Application of deep learning methods to high-energy astrophysics postprint

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High-energy gamma-ray astronomy, at frequencies of 100 MeV to 100 GeV, yields insights into the fields of compact objects, extreme processes, and particle propagation. Thousands of gamma-ray sources have been detected by the Fermi Gamma-ray Space Telescope, many without any known counterpart at other wavelengths or clear identification of the source. Deep learning algorithms have been successfully applied to a variety of problems in astronomy. In this paper, I give some typical examples for classifying Fermi sources with deep learning methods, to show how such techniques can improve capability to unveil the nature of high-energy gamma-ray sources.

Full Text

Preamble

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Application of deep learning methods to high-energy astrophysics

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Abstract

High-energy gamma-ray astronomy, at frequencies of 100 MeV to 100 GeV, yields insights into compact objects, extreme processes, and particle propagation. Thousands of gamma-ray sources have been detected by the Fermi Gamma-ray Space Telescope, many without any known counterpart at other wavelengths or clear identification of the source. Deep learning algorithms have been successfully applied to a variety of problems in astronomy. In this paper, I present some typical examples for classifying Fermi sources with deep learning methods, to show how such techniques can improve our capability to unveil the nature of high-energy gamma-ray sources.

Keywords: Gamma-ray astronomy; Pulsar; Active galactic nucleus; Deep learning

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1. INTRODUCTION

High-energy (HE) gamma-rays (100 MeV to 100 GeV) represent the most energetic and extreme non-thermal processes in the Universe. They can be produced by particle acceleration from compact objects and extreme environments, providing insight into the origin and propagation of cosmic rays. The Small Astronomy Satellite 2 (SAS-2)[1], the Celestial Observation Satellite B (COS-B)[2], and the Compton Gamma Ray Observatory (CGRO)[3] with its Energetic Gamma-Ray Experiment Telescope (EGRET) performed the first sensitive all-sky surveys at gamma-ray frequencies, which yielded many valuable results, such as the first observation that Active Galactic Nuclei (AGN) can emit high-energy gamma-rays. EGRET also increased the number of known pulsars and helped construct models to reveal how they accelerate particles. Since the launch of the Fermi Gamma-ray Space Telescope, HE gamma-ray astronomy has entered a golden age[4]. The Large Area Telescope (LAT), an instrument on board Fermi, covers an energy range from tens of MeV up to several TeV. Fermi-LAT surveys the sky in the high-energy regime approximately every 3 hours, performing excellently at monitoring persistent and transient sources with both galactic and extragalactic origins[5,6].

HE gamma-rays are mainly produced by two processes. In the leptonic process, HE electrons and positrons can interact with low-energy photons and boost them to high energies by Inverse Compton scattering. Electrons and positrons interacting with magnetic fields can also produce synchrotron photons. The other process is hadronic, in which the interaction between HE protons or nuclei in compact objects with protons in the dense interstellar medium often produces neutral mesons. Such mesons, resulting from nuclear interactions, quickly decay and produce gamma-rays. It is of key importance to determine whether leptonic or hadronic processes dominate the HE, very-high-energy (VHE, 100 GeV to 100 TeV) and even ultra-high-energy (UHE, above 100 TeV) ranges[7]. Since neutrinos are also the product of proton-proton interactions, hadronic processes are key for multi-messenger astronomy which links gamma-rays and neutrinos. For example, Fermi blazars (i.e., blazars detected by Fermi-LAT) are considered to give an important contribution to the diffuse TeV neutrino flux[8]. Consequently, observing HE gamma-rays from astrophysical sources is crucial to understanding particle acceleration in the Universe.

This paper is organized as follows: Section 2 describes HE gamma-ray astronomy, Section 3 briefly describes machine learning (ML) techniques in astronomy, Section 4 elaborates on the identification of gamma-ray sources, and Section 5 gives a summary of this paper.

