SModelS – from model constraints to the inverse problem

image courtesy of Jon Butterworth, Chris Wormell

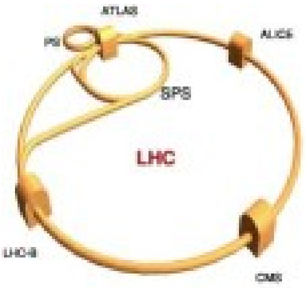
Wolfgang Waltenberger (ÖAW and Uni Vienna),
for the SModelS group

HEPHY
INSTITUT FÜR HOCHENERGIEPHYSIK

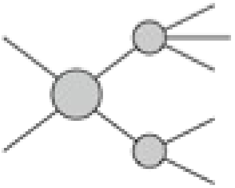
ATLAS-internal SUSY meeting, June 2020

Recap: simplified models

Back in the day, our community introduced simplified models with the intention of introducing an abstraction layer between the raw results and theoretical models.



simplified model

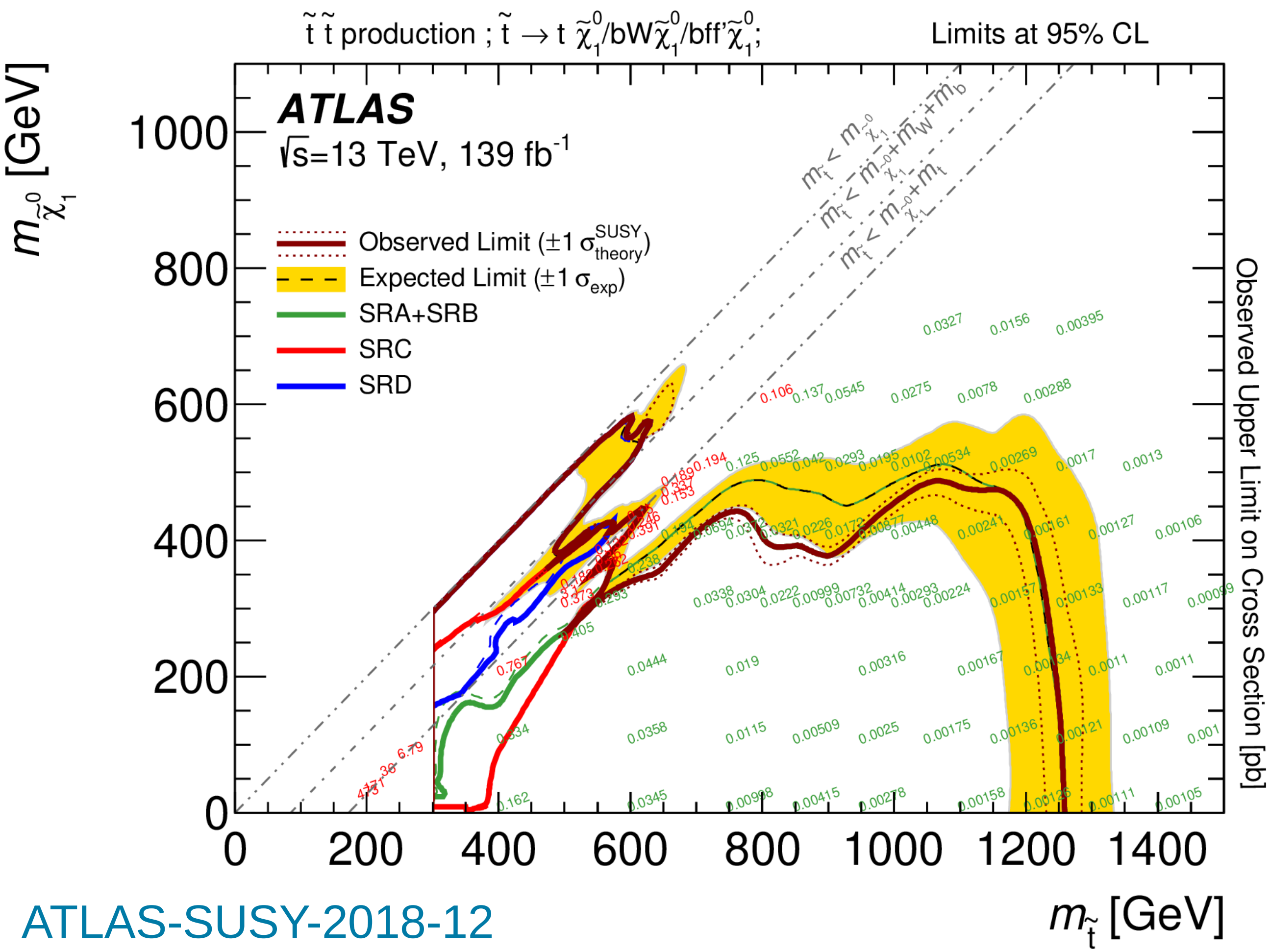


$\mathcal{L}$

The idea was, that instead of inferring the Next Standard Model (NSM) directly, we describe our findings with simplified models, and only then make the connection with fundamental theories.

Recap: simplified models

They have since served as a useful tool to contextualize our BSM searches, to give them a meaning.



ATLAS-SUSY-2018-12

This is one of your typical results.

Of such plots, we can make use of:

- the upper limits – the green and red numbers,
- the exclusion lines – to verify that we use the information correctly
- the "constraint" – the description of the simplified model, to understand which parts of a full theory we can apply the result to.

In this talk I will wish to convey how efficiency maps and full likelihoods majorly increase the usefulness of these results for us.

Our Inverse Problem

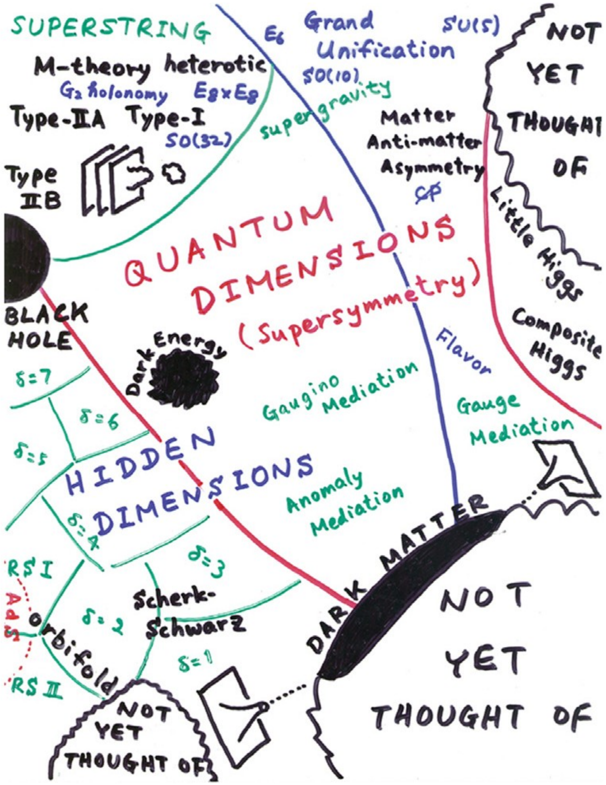
Obviously, our ultimate goal is not setting limits on (unphysical) models. Our ultimate goal must clearly be to arrive at a Next Standard Model (NSM), given LHC (and other) data.

This is a typical "Inverse Problem":
inductive reasoning with no clear recipe for success.

Q: Did we face similar situations in the past?

A: Not really. Our most recent big achievements (top discovery, Higgs discovery) were driven by highly predictive models. Think e.g. of the Higgs mechanism. It only had one free parameter, the Higgs mass. Classical hypothesis testing works very well in such a setting.

Searching for the NSM is a much more vague endeavour. The number of potential models is huge, many models come with an enormous amount of free parameters.

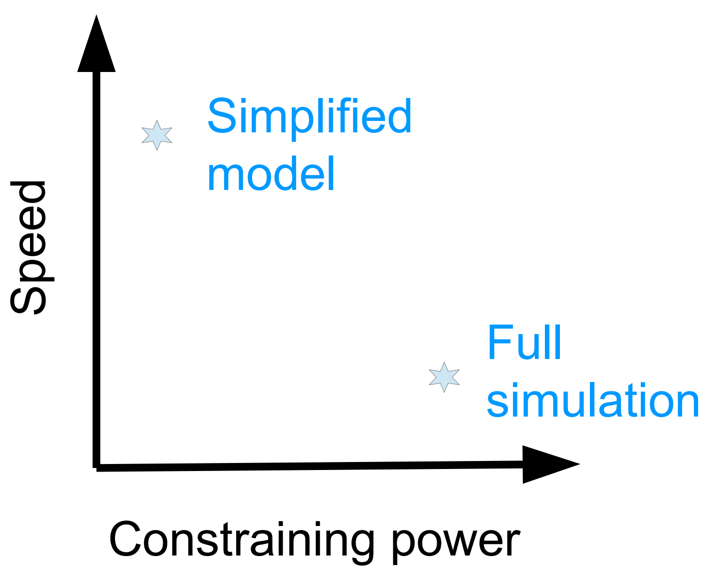


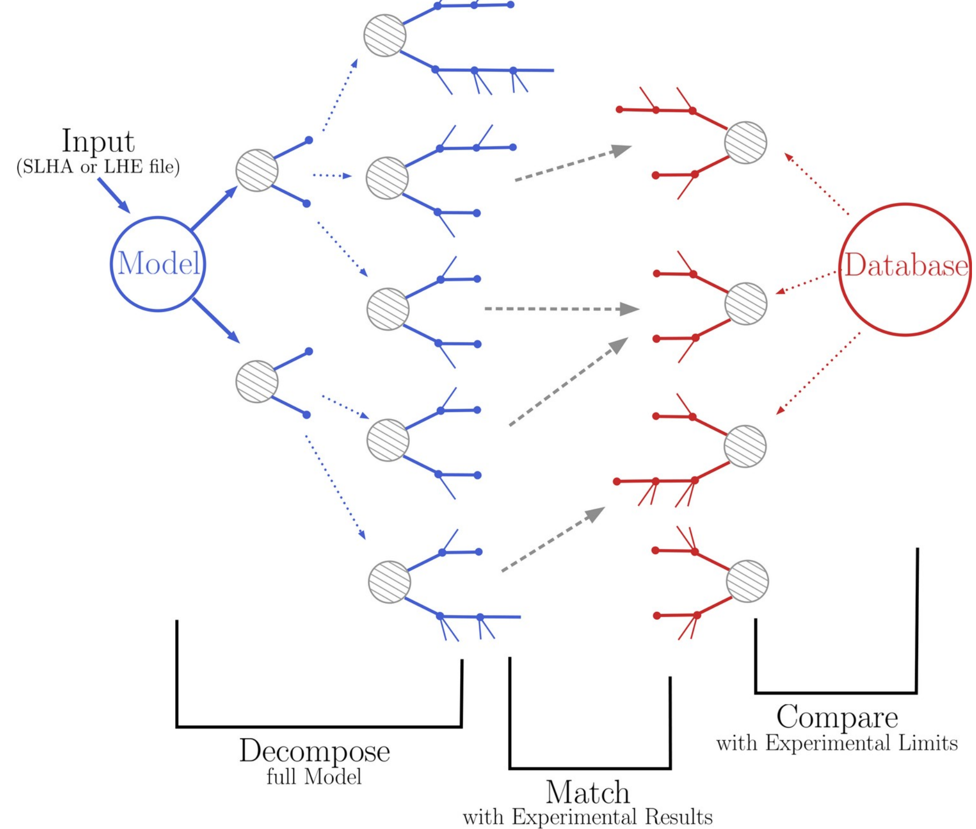
Hitoshi's impression of the theory landscape

How do we envisage we tackle our inverse problem?

