

Applying Contrastive Learning to Stellar Spectra

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Abstract

With its wide range of spectroscopic capabilities, the Near Infrared Spectrograph (NIRSpec) on the *James Webb* Space Telescope (JWST) is expected to usher in a new era of crowded-field extragalactic stellar spectroscopy. However, small sample sizes and limited overlap with ground-based surveys, such as APOGEE, pose challenges for NIRSpec data analysis. In this work, we present STARCLIP: a contrastive self-supervised learning framework that embeds observed APOGEE and *ab initio* NIRSpec spectra into a unified, physically meaningful latent space. Our approach consists of training convolutional neural networks (CNNs) to recover twenty fundamental stellar properties from single-modal spectroscopic data. We then adopt these pre-trained CNNs as encoders, aligning them via contrastive loss. To simulate realistic NIRSpec observations, we construct semi-empirical, stochastic NIRSpec catalogs and embed them into the shared latent space using MOCKSTARCLIP, a modified CLIP-based framework. Both models enable seamless transfer to downstream tasks, including cosine similarity search and stellar property recovery. Notably, a linear regressor applied to STARCLIP embeddings recovers all twenty stellar properties of interest with r^2 scores typically exceeding 0.88, including T_{eff} (with uncertainty $\lesssim 200$ K), $\log g$ ($\lesssim 0.07$ dex) and $[\text{Fe}/\text{H}]$ ($\lesssim 0.03$ dex) for RGB-like stars. Applying the regressor on MOCKSTARCLIP embeddings yields modestly reduced precision—approximately 450 K for T_{eff} , 0.11 dex for $\log g$ and 0.06 dex for $[\text{Fe}/\text{H}]$. Ultimately, our approach demonstrates that foundation models for NIRSpec and other spectral surveys with similar constraints is well within reach.

Key words: methods: data analysis – techniques: spectroscopic – stars: fundamental parameters

Glossary

\mathcal{A} Set of 19,001 qualified real APOGEE spectra.

\mathcal{J} Set of 19,001 *ab initio* JWST/NIRSpec spectra.

\mathcal{A} Set of 95,005 augmented APOGEE spectra derived from \mathcal{A} .

$[\mathcal{A}]$ Truncated version of \mathcal{A} to match the dimensionality of \mathcal{J} .

\mathcal{J} Set of 95,005 augmented, mock JWST/NIRSpec spectra derived from \mathcal{J} .

\mathcal{J}^{lo} Set of 250 spectra augmented, mock JWST/NIRSpec spectra derived from \mathcal{J} .

\mathcal{J}^{hi} Extended-mock version of \mathcal{J}_{lo} , enriched with 5,000 spectra in the test set.

$Z^{\mathcal{J}}$ JWST/NIRSpec embeddings generated by $f_{\Theta}(\tilde{\mathcal{J}})$.

$Z^{\mathcal{A}}$ APOGEE embeddings generated by $g_{\Phi}(\mathcal{A})$.

Z^{lo} JWST/NIRSpec embeddings from $f_{\Theta}(\mathcal{J}_{\text{lo}})$.

Z^{hi} JWST/NIRSpec embeddings from $f_{\Theta^*}(\mathcal{J}_{\text{hi}})$.

1 Introduction

Absorption features on a star’s spectrum encode its physical and chemical properties, which in turn provide a ‘fossil record’ of the formation history of its host galaxy [1]. The Near Infrared Spectroscopic Instrument (NIRSpec) [2, 3] on board the *James Webb* Space Telescope (JWST) [4] exhibits unique spectroscopic capabilities. With high angular resolution ($R = 2,700$) and sensitivity in the infrared (IR) range (0.6-5.3 μm), JWST/NIRSpec (hereafter, NIRSpec) enables efficient, high-quality resolved star spectroscopy of neighbouring galaxies that have so far been too distant, faint or crowded for previous instruments to detect. Although current datasets are limited in size ($n \sim 100$), these capabilities have motivated the launch of several recent astronomical programs, including (i) completed surveys of ~ 100 red giant branch (RGB) stars in M31 (JWST-GO-2609; PI: Nidever¹), (ii) an ongoing survey of ~ 200 RGB stars across three isolated dwarf galaxies (JWST-GO-3788; PI: Wiesz²) and (iii) an upcoming survey to observe ~ 200 more M31 disc stars (JWST-GO-4735; PI: Sandford³).

However, due to its novelty and uniqueness, the domain of JWST resolved-star spectroscopy remains largely unexplored, with open challenges in data collection, preprocessing, and analysis. In parallel, a growing number of astronomical surveys have adopted data-driven machine learning (ML) methods to extract insights from spectroscopic data. Broadly, these approaches fall into two categories:

- **Supervised** algorithms use input-output pairs to learn the mapping from a set of features (e.g., stellar spectra) to a set of target variables (e.g., stellar labels⁴) in order to perform discriminative tasks (e.g., stellar property recovery). These approaches perform well in data-rich regimes, but are ultimately constrained by the quality and quantity of labelled data available. Moreover, such models are often task-specific and generalise poorly to data distributions outside their training sets. Prominent data-driven models for inferring stellar labels from spectroscopic data include THE CANNON [5], STARNET [6], ASTRONN [7], DD-PAYNE [8] and BINGO [9].
- **Unsupervised** algorithms circumvent the need for labelled data by learning directly from raw input features and producing non-invertible outputs, such as: (i) clusters of similar objects, (ii) lists of detected anomalies, or (iii) low-dimensional representations of the data [10]. By revealing previously unknown structure in the data, these methods are arguably more useful for ‘AI for science’ research, as illustrated in [11, 12]. However, their performance often lags behind their supervised counterparts, limiting their adoption in practice [13, 14, 15].

Large-scale surveys such as Apache Point Observatory Galactic Evolution Experiment (APOGEE) [16, 17], Galactic Archaeology with HERMES (GALAH) [18] and Large Sky Area Multi-object Fiber Spectroscopic Telescope (LAMOST) [19] provide large ($n \sim 10^5\text{-}10^7$), homogeneous databases of labelled spectra that are virtually ideal for supervised ML. In contrast, NIRSpec programs generate much smaller samples ($n \sim 100$), limiting their suitability for supervised analysis. Moreover, substantial differences in field-of-view (FoV) and sensitivity between NIRSpec and ground-based surveys pose challenges in identifying cross-instrument targets that could inform NIRSpec analysis. For example, NIRSpec can resolve sources separated by ~ 1 arcsec within a compact 3.6×3.4 arcmin² FoV [2], while APOGEE imposes a minimum separation of ~ 1 arcmin across a broader 1.5° radius circular FoV [17]. NIRSpec also achieves superior faint-end sensitivity [2], detecting sources several magnitudes fainter than APOGEE’s limiting magnitude. Given the lack of overlap, one potential theory-driven strategy

¹<https://arxiv.org/pdf/2306.04688>

²<https://ui.adsabs.harvard.edu/abs/2023jwst.prop.3788W/abstract>

³<https://ui.adsabs.harvard.edu/abs/2024jwst.prop.4735S/abstract>

⁴In this context, ‘labels’ refers to physical quantities that characterise a stellar spectrum, including stellar parameters and chemical abundances.

is to generate a discrete set of *ab initio*, single-modal⁵ NIRSpec models. Frameworks like THE PAYNE [20] can then interpolate the ensemble of synthetic spectra to fit observed NIRSpec spectra, enabling the simultaneous recovery of multiple stellar parameters. Unfortunately, idealised instruments and physical assumptions in synthetic models often introduce a ‘*synthetic gap*’, causing systematic offsets between *ab initio* spectra and real observations [21]. We investigate a partial remedy: generating *ab initio*, semi-empirical NIRSpec data to pair with real APOGEE observations, resulting in a *cross-modal* dataset that can benefit from a synergistic analysis.⁶

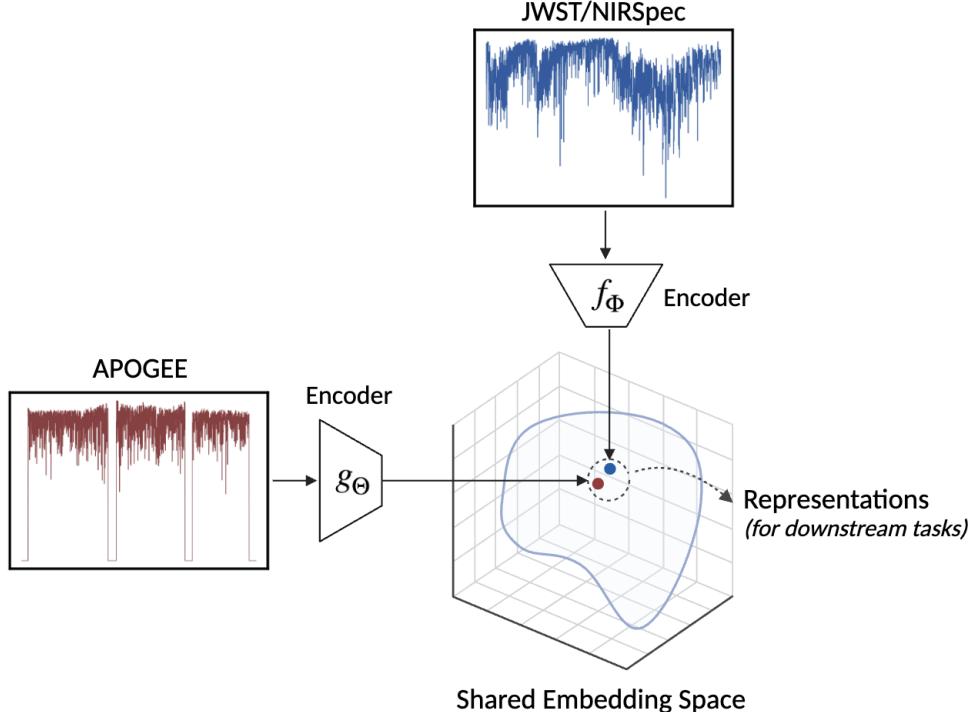


Figure 1: Illustration of STARCLIP model architecture; the MOCKSTARCLIP architecture is analogous. Two encoders, f_Φ and g_Θ , separately embed cross-modal JWST/NIRSpec and APOGEE spectra into a shared embedding space, where they are aligned under contrastive loss. The learned embeddings encode high-level physical information, enabling seamless transfer to downstream tasks. The two modalities are distinguished by colour, with JWST/NIRSpec in blue and APOGEE in red.

One promising ML approach to analyse cross-modal realisations is **self-supervised learning (SSL)**. SSL pre-trains models to solve a suite of auxiliary pretext tasks, in which the supervision signals are acquired directly from the data itself without explicit labels [24]. Once pre-trained, these models can extract high-quality latent representations that serve as a ‘foundation’ for improving performance [25, 26, 27], generalisation [28, 29] and robustness [30, 31] on downstream tasks. For this reason, they are often referred to as **foundation models** [32]. Foundation models have already closed the gap with supervised approaches across numerous tasks, particularly by leveraging *transfer learning* to support applications in settings that are insufficiently data-rich to train models from scratch [32].

⁵‘Modality’ refers to the type of data input. In this context, it refers to the astronomical program used to collect the spectra, such as APOGEE or JWST/NIRSpec.

⁶Our cross-modal approach is motivated, in part, by recent work [22, 23] showing that combining APOGEE and *Gaia* spectra in a unified ML framework improves stellar inferences over single-modal models, as noted in [29].

In this work, we introduce STARCLIP, and its variant MOCKSTARCLIP, cross-modal foundation models for stellar spectroscopy. Our approach consists of two stages. First, we train flexible 1-dimensional convolutional neural networks (1D-CNNs) on single-modal spectroscopic data to predict a set of stellar labels. Second, we repurpose the pre-trained CNNs as encoders to embed cross-modal data into a shared latent space. These encoders are jointly trained under a *contrastive* objective, whereby augmented⁷ views of the same underlying star are brought closer together while those of different stars are pushed apart. We show the resulting embeddings are seamlessly transferrable across a wide range of downstream tasks—including semantic similarity searches and stellar property estimation—ultimately facilitating analysis of NIRSpec data.

Spectroscopic data consist of 19,001 pairs of APOGEE Sloan Digital Sky Survey IV⁸ Data Release 17 (SDSS-IV DR17) [34] and theoretical NIRSpec spectra, the latter generated *ab initio* from stellar atmosphere and spectrum synthesis models maintained by R. Kurucz [35, 36, 37, 38, 39, 40]. Each pair is annotated with stellar labels, consisting of atmospheric parameters T_{eff} , $\log g$ and $[\text{Fe}/\text{H}]$ —the primary determinants of RGB spectral flux—along with 17 other elemental abundances $[\text{X}/\text{H}]$, including C, N, O, Na, Mg, Al, Si, S, K, Ca, Ti, V, Cr, Mn, Co, Ni and Ce. To bridge the ‘synthetic gap’, we apply a suite of semi-empirical, stochastic augmentations to the *ab initio* NIRSpec data, yielding a ‘mock’ dataset. To further approximate real NIRSpec observations, we select a representative subsample of 250 stars from the *ab initio* dataset and apply two levels of stochastic transformations, generating ‘mock’ and ‘extended-mock’ versions. A small sample ($n = 59$) of representative spectral traces from JWST-GO-3788 (PI: Weisz) is used to inform these transformations. STARCLIP and MOCKSTARCLIP result from applying our methodology to cross-modal datasets comprised of augmented APOGE × mock NIRSpec and subsampled mock-extended × mock NIRSpec pairs, respectively.

A schema of our approach is depicted in Figure 1. By combining a well-characterised set of real APOGEE observations with *ab initio* NIRSpec data, STARCLIP is poised to learn cross-modal representations that are more informative of stellar properties than either modality alone. By transferring the pre-trained weights of STARCLIP to MOCKSTARCLIP, we enable MOCKSTARCLIP to leverage prior knowledge from the larger training regime, while adjusting to a scaled-down setting that reflects observational characteristics expected of real NIRSpec data.

We summarise the contributions of this paper, as follows:

- To the best of our knowledge, we develop one of the first self-supervised foundation models for analysing NIRSpec data, along with a pipeline to ensure seamless integration with observed data.
- We train robust CNNs in a supervised setting to predict stellar parameters with high precision and accuracy.
- We apply cross-modal contrastive training to align pre-trained encoders around shared physical properties, creating a discriminative latent space.
- We apply dimension-reduction to the latent space, visualising its intrinsic local geometry in a lower-dimensional setting.
- With minimal processing, our models enable accurate transfer to downstream tasks, including (i) in-modal and cross-modal cosine similarity searches and (ii) stellar property estimation from spectra. These tasks empirically show that latent embeddings capture key physical properties of underlying stars.

