-Classification of Fermi-LAT sources with deep learning-

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Machine learning techniques are powerful tools for the classification of unidentified gamma-ray sources. We present a new approach based on dense and recurrent deep neural networks to classify unidentified or unassociated gamma-ray sources in the last release of the Fermi-LAT catalog (4FGL-DR2). Our method uses the actual measurements of the photon energy spectrum and time series as input for the classification, instead of specific, hand-crafted features. We focus on different classification tasks: the separation between extragalactic sources, i.e. Active Galactic Nuclei (AGN), and Galactic pulsars, the further classification of pulsars into young and millisecond pulsars and the sub-classification of AGN into different types. Since our method is very flexible, we generalise it to account for uncertainties in the predicted classes. Our list of high-confidence candidate sources labelled by the neural networks provides targets for further multiwavelength observations to identify their nature, as well as for population studies.

Introduction

Gamma-ray observatories as *Fermi*-LAT build catalogs of individual sources, collecting their main characteristics: measured position and flux at different energies and times + derived features, obtained from fits to data.

Dataset:
- Last release, 10 years of data: 4FGL-DR2 catalog [1]
- Traditional classification: multi-wavelenght observation, gamma-ray features
- $\sim 30\%$ of detected sources are not classified (UNC)

Our goal: predict source class and its uncertainty with deep learning using only photon energy spectrum and time series data

Impact: complement population studies; stimulate multi-wavelength follow ups

Fermi-LAT gamma-ray source populations

- Active Galactic Nuclei (**AGN**): jets originating from supermassive black hole at centre of a galaxy
- Most AGN are **blazars**: jets pointing towards line of sight, divided into BL Lacs (BLL), Flat Spectrum Radio Quasars (FSRQ) according to spectral characteristics; $\sim 40\%$ of uncertain type (BCU)
- Pulsars (**PSR**), divided into young pulsars (YNG) and millisecond pulsars (MSP)

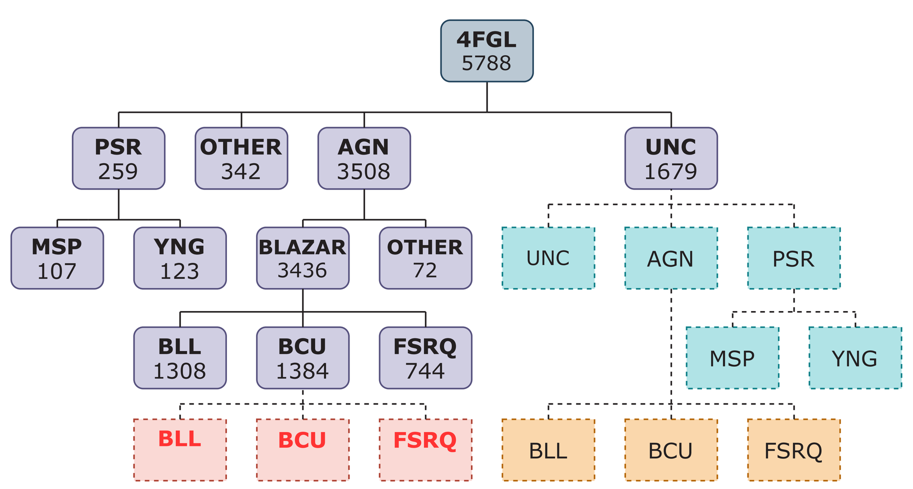

Fig.1: 4FGL-DR2 composition. Solid lines: class as reported in the catalog. Dashed linesL class predictions obtained using deep learning classifiers

Focus: features in AGN vs. PSR classification

Derived source features such as variability index (relative variability between different time bins wrt mean value) or curvature (significance for the log parabola spectral fit) were used in previous machine learning classification, see e.g. [2, 3].