Recap: SModelS

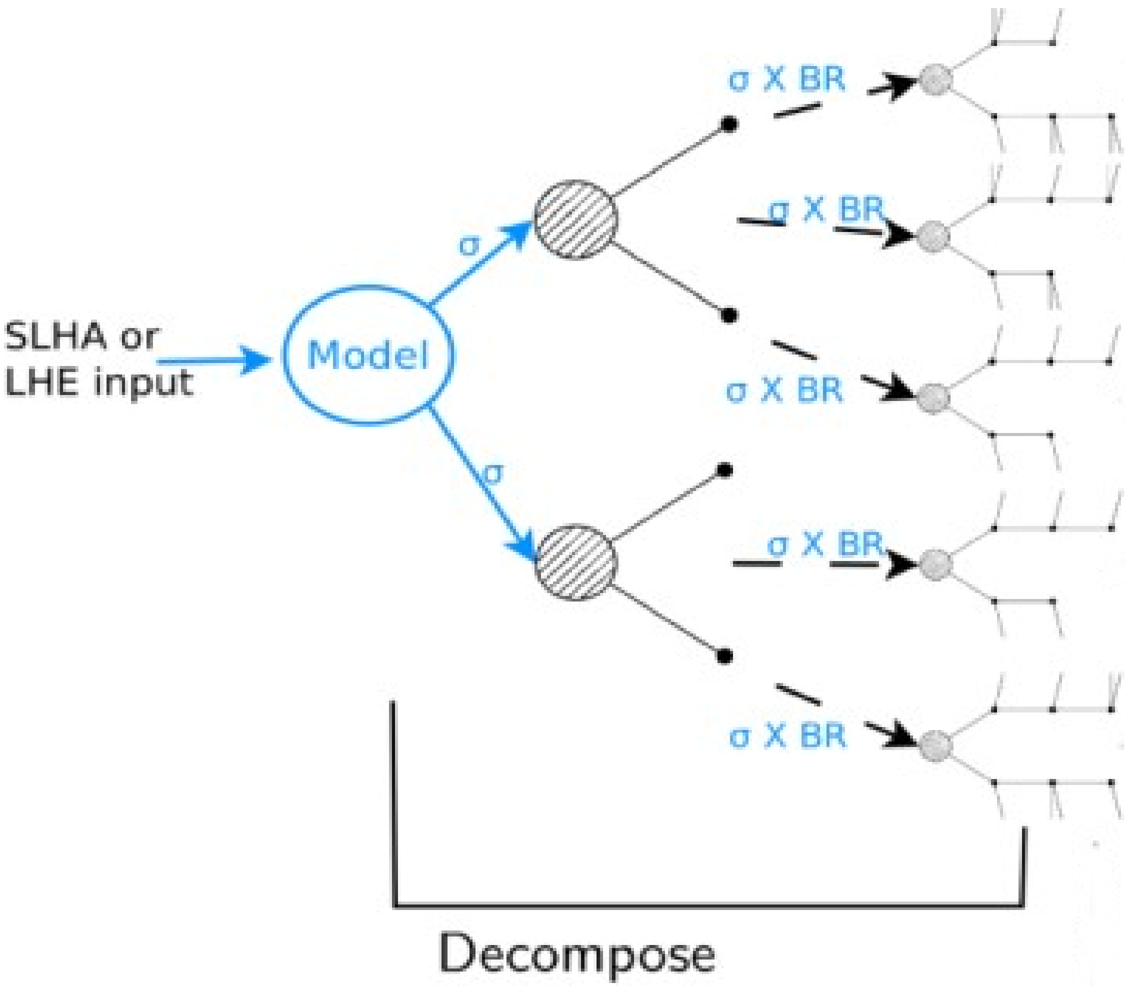
SModelS confronts theories beyond the Standard Model (BSM) with LHC search results by decomposing full models into their simplified models topologies, and comparing the cross section predictions of these individual topologies with a database of SMS results.





Recap: SModelS

1) Decomposition of a fundamental model



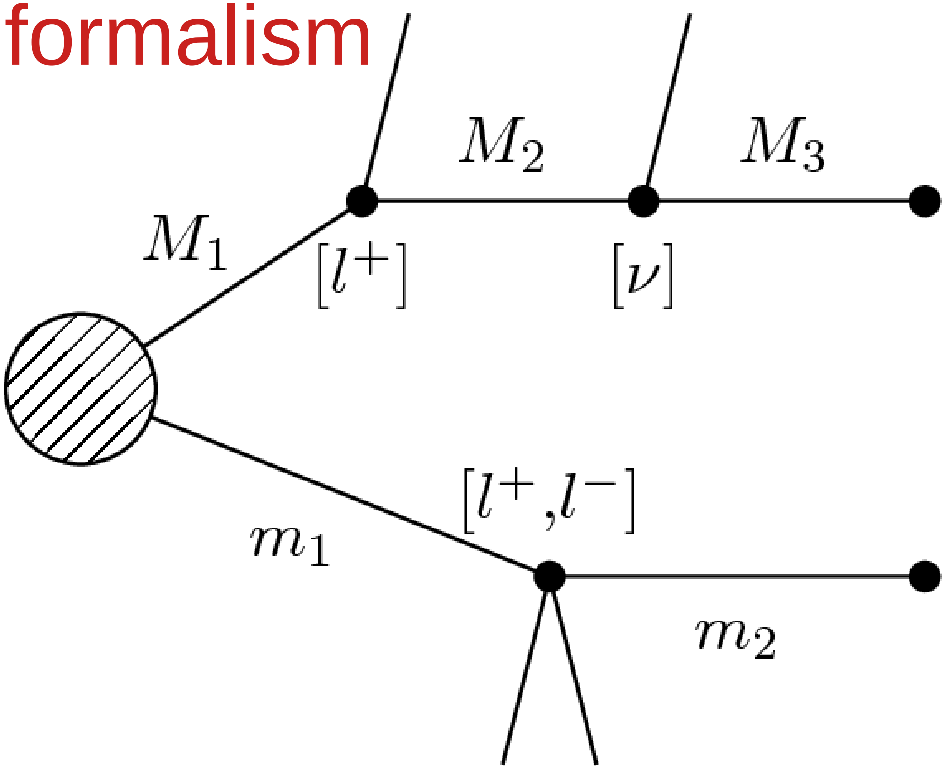
Input: SLHA file (mass spectrum, BRs) or LHE file (parton level)

Currently the model must have a $\mathbf{Z}_2$ symmetry

The decomposition produces a set of simplified model topologies (dubbed “elements”)

Recap: SModelS

2) Description of the topology in the SModelS formalism



$$= [[l^+],[\nu]]$$

$$= [\ [[l^+],[\nu]]\ ,\ [[l^+,l^-]]\ ]$$
$$([[M_1,M_2,M_3],[m_1,m_2]])$$

$$= [[l^+,l^-]]$$

Each topology is described by:

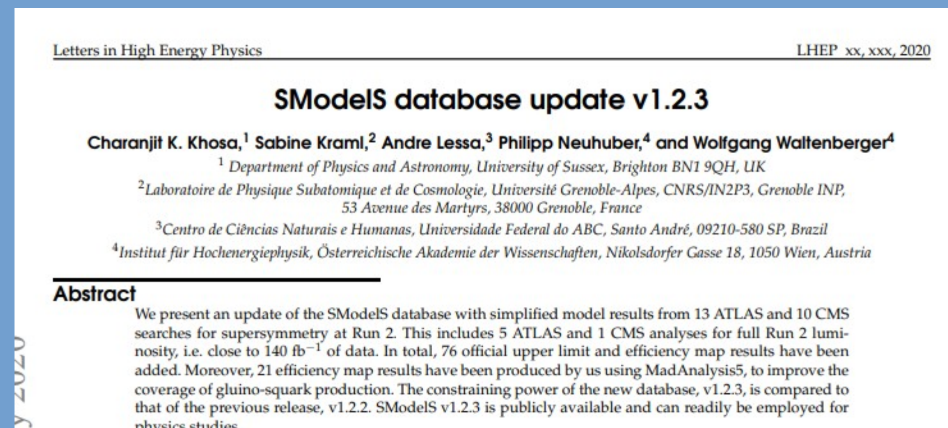
- Topology shape + final states
- BSM masses
- σ x BR

We (currently) ignore spin, color, etc of the BSM particles

It is model independent, there is no reference to the original model

Recap: SModelS

3) Matching elements with a database of ~ 50 ATLAS and ~ 50 CMS results



Letters in High Energy Physics LHEP xx, xxx, 2020

SModelS database update v1.2.3

Charanjit K. Khosa,[1] Sabine Kraml,[2] Andre Lessa,[3] Philipp Neuhuber,[4] and Wolfgang Waltenberger[4]
[1] Department of Physics and Astronomy, University of Sussex, Brighton BN1 9QH, UK
[2] Laboratoire de Physique Subatomique et de Cosmologie, Université Grenoble-Alpes, CNRS/IN2P3, Grenoble INP, 53 Avenue des Martyrs, 38000 Grenoble, France
[3] Centro de Ciências Naturais e Humanas, Universidade Federal do ABC, Santo André, 09210-580 SP, Brazil
[4] Institut für Hochenergiephysik, Österreichische Akademie der Wissenschaften, Nikolsdorfer Gasse 18, 1050 Wien, Austria

Abstract
We present an update of the SModelS database with simplified model results from 13 ATLAS and 10 CMS searches for supersymmetry at Run 2. This includes 5 ATLAS and 1 CMS analyses for full Run 2 luminosity, i.e. close to 140 fb^{-1} of data. In total, 76 official upper limit and efficiency map results have been added. Moreover, 21 efficiency map results have been produced by us using MadAnalysis5, to improve the coverage of gluino-squark production. The constraining power of the new database, v1.2.3, is compared to that of the previous release, v1.2.2. SModelS v1.2.3 is publicly available and can readily be employed for physics studies.

