Classification of Fermi-LAT unidentified gamma-ray sources using CatBoost gradient boosting decision trees

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ABSTRACT

The latest Fermi-LAT gamma-ray catalog, 4FGL–DR3, presents a large fraction of sources without clear association to known counterparts, i.e., unidentified sources (unIDs). In this paper, we aim to classify them using machine learning algorithms, which are trained with the spectral characteristics of associated sources to predict the class of the unID population. With the state-of-the-art CatBoost algorithm, based on gradient boosting decision trees, we are able to reach a 67% accuracy on a 23–class dataset. Removing a single of these classes –blazars of uncertain type– increases the accuracy to 81%. If interested only in a binary AGN/pulsar distinction, the model accuracy is boosted up to 99%. Additionally, we perform an unsupervised search among both known and unID population, and try to predict the number of clusters of similar sources, without prior knowledge of their classes. The full code used to perform all calculations is provided as an interactive Python notebook.

Key words: gamma-rays: general

1 INTRODUCTION

Since its launch on June 11, 2008, the Large Area Telescope on board the NASA Fermi Gamma-ray Space Telescope (Fermi-LAT) has been surveying the sky searching for gamma-ray sources The Fermi-LAT Collaboration & Atwood (2009). The Fermi-LAT is a pair conversion telescope designed to observe the energy band from ~20 MeV to more than 300 GeV. Several point-source Fermi-LAT catalogs have been released and contain hundreds to thousands of gamma-ray objects, many of them previously unknown The Fermi-LAT Collaboration (2015); Ackermann et al. (2016); The Fermi-LAT Collaboration (2017). The difference between such catalogs lies in the different energy ranges and exposure times, and the usage of the best available astrophysical diffuse emission model and instrumental response functions (IRFs) at the time.

The gamma-ray sky can be decomposed in several pieces, such as the interstellar gamma-ray emission, the isotropic gamma-ray background (IGRB) and individual point-like and extended sources. Both the Galactic diffuse emission and the IGRB are the main difficulties to detect point-sources, due to spectral confusion and photon spill over, given the poor angular resolution of the LAT Acero et al. (2016). This effect is especially strong near the Galactic plane, where the emission of the Milky Way (MW) dominates any other component.

Contrary to cosmic rays (CRs), the direction of propagation of gamma rays is (almost) unperturbed, and a precise location of sources can be made. These sources, which are not transient phenomena (although they can undergo flaring periods), are associated with astrophysical objects, which have mechanisms that accelerate particles up to these energies. These objects can be located in the MW or outside it.

Associating a gamma-ray source to a known astronomical object is not trivial, and requires a careful, multiwavelength analysis with several instruments Schinzel et al. (2017). The LAT is able to detect a rich variety of sources, being active galactic nuclei (AGN) the most frequent.

The current picture of the AGN landscape is a unified scheme, depending on the emission in the radio band and the existence of jets, as well as their orientation towards the Earth. This classification method gives rise to objects such as blazars (BLL), quasars, or Seyfert galaxies Urry & Padovani (1995). In particular BLLs, which are AGNs with a relativistic jet pointing directly towards the Earth, are the most numerous among all known gamma-ray sources.

Concerning Galactic sources, there is a much richer variety of objects, as their intrinsic low gamma-ray luminosity can be detected from the Earth, given their distances. Among them, we may find pulsars (PSRs), pulsar wind nebulae (PWNe), supernova remnants (SNRs), star-forming regions, globular clusters, high- and low-mass X-ray binaries, binary star systems, and nova Fermi-LAT Collaboration (2020). Among these, PSRs, PWNe, SNRs and binaries are the most common Galactic gamma-ray sources, as well as primary sources of accelerated CRs Koyama et al. (1995). This particle acceleration produces a gamma-ray spectrum which is typically best-fit by a power law –reflecting the non-thermal production of such energetic photons. Nevertheless, PSRs, SNRs, and PWNe present a curved spectrum Harding (2001); Takata et al. (2015).

