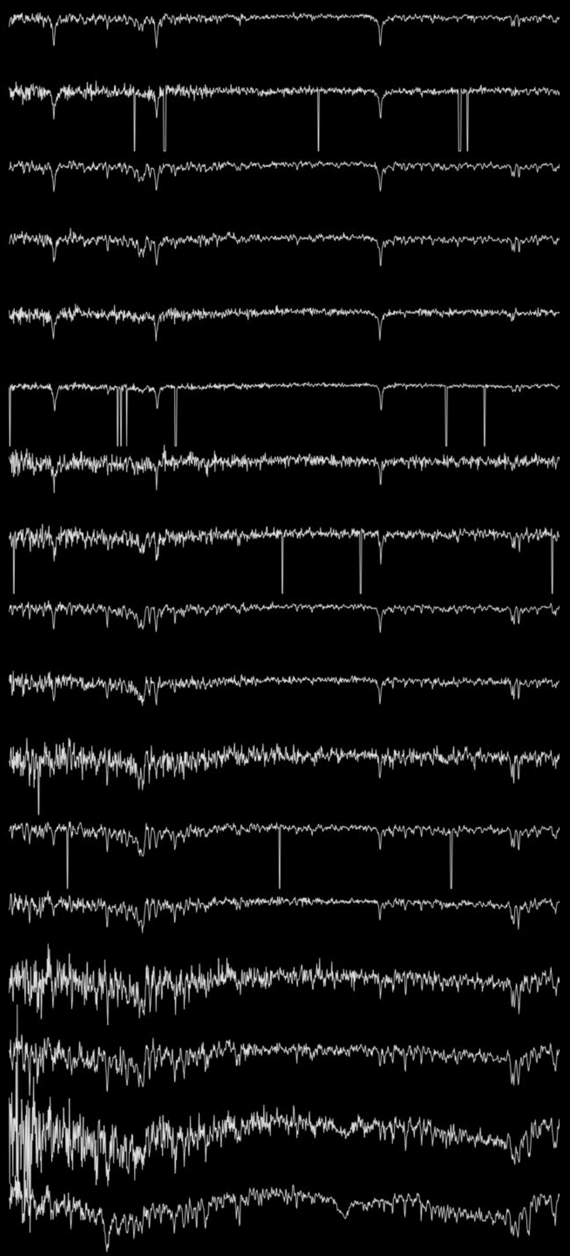
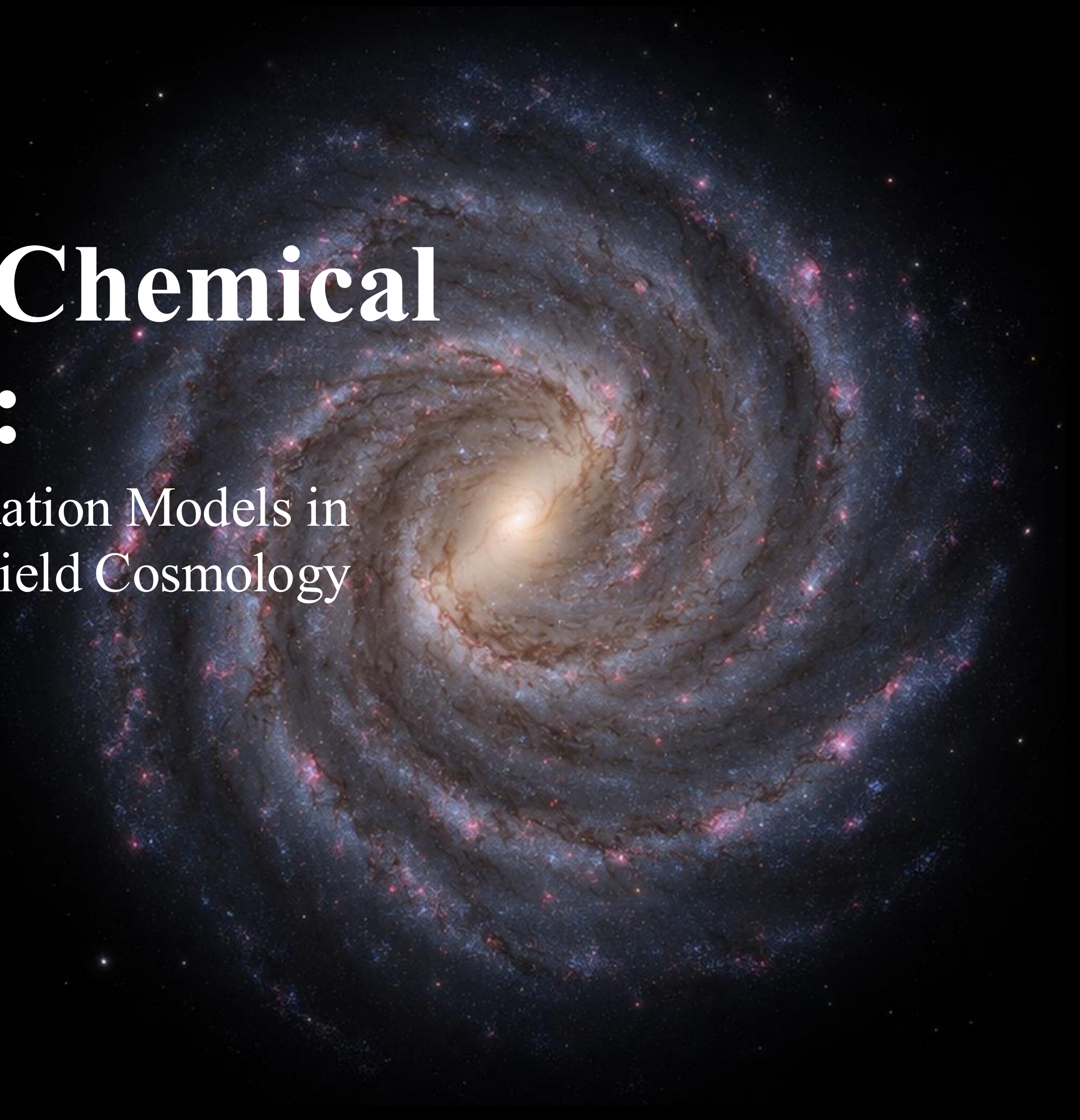


Decoding the Chemical Fossil Record:

Machine Learning and Foundation Models in Galactic Archaeology/Near-Field Cosmology

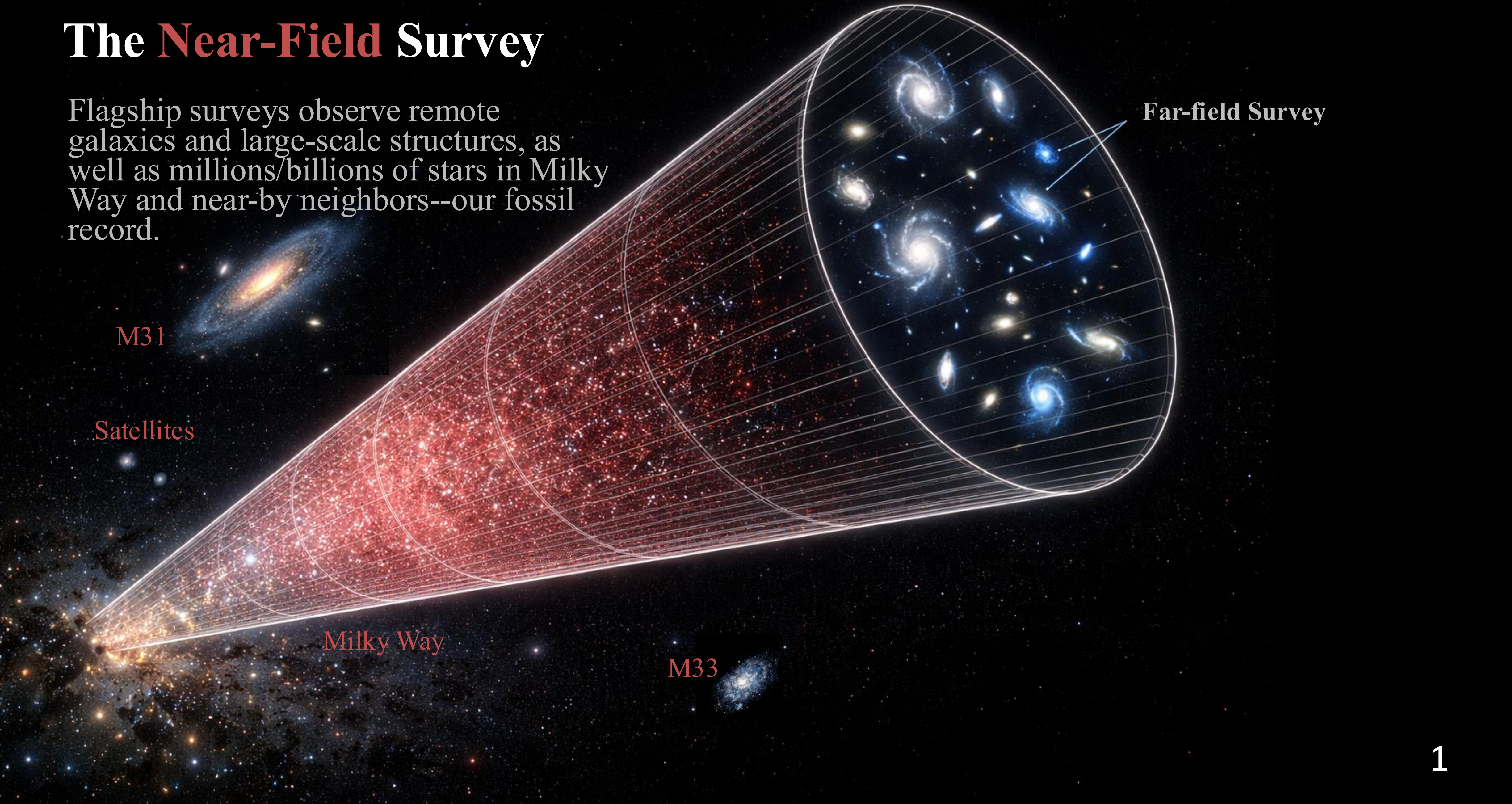


Xiaosheng Zhao (JHU)

