

Future lepton collider prospects for a composite pseudo-scalar

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Based on recent work

in collaboration with Alan Cornell, Aldo Deandrea, Benjamin Fuks

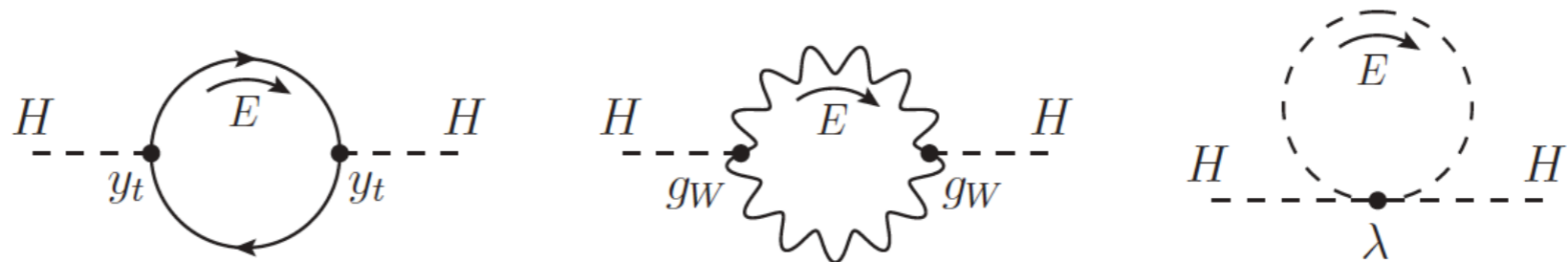
FCC-ee meeting

21 January 2021

Composite Higgs models at future colliders

- Composite Higgs models: new strong sector confining at low energies
- Higgs is a **bound state of fermions**
- Will be accompanied by **light** bound states
- First hints of compositeness?
- ‘Factories’ at new colliders can be used in targeted low mass searches

- Motivations for a composite Higgs model: addressing the hierarchy problem (Higgs sector unstable with respect to quantum corrections)



The FCC-ee may open the door to compositeness

In this talk

“Future lepton collider prospects for a ubiquitous composite pseudo-scalar”
in Physical Review D (10.1103/PhysRevD.102.035030) ([2004.09825](#))

A (brief) theory motivation

- Composite Higgs models predict the existence of a **light pseudo-scalar a , produced in association with the Higgs**
- Possibilities for global symmetries and gauge groups are broad: we will define 12 models (fundamental fermions)

Analysis outline

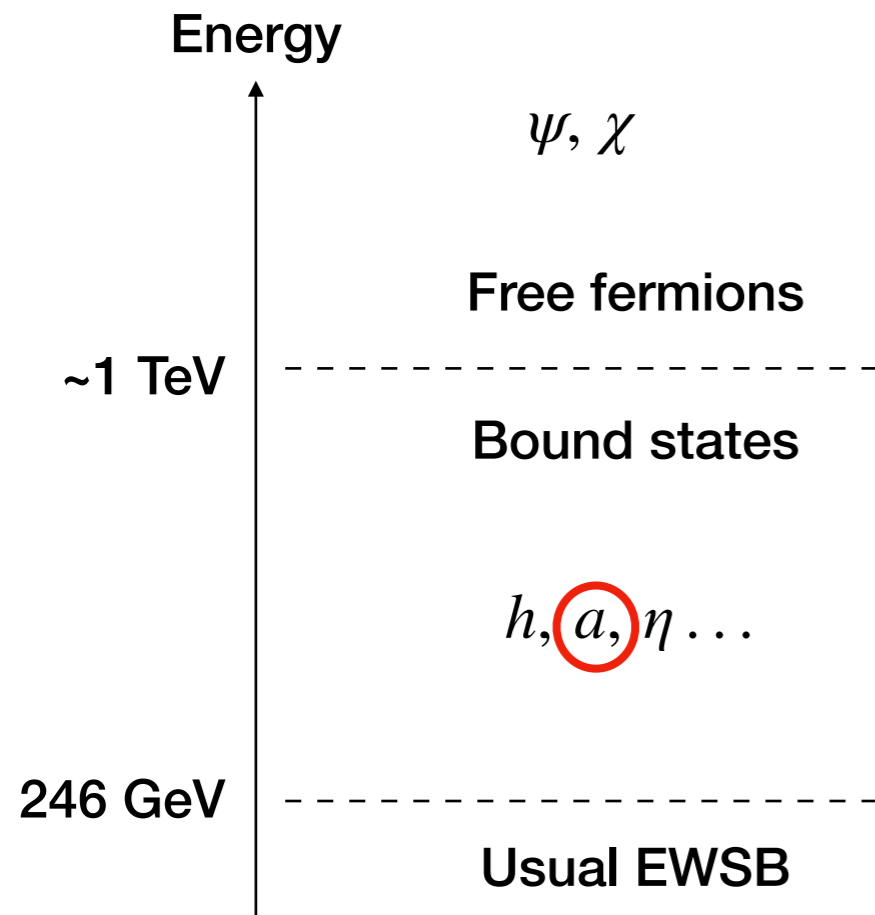
- Targeted low mass search for BSM physics:
- Consider $m_a \in [10,60]$ GeV: deficiency of (LHC) searches thus far
- **Possible search avenue at lepton colliders (FCC-ee)** with low c.m. + high integrated luminosity = possibility for detection of weakly interacting particles
- Z pole c.m. energy + 150 ab^{-1}
- **Cut and count vs machine learning using boosted decision trees**

A. A theoretical motivation

B. Building an analysis

- Cut and count
- Machine learning

Theoretical background



- A given model has a hypercolour gauge group (unbroken), and ψ, χ in two different irreps of the hypercolour group
- Global (flavour) symmetries of ψ, χ are broken on the order of 1 TeV
- Also broken (by the same mechanism) is a ubiquitous non-anomalous $U(1)$ symmetry

This talk: pseudo-scalar a which is always present in models of this nature

A $U(1)$ pseudo-scalar emerges

The non-anomalous $U(1)$ charge:

- Acts on both ψ, χ
- Broken by (at least) the chiral condensate in the EW (Higgs) sector of the theory
- Results in a **light pNGB**
- Need to make choices about the rest of group structure

M1-M12 First proposed
1312.5330/1610.06591

Ingredients: HC group, choice of fermion representations, EW coset, QCD coset (defined by flavour symmetry)

- We will employ a set of 12 models (M1-M12) spanning a variety of HC and flavour groups
- **Varying group structures + HC:** confining gauge interactions
- Coefficients determined, minimal set of fields
- Most minimal cosets:
 $SU(4)/Sp(4)$, $SU(5)/SO(5)$, $SU(4) \times SU(4)/SU(4)$

For example:

	G_{HC}	EW and QCD coset
M1	$SO(7)$	$\frac{SU(5)}{SO(5)} \times \frac{SU(6)}{SO(6)}$
M2	$SO(9)$	