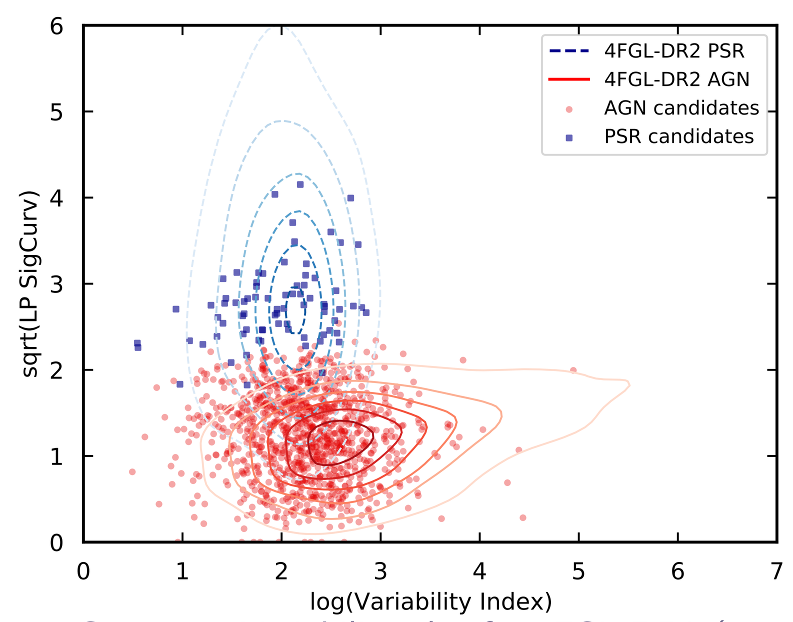

Fig.5: Curvature-Variability plot for 4FGL-DR2 (contours) and candidate sources (markers)

A-posteriori, our candidate sources follow expected clustering in variability-curvature plane: **deep networks extract relevant features from energy and time spectra**

Strategy

- Energy and time γ-ray spectra *only* as input data, instead of derived features: use full information contained in measurements, w/o bias from feature selection
- *Dense* and *recurrent* networks: catch correlations in sequential data
- *Bayesian networks* [4]: estimate uncertainties on predicted source class

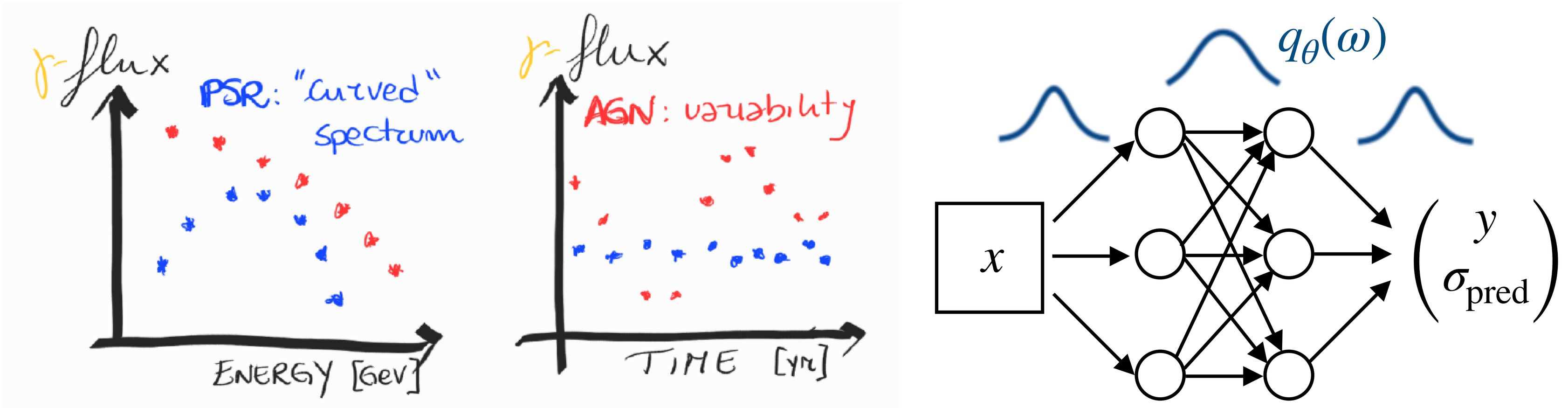

Fig.2: Left: Sketch of input data: energy spectrum and time series.
Right: Bayesian neural network concept: probability distribution assigned to weights instead of single value

Classification results

Benchmark: **accuracy** of 97.6% (AGN vs.PSR), 87% (YNG vs. MSP)

