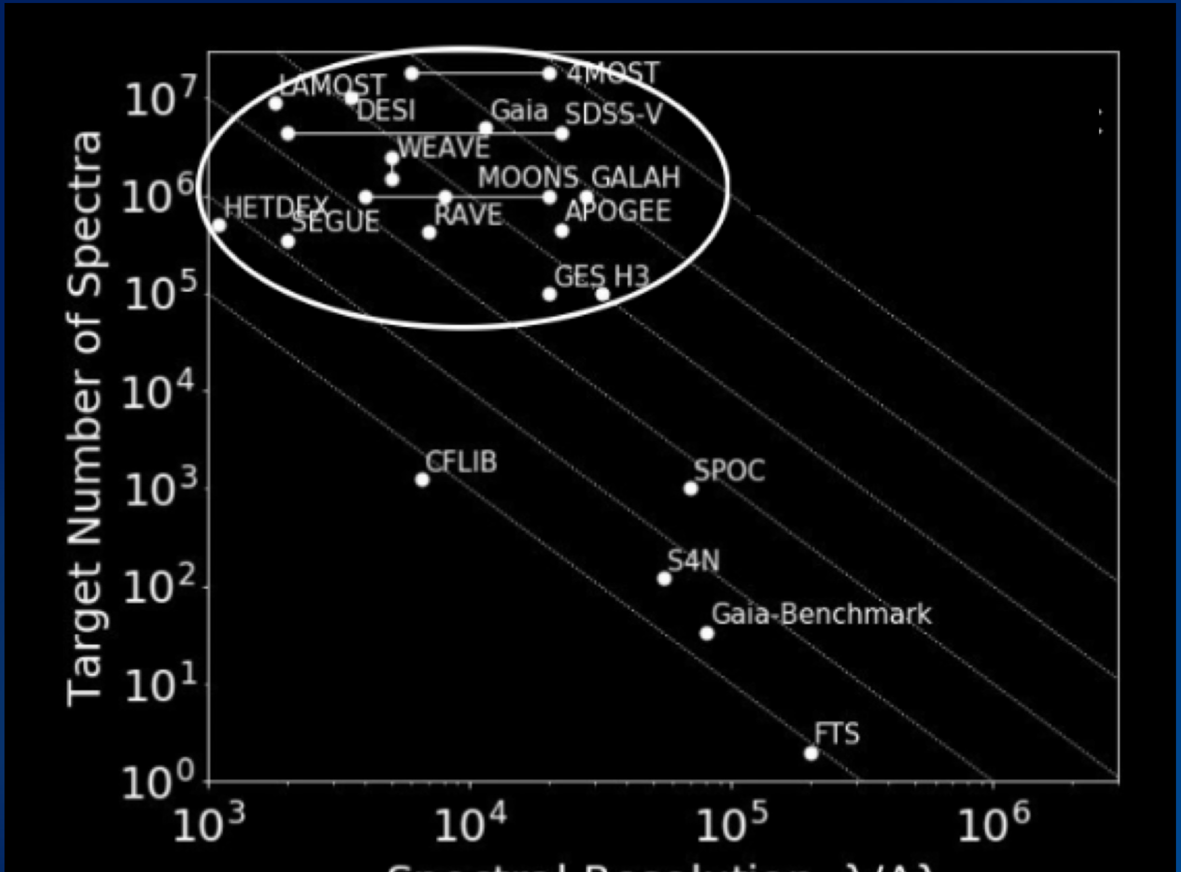
INAF
ISTITUTO NAZIONALE
DI ASTROFISICA

OSSERVATORIO ASTROFISICO DI ARCETRI

The evolving role of AI in (Stellar) Astronomy

G. SACCO

The need of AI for Astronomy



Credit: Y.S. Ting

Large amount of data

+

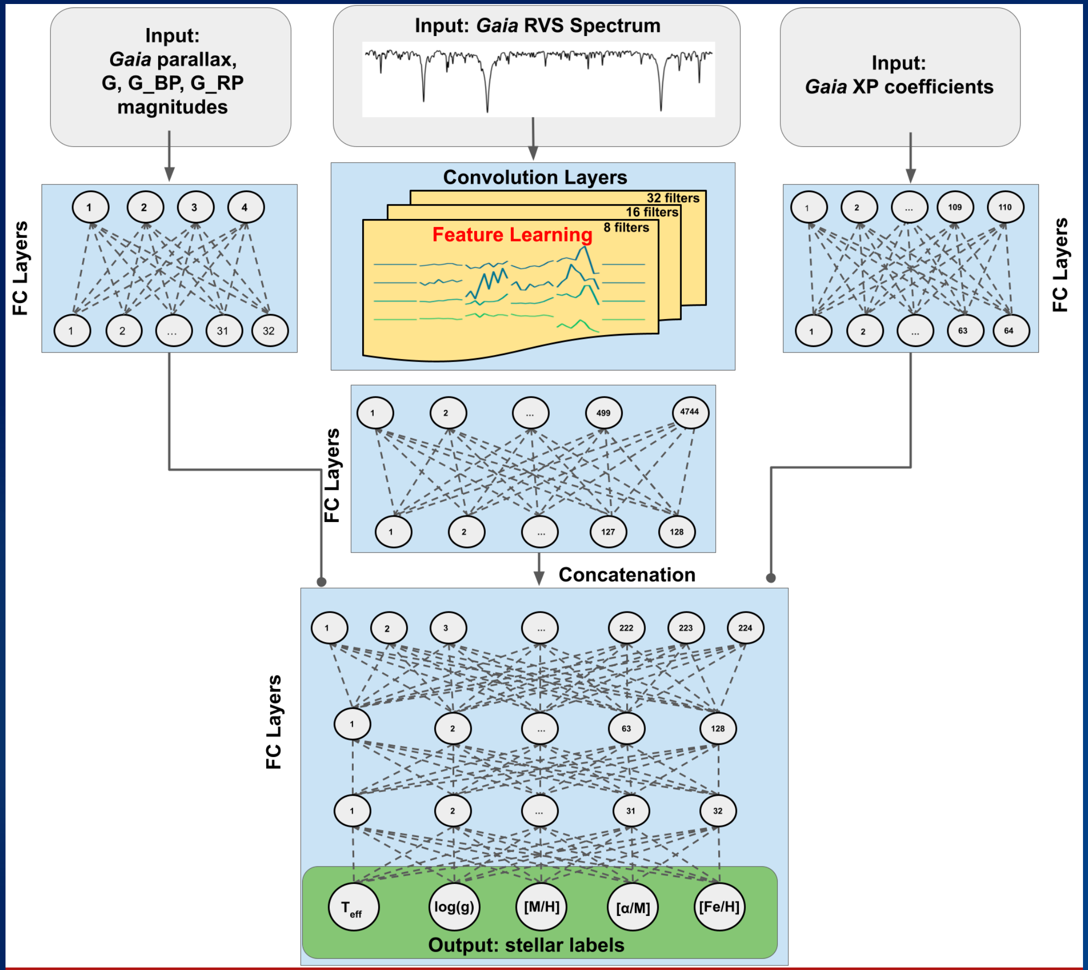
Complex physical models and multiple parameters

