



Searches for Exotic Objects among Fermi-LAT γ -Ray Sources with Weakly Supervised Machine Learning

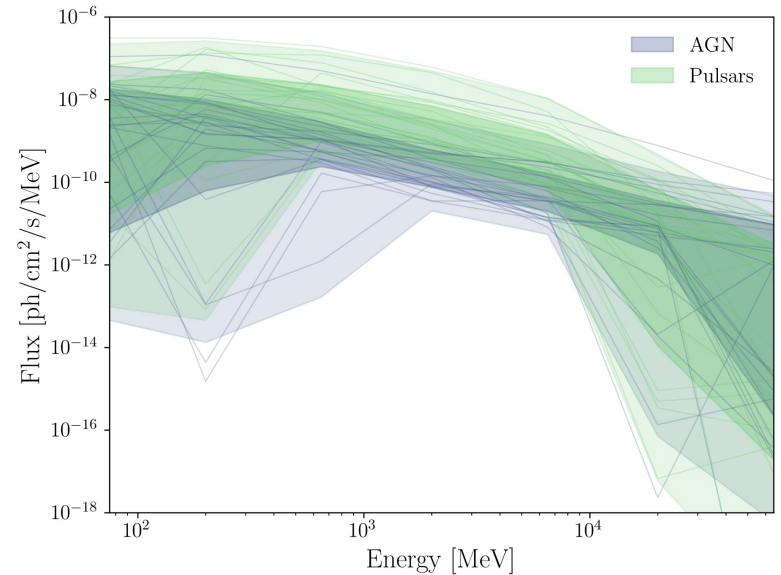
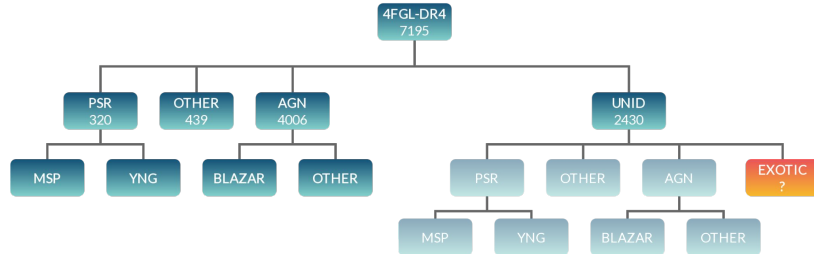
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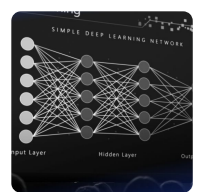


γ -Ray Observation with *Fermi*-LAT

- Wide field-of-view detector
- Covering the high-energy range of γ -ray energies
 - between about 20 MeV and up to a few TeV
- Observations since 2008, still ongoing
- Publicly available source catalog



Goal: Find **anomalies**/exotic sources among observed data



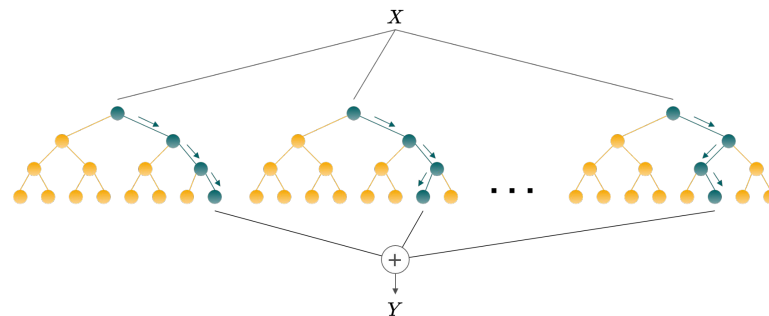
Classifier Setup for γ -Ray Classification

State-of-the-art γ -Ray classification:

- FFNN:
 - e.g.: AGN vs. Pulsar - *Finke et al. (2020) [2012.05251]*
 - Shows that flux spectrum of Fermi-LAT data is suitable for successful classification
 - Many other applications, e.g. multiclass, ...
- Bayesian NN:
 - Blazar Classification - *Butter et al. (2022) [2112.01403]*
 - Dark Matter Subhalos vs Astrophysical Sources - *Butter et al. (+KN) (2023) [2303.07362]*
 - Provides robust classification by additional consideration of classification uncertainty