#	ID	Pretty Name	Type	$\mathcal{L}$ [fb^{-1}]
1	CMS-PAS-EXO-16-036	hscp search	ul, eff	12.9
2	CMS-PAS-SUS-16-022	>= 3 l's + $\not{E}_T$	ul	12.9
3	CMS-PAS-SUS-16-052	soft l, <= 2 jets	ul, eff	35.9
4	CMS-PAS-SUS-17-004	multi-l EWK searches	ul	35.9
5	CMS-SUS-16-009	multijets + $\not{E}_T$, top tagging	ul	2.3
6	CMS-SUS-16-032	Sbottom and compressed stop	ul	35.9
7	CMS-SUS-16-033	0L + jets + $\not{E}_T$	ul, eff	35.9
8	CMS-SUS-16-034	2 OSSF l's	ul	35.9
9	CMS-SUS-16-035	2 SS l's	ul	35.9
10	CMS-SUS-16-036	0L + jets + $\not{E}_T$	ul	35.9
11	CMS-SUS-16-037	1L + jets + $\not{E}_T$ with MJ	ul	35.9
12	CMS-SUS-16-039	multi-l EWK searches	ul	35.9
13	CMS-SUS-16-041	multi-ls + jets + $\not{E}_T$	ul	35.9
14	CMS-SUS-16-042	1L + jets + $\not{E}_T$	ul	35.9
15	CMS-SUS-16-043	EWK WH	ul	35.9
16	CMS-SUS-16-045	Sbottom to bHbH and H $\to \gamma\gamma$	ul	35.9
17	CMS-SUS-16-046	$\gamma + \not{E}_T$	ul	35.9
18	CMS-SUS-16-047	γ + HT	ul	35.9
19	CMS-SUS-16-049	All hadronic stop	ul	35.9
20	CMS-SUS-16-050	0L + top tag	ul	35.9
21	CMS-SUS-16-051	1L stop	ul	35.9
22	CMS-SUS-17-001	Stop search in dil + jets + $\not{E}_T$	ul	35.9
23	CMS-SUS-17-003	2 taus + $\not{E}_T$	ul	35.9
24	CMS-SUS-17-004	EW-ino combination	ul	35.9
25	CMS-SUS-17-005	1L + multijets + $\not{E}_T$, top tagging	ul	35.9
26	CMS-SUS-17-006	jets + boosted H(bb) + $\not{E}_T$	ul	35.9
27	CMS-SUS-17-009	SFOS l's + $\not{E}_T$	ul	35.9
28	CMS-SUS-17-010	2L stop	ul	35.9
29	CMS-SUS-18-002	γ, jets, b-jets+ $\not{E}_T$, top tagging	ul	35.9
30	CMS-SUS-19-006	0L + jets, MHT	ul	137.0

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19.4 19.7 19.4 18.9 19.4 11.7 19.5 19.3 19.5 19.3 19.5 19.5 19.5 19.5 19.5

18	CMS-SUS-14-021	soft l's, low n_{jets}, high $\not{E}_T$	ul	19.7

#	ID	Pretty Name	Type	$\mathcal{L}$ [fb^{-1}]
1	ATLAS-SUSY-2015-01	2 b-jets + $\not{E}_T$	ul	3.2
2	ATLAS-SUSY-2015-02	single l stop	ul, eff	3.2
3	ATLAS-SUSY-2015-06	0 l's + 2-6 jets + $\not{E}_T$	eff	3.2
4	ATLAS-SUSY-2015-09	jets + 2 SS l's or >=3 l's	ul	3.2
5	ATLAS-SUSY-2016-07	0L + jets + $\not{E}_T$	ul, eff	36.1
6	ATLAS-SUSY-2016-14	2 SS or 3 l's + jets + $\not{E}_T$	ul	36.1
7	ATLAS-SUSY-2016-15	0L stop	ul, eff	36.1
8	ATLAS-SUSY-2016-16	1L stop	ul, eff	36.1
9	ATLAS-SUSY-2016-17	2 opposite sign l's + $\not{E}_T$	ul	36.1
10	ATLAS-SUSY-2016-19	stops to staus	ul	36.1
11	ATLAS-SUSY-2016-24	2-3 l's + $\not{E}_T$, EWino	ul, eff	36.1
12	ATLAS-SUSY-2016-26	>=2 c jets + $\not{E}_T$	ul	36.1
13	ATLAS-SUSY-2016-27	jets + γ + $\not{E}_T$	ul, eff	36.1
14	ATLAS-SUSY-2016-28	2 b-jets + $\not{E}_T$	ul	36.1
15	ATLAS-SUSY-2016-33	2 OSSF l's + $\not{E}_T$	ul	36.1
16	ATLAS-SUSY-2017-01	EWK WH(bb) + $\not{E}_T$	ul	36.1
17	ATLAS-SUSY-2017-02	0L + jets + $\not{E}_T$	ul	36.1
18	ATLAS-SUSY-2017-03	multi-l EWK searches	ul	36.1
19	ATLAS-SUSY-2018-04	2 hadronic taus	ul	139.0
20	ATLAS-SUSY-2018-06	3 l's EW-ino	ul	139.0
21	ATLAS-SUSY-2018-31	2b + 2H(bb) + $\not{E}_T$	ul	139.0
22	ATLAS-SUSY-2018-32	2 OS l's + $\not{E}_T$	ul	139.0
23	ATLAS-SUSY-2019-08	1L + higgs + $\not{E}_T$	ul	139.0

20.3 20.3 20.3 20.1 20.3 20.3 20.3 20.3 20.3 20.1 20.1 20.3 20.3 20.3 20.3

Work is in progress to cover wider range of experimental signatures, like LLPs, HSCPs, etc.

SModelS: input data

So what information goes into the database and how useful is what type of info?

- **Only exclusion lines**
  If only exclusion lines are given, without upper limits, we can do nothing

- **Observed 95% CL upper limits only:**
  cannot construct likelihood, binary decision "excluded" / "not-excluded" only

- **Expected and observed 95% CL upper limits**
  can construct an approximate likelihood with truncated Gaussian

- **Efficiency maps**
  can construct a better likelihood as Gaussian (for the nuisances) * Poissonian (for counting events in signal regions)

- **Cutflow tables, ADL descriptions**
  can produce "home-grown" efficiency maps via recasting frameworks (MA5, CutLang)

- **Efficiency maps + simplified likelihoods**
  can combine signal regions via multivariate Gaussian * Poissonians

- **Efficiency maps + pyhf likelihoods**
  can combine signal regions, in the long run potentially even analyses

Likelihoods

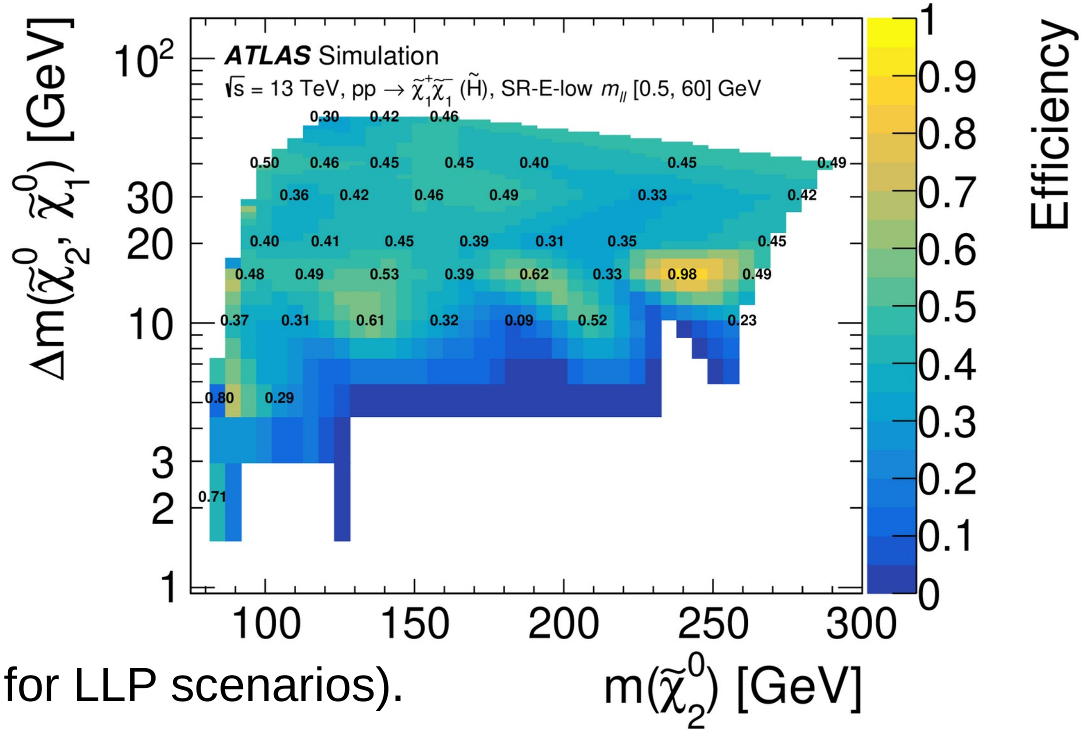
Combos

SModelS: input data

efficiency maps:

Apart from the very approximate likelihood obtained from expected+observed ULs, efficiency maps are needed. Often ATLAS and CMS provides them (thanks a ton!).

We can use all efficiency maps (per SR) given for “basic” simplified models. Efficiency maps for models with two or more cascade decays, and efficiency maps with “mixed” branchings will not enter the SModelS database.



While you guys need good showcases of simplified models and “mass planes”, we need good coverage: we are thus interested in also very extreme masses (high and low), and the whole phase space of particle masses (and widths, for LLP scenarios).

“Holes” in the maps can be a problem for us.

Phys. Rev. D 101 (2020) 052005

ATLAS-SUSY-2018-16

SModelS: input data

“home-grown” efficiency maps:

For the analyses without official efficiency maps, not all hope is lost for us. If there is a good description of the analyses with cut flow tables, or an ADL description (I come to that later), we can recast the analysis and produce the efficiency maps ourselves. Needless to say, we dont recast perfectly so this introduces another error – we prefer your maps.

ATLAS’ constraining power

SModelS’ power with home-grown maps

SModelS’ power without home-grown maps

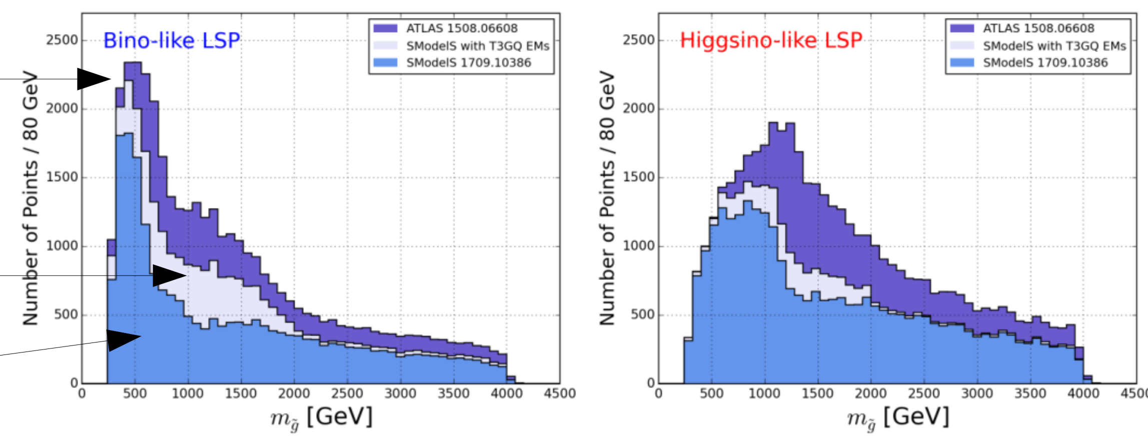


Figure 2. SModelS exclusion as a function of $m_{\tilde{g}}$ for the Bino(left) and Higgsino-like LSP (right): the points officially excluded by ATLAS are shown in purple, while in light blue the SModelS exclusion using the newly ‘homegrown’ maps for the *T2*, *T5* and *TGQ* (*T3GQ*) models is shown. The previous exclusion from [1], obtained without the EMs produced for this work, is shown in slate blue.

