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A Machine Learning Approach to Searching Dark Matter Subhalos in Fermi-LAT Sources

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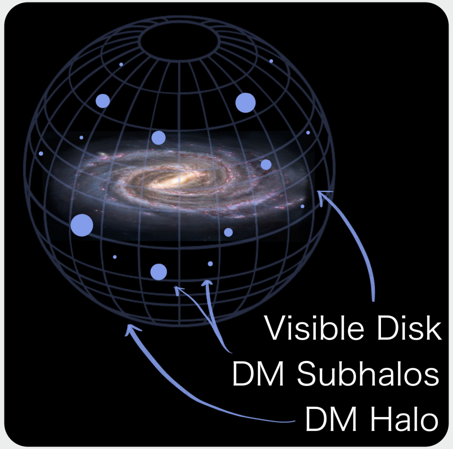
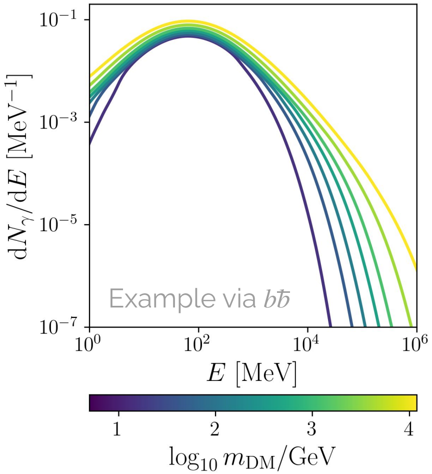
Motivation



- Galaxy populated by clumps of dark matter
  ➜ N-body simulations*

- Assuming WIMP dark matter:
  $\chi\chi \rightarrow$ SM SM ($\rightarrow \gamma$)
  ➜ A signal like this could already be detected among Fermi-LAT sources**



- The Fermi-LAT 4FGL source catalog can help constrain the properties of dark matter
  1. Create realistic set of subhalo simulations
  2. Assess detectability
  3. Look for subhalo-like spectra among unclassified sources

- Machine Learning is a powerful tool for classification tasks***
  ➜ We employ a neural network to effectively classify DM subhalos

This talk

* see e.g. Zavala, Frenk (2019) 1907.1175
Springel et al. (2008) 0809.0898

** see e.g. Hooper, Witte (2017) 1610.07587
Coronado-Blásquez et al (2019) 1910.14429
Calore et al. (2019) 1910.13722
Di Mauro et al. (2020) 2007.08535
Gammaldi et al. (2022) 2207.09307
...

*** see e.g. Finke et al. (2021) 2012.05251
Butter et al. (2022) 2112.01403

Motivation

4FGL Fermi-LAT source catalog

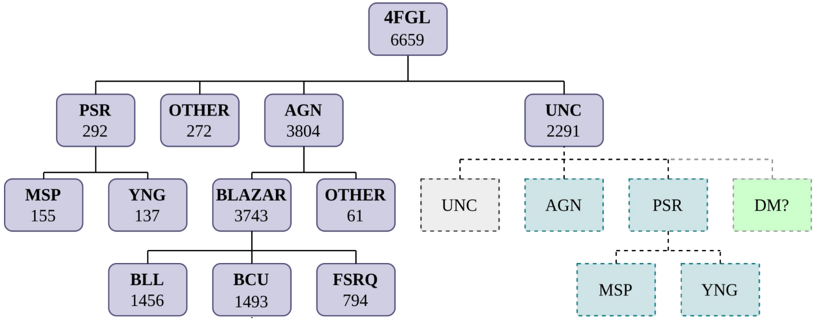


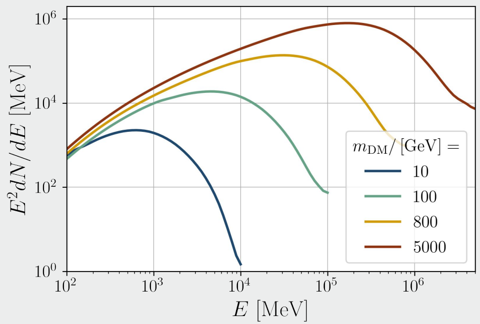
Figure adapted from arXiv:2112.01403

https://fermi.gsfc.nasa.gov/

- The Fermi Large Area Telescope (LAT) has collected data of the high-energy sky since 2008.
- Constantly increasing number of pulsars and AGN & discovery of new Galactic and extragalactic γ-ray emitters (1FGL (1 year) : 1451 sources)
- The 4FGL-DR3 (12 years) is the most recent catalog of γ-ray sources from the Fermi-LAT.