PSRs also present a very quickly-rotating subclass, with periods around the millisecond, and accordingly known as MilliSecond Pulssars (MSPs). These form when an old PSR is in a binary system, with a much less massive companion star, starts accreting material from it until it reignites with a quicker pulsation period. This leads to luminosities up to 20 times larger than in a young PSR, due to

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their fast rotation Calore et al. (2014). Due to their age and reignition kick velocity, MSPs tend to appear at higher Galactic latitudes than younger counterparts Cordes & Chernoff (1997).

All the source information is ultimately condensed in gamma-ray source catalogs. Depending on the instrument, the nomenclature may vary, but it is typically an alphanumeric chain which marks the instrument and data release, followed by the equatorial coordinates in format J2000, i.e., JHHMM.m+DDMMa, although notable sources may be named differently. This allows a quick cross-correlation between multiwavelength catalogs. Additional data such as detection significance, flux, positional error, spectral best-fit model parameters, variability and association(s) is provided.

All the gamma-ray source catalogs share a common feature: the large fraction of unidentified sources (unIDs). Indeed, ca. 1/3 of objects are of unknown nature. This is also the typical value in the TeV regime, where 26% of all sources are currently unassociated. The knowledge of the source class is critical to understand the underlying gamma-ray emission physics, as well as perform population studies Coronado-Blázquez et al. (2019a); Orlando et al. (2021).

In recent years, machine learning has become a widely used tool in data science for tasks such as regression, clustering, dimensionality reduction, feature extraction, and classification. Indeed, several well-established algorithms such as Logistic Regression (LR), K-Nearest Neighbours (KNN), Naive Bayes (NB), Support Vector Machines (SVMs), Artificial Neural Networks (ANN), Decision Trees (DT) or Random Forests (RF) are widely used for the latter (see, e.g., Ray (2019); Sarker (2021) for a review on these techniques). More recent implementations include eXtreme Gradient Boost (XGBoost) Chen & Guestrin (2016), LightGBM Ke et al. (2017), and CatBoost Prokhorenkova et al. (2017), currently the state-of-the-art in classification.

Some of the “classic” algorithms have been used for a classification of unIDs within gamma-ray catalogs (e.g., ANN by Salvetti et al. (2017), RF and LR by Saz Parkinson et al. (2016)), but only to distinguish between two different classes, such as PSR vs. AGN, or BLL vs. FSRQ.

In this paper, we perform a machine learning classification of the unIDs with three models: i) considering all 23 different classes; ii) excluding a single class, which induces confusion; and iii) establishing a binary PSR/AGN-like classification. Additionally, we perform an unsupervised clustering on both known and unID populations. This will allow to better understand the underlying population, as well as compare the statistical similarity between associated and unID sources.

The paper is structured as follows: In Section 2, we describe the latest LAT catalog, and select the features to take into account. In Section 3, we show the results of the classification with CatBoost within known sources as validation, and apply it to the unID population. In Section 4, we perform the unsupervised clustering among the known and unID population. We conclude in Section 5.

2 THE 4FGL–DR3 CATALOG

The 4FGL catalog was released in 2019, covering 8 years of LAT data (2008–2018) Fermi-LAT Collaboration (2020). A second release, 4FGL–DR2, was published a year later with two additional years of data Ballet et al. (2020), while a third one –and latest at this writing–, 4FGL–DR3, was published in January, 2022 covering 12 years of LAT operations Fermi-LAT Collaboration et al. (2022). It is therefore the most complete compendium of gamma-ray sources, as the LAT, being a space-borne telescope, covers the whole sky. We devote the interested reader to the LAT data repository for technical details on the construction of the catalog.

The 4FGL–DR3 contains 6659 individual sources, from which 2296 (34%) are unIDs. We obtain the table as an Excel-compatible file from here, where we exclude columns such as RA, DEC (yet, keeping GLON, GLAT), the alternative and extended gamma-ray names, as well as additional information of association (except 'source_type', which is out target variable).