⁷In this context, an ‘augmented view’ refers to a synthetically modified version of an original data point, generated to increase the number of positive pairs for training (see, e.g., [33] for details).

⁸<https://www.sdss4.org/>

1.1 Related Works

This paper builds on two recent works. First, Fabbro et al. [6] introduce STARNET, a CNN model capable of determining atmospheric stellar parameters— $T_{\text{eff.}}$, $\log g$, and $[\text{Fe}/\text{H}]$ —directly from observed APOGEE and *ab initio* APOGEE ATLAS9/ASSeT [41, 42] spectra. Second, Parker et al. [27] develop ASTROCLIP, a versatile foundation model that can embed cross-modal representations of galaxy images and spectra in a unified latent space. Their approach involves pre-training transformer-based encoders for images and spectra in a self-supervised setting, followed by aligning the encoders under contrastive loss. Parker et al. [27] show the resulting embeddings achieve state-of-the-art performance across a variety of downstream tasks—including photometric redshift estimation and physical property prediction—surpassing even supervised baselines. Both articles provide public access to their data and code on GitHub via the [StarNet](#) and [AstroCLIP](#) repositories.

In this work, we build our own foundation models in a two-step process involving carefully modified versions of STARNET and ASTROCLIP.

1.2 Outline

Code for our models is publicly available under an MIT License in the [StarCLIP](#) GitHub repository. Our paper is organised, as follows. In §2, we provide theoretical background on supervised and self-supervised methods relevant to this work, addressing their merits and disadvantages. In §3, we provide the spectroscopic datasets used for analysis. In §4, we discuss in detail the implementation and training process of the STARCLIP and MOCKSTARCLIP models. We present our results on in-modal and cross-modal similarity searches, dimension reduction and stellar property prediction in §5. Finally, §6 contains some concluding remarks and further extensions to our work.

1.3 Notations

In this paper, we use $[n]$, where $n \in \mathbb{N}$, to denote the set $\{1, \dots, n\}$. Given two datasets $\mathcal{X}, \mathcal{Y} \in \mathbb{R}^{n \times d}$ of equal size, we define their *elementwise* pairing as $\mathcal{X} \times \mathcal{Y} := \{(x_i, y_i) : i \in [n]\}$. We write $|\cdot|$ to denote the length of vectors and $\|\cdot\|$ to represent their Euclidean ℓ_2 -norm. We write $a \gg b$ whenever there exists a sufficiently small constant c such that $b/a < c$ holds. Finally, we denote by $a \otimes b$ the convolution operation between vectors A and b .

2 Machine Learning Methodology

In this section, we formalise the supervised and self-supervised methodologies underlying our models.

2.1 Supervised Learning

Let $X \in \mathcal{X} \subseteq \mathbb{R}^n$ and $Y \in \mathcal{Y} \subseteq \mathbb{R}^m$ be random variables, where $Y = f(X)$, for some unknown f . In supervised learning, the algorithm is provided with a set of training examples $\{(x_i, y_i)\}_{i=1}^T$, drawn from the joint distribution of X and Y . The goal is to learn a mapping $\hat{f} : \mathcal{X} \rightarrow \mathcal{Y}$ that minimises the expected loss, as measured by a specific *loss function* $L : \mathcal{Y}^2 \rightarrow \mathbb{R}$. Formally, this can be expressed as:

$$\hat{f} = \operatorname{argmin}_{f \in \mathcal{F}} \mathbb{E}[L(Y, f(X))], \quad (2.1)$$

where \mathcal{F} is the space of hypotheses functions (see, e.g., [43]). In regression tasks, choosing the mean squared error (MSE) loss gives: $\hat{f} = \operatorname{argmin}_{f \in \mathcal{F}} \mathbb{E}\|Y - f(X)\|^2$.

2.1.1 1D-CNNs: Feedforward Stage

1D-CNNs are a class of deep learning algorithms that solve equation (2.1) by adaptively learning spatial hierarchies of features in the input data. These networks process each training example $x \in X$ through a sequence of computational layers, which, in this analysis, consists of: (i) $N_{CL} = 2$ convolutional layers (CLs), (ii) an average-pooling layer and (iii) $N_{FCL} = 3$ fully connected layers (FCLs) (see Figure 5). Hereon, let $\zeta^{(l)}$ denote the output of the l th layer.

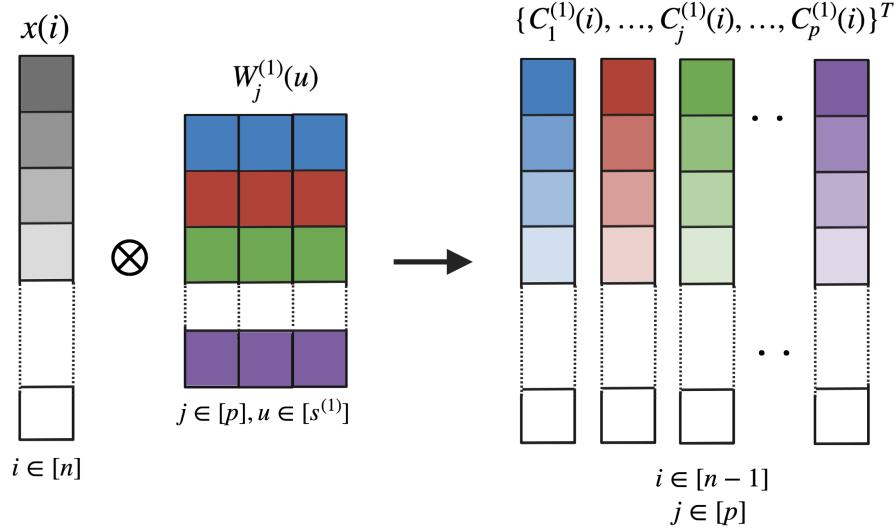


Figure 2: A 1D multi-filter convolution applied to an input signal x of length n , using a filter bank $\{W_j^{(1)}\}_{j=1}^p$ with p filters of size $s^{(1)}$. The result is a 2D matrix whose J th column $C_j^{(1)}$ is obtained by a single convolution (Equation 2.2). Illustration adapted from [44].

- (i) **Convolutional layers.** Let $\{W_j^{(1)}\}_{j=1}^p$ denote a set of p filters, each of size $s^{(1)}$. Each filter slides along the input signal x , aggregating local information from contiguous segments of $s^{(1)}$ elements. Assuming a stride of 1, the discrete *convolution* between the filter weights and the input is computed as:

$$C_j^{(1)}(i) = (x \otimes W^{(1)})(i) = \sum_{u=1}^{s^{(1)}} x_{i+u-1} W_j^{(1)}(u), \quad (2.2)$$

where $C_j^{(1)}$ is a vector of length $n - s^{(1)} + 1$. As illustrated in Figure 2, applying all p filters produces a matrix $C^{(1)} \in \mathbb{R}^{(n-s^{(1)})+1 \times p}$, where the J th column corresponds to the convolution output $C_j^{(1)}(i)$ defined in Equation 2.2. Adding a bias term $b_j^{(1)} \in \mathbb{R}$ and applying an activation map $\phi : \mathbb{R} \rightarrow \mathbb{R}$ to the ij th element of $C^{(1)}$ gives the ij th convolved feature of the feature map $\zeta^{(1)}$:

$$\zeta_j^{(1)}(i) = \phi \left(C_j^{(1)}(i) + b_j^{(1)} \right). \quad (2.3)$$

To capture higher-order features, a second convolution is applied independently to each of the p columns $\zeta_j^{(1)}$ using a multi-filter represented by a third-order tensor of shape $s^{(2)} \times p \times q$, where $s^{(2)}$ is the filter size and $p \times q$ is the number of filters. The result is a matrix $C^{(2)} \in \mathbb{R}^{(n-s^{(2)})+1 \times q}$, where

each column $C_j^{(2)}$ is computed by the sum of p convolutions:

$$C_j^{(2)}(i) = \sum_{l=1}^p \left(\zeta_l^{(1)} \otimes W_{l,j}^{(2)} \right) (i). \quad (2.4)$$

Adding bias $b_j^{(2)}$ and applying ϕ elementwise produces the feature map:

$$\zeta_j^{(2)}(i) = \phi \left(C_j^{(2)}(i) + b_j^{(2)} \right). \quad (2.5)$$

- (ii) **Average-pooling layer.** The pooling layer downsamples the feature map $\zeta^{(2)}$ by a factor of w , thereby compressing its size while retaining only the strongest features learned in the CLs. Average-pooling is performed by sliding a window of size w along each column of $\zeta^{(2)}$, extracting the average value from each windowed sub-region, as follows:

$$\zeta_j^{(3)}(i) = \frac{1}{w} \sum_{k=1}^w \zeta_j^{(2)}(wi - k + 1). \quad (2.6)$$

This operation produces a downsampled output $\zeta^{(3)}$ of shape $w \times q$.

- (iii) **Fully connected layers.** A flattening operation is applied to re-shape the 2D output $\zeta_j^{(3)}$ into a 1D vector f of length wq :

$$f(j + n(i - 1)) = \zeta_j^{(3)}(i), \quad (2.7)$$

which can be fed into the fully-connected network. Assuming each FCL is parameterised by weights and biases $(W^{(\ell)}, b^{(\ell)})$, then:

$$\zeta^{(\ell)}(i) = \phi \left(\sum_{j=1}^{|\zeta^{(\ell-1)}|} W^{(\ell)}(i, j)f(j) + b^{(\ell)}(j) \right), \quad (2.8)$$

where $|\zeta^{(3)}| = wq$ and $|\zeta^{(5)}|$ is equal to the length of the true label or ‘target’ associated to x .

The final output of the network is $\zeta_{\text{out}} := \zeta^{(6)}$, representing the network’s prediction of the target associated to x . While common activation functions include sigmoid, tanh and the rectified linear unit (ReLU), our work makes *ad hoc* use of the exponential linear unit (ELU) function:

$$\phi(z) = \begin{cases} z & \text{if } z > 0, \\ \alpha(e^z - 1) & \text{if } z \leq 0, \end{cases} \quad (2.9)$$

where $\alpha \in \mathbb{R}_{>0}$.

2.1.2 1D-CNNs: Backpropagation Stage

The layers of the network collectively transform the input x into a non-linear output $\hat{f}(x; \mathbf{W}, \mathbf{b})$, where \mathbf{W} and \mathbf{b} denote the set of filters/weights and biases, respectively. For each batch of T training examples $\{(x_i, y_i)\}_{i=1}^T$, \mathbf{W} and \mathbf{b} can be estimated by minimising the *empirical loss* between predictions and targets:

$$\hat{\mathbf{W}}, \hat{\mathbf{b}} = \operatorname{argmin}_{\mathbf{W}, \mathbf{b}} \frac{1}{T} \sum_{i=1}^T \|y_i - \hat{f}(x_i; \mathbf{W}, \mathbf{b})\|^2, \quad (2.10)$$

where regularisation is neglected for simplicity. During training, a suitable gradient-based optimiser is used to minimise the loss in Equation (2.10). Using *backpropagation*, the optimiser propagates the loss function backwards through the network, computing gradients of the loss with respect to each parameter via the chain rule. These gradients indicate the direction and magnitude by which each parameter should be adjusted to reduce the loss, enabling iterative updates until convergence. In this work, we use the *Adam* optimiser [45], which is particularly well-suited for optimising loss where the underlying datasets are large and/or the parameter spaces are high-dimensional. With low memory requirements, Adam efficiently minimises the objective function by leveraging adaptive estimates of first- and second-order moments to dynamically adjust learning rates [45].

Although 1D-CNNs have achieved state-of-the-art performance, particularly in computer vision tasks, their computational cost poses a challenge. Due to their high parameter count, these models typically require large volumes of labelled training data, which limits their applicability in settings where datasets are small [46, 47, 48] or where annotations are scarce, expensive or even unavailable [49].

2.2 Self-supervised Learning

An alternative to supervised learning, SSL has gained increasing attention for its ability to efficiently train large-scale models without explicit labels. Instead, SSL leverages the data *itself* as supervision by revealing complex structures and co-occurrence relationships between data components or augmented views of the same instance [50]. As summarised in [51], SSL methods can be broadly classified into three paradigms:

- **Contrastive:** trains an encoder to map input pairs (x_1, x_2) to embeddings (z_1, z_2) to measure the similarity between them.
- **Generative:** trains an encoder-decoder pair to map input x to an embedding z and then reconstruct x from z .
- **Adversarial:** trains an encoder-decoder pair to generate false samples and a discriminator to distinguish them from real samples.

In this work, we focus exclusively on contrastive SSL algorithms, which have recently outperformed even SL [52, 53, 54].

2.2.1 Contrastive Learning

As defined in [55], contrastive learning differentiates between semantically similar (positive) and dissimilar (negative) pairs of augmented views of data points, encouraging representations of positive pairs to be mapped closer together in latent space, while pushing those of negative pairs apart. These augmentations preserve the *semantic content* of the original observation while modifying other ‘nuisance’ aspects, promoting the learning of invariant features that enhance generalisation to downstream tasks [56, 57]. As an example, Contrastive Language-Image Pretraining (CLIP) [58] trains encoders to contrast images with their corresponding language-based descriptions, where the image is augmented with random square crops and the text with bi-grams with high pointwise *mutual information* (MI) for the pair.

To formalise this, let $\mathcal{X} \subseteq \mathbb{R}^n$ and $\mathcal{Y} \subseteq \mathbb{R}^m$ be the input space of two different modalities. Consider a batch of N unlabelled samples $\{(x_1, y_1), \dots, (x_N, y_N)\} \subseteq \mathcal{X} \times \mathcal{Y}$, where (x_i, y_i) is semantically related, e.g., a NIRSpec spectrum and its APOGEE pair. Apply random augmentations $A(\cdot)$ and $\tilde{A}(\cdot)$ to inputs x_i and y_j , respectively. CLIP’s objective is to learn a pair of encoders $f_\Phi : \mathcal{X} \rightarrow \mathbb{R}^d$ and $g_\Theta : \mathcal{Y} \rightarrow \mathbb{R}^d$, $d \ll \min(n, m)$, that compress the two modalities from raw space into a shared latent space, such that

$z_i^{\mathcal{X}} := f_{\Phi}(A(x_i))$ and $z_j^{\mathcal{Y}} := g_{\Theta}(\tilde{A}(y_j))$ are close to each other if they share ‘similar’ semantics, otherwise far away. For a given x_i , we refer to $z_i^{\mathcal{X}}$ as the *anchor* and to $z_j^{\mathcal{Y}}$ as a *positive sample* if $i = j$ and as a *negative sample* otherwise.

