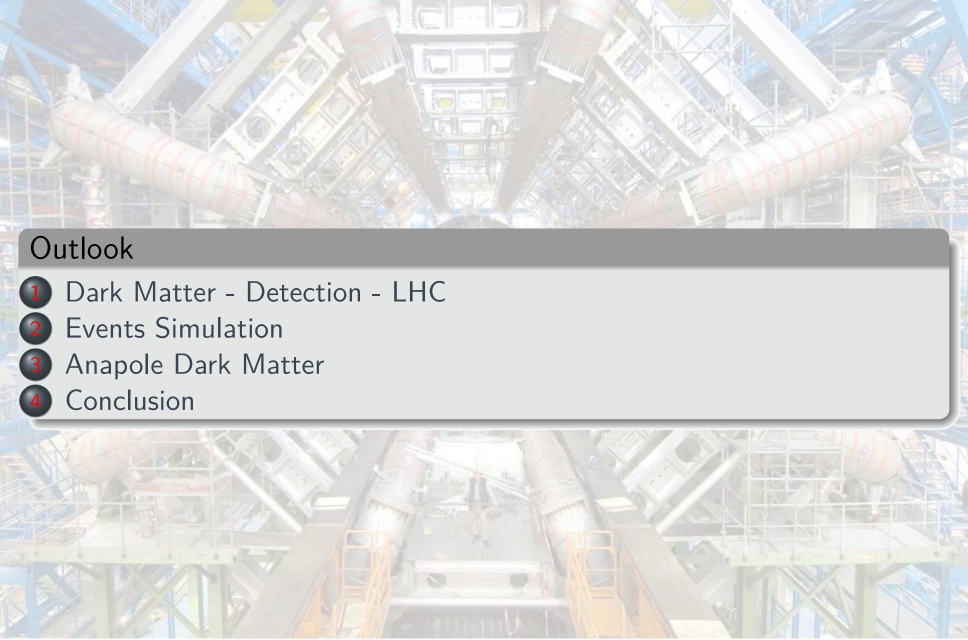
Anapole Dark Matter: A Collider Study using Machine Learning

Antonio C. O. Santos (UFPB)

Alexandre Alves (UNIFESP) and Kuver Sinha (Oklahoma U.)

September 6, 2019

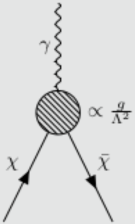


Outlook

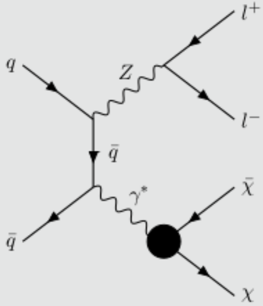
1. Dark Matter - Detection - LHC
2. Events Simulation
3. Anapole Dark Matter
4. Conclusion

Outline

Anapole Dark Matter



$$pp \to Z + \gamma^* \to \ell^+\ell^- + \chi\overline{\chi}$$



PHYSICAL REVIEW D **97,** 055023 (2018)

Collider detection of dark matter electromagnetic anapole moments

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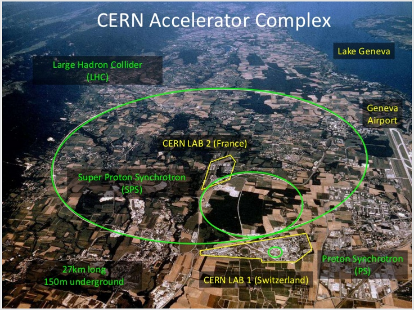
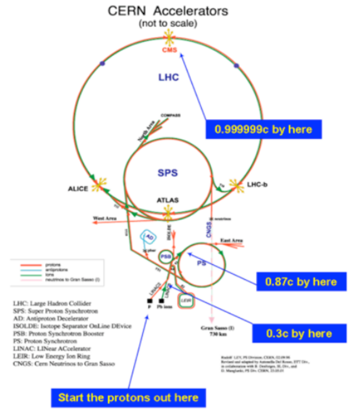
[2]*Departamento de Física, Universidade Federal da Paraíba, João Pessoa-PB, 58051-970, Brazil*
[3]*Centre for Cosmology, Particle Physics and Phenomenology (CP3), Universit catholique de Louvain, B-1348 Louvain-la-Neuve, Belgium*
[4]*Department of Physics and Astronomy, University of Oklahoma, Norman, Oklahoma 73019, USA*

Dark Matter Searches at Colliders - LHC

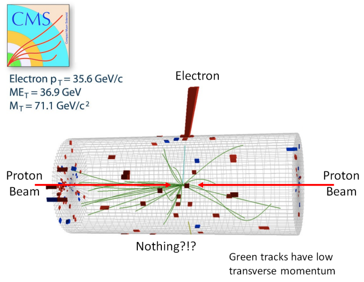


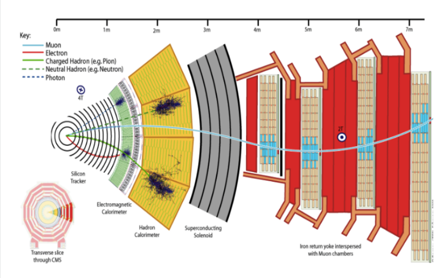


Dark Matter Searches at Colliders - LHC

$$p_1^\mu = (6.5 \text{ TeV}, 0, 0, 6.5 \text{ TeV}), \quad p_2^\mu = (6.5 \text{ TeV}, 0, 0, -6.5 \text{ TeV}),$$

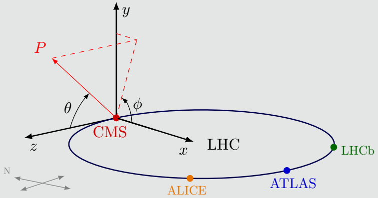
where $p^\mu = (E, p_x, p_y, p_z)$.

