Machine Learning for Adaptive Optics TO NAZIONALE G. Agapito^{1,2}, Fabio Rossi^{1,2}, Alessio Turchi¹

OSSERVATORIO ASTROFISICO DI ARCETRI

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DI ASTROFISICA

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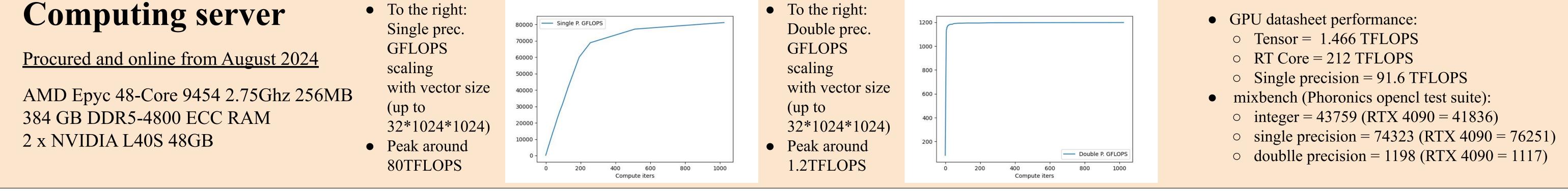
RSN5 2°Forum della Ricerca Sperimentale e Tecnologica in INAF

Introduction

The "Machine Learning for Adaptive Optics" Data Analysis Grant 2023, part of INAF's "astrofisica fondamentale" funding, is focused on identifying machine learning techniques that can make use of telemetry data streams from existing AO systems to improve the performance and/or optimize their behavior in different atmospheric conditions, but also leveraging machine learning technique to speed up numerical simulations computation. The project is also aimed at the improvement of future AO systems. A key support to this activity is the availability of large databases of telemetry data, such as those of SOUL at LBT and ERIS at VLT, collected during the commissioning carried out by INAF researchers. During the first year of activity we were able to achieve initial encouraging results on simulated data with excellent theoretical performance. The grant was used to finance the purchase of a computing server, which is necessary to provide the needed computational power, and the participation in two international conferences, SPIE in Yokohama and ML4ASTRO2 in Catania with one talk and the publication of two papers. In this poster we briefly present the activity carried out for the grant, its current status and its goals.

• To the right:

• To the right:



Goal of the project

The goal of the activity is to identify machine learning techniques that can use telemetry data from existing AO assisted instruments to enhance the performance of future AO systems. A key support to this activity is the availability of large databases of telemetry data such as those of SOUL at LBT and ERIS at VLT collected during the commissioning carried out by INAF researchers.

Long-term objectives (within and beyond the grant)

- Enhanced Optical Turbulence Prediction:
- 2. Wavefront sensing:
- 3. Turbulence reconstruction:
- 4. New approaches to tomography reconstruction:
- 5. Short time scale prediction of turbulence:
- 6. Optimization of temporal controllers:
- 7. PSF fitting and reconstruction:

enhance the previous results by using more complex ML algorithms and better training over the available databases. new ways to compute the slope of the wavefront sensor.

reconstruction from the measurements of the WFS to the residual wavefront and then to the incoming turbulence.

- tomographic turbulence reconstruction done by wide field adaptive optics systems.
- reduce wind driven halo in the PSF and improve vibration mitigation.
- optimization of the temporal controlleras a function of the observing conditions.
- enhance the data reduction pipelines of with PSF reconstruction using ML on the databases of on-sky PSFs.





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Efficient Asterism Selection for Wide Field Adaptive Optics Systems with TIPTOP

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Asterism Neural Network

Since the High Order (HO) part of the simulation is fixed, we can select the best asterism based only the Tip Tilt Jitter residual σ_{TT} , which is computed by the Low Order (LO) part of the simulation (even if this requires in as input the HO part output: the PSD of the high order modes residuals).

Our approach quickly evaluate asterisms is the following: 1. Using TIPTOP, we compute a large number of simulations (thousands) for the specific case, with randomly generated asterisms (varying positions and magnitudes of the NGSs) and we then evaluate σ^{A}_{TT} .

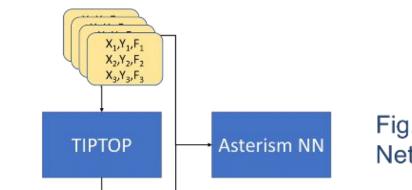


Fig. 2 Neural Network Training.

- 2. Train a Neural Network model to perform the regression from the input asterism features (9 scalar values: X, Y coordinates and Flux on the NGS sensors, for each of the 3 stars) to the associated output σ^{N}_{TT} .
 - 1. Asses the NN uncertainty in prediction U_N :
 - $\mathsf{E}_{\sigma} = (\sigma^{A}_{TT} \sigma^{N}_{TT}) / \sigma^{A}_{TT}$

A machine learning approach to AO parameters estimation on the wavefront sensor

Fabio Rossi¹, Alessio Turchi¹, Guido Agapito¹ ¹INAF - Osservatorio Astrofisico di Arcetri,

one of such networks is trained for each estimated quantit telemetry data. We focus on the following quantities: Strehl Ratio Wind Speed (per layer) GRU = Gated recurrent unit MAPE = Mean Absolute Percentage Error External Scale (L0) X_1 **GRU NN** X_2 MLP NN Many-to-Many 4 Hidden Layers, 5 Hidden Layers, 512 Neurons wide

Fig. 2 – Our Neural Network structure.

