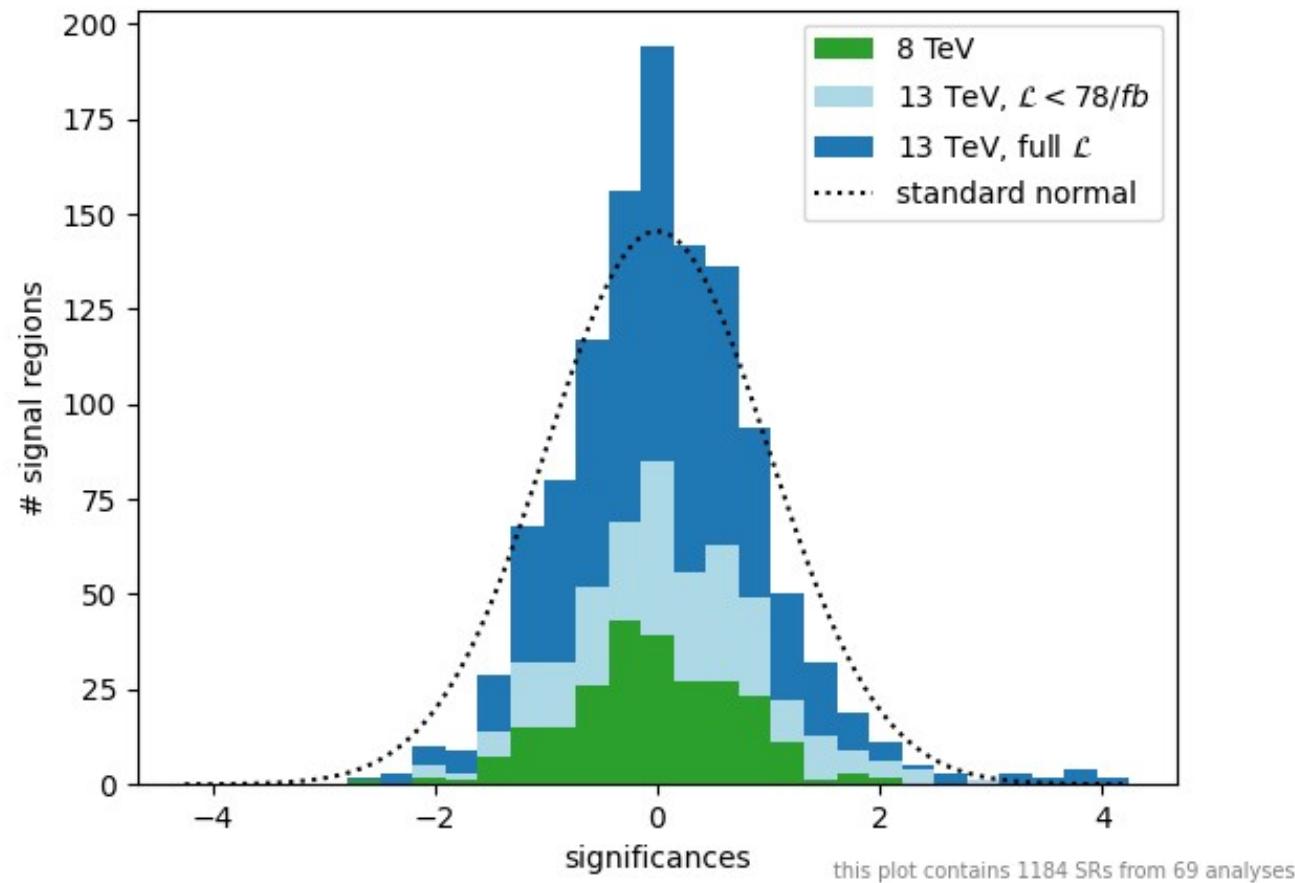
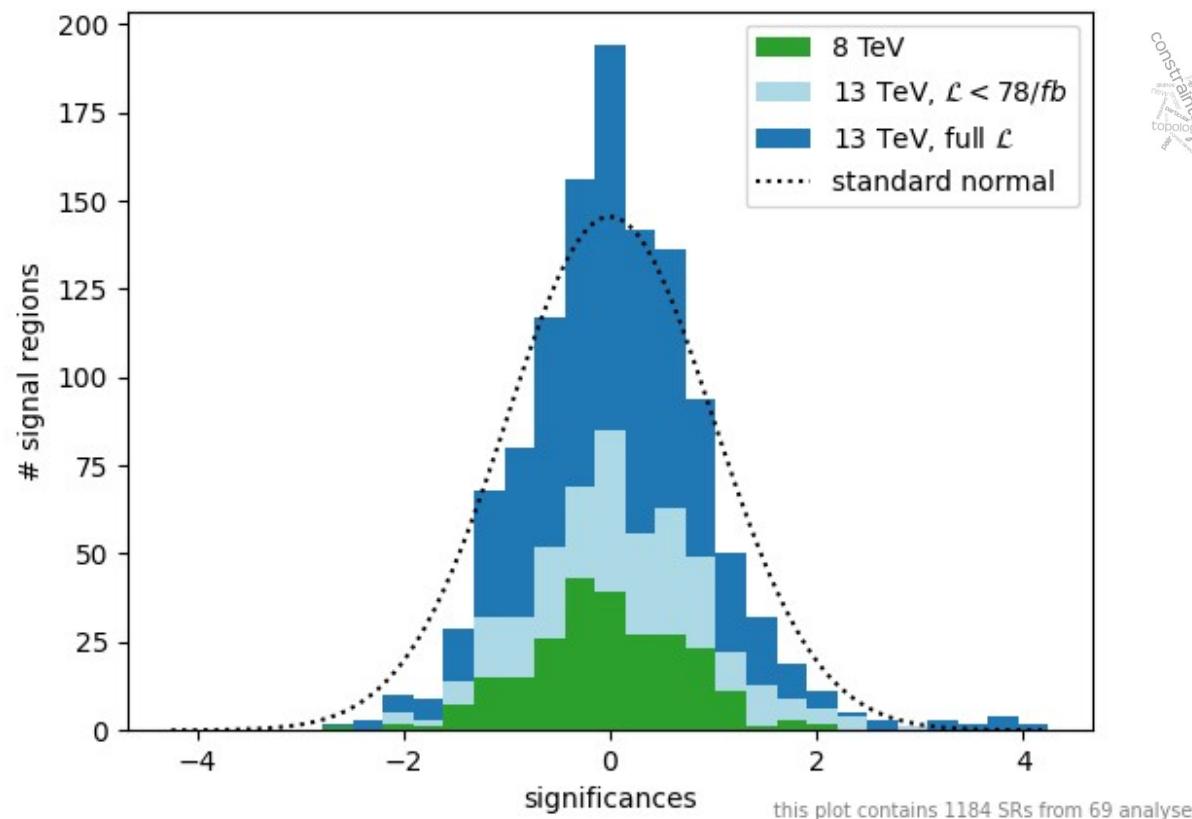


EXPERIMENTAL DATA AND SM_ODELS



Wolfgang Waltenberger (ÖAW and Uni Wien) for the SModelS collaboration



In SModelS v3.0.0 – to be released ~ next week, we will have the **results of a total of 160 publications in our database** (if we count really everything). They are all **ATLAS and CMS searches** for new (particle) physics.