+

Effects of atmosphere and instruments

Traditional methods for data analysis are not adequate

Deep learning in Galactic Astronomy



Guiglion+2024

Strengths

- Much faster
- Better with low res spectra
- Better with Low SNR spectra
- Capabilities to combine different dataset

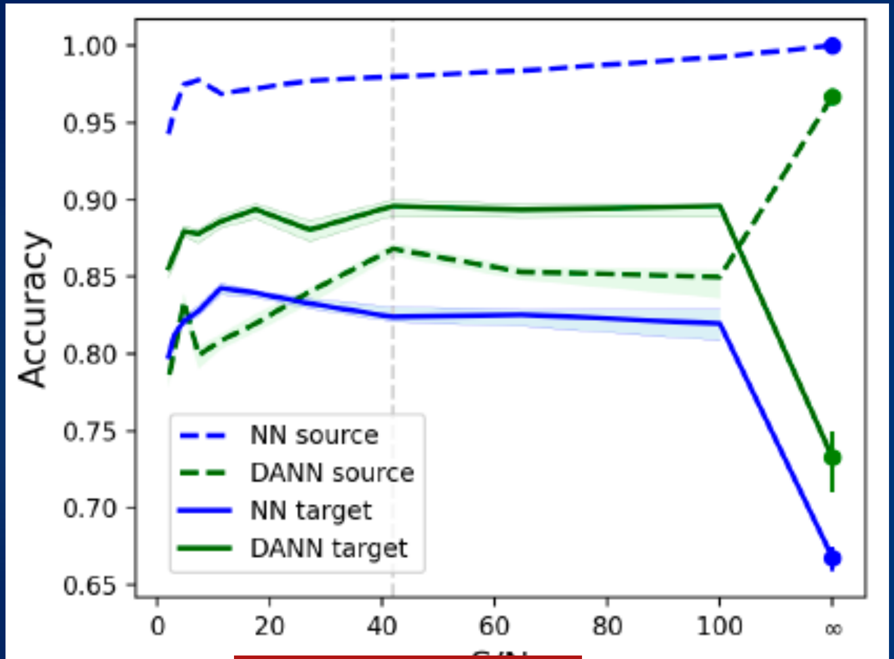
Weaknesses

- Results depend on the training sample
- Interpretability
- Error estimates

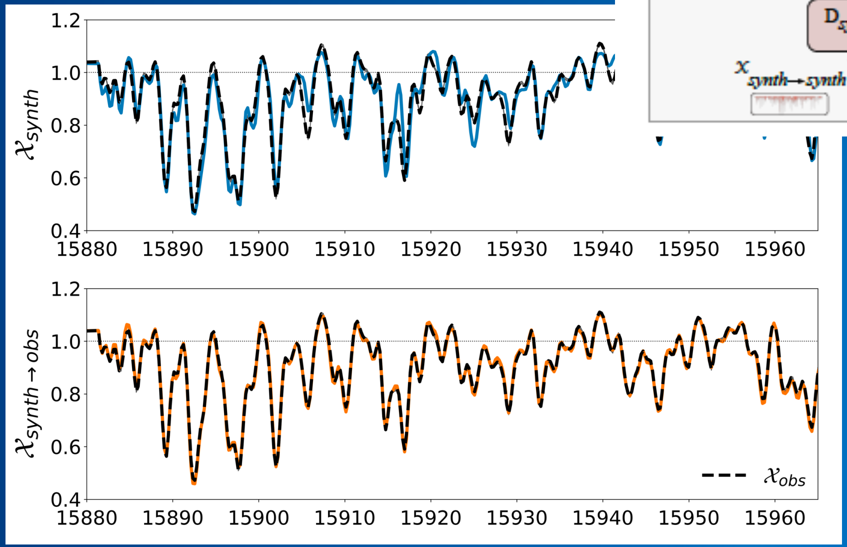
(e.g. Ness+2015, Zingales & Weidmann 2018, Ting+2019, Ambrosch+2023)

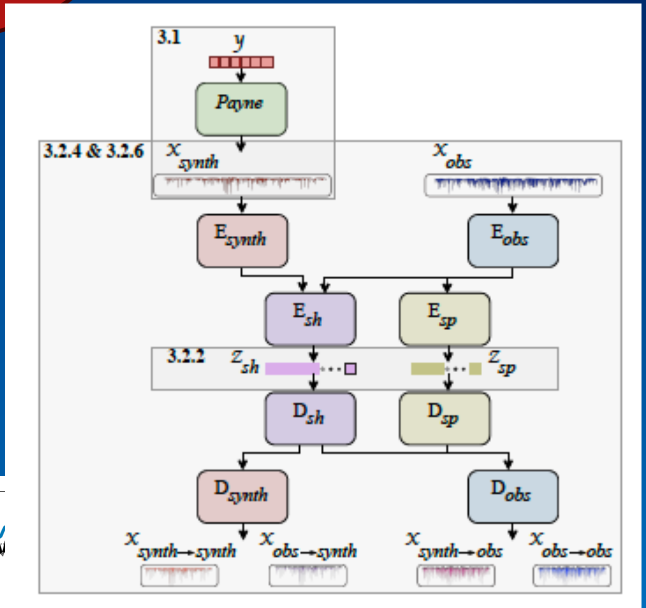
Scientific AI for astronomy: Domain adaptation

Domain adaptation to use models for training
(E.g. O'Brian+2021, Belfiore+2025)