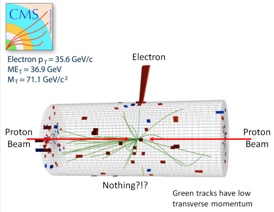


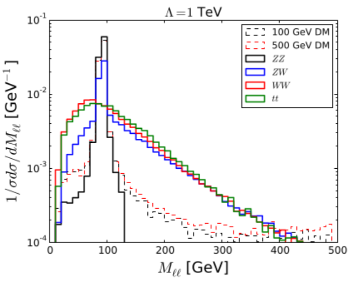


Dark Matter Searches at Colliders - LHC - Low level and High level features

$\vec{p}_T \equiv (p_x, p_y)$	$\phi \equiv \tan^{-1}\frac{p_x}{p_y}$	$\eta \equiv \ln\cot\frac{\theta}{2}$
$y = \frac{1}{2}\ln\left(\frac{E+p_Z}{E-p_Z}\right)$		$\Delta R = \sqrt{(\Delta\phi)^2 + (\Delta\eta)^2}$
$\not{\vec{p}}_T + \sum_i \vec{p}_{T_i} = 0$	$\not{E}_T \equiv \lvert\not{\vec{p}}_T\rvert$	$M_{\ell\ell} = \sqrt{E_{\ell\ell}^2 - \lvert\vec{p}_{\ell\ell}\rvert^2}$







Outline

Event Classification

- Sort blues vs red.
- How to discriminate?
- Decision boundary $y(\boldsymbol{x}) = y_{cut}$. What is best way to determine the boundary? Cuts over (x_1, x_2)?

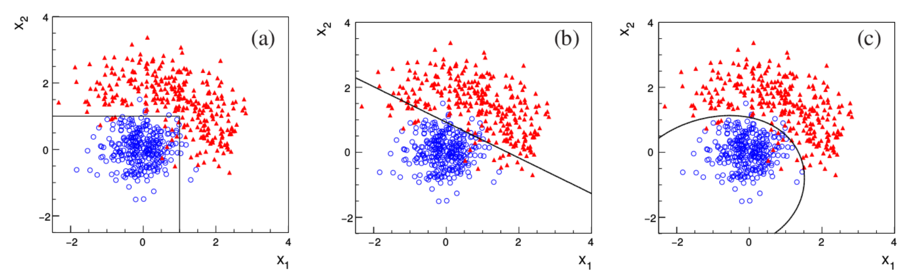
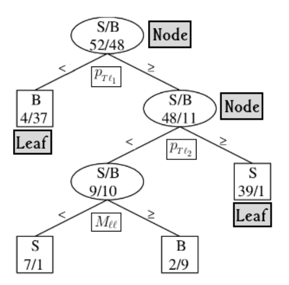


Figure: Proceedings, 69th Scottish Universities Summer School in Physics : LHC Phenomenology (SUSSP69): St.Andrews,Scotland, August 19-September 1, 2012

XGBoost - Artificial intelligence/Machine Learning

dmlc XGBoost

- Boosted Decision Trees (`https://github.com/dmlc/xgboost`)



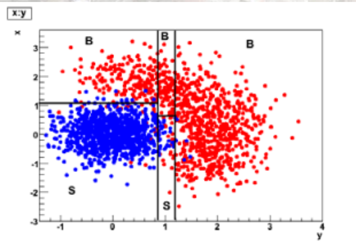


Figure: `https://machinelearningmastery.com/`

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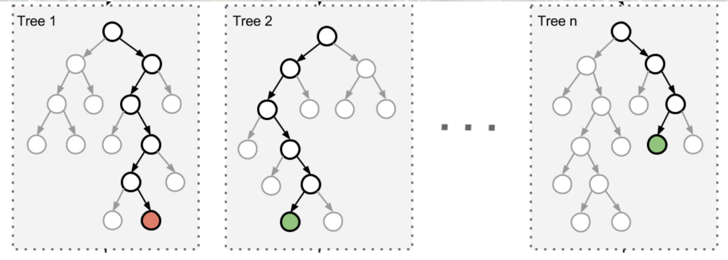

Figure: https://blog.statsbot.co/ensemble-learning-d1dcd548e936

Figure: https://machinelearningmastery.com/

XGBoost

- Boosted Decision Trees (`https://github.com/dmlc/xgboost`)

$$\hat{y}_i = \phi(\mathbf{x_i}) = \sum_{k=1}^{K} f_k(\mathbf{x_i})$$

$$Obj(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_K \Omega(f_k)$$

$$l(\hat{y}_i, y_i) = (y_i - \hat{y}_i)^2 \quad \text{(e.g)}$$

$$\Omega = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$$

$$Obj_{\text{split}} = \frac{1}{2}\left[\frac{\left(\sum_{iL} g_{iL}\right)^2}{\sum_{iL} h_{iL} + \lambda} + \frac{\left(\sum_{iR} g_{iR}\right)^2}{\sum_{iR} h_{iR} + \lambda} - \frac{\left(\sum_i g_i\right)^2}{\sum_i h_i + \lambda}\right] - \gamma$$

$$f_t(x) = w_{q(x)}$$

$$\rightarrow y^{\{t\}} = y^{\{t-1\}} + \epsilon f_t(x_i)$$

- Gradient Boosting Tree, Parameters:
  1. Number of trees;
  2. Maximum depth;
  3. Learning Rate;
  4. Minimum Child Weight.

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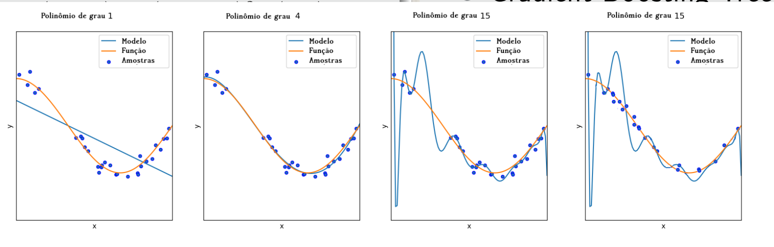

Obj_{split}

ight .

$\sum_i h_i + \lambda]$

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DARK MATTER AND WEAK INTERACTIONS (DARKWIN) CONFERENCE

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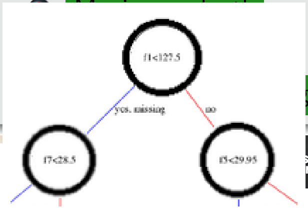