This work: **Boosted Decision Tree Classifier**

```
GradientBoostingClassifier(n_estimators = 200,  
                           max_depth = 4,  
                           learning_rate = 0.1)
```



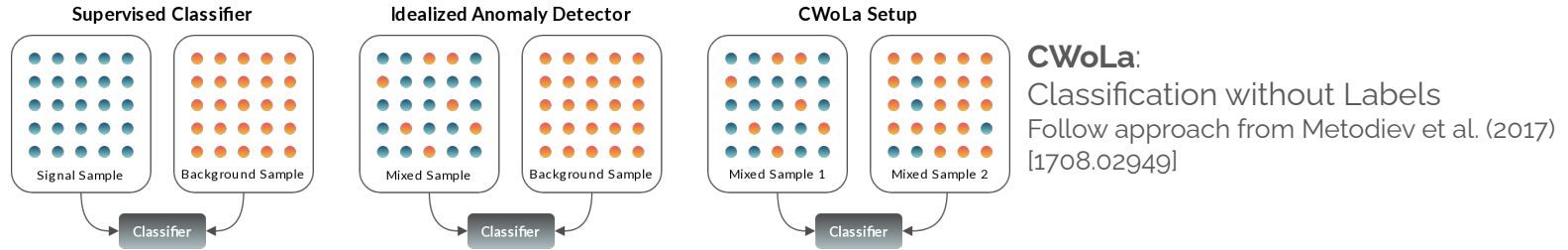
Inspiration: 'Back To The Roots: Tree-Based Algorithms for Weakly Supervised Anomaly Detection',
- *Finke et al. (2023) [2309.13111]*

Advantages of BDT approach:

- BDT works well on small data sets with strong class imbalances
- Trains very fast and can outperform DNN on 'simple' classification problems with tabular data



Searching for Anomalous γ -Ray Sources with Weakly Supervised Classification



An optimal classifier trained to distinguish the mixed samples is also optimal to distinguish signal from background objects

- Optimal classifier is given by the likelihood ratio, this relates to:

$$L_{M_1/M_2} = \frac{p_{M_1}}{p_{M_2}} = \frac{f_1 p_S + (1 - f_1) p_B}{f_2 p_S + (1 - f_2) p_B} = \frac{f_1 L_{S/B} + (1 - f_1)}{f_2 L_{S/B} + (1 - f_2)}$$

- Training a classifier to maximize L_{M_1/M_2} yields the optimal classifier also to discriminate signal and background if $f_1 > f_2$
- Pure background sample \leftrightarrow idealized anomaly detector

This work: Setup exemplary approaches where f can be controlled and supervised classification can be used as a benchmark



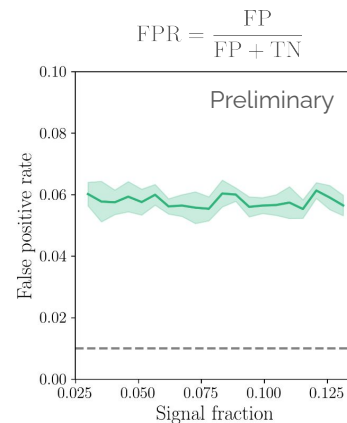
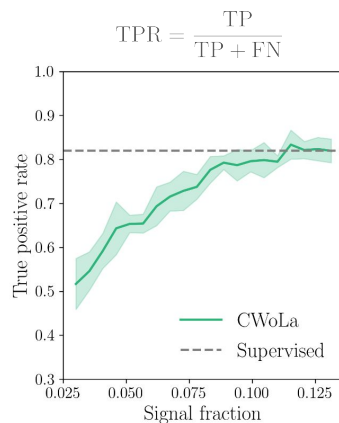
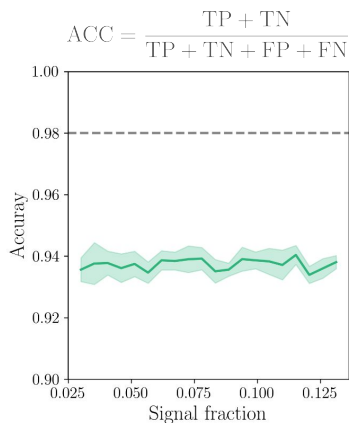
Case I - Astrophysical Sources