08/13/2026

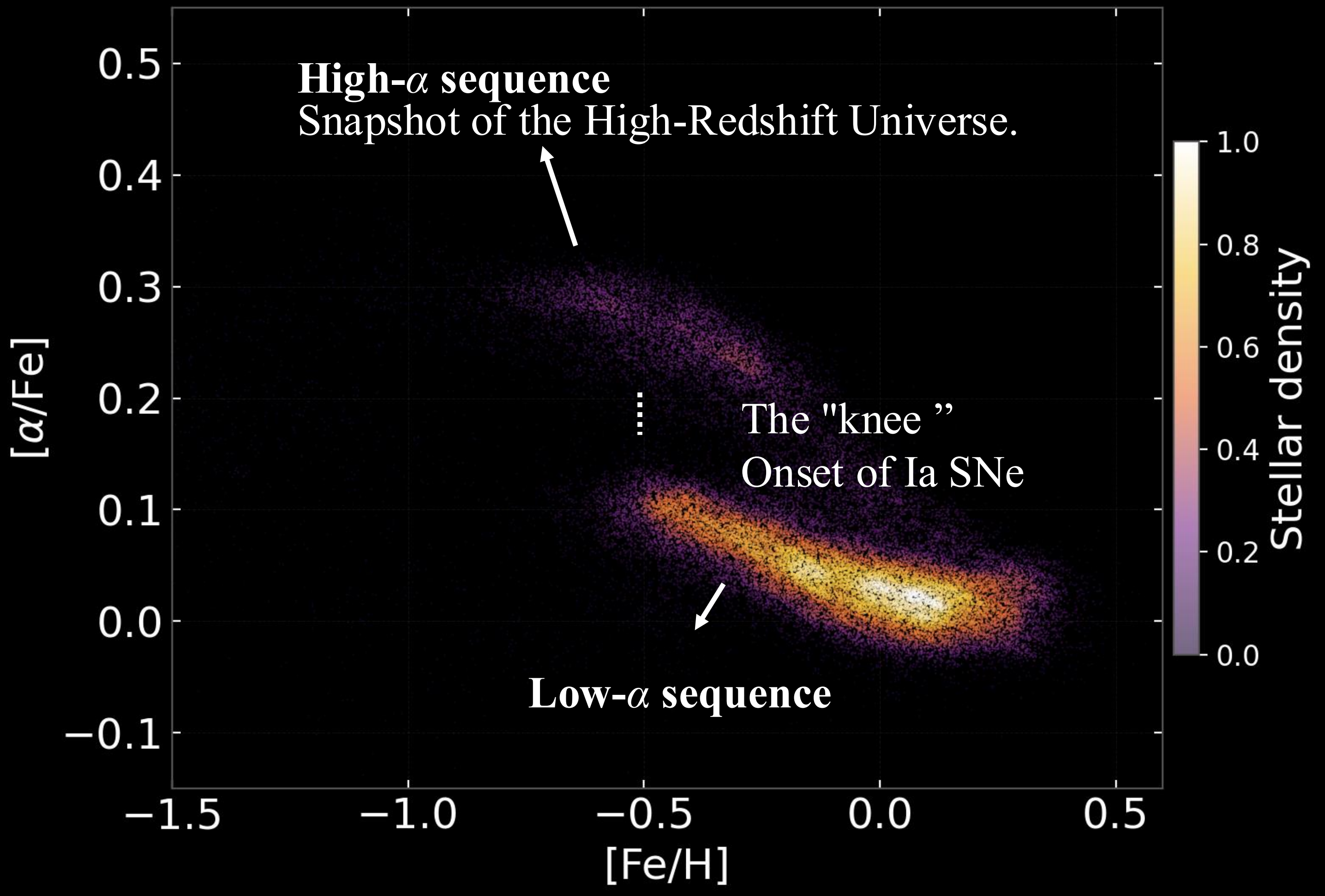
The Near-Field Survey

Flagship surveys observe remote galaxies and large-scale structures, as well as millions/billions of stars in Milky Way and near-by neighbors--our fossil record.



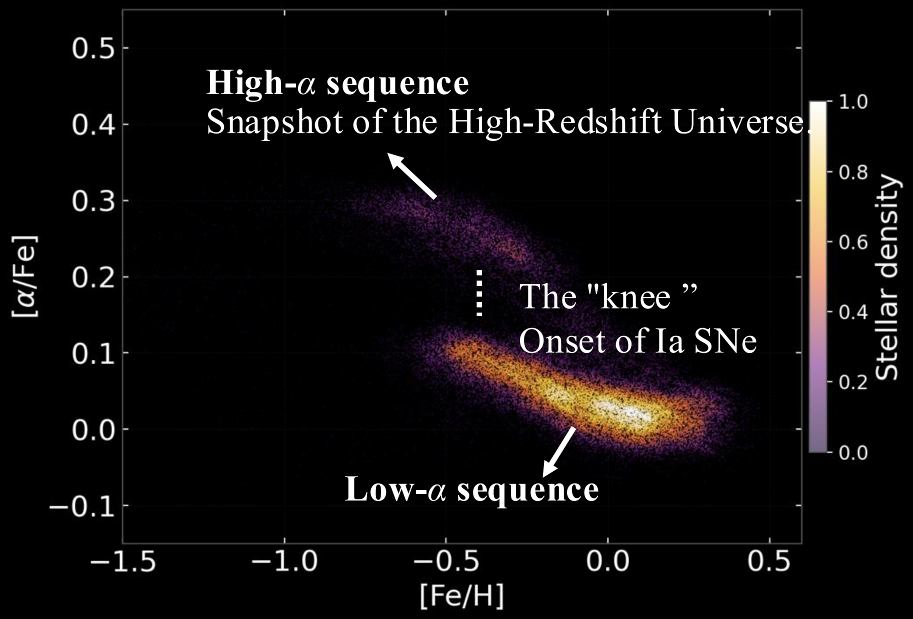
Chemical Tagging: Data-Mining the Galaxy using Stellar 'DNA'

Alpha-element Ratio
(Proxy for Star
Formation Speed)



Overall Metallicity (Proxy for Time/Generations)

Chemical Tagging: Data-Mining the Galaxy using Stellar 'DNA'



The Chemical Clock (Tracing Star Formation)

- **High-α:** rapid early burst; dominated by Type II SNe
- **The "knee"**— onset of delayed Type Ia enrichment; defines the transition epoch
- **Low-α:** slower, extended disk formation

COSMOLOGICAL LEVERAGE

Galaxy assembly & merger history

Accreted populations (e.g. GSE, Sequoia) carry distinct chemical fingerprints — a direct test of hierarchical clustering predictions.

Gas physics & feedback

The bimodality places direct constraints on gas inflow rates and supernova-driven outflow efficiency

Nucleosynthesis & early IMF

Metal-poor stars constrain the integrated yields of the first stellar generations, probing the early Universe IMF and Pop III enrichment channels.

Classical Pipelines are not Enough

WHERE CLASSICAL METHODS FAIL

Empirical library limits
Reference libraries have finite parameter coverage — the metal-poor regime is simply unreachable.

Pipeline varies across tasks/surveys
A pipeline is usually specific for tasks/surveys, hardly talk to each other.

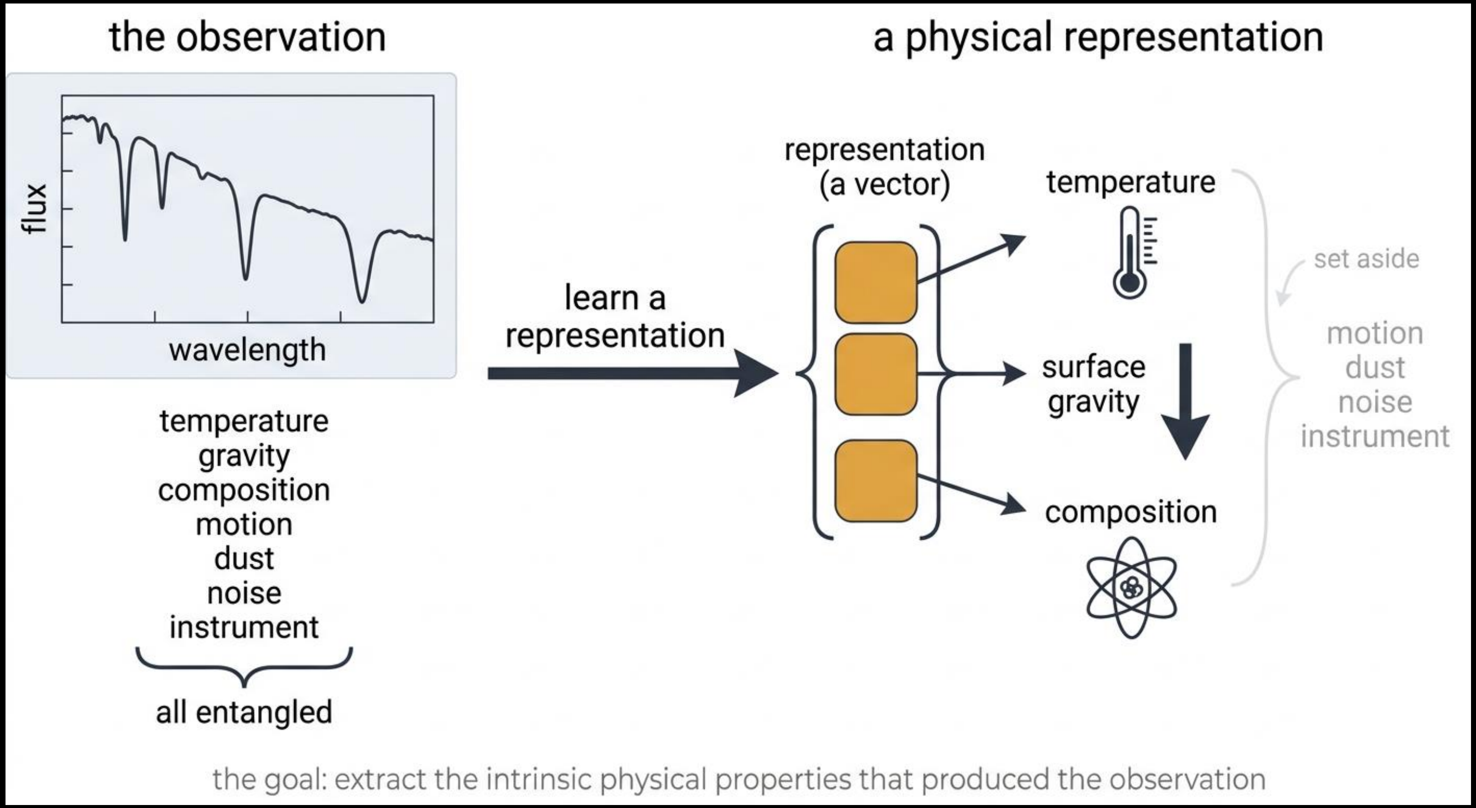
THE ML RESPONSE

Learn from data and high-res libraries
Train directly on millions of observed spectra — no reference library ceiling, except high-res library for labels (from, e.g., APOGEE)

Pre-train → fine-tune: *Foundation Models*
Pre-train on a large, label-rich survey once. A small label set in the target task/survey is enough to adapt — zero-shot or few-shot transfer.