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DARK MATTER AND WEAK INTERACTIONS (DARKWIN) CONFERENCE

Automatic Tuning of Hyperparameters

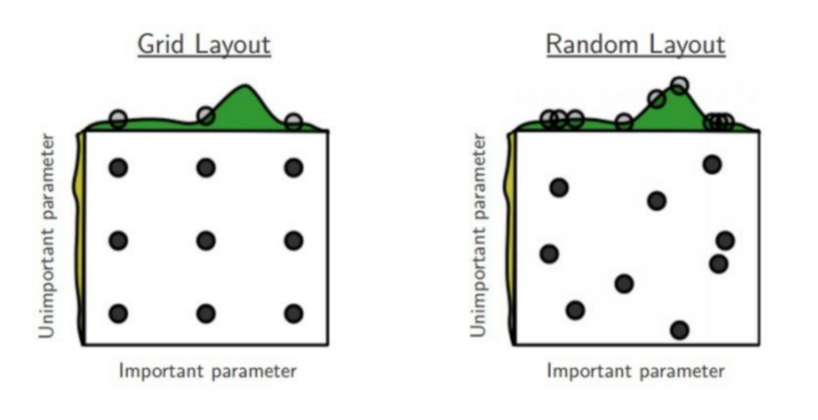


Figure: Hyperopt

Automatic Tuning of Hyperparameters - Hyperopt

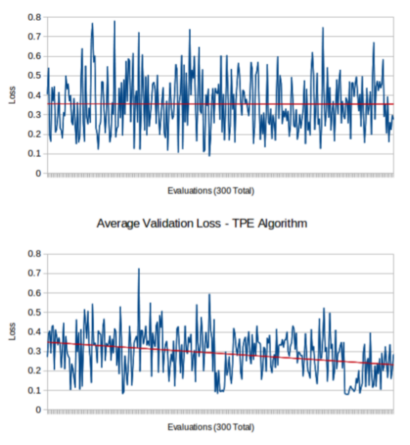


Figure: Hyperopt

Automatic Tuning of Hyperparameters - *Expected improvement* (EI)

$$\boxed{\mathrm{EI}(x) \propto \frac{l(x)}{g(x)}}$$

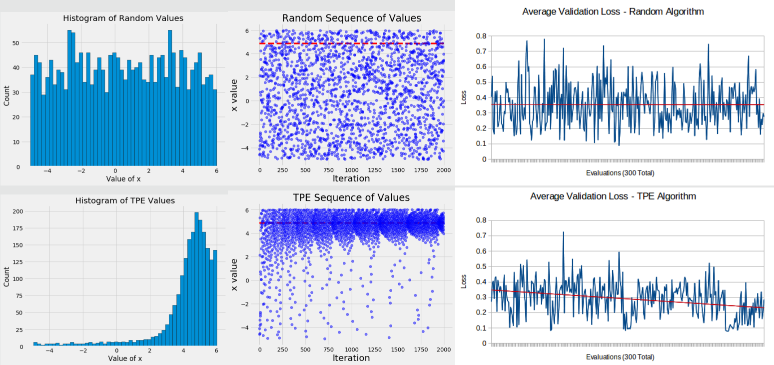


Figure: Hyperopt

Automatic Tuning of Hyperparameters - To optimize

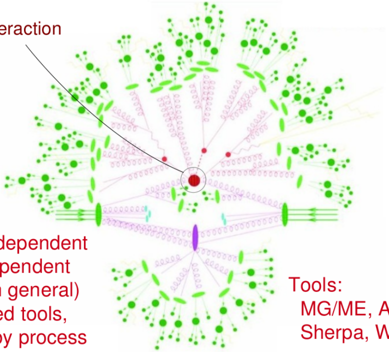
- `mlogloss` $= -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij}\log p_{ij}$
- $$N_\sigma = \begin{cases} \sqrt{2}\sqrt{(s+b)\log\left[\left(1+\frac{1}{b\,\epsilon^2}\right)\frac{s+b}{s+b+1/\epsilon^2}\right] + \frac{1}{\epsilon^2}\log\left[\frac{b+1/\epsilon^2}{s+b+1/\epsilon^2}\right]}, & \epsilon > 0 \\ \sqrt{2}\sqrt{-s+(s+b)\log\left(1+\frac{s}{b}\right)}, & \epsilon = 0 \end{cases}$$

Events Simulation

Model Theory → Model Build → Parton Level → Events Generator → Parton Shower Hadronization → Detector Simulation → Data Analyses → Model Theory

Elements of a simulation

1. Hard interaction



- Process dependent
- Model dependent
- Needs (in general) specialized tools, process by process

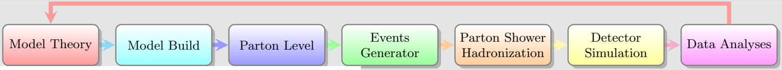
Tools:
MG/ME, AlpGen, Sherpa, Whizard, ...

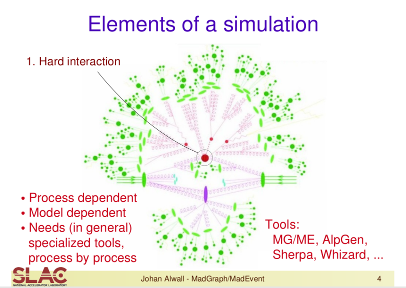
SLAC NATIONAL ACCELERATOR LABORATORY

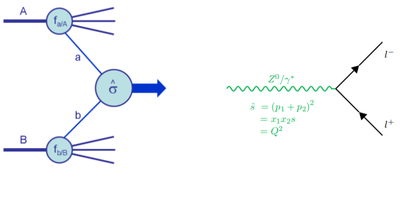
Johan Alwall - MadGraph/MadEvent 4

SEPTEMBER 02 to 13, 2019 - NATAL, BRAZIL

Events Simulation





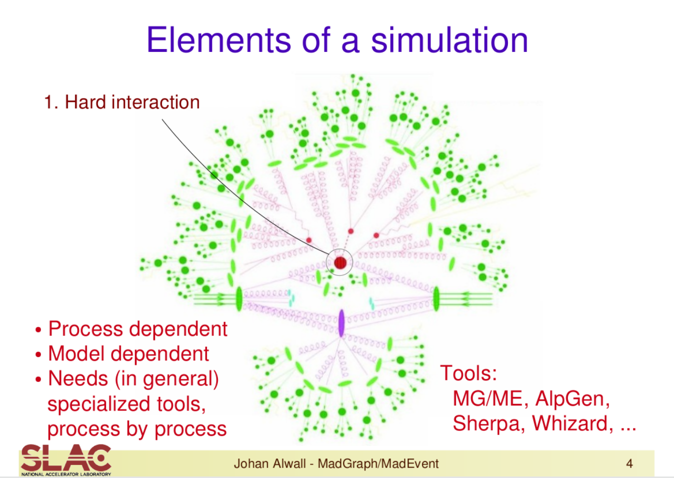


$$\sigma_{AB} = \int dx_a dx_b \; f_{q/p}(x_a, \mu_F^2) \; f_{\bar{q}/p}(x_b, \mu_F^2) \; [\hat{\sigma}_0 + \alpha_S(\mu_R^2)\hat{\sigma}_1 + \ldots]_{ab\to X}$$

$$d\hat{\sigma}^{(0)} = dP_{2f}\,\frac{1}{12}\sum |\mathcal{A}_\gamma^0 + \mathcal{A}_Z^0|^2(\hat{s},\hat{t},\hat{u}) \;,$$

