An exploration of the NMSSM using deep learning to fit hints of scalars and dark matter

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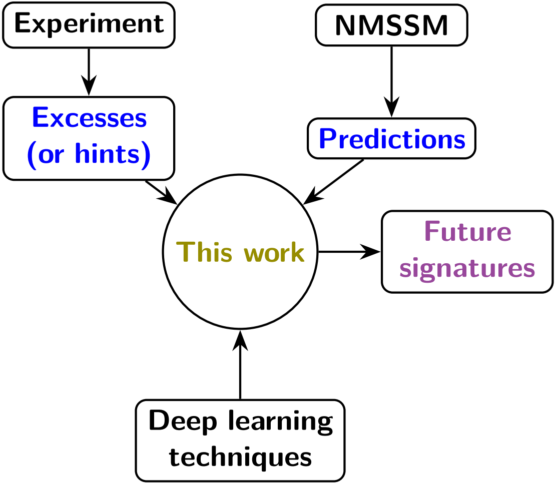
Based on:
A. Chakraborty, A. Hammad, P. Ko, S. Moretti and RR [JHEP 02 (2026) 077]
A. Hammad and RR, [CPC 314 (2025) 109659]

PASCOS 2026
Sheffield, June 25, 2026

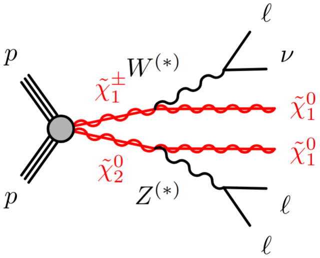
Main motivations

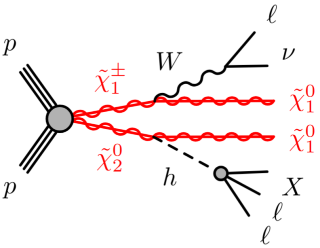


Disclaimer: In this talk I am mostly dealing with **hints** in experimental searches.

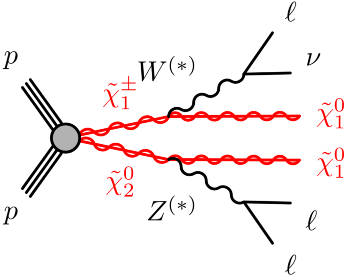
Experimental observations – Electroweakino searches [ATLAS 2106.01676]

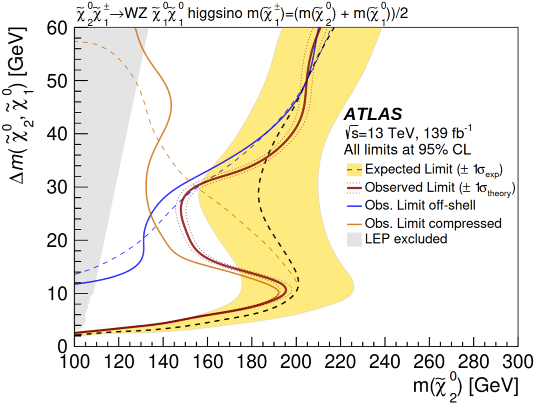
Simplified models



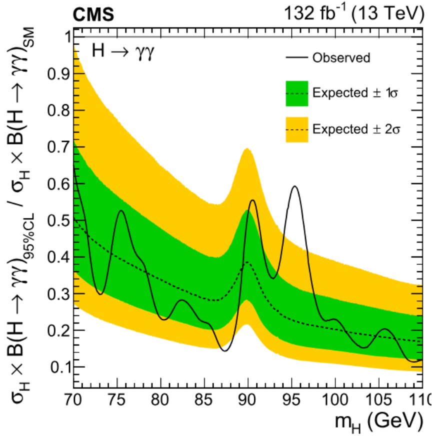


Experimental observations – Electroweakino searches [ATLAS 2106.01676]