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2. HE GAMMA-RAY ASTRONOMY

Detection of HE gamma-rays uses the conversion of photons to electron/positron pairs. Such secondary electrons and positrons can be recorded with tracking detectors. Thus, one can reconstruct the arrival direction and energy of primary gamma-rays according to the secondary particles produced, with the energy resolution being affected by fluctuations in the electron/positron cascade which develops in the detector. At several GeV, this technique has better energy resolution than at other energy ranges.

During its 16 years of operation, Fermi-LAT has created numerous catalogs including general sources[9-12], hard sources[13-15], solar flares[16], transients[17], gamma-ray bursts[18,19], low-energy sources[27], flaring sources[28], and supernova remnants[29]. These catalogs have significantly increased the number and variety of known HE gamma-ray sources, including pulsars[20-22] and AGN[23-26]. Fermi-LAT revealed that the high-energy gamma-ray sky is dominated by AGN and pulsars, which are prevalent as extragalactic and galactic sources, respectively.

AGN emit gamma-rays from collimated jets of charged particles with relativistic speeds[30]. As emissions from extragalactic sources, gamma-rays from AGN suffer attenuation due to the extragalactic background light (EBL) and produce electron/positron pairs[31]. Among AGN, blazars are a sub-class with extreme variability on timescales of seconds to years. Blazars show a spectroscopic structure with two bumps[32], which can be explained by the Doppler beaming effect observed in relativistic jets pointing at the observer, with a small viewing angle. According to emission lines in the optical band, blazars can be subdivided into BL Lacertae and flat-spectrum radio quasar (FSRQ) varieties. The distribution of photon index for Fermi blazars correlates with the blazar subclass[33].

Gamma-rays arise from cascades. Pulsar gamma-ray emissions originate from electromagnetic interactions between relativistic charged particles accelerated along magnetic field lines. Pulsars are stable, providing the most luminous gamma-ray sources in our galaxy. Spin-down power can be efficiently converted into gamma-rays via particle acceleration. Two types of magnetosphere models have been proposed to explain gamma-ray emission from pulsars. Polar cap models suggest that gamma-ray emissions originate from cascades of electron/positron pairs in the regions near the neutron star surface. Outer gap models, on the other hand, suggest that gamma-ray emissions originate from the outer part of the neutron star magnetosphere[34]. More than 3,130 of the associated or identified sources in the Fermi-LAT Fourth Source Catalog (4FGL) are AGN, while 239 are pulsars. However, for the total number of 5,064 4FGL sources, 1,336 (26.4%) remain unassociated. Most of them are faint sources with test statistics (TS) < 100.

Elucidating unidentified sources (UIDs) may greatly improve understanding of the gamma-ray sky. In addition, some identified sources are still of unknown subclass. For example, 1,312 sources are labeled as blazar candidates of uncertain type (BCU) in Fermi-LAT 4FGL data release 1 (DR1). Consequently, it is also important to identify the sub-class of progenitor AGN.

Identifying gamma-ray sources can yield information on the physical environment of their progenitors. In the extragalactic sky, the origin of the extragalactic gamma-ray background (EGB) is still an open question, and blazars and radio galaxies are thought to be substantial EGB contributors. Considering star formation activity and resulting cosmic ray acceleration, star-forming galaxies are also candidates for the EGB. Therefore, determining the class and number of extragalactic gamma-ray sources is important for resolving prospective components of the EGB[35].

Among galactic sources, pulsars dominate the high-energy range. Pulsar spin-down can be explained by various models[36-38], with wind or outflow expected to contribute to the process. The pulsar wind nebula (PWN) population is a promising contributor to galactic diffuse gamma-ray emissions (DGE). In addition, pulsar halos are recently discovered objects which also contribute to DGE[39]. These depend on the injection rate and injection spectral shape.

A primary strategy to identify UIDs in Fermi-LAT data concerns how to find suspected progenitors like AGN and/or pulsars. The population of UIDs can be assumed to follow the same distribution as associated/identified sources. Research into source identification aims to unveil the nature of UID gamma-ray sources. Classification requires up-to-date knowledge on different kinds of gamma-ray sources.

