Artificial Proto-Modelling for Dispersed Signals at the LHC

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in collaboration with:

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IRN Terascale Meeting – Montpellier – November 2025

Université Grenoble Alpes

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Outline

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Motivation

Experiments and theory point towards a theory beyond the Standard Model (of p.p.).
However, **no compelling signal of new physics** has shown up in the LHC data. **Why?**

- ▷ The new physics can only show up at higher energies.
- ▷ The new physics is too feebly coupled to the Standard Model.
- ▷ The new physics has been recorded but is hiding in the data.

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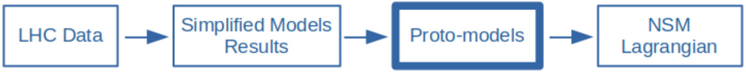
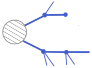
How to look for it? There are many well-motivated Standard Model extensions, many of which can have a significant number of free parameters.

Need to shift perspective, and adopt a
more model-independent and data-driven approach.



The proto-model machine

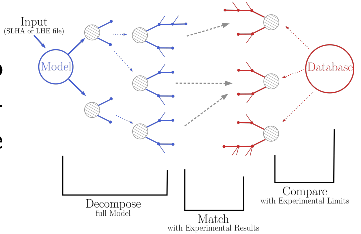
Proto-model: set of simplified models not tied to any theoretical assumption.
↳ m, σ and branching ratio (BR) of few BSM particles.



(typical framework of many LHC BSM searches)

Goal: search for the proto-models that violate the Standard Model the most, while being consistent with current LHC limits.

How: use reversible jump Markov chain Monte Carlo (RJMCMC)-type walk to generate proto-models and confront their signals to the simplified models results in the SModelS database (UL and EM-type results).



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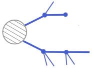

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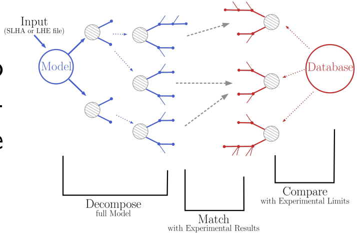


An initial concept has been published, comprising three building blocks:
(W. Waltenberger, A. Lessa, S. Kraml, JHEP03(2021)207)

- The builder
- The combiner
- The critic

Outline

The builder

It builds proto-models by adding/removing BSM particles, changing $m/\sigma/$BR.

The particles that can be added are SUSY-inspired:

new wrt initial concept

Particle	Decay Channels	Particle	Decay Channels
X_q	$qX_Z^j,\ q'X_W^i,\ qX_g$	X_W^1	$WX_Z^j,\ q\bar{q}'X_Z^1,\ \ell\nu_\ell X_Z^1$
X_t^1	$tX_Z^j,\ bX_W^i,\ WX_b^1,\ tX_g$	X_W^2	$WX_Z^j,\ ZX_W^1,\ hX_W^1,\ q\bar{q}X_Z^1,\ b\bar{b}X_Z^1,\ \ell\bar{\ell}X_Z^1$
X_b^1	$bX_Z^j,\ tX_W^i,\ WX_t^1,\ bX_g$	$X_Z^{j\neq 1}$	$WX_W^i,\ ZX_Z^k,\ hX_Z^k$
X_t^2	$tX_Z^j,\ bX_W^i,\ ZX_t^1,\ WX_b^1,\ tX_g$	X_ℓ	$\ell X_Z^j,\ \nu_\ell X_W^i$
X_b^2	$bX_Z^j,\ tX_W^i,\ ZX_b^1,\ WX_t^1,\ bX_g$	X_{ν_ℓ}	$\nu_\ell X_Z^j,\ \ell X_W^i$
X_g	$q\bar{q}X_Z^i,\ q\bar{q}'X_W^i,\ b\bar{b}X_Z^i,\ t\bar{t}X_Z^j,\ btX_W^i,\ qX_q,\ bX_b,\ tX_t$		

with:

- ▷ off-shell decays: $q, q' \in \{u, d, s, c\}$, $\ell \in \{e, \mu, \tau\}$ and flavor-democratic decays.
- ▷ $\mathbb{Z}_2$-odd particles.
- ▷ Only prompt decays and X_Z^1 lightest BSM particle $\Rightarrow$ final states with E_T^{miss}.

