# Probing a GeV-scale Scalar Boson and a TeV-scale Vector-like Quark Associated with $U(1)_{T3R}$ at the Large Hadron Collider using Machine Learning

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### Motivation: The Incompleteness of the Standard Model

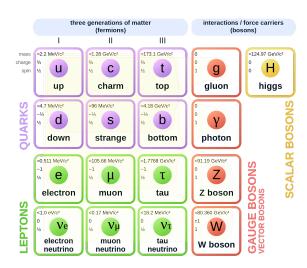


Figure 1: The Standard Model of Particle Physics.

### The Standard Model

The Standard Model (SM) of particle physics is a successful theory describing:

- Three of the four fundamental forces.
- All observed elementary matter particles.

### Incompleteness of the SM

However, it fails to account for:

- Gravity.
- Dark Matter and Dark Energy.
- The Hierarchy Problem.
- Neutrino Masses.
- A plethora of experimental anomalies.

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#### A $U(1)_{T3R}$ Extension of the Standard Model

- There has been recent interest in beyond-the-Standard Model (BSM) physics involving low-mass matter and mediator particles.
- For our study, we probe a  $U(1)_{T3R}$  extension of the SM. In our model,  $U(1)_{T3R}$  is not connected to electric charge and only couples to right-handed SM Fermions.
- The model in this formulation can address:
  - Thermal dark matter abundance.
  - Muon g 2,  $R_D$ , and  $R_{D^*}$  anomalies.
  - Lepton mass hierarchy.

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#### New Fields and Particles

- Three new matter fields are introduced:
  - One complex scalar  $\phi$ .
  - A left and right-handed fermion pair  $\eta_L$  and  $\eta_R$ .
- A set of new vector-like quarks  $(\chi_u, \chi_d, \chi_\mu, \chi_\nu)$  accessible at the LHC.
- A new dark Higgs (scalar boson)  $\phi'$  and a massive dark photon A'.

Our study focuses on the scalar boson  $\phi'$  and the first generation vector-like quark  $\chi_u$ .

#### Experimental Considerations

- The  $\phi'$  particles can be very light at  $\mathcal{O}(\text{MeV})$  or heavy at  $\mathcal{O}(\text{TeV})$ :
  - Mass scales below the electroweak scale have traditionally been difficult to probe at the LHC.
  - SM backgrounds dominate the phase space and are difficult to distinguish from signal.
- ATLAS and CMS Collaborations have excluded  $\chi_u$  (more generally, T) with masses m(T) < 1.3 TeV, for the assumption  $Br(T \rightarrow Ht) + Br(T \rightarrow Zt) + Br(T \rightarrow Wb) = 1$ .
- Since our model introduces an accompanying light scalar boson  $\phi'$ , these limits can be relaxed depending on the  $\chi_u$  branching fraction and  $\phi'$  mass.

#### **Previous Work**

Previous work has looked at  $\mathcal{O}(\text{MeV}) \phi'$  and the  $\phi' \to \gamma \gamma$  decay channel, in a merged diphoton system. This strategy is only effective for  $\mathcal{O}(\text{MeV}) \phi'$  and below.



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# Our Novel Analysis Strategy

### Signal Production

Sensitivity to  $\mathcal{O}(MeV)$  -  $\mathcal{O}(100GeV)$  scalars requires production mechanisms that create boosted topologies.

For this study, we target the production of  $pp \rightarrow t\chi_u \phi'$  through  $\chi_u t$  and gg fusion topologies that lead to:

- $\bullet~{\rm A}~{\rm boosted}~\phi'\to\mu^+\mu^-$
- $t \rightarrow bjj$

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$$\chi_u \to b \mu \nu_\ell$$

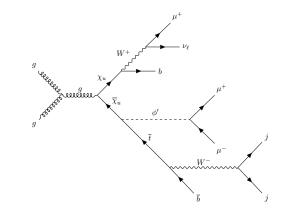
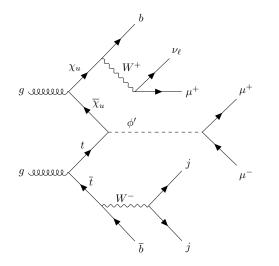


Figure 2: Representative Feynman Diagram for gg Fusion.