For (only) **69** of them do we have enough information to construct at least a simplified statistical model. Usually, a single result has multiple “signal regions”.

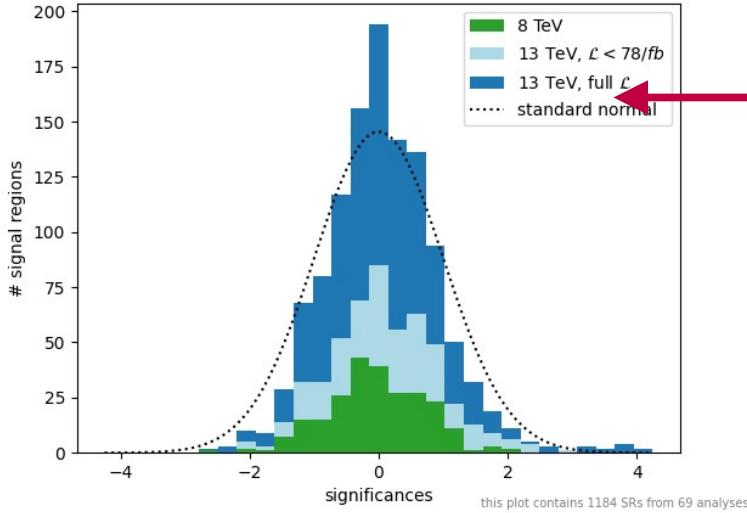
The plot above presents significances with respect to the Standard Model hypothesis, of all signal regions within these 69 publications.

If all is done correctly, and no new physics is in the data, the distribution should follow a **standard normal**. New physics would manifest itself as an overabundance of positive values.

AND WHAT DO WE DO WITH
THE INFORMATION CONTAINED
IN THESE STATISTICAL MODELS?

A NEXT STANDARD MODEL

SM models



from this ...

... we wish to infer this:



i.e. identify the One True Point
[*] (a.k.a. the Next Standard Model) in Hitoshi Murayama's landscape of theories

[*] obviously in reality we would actually want a posterior density, not one point

SModelS

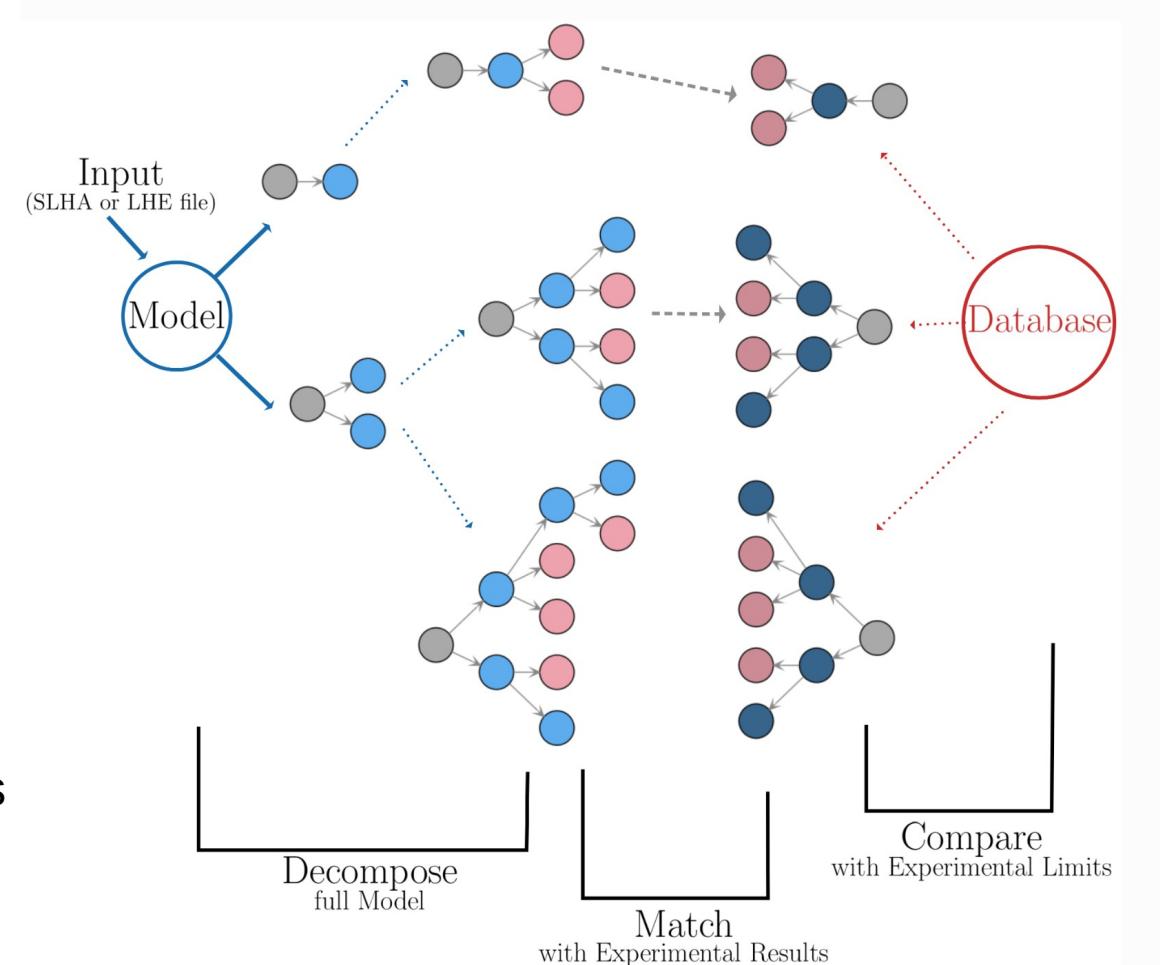
[GitHub](#) [pypi package](#) 2.3.3 [Open in Colab](#) [docs](#) main

<https://smodels.github.io>

19 December 2023: SModelS version 2.3.3 available ([what's new](#))

Paper for version 2.3: [arXiv:2306.17676](https://arxiv.org/abs/2306.17676)

- a tool to quickly compare a theory against a database of experimental results
- decomposes theory into its “simplified model spectrum”
- No expensive Monte Carlo event generation required!
- Database contains results from > 100 CMS and ATLAS publications