Events Simulation

Model Theory → Model Build → Parton Level → Events Generator → Parton Shower Hadronization → Detector Simulation → Data Analyses



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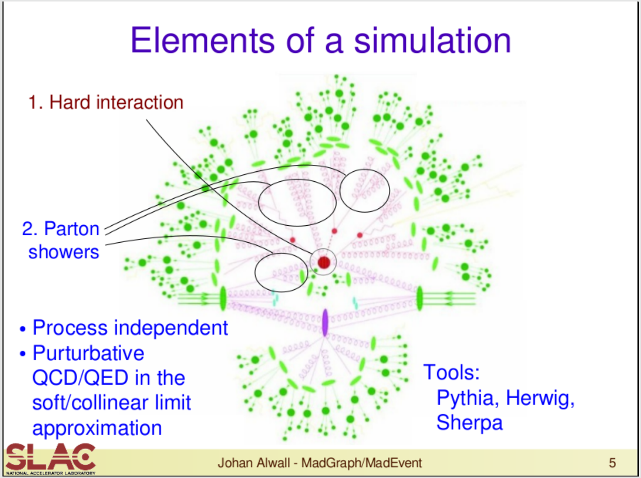

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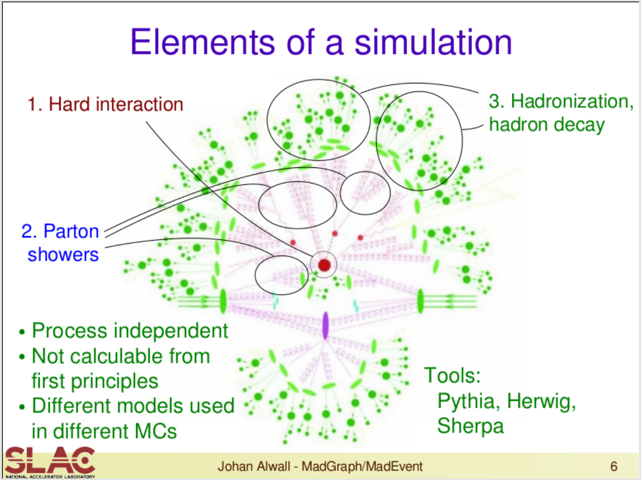

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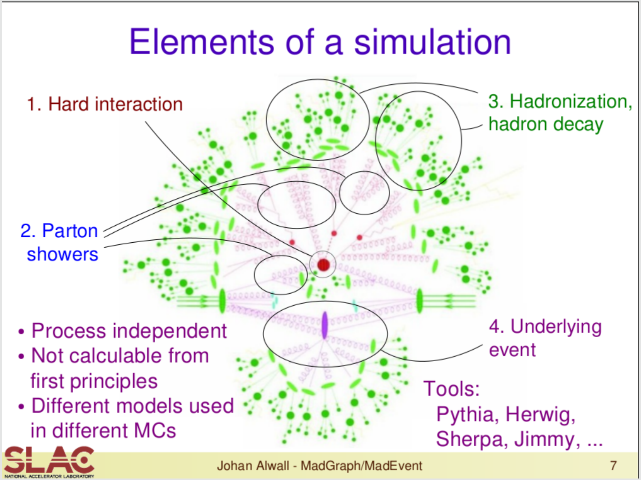

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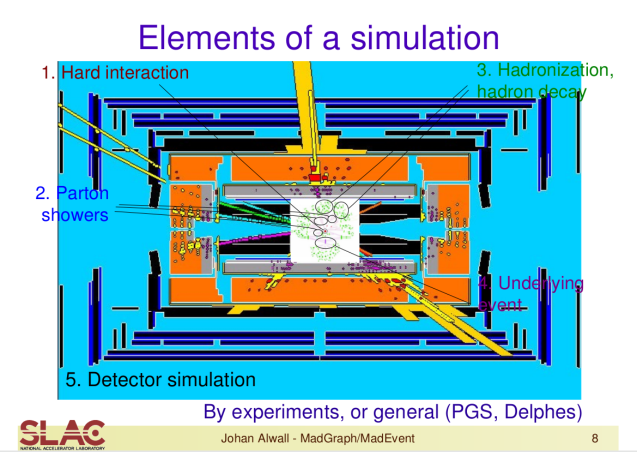


Events Simulation

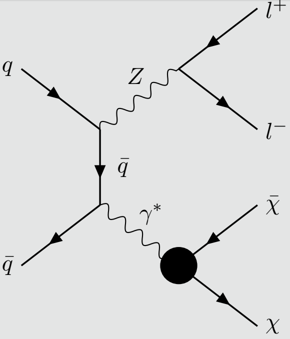
Model Theory → Model Build → Parton Level → Events Generator → Parton Shower Hadronization → Detector Simulation → Data Analyses → Model Theory

Model Theory → `FeynRules` → `MadGraph aMC@NLO` → `MadGraph aMC@NLO` → `Pythia` → `Delphes` → `Fortran` `Python` (**IA**) → Model Theory

Outline

Anapole Dark Matter

$$pp \to Z + \gamma^* \to \ell^+\ell^- + \chi\overline{\chi}$$



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[4]*Department of Physics and Astronomy, University of Oklahoma, Norman, Oklahoma 73019, USA*

Classical Physics

$$\mathcal{H} \propto -\mu(\vec{\sigma}\cdot\vec{B}) - d(\vec{\sigma}\cdot\vec{E}) - a(\vec{\sigma}\cdot(\vec{\nabla}\times\vec{B}))$$

$$\begin{aligned}\vec{A}(\vec{x}) &= \int d^3x' \frac{\vec{j}(\vec{x}')}{4\pi|\vec{x}-\vec{x}'|} \\ &= \int d^3x' \vec{j}(\vec{x}')\{1 - \vec{x}' \cdot \vec{\nabla} + \frac{1}{2}(\vec{x}' \cdot \vec{\nabla})^2 + \cdots\}\frac{1}{4\pi|\vec{x}|}.\end{aligned}$$

$$\vec{a} = \frac{M^2}{6}\int d^3x' \vec{x}' \times (\vec{x}' \times \vec{j}(\vec{x}')), \qquad \mu = \frac{1}{2}\int \vec{x}' \times \vec{j}(\vec{x}) d^3x.$$