Astrophysical data only:

- Background: AGN
- Signal: Pulsars
- Small signal fractions ($f_s \lesssim 0.1$)
- Background & mixed sample in \mathcal{O} (4FGL / UNID)

Data Augmentation:

- Use normalizing flow (rational quadratic spline) to generate additional AGN data
 - Realistic generated spectra: ACC $\leq 52.6\%$
- Used to probe small signal fractions without too sparse signal





Case II - Dark Matter Subhalos

- Dark matter is clustered hierarchically in galactic halos
 - According to cosmological simulations
 - Substructures ("Subhalos") form

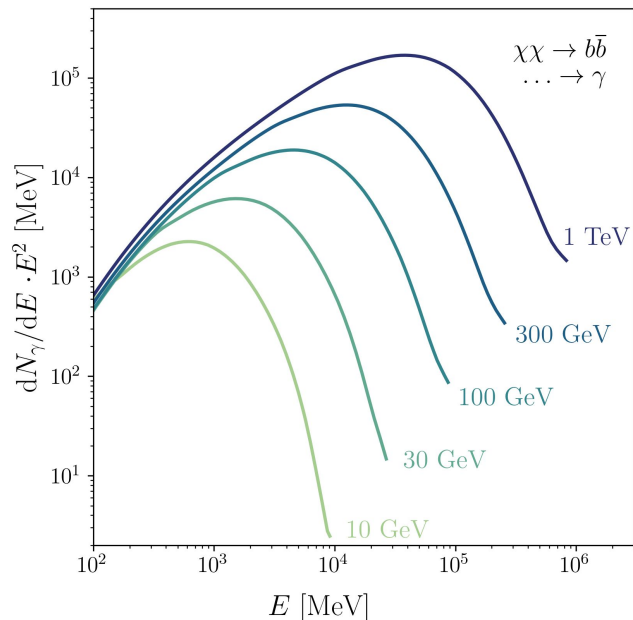
- Signal in γ -rays expected, following

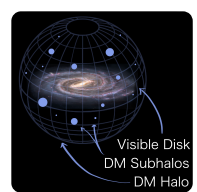
$$\phi = \frac{\langle \sigma v \rangle}{8 \cdot \pi \cdot m_{\text{DM}}} \cdot \mathcal{J} \cdot \frac{dN}{dE}, \quad \mathcal{J}(\Delta\Omega) = \int_{\Delta\Omega} d\Omega \int_{\text{l.o.s.}} ds \rho^2(x)$$

- We simulate subhalo population with CLUMPY



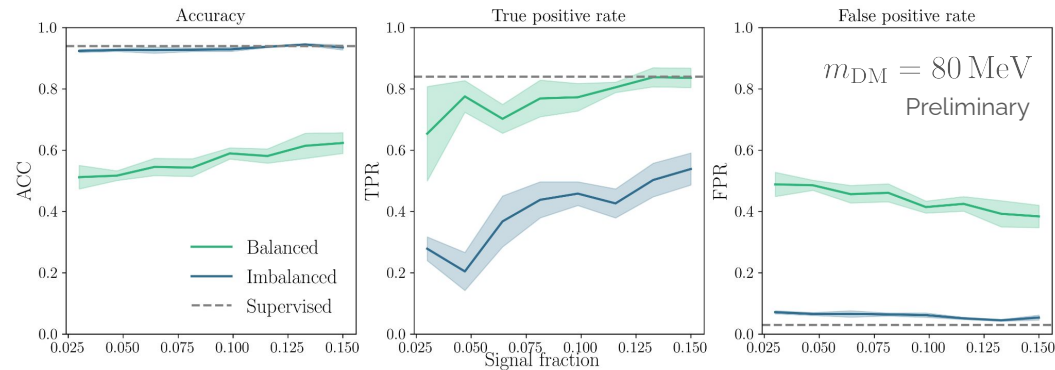
- Realistic simulation of observable signal using fermipy
 - Use detectable subset ($\sigma_d > 5$) of simulated subhalo population
 - For details on full simulation procedure see [2303.07362]