Foundation Models

Learn representations that are transferable



Foundation Models

Motivation of a foundation model

Why we explore foundation models?

MLP generalizes — but may shallowly
Pre-trained MLPs transfer across surveys, but treat each spectrum as a flat vector. Survey-specific systematics remain entangled with physical parameters.

Foundation models learn structure
Pre-trained on massive, diverse data, they learn the underlying spectral language — representations that are physically meaningful, not survey-specific.

Foundation Models

SpecCLIP: Aligning LAMOST LRS and Gaia XP. Using Contrastive Learning to push spectra of the same star together in vector space, with decoders to cross-predict and retain spectra-specific information

In what way to build?

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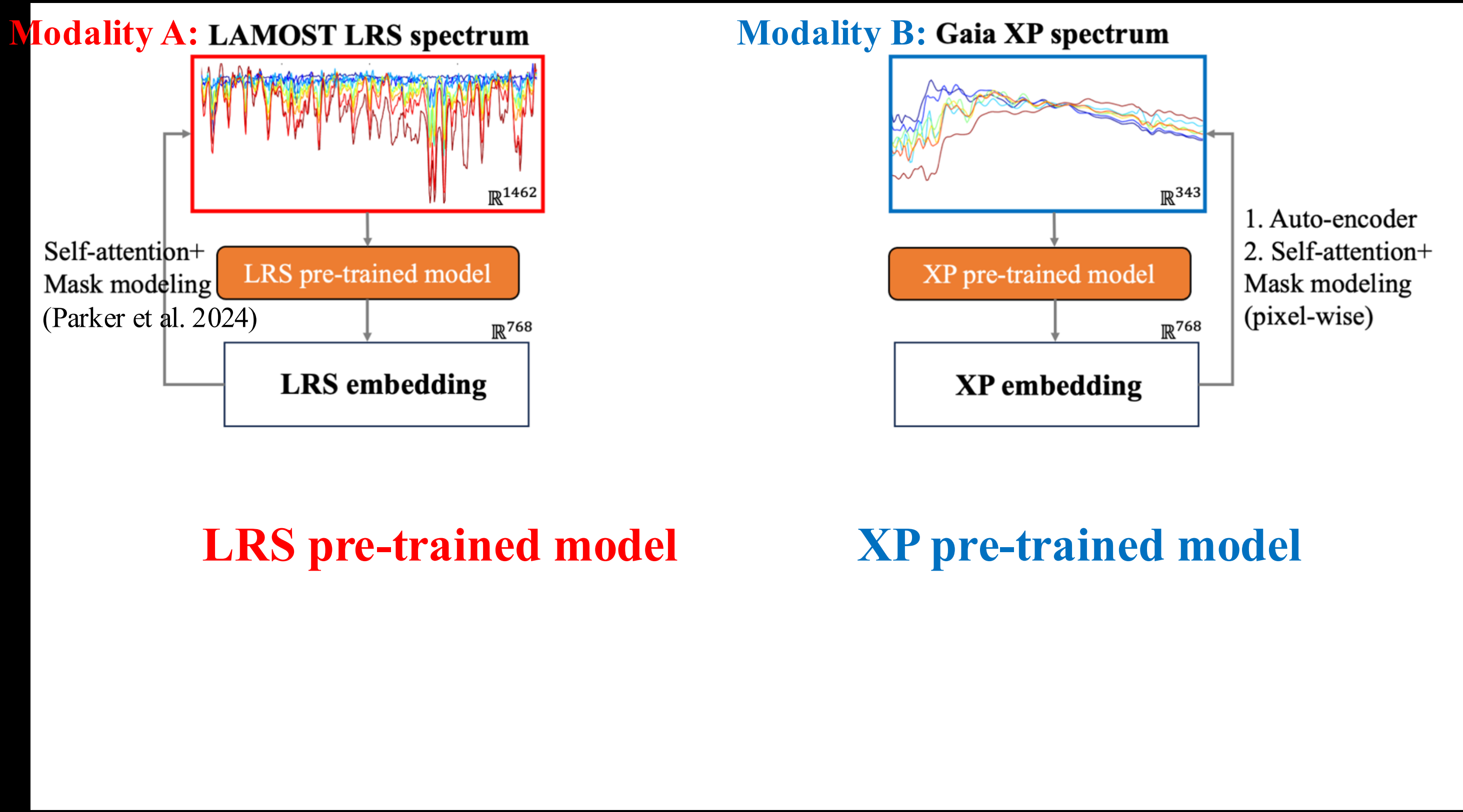

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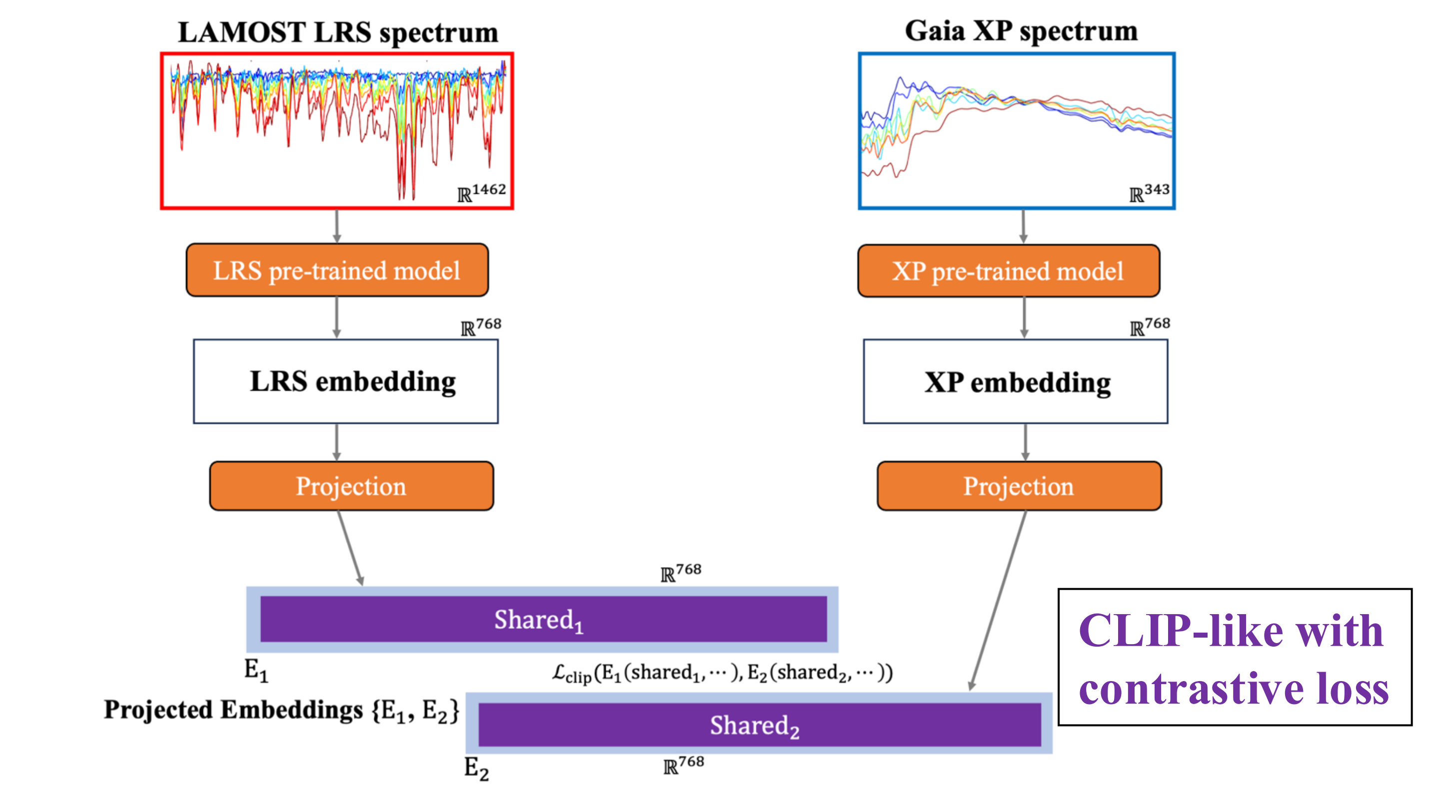

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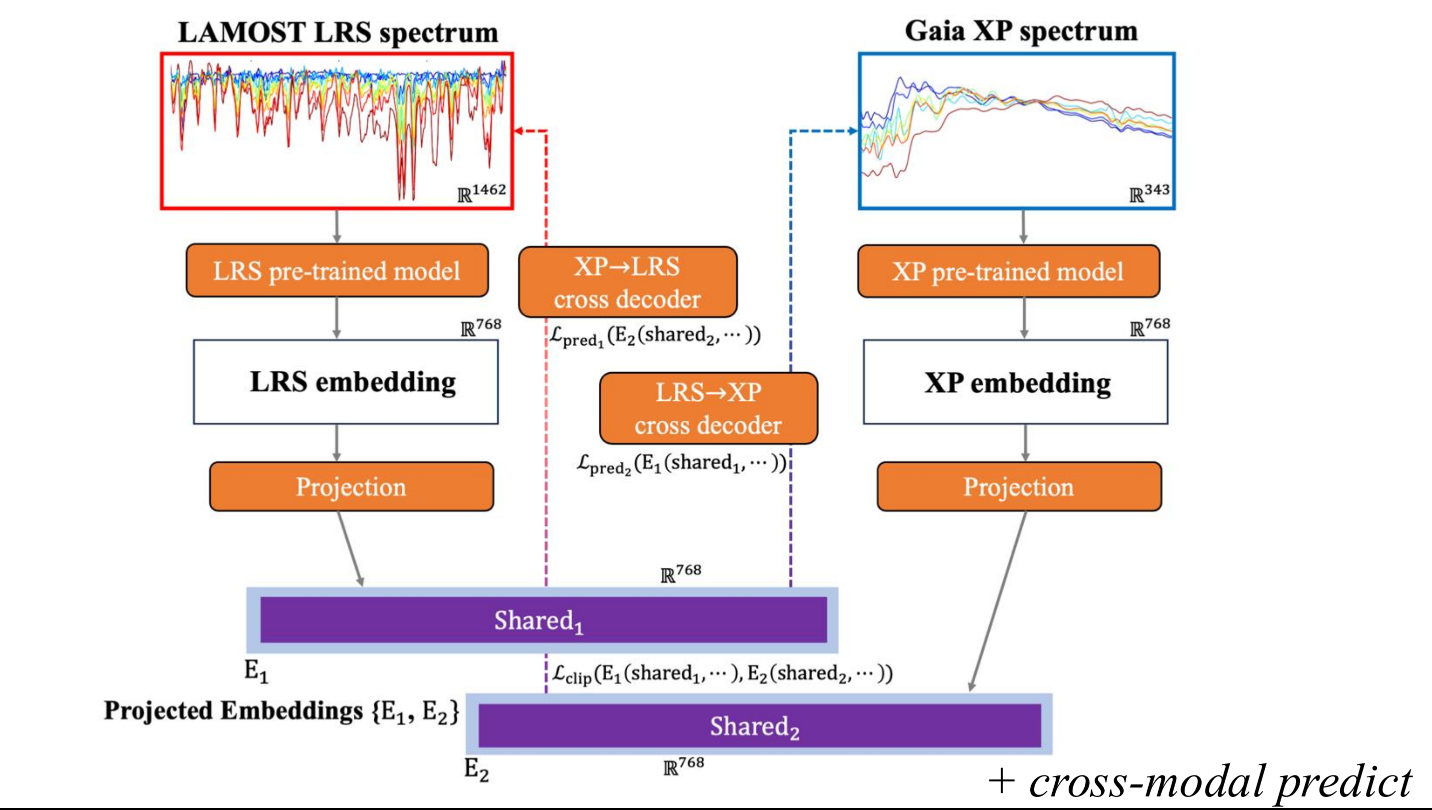