Our “home-grown” efficiency maps reduced the gap between our exclusion power and ATLAS’ exclusion power, for the pMSSM.

SModelS: input data

“home-grown” efficiency maps with ADL

Recently we have started to adopt the Analysis Description Language (ADL), which decouples the physics algorithm of an analysis from the analysis framework. If we have an ADL description of an analysis, we can produce efficiency maps for it, via tools that parse an ADL and run the analysis, e.g. “CutLang”.

Table 4. The "doublestep" algorithm

Step	Explanation	Commands in CutLang
1	name this algorithm "doublestep"	`algo doublestep`
2	execute preselection algorithm	`preselection`
3	minimize the Wχ^2	`cmd Wchi2 ~= 0`
4	minimize the top χ^2	`cmd topchi2 ~= 0`
5	mWH1 should be between 50 and 120 GeV	`cmd mWH1 [] 50 120`
6	mWH2 should be between 50 and 120 GeV	`cmd mWH2 [] 50 120`
7	WHbR1 should be greater than 0.6	`cmd WHbR1 > 0.6`
8	WHbR2 should be greater than 0.6	`cmd WHbR2 > 0.6`
9	Histogram the mass of WH1	`histo "mWHh1, W1 mass (GeV), 50, 50, 150, mWH1"`
10	Histogram the mass of WH2	`histo "mWHh2, W2 mass (GeV), 50, 50, 150, mWH2"`
11	Histogram the mass of TopH1	`histo "mTopHh1, top1 mass (GeV), 70, 0, 700, mTopH1"`
12	Histogram the mass of TopH2	`histo "mTopHh2, top2 mass (GeV), 70, 0, 700, mTopH2"`

But even if we have all efficiency maps in the world, we “underexclude”, because we cannot combine signal regions with this information only, …..

https://arxiv.org/abs/1605.02684
https://arxiv.org/abs/1803.10379
https://arxiv.org/abs/1801.05727
https://arxiv.org/abs/1909.10621

Likelihoods

Simplified likelihoods were introduced in 2017/2018 by CMS members. They are composed of individual Poissonians to model the counts in each signal region, together with a single multivariate Gaussian to model the envelope of all nuisances and the correlations between the signal regions.

Later, a skewness term was added.

Simplified likelihood, v1: All nuisances summarized in a single “all enveloping” multivariate Gaussian that “connects” all signal regions (which are Poissonian counting variables):

CMS-NOTE-2017-001

$$\mathcal{L}_S(\mu, \boldsymbol{\theta}) = \prod_{i=1}^{N} \frac{(\mu \cdot s_i + b_i + \theta_i)^{n_i} e^{-(\mu \cdot s_i + b_i + \theta_i)}}{n_i!} \cdot \exp\left(-\frac{1}{2}\boldsymbol{\theta}^T \mathbf{V}^{-1} \boldsymbol{\theta}\right)$$

Simplified likelihood, v2: a skewness term was proposed to allow for asymmetrical distributions.

arXiv:1809.05548

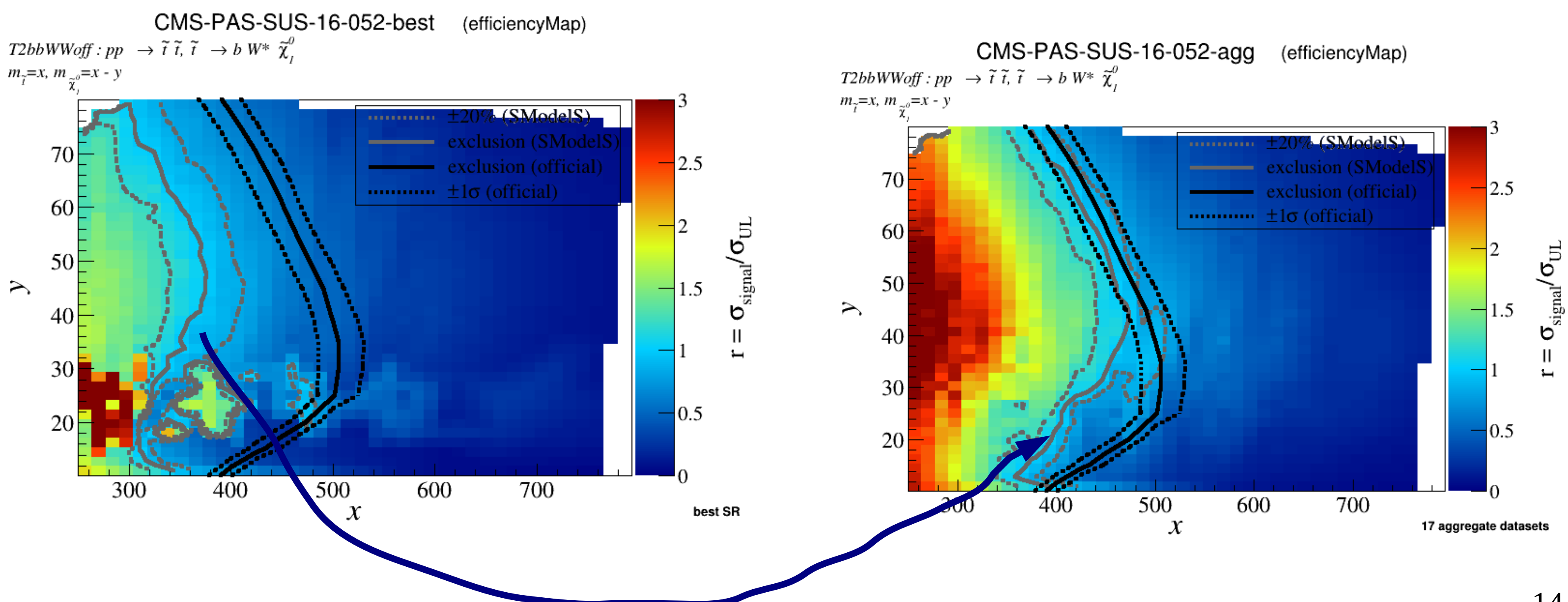
JHEP 04 (2019) 064

$$L_{\mathrm{S}}(\alpha, \theta) = \prod_{I=1}^{P} \Pr\left(n_I^{\mathrm{obs}} \,\middle|\, n_{s,I}(\alpha) + a_I + b_I\theta_I + c_I\theta_I^2\right) \cdot \frac{\mathrm{e}^{-\frac{1}{2}\theta^{\mathrm{T}}\rho^{-1}\theta}}{\sqrt{(2\pi)^P}}$$

SModelS: input data

Simplified likelihoods

For the first time in SModelS we could perform non-trivial combinations of signal regions. This significantly improved the constraining power of an analysis in SModelS:

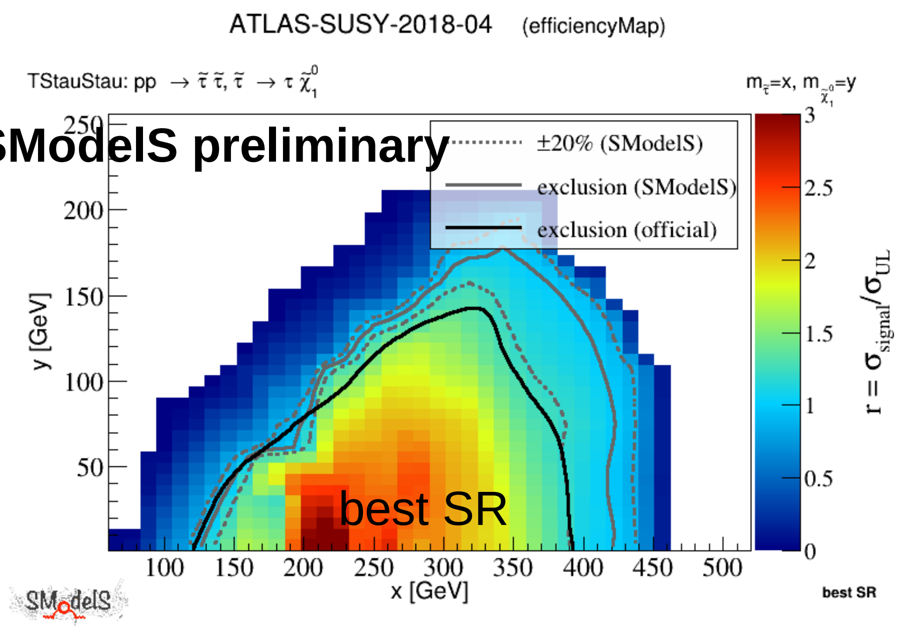


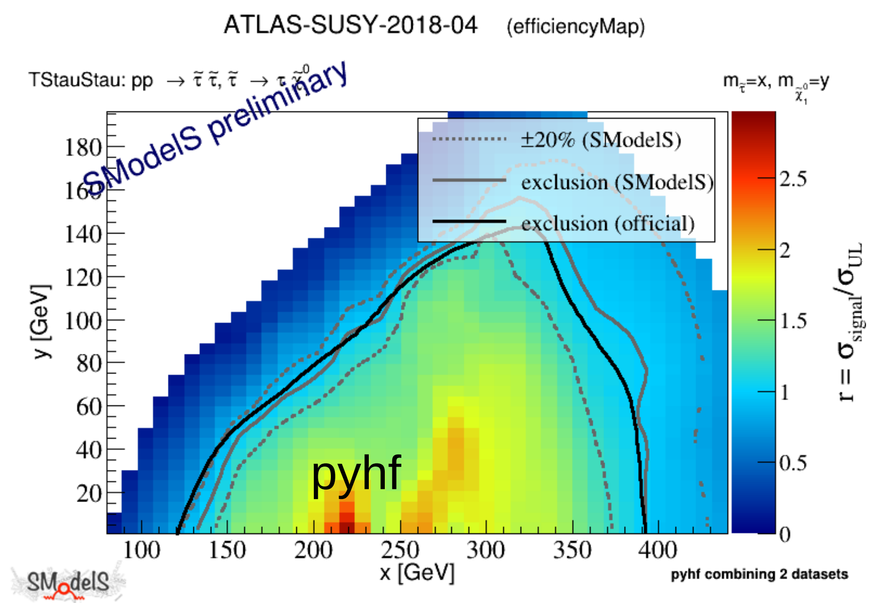
Improvement coming from combining signal regions via simplified likelihoods

SModelS: input data

Efficiency maps and pyhf

And now we have pyhf. Starting with SModelS v1.2.4, we will officially support it.