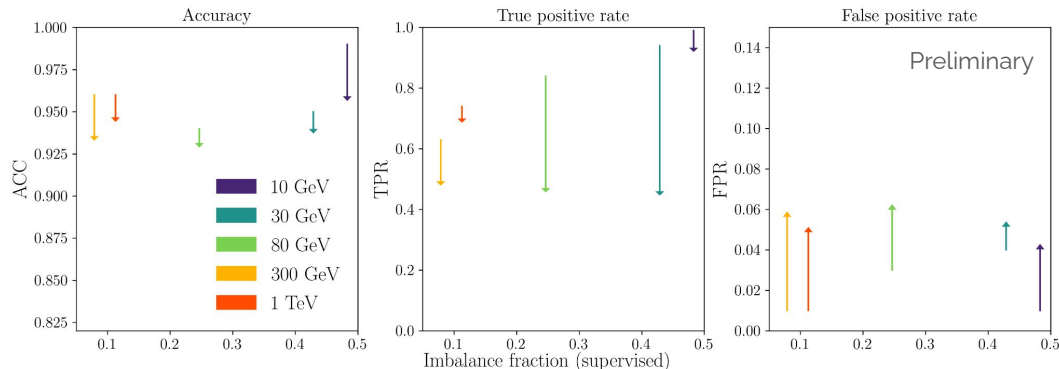


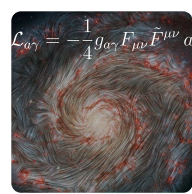
Searching for Subhalos with Weakly Supervised Classification

- Balanced: $N_{\text{Mixed}} = N_{\text{Background}}$
- Imbalanced: $N_{\text{Mixed}} = \frac{1}{2} N_{\text{Background}}$
- CWoLa performance dependent on training class imbalance



- Comparison for different dark matter masses
- Imbalance in supervised case relevant for TPR
- More 4FGL-similar halos (intermediate masses) lose most predictive power with CWoLa





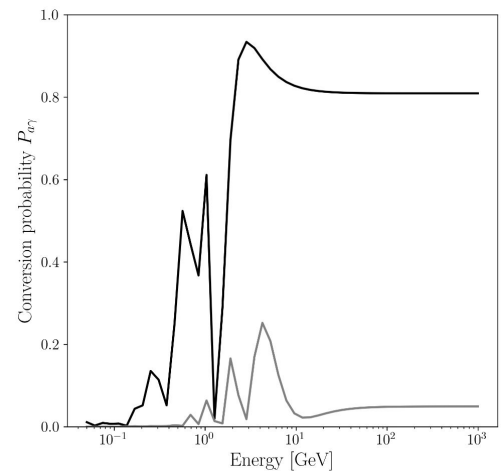
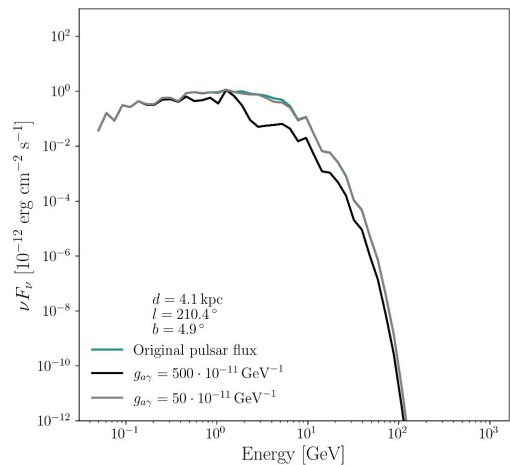
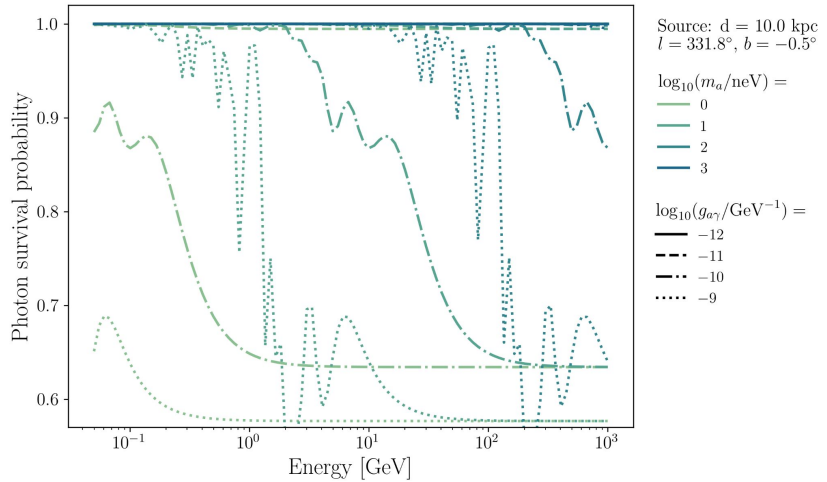
Case III - Axion-Photon Conversion