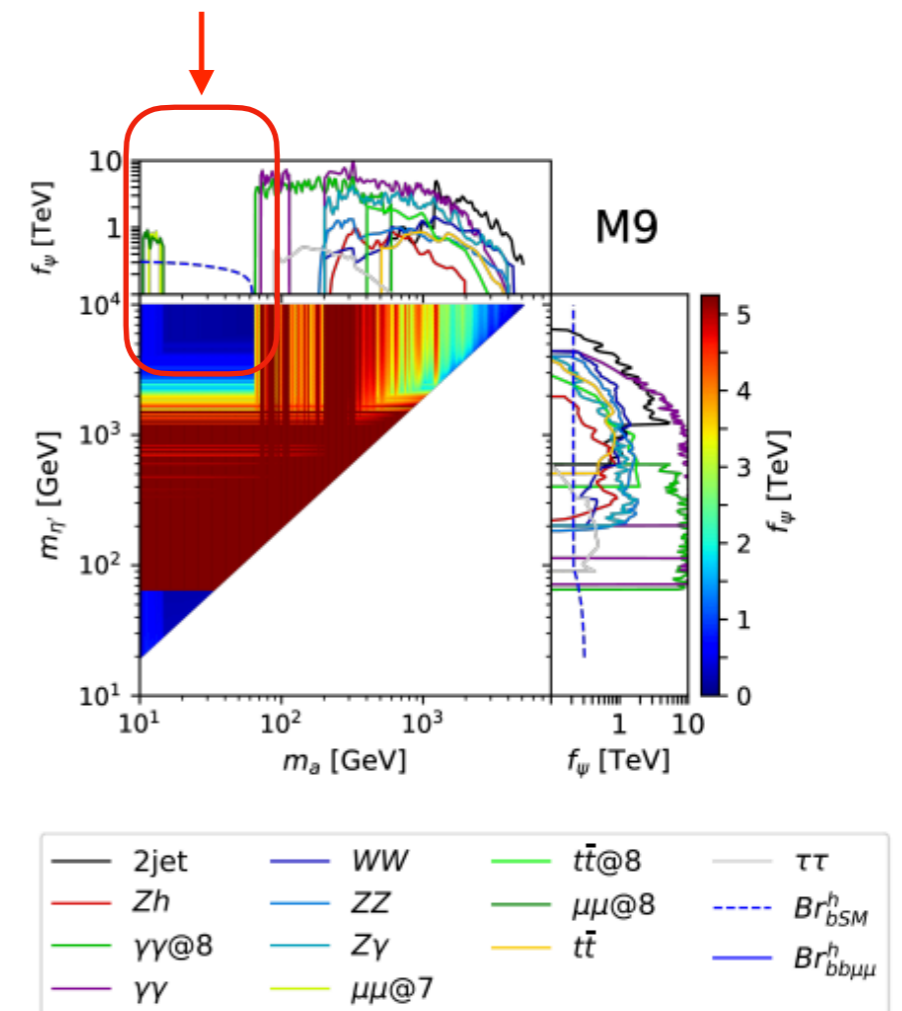
A U(1) pseudo-scalar emerges

How has it evaded detection so far?

- Needs to be weakly coupled - no strong or electric charge
- Small couplings
- Low mass

- Previous searches (di- j /di- μ /di- γ /di- τ) yield poor constraints in low pseudo-scalar mass region
- QCD backgrounds play a role in low mass searches at hadron colliders

Poorly constrained region



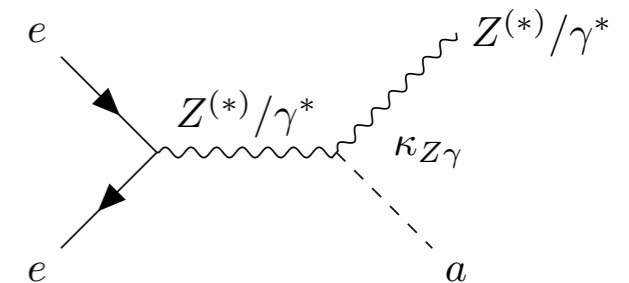
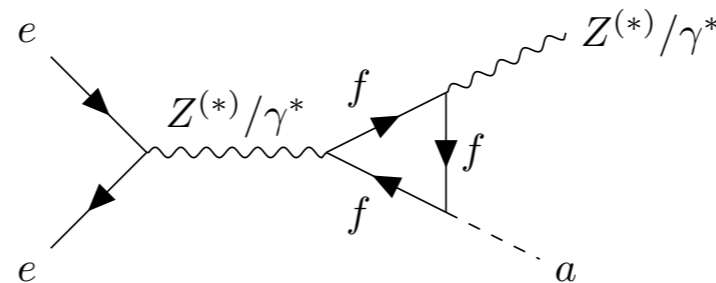
G. Cacciapaglia, G. Ferretti, T. Flacke, and H. Serôdio *Front. in Phys.*, vol. 7, p. 22, 2019.

U(1) pseudo-scalar

$$\mathcal{L} = \frac{1}{2} (\partial_\mu a) (\partial^\mu a) - \frac{1}{2} m_a^2 a^2 - \sum_f \frac{i C_f m_f}{f_a} a \bar{\Psi}_f \gamma^5 \Psi_f +$$

$$\frac{g_s^2 K_g}{16\pi^2 f_a} a G_{\mu\nu}^a \tilde{G}^{a\mu\nu} + \frac{g^2 K_W}{16\pi^2 f_a} a W_{\mu\nu}^i \tilde{W}^{i\mu\nu} + \frac{g'^2 K_B}{16\pi^2 f_a} a B_{\mu\nu} \tilde{B}^{\mu\nu},$$

- **Light**: mass up to 100 GeV
- Small couplings to SM particles
- **Singlet** under SM symmetries
- Couples directly to SM fermion
- Lagrangian input to FeynRules to create UFO



Coupling = SM component (loop of SM fermions)
+ BSM component (effective vertex)