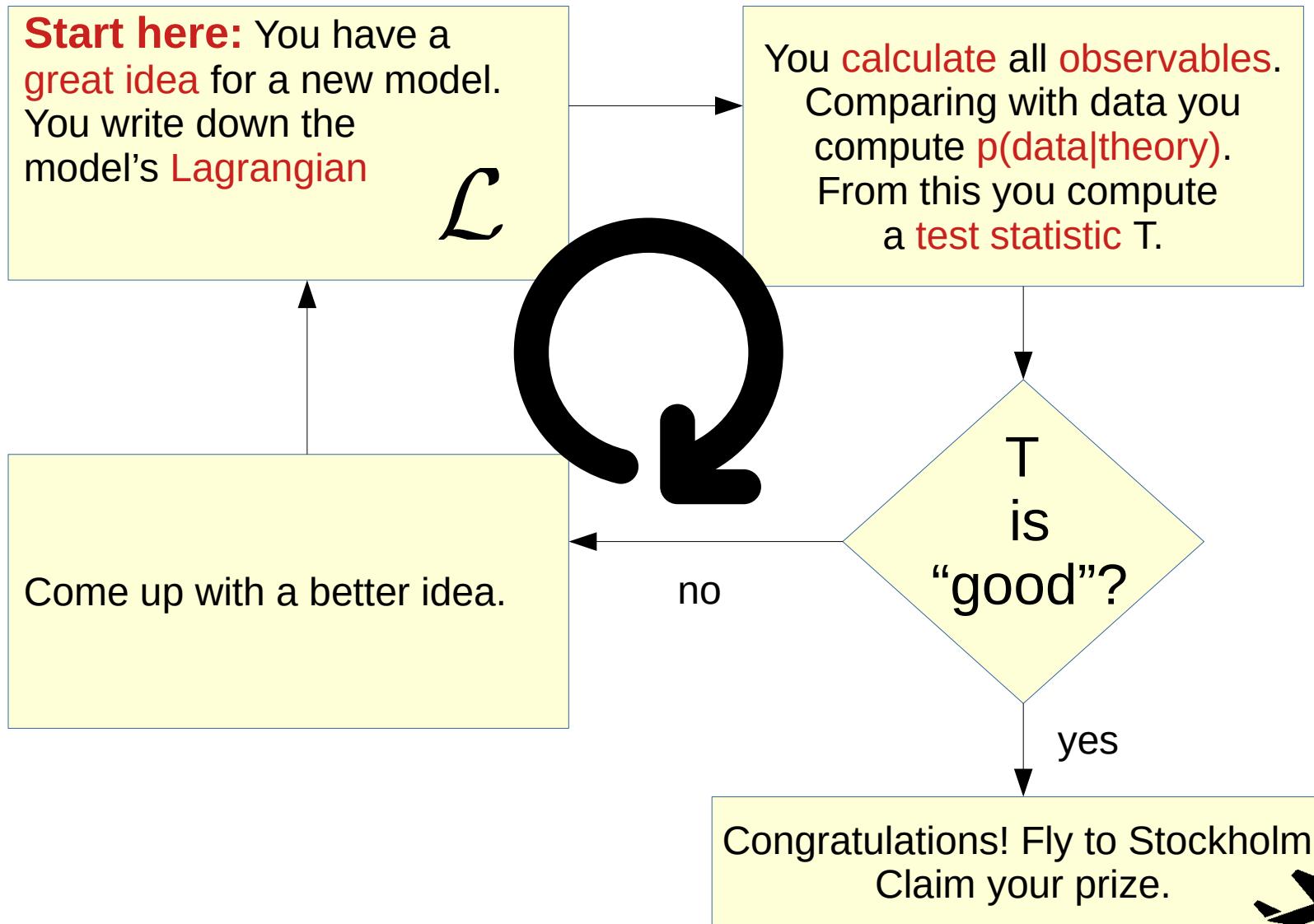
OUR INVERSE PROBLEM

To connect our observations with contender theories for the Next Standard Model,

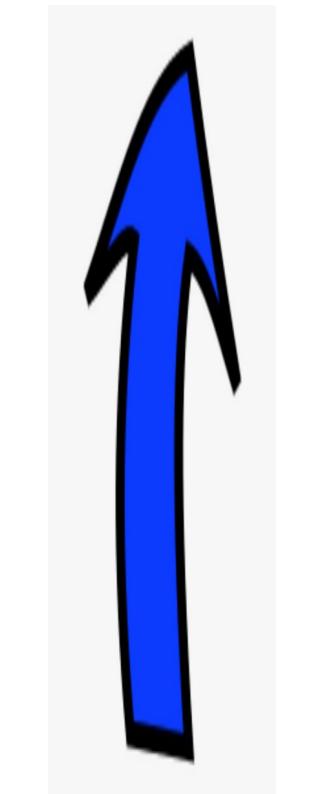
- In addition to lots of other information, we need statistical models (in one way or another)
- we can either start by:
postulating a theory, then fit its parameters
("top-down")
- or:
try to build our model directly from data
("bottom-up")

Top-down versus bottom-up

**Top-
Down:**



Top-down versus bottom-up



**Bottom-
Up:**

Start here: You describe your experimental findings in a language amenable to theoretical physics, e.g. simplified models for on-shell effects (“searches”), effective field theories for off-shell effects (“measurements”).

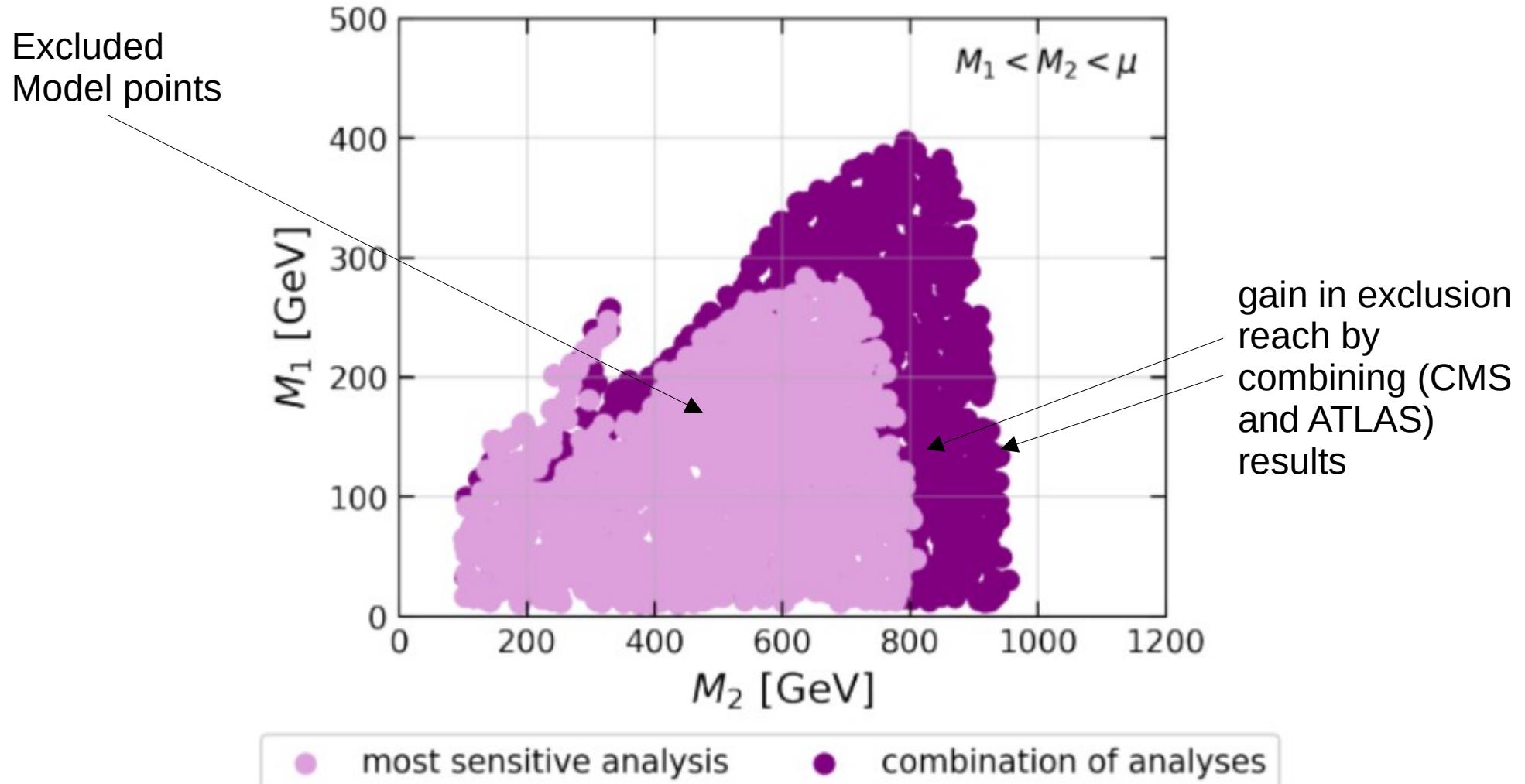
From the descriptions you try and construct precursor theories to the NSM that describe everything you really know about TeV-scale (and below) physics

Only now do you think about symmetries, gauge groups, etc that may underlie all observations. Construct your Lagrangian.

