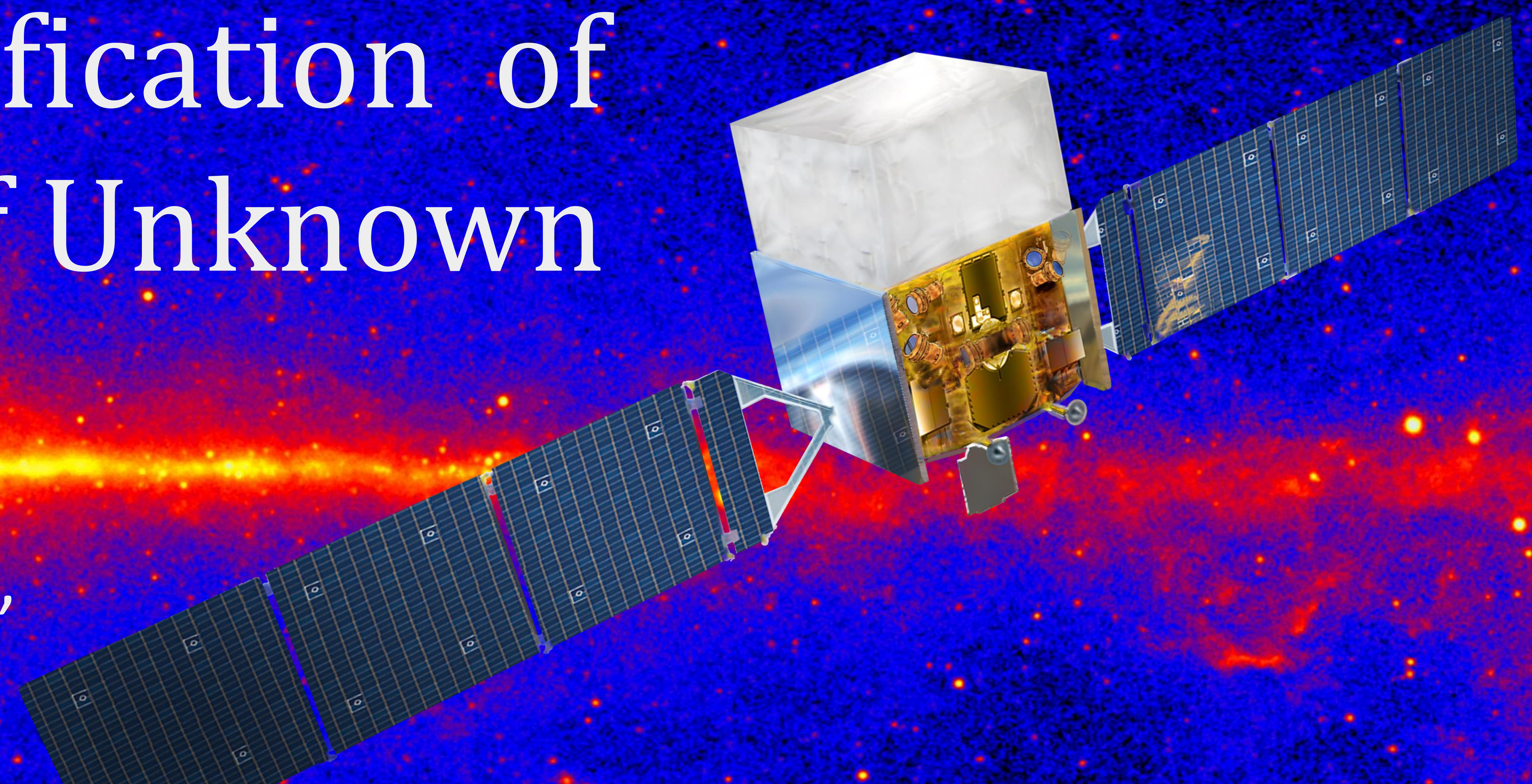
Artificial Neural Network Classification of the Fermi-LAT Catalog Blazars of Unknown Type and Unidentified Sources



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Abstract

The Fermi-LAT detected more than 7000 γ-ray sources in 14 years of operation. Many of these sources are still unassociated with counterparts in other wavelengths, others are associated to generic classes, such as blazar of unknown type, but their classification is still unclear. We consider a Machine Learning approach to the classification of Fermi-LAT unidentified sources and blazars of unknown type using multi-wavelength information. We present the artificial neural network method used to classify the blazars of unknown type and to find possible multi-wavelength counterparts for the Fermi-LAT unidentified γ-ray sources. We describe the multi-wavelength variables that characterized each source and the results obtained using them for the classification.

