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Searching for Dark Photon Production Using Genetic Algorithms

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The Dark Photon

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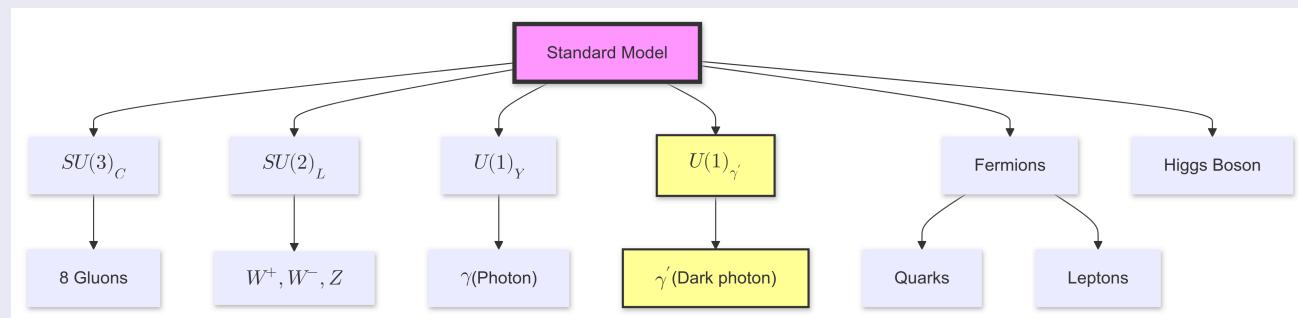
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- New particle can be introduced to the standard model by extending SM gauge group with new $U(1)$ gauge symmetry
- The dark photon interacts with the SM photon via kinetic mixing.

Extended Standard Model



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The Dark Photon, cont'd

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This U(1) gauge symmetry is associated with a new dark photon field, denoted as A'_μ . The Lagrangian that includes kinetic mixing between the photon and the dark photon is given by:

Kinetic Mixing Lagrangian

$$\mathcal{L} = -\frac{1}{4}F_{\mu\nu}F^{\mu\nu} - \frac{1}{4}F'_{\mu\nu}F'^{\mu\nu} + \frac{\epsilon}{2}F_{\mu\nu}F'^{\mu\nu} + \frac{1}{2}m_{A'}^2 A'_\mu A'^\mu$$

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- ϵ is the dimensionless kinetic mixing parameter.

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Diagonalizing Kinetic Terms

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- Redefinition must ensure the mixing term is eliminated and the fields are normalized.

Field Redefinition

$$\tilde{A}_\mu = A_\mu + \epsilon A'_\mu$$

$$\tilde{A}'_\mu = \sqrt{1 - \epsilon^2} A'_\mu$$

$$\mathcal{L} = -\frac{1}{4}\tilde{F}_{\mu\nu}\tilde{F}^{\mu\nu} - \frac{1}{4}\tilde{F}'_{\mu\nu}\tilde{F}'^{\mu\nu}$$

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Substitution

$$\mathcal{L}_{\text{int}} = e\tilde{A}_\mu J_{\text{em}}^\mu$$

$$\mathcal{L}_{\text{int}} = e(A_\mu + \epsilon A'_\mu)J_{\text{em}}^\mu$$

$$\mathcal{L}_{\text{int}} = eA_\mu J_{\text{em}}^\mu + e\epsilon A'_\mu J_{\text{em}}^\mu$$

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- The dark photon would contribute to missing energy signatures in experiments.

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Machine Learning Approach

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- The goal is to design an algorithm that can search for dark photons via missing/abnormal energy signatures.