### Our Novel Analysis Strategy



#### Figure 3: Representative Feynman Diagram for $\chi_u t$ Fusion.

#### **Final States**

As such, our final state contains:

- A merged dijet system.
- Two bottom tagged jets.
- Three muons.
- Large MET and MPT from neutrinos.



### Standard Model Backgrounds

#### **Background Determination**

Several SM background processes were considered. The two most important backgrounds are  $t\bar{t}$  with associated  $Z/\gamma^*$  radiation and diboson with  $b\bar{b}$  radiation as summarized in Table 1.

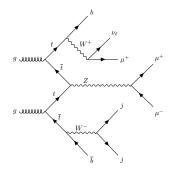


Figure 4: Feynman Diagram for  $t\bar{t}$  with Z radiation.

Process Information	Cross Section [pb]
$pp  ightarrow t\overline{t}\mu^+\mu^-, (t ightarrow W^+b, W^+ ightarrow jj), (\overline{t} ightarrow W^-\overline{b}, W^- ightarrow \mu^- u_\ell)$	0.002574
$pp  ightarrow b \overline{b} \mu \mu \mu  u_\ell$	0.0004692

Table 1: A summary of the dominant Standard Model backgrounds and their respective cross sections calculated using MadGraph with  $n = 10^6$  events.

# Simulating Signal and Background Events

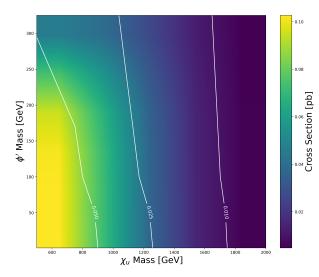


Figure 5: Cross Section vs.  $\phi'$  and  $\chi_u$  Masses.

#### Signal and Background Simulation

Samples  $n = 10^6$  are produced using:

- MadGraph5 for event generation.
- Pythia8 for parton showering and hadronization.
- Delphes for smearing and detector effects.
- The decay widths for  $\chi_u$  and  $\phi'$  are  $\mathcal{O}(\text{GeV})$ .
- The χ<sub>t</sub>tφ' and φ'μ<sup>+</sup>μ<sup>-</sup> couplings are assumed to be unity.

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### Kinematic Analysis

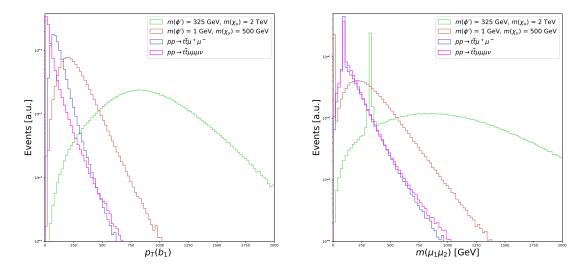


Figure 6:  $p_T(b_1)$  Kinematic Distribution

Figure 7:  $m(\mu_1\mu_2)$  Kinematic Distribution

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### Kinematic Analysis

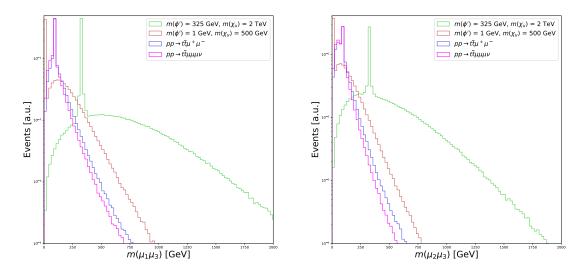


Figure 8:  $m(\mu_1\mu_3)$  Kinematic Distribution

Figure 9:  $m(\mu_2\mu_3)$  Kinematic Distribution

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### Machine Learning: Motivation and Workflow

### Motivation for Machine Learning (ML)

- ML offers sizable advantages over traditional event classification methods.
- In particular, machine learning algorithms consider all kinematic variables concurrently.
- This allows them to reverse the high-dimensional space of event kinematics and enact sophisticated selection criteria.
- This makes them ideal for hep-ph applications.

### Our Machine Learning Workflow

- The analysis of signal and background events is performed using ML algorithms.
- In particular, we consider various deep neural network (NN) architectures and a gradient boosted tree (BDT) classifier.



