

Can we “machine-learn” the Next Standard Model?

Wolfgang Waltenberger (ÖAW and Uni Vienna), Theory Seminar, Sussex,
May 2019

Obviously, the title of the talk has a few syntactic and semantic issues. Let's be a tad more concise:

employ
Bayesian
learning
hypothetical

Can we “~~machine-learn~~” the Next Standard Model?

from data
to infer

Wolfgang Waltenberger (ÖAW and Uni Vienna), Theory Seminar, Sussex,
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Can we use Bayesian inference to directly learn – that is, simultaneously build and “sample” – the Lagrangian of the hypothetical Next Standard Model (NSM) from heterogeneous High Energy Physics (HEP) Data?

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A frequentist's approach to finding the NSM

In frequentist statistics, we can only look at the “likelihood” of data,

$$p(\text{data}|\text{theory})$$

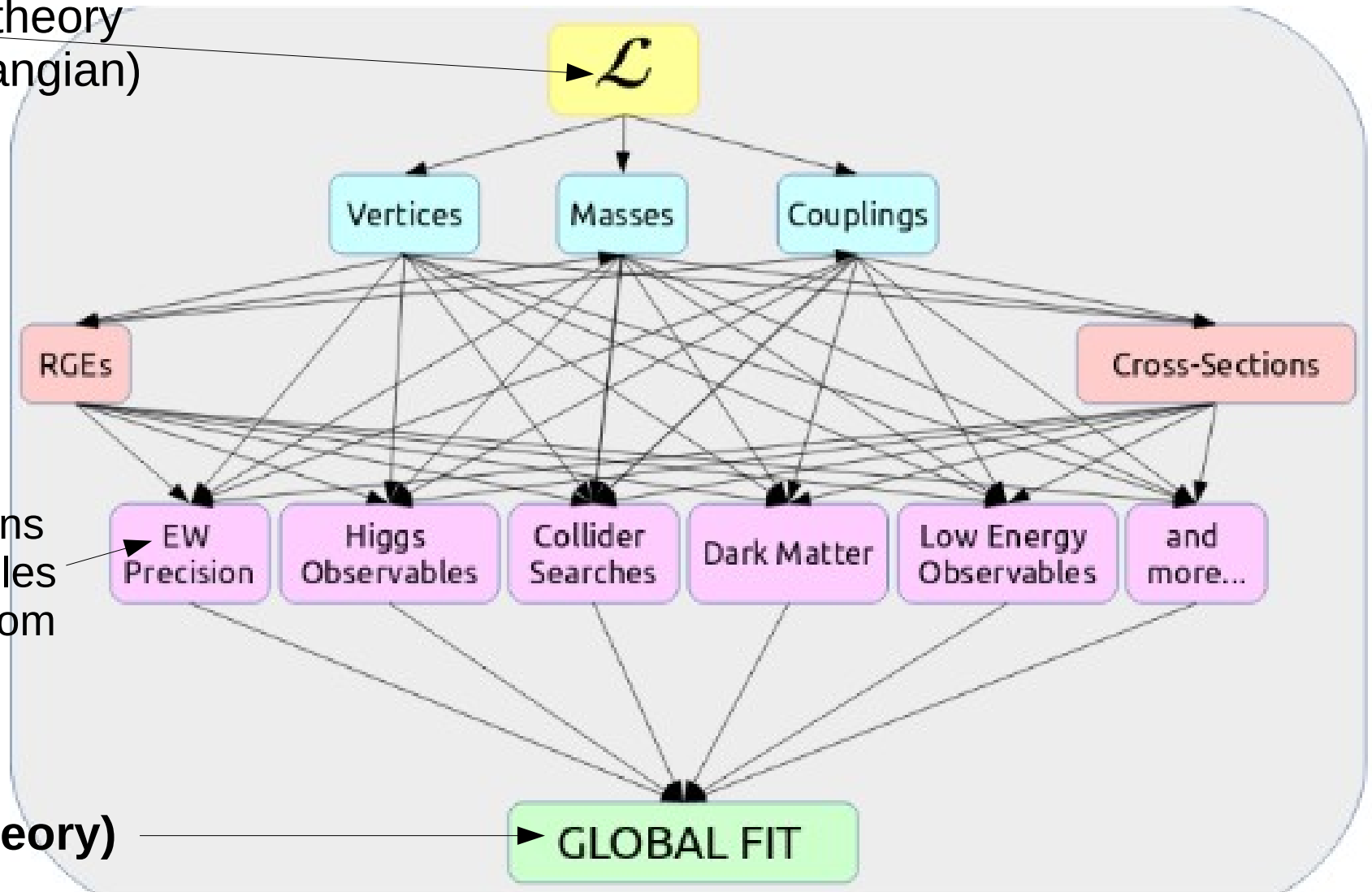
no statements of the type $p(\text{theory}|\text{data})$ are known to a frequentist.

Thus, a frequentist recipe for finding the NSM would read:

- Specify your favorite theory Beyond the Standard Model (BSM).
- Compute the likelihood of your observations, $p(\text{data}|\text{theory})$
- Compute a test statistic T based on your likelihood that quantifies how well your theory describes the data.
- If T is “bad”, come up with another theory. Repeat.
- If T is “good”, stop. You won. Fly to Stockholm, claim your Prize. You earned it.

A frequentist's approach to finding the NSM

your BSM theory
(as a Lagrangian)



the predictions
on observables
that follow from
the theory

$p(\text{data}|\text{theory})$

Frequentist approach: pros and cons

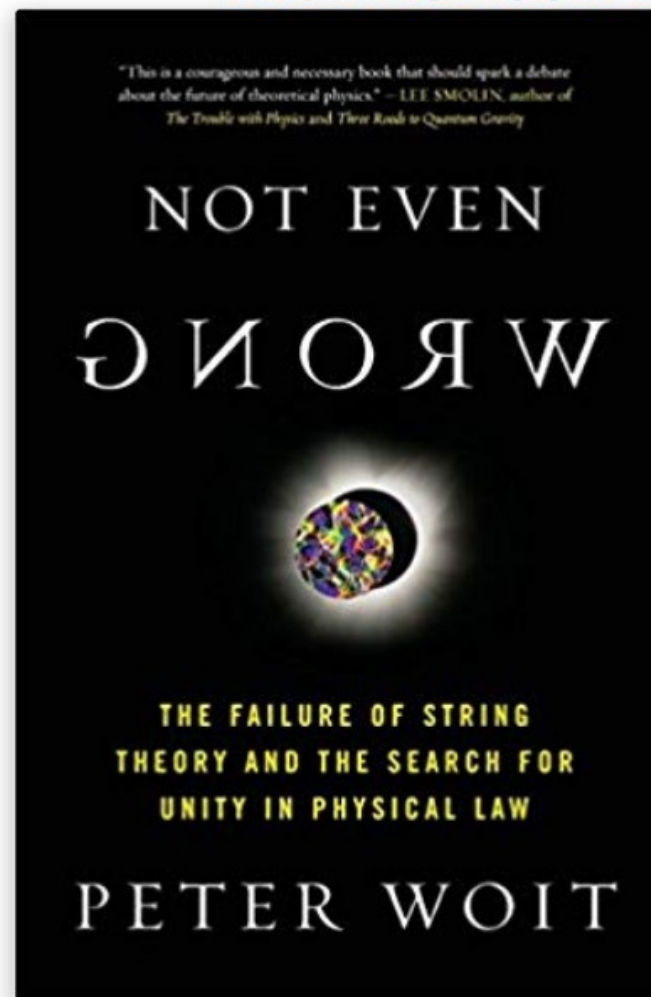
Pros:

- The statistical aspects of the procedure are well defined and reasonably simple
- We have many great ideas that we want tested (e.g. supersymmetry)
- The “right” procedure as long as we know what theory we want to test.

