Reinterpretation:
How can we maximise the science impact of SUSY searches?

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ATLAS SUSY workshop — Oslo, September 13, 2023

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As a community we can **learn far more physics** from an experimental result that is **reinterpretable** compared to one that is not.

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]

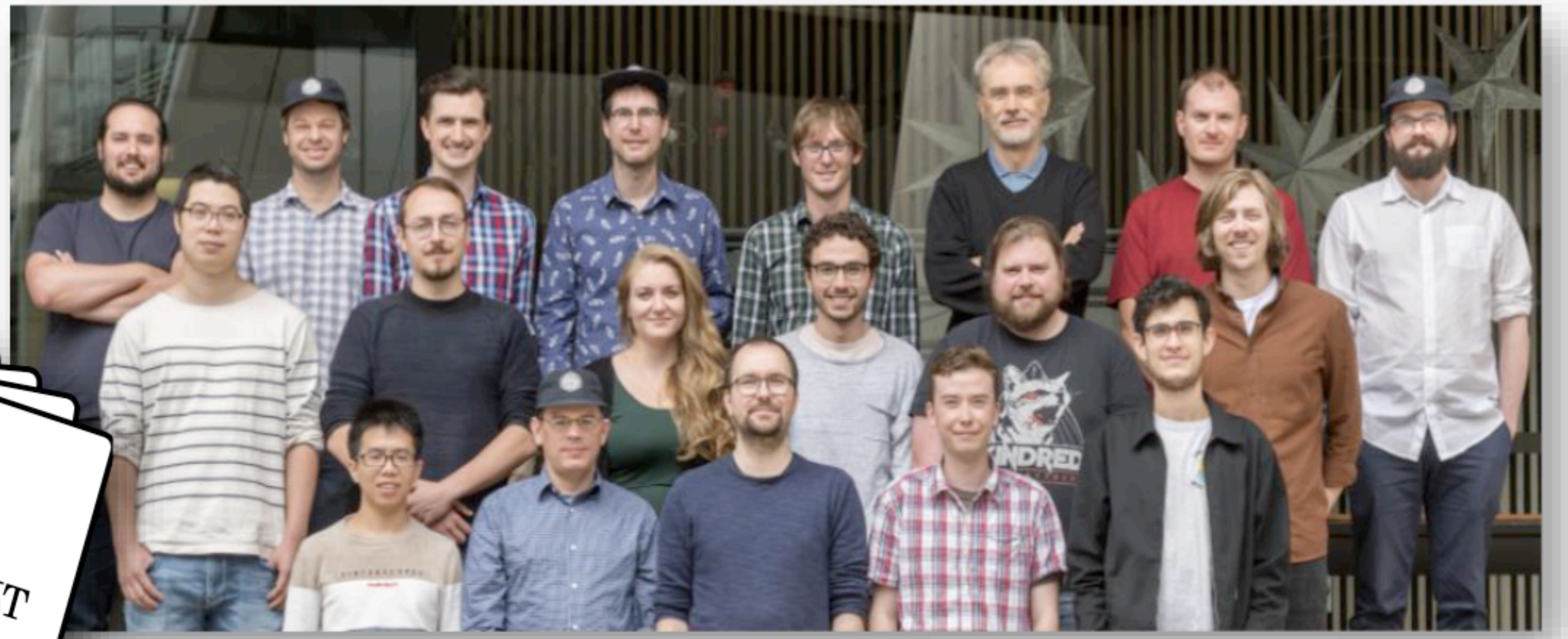
See also:

- *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]**

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
- Various statistical options (frequentist /Bayesian)
- Fast LHC likelihood calculator
- Massively parallel
- Fully open-source

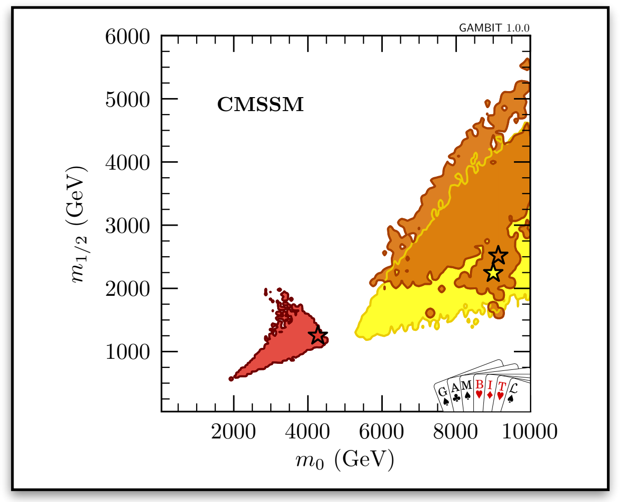


Members of: ATLAS, Belle-II, CLiC, CMS, CTA, Fermi-LAT, DARWIN, IceCube, LHCb, SHiP, XENON

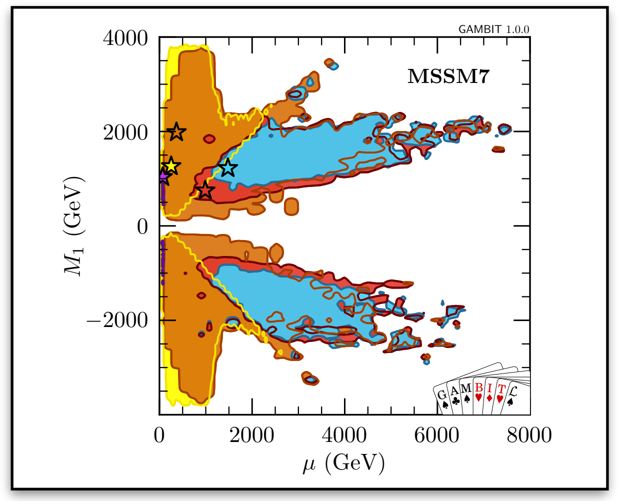
Authors of: BubbleProfiler, Capt'n General, Contur, DarkAges, DarkSUSY, DDCalc, DirectDM, Diver, EasyScanHEP, ExoCLASS, FlexibleSUSY, gamLike, GM2Calc, HEPLike, IsaTools, MARTY, nuLike, PhaseTracer, PolyChord, Rivet, SOFTSUSY, Superlso, SUSY-AI, xsec, Vevacious, WIMPSim

Recent collaborators: V Ananyev, P Athron, N Avis-Kozar, C Balázs, A Beniwal, S Bloor, LL Braseth, T Bringmann, A Buckley, J Butterworth, 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, M Lecroq, P Jackson, D Jacob, C Lin, FN Mahmoudi, G Martinez, H Pacey, MT Prim, T Procter, F Rajec, A Raklev, JJ Renk, R Ruiz, A Scaffidi, P Scott, N Serra, P Stöcker, W. Su, J Van den Abeele, A Vincent, C Weniger, A Woodcock, M White, Y Zhang ++

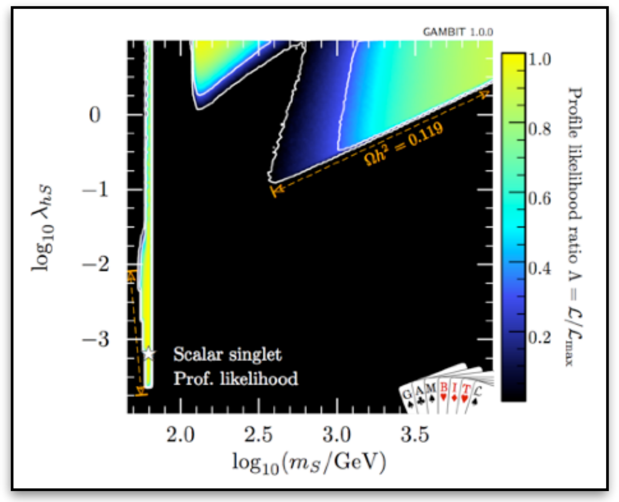
80+ participants in many experiments and numerous major theory codes



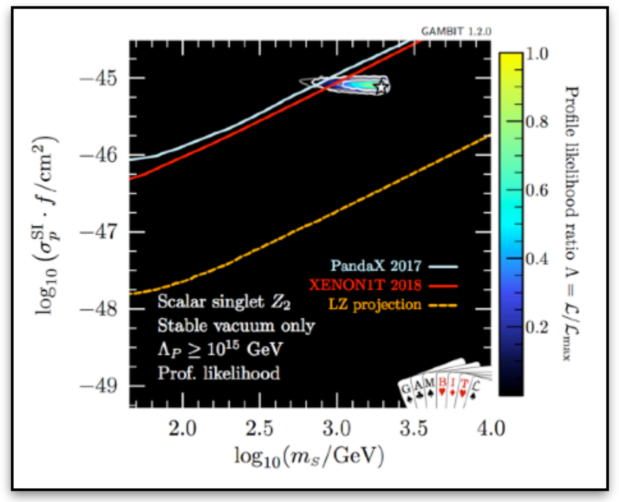
GUT-scale SUSY: 1705.07935



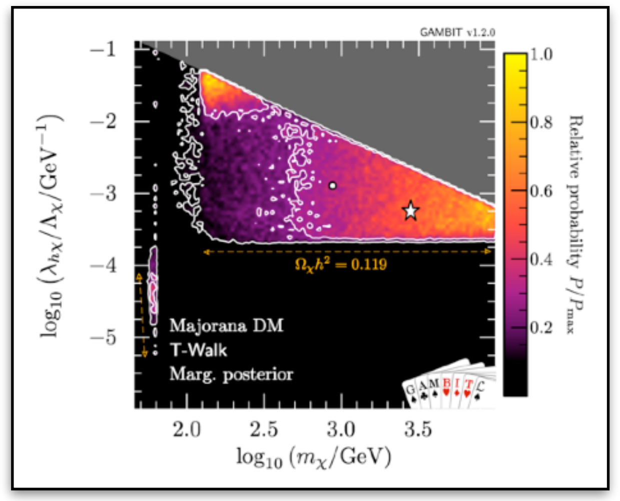
MSSM7: 1705.07917



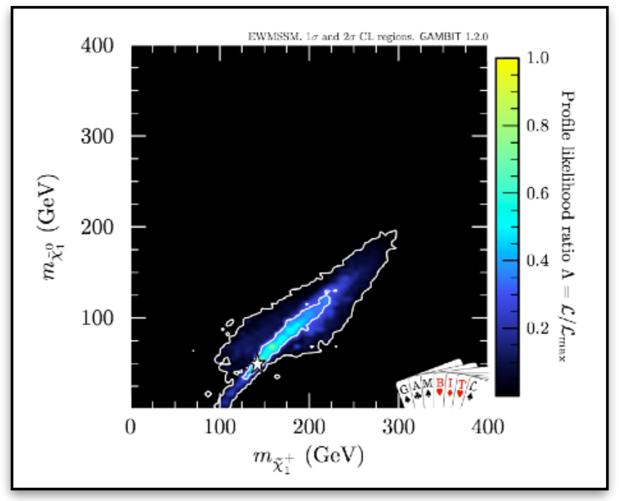
Scalar Higgs portal DM: 1705.07931



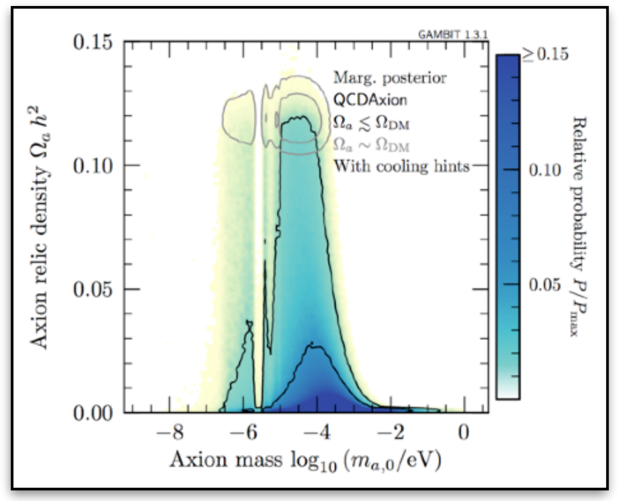
Scalar Higgs portal DM w/ vac. stability: 1806.11281



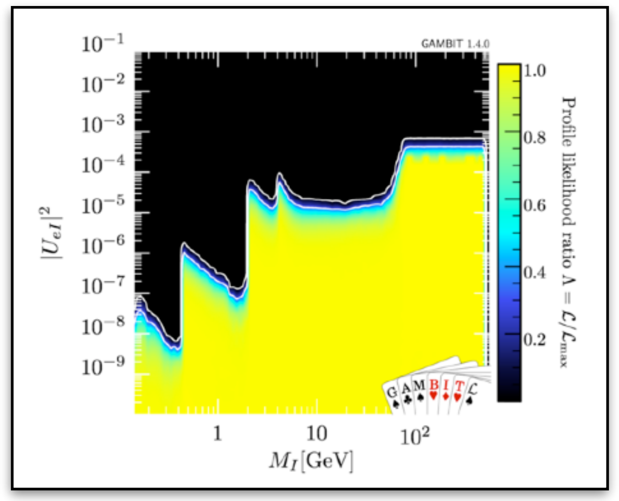
Vector and fermion Higgs portal DM: 1808.10465



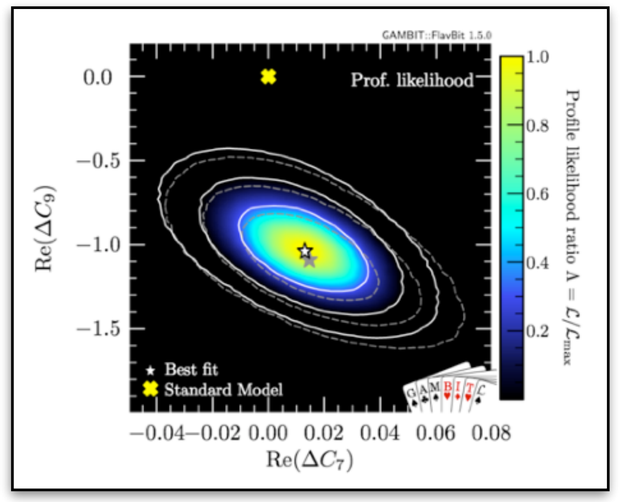
EW-MSSM: 1809.02097



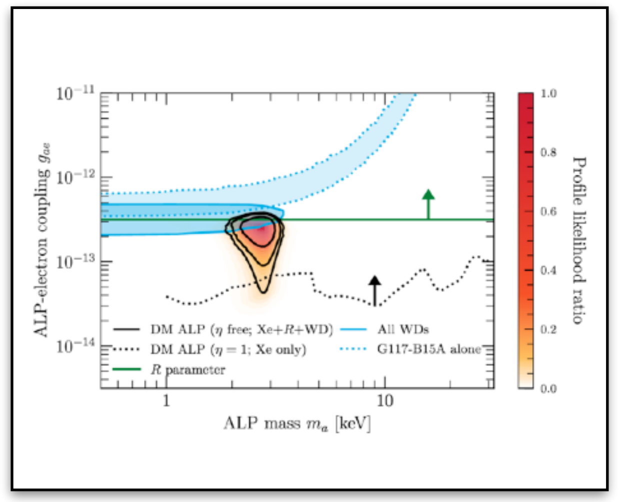
Axion-like particles: 1810.07192



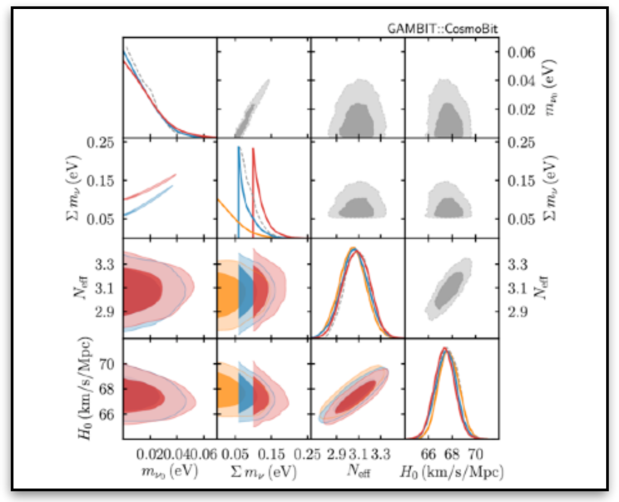
Right-handed neutrinos: 1908.02302



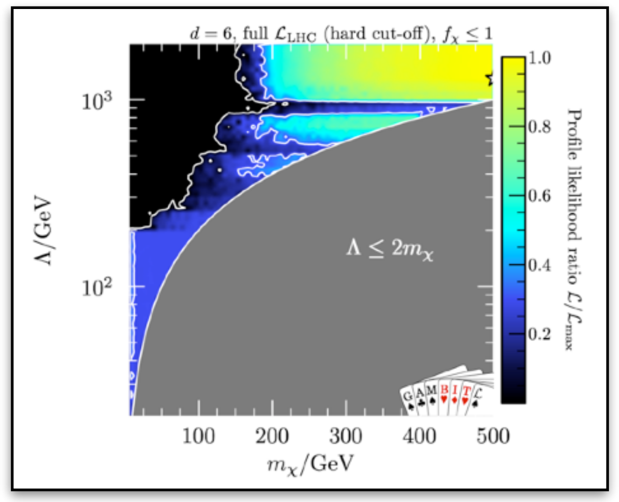
Flavour EFT: 2006.03489



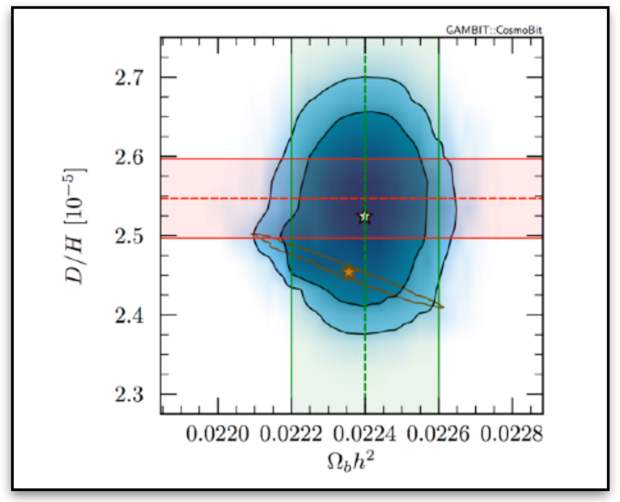
More axion-like particles: 2007.05517



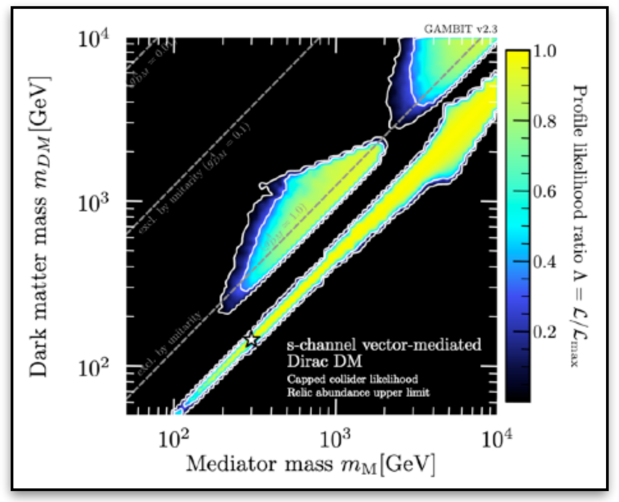
Neutrinos and cosmo: 2009.03287



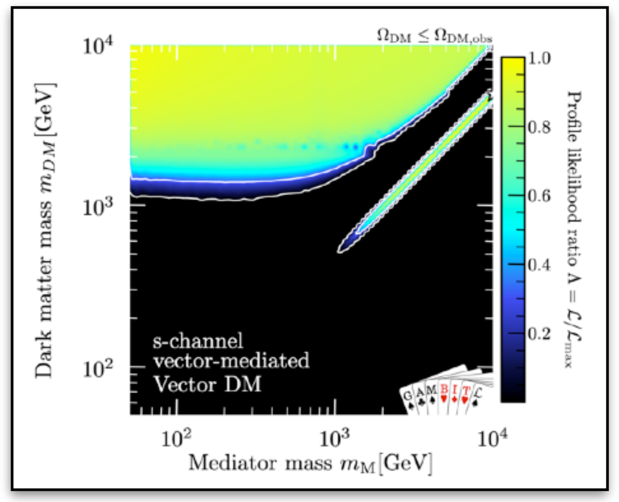
Dark matter EFTs: 2106.02056



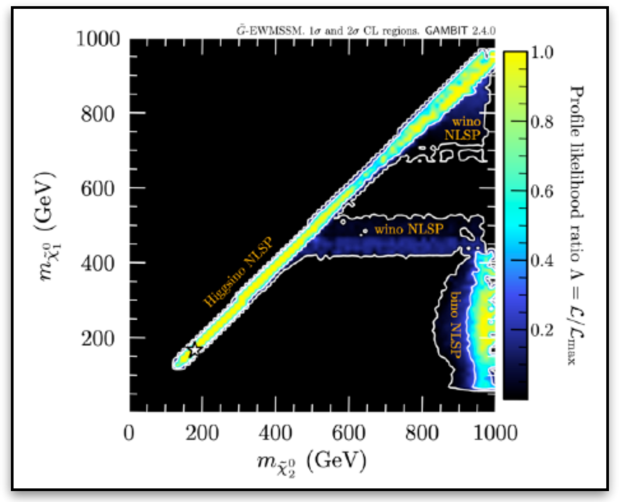
Cosmo ALPs: 2205.13549



Simplified DM, scalar/fermion: 2209.13266



Simplified DM, vector: 2303.08351



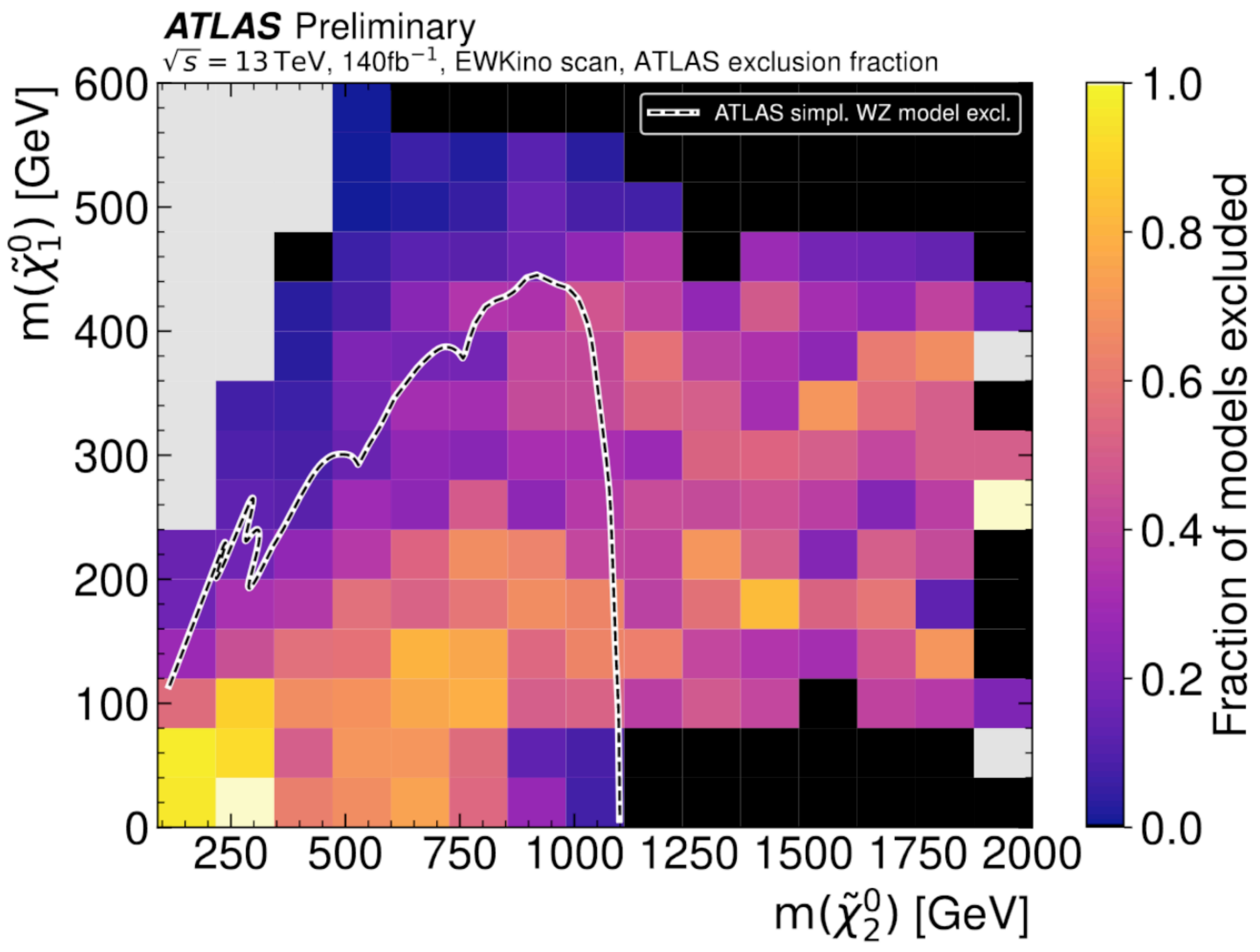
EW-MSSM w/ light gravitino: 2303.09082

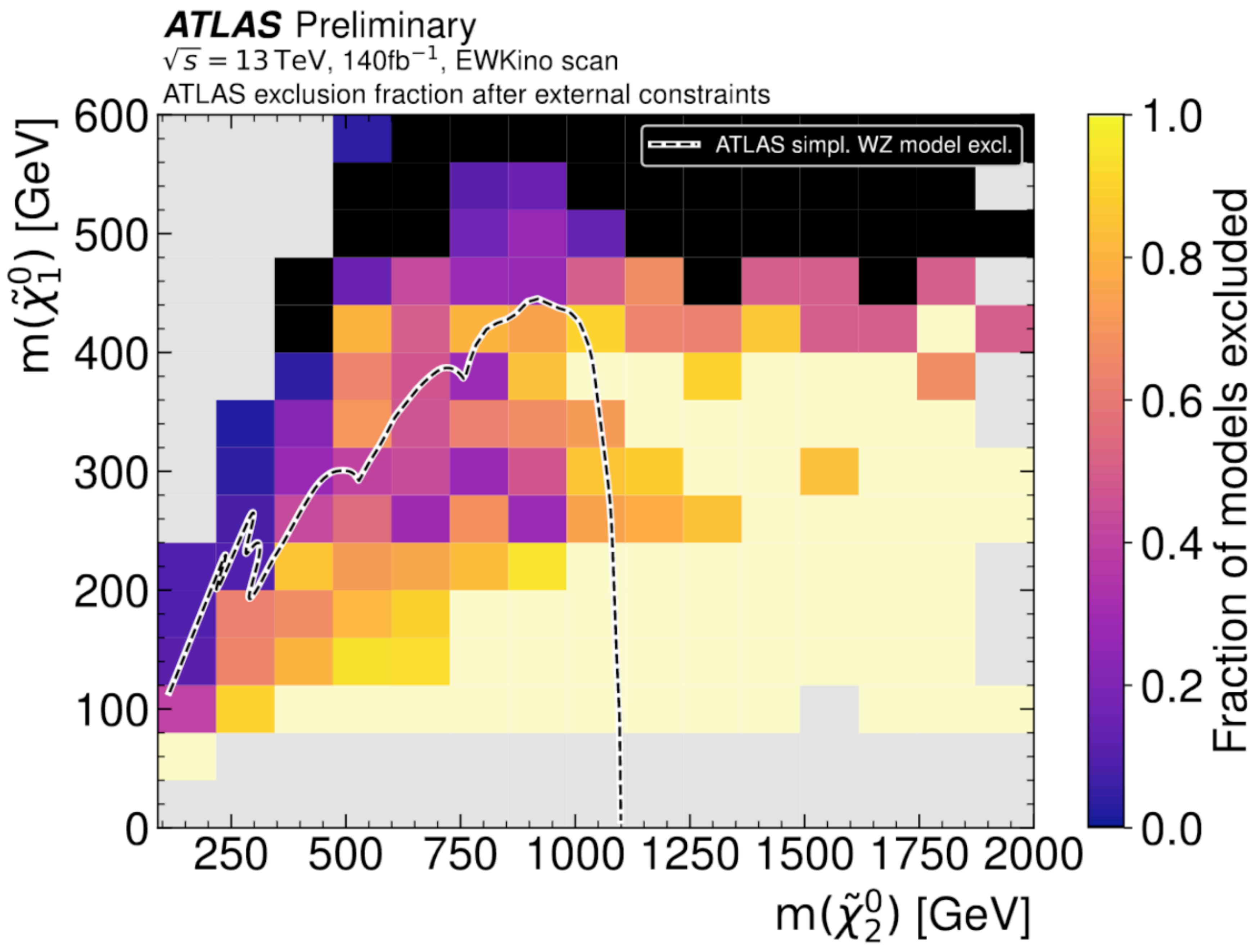
1. **The many interpretations of reinterpretation**
2. **How we can learn more**
3. **A recent SUSY reinterpretation example**
4. **Some challenges for reinterpretation**
5. **Moving forward: how to best help each other?**

1. The many interpretations of reinterpretation

There are many types of reinterpretation

- **Analysis preservation and reuse internally in an experiment**
  - High accuracy (full access to analysis details, full detector simulation, …)
  - High computational cost per model point

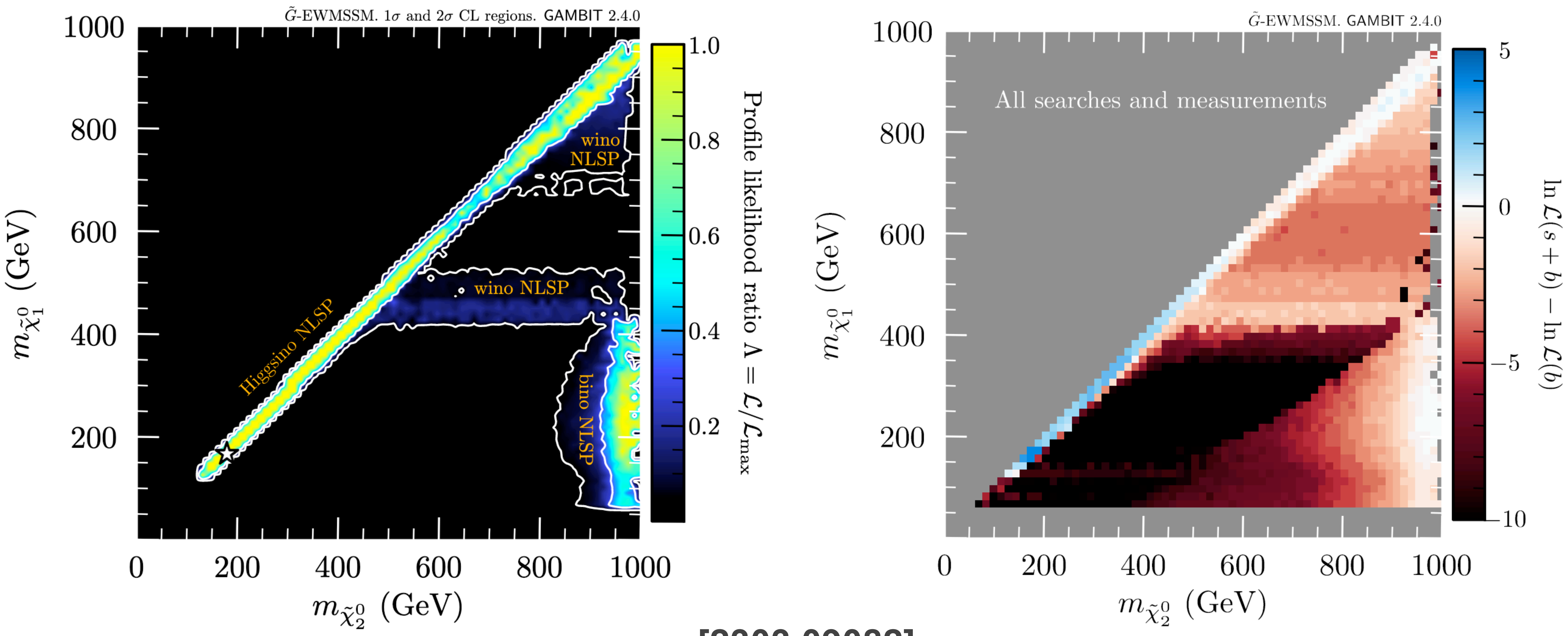




[ATLAS-CONF-2023-055]