### Machine Learning: Workflow Details

#### Feature Generation

A MadAnalysis Expert Mode (C++) script is used to generate a CSV file from the event kinematics in MadGraph LHE files. This data was used to train several ML models.

We use a 90-10 train-test split. The training is performed on an Nvidia A100 GPU using PyTorch and XGBoost libraries for the NNs and BDT, respectively. The results are summarized in Table 2.

### ML Model Selection

- BDT: A boosted decision tree with  $\eta = 0.3$ ,  $\gamma = 0$  and max\_depth = 64.
- NN1: 3 fully connected (FC) layers of widths 32, 64, and 1.
- NN2: A NN with 4 FC layers of widths 64, 128, 128, and 1.
- NN3: A NN with 5 FC layers of widths 64, 128, 512, 128, and 1.

All neural networks used a learning rate of 0.01 with an SGD optimizer and were trained for 100 epochs with a batch size of 8192. All layers used a ReLU activation function except for the final layer in each network, which used a sigmoid activation.

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### Machine Learning: Results

Model	Train/Test Accuracy	Training Time
BDT	N.A./0.9993	бs
NN1	0.9999/0.9997	1h 58m
NN2	0.9999/0.9998	2h 12m
NN3	0.9999/0.9998	2h 32m

Table 2: Train/test results for the ML models.

#### Remark

The BDT clearly provides significant training time improvements and greater explainability compared to the deep neural networks. In addition, all models performed similarly in terms of signal significance. Hence, we decided to use the BDT model for all proceeding analyses.



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# Computing Signal Significance

### Signal Significance

- The BDT output distributions are normalized to  $N = \mathcal{L}_{int} \cdot \sigma$  i.e. the integrated luminosity times the cross section.
- A bin-by-bin calculation is used to compute signal significance:

$$SS = \frac{\sum s_i w_i - n \sqrt{\sum b_i w_i^2}}{\sqrt{\sum (s_i + b_i) w_i^2} + \beta^2 \sum w_i^2 (s_i^2 + b_i^2)}$$

Where  $s_i$  and  $b_i$  are the number of signal and background events in the  $i^{\text{th}}$  bin,  $\beta$  is the systematic uncertainty, and  $w_i$  is the weight of the  $i^{\text{th}}$  bin defined as:

$$w_i = \ln\left(1 + \frac{s_i}{b_i}\right)$$

### Results: Signal Significance in Parameter Space

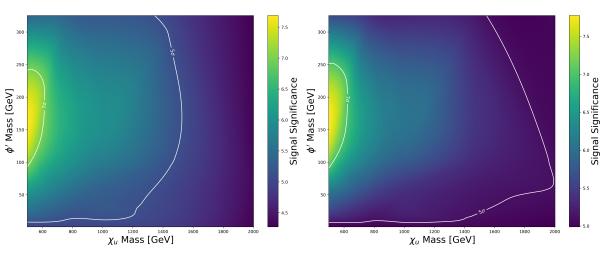


Figure 10:  $\mathcal{L}_{int} = 150 \text{ fb}^{-1}, \ \beta = 20\%$ 

Figure 11:  $\mathcal{L}_{int} = 3000 \text{ fb}^{-1}, \ \beta = 20\%$ 

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### Discussion and Conclusion

- In this work, we perform a phenomenology study on the production of a  $\phi'$  boson and a  $\chi_u$  vector-like quark associated with the  $U(1)_{T3R}$  model at the LHC.
- This model is well-motivated by modern problems in the SM, including the muon g 2 and *B*-Meson anomalies, thermal dark matter abundance, and the hierarchy problem.
- We consider production through gg and  $\chi_u t$  fusion and a decay mode that results in 3 muons, MET, and two *b*-tagged jets as final states.
- We achieve a  $\geq 5\sigma$  ( $3\sigma$ ) sensitivity for  $\phi'$  in the  $\mathcal{O}(\text{GeV}) \mathcal{O}(100\text{GeV})$  range with associated  $\chi_u$  masses in the  $\leq 1500$  (2000) GeV range for  $\mathcal{L}_{\text{int}} = 150 \text{ fb}^{-1}$ , and  $\geq 5\sigma$  sensitivity for effectively the entire parameter space with  $\mathcal{L}_{\text{int}} = 3000 \text{ fb}^{-1}$ .

# Thank you! Questions?



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