3.1. ML Algorithms

ML has a long history of application to astronomical research, such as identifying light curves[40,41], analyzing spectra[42,43], detecting absorbing species in interstellar gas[44] and classification[45,46]. Employing ML techniques improves the efficiency of classification methods by using prediction models based on training data. ML algorithms determine information directly from data rather than depending on predetermined formulation. As the sample size used in ML increases, the algorithm performance improves adaptively. The application of this kind of classification to HE gamma-ray astronomy is discussed in Section 4.

ML can be divided into supervised learning and unsupervised learning. Supervised learning aims to develop a predictive model based on both input and output data, for classification and regression. The relationship between input and output data must be known for optimal model training. The training data include features and labels, with the intention being for ML to determine the connection between these two values. Unsupervised learning aims to group and interpret data based only on input data. Input data provide the feature without the label, which can be applied to more complicated cases such as clustering. The intention is for the machine to learn by itself.

Several ML classification algorithms have been successfully applied to astronomy:

Decision Tree (DT): The features of a sample are split according to branches, towards predictors and targets. This model shows decision rules and classification results according to tree shape. As an induction method, disordered and cluttered data are converted into a model which can be applied to predict unknown data. Classification can deal with either discrete or continuous target values, and is based on the training of historical data.

Logistic Regression (LR): The LR method is a multivariate analysis model which predicts the probability of different classes, based on the values of a predictor. It is mainly used for classification related to dichotomies. The predictor variables do not need to follow a normal distribution. Such algorithms aim to find the best linear separation for input data.

Random Forest (RF): The RF method uses decision trees as building blocks for tasks such as regression and classification. It can be seen as the integration of multiple DTs. Based on a huge number of DTs, RF improves the predictions by gathering them together. RF can deal with nonlinear situations and large samples. The key parameters are the number of DTs and features.

Support Vector Machine (SVM): The SVM produces an optimal hyperplane that classifies new examples from training data. It uses a dichotomous approach to define the linear classifier with largest functional margin.

Boosted Decision Tree (BDT): Based on DT, the BDT classifier works by repeatedly applying yes/no decisions to separate positive and negative classes. By changing the weight of training samples to learn multiple classifiers, the capability of these classifiers can be improved.

Convolutional Neural Network (CNN): This is a popularly used ML algorithm which automatically extracts characteristics from high-dimensional data. CNN has been used extensively in image classification, because it learns underlying features from different layers and obtains spatial relations between pixels.

3.2. Deep Learning Method

Deep learning (DL) is a subclass of ML, using a model that consists of multiple processing layers. This allows it to process more complicated data and tasks. Samples used by DL need to be representative, ensuring training data and predicted samples are classified independently. This guarantees generalization ability and good prediction accuracy. DL has performed successfully in several fields in astronomy.

4.1. Classification Method of Fermi-LAT Sources

For training data, the feature of a sample must be known. Therefore, it is important to understand the feature to be used from the Fermi catalog, such as spectral models. For example, blazar spectra are modeled using a LogParabola relationship, as

$$\frac{dN}{dE} = N_0 \left(\frac{E}{E_b}\right)^{-[\alpha+\beta \ln(E/E_b)]} \quad ; \quad (1)$$

where N_0 is the normalization, α is the first index, β is the second index, and E_b is the scale parameter.

Pulsar spectra are modeled using a power law with an exponential cutoff, as

$$\frac{dN}{dE} = \begin{cases} N_0 \left(\frac{E}{E_0}\right)^{-\gamma_0} \exp\left[-\frac{d}{2}\ln\frac{E}{E_0} - \frac{db}{6}\ln^2\frac{E}{E_0} - \frac{db^2}{24}\ln^3\frac{E}{E_0}\right] & \text{if } \left|\frac{b}{\gamma_0}\ln\frac{E}{E_0}\right| < 1 \\ N_0 \left(\frac{E}{E_0}\right)^{-\gamma_0+d/b} \exp\left[-\frac{d}{b}\right] & \text{otherwise} \end{cases} \quad ; \quad (2)$$

where N_0 is the prefactor, γ_0 is the first spectral index, E_0 is the scale parameter, d is the local curvature parameter, and b is the second spectral index.