Cons:

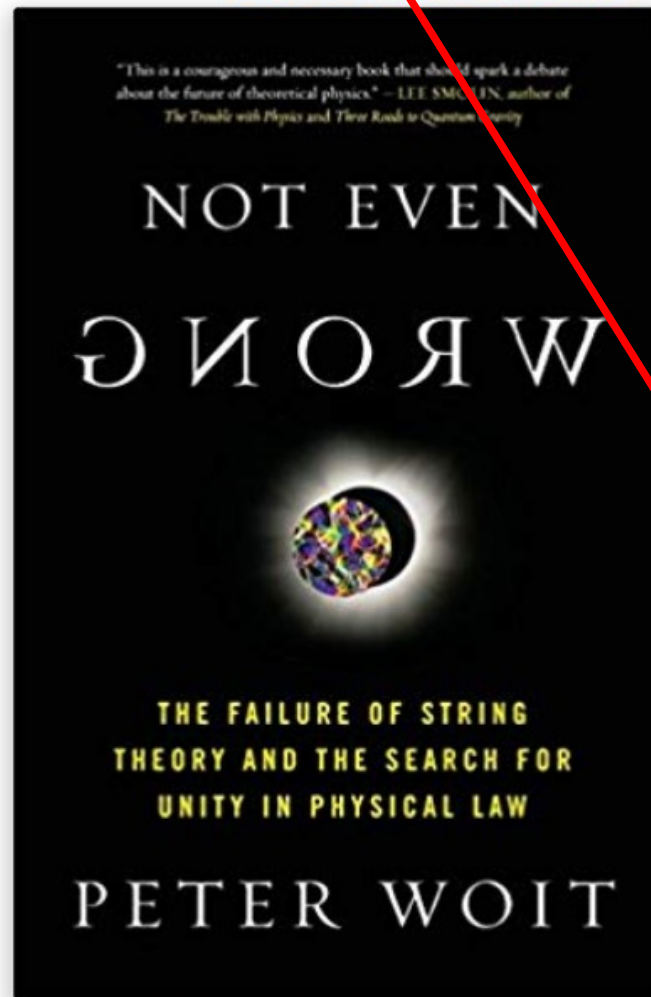
- We are driven by abstract theoretical ideas, not theory agnostic, not driven by observation. Choice of theories that we consider subject to our biases and preconceptions.
- Our – presumably – best ideas (e.g. natural supersymmetry) predicted that we find new physics at the TeV scale at the LHC. We did not.
- Does not cater to surprise. What if none of our preconceptions is correct?

The downsides of theory-driven approaches to finding the NSM have been fertile grounds for popular science books



(Independent of whether or not we agree with these authors)

Shall we, can we abandon “pretty” and allow for “ugly”? If yes, then how?



A little naming convention

For the remainder of this talk, I wish to distinguish between three types of models: pretty, simple, and ugly

- **pretty models:** well-defined, complete. Typically solve the Higgs hierarchy problem and aim at providing answers for many of our theoretical problems at once. Examples are **supersymmetry**, universal extra dimensions, little Higgs.
- **minimal models:** well-defined, simple, only minimal additions to the standard models. Do not solve the Higgs hierarchy problem. Aim at answering only individual questions. Examples: **dark photons**, two Higgs doublet models
- **ugly models:** ill-defined, possibly incomplete, possibly mathematically inconsistent (b/c incomplete), but may describe data.
→ At least “wrong” – see slide before :) ! And possibly useful?

Bayesian learning

- Let me propose a strategy for how we might be able to build up a prospective NSM that allows for “ugly”.
- My proposal will be based on the notion of Bayesian learning (as opposed to frequentist statistics).
- Please note that what I am presenting here is a **rough proposal**, not a finished study. (And, actually, I am actively looking for help on the theory side. Veronica to the rescue.).

Bayesian learning

Bayesian learning is simply an application of Bayes Theorem (sorry, no neural networks involved this time):

$$p(\text{theory}|\text{data}) \propto p(\text{data}|\text{theory})p(\text{theory})$$

... is proportional to ...

Our *a posteriori* knowledge of physics Beyond the Standard Model (BSM)

... the likelihood of the observed data, *given* the theory ...

... times our *prior* knowledge of BSM physics.

Bayesian learning

In the past, we have performed such a Bayesian analysis within CMS, for the phenomenological Minimal SuperSymmetric Model (pMSSM):

$$p(\text{pMSSM}|\text{CMS}) \propto L(\text{CMS}|\text{pMSSM})\pi(\text{pMSSM})$$

Our knowledge of the pMSSM
in light of the CMS search
results ...

... is proportional to ...

... the likelihood of our data,
given the pMSSM ...

... times our prior
knowledge of the
pMSSM

The pMSSM is a “stripped-down” version of the Minimal Supersymmetric Model (MSSM), with constraints put on all model parameters that have no big effect on LHC “phenomenology”. It has 18 or 19 free parameters.

Needless to say, many similar frequentist and Bayesian analyses have been performed within and outside the experimental collaborations.

Bayesian learning

$\pi(\text{pMSSM})$

– what’s our information on the pMSSM **prior** to looking at CMS’s search results?

i	Observable $\mu_i(\theta)$	Constraint $D_i^{\text{non-DCS}}$	Likelihood function $L[D_i^{\text{non-DCS}} \mu_i(\theta)]$	Comment
1	$\mathcal{B}(b \rightarrow s\gamma)$ [45]	$(3.43 \pm 0.21^{\text{stat}} \pm 0.24^{\text{th}} \pm 0.07^{\text{sys}}) \times 10^{-4}$	Gaussian	reweight
2	$\mathcal{B}(B_s \rightarrow \mu\mu)$ [46]	$(2.9 \pm 0.7 \pm 0.29^{\text{th}}) \times 10^{-9}$	Gaussian	reweight
3	$R(B \rightarrow \tau\nu)$ [45, 47]	1.04 ± 0.34	Gaussian	reweight
4	Δa_μ [48]	$(26.1 \pm 6.3^{\text{exp}} \pm 4.9^{\text{SM}} \pm 10.0^{\text{SUSY}}) \times 10^{-10}$	Gaussian	
5	$\alpha_s(m_Z)$ [49]	0.1184 ± 0.0007	Gaussian	
6	m_t [50]	$173.20 \pm 0.87^{\text{stat}} \pm 1.3^{\text{sys}} \text{ GeV}$	Gaussian	reweight
7	$m_b(m_b)$ [49]	$4.19^{+0.18}_{-0.06} \text{ GeV}$	Two-sided Gaussian	
8	m_h	LHC: $m_h^{\text{low}} = 120 \text{ GeV}$, $m_h^{\text{high}} = 130 \text{ GeV}$	1 if $m_h^{\text{low}} \leq m_h \leq m_h^{\text{high}}$ 0 if $m_h < m_h^{\text{low}}$ or $m_h > m_h^{\text{high}}$	reweight
9	μ_h	CMS and ATLAS in LHC Run 1, Tevatron	LILITH 1.01 [51, 52]	post-MCMC
10	sparticle masses	LEP [53] (via MICROMEAS [54–56])	1 if allowed 0 if excluded	

Bayesian learning

$\pi(\text{pMSSM})$ → what's our information on the pMSSM **prior** to looking at CMS'es search results?