A total of 50 columns are present in our data, with information such as the flux with uncertainty, detection significance, best-fit spectrum type, best-fit parameters, variability and other spectral parameters. Some columns, devoted to peak time range and energies for flaring sources, are null in most sources, and therefore are removed from the sample. These are the ['significance_peak', 'flux_peak', 'flux_peak_error', 'time_peak', 'time_peak_interval'] columns.

Given the distribution of null values, we decide to also remove the following columns: ['lp_beta_error', 'lp_epeak', 'lp_epeak_error', 'plec_exp_index_error', 'plec_epeak', 'plec_epeak_error']. In addition, we remove the 'name' column and the ['semi_major_axis_68', 'semi_minor_axis_68', 'position_angle_68'] columns, as they are redundant with the 68% values, also present in the catalog.

Therefore, we use 39 features as input for the classifier. Regarding the source class, encoded in the source_type column, the catalogs distinguishes between upper- and lower-case associations depending on them being firm associations or identifications. For our purposes, we homogenize the nomenclature to lower-case associations such as, BLAGN and BLL classes are merged as BLL). Also, sources labeled as unknown (‘unk’) and without source class (‘NaN’) are merged in ‘unk’.

We also perform a study of correlations between numerical variables via Pearson correlation, as shown in Figure 1. No significant correlations are found besides the spectral parameters and derived quantities.

3 CLASSIFICATION OF GAMMA-RAY SOURCES WITH CATBOOST ALGORITHM

To shed some light on the nature of 4FGL–DR3 unIDs, we rely on CatBoost algorithm for classification Prokhorenkova et al. (2017). CatBoost is based on a boosted decision tree with hyperparameter auto-tuning, native support for GPU executions and categorical labels (e.g., SpectrumType). At this writing it is the state-of-the-art algorithm for multiclass classification (see this page for more details), improving the results of XGBoost and LightGBM algorithms.

3.1 Validation on identified sources

To make predictions of the source class among the unIDs, first we must estimate the performance of the classifier in the identified sources, where we know the actual label. To do so, we generate a subset of sources taking into account only the ones with source_type

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2 Every LAT catalog ever published can be found here.
3 See TeVCat online tool.
4 https://catboost.ai/
As input we use 23 different classes: ['bcu', 'bll', 'fsrq', 'spp', 'psr', 'rdg', 'agn', 'msp', 'glc', 'smr', 'gal', 'sbg', 'sfr', 'bin', 'hmb', 'nlsy1', 'lmb', 'nov', 'css', 'pwn', 'ssrq', 'sey', 'gc']. We refer the reader to the Fermi webpage for a detailed explanation of each of these classes.

A 75/25% train/test split is performed on the subset of known sources. With the CatBoostClassifier class, we train the algorithm on the train set, this is, with knowledge of the class labels, and evaluate its performance in the test set, without prior knowledge on the source type. We also perform a cross-validation on 5 folds of the test set, and run the algorithm with 1000 iterations in each fold.

CatBoost obtains a $66.81 \pm 1.18\%$ accuracy on the 5–fold test set\footnote{If an algorithm randomly assigned a class, its expected average accuracy would be $100\%/23$ classes = $4.3\%$.}. In Figure 2, we show the confusion matrix of an average fold. Although the normalization may be misleading, with several "1s" (100\%) appearing off-diagonal, this is due to the fact that many of these "1s" reflect scarce source classes with just one or two members in the test set. If we plotted the confusion matrix with absolute numbers, it would be dominated by the bll class, as the catalog is, making very difficult to distinguish the non-zero off-diagonal elements. Nevertheless, we refer the reader to the provided notebook, where the option normalize='true' can be switched off in the confusion matrices generation.

We highlight the fact that most of the misclassified sources are labeled as BCUs, which are in fact a misclassified source class itself, as they are blazars of unknown nature Fermi-LAT Collaboration (2020). The performance of the algorithm will improve by taking into account this fact, which we will do in two different ways.