The gamma-ray spectra of pulsars are more curved than those of AGN. In addition, for the two sub-classes of blazar, flat-spectrum radio quasars (FSRQs) peak at a lower energy than BL Lacs. A prominent feature of blazars is variability, which hints at the mass of the supermassive black hole and radiation from jets. Variability in the timescale from radio waves to gamma-rays spans from years to minutes[47]. All these features in different objects can help to classify them. Strong correlation is found between gamma-ray photon index and log L for FSRQ and BL Lacs[48]. 2,863 objects (89% of total sources) are located at high Galactic latitudes in 4LAC ($|b| > 10°$), where AGN comprise almost four-fifths of the 4FGL sources. UID sources in this region share common spectral features with BCUs which suggests that, for the most part, they are AGN.

The number of detected sources has increased greatly because of data gathered by the Fermi Gamma-ray Space Telescope. 4FGL data release 3 (DR3) contains 6,658 point sources[49]. However, around one-third of these are unassociated with any counterparts at different wavelengths.

By considering two major classes of gamma-ray emitters, AGN and pulsars, the RF and LR algorithms have been applied to classify Fermi-LAT Third Source Catalog (3FGL) UIDs[50]. This work further develops the classification of pulsar candidate sub-classes (young and millisecond pulsars). Similarly, RF and extreme gradient boosting (XGBoost) have been used to determine that 34 unassociated Fermi sources at high galactic latitudes may potentially be pulsars[51].

Which parameters to consider in ML algorithms is an important consideration. Because not all 4FGL parameters are related to a special science case, more parameters may not necessarily improve accuracy.

A new method has been proposed, which directly trains on energy- and time-dependent photon fluxes from the 4FGL-DR2 catalog, rather than relying on specific or hand-crafted features[52]. This is a novel technique that uses a recurrent neural network to give good performance classifying gamma-ray sources, yielding results that are different to but compatible with a previous study related to human-crafted features. This aims to address sample selection bias, and can be applied to multi-wavelength data acquired from different facilities. Most pulsar candidates are distributed in the galactic plane, as shown in Fig. 1 [Figure 1: see original paper]. However, AGN candidates have a more random distribution than pulsars. As the variability-curvature plot illustrates, AGN and pulsars cluster in different regions, and pulsars tend to be non-variable while having spectra with significant curvature. The distribution of AGN and pulsar candidates cluster in the variability-curvature plot, confirming that the neural network extracts realistic features from spectra.

4.2. Classification of AGN sub-types

As blazars are the largest population among Fermi sources, there are still many blazar candidates of uncertain type (BCU). These objects display similar flat radio spectra with multi-wavelength spectral energy distributions (SEDs) showing the same two-humped shape as blazars. However, optical association is lacking to confirm their nature. Gradient-boosted decision trees have been used as BCU classifiers, because of the small set of available data[53]. Comparing the distribution of power law (PL) photon indices, it is clear that BL Lacs (2.03 $\pm$ 0.21) have harder spectra than those of FSRQs (2.47 $\pm$ 0.20), shown in Fig. 2 [Figure 2: see original paper]. The PL photon index of BL Lac candidates (2.09 $\pm$ 0.21) and FSRQ candidates (2.57 $\pm$ 0.14) show good agreement with known BL Lacs and FSRQs. The alternative plot for the difference in PL photon index between BL Lacs and FSRQs shows photon index versus luminosity. There is a clear correlation between photon index and probability. In this figure, the orange and blue dashed lines show the classification threshold defined for FSRQs and BL Lacs. Furthermore, the plot of PL photon index versus flux shows that different blazar classes are comparable.