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4	Δa_μ [48]	$(26.1 \pm 6.3^{\text{exp}} \pm 4.5^{\text{th}} \pm 10.1^{\text{sys}})$	Gaussian	(LHC) “Precision measurements”
5	$\alpha_s(m_Z)$ [49]	0.1181 ± 0.0007	Gaussian	
6	m_t [50]	$173.20 \pm 0.87^{\text{stat}} \pm 1.3^{\text{sys}}$ GeV	Gaussian	reweight
7	$m_b(m_b)$ [49]	$4.19^{+0.18}_{-0.06}$ GeV	Two-sided Gaussian	
8	m_h	$125.5 \pm 2.5^{\text{stat}} \pm 1.0^{\text{th}}$ GeV	1 if $m_h^{\text{low}} \leq m_h \leq m_h^{\text{high}}$ 0 if $m_h < m_h^{\text{low}}$ or $m_h > m_h^{\text{high}}$	reweight
9	μ_h	CMS and ATLAS in LHC Run 1, Tevatron	1 if $0.01 \leq \mu_h \leq 0.1$ 0 if $\mu_h < 0.01$ or $\mu_h > 0.1$	“The signal strength of the Higgs”
10	m_h	LEP [53] (via MICROLEGAS [94–96])	1 if allowed 0 if excluded	“Results from the Large Electron-Positron collider (LEP)”

- The argument of “naturalness” did not enter the prior (it is an argument for “pretty”)
- All particle masses were “cut off” at 3 TeV – we did not look into scenarios that are outside of the LHC’s reach!

Bayesian learning

$L(\text{CMS}|\text{pMSSM})$

→ what's the **likelihood** of CMS'es search results, given the pMSSM?

Analysis	\sqrt{s} [TeV]	\mathcal{L} [fb ⁻¹]	Likelihood
Hadronic $H_T + H_T^{\text{miss}}$ search [8]	7	4.98	counts
Hadronic $H_T + E_T^{\text{miss}}$ + b-jets search [9]	7	4.98	counts
Leptonic search for EW prod. of $\tilde{\chi}^0, \tilde{\chi}^\pm, \tilde{1}$ [10]	7	4.98	counts
Hadronic $H_T + H_T^{\text{miss}}$ search [11]	8	19.5	counts
Hadronic M_{T2} search [12]	8	19.5	counts
Hadronic $H_T + E_T^{\text{miss}}$ + b-jets search [13]	8	19.4	χ^2
Monojet searches [14]	8	19.7	binary
Hadronic third generation squark search [15]	8	19.4	counts
OS dilepton (OS ll) search [16] (counting experiment only)	8	19.4	counts
LS dilepton (LS ll) search [17] (only channels w/o third lepton veto)	8	19.5	counts
Leptonic search for EW prod. of $\tilde{\chi}^0, \tilde{\chi}^\pm, \tilde{1}$ [18] (only LS, 3 lepton, and 4 lepton channels)	8	19.5	counts
Combination of 7 TeV searches	7	—	binary
Combination of 7 and 8 TeV searches	7, 8	—	binary

Bayesian learning

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About 10 CMS searches for new physics!

$$L(\text{CMS}|\text{pMSSM}) = \int \text{Poisson}(N|s(\text{pMSSM}) + b)p(b)db$$

s: "Expected number of signal events" – need to simulate around 100,000 events, for every signal hypothesis! **Computationally very expensive!**

N: number of observed events in a search

b: number of Standard Model background events

p(b): likelihood for number of Standard Model background events

Bayesian learning

$L(\text{CMS}|\text{pMSSM})$

→ what's the **likelihood** of CMS'es search results, given the pMSSM?

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About 10 CMS searches for new physics!

$$L(\text{CMS}|\text{pMSSM}) = \int \text{Poisson}(N|s(\text{pMSSM}) + b)p(b)db$$

$p(b)$: our knowledge of the background for the search. Summarizes all the gigantic experimental effort (person-years!) that went into a specific search. We integrate out the dependency of the likelihood on such *nuisances*.

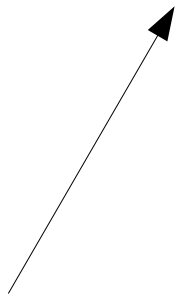
Bayesian learning

” \propto ”

→ “**proportional to**”: what’s the normalization constant and why don’t we have to compute it?

$$p(\text{pMSSM}|\text{CMS}) \propto L(\text{CMS}|\text{pMSSM})\pi(\text{pMSSM})$$

$$p(\text{pMSSM}|\text{CMS}) = \frac{L(\text{CMS}|\text{pMSSM})\pi(\text{pMSSM})}{\int d(\text{pMSSM})L(\text{CMS}|\text{pMSSM})\pi(\text{pMSSM})}$$



complicated 18-dimensional integral! Luckily we do not have to solve it, because we can **sample** the posterior, e.g. with Metropolis-Hastings algorithm, a **random walk** in the theory parameter space.

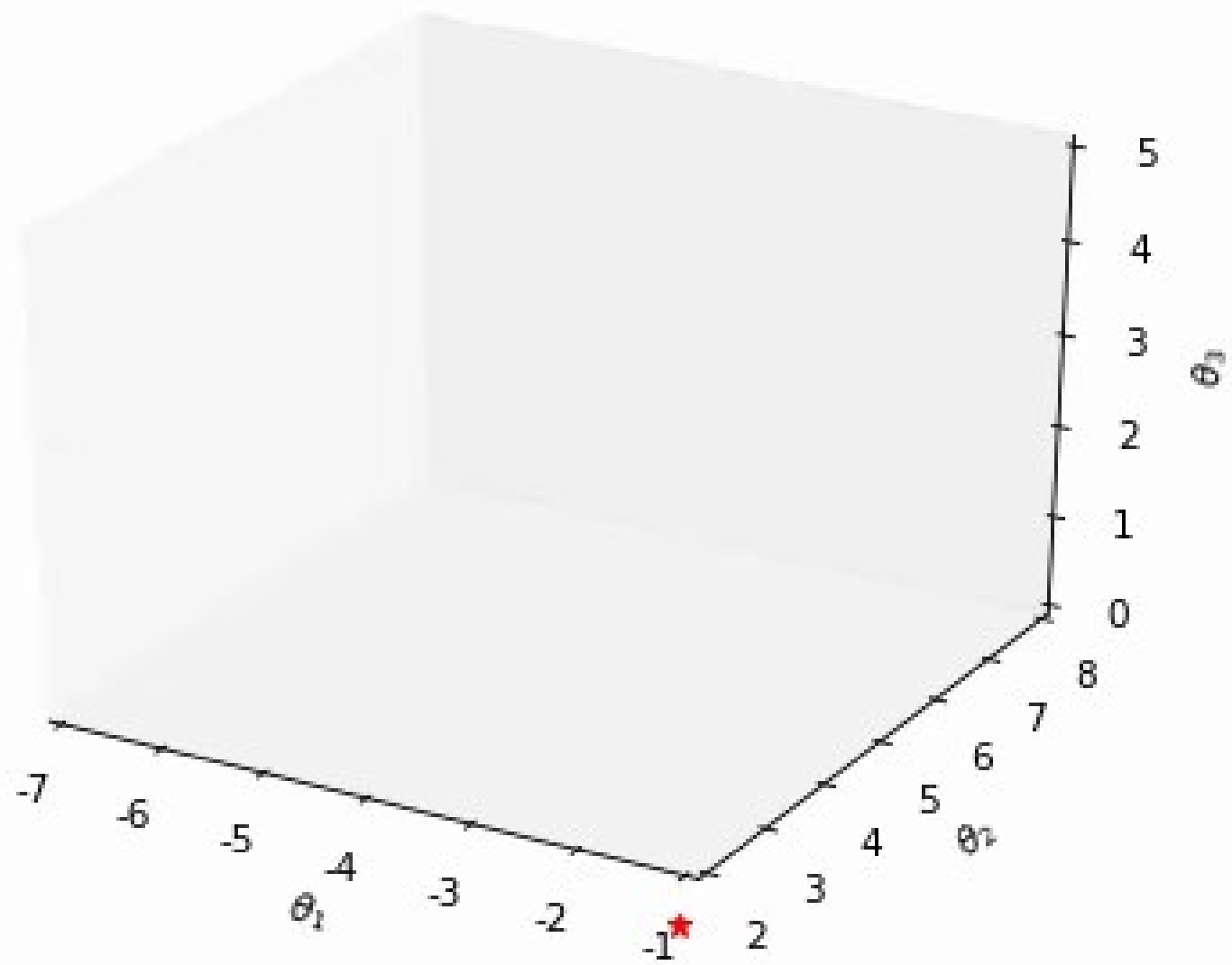
Bayesian random walk

$$p(\text{pMSSM}|\text{CMS}) = \frac{L(\text{CMS}|\text{pMSSM})\pi(\text{pMSSM})}{\int d(\text{pMSSM})L(\text{CMS}|\text{pMSSM})\pi(\text{pMSSM})}$$


