neutrinos so *extremely* light?
- What is dark matter? And dark energy?
- Why do the matter particles come in three «generations»?
- How did we end up with slightly more matter than antimatter?

Need beyond-Standard Model (BSM) physics to explain this

• ...

Understanding the full implications of [experimental] searches requires the interpretation of the experimental results in the context of many more theoretical models than are currently explored at the time of publication.

HEP Software Foundation [arxiv:1712.06982]

See also:

- Publishing statistical models: Getting the most out of particle physics experiments [arxiv:2109.04981]
- Reinterpretation of LHC Results for New Physics: Status and Recommendations after Run 2
   [arxiv:2003.07868]
- Simple and statistically sound strategies for analysing physical theories [arxiv:2012.09874]



1. Global fits

### 2. GAMBIT

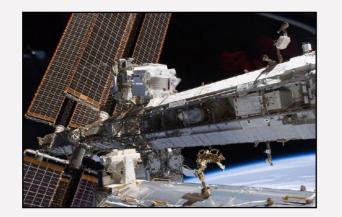
### **3. Applications of Bayesian inference**

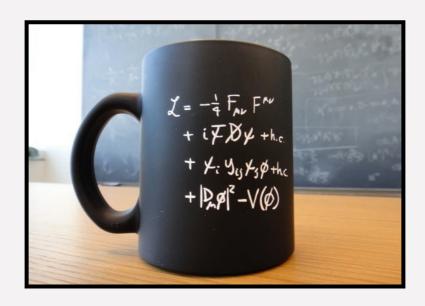
### 4. Summary

# 1. Global fits

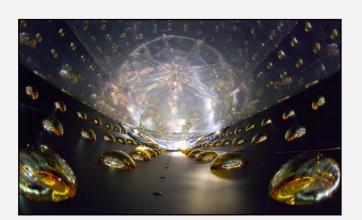








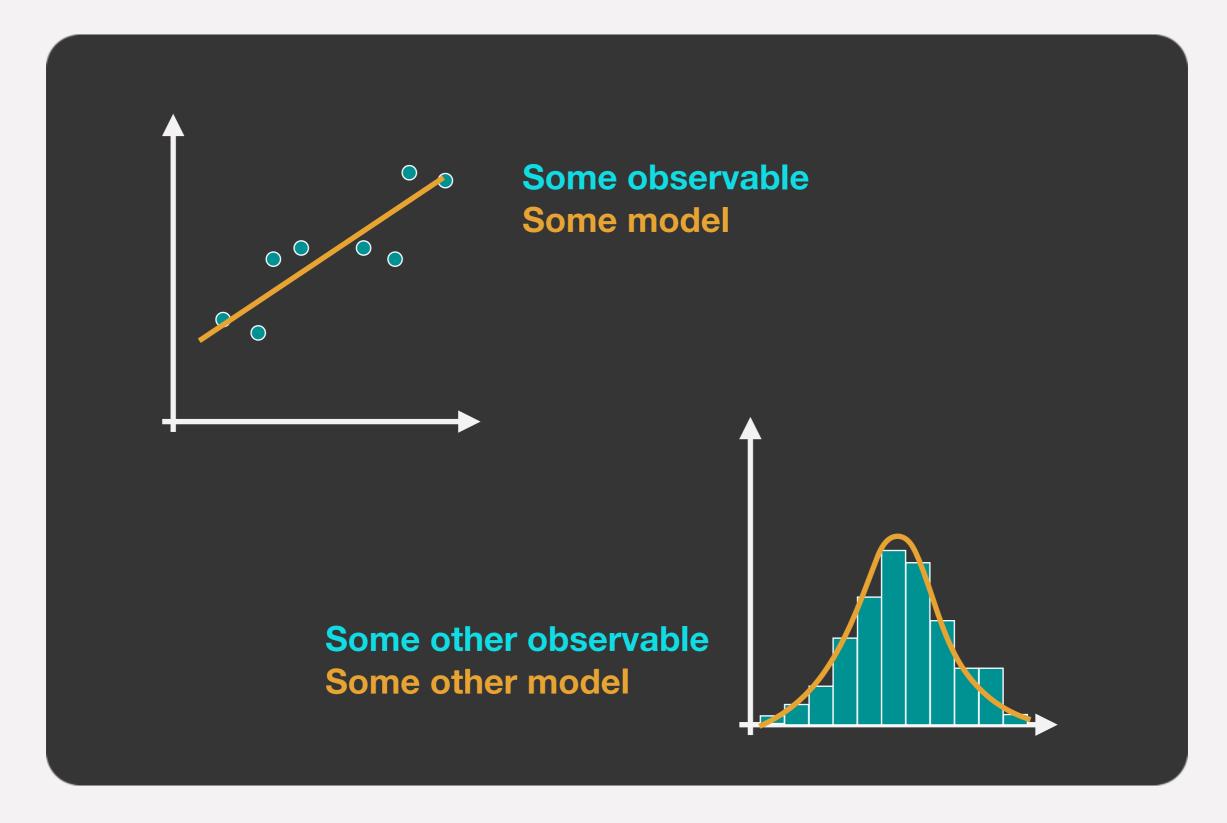




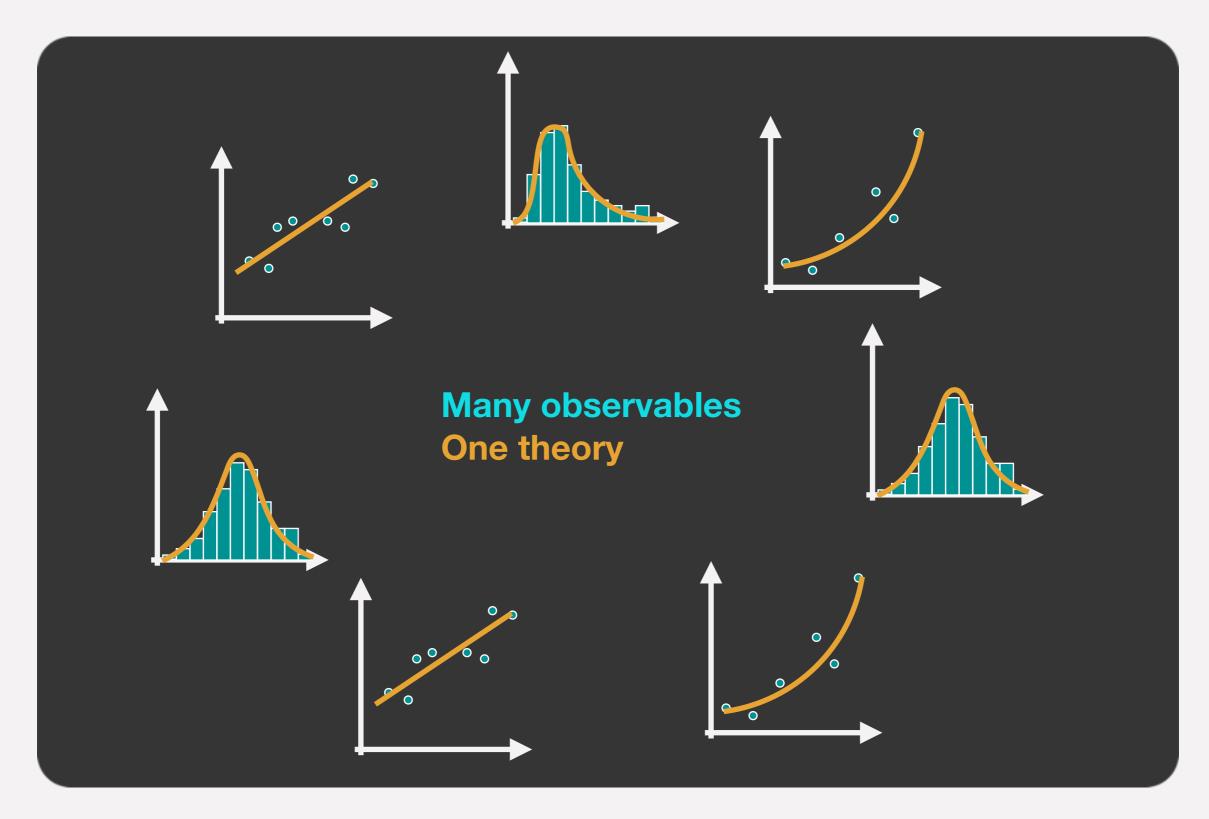