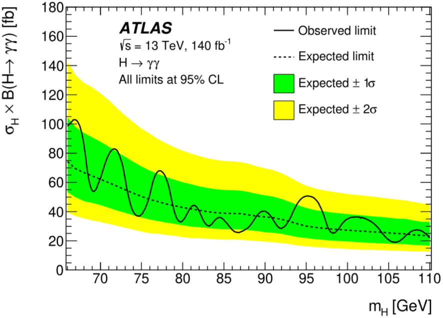




Experimental observations – 95.4 GeV

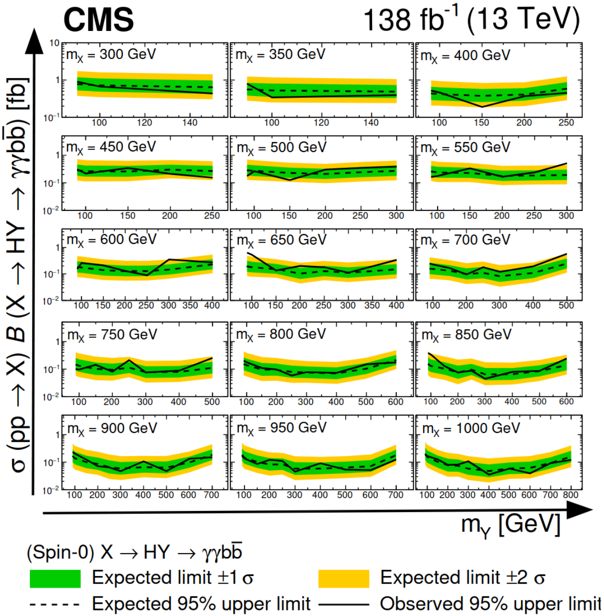


2.9σ local (1.3σ global)
[2405.18149]



1.7σ local
[2407.07546]

Experimental observations – 650 → 90 GeV [2310.01643]



Experimental observations – 650 $\to$ 90 GeV

CMS [2506.2312]:

X $\to$ YH $\to$Y($\gamma\gamma$)H($\tau\tau$)

(X, Y) with masses: (600, 95) GeV and (650, 95) GeV
local significances: 2.5σ and 2.3σ, respectively

Why SUSY and the NMSSM

Why Supersymmetry?

- Mass of the Higgs is protected by symmetry.
- Higgs potential generated dynamically
- Convergence of the coupling “constants” at a higher scale.
- Lightest supersymmetric particle (LSP) can be a dark matter candidate.

Why the next-to-minimal supersymmetryc standard model (NMSSM)?

- Minimal SUSY model plus an additional singlet superfield.
- μ term generated by additional singlet VEV.
- The 125 GeV Higgs mass is more natural
- Extension results in three CP-even Higgs bosons.

Relevant parameters to scan over the NMSSM

The NMSSM extends the superpotential of the MSSM

$$W_{\mathrm{NMSSM}} = W_{\mathrm{MSSM}} + \lambda \hat{H}_u \hat{H}_d \hat{S} + \frac{1}{3}\kappa \hat{S}^3,$$

where the MSSM superpotential has the μ term set to 0. The second term generates $\mu_{\mathrm{eff}} = \lambda s$ where $s = \langle S \rangle$.

The soft SUSY breaking part of the potential is

$$V_{\mathrm{soft}} = m_{H_u}^2 |H_u|^2 + m_{H_d}^2 |H_d|^2 + m_S^2 |S|^2 + \lambda A_\lambda \hat{H}_u \hat{H}_d \hat{S} + \frac{1}{3}\kappa A_\kappa \hat{S}^3,$$

`DLScanner`: streamline generic parameter scans

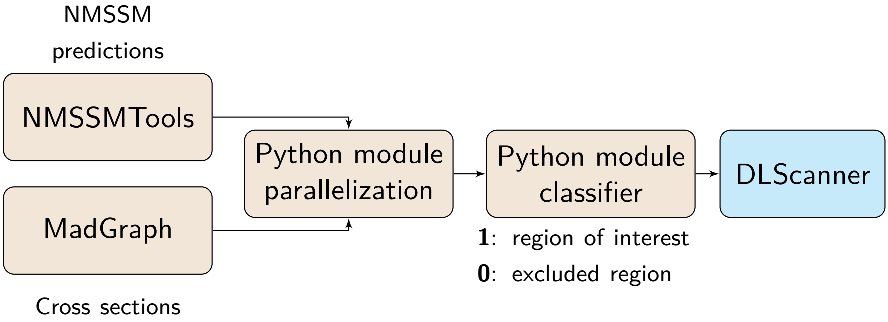
A. Hammad and RR, [CPC 314 (2025) 109659]

Install: `pip install DLScanner`
Code: `git clone https://github.com/raalraan/DLScanner.git`

- **Find regions** by binary classification or by regressing a custom function.
- Use tools like SPheno, micrOMEGAs, or **custom tools**.
- **Focus** on the HEP study and less on the deep learning setup.
- Possible to customize every aspect of the DL setup or the exploration of the parameter space.
- Use the default setup as starting point.

