Finanziato dall'Unione europea NextGenerationEU
Ministero dell'Università e della Ricerca
Italiadomani PIANO NAZIONALE DI RIPRESA E RESILIENZA
ICSC Centro Nazionale di Ricerca in HPC, Big Data and Quantum Computing

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# Centro Nazionale di Ricerca in HPC, Big Data e Quantum Computing

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| what | status |
|---|---|
| IACT Gamma/Hadron Discrimination and Energy Estimation (morphological parameters / Machine Learning) | |
| IACT Gamma/Hadron Discrimination and Energy Estimation (time parameters / Machine Learning) | |
| IACT Gamma/Hadron Discrimination and Energy Estimation (Deep Learning) | |
| X-ray Spectra Analysis in Low-mass X-ray binaries (Deep Learning/ Recurrent Neural Networks) | |
| Advancements in Cloud Masking Techniques for Multispectral Satellite Imagery (Deep Learning) | |
| Enhanced Financial Fraud Detection:Pattern Recognition from Historical Data (Machine Learning) | |

# Imaging Atmospheric Cherenkov Technique and Challenges

## Overview of IACTs:

The Imaging Atmospheric Cherenkov technique is essential for studying very high-energy (VHE) astrophysical radiation sources.

Significant in discovering and characterizing VHE gamma-ray emitters.

## Challenges in Data Analysis:

Data from Imaging Atmospheric Cherenkov Telescopes (IACTs) are largely overwhelmed by cosmic-rays background.

Necessitates highly efficient background rejection methods to distinguish gamma-ray signals by identifying unique shape features in their images.

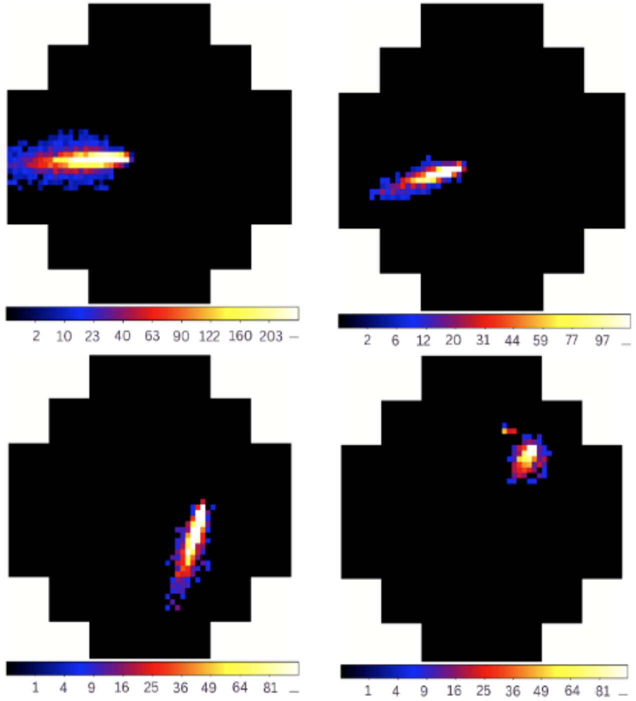



**Figure 1.** Cherenkov shower images simulated as observed by the ASTRI MiniArray telescopes, illustrating the morphological differences between different types of events (the contour matches that of the ASTRI telescope camera). The images include two gamma ray events (**Top**), a hadronic event with similarities to gammas (**Bottom Right**), and a distinct hadronic event (**Bottom Left**). These images showcase the often faint but discernible variations in the Cherenkov shower morphology.

# Machine Learning in Gamma/Hadron Separation and Energy Reconstruction

## Case Study Using ASTRI Mini-Array:

**Utilized simulated data to assess and compare various supervised Machine Learning methods, including Random Forest, Extra Trees, and Extreme Gradient Boosting (XGB).**

| | 1 LOG10 SIZE | 2 WIDTH | 3 LENGTH | 4 DENS | 5 CONC | 6 NUSED TEL | 7 M3 LONG | 8 TELIP |
|---|---|---|---|---|---|---|---|---|
| GH SET 0 | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ |
| GH SET 1 | ■ | ■ | ■ | ■ | ■ | ■ | | ■ |
| GH SET 2 | ■ | ■ | ■ | ■ | ■ | ■ | | ■ |
| GH SET 3 | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ |
| EN SET 0 | ■ | ■ | ■ | ■ | ■ | | | ■ |
| EN SET 1 | ■ | ■ | ■ | ■ | ■ | | | ■ |