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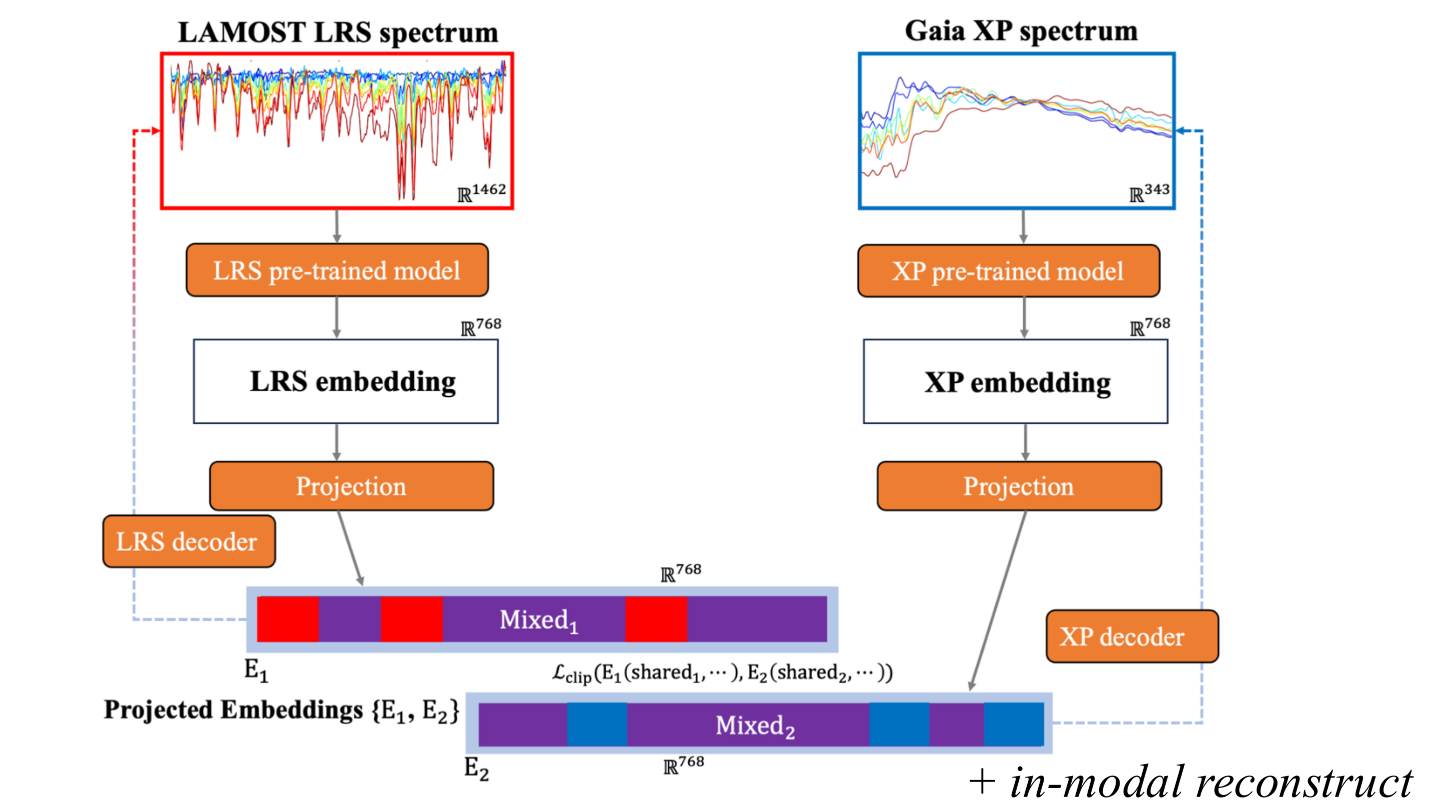

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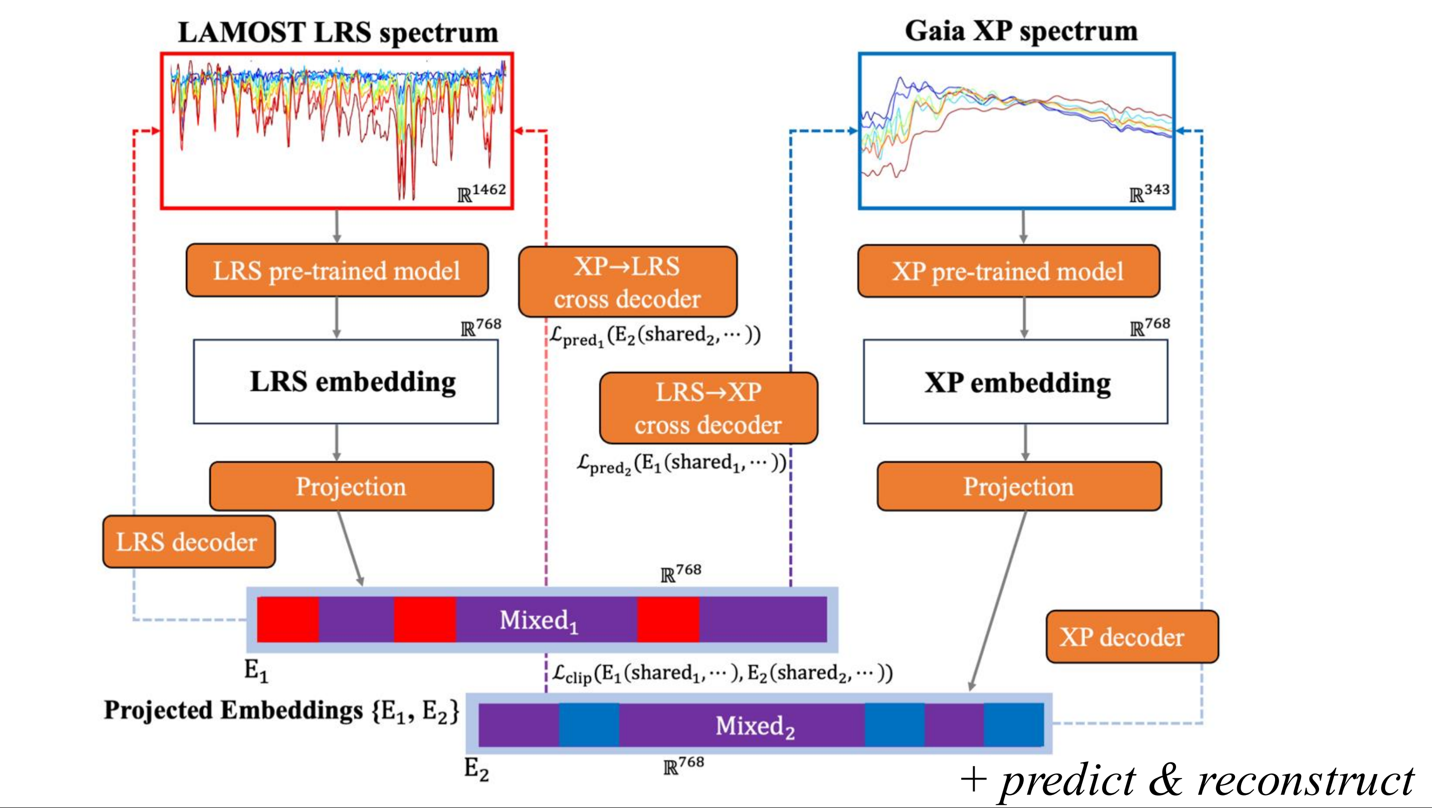

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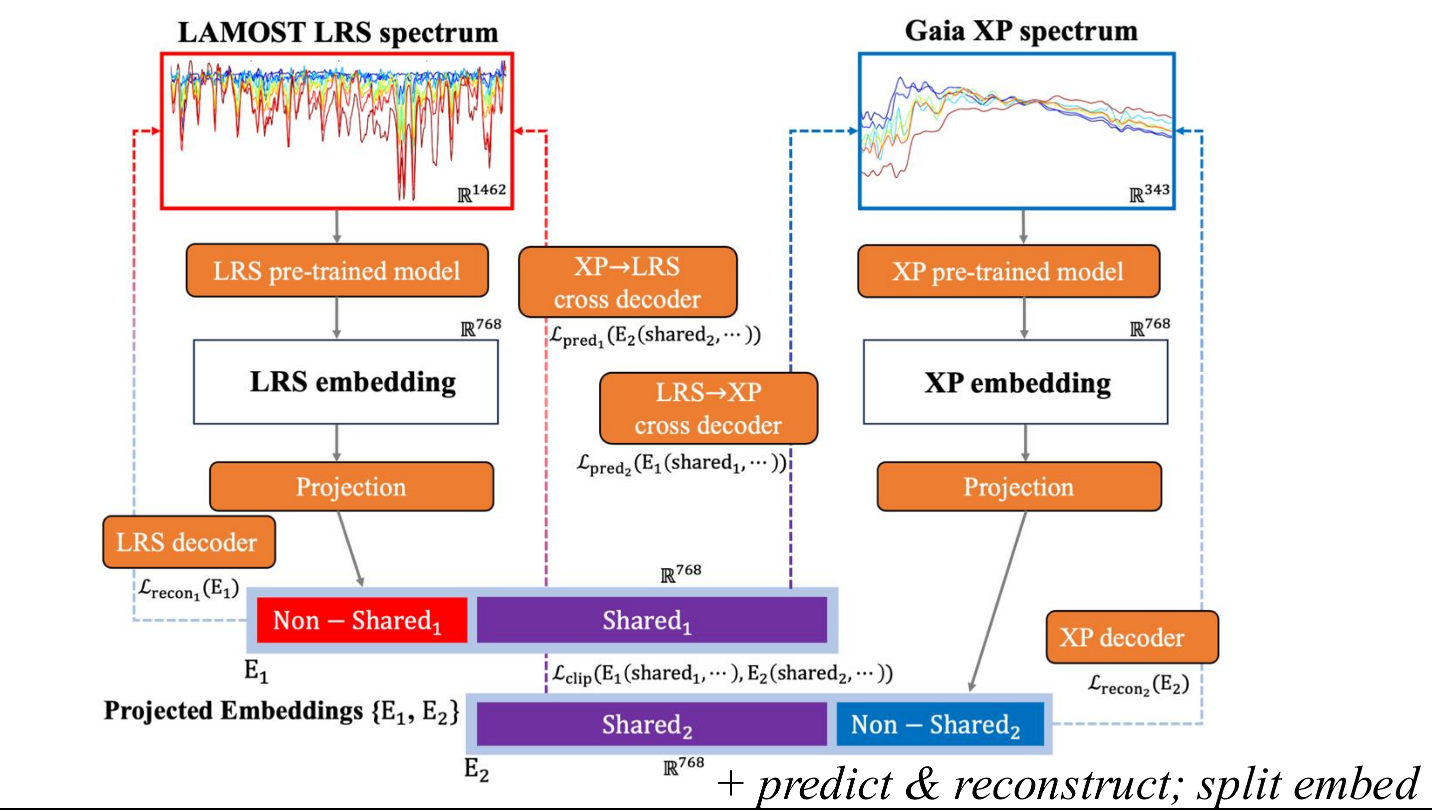
Zhao et al. 2026b