Setup of the DL scan

Calculations use `NMSSMTools` which coordinates a series of tools: `NMHDECAY`, `NMSPEC`, `NMGMSB`, `NMHDECAY_CPV`, `NMSDECAY`, `micrOMEGAs` and `SModelS`.



Setup of the DL scan

Preliminary scan in **wide** range.
Definitive scan in **narrow** range.

	$\tan\beta$	λ	κ	A_λ
wide	$[1.97,\ 10.9]$	$[0.013,\ 0.687]$	$[0.0058,\ 0.391]$	$[-5000,\ 480]$
narrow	$[3.2,\ 6.2]$	$[0.07,\ 0.42]$	$[0.05,\ 0.3]$	$[351,\ 834]$
	A_κ	μ_{eff}	M_1	M_2
wide	$[-621,\ 362]$	$[-244,\ 291]$	$[178,\ 3000]$	$[304,\ 10000]$
narrow	$[-300,\ -150]$	$[120,\ 220]$	$[500,\ 3000]$	$[750,\ 10000]$
	M_3	A_t	M_{Q_3}	M_{U_3}
	$[423,\ 5000]$	$[-5000,\ 1288]$	$[272,\ 10000]$	$[570,\ 10000]$

Setup of the DL scan

`DLScanner`: Binary classification is **stable** with small target spaces.

→ However, **small target** spaces are difficult to find on the first run!

Use a penalty function

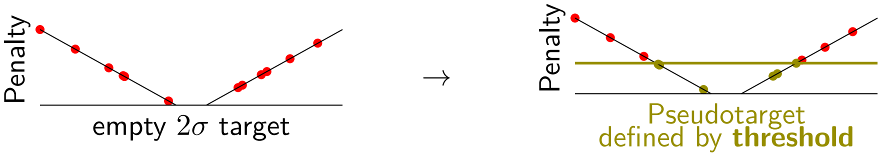
- If target region is not found, classify regions according to **low (1) and high (0) penalty**.
- Allows using deep learning to sequentially reduce the parameter space.

$$P_{\rm constraint}(O^{\rm th}, O^{\rm exp}_{\pm 2\sigma}) = \begin{cases} 0, & O^{\rm exp}_{-2\sigma} < O^{\rm th} < O^{\rm exp}_{+2\sigma}, \\ |O^{\rm exp}_{+2\sigma} - O^{\rm th}|^2, & O^{\rm th} > O^{\rm exp}_{+2\sigma},\ \text{if } O^{\rm exp}_{+2\sigma} \text{ exists}, \\ |O^{\rm th} - O^{\rm exp}_{-2\sigma}|^2, & O^{\rm th} < O^{\rm exp}_{-2\sigma},\ \text{if } O^{\rm exp}_{-2\sigma} \text{ exists}, \end{cases}$$

Individual penalties are weighted by 1σ
but we are **free to use any type of weighting**.

Setup of the DL scan

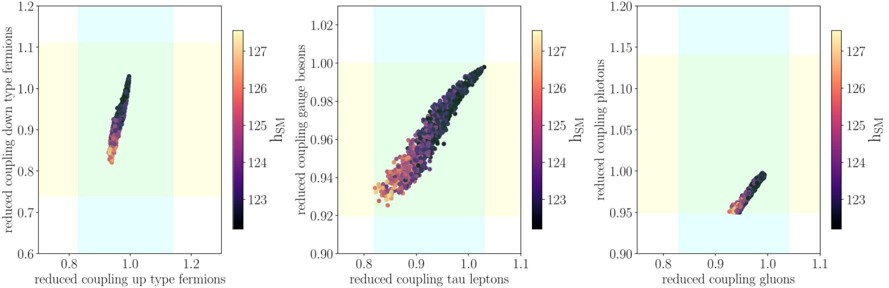
Small target: Dynamical classifier from penalty function



- If target is empty, define a *pseudotarget* from a penalty threshold for the next iteration
- In the next iteration, DLScanner will try to sample inside the *pseudotarget*
- Eventually, the penalty threshold is reduced to 0.