The sources in most ML classification tasks for Fermi-LAT UIDs are primarily those with high significance, but it is doubtful that this frame can be applied to all sources. While most UIDs are located at low Galactic latitude, confirmed AGN are mainly dominated by high galactic latitude sources. Because of the diffuse gamma-ray background and the difference between galactic and extragalactic source distribution at different latitudes, care should be taken over the application of training models. Therefore, different classification models (Fig. 3 [Figure 3: see original paper]) were established for low and high galactic latitude regions[54].

Based on the training set with 10 selected parameters, the performance of different ML models can be compared[55]. The parameter correlation coefficients are given in Fig. 4A [Figure 4: see original paper]. The average significance, flux, and energy flux show a strong correlation with each other. These three parameters reflect the features of gamma-ray radiation. Average significance, flux, and energy flux are also strongly correlated. Photon index is the most important feature for RF, as shown in Fig. 4B.

4.3. Classification of pulsar sub-types

Pulsars detected by Fermi arise from the First Fermi-LAT Catalog of Gamma-Ray Pulsars (1PC, 46 pulsars), the Second Fermi-LAT Catalog of Gamma-Ray Pulsars (2PC, 132 pulsars), and the Third Fermi-LAT Catalog of Gamma-Ray Pulsars (3PC, 294 pulsars). Observing gamma-ray pulses from radio pulsars may help with supplementation of multi-wavelength features in pulsars. On the other hand, gamma-ray blind searches of unidentified sources can find more radio-quiet pulsars. The development of pulsation detection techniques can further increase the number of known gamma-ray pulsars.

Although more than 3,000 pulsars are shown in the Australia Telescope National Facility (ATNF) Pulsar Catalog, less than 300 gamma-ray pulsars have been found by Fermi-LAT.

In the 3FGL era, ML techniques were applied to classify 3FGL sources[50]. The same techniques can also be applied to a sub-sample of gamma-ray pulsars, which includes young and millisecond pulsars. The "outlyingness"with respect to pulsar and AGN classes reveals the nature of the observed source (the definition of outlyingness can be found in Reference [50]). As can be seen, most AGN have large values of pulsar outlyingness. Similarly, most pulsars have large values of AGN outlyingness. For those with a large value of both pulsar and AGN outlyingness, they should be non-pulsar and non-AGN sources, which are shown in Fig. 5 [Figure 5: see original paper].

Aiming to search for pulsars in 3FHL, it is useful to label pulsar and non-pulsar to supervise classification methods[56]. As discussed above, gamma-ray flux variability is a crucial feature for distinguishing AGN from pulsars. Such variability features are included in the 4FGL catalog, but not in 3FHL. Therefore, this work employs an automatic algorithm to select features to determine the nature of the sample using recursive feature elimination (RFE). This is a backward selection approach which eliminates unimportant features. As Fig. 6 [Figure 6: see original paper] shows, for this ML technique, patterns and quality of selected data are ignored. This is owing to the limited knowledge available to be emphasized.

Here, the flux density error, power law index and pivot energy parameters are ranked, suggesting that the hardness of gamma-rays is important for distinguishing pulsars from other sources. Since a softer gamma-ray source has a smaller pivot energy, it anti-correlates with power law index. Fig. 6 shows two-dimensional projections of the parameter space for highly ranked parameters. This suggests that the hardness (ratio of soft to hard photons) is an important factor for identifying pulsar candidates.

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5. SUMMARY

DL algorithms are applied in HE gamma-ray astronomy for the classification of Fermi-LAT sources and their sub-classes. The application of DL has increased the efficiency of gamma-ray source classification, compared with previous techniques. Such automatic analysis shortens the time cycle required to identify the nature of sources. Several examples mentioned in this review have been corroborated by subsequent multi-wavelength observations. However, current progress on classification is mainly based on observational properties. An increasing number of new kinds of astrophysical objects have also been found in the HE gamma-ray band. Furthermore, DL techniques are computationally intensive, owing to complicated model design.

Future classification methods will require a greater number of physical parameters related to different theories and/or new populations.

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Note: Figure translations are in progress. See original paper for figures.