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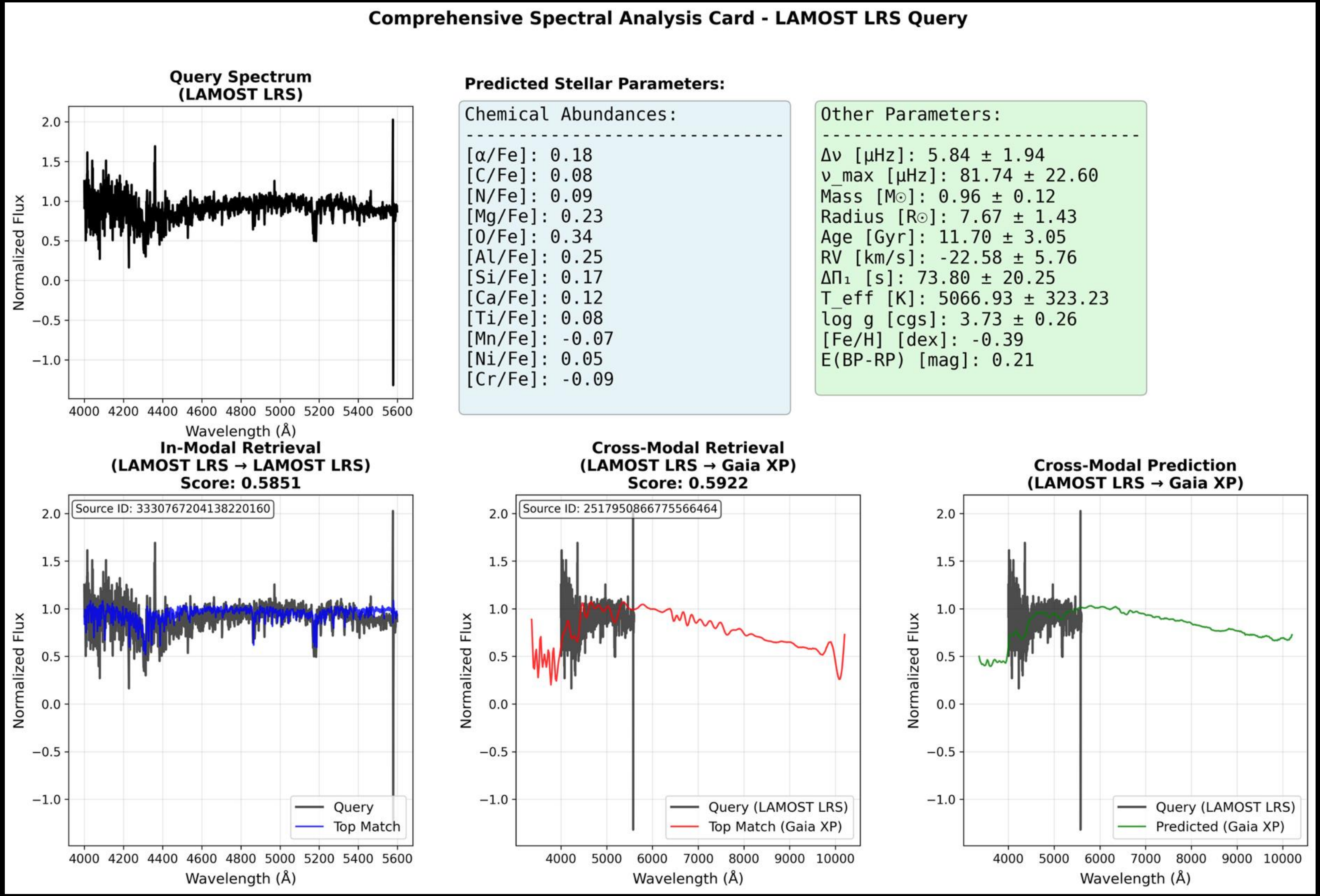
Downstream Tasks Overview



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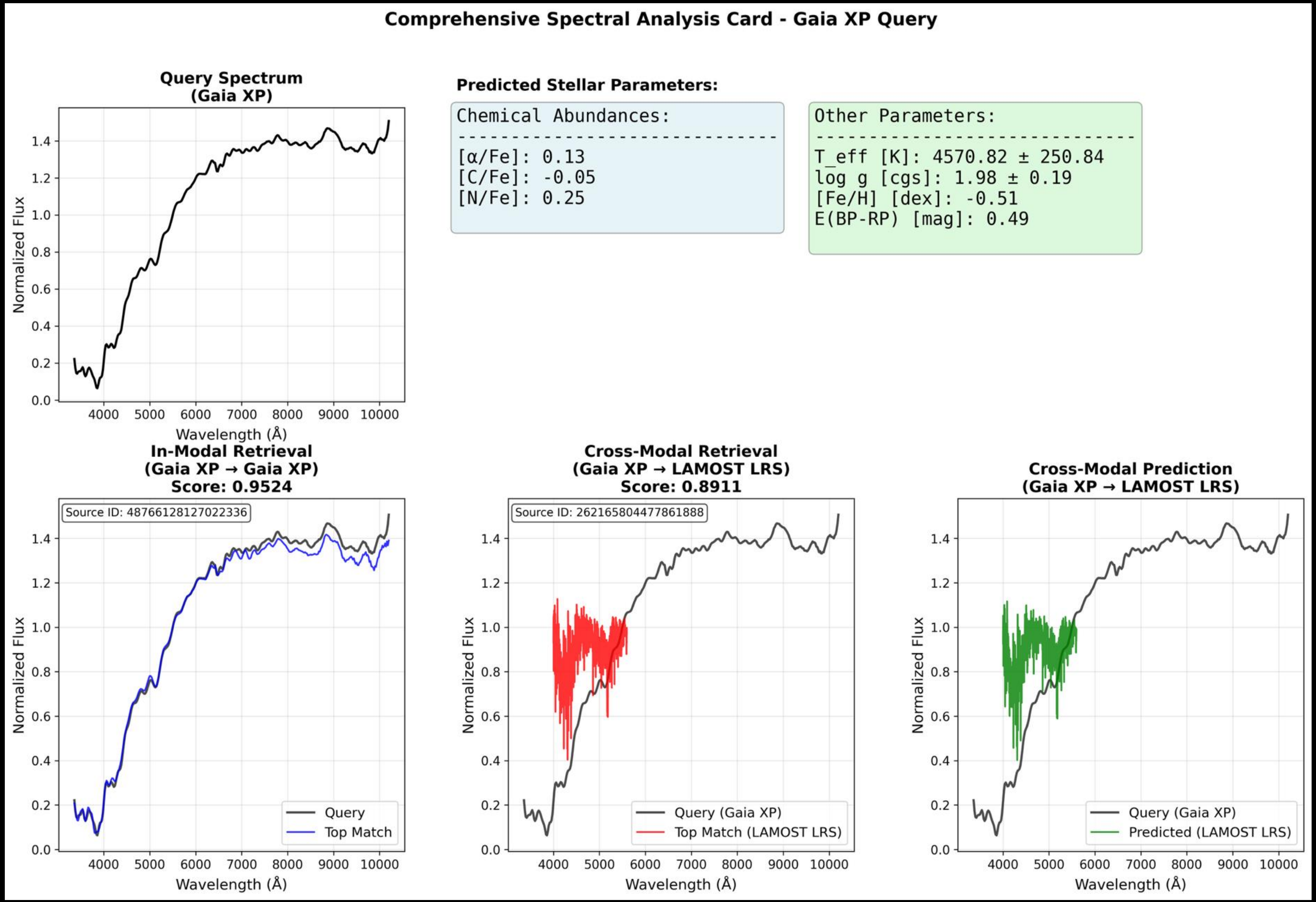
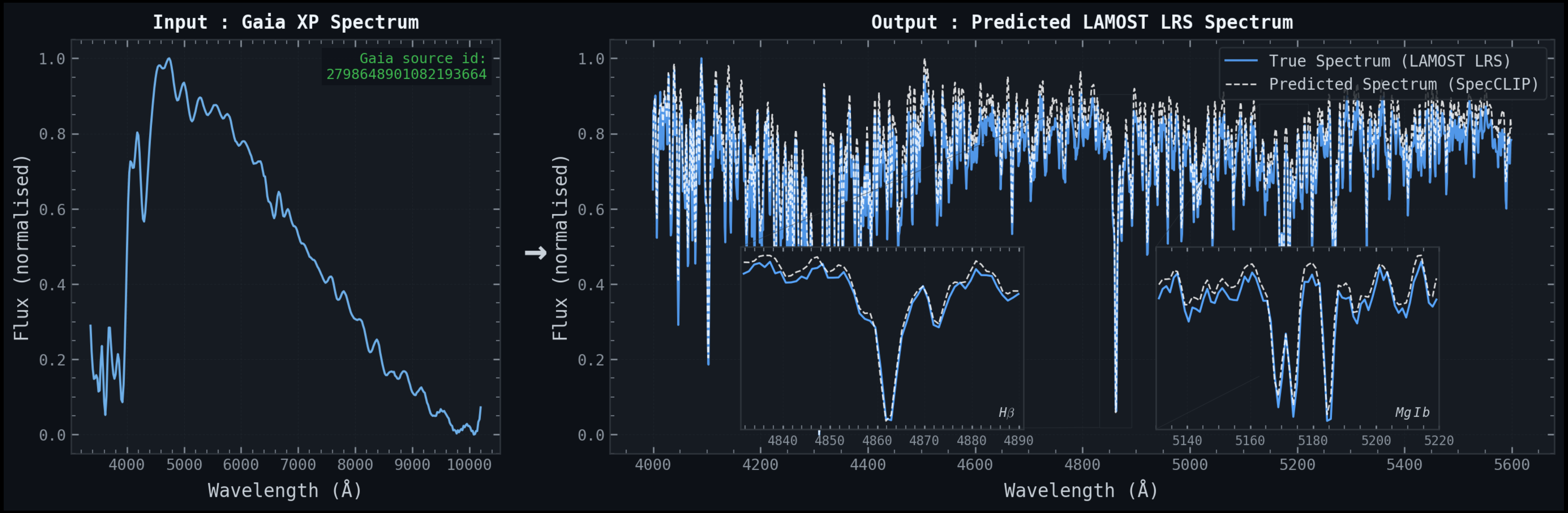