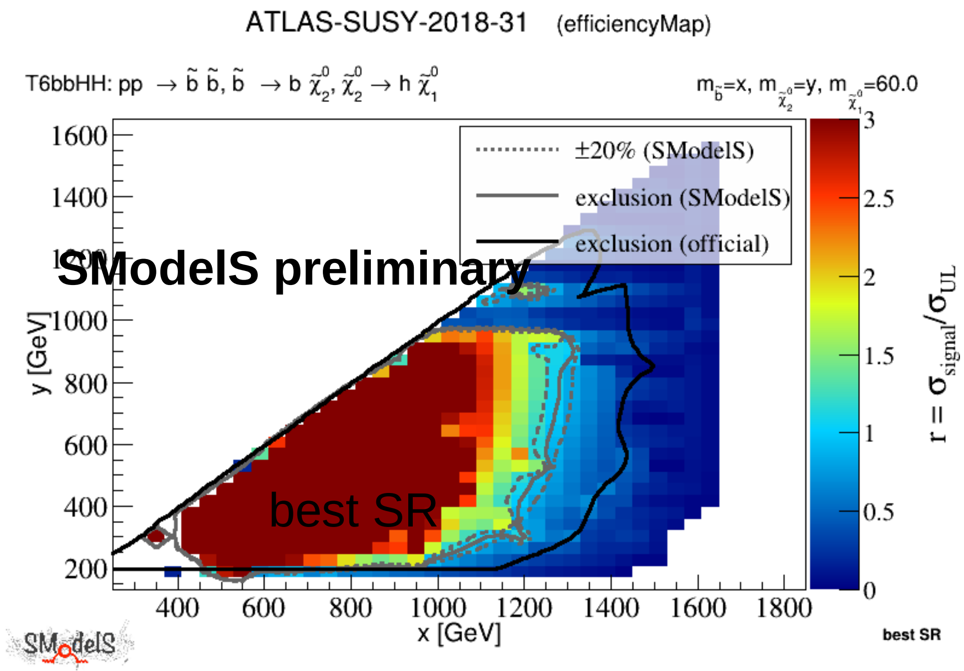


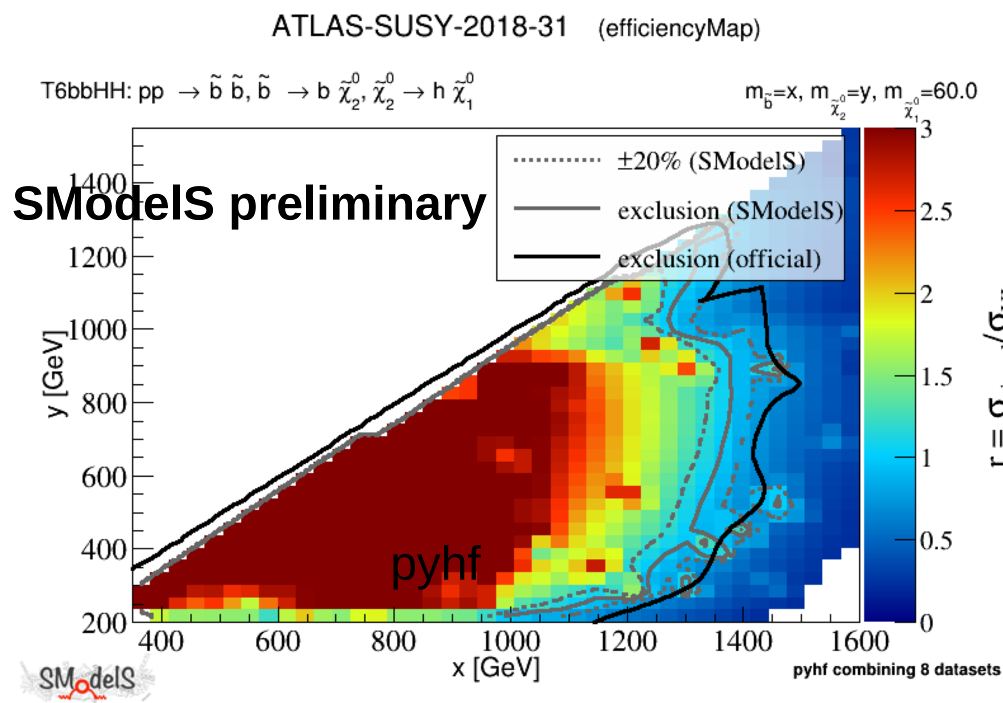
ATLAS result with two signal regions, showing a “poor person’s combination” – best expected SR on the left. Combination via pyhf on the right: we can reproduce your official exclusion lines.

https://github.com/scikit-hep/pyhf
doi:10.5281/zenodo.1169739

SModelS: input data

Efficiency maps and pyhf





ATLAS result with eight signal regions, showing a “poor person’s combination” – best expected SR on the left. Combination via pyhf on the right.

https://github.com/scikit-hep/pyhf
doi:10.5281/zenodo.1169739

correlations, combinations

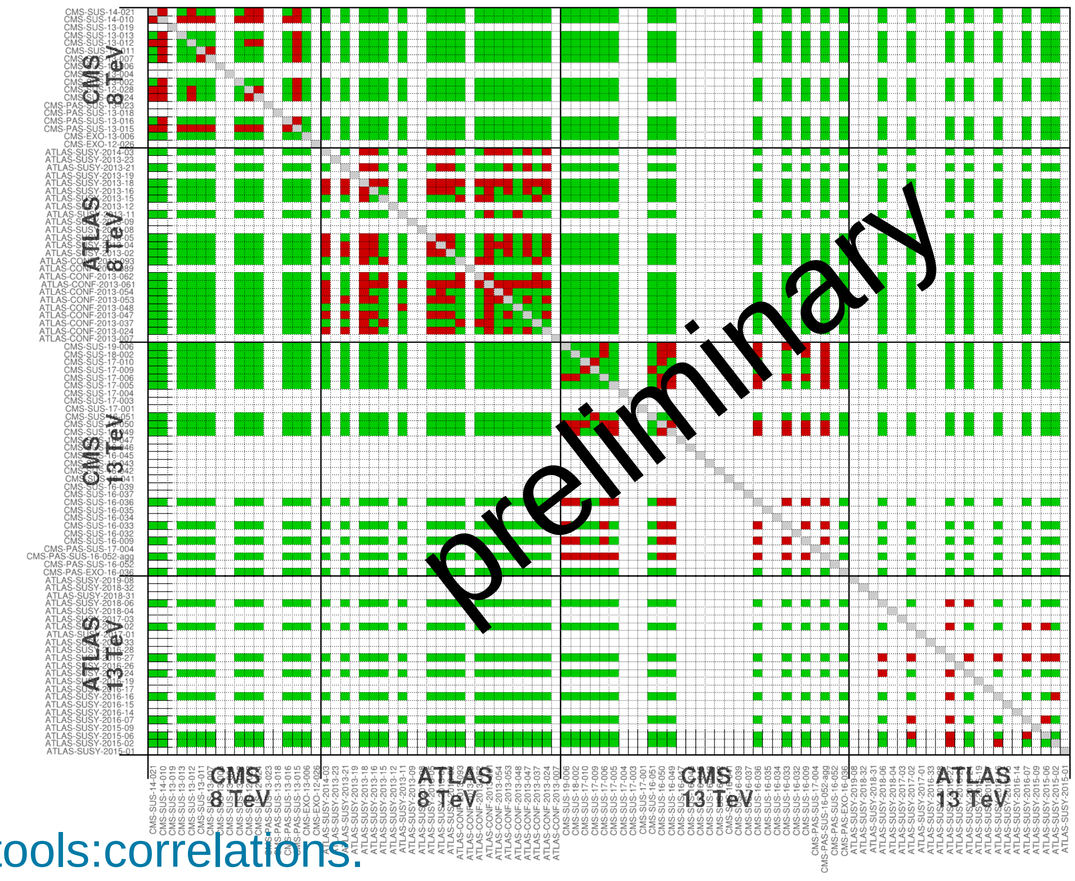
Once we have likelihoods, the question arises: which of the 100 analyses in our database can be combined – which are approximately uncorrelated, and which are not.

E.g. In good approximation, we can safely combine results from different runs and different experiments. We cannot combine results for which we have no likelihoods.

The matrix on the right was determined by eye – by looking at descriptions of the final states in the signal regions: Error-prone and ineffective!

Les Houches efforts have started to determine this matrix in an automated way, making use of MadAnalysis5 and ADL.

(This is a simplified, “binary” version of a matrix that CMS and ATLAS need for their internal combination efforts. Is it conceivable that the experiments publish such a correlation matrix? Alternatively, if we had pyhf likelihoods for many results, we could construct this ourselves)



https://phystev.cnrs.fr/wiki/2019:groups:tools:correlations.

Proto-models

One thing we have recently been working on in SModelS – apart from extending the framework to scenarios with long-lived particles – is setting up an algorithm that finds potentially dispersed signals in the SModelS database – signals that only become evident when combining all data.
It does so by “stacking up” simplified models (dubbed “proto-models”) to build potential precursors of the NSM, constructed from the SModelS database.

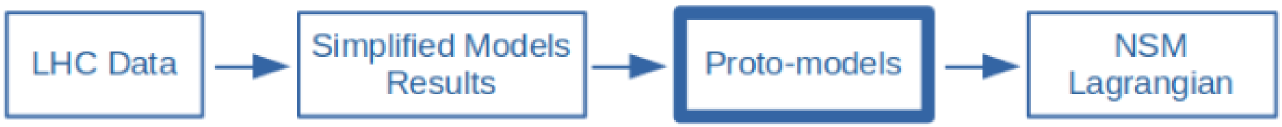


Figure 2: The overall strategy at how we envisage to construct the NSM from LHC Data: the raw data are described via Simplified Models results. From these, we shall construct proto-models. These proto-models are intended to serve as the input to constructing the NSM. The construction of proto-models is subject of this publication.

