Searching for Dark Photon Production Using Genetic Algorithms

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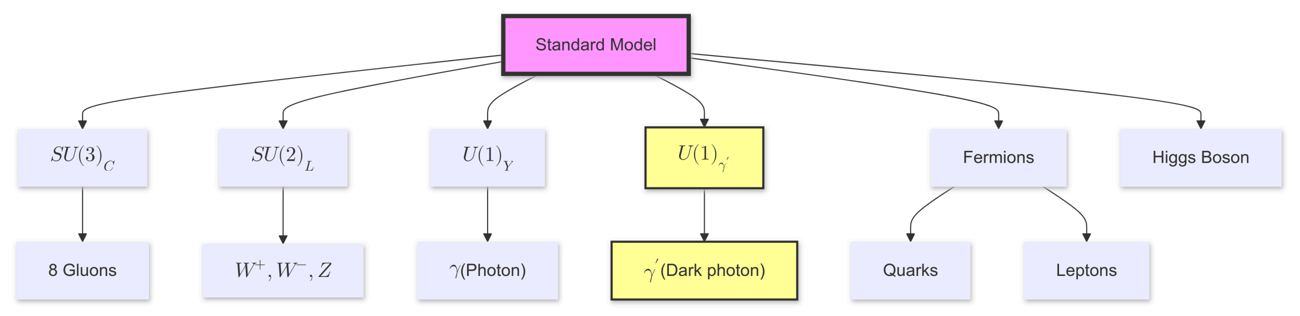
The Dark Photon

- Dark matter makes up 27% of the energy density and 85% of the matter density of the universe.
- The Standard Model does not account for dark matter, a separate dark sector is proposed
- The dark photon is a force carrier for the dark sector, similar to the photon
- 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



The Dark Photon, cont'd

Kinetic Mixing/Interaction Lagrangian

$$\mathcal{L}_0 = -\frac{1}{4}F_{\mu\nu}F^{\mu\nu} - \frac{1}{4}F'_{\mu\nu}F'^{\mu\nu} + \frac{\epsilon}{2}F_{\mu\nu}F'^{\mu\nu}$$

$$\mathcal{L}_{int} = eJ_\mu A^\mu + e'J'_\mu A'^\mu$$

Where:

- $F_{\mu\nu} = \partial_\mu A_\nu - \partial_\nu A_\mu$ is the electromagnetic field strength tensor, where A_μ is the SM photon field.
- $F'_{\mu\nu} = \partial_\mu A'_\nu - \partial_\nu A'_\mu$ is the dark photon field strength tensor, where A'_μ is the dark photon field.
- ϵ is the dimensionless kinetic mixing parameter.

Diagonalizing Kinetic Terms

- Need to remove the mixing term so the kinetic terms only consist of parameters from one field.

Rotating Fields

$$\begin{pmatrix} A_a^\mu \\ A_b^\mu \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{1-\epsilon^2}} & 0 \\ -\frac{\epsilon}{\sqrt{1-\epsilon^2}} & 1 \end{pmatrix} \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} A'^\mu \\ A^\mu \end{pmatrix},$$

- After this rotation, if the dark photon has mass, we end up with the Lagrangian containing this term:

Charge Interaction

$$\mathcal{L} \supset -\frac{e\epsilon}{\sqrt{1-\epsilon^2}} J_\mu A'^\mu \simeq -e\epsilon J_\mu A'^\mu,$$

Consequences

- Based on the equation, the dark photon can interact with the same particles as a photon (suppressed by a factor ϵ)
- This interaction is called the dark photon portal
- This portal opens up new interaction/production channels.
- For instance, in meson decays, a neutral pion π^0 can decay into a photon and a dark photon:

Production of Dark Photon

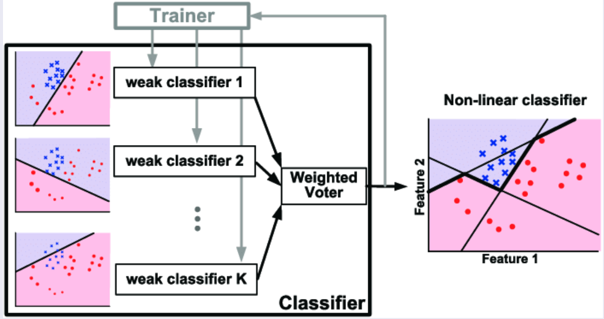
$$\pi^0 \to \gamma + \gamma'$$

- The rate of such a process is proportional to ϵ^2 $(\approx 10^{-6})$.
- The dark photon would contribute to missing energy signatures in experiments.

