

Machine learning methods for classification of unassociated *Fermi* LAT sources

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ABSTRACT

Context. Classification of sources is one of the most important tasks in astronomy. Sources detected in one wavelength band, e.g., in gamma rays, may have several possible associations in other wavebands or there may be no plausible association candidates.

Aims. In this work, we take unassociated sources in the third *Fermi*-LAT point source catalog (3FGL) and suggest associations to known classes of gamma-ray sources using machine learning methods trained on associated sources in the 3FGL.

Methods. We use several machine learning methods to separate *Fermi*-LAT sources into two major classes: pulsars and active galactic nuclei (AGNs). We evaluate the dependence of results on meta-parameters of the ML methods, such as the depth of the tree in tree-based classification methods and the number of layers in neural networks. We test the performance of the methods with a test sample drawn from the associated sources in 3FGL. We compare the predictions with the preliminary forth *Fermi*-LAT catalog (4FGL).

Results. Summary of results

Key words. Methods: statistical – Catalogs

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11 1. Introduction

12 2. Methods

13 The purpose of this section is to describe the ML meth-
14 ods that we use for the classification: random forests,

15 boosted decision trees, (simple decision trees?), neural
16 networks, logistic regression, support vector machine.

17 Methodology

18 1. Split the PS with known classification into learning
19 and test samples.

20 2. Use the learning sample for training and for selec-
21 tion of features. In particular, continuous parameters,
22 such as the thresholds in the decision trees or mixing
23 matrices in neural networks, are determined from the
24 leaning sample.

25 3. Meta-parameters, which encode the complexity of the
26 methods, such as the depth of the decision trees, are
27 determined from the best performance on the test
28 sample.

29 2.1. Details of the analysis

30 In this subsection we give more details on the analysis:

- 31 1. Describe the features that we use for the analysis.
- 32 2. Describe the objective function for minimization (ac-
33 curacy of classification on learning sample). Weighted
34 objective function: give more weight to pulsars, since
35 there are fewer of them in the catalog.

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- 36 3. Learning curve using all features? *Plot: classification*
37 *accuracy using the total list of features for learning*
38 *and test sample as a function of complexity param-*
39 *eter.*
- 40 4. Selection of the most important features. *Table: fea-*
41 *tures vs algorithms. Columns: algorithms, rows: fea-*
42 *tures, values: significance.*
- 43 5. Selection of meta-parameters. *Plot: classification re-*
44 *sults for the test sample using a subset of features.*
- 45 6. Train the final classifier. *Table: classification accuracy*
46 *of the final classifiers for different algorithms using*
47 *the test sample from 3FGL.*

48 Discuss the general features of the optimal algo-
49 rithms: which features turn out to be important, what
50 is the depth of the trees, the number of trees in random
51 forests, the depth and number of internal nodes in the
52 neural networks.

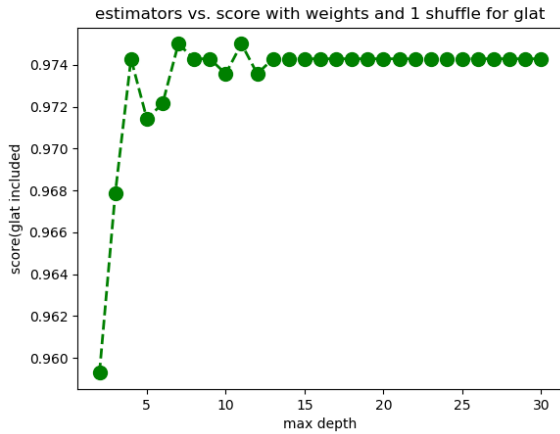


Fig. 1. Example of a figure for one column.

53 2.2. Comparison of the classification algorithms

54 *Plot: classification domains for a pair of features (or dif-*
55 *ferent pairs of features, e.g., latitude vs index, index vs*
56 *curvature, latitude vs variability).*

57 Probabilistic classification? Result: probability for a
58 source to belong to a particular class. Result of classi-
59 fication: table of sources with probabilities for different
60 algorithms. Final probability: the probability for one of
61 the algorithms (for the most precise one?) and uncertain-
62 ties determined from the other algorithms.

63 Discuss a few examples where algorithms give differ-
64 ent predictions (are these sources at the boundaries of
65 the domains).

66 Discuss examples where algorithms misclassify
67 sources from the test sample.

68 3. Prediction for unassociated sources in 3FGL 69 and comparison with 4FGL

70 Apply the algorithms on unassociated sources in 3FGL.
71 *Plot: add unassociated sources on the plots with do-*
72 *main for the best algorithm.*

73 Create a table with sources which are more likely to
74 be pulsars (select about 20 the most likely candidates).
75 Compare the accuracy of the algorithm for the sources
76 which have an associate now in the 4FGL catalog.

77 4. Comparison with 4FGL

78 5. Conclusions

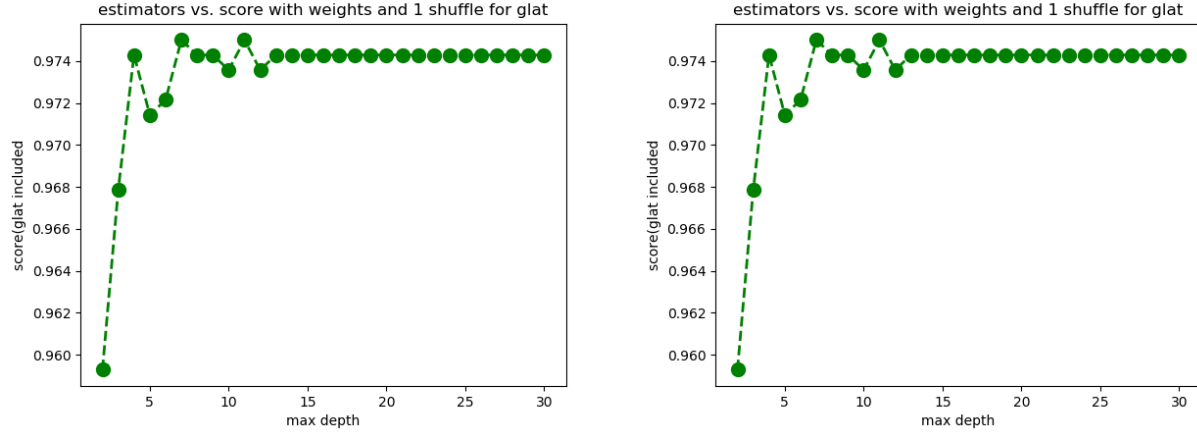


Fig. 2. Example of a figure for both columns.

79 **Appendix A: Appendix**

80 If we need one.