There are many types of reinterpretation

- **Simulation-based reinterpretation by outside groups**
  - Medium accuracy (faster simulations, reimplementing analyses from public info, …)
  - Medium-to-high computational cost per model point



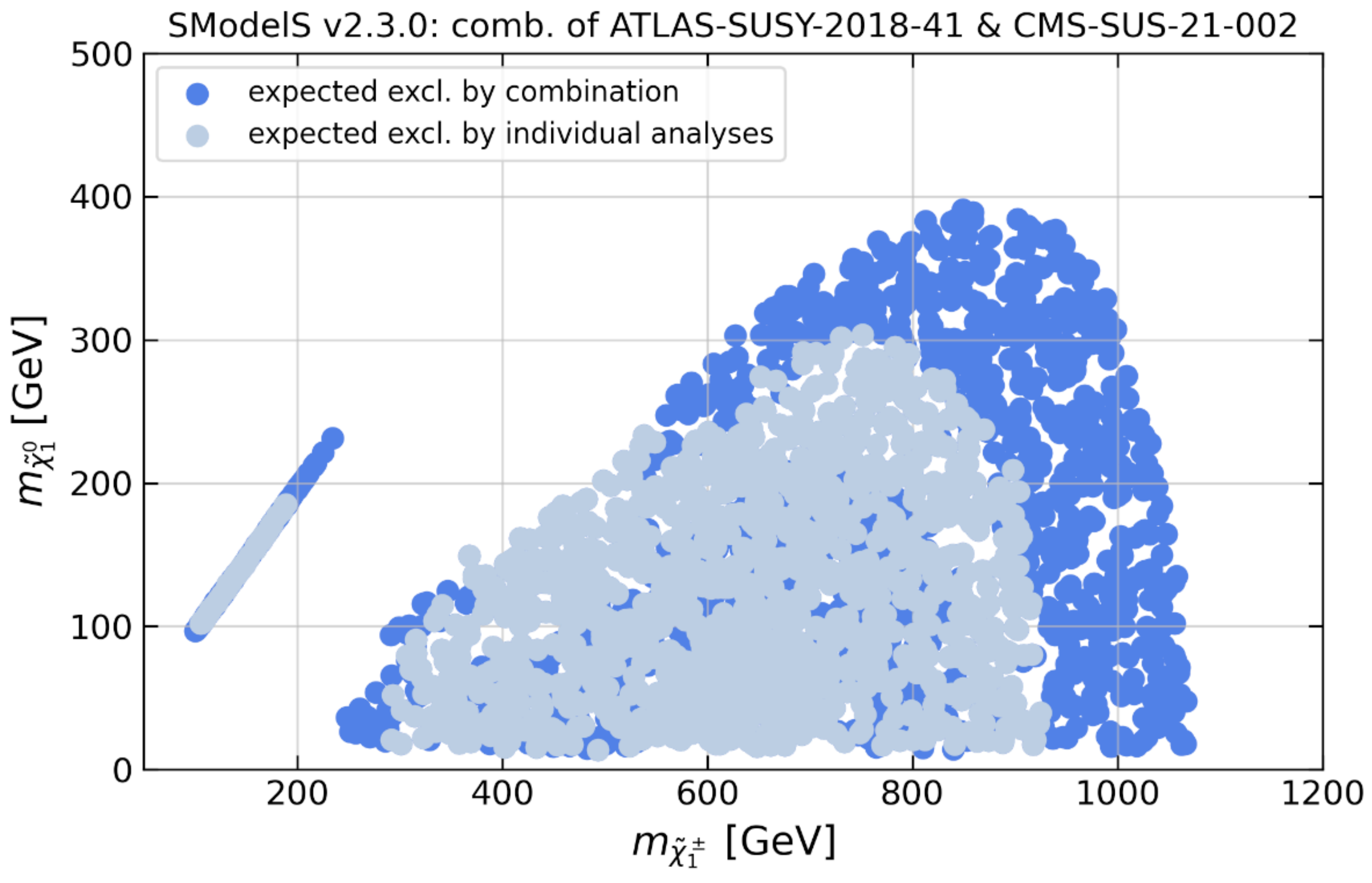
[2303.09082]

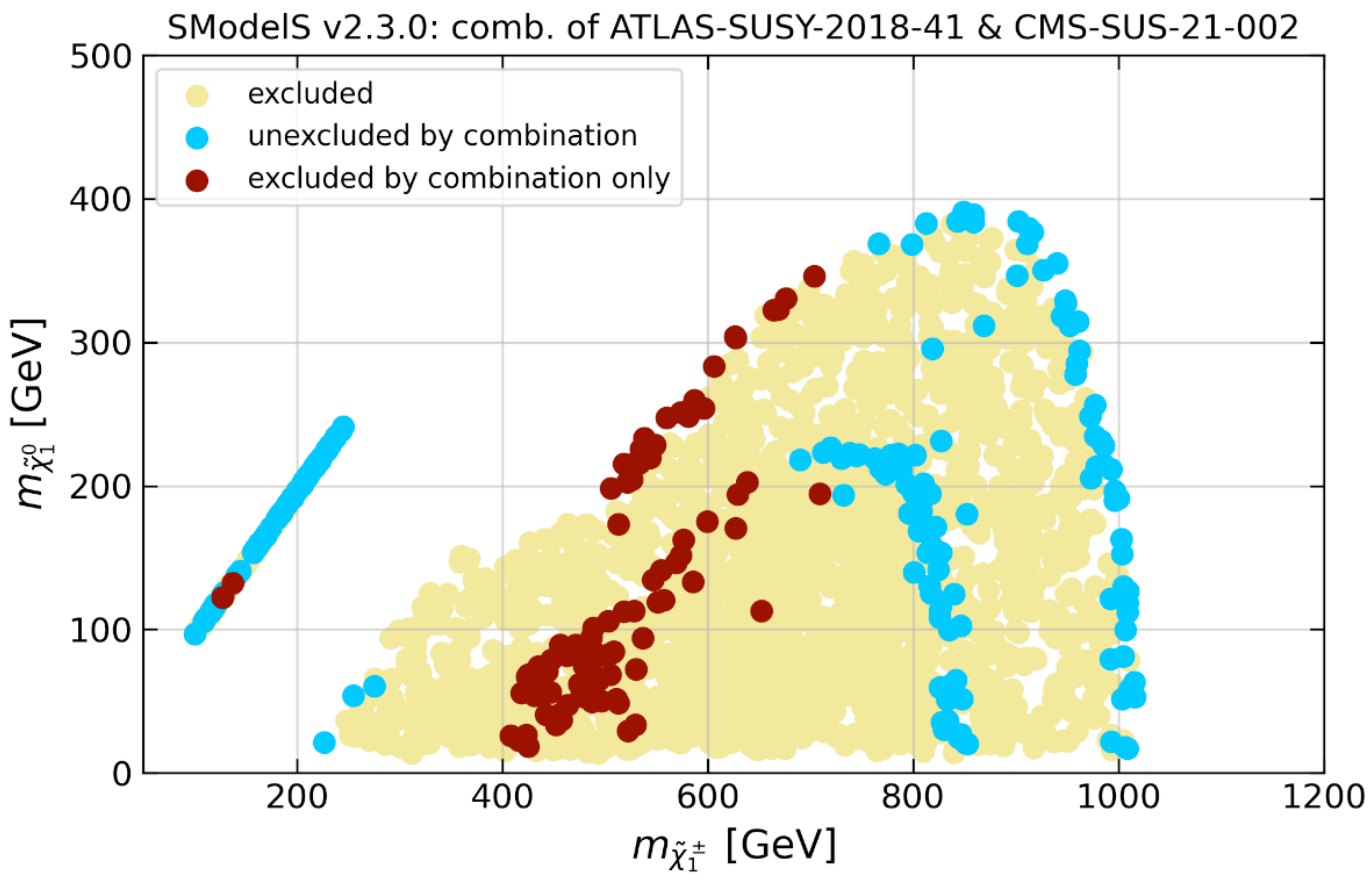
- MadAnalysis
- CheckMATE
- GAMBIT (ColliderBit)
- Contur+Rivet
- …

There are many types of reinterpretation

- **Simulation-less reinterpretation by outside groups**
  - Medium accuracy
  - Reduced exclusion sensitivity compared to simulation-based methods
  - (Very) low computational cost per model point

- SModelS
- HiggsTools
- DarkCast
- …

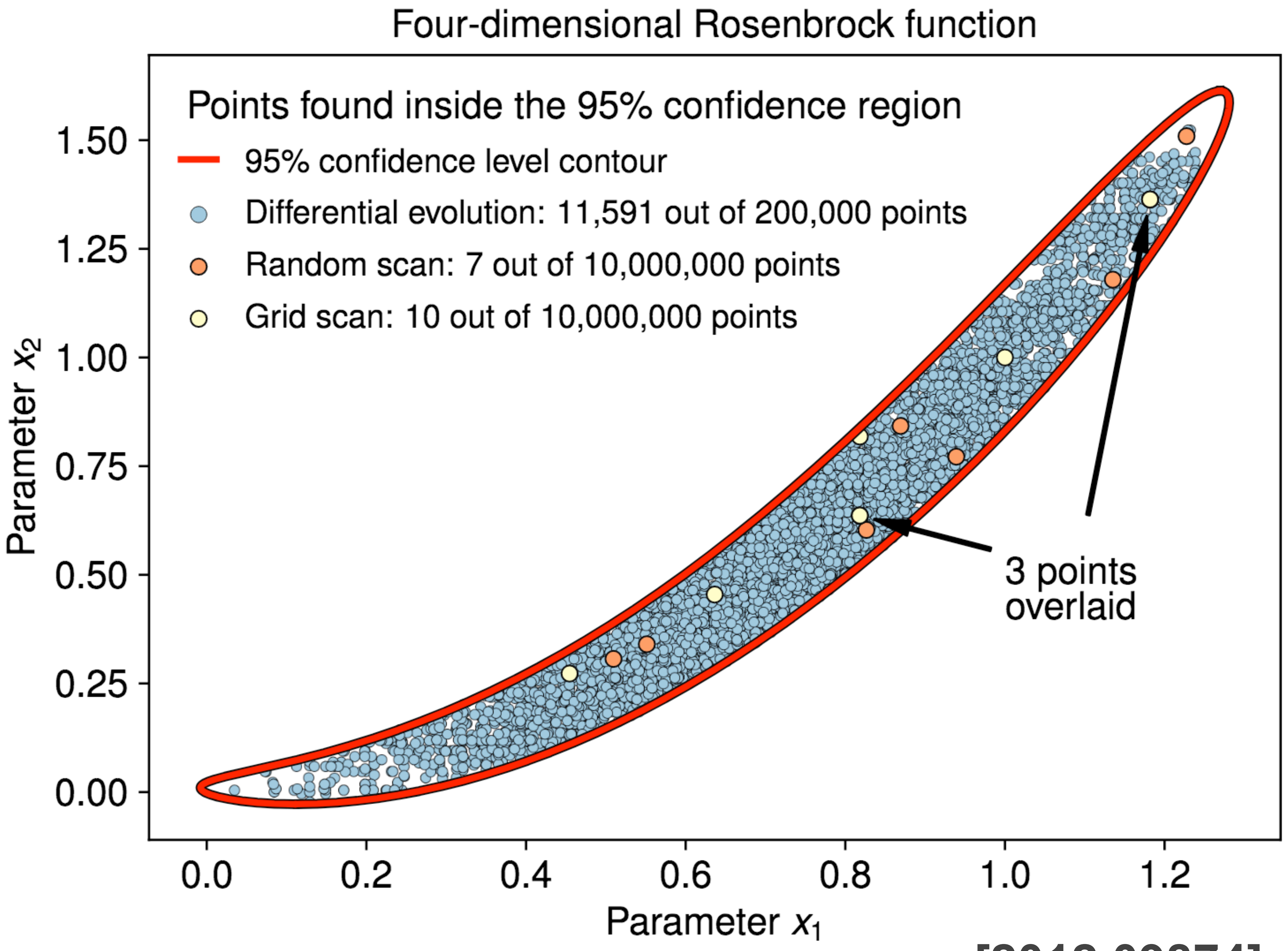




[2306.17676]

Why the need for speed?

- First, BSM parameter spaces are **high-dimensional**!
  - And theorists have limited CPU resources :)
- Second, in **global fits** we seek statistically rigorous conclusions about **regions of BSM parameter spaces**
  - Need properly **converged** explorations of the **likelihood function / posterior distribution**
  - Must use **adaptive sampling algorithms**, that focus on higher-likelihood regions
  - So the problem is **not trivially parallelisable** (we can't just sample first, simulate later)



[2012.09874]

2. How we can learn more

- From Roberto Franceschini’s talk on Monday:

When I say “complete” I mean that

- it is quite hard to find an experimental signature that can be attained in another model and cannot be attained in SUSY (including possible R-parity breaking)
- the model also comes with “some” way to judge how likely it is the particular signal at hand (how much do I have to sweat to get this signal in a particular model)
- the model allows to derive the experimental implications of observing such signal (what other signals should I see besides this?)

ROBERTO FRANCESCHINI - 2023 OSLO ATLAS SUSY WORKSHOP - HTTPS://INDICO.CERN.CH/EVENT/1322199/

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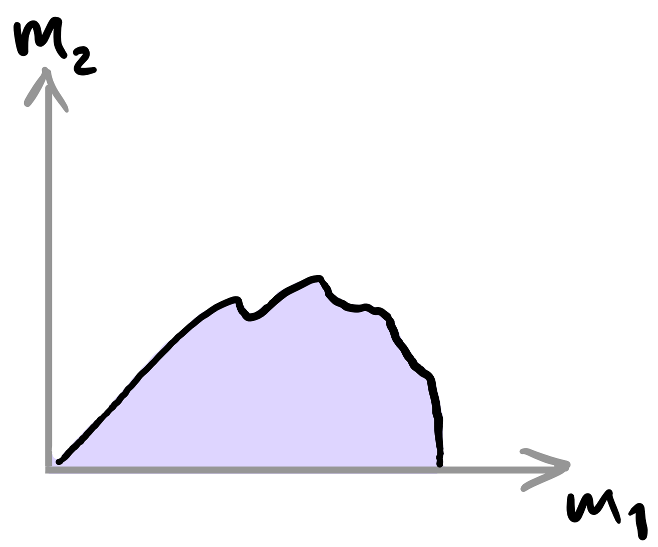
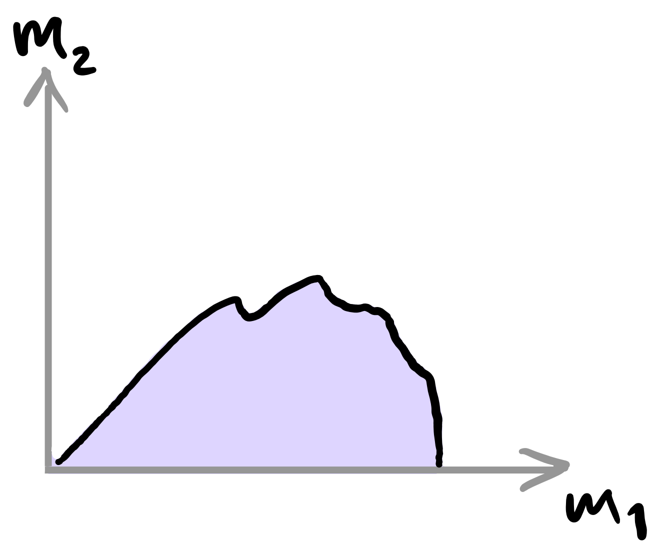
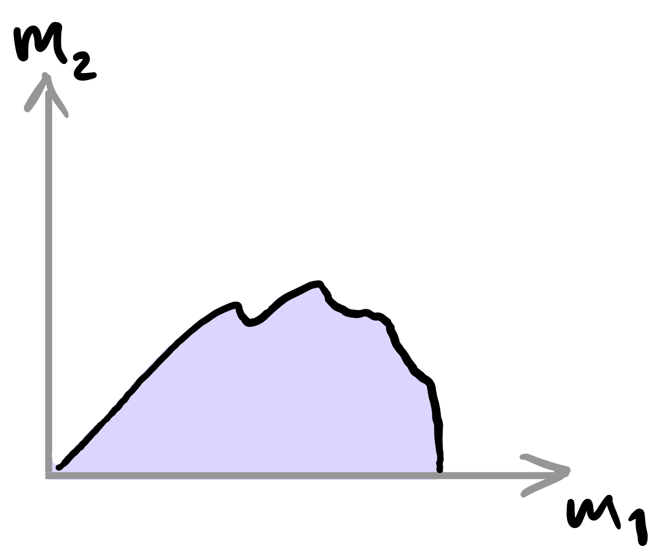
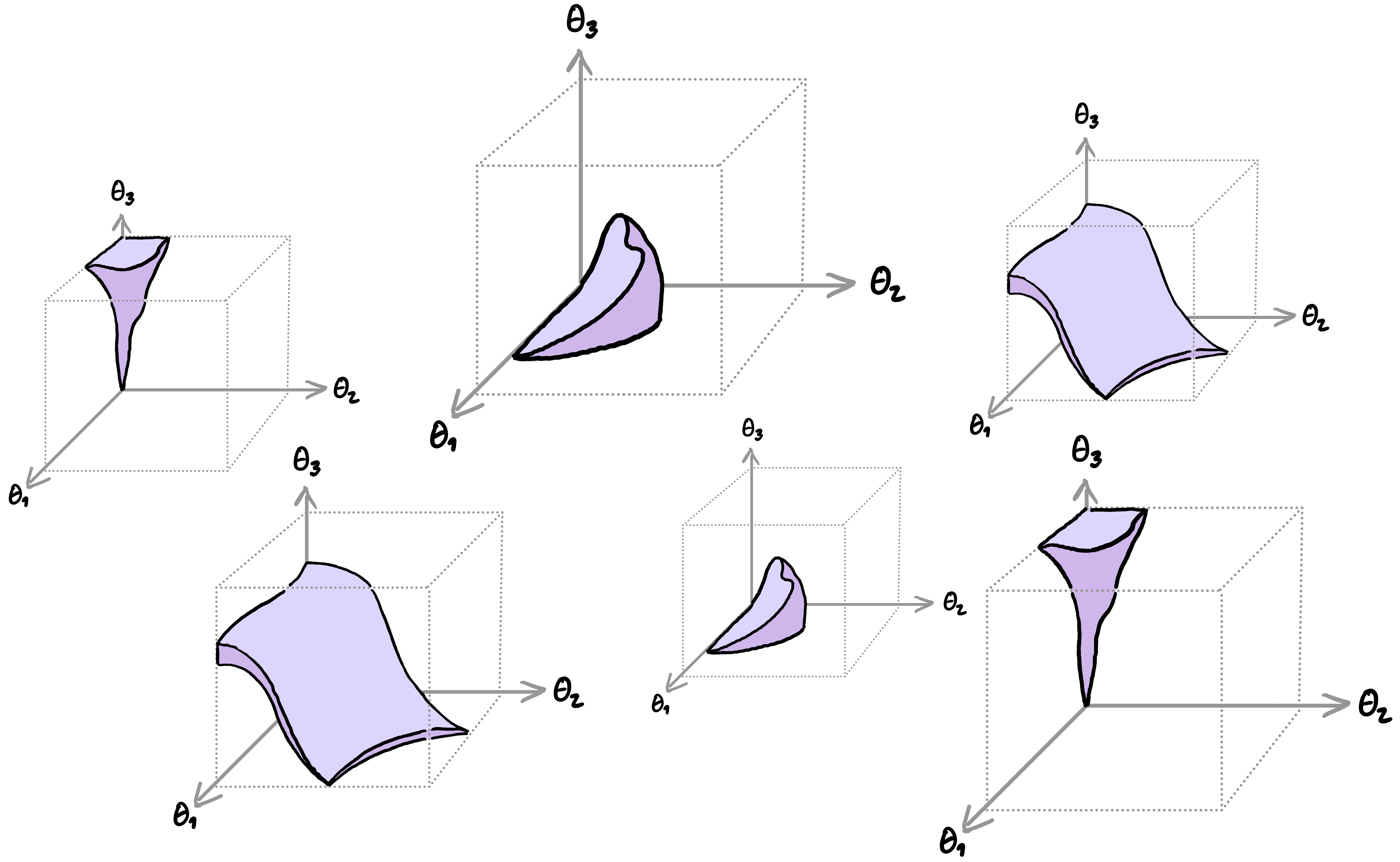
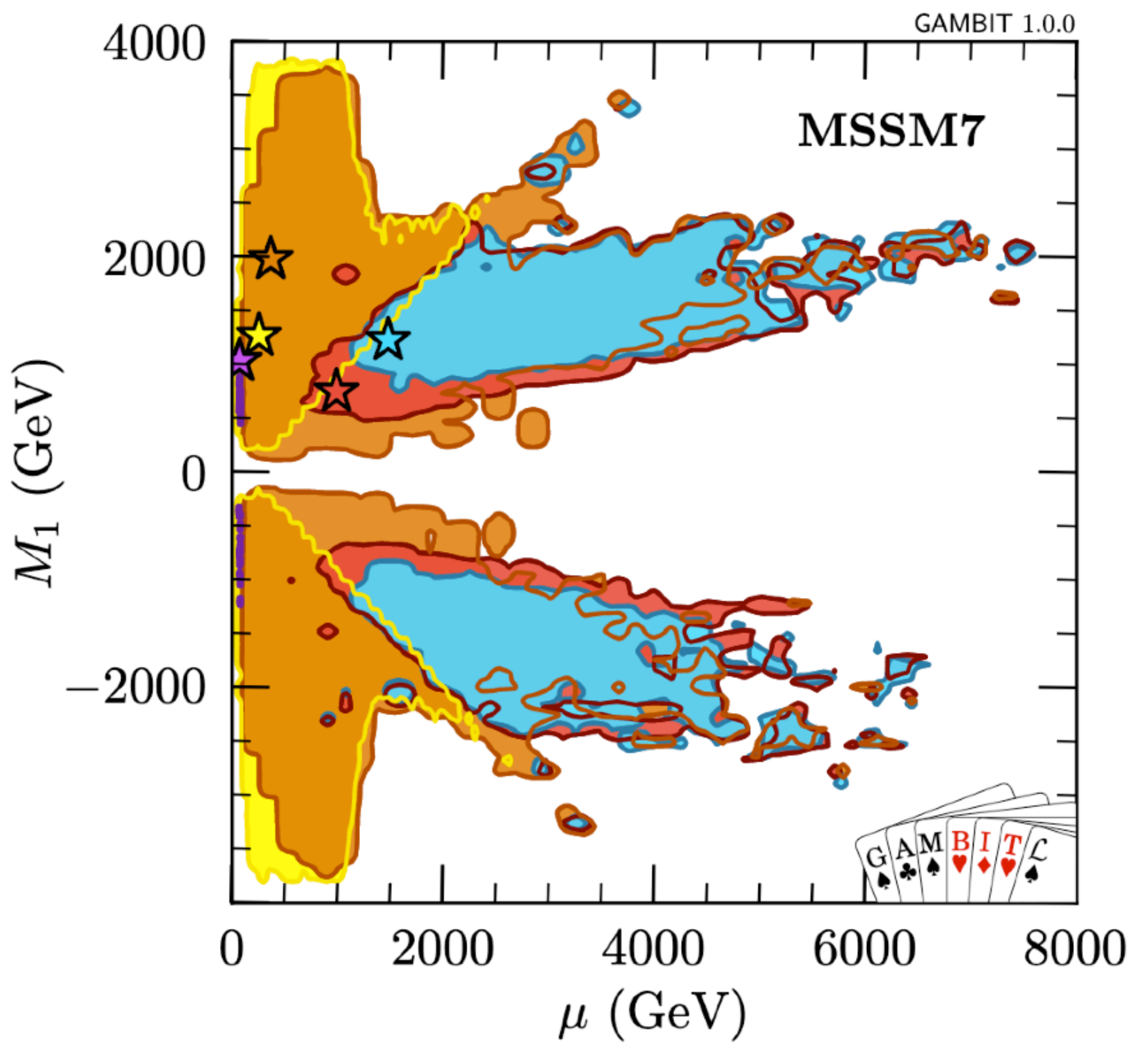
All the hard-won event counts with background estimates from the LHC SUSY programme hold **a lot** of information about BSM theory space.

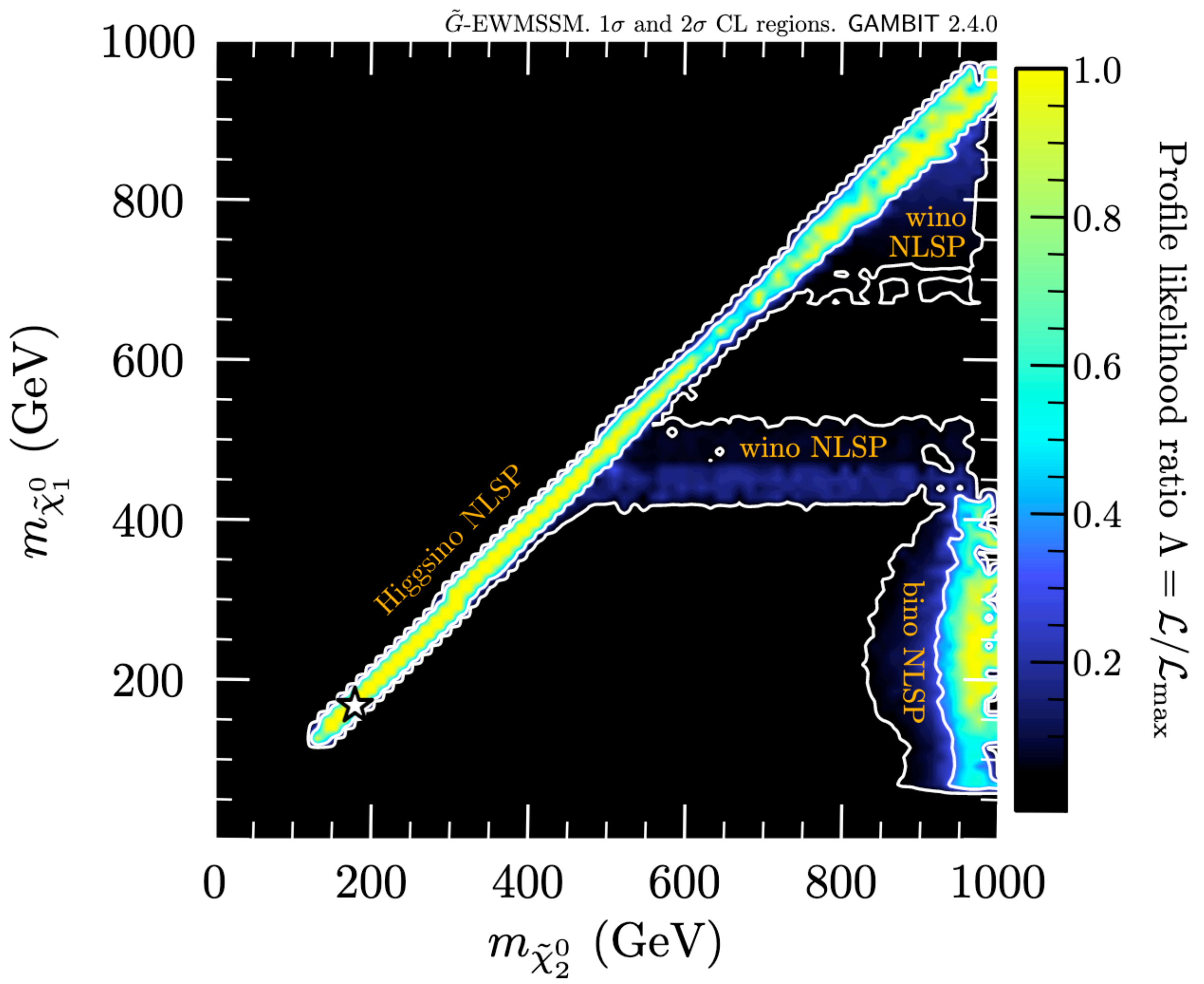
	What we have learned at time of publication		What we have learned long after publication
Impossible to reinterpret		→	
Possible to reinterpret		→	

Learning more #1:

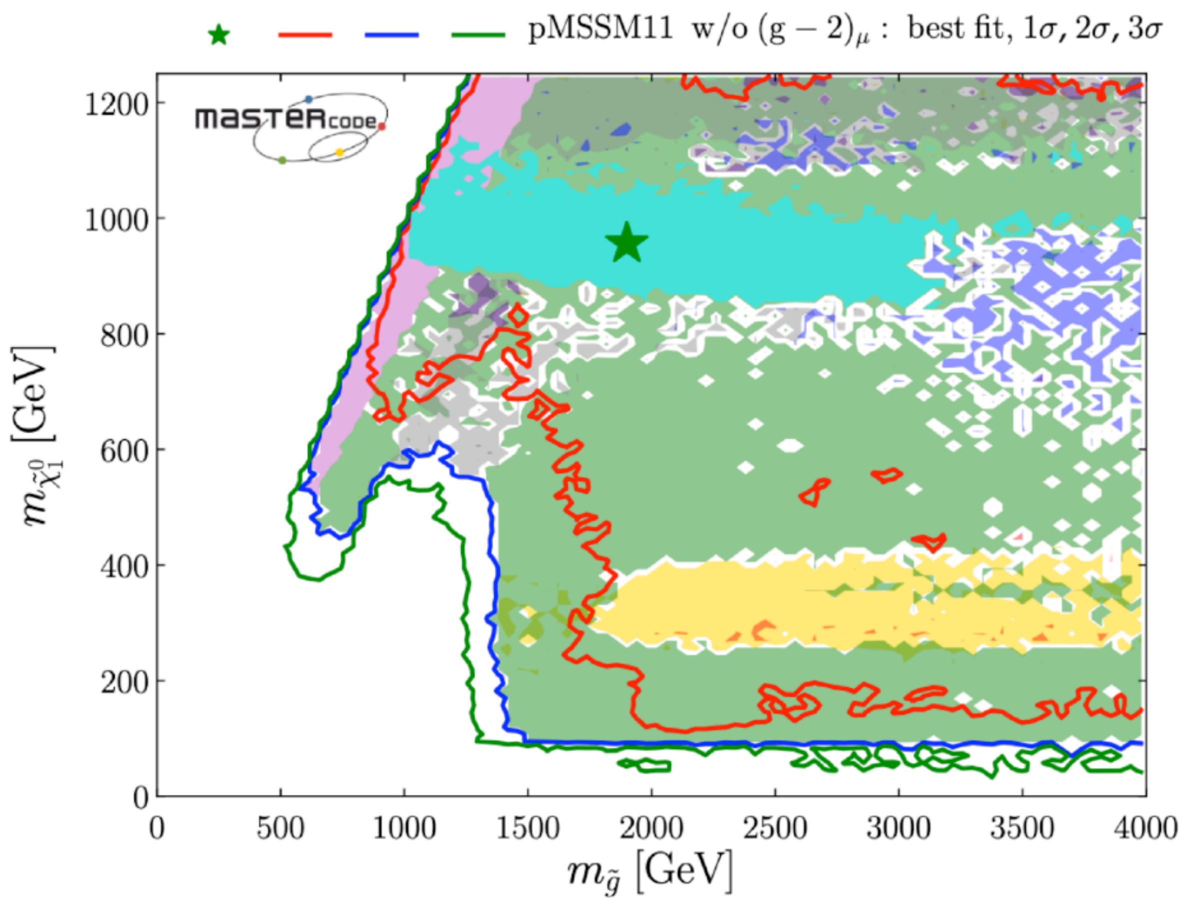
We can probe much more of SUSY theory space