\mathcal{L}

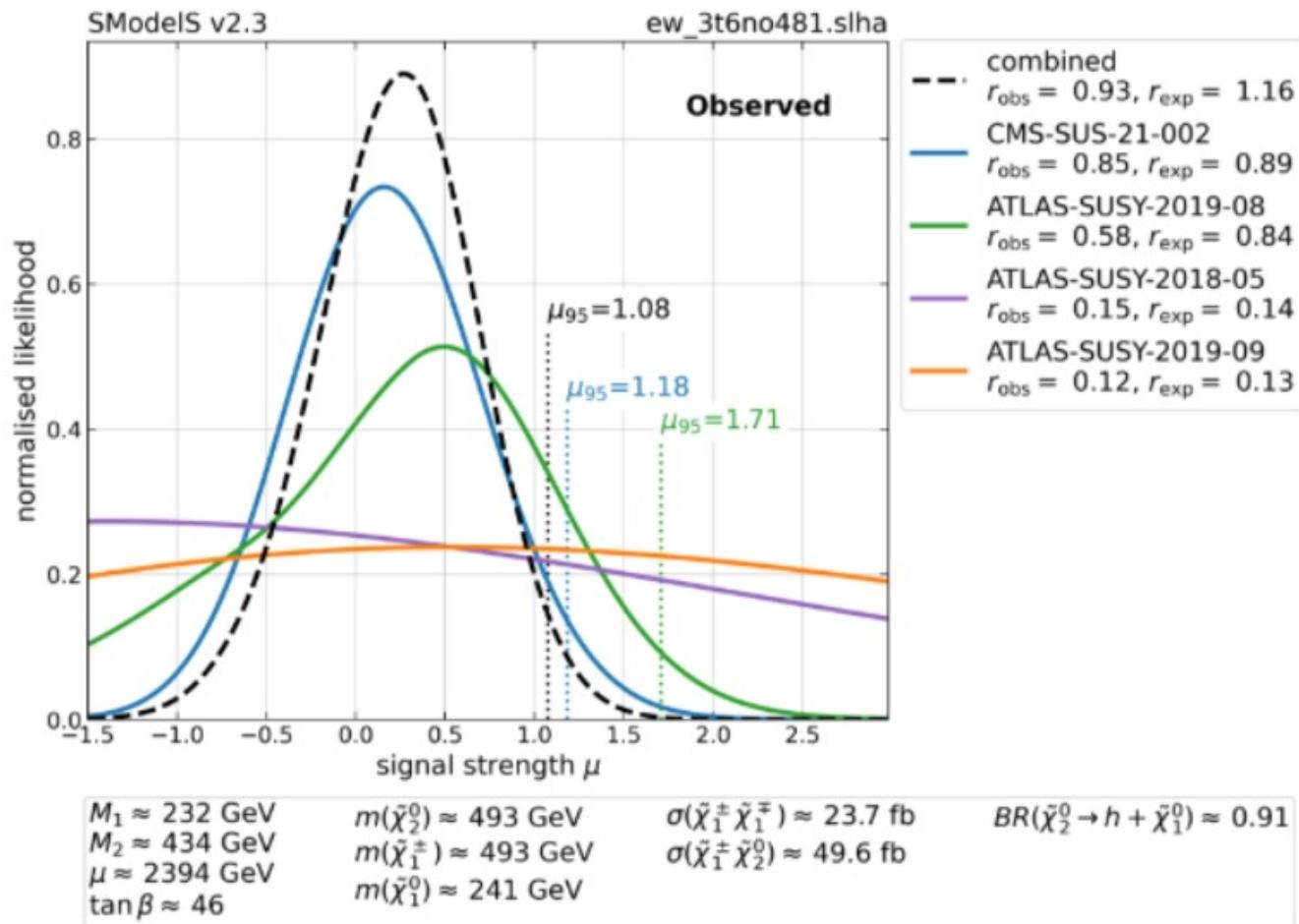
Top-down: example

“Global LHC constraints on electroweakinos with SModelS v2.3”
Model: MSSM, but looking at its charginos and neutralinos only