Cross-Modal Retrieval

Retrieve a similar star in another survey

Cross-Modal Spectral Translation

SpecCLIP predict a higher-res spectrum from the spectrophotometry (via shared physical information)



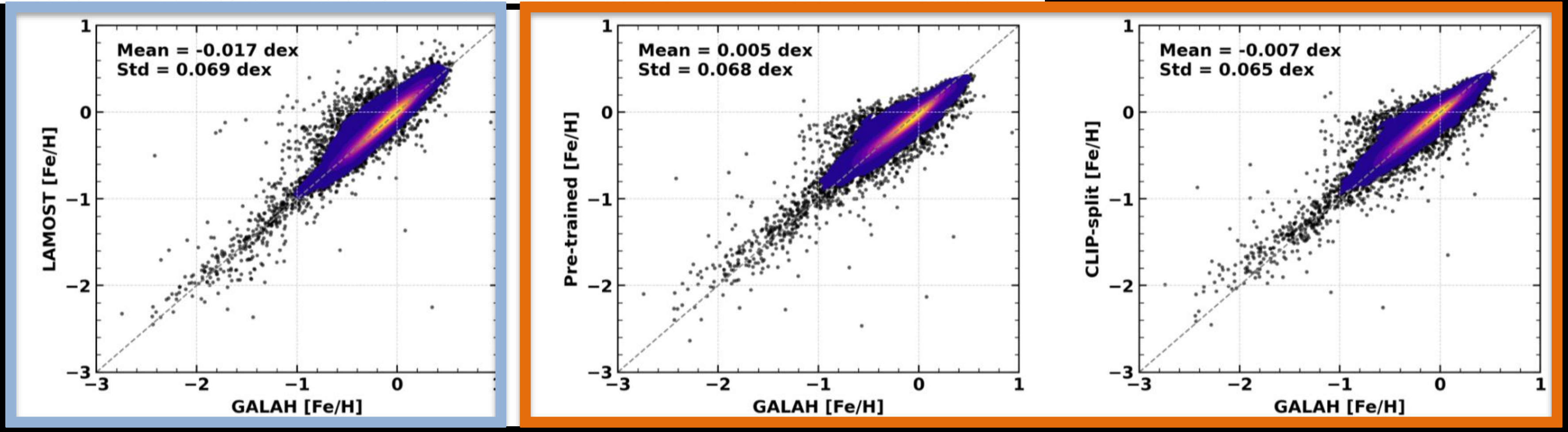
Chemical Abundance Estimation

			LRS Models				
Parameter	Raw Spectra σ / R^2	Pre-trained σ / R^2	CLIP σ / R^2	CLIP-r σ / R^2	CLIP-p σ / R^2	CLIP-pr σ / R^2	CLIP-split σ / R^2
Atmospheric Parameters							
[Fe/H]	0.070 / −0.882	0.066 / 0.939	0.058 / 0.949	0.057/0.949	0.058 / 0.949	0.057 / 0.949	**0.056 / 0.954**
[α/Fe]	0.023 / 0.872	0.021 / 0.906	**0.020** / 0.912	**0.020**/0.913	**0.020** / 0.911	**0.020 / 0.916**	**0.020** / 0.911

Raw spectra < Embeddings

Full table in Zhao et al. 2026b

LAMOST LRS Comparable or better than official pipeline



LAMOST official

Ours

Chemical Abundance Estimation

	LRS Models						
Parameter	Raw Spectra σ / R^2	Pre-trained σ / R^2	CLIP σ / R^2	CLIP-r σ / R^2	CLIP-p σ / R^2	CLIP-pr σ / R^2	CLIP-split σ / R^2
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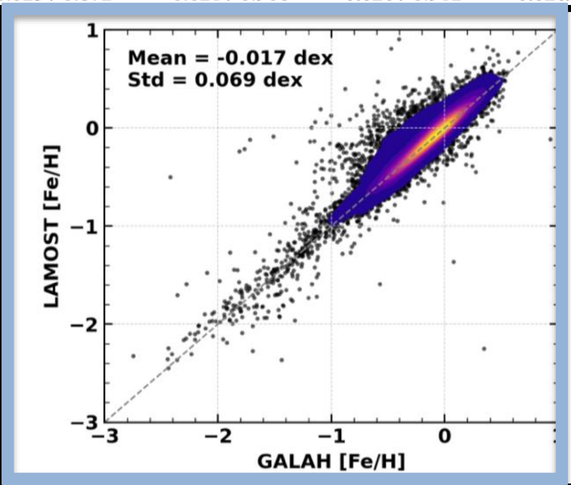

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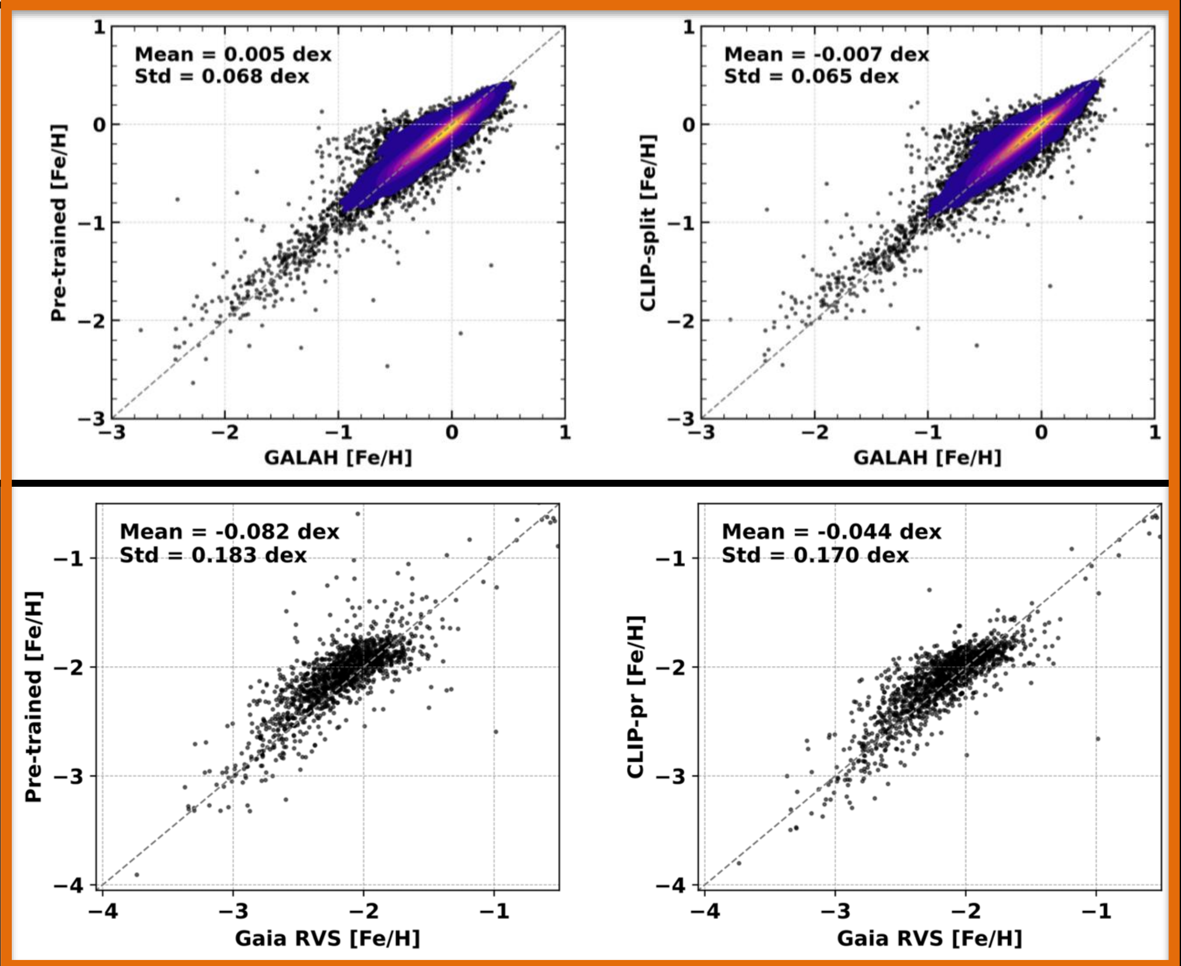