Axion-photon coupling leads to conversion in magnetic field

$$\mathcal{L}_{a\gamma} = -\frac{1}{4}g_{a\gamma}F_{\mu\nu}\tilde{F}^{\mu\nu} a$$

→ Energy dependent oscillatory suppression of γ -ray flux

- Signal: Pulsars with oscillatory pattern from ALP-photon conversion in the GMF
 - Assume fixed axion mass and axion-photon coupling strength
- Background: Unmodulated pulsar spectra





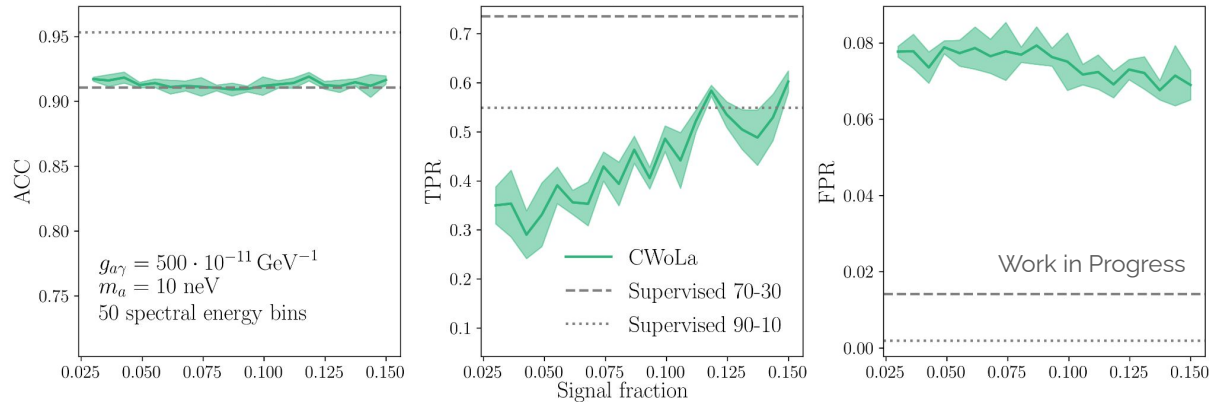
Case III - Axion-Photon Conversion

Pick parameters leading to sufficiently strong modulation:

- Mass: $m_a = 10 \text{ neV}$
- Coupling: $g_{a\gamma} = 5 \cdot 10^{-9} \text{ GeV}^{-1}$

Supervised benchmark: Different initial class imbalances

- CWoLa Training class imbalance: 70/30%
- 'Low signal fraction' setup: 90/10%



Complex setup also for supervised classification (depends on ALP parameters)

→ In such cases, CWoLa leads to larger FPR // other features in data might overshadow signal

Conclusion and Outlook

Application of CWoLa in search for anomalous γ -ray sources

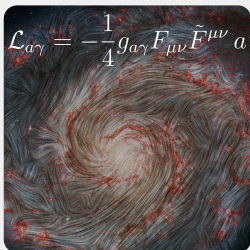
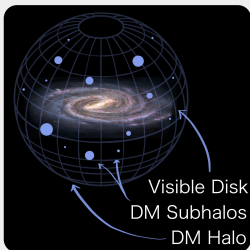
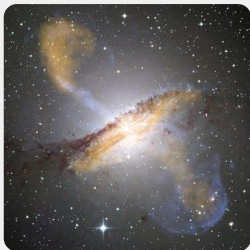
- Demonstrated potential on three exemplary cases
- Supervised limit can be reached at small signal fractions

Challenges:

- Small data sets - few signal samples overall
- Results depend on how 'well-defined' classification setup is also in supervised case

Take-aways:

- Method useful to point out interesting sources for further investigation
- Findings of test setups can help guide CWoLa setup on unlabeled data



Thank you for your attention!