Introduction

The classification of identified sources and the identification of observed sources with counterparts at other wavelengths have been significant issues in γ-ray astrophysics since its beginnings. The *Fermi*-LAT has detected more than 7000 γ-ray sources in 14 years observation of which about one third are not associated with already known objects (UID), and approximately one fifth are associated with blazars of uncertain nature (BCU). We developed a machine learning method that uses an artificial neural network (ANN) trained with multi-wavelength data. We used this method to classify BCUs into BL Lacs (BLL) or Flat Spectrum Radio Quasar (FSRQ). Then we considered all the possible UIDs multi-wavelength counterparts and we implemented an ANN to find which one was the best candidate and to classify them in Blazar or Not-Blazar sources. To implement the ANN, we used the Python based *Keras* Application Programming Interface [1] and the *TensorFlow* platform [2].

UIDs Counterparts Selection

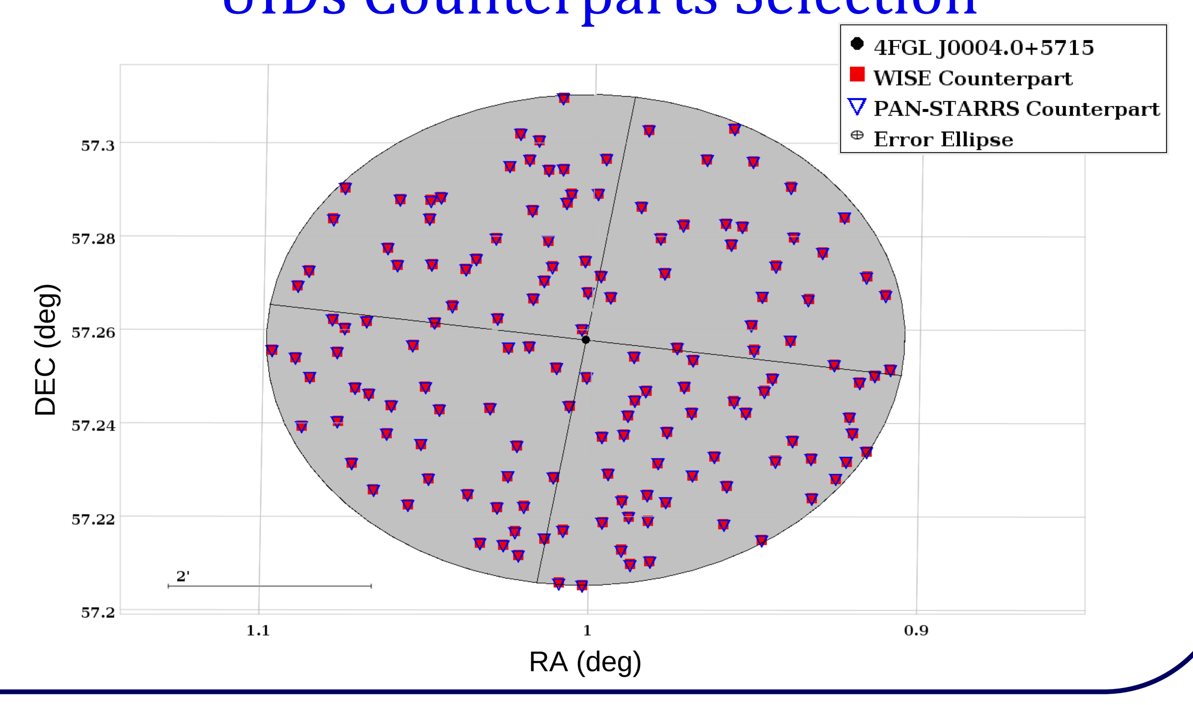

Fig 1: Plot of the counterparts from the WISE and Pan-STARRS catalogs that are in the Error Ellipse of the 4FGL J0004.0+5715 source.