Previous pheno by others in 1710.11142, 1902.06890, focusing on LHC searches

A. A theoretical motivation

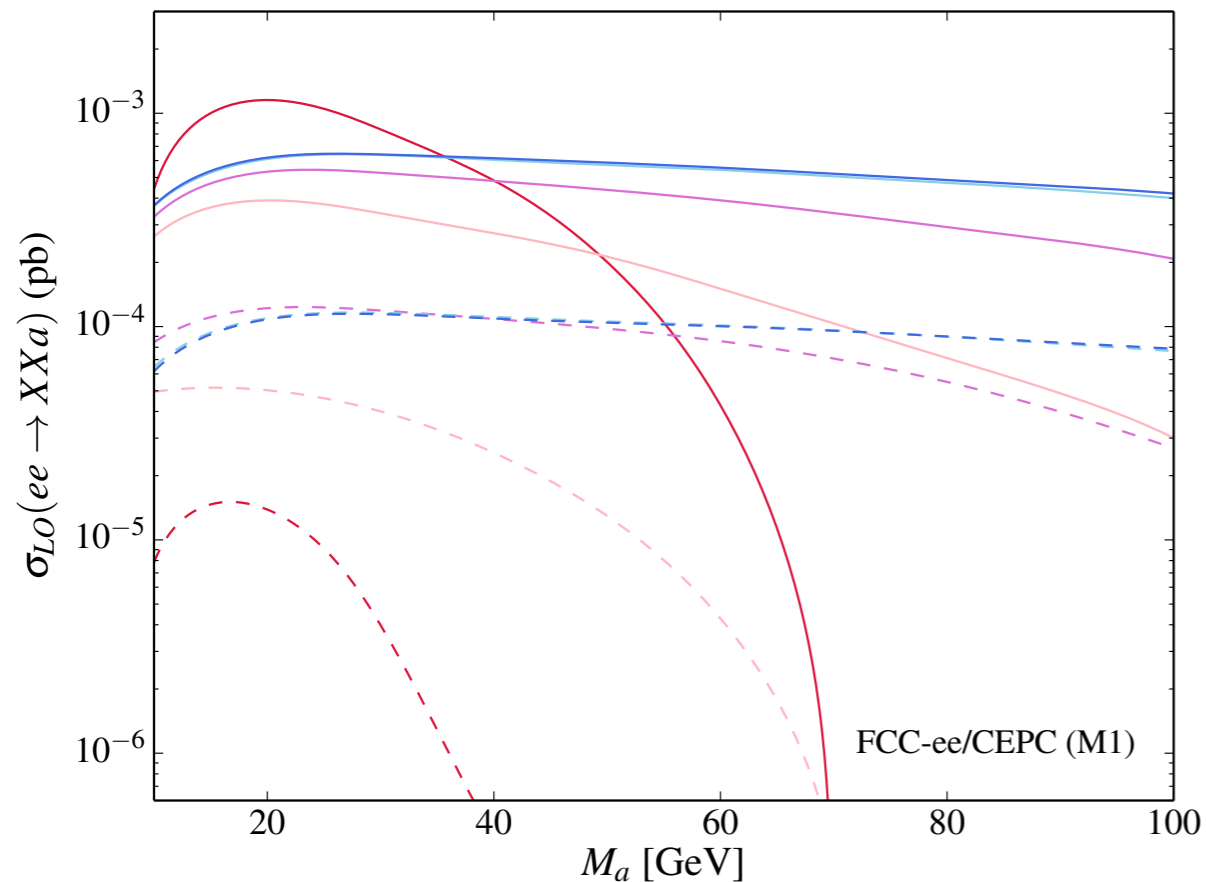
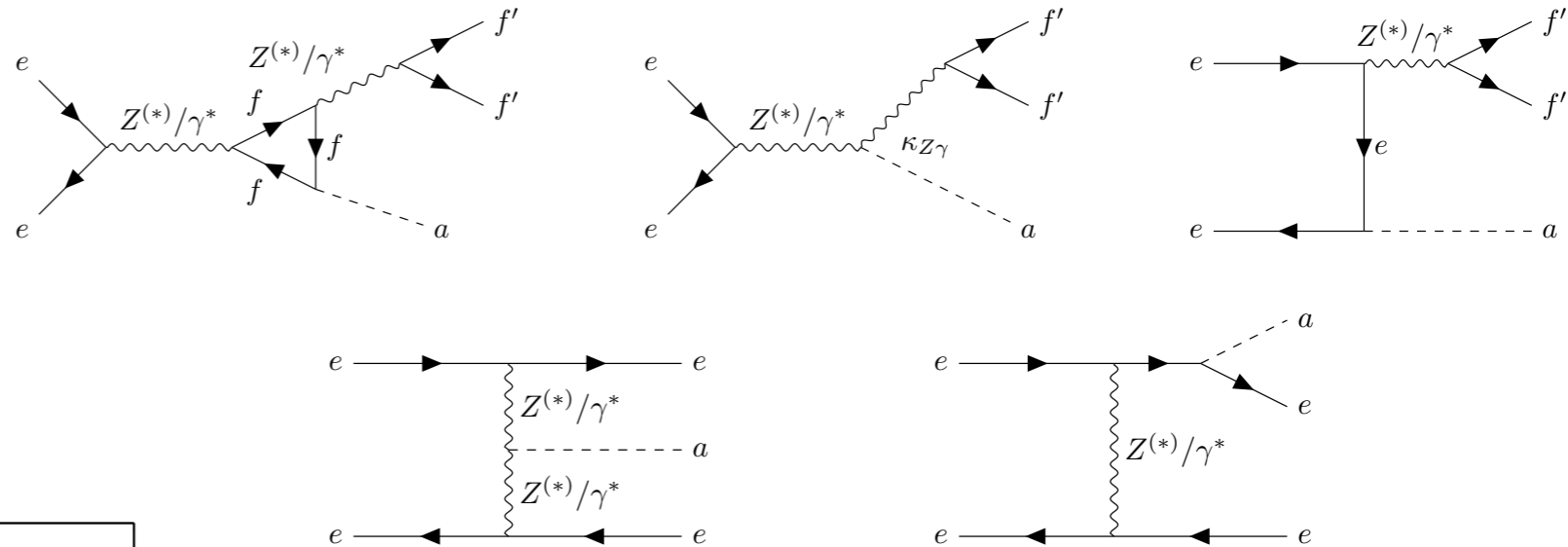
B. Building an analysis

- Cut and count
- Machine learning

Production at lepton colliders

We consider production in association with a (virtual or real) boson at circular colliders:

$$e^+e^- \rightarrow \ell^+\ell^-a, \quad e^+e^- \rightarrow jj a$$



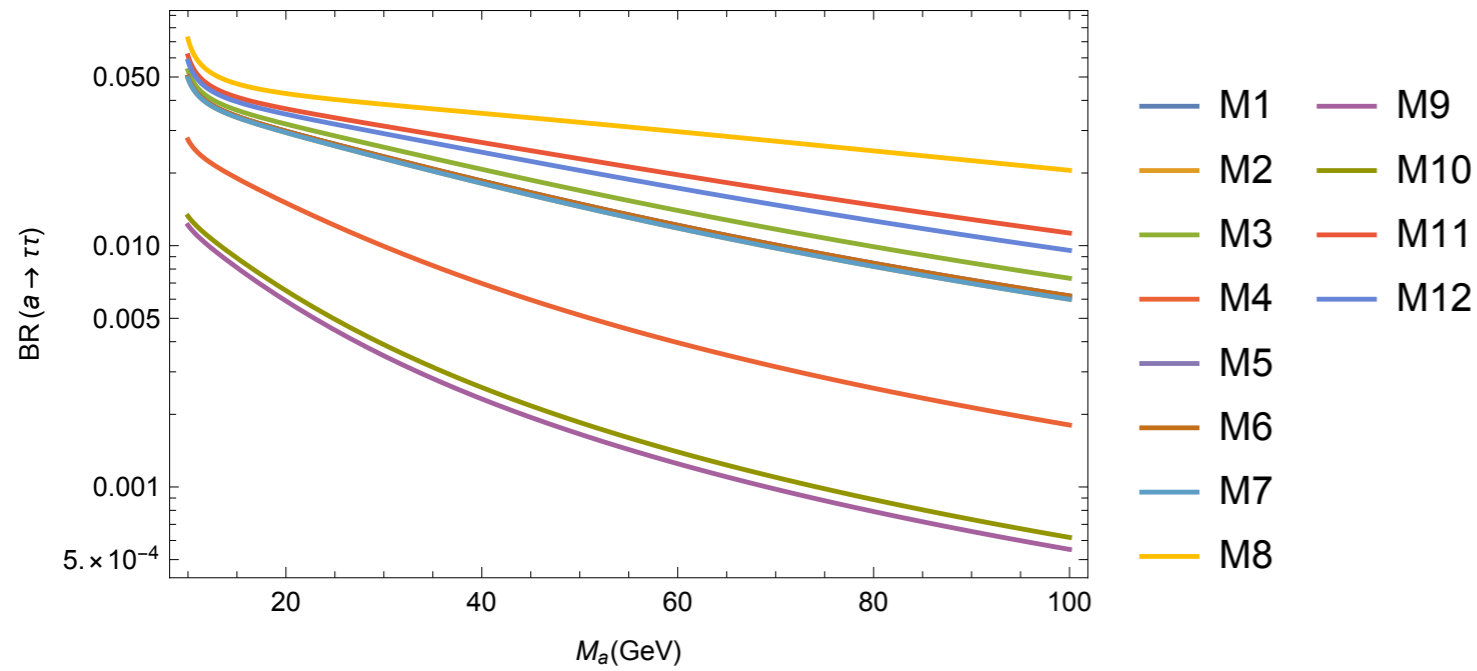
- $\ell^+\ell^-$ 91.2 GeV ($\times 15$)
- $\ell^+\ell^-$ 161 GeV ($\times 15$)
- $\ell^+\ell^-$ 240 GeV ($\times 15$)
- $\ell^+\ell^-$ 350 GeV ($\times 15$)
- $\ell^+\ell^-$ 365 GeV ($\times 15$)
- - - jj 91.2 GeV
- - - jj 161 GeV
- - - jj 240 GeV
- - - jj 350 GeV
- - - jj 365 GeV