Belfiore+2025



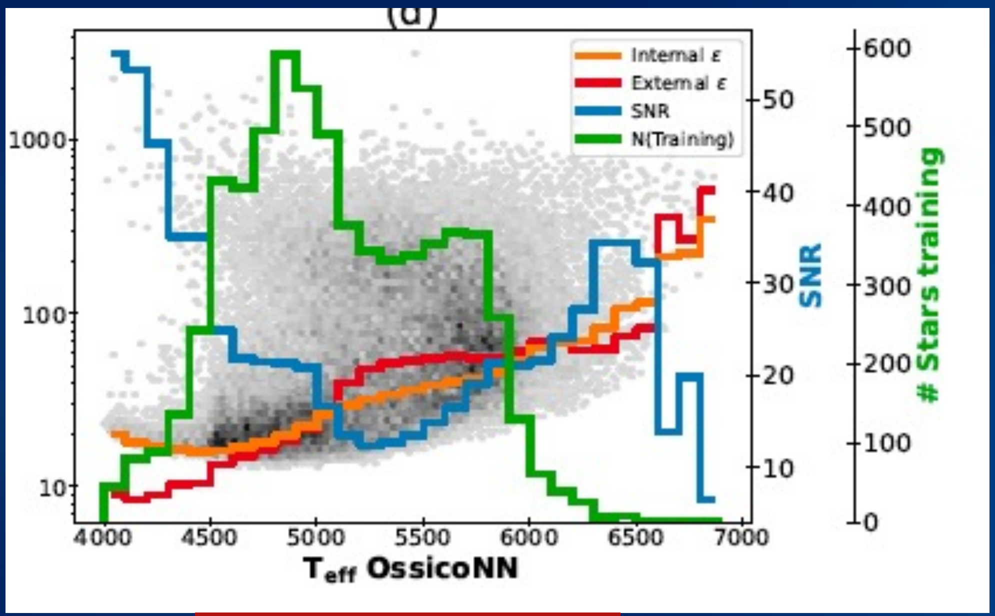


O'Brien+2021

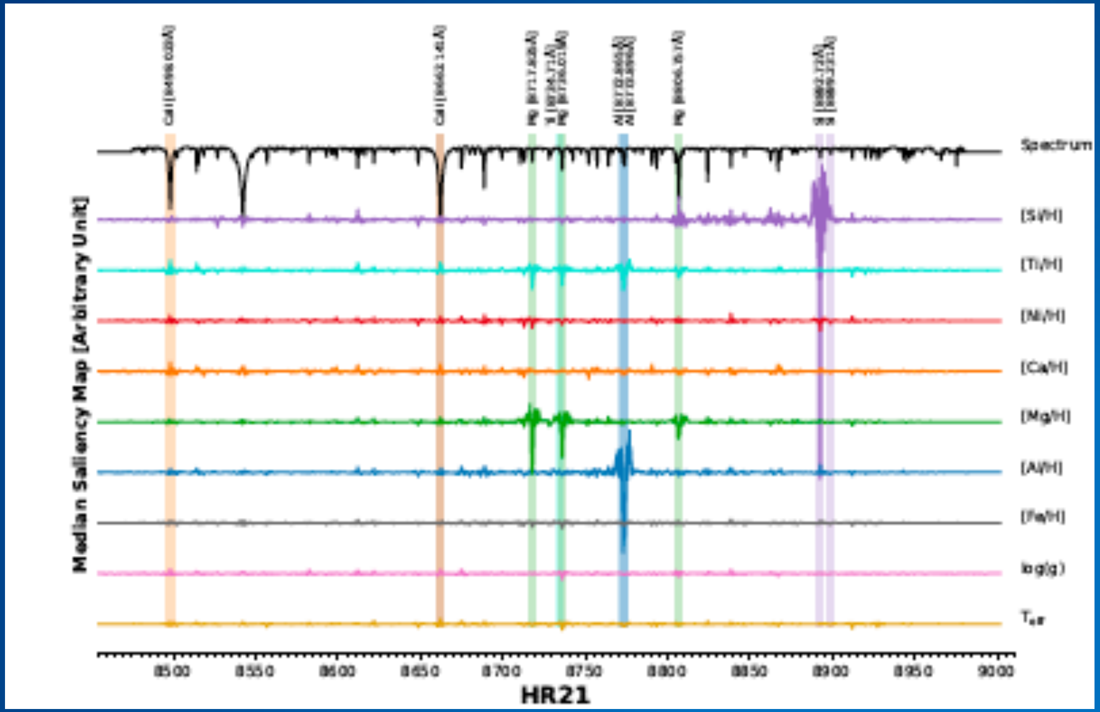
Scientific AI for astronomy

Normalizing flows to calculate posterior distribution (e.g. Kang+2022, 2023, Iglesias-Navarro+2024 Candebat+ 2024)

New tools for interpretability (e. g., Ambrosch+2023, Candebat, Sacco+2024)