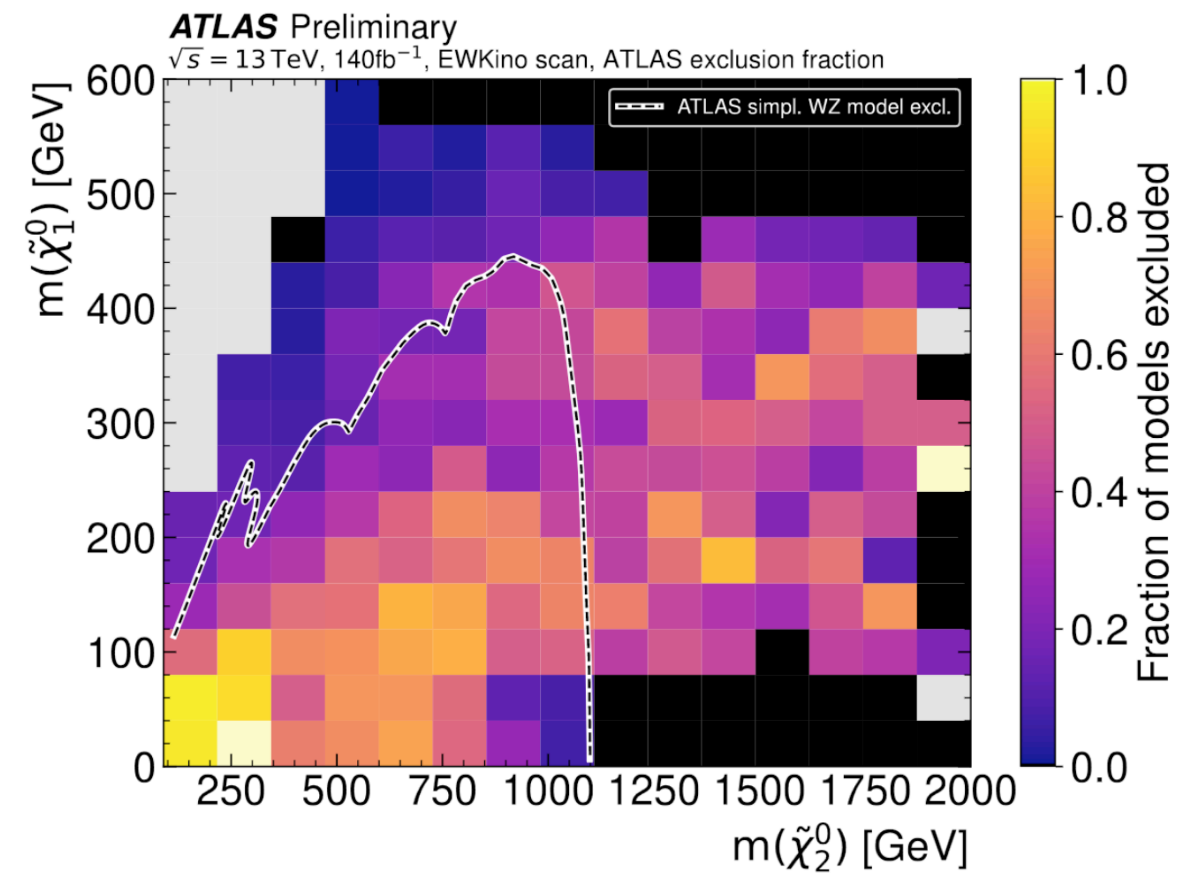
[1705.07917]



[2303.09082]



[1710.11091]



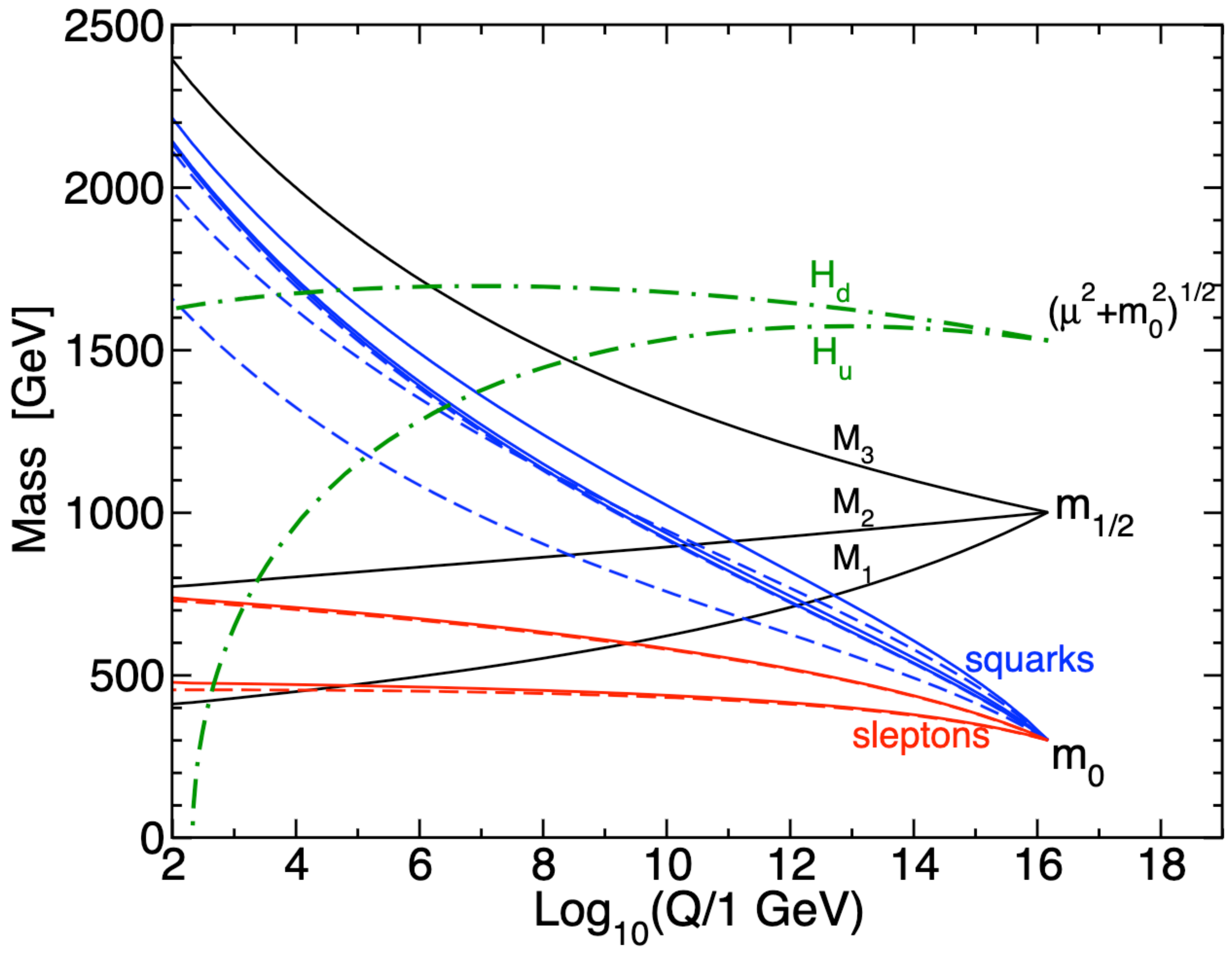
[ATLAS-CONF-2023-055]

Reminder:
Theory space is a strange, implausible place

- «Everyone» would assign **negligible prior belief** to **almost all points** in the **low-scale MSSM parameter space**
- MSSM expresses our ignorance of SUSY breaking
- Any «elegant»/«economic»/«reasonable» high-scale model maps to some tiny subspace of the low-scale MSSM
- And any simplified model plane maps to some strange hypersurface through low-scale MSSM

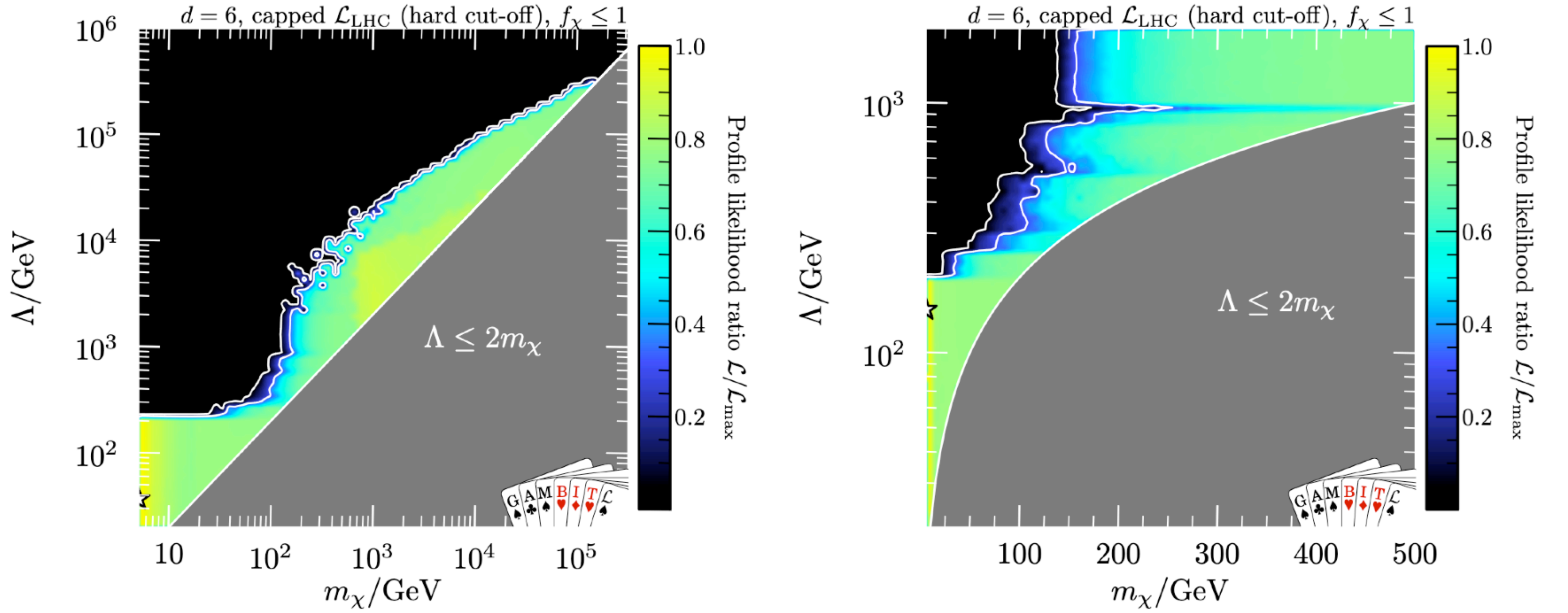
- A «large» exclusion in simplified model space:
    - **Maybe large**, **maybe small** impact on MSSM

- A «large» exclusion in low-scale MSSM
    - **Maybe decisive**, **maybe negligible** impact on the space of plausible high-scale models

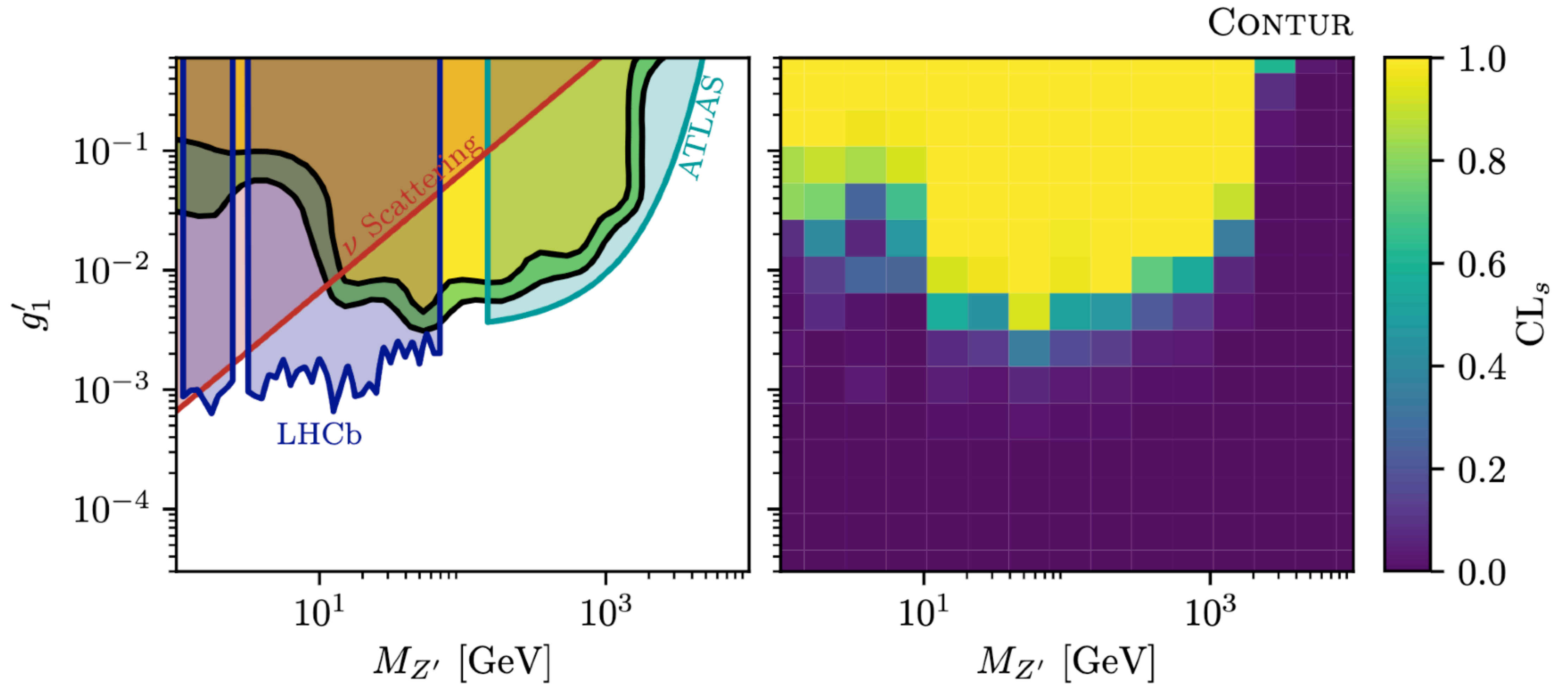


[hep-ph/9709356]

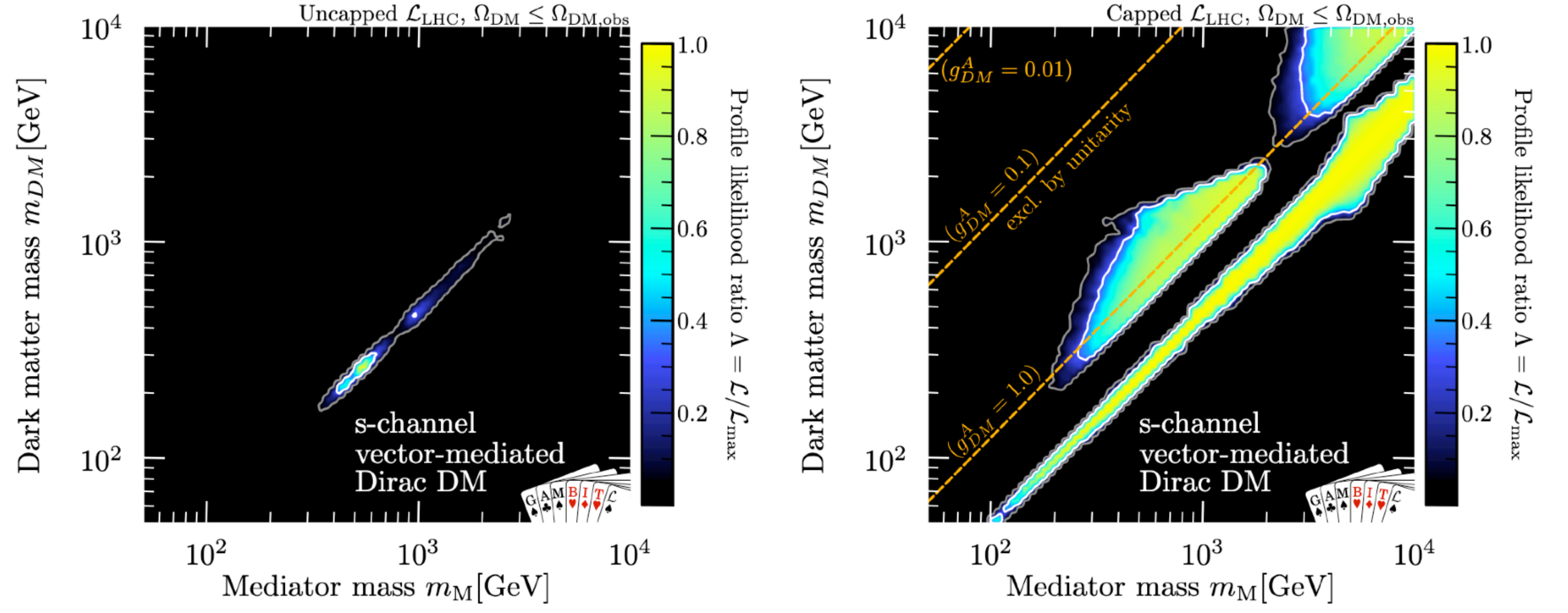
Learning more #2:
We can probe much more of BSM theory space



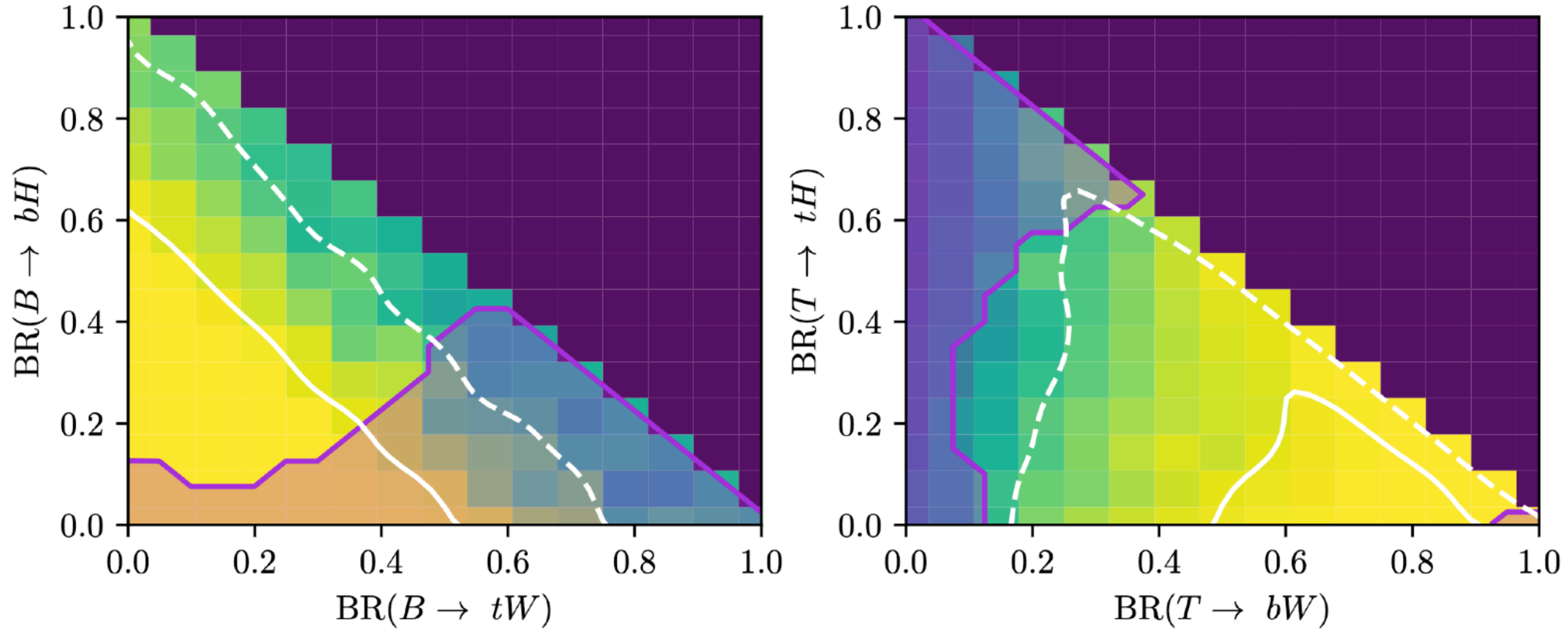
DM EFTs [2106.02056]



B-L gauge model [1811.11452]

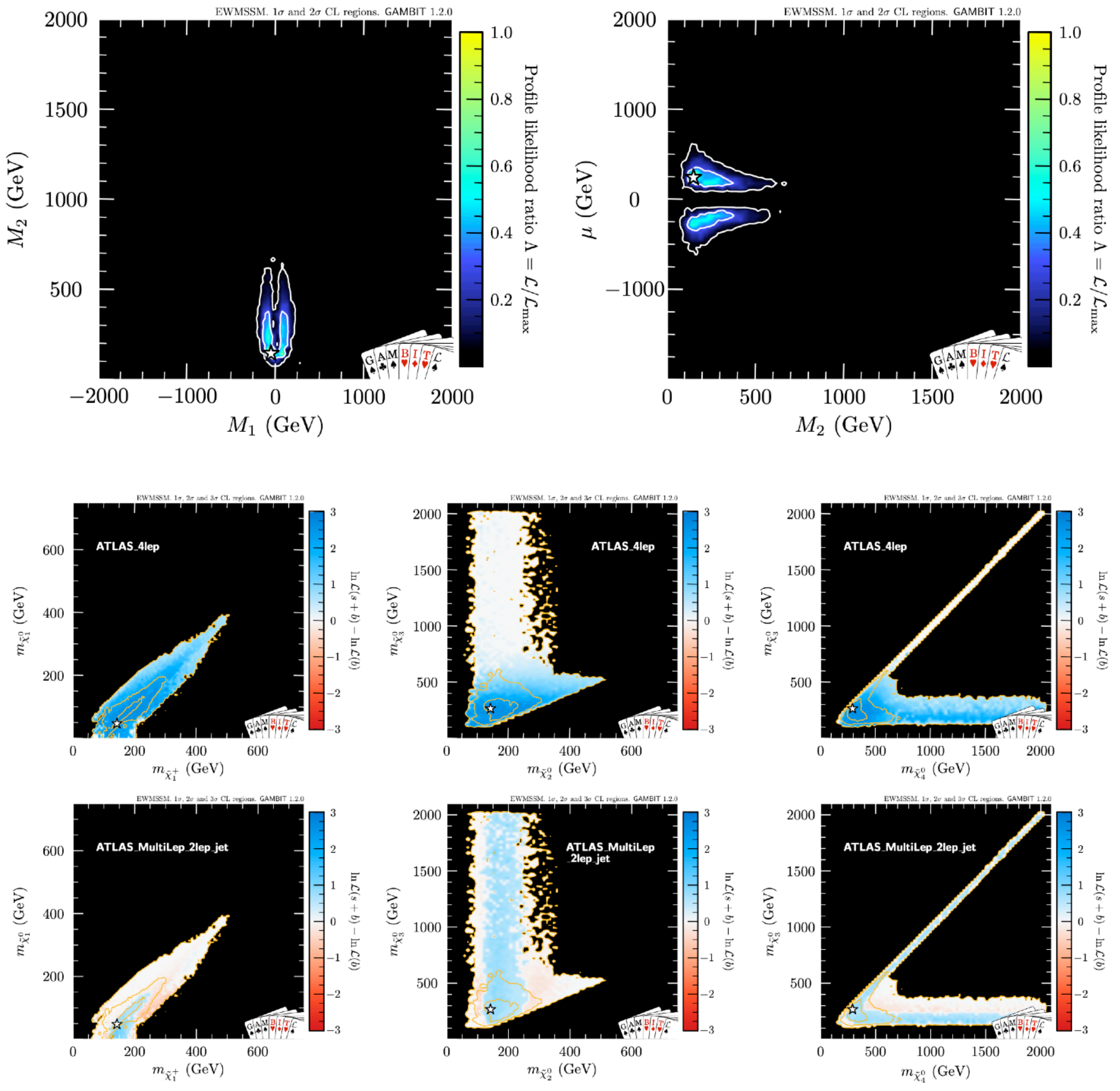


DM w/ vector mediator [2209.13266]

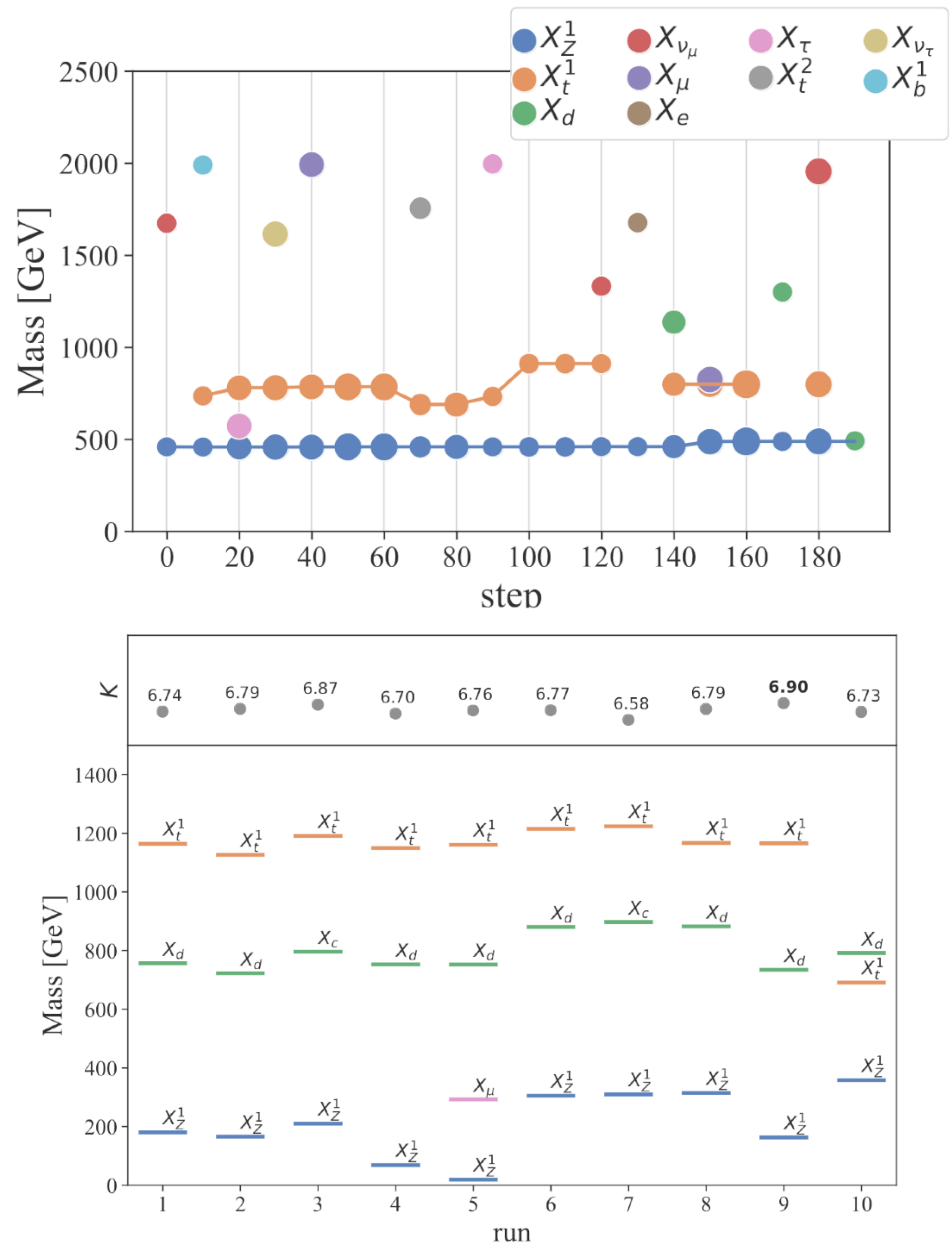


Vector-like quarks [2006.07172]

Learning more #3:
We can identify best-fit scenarios

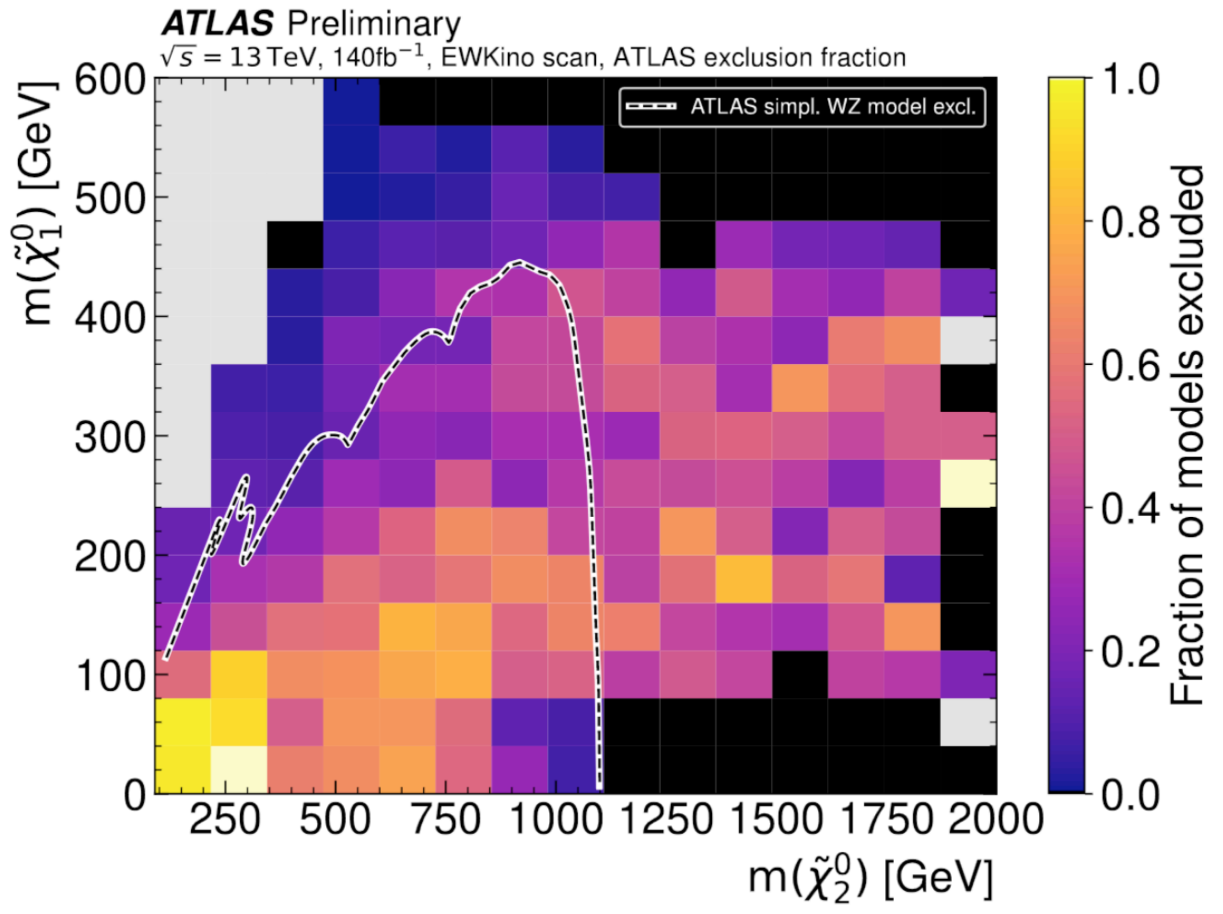


Explore MSSM EWino sector [1809.02097]