| | 9 ST MAXH | 10 LEAK | 11 NUM CORE | 12 NUM BOUND | 13 DELTA | 14 ASYM | 15 ECCE | 16 ELONG |
|---|---|---|---|---|---|---|---|---|
| GH SET 0 | ■ | ■ | ■ | ■ | | | | |
| GH SET 1 | ■ | ■ | | ■ | ■ | ■ | | |
| GH SET 2 | ■ | ■ | ■ | ■ | ■ | ■ | ■ | ■ |
| GH SET 3 | ■ | ■ | ■ | ■ | ■ | ■ | | |
| EN SET 0 | ■ | ■ | | | | | | |
| EN SET 1 | ■ | ■ | | | ■ | | ■ | ■ |

**Table 1.** Sets of parameters used in our analysis. "GH SET" refers to sets used in gamma/hadron discrimination while "EN SET" refers to sets used in energy estimation. A full box indicates that the corresponding parameter is part of the set. "GH SET 3" and "EN SET 1" are highlighted since they are our top-performing sets, as we will discuss in Sections 5.5 and 6.3.

# Machine Learning in Gamma/Hadron Separation and Energy Reconstruction

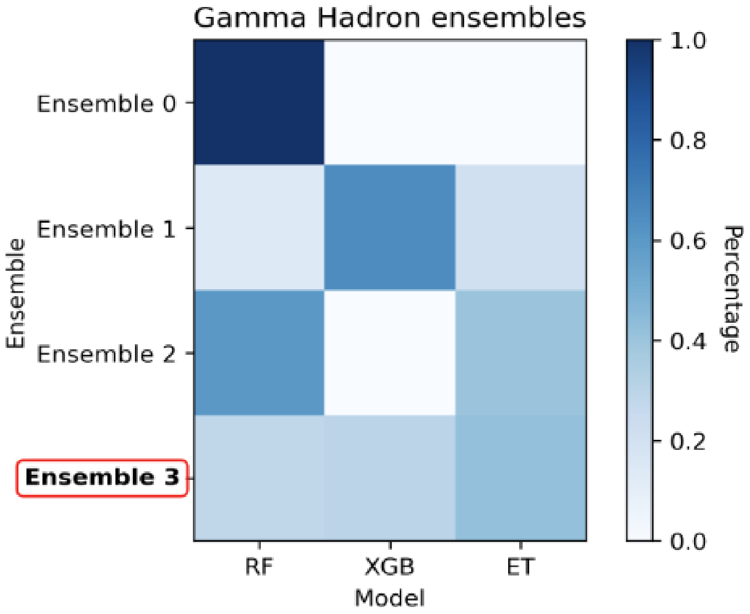



**Figure 3.** Heatmap of gamma/hadron separation Stacking Ensembles. The figure displays the percentage of each Machine Learning model in four different Stacking Ensembles consisting of Random Forest (RF), XGB, and Extra Trees (ET) models. The ensembles were chosen through a series of tests aimed at optimizing the Quality factor of the models. Our best model is ensemble 3. The heatmap visualization provides an easy-to-read overview of the model composition of each ensemble, with darker shades of blue indicating a higher percentage of the model.