$$p_T(j) > 20 \text{ GeV}, \quad |\eta(j)| < 5$$

$$p_T(\ell) > 5 \text{ GeV}, \quad |\eta(\ell)| < 2.5$$

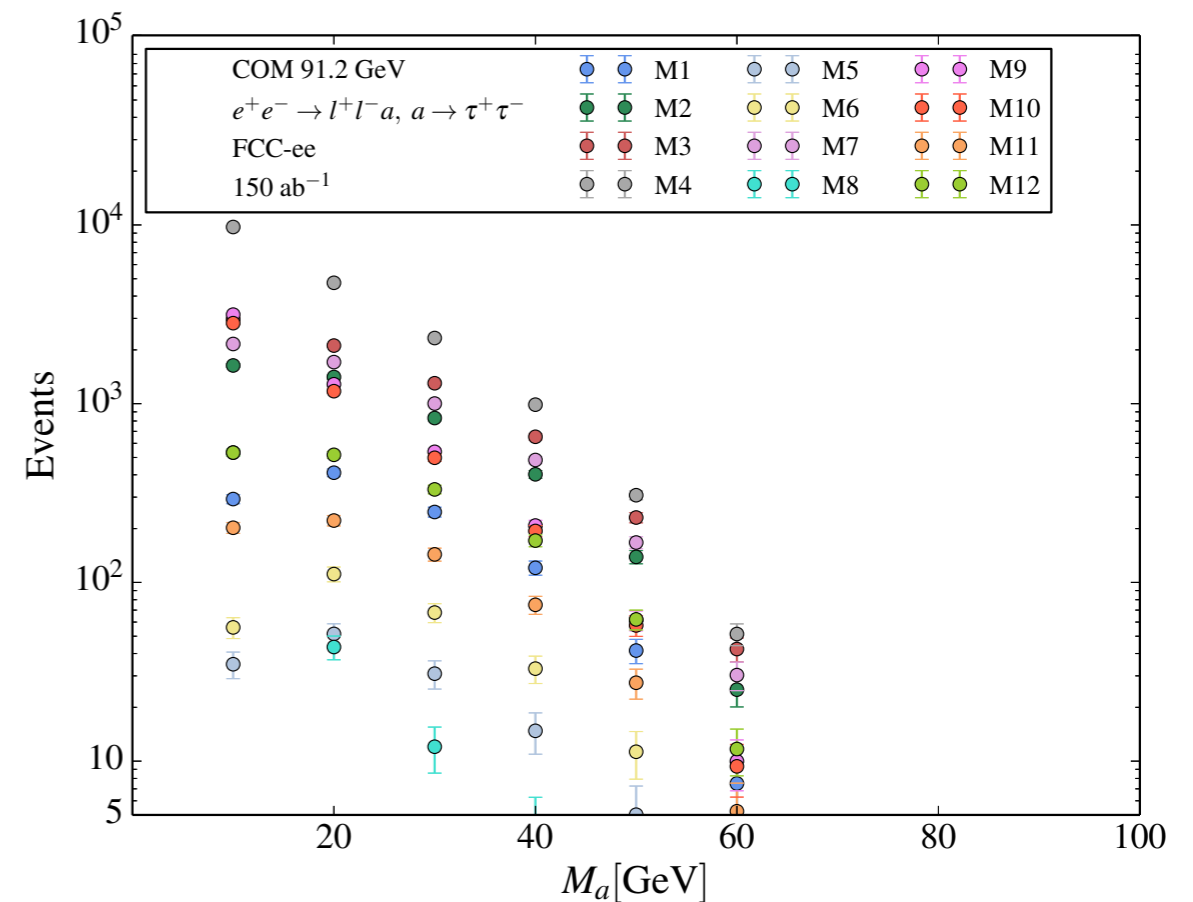
$$\Delta R(\ell, \ell') > 0.4, \quad \Delta R(j, j') > 0.4.$$

FCC-ee: $\tau\tau$ decay



Branching to taus and b-quarks highest
(coupling proportional to fermion mass)

- Consider a produced in conjunction with a pair of OS leptons (avoid multi jet background)
- Signal events expected for subsequent decay to hadronic tau pair
- Sensitivity of machine depends on specifics of model



Analysis

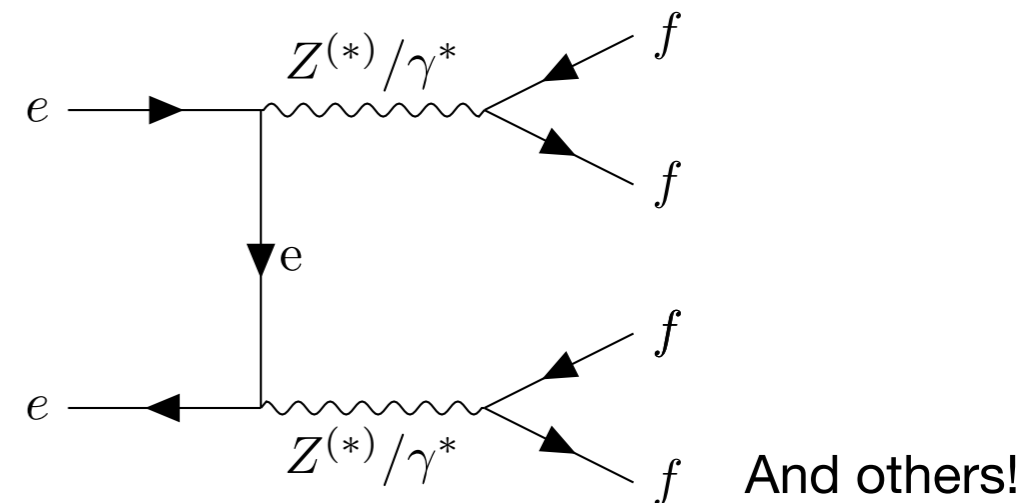
- Signal: $e^+e^- \rightarrow a \ell^+\ell^-$, $a \rightarrow \tau^+\tau^-$ (hadronic taus)

Using MG5_aMC + Pythia

- Z pole: low c.m energy means fewer background processes with 150 ab^{-1}

- FCC-ee IDEA detector concept in Delphes

- Background resulting from (virtual) Z/γ events



Preselection

$$N_{\ell} \geq 2 \text{ with } p_T(\ell) > 10 \text{ GeV}; \quad N_{\tau} \geq 2 \text{ with } p_T(\tau) > 5 \text{ GeV}; \quad M_{\ell\ell} > 12 \text{ GeV}; \quad M_{\tau\tau} > 10 \text{ GeV}.$$