Machine Learning Approach

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

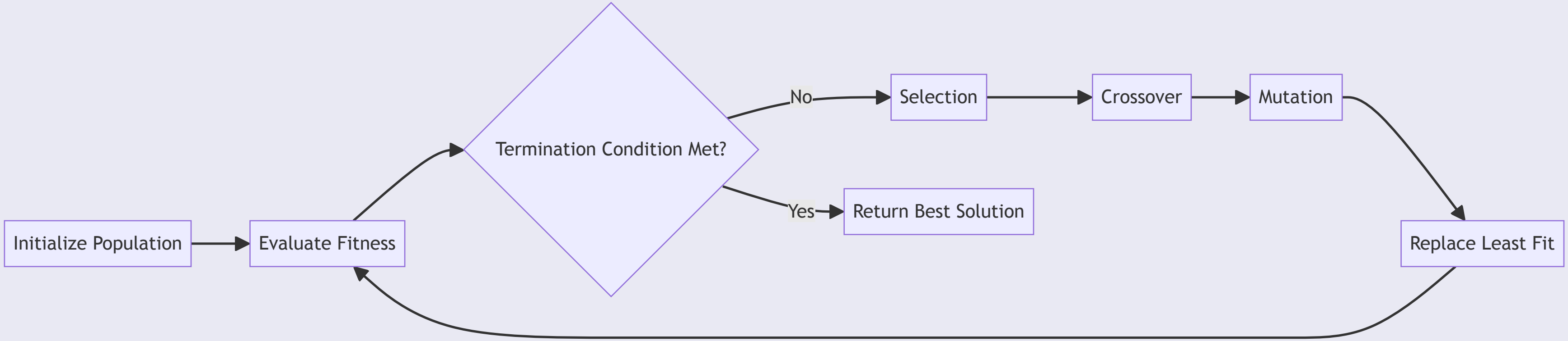
AdaBoost Diagram



Why Genetic Algorithms?

- 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



Data Simulation

- Simulated proton-proton collisions at 14 TeV using `Pythia3.8` on a 2021 MacBook Pro (M1 Pro, 32 GB RAM)
- The simulation was modified to add a decay channel $(\pi^0 \to \gamma + \gamma')$ with a branching ratio of 10^{-6}
- The dark photon was defined as a stable particle that is color neutral, chargeless, has a spin of 1 and a mass of 10^{-20} eV
- 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