Artificial Proto-Modelling: Building Precursors of a Next Standard Model from Simplified Models Results

to appear on arXiv hopefully soon

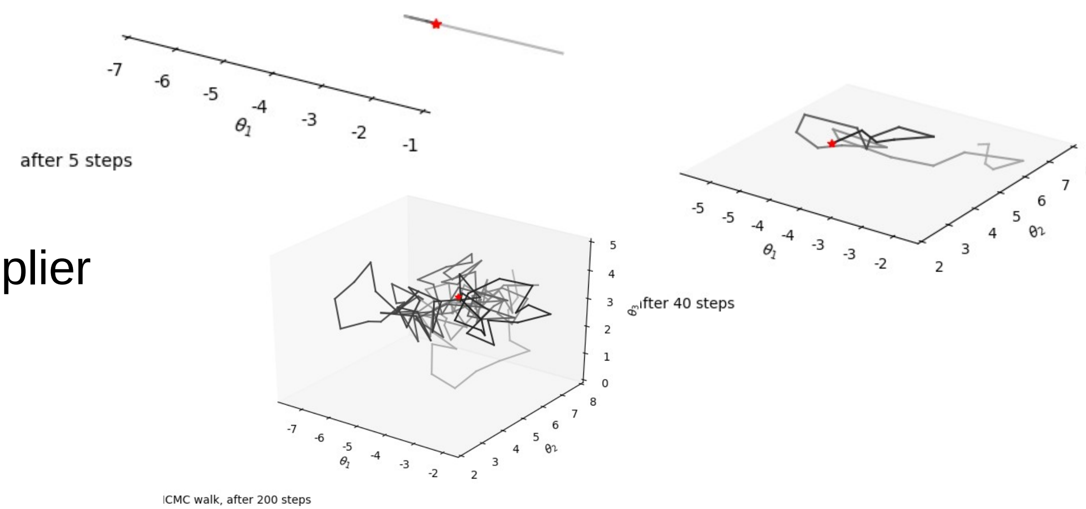
http://www.hephy.at/user/wwaltenberger/models/mcmc.webm

Proto-models

One thing we have recently been working on in SModelS (apart from extending the framework to scenarios with long-lived particles), setting up an algorithm that finds potentially dispersed signals in the SModelS database, while respecting all SMS constraints. It does that by “stacking up” simplified models in an MCMC-type walk, and checking if there are hints for a dispersed signal in “legal” combinations of results.

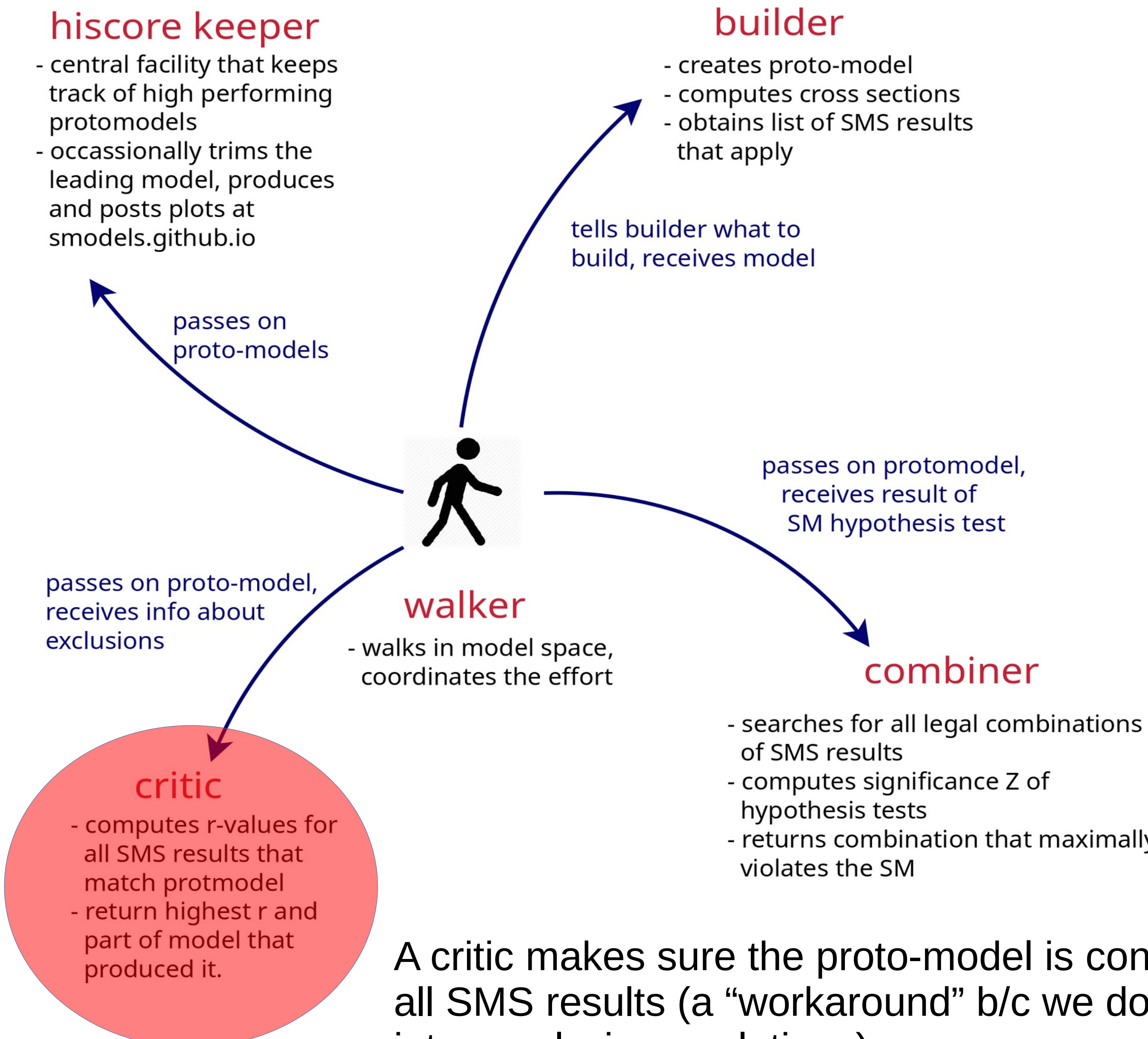
Possible actions being taken within the MCMC walk:

- randomly add a particle
- randomly remove a particle
- randomly change a branching
- randomly change a signal strength multiplier
- ….



http://www.hephy.at/user/wwaltenberger/models/mcmc.webm

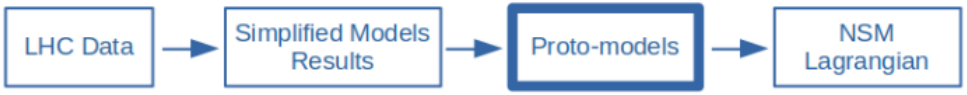
Proto-models



A critic makes sure the proto-model is consistent with all SMS results (a “workaround” b/c we dont have inter-analysis correlations)

Proto-models

The overall vision of this being that instead of postulating NSM candidates and then falsifying them (or failing to do so), we put the model building into the statistical procedure itself. A slow, bottom-up procedure, starting from data.



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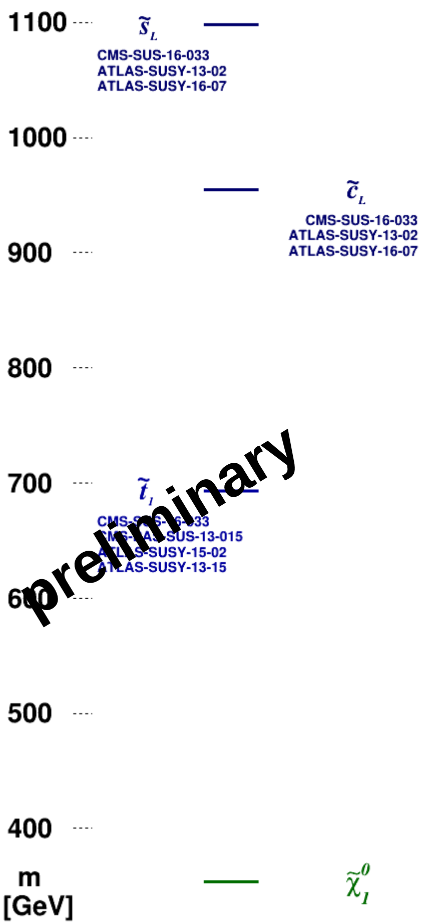


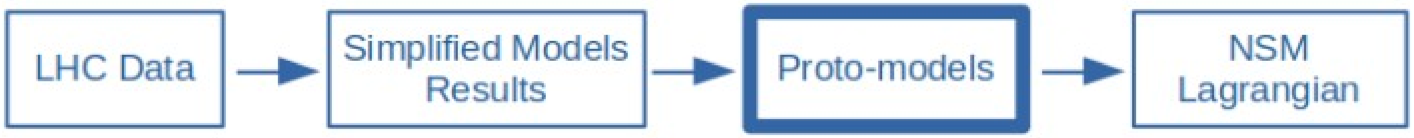
Analysis Name	Type	Dataset	Observed	Expected	Approx σ	Particles
ATLAS-SUSY-2015-02	em	SR1	12	5.5 +/- 0.72	2.6 σ	$\sim t_1$
ATLAS-SUSY-2016-07	em	2j_Meff_1200	611	526 +/- 31	2.2 σ	$\sim s_L, \sim c_L$
CMS-SUS-16-033	em	SR2_Njet3_Nb0_H ...	71	55.2 +/- 11.5	1.2 σ	$\sim s_L, \sim c_L, \sim t_1$
ATLAS-SUSY-2013-02	em	SR6jtp	6	4.9 +/- 1.6	0.4 σ	$\sim s_L, \sim c_L$
ATLAS-SUSY-2013-15	em	tNboost	5	3.3 +/- 0.7	0.9 σ	$\sim t_1$
CMS-PAS-SUS-13-015	em	pTmiss350_Nb2	15	8.6 +/- 7.1	0.8 σ	$\sim t_1$

preliminary

Identifying a potential dispersed signal and constructing a theoretical context for it that is consistent with all SMS results.

Proto-models

The overall vision of this being that instead of postulating NSM candidates and then falsifying them (or failing to do so), we put the model building into the statistical procedure itself. A slow, bottom-up procedure, starting from data.



Proto-models

But our MCMC walk is but a crutch, a burden we must carry because we do not have derivatives, i.e. gradients and Hessians.

If we had gradients we could instead perform gradient descent to find the best model, and we could use the Fisher information to infer the error on its parameters.

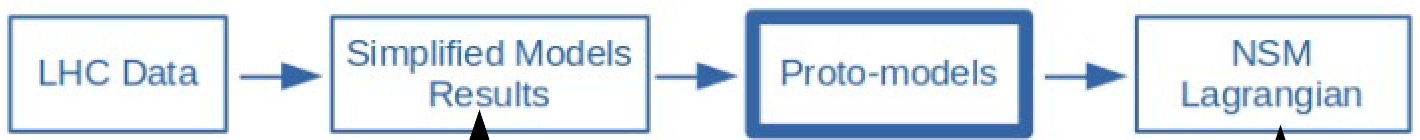
So, how about we make the whole chain differentiable?

Differentiable induction

Our MCMC walks are but a crutch, a burden we must carry because we do not have derivatives, i.e. gradients and Hessians.