- Following preselection, we expect about **50,000 background events** and up to **40 signal events** (maximal production at $M_a = 20/30 \text{ GeV}$)
- Signal looks swamped by background
- In the following analysis we will proceed with cut and count, and compare with ML
- Choose a sample of models with varying group structures for illustrative purposes

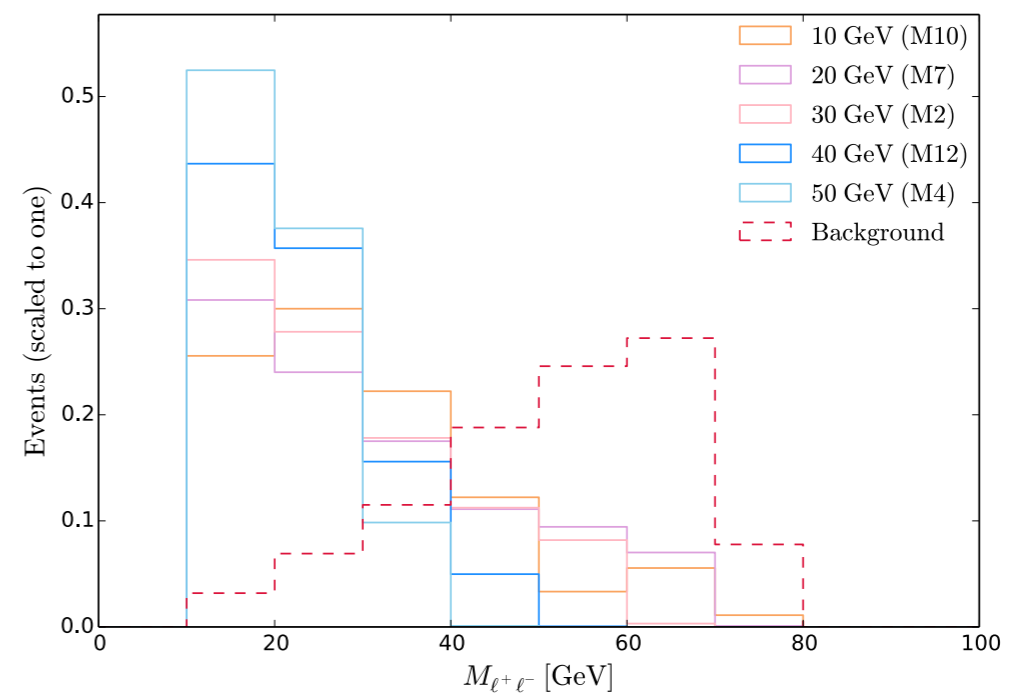
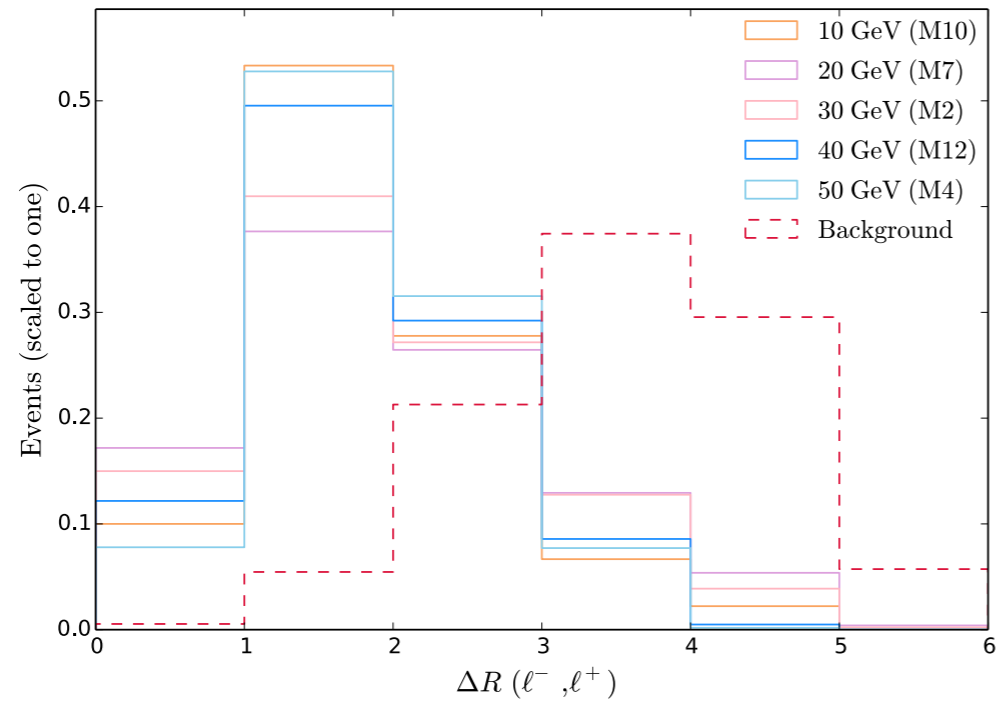
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B. Building an analysis