The standard loss used to train these encoders is the Information Noise Contrastive Estimation (InfoNCE) [59]:

$$\mathcal{L}_{\text{InfoNCE}}(f_{\Phi}, g_{\Theta}, \tau) = -\mathbb{E} \left[\log \frac{\exp(s_{ii}/\tau)}{\exp(s_{ii}/\tau) + \sum_{j \neq i}^N \exp(s_{ij}/\tau)} \right]. \quad (2.11)$$

Here, $\tau \in \mathbb{R}_{>0}$ denotes a trainable temperature parameter, discussed in §2.2.2, and $s_{ij} := s(z_i^{\mathcal{X}}, z_j^{\mathcal{Y}})$ is a similarity measure between the features $z_i^{\mathcal{X}}$ and $z_j^{\mathcal{Y}}$. In our setting, we use cosine similarity:

$$s_{ij} := \frac{\langle z_i^{\mathcal{X}}, z_j^{\mathcal{Y}} \rangle}{\|z_i^{\mathcal{X}}\| \|z_j^{\mathcal{Y}}\|}. \quad (2.12)$$

Minimising Equation (2.11) encourages alignment for positive pairs $(z_i^{\mathcal{X}}, z_i^{\mathcal{Y}})$ while penalising similarity with negative ones $(z_i^{\mathcal{X}}, z_j^{\mathcal{Y}}), j \neq i$.

Of note, InfoNCE has an insightful connection to MI. A formal proof given by [59] and [60] shows that, for any two vectors $x_i \in \mathcal{X}$ and $y_j \in \mathcal{Y}$, with representations z_i and z'_j , respectively,

$$I(z_i^{\mathcal{X}}; z_j^{\mathcal{Y}}) \geq \log(k) - \mathcal{L}_{\text{InfoNCE}}, \quad (2.13)$$

where k is the number of negative samples associated to a given sample x_i . This shows that minimising $\mathcal{L}_{\text{InfoNCE}}$ maximises the variational lower bound on the MI $I(z_i; z'_j)$, which is itself bounded above by $I(x_i; y_j)$ through the data-processing inequality. Moreover, the log-dependency on k implies that having more negative samples leads to improved representations, a fact formally proved by Tian et al. [61]. Altogether, InfoNCE provides a good lower bound approximation to MI, enjoying greater stability and lower variance than most other competing approaches [62].

2.2.2 Role of Temperature in Contrastive Learning

Intuitively, the temperature τ controls the sensitivity of the InfoNCE loss. A smaller τ tends to penalise much more on *hard*⁹ negative samples (HNS), pushing their latent features further away from those of the anchor [63]. As a result, the local structure of each anchor tends to be more separated, and the embedding distribution appears to be more uniform [63]. Conversely, a larger τ reduces the loss’ sensitivity to HNS, resulting in more compact, clustered latent features [64]. In practice, τ has been shown to crucially impact the quality of a model’s learned embeddings (e.g., [19, 65, 66]).

The phenomenon of larger τ inducing semantic structure in representation space has been demonstrated empirically (e.g., [19, 66]), but is otherwise poorly understood. To gain a little insight, we follow the setup of [67] and perform a change-of-variables in Equation (2.11), in which similarities s_{ij} are replaced by ‘distances’ d_{ij} :

$$d_{ij} = \frac{1 - s_{ij}}{\tau} \quad (2.14)$$

$$c_{ii} = \exp(d_{ii}), \quad (2.15)$$

⁹A *hard negative sample* (HNS) is defined as a negative sample with high cosine similarity to the anchor; consequently, it appears as a *nearest neighbour* to the anchor. Conversely, *easy negative samples* (ENS) are easily distinguishable from the anchor by simple patterns and are therefore more distant in embedding space.

where it is clear $0 \leq d_{ij} \leq 2/\tau$. This allows us to rewrite each summand, \mathcal{L}_c^i , of the InfoNCE loss as:

$$\mathcal{L}_c^i = -\log \left[\frac{\exp(-d_{ii})}{\exp(-d_{ii}) + \sum_{j \neq i}^N \exp(-d_{ij})} \right] = \log \left[1 + c_{ii} \sum_{j \neq i}^N \exp(-d_{ij}) \right]. \quad (2.16)$$

Hence, the loss increases monotonically with the sum of exponentiated distances $S_i := \sum_{j \neq i}^N \exp(-d_{ij})$. This means it is enough to examine the behaviour of S_i in the regimes of small and large τ :

- **Small τ .** When $\tau \ll 1$, the dominant contributions to S_i arise from distances d_{ij} where $s_{ij} \sim 1$, corresponding to HNS of the anchor. As a result, the loss function can be interpreted as maximising the average distance to these HNS, encouraging the model to push embeddings further apart. This leads to a more uniform and isotropic distribution in embedding space.
- **Large τ .** When $\tau \geq 1$, say, all distances d_{ij} are of comparable magnitude, contributing roughly equally to S_i . Hence, the loss function can be interpreted as maximising the average distance over a broader range of neighbours. Since the number of ENS typically exceeds the number of HNS, ENS collectively have a greater influence on the loss. Rather than learning ‘hard’ features that enable better *instance-discrimination* among HNS, the model is instead encouraged to learn ‘easier’ patterns that allow for better *group-wise discrimination*. With this biased approach, the model tends to increase the margin between clusters of samples, inducing semantic structure in representation space.

3 Data¹⁰

3.1 APOGEE Spectra

We use spectra and stellar parameters from APOGEE SDSS-IV DR17 [16, 34]. Observations were captured with two high-resolution APOGEE spectrographs [68]: one on the 2.5 m Sloan Foundation telescope [69] at Apache Point Observatory (APO), and another on the 2.5 m Irénée du Pont telescope [70] at Las Campanas Observatory (LCO). Both spectrographs operate in the near-IR *H*-band (1.51–1.7 μ m) at a high spectral resolution of $R \sim 22,500$ and can observe up to 300 objects simultaneously within 3° and 2° diameter FoVs, respectively [17, 71, 68]. Throughout the survey, APOGEE preferentially targets RGB stars and other luminous post-main-sequence stars across the Milky Way (MW), particularly in heavily dust-obscured parts of the Galactic bulge, disc and halo [72]. Raw data are processed by an automated pipeline [73], which calibrates and subsamples them onto a common wavelength grid with spacing $\Delta\lambda/nR$, where $n \sim 3.2$ is the number of pixels per resolution element. The final wavelength grid spans $\lambda_{\min.} = 15,100\text{\AA}$ to $\lambda_{\max.} = 17,000\text{\AA}$.

Stellar parameters and chemical abundances are derived using the APOGEE Stellar Parameter and Chemical Abundances Pipeline (ASPCAP) [74] in a two-step process. First, each observed APOGEE spectrum is compared to a grid of synthetic spectra and χ^2 -minimisation is used to identify the best-fit parameters: T_{eff} , $\log g$, [M/H], [C/H], [N/Fe], [α /Fe] and v_{micro} . The synthetic grid is generated via the 1D local thermodynamic equilibrium (LTE) branch of the ATLAS9/ASS ϵ T synthesis code, developed by R. Kurucz [41, 42]. Second, ASPCAP estimates individual element abundances—C, N, O, Na, Mg, Al, Si, S, K, Ca, Ti, V, Mn, Fe, and Ni—by minimising residuals in selected spectral windows sensitive to each element. A wrapper sets quality flags when fits are deemed unreliable, particularly when estimated parameters lie near the edges of the grid, where interpolation or extrapolation can degrade accuracy.

¹⁰All datasets have been provided via private communication by Dr Nathan Sandford (nathan.sandford@utoronto.ca).

To minimise the propagation of ASPCAP errors, we exclude stars flagged for unreliable chemical abundance measurements. We further restrict the dataset to high-quality, upper RGB stars—the primary targets of NIRSpec spectroscopy—that meet the following criteria: $\text{SNR} > 200$, $4000 < T_{\text{eff}} < 5000 \text{ K}$, $0.5 < \log(g) < 2.0$ and $v_{\text{scatter}} < 1.0 \text{ km/s}$. Notably, high v_{scatter} values are typically indicative of unresolved binaries [73], whose duplicated or blended spectral lines can degrade ASPCAP abundance measurements. Applying these selection criteria to the full APOGEE survey yields a refined sample of 19,001 stars, denoted **A**. Figure 3 shows a Kiel diagram, i.e., the $\log(g)$ versus T_{eff} plane, for the APOGEE spectra in **A**.

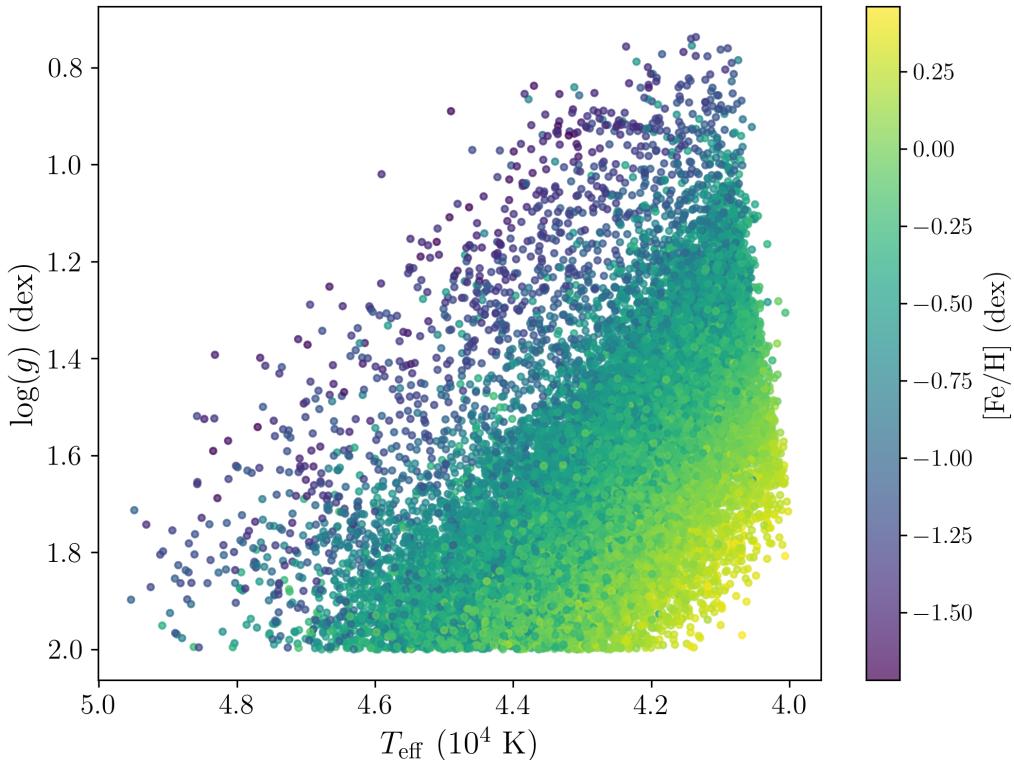


Figure 3: Kiel diagram of qualified APOGEE spectra, whose parameters are derived from ASPCAP. Note different colours indicate different values of $[\text{Fe}/\text{H}]$ metallicity.

We split **A** into training, validation and test sets in a 5:1:2 ratio. This split is chosen to maximise the number of stars in the training set, while having at least 2,000 stars in the validation and tests sets to be representative of the full stellar parameter range.

3.2 JWST/NIRSpec Spectra

3.2.1 *Ab initio* Data

Ab initio spectra are generated using the same method as described in Ting et al. [75] and Sandford et al. [76]. Briefly, 1D LTE model atmospheres are computed using the ATLAS12 program, developed and maintained by R. Kurucz [35, 36, 37, 38, 39, 40]. Each model adopts one of 19,001 sets of APOGEE stellar parameters, along with solar abundances obtained from Asplund et al. [77]. Convection is modelled according to standard 1D mixing length theory (MLT) with $\alpha = 1.25$ and no overshooting. Spectra are computed with the SYNTHE program, also due to R. Kurucz, at a nominal resolution of $R = 300,000$. They are subsequently continuum-normalised, convolved down to the average resolution

of NIRSpec ($R = 2,700$) and subsampled onto a common wavelength grid with $\Delta\lambda/nR$, where $n \sim 4.6$ is the number of pixels per resolution element. The final wavelength grid covers $\lambda_{\min.} = 9,000\text{\AA}$ to $\lambda_{\max.} = 18,000\text{\AA}$. We denote the set of synthetic NIRSpec spectra as \mathbf{J} , which we split into training, validation and test sets in a 5:1:2 ratio.

In this way, we obtain a database $\mathbf{J} \times \mathbf{A}$, consisting of 19,001 paired NIRSpec and APOGEE spectra, each characterised by a common set of stellar labels.

3.2.2 Observed Data

We use a small sample ($n = 59$) of representative traces on the NIRSpec detector. The multi-object spectroscopic (MOS) observations are collected as part of the JWST-GO-3788 program (PI: Wiesz), using microshutter array (MSA) in a 3.6×3.4 arcmin 2 FoV over near-IR wavelength ranges (0.97-1.82 μm) at a resolution $R = 2,700$ [2]. Targets are predominately stars on the upper RGB branch in three isolated dwarf galaxies—Tucana, Leo A and IC 1613—for which $[\alpha/\text{Fe}]$ and $[\text{Fe}/\text{H}]$ can be measured to 0.1-0.3 dex precision.

As shown in Figure 4(a), the MSA occupies NIRSpec’s slit plane in a 2×2 mosaic of micro-shutter quadrants. It is further mounted on the detector plane, which consists of two adjacent detector arrays, NRS1 and NRS2, separated by a 2.8 mm horizontal gap in the direction of dispersion. As shown in Figure 4(b), the presence of this gap causes portions of NIRSpec spectra to be lost if they happen to project onto it.

