UNIVERSITÉ Grenoble Alpes

LPSC Grenoble

CONACYT

Beyond vanilla new physics at the LHC

PhD defense of

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General outline.

- **Introduction.**
- **Constraining the Minimal Dirac Gaugino Model.**

  - The model.

  - LHC limits on gluinos and squarks.

  - Constraining the electroweakino sector.
- **Tools (Contributions to Les Houches 2019)**.

  - Determining the orthogonality of LHC analyses.

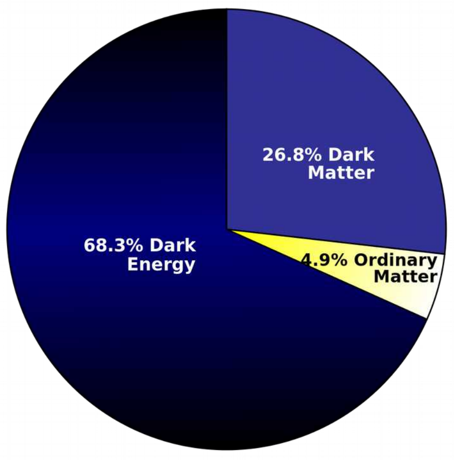
  - (Machine) Learning the cross sections of the IDM.
- **Conclusion.**

Introduction.

Why new physics?

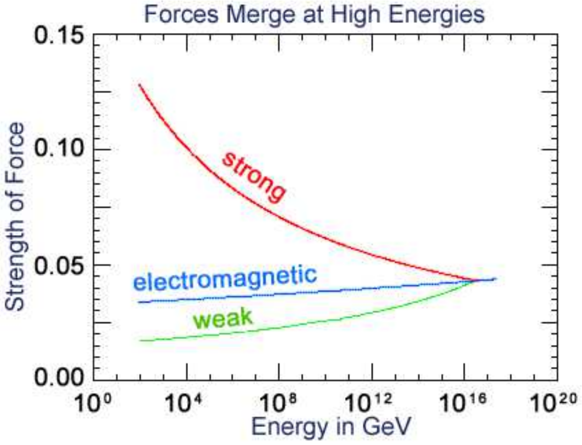
Astrophysics and cosmology

- Dark Matter
- Dark energy
- Matter-antimatter asymmetry
- Neutrino masses

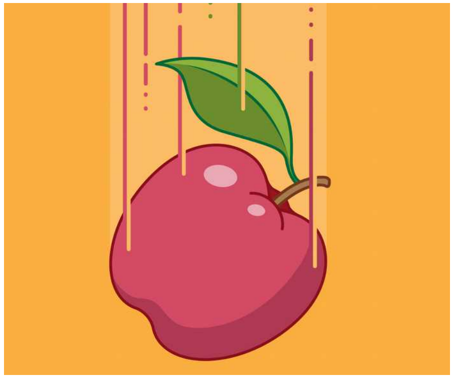


Intrinsic questions.

- The hierarchy problem
- Gauge coupling unification
- Strong CP problem
- Why three families?

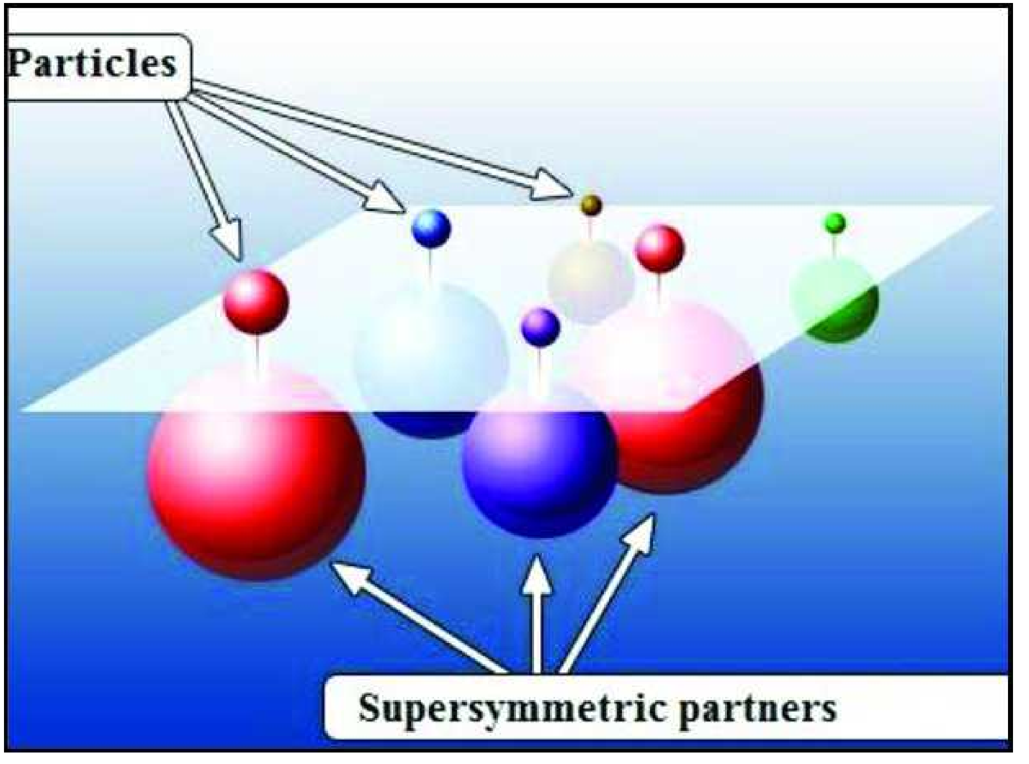


- **Gravity**



Where to go? Supersymmetry*

- In supersymmetry (SUSY), fermionic generators transform the spin of the fields by ½.
- Thus, ***for each fermion there is a bosonic superpartner and viceversa.***

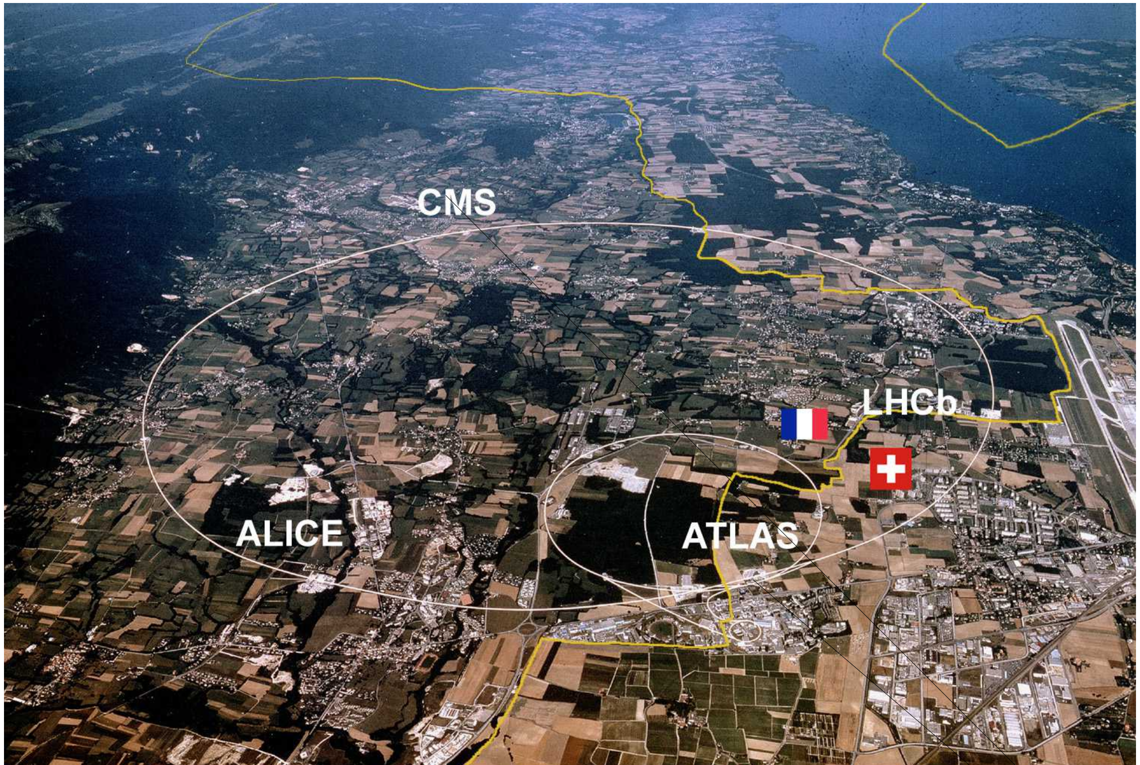


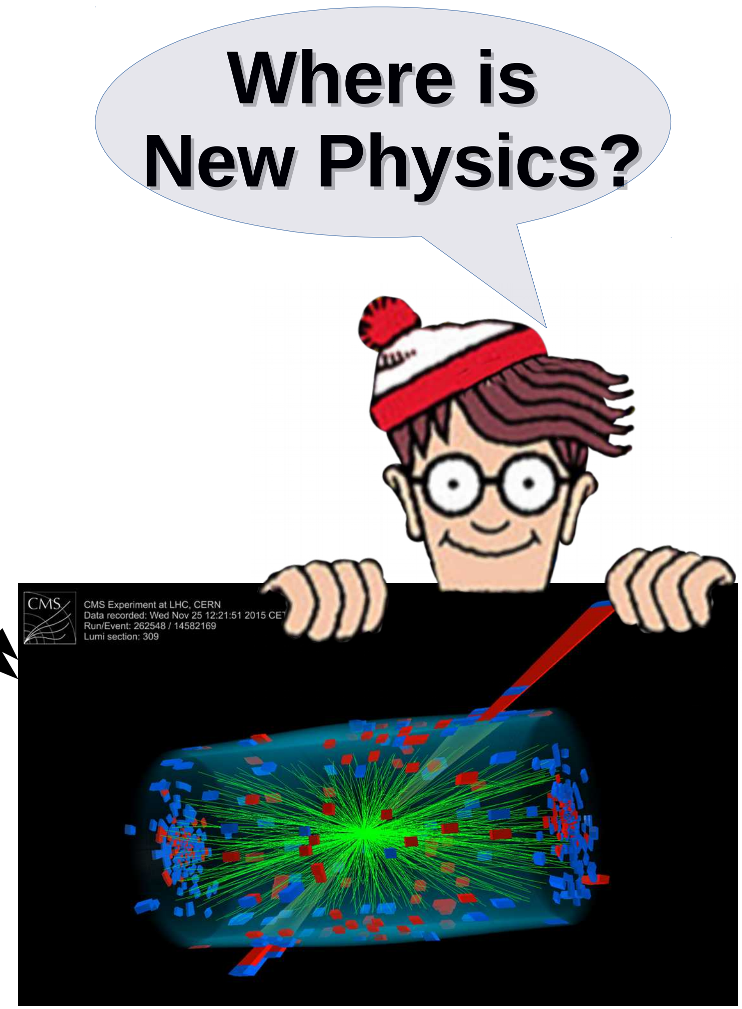
MOTIVATIONS:

- Only way to extend the Poincaré space-time symmetries.
- Natural solution to hierarchy problem.
- Unification of electroweak and strong forces.
- Can include Dark Matter candidates.
- Connection with quantum gravity.

***Other possibilities are: Extra dimensions, Multi-Higgs models, Axions,...**

The Large Hadron Collider.





- **Run 1 (2009-2013): 7-8 TeV c.o.m.; 30/fb t.i.l**
- **Run 2 (2015-2018): 13 TeV c.o.m. ; 150/fb t.i.l.**
- **Run 3: Under preparation.**

New physics searches at LHC.

SUSY searches

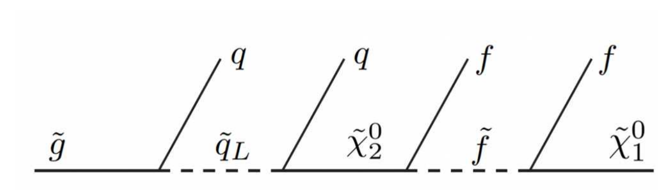
SUSY theories have a rich phenomenology which inspire searches in multiple signal regions!

- Is commonly assumed that they conserve R-parity

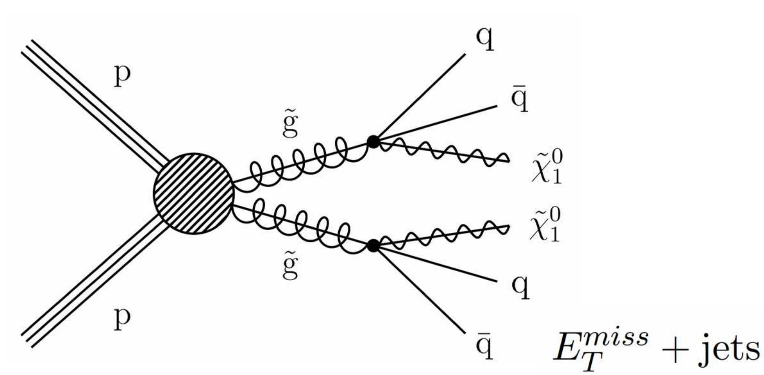
$$R = (-1)^{3(B-L)+2s}$$ → **(Imposed for baryon B and lepton L number conservation.)**

As a consequence

- SUSY particles would always be pair produced at LHC .
- They cascade decay into the Lightest SUSY Particle LSP.
- The LSP is stable.
- If neutral, the LSP can be Dark Matter candidate.
- A neutral LSP leaves a missing energy E_T^{miss} signature.



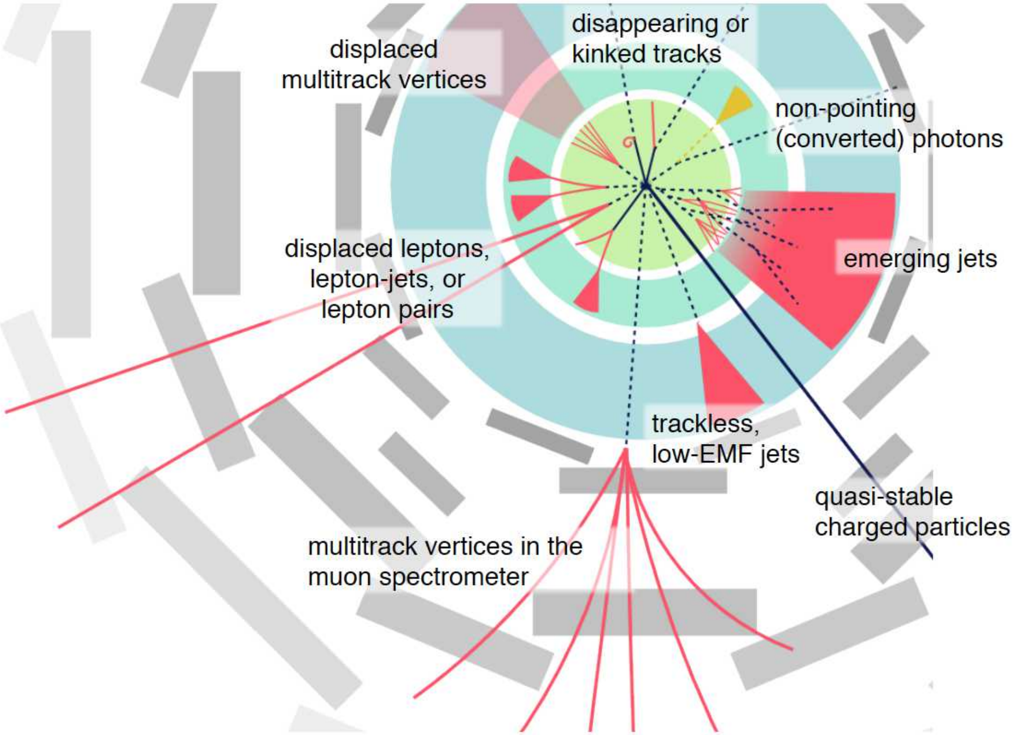
→ **SUSY would be observed as SM final states plus missing energy:**



New physics searches at LHC.

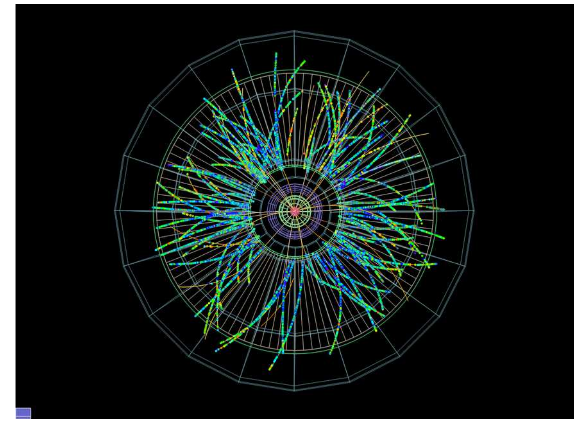
LLP searches

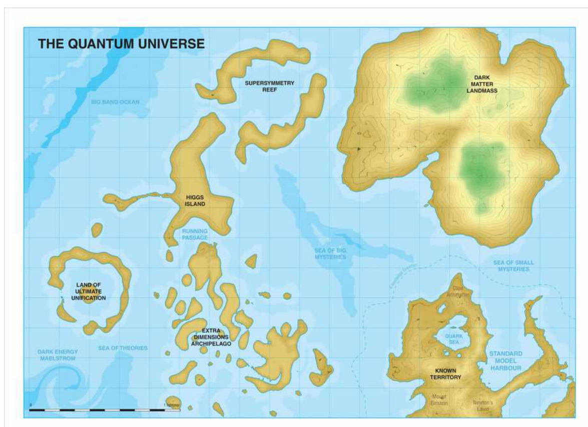
- Long Lived Particles (LLP) are BSM particles with lifetimes >= of the order of the detector.
- They are realized in SUSY theories with approximate R-symmetry, models with quasi-degenerate mass spectra, in FIMP dark matter theories, etc.
- Impose new challenges for their observation.
- Distinctive signatures expected from those of SM.



Why beyond vanilla?

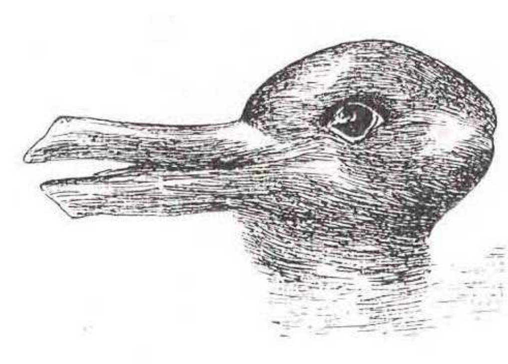
- ATLAS and CMS has an extensive program of searches for new physics.
- Experimental analyses are often optimized and interpreted for popular or 'vanilla' BSM models.





- However, there is a sea of proposed theories/scenarios for new physics,
- Many are non-minimal, less-known, not-thought-of-yet… theories that are not directly interpreted by LHC searches.
- We call them **beyond vanilla new physics.**

- The aim of the **LHC reinterpretation framework** is to be able to test any BSM theory against LHC results.
- A very active field with strong communication between theorists and experimenters.



Reinterpretation of LHC searches

Simplified model approach.

- Most LHC new physics searches present their results as upper limit and efficiency maps in the context of simplified model spectra (SMS).
- SMS results are relatively straightforward to reinterpret
- Direct comparison of $\sigma \times \mathcal{B}$ of theory vs corresponding $[\sigma \times \mathcal{B}]_{UL}$ from exp.