Candebat+2024



AI 2.0: Transformers and Foundation Models

Specific and small dataset

Very large Dataset

LLM Architecture

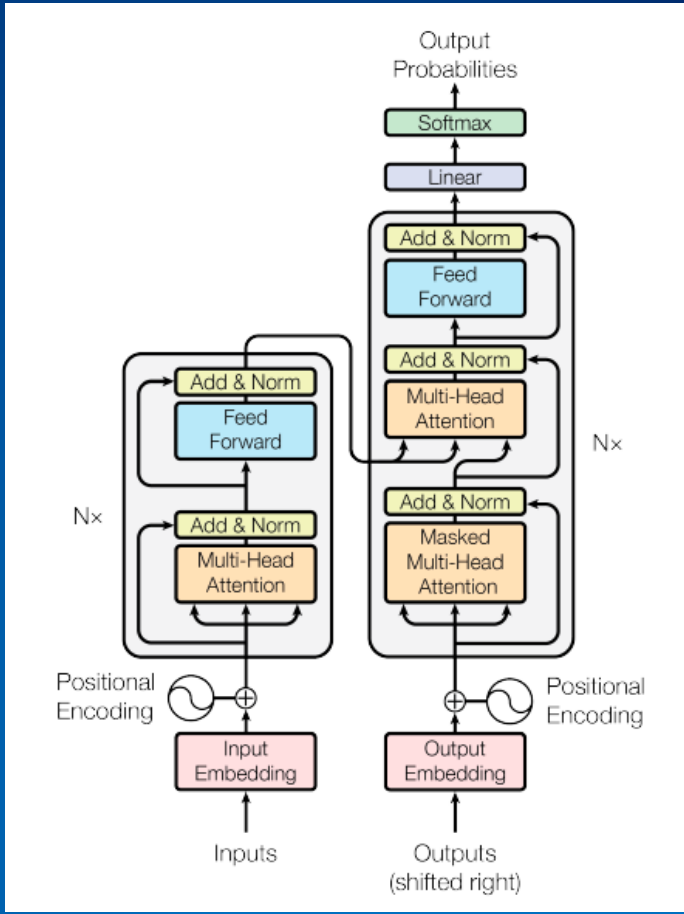
Pretraining

Foundation Model

Finetuning

Finetuned LLM

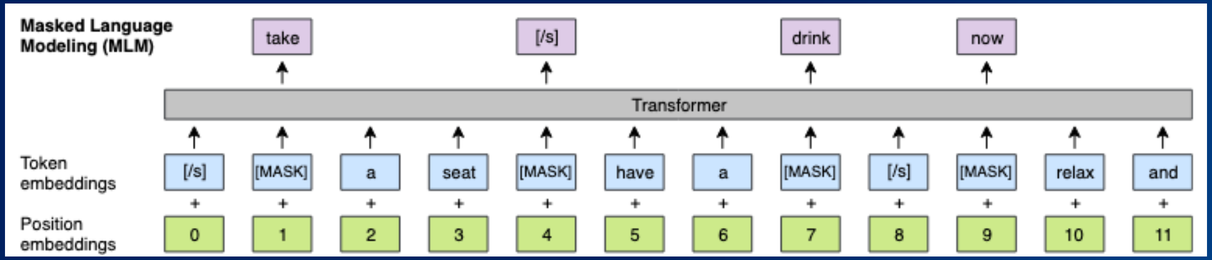
Attention is all you need



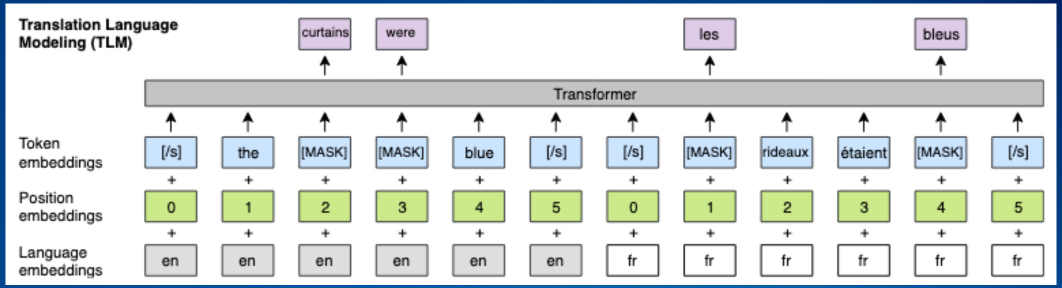
Vaswani+2017

AI 2.0: Transformers and Foundation models

Self-Supervised Learning pre-training

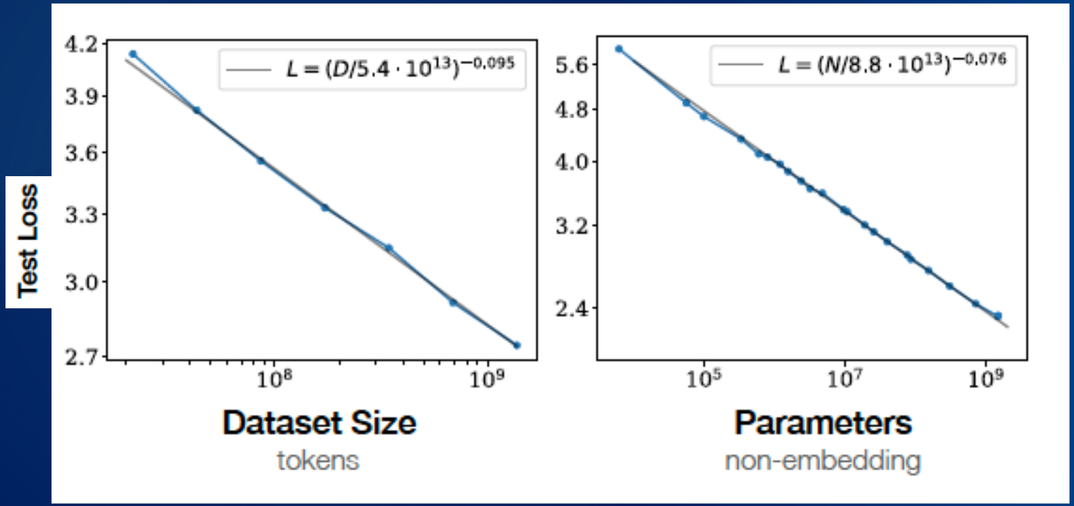


Cross-Domain Generalization



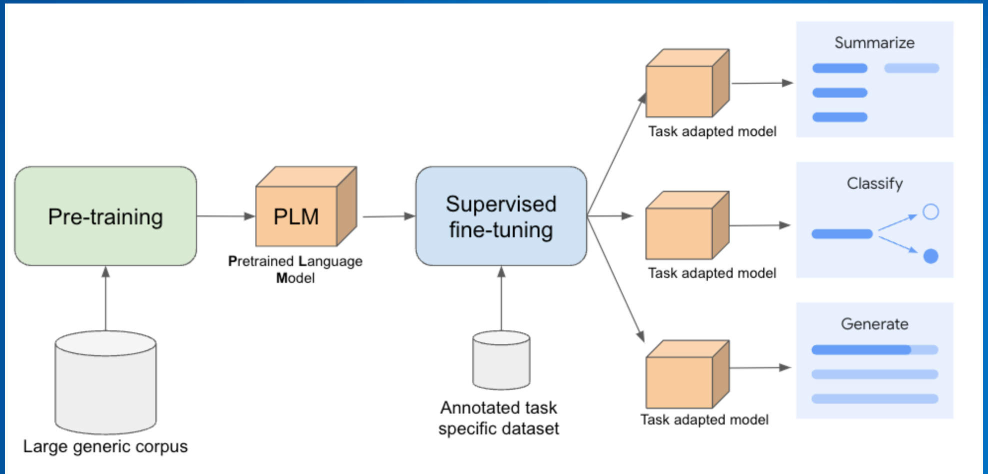
Lample & Conneau 2019

Scalling Law

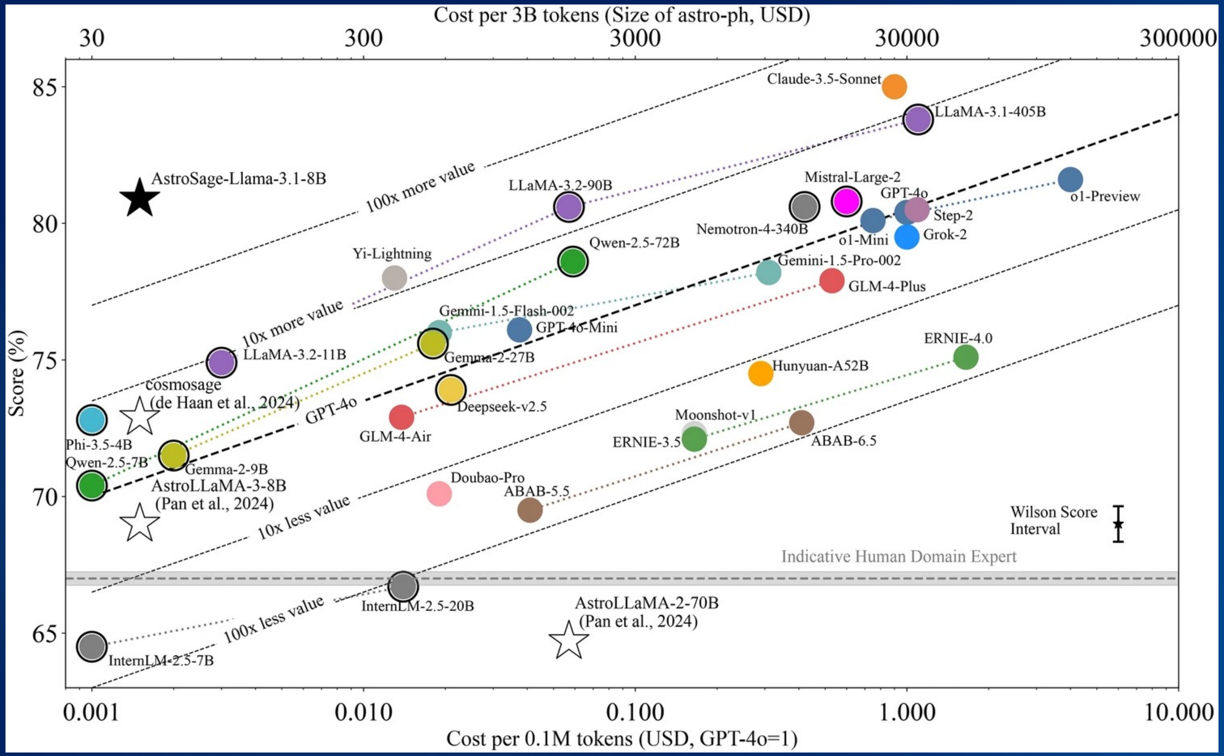


Kaplan et al. 2020

Versatility



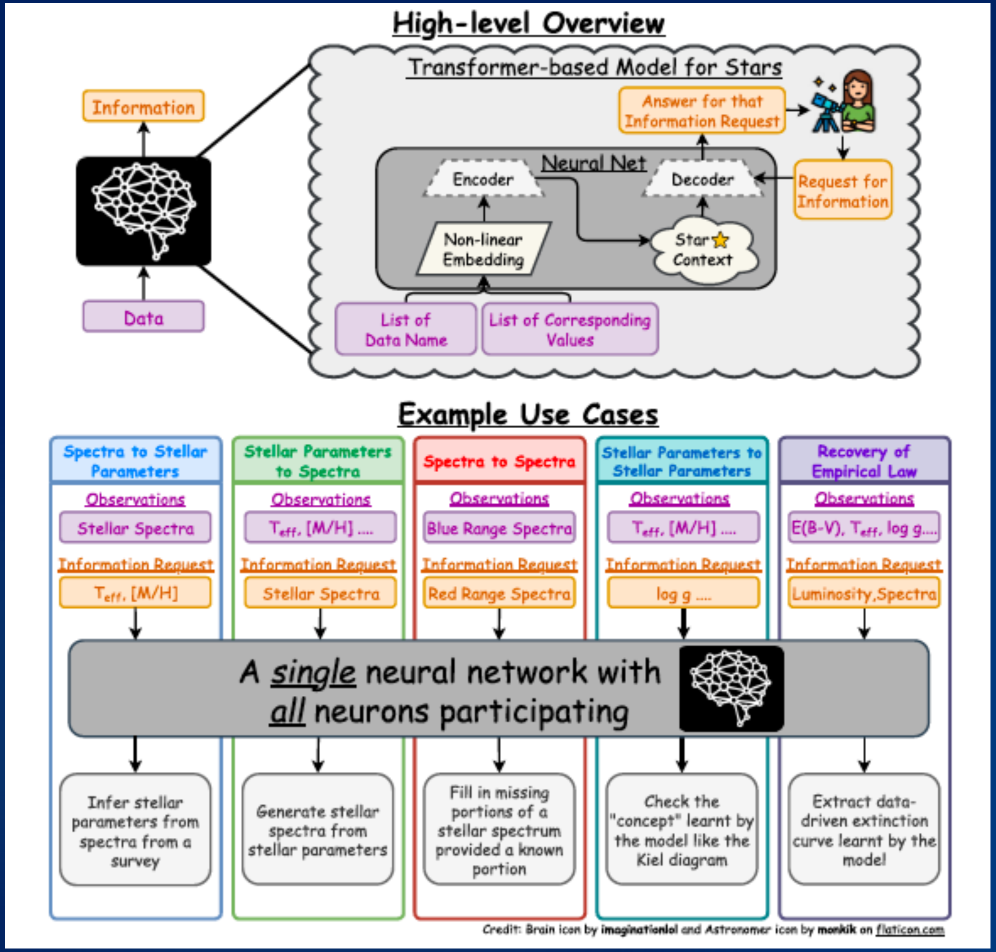
Foundation models in astronomy

