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Unveiling dark matter subhalos in gamma ray catalogs with machine learning

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Using the data from the Large Area Telescope (LAT), the Fermi-LAT collaboration continuously updates their catalogs, which now contain a few thousands of detected gamma-ray sources. Among them, around one third are of not yet identified origin, and they could contain signals from established source types or, most intriguing, new source types such as dark matter subhalos producing gamma-rays from dark matter self-annihilation. We apply state-of-the-art machine learning methods for classification to the sources in Fermi-LAT catalogs with the aim of identifying possible candidates of exotic gamma-ray sources, namely dark matter subhalos. We first simulate the properties of dark matter subhalo gamma-ray sources by using established models from both N-body simulations and semi-analytical approaches for the subhalo distribution. We then carefully assess the detectability of this sample by using Fermi-LAT simulations. We discuss results of our machine learning analysis performed on the unidentified sources in the 4FGL-DR3, and present conservative limits on the dark matter annihilation cross-section from the exclusion of the unidentified sources classified as astrophysical-like by our networks.

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1. Introduction

The Fermi Large Area Telescope (*Fermi*-LAT) has detected over six thousand γ-ray point sources, collected in incremental catalogs [1]. Most sources in *Fermi*-LAT catalogs are blazars and pulsars. However, more than two thousand sources in the most recent 4FGL-DR3 catalog remain without clear identification or counterparts at other wavelengths. Some of these unidentified (UNID) sources could potentially be attributed to exotic new sources, such as dark matter annihilation or decay in subhalos. Cosmological simulations suggest that dark matter structures form hierarchically. Dark matter halos are thus expected to contain a large number of smaller substructures known as subhalos (see e.g. [2]), among which a significant fraction are invisible at optical wavelengths because they lack baryonic matter. However, dark matter subhalos in the Milky Way could be detected as γ-ray point sources due to the annihilation or decay of dark matter particles into Standard Model final states. Signatures of dark subhalo populations have been searched for within individual γ-ray sources in *Fermi*-LAT catalogs [3–6]. Subhalos are expected to appear in *Fermi*-LAT surveys as steady sources of γ rays, predominantly point-like with possibly few extended nearby representatives [7]. Furthermore, subhalos should have no counterpart emission at other wavelengths, and their γ-ray emission is expected to be signal dominated, with little background from other astrophysical mechanisms. Machine learning classifiers have been used in recent years as useful tool for γ-ray source classification, both to study UNID sources as well as to search for potential dark subhalos [8–14]. However, all previous results on dark subhalos were based on machine learning classifiers that were not trained on realistic subhalo simulations, but only using their expected similarities to observed astrophysical sources.

This contribution is based on Ref. [15], in which we extends previous works in several directions. Our novelties can be summarized as follows: (i) We train our networks on realistic dark matter subhalo simulations, taking into account the specific spectral properties produced by different dark matter masses. (ii) We base the classification on the measured flux as a function of energy, instead of using derived features, i.e. we use the full information contained in the measured energy spectra. (iii) We use Bayesian neural networks, which allow us to account for uncertainties in the network weights and make robust predictions about subhalo-like sources.

2. Models & methods

2.1 Dark matter modeling

Subhalos are structures predominantly composed of dark matter. If dark matter particles are weakly interacting massive particles (WIMPs) that can self-annihilate into Standard Model particles, then individual subhalos could shine as sources of emission in the sky, potentially offering a signal for dark matter. According to the WIMP paradigm, natural dark matter candidates with masses in the GeV-TeV range could produce γ rays through annihilation into hadronic or leptonic final states. The differential γ-ray flux, ϕ_γ, from the annihilation of (Majorana) WIMP particles from a dark matter subhalo is computed as:

$$\phi_\gamma := \frac{\mathrm{d}\Phi_\gamma}{\mathrm{d}E}(E, \Delta\Omega) = \frac{\langle \sigma v \rangle}{8\pi m_{\mathrm{DM}}^2}\, \mathcal{J}(\Delta\Omega)\, \frac{\mathrm{d}N_\gamma^i}{\mathrm{d}E}(E), \tag{1}$$

where m_{DM} is the dark matter mass, $\langle \sigma v \rangle$ is the thermally averaged annihilation cross section, $\mathcal{J}$ is the so-called $\mathcal{J}$-factor, which is the integral along the line of sight of the subhalo dark matter density over the solid angle $\Delta\Omega$, and $\mathrm{d}N_\gamma^i(E)/\mathrm{d}E$ is the energy spectrum of γ rays produced by dark matter annihilation in a given annihilation channel i.