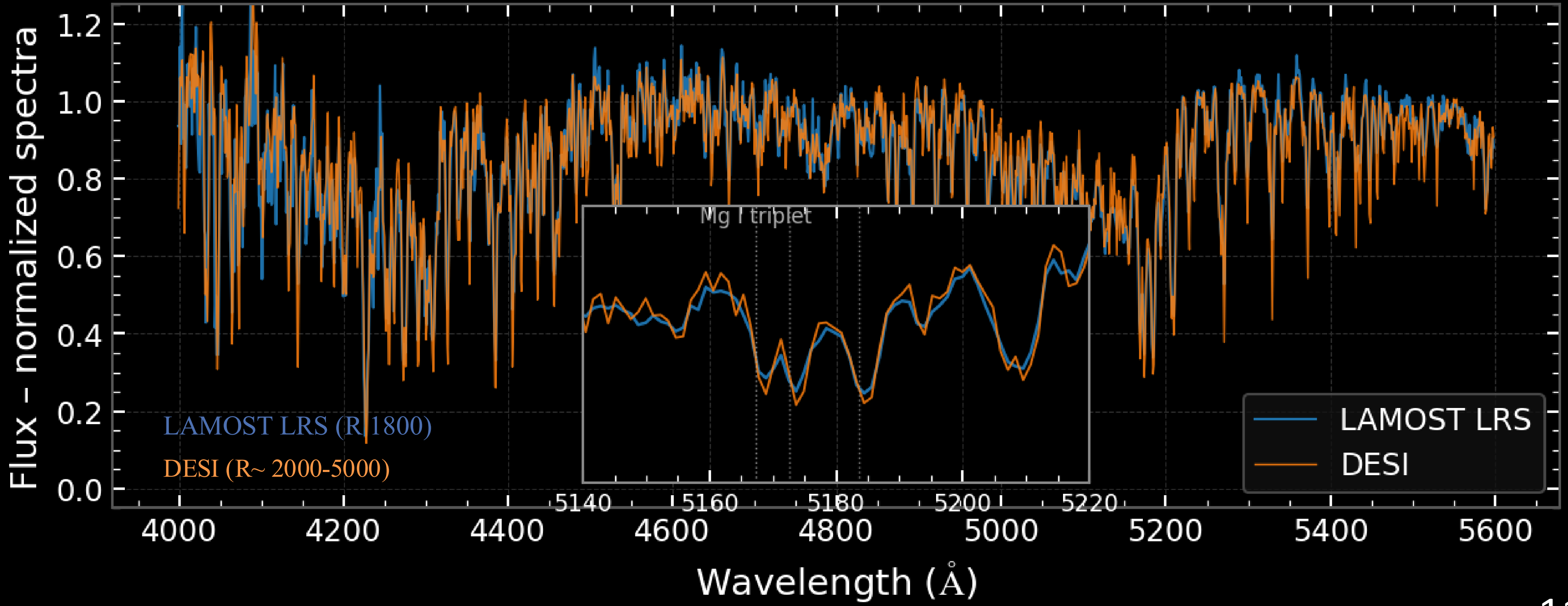
Ours

Gaia XP
Effectiveness
extending to metal-poor

How do foundation models help to generalize from one survey to a **brand-new** one?

The Challenge of Heterogeneous Surveys

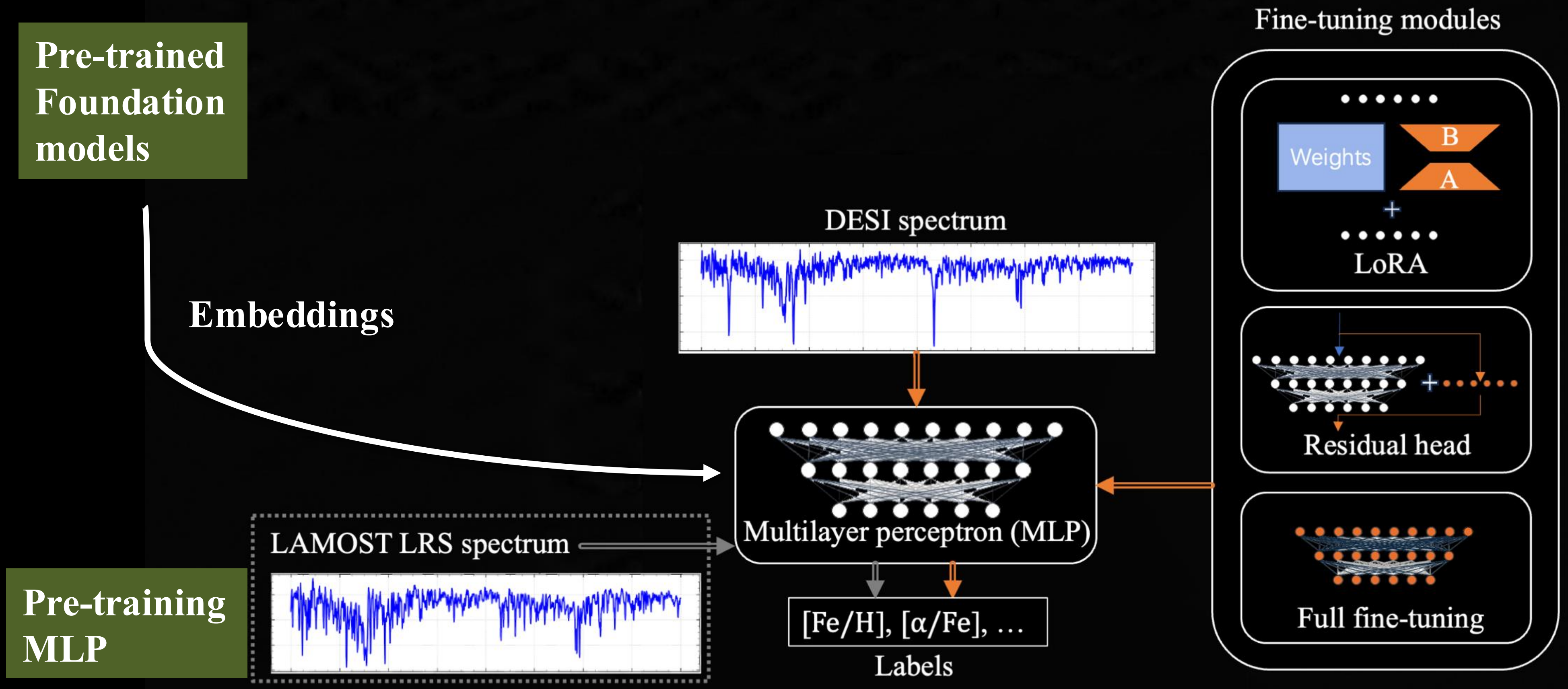
The Challenge: How do we transfer models measuring physical labels ([Fe/H], [alpha/Fe]) from a well-studied, low-res survey to a new, massive, medium-res survey without re-measuring everything?



Pre-trained on LAMOST LRS → Fine-tuned on DESI

Explore the Embedding from a Foundation Model

How could embeddings from a pre-trained foundation model perform?



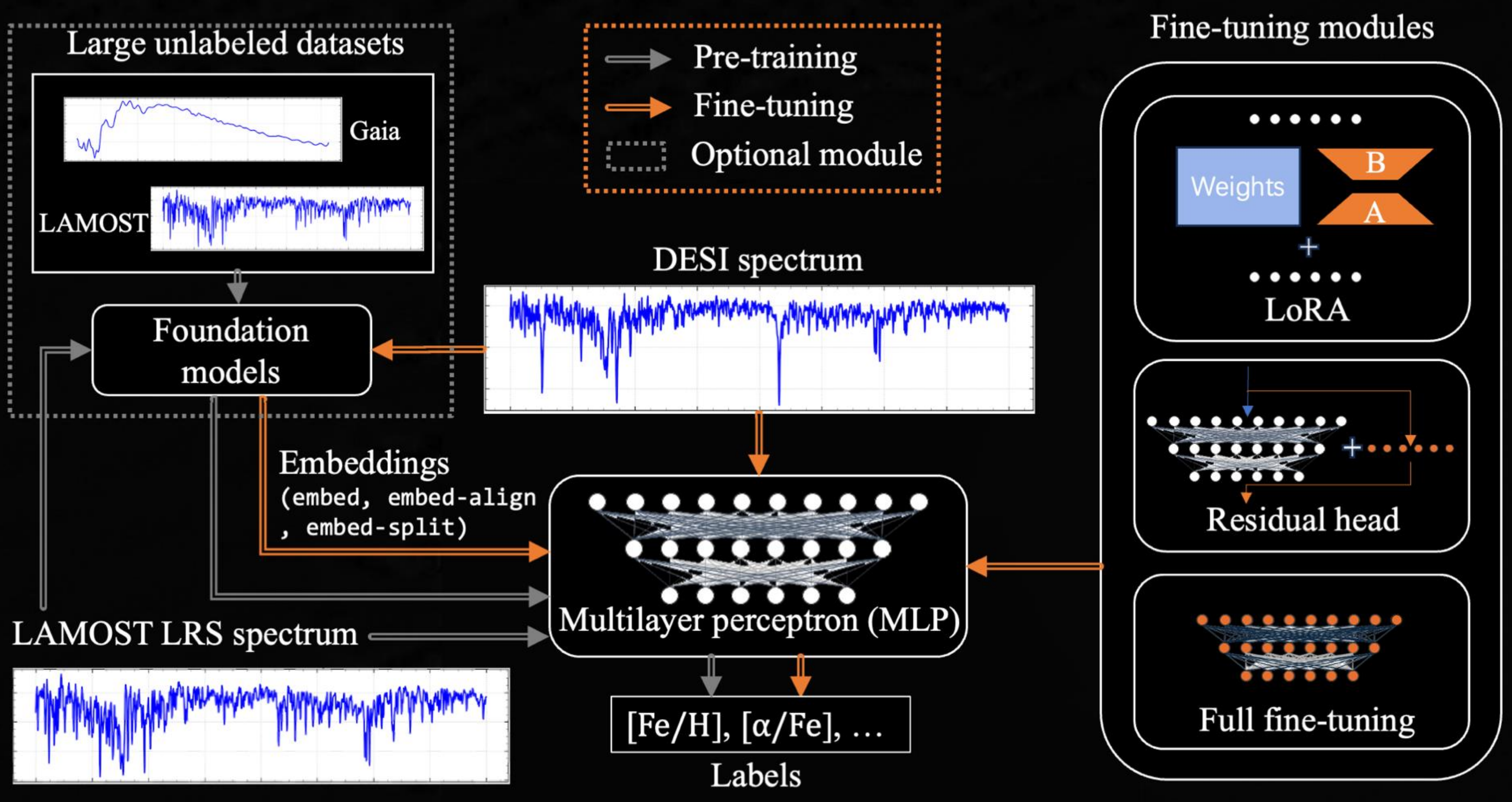
Explore the Embedding from a Foundation Model

How could embeddings from a pre-trained foundation model perform?

Zhao et al. 2026a

Pre-trained Foundation models

Pre-training MLP



The Model Showdown

Zhao et al. 2026a

(Full/Metal-poor/Metal-rich)

Table 1. Coefficient of determination (R^2) for MLPs with different fine-tuning strategies and input types in [Fe/H] and [α/Fe] estimation on DESI spectra.