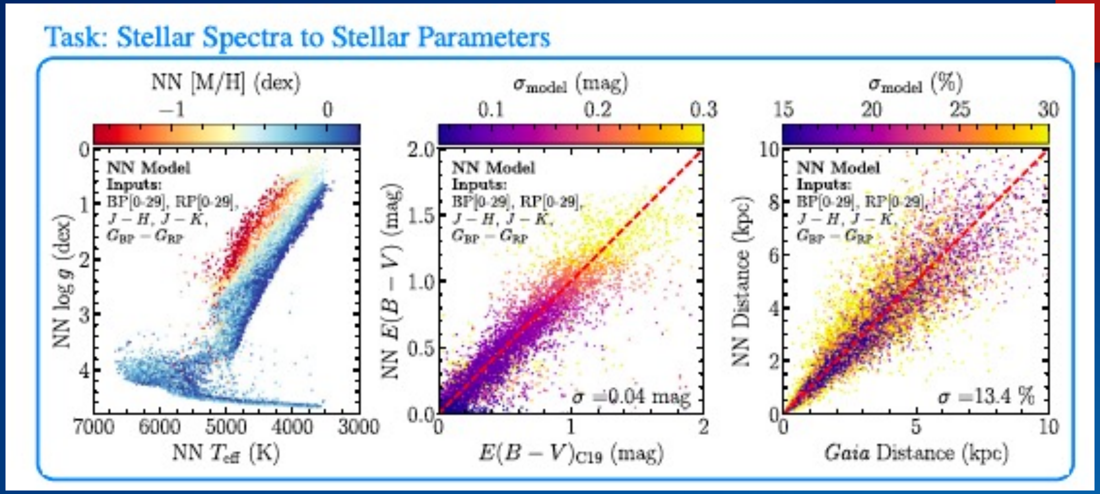


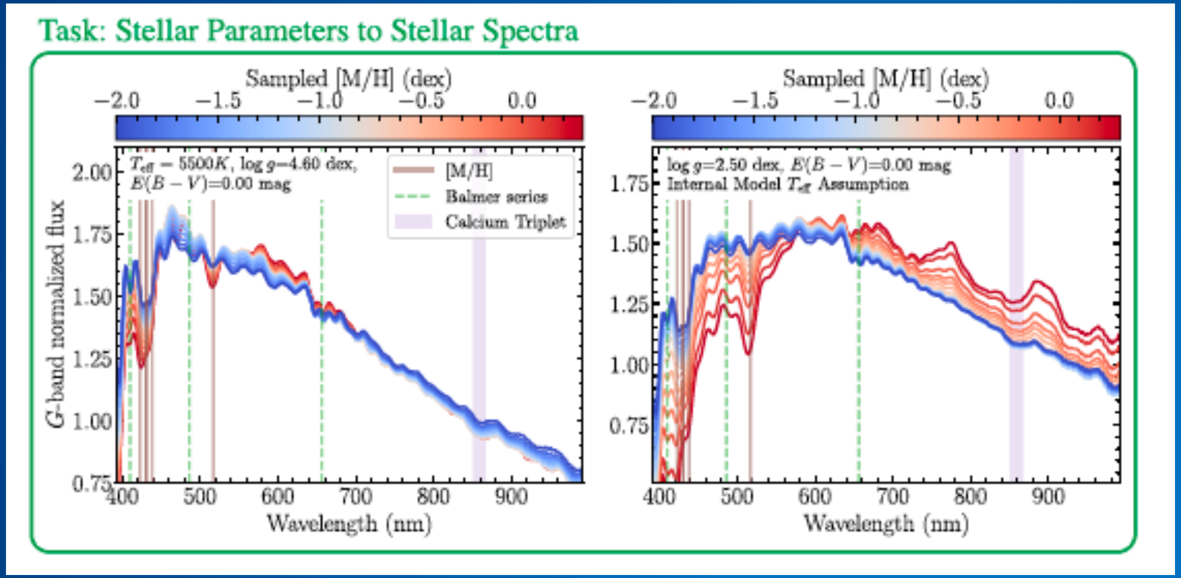
de Haan et al. 2025

Specialized AI assistant in Astronomy

Foundation models in astronomy



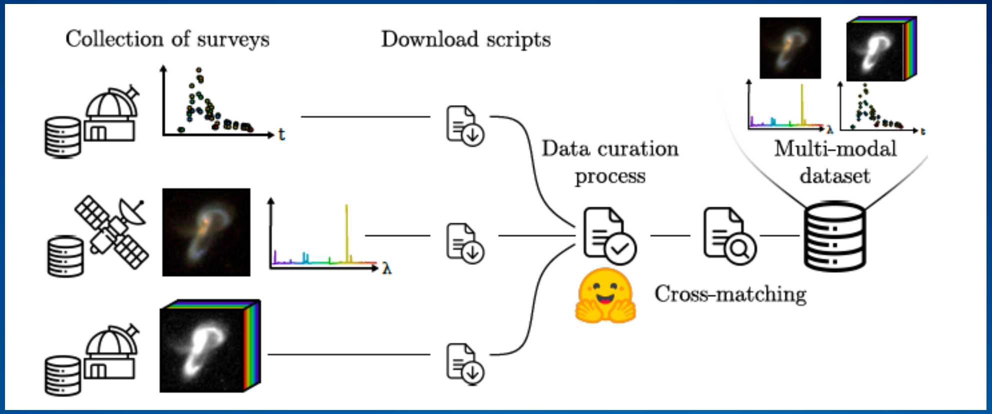




(Leung & Bovy 2023, 2024)

The multi-modal universe

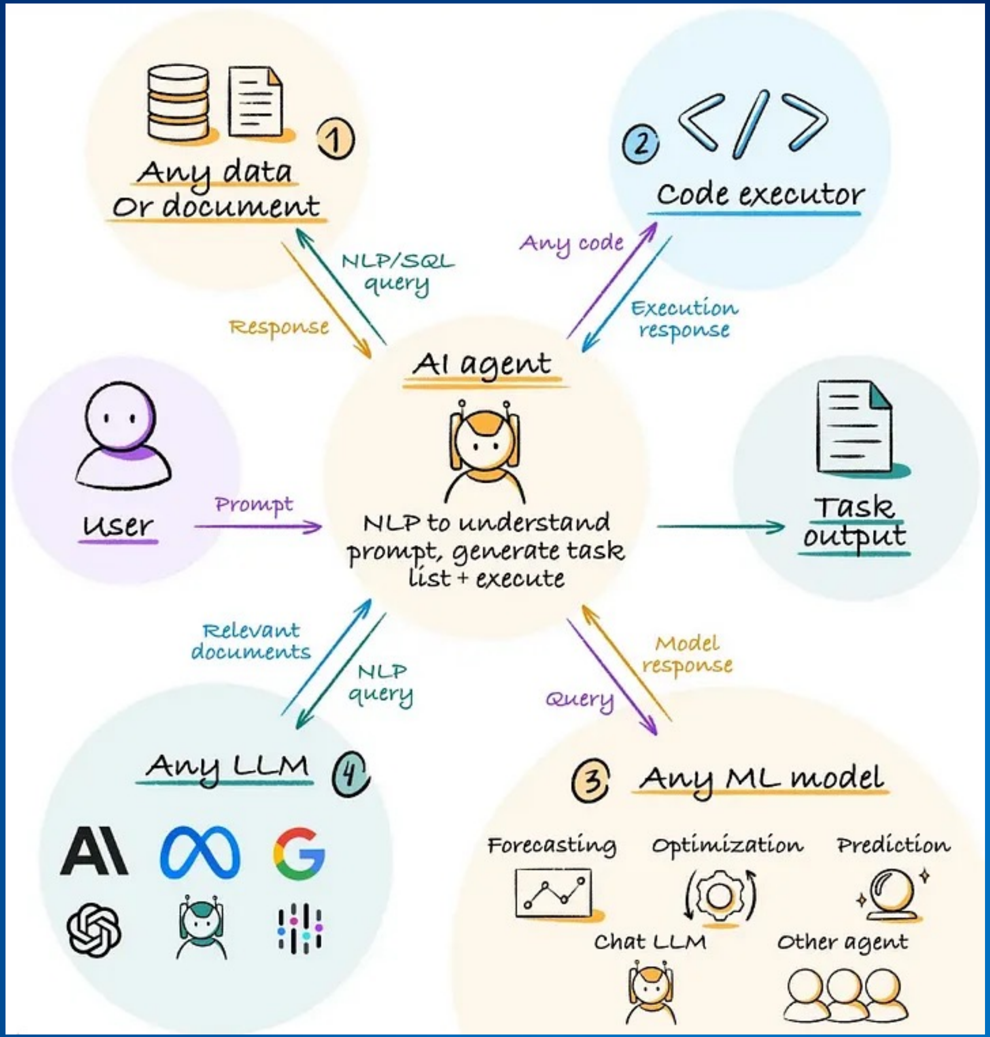
Modality	Source Survey	N_c	Shape	Number of samples	Main science
	Legacy Surveys DR10 [43]	4	160×160	124M	Galaxies
	Legacy Surveys North [43, 134]	3	152×152	15M	Galaxies
Images	HSC [5, 3]	5	160×160	477K	Galaxies
	BTS [56, 114, 120]	3	63×63	400K	Supernovae
	JWST[13, 14, 50]	6-7	96×96	300K	Galaxies
	Gaia BP/RP [59]	-	110[1]	220M	Stars
	SDSS-II [1]	-	Variable	4M	Galaxies, Stars
Spectra	DESI [41]	-	7081	1M	Galaxies
	APOGEE SDSS-III [6]	-	7514	716k	Stars
	GALAH [28]	-	Variable	325k	Stars
	Chandra [51]	-	Variable	129K	Galaxies, Stars
	VIPERS [126]	-	557	91K	Galaxies
Hyperspectral Image	MaNGA SDSS-IV [2]	4563	96×96	12k	Galaxies
	PLAsTiCC[2][138]	6	Variable	3.5M	Time-varying objects
	TESS [121, 33]	1	Variable	1M	Exoplanets, Stars
	CfA Sample [68, 69, 18, 70]	5-11	Variable	1K	Supernovae
	YSE [7]	6	Variable	2K	Supernovae
	PS1 SNe Ia [127]	4	Variable	369	Supernovae
Time Series	DES Y3 SNe Ia [24]	4	Variable	248	Supernovae
	SNLS [63]	4	Variable	239	Supernovae
	Foundation [53, 81]	4	Variable	180	Supernovae
	CSP SNe Ia [36, 135, 86]	9	Variable	134	Supernovae
	Swift SNe Ia[26]	6	Variable	117	Supernovae
	Gaia [59]	-	-	220M	Stars
Tabular	PROVABGS [65]	-	-	221K	Galaxy
	Galaxy10 DECaLS [147, 92]	-	-	15K	Galaxy