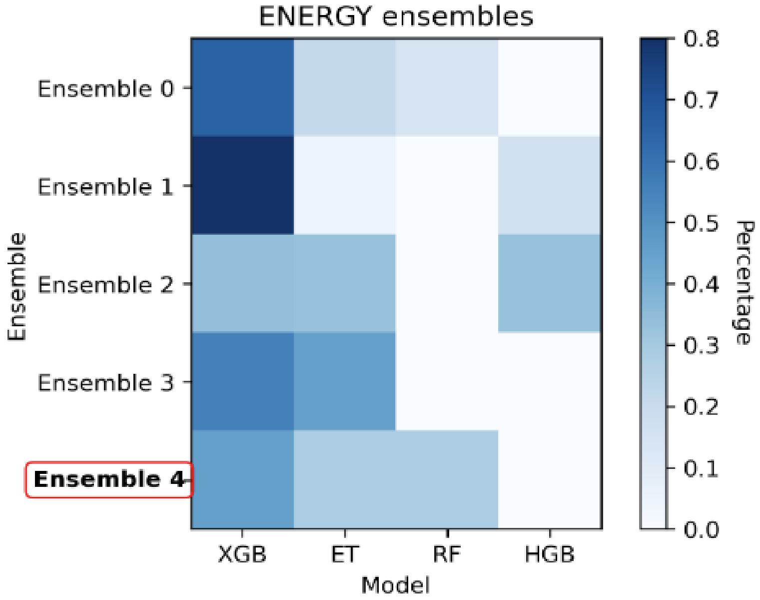



**Figure 10.** Heatmap of energy Stacking Ensembles. The figure presents the percentage of each Machine Learning model in five different Stacking Ensembles consisting of XGB, Extra Trees (ET), Random Forest (RF) and HGB models. The ensembles and their weights were selected to optimize the bias. Our best model is ensemble 4. The heatmap visualization provides a clear representation of the relative contribution of each model to each ensemble, with darker shades of blue indicating a higher percentage of the model.

# Machine Learning in Gamma/Hadron Separation and Energy Reconstruction

## Optimal Techniques and Weighting:

**Gamma/Hadron Separation:**

- **Most effective technique: Stacking Ensemble Method.**
- **Composition: 42% Extra Trees, 28% Random Forest, 30% XGB.**

**Energy Estimation:**

- **Best performing technique: Stacking Ensemble Method.**
- **Composition: 45% XGB, 27.5% Extra Trees, 27.5% Random Forest.**