Simulations
Subhalo Population

DM annihilation spectra

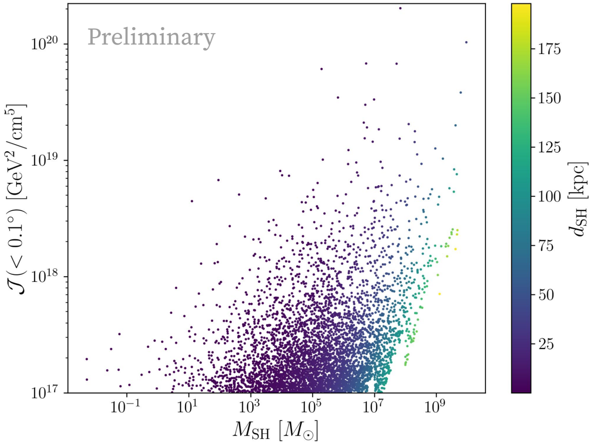


DM model dependent

$$\phi = \overbrace{\frac{\langle \sigma v \rangle}{8 \cdot \pi \cdot m_{\mathrm{DM}}}}^{\text{Prefactor}} \cdot \underbrace{\mathcal{J}}_{\text{CLUMPY}} \cdot \overbrace{\frac{\mathrm{d}N}{\mathrm{d}E}}^{\text{PPPC 4 DM ID}}$$

Halo model dependent

J-Factor distribution



PPPC 4 DM ID: *Cirelli et al. (2012)*

DM annihilation spectra for each mass, and primary annihilation channel, assuming WIMPs

CLUMPY V3: *Hütten et al. (2018)*

J-factor and sky position of galactic subhalos

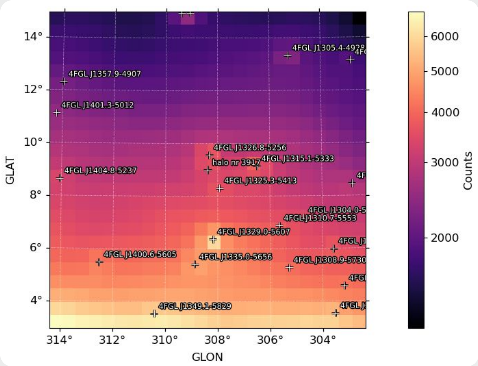
https://clumpy.gitlab.io/CLUMPY/

Simulations
Detector Effects

Next Step: Assess detectability and simulate flux detected by Fermi-LAT

Use **fermipy** for simulating 12 years of Fermi-LAT data

ROI counts map



Input: Individual subhalo with given position in sky & flux fitted with 'PLSuperExpCutoff'*

$$\phi = \phi_0 \left(\frac{E}{E_0}\right)^{\gamma} \exp\left(-\left(\frac{E}{E_0}\right)^{\beta}\right)$$

Define ROI around subhalo

Fit source among background (diffuse + isotropic) & point sources (4FGL-DR3)

Detection threshold

$$\mathrm{TS} = 2\log\left(\mathcal{L}/\mathcal{L}_0\right) \overset{!}{\geq} 25$$

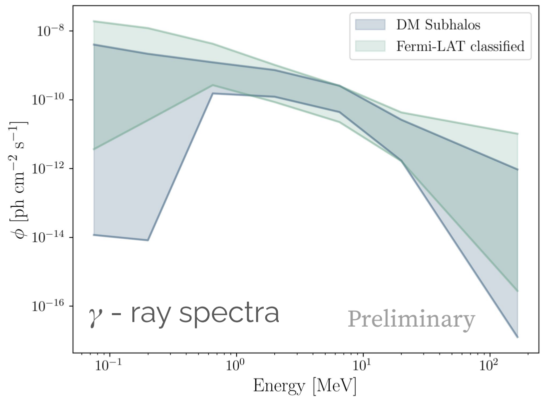
Result: Realistic training set consisting of the flux of each subhalo with same systematics as astrophysical sources + detection significance

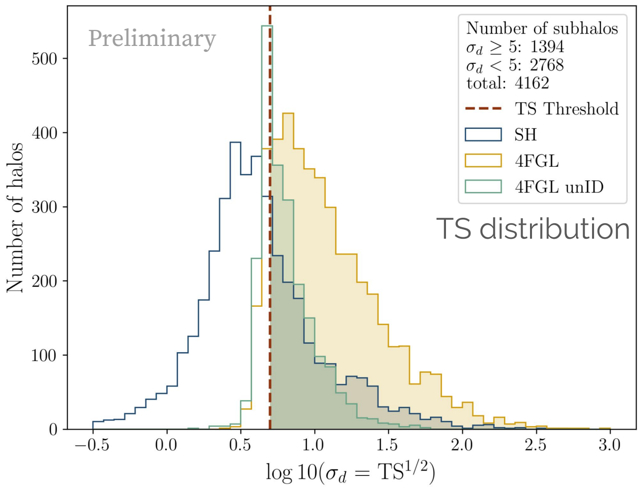
* see also Calore et al. (2017) 1611.03503