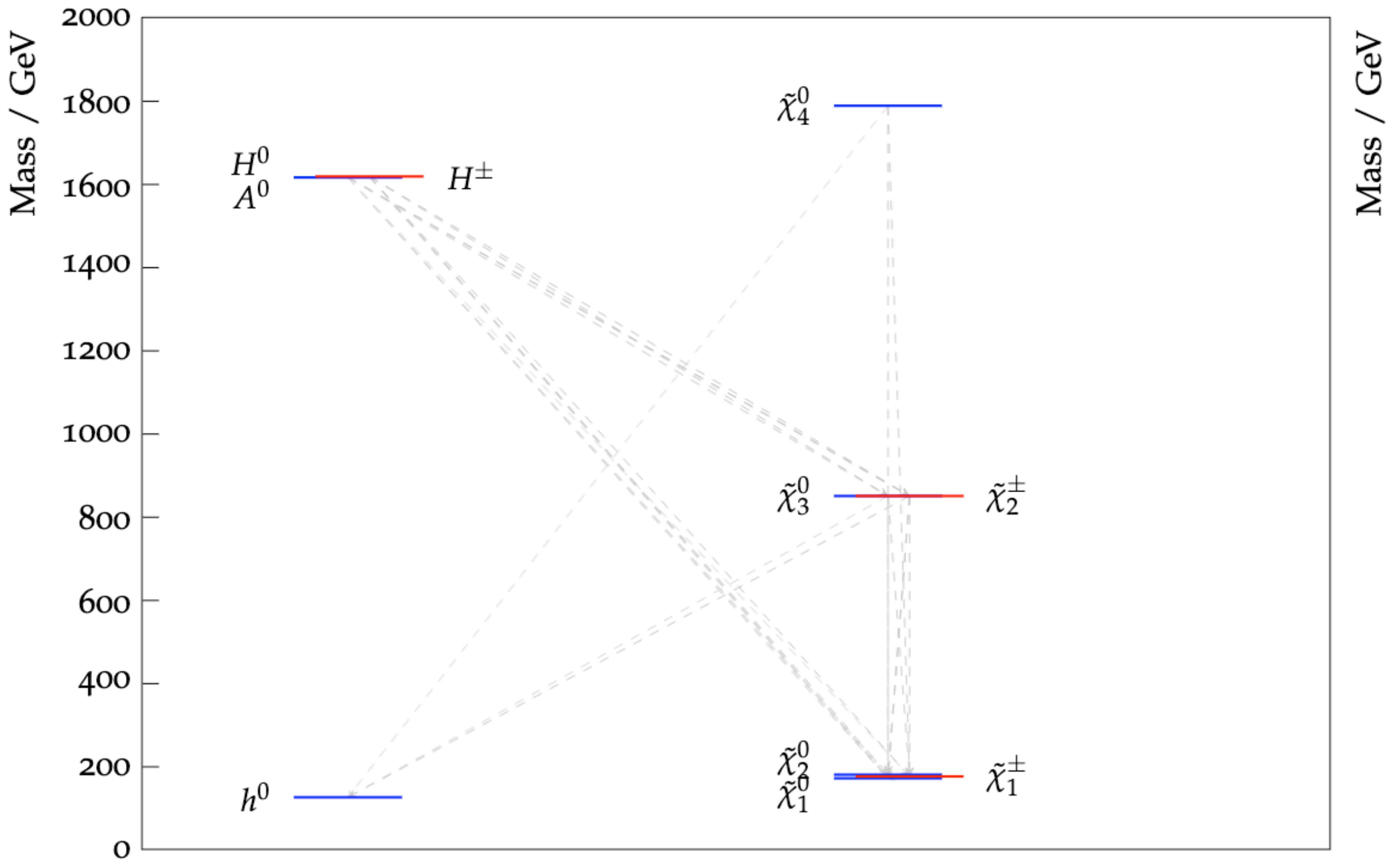


Explore space of simplified models [2012.12246]

Learning more #4:
We can learn how to plug «holes» in theory space

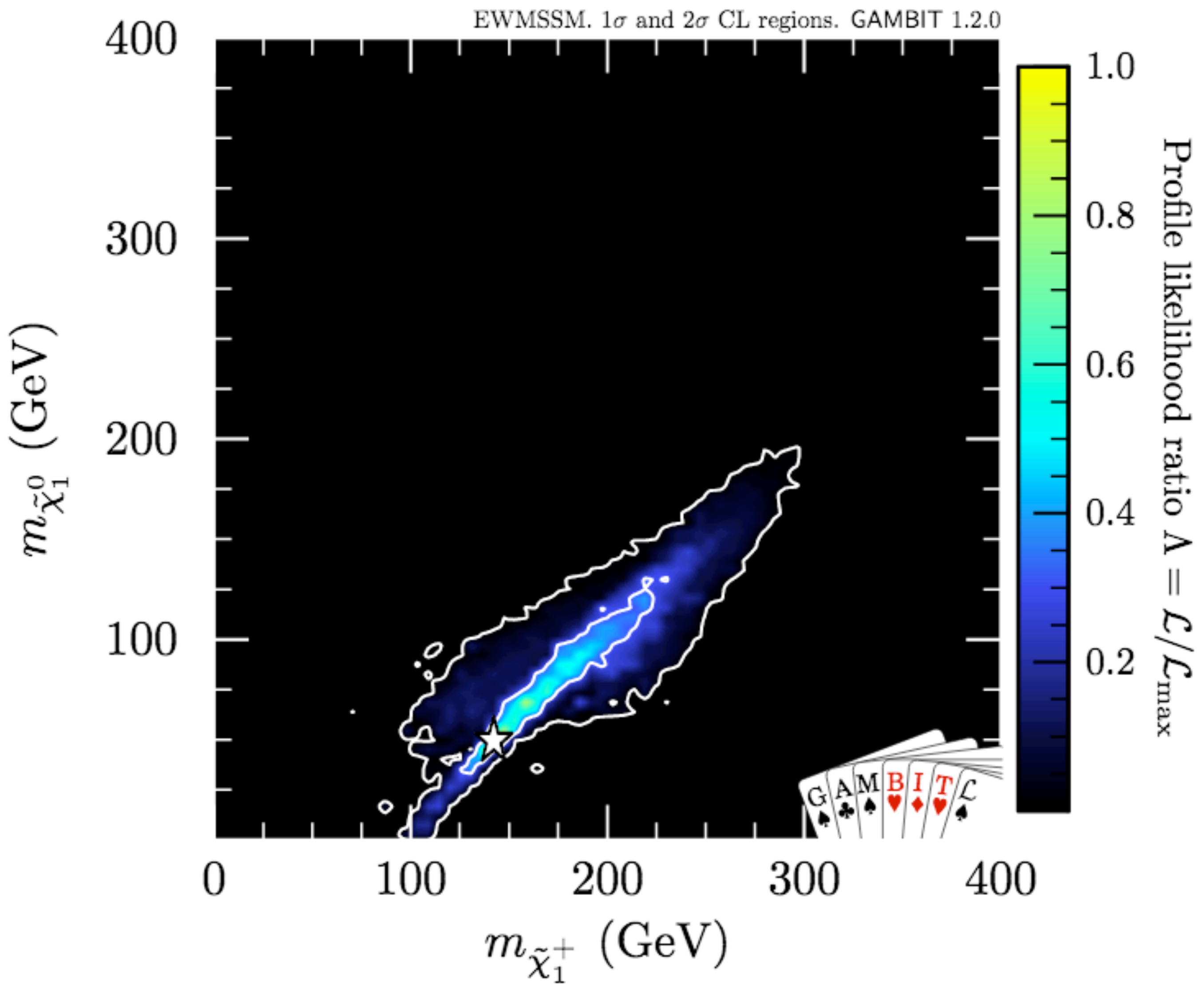


[ATLAS-CONF-2023-055]

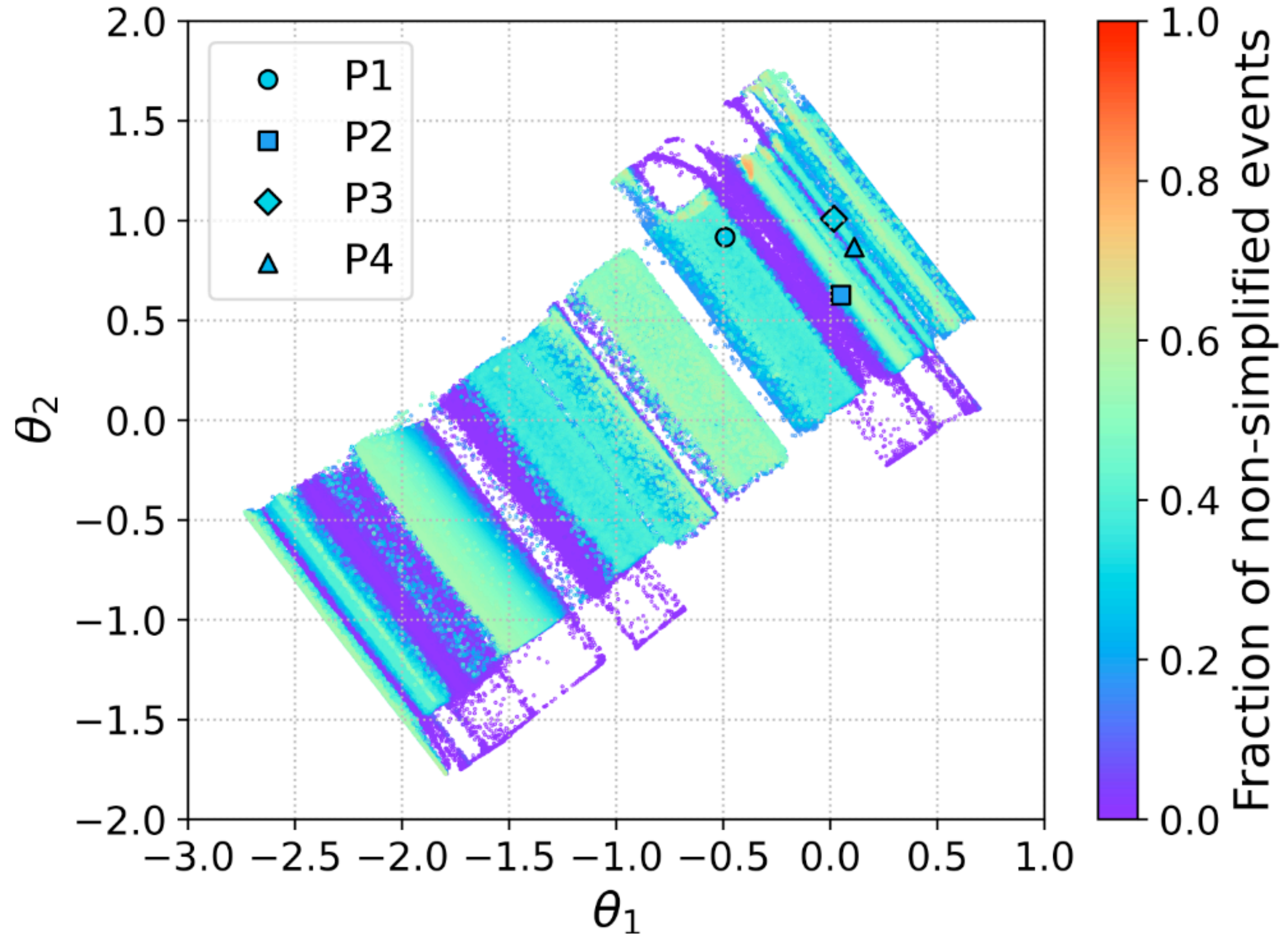


- Example:
  - Light Higgsinos, heavier winos
  - Dominant production mode can be the heavier wino pair (if not too heavy)

Learning more #4:
We can learn how to plug «holes» in theory space



[1809.02097]



[2305.01835]

- Studied benchmark points that survived 36 fb^{-1} searches. Example:
    - 3 Higgsinos ~200 GeV, Δm ~ 40 GeV
    - 2 winos ~ 300 GeV
- Compare to wino/bino simplified model with Δm ~ 100 GeV
    - Main signature is similar: on-shell W + Z + MET
    - But gives **less clean final states**, due to not-necessarily-soft products from decays between higgsinos
    - Replace «simplified model cut» $\mathbf{n_{jets} = 0}$ with a «less simplified» cut $\mathbf{H_T < X}$?

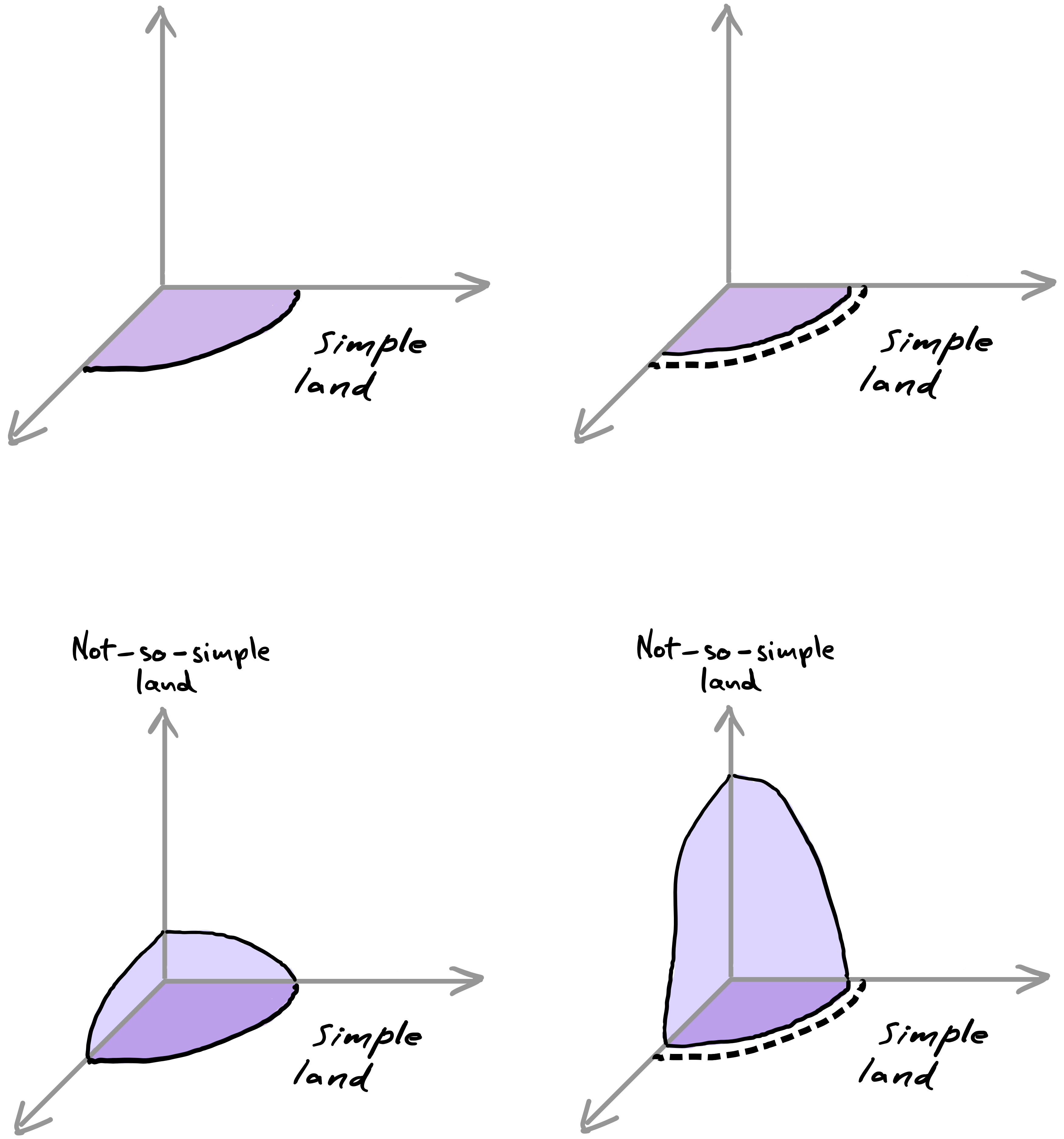
Learning more #4:

W

fb-1

400
300
200
100
$m_{\tilde{\chi}_1^0}$ (GeV)

When optimising searches on simplified models, at what point do we start losing rather than gaining sensitivity to volumes of «similar» theory space?

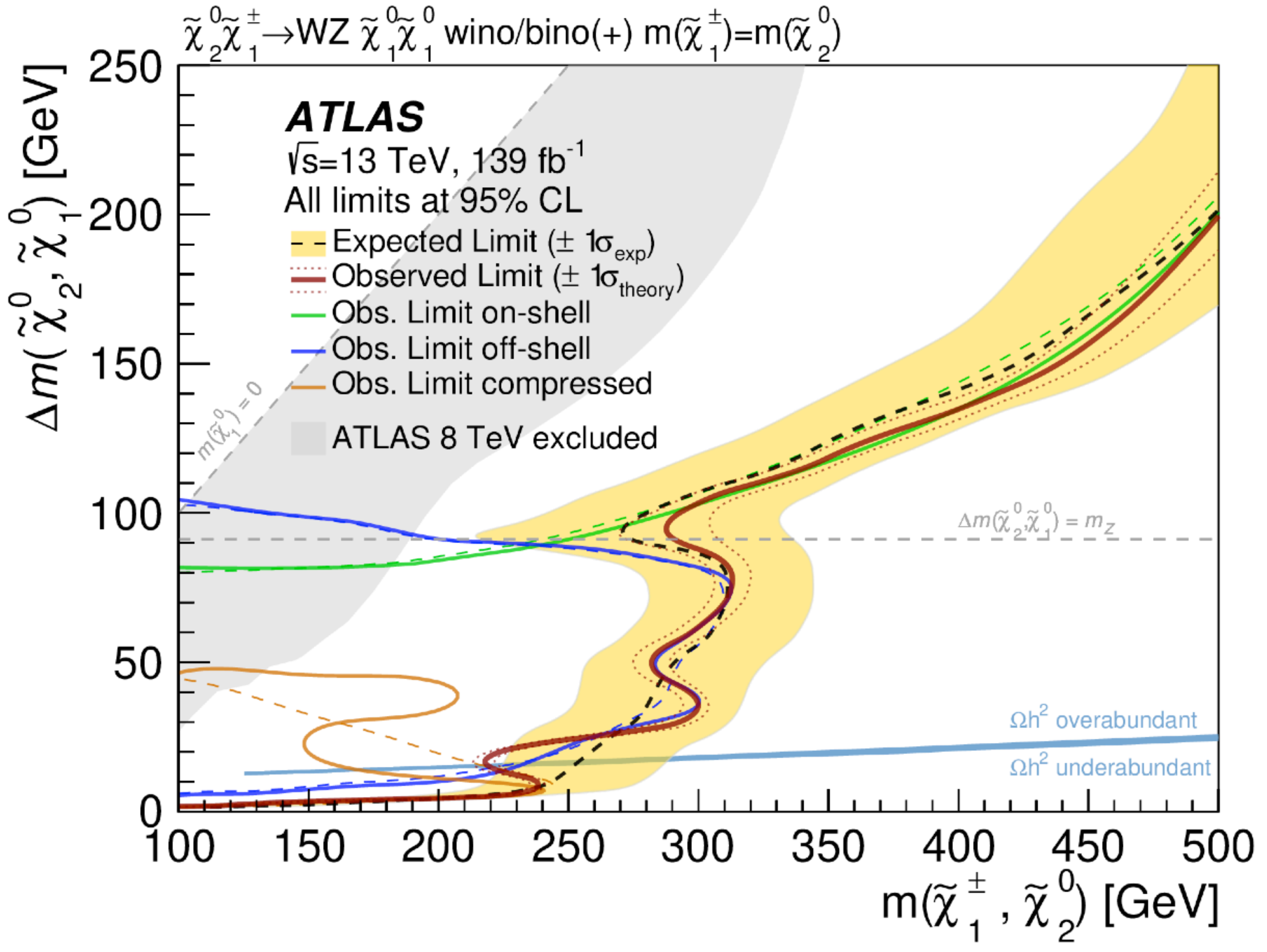


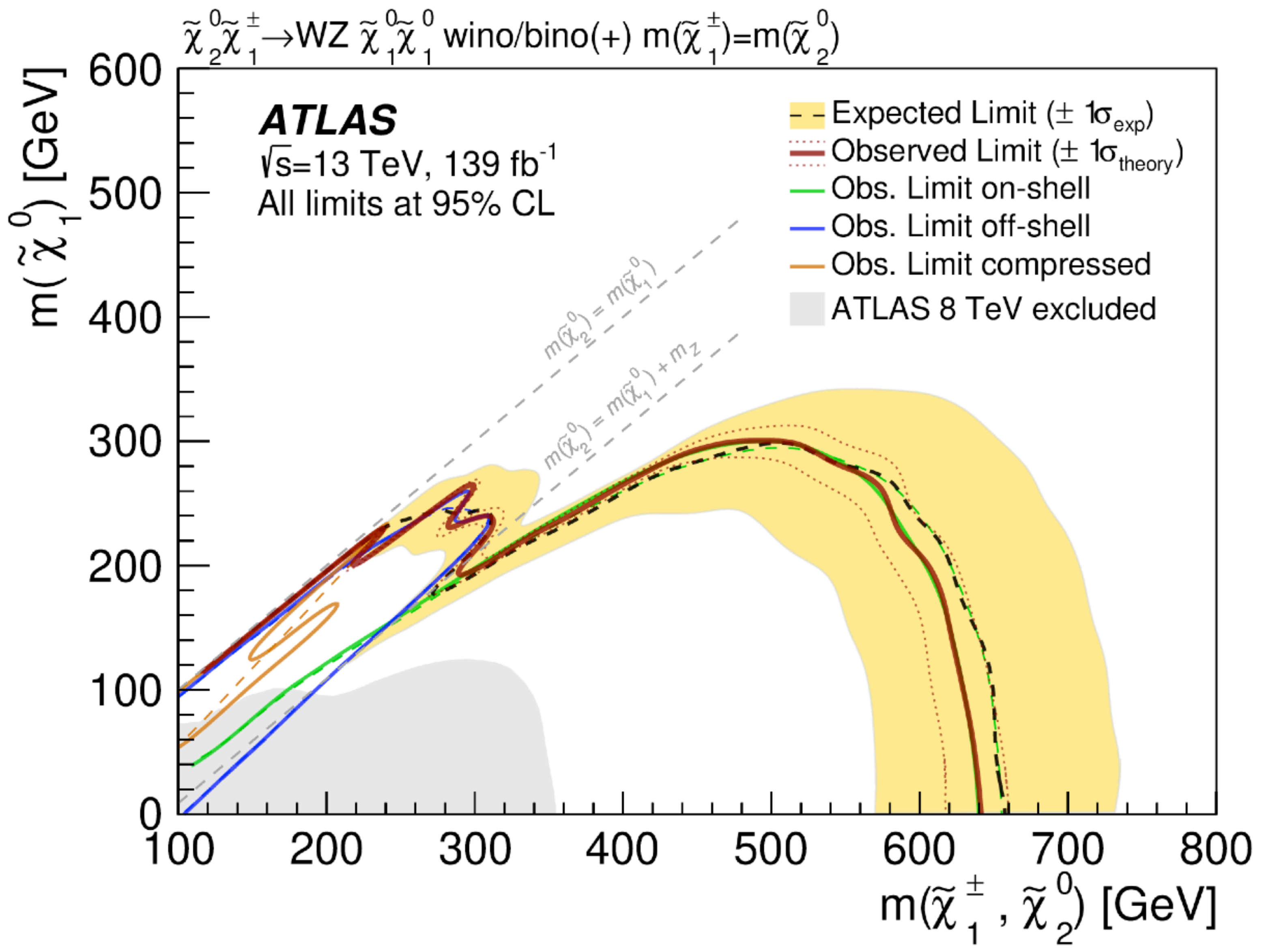
Δm

to
cays

with a «less simplified» cut $\mathbf{H_T < X}$?

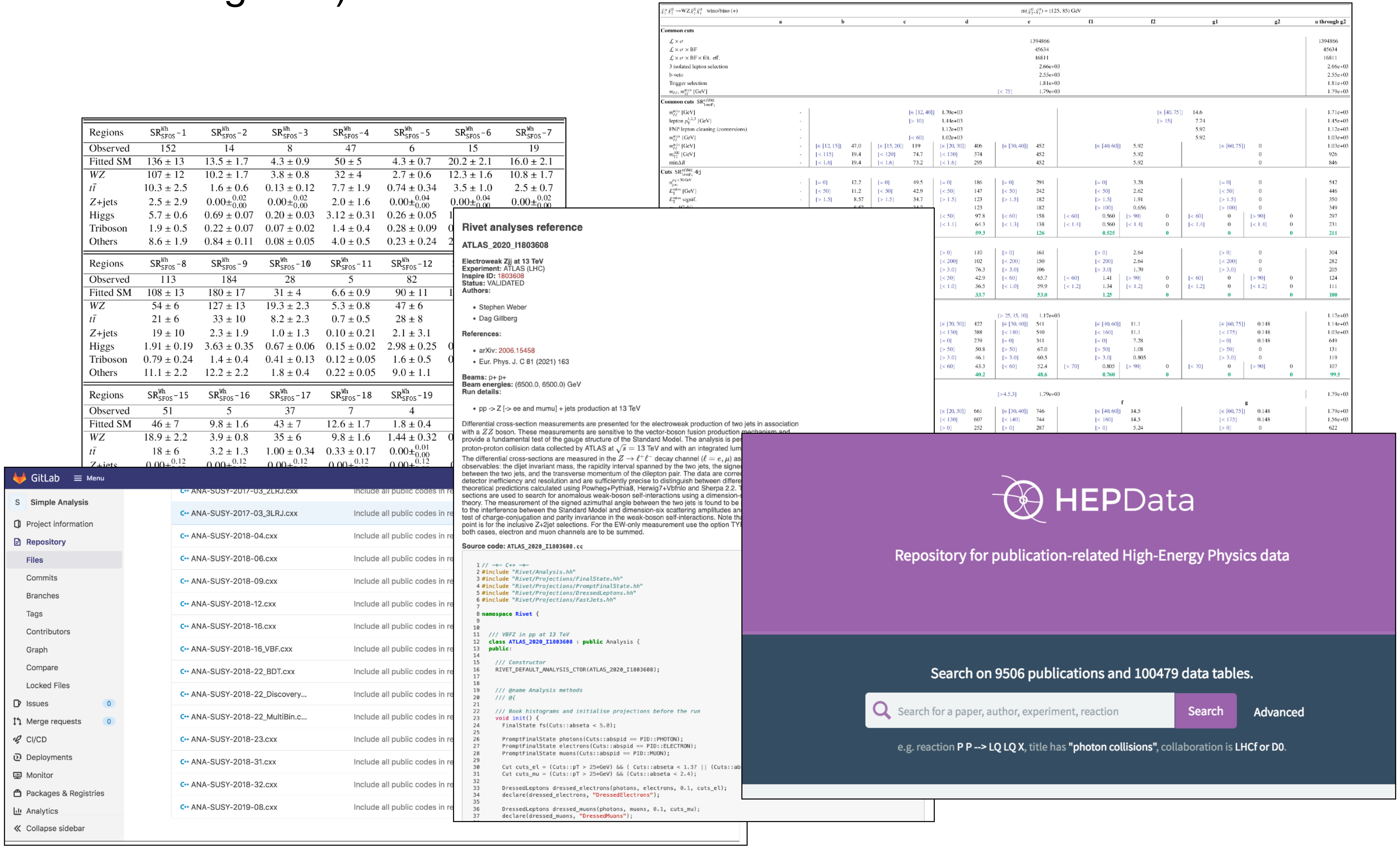
In short:
Given a null-result, the exclusion limits are very interesting and useful…





[ATLAS, 2106.01676]

…but **this** is the real gold! :)



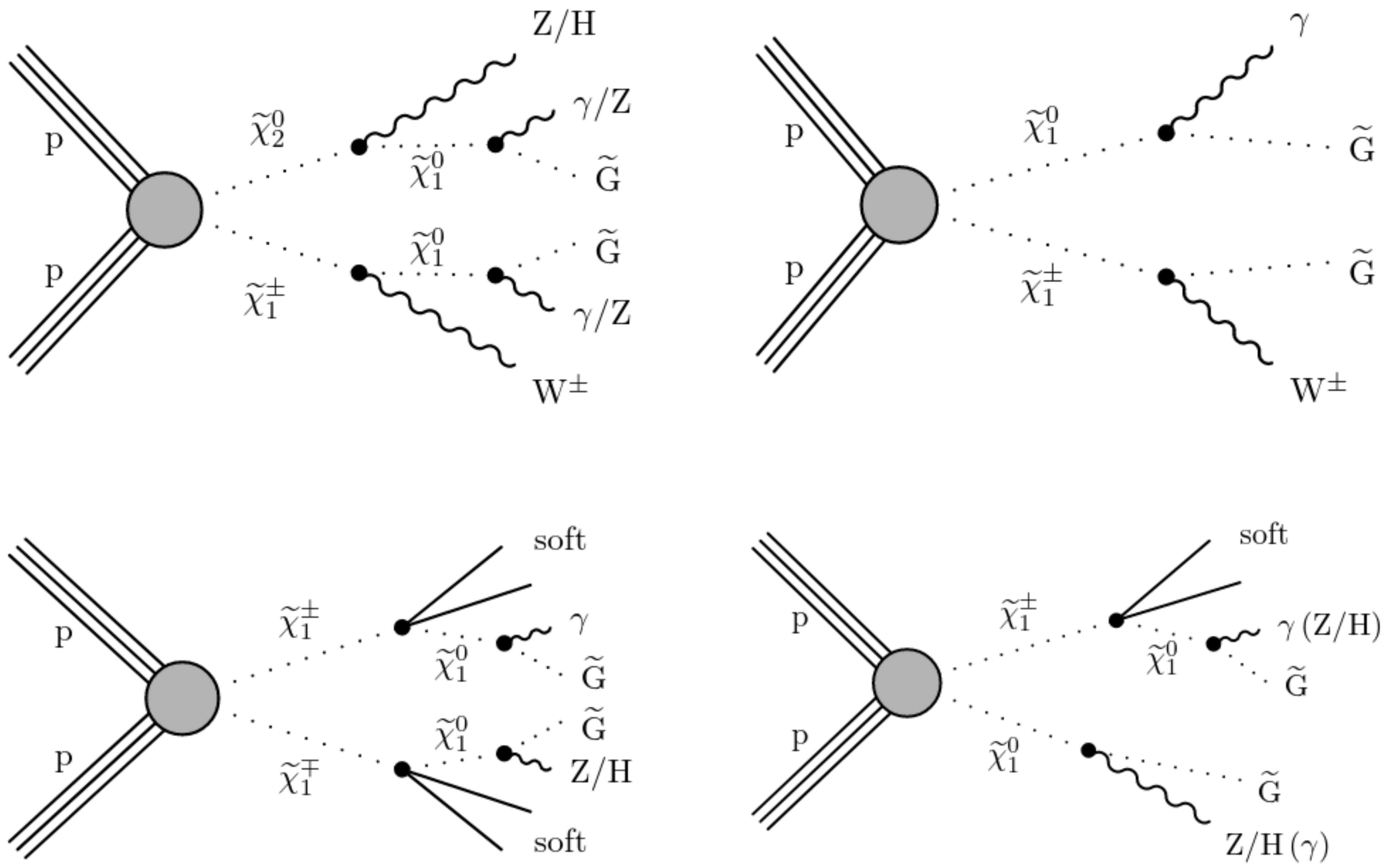
A **huge thank you** to everyone who works hard to produce some cutflow, a SimpleAnalysis code snippet, an efficiency map, a JSON likelihood file, …