**Derived from extensive experiments, trials, and cross-validation to ensure maximum performance.**

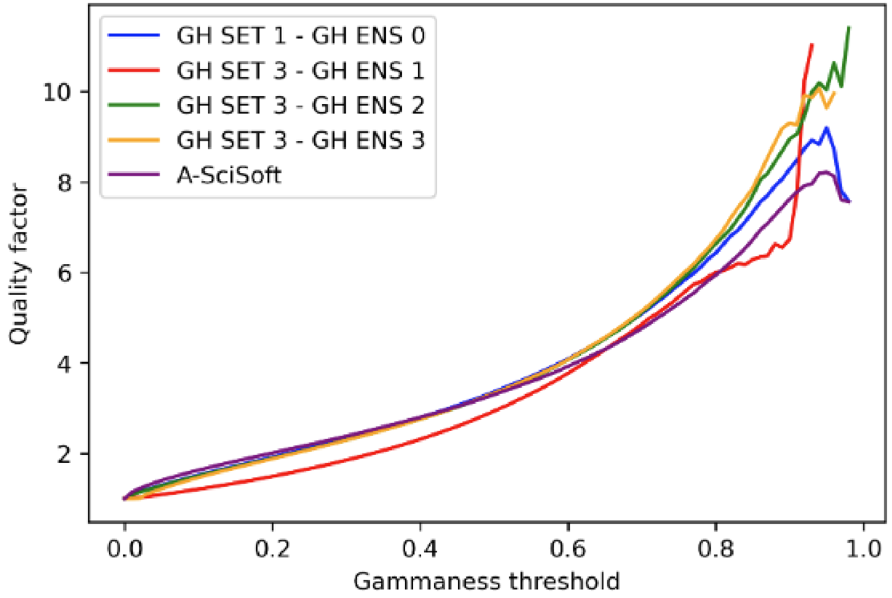



**Figure 6.** Quality factor for different gammaness threshold and for different models and sets of parameters.

# Machine Learning in Gamma/Hadron Separation and Energy Reconstruction

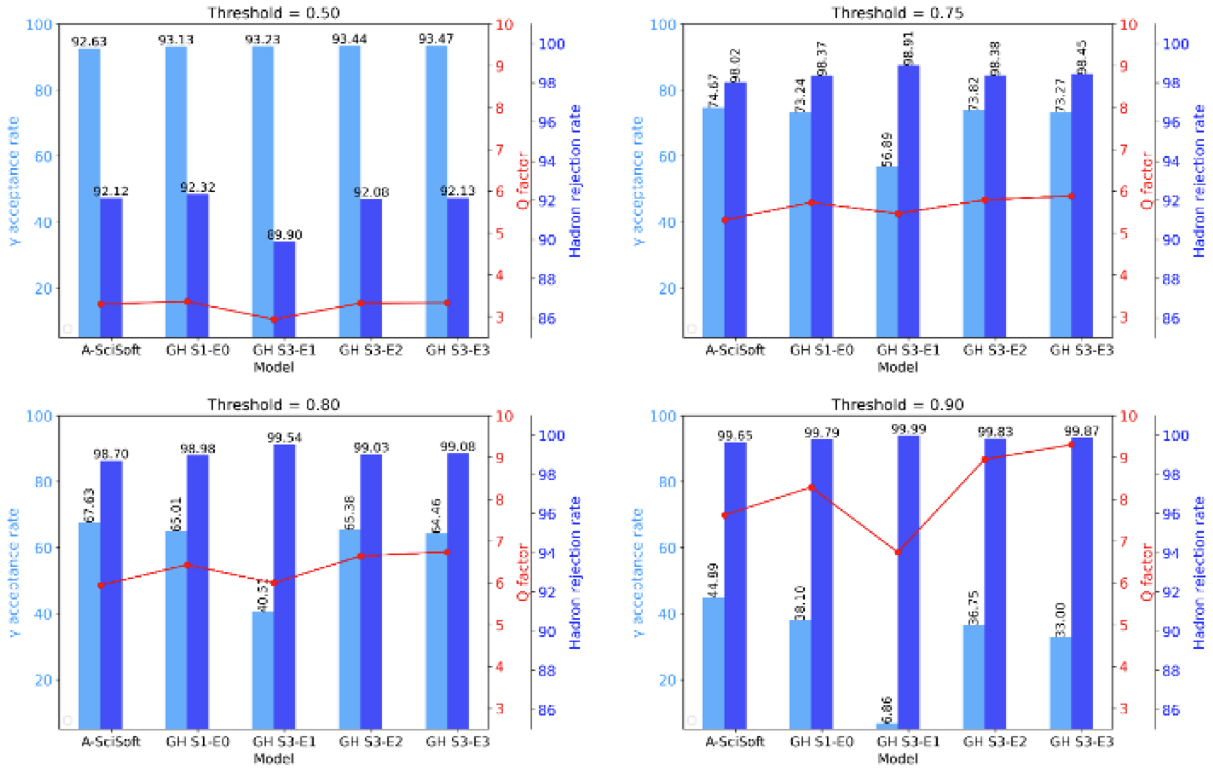



**Figure 7.** Bar plots showing the performance of five models in terms of true identification rate ($\gamma$ acceptance rate, in dodgerblue) and rejection rate of impostor matches (Hadron rejection rate, in blue), along with the quality factor (in red) for each model for four different gammaness thresholds (0.5, 0.75, 0.8 and 0.9).

# Machine Learning in Gamma/Hadron Separation and Energy Reconstruction

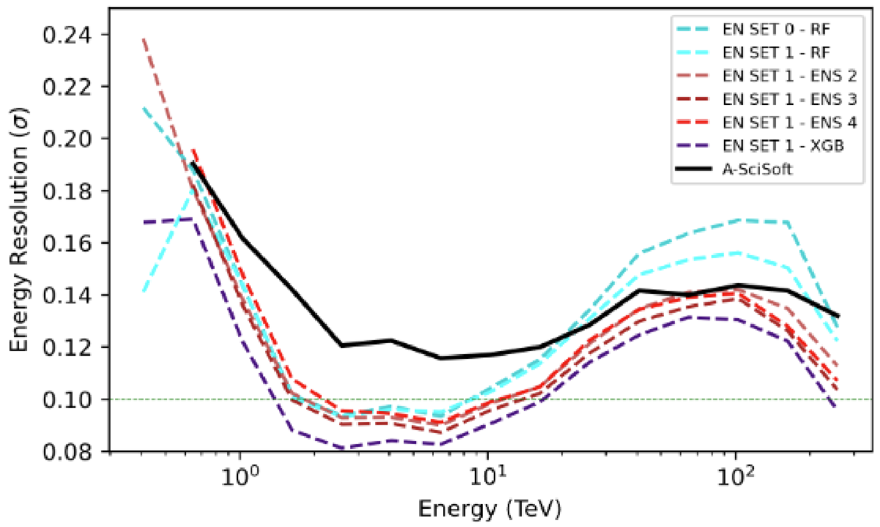



**Figure 11.** Energy resolution for different Machine Learning methods and two different sets of parameters against the benchmark (A-SciSoft).