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- Machine learning

Cut and count



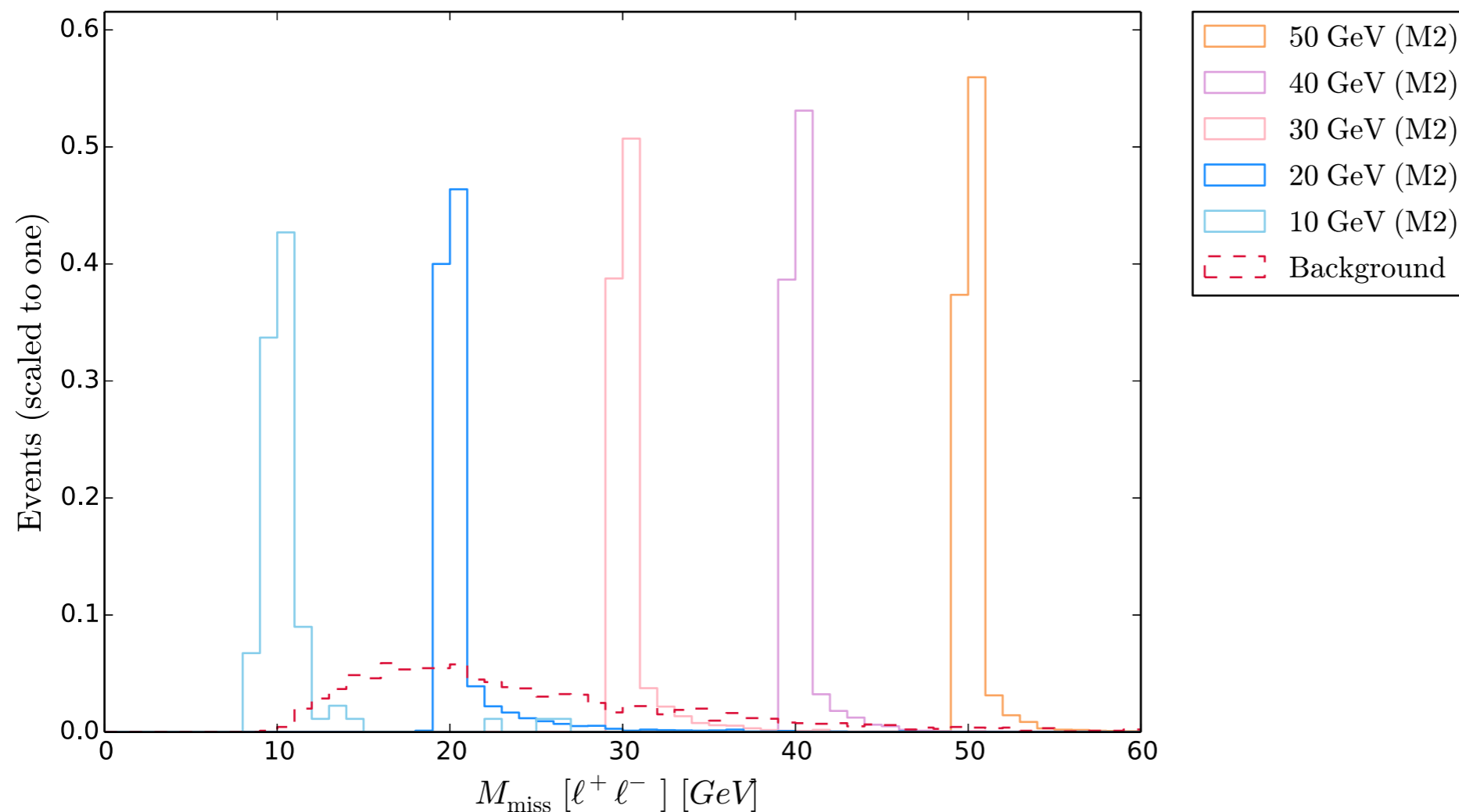
$$\Delta R(\ell^+, \ell^-) < 3 ;$$

$$M_{\ell\ell} < 40 \text{ GeV} .$$

Cut and count with MadAnalysis5

Model	$M_a = 10 \text{ GeV}$	$M_a = 20 \text{ GeV}$	$M_a = 30 \text{ GeV}$	$M_a = 40 \text{ GeV}$	$M_a = 50 \text{ GeV}$
M2	0.0015	0.13	0.090	0.049	0.020
M4	0.0013	0.42	0.26	0.12	0.040
M7	0.0024	0.14	0.11	0.061	0.023
M10	0.0042	0.11	0.055	0.023	0.0078
M12	0.00061	0.047	0.035	0.021	0.017

Cut and count: missing mass



Look promising, but..

Signal dwarfed by sheer scale of background

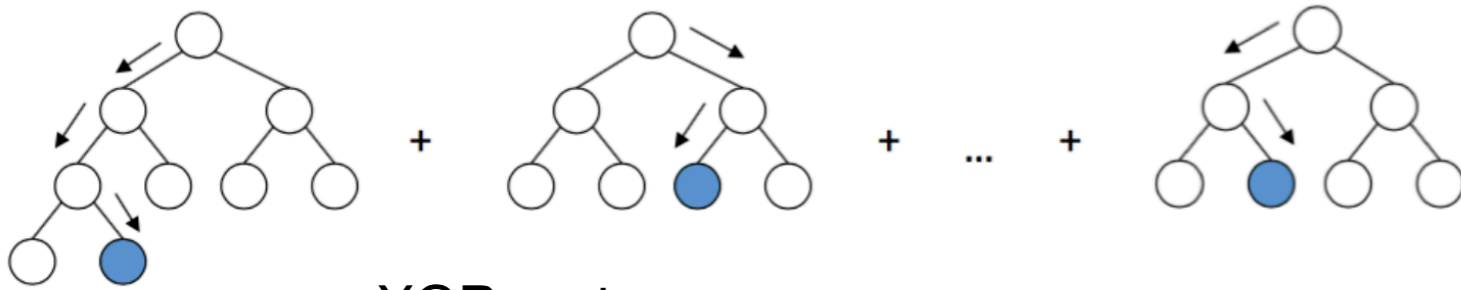
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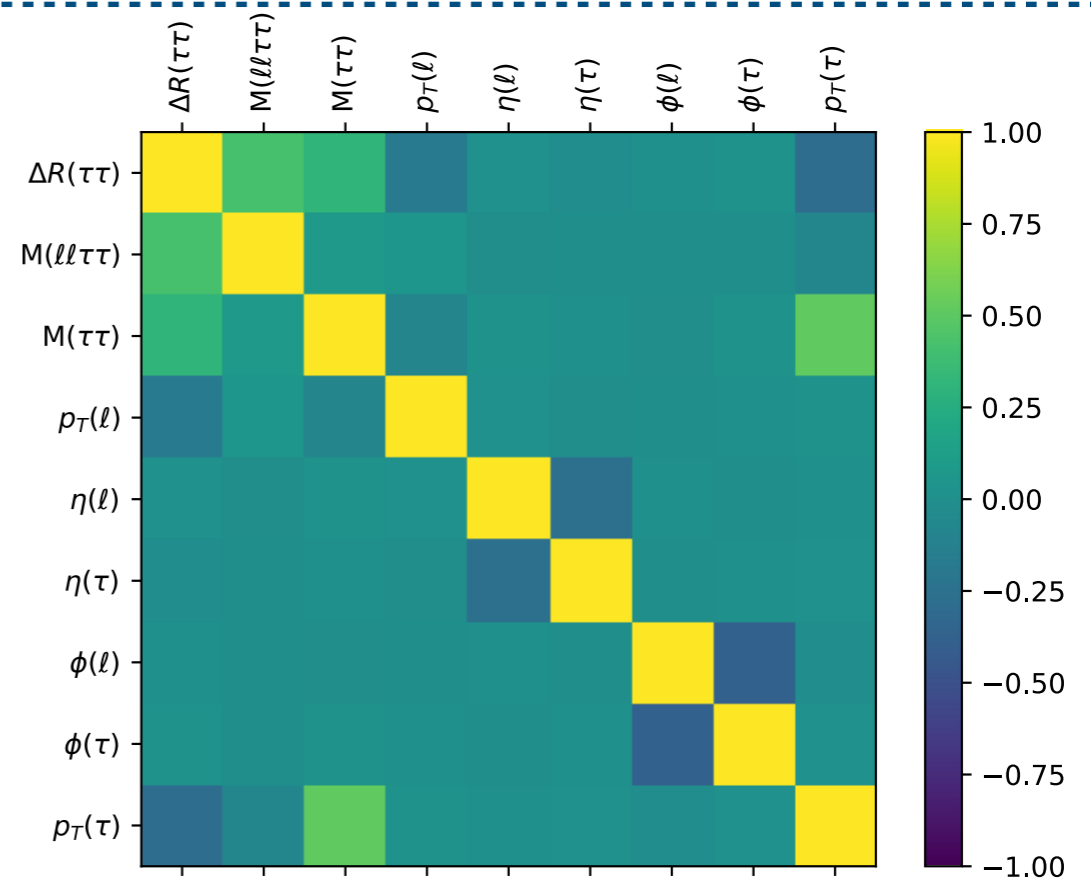
Machine learning: XGBoost



XGBoost:

- Gradient boosting machine learning algorithm
- **Classify signal or background** : Logistic regression for binary classification

- Features optimised to **maximise performance without being too correlated**
- 1:5 test/train split
- Good handling of sparse data
- Trained by maximising *auc*, then calculated significance
- One hyperparameter choice across masses in a given model



Machine learning: XGBoost

- We see a variation across models, with **maximal significance** for $M_a = 20$ GeV