3. A recent SUSY reinterpretation example

Collider constraints on electroweakinos in the presence of a light gravitino

The GAMBIT Collaboration: Viktor Ananyev[1], Csaba Balázs[2], Ankit Beniwal[3], Lasse Lorentz Braseth[1], Andy Buckley[4], Jonathan Butterworth[5], Christopher Chang[6], Matthias Danninger[7], Andrew Fowlie[8], Tomás E. Gonzalo[9], Anders Kvellestad[1], Farvah Mahmoudi[10,11], Gregory D. Martinez[12], Markus T. Prim[13], Tomasz Procter[4], Are Raklev[1], Pat Scott[14], Patrick Stöcker[15], Jeriek Van den Abeele[1], Martin White[16], Yang Zhang[17,18]

EW SUSY w/ light gravitino at the LHC



Usual ATLAS/CMS simplified model:

- Production of lightest neutralinos/charginos
- 1-2 fixed branching ratios
- Near massless gravitino as LSP

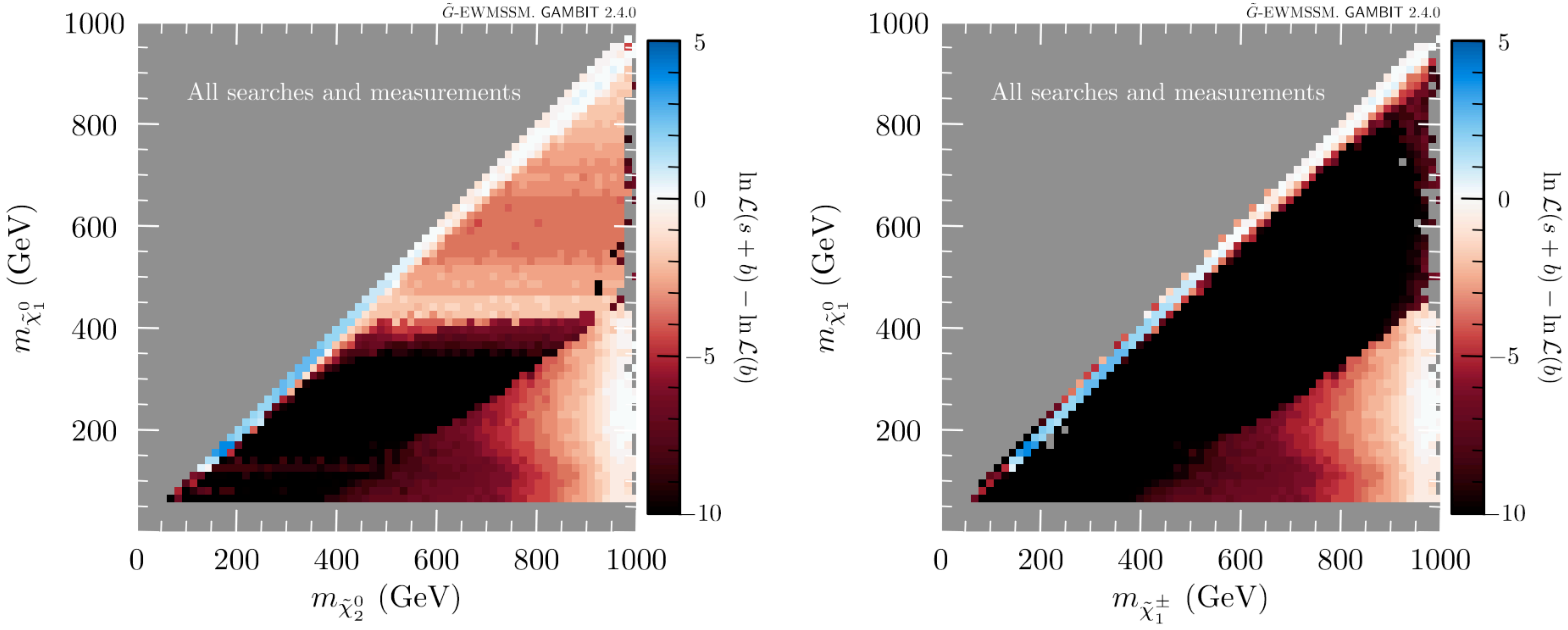
Our model: all EWinos + light gravitino

- **Model**: MSSM w/ neutralinos, charginos and gravitino within LHC reach
- **7 SUSY particles below 1 TeV**: 4 neutralinos, 2 charginos, light gravitino
- **4D theory parameter space**: M1, M2, mu, tan beta
- **Why a gravitino?**
  - necessary consequence of supergravity
  - gauge-mediated symmetry breaking (GMSB): gravitino likely the LSP
- Distinct collider pheno: **the lightest neutralino/chargino will decay**
- Gravitino mass fixed to 1 eV → **prompt decay** of lightest neutralino/chargino

Analysis

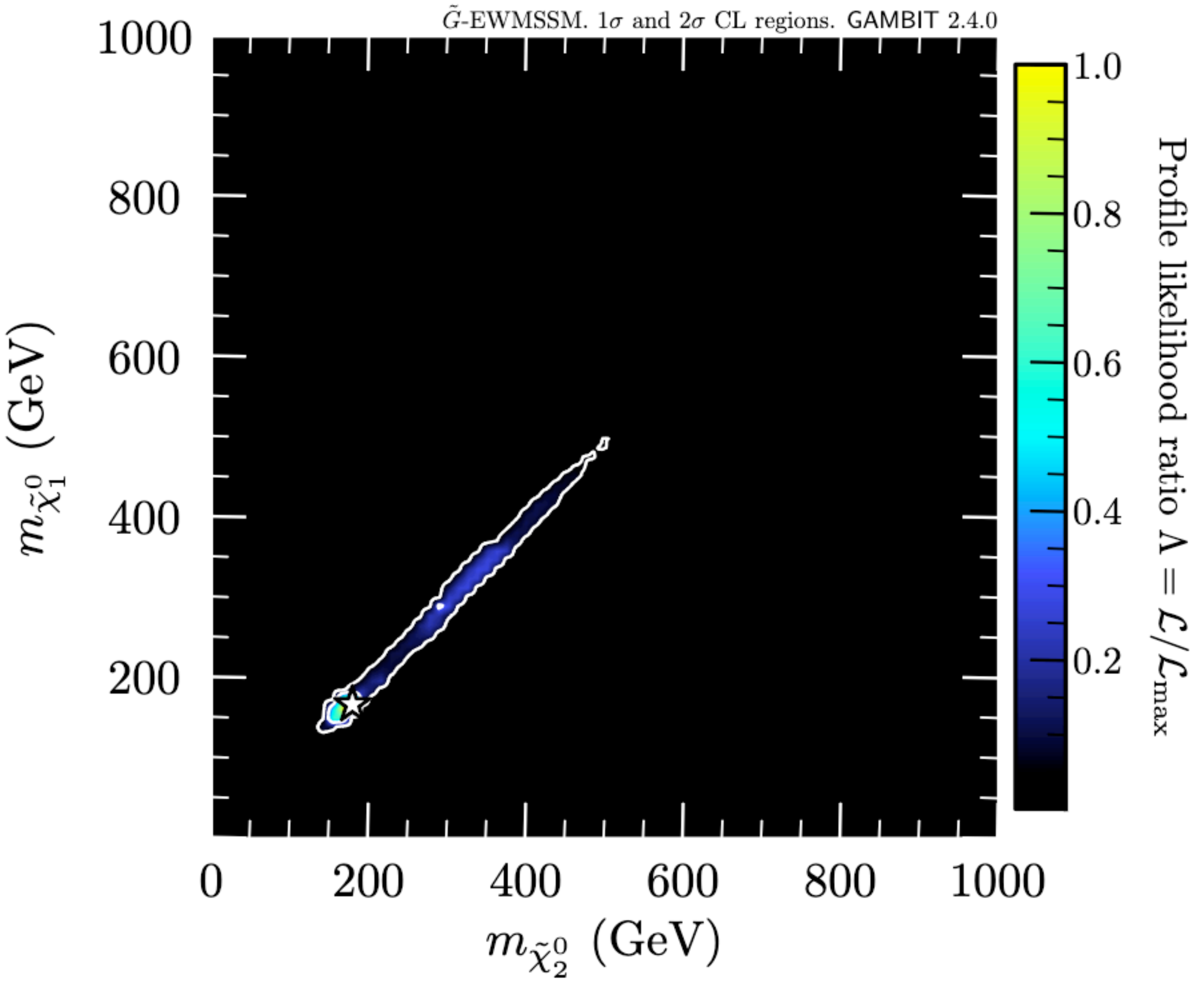
- Series of parameter scans w/ GAMBIT
- Scanner: **Diver** (differential evolution)
- Per point: **simulate 16M SUSY events** (Pythia, via ColliderBit)
- CPU cost: tens of millions of CPU hours…
- **Likelihoods**:
    - **15 ATLAS + 12 CMS searches** (in ColliderBit)
    - **22 «pools» of 45 ATLAS, CMS and LHCB measurements** (Contur+Rivet, via ColliderBit)
    - apply relevant LEP cross-section limits (in ColliderBit)