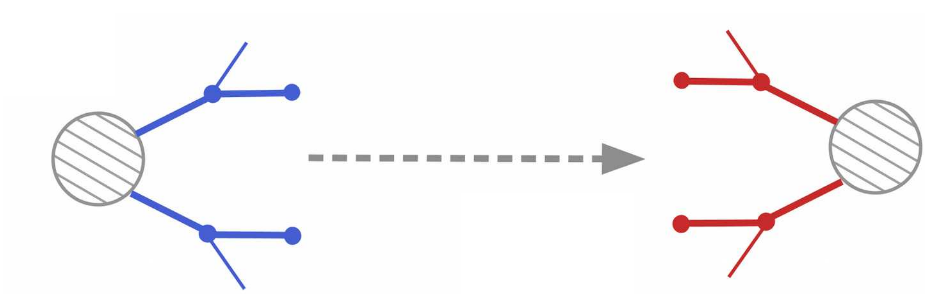
Pros and cons:
Fast but more conservative.
My contribution:
SModelS' Interactive Plots Maker

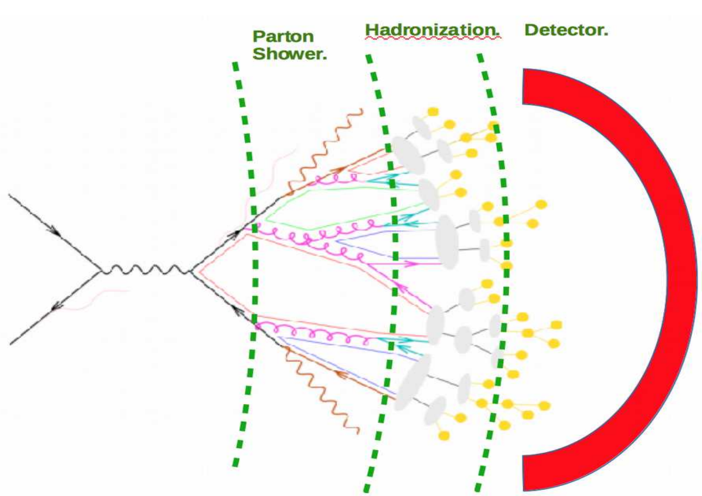
Full recasting approach.

- Full event simulation with MC event generators followed by emulation of detector response.
- implementation of SRs of LHC analyses.
- Computation of expected signal efficiencies.

Pros and cons:
- More precise but time consuming.

My contribution:
Implementation of ATLAS 13TeV multijet (36/fb) search in MadAnalysis 5.





Constraining the Minimal Dirac Gaugino Model

1. *The model*

The MDGSSM model

- Most of SUSY searches at the LHC are optimized for the MSSM, where gauginos are Majorana particles.
- We can introduce Dirac gaugino states by adding a Weyl fermion in the adjoint representation of each gauge group. Embedded in a scalar **S**, triplet **T** and octet **O** superfields.

$$\mathcal{L}_{\text{supersoft}} = \int d^2\theta \Big[\sqrt{2}\, m_{DB} \theta^\alpha \mathbf{W}_{1\alpha} \mathbf{S} + 2\sqrt{2}\, m_{DW} \theta^\alpha \mathrm{tr}\left(\mathbf{W}_{2\alpha} \mathbf{T}\right) + 2\sqrt{2}\, m_{D3} \theta^\alpha \mathrm{tr}\left(\mathbf{W}_{3\alpha} \mathbf{O}\right) \Big] + \text{h.c.}$$

Properties:

- Only *supersoft* terms that don’t appear in the RG equations of the other operators.
- Only a finite shift is induced to the sfermion masses.
- Tree level enhancement of Higgs mass

->Here we consider the **Minimal Dirac Gaugino Supersymmetric Standard Model (MDGSSM)** where

- The only added superfields are **S**, **T** and **O**.
- Explicit R-symmetry breaking in the Higgs sector.

MDGSSM particle content

Names		Spin 0	Spin 1/2	Spin 1	$SU(3)$, $SU(2)$, $U(1)_Y$
Quarks	$\mathbf{Q}$	$\tilde{Q} = (\tilde{u}_L, \tilde{d}_L)$	(u_L, d_L)		$(\mathbf{3}, \mathbf{2}, 1/6)$
	$\mathbf{u^c}$	$\tilde{u}^c_R$	u^c_R		$(\overline{\mathbf{3}}, \mathbf{1}, -2/3)$
(×3 families)	$\mathbf{d^c}$	$\tilde{d}^c_R$	d^c_R		$(\overline{\mathbf{3}}, \mathbf{1}, 1/3)$
Leptons	$\mathbf{L}$	$(\tilde{\nu}_{eL}, \tilde{e}_L)$	(ν_{eL}, e_L)		$(\mathbf{1}, \mathbf{2}, -1/2)$
(×3 families)	$\mathbf{e^c}$	$\tilde{e}^c_R$	e^c_R		$(\mathbf{1}, \mathbf{1}, 1)$
Higgs	$\mathbf{H_u}$	(H^+_u, H^0_u)	$(\tilde{H}^+_u, \tilde{H}^0_u)$		$(\mathbf{1}, \mathbf{2}, 1/2)$
	$\mathbf{H_d}$	(H^0_d, H^-_d)	$(\tilde{H}^0_d, \tilde{H}^-_d)$		$(\mathbf{1}, \mathbf{2}, -1/2)$
Gluons	$\mathbf{W_{3\alpha}}$		$\tilde{g}_\alpha$	g	$(\mathbf{8}, \mathbf{1}, 0)$
W	$\mathbf{W_{2\alpha}}$		$\tilde{W}^\pm, \tilde{W}^0$	$W^\pm, W^0$	$(\mathbf{1}, \mathbf{3}, 0)$
B	$\mathbf{W_{1\alpha}}$		$\tilde{B}$	B	$(\mathbf{1}, \mathbf{1}, 0)$
DG-octet	$\mathbf{O_g}$	O_g	$\tilde{g}'$		$(\mathbf{8}, \mathbf{1}, 0)$
DG-triplet	$\mathbf{T}$	$\{T^0, T^\pm\}$	$\{\tilde{W}'^\pm, \tilde{W}'^0\}$		$(\mathbf{1}, \mathbf{3}, 0)$
DG-singlet	$\mathbf{S}$	S	$\tilde{B}'$		$(\mathbf{1}, \mathbf{1}, 0)$

MSSM

MDGSSM

MDGSSM electroweakino spectrum.

In the MDGSSM we have 6 neutralinos and 3 charginos:

$$\begin{pmatrix} 0 & M_{DB} & 0 & 0 & -\frac{\sqrt{2}\lambda_S}{g_Y} m_Z s_W s_\beta & -\frac{\sqrt{2}\lambda_S}{g_Y} m_Z s_W c_\beta \\ M_{DB} & 0 & 0 & 0 & -m_Z s_W c_\beta & m_Z s_W s_\beta \\ 0 & 0 & 0 & M_{DW} & -\frac{\sqrt{2}\lambda_T}{g_2} m_Z c_W s_\beta & -\frac{\sqrt{2}\lambda_T}{g_2} m_Z c_W c_\beta \\ 0 & 0 & M_{DW} & 0 & m_Z c_W c_\beta & -m_Z c_W s_\beta \\ -\frac{\sqrt{2}\lambda_S}{g_Y} m_Z s_W s_\beta & -m_Z s_W c_\beta & -\frac{\sqrt{2}\lambda_T}{g_2} m_Z c_W s_\beta & m_Z c_W c_\beta & 0 & -\mu \\ -\frac{\sqrt{2}\lambda_S}{g_Y} m_Z s_W c_\beta & m_Z s_W s_\beta & -\frac{\sqrt{2}\lambda_T}{g_2} m_Z c_W c_\beta & -m_Z c_W s_\beta & -\mu & 0 \end{pmatrix}$$

Neutralinos

$$\begin{pmatrix} 0 & M_{DW} & \frac{2\lambda_T}{g} m_W c_\beta \\ M_{DW} & 0 & \sqrt{2} m_W s_\beta \\ -\frac{2\lambda_T}{g} m_W s_\beta & \sqrt{2} m_W c_\beta & \mu \end{pmatrix}$$

Charginos

Binos
Winos
Higgsinos

λ_S and λ_T are the couplings between the scalar and triplet DG-adjoint fermions and the Higgs superfields

$$W \supset \lambda_S \mathbf{S}\, \mathbf{H_u} \cdot \mathbf{H_d} + 2\lambda_T\, \mathbf{H_d} \cdot \mathbf{T}\mathbf{H_u}$$

They induce small-mass splittings between binos and winos, e.g. if M_{DB} << M_{DW}, μ

$$m_{\tilde{\chi}_2^0} - m_{\tilde{\chi}_1^0} = \left| 2 \frac{M_Z^2 s_W^2}{\mu} \frac{(2\lambda_S^2 - g_Y^2)}{g_Y^2} c_\beta s_\beta \right|$$

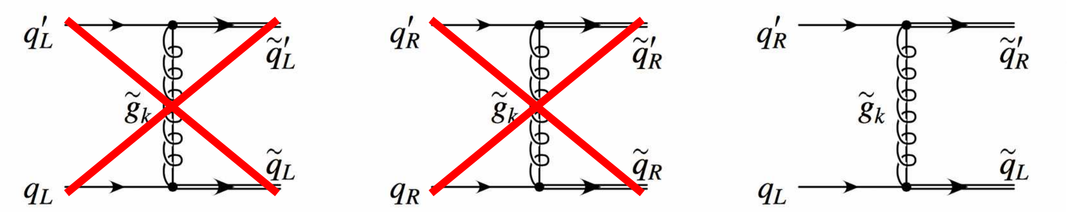
Constraining the Minimal Dirac Gaugino Model.

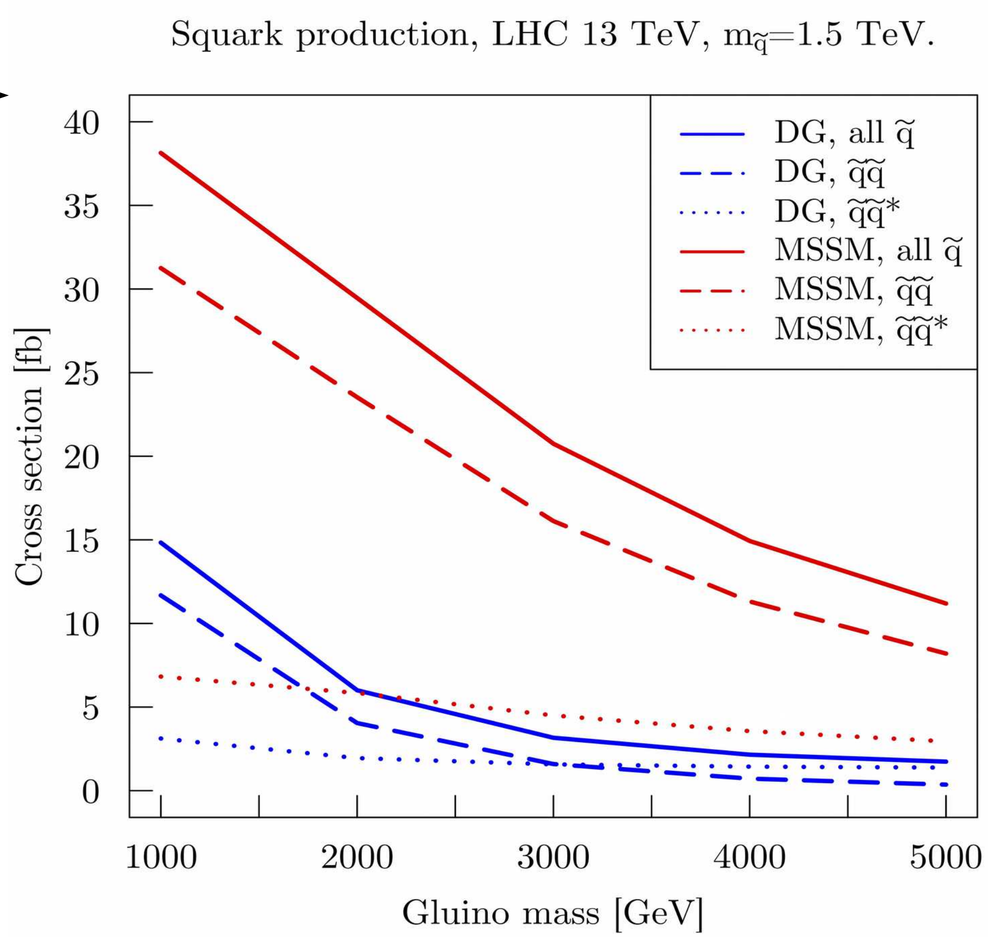
2. ***LHC limits on gluinos and squarks.***

Gluino and squark production.

- **Squark production.**

  t-channel exchange via Dirac gluino forbids final states of same helicity, reducing squark production cross sections.





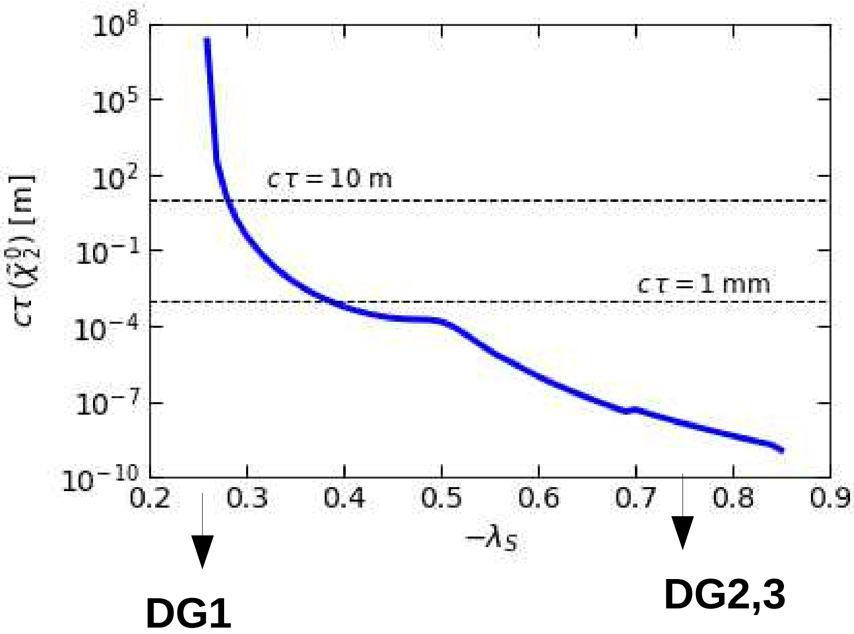
- **Gluino production.**

  Augmented number of gluino degrees of freedom enhance their production cross sections.

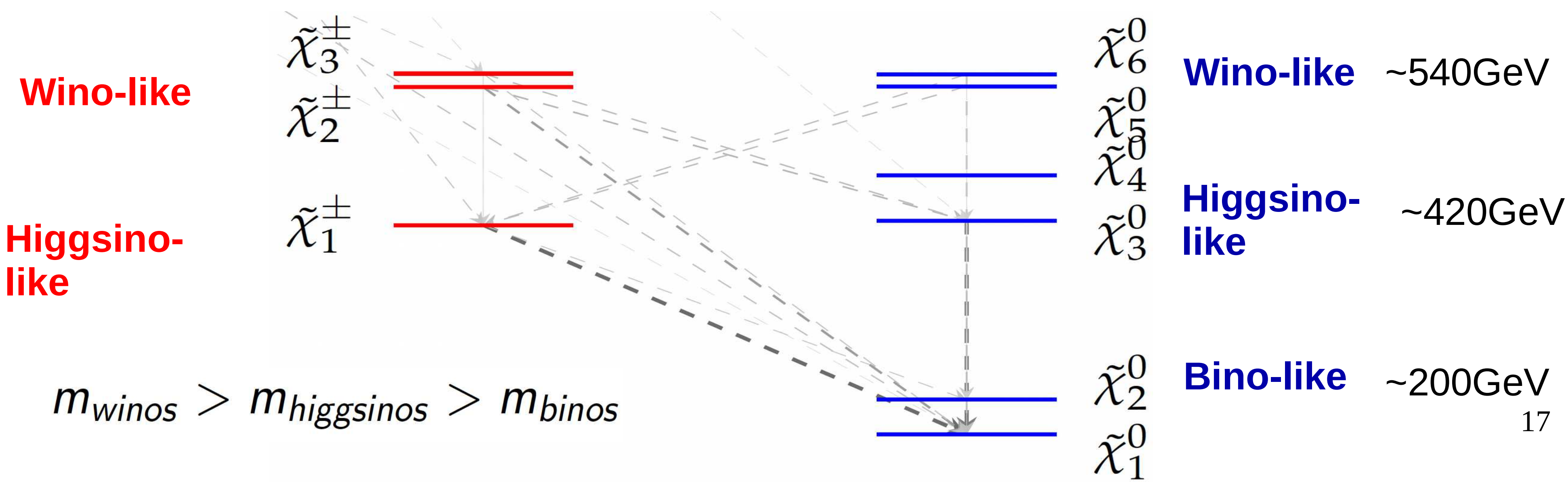
- **Gluino-squark production**

  Similar to Majorana case.

Benchmark scenarios.

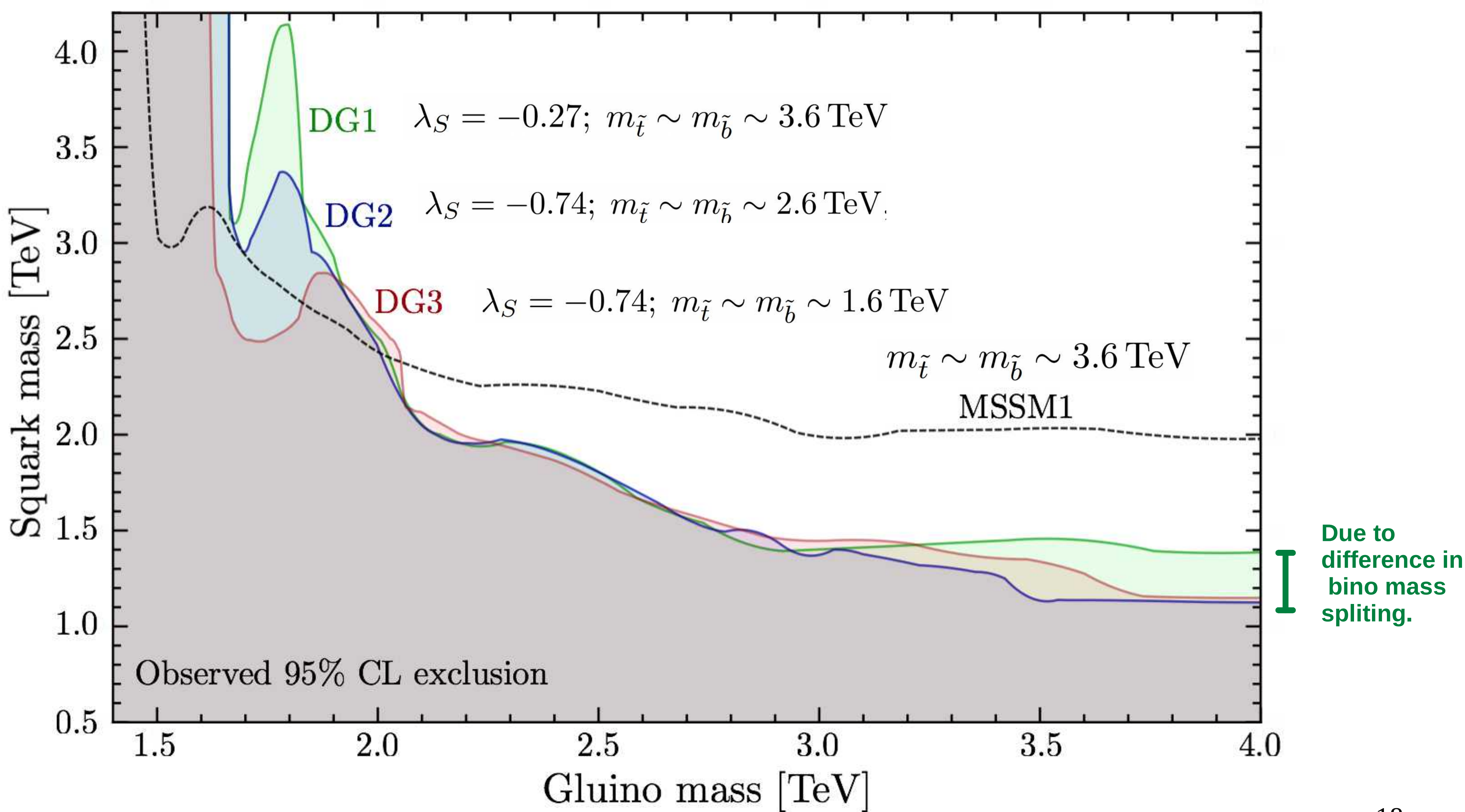


	Bino mass-splitting	NLSP lifetime	3rd gen squark mass
DG1	small	large	3.6 TeV
DG2	large	small	2.6 TeV
DG3	large	small	1.6 TeV



Full recasting results. DG vs MSSM.