Candidate sources follow the expected Galactic latitude distribution

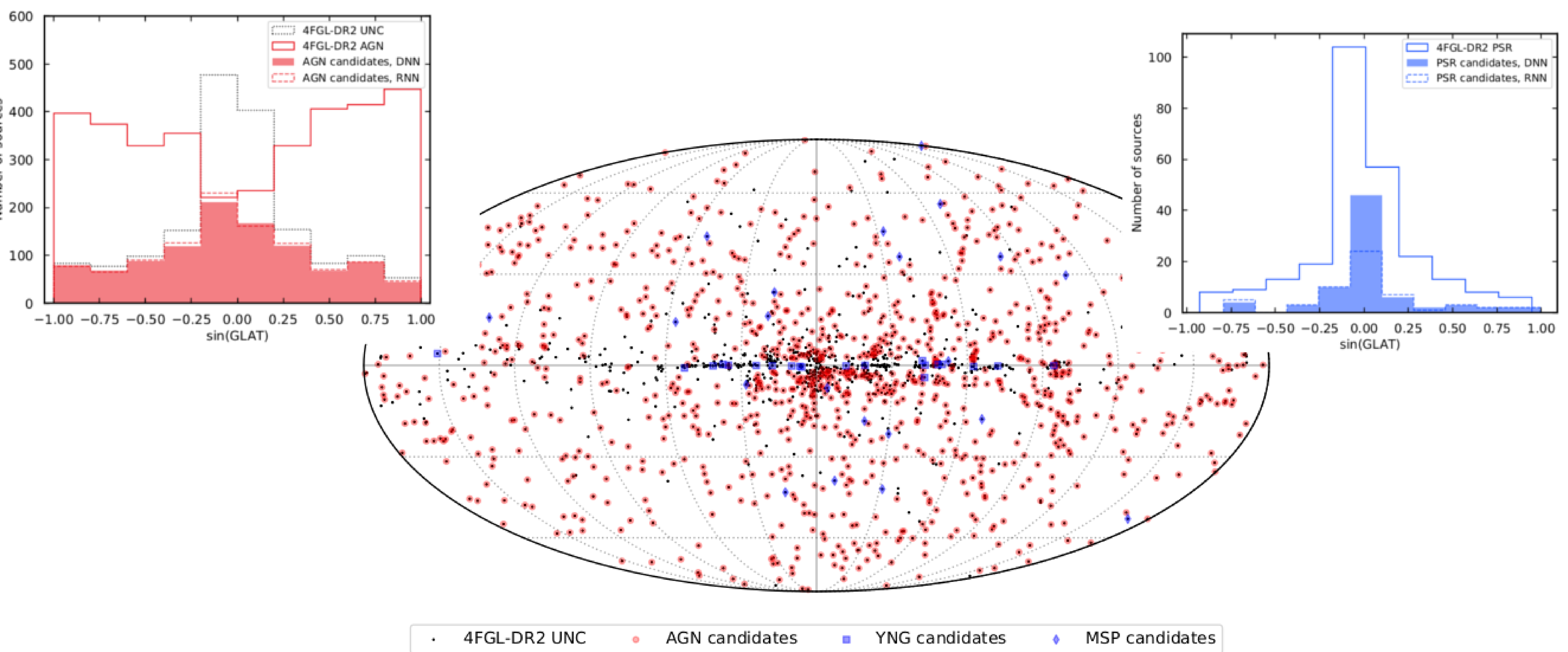

Fig.4:Sky distribution (Galactic coordinates) of: unclassified sources (black), AGN candidates (1050 in total, red), YNG pulsar and MSP candidates (78 in total, blue).

Confusion matrix : [on Test set of 1053 AGN, 78 PSR]

	True AGN	True PSR
Predicted AGN	1042.1 ± 3.7	16.4 ± 5.4
Predicted PSR	10.9 ± 3.7	61.6 ± 5.4

Architecture, training, testing

- Input data: energy spectrum (7) + time spectrum (10)
- Classified 4FGL-DR2: used for training (70%), testing (30%)
- Optimized performance: ten-fold cross-validation
- Complementary performance measures: accuracy, confusion matrix, ROC/AUC [6]