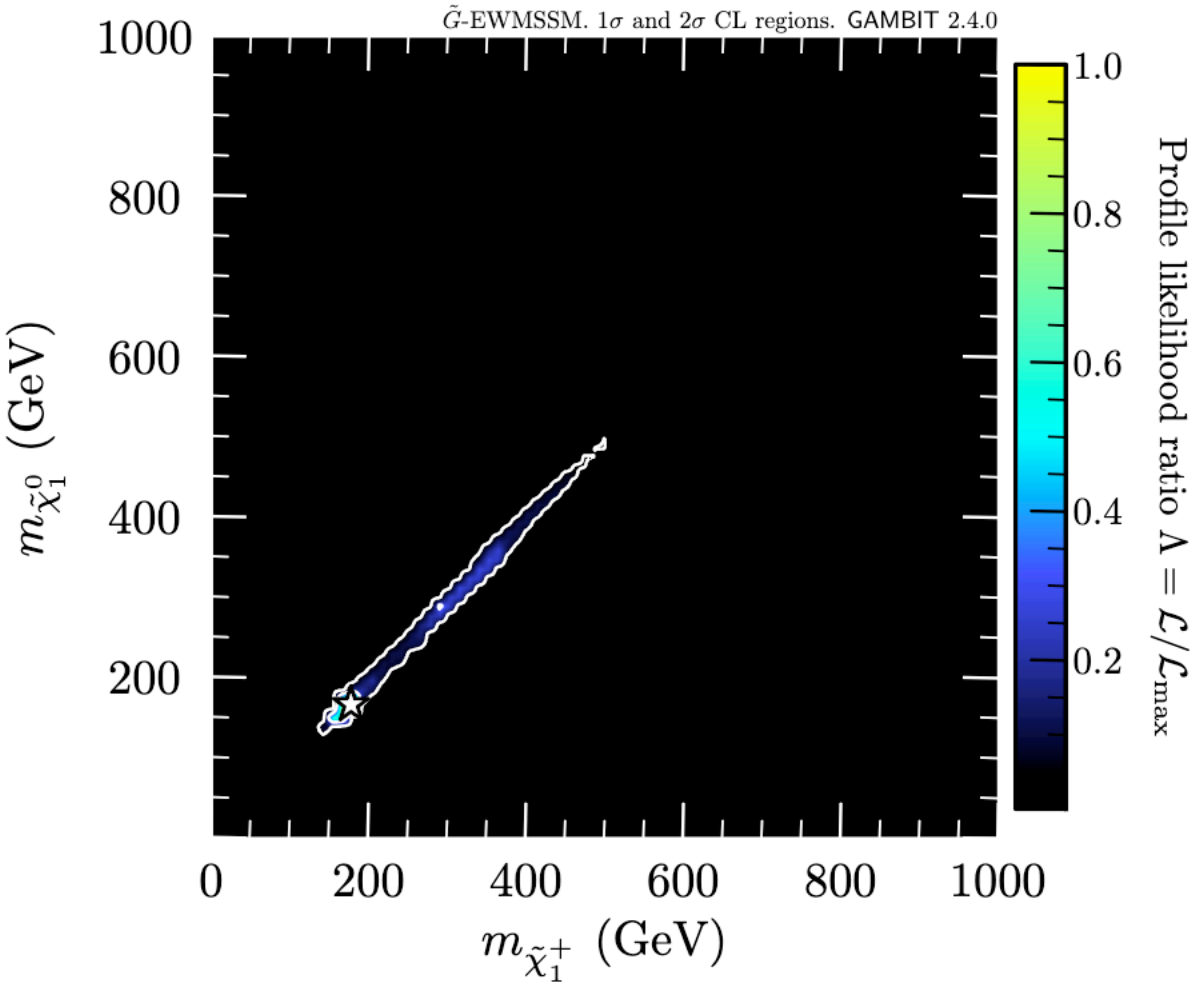
It’s a complicated profile likelihood…



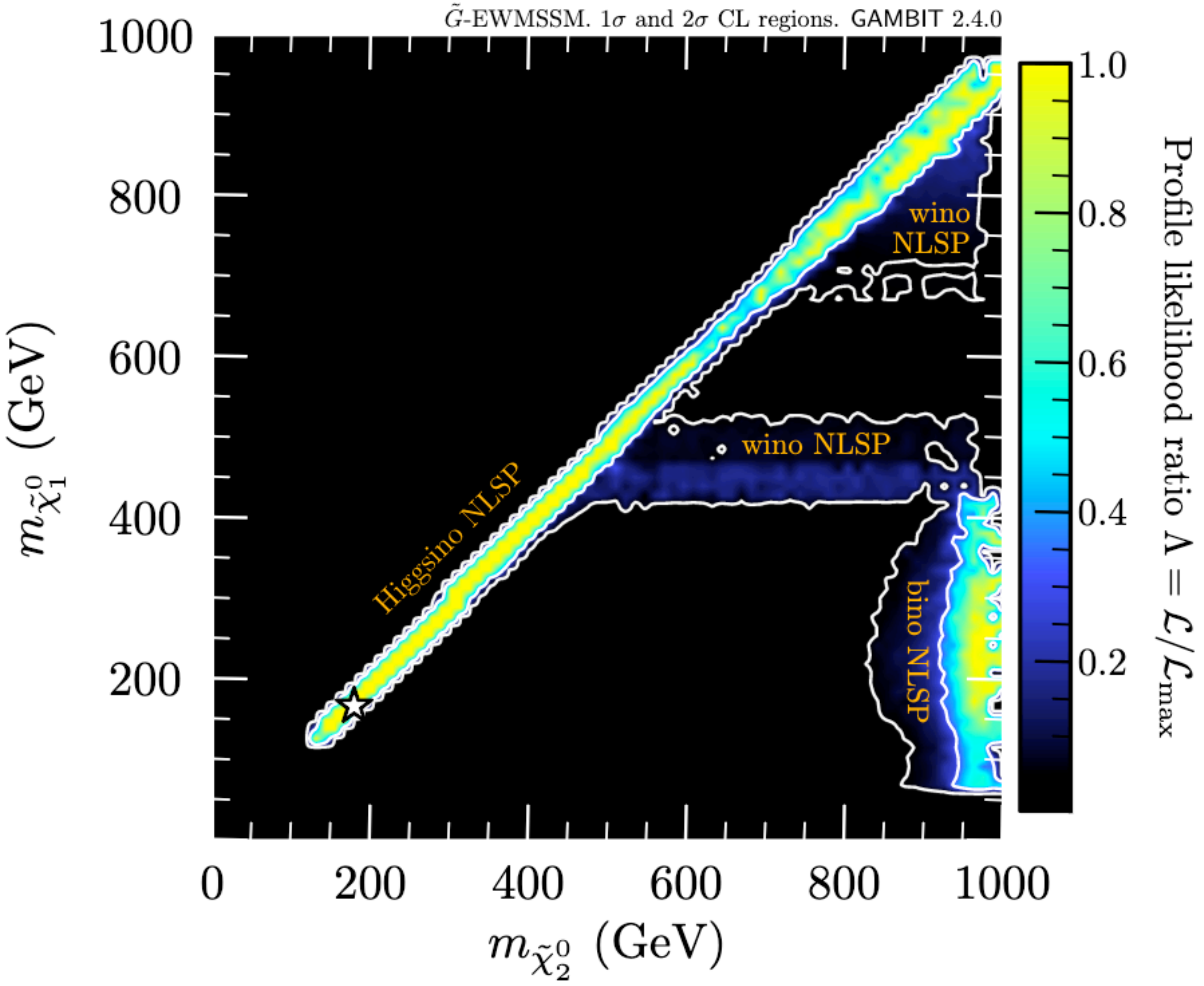
It’s a complicated profile likelihood…

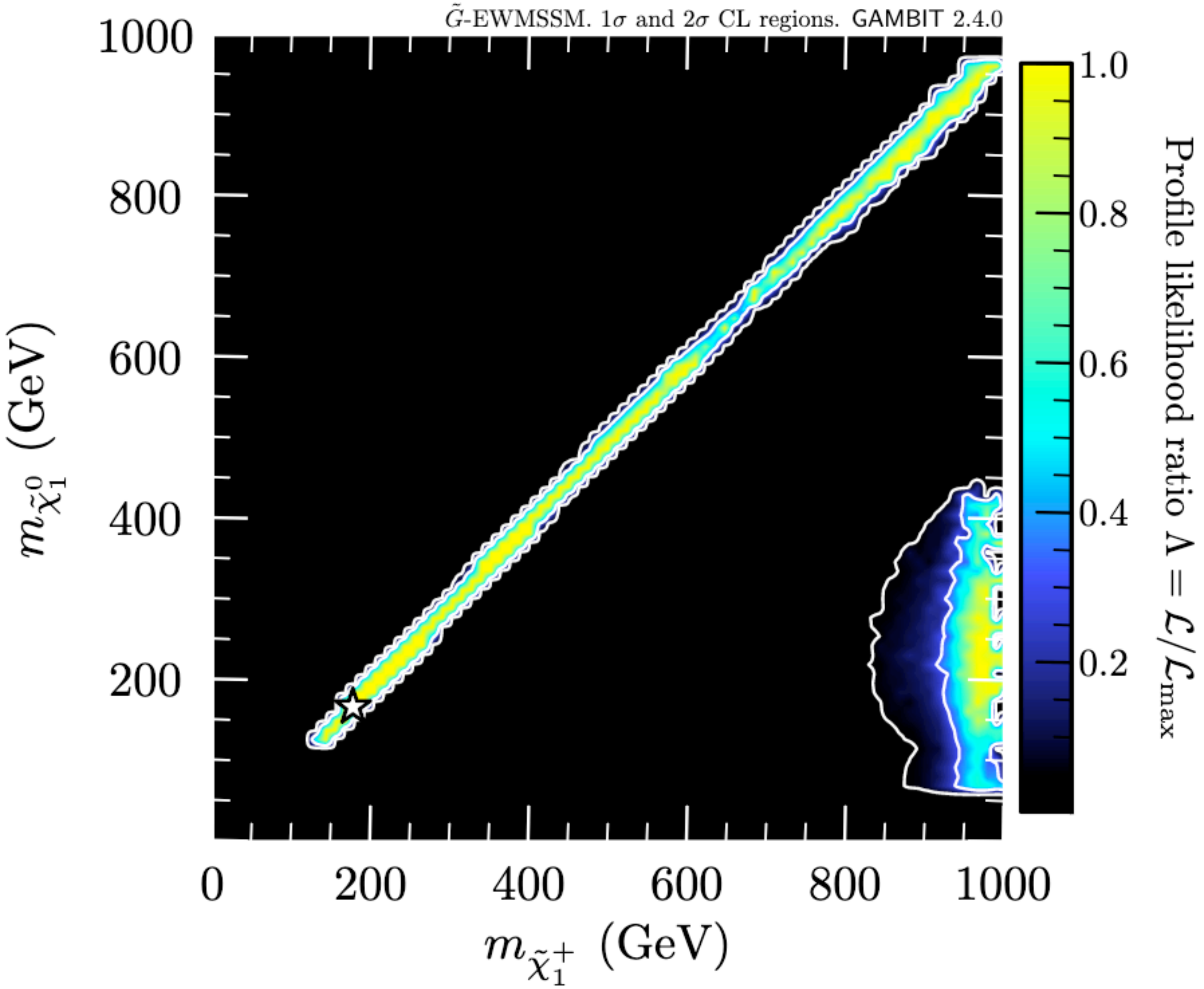
Best fit for light higgsino scenarios

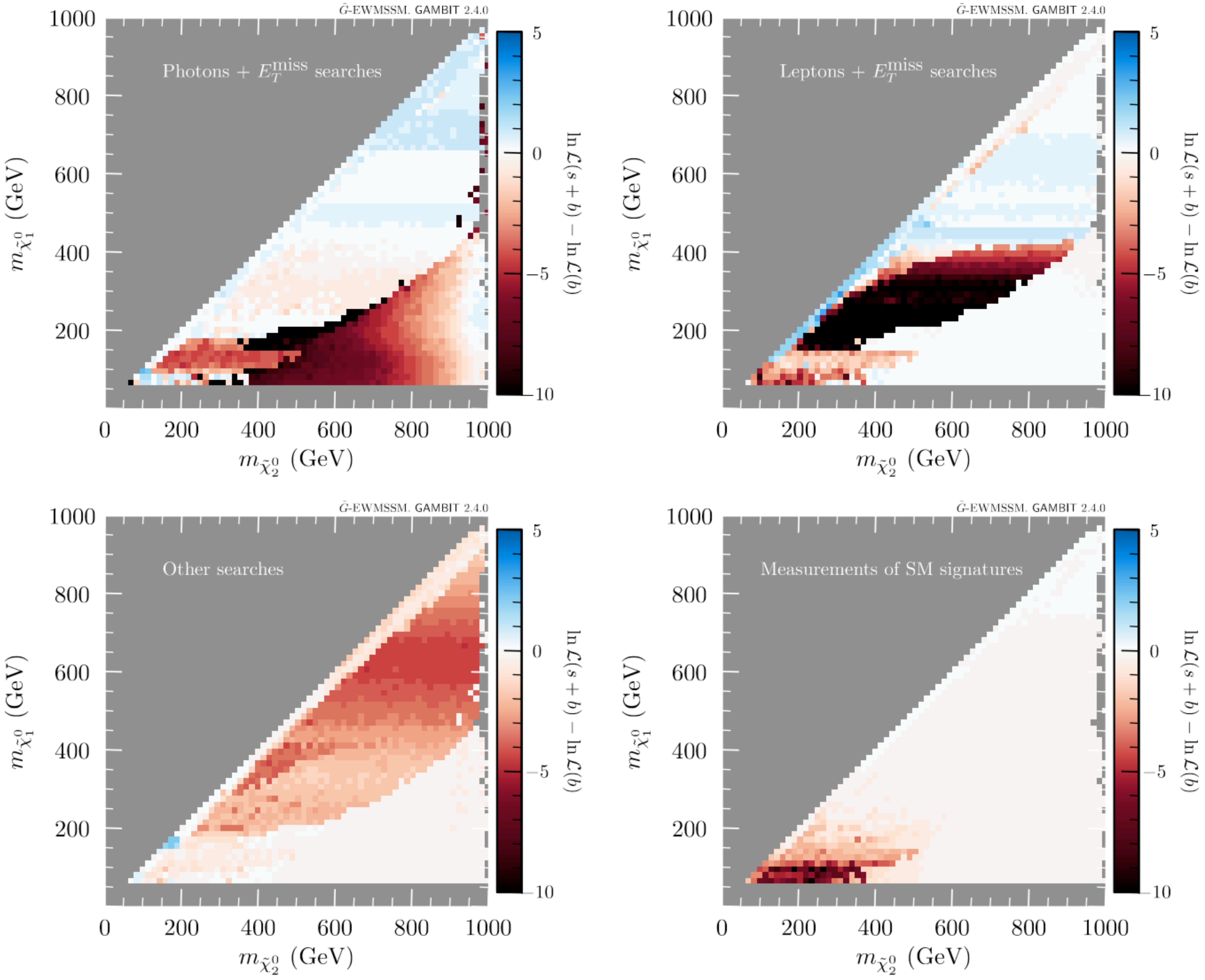




Several different surviving scenarios







$\tilde{G}$-EWMSSM, GAMBIT 2.4.0
Photons + $E_T^{\rm miss}$ searches
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Measurements of SM signatures
$m_{\tilde{\chi}_1^0}$ (GeV)
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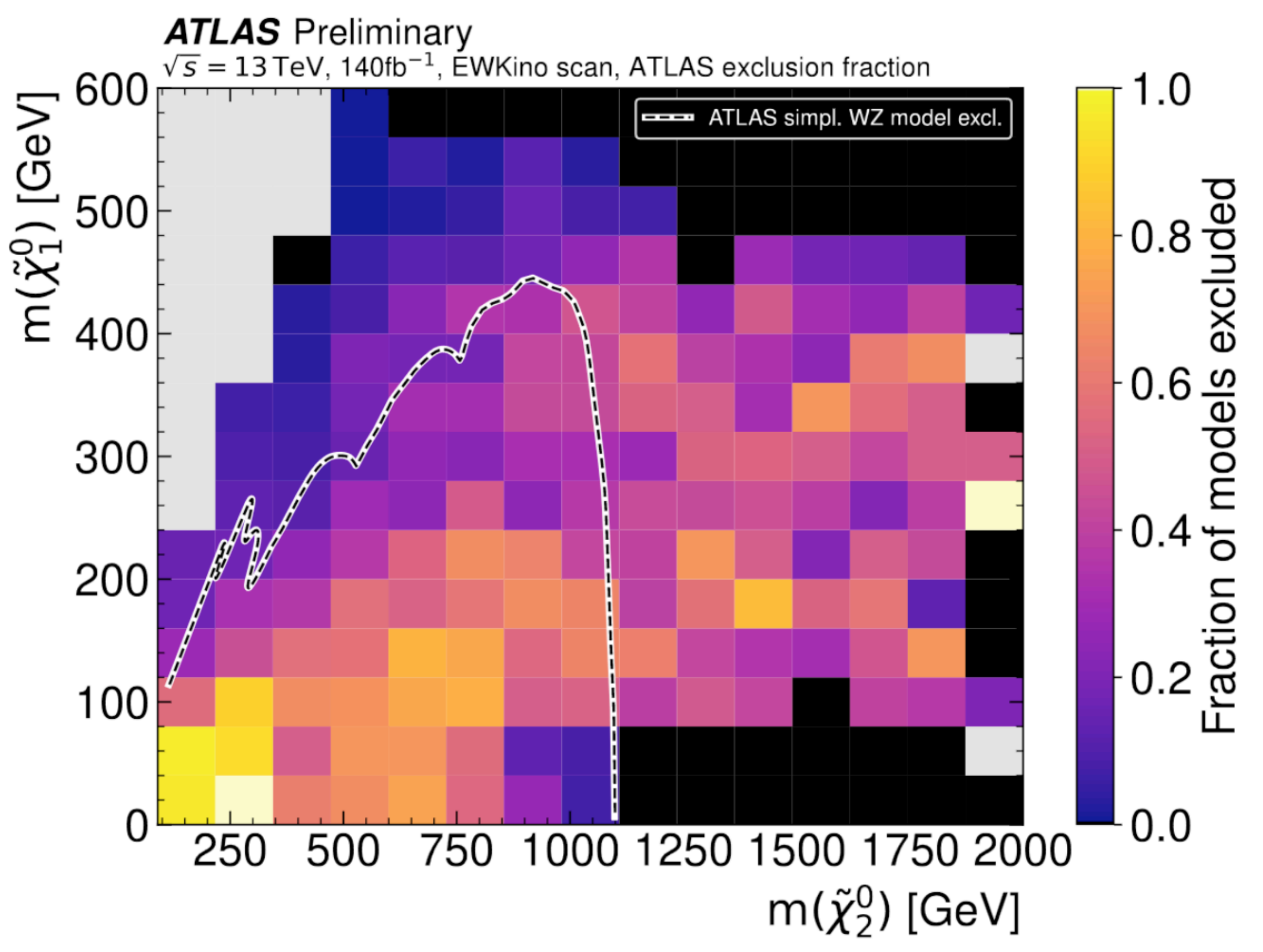
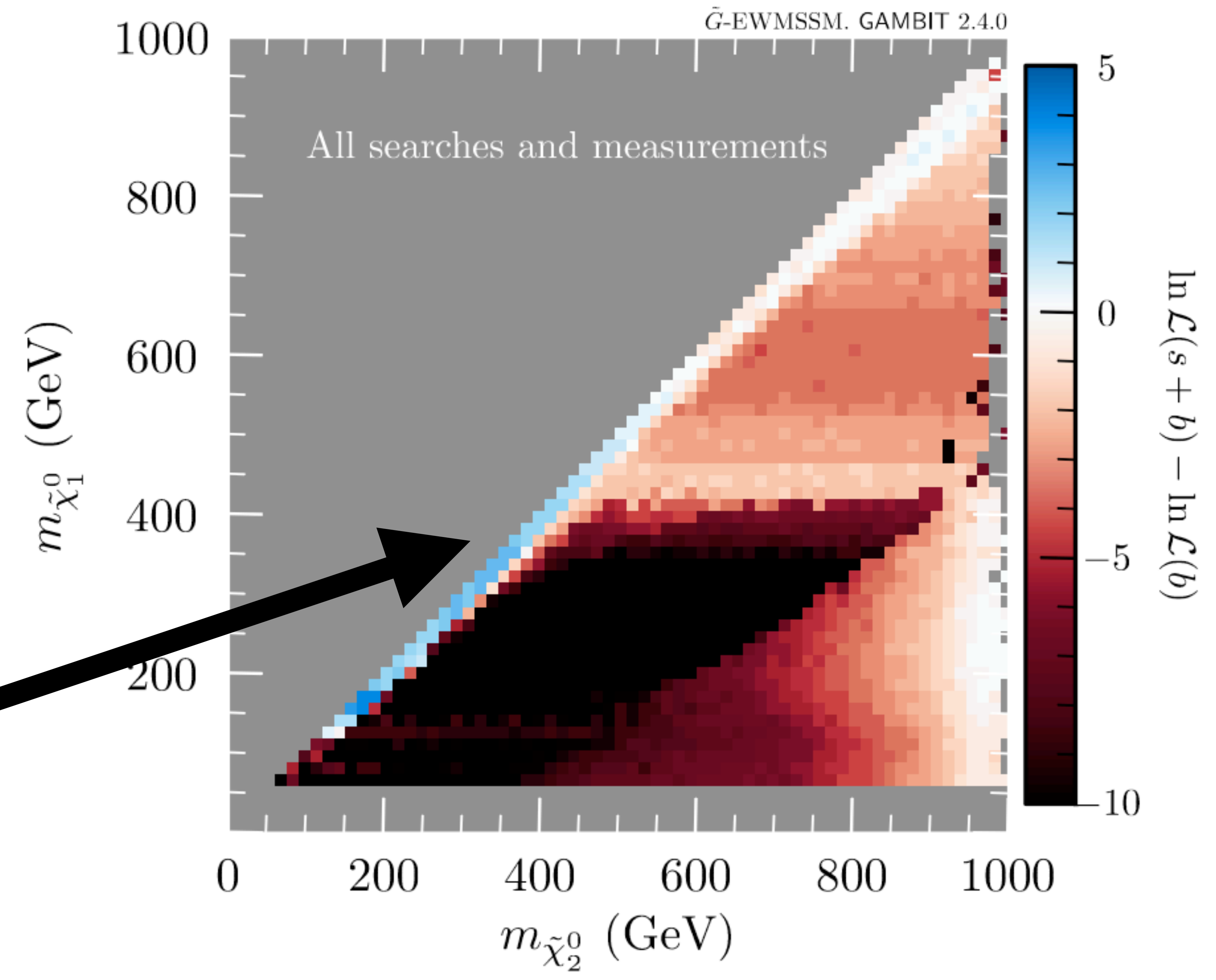
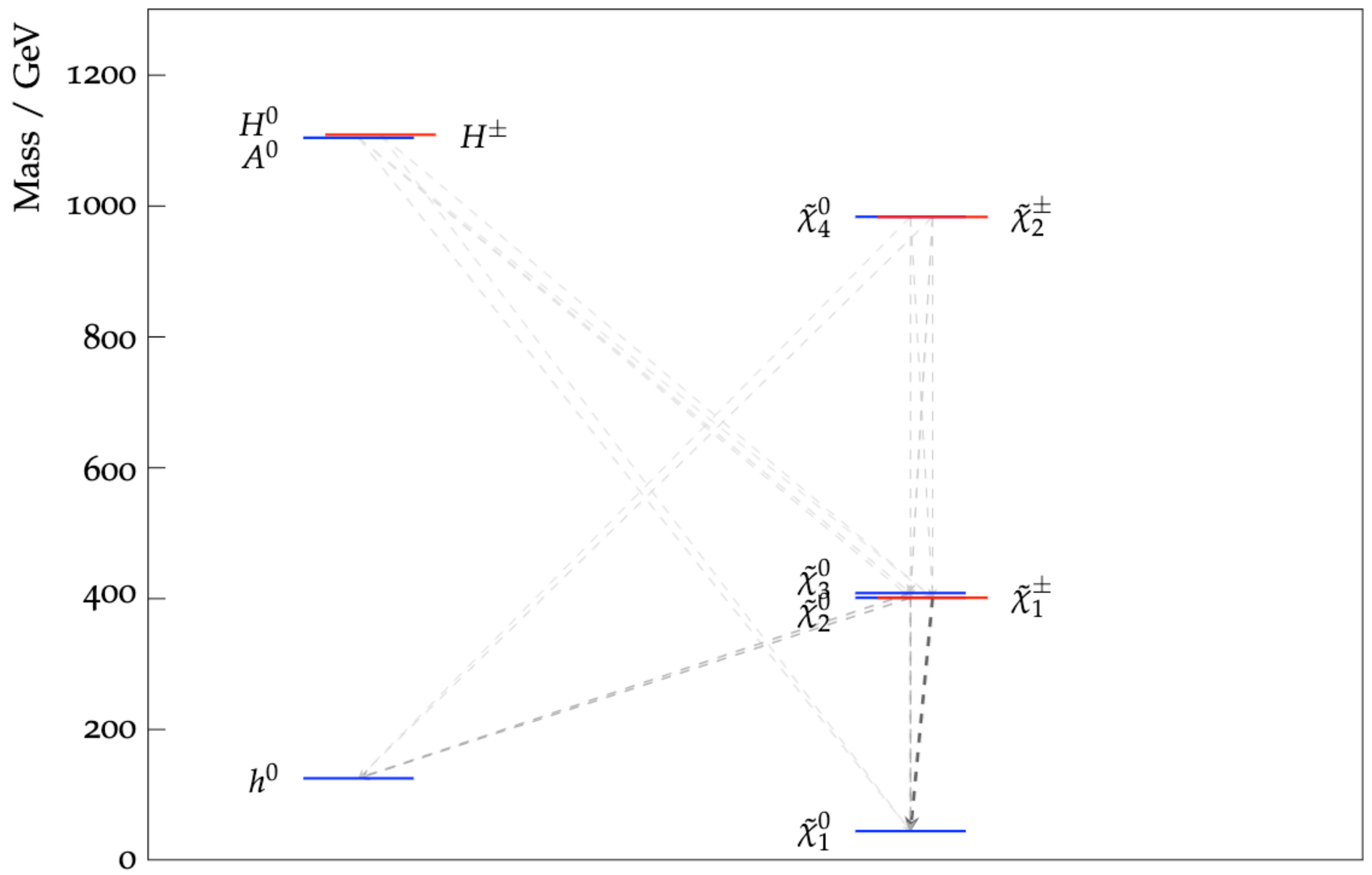
$\ln \mathcal{L}(s+b) - \ln \mathcal{L}(b)$
0
200
400
600
800
1000
5
0
−5
−10

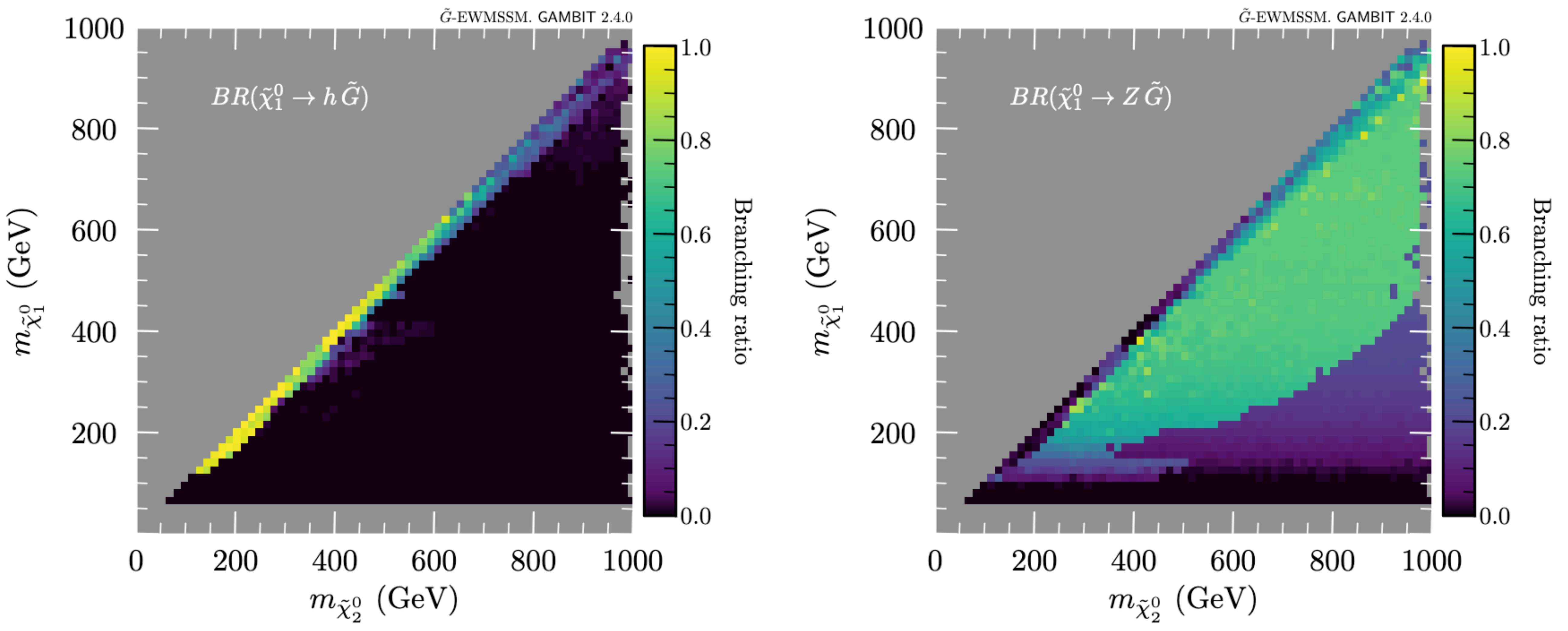


[ATLAS-CONF-2023-055]

Quite similar scenarios







Anders Kvellestad

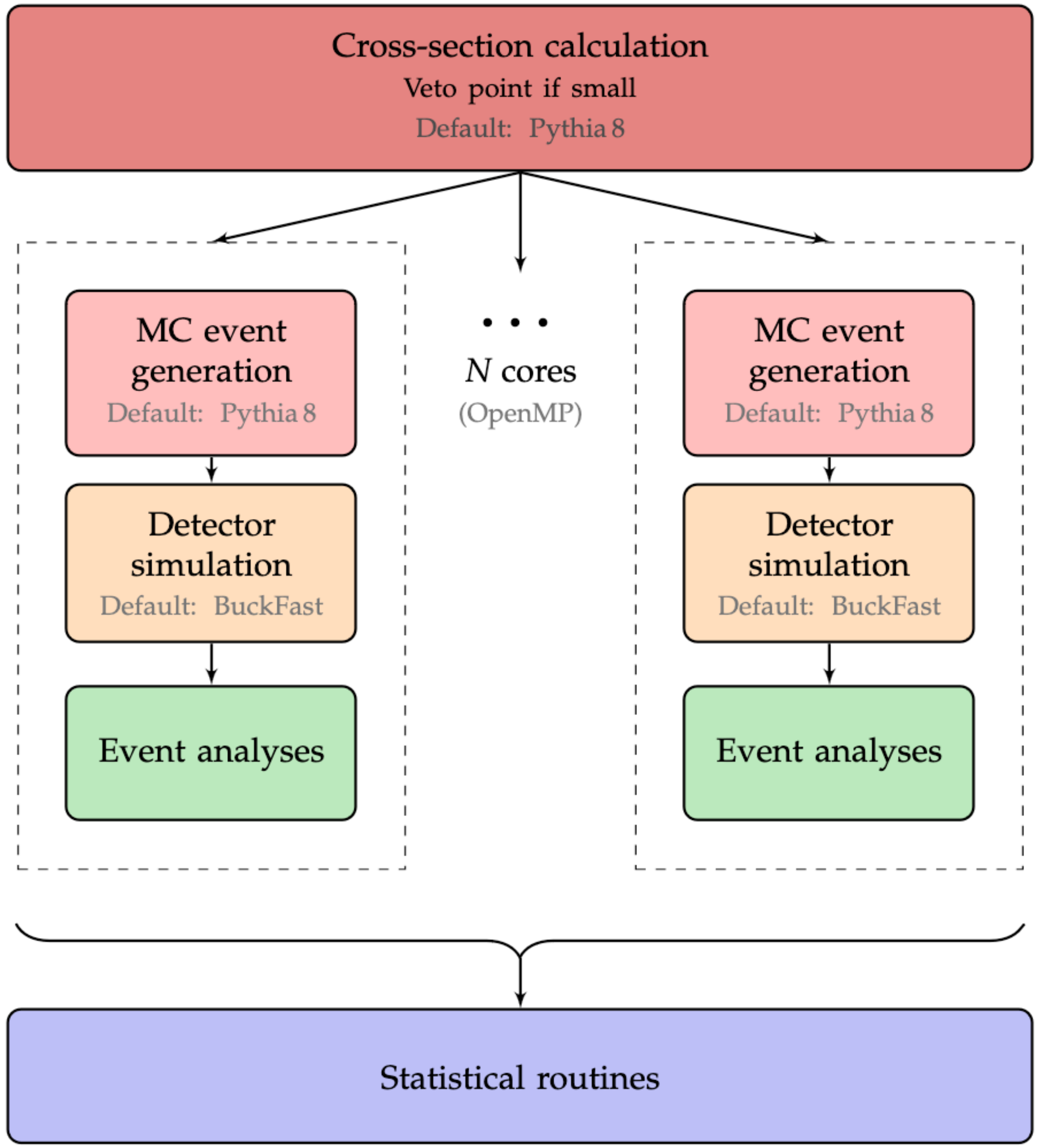
4. Some challenges for reinterpretation

The ATLAS and CMS SUSY groups are overall doing a really good job at providing public material for reinterpretation!

(Reinterpretation of experiments in other areas of particle physics still often involves scraping data from Figure 73 in Appendix B of an old PhD thesis…)

What we do in ColliderBit

- For **each parameter point** in a scan:
  - Run **Pythia simulations** of all relevant SUSY processes
  - Pass events through **fast detector simulation** (four-vector smearing + efficiencies)
  - Pass events through **our implementations of ATLAS and CMS searches**
    - → signal predictions for all SRs
  - Compute **a combined likelihood** for the parameter point
    - We combine as many analyses and SRs as we reasonably can, given available info
  - Plus an analogous pipeline for measurements, using Rivet + Contur

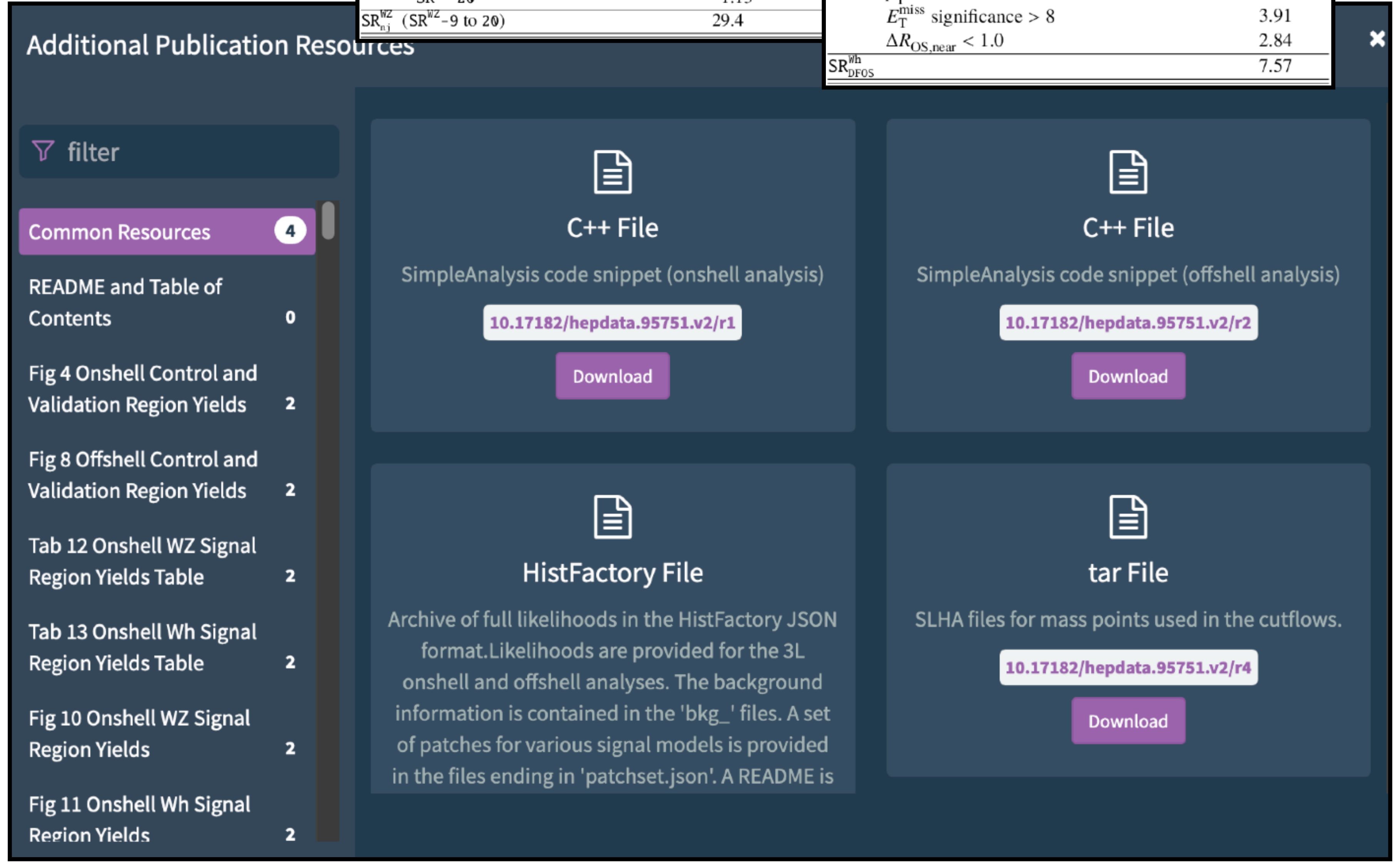


The information we need to do this

- **Implementing the analysis:**
  - Clear analysis description in the paper
  - SimpleAnalysis code snippets
  - Reusable NNs?
- **Validating our implementation:**
  - Cutflows for benchmark points
    - Clear definition of signal model (SLHA file)
    - Any preselections not mentioned in cutflow?
    - How many MC events generated?
- **Fully utilising the data (and improving stability):**
  - Full likelihoods, JSON (ATLAS)
  - Correlation matrices for simplified likelihoods (CMS)

Selection	$m(\tilde{\chi}^0_2,\tilde{\chi}^0_1)$ [GeV] (300, 200)	(600, 100)
$\mathcal{L}\times\sigma$	53784	2799
$\mathcal{L}\times\sigma\times$ BF	1760	
$\mathcal{L}\times\sigma\times$ BF $\times$ filt. eff.	1322	
3 isolated lepton selection, lepton $p_T^{1,2,3} > 25, 20, 10$ GeV, $E_T^{miss} > 50$ GeV	227	
$n_{SFOS} \geq 1$	226	
Trigger selection	222	
$n_{b-jets} = 0$	209	
Resonance veto $m_{\ell\ell} > 12$ GeV	209	
$\lvert m_{3\ell} - m_Z\rvert > 15$ GeV	203	
$m_{\ell\ell} \in [75, 105]$ GeV	196	
with MC to data weight	186	
$n_{jets} = 0$	76.4	
with MC to data weight	73.3	
$m_T \in [100, 160]$ GeV	26.7	
SR^{WZ}-1	20.9	
SR^{WZ}-2	4.86	
SR^{WZ}-3	0.78	
SR^{WZ}-4	0.14	
$m_T > 160$ GeV	5.80	
SR^{WZ}-5	4.64	
SR^{WZ}-6	0.16	
SR^{WZ}-7	0	
SR^{WZ}-8	0	
SR^{WZ}_{0j} (SR^{WZ}-1 to 8)	31.4	
$n_{jets} > 0$, $H_T < 200$ GeV	97.5	
with MC to data weight	91.8	
$m_T \in [100, 160]$ GeV	29.6	
SR^{WZ}-9	8.75	
SR^{WZ}-10	3.46	
SR^{WZ}-11	0.54	
SR^{WZ}-12	0	
$m_T > 160$ GeV	9.50	
SR^{WZ}-13	7.19	
SR^{WZ}-14	1.53	
SR^{WZ}-15	0.09	
SR^{WZ}-16	0	
$n_{jets} > 0$, $H_T > 200$ GeV	22.2	
$H_T^{lep} < 350$ GeV	20.9	
with MC to data weight	19.3	
$m_T > 100$ GeV	10.8	
SR^{WZ}-17	2.53	
SR^{WZ}-18	3.12	
SR^{WZ}-19	1.09	
SR^{WZ}-20	1.13	
SR^{WZ}_{nj} (SR^{WZ}-9 to 20)	29.4	

Selection	$m(\tilde{\chi}^0_2,\tilde{\chi}^0_1)$ [GeV] (190, 60)
$\mathcal{L}\times\sigma$	303527
$\mathcal{L}\times\sigma\times$ BF	10927
$\mathcal{L}\times\sigma\times$ BF $\times$ filt. eff.	1174
3 isolated lepton selection, lepton $p_T^{1,2,3} > 25, 20, 10$ GeV, $E_T^{miss} > 50$ GeV	192
Trigger selection	186
$n_{b-jets} = 0$	171
$n_{SFOS} \geq 1$	137
Resonance veto $m_{\ell\ell} > 12$ GeV	133
$\lvert m_{3\ell} - m_Z\rvert > 15$ GeV	110
with MC to data weight	104
$m_{\ell\ell} < 75$ GeV	56.2
$n_{jets} = 0$ ($SR^{Wh}_{low-m_{\ell\ell}-0j}$)	22.3
SR^{Wh}_{SFOS}-1	8.26
SR^{Wh}_{SFOS}-2	1.57
SR^{Wh}_{SFOS}-3	0.50
SR^{Wh}_{SFOS}-4	5.97
SR^{Wh}_{SFOS}-5	0.64
SR^{Wh}_{SFOS}-6	2.67
SR^{Wh}_{SFOS}-7	2.75
$n_{jets} > 0$, $H_T < 200$ GeV ($SR^{Wh}_{low-m_{\ell\ell}-nj}$)	26.5
SR^{Wh}_{SFOS}-8	2.95
SR^{Wh}_{SFOS}-9	5.28
SR^{Wh}_{SFOS}-10	1.59
SR^{Wh}_{SFOS}-11	0.63
SR^{Wh}_{SFOS}-12	5.55
SR^{Wh}_{SFOS}-13	2.91
SR^{Wh}_{SFOS}-14	0.68
SR^{Wh}_{SFOS}-15	5.48
SR^{Wh}_{SFOS}-16	1.39
$n_{SFOS} = 0$	34
with MC to data weight	33.5
$n_{jets} = 0$	14.8
$p_T^{\ell_3} > 15$ GeV	12.2
E_T^{miss} significance > 8	5.36
$\Delta R_{OS,near} < 1.2$	4.73
$n_{jets} \in [1, 2]$	15.6
$p_T^{\ell_3} > 20$ GeV	9.4
E_T^{miss} significance > 8	3.91
$\Delta R_{OS,near} < 1.0$	2.84
SR^{Wh}_{DFOS}	7.57



[SUSY-2019-09]

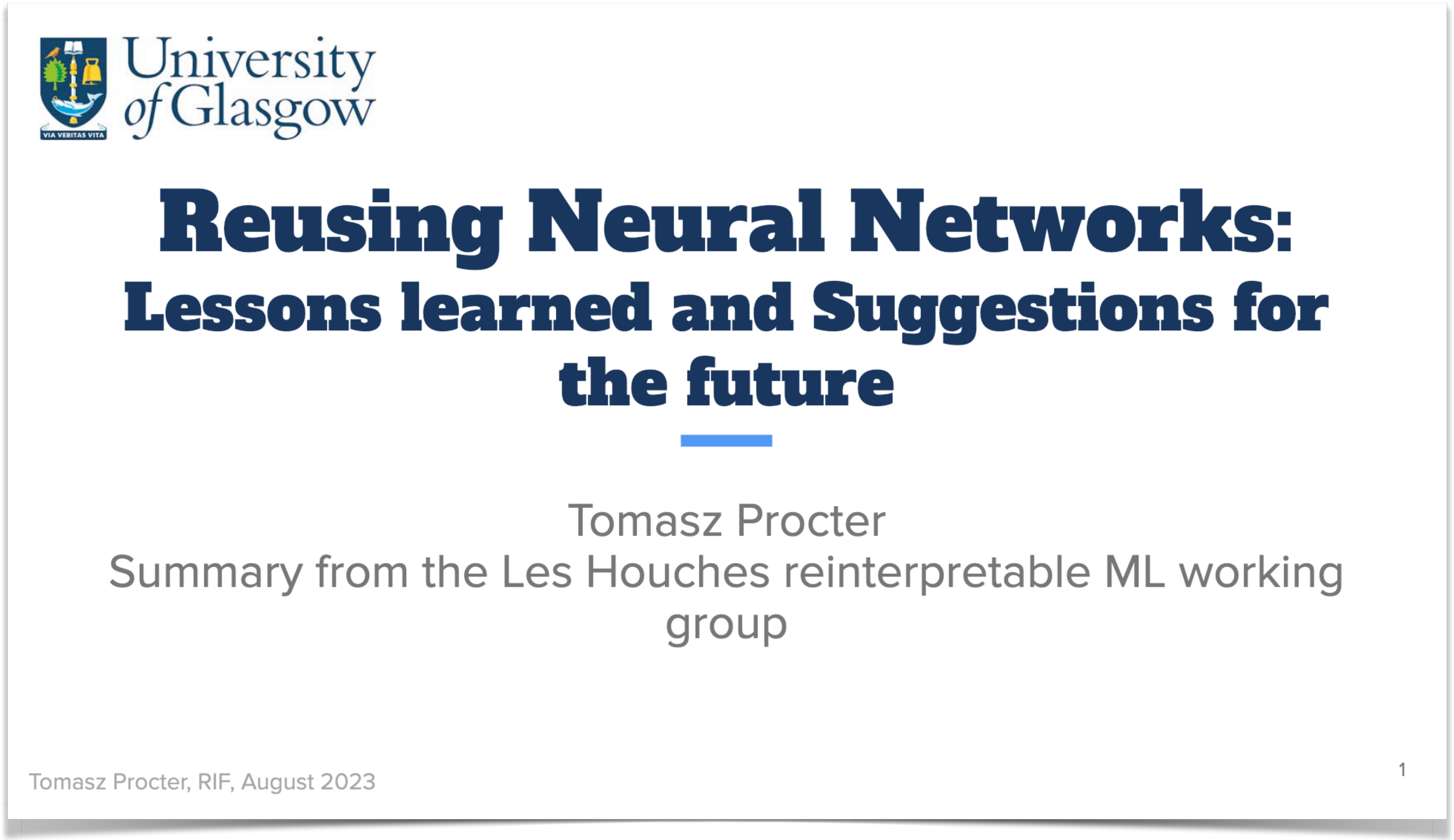
The main challenges we encounter

- **Limited public information**
  - Limits our ability to validate our implementation
  - Forces us to identify best-expected SR at each point

- **Detector-level variables**
  - We can’t do sophisticated detector simulation when mapping out high-dimensional theory spaces

- The big one: **neural networks**

See this talk by **Tomasz Procter**, from the LHC Reinterpretation Forum:



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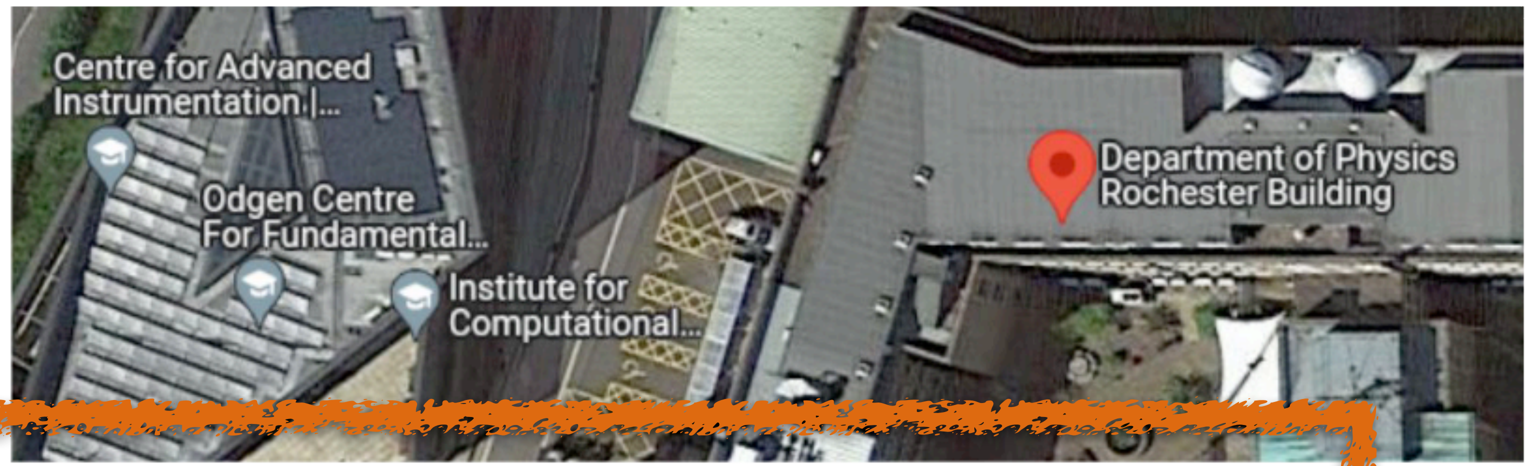

Where we are

- Two publicly available LHC analysis ML networks - both from ATLAS SUSY:
  - ANA-SUSY-2019-04 was discussed at last RiF
  - ANA-SUSY-2018-30 seems to have worked a lot better in multiple frameworks - good to see!
- Nothing from CMS
- Nothing from ATLAS groups beyond SUSY.
- Clearly ATLAS SUSY group policies concerning simpleAnalysis have been very useful - do other groups need to take note?
- Personal comment: trying to get approval to add an .lwtnn file to hepdata has been...prolonged..., and exact procedures seem unclear to everyone*.

* If you think you could help me get this out I'd appreciate it!

Tomasz Procter, RIF, August 2023 4

See <u>this talk</u> by **Tomasz Procter**, from the LHC Reinterpretation Forum:

Analysis Design

- Use an open-source framework (tensorflow, pytorch, etc)
- Ensure the network can be saved in a useful preservation format for inference (e.g. ONNX or lwtnn).
    - Just leaving in a `.h5` file or `.pkl` file is unlikely to be stable
- Be considerate with choice of inputs - if a tagger depends entirely on detector level inputs, that's fine (but please provide detailed efficiencies – including misstags – or surrogates), but 10 truth-level quantities + pseudo-continuous b-score is frustrating.

Tomasz Procter, RIF, August 2023

6

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Tomasz Procter, RIF, August 2023

A «**Les Houches guide to reusable ML models**» document is in preparation!

More complicated selection variables

Easier and more accurate reinterpretation

5. Moving forward: how to best help each other?

Join the discussions in the LHC Reinterpretation Forum!