The posterior is a probability – it is normalized! (That’s what the denominator on the r.h.s. is actually doing). So if I can “sample” the posterior (i.e. draw random samples from it), I am done!

Metropolis algorithm:

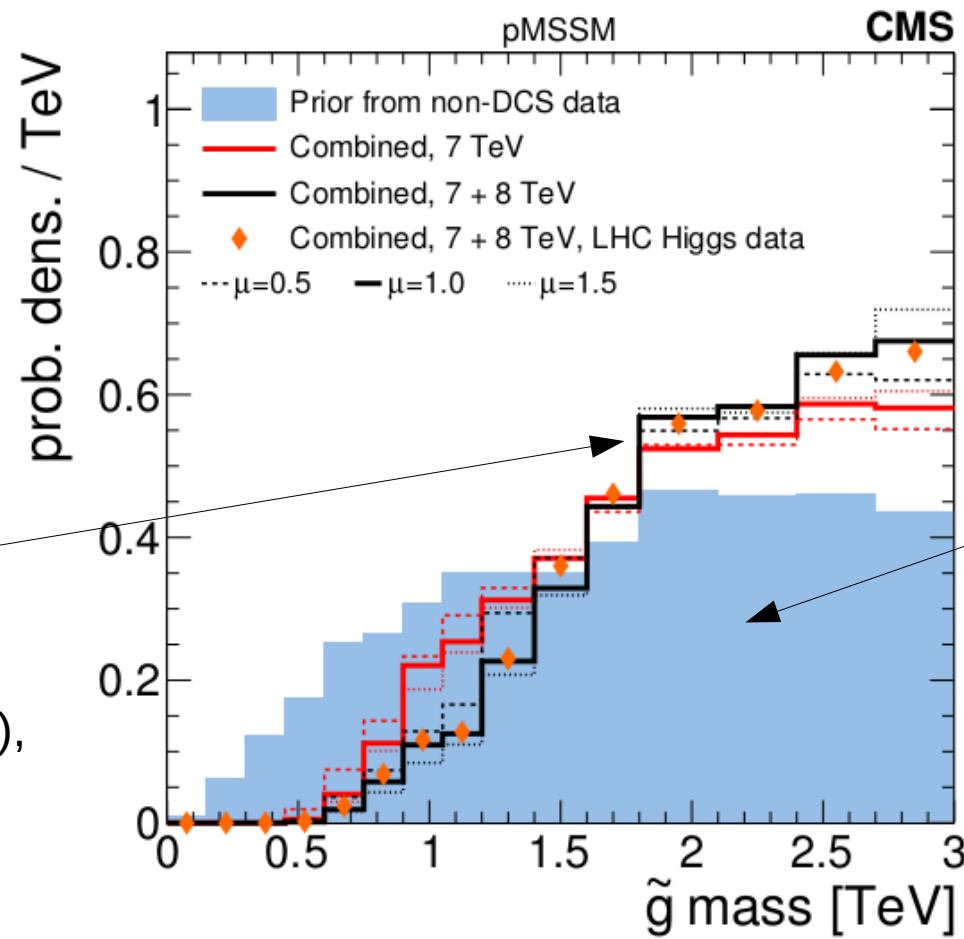
- **initialisation:** start with a random pMSSM point x . Compute the numerator $f(x)$ of the posterior (likelihood times prior).
- **generation:** now take a random step in a random direction in the 18-dimensional space. Compute the numerator for that point, $f(x')$.
- **acceptance:** compute $\alpha = f(x')/f(x)$, i.e. the ratio of the posteriors. Draw a uniformly distributed random number u on $[0,1]$. If $u > \alpha$, reject the last step, go back to the step before. Else, accept.



Bayesian learning

$$L(\text{pMSSM}|\text{CMS})$$

→ what did CMS's searches teach us about the pMSSM? Prior versus **posterior**!



Our *a posteriori* knowledge of the mass of the gluino, after the first LHC “run” (red line), and the second run (black line).

Blue area: Our *prior* knowledge about the mass of the partner particle of the gluon, the *gluino*

“What have we learned about the supersymmetric partner of the gluon partner, the *gluino*”?
Qualitative summary of the plot:

“we had a realistic chance of finding something, but we didn’t.”

Let's do ugly!

But the pMSSM would still count as a “pretty” theory. How can we move to “ugly”?

Proposal: we switch from models like the pMSSM to the space of *sensible* BSM Lagrangians.

Obvious, difficult question: what's a sensible Lagrangian? (Let's for now put this question aside, assume that it can be answered. Will come back to this later)

Let's do ugly!

Idea: we “parametrize” the space of all sensible Lagrangians by the modifications on the SM that it takes to obtain that particular Lagrangian.

Mindset very much like that of (e.g. dark matter) model builders.

Examples for modifications:

- add a scalar / fermion / vector
- add couplings
- add a second Higgs doublet mode
- add kinetic mixings

Let's do ugly!

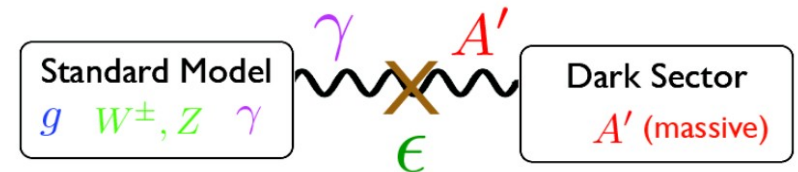
What are typical modifications to the SM Lagrangian, that the algorithm should consider?