If we had gradients we could instead perform gradient descent to find the best model, and we could use the Fisher information to infer the error on its parameters (if you want non-Gaussian posteriors you can then still MCMC-sample if you wish).

So, how about we make the whole chain differentiable?



described as likelihoods L that are differentiable with respect to the yields y_i

we have started an effort to make SModelS differentiable w.r.t SMS parameters p_j, by learning our entire database:

thats just a sum of simplified models → differentiable!

for individual candidates we can make this differentiable w.r.t fundamental parameters Θ_l, via neural networks, with efforts similar to DeepXS, or “TheoryGANs” [*]:

$$\frac{\partial L}{\partial \theta_l} = \frac{\partial L}{\partial y_i} \cdot \frac{\partial y_i}{\partial p_j} \cdot \frac{\partial p_j}{\partial (m_k, \Gamma_k, \sigma_k)} \cdot \frac{\partial (m_k, \Gamma_k, \sigma_k)}{\partial \theta_l}$$

Needless to say, the data pipeline sketched above is not the only feasible one. Differentiability however would be a helpful tool for all possible data pipelines. A similar rationale would apply also to EFTs, Wilson coefficients and data from measurements.

https://arxiv.org/abs/1810.08312

LHC Data → Simplified Models Results → Proto-models → NSM Lagrangian

$$\frac{\partial L}{\partial \theta_l} = \frac{\partial L}{\partial y_i} \cdot \frac{\partial y_i}{\partial p_j} \cdot \frac{\partial p_j}{\partial (m_k, \Gamma_k, \sigma_k)} \cdot \frac{\partial (m_k, \Gamma_k, \sigma_k)}{\partial \theta_l}$$

All of this is to say, that we realistically can try to “learn” the fundamental laws of the universe from data, as opposed to postulating them. Gradient-free for starters, adding gradients in the long run:

“differentiable inductive reasoning”, if you wish.

Thanks for your attention!

“Reinterpretation of LHC Results for New Physics: Status and Recommendations after Run 2”, community-wide effort, signed also by a few ATLAS members, 2003.07868

In order to enable a systematic and powerful reuse of simplified model results, we hence give the following recommendations:

1. Simplified model topologies should aim to be as unbiased as possible by an underlying UV model, even when a specific model is used to generate the signal samples. In particular, individual results should be provided for each topology and final state. As an example, consider pair production of gluinos, each of which can decay to $b\bar{b}$ or $t\bar{t}$ plus the lightest neutralino. In this case we propose that efficiency maps be provided for the $4b$, $4t$, and $2t2b + E_T^{\rm miss}$ final states separately rather than their mixture resulting from fixed branching ratios. We stress that only with this information can one apply the experimental results to arbitrary models.

2. For a higher-dimensional parameter space (three or more mass parameters), occurring e.g. in cascade decays with more than one step, a full exploration of the parameter space is sometimes not feasible and, hence, fixed mass relations for intermediate particles in cascades are used. We suggest here to provide at least three values for each of the respective mass relations, in order to assess the dependence of the analysis' sensitivity on these parameters. In the case of LLP searches, it is also important to present results for distinct LLP lifetime values, since they strongly affect the signal efficiency. Generally, for the auxiliary material it would be preferable if efficiencies were released in a format that goes beyond the two-dimensional parameterisation suitable for paper figures whenever necessary – we suggest multidimensional data tables instead of a proliferation of two-dimensional projections of the parameter space.

3. We recommend that efficiency maps be provided *for all* signal regions (or appropriately aggregated signal regions). This is relevant because the sensitivity of specific regions may change for different signal models.

“Reinterpretation of LHC Results for New Physics: Status and Recommendations after Run 2”, community-wide effort, signed also by a few ATLAS members, 2003.07868

4. For upper limits, it is useful to report both the observed *and* the expected limits as functions of the simplified model parameters, as this allows for selecting the most sensitive result and/or for computing an approximate likelihood as a truncated Gaussian [38]. If results are given in terms of signal strength (i.e. normalised to a theory expectation) instead of absolute total cross-section, the reference cross-sections should be provided in addition.

5. The presentation of results for various simplified models can significantly enhance the (re)applicability of the search. Since distinct topologies and final states can drastically change signal efficiencies, it is desirable to derive results for multiple simplified models for a given search.

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observed and expected 95% CL upper limits:

If in addition to the observed 95% limits we are also being given the expected limits, we can construct an approximate likelihood as a truncated Gaussian:

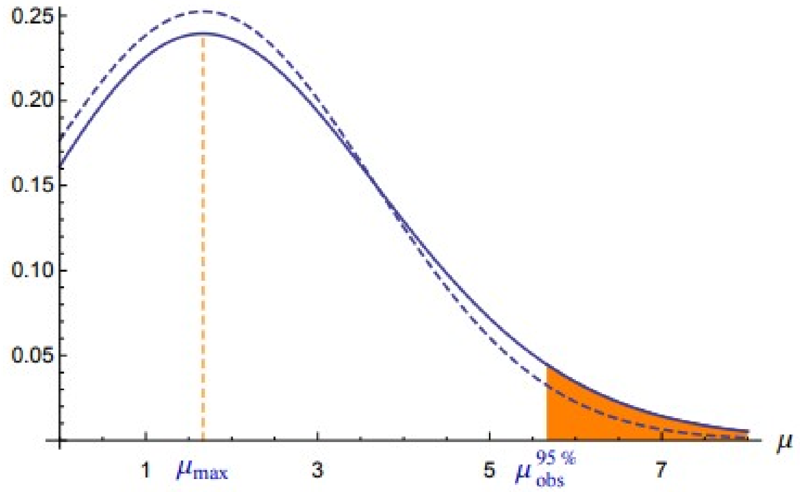


Figure 2: Posterior probability $p(\mu|n_{obs})$ obtained for $n_{obs} = 35$, $n_b = 30$, $n_s^{SM} = 3$ (continuous curve). In this example the maximum is at $\mu_{max} = 5/3$, and the 95% CL limit on μ is $\mu_{obs}^{95\%} = 5.66$. The dashed curve shows the approximating Gaussian with mean μ_{max} and standard deviation $\sigma_{obs} = \sqrt{35}/3$.

https://arxiv.org/abs/1202.3415

Second new SModelS ingredient: model builder

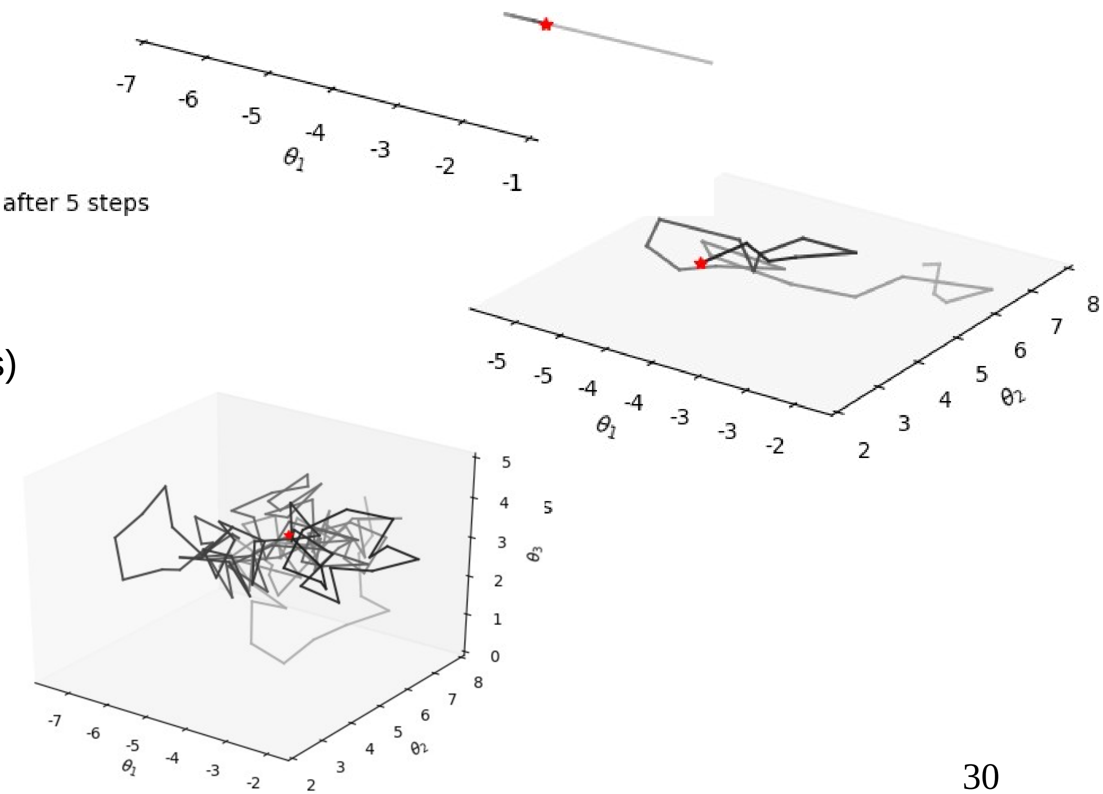
- currently a Metropolis-Hastings-type random walk in the space of all models that can be described with semantically correct SLHA files (actually currently only a subset).

- in the future will want to try a neural network that learns “Z”. Should be faster, as long was we want only central values, and not complete distributions.

- We begin with the standard model, all BSM particles being “frozen out” (put to high masses). We then take random steps in model space.
  Possible random steps:
  - freezing a particle out
  - unfreezing a particle
  - changing a particle’s mass
  - changing a particle’s branchings
  - changing a particle’s signal strength modifier
    (we use the NLO SUSY cross sections for defaults)

- All models need to obey all (relaxed) SModelS exclusions. So both antagonists (the “excluder” and the “excess finder”) experience the same biasses from the incomplete SModelS database.

- We can punish the algorithm for introducing new particles.