Simulations
Results

- ‘DM-only simulation: Based on the Aquarius DM-only N-body simulation*
  - Einasto profile
  - Subhalos follow mass- concentration relation**

	Initial / Benchmark Setup
Halo model	DM only
$m_{\rm DM}$	80 GeV
$\langle\sigma v\rangle$	10^{-23} cm^3 s^{-1}
Final state	$b\bar{b}$





➜ Benchmark classification training set for comparing subhalos with 4FGL catalog

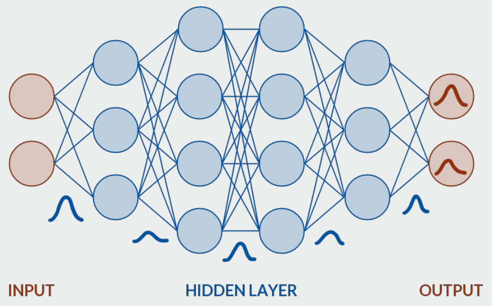
➜ Realistic scenario with simulations as close as possible to real sources

➜ Number of detectable subhalos sufficient for ML approach

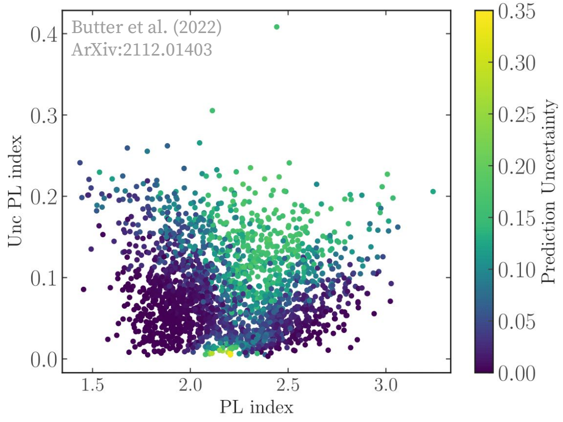
* see e.g. Springel et al. (2008) 0809.0898
Hütten et al. (2016) 1606.08498

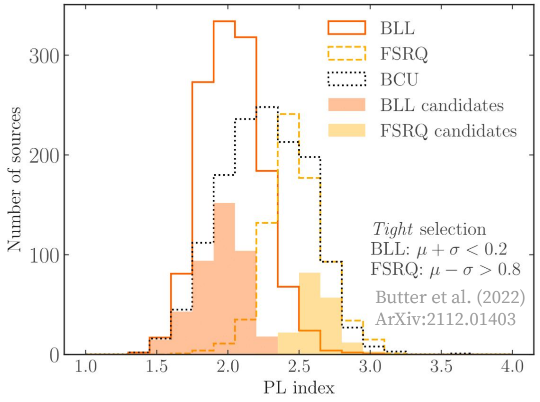
** see Moliné et al. (2017) 1603.04057

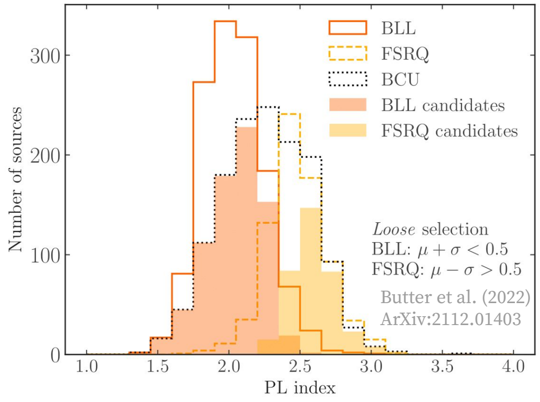
Neural Networks for γ-Ray Source Classification (Butter et al. (2022) 2112.01403)



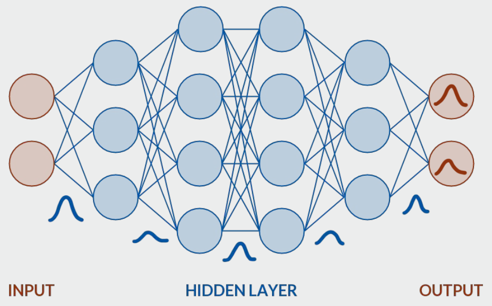
- Classification of AGN (BLL vs FSRQ) within Fermi-LAT 4FGL-DR2 based on spectra only
- Use Bayesian Neural Network for reliable uncertainty estimates of classification
- Accuracy: 88.9%