ANN Validation

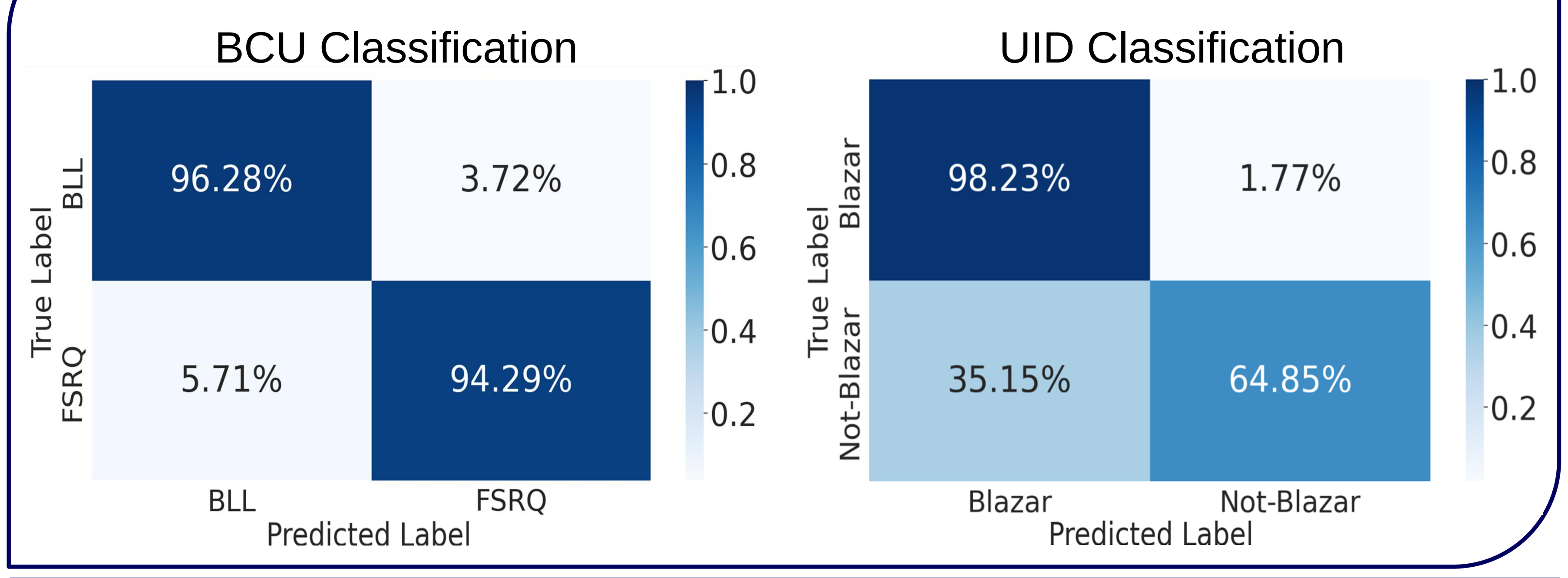

Fig. 2: Confusion Matrices. **Left**: confusion matrix of the ANN used for BCU classification. **Right**: confusion matrix of the ANN used for UID classification.

Multi-Wavelength Variables

To classify the sources an ANN must recognize the features that differentiate the classes. We select the physical information that can better distinguish the classes and we use them as input dataset for the ANN training. We considered NVSS catalog [3] for radio data, Pan-STARRS PS1 catalog [4] for optical data, WISE All-Sky Data Release catalog [5] for infrared data, and 4FGL-DR4 [6] catalog for γ-ray data. We used for the analysis only the 4FGL-DR4 sources that have counterparts in all the other three catalogs. For the identified γ-ray sources we used the known counterparts in the cited catalogs. For the UID we considered all the counterparts from the catalogs that are in the 95% confidence Error Ellipse [Fig 1]. Each of these sources is then characterized by 28 parameters: 14 normalized annual fluxes sorted in ascending order, 6 SED values in γ energy bands, 5 SED values in optical energy bands, 2 infrared color indexes and the base-10 logarithm of the flux density in radio.

ANN Classification

To evaluate the effectiveness of the model, we calculated various metrics using a test set. As shown in [Fig. 2] the first ANN is able to correctly identify 96% of the BLLs and 94% of the FSRQs in the test set, while the second one is able to correctly identify 98% of the Blazars and 65% of the Not-Blazars in the test set. The ANN calculates the likelihood of a source to belong to a class (e.g. the likelihood of being a BLL or a FSRQ). To effectively classify the BCUs and the UIDs, we applied thresholds on the likelihood that are found using the test sample; of 723 BCUs, 432 are classified as BL Lacs, 237 as FSRQs and 54 (i.e. 6%) remain unclassified [Fig 3a]. We did the same for the 1036 UIDs: 709 are associated with a Blazar counterpart and 237 are associated with a Not-Blazar counterpart [Fig 3c]. The distributions in the sky of the classified sources are shown in [Fig 3b] and [Fig 3d] in Aitoff projection in galactic coordinates.