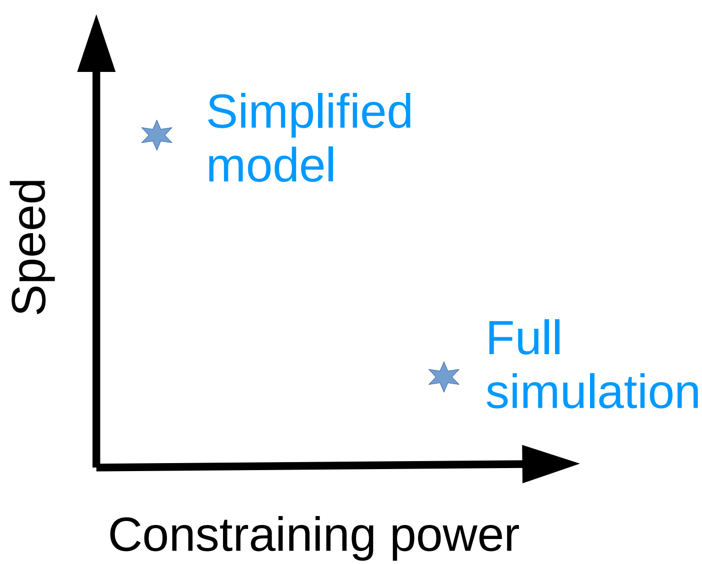
after 5 steps

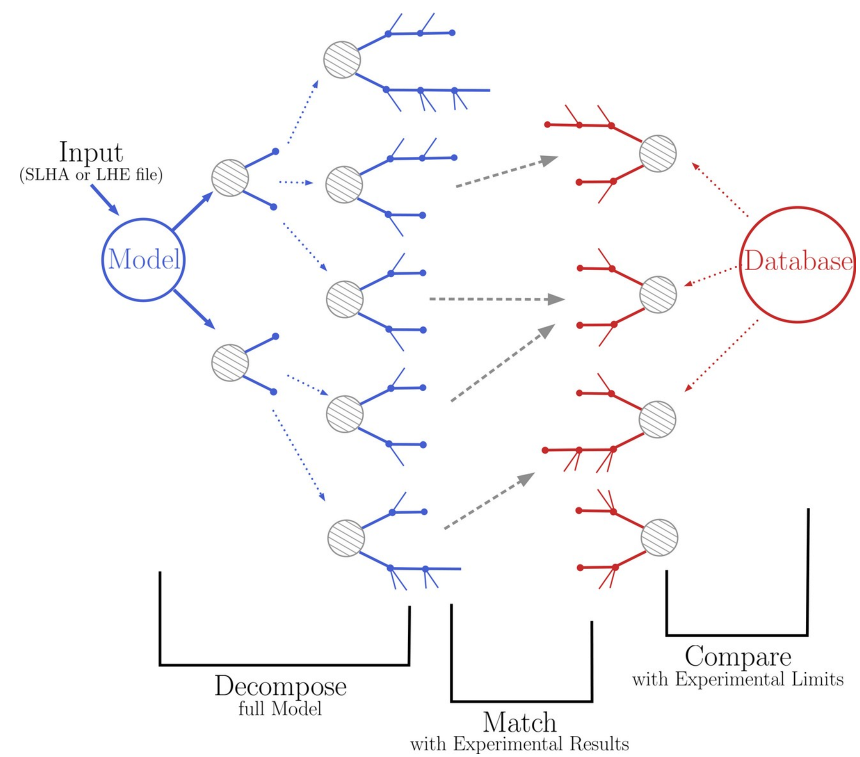
ICMC walk, after 200 steps

http://www.hephy.at/user/wwaltenberger/models/mcmc.webm

Recap: the Idea behind SModelS

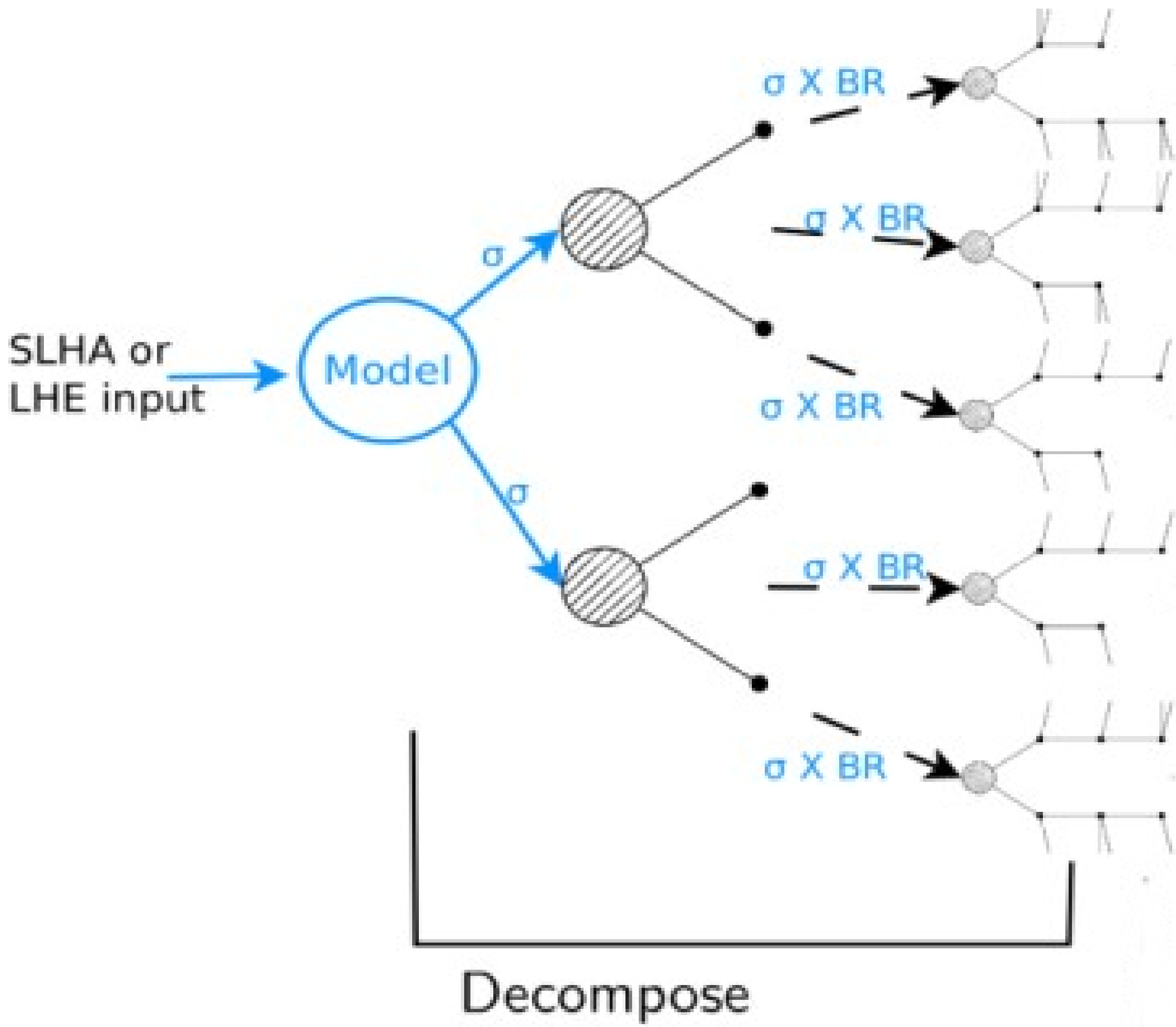
SModelS confronts theories beyond the Standard Model (BSM) with LHC search results by decomposing full models into their simplified models topologies, and comparing the cross section predictions of these individual topologies with a database of SMS results.





Recap: How SModelS works

1) Decomposition of a fundamental model



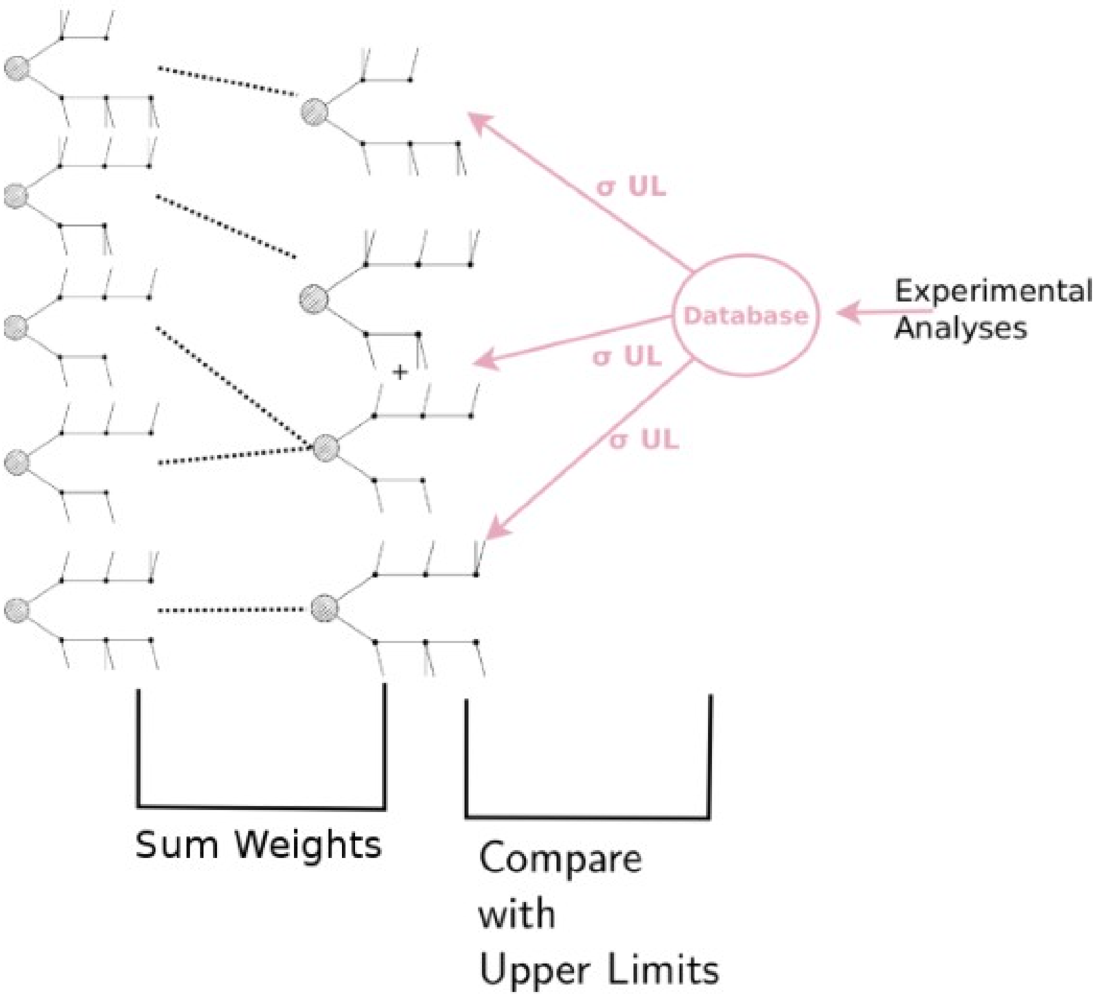
Input: SLHA file (mass spectrum, BRs) or LHE file (parton level)

Currently the model must have a $\mathbf{Z}_2$ symmetry

The decomposition produces a set of simplified model topologies (dubbed “elements”)

Recap: How SModelS works

3) Comparison of predicted signal strengths with experimental result:



- **Upper Limit Results:**
  Predicted signal strength = σ x BR
  Experimental result: σ_{UL}

- **Efficiency Map Results:**
  Predicted signal strength = ∑ σ x BR x ε
  Experimental result: $\sigma_{UL}=N_{UL}/L$ from $N_{observed}$, expected(BG), error(BG)

- r = predicted / σ_{UL}

- Model is excluded if most constraining analysis has r > 1