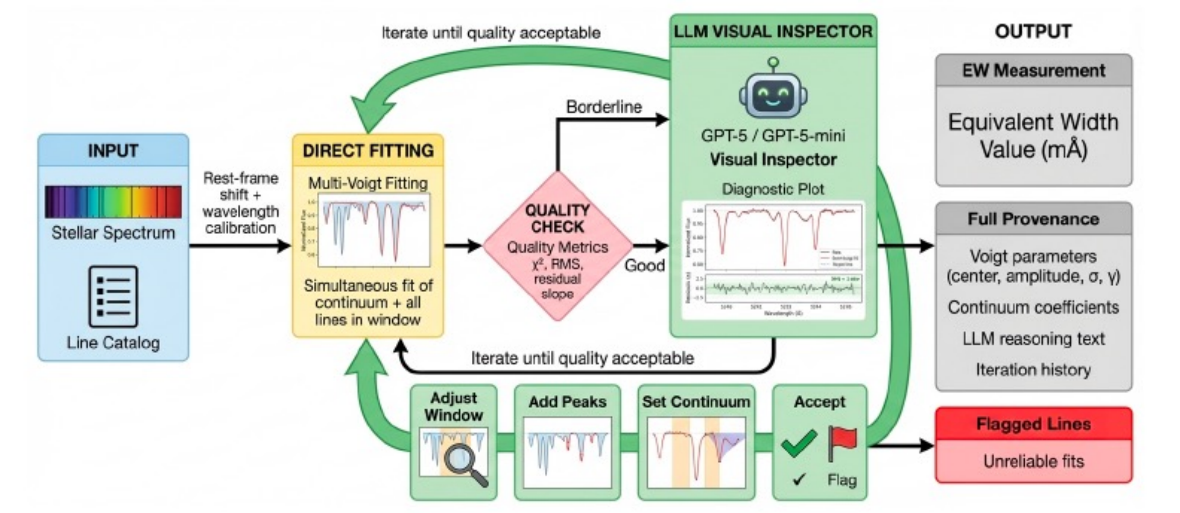
A massive dataset to develop Large Multi Modal Model for astronomy

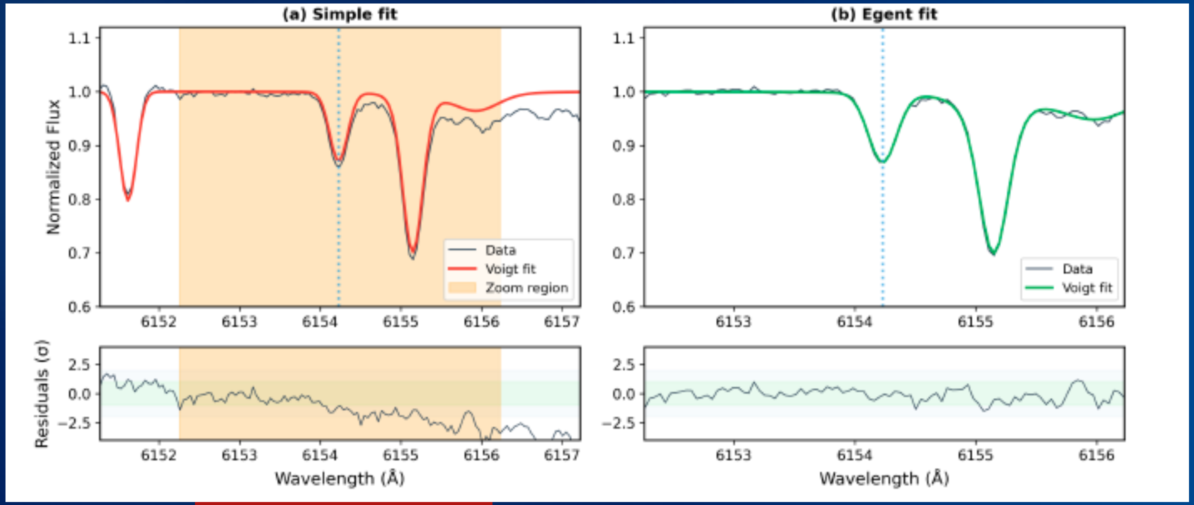
(The multimodal Universe Collaboration 2024)