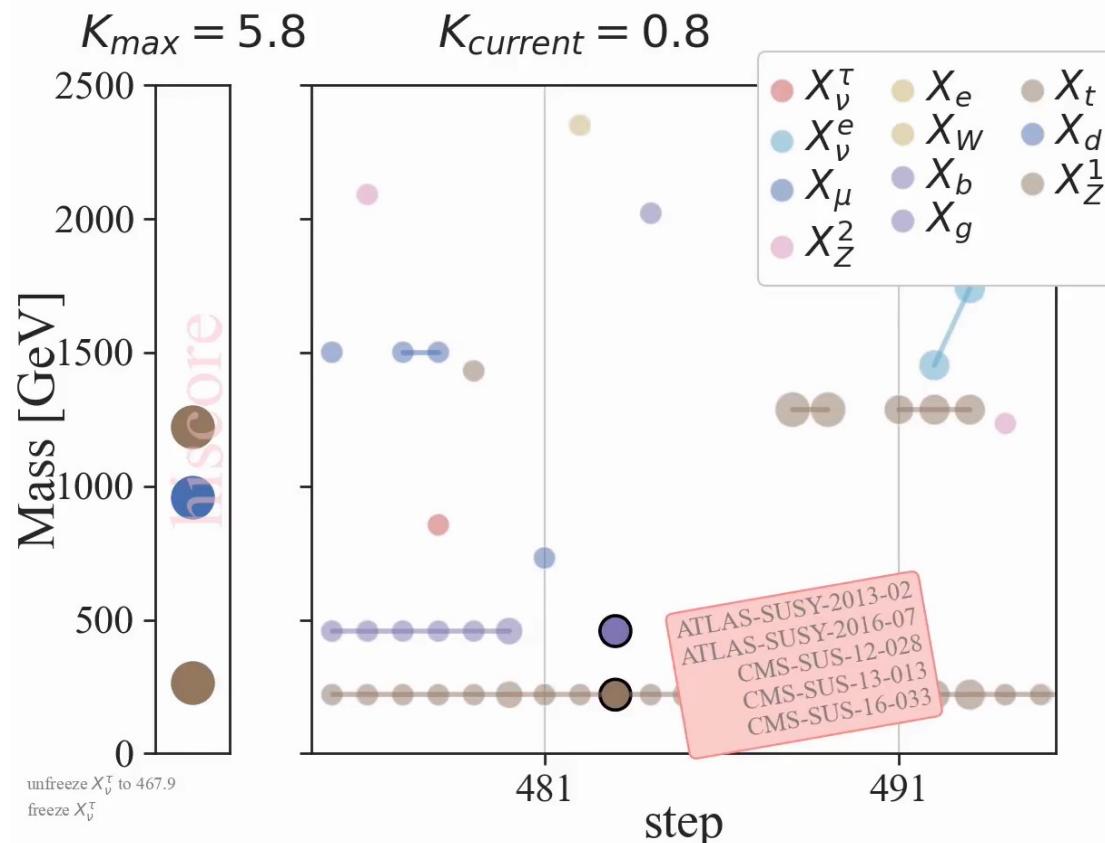
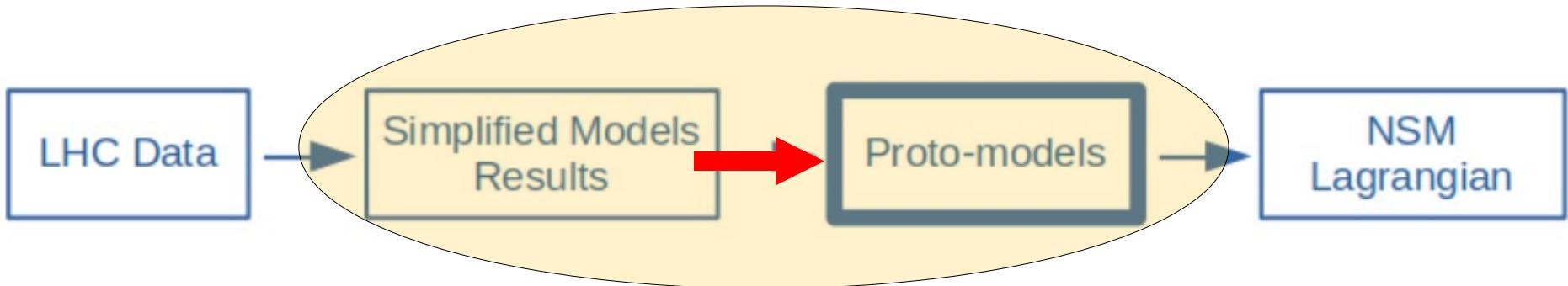
Top-down: example

P3



Combination at work, for one model point. Likelihoods here are functions of a single parameter (the overall “signal strength”). Combining several likelihoods (colored lines) results in a narrower combined likelihood (dashed line).

BOTTOM-UP: PROTOMODELS



“Likelihood-based automated model building” (in a wider sense of the words)

STATISTICAL MODELS IN THE SMODELS DATABASE

ATLAS, Run-2, Full Lumi only:

ID	Short Description	\mathcal{L} [fb $^{-1}$]	UL _{obs}	UL _{exp}	EM	comb.
ATLAS-EXOT-2018-48	di-top resonance	139.0	✓	✓		
ATLAS-EXOT-2019-03	dijet resonance	139.0	✓	✓		
ATLAS-SUSY-2018-04	2 hadronic τ	139.0	✓		✓	PYHF
ATLAS-SUSY-2018-05	2 ℓ + jets, EWK	139.0	✓		✓	PYHF
ATLAS-SUSY-2018-06	3 ℓ , EWK	139.0	✓	✓	✓	
ATLAS-SUSY-2018-08	2 OS ℓ	139.0	✓		✓	
ATLAS-SUSY-2018-09	2 SS ℓ	139.0	✓			
ATLAS-SUSY-2018-10	1 ℓ + jets	139.0	✓		✓	
ATLAS-SUSY-2018-12	0 ℓ + jets	139.0	✓	✓	✓	
ATLAS-SUSY-2018-13	displaced jets	139.0			✓	SLv1
ATLAS-SUSY-2018-14	displaced vertices	139.0			✓	PYHF
ATLAS-SUSY-2018-16	2 soft ℓ + jets, EWK	139.0	✓	✓	✓	PYHF
ATLAS-SUSY-2018-22	multi-jets	139.0	✓		✓	
ATLAS-SUSY-2018-23	$Wh(\gamma\gamma)$, EWK	139.0	✓	✓		
ATLAS-SUSY-2018-31	2 b-jets + 2 h	139.0	✓		✓	PYHF
ATLAS-SUSY-2018-32	2 OS ℓ	139.0	✓		✓	PYHF
ATLAS-SUSY-2018-40	2 b-jets + 2 h	139.0	✓	✓	✓	
ATLAS-SUSY-2018-41	hadr. EWK	139.0	✓	✓	✓	SLv1
ATLAS-SUSY-2018-42	charged LLPs, dE/dx	139.0	✓	✓	✓	
ATLAS-SUSY-2019-02	2 soft ℓ , EWK	139.0	✓		✓	SLv1
ATLAS-SUSY-2019-08	1 ℓ + $h(bb)$, EWK	139.0	✓		✓	PYHF
ATLAS-SUSY-2019-09	3 ℓ , EWK	139.0	✓	✓	✓	PYHF

Type of statistical model

STATISTICAL MODELS

- Only exclusions for particular models

If only “exclusion lines” are given, without upper limits, we can do nothing

- Observed 95% CL upper limits on production cross sections only:

cannot construct likelihood, binary decision “excluded” / “not-excluded” only (“critic”)

- Expected and observed 95% CL upper limits

can construct an approximate likelihood with truncated Gaussian,
cannot combine topologies, very crude approximation

- Signal Efficiency “maps” for “simplified models”

can construct a likelihood as Gaussian (for the nuisances) * Poissonian
(for yields), can work per SR, and combine topologies in each SR [*]

- Efficiency maps + correlation matrices

can combine signal regions via multivariate Gaussian * Poissonians

- Efficiency maps + full likelihoods

full realism, correct statistical model

- Efficiency maps + full likelihoods + naming convention

+ knowledge about “data overlaps”

can combine publications at full realism

Likelihoods
Combos



BETTER

[*] if efficiency maps are not supplied, we can try to produce them with recasting frameworks

HEPDATA



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Tumasyan, Armen et al.

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Search for new particles in events with energetic jets and large missing transverse momentum in proton-proton collisions at $\sqrt{s} = 13$ TeV

The CMS collaboration

Tumasyan, Armen , Adam, Wolfgang , Andrejkovic, Janik
Walter , Bergauer, Thomas , Chatterjee, Suman , Dragicevic,
Marko , Escalante Del Valle, Alberto , Fruehwirth, Rudolf ,
Jeitler, Manfred , Krammer, Natascha

JHEP 11 (2021) 153, 2021.

<https://doi.org/10.17182/hepdata.106115.v2>

[Journal](#) [INSPIRE](#) [Resources](#)

Abstract

A search is presented for new particles produced at the LHC in proton-proton collisions at $\sqrt{s} = 13$ TeV, using events with energetic jets and large missing transverse momentum. The analysis is based on a data sample corresponding to an integrated luminosity of 101 fb^{-1} , collected in 2017–2018 with the CMS detector. Machine learning techniques are used to define separate categories for events with narrow jets from initial-state radiation and events with large-radius jets consistent with a hadronic decay of a W or Z boson. A statistical

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Version 2 ▾

[Filter 55 data tables](#)

Background prediction and observed data yields in the signal region bins. The background yields are obtained from the background-only fit...