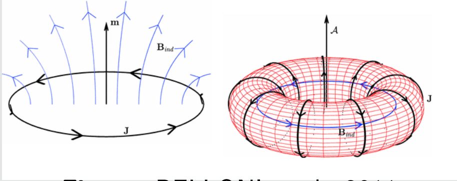


Figure: PELLONI et al., 2011

Anapole Dark Matter

Current term $\overline{u}(\mathbf{p})\Gamma_\mu(q)u(\mathbf{p})$

$$\bar{u}(p_1)\mathcal{O}^\mu(q)u(p_2) = \bar{u}(p_1)\left\{F_1(q^2)\gamma^\mu + \frac{i\sigma^{\mu\nu}}{2m}q_\nu F_2(q^2) + \right.$$

$$\left. i\epsilon^{\mu\nu\alpha\beta}\frac{\sigma_{\alpha\beta}}{4m}q_\nu F_3(q^2) + \frac{1}{2m}\left(q^\mu - \frac{q^2}{2m}\gamma^\mu\right)\gamma_5 F_4(q^2)\right\}u(p_2).$$

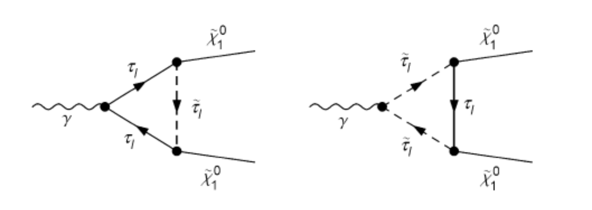


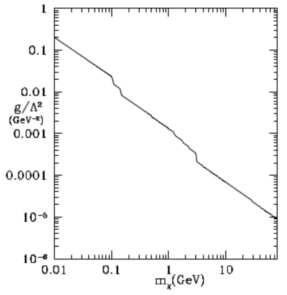
Figure: Anapole Dark Matter (CABRAL-ROSETTI; MONDRAGÓN; REYES-PÉREZ, 2016).

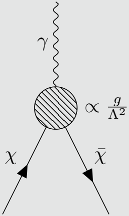
Chiu Man Ho and Robert J. Scherrer (e-print 1211.0503)

$$\mathcal{L}_{int} = \frac{g}{\Lambda^2}\, \bar{\chi}\gamma^{\mu}\gamma^{5}\chi\, \partial^{\nu} F_{\mu\nu}\,,$$

$$\Omega_\chi h^2 = (\,2.14 \times 10^9\,)\, \frac{x_f^2\, (\mathrm{GeV})^{-1}}{g_*^{1/2}\, M_{Pl}\sigma_0} \qquad \langle\, \sigma_{\chi\bar{\chi}\to f\bar{f}}\, v_{\mathrm{rel}} \rangle = \frac{4g^2 \alpha m_\chi^2}{\Lambda^4} \left(\frac{T}{m_\chi}\right),$$

$$x_f = \ln\left[0.076\left(\frac{g_\chi}{g_*^{1/2}}\right) M_{Pl}\, m_\chi \sigma_0\right] - \frac{3}{2}\ln\ln\left[0.076\left(\frac{g_\chi}{g_*^{1/2}}\right) M_{Pl}\, m_\chi \sigma_0\right].$$





Anapole Dark Matter

Thus, we perform a mono-Z search in the leptonic channel at the LHC. Our signal is.

$$pp \to Z + \gamma^* \to \ell^+\ell^- + \chi\overline{\chi}$$

where $\ell = \mu, e$ come from the Z boson and the dark matter pair from the virtual photon. The backgrounds considered in this work are

$$\begin{array}{ll}
\text{Irreducible:} & ZZ(\gamma^*) \to \ell^+\ell^- + \nu_\ell\overline{\nu}_\ell \\
\text{Irreducible:} & W^+W^- \to \ell^+\ell'^- + \nu_\ell\overline{\nu}_{\ell'} \\
\text{Reducible:} & ZW \to \ell^\pm\ell^\mp\ell'^\pm + \nu_{\ell'} \\
\text{Reducible:} & t\bar{t} \to W^+W^-b\bar{b} \to \ell^+\ell'^- + \nu_\ell\overline{\nu}_{\ell'} + jj
\end{array}$$

Triggers

$$p_T(\ell) > 20 \text{ GeV}, \quad |\eta_\ell| < 2.5, \quad \Delta R_{\ell\ell} > 0.4, \quad \not{E} > 20 \text{ GeV}$$

Anapole Dark Matter

$$p_T(\ell) > 20\ \text{GeV}, \quad |\eta_\ell| < 2.5, \quad \Delta R_{\ell\ell} > 0.4, \quad \not{E} > 20\ \text{GeV}$$

Signals	100 GeV	200 GeV	300 GeV	400 GeV	500 GeV
σ(fb)	0.143	0.119	0.095	0.073	0.056
Backgrounds	ZZ	WW	ZW	$t\bar{t}$	Wt
σ(fb)	152.4	1.5×10^3	236.2	1.4×10^4	584.9

Table: $\mathcal{L} = 3\text{ab}^{-1}$, $m_\chi = (100 - 500)\,\text{GeV}$ with $\Lambda = 1\,\text{TeV}$ e $\sqrt{s} = 13\,\text{TeV}$ (*LHC*).

$$N_{\text{events}} = \epsilon \times \sigma \times \mathcal{L}_{\text{int}},$$

$$\begin{aligned}
&\text{Sinal:} && pp \to Z + \gamma^* \to \ell^+\ell^- + \chi\bar{\chi} \\
&\text{Irreducible:} && ZZ(\gamma^*) \to \ell^+\ell^- + \nu_\ell\bar{\nu}_\ell \\
&\text{Irreducible:} && W^+W^- \to \ell^+\ell'^- + \nu_\ell\bar{\nu}_{\ell'} \\
&\text{Reducible:} && ZW \to \ell^\pm\ell^\mp\ell'^\pm + \nu_{\ell'} \\
&\text{Reducible:} && t\bar{t} \to W^+W^-b\bar{b} \to \ell^+\ell'^- + \nu_\ell\bar{\nu}_{\ell'} + jj.
\end{aligned}$$