(Re)interpretation of the LHC results for new physics

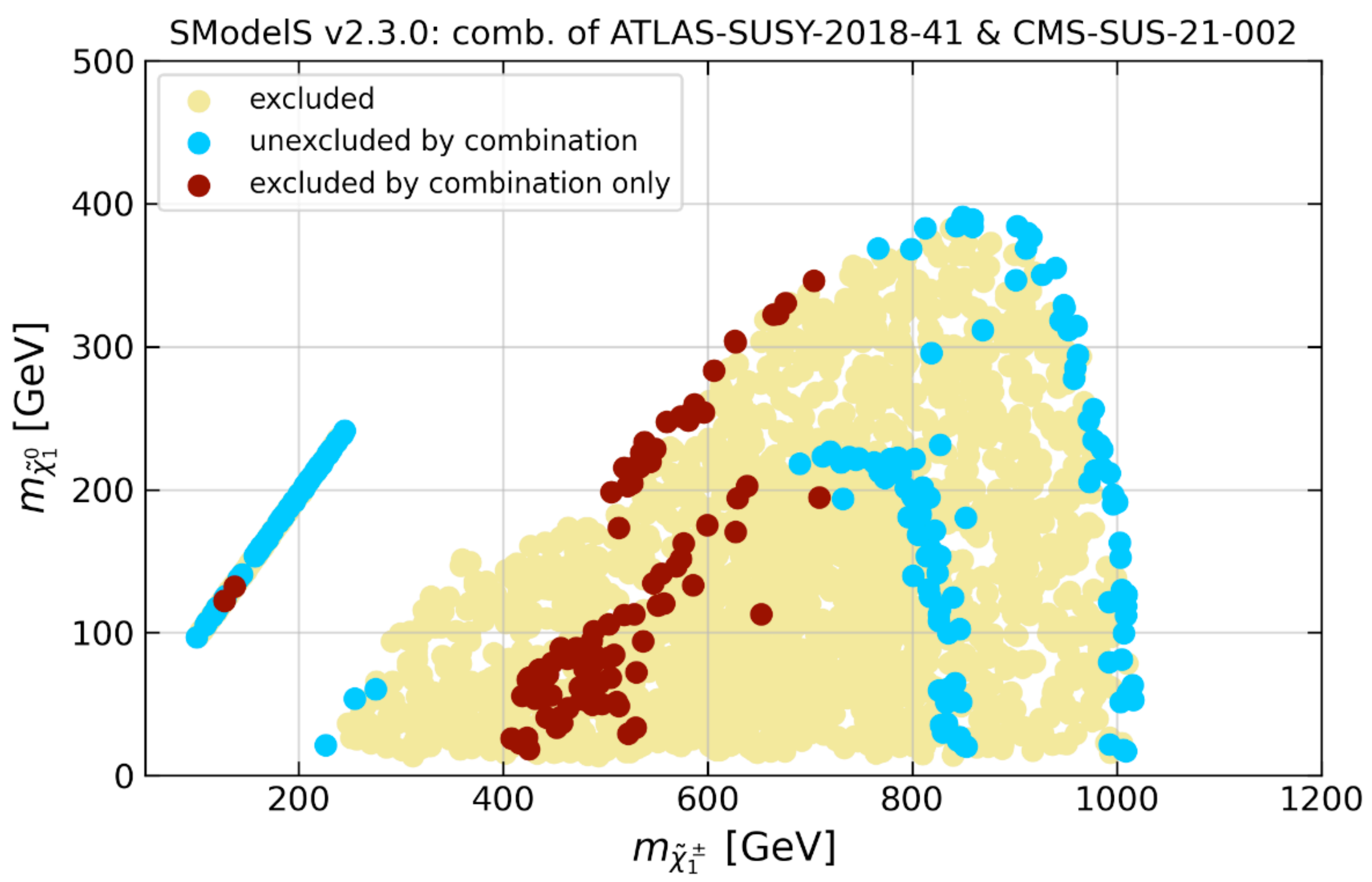
August 29, 2023 to September 1, 2023
Durham University
Europe/London timezone

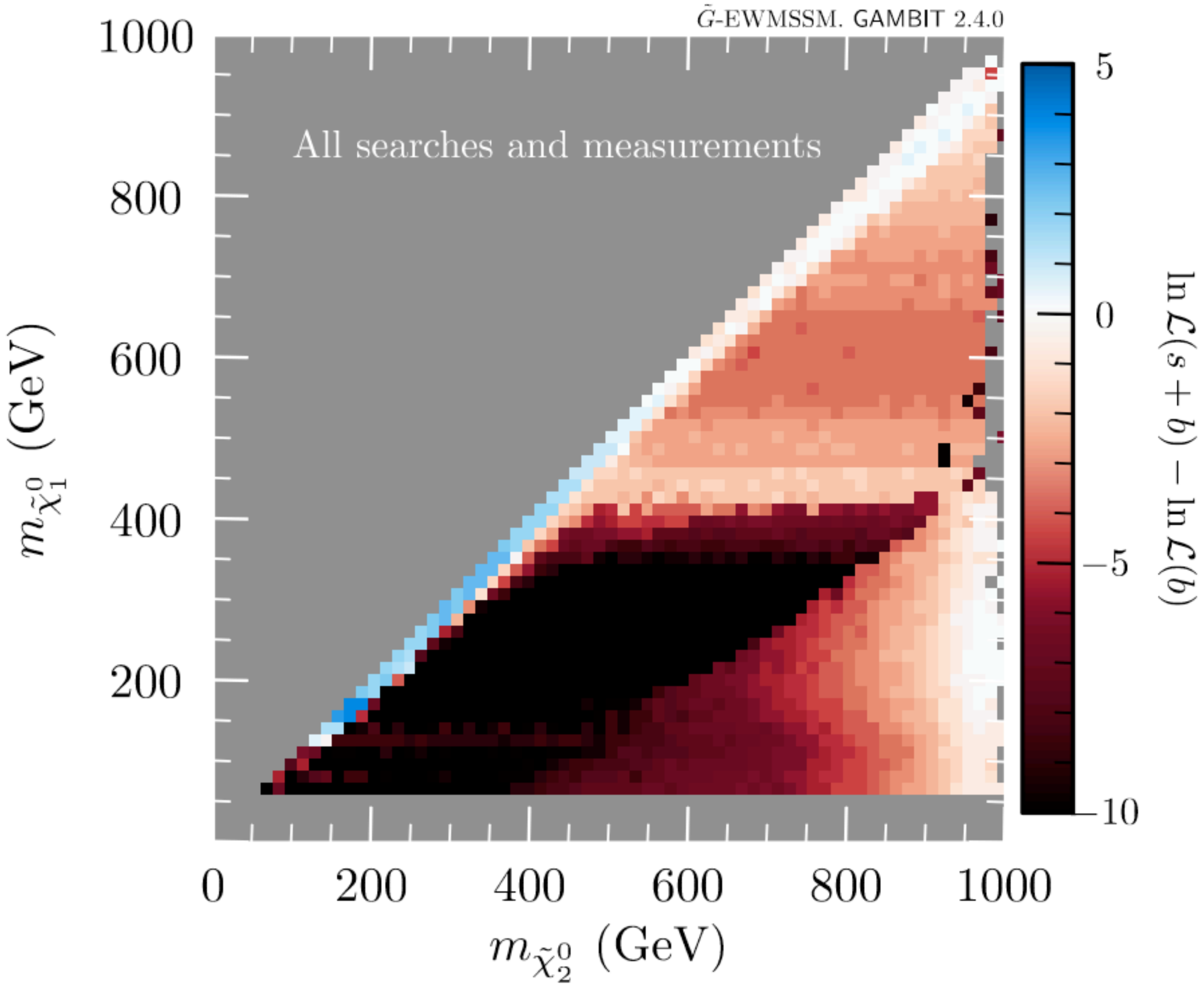
What would you like from reinterpretation studies?

- Assuming that we theorists can do reinterpretation in **fairly high-dimensional theory spaces** at **medium accuracy**…

- …what output is most useful for you?

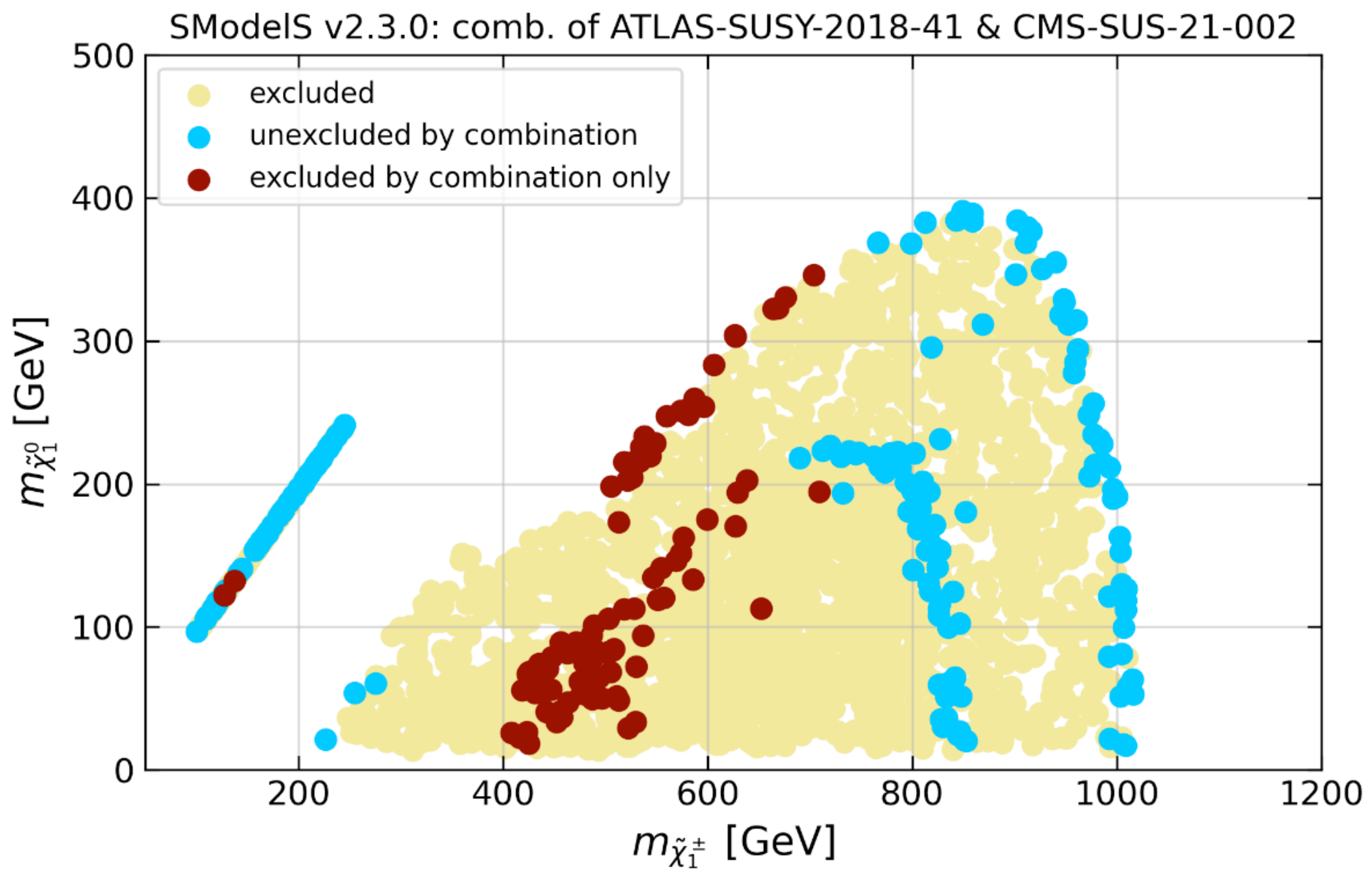
  - Maps of impact of current searches?
  - Benchmark points from surviving scenarios?
  - New low-dimensional planes for analysis optimisation?
  - New simplified models?
  - Suggested event selection strategies?
  - Forecasting for higher luminosity or new colliders?
  - Other things? All of the above?

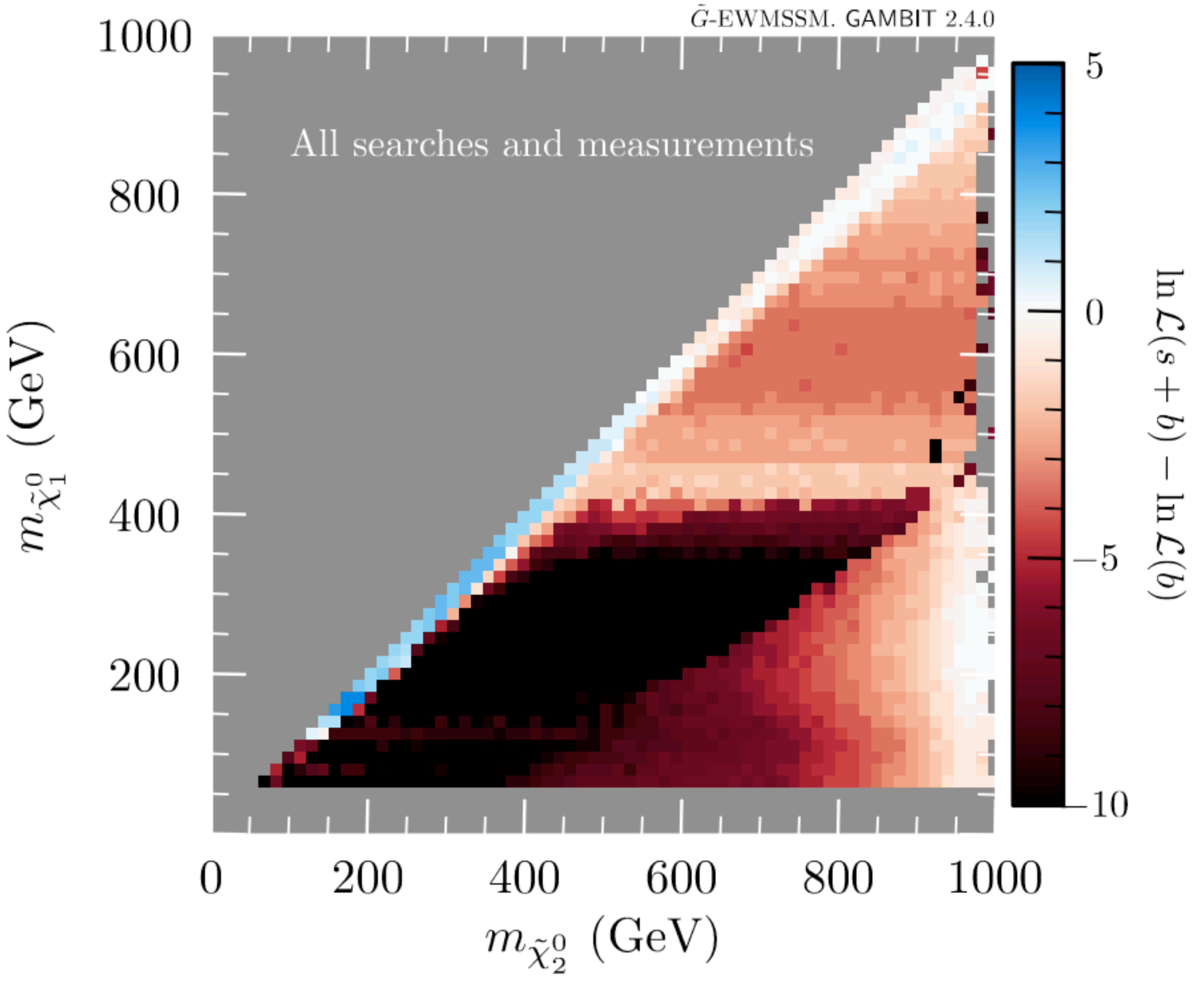




What experiments can do to help reinterpretations

- Consider tradeoff between gain from complicated selection variables and loss of reinterpretability
- Keep in mind that sensitivity in simplified model plane ≠ sensitivity in BSM theory space
  - Can we e.g. use a «less simplified» SR definition?
  - Reach out to your friendly neighbourhood theorist!
- Consider reinterpretation by outside teams when designing new searches
  - Maybe include alternative, easy-to-reinterpret SRs?
- Support existing ATLAS efforts for reinterpretation
  - SimpleAnalysis code snippets
  - Full likelihoods
  - Reusable NNs
  - …





So how can we maximise the science impact of SUSY searches?

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We can make sure that physicists in our community will be able to compute **reasonably accurate predictions** for **as many of the SRs as possible**, and that this can happen **as efficiently as possible** both in **human hours** and **CPU hours.**

So how can we maximise the science impact of SUSY searches?

We can make sure that physicists in our community will be able to compute **reasonably accurate predictions** for **as many of the SRs as possible**, and that this can happen **as efficiently as possible** both in **human hours** and **CPU hours.**

(And of course, discover SUSY.)

Bonus tracks

Parameter space

M_1 M_2 μ $\tan\beta$

Neutralinos

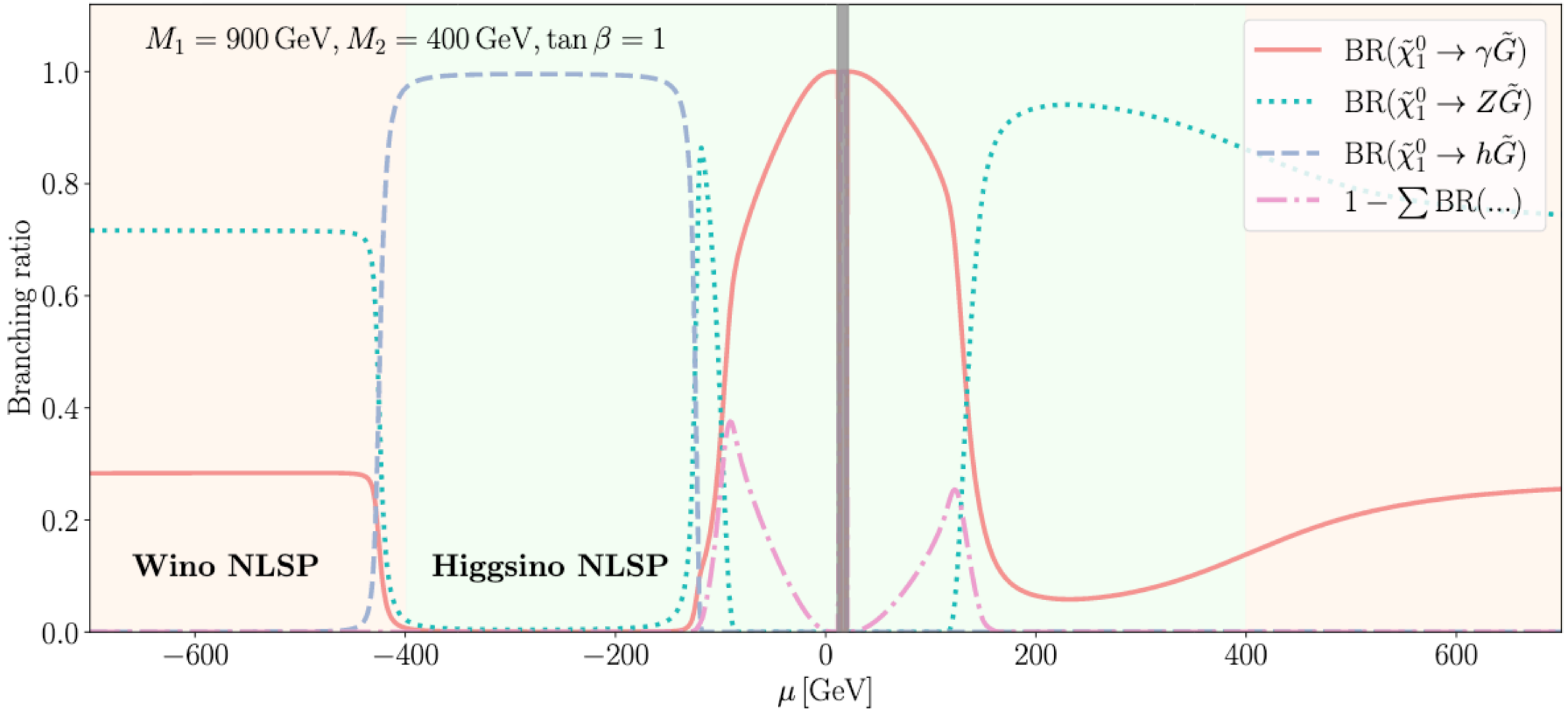
$$\psi^0 = (\tilde{B}, \tilde{W}^0, \tilde{H}_d^0, \tilde{H}_u^0)$$

$$M_N = \begin{pmatrix} M_1 & 0 & -\frac{1}{2}g'vc_\beta & \frac{1}{2}g'vs_\beta \\ 0 & M_2 & \frac{1}{2}gvc_\beta & -\frac{1}{2}gvs_\beta \\ -\frac{1}{2}g'vc_\beta & \frac{1}{2}gvc_\beta & 0 & -\mu \\ \frac{1}{2}g'vs_\beta & -\frac{1}{2}gvs_\beta & -\mu & 0 \end{pmatrix}$$

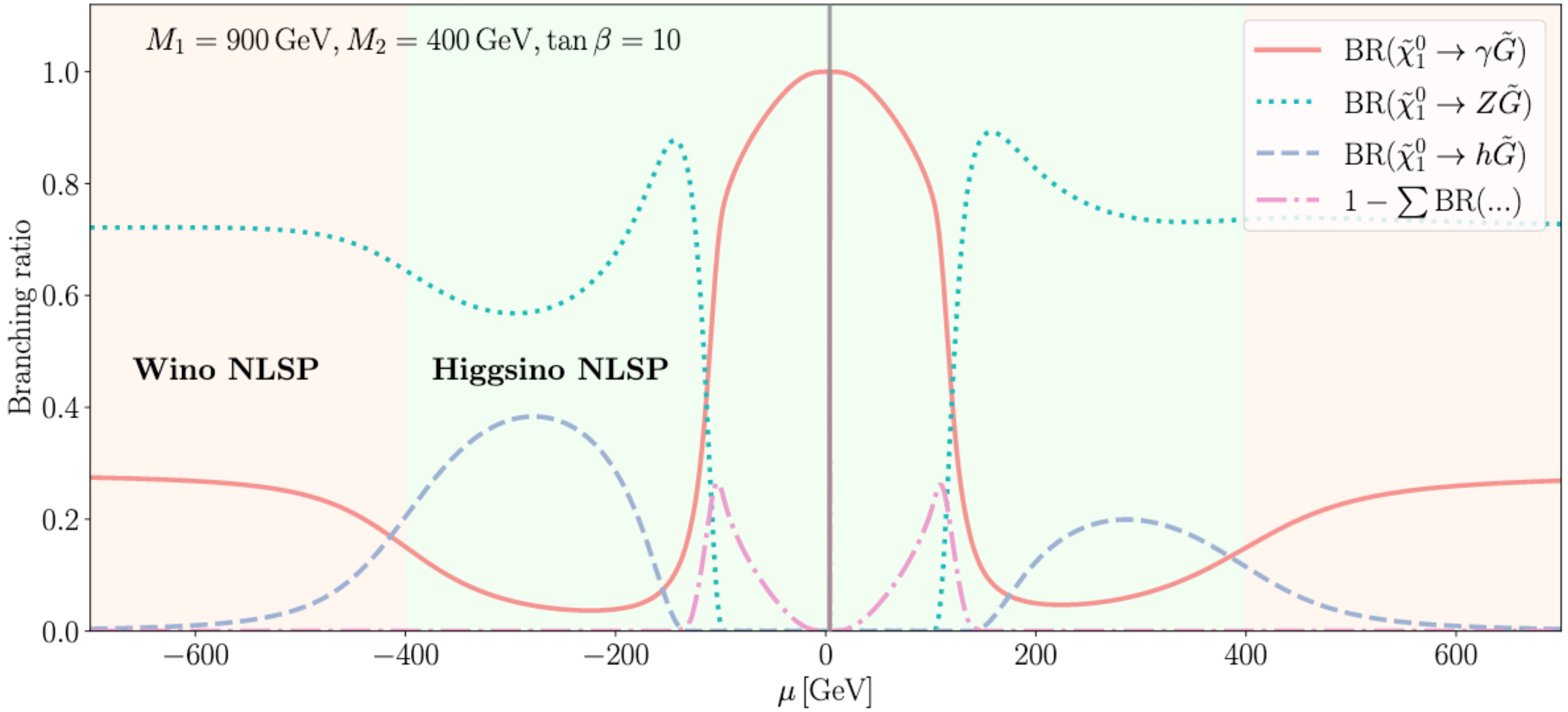
Charginos

$$\psi^\pm = (\tilde{W}^+, \tilde{H}_u^+, \tilde{W}^-, \tilde{H}_d^-)$$

$$M_C = \begin{pmatrix} 0 & X^T \\ X & 0 \end{pmatrix}, \quad \text{where} \quad X = \begin{pmatrix} M_2 & \frac{gvs_\beta}{\sqrt{2}} \\ \frac{gvc_\beta}{\sqrt{2}} & \mu \end{pmatrix}.$$

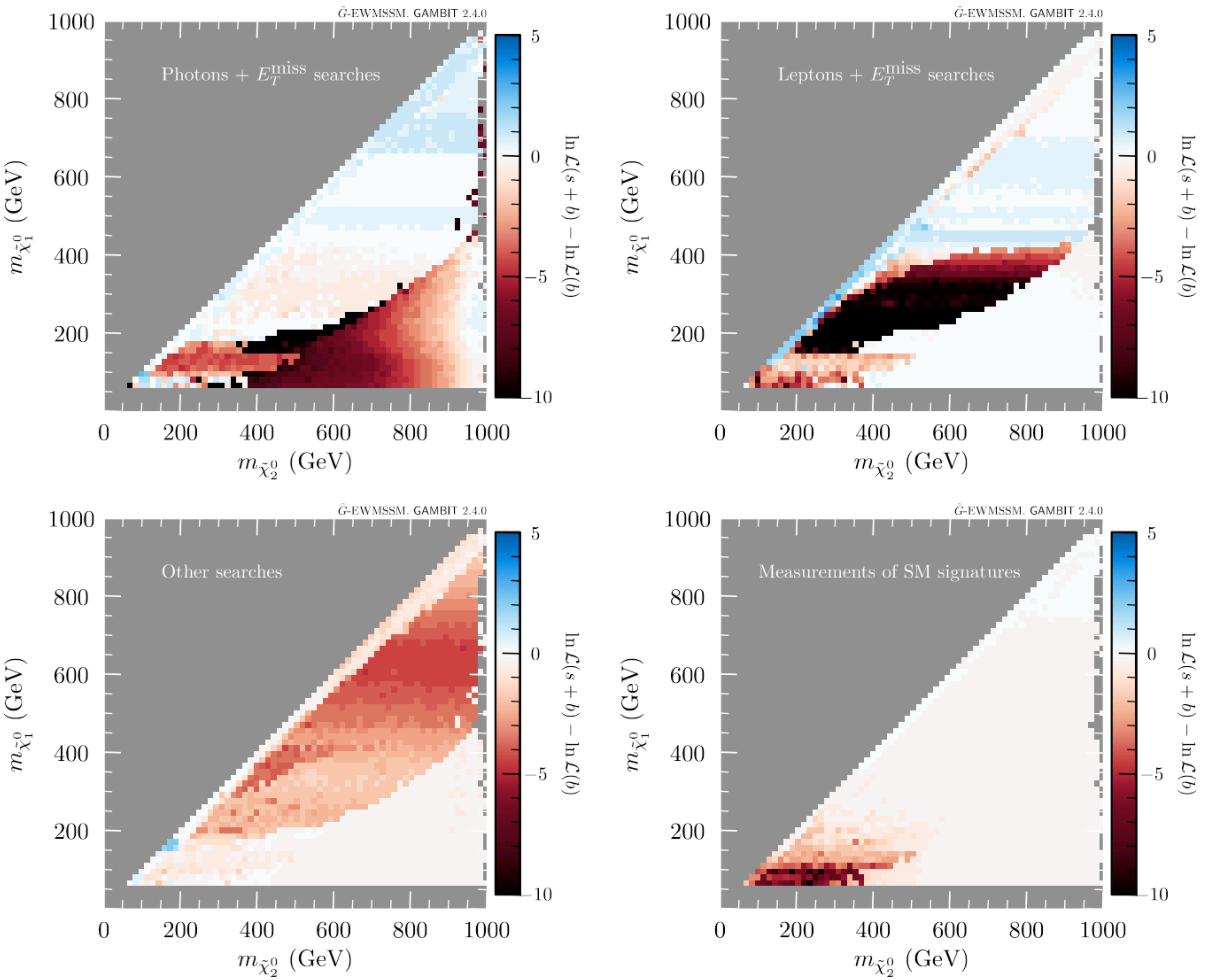


$M_1 = 900\,\text{GeV}, M_2 = 400\,\text{GeV}, \tan\beta = 1$
$\text{BR}(\tilde{\chi}_1^0 \to \gamma\tilde{G})$
$\text{BR}(\tilde{\chi}_1^0 \to Z\tilde{G})$
$\text{BR}(\tilde{\chi}_1^0 \to h\tilde{G})$
$1 - \sum \text{BR}(...)$
Wino NLSP
Higgsino NLSP
Branching ratio
μ [GeV]



$M_1 = 900\,\text{GeV}, M_2 = 400\,\text{GeV}, \tan\beta = 10$
$\text{BR}(\tilde{\chi}_1^0 \to \gamma\tilde{G})$
$\text{BR}(\tilde{\chi}_1^0 \to Z\tilde{G})$
$\text{BR}(\tilde{\chi}_1^0 \to h\tilde{G})$
$1 - \sum \text{BR}(...)$
Wino NLSP
Higgsino NLSP
Branching ratio
μ [GeV]

Search label	Luminosity	Source
ATLAS_2BoostedBosons	$139\,\mathrm{fb}^{-1}$	ATLAS hadronic chargino/neutralino search [100]
ATLAS_0lep	$139\,\mathrm{fb}^{-1}$	ATLAS 0-lepton search [101]
ATLAS_0lep_stop	$36\,\mathrm{fb}^{-1}$	ATLAS 0-lepton stop search [102]
ATLAS_1lep_stop	$36\,\mathrm{fb}^{-1}$	ATLAS 1-lepton stop search [103]
ATLAS_2lep_stop	$139\,\mathrm{fb}^{-1}$	ATLAS 2-lepton stop search [104]
ATLAS_2OSlep_Z	$139\,\mathrm{fb}^{-1}$	ATLAS stop search with Z/H final states [105]
ATLAS_2OSlep_chargino	$139\,\mathrm{fb}^{-1}$	ATLAS 2-lepton chargino search [106]
ATLAS_2b	$36\,\mathrm{fb}^{-1}$	ATLAS 2-b-jet stop/sbottom search [107]
ATLAS_3b	$24\,\mathrm{fb}^{-1}$	ATLAS 3-b-jet Higgsino search [108]
ATLAS_3lep	$139\,\mathrm{fb}^{-1}$	ATLAS 3-lepton chargino/neutralino search [109]
ATLAS_4lep	$139\,\mathrm{fb}^{-1}$	ATLAS 4-lepton search [110]
ATLAS_MultiLep_strong	$139\,\mathrm{fb}^{-1}$	ATLAS leptons + jets search [111]
ATLAS_PhotonGGM_1photon	$139\,\mathrm{fb}^{-1}$	ATLAS 1-photon GGM search [112]
ATLAS_PhotonGGM_2photon	$36\,\mathrm{fb}^{-1}$	ATLAS 2-photon GGM search [113]
ATLAS_Z_photon	$80\,\mathrm{fb}^{-1}$	ATLAS Z + photon search [114]
CMS_0lep	$137\,\mathrm{fb}^{-1}$	CMS 0-lepton search [115]
CMS_1lep_bb	$36\,\mathrm{fb}^{-1}$	CMS 1-lepton + b-jets chargino/neutralino search [116]
CMS_1lep_stop	$36\,\mathrm{fb}^{-1}$	CMS 1-lepton stop search [117]
CMS_2lep_stop	$36\,\mathrm{fb}^{-1}$	CMS 2-lepton stop search [118]
CMS_2lep_soft	$36\,\mathrm{fb}^{-1}$	CMS 2 soft lepton search [119]
CMS_2OSlep	$137\,\mathrm{fb}^{-1}$	CMS 2-lepton search [120]
CMS_2OSlep_chargino_stop	$36\,\mathrm{fb}^{-1}$	CMS 2-lepton chargino/stop search [121]
CMS_2SSlep_stop	$137\,\mathrm{fb}^{-1}$	CMS 2 same-sign lepton stop search [122]
CMS_MultiLep	$137\,\mathrm{fb}^{-1}$	CMS multilepton chargino/neutralino search [123]
CMS_photon	$36\,\mathrm{fb}^{-1}$	CMS 1-photon GMSB search [124]
CMS_2photon	$36\,\mathrm{fb}^{-1}$	CMS 2-photon GMSB search [125]
CMS_1photon_1lepton	$36\,\mathrm{fb}^{-1}$	CMS 1-photon + 1-lepton GMSB search [126]