A few of the simpler cases:

- **Dark photons**, kinetic mixing between photon and

dark photon:

only two new parameters: the mixing angle and the mass of the dark photon



$$\Delta\mathcal{L} = \frac{\epsilon}{2} F^{Y,\mu\nu} F'_{\mu\nu}$$

“Kinetic Mixing”

Holdom
Gaision, Manohar

Plot taken from [talk](#) by P. Crivelli

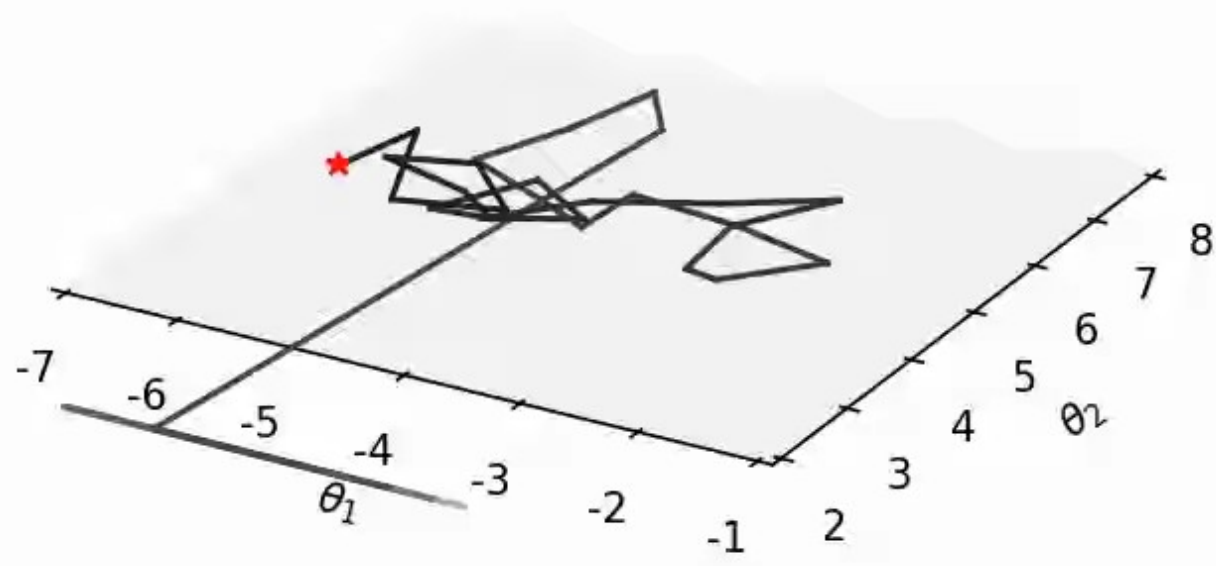
- **Extra scalar** with hypercharge 0

can implement a dark matter candidate through a Higgs portal

$$\mathcal{L}_{\text{SHP}} = \mathcal{L}_{\text{SM}} + \frac{1}{2} \partial_\mu S \partial^\mu S - \frac{1}{2} m_0^2 S^2 - \frac{1}{2} \lambda_S |H|^2 S^2 - \frac{1}{4!} \lambda_4 S^4$$

- **Extra Higgs doublet**, with or without a “Z₂” symmetry

we could even take out the first Higgs doublet from the SM (ignoring the fact that this becomes a theory that violates unitarity) feed it the Higgs measurements, and if see the algorithm correctly reproduces the Standard Model.



MCMC walk, after 140 steps

Let's do ugly!

Under what circumstances does this proposal **not** make sense?

- if/when the pretty models seem to work (though the “usual” natural ones do not, we know that by now).
- if/when the minimal models seem to work (think e.g. a Z' -like resonance is found at the LHC, but nothing else. Just add a $U(1)$ symmetry to the standard model, then.)

When would this proposal have its maximum benefit?

- when neither “pretty” nor “minimal” works
- when no clear, simple signal shows up in any of the individual experiments: “dispersed” signals with unclear and not trivial interpretation

Of the tools and theory calculations needed for this proposal, what is already done?

Task	Description	Status
Predictions, precision measurements	Calculation of various observables of precision measurements for arbitrary Lagrangians at high enough perturbation orders	Probably only partially?
Generic “global fitting” framework	A generic framework that allows to perform “global fits” of data to arbitrary models	Exists (e.g. GAMBIT)
Model building random walk	A “scanner bit” that performs a Metropolis-Hastings random walk, but includes model building	Does not exist
Fast likelihood for searches	A fast method to compute likelihoods for searches for new physics, for arbitrary Lagrangians	Mostly (SModelS)
Fast likelihood for precision measurements	A fast method to compute likelihoods for precision measurements, for arbitrary Lagrangians	Contur? Can we exploit effective field theories? SMEFT?
Fast likelihood for astrophysical observations	Fast likelihoods for astrophysical observations, for arbitrary Lagrangians	Micromegas? MadDM? ... ?
Global combination	Global combination of all likelihoods involved	Done in GAMBIT

What conditions would we require even of an ugly Lagrangian?

Condition	Is required?
Lorentz invariance	yes
Renormalizability	No (we anyhow don't pretend to have a "complete" theory)
Unitarity	Not necessarily (same as above)
Conservation of charges	yes
Vacuum (meta) stability	Probably not?
Perturbativity	Conceptually no, technically yes?

Near-term goals

Admittedly, directly learning BSM Lagrangians is not yet feasible in the near future for many types of measurements. (Think e.g. we will need predictions at good enough perturbation order for arbitrary Lagrangians. Challenging!)

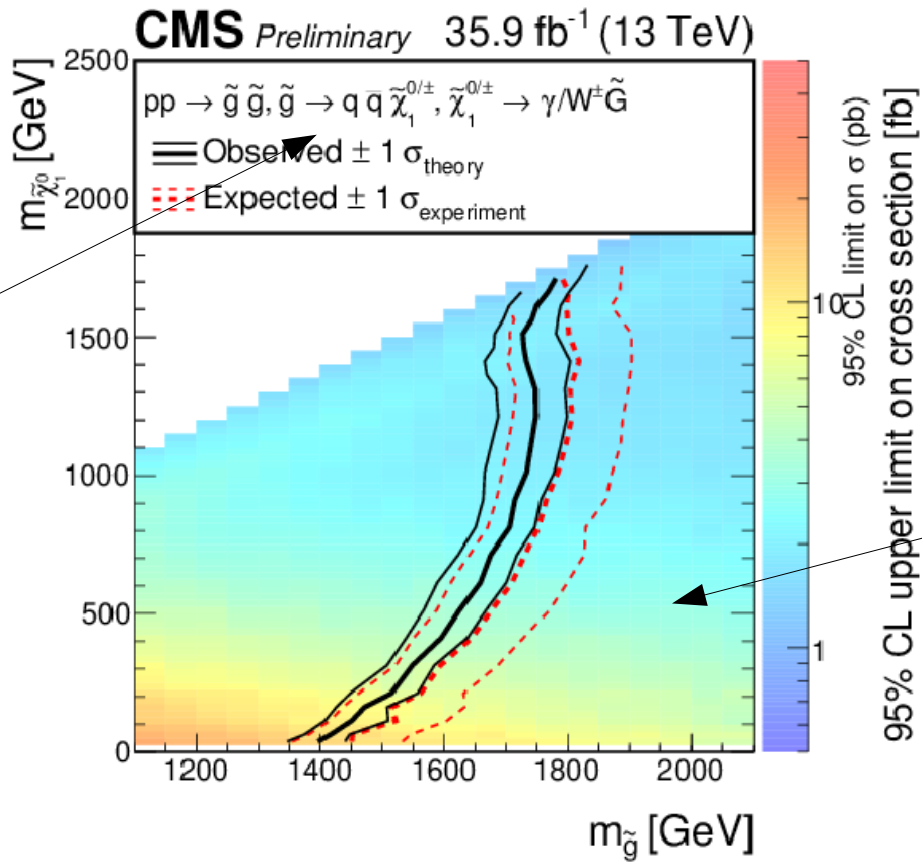
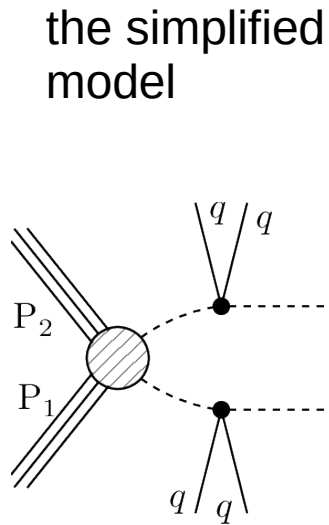
A trimmed-down version of this idea that I would like to work on that can be implemented in O(months), is to

- restrict the space of models to ones that can be properly described with SLHA files (a.k.a. SUSY-like models)
- start with direct searches, use simplified models and SModelS for a quick confrontation of the models with O(100) LHC search results.
- That way, we can search for “dispersed signals” – signals that become evident when combining searches – in the existing results.
- If now dispersed signals can be identified, we can search for maximally “spectacular” signatures that should be within reach of the LHC but have nevertheless been missed, at by the simplified models results. We can encode the notion of “spectacularity” in our prior.
- Of course, such an approach could be combined with a likelihood on Wilson coefficients, and thus LHC precision measurements.