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

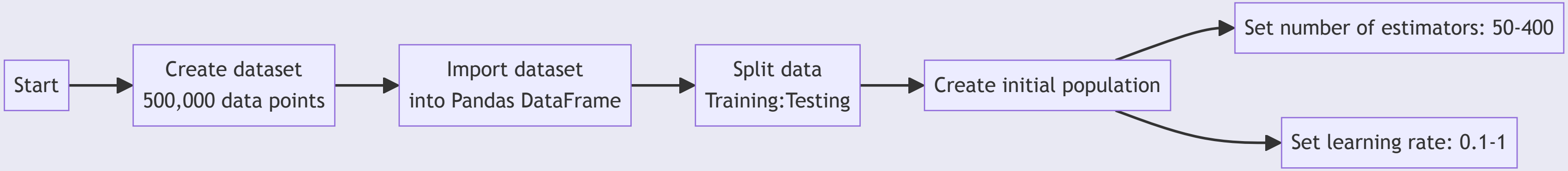
R2 Formula

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

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

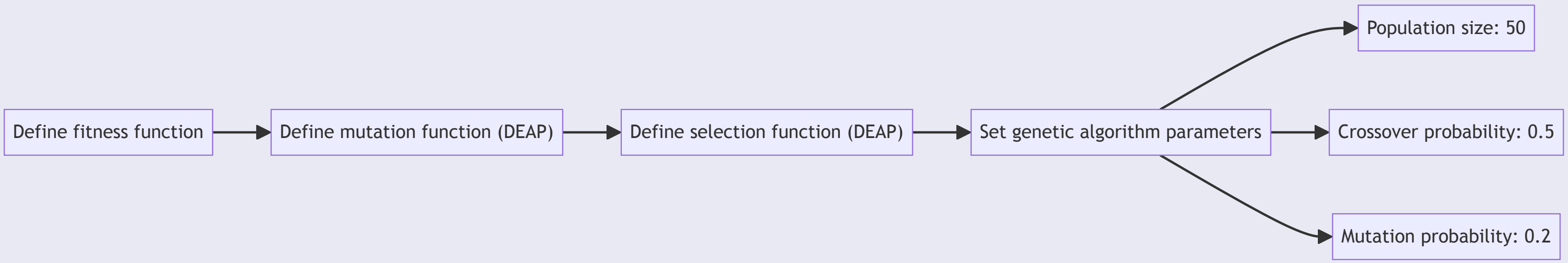
Algorithm, Pt. 1

Initialization



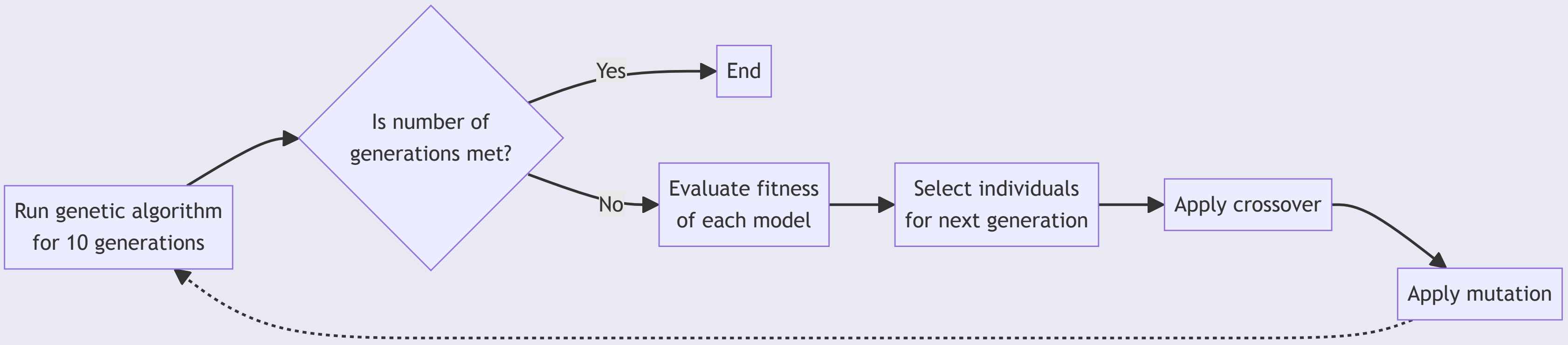
Algorithm, Pt. 2

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	HT	MET	MR	R^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. Evals	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

Final Model Results

- After algorithm execution, the algorithm converged on a solution with a fitness of 0.99995.
- The hyperparameters of the model are:

Final Model Hyperparameters

Number of Estimators	Learning Rate
319	0.1

- Evaluating the model on the testing dataset resulted in an accuracy of 99.995%.
- However, the accuracy for instances where a dark photon was produced stood at 80%.
- Model had no false positives.

Conclusions

- The GA was successful in finding a model with a high accuracy, as shown by a model accuracy of 99.995% on the testing dataset.
- However, the accuracy for instances where a dark photon was produced stood at 80%.
- 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.

Summary: Dark Photon Search Using Genetic Algorithms

- Dark photon: Proposed force carrier for dark matter, interacts with SM photon via kinetic mixing
- Simulation: Proton-proton collisions at 14 TeV, added decay channel ($\pi^0 \rightarrow \gamma + \gamma'$)
- ML approach: AdaBoost model for binary classification, genetic algorithm for hyperparameter tuning
  - Hyperparameters optimized: number of estimators, learning rate
- Dataset: 500,000 points, only 25 with dark photon production (extreme imbalance)
- Results:
  - Overall accuracy: 99.995%
  - Accuracy for dark photon events: 80%, no false positives
- Conclusion: Promising for beam experiments, but advanced techniques needed to address imbalance
  - Potential improvements: Reinforcement Learning, XGBoost

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Questions?

Citations

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