Model	Metric	$M_a = 10$ GeV	$M_a = 20$ GeV	$M_a = 30$ GeV	$M_a = 40$ GeV	$M_a = 50$ GeV
M2	<i>auc</i>	0.98 ± 0.003	0.87 ± 0.006	0.84 ± 0.0013	0.94 ± 0.0058	0.95 ± 0.0066
	<i>ams</i>	0.22	2.96	2.41	0.29	0.11
M4	<i>auc</i>	0.98 ± 0.0045	0.95 ± 0.0029	0.87 ± 0.020	0.88 ± 0.042	0.89 ± 0.061
	<i>ams</i>	1.16	2.83	1.69	0.54	0.15
M7	<i>auc</i>	0.98 ± 0.0018	0.86 ± 0.0082	0.88 ± 0.0011	0.90 ± 0.0012	0.94 ± 0.019
	<i>ams</i>	0.22	3.20	2.58	0.27	0.14
M10	<i>auc</i>	0.98 ± 0.003	0.92 ± 0.0057	0.90 ± 0.019	0.96 ± 0.0078	0.96 ± 0.0050
	<i>ams</i>	0.37	4.08	2.35	0.14	0.042
M12	<i>auc</i>	0.98 ± 0.0075	0.92 ± 0.003	0.92 ± 0.013	0.95 ± 0.0044	0.96 ± 0.0082
	<i>ams</i>	0.066	1.26	0.98	0.11	0.046

A reminder of the cut and count significances:

Model	$M_a = 10$ GeV	$M_a = 20$ GeV	$M_a = 30$ GeV	$M_a = 40$ GeV	$M_a = 50$ GeV
M2	0.0015	0.13	0.090	0.049	0.020
M4	0.0013	0.42	0.26	0.12	0.040
M7	0.0024	0.14	0.11	0.061	0.023
M10	0.0042	0.11	0.055	0.023	0.0078
M12	0.00061	0.047	0.035	0.021	0.017

Future prospects and conclusion

What luminosities are needed?

Model	M_a (GeV)	Cut and Count		Machine Learning	
		2σ	3σ	2σ	3σ
M2	10	2.67×10^8	6.00×10^8	1.24×10^4	2.79×10^4
	20	3.55×10^4	7.99×10^4	68.5	154
	30	7.41×10^4	1.67×10^5	103	232
	40	2.50×10^5	5.62×10^5	7.13×10^3	1.61×10^4
	50	1.50×10^6	3.38×10^6	4.96×10^4	1.12×10^5
M4	10	3.55×10^8	7.99×10^8	446	1.00×10^3
	20	3.40×10^3	7.65×10^3	74.9	169
	30	8.88×10^3	2.00×10^4	210	473
	40	4.17×10^4	9.38×10^4	2.06×10^3	4.63×10^3
	50	3.75×10^5	8.44×10^5	2.67×10^4	6.00×10^4
M7	10	1.04×10^8	2.34×10^8	1.24×10^4	2.79×10^4
	20	3.06×10^4	6.89×10^4	58.5	132
	30	4.96×10^4	1.12×10^5	90.1	203
	40	1.61×10^5	3.63×10^5	8.23×10^3	1.85×10^4
	50	1.13×10^6	2.55×10^6	3.06×10^4	6.89×10^4
M10	10	3.40×10^7	7.65×10^7	4.38×10^3	9.86×10^3
	20	4.96×10^4	1.12×10^5	36.0	81.1
	30	1.98×10^5	4.46×10^5	109	244
	40	1.13×10^6	2.55×10^6	3.06×10^4	6.89×10^4
	50	9.86×10^6	2.22×10^7	3.40×10^5	7.65×10^5
M12	10	1.61×10^9	3.63×10^9	1.38×10^5	3.10×10^5
	20	2.72×10^5	6.11×10^5	378	850
	30	4.90×10^5	1.10×10^6	624	1.41×10^3
	40	1.36×10^6	3.06×10^6	4.96×10^4	1.12×10^5
	50	2.08×10^6	4.67×10^6	2.84×10^5	6.38×10^5

- Significant gains by gradient boosting methods
- Highest and lowest masses remain out of reach
- Possibility to achieve 2σ or even 3σ for several models

Search complementary (parameter space unconstrained) to axionlike searches presented in

M. Bauer et al, Eur. Phys. J. C 79, 74 (2019). [58]

M. Bauer et al, Collider probes of axion-like particles, J. High Energy Phys. 12 (2017) 044.

And to existing diphoton searches A. Mariotti et al, Phys. Lett. B 783, 13 (2018).

- A direct search for a light composite pseudo-scalar at high integrated luminosity lepton colliders should be considered
- Could be separately optimised for the heavier configurations by considering higher c.m. energies.

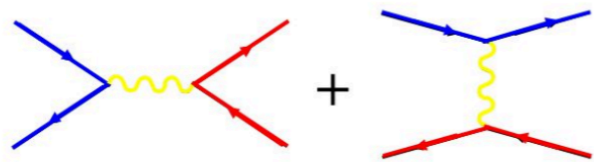
Thank you

Model implementation tools

FEYNRULES 2.0- A complete toolbox for tree-level phenomenology

Adam Alloul^a, Neil D. Christensen^b, Céline Degrande^{c,d},
Claude Duhr^d, Benjamin Fuks^{e,f}

MadGraph + MadEvent



Automated Tree-Level
Feynman Diagram, Helicity Amplitude,
and Event Generation



FeynRules for model building

MG5_aMC for simulation of signal and background processes

Pythia for parton showering and hadronisation

Delphes (+ FastJet) for detector response

Analysis:

MadAnalysis: cut and count

XGBoost: machine learning

Models

- We have ψ, χ in two different irreps of the hypercolour group
- Minimal set of fields
- **M1-M12** including partial compositeness for the top
- **Varying group structures + HC**: confining gauge interactions
- Coefficients determined

First proposed
1312.5330/1610.06591

Ingredients: HC group, choice of fermion representations, EW coset, QCD coset

	G_{HC}	EW and QCD coset	ψ	χ	q_χ/q_ψ
M1	$SO(7)$	$\frac{SU(5)}{SO(5)} \times \frac{SU(6)}{SO(6)}$	$5 \times \mathbf{F}$	$6 \times \mathbf{Sp}$	$-5/6$
M2	$SO(9)$	$\frac{SU(5)}{SO(5)} \times \frac{SU(6)}{SO(6)}$	$5 \times \mathbf{F}$	$6 \times \mathbf{Sp}$	$-5/12$
M3	$SO(7)$	$\frac{SU(5)}{SO(5)} \times \frac{SU(6)}{SO(6)}$	$5 \times \mathbf{Sp}$	$6 \times \mathbf{F}$	$-5/6$
M4	$SO(9)$	$\frac{SU(5)}{SO(5)} \times \frac{SU(6)}{SO(6)}$	$5 \times \mathbf{Sp}$	$6 \times \mathbf{F}$	$-5/3$
M5	$Sp(4)$	$\frac{SU(5)}{SO(5)} \times \frac{SU(6)}{SO(6)}$	$5 \times \mathbf{A}_2$	$6 \times \mathbf{F}$	$-5/3$
M6	$SU(4)$	$\frac{SU(5)}{SO(5)} \times \frac{SU(3)^2}{SU(3)}$	$5 \times \mathbf{A}_2$	$3 \times (\mathbf{F}, \bar{\mathbf{F}})$	$-5/3$
M7	$SO(10)$	$\frac{SU(5)}{SO(5)} \times \frac{SU(3)^2}{SU(3)}$	$5 \times \mathbf{F}$	$3 \times (\mathbf{Sp}, \bar{\mathbf{Sp}})$	$-5/12$
M8	$Sp(4)$	$\frac{SU(4)}{Sp(4)} \times \frac{SU(6)}{SO(6)}$	$4 \times \mathbf{F}_2$	$6 \times \mathbf{A}_2$	$-1/3$
M9	$SO(11)$	$\frac{SU(4)}{Sp(4)} \times \frac{SU(6)}{SO(6)}$	$4 \times \mathbf{Sp}$	$6 \times \mathbf{F}$,	$-8/3$
M10	$SO(10)$	$\frac{SU(4)^2}{SU(4)} \times \frac{SU(6)}{SO(6)}$	$4 \times (\mathbf{Sp}, \bar{\mathbf{Sp}})$	$6 \times \mathbf{F}$	$-8/3$
M11	$SU(4)$	$\frac{SU(4)^2}{SU(4)} \times \frac{SU(6)}{SO(6)}$	$4 \times (\mathbf{F}, \bar{\mathbf{F}})$	$6 \times \mathbf{A}_2$	$-2/3$
M12	$SU(5)$	$\frac{SU(4)^2}{SU(4)} \times \frac{SU(3)^2}{SU(3)}$	$4 \times (\mathbf{F}, \bar{\mathbf{F}})$	$3 \times (\mathbf{A}_2, \bar{\mathbf{A}}_2)$	$-4/9$