Results Multivariate Analysis: Cuts + BDT

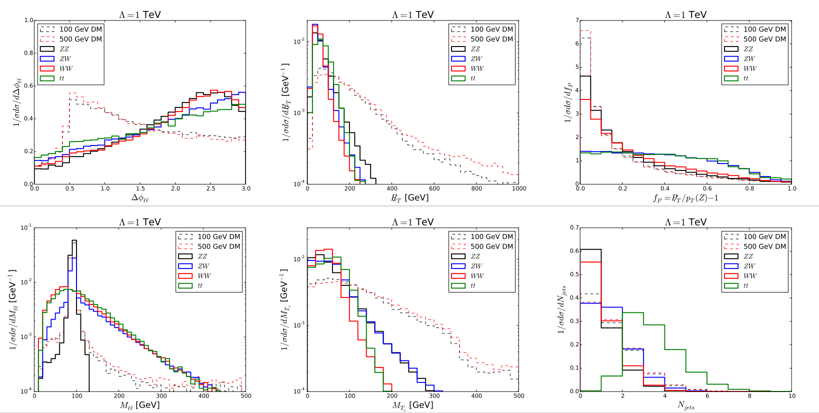


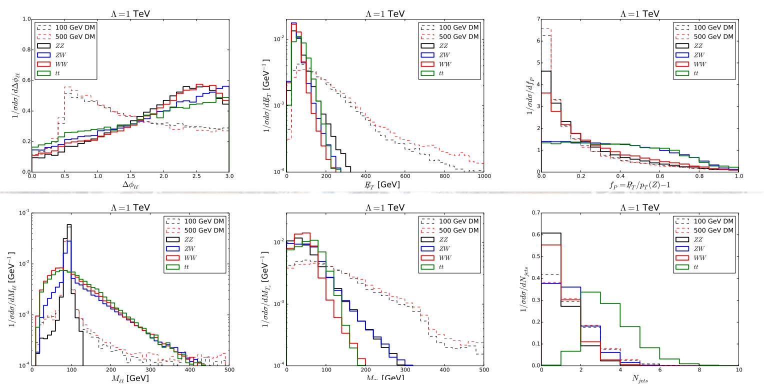
Figure: 10.1103/PhysRevD.97.055023

Results Multivariate Analysis: Cuts + BDT

Variable	min	max	step
$\not{E}_T(>)$	50	150	1
$n_j(\leq)$	0	8	1
`Number of Trees` $(\geq)$	70	250	1
`Maximum depth` $(\leq)$	5	10	1
`Learning Rate` $(=)$	0.01	0.5	0.02
`Minimum Child Weight` $(\leq)$	1	10	1.

`Hyperopt`

- Missing Energy $\not{E}_T$.
- Invariant Mass of the opposite sign leptons
- $\not{E}_T \times \cos\left(\Delta\phi(\vec{E}_T^{miss}, \vec{p}_T^Z)\right)$.
- $|\not{E}_T - p_T^Z|/p_T^Z$.
- $\Delta\phi(\ell^+, \ell^-)$.
- $\alpha_T = E_T(\ell_2)/M_T$.
- $\cos(\theta^*)$.
- $M_{T_c} = \sqrt{2\left(\vec{p}_{T_\ell} \cdot \vec{p}_{T_\ell} + p_{T_\ell} p_{T_\ell}\right)}$.
- n_ℓ, number of leptons.
- n_j, number jets.



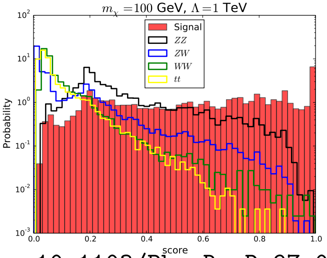
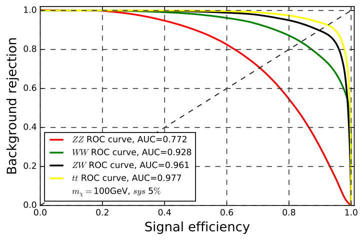
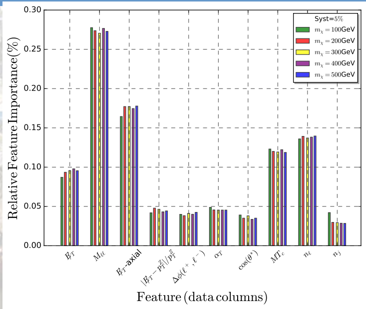
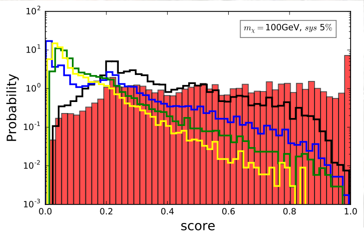


Figure: 10.1103/PhysRevD.97.055023

Results Multivariate Analysis: Cuts + BDT







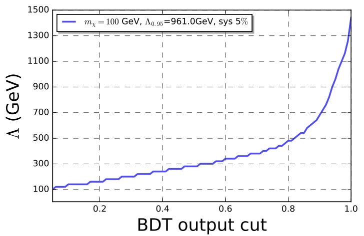


Figure: *BDT* Performance.

Results Multivariate Analysis: Cuts + BDT

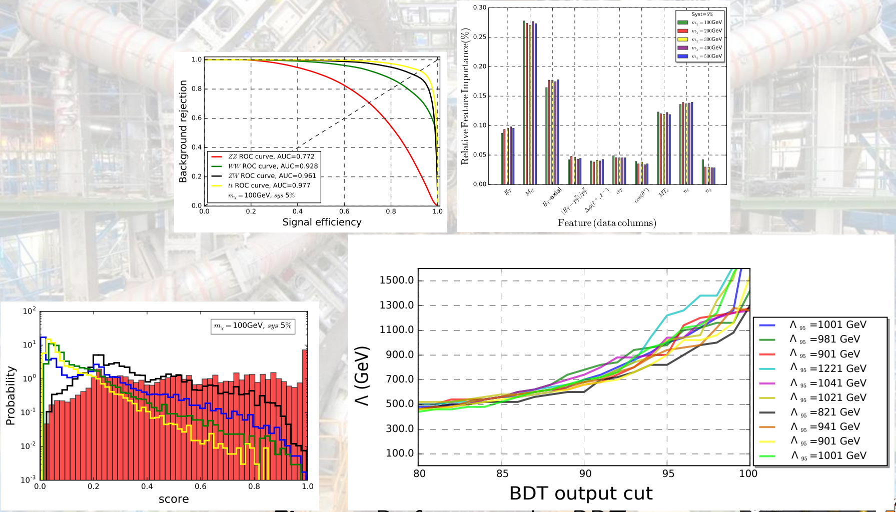
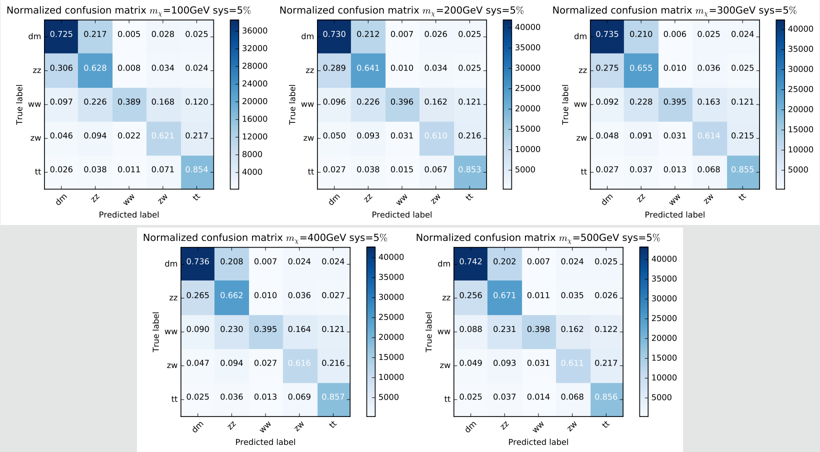