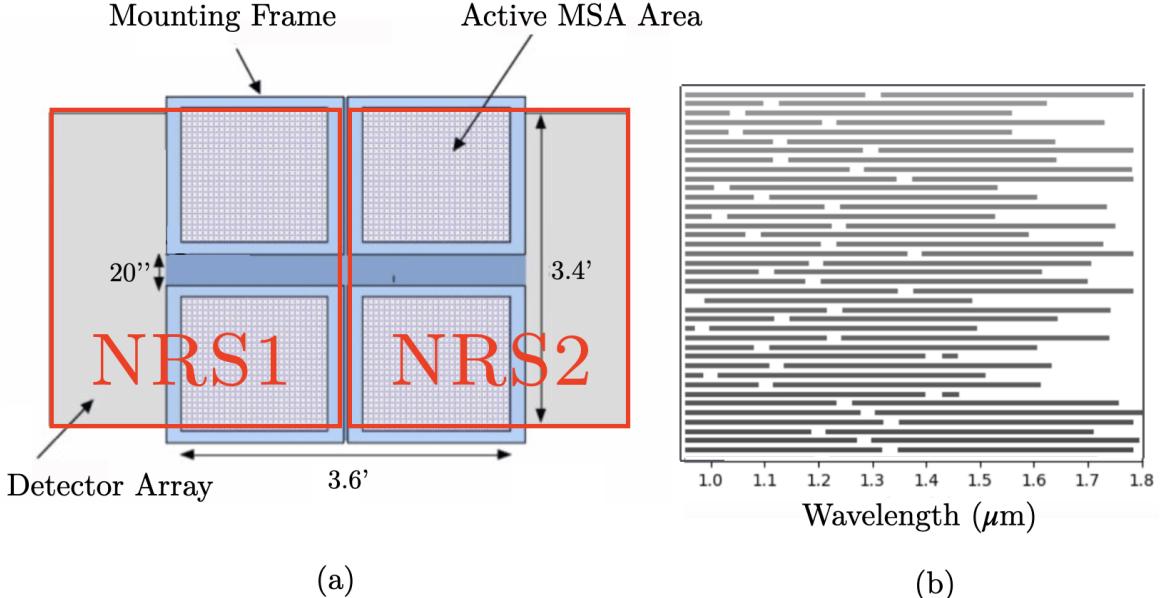


Figure 4: (a) Layout of the NIRSpec slit plane, adapted from [78]. The four MSA quadrants covering 3.6×3.4 arcmin 2 on the sky, are mounted via a frame onto the detector plane. The two large squares mark the outer boundaries of the active areas of the two detector arrays, NRS1 and NRS2. The dispersion direction is horizontal. (b) Sample representative spectral traces on the NIRSpec detector, adapted from [79]. Each trace, widened for clarity, exhibits missing wavelength segments lost to the detector gaps.

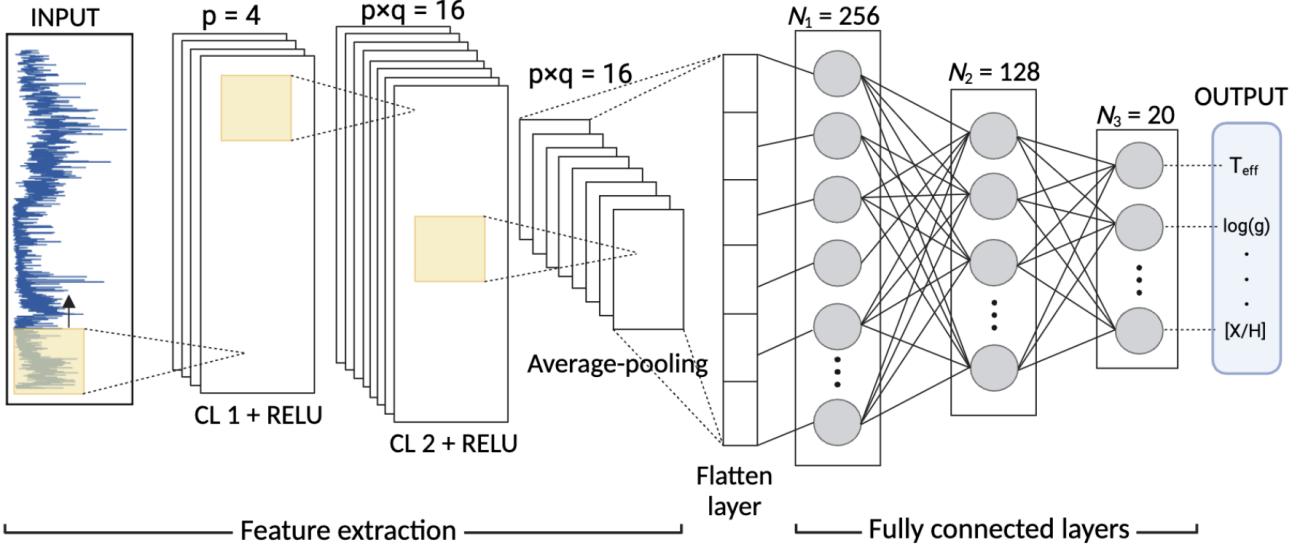


Figure 5: Schematic of the CNN architecture used to predict stellar properties from single-modal spectra. The input layer is followed by pooling layers with 4 and 16 filters, respectively. An average-pooling layer with a window length of 4 is applied next, followed by three fully connected layers with 256, 128, and 20 nodes. The final output layer provides the predicted stellar properties: T_{eff} , $\log g$ and 18 elemental abundances [X/H].

4 Model Implementation

We present a two-step procedure to train our cross-modal spectral encoders *in silico*:

- (i) We pre-train single-modal CNNs in a supervised setting to predict stellar labels from spectroscopic data, using a modified STARNET [6].
- (ii) We fine-tune our pre-trained CNNs in a contrastive setting, aligning their cross-modal embeddings in a shared latent space, using a modified ASTROCLIP [27].

Notably, our strategy to initialise CLIP with pre-trained models—rather than to train the entire SSL framework from scratch—has been shown to stabilise training and reduce the computational costs associated with CLIP [80]. Further details on the implementation and training of these models are provided below.

4.1 Spectral Encoder Model

4.1.1 Implementation

Our spectral encoder is closely modelled after STARNET [6]. In particular, the CNN model we implement has $N_{\text{CL}} = 2$ convolutional and $N_{\text{FCL}} = 3$ fully-connected layers, which together perform stellar property prediction of 20 stellar parameters.

Figure 5 shows the sequential operations required to transform single-modal spectra to a stellar property prediction. The leftmost block represents the input spectra, either obtained from A or J. The first operation applied to the input is a 1D-convolution using 1 input channel and $p = 4$ output channels, corresponding to the number of learnable filters of size $s^{(1)} = 8$ (and stride = 1). An additional 1D-convolution is performed on each channel of the previous layer, resulting in $p \times q = 16$ output channels,

using 16 learnable filters of size $s^{(2)} = 8$. After each convolution, the ELU activation function is applied to introduce non-linearities into the model.

The output channels produced by the second convolution are then downsampled via average-pooling, with a window length of $w = 4$, and flattened to a single dimension. The flattened vectors are then passed to the fully connected part of the network. Here, they are mapped to three multiperceptron (MLP) layers with $N_1 = 256$, $N_2 = 128$ and $N_3 = 20$ hidden units, successively, each with their own learnable sets of weights and biases. After the first two MLP layers, ELU activation is applied. After the last MLP layer, the model outputs the stellar property estimation \hat{Y} .

Though we adopt the model architecture and hyperparameter selection (p, q, w, N_1, N_2) from [6], we distinguish our work in the following ways:

- We use ELU rather than ReLU (or sigmoid or tanh), having found that it promotes training stability and enables convergence to lower loss values.
- We use average-pooling rather than max-pooling, having found that it better preserves features relevant to regression.
- We introduce a learning rate scheduler to reduce training time.
- We implement an early stopping criterion based on the validation loss to mitigate overfitting.
- We predict $N_3 = 20$ rather than 3 stellar parameters with high precision and accuracy.

4.1.2 Training Procedure

We implement our model architecture and training procedure in PyTorch [81]. For our training task, which is to regress stellar properties, the loss function we optimise is the MSE:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N_{\text{batch}}} \sum_{i=1}^N (Y_i - \hat{Y}_i)^2, \quad (4.1)$$

where N_{batch} is the number of spectra in the batch, and Y_i and \hat{Y}_i denote the true and predicted stellar property of interest, respectively. Note each Y_i is Z-score normalised to have zero mean and unit variance, ensuring that all properties are roughly equally weighted in \mathcal{L}_{MSE} .

We train two single-modal encoders, f_ϕ and g_θ , on APOGEE A and NIRSpec J data, respectively. For each encoder we train, the corresponding training data are batched into sets of $N_{\text{batch}}^{\text{train}} = 64$ stars. While the model weights ϕ (or θ) are randomly initialised, the network implements a training procedure to update these weights, as follows (see [82]):

- (1) forward pass the batch through the network to compute \hat{Y}_{batch} ,
- (2) compute \mathcal{L}_{MSE} according to Equation (4.1),
- (3) backpropagate \mathcal{L}_{MSE} through each layer of the network,
- (4) compute the gradient $\Delta_\phi \mathcal{L}_{\text{MSE}}$ (or $\Delta_\theta \mathcal{L}_{\text{MSE}}$),
- (5) update the weights to minimise \mathcal{L}_{MSE} .

Steps (1) through (5) are repeated for each training batch iteration, resulting in a steady convergence of the training loss over $N_{\text{epochs}} = 15$ or until an early stopping criterion is met. Specifically, step (5) is carried out using PyTorch’s Adam optimiser ($\eta_0 = 0.001$), with a StepLR scheduler ($T_{\text{step}} = 5$, $\gamma = 0.1$). Altogether, for 11,875 training spectra of either modality and 8.4 million NN parameters, training proceeded in $N_{\text{steps}} = 2,775$ steps and converged in ~ 20 seconds, using 1 NVIDIA TITAN Xp GPU.

During training, we also monitor the validation loss. Specifically, at the start of each training epoch, we carry out steps (1) and (2) on the validation set of 2,375 spectra, processed in batches of size $N_{\text{batch}}^{\text{val.}} = 128$. This provides a *diagnostic* of how generalisable the model is to unseen data. To mitigate overfitting, we also implement an early stopping criterion with the following policy: Should the validation loss not improve for $N_{\text{stop}} = 3$ consecutive epochs within a tolerance of $\epsilon_{\text{tol}} = 10^{-3}$, training is halted. Future work could explore performing grid searches over a heuristic choice of hyperparameters $\{(\eta_0, T_{\text{step}}, \gamma)\}$, choosing the combination that yields the best performance on the validation set—a clear improvement over choosing the hyperparameters *ad hoc*.

All model and training parameters are summarised in Table 1.

Table 1: Model and training parameters for CNN Encoders

	Parameter	Setting(s)	Description
Architecture	n	8,575 (8,192)	number of pixels in each spectrum in A (J)
	N_{CL}	2	number of convolutional layers (CL)
	p	4	number of output channels of CL1
	$s^{(1)}$	8	filter size of CL1
	$p \times q$	16	number of output channels of CL2
	$s^{(2)}$	8	filter size of CL2
	stride	1	convolution stride of both CLs
	w	4	width of pooling kernel
	N_{FCL}	3	number of fully connected layers (FCL)
	N_1	256	number of hidden units in FCL1
	N_2	128	number of hidden units in FCL2
	N_3	20	number of hidden units in FCL3
Optimisation	ϕ	ELU	activation function
	optimiser	Adam	—
	η_0	10^{-3}	base learning rate (LR)
	T_{step}	5	LR decay period/step size
	γ	10^{-1}	LR decay multiplicative factor
Training	\mathcal{L}_{MSE}	MSE	loss function
	$N_{\text{batch}}^{\text{train}}$	64	training batch size
	N_{epochs}	15	number of training epochs
	N_{steps}	2,775	number of training steps
	N_{stop}	3	number of epochs to halt training if no improvement
	ϵ_{tol}	10^{-2}	early stopping tolerance

4.1.3 Model Evaluation

Each single-modal encoder is evaluated on its corresponding held-out test set of 4,751 spectra, batched into sets of $N_{\text{batch}}^{\text{test}} = 128$. The residuals between true and predicted targets are then computed, as shown in Figure 7. To quantify the model performance, we compute three evaluation metrics: the coefficient of determination r^2 , the bias Δ and the root-mean-squared error (RMSE), respectively given

as:

$$r^2 = 1 - \frac{1}{N\sigma^2} \sum_i (Y_i - \hat{Y}_i)^2 \quad (4.2)$$

$$\Delta = \frac{1}{N} \sum_i (\hat{Y}_i - Y_i) \quad (4.3)$$

$$\text{RMSE} = \left[\frac{1}{N} \sum_i (Y_i - \hat{Y}_i)^2 \right]^{\frac{1}{2}}, \quad (4.4)$$

where N is the number of observations in the test set and Y and \hat{Y} are the true and predicted targets of the stellar property of interest, respectively. The term σ^2 denotes the variance of $\vec{Y} = (Y_1, \dots, Y_N)$. In general, $r^2 \simeq 1$ indicates the model explains most of the variation in Y , while $r^2 \simeq 0$ indicates it captures little to no variation. Additionally, in general, smaller bias and RMSE values indicate better model performance.

4.2 StarCLIP Model

4.2.1 Spectrum Preprocessing

To simulate physical corruptions in observed NIRSpec data, we apply a (sub)set of the following semi-empirical, stochastic transformations to each spectrum in J :

- (i) *Fixed-data Substitution.* The Paschen series have been long used for the determination of fundamental parameters of stellar atmospheres [83, 84, 85]. In fact, the Paschen H -lines contain some of the most informative pixels for estimating T_{eff} and $\log g$ (see, e.g., [86]). However, observational challenges, large uncertainties in absorption-line measurements and limitations of LTE modelling can potentially introduce important systematic and model-dependent errors near the Paschen lines. As such, a *desideratum* in this work is to reduce the model's sensitivity to potentially poorly modelled or corrupted data near these regions. To this end, we fix an arbitrary spectrum in J and isolate four ‘reference’ neighbourhoods of radius $\sim 10\text{\AA}$ centred on the Paschen lines: 9,548.6, 10,052.1, 10,941.1 and 12,821.6 \AA . Given another spectrum in J , we replace its flux values in these neighbourhoods with the reference values just obtained.
- (ii) *Pixel Masking.* We select uniformly at random 0.1% of pixels to set to unity¹¹, roughly the expected fraction of non-operable pixels in the NIRSpec detectors [3].
- (iii) *Denormalisation.* Observed spectra are distorted by broad telluric bands, instrumental effects of the spectrograph, and artifacts introduced during the pipeline reduction process (see, e.g., [87]). To emulate imperfections in continuum normalisation, we multiply the given spectrum in J by a low-amplitude eighth-order polynomial perturbation P , defined as follows:

$$P(\lambda) = 1 + \alpha \left(\frac{p(\lambda') - \mu_p}{\max |p(\lambda') - \mu_p|} \right), \quad (4.5)$$

where

$$p(\lambda) = \sum_{i=0}^d c_i (\lambda')^i, \quad \lambda' = \frac{\lambda_i - \lambda_{\min}}{\lambda_{\max} - \lambda_{\min}} \in [0, 1], \quad \mu_p = \frac{1}{n} \sum_{i=1}^n p(\lambda'_i) \quad (4.6)$$

and $\alpha = 0.01$, $d = 8$, $c_i \sim \mathcal{U}(-1, 1)$, $\lambda_{\min} = 9,000\text{\AA}$, $\lambda_{\max} = 18,000\text{\AA}$, $n = 8,192$. Note the choice of P is *heuristic*, serving as an initial approximation for modelling normalisation errors.