Analysis: ATLAS 13TeV Multijet+MET (36/fb) search



Dashed line (MSSM1) is the limit one finds in the MSSM.

Constraining the Minimal Dirac Gaugino Model.

3. *Electroweak-ino sector.*

Finding regions with good DM.

$$0 < m_{DY},\, m_{D2},\, \mu < 2\ \text{TeV}; \quad 1.7 < \tan\beta < 60; \quad -3 < \lambda_S,\, \lambda_T < 3.$$

We implemented an MCMC Metropolis-Hastings algorithm (with a small probability of random uniform jump) that walks toward the minimum of

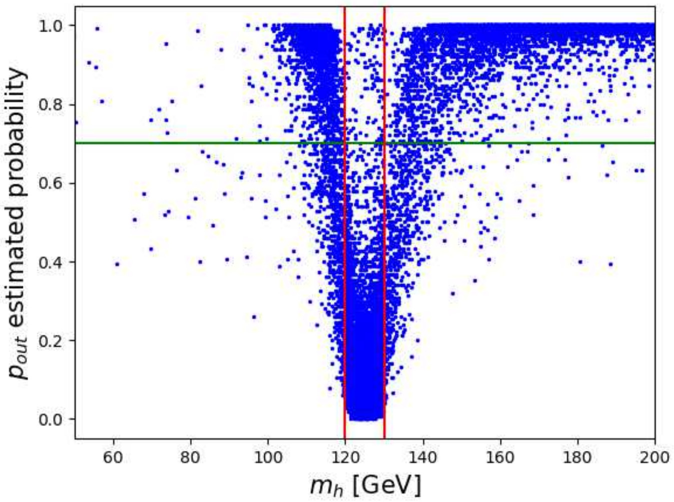
$$-\log(L) = \chi^2_{\Omega h^2} - \log(p_{\mathrm{X1T}}) + \log(m_{\mathrm{LSP}})$$

$$\chi^2_{\Omega h^2} = \frac{(\Omega h^2 - \Omega h^2_{\text{Planck}})^2}{\Delta^2_\Omega}$$

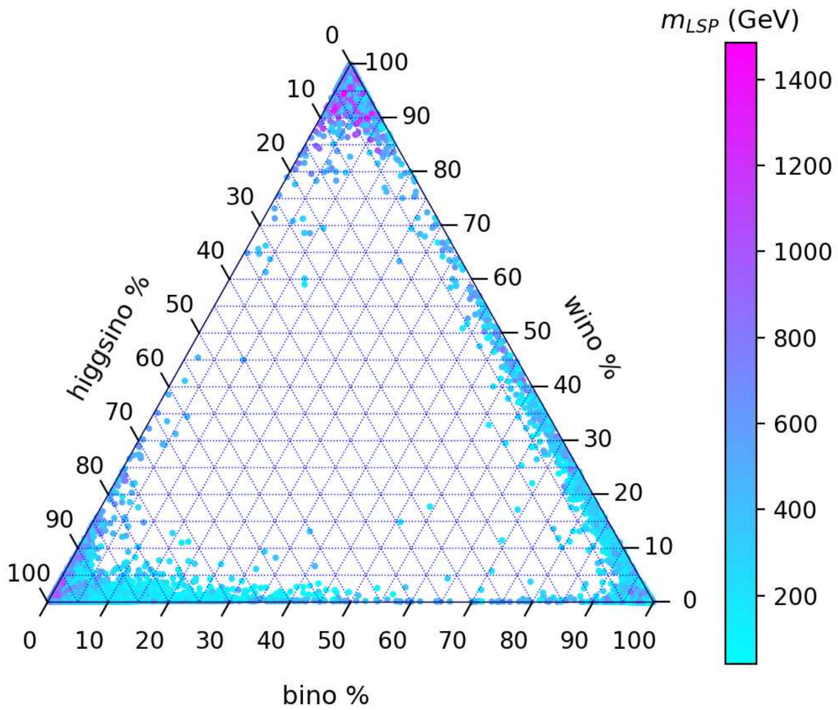
P-value of Xenon1T exclusion

Mass of LSP

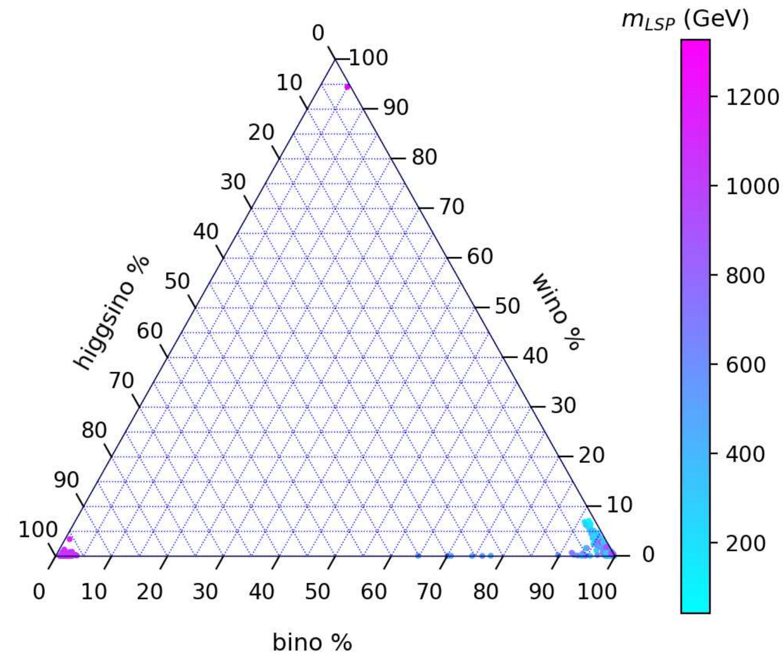
To efficiently find the points with A Higgs mass in good range we Implemented a Random Forest Classifier **yielding a ~4 times faster scan!**



Scan results.



$$\Omega h^2 < 1.1\,\Omega h^2{}_{\text{Planck}}$$



$$\Omega h^2 = \Omega h^2{}_{\text{Planck}} \pm 10\%$$

Constraints included so far:

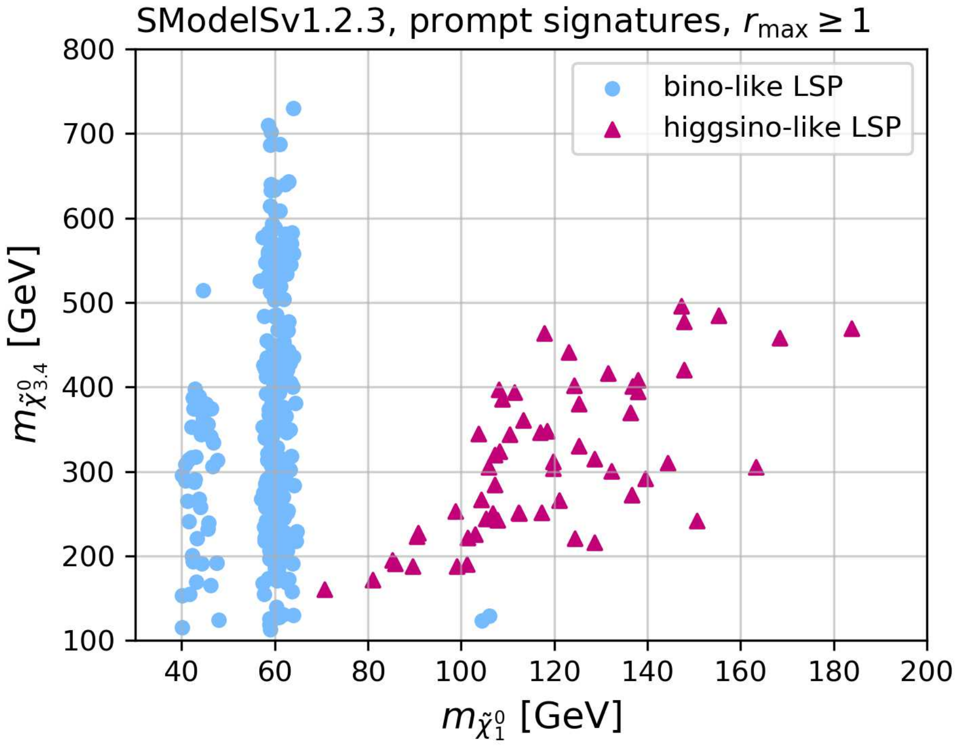
- LSP is at least a fraction of observed DM content.
- LEP limits
- Z invisible decays
- H invisible decays
- XENON1T direct detection constraints.

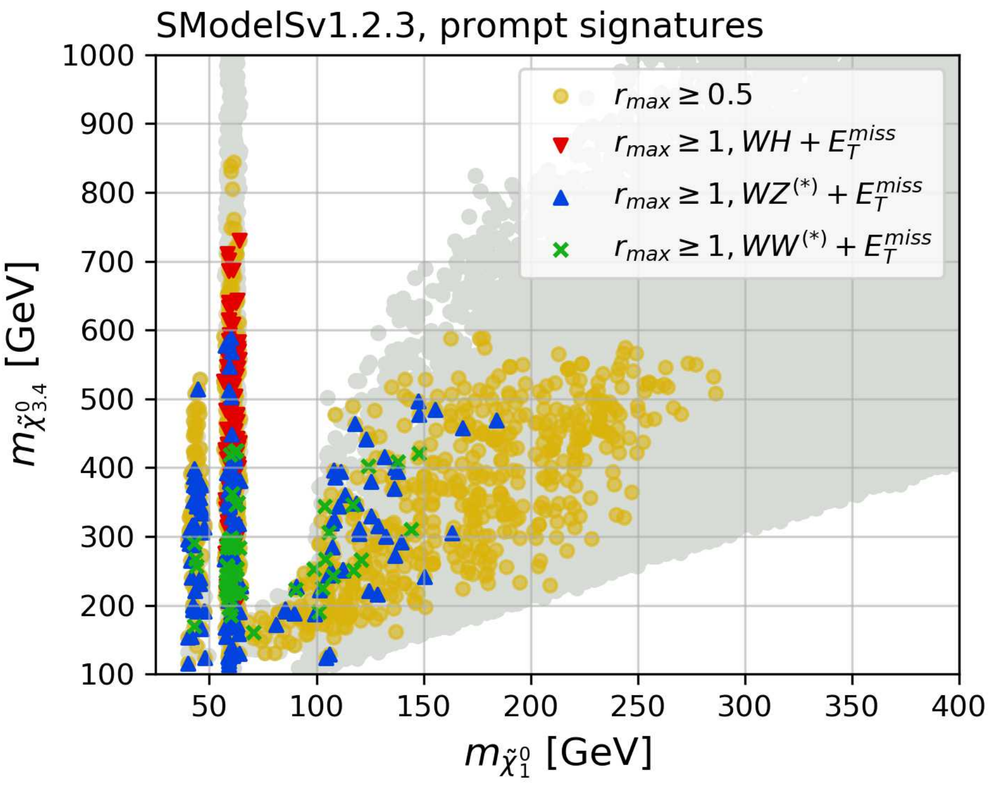
LHC constraints. Prompt searches.

- Limits derived from simplified model reinterpretation using SModelS.

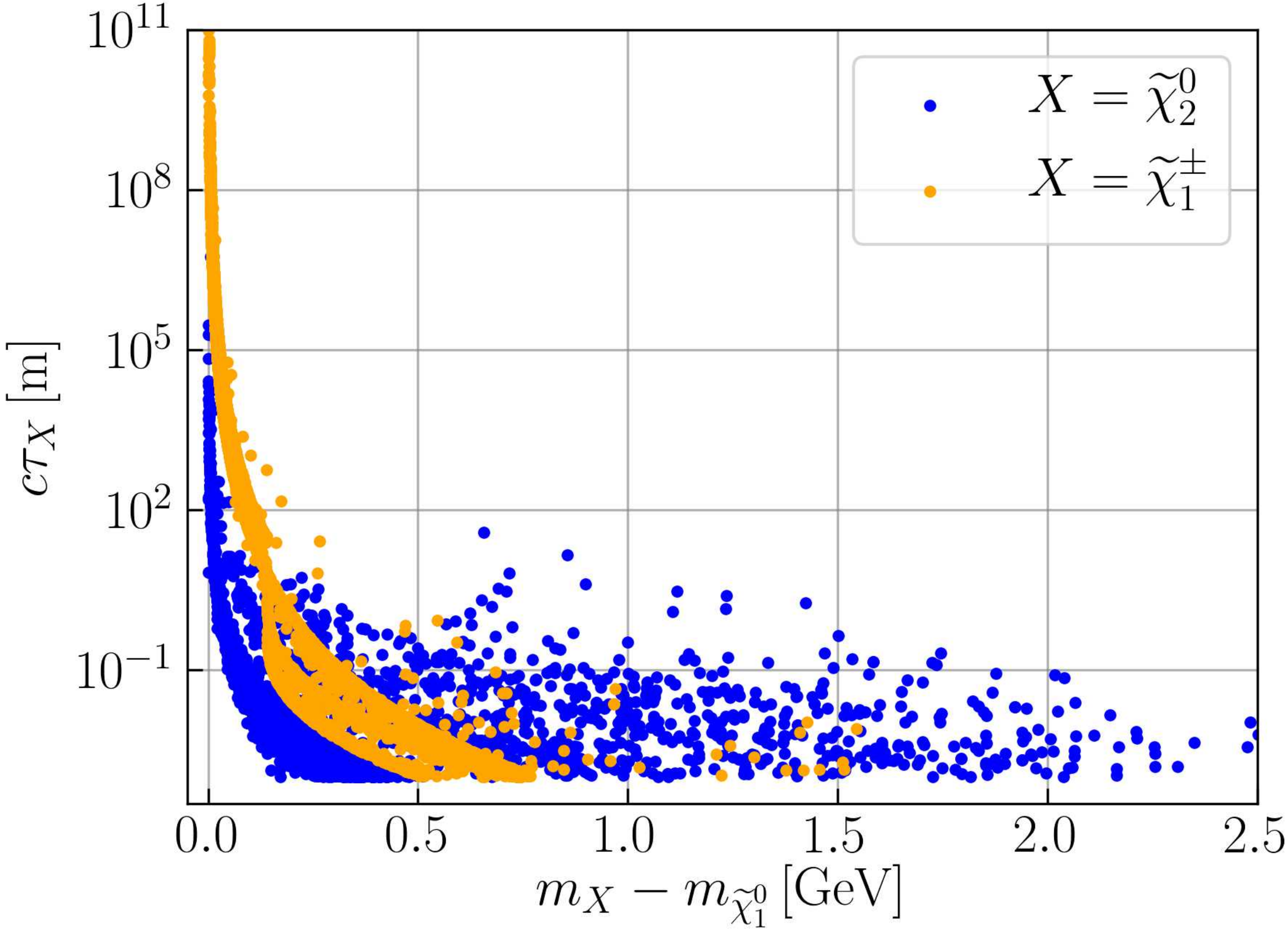
Included analyses:

- ATLAS EW-ino searches with 139/fb, constraining WZ(*), WH, WW(*)+ MET signatures.
- CMS EW-ino combination from 35/fb, constraining WZ(*) and WH + MET signatures.



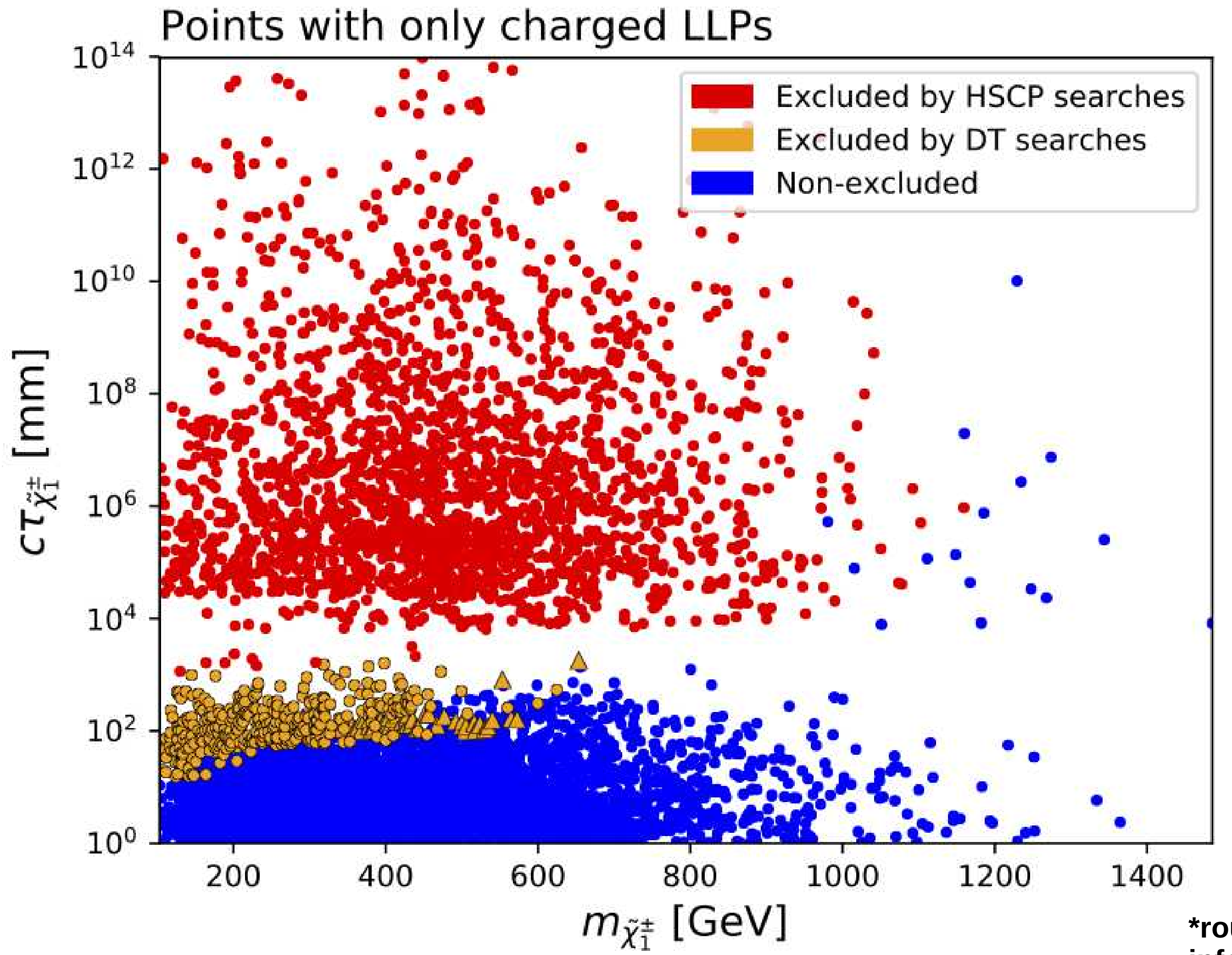


LLP scenarios.