512 Neurons wide

Quantity	Analytical - from references (SH WFS)	Analytical - Our Implementation (PWFS)	Our Method - Test Set (PWFS)
Strehl Ratio	7.3%+2.6% Bias ^[6]	31.84%	5.72%
Seeing	>22% ^[7] , 6.4% ^[6]	12.91%	2.29%
Wind Speed (Layer 0)	N.A.	23,81% ~[6]	12.2%
External Scale (L0)	N.A.	N.A.	3.32%

Table 1 – MAPE Errors to summarize methods results.

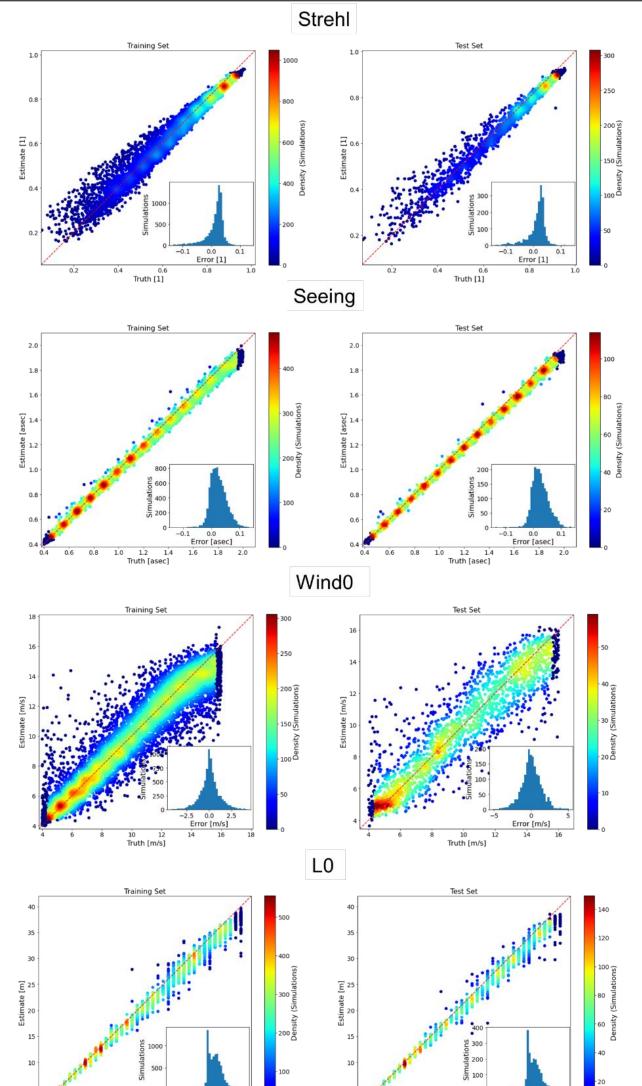
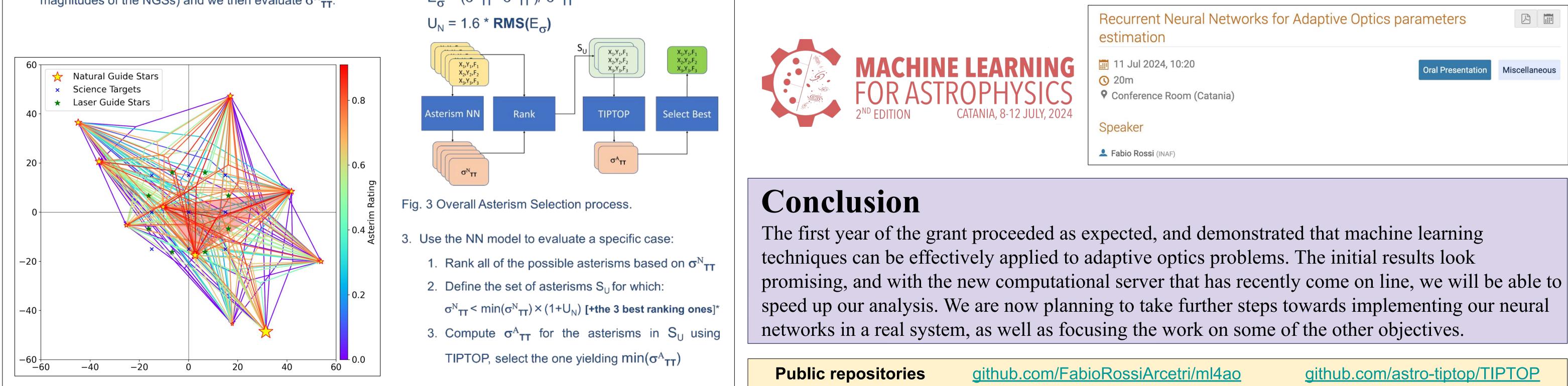


Fig. 3 – Distributions and scatter plots of the errors



X₄₂₅