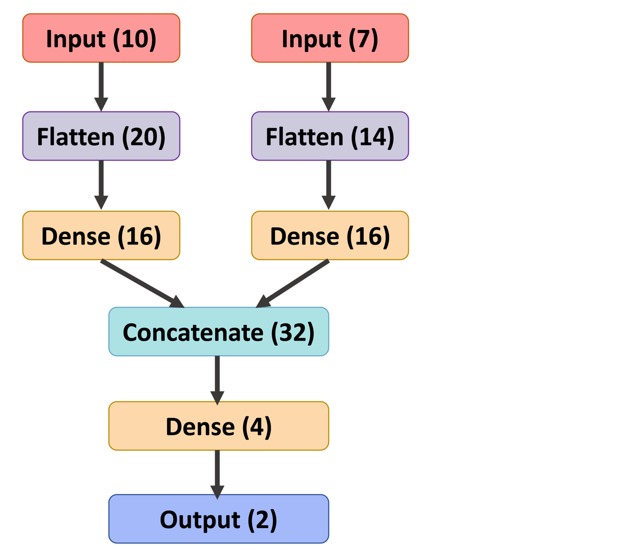

Fig.3: Sketch of architecture for AGN vs. PSR classification. Each box illustrates one layer (type, output shape). Dense layers are also substituted with recurrent or Bayesian layers.

Focus: Bayesian classification of BCU

Uncertainties on predicted gamma-ray source classes so far never estimated.
We are investigating Bayesian classification of blazars of uncertain type (BCU) in BLL vs. FSRQ [4, 5]

- Simplest architecture: dense neural network on energy spectrum only
- Dense layers substituted by Bayesian layers
- Data augmentation to stabilize the Bayesian classifier

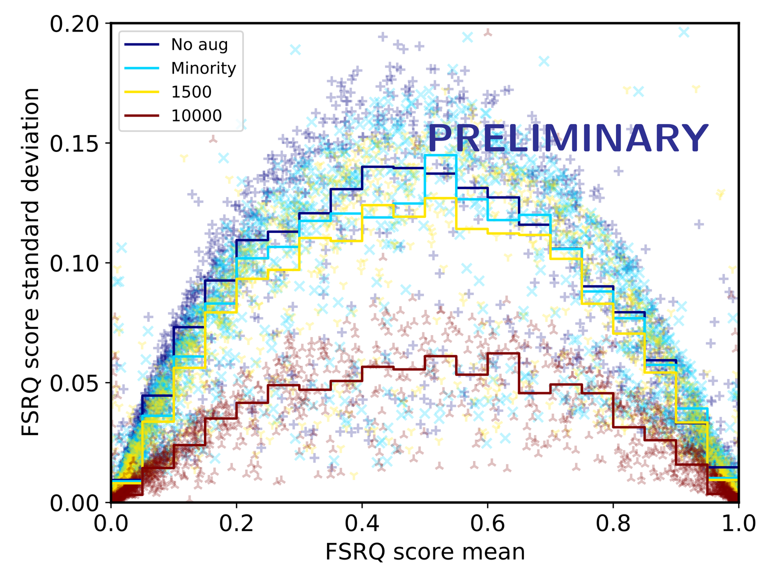

Fig.6: distribution of FSRQ classification uncertainties for different data augmentation setups.

Classification uncertainties estimate for candidate BLL and FSRQ

Conclusions & outlook

A novel deep learning approach to classify unidentified or unassociated gamma-ray sources in the last release of the Fermi-LAT catalog (4FGL-DR2) was presented.

- **Main novelties and results**:
  1. Deep and recurrent networks using energy and time spectra data only successfully used to predict source classes for 4FGL-DR2 unclassified sources
  2. Bayesian networks explored to estimate classification uncertainty.
- **Outlook**:
  1. Use predicted classification with uncertainties to complement population studies of extragalactic and Galactic sources
  2. Extend energy and time spectra with data from other observatories.

References

[1] Ballet et al., arXiv:2005.11208
[2] Saz Parkinson et al, ApJ 820 (2016)
[3] Luo et al, MNRAS 492 (2020)
[4] C.M. Bishop, J.Braz.Comp.Soc.4 (1) 1997
[5] Butter et al, in preparation (2021)
[6] Finke et al, arXiv:2012.05251

Resources & contacts

Preprint: **arXiv:2012.05251**
Full list of predictions:
https://github.com/manconi/agn-psr-nn-classification
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