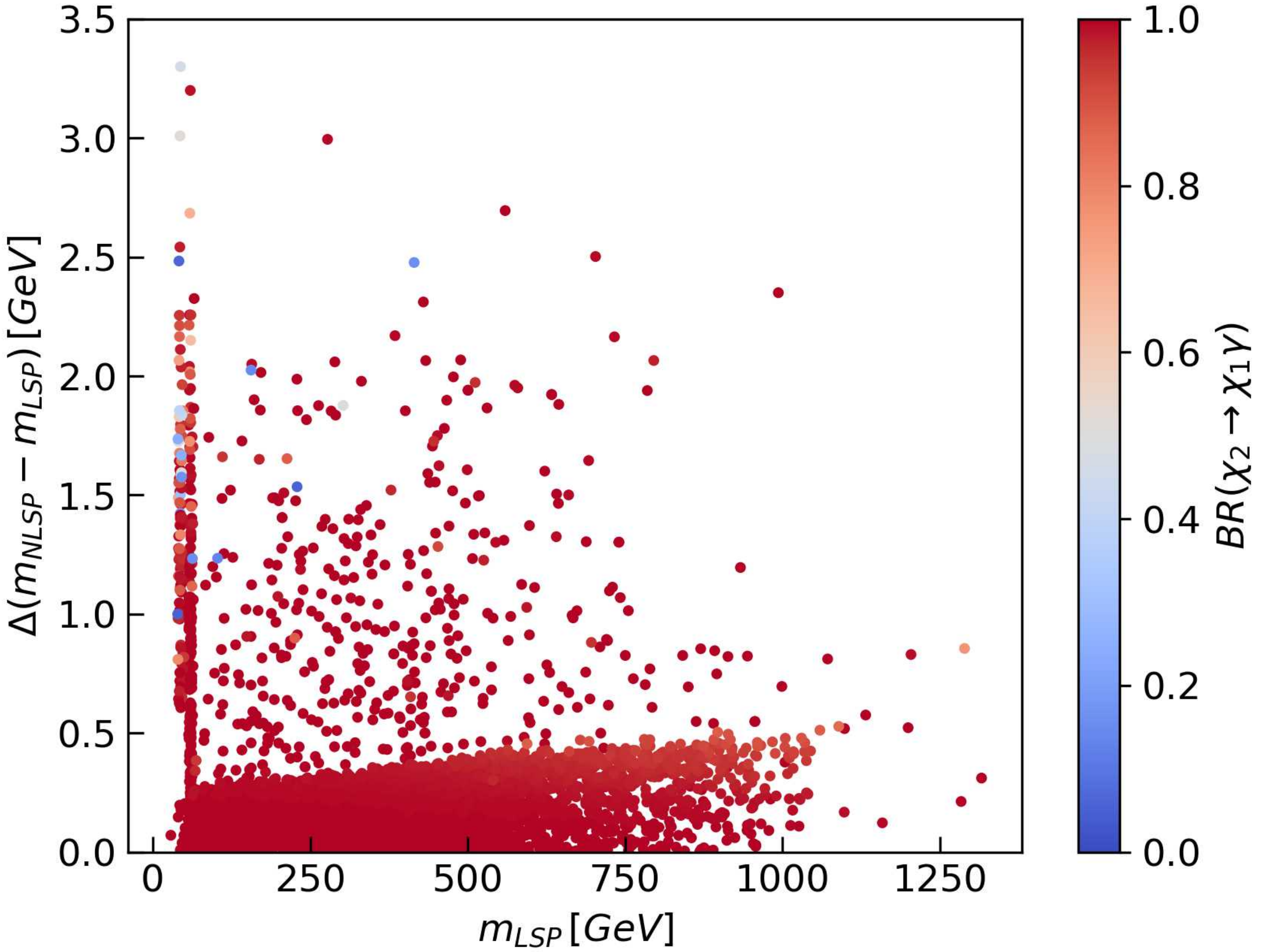
LHC constrains. Charged LLPs.

- Heavy Stable Charged Particle (HSCP) limits derived using SModelS (CMS 8TeV and 13TeV-13/fb).
- Disappearing Track (DT) limits derived using independent interpolation of upper limits (ATLAS and CMS 13TeV-36/fb, CMS 13TeV-140/fb*).



***rough interpolation, no full info provided yet.**

Neutral LLP signatures.



- Loop decays into soft photons dominate.
- Signature not covered at LHC!

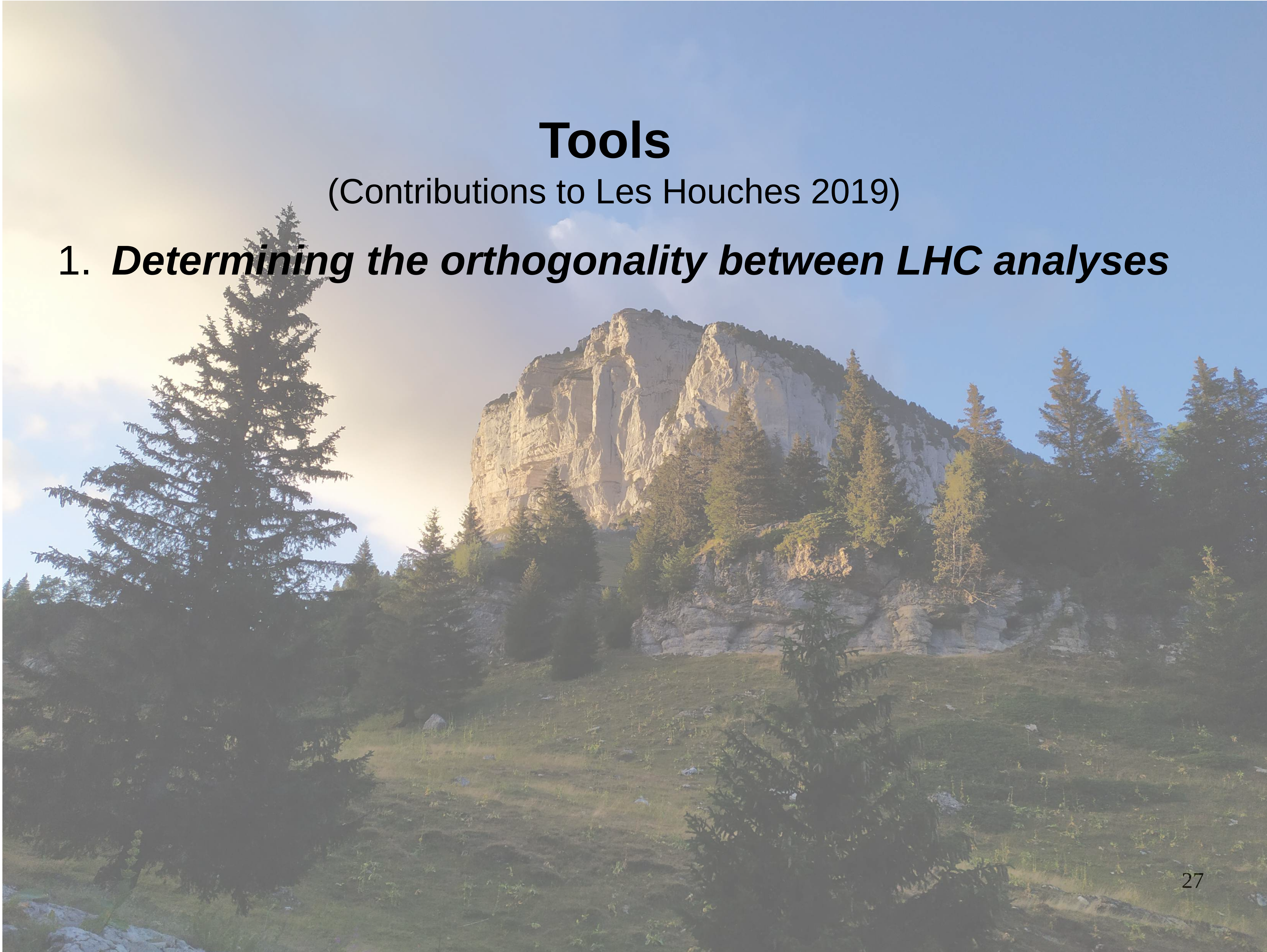
MDGSSM: Summary

Gluinos and squarks:

- Results were as expected from the differences between MDGSSM and MSSM regarding gluino and squark production.
- Stronger constrains when gluino production is dominant and weaker ones in the region where squark production dominates.
- We observed relaxed constraints in the scenarios with large bino mass-splitting due to extra steps in the decay chain.

Electroweakino sector.

- We found a significant number of scenarios with long-lived charginos and/or neutralinos which survive DM constraints.
- Prompt searches only excluded certain points with LSP masses below 200 GeV.
- HSCP and DT searches provide strong constraints on scenarios with charged LLPs.
- Scenarios with neutral LLPs currently escape exclusion as their distinctive signature (soft photons plus missing energy) is not covered at the LHC.



Tools

(Contributions to Les Houches 2019)

1. ***Determining the orthogonality between LHC analyses***

Motivation.

- We want know **which LHC analyses are uncorrelated?**
- Uncorrelated analyses can be trivially combined to derive potentially stronger bounds.
- We propose a statistical method to determine the orthogonality between signal regions of different analyses.

Strategy:

- Select the intersection of LHC analyses between SModelS and MadAnalysis 5.
- From the SModelS database extract the simplified models and BSM mass ranges for which the analyses are sensitive.
- Generate events by sampling the space of simplified model mass parameters, using MadGraph.
- Determine if events survive the SR cuts in the considered analyses.
- A **statistical bootstrap procedure** to extract the correlation matrix

$$\rho_{ij} = \mathrm{cov}_{ij} / \sqrt{\mathrm{cov}_{ii}\mathrm{cov}_{jj}}$$

- SRs are determined as approximately independent if

$$|\rho_{ij}| < \rho_{\mathrm{max}}.$$

Bootstrap procedure

Step 1: Collect the events.

	SR1	SR2	SR3
EV1	0	1	0
EV2	1	1	0
EV3	0	1	1

Bootstrap procedure

Step 2: Multiply each event by a value from Poisson distribution (EVi X POISi). Each iteration (j) creates a matrix (M_j) of ‘Poissoned’ events.

	SR1	SR2	SR3
EV1	0	1	0
EV2	1	1	0
EV3	0	1	1

X

POIS1
0
2
1

,

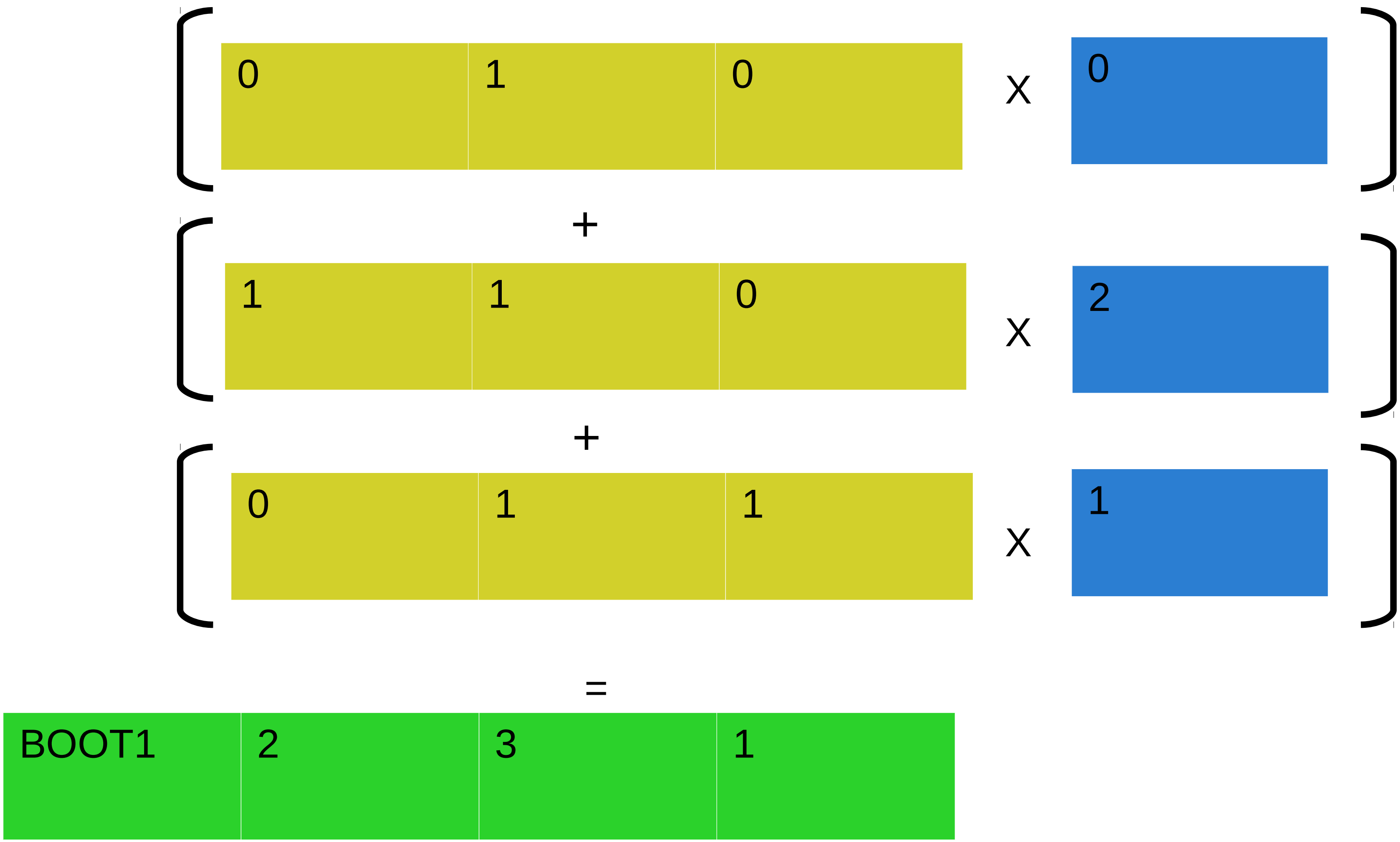
POIS2
1
1
0

,

POIS3
1
0
1

Bootstrap procedure

Step 3: Sum over ‘poissoned’ rows to obtain the bootstrapped rows (BOOTi)



Bootstrap procedure

Step 4: Sum over rows of each 'poissoned' matrix.
BOOTj= Sum_rows(M_j).

	SR1	SR2	SR3
BOOT1	2	3	1
BOOT2	1	2	0
BOOT3	0	2	1

Bootstrap procedure

Step 5: Compute the correlation matrix.

	SR1	SR2	SR3
SR1	1	.86	0
SR2	.86	1	.5
SR3	0	.5	1

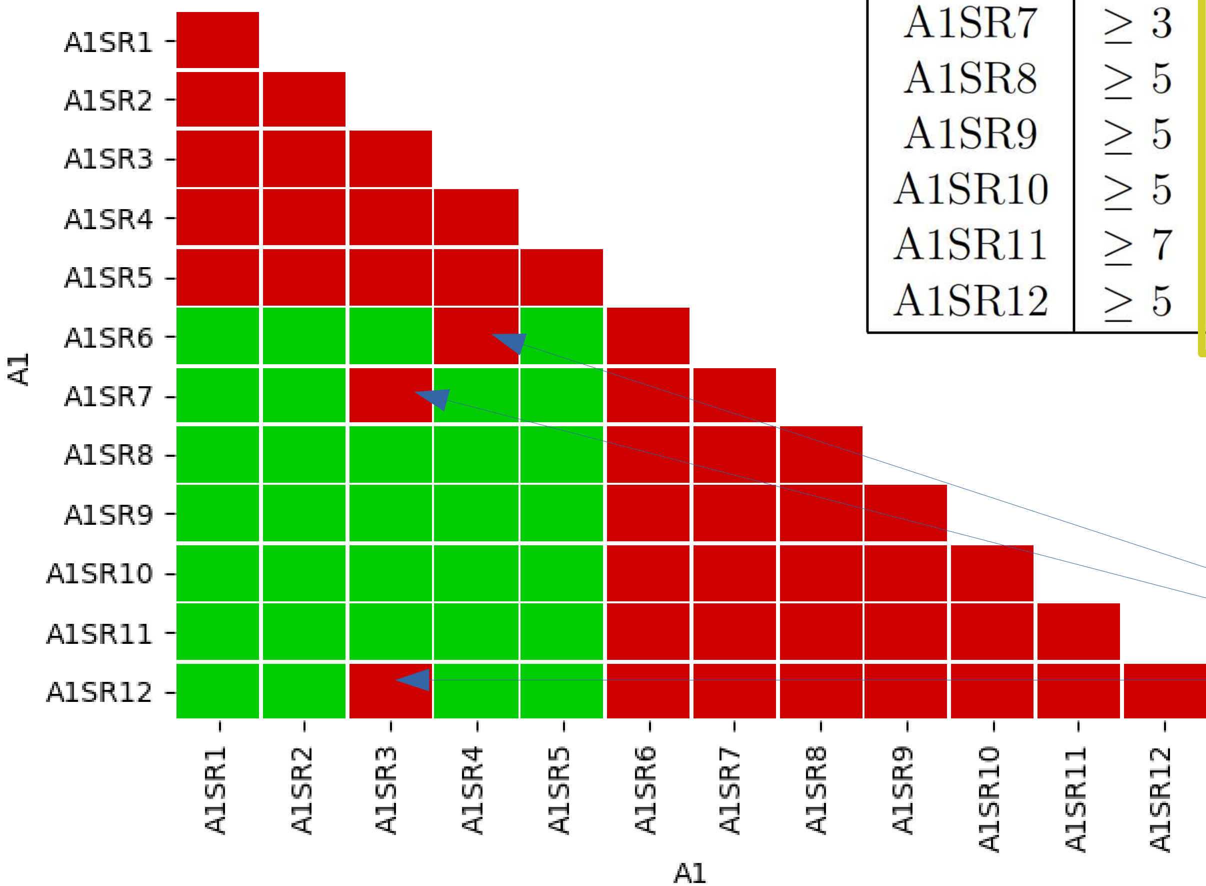
Bootstrap procedure

Step 6: Determine independent SRs with a correlation cutoff ($|\rho_{ij}| < \rho_{\max}$)