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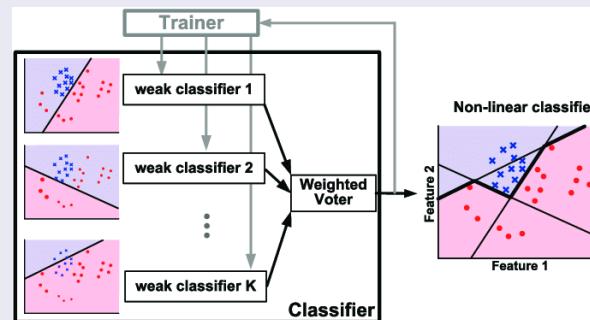
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- A binary classification model can be used to evaluate a data point if a dark photon is produced or not.
- Due to the nature of dark photon production, the resulting dataset will be imbalanced, with a majority of interaction not producing a dark photon.
- This imbalance can be accounted for with an AdaBoost model.

AdaBoost Diagram



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Why Genetic Algorithms?

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- The AdaBoost model has a set of hyperparameters (the number of estimators and the learning rate).

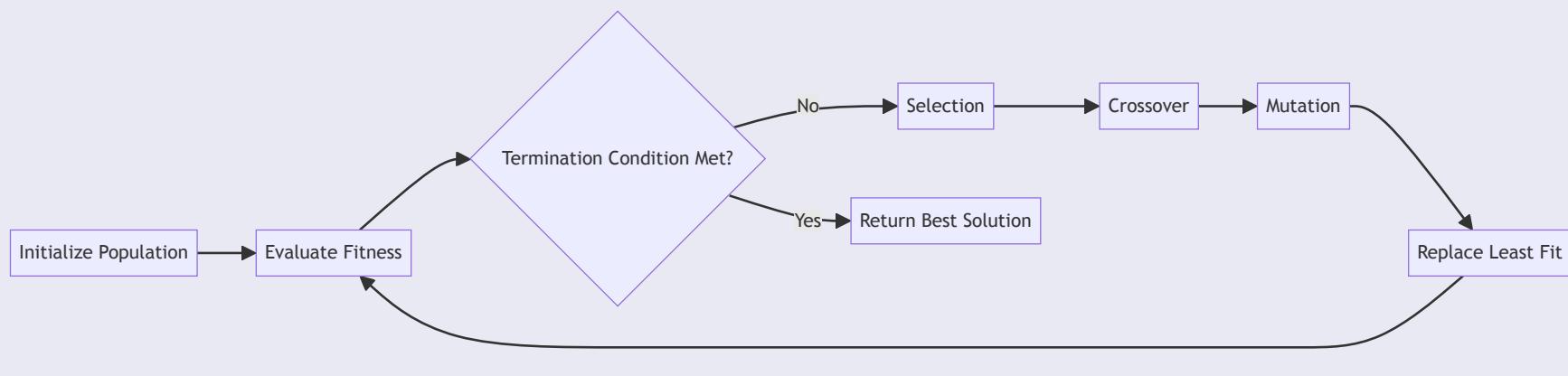
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- The AdaBoost model has a set of hyperparameters (the number of estimators and the learning rate).
- Tuning the hyperparameters manually can take a lot of time to approach an optimal solution.
- An optimal solution to this problem can be reached with a genetic algorithm.

Genetic Algorithm Flowchart



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Data Simulation

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- The simulation was modified to add a decay channel ($\pi^0 \rightarrow \gamma + \gamma'$) with a branching ratio of 10^{-6}
- The dark photon was defined as a stable massless particle that is color neutral, chargeless, and has a spin of 1
- To gather data from the simulation, the program calculated:
 - the scalar sum of jet transverse momenta (HT) by summing the total visible energy
 - the missing transverse energy (MET) by summing total energy produced by neutrinos and dark photons
 - the razor variable of mass scale (MR)
 - the razor variable (R^2), which quantifies the balance of energy and momentum.
 - boolean flag that checked if a dark photon was produced.