A $U(1)$ pseudo-scalar emerges

We will always have singlet pseudo-scalars associated to global $U(1)$ symmetries, (and a coloured octet arising from the presence of coloured underlying fermions)

$$a, \eta', \pi_8$$

a, η' undergo non-trivial mixing. In the decoupling limit,

$$\sin \alpha_{dec} = \frac{1}{\sqrt{1 + \frac{q_\psi^2 N_\psi f_\psi^2}{q_\chi^2 N_\chi f_\chi^2}}}$$

The pNGB \tilde{a} is naturally **lighter** than the typical confinement scale, and the orthogonal $\tilde{\eta}$ is heavier

ψ condensing: the axial $U(1)_\psi$ would be spontaneously broken, but also explicitly broken by a ABJ anomaly

\implies heavy Goldstone.

Also have χ fermions condensing \implies additional axial $U(1)_\chi$ spontaneously broken.

Possible to construct an ABJ anomaly free linear combination $U(1)_a$: associated pseudo-scalar will be light

Machine learning

- Remember the matrix of objects we got from our detector
- The simple cuts in variables weren't enough
- What if we can build an **algorithm** to differentiate the signal from background?

$$X = \begin{array}{c} \xrightarrow{\text{features}} \\ \left[\begin{array}{cccc} x_1^1 & x_1^2 & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^d \\ \vdots & \vdots & \ddots & \vdots \\ x_N^1 & x_N^2 & \cdots & x_N^d \end{array} \right] \\ \downarrow \text{objects} \end{array}$$

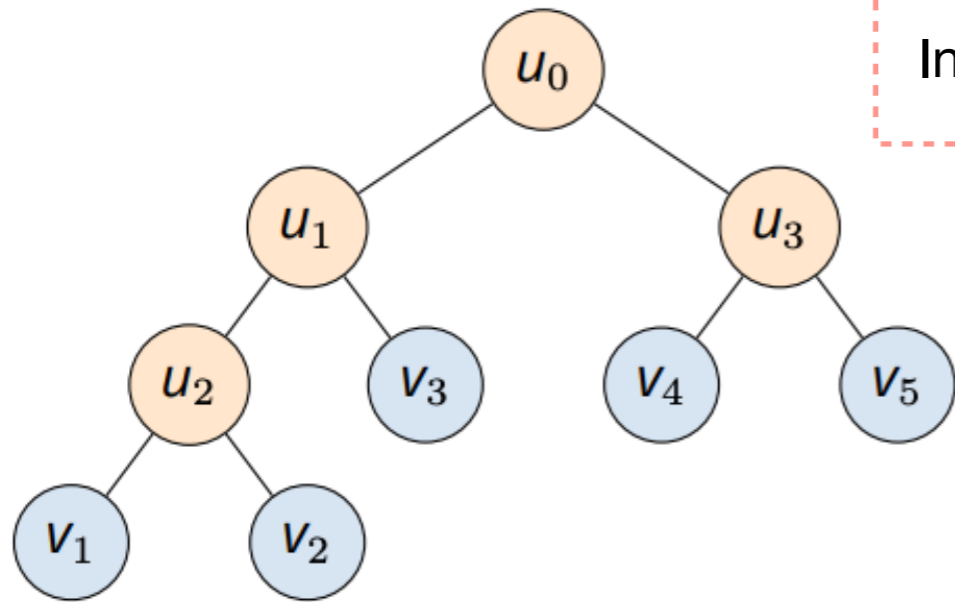
Simulated labelled
(training) data
 $\mathcal{D} = \{x_i, y_i\}, y_i = f(x_i)$

Model: $\hat{f} = \mathcal{A}(\mathcal{D})$

Predicted labels
for our test data: $\{x_j, y_j\}$

Simulated un-labelled
(test) data $\{x_j\}$

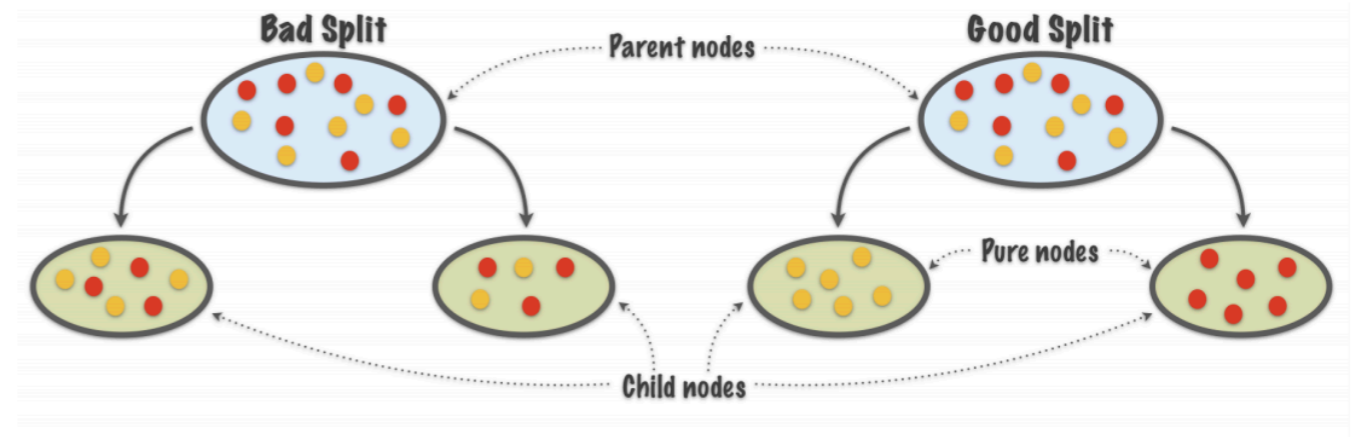
Decision trees



Internal nodes: check value and compare to a threshold

Leaves: allow us to make predictions

- We want to train our tree so that at each node
- we split our data in a sensible way.
- Once the tree is trained, a given object will traverse the tree until it hits a leaf and is classified.



Picture credit: <https://alanjeffares.wordpress.com/tutorials/decision-tree/>

While decision trees are interpretable, they are often not very powerful and can be unstable. A more advanced class of algorithms, ensembles, build on this idea..