¹¹We choose unity rather than to 0 (or NaN), so to help mitigate discontinuities in the flux profile of the data.

- (iv) *Gaussian Noise*. We randomly add Gaussian noise to the spectrum by sampling the noise level from a normal distribution $\mathcal{N}(0, \text{SNR}^{-1})$, where $\text{SNR} \sim \mathcal{U}(30, 300)$, roughly the expected signal-to-noise (SNR) range for NIRSpec detectors [2].
- (v) *Wavelength Masking*. We use an automated routine in Python’s OpenCV [88] to detect gap boundaries in a grayscale image of 59 spectral traces, as exemplified in Figure 4(b). Each trace admits two gaps: the first is characterised by its leftmost x -position $x_{\text{gap},1}$ and width $w_{\text{gap},1}$, while the second is defined by its width $w_{\text{gap},2}$, as its rightmost endpoint is fixed at $\lambda_{\text{max}} = 18,000\text{\AA}$. To model the distribution of these gaps, we fit nonparametric distributions to the empirical measurements $\{x_{\text{gap},1}\}$, $\{w_{\text{gap},1}\}$ and $\{w_{\text{gap},2}\}$ using Gaussian kernel density estimation (KDE). When sampling new x -positions and widths of gaps from the KDEs, we apply a ReLU transformation to enforce non-negativity:

$$x'_{\text{gap},1} = \max(0, x_{\text{gap},1}) \quad (4.7)$$

$$w'_{\text{gap},i} = \max(0, w_{\text{gap},i}), \quad (4.8)$$

$i = 1, 2$. The sampled gaps are then applied to a given spectrum in \mathbf{J} , replacing the corresponding flux values within these missing intervals with unity.

The mock dataset \mathcal{J} is created by replicating each entry in \mathbf{J} five times and augmenting each instance with observational signatures (iv) and (v). Its pair, \mathcal{A} , is similarly defined by replicating each entry in \mathbf{A} five times without additional transformation. This results in an augmented dataset $\mathcal{J} \times \mathcal{A}$ of 95,005 paired mock NIRSpec \times APOGEE spectra. We partition $\mathcal{J} \times \mathcal{A}$ into training, validation and test subsets using a 5:1:2 split at the *instance-group level*, ensuring all augmented views of a given original spectrum are assigned to the same subset.

To mimic the low-data regime of JWST, we partition \mathbf{J} into 30 bins based on [Fe/H] values, where the number of bins is determined with Freedman-Diaconis’ rule [89]. We then randomly subsample $n = 250$ spectra from \mathbf{J} , whose [Fe/H] values are distributed approximately uniformly across all bins. Applying transformations (iv) and (v) to this subset gives the mock sample \mathcal{J}^{lo} ; applying all transformations from (i) to (v) gives the extended-mock sample \mathcal{J}^{hi} . We split $\mathcal{J}^{\text{lo}} \times \mathcal{J}^{\text{hi}}$ into training, validation and test sets in a 5:1:2 ratio.

We further enrich the test split of \mathcal{J}^{hi} by generating an additional 5,000 extended-mock spectra, whose [Fe/H] values remain approximately uniformly distributed across all bins. The resulting augmented test split, now comprising 5,062 spectra, reduces sparsity in visualisations and enhances the representativeness of the test set across the entire stellar parameter range.

Figure 6 illustrates the complete sequence of stochastic transformations (i)-(v) applied to a NIRSpec spectrum in \mathcal{J}_{hi} . It provides a close view of the fixed-data substitution process, described in (i), demonstrating how spectral regions near Paschen lines are replaced by fixed values from a reference spectrum in \mathbf{J} .

4.2.2 Implementation

Our CLIP models are closely modified versions of ASTROCLIP [27]. As illustrated in Figure 1, each network is a sort of *compositional* model, consisting of a pair of cross-modal spectral encoders with 20 embedding dimensions. The output of each network is a pair of cross-modal embeddings that reside in a shared, CLIP-aligned latent space.

We train two versions of the model. The first, STARCLIP, employs pre-trained encoders f_θ and g_ϕ to initialise the mapping of \mathcal{J} and \mathcal{A} into latent space. Both encoders remain unfrozen, allowing

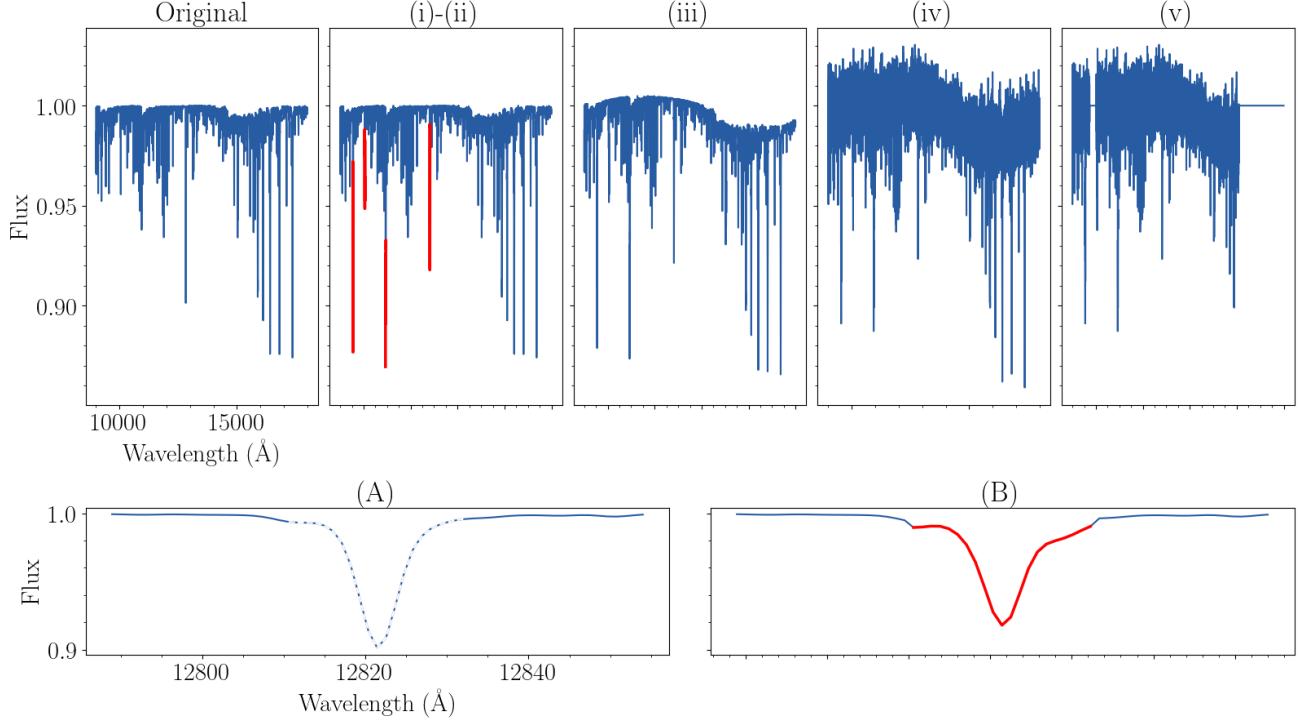


Figure 6: Sequence of stochastic transformations applied to a representative spectrum from J , mapping it to an element of \mathcal{J}^{hi} . The **top panels** show the original spectrum, successively transformed through (i)-(ii) fixed-data substitution and pixel masking, (iii) denormalisation, (iv) Gaussian noise addition, and (v) wavelength masking. The red lines in panel (i)-(ii) indicate the four neighbourhoods substituted using the arbitrarily-chosen ‘reference’ spectrum in J , thickened for clarity. The **bottom panel** (A) highlights the spectrum’s original neighbourhood of radius $\sim 10\text{\AA}$ centred on the Paschen line $12,821.6\text{\AA}$, marked with dashed lines. Panel (B) shows the same neighbourhood after applying (i)-(ii), with the substituted region from the reference spectrum highlighted in red.

STARCLIP to align the representation spaces of the two modalities (see, e.g., [90]). After training, the initial weights θ and ϕ are updated to learned weights Θ and Φ . The second version, MOCKSTARCLIP, uses a pair of identically initialised encoders, both denoted f_Θ , to map \mathcal{J}^{lo} and \mathcal{J}^{hi} into the *same* latent space. While the encoder for \mathcal{J}^{lo} is frozen, the fully-connected part of the encoder for \mathcal{J}^{hi} is unfrozen, enabling MOCKSTARCLIP to be fine-tuned on physical corruptions in the extended-mock data. After training, the learned weights of this latter encoder are thus updated from Θ to Θ^* .

4.2.3 Training Procedure

We implement our training procedure in PyTorch [81]. We first batch the training splits of $\mathcal{J} \times \mathcal{A}$ ($\mathcal{J}^{\text{lo}} \times \mathcal{J}^{\text{hi}}$) into mini-batches of $N_{\text{batch}}^{\text{train}} = 16$ (8) pairs of stars. Optimisation is performed using the Adam optimiser with base learning rates of $\eta_0 = 1 \times 10^{-4}$ (1×10^{-3}), controlled by a cosine annealing scheduler and weight decay parameter of $\lambda = 0.2$ (0). We train our models for $N_{\text{epochs}} = 30$ on 1 NVIDIA TITAN Xp GPU, which results roughly in $T_{\text{train}} \sim 1$ h (~ 20 min.) of training time.

Similar to the findings in Parker et al. [27], we observe that STARCLIP performs best when the value of τ in Equation (2.11) is fixed to 15.5. In contrast, following the approach of Radford et al. [58], we find MOCKSTARCLIP achieves better performance when τ is treated as a learnable parameter in gradient

descent, initialised to 0.07—the default starting value in CLIP. In view of §2.2.2, these choices of τ are well-motivated: augmented views with frequent semantics in $\mathcal{J} \times \mathcal{A}$ benefit from a larger τ to preserve local semantic structure, whereas a smaller τ would undesirably push semantically consistent samples apart. Conversely, the samples in $\mathcal{J}_{\text{lo}} \times \mathcal{J}_{\text{hi}}$, which exhibit rarer semantics, benefit from a smaller τ to make their features more discriminative and separable. By computing Equation (2.11) between all cross-modal pairs in $\mathcal{J} \times \mathcal{A}$ and $\mathcal{J}^{\text{lo}} \times \mathcal{J}^{\text{hi}}$, we maximise the similarity of embeddings corresponding to (augmented views of) the same spectrum while minimising similarity with embeddings of other spectra.

All model and training parameters are summarised in Table 2.

Table 2: Model and training parameters for CLIP models

	Parameter	Value(s)/Setting(s)		Description
		STARCLIP	MOCKSTARCLIP	
Architecture	$\mathcal{X} \times \mathcal{Y}$	$\mathcal{J} \times \mathcal{A}$	$\mathcal{J}^{\text{lo}} \times \mathcal{J}^{\text{hi}}$	cross-modal input data
	$\mathcal{W}_{\text{init},1}$	f_θ	f_Θ	encoder 1 weight init.
	$\mathcal{W}_{\text{init},2}$	g_ϕ	f_Θ	encoder 2 weight init.
	τ	15.5 (fixed)	0.07 (learnable)	temperature parameter
Optimisation	optimiser	Adam	Adam	—
	η_0	10^{-4}	10^{-3}	base learning rate (LR)
	λ	0.2	0	LR weight decay
	scheduler	Cosine Annealing	Cosine Annealing	—
	T_{max}	80	80	max number of iterations
Training	η_{min}	5×10^{-6}	5×10^{-6}	minimum LR
	\mathcal{L}	InfoNCE	InfoNCE	loss function
	$N_{\text{batch}}^{\text{train}}$	16	8	training batch size
	N_{epochs}	30	30	number of training epochs

4.2.4 Model Evaluation

We embed the held-out test spectra, generating discriminative representations that generalise to downstream tasks without the need for fine-tuning. We denote the elementwise-paired set of STARCLIP embeddings by $Z^{\mathcal{J}} \times Z^{\mathcal{A}}$, and the corresponding set of MOCKSTARCLIP embeddings by $Z^{\text{lo}} \times Z^{\text{hi}}$, where:

$$Z^{\mathcal{J}} := f_\Theta(\mathcal{J}), \quad Z^{\mathcal{A}} := g_\Phi(\mathcal{A}), \quad (4.9)$$

$$Z^{\text{lo}} := f_\Theta(\mathcal{J}^{\text{lo}}), \quad Z^{\text{hi}} := f_{\Theta^*}(\mathcal{J}^{\text{hi}}). \quad (4.10)$$

To evaluate the effectiveness of similarity search, we adopt *ad hoc* versions of two widely used evaluation metrics in information retrieval: *SuccessRate@k* and Mean Reciprocal Rank (MRR) [91, 92, 93]. In our work, *SuccessRate@k* measures the proportion of queries for which the *true* cross-modal pair or any of its augmented views appear in the top k ranked results. Specifically,

$$\text{SuccessRate}@k = \frac{1}{|Q|} \sum_{q=1}^{|Q|} \delta(FRank_q \leq k), \quad (4.11)$$

where Q is a set of tested queries and $\delta(\cdot)$ is the indicator function, and $FRank_q$ [94] denotes the rank of the first correct match (i.e., the true cross-modal pair or any of its augmented views) in the result list for query q . We report $SuccessRate@k$ for $k = 1, 5, 10$ and 50 , reflecting the typical sizes of results users consider in retrieval tasks [93]. The MRR is the average of the reciprocal ranks of results of Q , where the reciprocal rank is the inverse of the rank of the $FRank$. Thus, the formula is:

$$\text{MRR} = \frac{1}{|Q|} \sum_{q=1}^{|Q|} \frac{1}{|FRank_q|}. \quad (4.12)$$

In general, higher $SuccessRate@k$ and MRR values imply better search code performance. To assess the accuracy of stellar property inference, we compute the three evaluation metrics in Equations (4.2) to (4.4).