Recap: simplified models



Simplified models are models meant to describe physics Beyond the Standard Model (BSM). Contrary to a “full” model like supersymmetry, however, they only introduce a small number (2 or 3) of new particles, allow them to decay only in one specific channel. They are meant as a tool, or a “abstraction interface” for a theorist to the results of the searches of CMS and ATLAS.

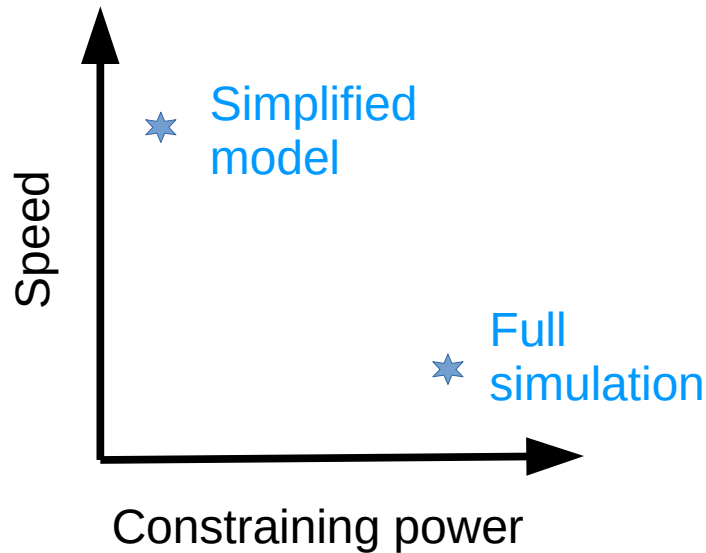
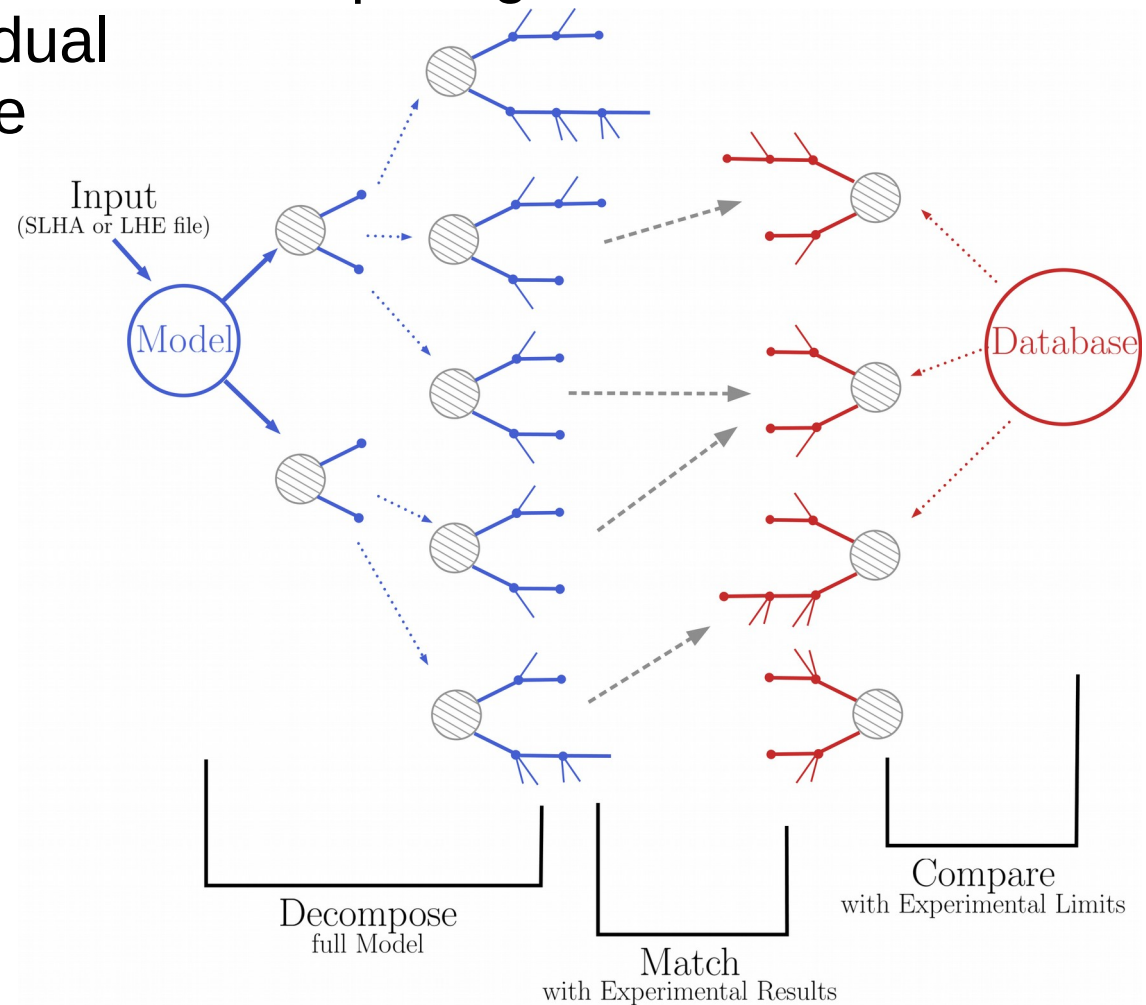


A typical simplified models result, as presented by CMS. Two massive particles ($\tilde{g}, \tilde{\chi}$) were introduced. The upper limits on production cross sections (the heatmap) are given as a function of the masses of these two particles.

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.