The constraints: SM-like Higgs properties

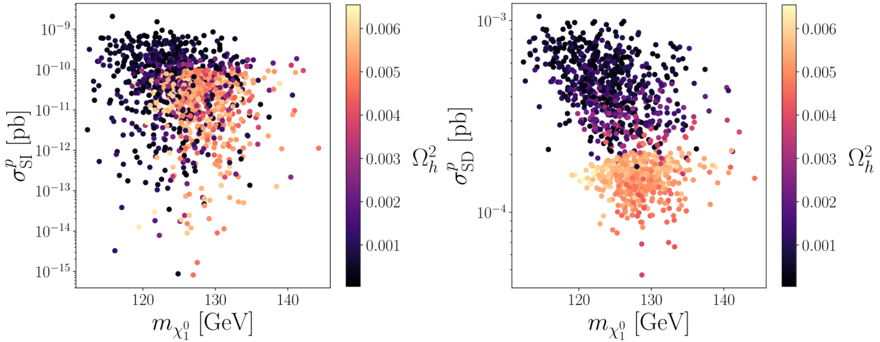
$m_{h125} = 125.2 \pm 3$ GeV due to theoretical uncertainty



The constraints: Dark matter measurements

$$\Omega_{\mathrm{CDM}} h^2 < 0.122$$

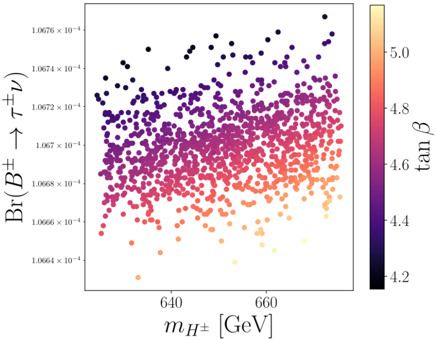
σ^p_{SI} below LZ limits [2207.03764]

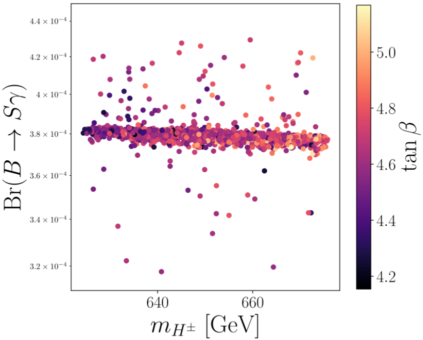


Relic density consistent with other studies: Ellwanger and Hugonie [2309.07838]

The constraints: Low energy observables

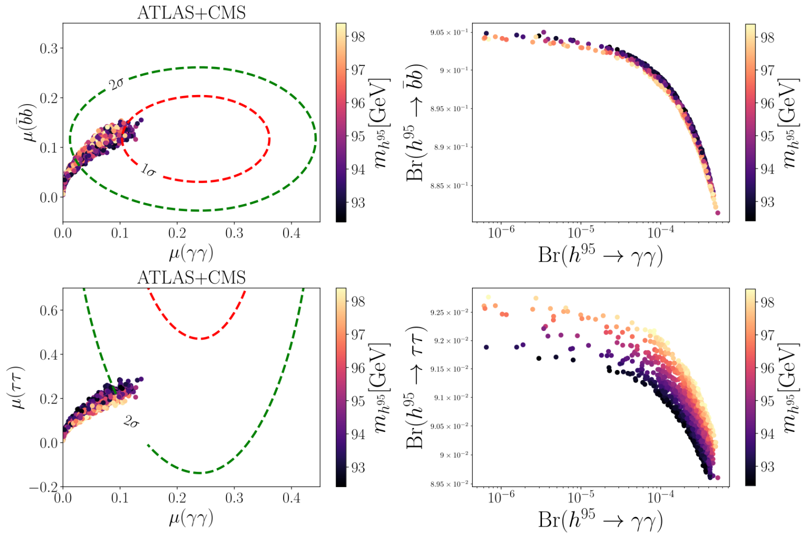
$$\mathrm{BR}(B \to X_s\gamma)_{E_\gamma \geq 1.6\ \mathrm{GeV}} = (3.32 \pm 0.15) \times 10^{-4}\,,$$
$$\mathrm{BR}(B^\pm \to \tau^\pm \nu_\tau) = (1.11 \pm 0.165) \times 10^{-4}\,.$$