5 Results

5.1 CNN Stellar Property Recovery

We evaluate the performance of the NIRSpec and APOGEE CNN models in recovering 20 stellar parameters from 2,375 test spectra in J and A, respectively. Figure 7 shows the predictions for *six* stellar properties derived from both CNNs, including three atmospheric parameters (T_{eff} , $\log(g)$, [Fe/H]), along with three chemical abundances [X/H] selected to represent high, median and low RMSE scores. Following the approach of [82], the top panel in Figure 7 shows model-based predictions against the true targets, while the bottom panel displays residuals, highlighting regions where the models are biased. In this panel, we also mark the region within 1 standard deviation of a perfect prediction. For completeness, Table 4 in the Appendix reports the evaluation metrics $\{r^2, \Delta, \text{RMSE}\}$ for all 20 stellar parameters derived from both CNNs. Note these parameters are not independent but exhibit intrinsic degeneracies, as exemplified by the correlation between T_{eff} and $\log g$ in Figure 3.

As shown in Table 4, both CNNs recover all stellar properties well, with r^2 scores exceeding ~ 0.88 and RMSE precisions *comparable* to—if not better than—the estimated precisions of the SDSS-IV DR17 APOGEE/APSCAP measurements [95]. In particular, the NIRSpec (APOGEE) model predicts $T_{\text{eff}}, \log g$ and metallicities to RMSE precisions of 280 (270) K, 0.09 (0.09) dex and $\lesssim 0.1$ dex, respectively. These are in strong agreement with the estimated precisions of calibrated ASPCAP results, which find T_{eff} is measured with a precision better than 150 K, $\log g$ better than 0.2 dex and metallicites better than 0.1 dex. Moreover, the overall biases are negligible, typically an order of magnitude smaller than the RMSEs. As shown in the bottom panels of Figure 7, most of the model bias occurs at the limits of parameter space, where predictions exhibit ‘regression towards the mean’, in which low values tend to be over-predicted and high values under-predicted. A potential reason for this behaviour is that stars with extreme values are underrepresented and of lower quality (i.e., low SNR, weak spectral features) in our catalogs, making it difficult for the models to learn this region of parameter space sufficiently well at training time. Another contributing factor may be due to degeneracies between data and labels or any discrete, abrupt changes in data-label relationships due to underlying physical processes [82]. To illustrate, for T_{eff} values larger than $\sim 4.5 \times 10^4$ K, the predictions are systematically negatively biased, especially for stars with relatively low SNR. This is likely caused by the reduced number of spectral features in hotter spectra and the increasing degeneracy between temperature and gravity measurements in warmer stars.

In general, the NIRSpec CNN is capable of predicting values closer to the ASPCAP stellar parameters than the APOGEE CNN. This arises from variations in the training data: observed spectra in A

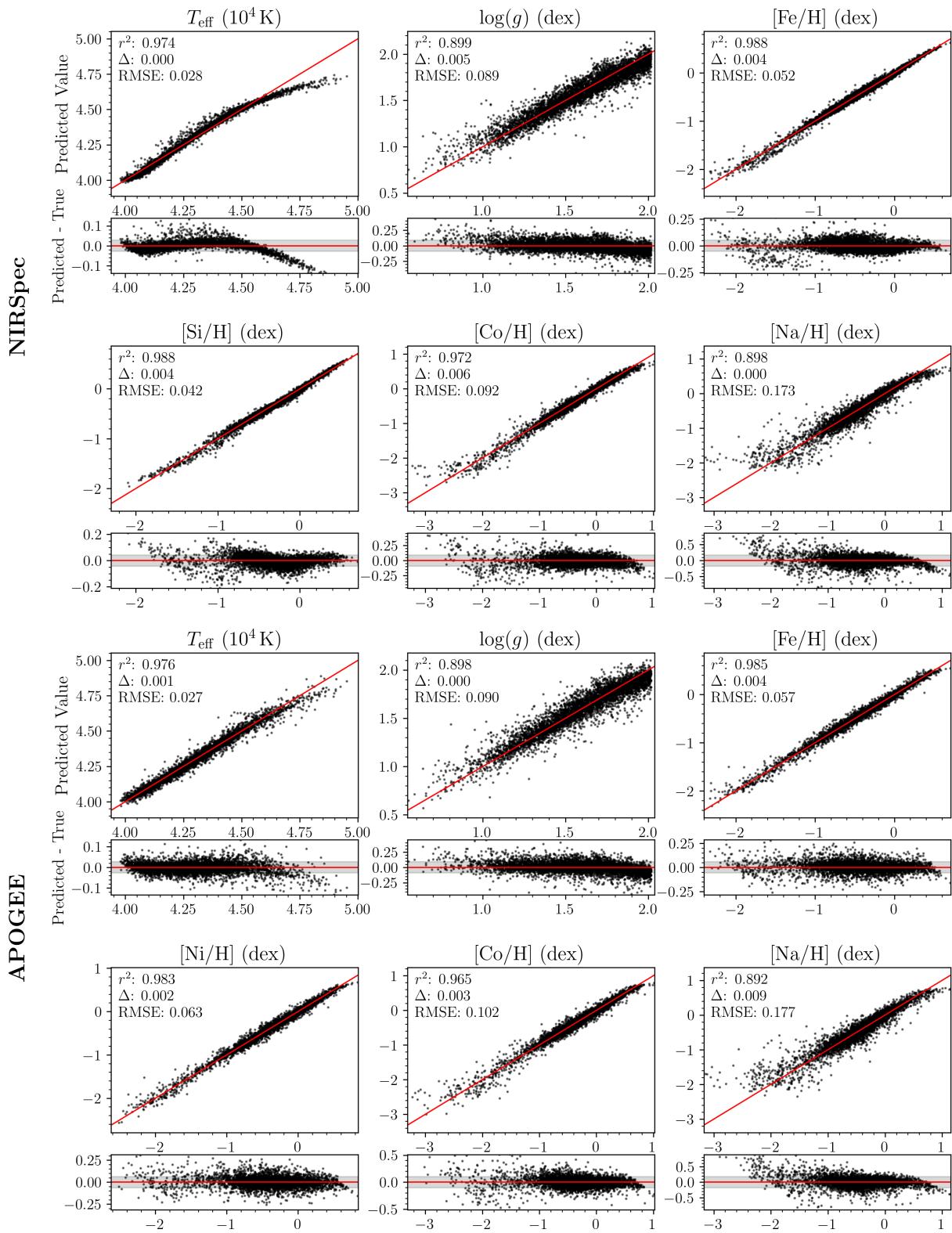


Figure 7: Performance of the single-modal CNN models in predicting fundamental atmospheric parameters along with three chemical abundances representative of high, median, and low RMSE scores. The **top subpanels** report the r^2 , Δ , and RMSE of the predictions. The **bottom subpanels** show residuals, with shaded regions indicating one standard deviation. The red line denotes perfect prediction. Adapted from [82].

have different shapes and profiles than synthetic spectra in \mathcal{J} , characterised by noise, missingness, instrumental broadening, and other signature effects, which *ab initio* models can at most partially capture. As such, the NIRSpec CNN is better poised to capture relevant spectral features in the data, leading to more accurate parameter estimates. In §4.2.1, we describe a pipeline aimed at minimising the *synthetic gap* between the feature distributions of synthetic and observed spectra.

5.2 SSL Downstream Tasks

5.2.1 Cosine Similarity Search

We evaluate the retrieval performance of *Cross-modal Cosine Similarity Search* (CrossCSS) on test embeddings generated by STARCLIP and MOCKSTARCLIP. Briefly, given a search query from one modality (e.g., $Z^{\mathcal{J}}$), CrossCSS computes its cosine similarity with all embeddings from the complementary modality (e.g., $Z^{\mathcal{A}}$), ranks the results by similarity, and retrieves the top- k most relevant matches. To assess the impact of CLIP alignment, we compare CrossCSS performance on CLIP-aligned embeddings against corresponding baseline searches using raw spectra: $\mathcal{J} \times [\mathcal{A}]$ and $\mathcal{J}^{\text{lo}} \times \mathcal{J}^{\text{hi}}$, respectively.¹²

Table 3: Overall Performance of CrossCSS on CLIP Embeddings and Baselines (best scores in boldface)

Model	Query	Retrieved	R@1	R@5	R@10	R@50	MRR
STARCLIP	$Z^{\mathcal{J}}$	$Z^{\mathcal{A}}$	0.14	0.14	0.24	0.57	0.17
	$Z^{\mathcal{A}}$	$Z^{\mathcal{J}}$	0.15	0.41	0.56	0.86	0.28
<i>Baseline</i>	\mathcal{J}	$[\mathcal{A}]$	0.00	0.00	0.00	0.00	0.00
	$[\mathcal{A}]$	\mathcal{J}	0.00	0.00	0.00	0.01	0.00
MOCKSTARCLIP	Z^{lo}	Z^{hi}	0.06	0.22	0.35	0.75	0.19
	Z^{hi}	Z^{lo}	0.08	0.27	0.40	0.75	0.16
<i>Baseline</i>	\mathcal{J}^{lo}	\mathcal{J}^{hi}	0.00	0.02	0.03	0.11	0.02
	\mathcal{J}	\mathcal{J}^{lo}	0.00	0.02	0.03	0.11	0.02

Table 3 reports CrossCSS retrieval performance for both CLIP models against their respective baselines, measured in terms of *SuccessRate@k* and MRR. Columns $R@1$, $R@5$, $R@10$ and $R@50$ correspond to *SuccessRate@k* at $k = 1, 5, 10$ and 50 , respectively. For each model, the first two rows report CrossCSS on CLIP-aligned embeddings, with query and retrieved modalities alternated; the next two rows report baseline performance on raw spectra.

As shown in Table 3, CrossCSS applied to CLIP-aligned embeddings consistently outperforms all baseline methods. In contrast, CrossCSS on raw spectra often *fails* to retrieve meaningful matches, indicating that CLIP alignment is essential for enabling CrossCSS to retrieve semantically meaningful cross-modal pairs. Indeed, averaged across both query directions, CrossCSS with MOCKSTARCLIP embeddings improves *SuccessRate@k* by 1,000%, 1,067% and 582% for k is 5, 10 and 50, respectively, relative to its unaligned baseline. These improvements reflect at least an order-of-magnitude increase in successful retrievals—i.e., instances where the true cross-modal pair (or one of its augmentations) appears within the top- k results. These findings demonstrate that CLIP alignment enhances shared

¹²We define $[\mathcal{A}]$ as the truncated version of \mathcal{A} , obtained by cropping each spectrum by $8,575 - 8,192 = 383$ pixels to remove missing regions (15,100–15,152 Å and 16,969–17,000 Å), ensuring dimensional agreement with \mathcal{J} for computing cosine similarity in Equation (2.12).

semantic structure across modalities, enabling CrossCSS to retrieve results that more faithfully reflect the user’s query intent.

Interestingly, while both query directions yield comparable performance for MOCKSTARCLIP and its baseline, we observe a notable asymmetry in retrieval results for STARCLIP. Specifically, querying APOGEE embeddings in Z^A to retrieve NIRSpec embeddings in Z^J consistently outperforms the reverse. This suggests that the APOGEE encoder g_Φ produces more discriminative or higher-quality embeddings than the NIRSpec encoder f_Θ , potentially due to inherent differences in the spectral characteristics of APOGEE and NIRSpec data.

5.2.2 Dimensionality Reduction

Parameterised models with many correlated parameters often amenable to dimensionality reduction (DR) methods, which aim to identify a lower-rank latent space more directly aligned with the underlying physical variables governing the system (see, e.g., [96]). We apply Principal Component Analysis (PCA) [97] to the *joint* test embeddings of STARCLIP ($Z^J \cup Z^A$) and MOCKSTARCLIP ($Z^{\text{lo}} \cup Z^{\text{hi}}$) to assess whether they encode core stellar properties. Briefly, given a set of test embeddings, PCA decomposes the sample covariance matrix into a set of orthogonal eigenvectors ranked by their associated eigenvalues—or, equivalently, by the variance they account for. Eigenvectors accounting for most of the variance are assumed to reflect real correlations between physical parameters, while those explaining minimal variance are typically attributed to measurement noise and are thus discarded [96]. This yields a reduced embedding space, in which the distribution of stellar fundamental parameters can be more easily visualised.

Using the `scikit-learn` [98] PCA implementation, we project the test embeddings of STARCLIP and MOCKSTARCLIP onto the linear subspace spanned by their top two principal components, which together account for $\sim 41\%$ and $\sim 50\%$ of the total sample variance, respectively. Figure 8 shows the resulting projections, with each compressed embedding colour-coded by one of three atmospheric parameters (T_{eff} , $\log g$, $[\text{Fe}/\text{H}]$) or a representative chemical abundance ($[\text{Mg}/\text{Fe}]$). In general, T_{eff} and $\log g$ are fundamental parameters for classifying stars, while $[\text{Fe}/\text{H}]$ and $[\text{Mg}/\text{Fe}]$ are key tracers of the chemical and dynamic evolution of galaxies (see, e.g., [29]), and therefore are listed among the top-priority elements targeted by the APOGEE survey.

The projections exhibit a noisy but broadly continuous evolution of stellar parameters across the reduced embedding space, suggesting that STARCLIP and MOCKSTARCLIP arrange embeddings around shared physical semantics in the higher-dimensional latent space. Interestingly, MOCKSTARCLIP projections exhibit clearer structure, characterised by two stellar parameter gradients that are closely aligned with its principal component axes. This suggests MOCKSTARCLIP has learned more *disentangled* latent representations in the higher-dimensional space, in which individual axes correspond more directly to underlying astrophysical variables. Altogether, the roughly continuous variation of stellar parameters across the reduce space offers a qualitative indication that regression from CLIP-aligned embeddings to stellar labels should be possible. Equipped with this insight, we proceed in §5.2.3 to quantitatively recover stellar properties from the learned embeddings.