The combiner

$$\text{Poiss}(\mu s + b + \theta)\text{p}(\theta)$$

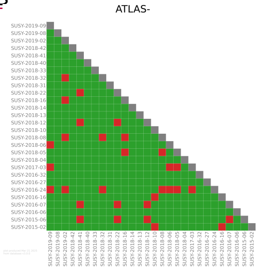
It finds all allowed analysis combinations.

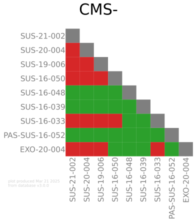
$$L_c(\mu) = \Pi_i L_i(\mu)$$

Binary combinability: two analyses are approximately uncorrelated if from different runs, experiments, or with non-overlapping SRs.

A likelihood can be built for
25 ATLAS and 8 CMS prompt,
$\mathbb{Z}_2$-preserving, searches.
18 use full Run 2 luminosity.

Combination of maximal length.





Combination of SRs: 9 ana. with full HistFactory model, 11 ana. with cov. matrix.

An optimized pathfinder: now relies on the "pathfinder" algorithm developed in J. Y. Araz et al., SciPost Phys. 14 (4) (2023) 077 → (much faster).

The test statistic

The combiner is used to find

$$\pi_{\mathrm{BSM}} = \exp\left[-\left(\frac{n_{\mathrm{particles}}}{2} + \frac{n_{\mathrm{BRs}}}{4} + \frac{n_\sigma}{8}\right)\right]$$

$\times\,\pi_{\text{missing ana}}$

$\times\,\pi_{\text{large or small }\sigma}$

Penalise for complexity and over-fitting

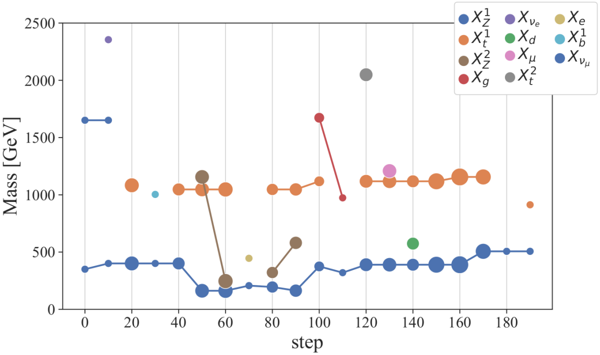
$$K := \max_{c\in C}\left[2\ln\left(\frac{L^c_{\mathrm{BSM}}(\hat\mu)\cdot\pi_{\mathrm{BSM}}}{L^c_{\mathrm{SM}}\cdot\pi_{\mathrm{SM}}}\right)\right]$$

Set of allowed combinations

$$L^c_{\mathrm{SM}} = L^c_{\mathrm{BSM}}(\mu=0)$$

$$\pi_{\mathrm{SM}} = 1$$

The algorithm tries to maximise K through the RJMCMC-type walk (most significant combination).



The critic

It uses limits of analyses not entering the combination to ensure they are not violated. Acts as an adversarial to the builder.

Two critics: each giving a binary output: the proto-model is excluded or not.

The fast critic: uses UL-type results. No likelihood is built; approximation but fast. Number of analyses allowed to exclude: number of analyses giving 66% of CDF of $\mathcal{B}(n, p = 0.05)$, where n is the number of sensitive analyses (i.e. with $\frac{\sigma}{\sigma_{95}^{\text{exp}}} \geqslant 0.7$). If more analyses exclude the proto-model, rejected by fast critic.