Simplified likelihood:
covariance matrix
(Monojet)

Supplementary material
[10.17182/hepdata.106115.v2/t14](https://doi.org/10.17182/hepdata.106115.v2/t14)
Matrix of covariance coefficients between signal region bins. The coefficients are obtained from the background-only fit to the control regions,...

[Simplified likelihood: Yields \(Monojet\)](#) ▾

Supplementary material
[10.17182/hepdata.106115.v2/t15](https://doi.org/10.17182/hepdata.106115.v2/t15)
Background prediction and observed data yields in the signal region bins. The background yields are obtained from the background-only fit...

cmenergies

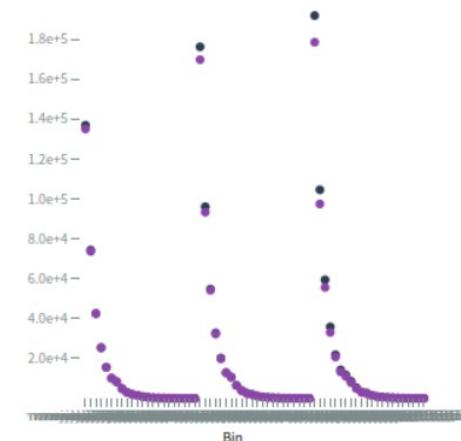
13000.0

Showing 50 of 66 values

[Show All 66 values](#)

Bin	Background yield	Data yield
monojet_2016_bin0	135004.8633	136865
monojet_2016_bin1	73681.17188	74340
monojet_2016_bin2	42448.17627	42540
monojet_2016_bin3	25541.23718	25316
monojet_2016_bin4	15454.10522	15653
monojet_2016_bin5	10162.67578	10092
monojet_2016_bin6	8473.070068	8298
monojet_2016_bin7	4853.264771	4906
monojet_2016_bin8	2960.103455	2987
monojet_2016_bin9	1906.687012	2032
monojet_2016_bin10	1498.361874	1514

Visualize



Deselect variables or hide different error bars by clicking on them.

(CMS monojet search)

SERIALIZED STATISTICAL MODELS

(Lukas is of course the authority here but) pyhf serializes the models into json files:

```
{
  "channel": {
    "type": "object",
    "properties": {
      "name": { "type": "string" },
      "samples": { "type": "array", "items": {"$ref": "#/definitions/sample"}, "minItems": 1 }
    },
    "required": ["name", "samples"],
    "additionalProperties": false
  },
}
```

Posterior distributions on nuisance parameters (such as jet energy scales, pdf uncertainties, reconstruction inefficiencies, etc etc) are described via “auxiliary measurements” → keeping things frequentist (if we wish)!

Statistics Standardization committee formed: **HS3**

<https://github.com/hep-statistics-serialization-standard/hep-statistics-serialization-standard>

These “closed world” approaches are general enough for users!

IN “USER SPACE”: MACHINE LEARNING SURROGATE MODELS

If speed and/or memory footprint become an issue, users can always also machine-learn surrogate models.

If only likelihood is needed: simple, fully connected neural networks (Bayesian neural networks for adding errors on the estimates), e.g.:

CERN-TH-2019-187

The DNNLikelihood: enhancing likelihood distribution with Deep Learning

Andrea Coccato^a, Maurizio Pierini^b, Luca Silvestrini^{b,c}, and Riccardo Torre^{a,b}

^a INFN, Sezione di Genova, Via Dodecaneso 33, I-16146 Genova, Italy

^b CERN, 1211 Geneva 23, Switzerland

^c INFN, Sezione di Roma, P.le A. Moro, 2, I-00185 Roma, Italy

If full statistical model including toys is needed as well: generative network such as normalizing flows. e.g:

SciPost Physics

Submission

The NFLikelihood: an unsupervised DNNLikelihood from Normalizing Flows

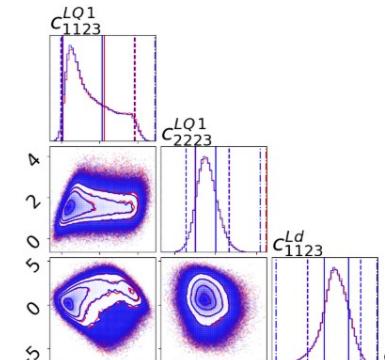
Humberto Reyes-González^{1,2,*} and Riccardo Torre^{2,†}

1 Department of Physics, University of Genova, Via Dodecaneso 33, 16146 Genova, Italy

2 INFN, Sezione di Genova, Via Dodecaneso 33, I-16146 Genova, Italy

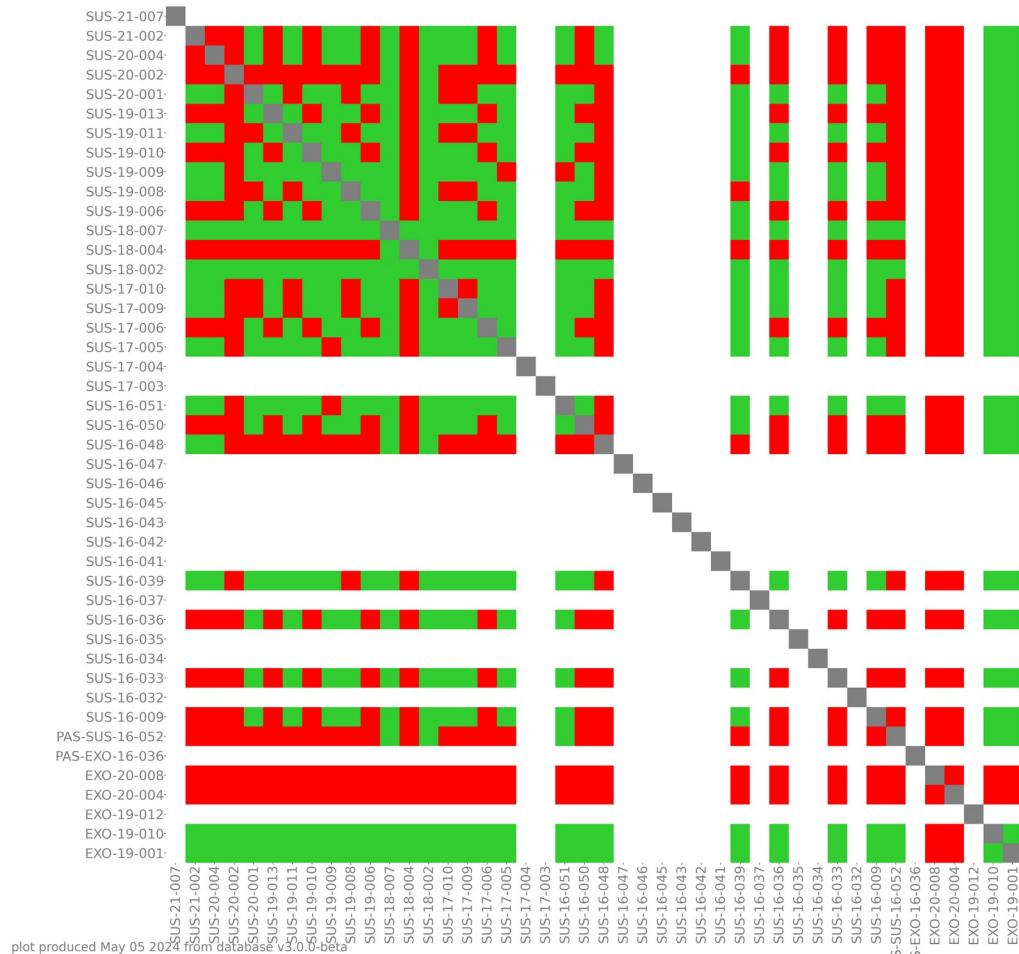
* humberto.reyes@rwth-aachen.de

† riccardo.torre@ge.infn.it



COMBINABILITY MATRIX, AND “RECASTS”