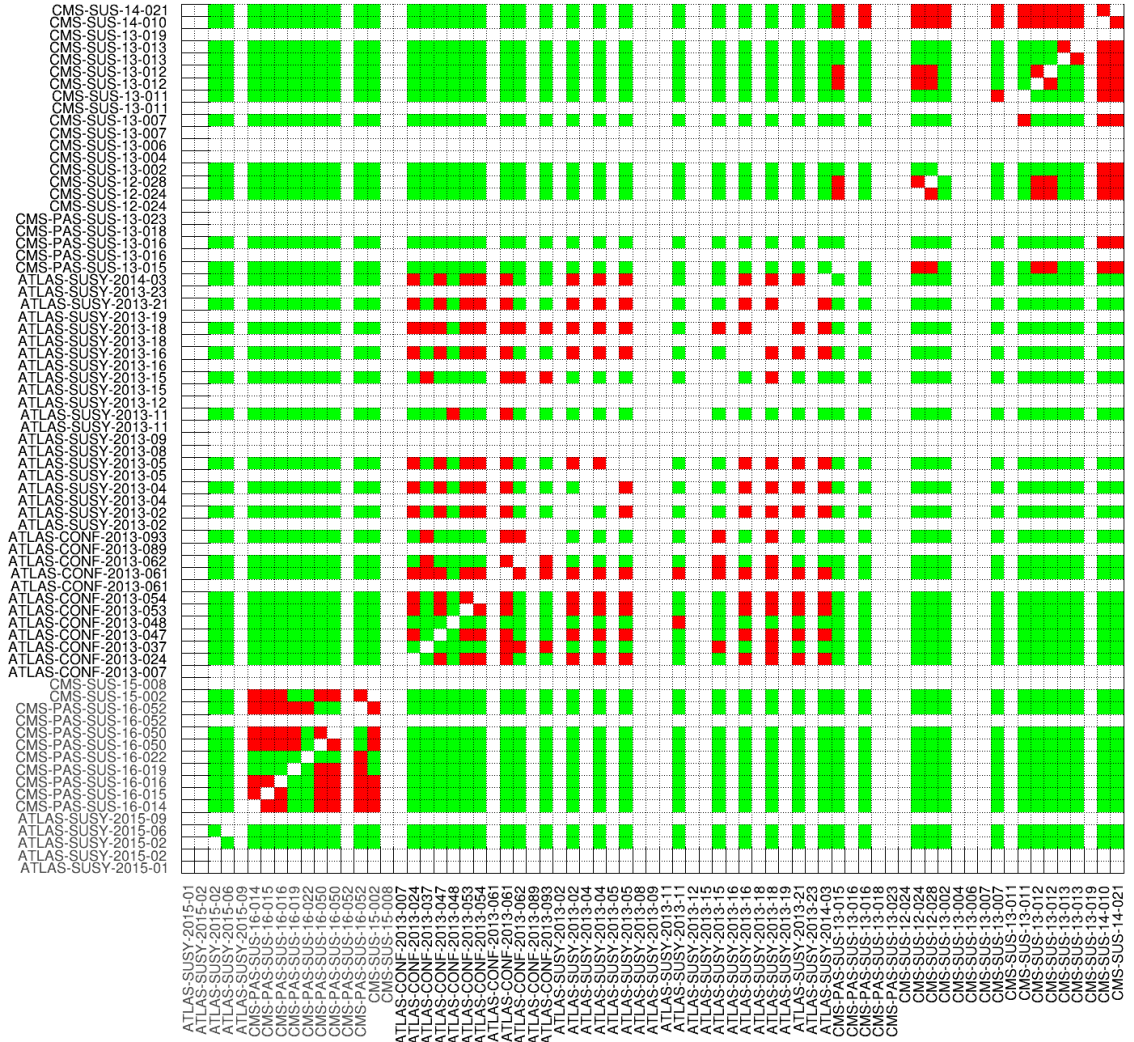
Combination of analyses



Joint likelihoods for combining analyses

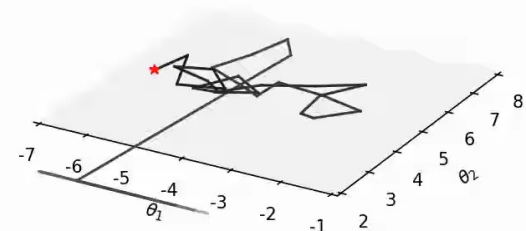
many pairs of analyses can be treated as **approximately uncorrelated** (the **green** blocks, think e.g. of a 8 TeV ATLAS result and a 13 TeV CMS result)

Correlations between analyses (green is uncorrelated)



Summary

- Why don't we mechanize the task of model building, and treat it as random steps in a Bayesian random walk!
- We can encode many types of “goals”, (theoretical) constraints and desirable features in our prior.
- In order to avoid the cost of recasting LHC searches, we can use the conservative but fast SModelS.
- Constraints from measurements may be added via likelihoods on Wilson coefficients.

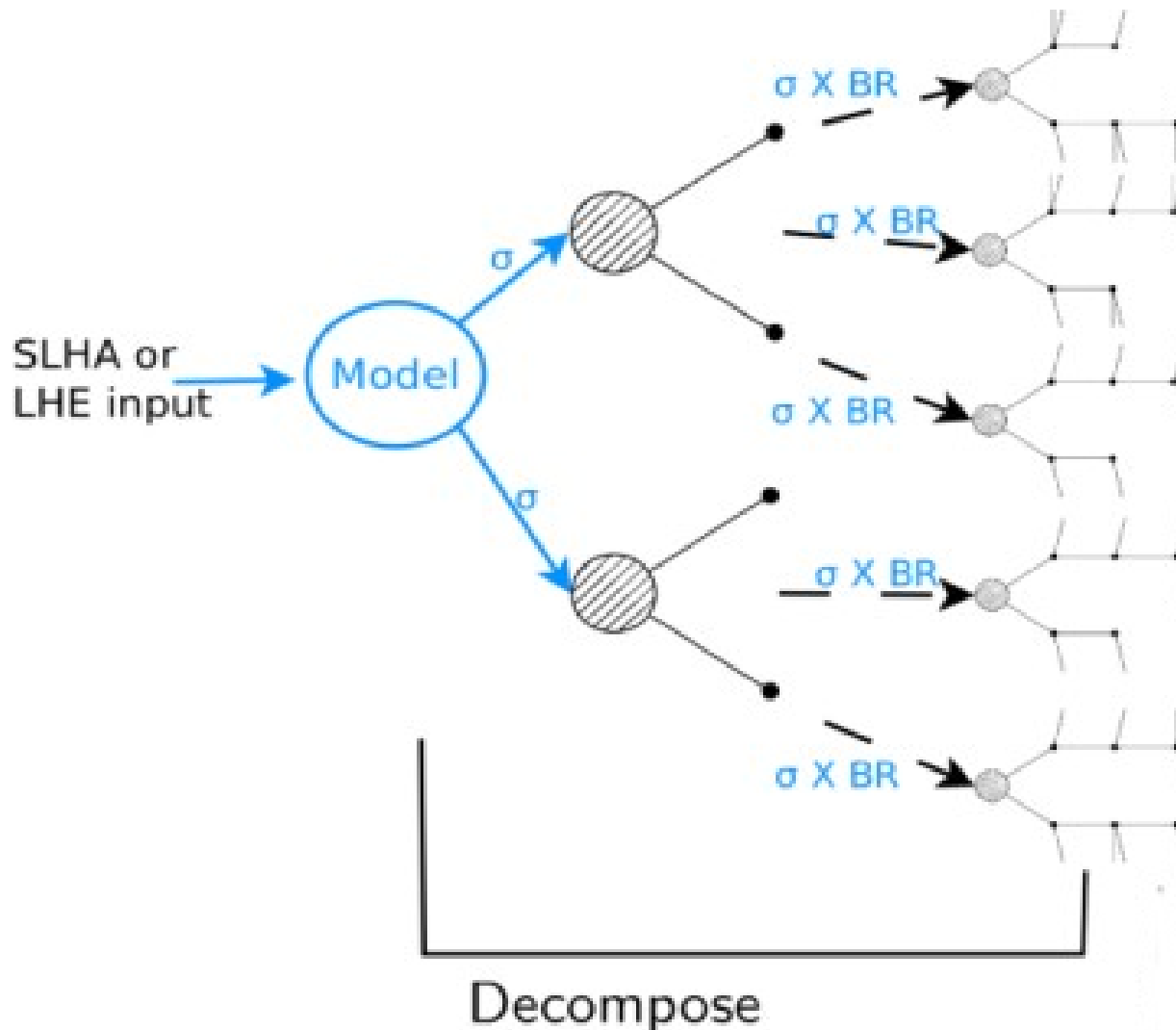


MCMC walk, after 140 steps

Recap: How SModels works



1) Decomposition of a fundamental model

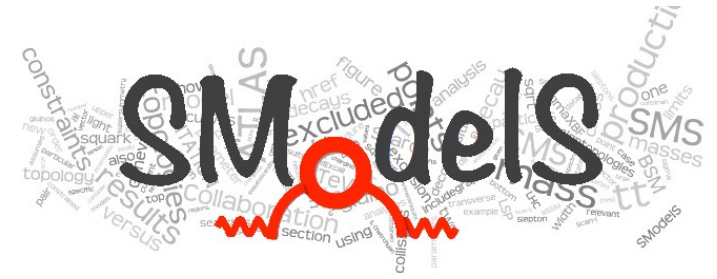


Input: SLHA file (mass spectrum, BRs) or LHE file (parton level)