	SR1	SR2	SR3
SR1			
SR2			
SR3			

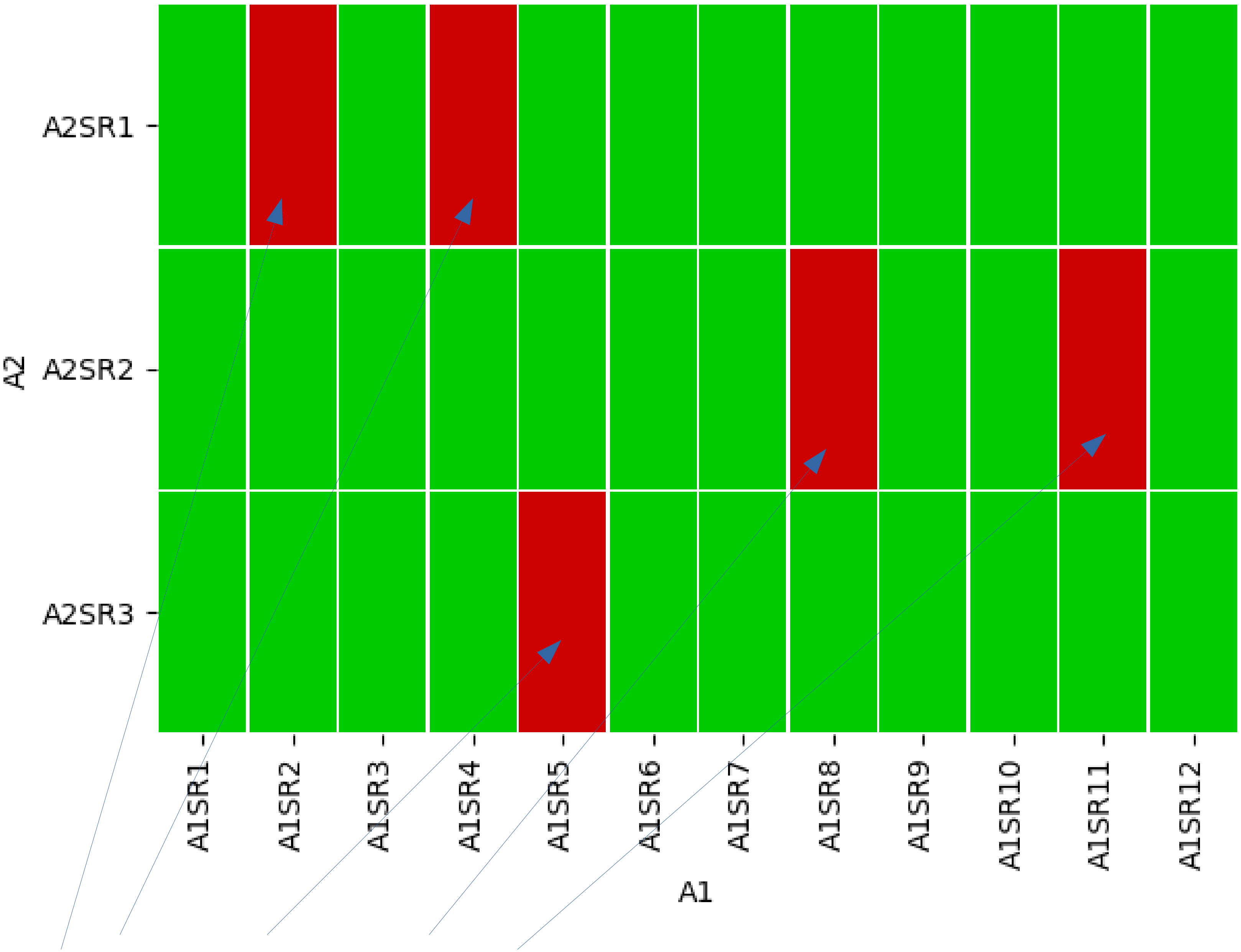
Example: CMS jets+MET search

	N_{jet}	$N_{b\text{-jet}}$	H_T [GeV]	H_T^{miss} [GeV]
A1SR1	≥ 2	0	≥ 500	≥ 500
A1SR2	≥ 3	0	≥ 1500	≥ 750
A1SR3	≥ 5	0	≥ 500	≥ 500
A1SR4	≥ 5	0	≥ 1500	≥ 750
A1SR5	≥ 9	0	≥ 1500	≥ 750
A1SR6	≥ 2	≥ 2	≥ 500	≥ 500
A1SR7	≥ 3	≥ 1	≥ 750	≥ 750
A1SR8	≥ 5	≥ 3	≥ 500	≥ 500
A1SR9	≥ 5	≥ 2	≥ 1500	≥ 750
A1SR10	≥ 5	≥ 3	≥ 750	≥ 750
A1SR11	≥ 7	≥ 1	≥ 300	≥ 300
A1SR12	≥ 5	≥ 1	≥ 750	≥ 750



Close to independency threshold

CMS Multijet+MET vs CMS Dilepton+MET



Close to independency threshold

Tools

(Contributions to Les Houches 2019)

2. ***Machine Learning cross sections.***

Machine learning cross sections …

MISSION:

- To build neural networks that can **precisely** predict, with an **uncertainty estimation,** the cross sections of the production processes.
- In this case those in the Inert Doublet Model (IDM).

MOTIVATION:

- The computation of production cross sections over large parameter spaces usually takes a large amount of time.
- Training DNNs to predict these cross sections could substantially save computational costs.

CHALLENGES:

- High level of precision is required.
- Small uncertainty desired.
- The values of the cross sections range over several order of magnitudes.
- The relation between the input parameters and the cross sections is not always linear, specially resonance regions.

The IDM.

The potential:

$$V = \mu_1^2|\mathbf{H_1}|^2 + \mu_2^2|\mathbf{H_2}|^2 + \lambda_1|\mathbf{H_1}|^4 + \lambda_2|\mathbf{H_2}|^4 + \lambda_3|\mathbf{H_1}|^2|\mathbf{H_2}|^2$$
$$+\lambda_4|\mathbf{H_1}^\dagger\mathbf{H_2}|^2 + \frac{\lambda_5}{2}[(\mathbf{H_1}^\dagger\mathbf{H_2})^2 + \mathrm{h.c.}]\,.$$

Five free parameters:

$$M_{H^0}^2 = \mu_2^2 + \frac{1}{2}(\lambda_3+\lambda_4+\lambda_5)v^2\,,$$
$$M_{A^0}^2 = \mu_2^2 + \frac{1}{2}(\lambda_3+\lambda_4-\lambda_5)v^2\,,$$
$$M_{H^\pm}^2 = \mu_2^2 + \frac{1}{2}\lambda_3 v^2\,,$$

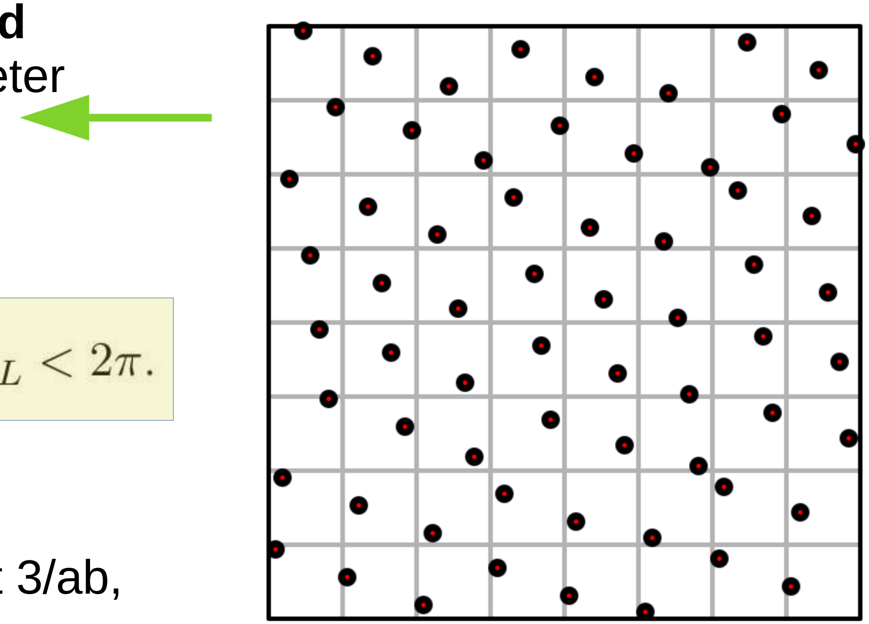
$$\lambda_2 \text{ and } \lambda_L \equiv \lambda_3+\lambda_4+\lambda_5\,.$$

8 production processes to learn:

$$pp \to H^0H^0,\ A^0A^0,\ H^0A^0,\ H^0H^+,\ A^0H^+,\ H^+H^-,\ H^0H^- \text{ and } A^0H^-.$$

Acquiring the training data.

→ 50,000 samples were generated using the **Jittered Sampling Method,** to evenly cover the input parameter space:



$$50 < M_{H^0},\, M_{A^0},\, M_{H^\pm} < 3000\ \mathrm{GeV}; \quad -2\pi < \lambda_2,\, \lambda_L < 2\pi.$$

→ Since the expected luminosity at HL-LHC is about 3/ab, we imposed a lower limit on the cross section of our dataset of

$$\sigma_{\min} = 10^{-7}\mathrm{pb}$$

→ The remaining data was divided as training and test data set in a 70:30 split.

Data preprocessing and loss function.

For the input parameters, we implemented a z-score transformation.

$$x'_{\text{IDM}} = \frac{x_{\text{IDM}} - \mu(x_{\text{IDM}})}{\sigma(x_{\text{IDM}})} \,,$$

For the cross sections we chose a log transformation, to reduce the range of the target values.

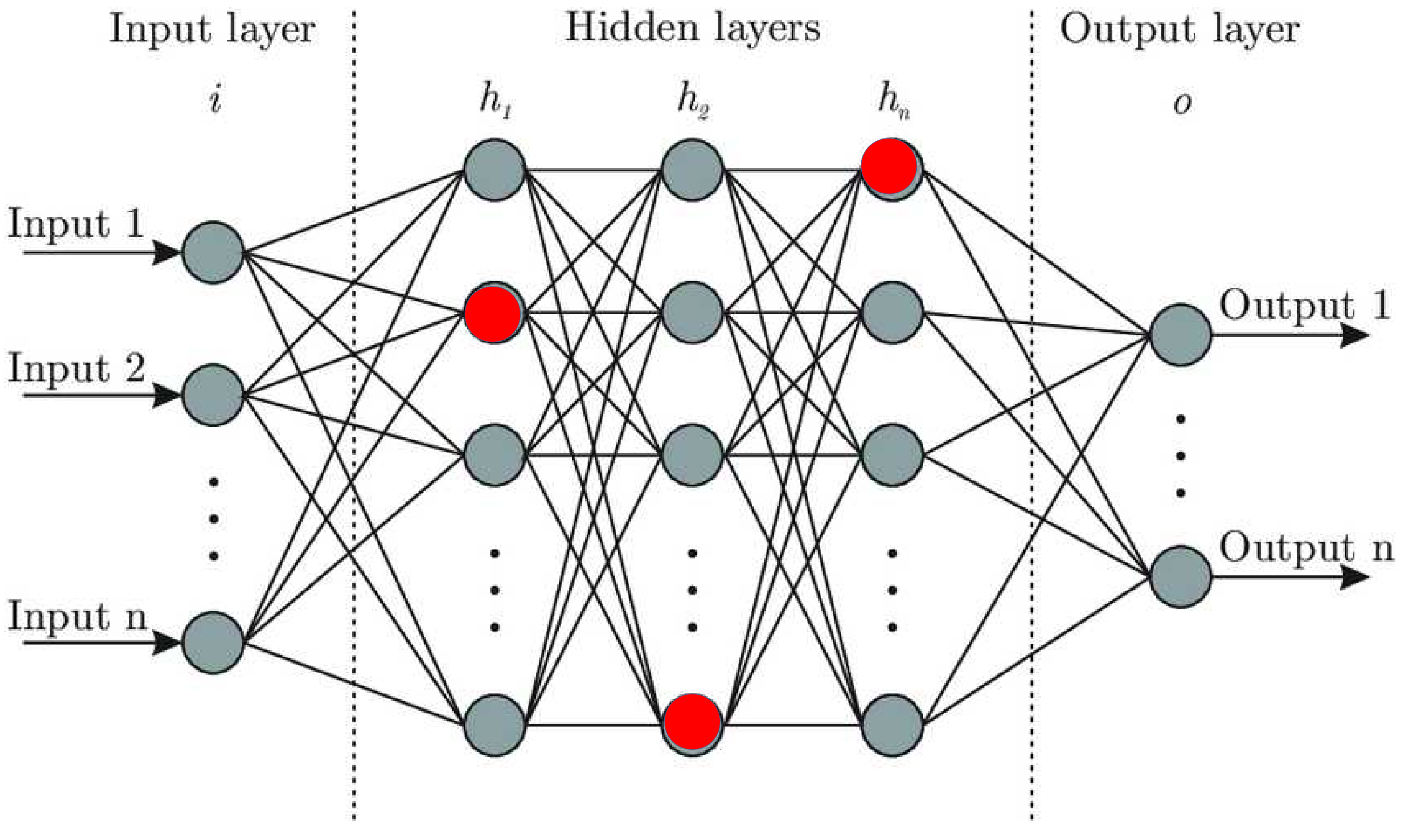
$$\sigma'_{\text{IDM}} = \log\left[\frac{\sigma_{\text{IDM}}}{\min(\sigma_{\text{IDM}})}\right] .$$

To take into account the preprocessing of the target values we used a custom loss function that minimizes the MAPE of the original cross sections.

$$L(\sigma'_{\text{true}}, \sigma'_{\text{pred}}) = \frac{1}{N}\sum_{i=1}^{N} |1 - \exp(\sigma'_{\text{pred}} - \sigma'_{\text{true}})| \,,$$

Uncertainty estimation.

- For uncertainty estimation, **permanent dropout** was implemented.
- Fixed rate of randomly turned-off neurons in each hidden layer.
- At each iteration/prediction a different configuration trained/predicts.
- Several predictions are drawn from the same set of inputs and the corresponding mean and standard deviation is computed.



Accuracy measurements

1) The coefficient of variance (CV) of the prediction

$$\mathrm{CV} = \frac{\mathrm{std}(\sigma_{pred})}{\mu(\sigma_{pred})}$$

2) The relative error of the prediction

$$\mathrm{RE} = \left| \frac{(\sigma_{pred} - \sigma_{true})}{\sigma_{true}} \right|$$

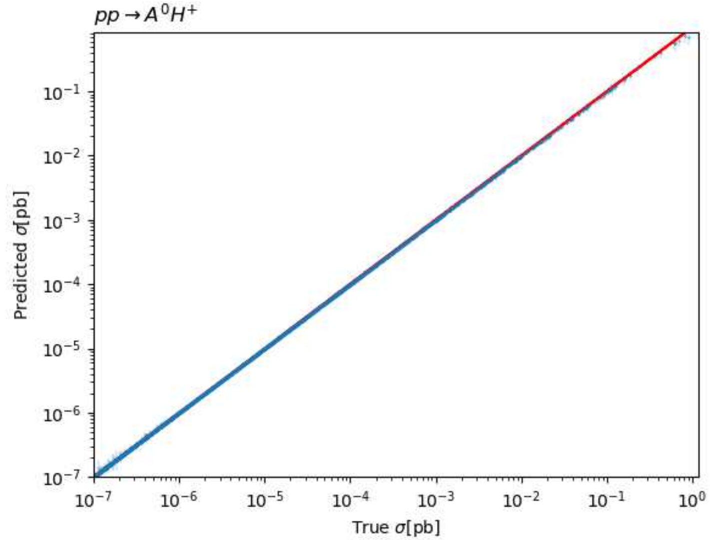
3) Fraction of test points whose true values lie **within 1 std** from the mean correspondent prediction

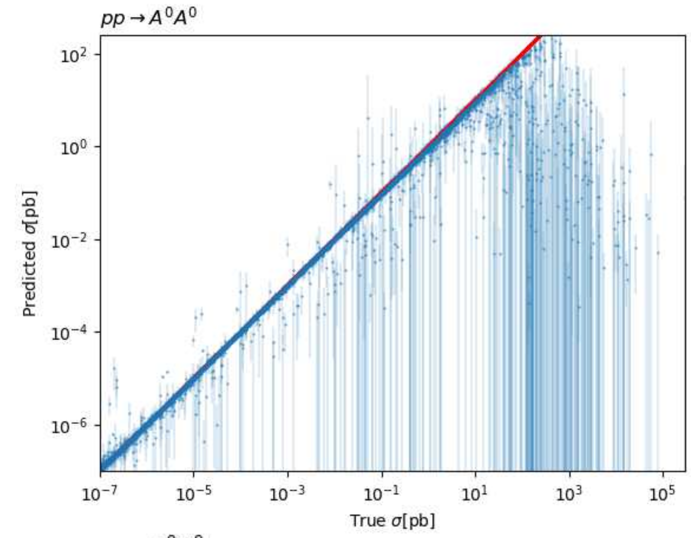
	H^0H^0	A^0A^0	H^+H^-	H^0A^0	H^0H^+	A^0H^+	H^0H^-	A^0H^-
$\mu(\mathrm{RE})$	0.0303	0.1049	0.2259	0.0058	0.0076	0.0048	0.0057	0.0072
$\mu(\mathrm{CV})$	0.0850	0.1880	0.1508	0.0272	0.0402	0.0276	0.0276	0.0287
within 1 std	0.9833	0.9509	0.9812	0.9981	0.9995	0.9997	0.9886	0.9817

The best and the worst

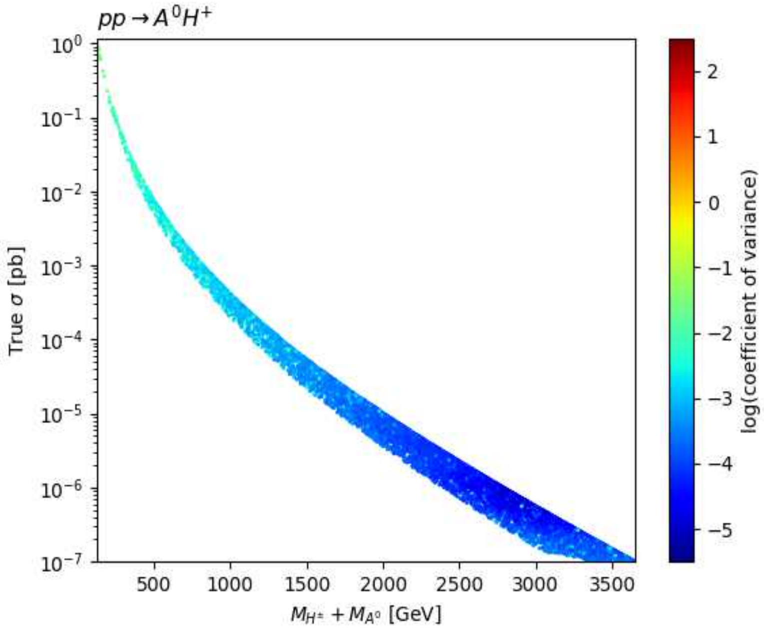
p p → $A^0 H^+$ | **p p → $A^0 A^0$**

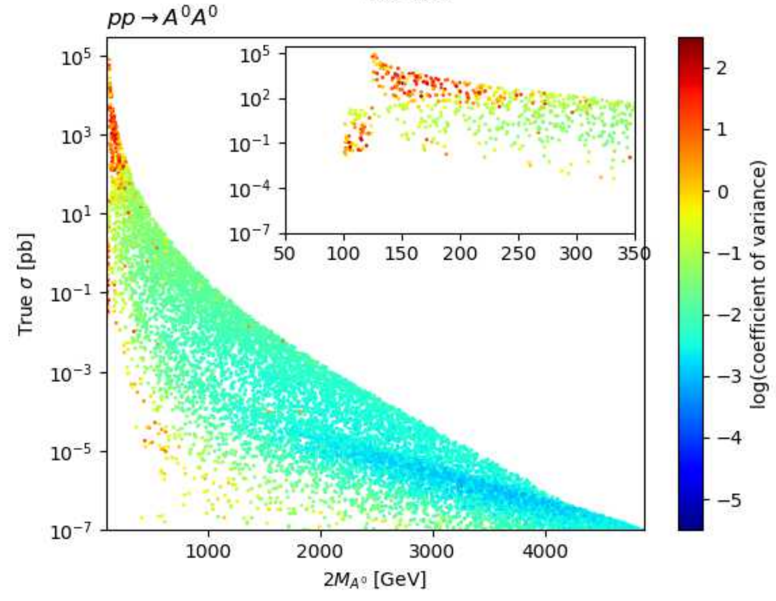
True vs predicted





log(CV), mass vs true





Tools summary

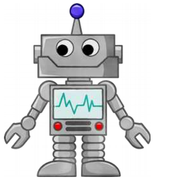
Determining between orthogonality LHC analyses.

- We present an statistical procedure to determine the orthogonality between SRs of different analyses.
- It is implemented in a Python program we call **TACO (Testing Analyses' Correlations)**, available at https://github.com/hreyes91/TACO

- Outlook 1: to generate more complicated events to uncover potential correlations that might be missed.
- Outlook 2: Include more analyses.
- Outlook 3: Implement results in recasting tools.

Machine learning cross sections.