CMS, 13 TeV



- We keep track of which pairs of analyses have no overlaps in what LHC collision events enter the signal regions. In the “pheno community”, we combine only if no overlap.
- Currently most reliable source for the combinations matrix: **analysis recast frameworks**: generating events, track which signal regions are populated by which events
- Requires detailed documentation about the analysis
- Experimental collaborations could in principle produce this information as well (and better)

Strength in numbers: Optimal and scalable combination of LHC new-physics searches

Jack Y. Araz, Andy Buckley, Benjamin Fuks, Humberto Reyes-Gonzalez, Wolfgang Waltenberger, Sophie L. Williamson, Jamie Yellen
SciPost Phys. 14, 077 (2023) · published 20 April 2023

doi: 10.21468/SciPostPhys.14.4.077

pdf

BiBTeX

RIS

Submissions/Reports

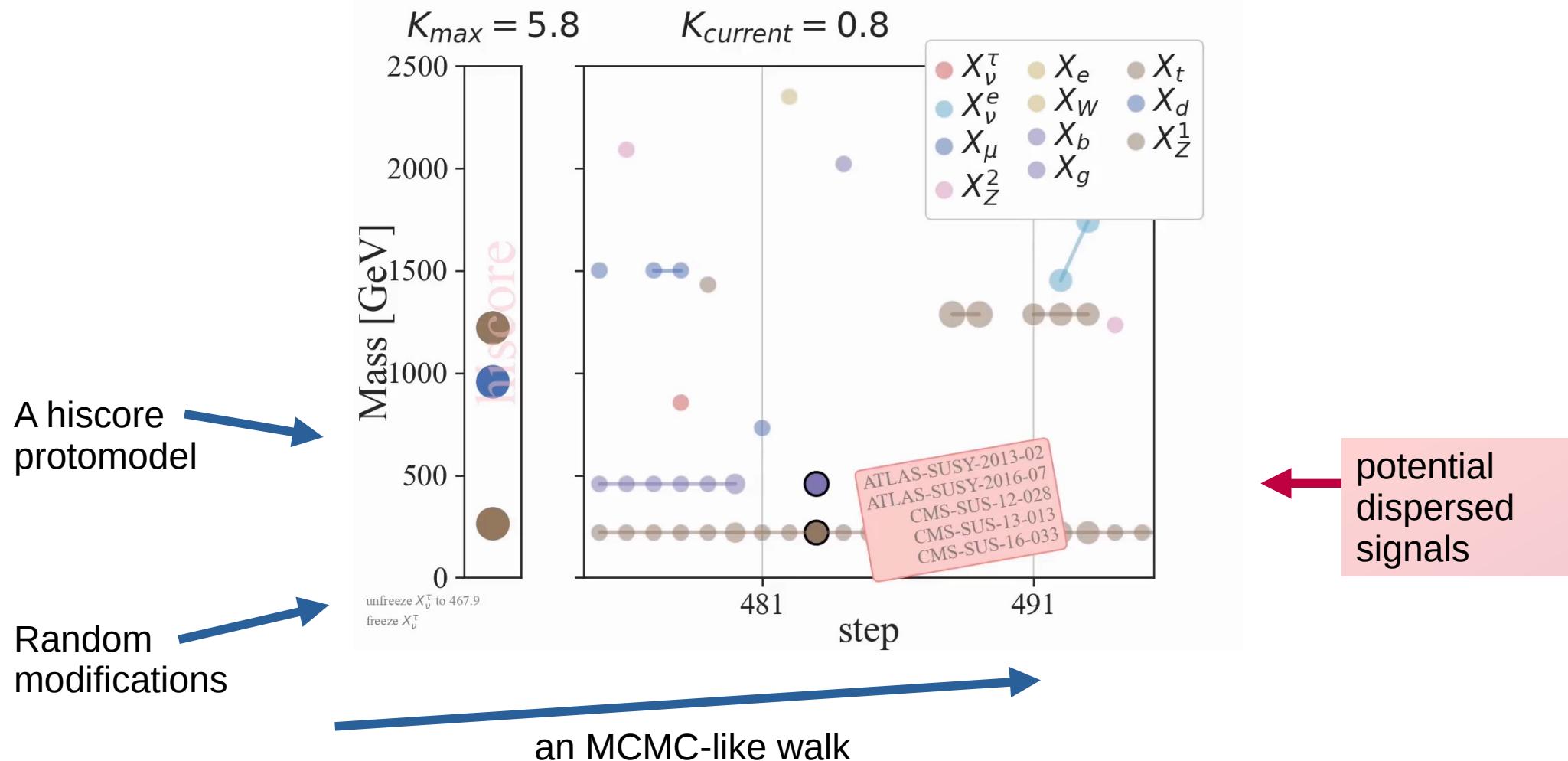
Check for updates

REPRODUCING AN ANALYSIS

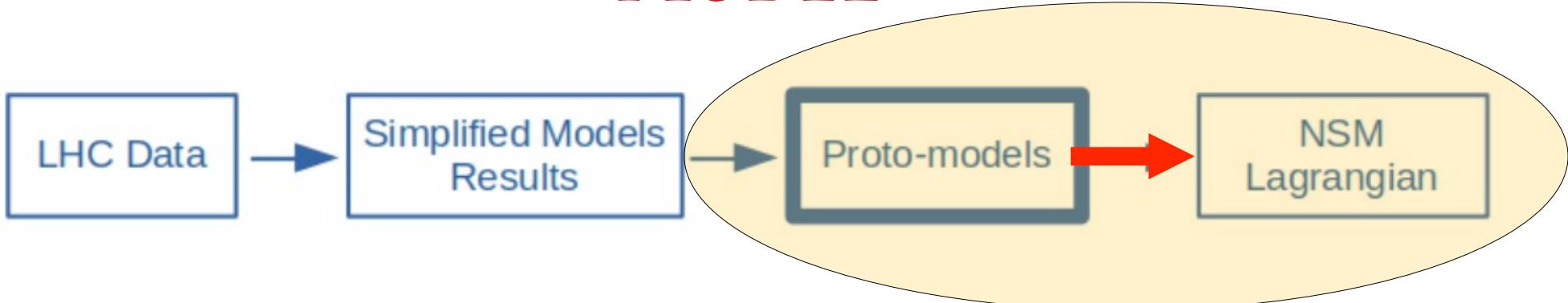
In order to facilitate reproduction of an entire analysis – to e.g. apply it to a new model, or to study analysis overlap (previous slide), the analysis needs to be documented in great detail:

- **Cutflow tables** of the analysis cuts, **reconstruction object efficiencies**, machine-learning models (e.g. as onnx files) need to be given in digitized form, for e.g. recasts, studies of analysis overlaps.
- Implementation in a simple framework / language: e.g. **SimpleAnalysis** or Analysis Description Language (**ADL**)
- For Monte Carlo samples used in publication: **generator datacards**, etc
- Upper limit plots, **signal efficiency maps** (of simplified models) **in digitized form**
- **Statistical models in reusable digitized form**

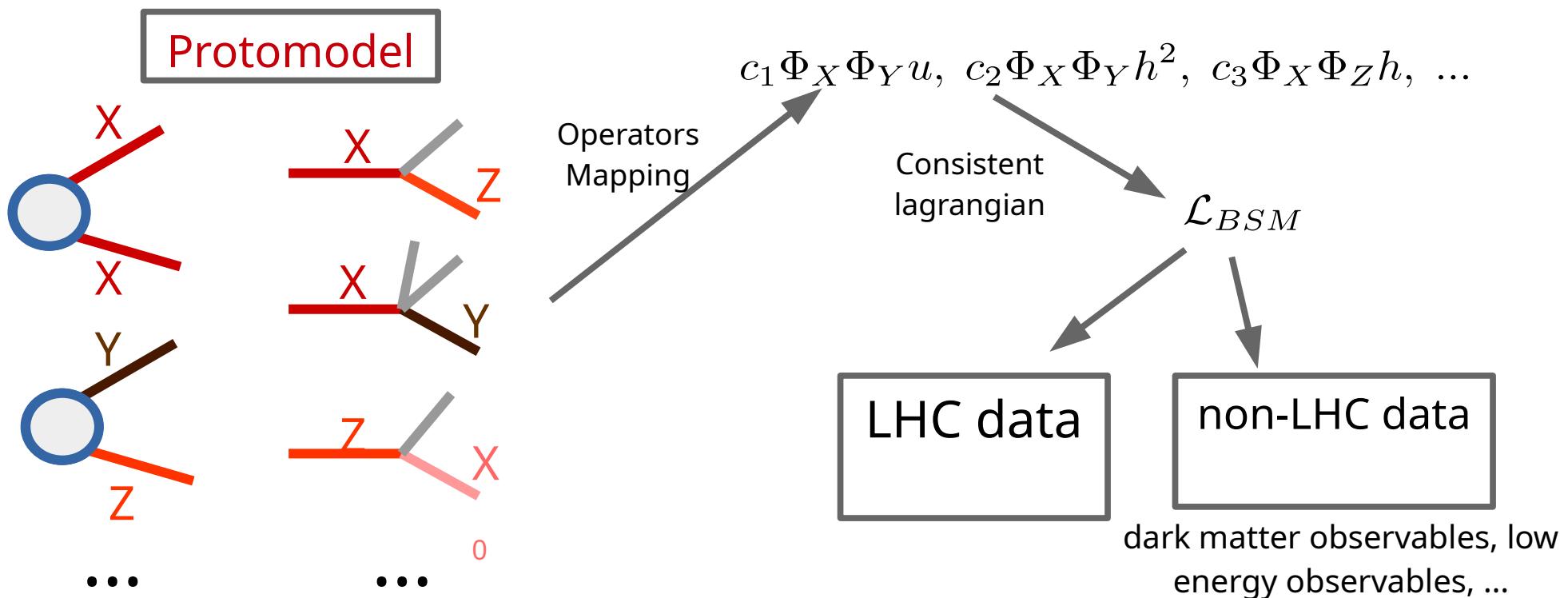
EXPERIMENTAL RESULTS → PROTOMODELS



PROTOMODELS → NEXT STANDARD MODEL



Work from protomodels to UV complete theories has begun
(John Gargalionis, PostDoc in Valencia) – lot's of combinatorics!



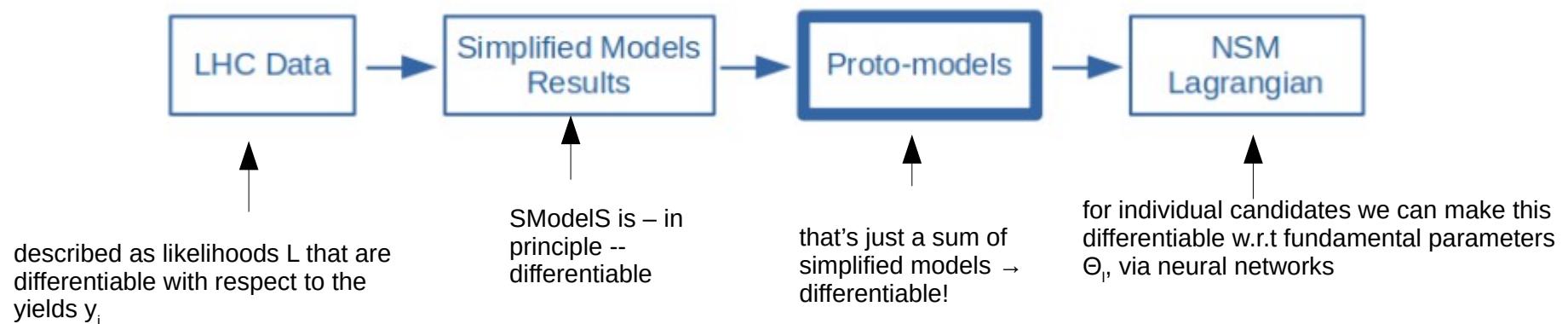
SUMMARY

- Ideally, **all important aspects of a physics result get published**: cutflow tables, reconstruction object efficiencies, machine learned models, generator datacards, for SModelS: efficiency maps and: **serialized statistical models!**
- **HEPdata** is the collider physics results platform of choice
- **DOIs** for all digital objects
- **Global fits** are still an indispensable tool for the “big picture” (see also gambit’s talk)
- The SModelS collaboration recently started to **automate model building based on the statistical models**

DIFFERENTIABLY IF POSSIBLE



If we had gradients we could perform gradient descent to find the best model, and we could use e.g. the Fisher information to infer the error on its parameters (or, alternatively we can then MCMC-sample).



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

Not yet required (theory space as well as space of measurements are still low-dimensional enough). Action item for now: keep choosing, supporting, developing technologies that support autograd

THE TEST STATISTIC

The test statistic K^c is a likelihood-ratio test that quantifies how much better the proto-model describes the data than the Standard-Model (plus a penalty for model complexity).

The diagram shows the formula for the test statistic K^c with three annotations:

- A blue arrow points from the text "Quantifies violation of Standard Model hypothesis" to the term $\frac{L_{\text{SM}}^c}{L_{\text{BSM}}^c(\hat{\mu})}$.
- A green arrow points from the text "Quantifies violation of Standard Model hypothesis" to the term $\cdot \pi(\text{SM})$.
- A red arrow points from the text "Penalizes for model complexity" to the term $\cdot \pi(\text{BSM})$.

$$K^c := -2 \ln \frac{L_{\text{SM}}^c \cdot \pi(\text{SM})}{L_{\text{BSM}}^c(\hat{\mu}) \cdot \pi(\text{BSM})}$$

We search for proto-models and combinations of results / likelihoods that maximize K^c
while remaining compatible with all negative results in our database.