Data Calculations

More in-depth calculations:

MR Formula

$$MR = \sqrt{(E_1 + E_2)^2 - (p_1^z + p_2^z)^2}$$

R2 Formula

$$R^2 = \left(\frac{M_T}{MR} \right)^2$$

$$M_T = \sqrt{2|\vec{p}_T^{vis}| |\vec{MET}| (1 - \cos(\Delta\phi))}$$

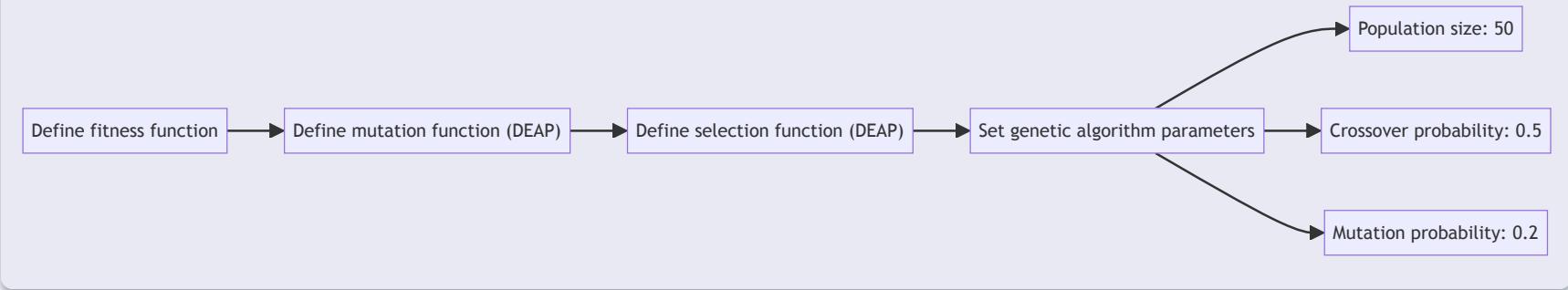
Algorithm, Pt. 1

Initialization



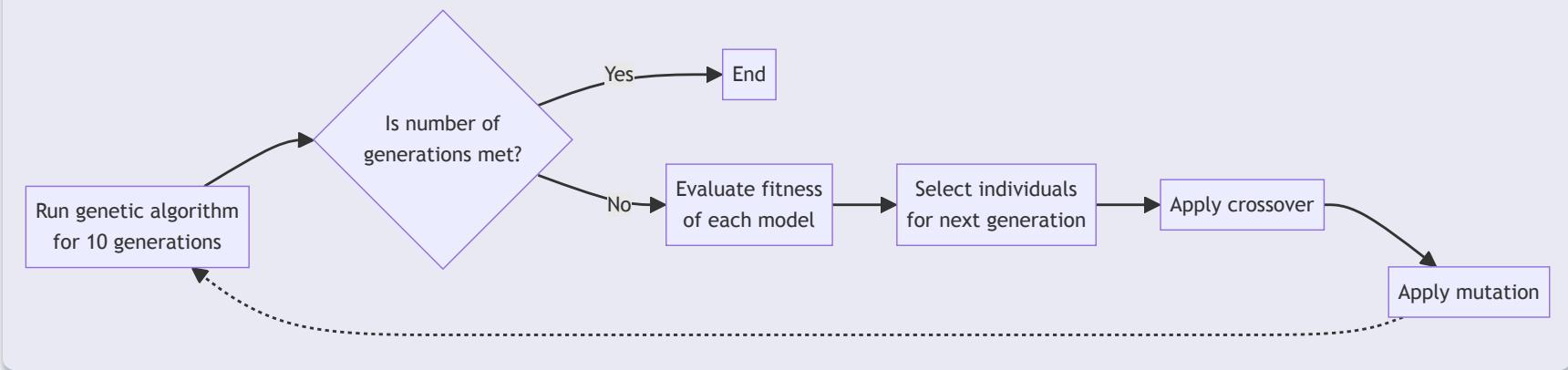
Algorithm, Pt. 2

Genetic Algorithm Creation



Algorithm, Pt. 3

GA Execution



Data Snapshot

- In the data set, only 25 out of 500,000 data points indicated that a dark photon was produced.