We model the dark matter subhalo population using the `CLUMPY` [16] code based on dark matter-only cosmological simulations [17, 18]. We compute the $\mathcal{J}$-factor for each subhalo by integrating the square of the dark matter density, and treat each subhalo as a point-like source by setting the integration angle $\theta_{\rm int} = 0.5$ deg. We only consider subhalos with $\mathcal{J}_{\rm sub}(< 0.5\,\mathrm{deg})$ values greater than 10^{17} GeV^{2}cm^{-5} [18].

We calculate the expected flux of γ rays in the *Fermi*-LAT energy range for each subhalo using different dark matter spectral models. We focus on the hadronic annihilation channel $b\bar{b}$ with a branching ratio of one. This channel produces energy spectra similar to those of other astrophysical sources, such as pulsars, and represents the most challenging setup for our machine learning classifiers. We use the γ-ray energy spectra $\mathrm{d}N_\gamma^i(E)/\mathrm{d}E$ as provided in [19], which is represented within the simulations illustrated below by a fit with a power law with a super-exponential cutoff. Comparing the pulsar and dark matter spectra (see Fig.2 in Ref. [15]), we observe that their shapes become very similar for the $b\bar{b}$-channel and dark matter masses around a few tens of GeV. Following this observation, some studies [20, 21] have used machine learning classifiers that were trained to identify pulsars among *Fermi*-LAT unidentified sources to estimate the number of dark matter subhalo candidates. However, it is important to note that the similarity between the dark matter and pulsar spectra is limited to a specific range of dark matter masses and specific annihilation channels. Furthermore, it is necessary to include realistic subhalo sources in the training set of the algorithms to ensure consistency when using machine learning classifiers.

2.2 *Fermi*-LAT simulation

The measurement of γ rays from dark matter subhalos with *Fermi*-LAT is simulated as explained in this section. Our objectives are twofold: (1) to update the detection prospects for point-like dark matter subhalos for the 4FGL-DR3 catalog, and (2) to produce a realistic training set for our neural networks. To achieve these objectives, our simulation must produce the following outcomes: (i) The number of detectable subhalos in the 4FGL-DR3 catalog as a function of the annihilation cross section and the dark matter mass; (ii) The energy spectrum that would be detected by Fermi-LAT for each subhalo, taking into account realistic systematic uncertainties from diffuse and point-source backgrounds, the *Fermi*-LAT instrument response function, and using detection pipelines typically employed in *Fermi*-LAT source analysis. Thus, we have extended our simulation strategy, building upon previous work [5, 18], to create realistic training data. In particular we use the latest published data, include the full information from the energy spectra and optimise the fitting procedure to extract these spectra. By processing complete spectra, we can leverage the ability of neural networks to extract all relevant information from low-level features. Our work thus differs from previous studies, such as [14], which used synthetic features to search for dark matter subhalo candidates.

We simulate 12 years of *Fermi*-LAT data and apply cut selections compatible with the most recent release of the public *Fermi*-LAT source catalog, the 4FGL-DR3 catalog [1]. The simulations and subsequent data analysis are performed using FERMIPY, a Python interface to the official analysis tools developed by the *Fermi*-LAT collaboration[1].