The first strategy consists on ignoring the BCU class. This will reduce the sample of known sources from 4363 down to 2763 (37\% of rejections), while retaining 22 classes. By repeating the steps in the previous, full 23-class model, we now reach a $80.70 \pm 2.41\%$ accuracy in the test set with 5–fold cross-validation and 1000 iterations. We plot the confusion matrix in Figure 3, where the main source of confusion is now the bll class. Nevertheless, this model performs a factor $\sim 18$ better than a random classifier, and can provide hints for unIDs specific classes.

As a second approach, we group the sources in two general categories, g-AGNs (containing bcu, bll, fsrq, agn classes) and g-PSR...
We predict the labels of each of the classes in the three models previously introduced. We use the predict method based on the trained data for each model. In the following, we discuss the results for each of them, according to the output distribution.

| Class      | Count | Class    | Count | Class      | Count |
|------------|-------|----------|-------|------------|-------|
| bcu        | 1516  | spp      | 812   | AGN-like   | 2189  |
| spp        | 479   | bll      | 752   | PSR-like   | 107   |
| bll        | 133   | fsrq     | 460   |            |       |
| fsrq       | 56    | msp      | 132   |            |       |
| msp        | 50    | glc      | 113   |            |       |
| glc        | 41    | snr      | 22    |            |       |
| snr        | 16    | pwn      | 3     |            |       |
| pwn        | 3     | rdg      | 2     |            |       |
| rdg        | 1     |          |       |            |       |

Table 2: Distribution of source predicted classes for each of the three considered models.

The prediction of the two first models, with 23 and 22 classes, yields spp as the most or second most predicted source among unIDs, mounting up to 21 and 35% of the whole unID class prediction, respectively. In the 23-class model, spp represents a 3% of the total known sources, and a 4% in the 22-class model. This class is defined in the catalog as “special case – potential association with SNR or PWN” Fermi-LAT Collaboration (2020). Therefore, it is difficult to predict the actual class of these unIDs rather than pinning them down to these possibilities.

While we must stress that associated test set accuracies for these two models are 67 and 81%, it is interesting to note that their confusion matrices (Figures 2 and 3) do not present Type I errors for the spp class except for marginal source types, i.e., this class is not overrepresented in the output of the known sample run.

The rest of sources are associated with AGNs or pulsars, with specific sub-types. Classes which are underrepresented in the associated dataset, such as rdg, are also very scarce in the predicted set, while many are not predicted at all.

Regarding the Galactic longitude/latitude distribution, we plot them in Figures 5 and 6 for each of the three models. Only classes with more than one predicted member appear. As the unIDs are clustered around low latitudes, the predictions will also be; nevertheless, we find interesting differences depending on the predicted class and model.

All three models present distributions peaked around low latitudes, where most of unIDs are present, due to source confusion induced by the intense Galactic diffuse emission. It is interesting to note that, in the binary model, AGN-like sources are more spread across higher latitudes, while PSR-like’s probability distribution decreases quicker towards high latitudes. This is consistent with the latitude distribution of known sources, where psr-like sources cluster around high latitudes, while AGN-like’s distribution is more spread across all latitudes.

(As in the rest of the paper, we will not distinguish upper- and lower-case classes.)

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**Figure 4.** Normalized confusion matrix of the classifier performance on the test set of known sources, for the binary aggregation of AGN-like (g-agn, composed of bcu, bll, fsrq, agn classes) and pulsar-like (g-psr, composed of psr and msp classes). Note the algorithm perfectly classifies the AGN-like sources.

**Table 1.** Summary of the three models trained with CatBoost, according to the number of classes considered. The reported test set accuracy is computed with a 5-fold cross-validation on a 25% test split and 1000 iterations.

| Classes | Definition       | Test set accuracy |
|---------|------------------|-------------------|
| 23      | All classes      | 66.81 ± 1.18%     |
| 22      | No BCUs          | 80.70 ± 2.41%     |
| 2       | PSR/AGN-like     | 99.21 ± 0.19%     |

**3.2 Prediction of unIDs classes**

The results of this model using CatBoost is an important improvement with respect to both the 23- and 22- types classification, reaching a test accuracy of 99.21 ± 0.19% over a 5-fold cross-validation and 1000 iterations. The confusion matrix is shown in Figure 4.