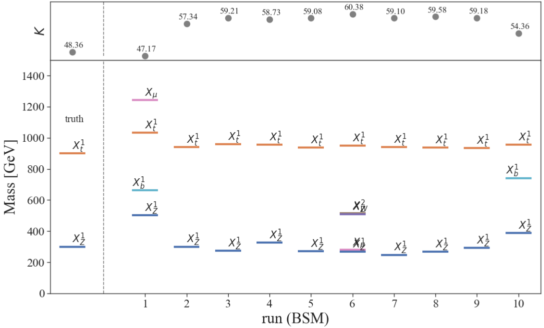
The slow critic: uses the combiner to get the most sensitive combination of analysis. The proto-model is excluded if $\frac{\sigma}{\sigma_{95}^{\text{comb}}} \geqslant 1$.

108 (+25) prompt, $\mathbb{Z}_2$-preserving, searches are available.
29 (+23) use full Run 2 luminosity.

Outline

Closure test

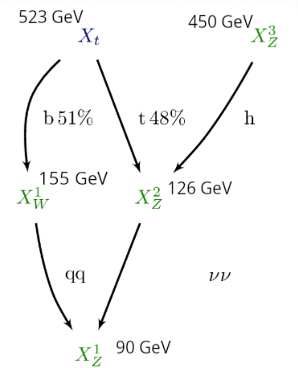
1. Create a "fake database" by sampling from the SM hypothesis.
2. Inject a signal (here X_t^1 and X_Z^1).
3. Let many "walkers" search for it.
4. Did the step with the highest K of each walker find the signal?



Every walker found the 2 BSM particles, most with correct masses.

Additional particles and higher K come from fitting other SM deviations (introduced during sampling from SM).

Current best result



After many walkers and steps, proto-model with the highest K:
$K = 32.50$ and $Z \approx 6.25$(!)
↳ need K distrib. under SM hypothesis for p-value.

11 analyses enter the most significant combination.
The most significant 5 (all using full Run 2 luminosity):

Analysis Name	**Dataset**	**Obs**	**Expected**	**Z**	**Process** ($pp \to$)
monojet (CMS-EXO-20-004)	comb.	180.8 fb	136.7 fb	4.6 σ	$X_Z^2 X_Z^2 / X_Z^2 X_Z^1 \to E_T^{\text{miss}}$ $X_Z^2 X_W^1 / X_W^1 X_Z^1 \to qq + E_T^{\text{miss}}$
monojet (ATLAS-EXOT-2018-06)	EM10	413	359 $\pm$ 10	2.5 σ	$X_Z^2 X_Z^2 / X_Z^2 X_Z^1 \to E_T^{\text{miss}}$ $X_Z^2 X_W^1 / X_W^1 X_Z^1 \to qq + E_T^{\text{miss}}$
2 $h(bb)$, EWK (CMS-SUS-20-004)	comb.	0.3 fb	0.2 fb	2.0 σ	$X_Z^3 X_Z^3 \to hh + E_T^{\text{miss}}$
0 ℓ+ jets (ATLAS-SUSY-2018-12)	SRBTT	67	46 $\pm$ 7	2.0 σ	$X_t X_t \to tt + E_T^{\text{miss}}$
2 OS ℓ (ATLAS-SUSY-2018-08)	SRSF140	9	5.1 $\pm$ 0.9	1.5 σ	$X_t X_t \to tt + E_T^{\text{miss}}$

Why BR($X_t \to b X_W^1$) $\neq 0$? Maybe penalty term not strict enough?

Current best result – The critics

This proto-model passes both critics.

30 analyses are sensitive to the current best proto-model.
The 4 most sensitive datasets entering the fast critic:

Analysis Name	**Dataset**	$\sigma/\sigma_{\mathbf{95}}$	$\sigma/\sigma_{\mathbf{95}}^{\text{exp}}$	**Process** ($pp \rightarrow$)
monojet (ATLAS-EXOT-2018-06)	EM8	1.49	1.62	$X_Z^2 X_Z^2 / X_Z^2 X_Z^1 \rightarrow E_T^{\text{miss}}$ $X_Z^2 X_W^1 / X_W^1 X_Z^1 \rightarrow qq + E_T^{\text{miss}}$
stop comb. (CMS-SUS-20-002)	UL	1.32	1.20	$X_t X_t \rightarrow tt + E_T^{\text{miss}}$
jets + t- and W-tag (CMS-SUS-19-010)	UL	0.98	0.93	$X_t X_t \rightarrow tt + E_T^{\text{miss}}$
1 ℓ + jets (CMS-SUS-19-009)	UL	0.83	0.84	$X_t X_t \rightarrow tt + E_T^{\text{miss}}$

Excluded if $\sigma/\sigma_{95} \geqslant 1$ but allow for some leeway.