## **Statistical fits**



# **Global fits**



# The basic steps of a BSM global fit

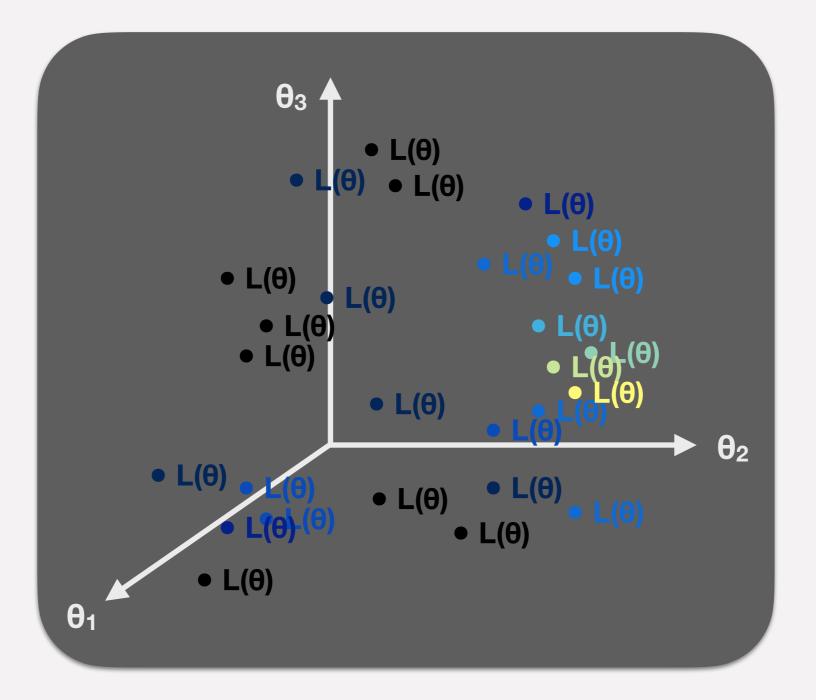
Choose your **BSM theory and parameterisation**

 Construct the joint likelihood function including observables from collider physics, dark matter, flavor physics, +++

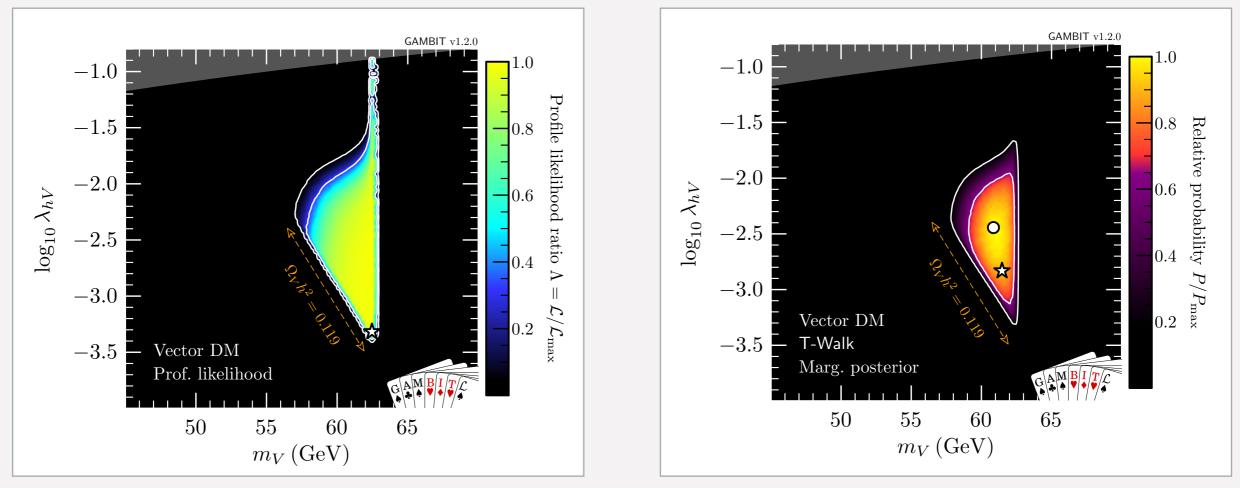
$$\mathcal{L} = \mathcal{L}_{collider} \mathcal{L}_{DM} \mathcal{L}_{flavor} \mathcal{L}_{EWPO} \dots$$

- Use sophisticated scanning techniques to explore the likelihood function across the parameter space of the theory
- From likelihood samples, carry out frequentist or Bayesian inference (parameter estimation, model comparison, ...)

- Explore the model parameter space ( $\theta_1, \theta_2, \theta_3, ...$ )
- At every point  $\theta$ : calculate predictions( $\theta$ )  $\rightarrow$  evaluate joint likelihood L( $\theta$ )



# *Typical result:* Parameter estimation, presented as **profile likelihood** and/or **posterior density** plots



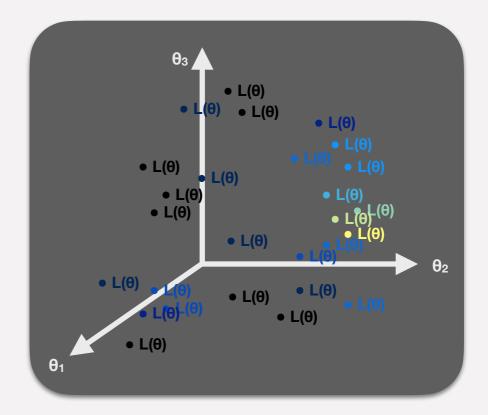
<sup>[</sup>arxiv:1808.10465]

**Computational challenges:** 

- Need **smart exploration** of parameter space
- Need fast theory calculations
- Need fast simulations of experiments (e.g. LHC)
- Need sufficiently detailed likelihoods or full statistical models