Blazar of Unknown Type Classification

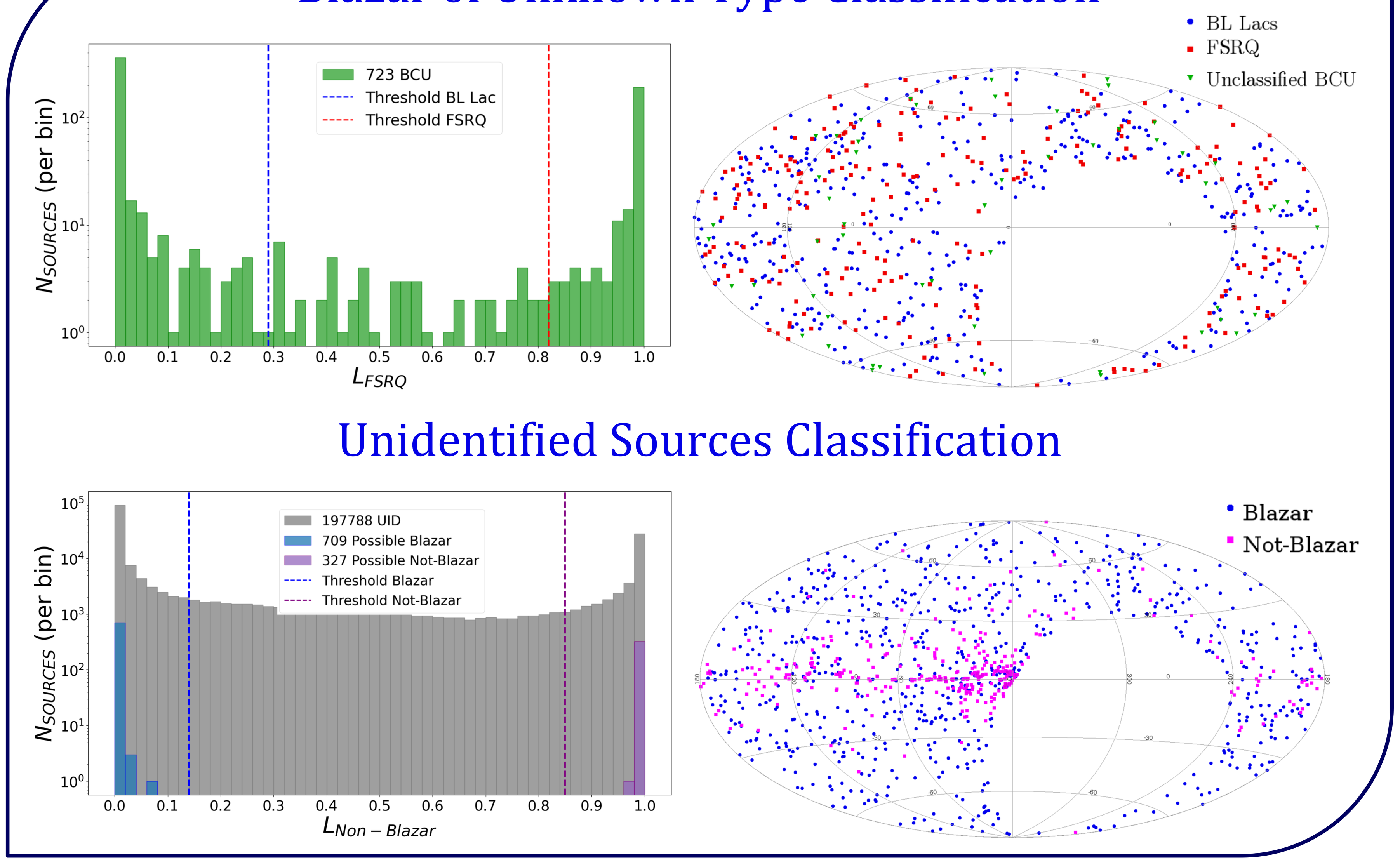

Fig 3: Results of the classification. **a**: likelihood of being a Flat Spectrum Radio Quasar source. The histogram is in logarithmic scale. **b**: distribution of the 723 classified BCUs in Aitoff projection in galactic coordinates. **c**: likelihood of being a Not-Blazar source. In grey are shown all the counterparts, while the best counterpart found by the ANN for each of the 1036 UIDs is shown in blue (if classified as Blazar) and purple (if classified as Not-Blazar). The histogram is in logarithmic scale **d**: distribution of the 1036 classified UIDs counterparts in Aitoff projection in galactic coordinates.

Conclusions

Using the ANNs trained with this multi-wavelength dataset we are able to achieve both goals described in the introduction. The first ANN is able to classify 96% of the 723 BCUs considered. Then, using the second ANN on the 1036 considered UIDs, we can propose a multi-wavelength counterpart for every UIDs and to classify them as Blazar or Not-Blazar. The distribution of possible UIDs counterparts follows the expected pattern in galactic coordinates although no positional information is given to the ANN. These potential multi-wavelength UIDs counterparts can be further studied through dedicated follow up campaigns from other observatories.

Bibliography

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