- We trained neural networks to predict the production xsections in the IDM with an uncertainty estimation.
- Results are promising but they can definitely be improved.
- Our training data should be more evenly distributed over the target values. Possible solution: dropout-based active learning.
- The coefficient of variance and relative error seem to be correlated.
- All the material of the project is open: https://github.com/SydneyOtten/IDM_XS



Conclusions.

Conclusions.

- There are a number of reasons to journey beyond the Standard Model.
- A plethora of theories on the market.
- Reinterpretation of LHC data is a very active and relevant field.
- Is composed by a great community of theorist and experimenters. I have enjoyed being part of it!
- Current improvements undergoing at LHC and future experiments may lead to exciting news in upcoming years.
- Modern data science will definitely play a role in future developments.
- I have really enjoyed working on these topics here and I’m grateful to all the people I have interacted during the last 3 years.
- La métropole grenoblois est superbe!

Thank you!!!

Back up

The Minimal Supersymmetric Standard Model.

Names	Superfield	Spin 0	Spin 1/2	Spin 1	$SU(3), SU(2), U(1)_Y$
Quarks	$\hat{Q}$	$\tilde{Q} = (\tilde{u}_L, \tilde{d}_L)$	(u_L, d_L)		$(\mathbf{3}, \mathbf{2}, 1/6)$
	$\hat{u}^c$	$\tilde{u}^c_R$	u^c_R		$(\overline{\mathbf{3}}, \mathbf{1}, -2/3)$
(×3 families)	$\hat{d}^c$	$\tilde{d}^c_R$	d^c_R		$(\overline{\mathbf{3}}, \mathbf{1}, 1/3)$
Leptons	$\hat{L}$	$(\tilde{\nu}_{eL}, \tilde{e}_L)$	(ν_{eL}, e_L)		$(\mathbf{1}, \mathbf{2}, -1/2)$
(×3 families)	$\hat{e}^c$	$\tilde{e}^c_R$	e^c_R		$(\mathbf{1}, \mathbf{1}, 1)$
Higgs	$\hat{H}_u$	(H^+_u, H^0_u)	$(\tilde{H}^+_u, \tilde{H}^0_u)$		$(\mathbf{1}, \mathbf{2}, 1/2)$
	$\hat{H}_d$	(H^0_d, H^-_d)	$(\tilde{H}^0_d, \tilde{H}^-_d)$		$(\mathbf{1}, \mathbf{2}, -1/2)$
Gluons	$\hat{G}$		$\tilde{g}$	g	$(\mathbf{8}, \mathbf{1}, 0)$
W	$\hat{W}$		$\tilde{W}^\pm, \tilde{W}^0$	$W^\pm, W^0$	$(\mathbf{1}, \mathbf{3}, 0)$
B	$\hat{B}$		$\tilde{B}$	B	$(\mathbf{1}, \mathbf{1}, 0)$

Higgsinos and **electroweak gauginos** mix forming 4 neutralino and 2 chargino mass eigenstates:

$$M_{\tilde{\chi}^0} = \begin{pmatrix} M_1 & 0 & -g'v_d/2 & g'v_u/2 \\ 0 & M_2 & gv_d/2 & -gv_u/2 \\ -g'v_d/2 & gv_d/2 & 0 & \mu \\ g'v_u/2 & -gv_u/2 & \mu & 0 \end{pmatrix} \qquad M_{\tilde{\chi}^\pm} = \begin{pmatrix} M_2 & -gv_d/\sqrt{2} \\ -gv_u/\sqrt{2} & -\mu \end{pmatrix}$$

L and B conservation is ensured by $R = (-1)^{3(B-L)+2s}$, thus obtaining an LSP.

SUSY at colliders.

Gluinos and squarks

PRODUCTION

$$gg \to \tilde{g}\tilde{g},\ \ \tilde{q}_i\tilde{q}_j$$

$$gq \to \tilde{g}\tilde{q}_i,$$

$$q\bar{q} \to \tilde{g}\tilde{g},\ \ \tilde{q}_i\tilde{q}_j^*,$$

$$qq \to \tilde{q}_i\tilde{q}_j$$

s-channel

t-channel

s-channel

DECAYS

$$\tilde{g} \to q\tilde{q} \qquad\qquad \tilde{q} \to q\tilde{g}$$

$$\tilde{g} \to q\bar{q}\tilde{\chi}_i^0,\ \ qq'\tilde{\chi}_j^\pm \qquad\qquad \tilde{q} \to q\tilde{\chi}_i^0,\ \ \tilde{q} \to q'\tilde{\chi}_j^\pm$$

SUSY at colliders.

Electroweakinos

PRODUCTION:

$$q\bar{q} \to \tilde{\chi}_i^+ \tilde{\chi}_j^-,\ \tilde{\chi}_k^0 \tilde{\chi}_l^0,$$
$$u\bar{d} \to \tilde{\chi}_i^+ \tilde{\chi}_k^0\ d\bar{u} \to \tilde{\chi}_i^- \tilde{\chi}_k^0$$

Predominantly s-channel

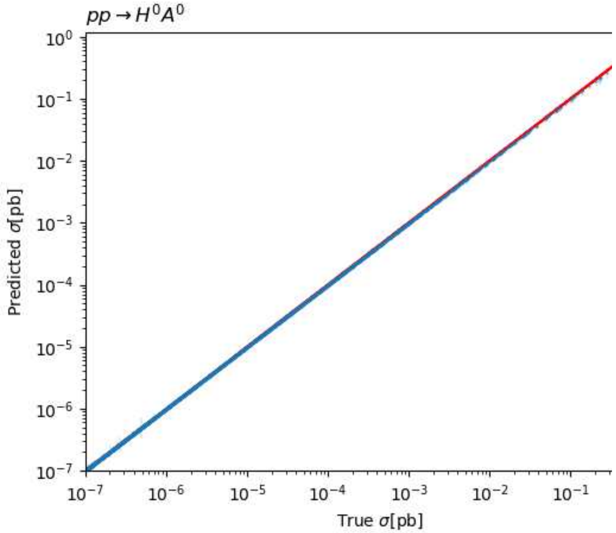
DECAYS:

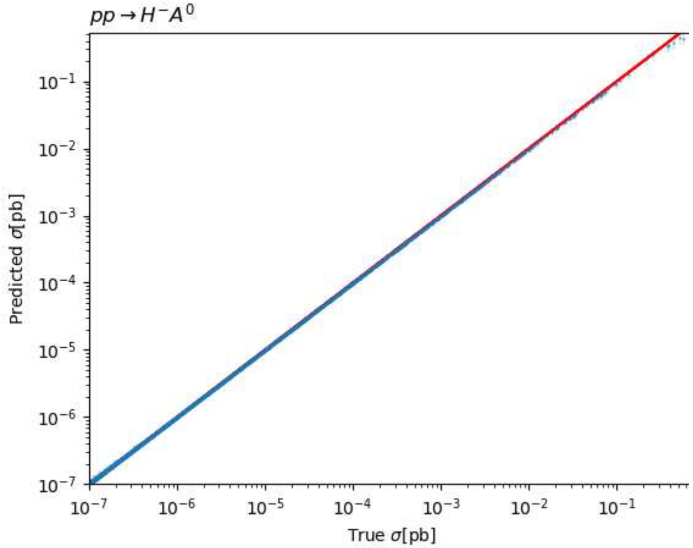
Usually subdominant

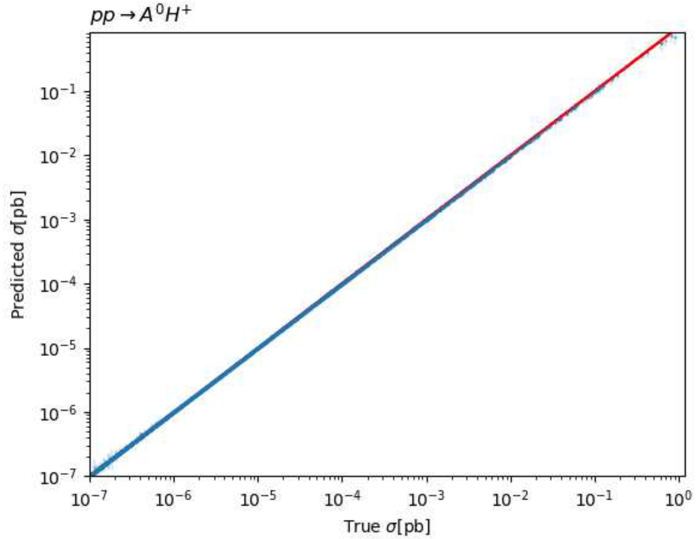
$$\tilde{\chi}_i^0 \to Z\tilde{\chi}_k^0,\ W\tilde{\chi}_j^\pm,\ h\tilde{\chi}_k^0,\ l\tilde{l}, \nu\tilde{\nu},\ q\tilde{q}, [H\tilde{\chi}_k^0,\ A\tilde{\chi}_k^0, H^\pm\tilde{\chi}_k^\mp, q\tilde{q}],$$
$$\tilde{\chi}_j^\pm \to W\tilde{\chi}_l^0,\ Z\tilde{\chi}_1^\pm,\ l\tilde{\nu},\ \nu\tilde{l}, q\tilde{q}', [H\tilde{\chi}_1^\pm,\ A\tilde{\chi}_1^\pm, H^\pm\tilde{\chi}_l^0, q\tilde{q}']$$

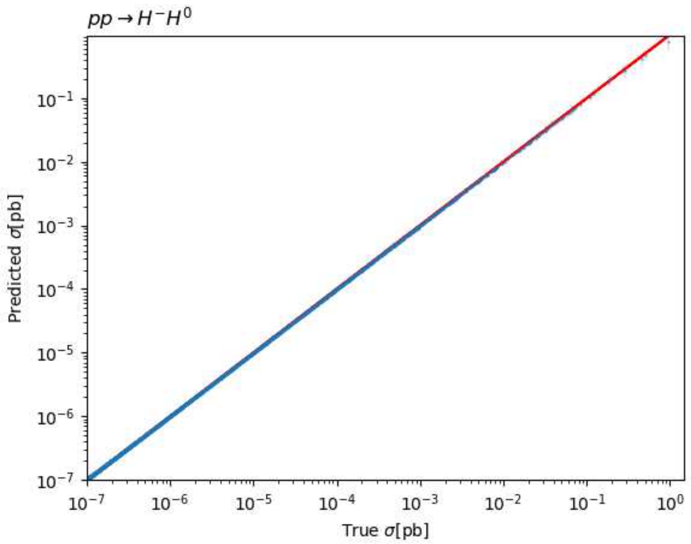
$$\tilde{\chi}_i^0 \to ff\tilde{\chi}_j^0,\ \tilde{\chi}_i^0 \to ff'\tilde{\chi}_j^\pm,\ \tilde{\chi}_i^\pm \to ff'\tilde{\chi}_j^0 \text{ and } \tilde{\chi}_2^\pm \to ff\tilde{\chi}_1^\pm$$

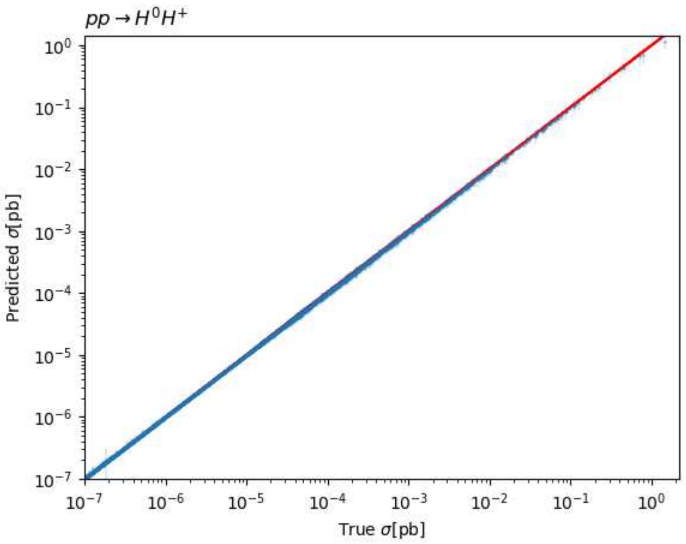
First the best results...



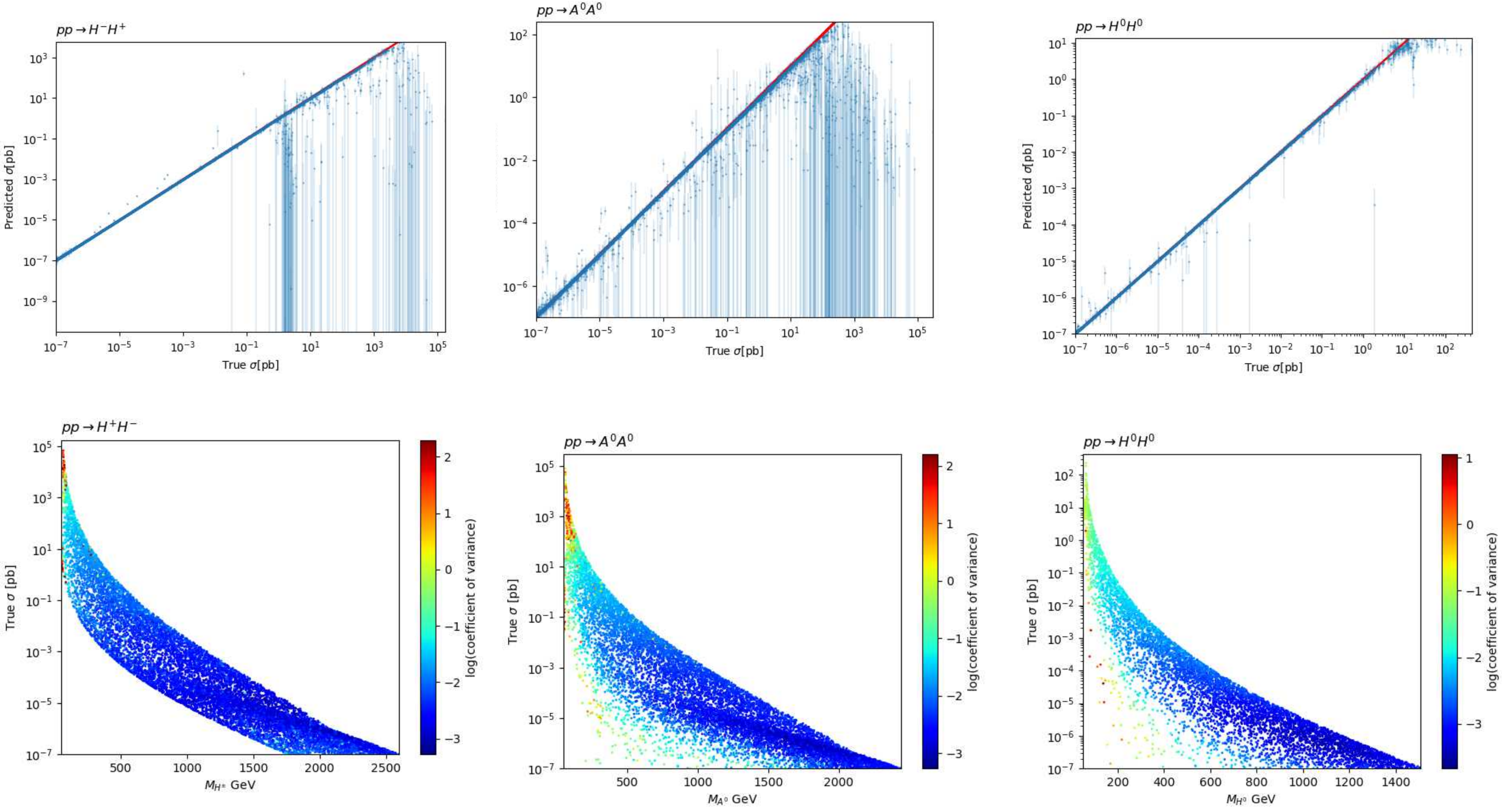






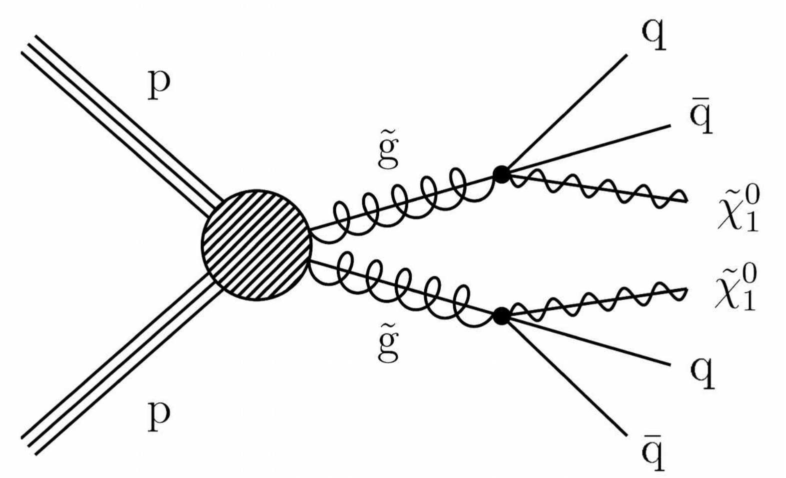


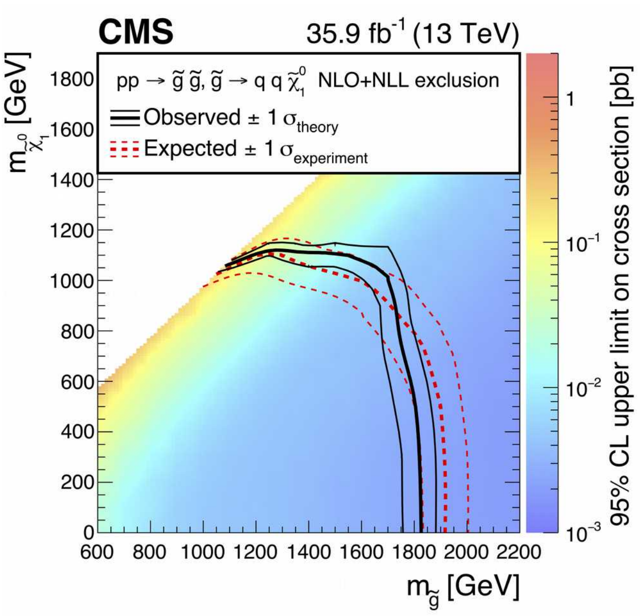
...and now the next to best ones.

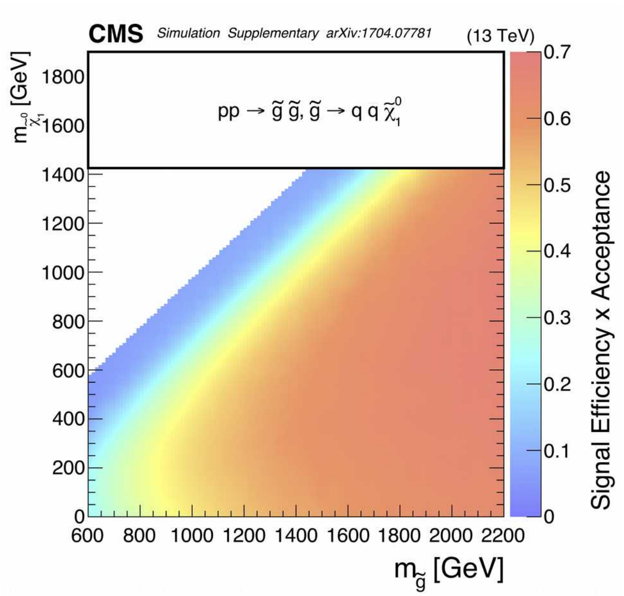


Simplified model framework.