<pre>// Increment signal region counters: 2 same-sign leptons if (preselection &amp;&amp; nSignalLeptons==2 &amp;&amp; nSignalTaus==0 &amp;&amp; met&gt;60 &amp;&amp; conversion_veto) if (signalLeptons.at(0)-&gt;pid()*signalLeptons.at(1)-&gt;pid()&gt;0 {     if ((signalLeptons.at(0)-&gt;abspid()==11 &amp;&amp; signalLeptons.at(0)-&gt;pT()&gt;25)    (signalLeptons.at(0)-&gt;pT()&gt;25)    (signalLeptons.at(0)-&gt;p</pre>
<pre>bool pp = false; bool mm = false; if(signalLeptons.at(0)-&gt;pid() &gt; 0)pp = true; if(signalLeptons.at(0)-&gt;pid() &lt; 0)mm = true;</pre>
<pre>if (num_ISRjets==0) {</pre>
<pre>// The 0 jet regions if(mT &lt; 100 &amp;&amp; pT_ll &lt; 50 &amp;&amp; met &lt; 100) _numSR["SS01"]++; if(mT &lt; 100 &amp;&amp; pT_ll &lt; 50 &amp;&amp; met &gt;= 100 &amp;&amp; met &lt; 150 &amp;&amp; pDnumSR["SS02"]++; if(mT &lt; 100 &amp;&amp; pT_ll &lt; 50 &amp;&amp; met &gt;= 100 &amp;&amp; met &lt; 150 &amp;&amp; mm) _numSR["SS03"]++; if(mT &lt; 100 &amp;&amp; pT_ll &lt; 50 &amp;&amp; met &gt;= 150 &amp;&amp; met &lt; 200) _numSR["SS04"]++; if(mT &lt; 100 &amp;&amp; pT_ll &gt; 50 &amp;&amp; met &gt;= 100 &amp;&amp; met &lt; 200) _numSR["SS04"]++; if(mT &lt; 100 &amp;&amp; pT_ll &gt; 50 &amp;&amp; met &gt;= 100 &amp;&amp; met &lt; 150 &amp;&amp; pT_lt = 100 &amp;&amp; met &lt; 150 &amp;&amp; pT_lt = 100 &amp;&amp; met &lt; 150 &amp;&amp; pT_lt = 100 &amp;&amp; met &lt; 150 &amp;&amp; met &lt; 150 &amp;&amp; pT_lt = 100 &amp;&amp; met &lt; 150 &amp;&amp; pT_lt &gt; 50 &amp;&amp; met &gt;= 100 &amp;&amp; met &lt; 150 &amp;&amp; met &lt; 150</pre>



Some code infrastructure challenges:

- Need different parameter scanning algorithms
- Need model-agnostic core framework
- Need to interface *many* external physics codes
- Need massive parallelisation...
- ...which implies a need for diskless interfacing
- ...which implies a need to stop external codes from calling STOP and kill your 10,000-CPU scan... :)

# 2. GAMBIT



### GAMBIT: The Global And Modular BSM Inference Tool

gambit.hepforge.org

github.com/GambitBSM EPJC 77 (2017) 784

arXiv:1705.07908

- Extensive model database, beyond SUSY
- Fast definition of new datasets, theories
- Extensive observable/data libraries
- Plug&play scanning/physics/likelihood packages GAMBI
- Various statistical options (frequentist /Bayesian)
- Fast LHC likelihood calculator
- Massively parallel
- Fully open-source

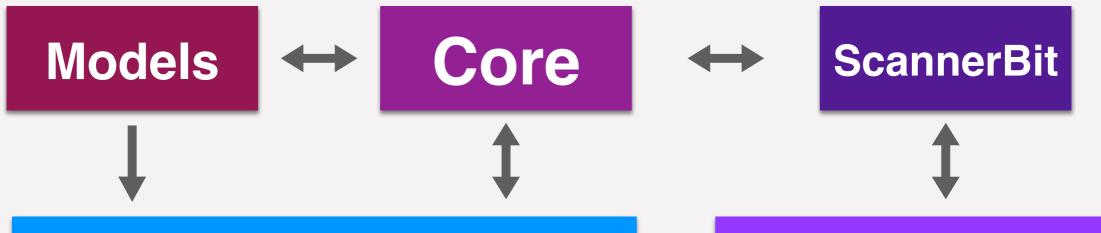
Members of: ATLAS, Belle-II, CLiC, CMS, CTA, Fermi-LAT, DARWIN, IceCube, LHCb, SHiP, XENON

Authors of: BubbleProfiler, Capt'n General, Contur, DarkAges, DarkSUSY, DDCalc, DirectDM, Diver, EasyScanHEP, ExoCLASS, FlexibleSUSY, gamLike, GM2Calc, HEPLike, IsaTools, MARTY, nuLike, PhaseTracer, PolyChord, Rivet, SOFTSUSY, Superlso, SUSY-AI, xsec, Vevacious, **WIMPSim** 

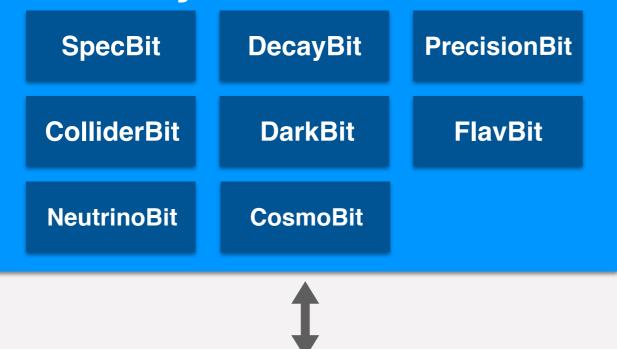
Recent collaborators: P Athron, C Balázs, A Beniwal, S Bloor, T Bringmann, A Buckley, J-E Camargo-Molina, C Chang, M Chrzaszcz, J Conrad, J Cornell, M Danninger, J Edsjö, T Emken, A Fowlie, T Gonzalo, W Handley, J Harz, S Hoof, F Kahlhoefer, A Kvellestad, P Jackson, D Jacob, C Lin, N Mahmoudi, G Martinez, MT Prim, A Raklev, C Rogan, R Ruiz, P Scott, N Serra, P Stöcker, W. Su, A Vincent, C Weniger, M White, Y Zhang, ++

70+ participants in many experiments and numerous major theory codes





### **Physics modules**



### **Scanners**

Diver, GreAT, MultiNest, PolyChord, TWalk, grid, random, postprocessor, ...

### Backends

CaptnGeneral, DarkSUSY, DDCalc, FeynHiggs, FlexibleSUSY, gamLike, gm2calc, HEPLike, HiggsBounds, HiggsSignals, MicrOmegas, nulike, Pythia, SPheno, SUSYHD, SUSYHIT, SuperIso, Vevacious, MontePython, CLASS, AlterBBN, ...