Photons + E_T^{miss} searches
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$m_{\tilde{\chi}_1^0}$ (GeV)
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0
200
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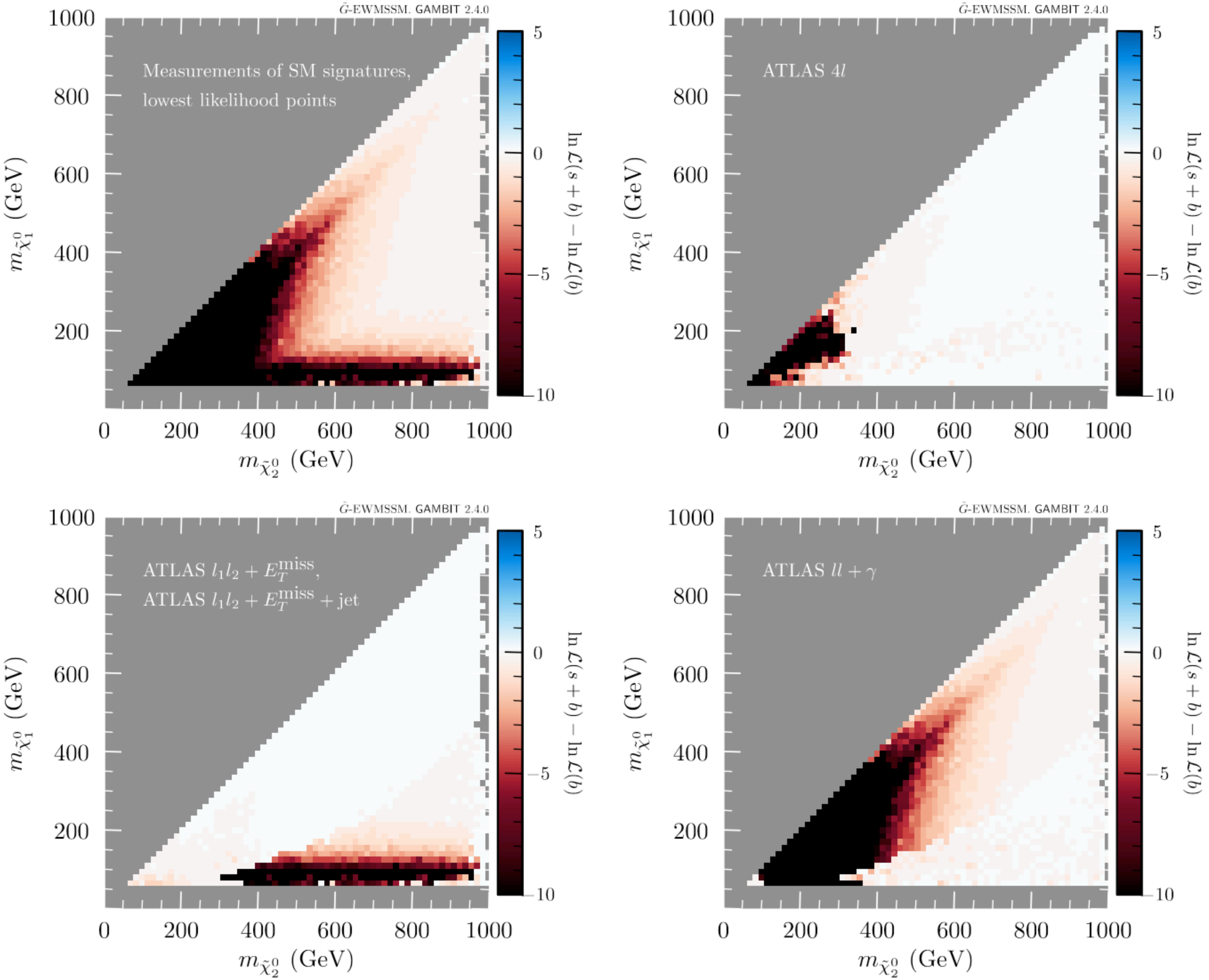
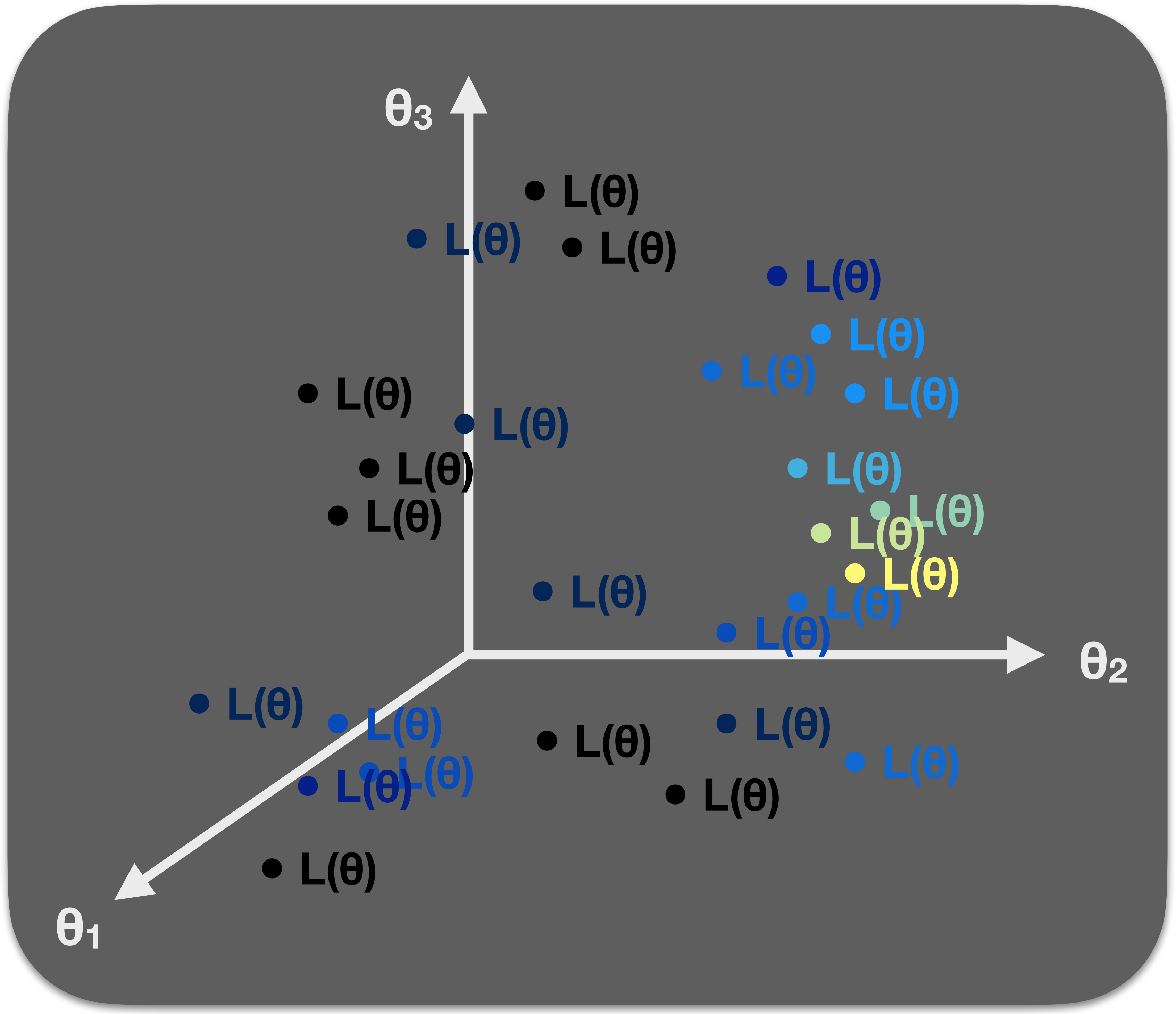


$\tilde{G}$-EWMSSM, GAMBIT 2.4.0
Measurements of SM signatures, lowest likelihood points
ATLAS $4l$
ATLAS $l_1l_2 + E_T^{\text{miss}}$, ATLAS $l_1l_2 + E_T^{\text{miss}} + \text{jet}$
ATLAS $ll + \gamma$
$m_{\tilde{\chi}_1^0}$ (GeV)
$m_{\tilde{\chi}_2^0}$ (GeV)
$\ln \mathcal{L}(s+b) - \ln \mathcal{L}(b)$

- **Explore the model parameter space** (θ_1, θ_2, θ_3, …)
- At every point θ: **compute all predictions(θ) → evaluate likelihood L(θ)**



- Region of highest L(θ) or lnL(θ): **model's best simultaneous fit to all data**
(but not necessarily a *good* fit, or the most probable θ…)

Detailed model → many parameters → high-dimensional parameter space

High-dimensional spaces are exponentially tricky to explore…

- For given sample density, the number of required samples increases exponentially
  - 0.01 resolution for a 1D unit interval: 100 points
  - 0.01 resolution for a 10D unit cube: $100^{10} = 10^{20}$ points
- The volume of any interesting region decreases exponentially fast with D
- A uniformly sampled point is «always» near at least *one* of the walls…
- …and it's also «always» the surface of a sphere with radius sqrt(D/3)
- Relative differences in distances between points vanish («loss of contrast»)

Detailed model → many parameters → high-dimensional parameter space

High-dime

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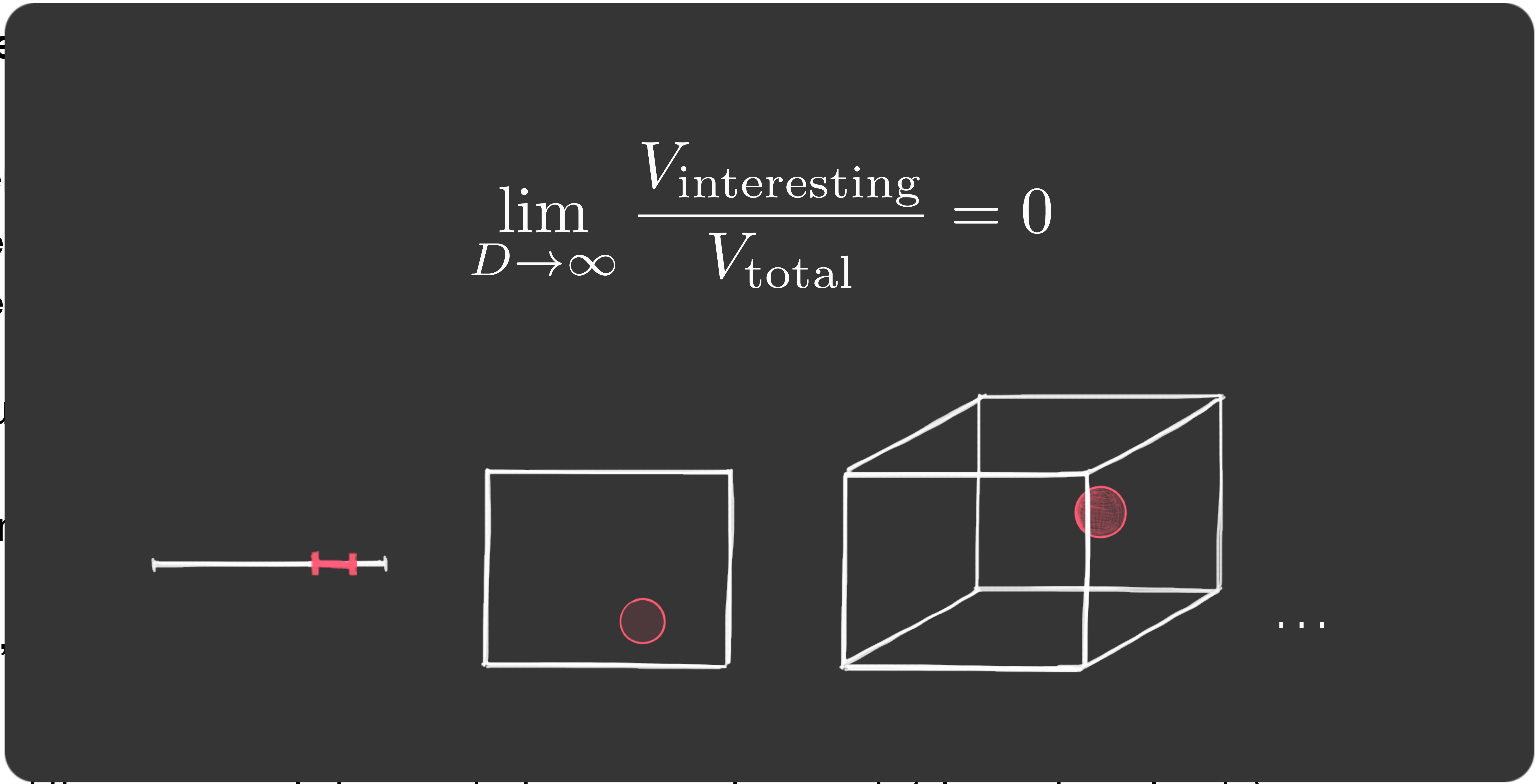

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  - 0.01 resolution fo
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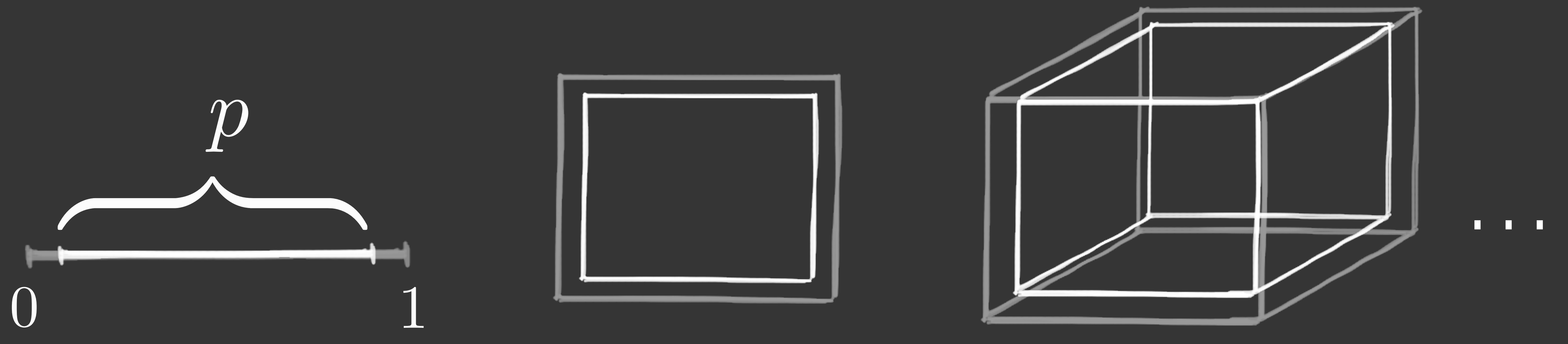
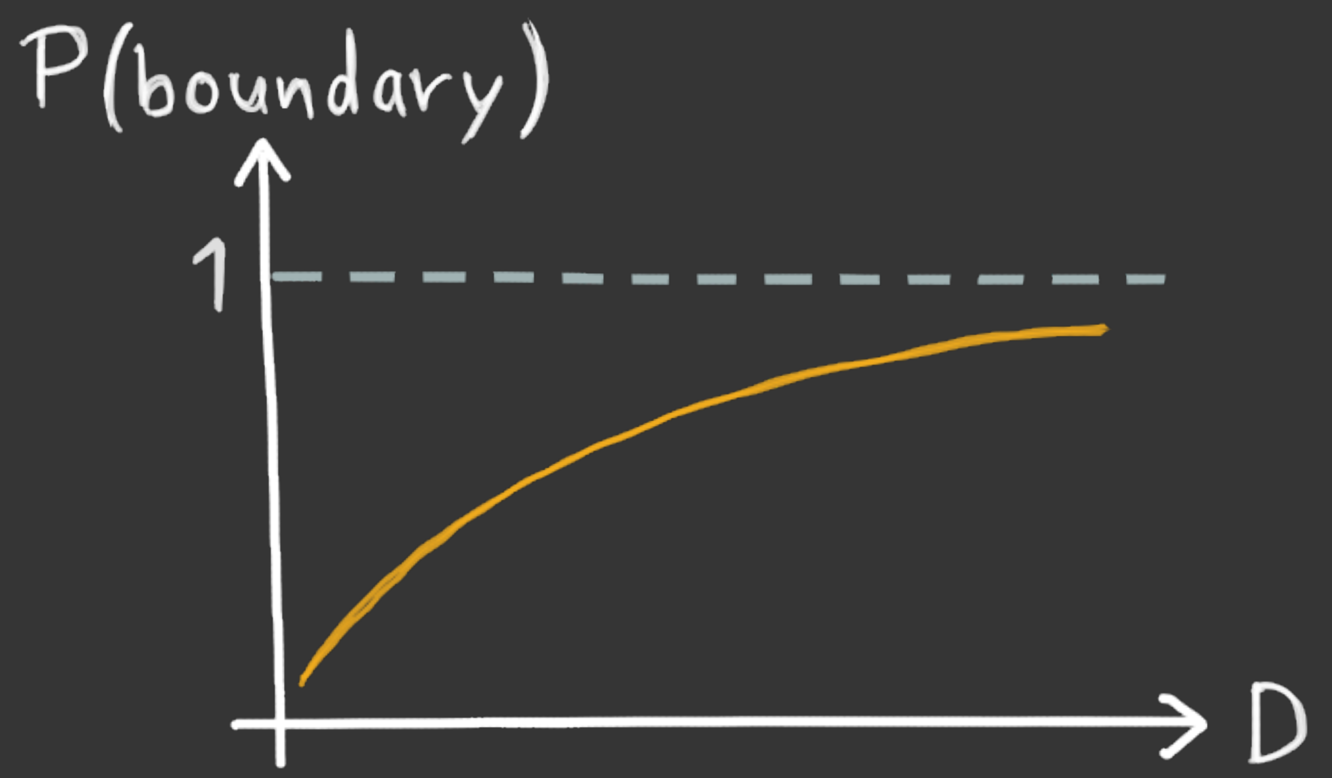
- …and it’s also «a
- Relative differenc

$$\vec{x} = (x_1, x_2, \dots, x_D) \quad x_i \sim U(0,1)$$



$$P(\text{boundary}) = 1 - P(\text{not boundary}) = 1 - p^D$$



Detailed model → many parameters → high-dimensional parameter space

High-dimensional spaces are exponentially tricky to explore…

- For given sample density, the number of required samples increases exponentially
  - 0.01 resolution for a 1D unit interval: 100 points
  - 0.01 resolution for a 10D unit cube: $100^{10} = 10^{20}$ points
- The volume of any interesting region decreases exponentially fast with D
- A uniformly sampled point is «always» near at least *one* of the walls…
- …and it's also «always» the surface of a sphere with radius sqrt(D/3)
- Relative differences in distances between points vanish («loss of contrast»)

Consequence:
Detailed physics models → huge computational challenge

[large number of observables]

$$\times$$

[long calculation time per observable per parameter point]

$$\times$$

[huge number of points required to explore parameter space]

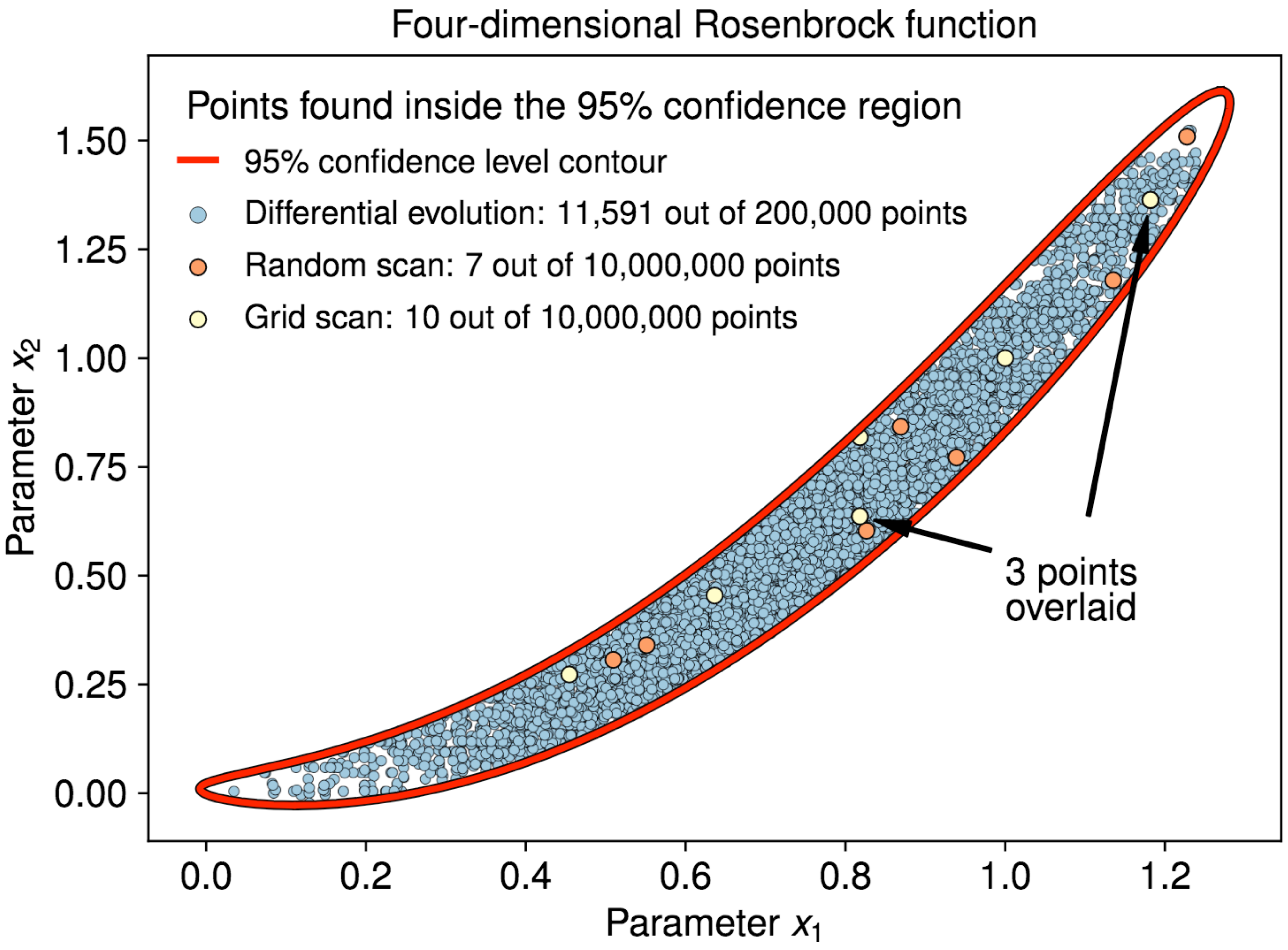
$$\approx$$

$$\infty$$

So we must:

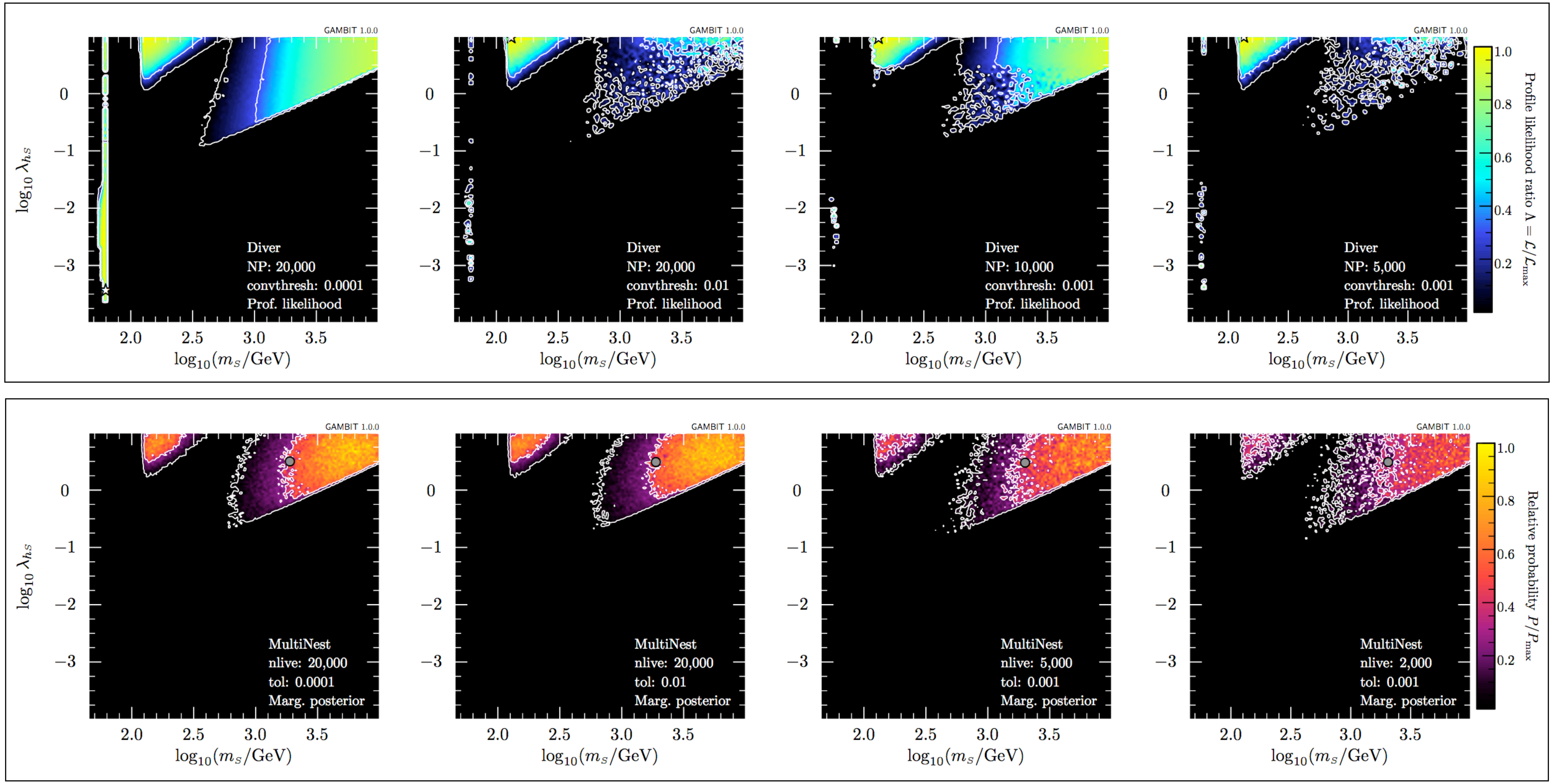
- speed up our physics computations where we can
- pick our parameter samples wisely
- maximise the usefulness of the CPU hours we spend

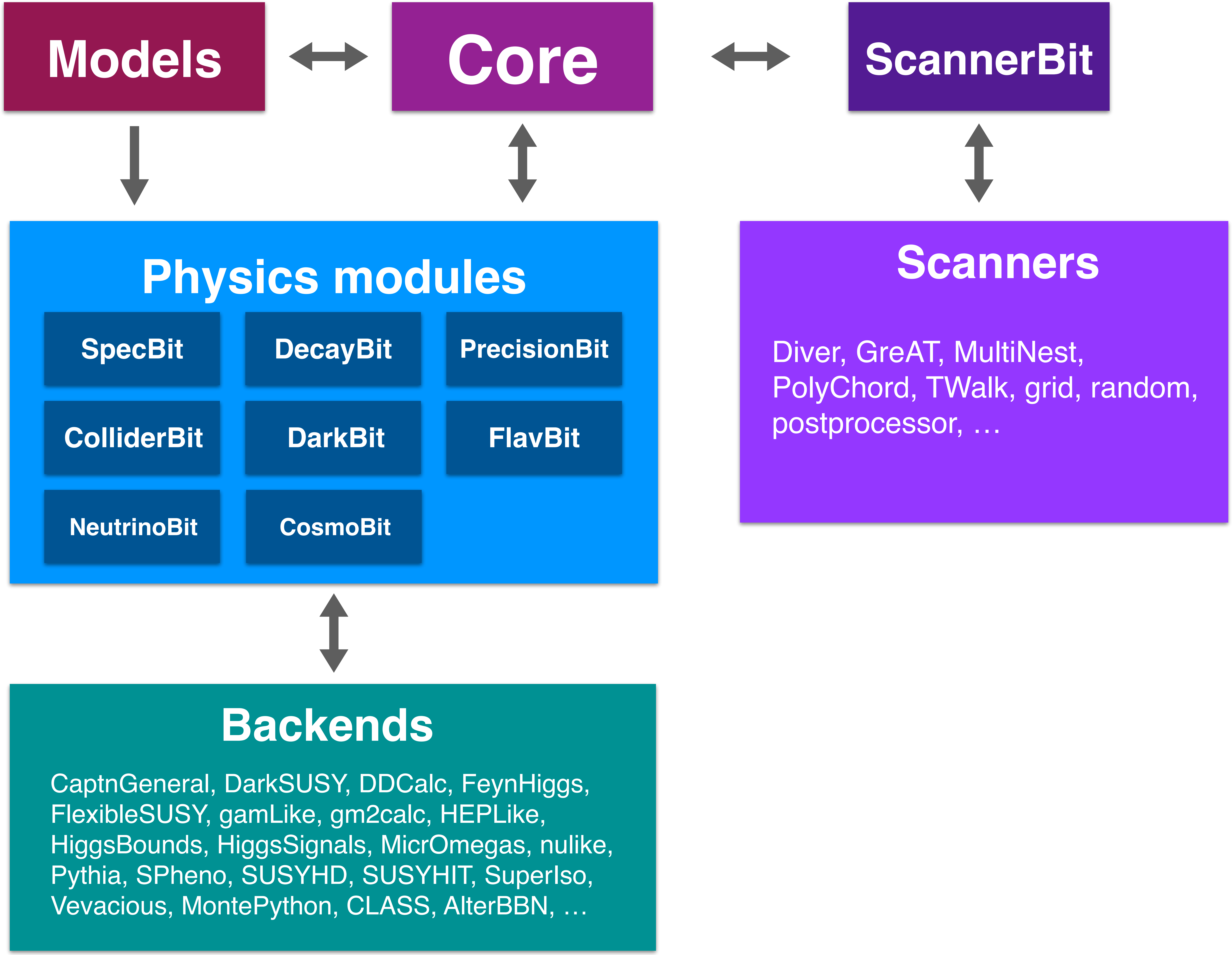
Parameter space exploration



[2012.09874]

Parameter space exploration




Models
Core
ScannerBit
Physics modules
SpecBit
DecayBit
PrecisionBit
ColliderBit
DarkBit
FlavBit
NeutrinoBit
CosmoBit
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, …