[1]https://fermipy.readthedocs.io/en/latest/

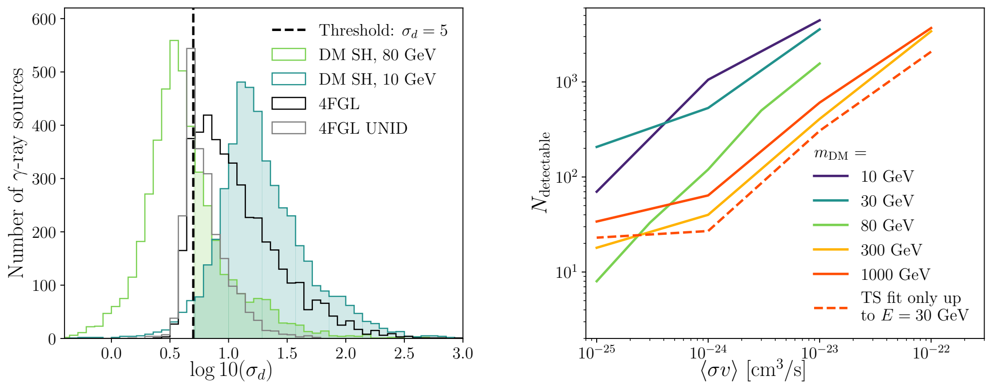

Figure 1: *Left:* Detection significance distribution for two dark matter masses at a fixed cross-section. The distribution of 4FGL classified and UNID sources are added for comparison. *Right:* Number of detectable sources as function of the annihilation cross-section for different dark matter masses.

For each subhalo, we perform the following steps: We (i) select $12^\circ \times 12^\circ$ sky patch (ROI) around the simulated source position; (ii) include a source model fit to the γ-ray spectrum following the respective $\mathcal{J}$-factor, dark matter model, and a choice for the dark matter annihilation cross-section; (iii) fit ROI including point sources, diffuse & isotropic background; (iv) calculate the spectral energy distribution (SED) of each subhalo by fitting the flux normalisation of the source in each energy bin defined by the 4FGL-DR3 catalog. At the end of our analysis chain, we obtain for each dark matter subhalo: the detection significance (TS) over the full energy range, the detection significance in each energy bin, and the spectral energy distribution that would be measured by *Fermi*-LAT catalogs. See Sec.3 and Appendix A in Ref. [15] for technical details.

3. Results

3.1 Detectability of dark matter subhalos

To assess the detectability of dark matter subhalos, we focus on WIMP annihilation into $b\bar{b}$ final states and consider a wide range of annihilation cross sections $\langle \sigma v \rangle$ and masses m_{DM}.

In figure 1 (left), we present the distribution of simulated γ-ray subhalos as a function of detection significance ($\sigma_d = \sqrt{\mathrm{TS}}$) for two exemplary setups, in comparison to the distributions of both detected and unidentified (UNID) sources in the 4FGL-DR3 catalog. For the dark matter model corresponding to $m_{\mathrm{DM}} = 80\,\mathrm{GeV}$, 40% of the original subhalo population is detectable by *Fermi*-LAT. Note that the number of detectable subhalos is significantly enhanced by the large annihilation cross section we assume for the benchmark setup. The σ_d-distribution for our dark matter subhalos is similar to that of the UNID sources, with a noticeable difference at higher significances ($\sigma_d > 10$). We observe that varying the dark matter mass has a strong effect on the number and distribution of detectable subhalos for a fixed annihilation cross section. Lower masses have a higher detection rate due to a larger overall normalisation and a peak in the annihilation spectrum at lower energies. Our results show that the distribution of the detection significance σ_d for a realistic simulation of dark matter subhalos is highly model-dependent, and that it differs from that of 4FGL sources, considering both classified and UNID sources. It roughly approaches that of the 4FGL UNID sources for specific dark matter masses, a specific annihilation channel and specific cross section values.

The number of detectable subhalos in our simulation setup decreases approximately linearly with decreasing annihilation cross section as shown in figure 1 (right panel). This effect has been quantified in previous work [4, 5] and is reproduced also in our setup for the 4FGL-DR3 catalog. The number of detectable subhalos, i.e. subhalos for which $\sigma_d > 5$, ranges from 8 at $\langle\sigma v\rangle = 10^{-25}$ cm^3/s to about 10^3 at $\langle\sigma v\rangle = 10^{-23}$ cm^3/s for $m_{\rm DM} = 80$ GeV. Fewer subhalos are detected at higher dark matter masses because the γ-ray flux decreases proportional to ${m_{\rm DM}}^{-2}$. However, the decrease in flux is partially offset by the fact that the energy spectrum is harder and thus easier to detect at larger dark matter masses. This is why the number of detectable sources for dark matter masses around 1 TeV is higher than that for 300 GeV, for a given annihilation cross section. If we look at the TS obtained by fitting the energy spectrum only up to 30 GeV (red dashed line), we indeed find fewer detectable sources at 1 TeV compared to dark matter masses of 300 GeV.