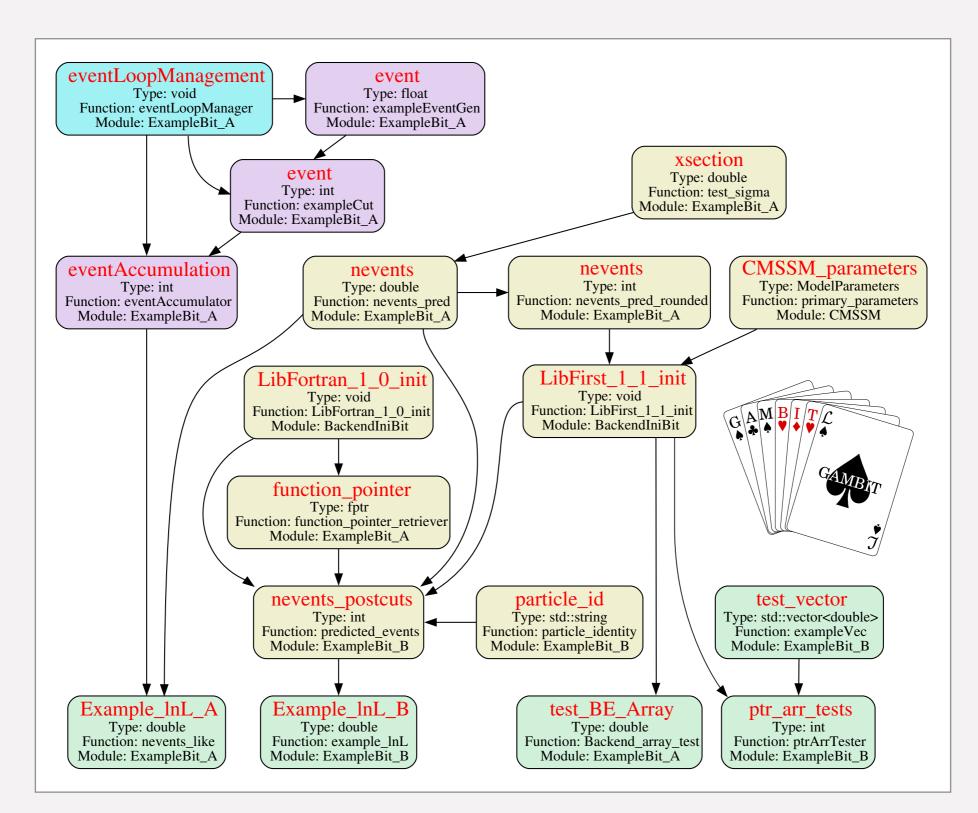


# **Some technical features**

### • Two-level parallelisation:

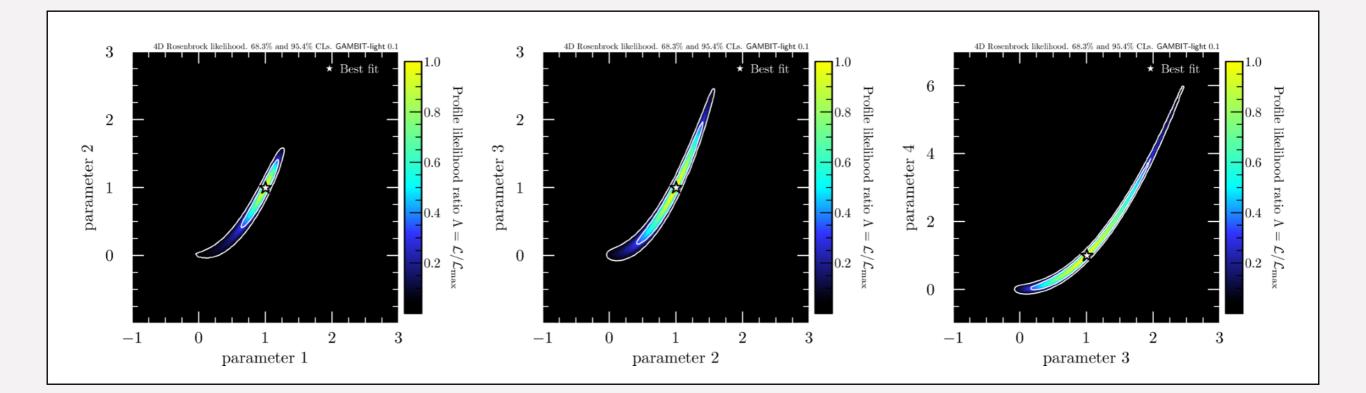
- **MPI** for parameter sampling algorithm
- OpenMP for per-point physics computations
- Collection of sampling algorithms as plug-ins
- Backend system for using C, C++, Fortran, Python and Mathematica codes as runtime plug-ins for physics computations
- Run configuration through YAML input file
- **Dynamic dependency resolution**: order of computations not hard-coded
- GAMBIT Universal Model machine (GUM): code auto-generation for new physics models

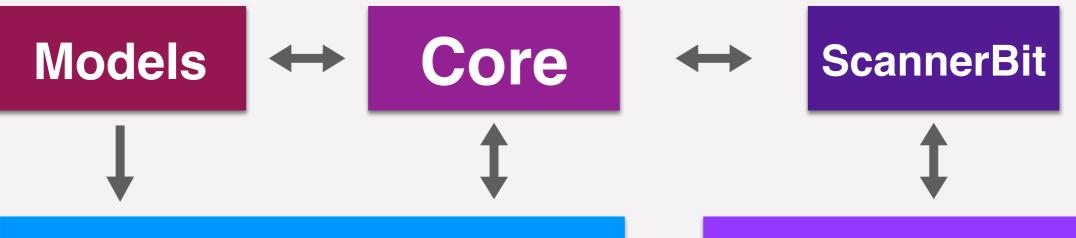




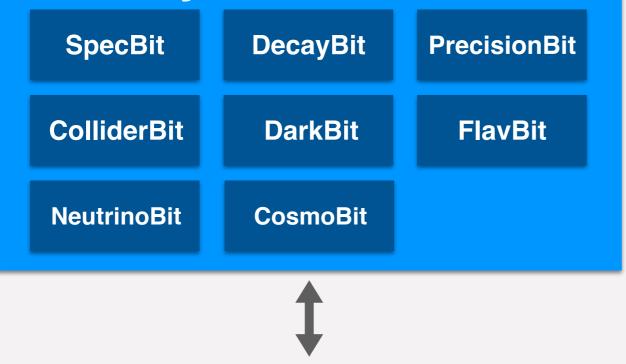
# **GAMBIT-light**

- GAMBIT can be used beyond particle physics
- At its core: A general tool for computationally heavy optimisation and parameter estimation tasks
- Coming soon: GAMBIT-light
   A lightweight GAMBIT without the particle physics





### **Physics modules**



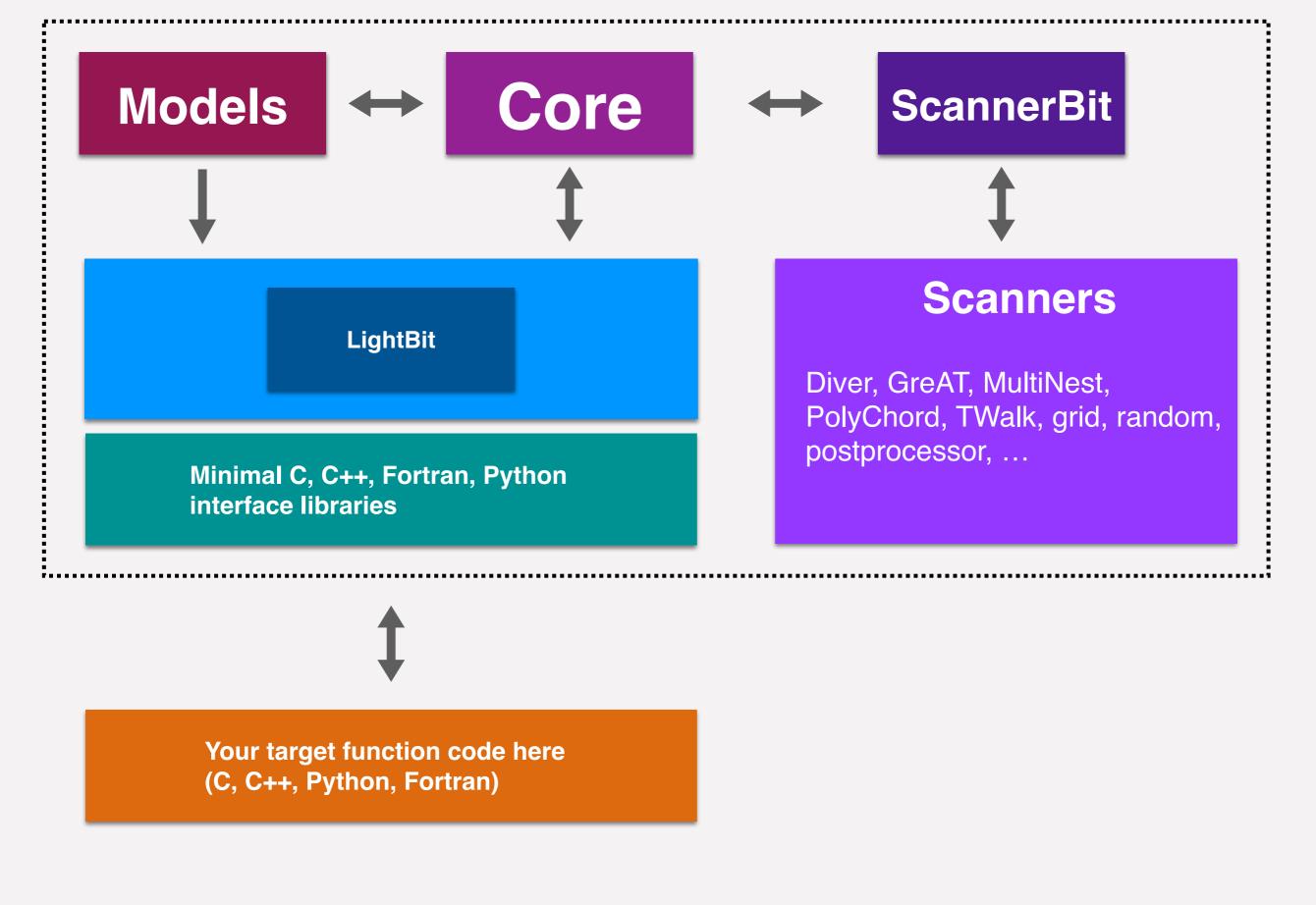
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#### UserModel:

#### p1

name: param\_name\_1
prior\_type: flat
range: [0.0, 1.0]

#### p2:

name: param\_name\_2
prior\_type: log
range: [1.0e-2, 1.0e2]

#### р3:

name: param\_name\_3
fixed value: 3.0

#### p4:

name: param\_name\_4
fixed\_value: 4.0

#### UserLogLikes:

user lib: Backends/light interface/libuser c.so init fun: init user loglike - param name 1 - param name 2 - param name 3 my\_library\_A\_output\_1 my\_library\_A\_output\_2 - my library A output 3 lang: fortran user lib: Backends/light interface/libuser fortran.so init fun: init user loglike - param name 1 - param name 2 my library\_B\_output\_1 lang: python
user\_lib: Backends/light\_interface/libuser.py init fun: init user\_loglike - param\_name\_1 - param name 2 - param\_name\_4
output: - my library C output 1 - my library C output 2

#### Printer

printer: hdf5
options:
 output\_file: "results.hdf5"
 group: "/data"
 buffer\_length: 1000
 delete\_file\_on\_restart: true

#### Scanner

use\_scanner: polychord

#### scanners:

de: plugin: diver NP: 200 convthresh: 1e-4 verbosity: 1 lambdajDE: false

#### multinest: plugin: multinest nlive: 2000 tol: 0.01

twalk: plugin: twalk sqrtR: 1.001

polychord: plugin: polychord tol: 0.01

minuit2: plugin: minuit2 tolerance: 0.0001 precision: 0.0001 max\_loglike\_calls: 100000 max\_iterations: 100000 algorithm: combined

#### KeyValues

default\_output\_path: "runs/gambit\_light\_test"

ebug: false

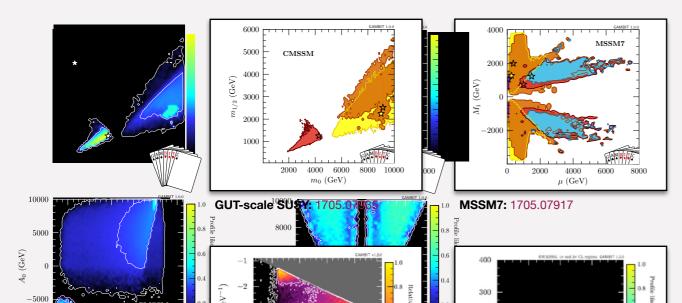
#### print\_scanID: true

ng: generator: ranlux48 seed: -1

likelihood: model\_invalid\_for\_lnlike\_below: -5e5 print\_invalid\_points: false

### **3. Applications of Bayesian inference**





2.5 3.0 3.5

Prof. like

-0.04-0.02 0.00 0.02 0.04 0.06 0.08

 $\operatorname{Re}(\Delta C_7)$ 

Flavour EFT: 2006.03489

 $\log_{10} (m_{\chi}/\text{GeV})$ 

Vector and fermion Higgs portal

2.0

DM: 1808.10465

0.0

-1.1

-1.5

2.7

2.6<u>م</u>

2.5

2.4

2.3

Cosmo ALPs: 2205.13549

D/H [10-

 $\operatorname{Re}(\Delta C_9)$ 

 $\log_{10} (\lambda_{h\chi}/\Lambda_{\chi}/Ge)$ 

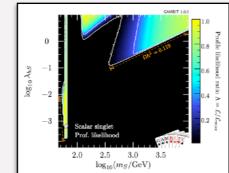
10

20

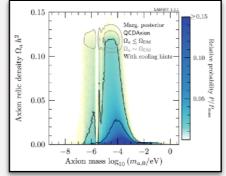
30 40

 $\tan \beta$ 

 $\blacksquare$   $\tilde{t}_1$  co-annihilation



Scalar Higgs portal DM: 1705.07931



Axion-like particles: 1810.07192

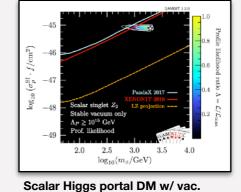
 $0.020.040.06 \ 0.05 \ 0.15 \ 0.25 \ 2.93.13.3 = 66 \ 68 \ 70$  $m_{\nu_1} (eV) = \sum m_{\nu} (eV) = N_{eff} = H_0 (km/s/M_f)$ 

Neutrinos and cosmo: 2009.03287

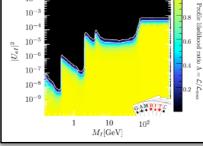
 $0^2$   $10^3$ Mediator mass  $m_M$ [GeV]

Simplified DM, vector: 2303.08351

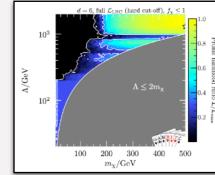
 $10^{4}$ 

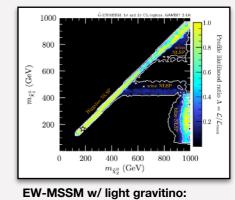


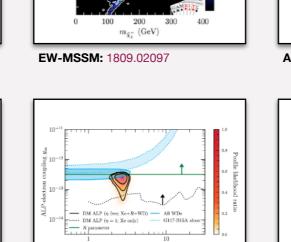
stability: 1806.11281  $10^{-}$ 10 10 GAMBITC



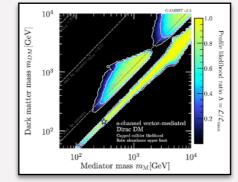
**Right-handed neutrinos:** 1908.02302



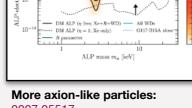




More axion-like particles:



2209.13266

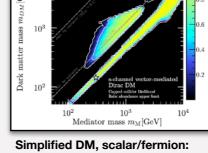


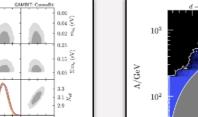
2007.05517

(GeV)