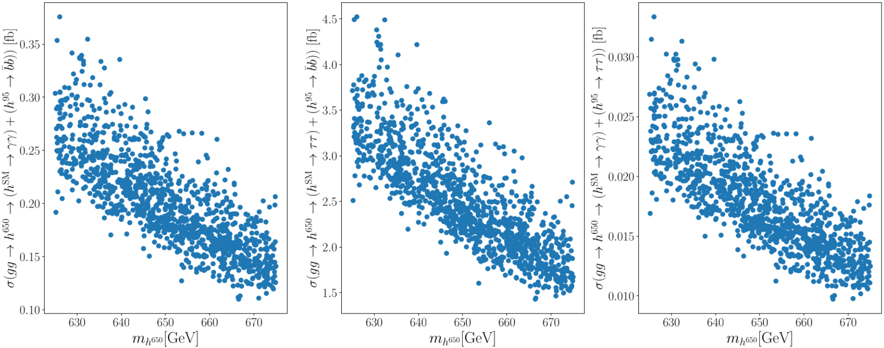


Finding a 95 GeV scalar

$$\mu_{\gamma\gamma} = \frac{\sigma(gg \to h_{95} \to \gamma\gamma)}{\sigma(gg \to h_{95}^{\rm SM} \to \gamma\gamma)}, \quad \mu_{b\bar{b}} = \frac{\sigma(e^+e^- \to Zh_{95} \to Zb\bar{b})}{\sigma(e^+e^- \to Zh_{95}^{\rm SM} \to Zb\bar{b})}, \quad \mu_{\tau^+\tau^-} = \frac{\sigma(gg \to h_{95} \to \tau^+\tau^-)}{\sigma(gg \to h_{95}^{\rm SM} \to \tau^+\tau^-)}.$$



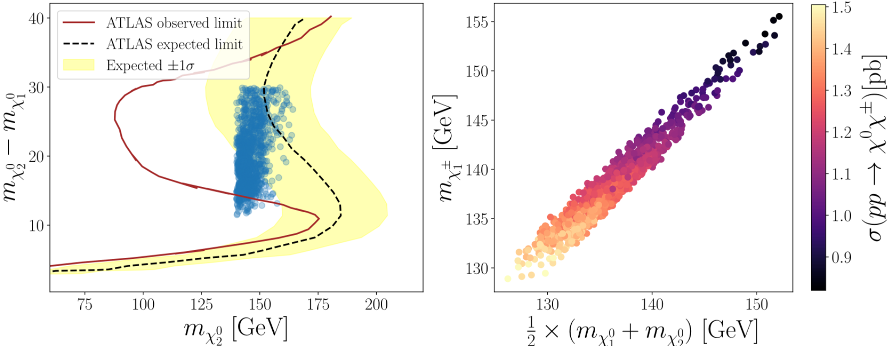
Finding a 650 GeV scalar



Remember that local significances are still low in the 2-3σ range.

Finding electroweakinos

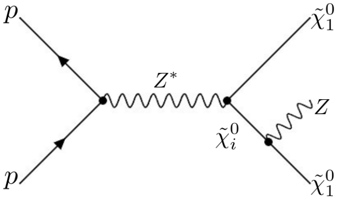
Get EWino in the discrepant region

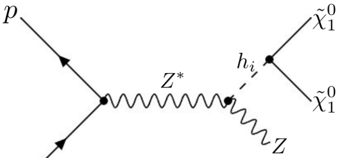


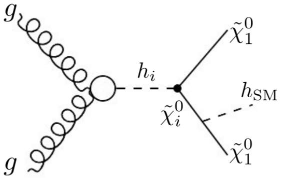
Signatures for mono-H and Z

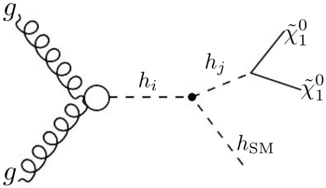
We study the following processes

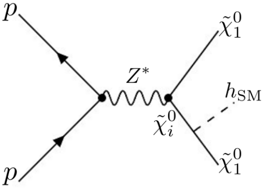
$$pp \to \tilde{\chi}_1^0 \tilde{\chi}_1^0 H \quad \text{and} \quad pp \to \tilde{\chi}_1^0 \tilde{\chi}_1^0 Z,$$