Snapshot of Simulation Data

Event Number	<i>HT</i>	<i>MET</i>	<i>MR</i>	<i>R</i> ²	Dark Photon Produced?
352806	94.775	0.000	14000.000	0.000000	False
417824	48.964	0.000	14000.000	0.000000	False
469847	196.721	0.000	14000.000	0.000000	False
407746	118.227	1.069	13983.157	2.585e-06	False
469848	105.605	0.000	14000.000	0.000000	False

Genetic Algorithm Output Data

Genetic Algorithm Data

Generation	Num. Eval	Avg. Fitness	Std. Dev Of Fitness	Min Fitness	Max Fitness
1	33	0.999929	1.91844e-05	0.99988	0.99995
3	27	0.999949	6.00333e-06	0.99992	0.99995
5	28	0.99995	1.11022e-16	0.99995	0.99995
7	34	0.999949	4.58258e-06	0.99992	0.99995
9	28	0.999949	4.58258e-06	0.99992	0.99995
10	40	0.99995	1.4e-06	0.99994	0.99995

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Final Model Results

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Final Model Hyperparameters

Number of Estimators

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- This dataset had an extreme imbalance, explaining the 80% accuracy on data points where a dark photon was produced in the testing set.
- This can be countered with using more advanced classification techniques (RL, XGBoost, etc.)
- However, there were no false positives, meaning that this algorithm could be used in beam experiments to find data to support the idea that dark photons are produced in these proton-proton experiments.

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- Dr. Richard Oppenheim and Dr. Bruce Cortez (ex-AT&T Research) for their feedback and guidance for this project.
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- Aguilar-Arevalo, A.A.: Search for Dark Matter in the Beam-Dump of a Proton Beam with MiniBooNE. *Journal of Physics: Conference Series* **912**, 012017 (2017).
<https://doi.org/10.1088/1742-6596/912/1/012017>
- Batley, J., et al.: Search for the dark photon in decays. *Physics Letters B* **746**, 178–185 (2015). <https://doi.org/10.1016/j.physletb.2015.04.068>
- Battaglieri, M., et al.: Dark Matter Search in a Beam-Dump EXperiment (BDX) at Jefferson Lab an Update on PR12-16-001 the BDX Collaboration. (2018).
- Berkane, A., Boussahel, M.: Dark Photon as an Extra U(1) Extension to the Standard Model with General Rotation in Kinetic Mixing. (2021).
- Celentano, A., et al.: New Production Channels for Light Dark Matter in Hadronic Showers. *Physical Review D* **102**(7), 075026 (2020).
<https://doi.org/10.1103/physrevd.102.075026>
- Chatrchyan, S., et al.: Search for Supersymmetry with Razor Variables In PP Collisions At \sqrt{s} =7 TeV. *Physical Review D* **90**(11), 112001 (2014).
<https://doi.org/10.1103/physrevd.90.112001>
- Cushman, P., et al.: Snowmass CF1 Summary: WIMP Dark Matter Direct Detection. (2013). <https://doi.org/10.48550/arxiv.1310.8327>
- De Napoli, M.: Production and Detection of Light Dark Matter at Jefferson Lab: The BDX Experiment. *Universe* **5**(5), 120 (2019). <https://doi.org/10.3390/universe5050120>
- Deb, K.: Genetic Algorithm in Search and Optimization: The Technique and Applications. (1998). <http://repository.ias.ac.in/82743/>
- Dutra, M., et al.: MeV Dark Matter Complementarity and the Dark Photon Portal. *Journal of Cosmology and Astroparticle Physics* **2018**(03), 037–037 (2018).
<https://doi.org/10.1088/1475-7516/2018/03/037>
- Fabbrichesi, M., et al.: The Dark Photon. (2020).
- Leung, Y., et al.: Degree of Population Diversity - a Perspective on Premature Convergence in Genetic Algorithms and Its Markov Chain Analysis. *IEEE Transactions on Neural Networks* **8**(5), 1165–1176 (1997). <https://doi.org/10.1109/72.623217>
- Novaes, S.: Standard Model: An Introduction. (2000). <https://arxiv.org/pdf/hep-ph/0001283v1.pdf>
- Tong, D.: Gauge Theory.