3.2 Dark matter subhalo classification with neural networks

In order to identify UNID sources that have the same spectral properties as our dark matter models predict for subhalos, but differ from known astrophysical sources, we have implemented a Bayesian Neural Network (BNN). Our setup is based on Ref. [13] where the advantages of using such a BNN on the energy spectra of γ-ray sources were shown for classifying blazars of uncertain type. Most notable is the benefit of the uncertainty in the network prediction that can be inferred from the network output. The training data consists of the 8 values of the source spectra as a function of energy of the 4FGL-DR3 classified sources (`'Flux_Band'` in the catalog) and the simulated dark matter subhalos. The network consists of four dense Bayesian layers with 16 nodes, each with a Gaussian prior on the kernel, ReLU activation and a dropout fraction of 5 %. The final layer is fed through a softmax activation. We use the logarithm of the fluxes as inputs and pre-process them so that for each energy bin the inputs are distributed around a mean of zero with a standard deviation of one. For the training process we use the Adam optimiser with a learning rate of 10^{-3} and stop the training when the validation loss converges. We leave 10% of the training set, not used during training, as test sets. Depending on the similarity of the shape of the subhalo spectra to subsets of the 4FGL sources, the accuracy of our network on the respective test sets ranges from $\sim 90\%$ to $\sim 97\%$ and is consistent for each model with each new training. For the final results, we use the full dataset for training. The lower end of this accuracy range corresponds to the setups with $m_{\rm DM} = 30$ GeV and $m_{\rm DM} = 80$ GeV, and is comparable to the accuracy achieved when learning classification between different classes within the 4FGL catalog, as in [13].

We use the classification algorithm introduced to estimate the number of γ-ray spectra among the UNID sources observed by *Fermi*-LAT that exhibit characteristics similar to those expected from dark matter subhalos. We apply conservative selection criteria to avoid counting sources that can be reasonably discarded as subhalo objects, removing all sources showing time variability (variability index greater than 24.725 [1]) and discarding "low confidence association" with any astrophysical source type, leaving 1788 UNID sources for classification with our BNN. We further distinguish on-plane and off-plane sources based on their location within and outside the Galactic plane, respectively, using the threshold $|b| = 10°$. We expect the dark matter subhalos to be more evenly distributed across the Galactic halo, rather than clustering predominantly in the Galactic

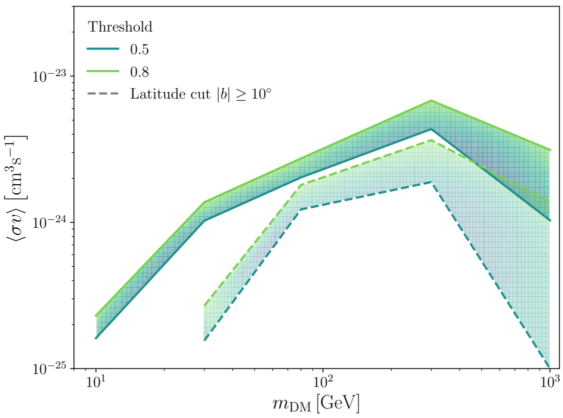

Figure 2: Our limits on annihilating dark matter as a function of dark matter mass assuming $\bar{b}b$ channel for different classification thresholds and cutting or not low-latitude sources.

plane. In particular, because we expect pulsars with an energy spectrum similar to that expected from dark matter annihilation to be predominantly in the Galactic plane, the number of off-plane sources classified as subhalos is a more conservative estimate. We use the class predictions from our network to distinguish between astrophysical sources and dark matter subhalos. By setting a threshold on the mean prediction μ minus the standard deviation σ, we can estimate the number of potential dark matter subhalos among the UNID sources. We apply a range of thresholds ($\mu - \sigma \geq [0.5, 0.8]$) to capture the behaviour of the predictions within a loose and tight selection threshold, as described in [13]. Comparing the different thresholds allows us to understand the range of candidates, from a more conservative lower limit to a more optimistic upper limit. We use a threshold to determine the number of subhalo candidates, i.e. UNID sources that survive our cuts and have a predicted class label above the threshold. The number of candidates individually for on-plane and off-plane sources for different dark matter masses and thresholds is detailed in Ref. [15], Table 1. Furthermore, we make the network predictions for the UNID sources publicly available for each model.[2]