AI 2.0: AI agents



AI agents in Astronomy





(Ting+2025)

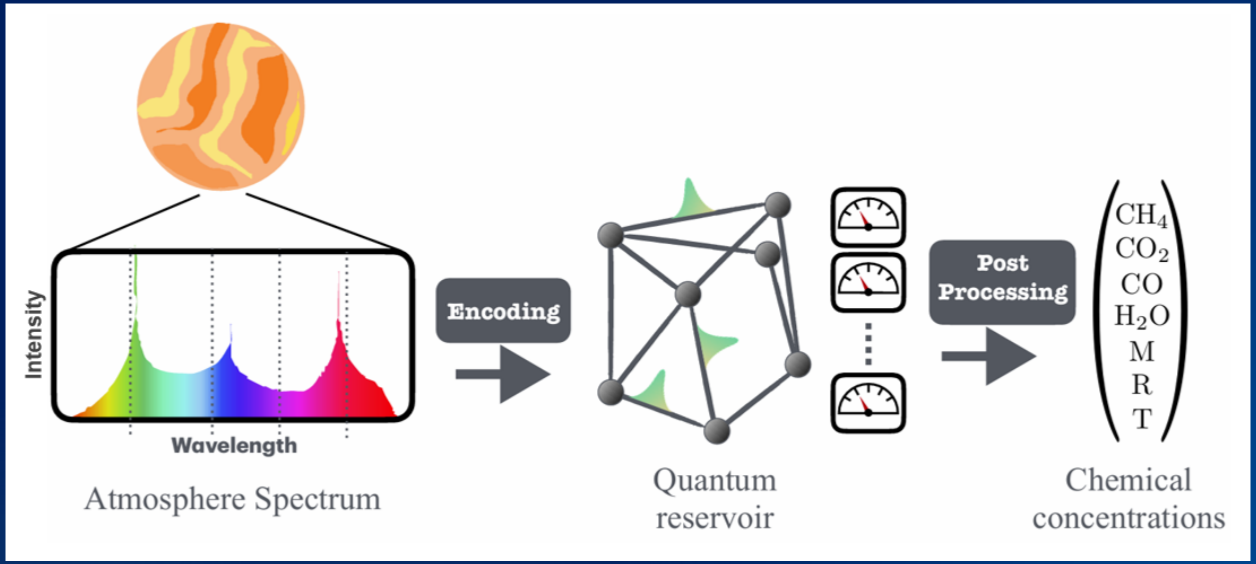
Case 1: Blend Detection (Ca I 6696.02 Å)

"The residuals show a pronounced W-shaped pattern centered at the target (a positive excursion just blueward of 6696.02 Å and negative residuals at/just redward), indicating a missed blend very close to the target. The red fit looks symmetric while the data shows asymmetry (suggesting two close components). I will add an extra Voigt component to deblend the pair at the blue-side shoulder near 6695.9 Å."

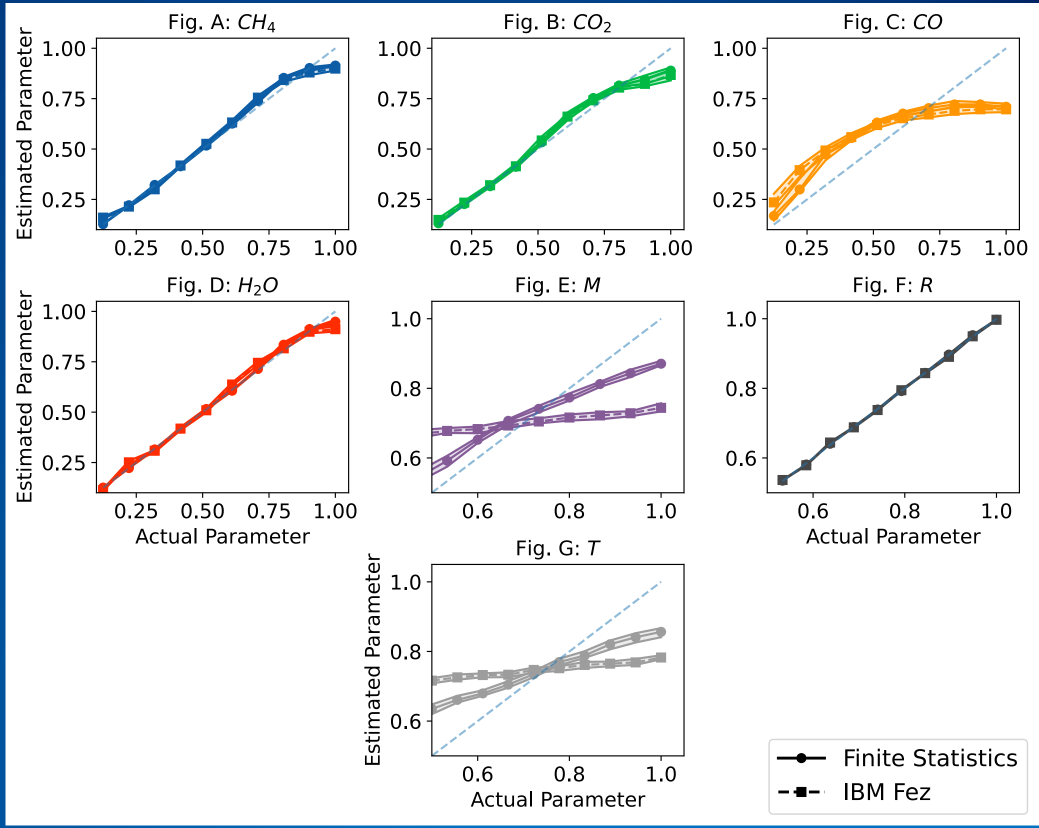
After adding peak: "The residuals no longer show a W-shape at the target and the central RMS is 1.64σ, which is within the acceptable range."

The Capabilities of an LLM to analyze plot and define a strategy are used to improve the fit

Quantum Artificial Intelligence



The Quantum computer of the IBM has been used to analyse simulated spectra of JWST



(Vetrano+2025)

Conclusions

- **Deep learning algorithms are commonly used for astrophysical data**
  1. Develop libraries of training set + domain adaptation to fill the observational gap
  2. Analyse NN output should be standard practices
  3. Normalizing flow and other techniques allow us to properly estimates errors

- **Tools for data analysis (and not only) based on LLMs and Agents are starting to emerge and may have a large impact in the near future**

- **AI technologies are evolving very quickly and, as community, we should invest to exploit them, to define best practices and built up a know-how**