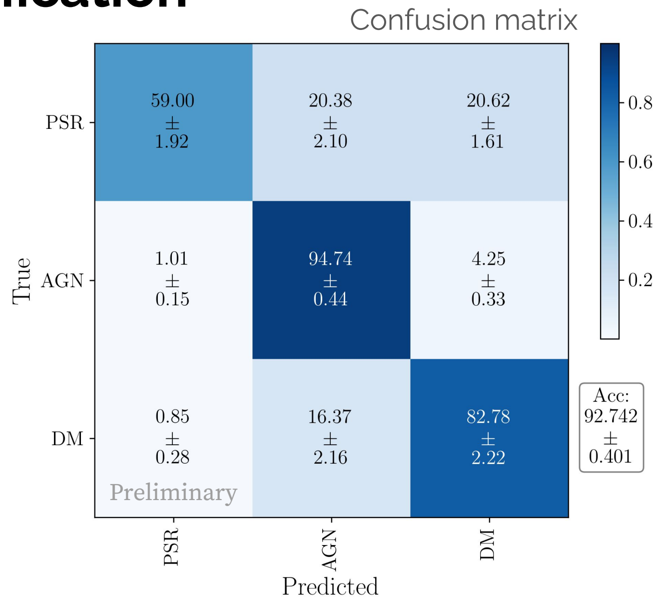




Preliminary Results
Subhalo vs 4FGL Classification



- Classification accuracy synthetic subhalos vs real 4FGL data compatible with classifications among real source types

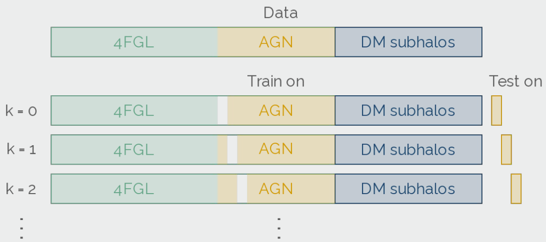


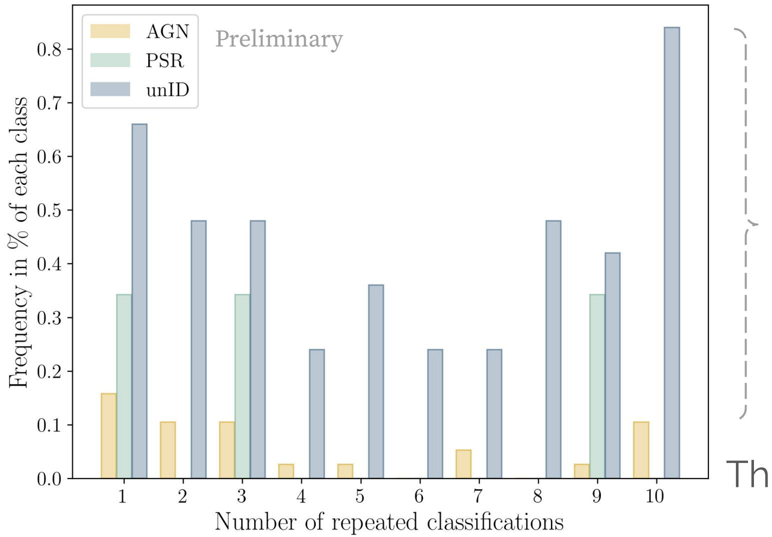
- Limits of accuracy: Statistical fluctuation and imbalance within data

➜ Achieved sweet spot between realistic data set and efficient neural network

  ➜ Trained network can give reliable estimate on which unclassified sources in 4FGL are compatible with DM subhalo model at hand

Preliminary Results
4FGL UnID Sources Classified as Subhalos





$N_{candidate}$ = 12

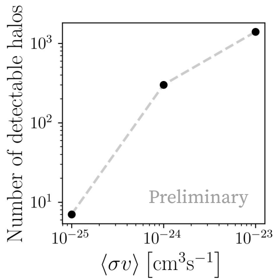
Threshold: μ - σ > 0.8

- k-fold cross validation approach to training and testing on AGN/PSR
- Fraction of misclassification of known sources smaller than unIDs classified as SH

Conclusions & Outlook

- Using CLUMPY, PPPC 4 DM ID and **fermipy**, we have constructed a set of realistic DM subhalo simulations for a given model

- We have carefully evaluated the detectability using complete simulations of 12 years of Fermi-LAT data and used this to compare to the 4FGL-DR3 source catalog



- We use a Bayesian Neural Network classification approach to conservatively estimate the number of DM subhalo candidates among unclassified 4FGL sources

- This approach can be extended to any DM model

astro-ph-leaks
@LeaksPh

BUT I MAY BE WRONG THIS IS JUST MY OWN UNDERSTANDING AT THE MOMENT.

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Are we seeing new physics already?