Depending on the requested level of detail of the source class, we can opt for a broad, binary classification between PSR-like and AGN-like sources, a detailed 22-class, or a 23-class (including BCUs) model, reproducing the original catalog. The assumptions and reached accuracies in the test set are summarized in Table 1.

With these three models, we can now predict the classes of the unIDs, and study the distribution and differences between them.
Galactic latitude probability distribution of the predicted classes in each of the three models. **Top row:** 23–class model. **Middle row:** 22–class model. **Bottom row:** 2–class model. As the Figure depicts the mathematical probabilistic density function, it may overcome the physical range \([-90, 90]\).

In the 22-class model, without BCUs, we note a symmetry of the distributions with respect to the central latitude, with the two predicted PWNs very peaked at zero latitude. Nevertheless, in the full, 23-class model, we note BLL and FSRQ distributions are shifted towards positive latitudes.

Regarding the longitude distribution, most classes present a double-peaked distribution with a local minimum around the Galactic anti-center (180 deg), as expected. There are some exceptions to this, such as FSRQs and BLLs, which do not decay towards the anti-center as they are extragalactic sources and do not follow a Galactic distribution. The eccentric distribution of PWNs is due to be composed only of three sources in both 23- and 22-class models.

The full prediction tables for each unID and model including the source name, Galactic coordinates, and predicted class are available as interactive arrays in the provided notebook.

**4 CLUSTERING OF ASSOCIATED AND UNID POPULATIONS OF GAMMA-RAY SOURCES**

The classification of sources requires a label, i.e., a target variable. Another possible approach is to perform an unsupervised learning of the LAT gamma-ray sources, known as clustering. In this case, no source class information is required, as the algorithm will assign each
source to different clusters, maximizing the intra-cluster similarity and differences between clusters. This blind search will allow us to compare both associated and unID samples to search for possible statistical differences between them. If an extra cluster was found in the case of the unIDs, it would point towards the potential existence of a new class of gamma-ray emitter, difficult to associate to a known source in other wavelength and therefore only present in the unID sample. Therefore, no classification is attempted in this Section, but rather a statistical study of both associated and unID populations in order to compare their similarities.

To do so, we will use the k–means method Lloyd (1982). This is preferred over hierarchical, agglomerative clustering Ackermann et al. (2010) due to the number of features considered, as well as the high number of individual sources. The main input is the number of clusters, which is not decided by the algorithm, but defined by the user.

We use the scikit-learn Pedregosa et al. (2012) implementation of k–means with k–means++ initialization\(^8\). The same features as in Section 3 are removed, plus the 'name', 'source_type' and categorical variables, resulting in a 32–dimensional clustering. We divide the LAT sources in associated and unIDs, as our main goal in this section is to compare the number of predicted clusters, which could be interpreted as groups of sources with similar characteristics (not necessarily belonging to the same classes).

To decide the optimal number of clusters \(k\), we implement the Within-Cluster Sum of Squares (WCSS) and the so-called “elbow method” Marutho et al. (2018). It consists on computing the sum of squares of the distances of each source to all clusters to their respective centroids. This will output a monotonically decreasing function, which will be null in the limit of \(k = d\), where \(d\) is the number of sources. Nevertheless, by evaluating the improvement on WCSS as we increase \(k\), the curve will show an “elbow” on the optimal value \(k_{\text{opt}}\), and for \(k > k_{\text{opt}}\) the decrease will be less pronounced. The result of the WCSS curve for LAT sources clustering in both populations is shown in Figure 7.