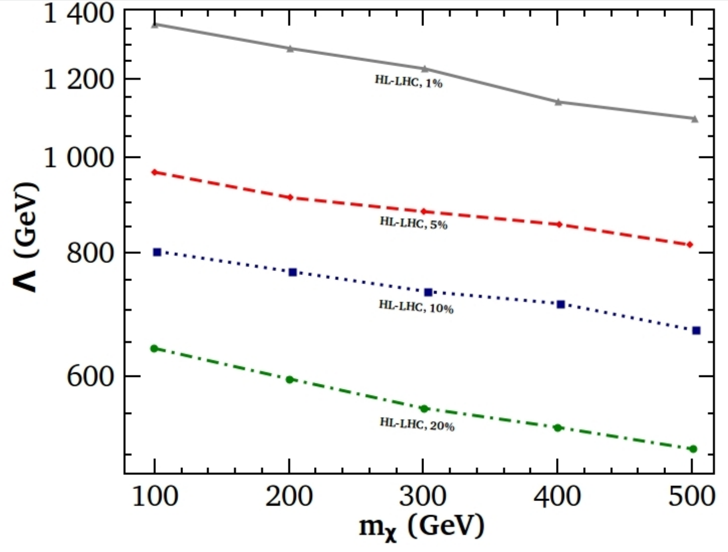
Figure: Performance das *BDT*

DARK MATTER AND WEAK INTERACTIONS (DARKWIN) CONFERENCE

Results Multivariate Analysis: Cuts + BDT



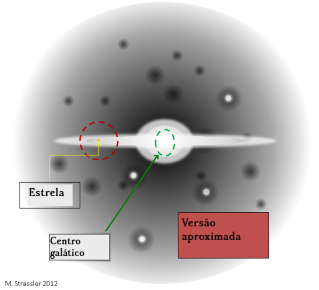
Results Multivariate Analysis: Cuts + BDT

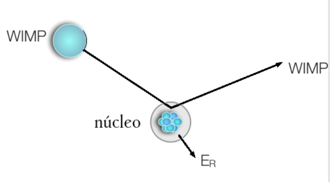


Direct Detection

$$\frac{dR}{dE}(E,t) = \frac{\rho_{\mathrm{ME}}}{m_{\mathrm{ME}} m_A} \int d^3v \; v f(\boldsymbol{v},t) \frac{d\sigma_{MN}}{dE}(E,v),$$

$$\mathcal{L}_{CI} = \alpha_q \, \bar{\chi}\chi \, \bar{q}q \neq \frac{g}{\Lambda^2} \, \bar{\chi}\gamma^\mu\gamma^5\chi \, \partial^\nu F_{\mu\nu}$$





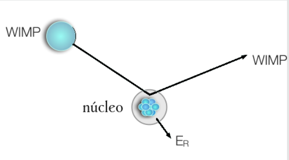
Direct Detection

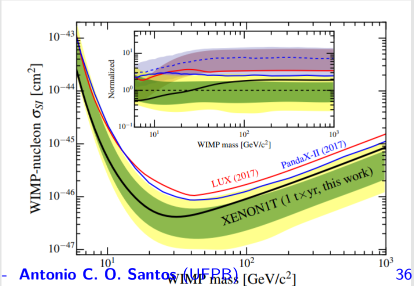
$$\frac{dR}{dE}(E,t) = \frac{\rho_{\rm ME}}{m_{\rm ME} m_A} \int d^3v \; v f(\boldsymbol{v},t) \frac{d\sigma_{MN}}{dE}(E,v),$$

$$\mathcal{L}_{CI} = \alpha_q \, \bar{\chi}\chi \, \bar{q}q \;\; \neq \;\; \frac{g}{\Lambda^2} \, \bar{\chi}\gamma^\mu\gamma^5\chi \, \partial^\nu F_{\mu\nu}.$$

$$\frac{d\sigma}{dE_R}_{\text{Anapole}} = \frac{1}{2\,\pi}\left(\frac{g}{\Lambda^2}\right)^2 Z^2\, e^2\, m_N \left\{ 1 - \left(1 - \frac{2\,M_{\chi N}^2}{m_N^2} \right) \frac{m_N\, E_R}{2\,M_{\chi N}^2\, v^2} \right\} |F_c(E_R)|^2 \; ,$$

$$\frac{d\sigma_{MN}}{dE}(E,v)_{\rm CI} = \frac{m_N}{2\mu_A^2 v^2} \sigma_0^{\rm SI} |F_c(E_R)|^2.$$

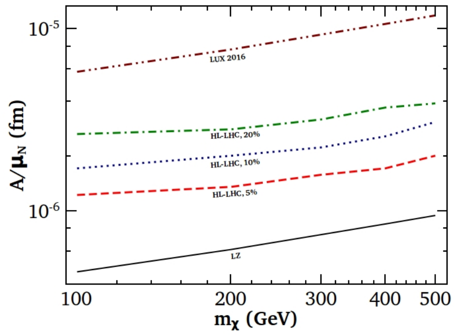




Results - Direct Detection

Considering an effective Lagrangian,

$$\mathcal{L}_{\text{DM-nucleon}} = \frac{i\mathcal{A}}{2}\overline{\chi}\gamma^{\mu}\gamma^{5}\chi\partial^{\nu}F_{\mu\nu} + eA_{\mu}J^{\mu}.$$