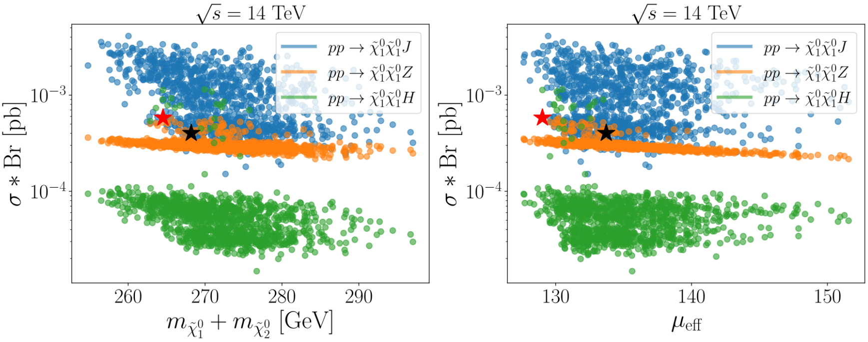






Signatures for mono-H and Z

Production cross sections



Red star: mono-Z benchmark point

Black star: mono-H benchmark point

	$\tan\beta$	λ	κ	A_λ	A_κ	μ_{eff}	M_1	M_2	M_3	A_t	$m_{\tilde{\chi}_1^0}$
mono-H	4.62	2.6×10^{-1}	2.0×10^{-1}	6.1×10^2	-2.97×10^2	1.33×10^2	2.7×10^3	1.08×10^3	3×10^3	-4.9×10^3	1.26×10^2
mono-Z	4.62	2.9×10^{-1}	2.3×10^{-1}	5.6×10^2	2.94×10^2	1.29×10^2	2.49×10^3	9.1×10^2	1.4×10^3	-4.6×10^3	1.2×10^2

Signatures for mono-H and Z: efficiencies

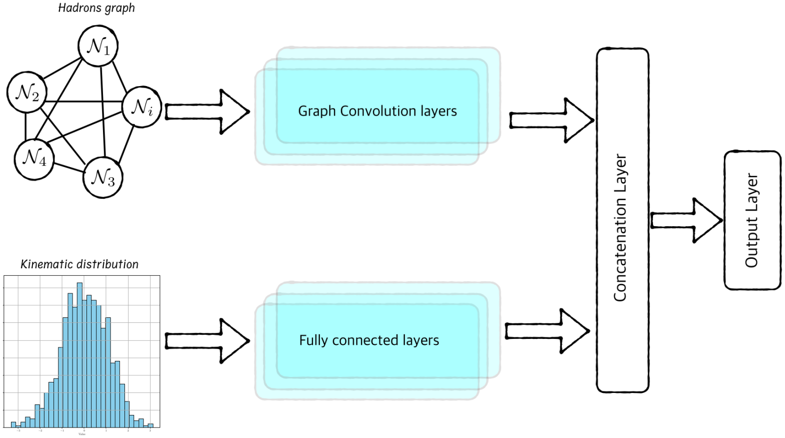
Selection cuts	$\bar{t}t$ leptonic	$V + jj$	VV	Zh_{SM}	mono-H
Cross-section [pb]	26.9	516	0.587	0.106	4×10^{-4}
$\not{E}_T \geq 200$ GeV	1.5×10^{-2}	1.5×10^{-3}	2×10^{-2}	4.7×10^{-2}	0.436
$N(b) \geq 2$	1.2×10^{-2}	1.1×10^{-3}	1.4×10^{-2}	3.5×10^{-2}	0.325
$p_T(b_1) \geq 50$, $p_T(b_2) \geq 30$ GeV	1.8×10^{-3}	1.7×10^{-4}	3×10^{-3}	1.4×10^{-2}	0.13
80 GeV $\leq m(b\bar{b}) \leq$ 140 GeV	5×10^{-4}	6×10^{-5}	2.6×10^{-3}	1.2×10^{-2}	0.121
$\Delta\phi(b_{1,2}, \not{E}) > 0.35$	4×10^{-4}	4×10^{-5}	2.4×10^{-3}	1.1×10^{-2}	0.120