- Most ATLAS and CMS searches interpret their results in the context of Simplified model spectra (SMS).
- SMS are sets of *effective* Lagrangians that characterize new physics models with a small set of kinematic parameters (masses xsections, Brs,τ)
- They show clear relation between model parameters and detector signatures.
- Reduced model dependence.
- Allow potential reinterpretation.







SMS results are presented as Upper Limit (UL) and Efficiency maps

Benchmark scenarios.

Parameters				
	DG1	DG2	DG3	DG4
m_{1D}	200	200	200	200
m_{2D}	500	500	500	1175
μ	400	400	400	400
$\tan\beta$	2	2	2	2
$-\lambda_S$	0.27	0.74	0.74	0.79
$\sqrt{2}\,\lambda_T$	0.14	0.14	0.14	-0.26
$m^2_{\tilde{Q}_3}$	1.25e7	6.5e6	2.26e6	8.26e6
$m^2_{\tilde{Q}_1}$	6.25e6	6.25e6	6.25e6	6.25e6
m_{3D}	1750	1750	1750	1750

Masses				
	DG1	DG2	DG3	DG4
$\tilde{\chi}^0_1$	201.35	182.1	181.8	182.4
$\tilde{\chi}^0_2$	201.72	218.0	216.6	213.2
$\tilde{\chi}^0_3$	403	400	396	408
$\tilde{\chi}^0_4$	419	445	441	437
$\tilde{\chi}^0_5$	537	536	535	1226
$\tilde{\chi}^0_6$	548	548	546	1227
$\tilde{\chi}^\pm_1$	400	395	391	398
$\tilde{\chi}^\pm_2$	536	536	534	1224
$\tilde{\chi}^\pm_3$	549	548	547	1229
$\tilde{t}_1$	3604	2607	1590	2894
$\tilde{t}_2$	3613	2637	1613	2927
h_1	124.0	125.0	125.3	125.2

Small bino mass splitting.
Large bino mass splitting.
Light winos.
Heavy winos.

We scanned over the gluino and squark mass spectrum.

ATLAS SUSY 2016-07: The recasted analysis.

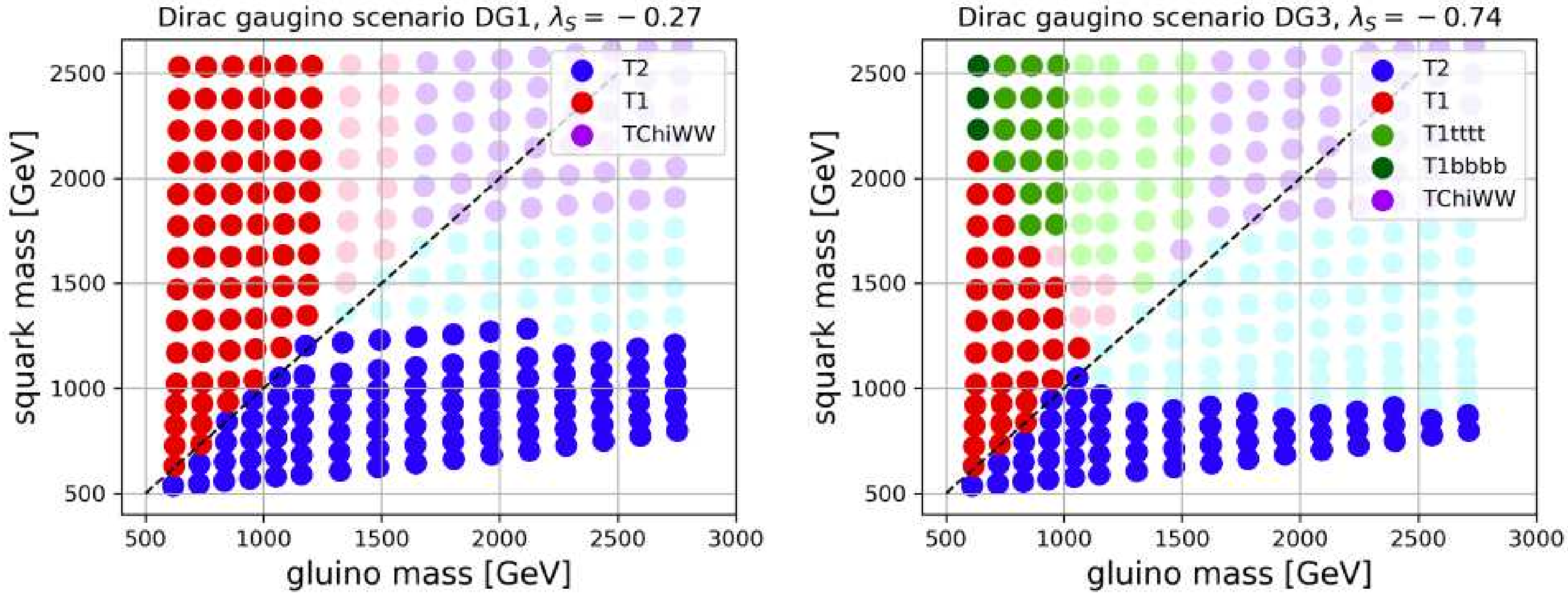
Search for squarks and gluinos in final states with jets and missing transverse momentum using 36 fb^{-1} of $\sqrt{s}$ =13 TeV *pp* collision data with the ATLAS detector

ATLAS analyses, 13 TeV

Analysis	Short Description	Implemented by	Code	Validation note	Version
ATLAS-SUSY-2015-06	Multijet + missing transverse momentum	S. Banerjee, B. Fuks, B. Zaldivar	Inspire	PDF	v1.3/Delphes3
ATLAS-SUSY-2016-07	Multijet + missing transverse momentum (36.1 fb-1)	G. Chalons, H. Reyes-Gonzalez	Inspire	PDF Pythia files	v1.7/Delphes3
ATLAS-EXOT-2015-03	Monojet (3.2 fb-1)	D. Sengupta	Inspire	PDF	v1.3/Delphes3
ATLAS-EXOT-2016-25	Mono-Higgs (36.1 fb-1)	S. Jeon, Y. Kang, G. Lee, C. Yu	Inspire	PDF	v1.6/Delphes3
ATLAS-EXOT-2016-27	Monojet (36.2 fb-1)	D. Sengupta	Inspire	PDF	v1.6/Delphes3
ATLAS-EXOT-2016-32	Monophoton (36.1 fb-1)	S. Baek, T.H. Jung	Inspire	PDF	v1.6/Delphes3
ATLAS-CONF-2016-086	b-pair + missing transverse momentum	B. Fuks & M. Zumbihl	Inspire	PDF	v1.6/Delphes3

http://madanalysis.irmp.ucl.ac.be/wiki/PublicAnalysisDatabase

Results from SModelS.

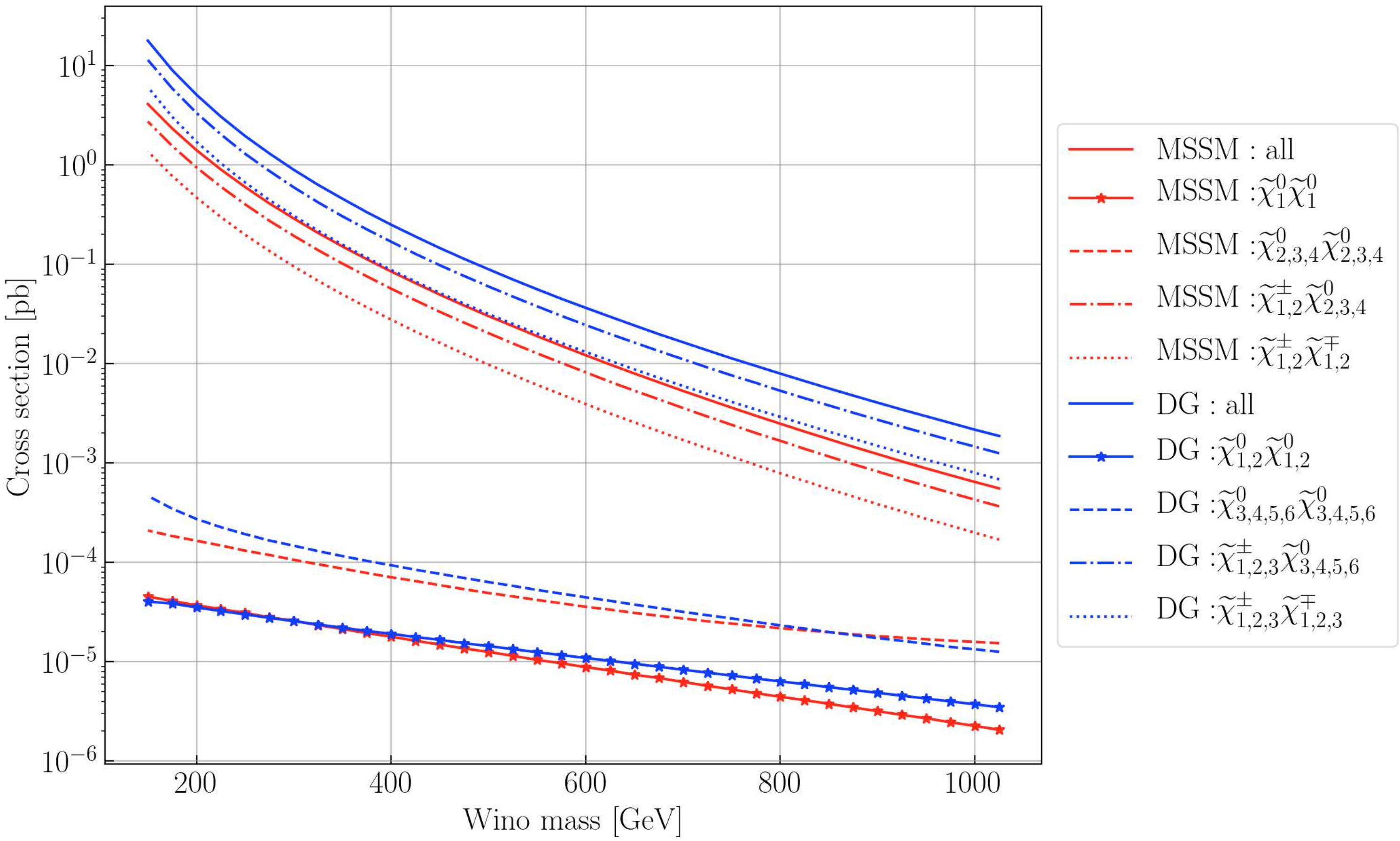


Gluino vs squark masses map of the SModelS limits. Hard coloured points means exclusion.

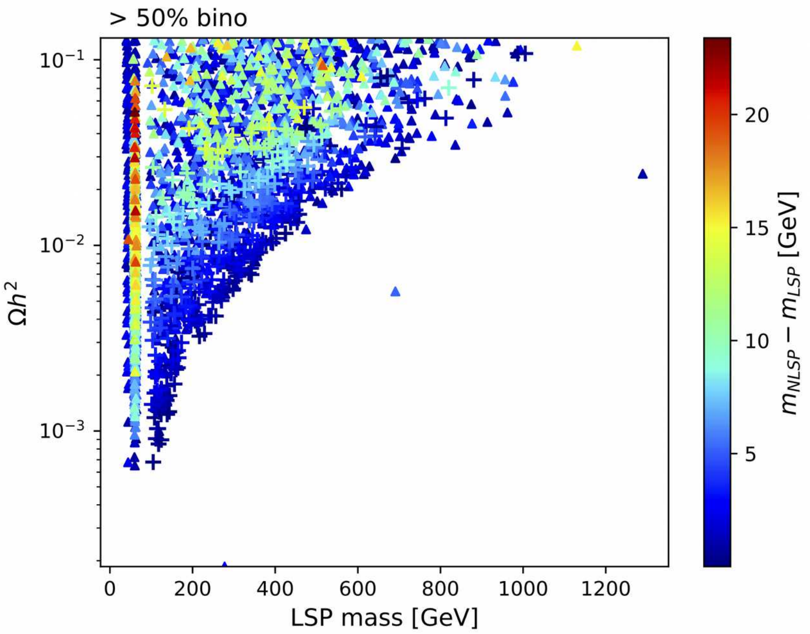
T1: $pp \to \tilde{g}\tilde{g},\ \tilde{g} \to q\bar{q}\tilde{\chi}_1^0$; T1tttt: $pp \to \tilde{g}\tilde{g},\ t\bar{t}\tilde{\chi}_1^0$; T2: $pp \to \tilde{q}\tilde{q}^{(*)}, \tilde{q} \to q\tilde{\chi}_1^0$; TChiWW: $pp \to \tilde{\chi}_i^{\pm}\tilde{\chi}_i^{\pm},\ \tilde{\chi}_i^{\pm} \to W^{\pm}\tilde{\chi}_1^0$

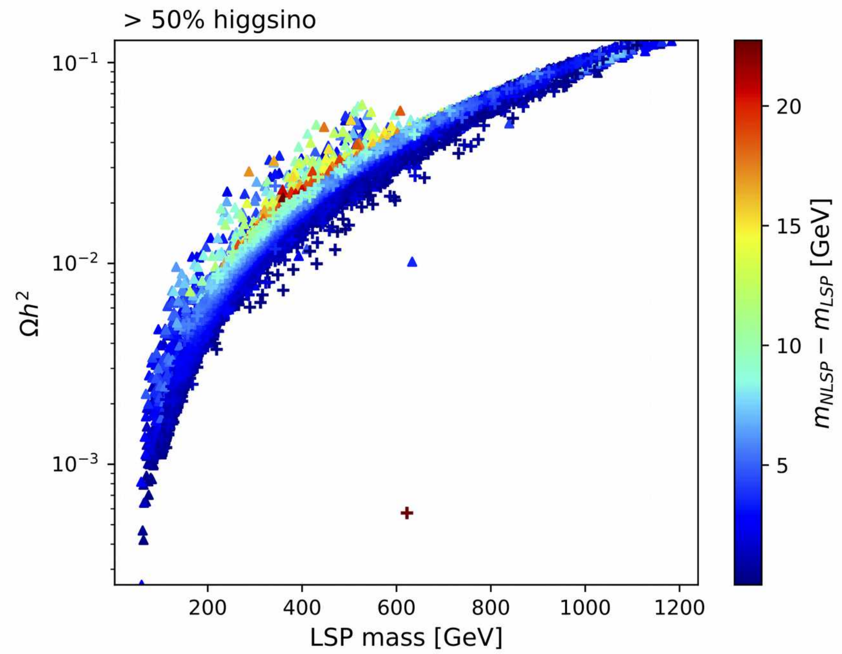
Due to the complexity of the model, constraints from SMS are weaker. E.g. The effective cross section from the T1 topology above is roughly 1% of the total.

Collider signals



Scan results.

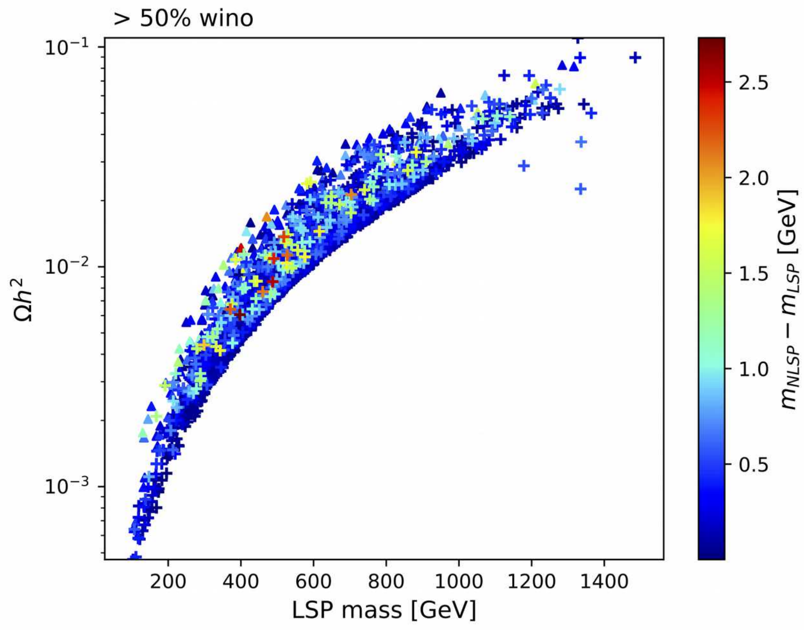




- General small NLSP-LSP mass splittings.
- Two possible mass orderings

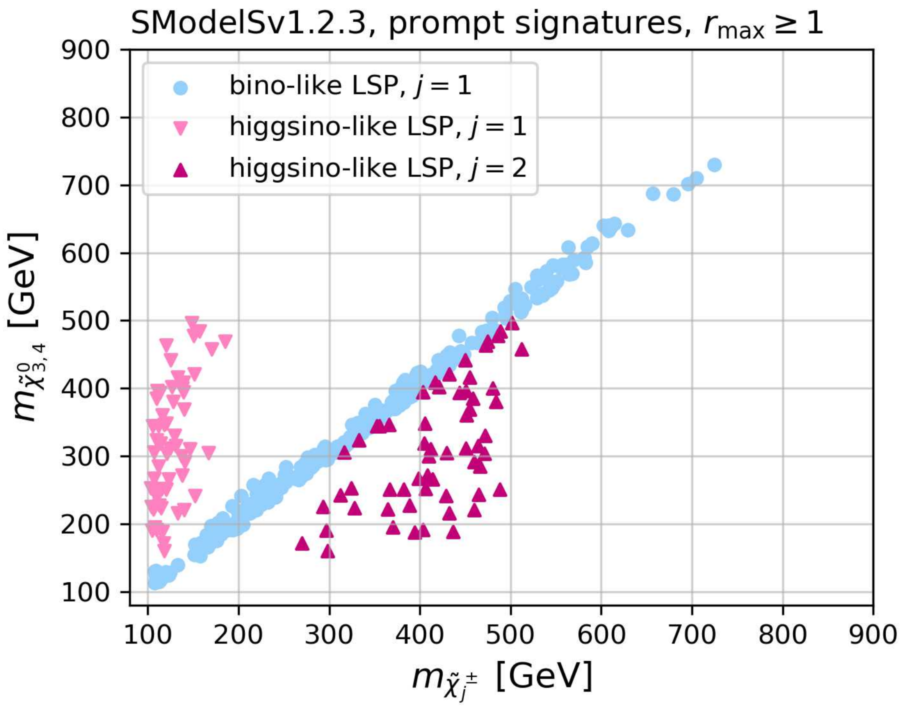
$$\tilde{\chi}_1^0 < \tilde{\chi}_1^\pm < \tilde{\chi}_2^0$$