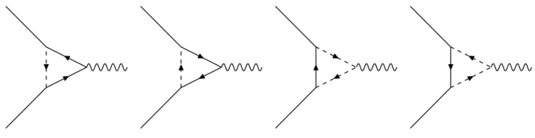
Simplified Model

$$\mathcal{L}_{\text{int}} = \lambda_L \widetilde{f}_L^* \overline{\chi} P_L f + \lambda_R \widetilde{f}_R^* \overline{\chi} P_R f + \text{c.c.}. \quad m_{\widetilde{f}} \sim 250\,\text{GeV} \to \Lambda \sim 800\,\text{GeV}$$

$$\begin{pmatrix} \widetilde{f}_1 \\ \widetilde{f}_2 \end{pmatrix} = \begin{pmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{pmatrix} \begin{pmatrix} \widetilde{f}_L \\ \widetilde{f}_R \end{pmatrix}.$$

$$\mathcal{M}^\mu = i\mathcal{A}(q^2)\overline{u}(p')\left(q^2\gamma^\mu - \not{q}\, q^\mu\right)\gamma^5 u(p).$$

$$\begin{aligned}\mathcal{A}(q^2) = {} & e\left(|\lambda_L|^2\cos^2\alpha - |\lambda_R|^2\sin^2\alpha\right) X_1(q^2) \\ & + e\left(|\lambda_L|^2\sin^2\alpha - |\lambda_R|^2\cos^2\alpha\right) X_2(q^2).\end{aligned}$$

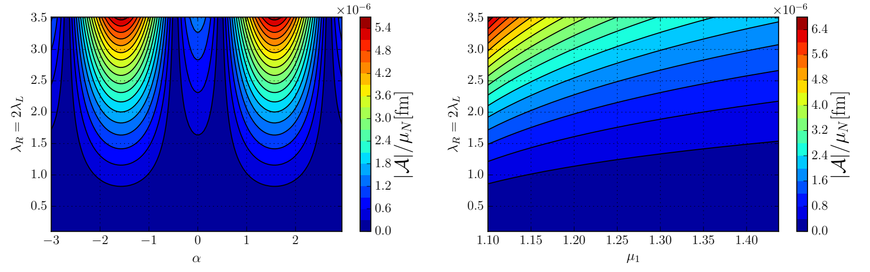


(a) $\mathcal{M}_1$ (b) $\mathcal{M}_2$ (c) $\mathcal{M}_3$ (d) $\mathcal{M}_4$

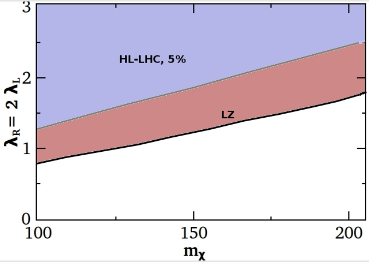
Simplified Model

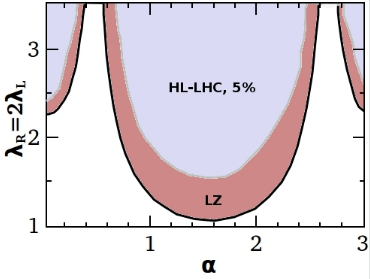
$$\mathcal{A}(q^2) = e\left(|\lambda_L|^2\cos^2\alpha - |\lambda_R|^2\sin^2\alpha\right)X_1(q^2) + e\left(|\lambda_L|^2\sin^2\alpha - |\lambda_R|^2\cos^2\alpha\right)X_2(q^2)$$

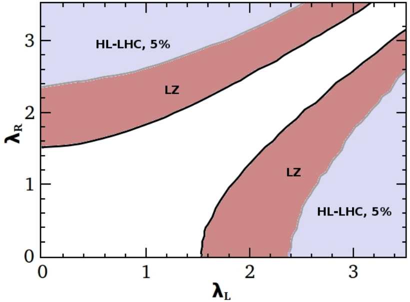
$$\begin{cases} \Lambda^2 \sim 96\pi m_{\tilde{f}_1}^2, \\ g \sim \mu_1/\sqrt{\delta} \sim \mathcal{O}(1). \end{cases}$$



Anapole DM - Discovery Potential in *LHC*- Simplified Model







Outline

Conclusions

- Considering 1% of systematics uncertainties, for a DM mass equal to $100\,\mathrm{GeV}$, *LHC* can probe $\Lambda \lesssim 1.1\,\mathrm{TeV}$, and for 5%, $\Lambda \lesssim 900\,\mathrm{GeV}$, considering $\mathcal{L}_{\text{int}} = 3\,ab^{-1}$[a]. The discovery reach (5σ) in Λ decreases approximately by $200\,\mathrm{GeV}$ for a given heavier DM mass.
- We compare the EFT with a simplified model. We choose a weakly coupled UV completion in which the DM is a Majorana fermion χ that couples to an uncolored fermion f (with mass m_f) and a pair of charged scalars $\widetilde{f}_{L,R}$. At one loop, the DM couples to the photon through an anapole moment interaction.
- The *LHC* discovery potential were compared with the next generation of direct detection experiment, in particular, as an example, the LUX-ZEPLIN (2025). **Showing that the *LHC* has competitive results.**

[a] https://project-hl-lhc-industry.web.cern.ch/content/project-schedule

Conclusions - Confirmed improvement

ML in HEP

- Use of Machine Learning (a.k.a Multi Variate Analysis as we call it) already at LEP somewhat, much more at Tevatron (Trees)
- At LHC, Machine Learning used almost since first data taking (2010) for reconstruction and analysis
- In most cases, Boosted Decision Tree with Root-TMVA, on ~10 variables
- For example, impact on Higgs boson sensitivity at LHC:

analysis	data taking year	no ML sensitivity	ML sensitivity	ML data gain
ATLAS $H \to \gamma\gamma$ [16]	2011-2012	4.3	-	-
CMS $H \to \gamma\gamma$ [17]	2011-2012	?	2.7	?
ATLAS $H \to \tau^+\tau^-$ [18]	2012	2.5	3.4	85%
CMS $H \to \tau^+\tau^-$ [19]	2012	3.7	-	-
ATLAS $VH \to bb$ [20]	2012	1.9	2.5	73%
ATLAS $VH \to bb$ [21]	2015-2016	2.8	3.0	15%
CMS $VH \to bb$ [22]	2012	1.4	2.1	125%
CMS $VH \to bb$ [23]	2015-2016	-	2.8	-

➔~50% gain on LHC running

Advances in ML in HEP, David Rousseau, Uppsala seminar, 25 Oct 2017 3

Figure: From David Rousseau LaL-Orsay

Discovery

Figure: http://static6.businessinsider.com/

Figure: https://www.marketwatch.com/story/