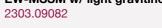
200  $i_{\tilde{X}_1^0}$ 

100





Dark matter EFTs: 2106.02056



G

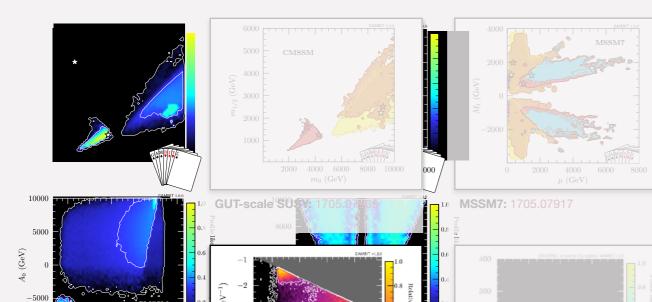


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 $10^{2}$ 

 $10^{2}$ 

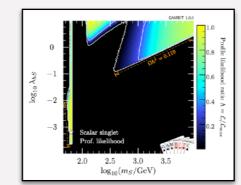
Dark



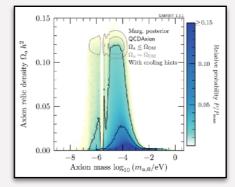
2.5 3.0 3.5

 $\log_{10} (m_{\chi}/\text{GeV})$ 

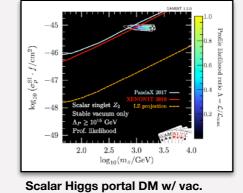
Vector and fermion Higgs portal

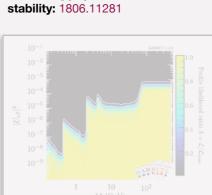


Scalar Higgs portal DM: 1705.07931

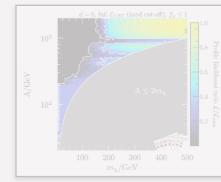


Axion-like particles: 1810.07192

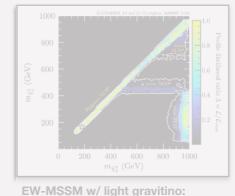




**Right-handed neutrinos:** 



Dark matter EFTs: 2106.02056



Flavour EFT: 2006.03489

 $\log_{10} (\lambda_{h\chi}/\Lambda_{\chi}/Ge)$ 

\_3

2.0

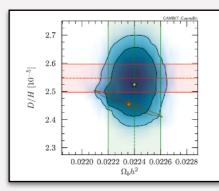
DM: 1808.10465

30 40

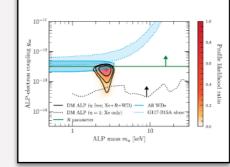
 $\tan \beta$ 

 $\blacksquare$   $\tilde{t}_1$  co-annihilation

1020

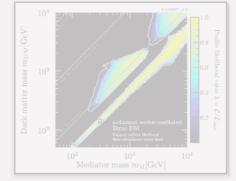


Cosmo ALPs: 2205.13549

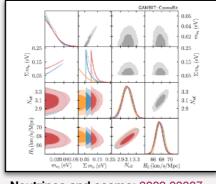


More axion-like particles: 2007.05517

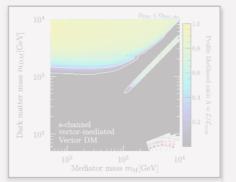
EW-MSSM: 1809.02097



Simplified DM, scalar/fermion:



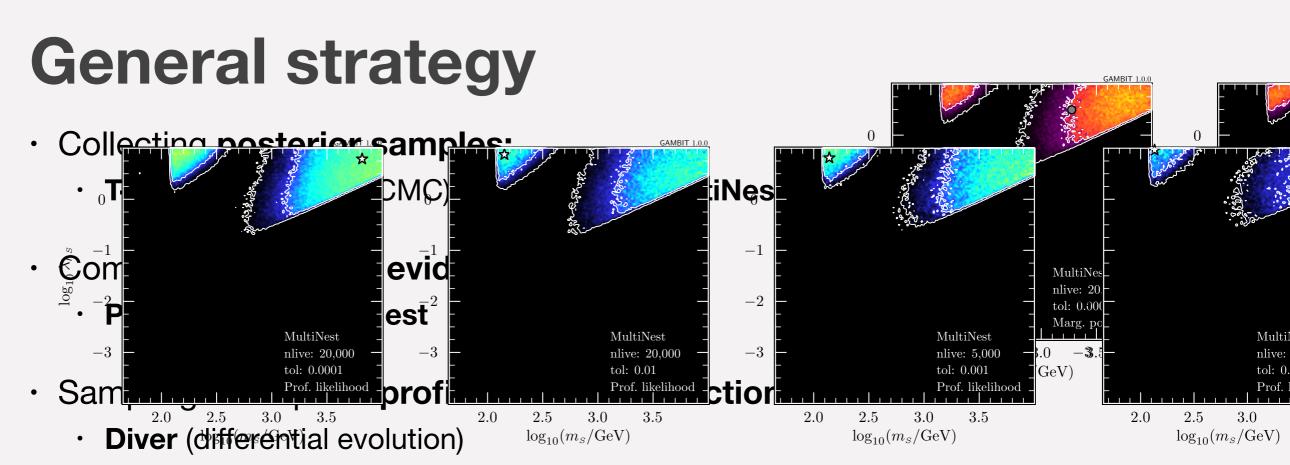
Neutrinos and cosmo: 2009.03287



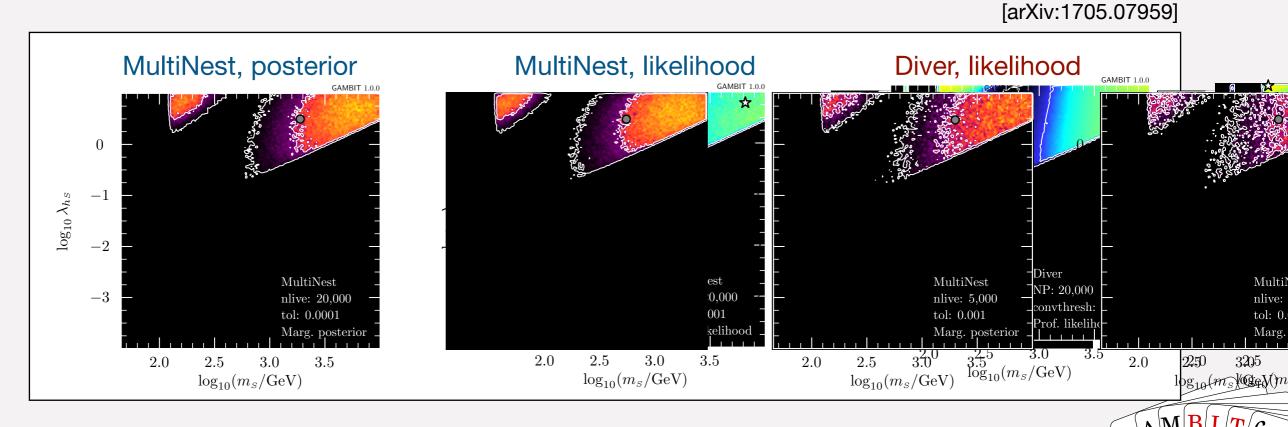
Simplified DM, vector: 2303.08351







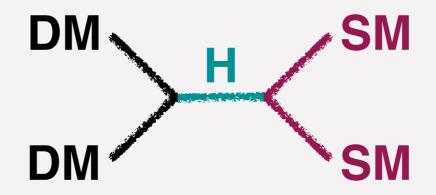
And add all samples from the Bayesian scans