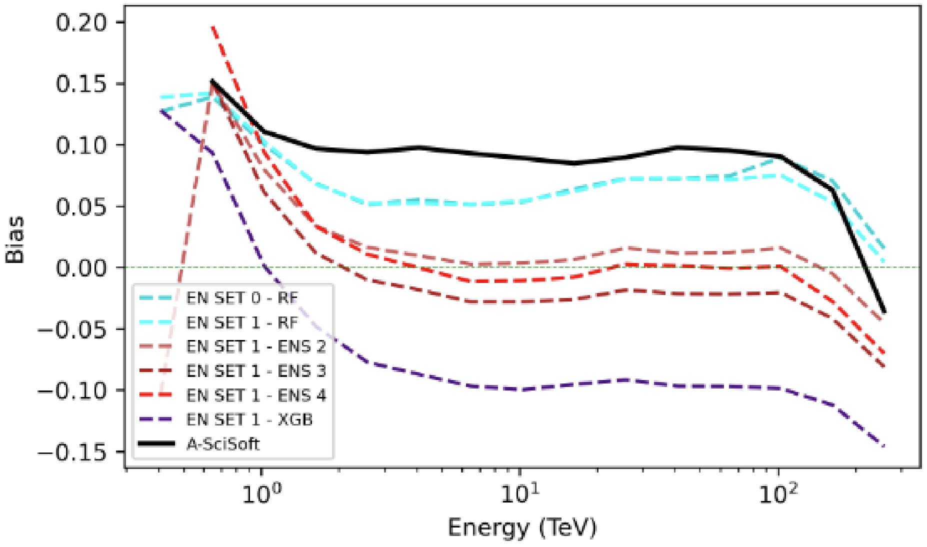



**Figure 12.** Energy bias for different Machine Learning methods and two different sets of parameters against the benchmark (A-SciSoft).

**Machine Learning, especially Stacking Ensemble methods, has proven effective for gamma/hadron segregation and energy estimation in ASTRI Mini-Array data, outperforming traditional methods like Random Forest.**

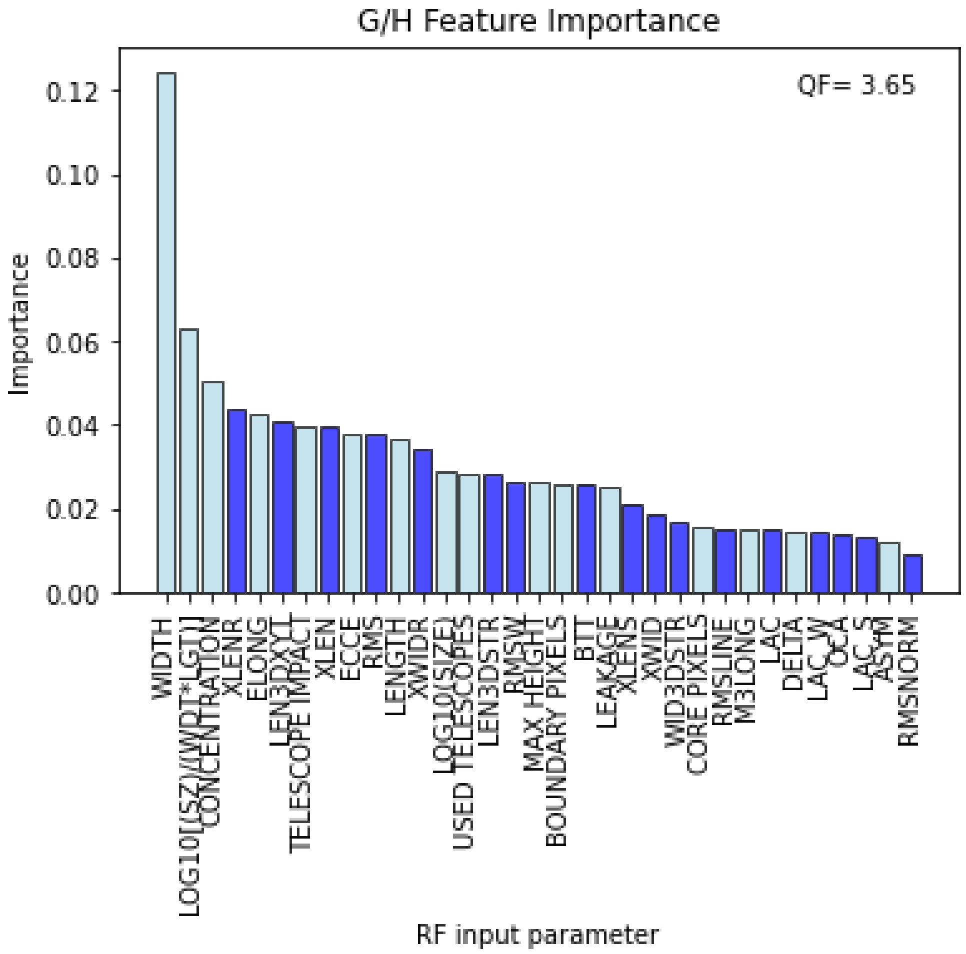
**These methods reduce energy bias significantly, validating the robustness of the current reconstruction chain and suggesting potential integration into ASTRI's official analysis pipeline.**