7 analyses enter the slow, likelihood-based, critic (most sensitive combination of ana.)
↳ Does not exclude proto-model: $\sigma/\sigma_{95} = 0.98$ (large over-fluctuation: $\sigma/\sigma_{95}^{\text{exp}} = 3.48$).

Conclusions

- ▷ The absence of positive result and the stringent constraints reflect the need to **shift from the usual top-bottom approach**.

- ▷ The proto-model machine proposes a more model-independent, **data-driven approach**.

- ▷ Promising preliminary results but **further work** is required:
  - Scrutinise the walk more deeply
  - More complex closure tests
  - Posterior distribution wrt model parameters
  - K distribution under the SM hypothesis
  - Add LLP and non-$\mathbb{Z}_2$ topologies
  - Match proto-models to higher order theory

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  - Match proto-models to higher order theory
- These studies completely rely on the possibility to build **likelihoods**.
  Many thanks to the experimental collaborations for publishing and preserving all the valuable information needed for reinterpretation studies.

Thank you for your attention!

Acceptance probability

To account for dimension jump, introduce latent variables u and v: $d_{M_i} + d_u = d_{M_j} + d_v$.

To converge towards a stationary distribution for K, take step if $x \sim \mathcal{U}(0,1) \leqslant \alpha$:

$$\alpha(M_i, M_j) = \min\left\{1, \underbrace{\frac{L^c_{\mathrm{BSM}}(\hat{\mu}|M_j)}{L^c_{\mathrm{SM}}(M_j)} \frac{L^{c'}_{\mathrm{SM}}(M_i)}{L^{c'}_{\mathrm{BSM}}(\hat{\mu}|M_i)}}_{\text{likelihood ratio}} \underbrace{\frac{\pi_{\mathrm{BSM}}(M_j)}{\pi_{\mathrm{BSM}}(M_i)}}_{\substack{\text{model}\\ \text{prior ratio}}} \underbrace{\frac{\pi(\theta_j|M_j)}{\pi(\theta_i|M_i)}}_{\substack{\text{parameter}\\ \text{prior ratio}}} \frac{p_V(v)}{p_U(u)} \prod_m \underbrace{\frac{q_m(M_j \to M_i)}{q_m(M_i \to M_j)}}_{\text{proposal ratio}}\right\}$$

with θ model parameters (m, σ, BR). We take u and v from same distributions as θ:

$$\alpha(M_i, M_j) \approx \min\left\{1, \frac{L^c_{\mathrm{BSM}}(\hat{\mu}|M_j)}{L^c_{\mathrm{SM}}(M_j)} \frac{L^{c'}_{\mathrm{SM}}(M_i)}{L^{c'}_{\mathrm{BSM}}(\hat{\mu}|M_i)} \frac{\pi_{\mathrm{BSM}}(M_j)}{\pi_{\mathrm{BSM}}(M_i)} \underbrace{\frac{p(M_j \to M_i)}{p(M_i \to M_j)}}_{\text{probability ratio}}\right\}$$

Example for adding/removing a particle

$$p_{\text{add}}(M_i \to M_j) = \frac{1 + \exp(z_{M_i})}{1 + \exp(z_{M_j})}$$

$$p_{\text{rem}}(M_i \to M_j) = \frac{1 + \exp(-z_{M_j})}{1 + \exp(-z_{M_i})}$$

where

$$z_M = \left(\frac{n_{\text{particles}} - 8}{2} + \frac{n_{\text{BRs}}}{4} + \frac{n_\sigma}{8} \right)_M$$