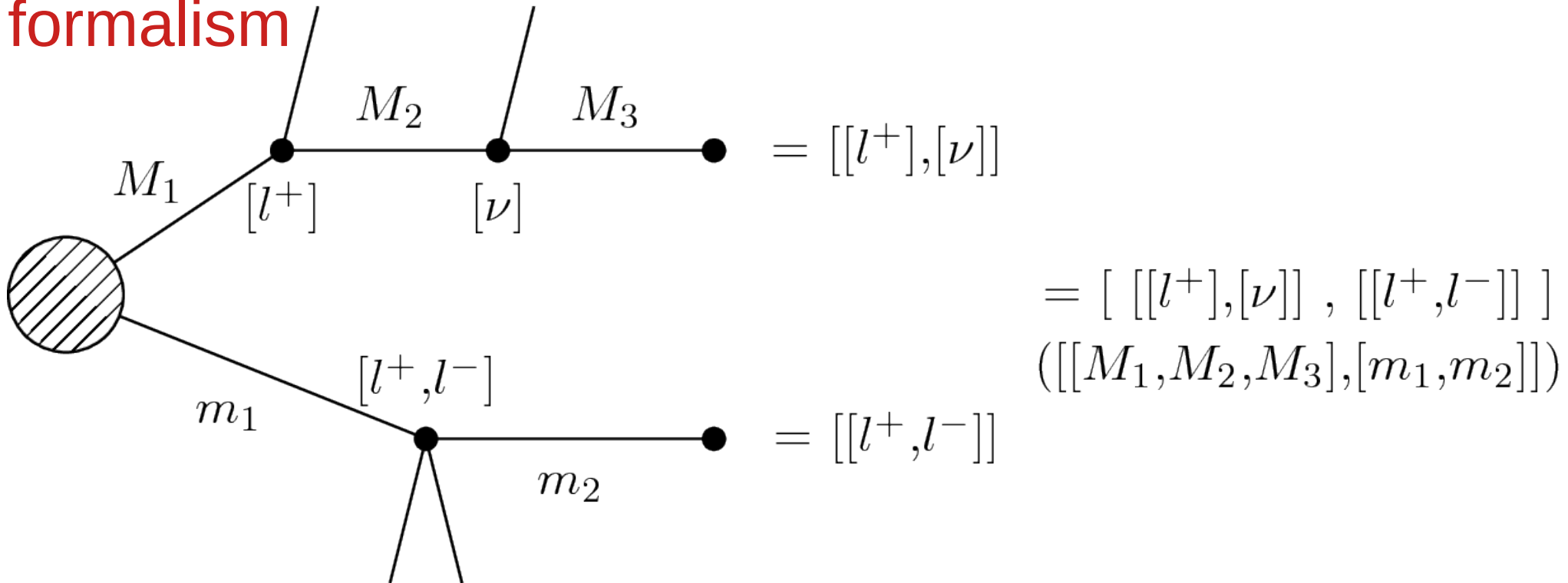
Currently the model must have a Z_2 symmetry

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

Recap: How SModels works



2) Description of the topology in the SModels formalism



Each topology is described by:

- Topology shape + final states
- BSM masses
- $\sigma \times \text{BR}$

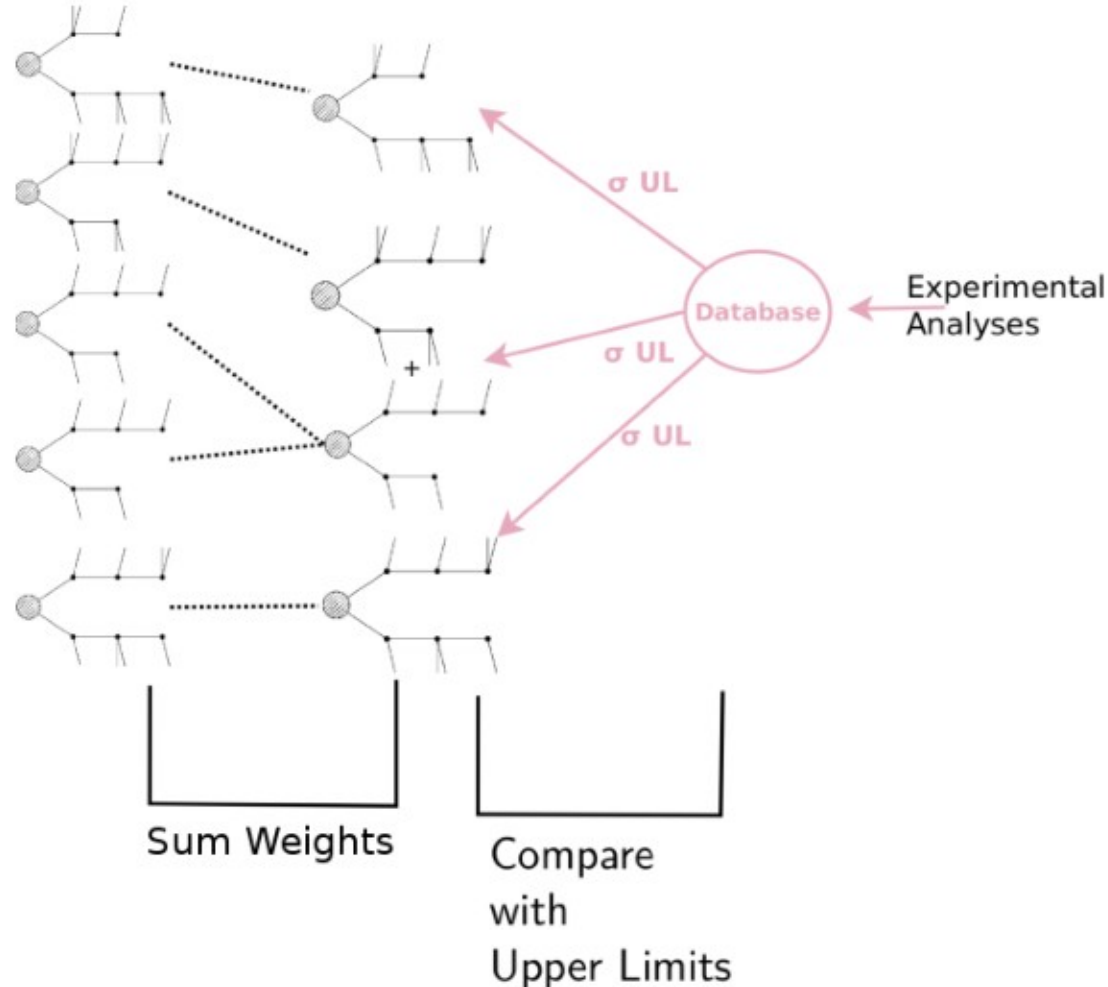
We (currently) ignore spin, color, etc of the BSM particles

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

Recap: How SModels works



3) Comparison of predicted signal strengths with experimental result:



- **Upper Limit Results:**
Predicted signal strength = $\sigma \times BR$
Experimental result: σ_{UL}
- **Efficiency Map Results:**
Predicted signal strength = $\sum \sigma \times BR \times \epsilon$
Experimental result: $\sigma_{UL} = N_{UL} / L$ from $N_{observed}$, $expected(BG)$, $error(BG)$
- $r = \text{predicted} / \sigma_{UL}$
- Model is excluded if most constraining analysis has $r > 1$