3.3 Limits on annihilating dark matter

Our classification algorithm are finally used to set upper limits on the dark matter annihilation cross section. To do this, we distinguish between sources that are confidently astrophysical in origin and those that are considered exotic. Exotic sources include γ-ray sources that are confidently identified as subhalos, as well as sources that cannot be attributed to either dark matter subhalos or astrophysical objects. We select these sources using a threshold t such that $(1 - \mu) - \sigma \leq t$. The quantity $1 - \mu$ corresponds to the classification score for astrophysical sources, and switching the labels provides a more conservative selection of sources (table 2 in Ref.[15]). To place a conservative upper limit on the dark matter annihilation cross section, we adopt the criterion that the number of detectable subhalo candidates should not exceed the number of exotic sources, i.e. those sources that cannot be confidently classified as astrophysical. Using the relationship between the annihilation cross section $\langle \sigma v \rangle$ and the number of detectable subhalo candidates, we can translate

[2] https://github.com/kathrinnp/bnn-subhalo-candidates

the limit on the number of subhalo candidates into an upper limit on the annihilation cross section $\langle\sigma v\rangle$. The resulting limits on the dark matter annihilation cross section are shown in figure 2 for different classification thresholds as a function of the dark matter mass. As expected, more stringent classifications of the spectra as astrophysical lead to weaker limits. In figure 2, the upper limits on the dark matter annihilation cross section are shown using all exotic sources (solid lines) and only off-plane sources (dashed lines). Since the off-plane sources are expected to have less contamination from astrophysical sources, they are a better representation of the potential dark matter subhalos. However, the latitude cut applied to obtain the off-plane sample also removes a significant number of UNID sources. Therefore, the all-sky results should be considered conservative, while the off-plane results represent a complementary approach with less contamination from pulsars or other astrophysical γ-ray sources. Our results show particularly strong limits for the large dark matter mass model $m_{\rm DM} = 1$ TeV, with $\langle\sigma v\rangle < 10^{-24}$ cm^{3}s^{-1} excluded for the loose selection. Comparing our our conservative limits ($(1-\mu)-\sigma \leq t = 0.8$) with previous research on dark matter subhalo searches, such as the studies by Coronado-Blazquez et al. (2019a,b) [6, 21] and Calore et al. (2019) [18], our limits are weaker in the central energy range, but become stronger and more competitive at low and high dark matter masses, where the subhalo spectra differ more from astrophysical sources. Unlike previous studies where the number of candidates was fixed for all dark matter masses studied, we vary the number of sources as a function of dark matter mass, highlighting the advantage of using γ-ray energy spectra and the importance of a well-trained neural network on known astrophysical sources, as well as carefully constructed subhalo simulations. In addition, we anticipate more constraining results for annihilation channels for which the dark matter spectrum has a more distinct shape with respect to observed astrophysical source, e.g. $\tau^+\tau^-$.

4. Conclusions

In this contribution we have presented a machine learning supported analysis of dark matter subhalo detection in *Fermi*-LAT 4FGL-DR3. In order to train our networks, we have performed careful, realistic simulation of dark matter subhalo detectability and observable flux. We have estimated the detectability of dark matter subhalos with different dark matter models using 12 years of *Fermi*-LAT data. The detectability decreases with increasing dark matter mass due to the spectral form of the dark matter annihilation fluxes. However, at larger masses, the spectra peak at energies where the astrophysical γ-ray background is less prevalent, increasing the subhalo detectability. The main innovation of this study is the use of Bayesian neural networks to classify the unidentified *Fermi*-LAT sources. We have identified numerous dark matter subhalo candidates, particularly in the mass range of a few tens of GeV. We are making this list of candidate sources publicly available to allow further investigation of their nature using multi-wavelength observations. In addition, we have used the number of γ-ray sources that the network could not confidently classify as astrophysical to derive conservative upper bounds on the dark matter annihilation cross sections. Our limits are particularly competitive at large dark matter masses, where subhalo spectra are more distinct from astrophysical sources. We therefore demonstrate the importance of separately evaluating the number of subhalo candidates in *Fermi*-LAT catalogs for each dark matter model in order to fully exploit the information contained in the spectra. Further work could explore more sophisticated models of subhalo formation, including for example baryonic effects, or more complex particle physics scenarios involving alternative or multiple annihilation channels. In addition, the application of

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unsupervised and weakly supervised machine learning techniques could enable the identification of anomalous γ-ray sources in a more model-independent way.

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