5.2.3 Stellar Property Recovery

We show STARCLIP and MOCKSTARCLIP are capable of inferring stellar properties from learned embeddings in Z^J and Z^{hi} , respectively. Conventional ML approaches to this task would typically rely on bespoke CNNs, entailing the development of an end-to-end pipeline from scratch [6, 82]. In contrast, CLIP-aligned embeddings already capture expressive features of the input stars, enabling us to apply a

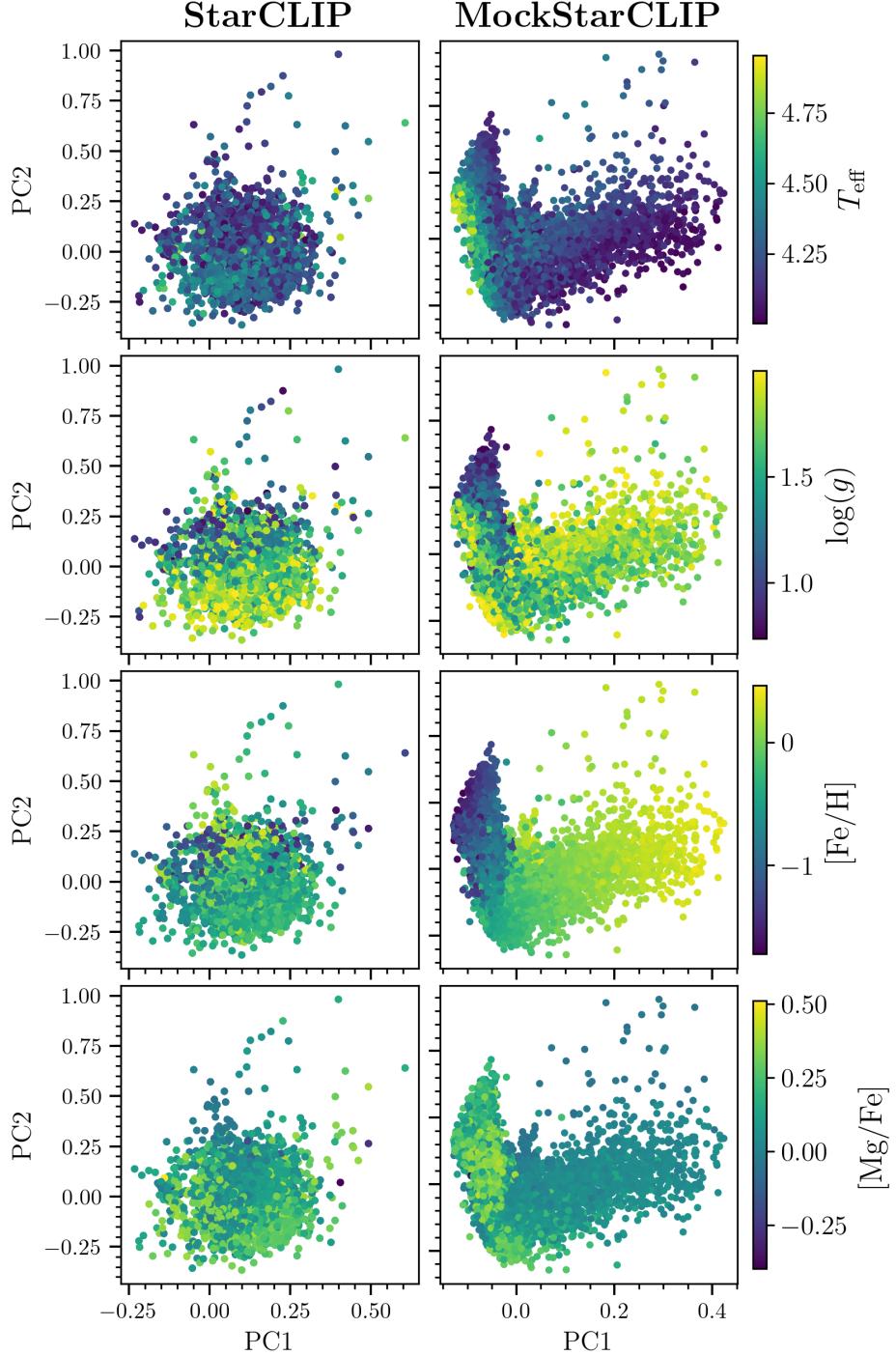


Figure 8: PCA projections of STARCLIP (*left*) and MOCKSTARCLIP (*right*) test embeddings onto their first two principal components (PC). Each point represents a compressed embedding, colour-coded by one of four stellar parameters: T_{eff} , $\log g$, $[\text{Fe}/\text{H}]$, or $[\text{Mg}/\text{Fe}]$, as indicated.

simple multi-output linear probe to regress catalog-reported stellar properties directly from the CLIP embeddings. As a supervised baseline, we include a modified STARNET CNN [6], described in §4.1.1, trained end-to-end on the spectral databases \mathcal{J} and \mathcal{J}^{hi} . To account for differences in dataset size, we

adjust the following training hyperparameters:

- For the CNN trained on \mathcal{J} , we use a reduced learning rate $\eta' = 5 \times 10^{-4}$.
- For the CNN trained on \mathcal{J}^{hi} , we enable weight decay at a rate of $\lambda' = 5 \times 10^{-4}$ and use batch sizes of $N_{\text{batch}}^{\text{train}} = 16$, $N_{\text{batch}}^{\text{val.}} = 4$ and $N_{\text{batch}}^{\text{train}} = 128$.

To mimic the MOCKSTARCLIP setup, the CNN trained on \mathcal{J}^{hi} is also initialised with weights pretrained on \mathcal{J} and its convolutional layers are frozen at training time. Importantly, in all analyses involving the augmented datasets $Z^{\mathcal{J}}$ and \mathcal{J} , we perform probing at the *instance-group level*: we mean-aggregate the predictions from all augmented views of the same star, ensuring each star contributes exactly one prediction in downstream evaluation. An empirical spread s is computed from the five predictions and added in quadrature, element-wise, to the estimated intrinsic scatter σ_{int} from SDSS-IV DR17 APOGEE measurements [95]. This gives a total estimated uncertainty:

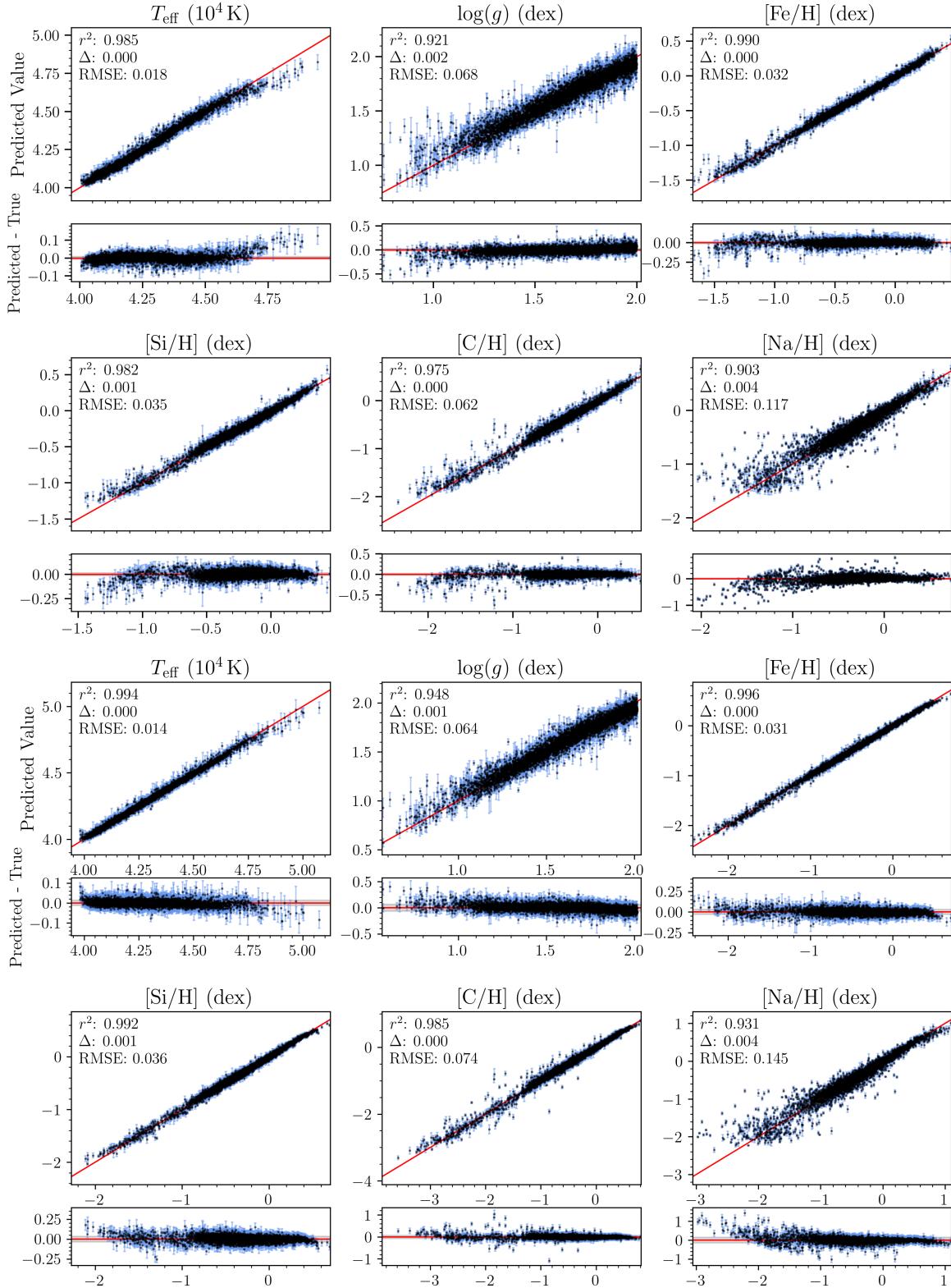
$$\sigma = \sqrt{s^2 + \sigma_{\text{int}}^2}. \quad (5.1)$$

Figure 9 shows the predictions derived from (a) STARCLIP and (b) MOCKSTARCLIP, along with their respective CNN baselines, across six representative stellar properties: three atmospheric parameters and three chemical abundances with high, median and low RMSE scores. Complete evaluation metrics for all 20 stellar parameters are provided in Tables 5 and 6 and Figures 10 and 11 in the Appendix. Again, we find that both CLIP-based models recover all stellar properties with high accuracy, achieving r^2 scores typically exceeding ~ 0.90 , RMSE scores comparable to the estimated precisions of SDSS-IV DR17 APOGEE measurements [95], and minimal biases—generally one to two orders smaller than the corresponding RMSE values. Consistent with the findings of [27], our CLIP-based models successfully demonstrate an ability to encode core physical attributes of the input stars in their embeddings, despite undergoing no task-specific fine-tuning. Interestingly, while STARCLIP outperforms MOCKSTARCLIP across most tasks, as anticipated, it achieves equal or slightly lower r^2 scores for [S/H], [Cr/H], [Co/H] and [Ce/H]. One potential reason for this behaviour is that MOCKSTARCLIP, trained with smaller τ , induces a more separable and discriminative embedding space, which may help to resolve subtle or degenerate spectral features—and thereby improve predictions for parameters with weaker spectral signatures. Finally, although both CLIP-based models perform competitively, they typically underperform relative to their supervised counterparts, particularly in terms of r^2 . Consistent with [99], [100] and [101], these findings suggest that specialised, pre-trained foundation models have not yet surpassed traditional supervised approaches trained directly on downstream task data. Nonetheless, the ability of our CLIP-based models to generalise well in low-data regimes, enrich shared semantic information, and transfer to downstream tasks without fine-tuning highlights important advantages of our approach over supervised analysis.

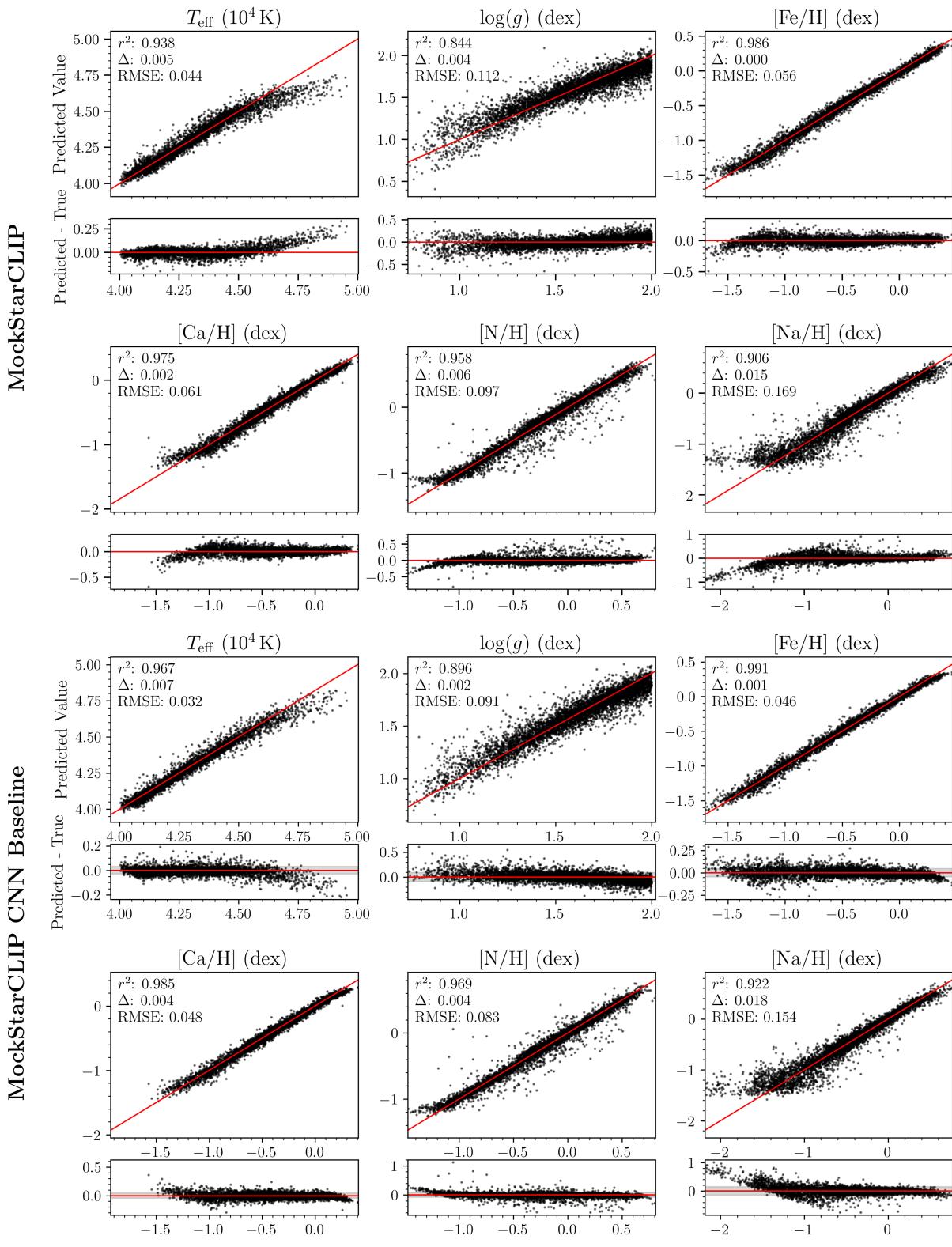
6 Conclusion

We have presented STARCLIP, and its variant MOCKSTARCLIP, versatile cross-modal foundation models for stellar spectroscopy. Both models encode in their embeddings core physical information about the underlying stars, leading to strong performance across a variety of downstream tasks, including cosine similarity search and stellar property estimation. We believe these rich embeddings have the potential to serve as off-the-shelf tools for building higher-level models, facilitating analysis of NIRSpec

StarCLIP



(a) STARCLIP and Supervised CNN Baseline Performance



(b) MOCKSTARCLIP and Supervised CNN Baseline Performance

Figure 9: Performance of (a) STARCLIP and (b) MOCKSTARCLIP, and their respective baselines, in predicting a common set of fundamental atmospheric parameters and representative chemical abundances. Error bars denote standard deviations computed via Equation (5.1). In general, both models are in agreement with but underperform relative to their respective supervised counterparts.

data. This, in turn, will make accessible a vast wealth of chemical information in the spectra of stars outside the MW. In the future, we plan to extend MOCKSTARCLIP’s capabilities to integrate observed NIRSpec data, validating its real-world applicability. While our pipeline implements semi-empirical, stochastic transformations to simulate physical corruptions in observed data, the fidelity of these simulations is not yet clear. Ultimately, fine-tuning the model to work well with observed datasets would help set the stage for the broader adoption of foundation models in extragalactic stellar spectroscopy, poising the field for transformative growth.