In the case of the associated sample, it is hard to decide whether 4 or 6 is the optimal number of clusters with the red curve (in linear scale). Yet, by drawing it in log-scale, the value of \(k_{\text{opt}}\) = 6 is preferred over 4. On the other hand, the unID WCSS curve has a clear “elbow” for \(k = 4\). Analytically, the computation of \(k_{\text{opt}}\) is obtained computing the second derivative of a spline interpolation of the WCSS: the lowest \(k\) in which the second derivative drops near zero will be \(k_{\text{opt}}\). The values obtained this way match the aforementioned ones.

The possible mismatch between the predicted clusters on associated sources and unIDs suggests the former contains a few unique sources not present in the latter. By taking a look at the distribution of sources in each cluster, for both populations, we obtain 3902–303–142–13–2–1 (\(\sim 89\%–7\%–3\%–0.3\%–0.05\%–0.02\%\)) for the associated sample and 1993–272–27–4 (\(\sim 87\%–12\%–1\%–0.2\%\)) for the unIDs.

If we used \(k_{\text{opt}} = 4\) in the associated sample, the proportion would be 4324–30–2–1, with the two intermediate clusters of 303 and 142 sources being incorporated to the 3902- and 13-source clusters. The last two, exotic clusters are still present and therefore are not a result of over-estimating the \(k_{\text{opt}}\).

Indeed, the two-member cluster is composed by the Vela Abdo et al. (2010) and Geminga MAGIC Collaboration et al. (2020) pulsars, among the first detected gamma-ray sources due to their proximity to the Solar System. The single-member cluster contains 4FGL J1533.9–5712e, an extended source classified as SNR with H.E.S.S. counterpart Araya (2017), which the k-means algorithm renders as unique. These are exceptional sources which are very easily associated, and not expected in the unIDs pool. Without these three rare sources, we would have four clusters with similar proportions (as discussed in the previous paragraph) in both the associated and unID samples, suggesting their underlying populations are statistically the same, according to the resulting gamma-ray spectral characteristics.

Additionally, we show in Table 3 the distribution of source classes across all 6 clusters for the known sample. Clusters #0 and #1 present similar proportion of sources, yet the first does not contain g-psr sources, but the latter contains more than an order of magnitude more sources. Clusters #3 and #4 present similar distribution of sources among them, more balanced than #0 and #1, and again the latter presents a factor \(\sim 10\) more sources than the former. Finally, clusters #2 and #5 are the two- and one-member aggregations already discussed.

We refer the interested reader to the full notebook to find a 2D plotting function which takes all possible combinations of variables and plots them against each other, with individual sources colored by cluster and the centroids marked in black. As an example, we show in Figure 8 the scatter relation between two variables for the associated sample.

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8 See scikit-learn webpage for more details on this method.
This may be discouraging, as no exotic source – such as WIMP dark matter (DM) annihilation or decay Conrad (2014); Funk (2015) – would be expected to appear within the unIDs. Yet, the clustering results only tell us that there seems to be no extremely unique unID, but says nothing about their underlying physics. For example, low-mass DM annihilation in certain hadronic channels such as $bb$ or $cc$ can mimic PSR spectra Mirabal (2013); Mirabal et al. (2016); Coronado-Blázquez et al. (2019b). Therefore, even if not exhibiting any exotic characteristic according to the 32 considered variables, it would constitute a new class of gamma-ray source.

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**DATA AVAILABILITY**

The datasets in csv and Excel format, and the full code to obtain the results presented in this paper can be obtained from this link, as well as online supplementary material from MNRAS. The code is written in Python as an interactive, pre-computed notebook which can be opened and executed with Google Colab or Jupyter.
REFERENCES