# Innovative Approach Using Pixel Time Tags

**Introduces a new dimension to the analysis by considering the time evolution of showers.**

**Pixel time tags record the activation time of each camera pixel during a shower, providing critical temporal information.**

**This temporal data, combined with morphological analysis, enhances the discrimination between photonic (gamma-ray) and hadronic showers, potentially improving hadron rejection and overall IACT sensitivity.**

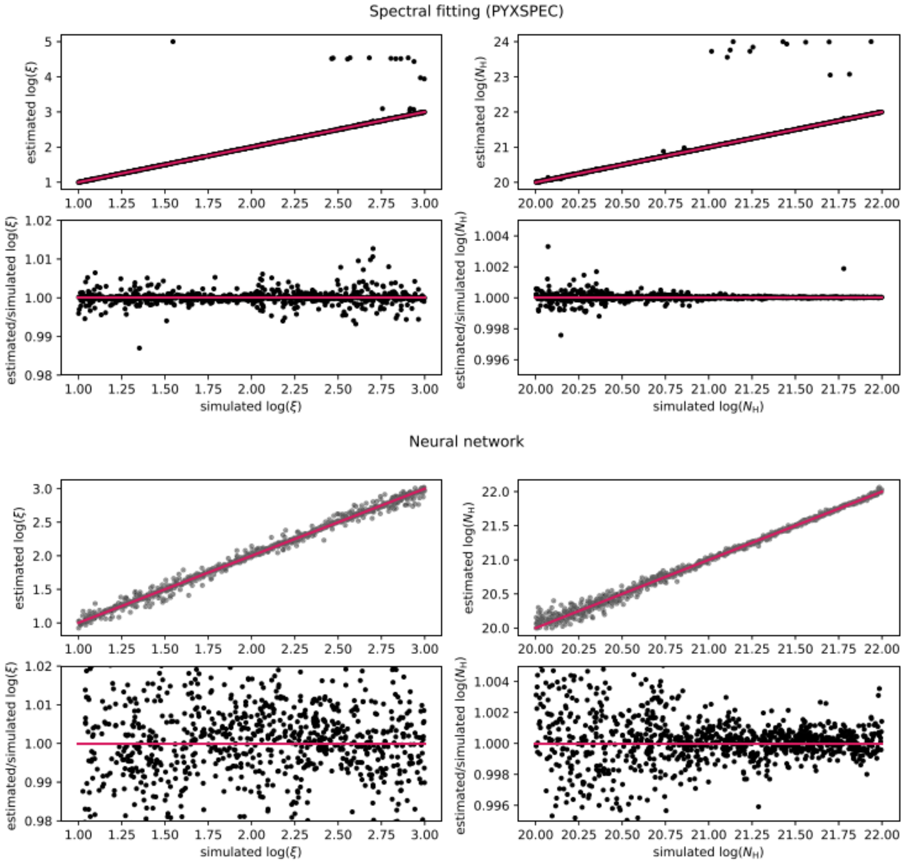


# Dropout as a Bayesian Approximation applied to X-ray spectral fitting

**We aim to investigate the neural networks ability to recover a model parameters but also their associated uncertainties, and compare its performance with standard X-ray spectral fitting.**

**The advantages of using a neural network are:**

- **Less sensitive to local minima trapping than standard fit statistic minimization techniques**
- **Substantial decrease in computation time**




Parker et al. 2022

# Dropout as a Bayesian Approximation applied to X-ray spectral fitting

**Our strategy is to use Dropout both in training and inference.**
**We simulated 100k models and used them to perform the training of an ANN. To predict the parameters of a given spectrum, we perform the prediction 1k times and from the distribution of predictions we get the best estimate and errors.**

**TBD:**

- **Exploring hyperparameters**
- **Testing more complex models**
- **Compare results with other software (XSPEC)**

| Model: tbabs x ( powerlaw + bbodyrad ) | | |
|---|---|---|
| Nh | [.15, .35] | Uniform |
| Gamma | [1, 3] | Uniform |
| NormPL | [.01, 10] | Log Uniform |
| kTbb | [.3, 3] | Uniform |
| NormBB | [1, $10^4$] | Log Uniform |