Selection cuts	$\bar{t}t$ leptonic	$V + jj$	VV	Zh_{SM}	mono-Z
Cross-section [pb]	26.9	516	0.587	0.106	5×10^{-4}
$\not{E}_T \geq 200$ GeV	1.5×10^{-2}	1.5×10^{-3}	2×10^{-2}	4.7×10^{-2}	0.38
$N(b) \geq 2$	1.2×10^{-2}	1.1×10^{-3}	1.4×10^{-2}	3.5×10^{-2}	0.29
$p_T(b_1) \geq 30$, $p_T(b_2) \geq 20$ GeV	1.1×10^{-2}	5.5×10^{-4}	4.8×10^{-2}	2.8×10^{-2}	0.182
50 GeV $\leq m(b\bar{b}) \leq$ 120 GeV	6×10^{-3}	3×10^{-4}	4.3×10^{-2}	2.6×10^{-2}	0.12
$\Delta\phi(b_{1,2}, \not{E}) > 0.35$	5.5×10^{-3}	3×10^{-4}	2.5×10^{-2}	1.1×10^{-2}	0.11

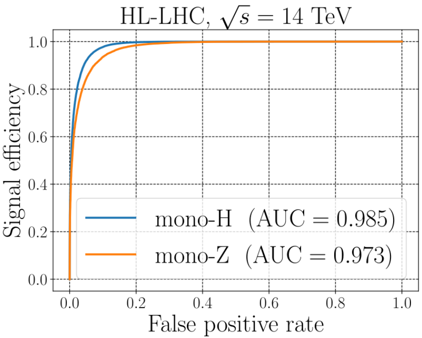
Signatures for mono-H and Z: deep learning setup

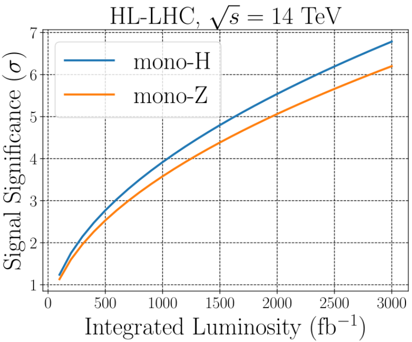
Final state hadrons $\rightarrow$ fully connected graph
each hadron has $(M, p_T, E, \eta, \phi,$ charge$)$

Kinematical input: MET, $p_T(b_{1,2})$, $\eta_T(b_{1,2})$, $p_T(b\bar{b})$, $\eta_T(b\bar{b})$, $m(b\bar{b})$,
$\Delta R(b,\bar{b}) = \sqrt{\Delta_\eta(b,\bar{b})^2 + \Delta_\phi(b,\bar{b})^2}$



Signatures for mono-H and Z: HL-LHC





$$\sigma = \left[2\left((N_s + N_b)\ln\frac{(N_s+N_b)(N_b+\sigma_b^2)}{N_b^2+(N_s+N_b)\sigma_b^2} - \frac{N_b^2}{\sigma_b^2}\ln(1+\frac{\sigma_b^2 N_s}{N_b(N_b+\sigma_b^2)})\right)\right]^{1/2},$$

N_s, N_b number of signal and background events, respectively
σ_b systematic uncertainty, assumed 10%

Summary

- Supersymmetry is still alive and well motivated, with the NMSSM gaining popularity
- New observations may point the way for new theoretical explorations but add work to the numerical work.
- New data analysis techniques may be needed. Machine learning is recently stepping up as a great candidate.
- We performed an scan of the parameter space of the NMSSM in search for a number of recent observations and found regions that successfully satisfy all the constraints.
- We also applied deep learning to the search for mono-H and Z signals and found points that deserve further exploration.
- In the future we hope that `DLScanner` can be used in more studies that have to deal with costly and time-consuming computations.

Useful links

`DLScanner`:
https://github.com/raalraan/DLScanner

Example code for this work:
https://github.com/raalraan/DLScanner/tree/main/tests/examples/2508_13912

Thanks for listening!