Abdo A. A., et al., 2010, ApJ, 713, 154
Acero F., et al., 2016, ApJS, 223, 26
Ackermann M. R., Blömer J., Kuntze D., Sohler C., 2010, arXiv e-prints, p. arXiv:1012.3697
Ackermann M., et al., 2016, APJS, 222, 5
Araya M., 2017, ApJ, 843, 12
Ballet J., Burnett T. H., Digel S. W., Lott B., 2020, arXiv e-prints, p. arXiv:2005.11208
Calore F., Di Mauro M., Donato F., 2014, The Astrophysical Journal, 796, 14
Chen T., Guestrin C., 2016, arXiv e-prints, p. arXiv:1603.02754
Conrad J., 2014, arXiv e-prints, p. arXiv:1411.1925
Cordes J. M., Chernoff D. F., 1997, The Astrophysical Journal, 482, 971–992
Coronado-Blázquez J., Sánchez-Conde M. A., Domínguez A., Aguirre-Santaella A., Di Mauro M., Mirabal N., Nieto D., Charles E., 2019a, J. Cosmology Astropart. Phys., 2019, 020
Coronado-Blázquez J., Sánchez-Conde M. A., Di Mauro M., Aguirre-Santaella A., Ciucă I., Domínguez A., Kawata D., Mirabal N., 2019b, J. Cosmology Astropart. Phys., 2019, 045
Fermi-LAT Collaboration 2012, The Astrophysical Journal, 750, 3
Fermi-LAT Collaboration 2020, The Astrophysical Journal Supplement Series, 247, 33
Fermi-LAT Collaboration et al., 2022, arXiv e-prints, p. arXiv:2201.11184
Funk S., 2015, Proceedings of the National Academy of Science, 112, 12264
Harding A. K., 2001, in Aharonian F. A., Völk H. J., eds, American Institute of Physics Conference Series Vol. 558, High Energy Gamma-Ray Astronomy: International Symposium. pp 115–126 (arXiv:astro-ph/0012268), doi:10.1063/1.1370785
Ke G., Meng Q., Finley T., Wang T., Chen W., Ma W., Ye Q., Liu T.-Y., 2017, in NIPS.
Koyama K., Petre R., Gotthelf E. V., Hwang U., Matsuura M., Ozaki M., Holt S. S., 1995, Nature, 378, 255
Lloyd S., 1982, IEEE Transactions on Information Theory, 28, 129
MAGIC Collaboration et al., 2020, A&A, 643, L14
Marutho D., Hendra Handaka S., Wijaya E., Muljono 2018, in 2018 International Seminar on Application for Technology of Information and Communication. pp 533–538, doi:10.1109/ISEMANTIC.2018.8549751
Mirabal N., 2013, Mon. Not. Roy. Astron. Soc., 436, 2461
Mirabal N., Charles E., Ferrara E. C., Gonthier P. L., Harding A. K., Sánchez-Conde M. A., Thompson D. J., 2016, Astrophys. J., 825, 69
Orlando E., Rasmussen M., Strong A. W., 2021, PoS, ICRC2021, 662
Pedregosa F., et al., 2012, arXiv e-prints, p. arXiv:1201.0490
Prokhorenkova L., Gusev G., Vorobev A., Veronika Dorogush A., Gulin A., 2017, arXiv e-prints, p. arXiv:1706.09516
Ray S., 2019, in 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon). pp 35–39, doi:10.1109/COMITCon.2019.8862451
Salvetti D., Chiaro G., La Mura G., Thompson D. J., 2017, MNRAS, 470, 1291
Sarker I. H., 2021, SN Computer Science, 2
Saz Parkinson P. M., Xu H., Yu P. L. H., Salvetti D., Marelli M., Falcone A. D., 2016, ApJ, 820, 8
Schinzel F. K., Petrov L., Taylor G. B., Edwards P. G., 2017, ApJ, 838, 139
Takata J., Ng C. W., Cheng K. S., 2015, Monthly Notices of the Royal Astronomical Society, 455, 4249–4266
The Fermi-LAT Collaboration 2015, APJS
The Fermi-LAT Collaboration 2017, APJS, 232, 18
The Fermi-LAT Collaboration Atwood W. B., 2009, APJ
Urry C. M., Padovani P., 1995, Publications of the Astronomical Society of the Pacific, 107, 803

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