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25

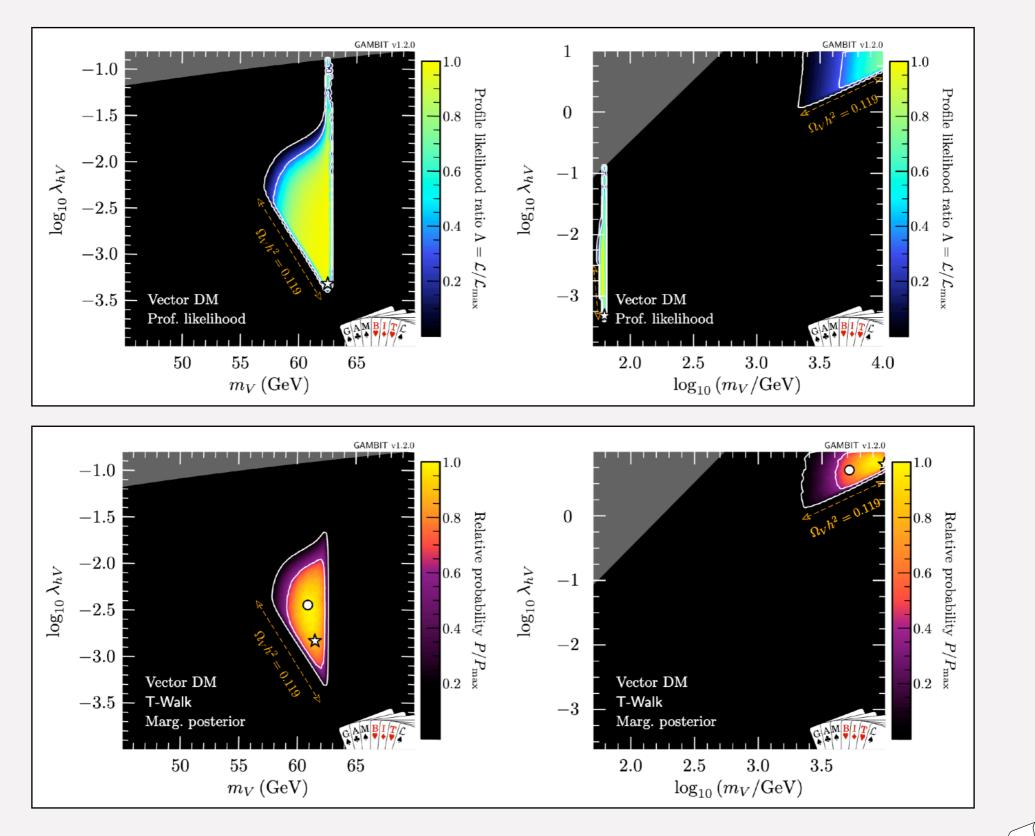
### **Example: «Higgs portal» dark matter** [arxiv:1808.10465]



- Study of three models where the dark matter (DM) field only interacts with the Standard Model fields through interactions with the Higgs field
- 1) Vector DM 2) Dirac fermion DM 3) Majorana fermion DM
- Parameter space
  - DM mass
  - 1−2 parameters for the DM-Higgs interaction
  - 7 nuisance parameters
- Likelihoods for DM density, Higgs «invisible decay width», and many experimental searches for DM signals (indirect and direct)
- $\cdot$  Intended here as an example the results are now somewhat outdated



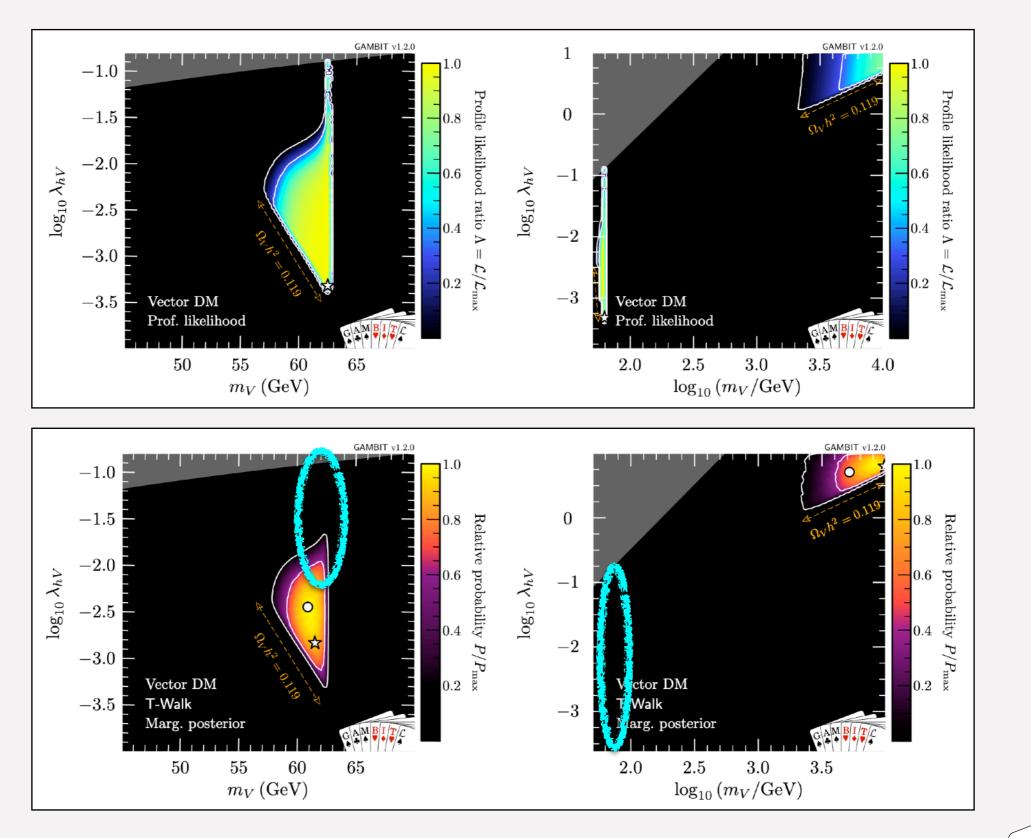
- Both profile likelihoods and posteriors
- · Helps disentangle «low likelihood» vs «high likelihood but fine-tuned»



M

G

- Both profile likelihoods and posteriors
- · Helps disentangle «Iow likelihood» vs «high likelihood but fine-tuned»



M

G

#### **Bayesian model comparisons**

Model	Compar	rison model a	and priors	Odds
$\xi = 0$	$m_{\chi}$ : log	$\lambda_{h\chi}/\Lambda_{\chi}$ : lo	$\log \xi$ : flat	70:1
$g_{ m p}/\Lambda_{ m p}=0$	$m_{\chi}$ : log	$g_{ m s}/\Lambda_{ m s}$ : log	$g_{\mathrm{p}}/\Lambda_{\mathrm{p}}$ : log	140:1

**Table 8:** Odds ratios for CP violation for the singlet Majorana fermion Higgs portal model. Here the odds ratios are those against a pure CP-even Higgs portal coupling, as compared to two different parametrisations (and thus priors) of the model in which the CP nature of the Higgs portal can vary freely.