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Disclaimer. All code was written solely by the author between May 1st, 2024 and May 1st, 2025. All writing of this paper was undertaken solely by the author, strictly begun after the publication of the Part III essay titles.

Data Availability. The data and code underlying this article are available in a GITHUB repository at this [link](#).

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¹³<https://www.biorender.com/>

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A Appendix

Table 4: Single-modal CNN Performance on Stellar Property Recovery

Parameter	NIRSpec			APOGEE		
	r^2	Δ	RMSE	r^2	Δ	RMSE
T_{eff}	0.974	0.000	0.028	0.976	0.001	0.027
$\log(g)$	0.899	0.005	0.089	0.898	0.000	0.090
[C/H]	0.976	0.004	0.090	0.970	0.003	0.102
[N/H]	0.947	0.000	0.107	0.944	0.008	0.109
[O/H]	0.982	0.001	0.051	0.969	0.003	0.068
[Na/H]	0.898	0.000	0.173	0.892	0.009	0.177
[Mg/H]	0.982	0.002	0.053	0.965	0.003	0.075
[Al/H]	0.952	0.002	0.105	0.939	0.008	0.119
[Si/H]	0.988	0.004	0.042	0.971	0.004	0.065
[S/H]	0.911	0.001	0.101	0.906	0.004	0.103
[K/H]	0.902	0.002	0.132	0.888	0.004	0.141
[Ca/H]	0.981	0.005	0.052	0.969	0.003	0.067

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Parameter	NIRSpec			APOGEE		
	r^2	Δ	RMSE	r^2	Δ	RMSE
[Ti/H]	0.981	0.003	0.070	0.969	0.004	0.092
[V/H]	0.898	0.001	0.151	0.899	0.007	0.151
[Cr/H]	0.958	0.007	0.107	0.954	0.000	0.112
[Mn/H]	0.980	0.003	0.085	0.980	0.004	0.085
[Fe/H]	0.988	0.004	0.051	0.984	0.004	0.058
[Co/H]	0.972	0.006	0.092	0.965	0.003	0.102
[Ni/H]	0.989	0.003	0.049	0.983	0.002	0.063
[Ce/H]	0.877	0.005	0.170	0.906	0.003	0.149

Table 5: STARCLIP and Supervised CNN Baseline Performance on Stellar Property Recovery

Parameter	STARCLIP			Supervised CNN		
	r^2	Δ	RMSE	r^2	Δ	RMSE
T_{eff}	0.985	0.000	0.018	0.994	0.000	0.014
$\log(g)$	0.921	0.002	0.068	0.948	0.001	0.064
[Fe/H]	0.990	0.000	0.032	0.996	0.000	0.031
[C/H]	0.975	0.000	0.062	0.985	0.000	0.074
[N/H]	0.957	0.000	0.068	0.973	0.000	0.077
[O/H]	0.977	0.001	0.041	0.990	0.001	0.040
[Na/H]	0.903	0.004	0.117	0.931	0.004	0.145
[Mg/H]	0.978	0.000	0.041	0.990	0.000	0.042
[Al/H]	0.963	0.001	0.061	0.974	0.001	0.078
[Si/H]	0.982	0.001	0.035	0.992	0.001	0.036
[S/H]	0.916	0.001	0.069	0.931	0.002	0.092
[K/H]	0.906	0.001	0.090	0.921	0.002	0.121
[Ca/H]	0.982	0.000	0.035	0.989	0.000	0.041
[Ti/H]	0.984	0.000	0.045	0.990	0.000	0.053
[V/H]	0.917	0.001	0.093	0.923	0.002	0.130
[Cr/H]	0.962	0.002	0.071	0.970	0.003	0.093
[Mn/H]	0.988	0.001	0.047	0.993	0.001	0.051
[Co/H]	0.963	0.002	0.071	0.973	0.003	0.093
[Ni/H]	0.987	0.001	0.037	0.994	0.000	0.037
[Ce/H]	0.910	0.002	0.109	0.921	0.003	0.141

Table 6: MOCKSTARCLIP and Supervised CNN Baseline Performance on Stellar Property Recovery

Parameter	MOCKSTARCLIP			Supervised CNN		
	r^2	Δ	RMSE	r^2	Δ	RMSE
T_{eff}	0.938	0.005	0.044	0.968	0.006	0.032
$\log(g)$	0.844	0.004	0.112	0.901	0.002	0.089
[Fe/H]	0.965	0.004	0.074	0.981	0.004	0.054
[C/H]	0.965	0.006	0.112	0.981	0.007	0.083
[N/H]	0.958	0.006	0.097	0.970	0.005	0.083
[O/H]	0.965	0.004	0.074	0.981	0.003	0.054
[Na/H]	0.906	0.015	0.169	0.921	0.015	0.155
[Mg/H]	0.969	0.004	0.073	0.985	0.004	0.051
[Al/H]	0.943	0.015	0.118	0.968	0.012	0.090
[Si/H]	0.973	0.003	0.064	0.986	0.002	0.047
[S/H]	0.928	0.006	0.092	0.944	0.006	0.082
[K/H]	0.926	0.017	0.116	0.948	0.007	0.098
[Ca/H]	0.975	0.002	0.061	0.985	0.003	0.048
[Ti/H]	0.977	0.003	0.081	0.985	0.000	0.066
[V/H]	0.895	0.009	0.154	0.919	0.016	0.137
[Cr/H]	0.952	0.008	0.117	0.961	0.013	0.107
[Mn/H]	0.984	0.005	0.077	0.989	0.003	0.064
[Co/H]	0.962	0.011	0.110	0.970	0.003	0.098
[Ni/H]	0.983	0.003	0.064	0.991	0.002	0.047
[Ce/H]	0.928	0.002	0.135	0.940	0.006	0.124

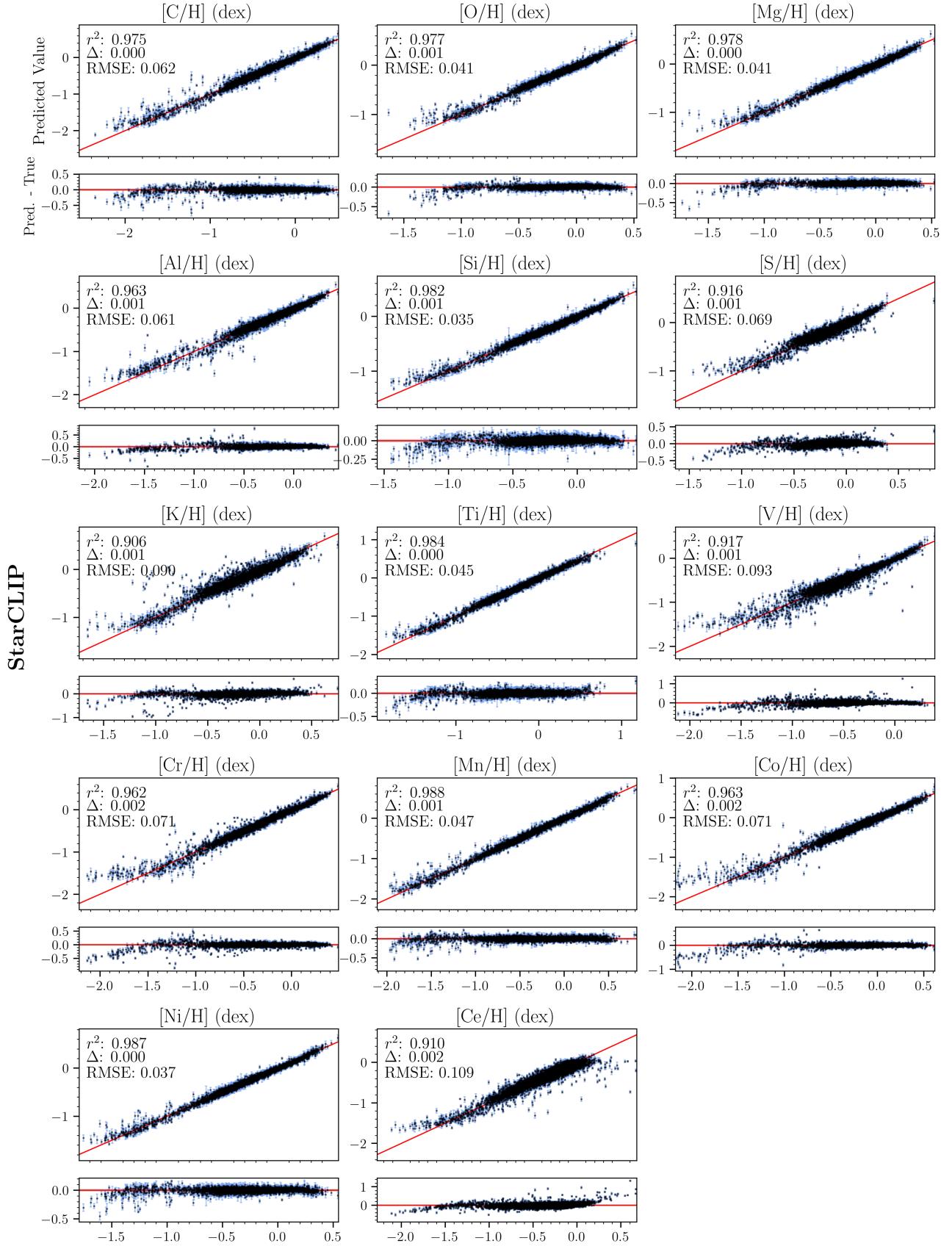


Figure 10: Performance of STARCLIP in predicting the remaining 14 chemical abundances.

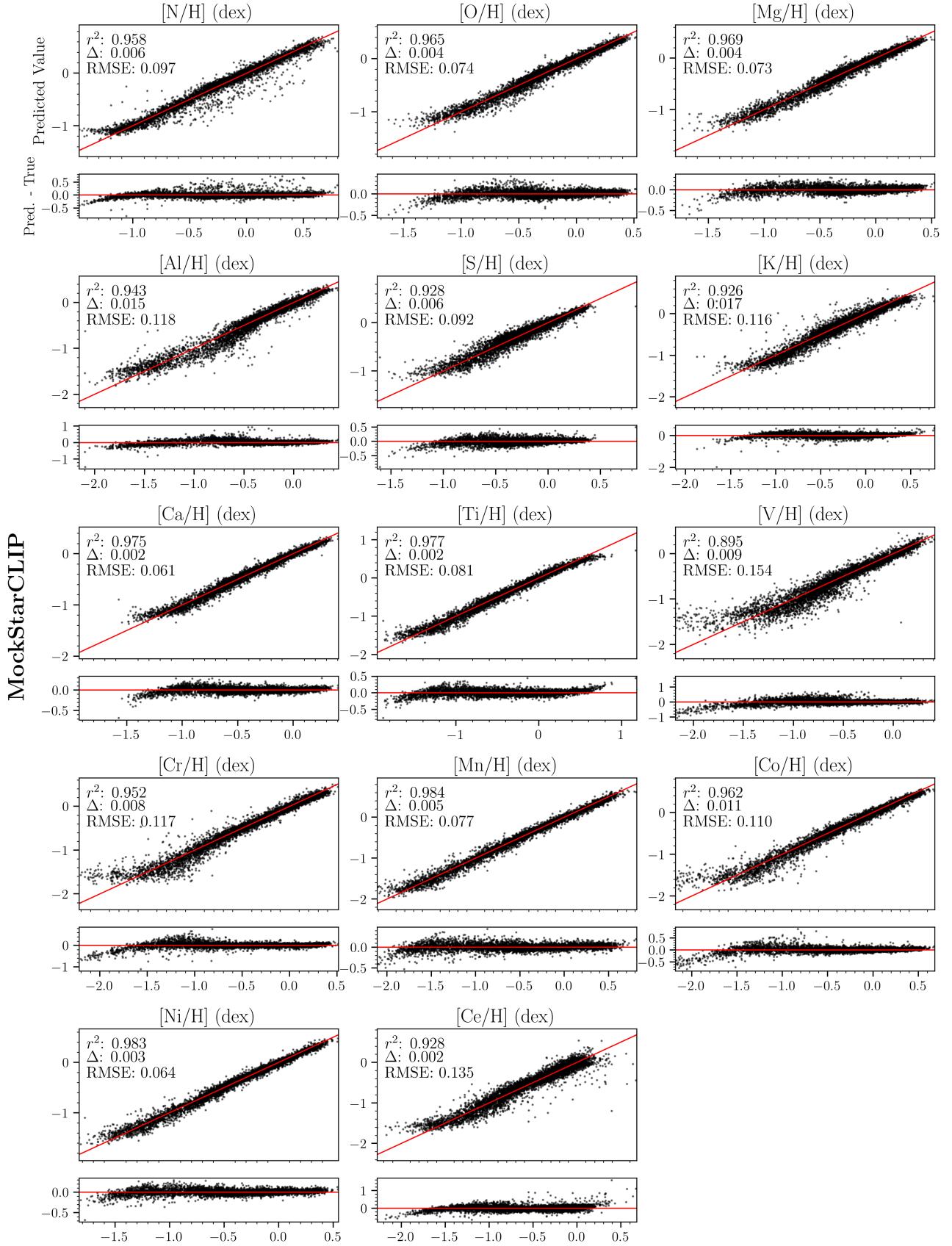


Figure 11: Performance of MOCKSTARCLIP in predicting the remaining 14 chemical abundances.