Machine Learning used in Interstellar Medium

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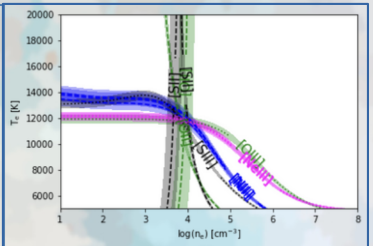
Machine Learning technics are widely used in astrophysics, mainly based on **classification** tools. I show here a few examples of the use of **regressors**, obtained with Scikit-learn (Pedregosa+11), TensorFlow (Abadi+15) or XGBOOST (Chen+16) python libraries, controlled by **AI4neb** (*Morisset, in dev.*) interface.

PyNeb

The **PyNeb** library (scan QR code) is dedicated to the analysis of emission lines from astrophysical nebula. It is used to determine the physical and chemical properties (such as the electron temperature Te and density Ne) from line ratios. To accelerate the determination of these 2 parameters, an **Artificial Neural Network** is trained to predict Te-Ne.
In case of IFUs images with Monte-Carlo distribution, millions of line ratios are used, and the CPU time to determine Te-Ne is reduced from hours to a few seconds.
Stay tuned to *Garcia-Rojas+22 subm.*



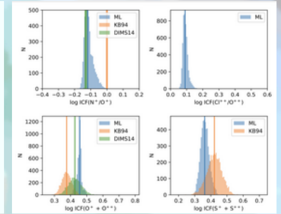
The **Ionization Correction Factors** (ICFs) are needed when one wants to determined elemental abundances from ionic abundances, and some ions are missing (mostly because unobserved). The ICFs can be obtained by training **XGBoost** algorithms. One can use the feature importances to determine which line ratio is important in the determination of each ICF.
Examples from *Sabin+22, subm. and Morisset+22, in prep.*:

The input vector X is build from a 6D vector of the logarithmic values of the following line ratios:

- He II λ4686 / He I λ5876
- [O III] λ5007 / [O II] λ3727
- [Ne V] λλ3426, 3346 / [Ne IV] λ4726
- [Ne IV] λ4726 / [Ne III] λ3869
- [Ar V] λ6435 / [Ar IV] λλ4711, 4740
- [O III] λλ4363/5007

The output vector y is directly the set of the following ICFs (logarithmic values are used):

- $O / (O^{+} + O^{++})$
- $N/O \times O^{+} / N^{+}$
- $Ne / (Ne^{++} + Ne^{4+})$
- $Ne / (Ne^{++} + Ne^{3+} + Ne^{4+})$
- $Ne / O \times O^{++} / Ne^{++}$
- $S / (S^{+} + S^{++})$
- $S / O \times O^{+} / (S^{+} + S^{++})$
- $S / O \times O^{++} / (S^{+} + S^{++})$
- $Cl / O \times O^{+} / Cl^{++}$
- $Cl / O \times O^{++} / Cl^{++}$
- $Ar / (Ar^{3+} + Ar^{4+})$



Feature Importances

	Observed line ratio					
	[OIII]/[OII]	[NeV]/[NeIV]	[NeIV]/[NeIII]	[ArV]/[ArIV]	HeII/HeI	[OIII]5007/4363
O+ + O++	0.00	0.01	0.05	0.17	**0.75**	0.01
N+/O+	0.16	0.03	0.03	0.14	0.30	0.34
Ne2+ + Ne4+	0.06	0.09	0.01	0.03	**0.75**	0.07
Ne2+ + Ne3+ + Ne4+	0.08	0.05	0.02	0.60	0.02	0.22
Ne2+/O2+	0.10	0.09	0.03	0.06	0.49	0.23
S+ + S++/O++	0.18	0.06	0.03	0.10	0.17	0.46
Cl2+/O2+	0.24	0.05	0.03	0.09	0.14	0.46
S+ + S2+	0.12	0.10	0.02	0.18	0.39	0.18
Ar3+ + Ar4+	0.17	0.03	0.02	0.11	0.52	0.16
S+ + S2+/O+	0.08	0.01	0.00	0.12	**0.69**	0.09
Cl2+/O+	0.10	0.01	0.00	0.12	**0.66**	0.10

Strong lines

ANN is trained using e-BOND photoionization models from 3MdB (see QR code) to predict strong lines like [NII], [OII], [OIII], giving O/H, N/O, logU, and age.

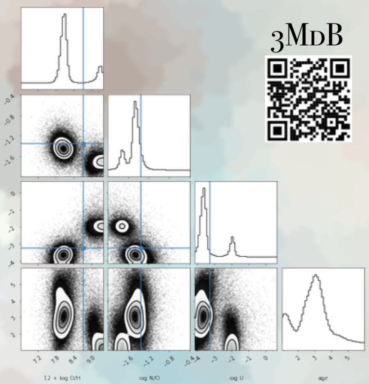
A **Genetic Evolution** algorithm uses this ANN to look for the sets of parameters simultaneously fitting the observations of IC 2574. 370,000 calls to ANN are performed in a few seconds, really faster than calling Cloudy (Ferland+) each time.

All the points in the contours correspond to values of parameters leading to reasonable fit to the observed data → degeneracy of O/H.

The "Best Model" is a meaningless concept.

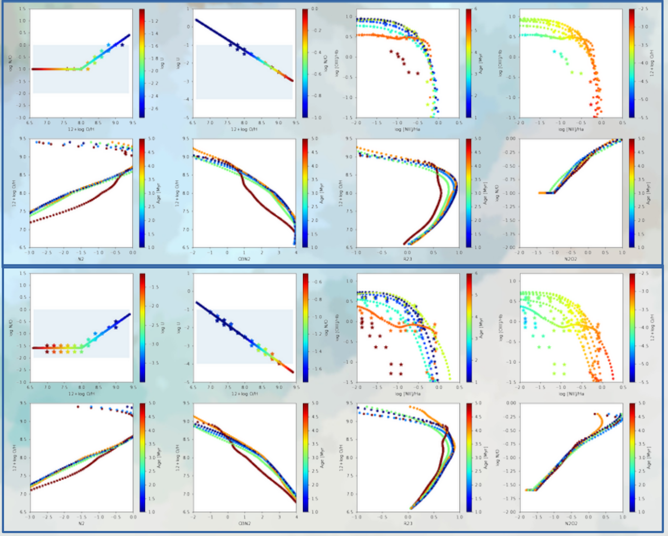
The "weighted mean value" is rather risky.

Morisset+22 in prep.



3MdB

Training a Neural Network to reproduce the predictions of Cloudy photoionization code (Ferland+) allows to increase the resolution of a given grid of models. The 3MdB database is used to train an ANN and to explore the behavior of different diagnostics when changing the relation between N/O and logU with O/H.
Examples from *Espinosa-Ponce+22, in prep.*



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