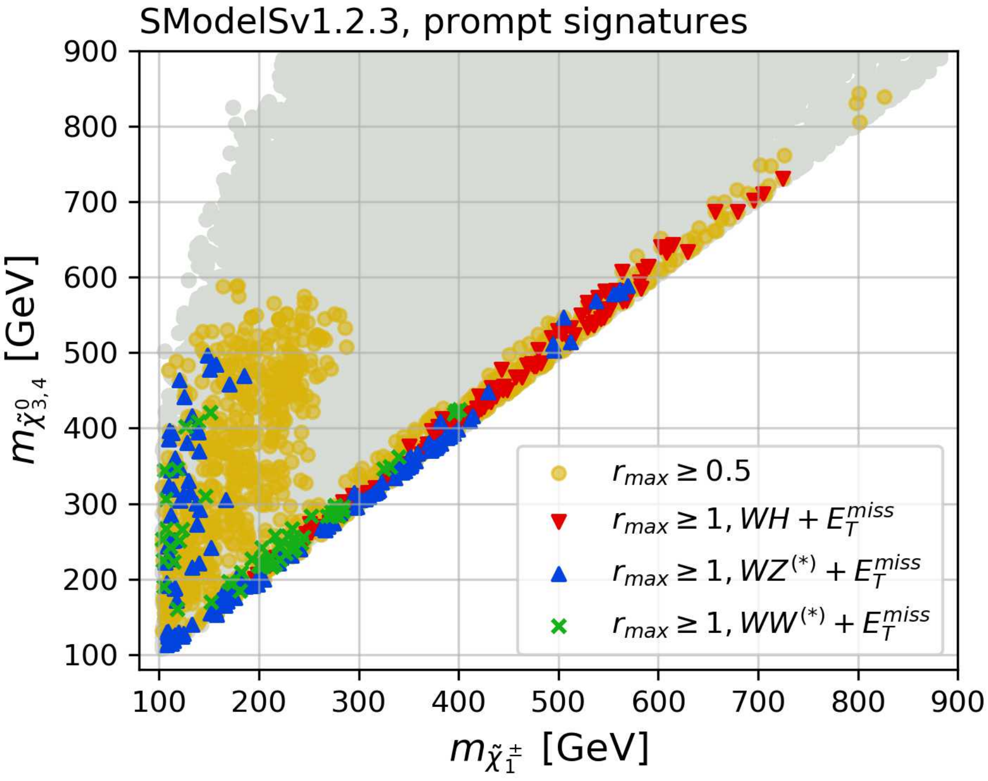
$$\tilde{\chi}_1^0 < \tilde{\chi}_2^0 < \tilde{\chi}_1^\pm$$



neutral NLSP

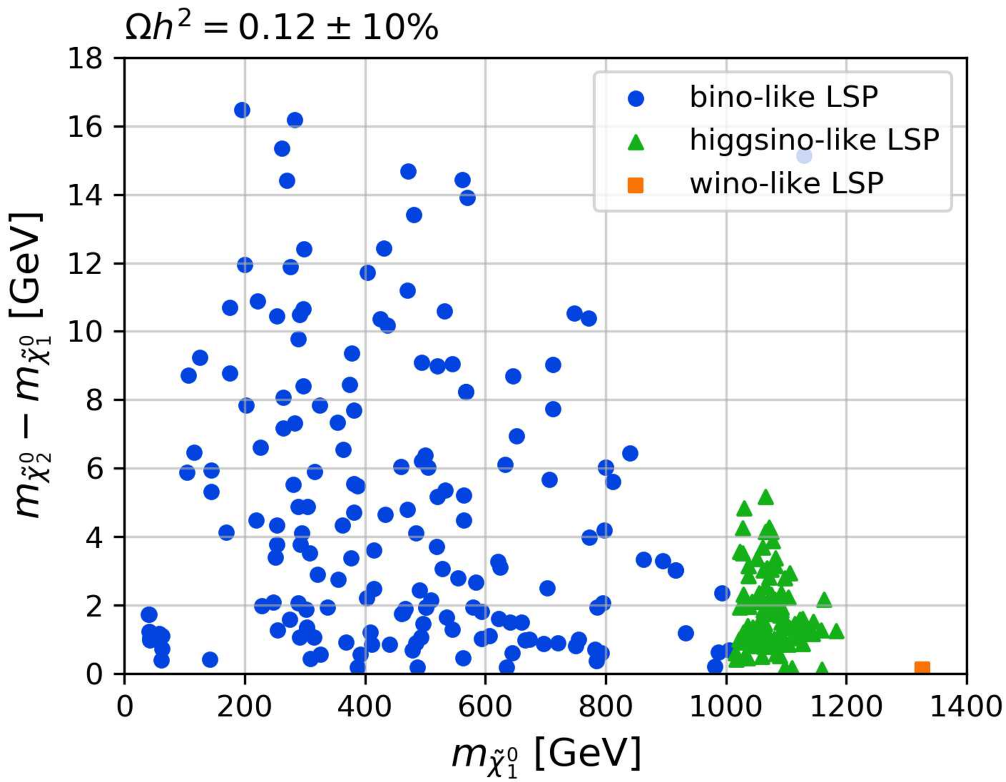
charged NLSP

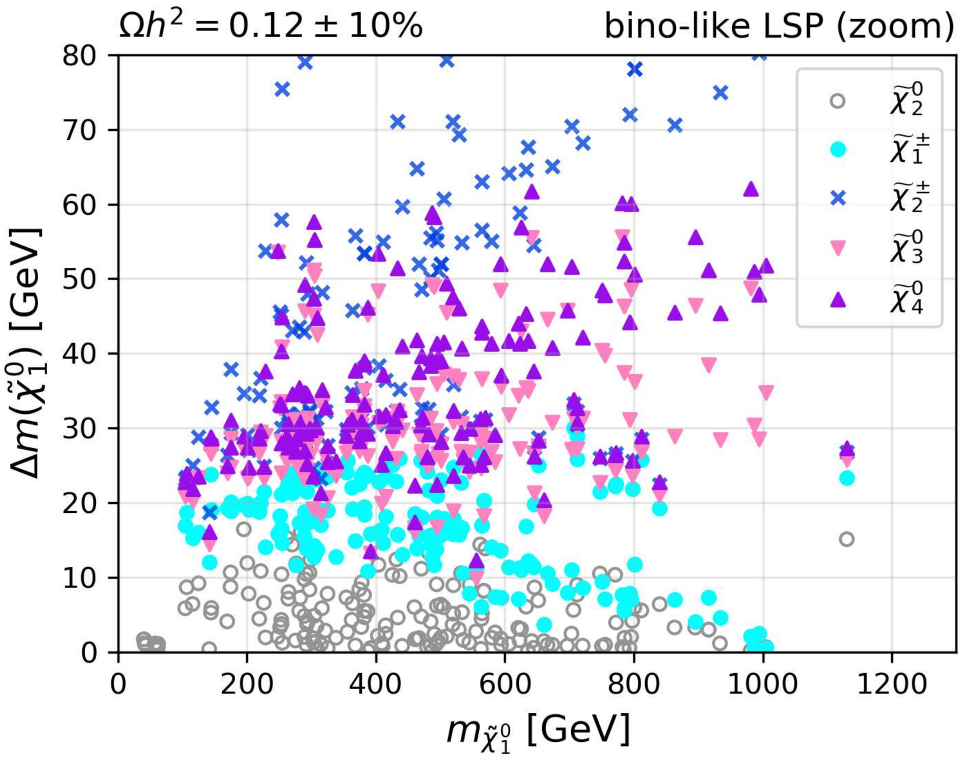

SModelSv1.2.3, prompt signatures, $r_{\max} \geq 1$
bino-like LSP, $j = 1$
higgsino-like LSP, $j = 1$
higgsino-like LSP, $j = 2$
$m_{\tilde{\chi}^0_{3,4}}$ [GeV]
$m_{\tilde{\chi}^\pm_j}$ [GeV]
100
200
300
400
500
600
700
800
900


SModelSv1.2.3, prompt signatures
$r_{max} \geq 0.5$
$r_{max} \geq 1, WH + E_T^{miss}$
$r_{max} \geq 1, WZ^{(*)} + E_T^{miss}$
$r_{max} \geq 1, WW^{(*)} + E_T^{miss}$
$m_{\tilde{\chi}^0_{3,4}}$ [GeV]
$m_{\tilde{\chi}^\pm_1}$ [GeV]
100
200
300
400
500
600
700
800
900

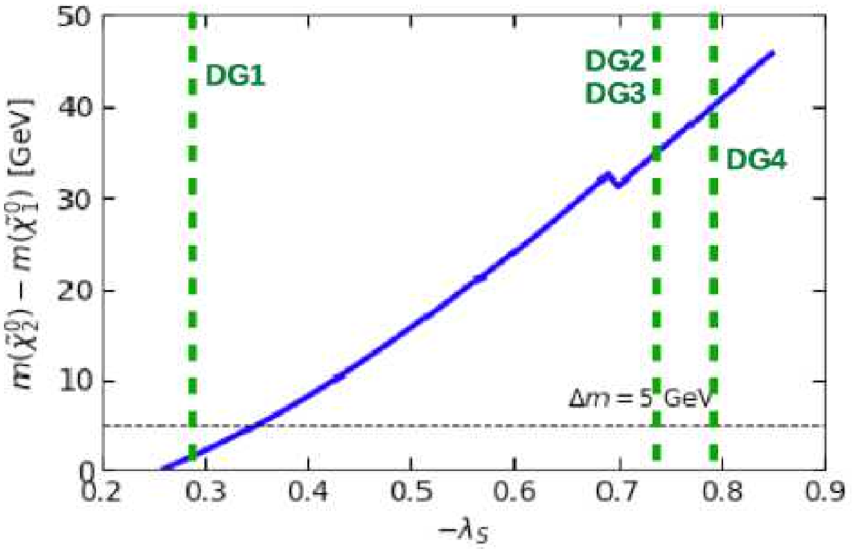
Scan results.

$$\Omega h^2 = \Omega h^2{}_{\text{Planck}} \pm 10\%$$

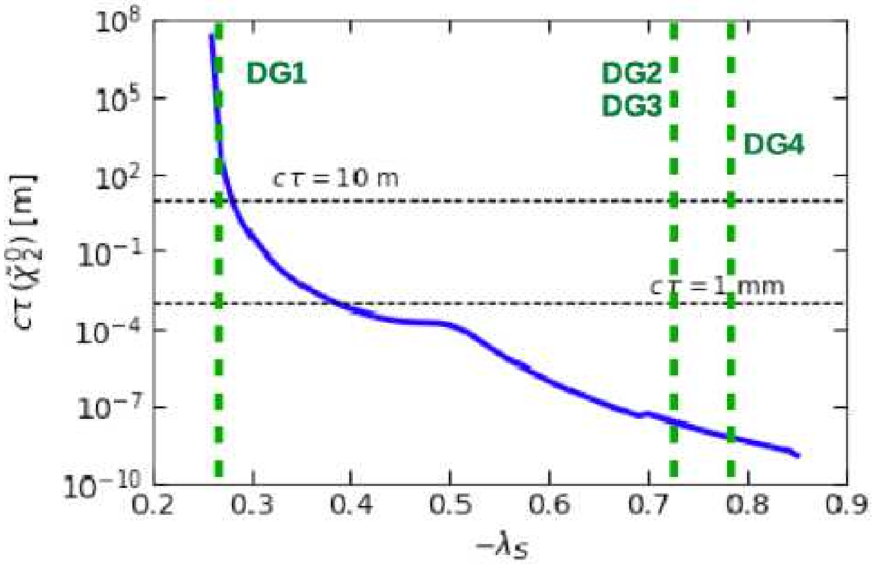




Lifetime and mass splitting of binos: motivation of benchmark choices.



Mass splitting between $\tilde{\chi}^0_{1,2}$.

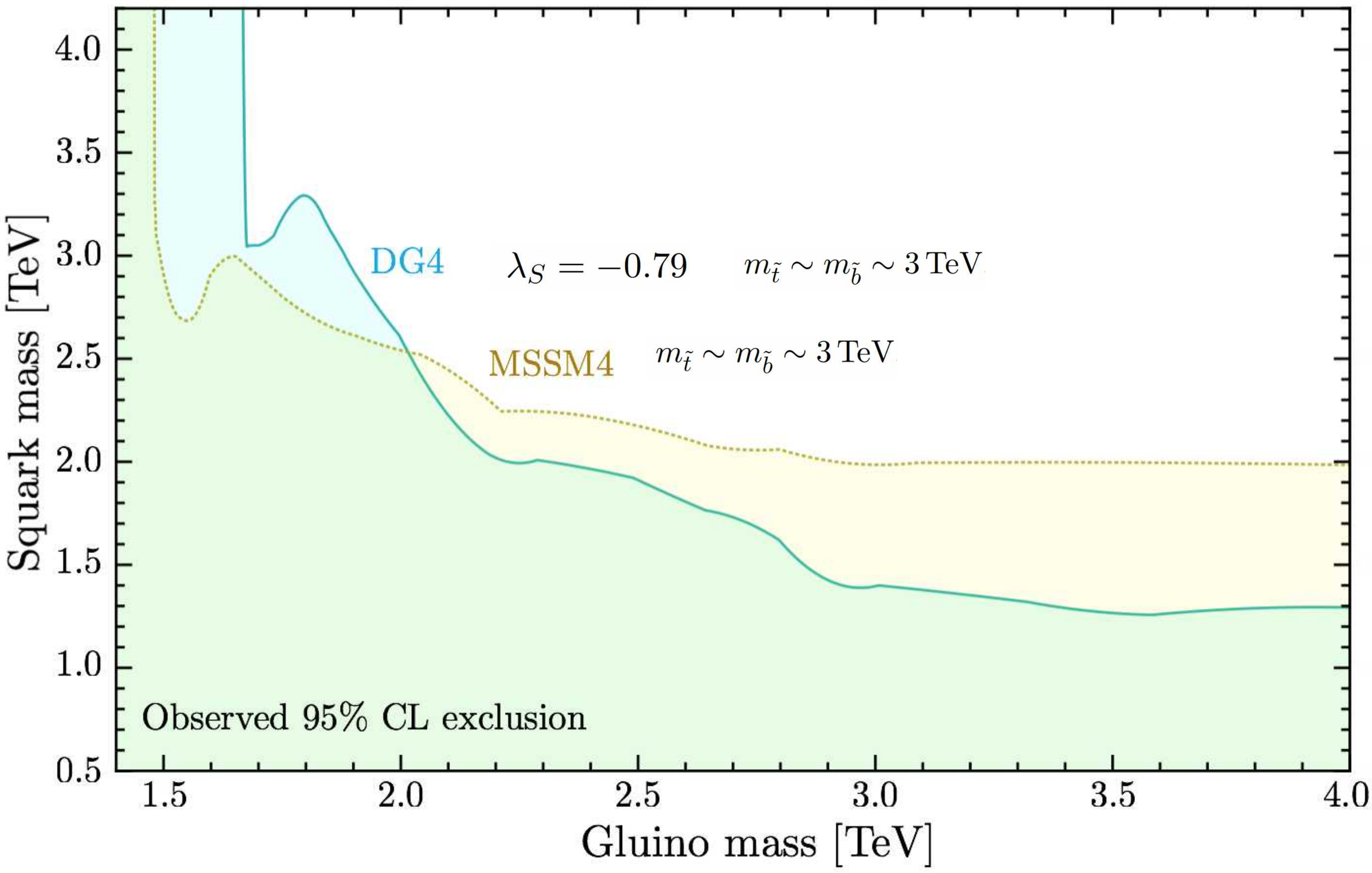


The lifetime of $\tilde{\chi}^0_2$.

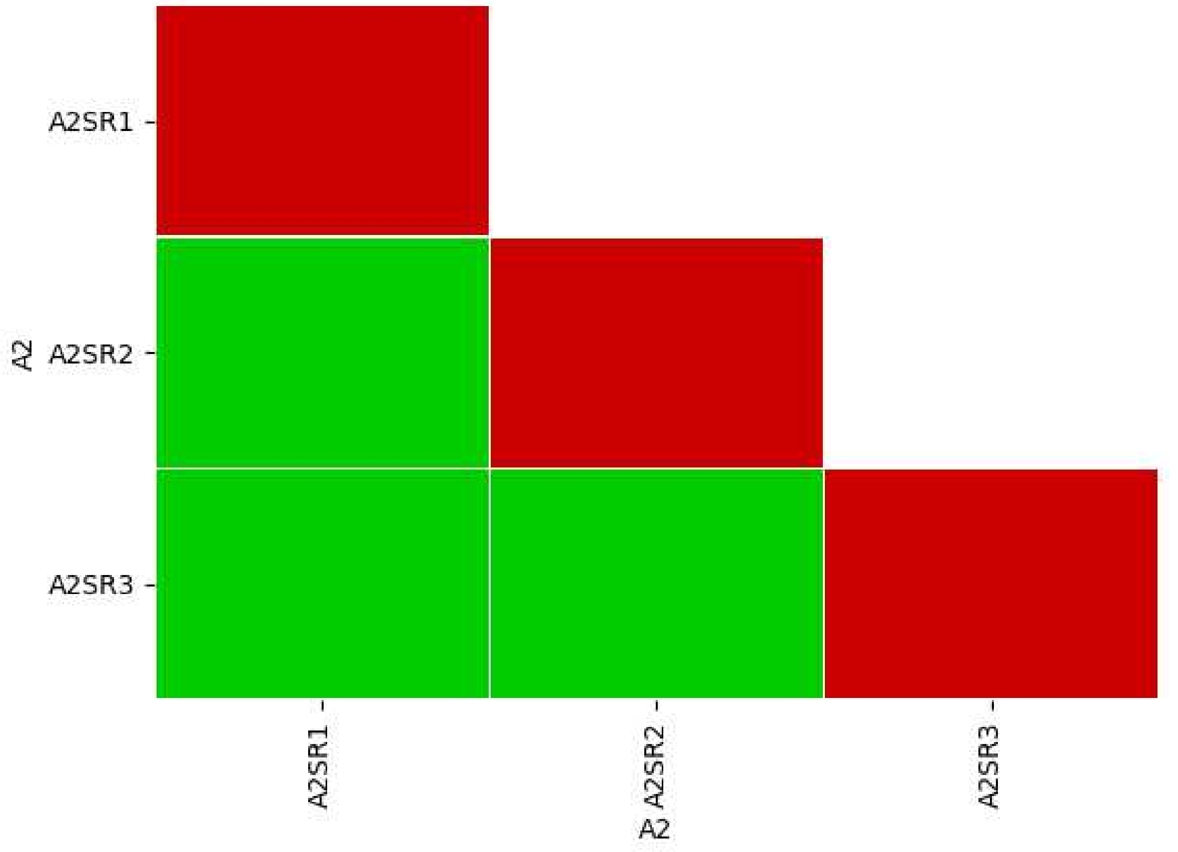
Constraints for four benchmark scenarios will be shown:

- One with small $\tilde{\chi}^0_{1,2}$ mass spliting/long $\tilde{\chi}^0_2$ lifetime: DG1 where λ_S=-0.27 .
- Three with a large $\tilde{\chi}^0_{1,2}$ mass spliting/short $\tilde{\chi}^0_2$ lifetime: DG2,DG3 with λ_S =-0.74 and DG4 with λ_S =-0.79.

Results from Recasting : DG4 vs MSSM4 (heavy winos).



CMS Dilepton+MET search (CMS-SUS-17-001)



$m_{T2}(l_1 l_2)$ [GeV]	$100 - 140$	$140 - 240$	> 240
$E_T^{\text{miss}} > 200$ GeV	A2SR1	A2SR2	A2SR3

The training algorithm.

Fixed hyperparameters: Initializer → He Normal, Activation function in each hidden layer → LeakyReLu, Optimizer → Adam.

```
model.add(Dense(neurons, kernel_initializer = he_normal(seed=42), kernel_regularizer=l2(L2lambda)))
model.add(LeakyReLU(alpha=0.2))
model.add(PermaDropout(dropout_fraction))
```

```
from keras import backend as K
from keras.layers.core import Lambda

def PermaDropout(rate):
    return Lambda(lambda x: K.dropout(x, level=rate))
```

In order to obtain an approximation of the **Bayesian uncertainties** as Monte Carlo dropout a **"permanent" dropout layer** was implemented after each hidden layer, this means that the dropout is present not only during training, but also for inferences.

We implemented EarlyStopping callback with a patience of 50. After 500 epochs have ended or EarlyStopping has terminated the iteration, the learning rate was divided by 2 and the training continues until 10 of those iterations were completed.

To choose the best configuration, we ran a scan over the rest of the hyperparameter and trained a neural network with each combination for the $pp \to H_0 H_0$. This configuration is formed by 6 hidden layers with 192 artificial neurons, λ of L2 regularization= 10^−5 and a dropout fraction of 1 %

An open library of classifiers and regressors for HEP phenomenology.

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GOAL: To build a framework in which all material regarding ML applications for particle physics phenomenology can be shared and found for the purpose of education, reproducibility, etc...

Mainly we want:

- A collection of Machine Learning models.
- A collection of Training Data.
- A collection of code to build Machine Learning models.