(Full/MP/MR)	lrs	embed	embed-align	embed-split
[Fe/H]				
residual	0.923 / 0.636 / 0.904	0.922 / 0.196 / 0.913	0.922 / 0.003 / 0.918	0.933 / 0.219 / 0.927
LoRA	0.922 / 0.571 / 0.904	0.921 / 0.031 / 0.916	0.928 / 0.131 / 0.922	0.933 / 0.133 / 0.930
full fine-tune	0.923 / 0.329 / 0.911	0.926 / 0.173 / 0.918	0.927 / 0.085 / 0.922	0.933 / 0.079 / 0.931
zero-shot	0.873 / 0.678 / 0.833	0.833 / 0.694 / 0.779	0.851 / 0.465 / 0.810	0.839 / 0.537 / 0.791
from scratch	0.880 / -0.736 / 0.878	0.877 / -1.246 / 0.886	0.647 / -0.072 / 0.542	0.794 / -0.649 / 0.759
[α/Fe]				
residual	0.799 / 0.366 / 0.802	0.790 / 0.396 / 0.792	0.796 / 0.232 / 0.801	0.796 / 0.335 / 0.800
LoRA	0.829 / 0.418 / 0.831	0.807 / 0.370 / 0.810	0.769 / 0.290 / 0.772	0.733 / 0.205 / 0.736
full-finetune	0.816 / 0.381 / 0.819	0.810 / 0.315 / 0.813	0.784 / 0.247 / 0.787	0.773 / 0.231 / 0.777
zero-shot	0.776 / 0.318 / 0.778	0.730 / 0.183 / 0.733	0.772 / 0.202 / 0.776	0.681 / 0.105 / 0.685
from scratch	0.761 / 0.067 / 0.766	0.729 / 0.401 / 0.730	0.611 / 0.144 / 0.612	0.749 / 0.374 / 0.751

Raw spectra as input **Embeddings as input**

Foundation models perform well at metal-rich regime, though underperform at the metal-poor regime for [Fe/H]; consistently degraded performance on [α/Fe].

The Model Showdown: Where Foundation Model Wins

METAL-POOR ([Fe/H] < - 1.0)

Winner: Simple MLP

Direct training captures faint features better.

METAL-RICH ([Fe/H] > -1.0)

Winner: SpecCLIP

Embeddings capture complex correlations best.

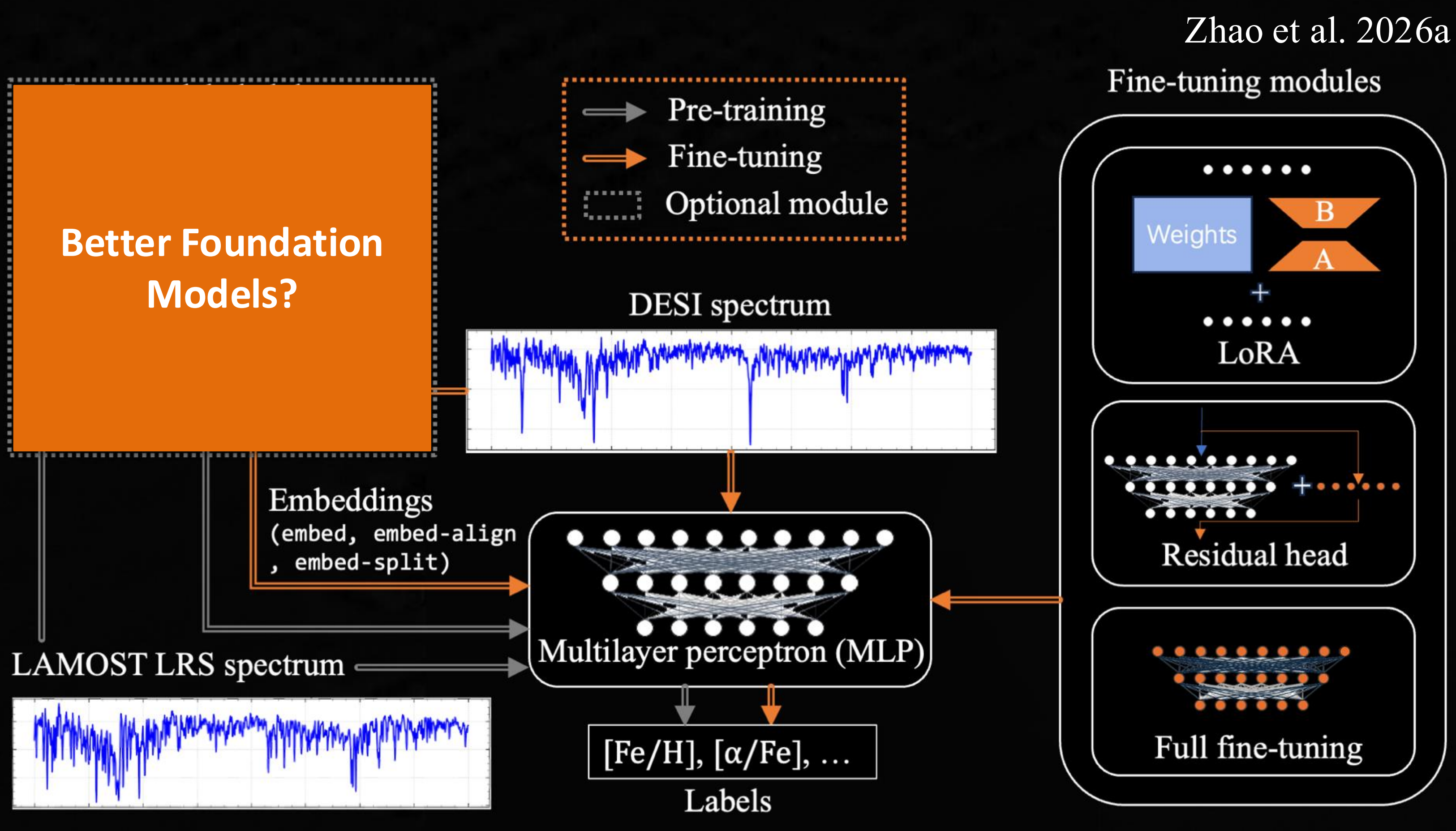
Nuance matters. Key is generalization.

TOOL B: Explore the Embedding from a Foundation Model

How could embeddings from a pre-trained foundation model perform?

Pre-trained Foundation models

Pre-training MLP



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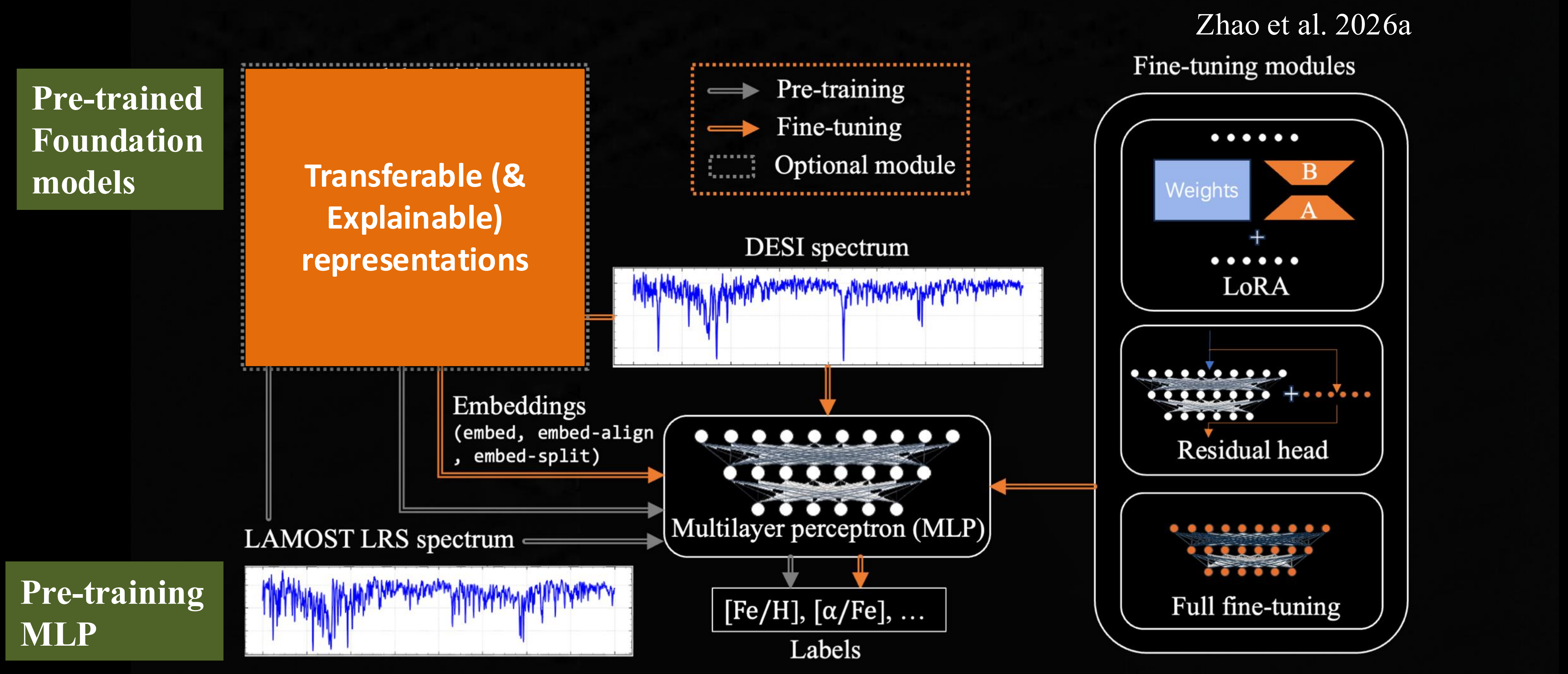
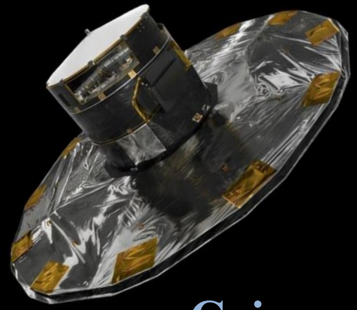
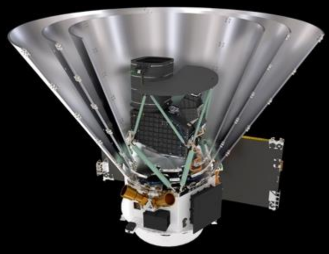


The Blueprint for the Upcoming Years…

Building multi-modal pipeline. As data volume grows, ML/foundation model-driven analysis/discovery may be a key complement.



Gaia



+ LAMOST, Via, Roman…

SPHEREx

DESI

PFS

SDSS

LSST

Summary

The Method:

- Foundation model bring robust embeddings at some parameter regions and unlocks cross-modal search and prediction, benefiting parameter estimation and anomaly detections at large scale.

The Yield:

- Value-added catalogs and related science
- Provides broader implications for multi-modal transfer learning in any domain where instruments are mismatched and labels are scarce.

Caveat:

- The embeddings from SpecCLIP struggle at some physical contents and some physical parameter regime for cross-survey generalization to a brand-new domain
- “Foundation model” should prove its transferability across instruments, populations, and tasks