Within the fermion DM models:

Strong evidence for model that allows a CP-violating H-DM interaction, i.e. a more complicated model

(Nested models)

No particular preference in comparisons between the different classes of DM models

(Non-nested models)

Model	Parameters and priors				Odds
S	$m_S$	: log	$\lambda_{hS}$ : lo	g	1:1
$V_{\mu}$	$m_V: \log  \lambda_{hV}: \log$			6:1	
$\chi$	$m_{\chi}$ : log	$\lambda_{h\chi}/$	$\Lambda_{\chi}$ : log	$\xi$ : flat	1:1
$\psi$	$m_\psi \colon \log$	$\lambda_{h\psi}/$	$\Lambda_\psi \colon \log$	$\xi$ : flat	1:1

**Table 9:** Odds ratios against each singlet Higgs portal DM model with  $\mathbb{Z}_2$  symmetry, relative to the scalar model.

# More examples of Bayesian applications in BSM phenomenology

(by no means an exhaustive list)

- · Fast theory emulators, fast marginalised likelihoods, ...
  - Fast AMS-02 antiproton likelihoods: [arxiv:2303.07362]
  - Fast higher-order LHC cross-section predictions: [arxiv:2006.16273]
- Bayesian takes on fine-tuning questions in BSM physics [arxiv:1204.4940], [arxiv:1709.07895] (and many more...)
- Bayesian uncertainties for missing higher-order terms in QFT calculations: [arxiv:2006.16293]
- Creative applications of (originally) Bayesian methods
  - Nested sampling for **estimating small p-values** [arxiv:2105.13923]
  - Nested sampling for event generation [arxiv:2205.02030]
- + many applications of Bayesian parameter estimation and model comparison...

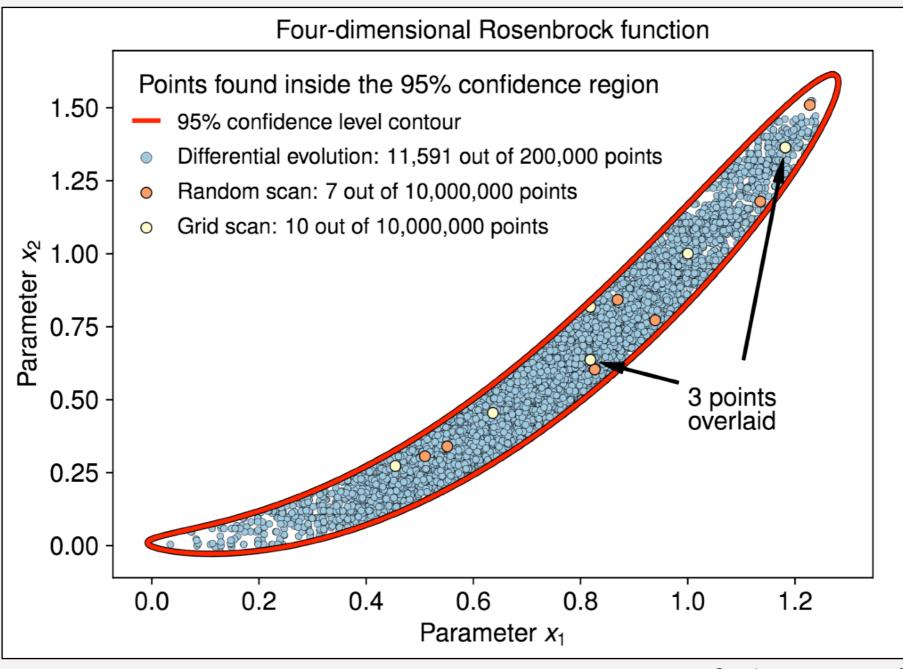
# Summary

# Summary

- How can we **learn the most physics from our experimental results?** *Test all the results against all interesting theories!*
- GAMBIT is an open-source tool for large-scale global fits of new theories in particle physics
- A modular and model-independent core software framework
   → GAMBIT has been used to investigate a wide range of new theories
- Bayesian approaches widely used in BSM physics: parameter estimation, model comparison, emulation, theory uncertainties
- **Different questions, different answers:** Useful to perform both Bayesian and frequentist analyses (if computationally feasible)
- Coming soon: GAMBIT-light
- gambit.hepforge.org and github.com/GambitBSM/gambit\_2.4
- GAMBIT results are publicly available: zenodo.org/communities/gambit-official

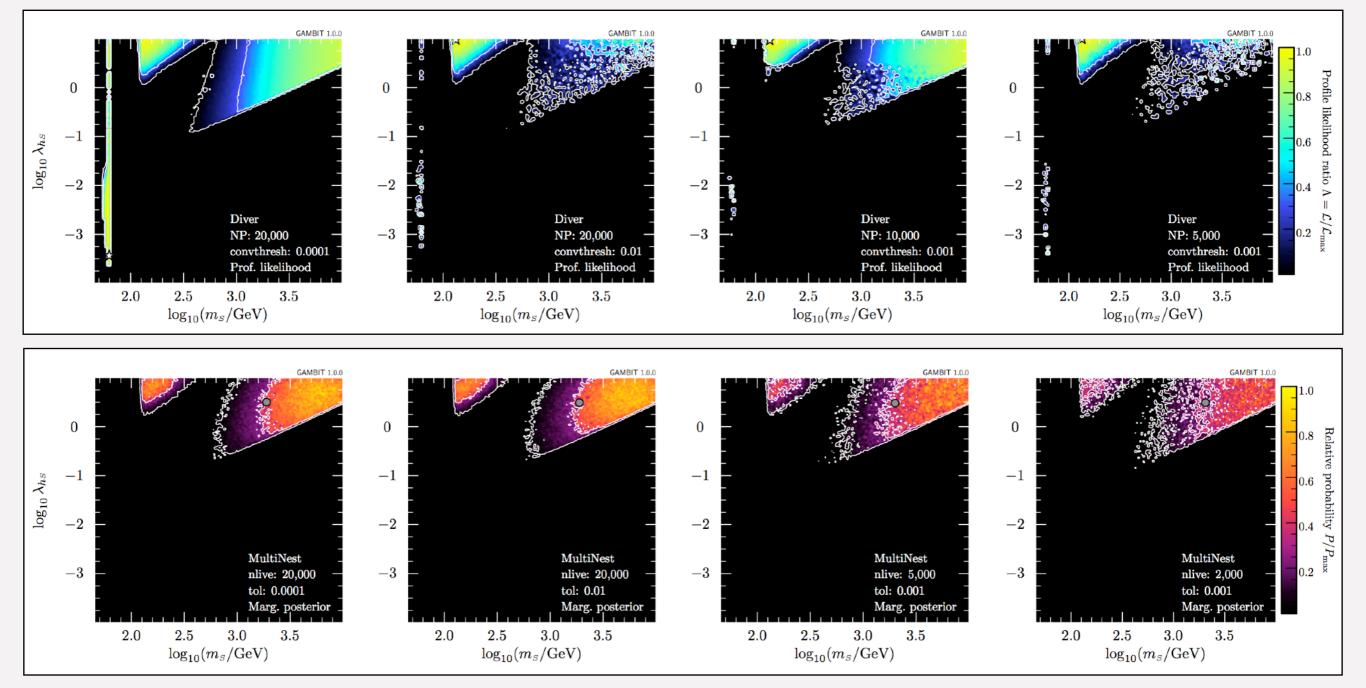
# **Bonus tracks**

# **Parameter space exploration**



[arxiv:2012.09874]

## **Parameter space exploration**



<sup>[</sup>arxiv:1705.07959]



- Basic building blocks: module functions
- A physics module: a collection of module functions related to the same physics topic
- Each module function has a single capability (what it calculates)
- A module function can have dependencies on the results of other module functions
- A module function can declare which models it can work with
- GAMBIT determines which module functions should be run in which order for a given scan (dependency resolution)

```
void function_name(double &result)
{
    ...
    result = ... // something useful
}
```

