Applying Contrastive Learning to JWST Stellar Spectra

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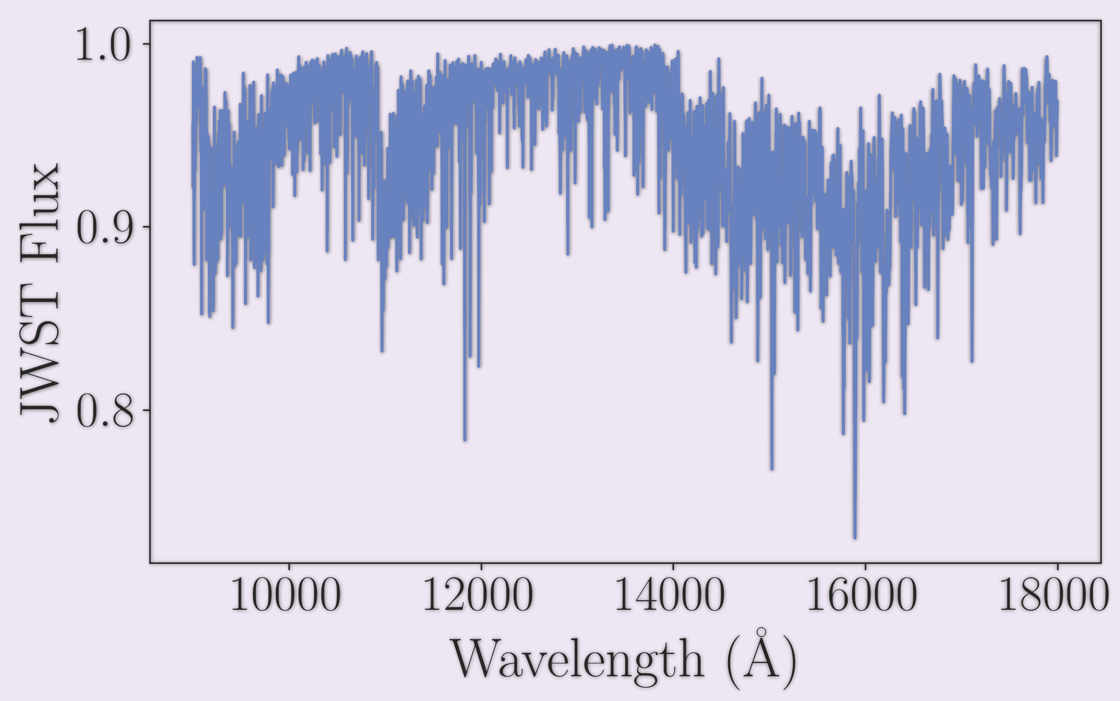
ABSTRACT

Objective

The domain of JWST resolved star spectroscopy remains largely unexplored. This work seeks to analyse this valuable data by means of novel ML approaches.

Data

We analyse 19,000 pairs of synthetic JWST and real APOGEE spectra of the Milky Way, each with 20 stellar labels.



Research Methods

1. Deep CNN is trained on JWST spectra to predict stellar labels.
2. CLIP uses pre-trained CNN as an encoder to embed JWST-APOGEE pairs into a physically meaningful, shared 20-dim. latent space.
3. InfoNCE Loss aligns the encoders around shared semantics.

4-6 Embeddings are used in downstream tasks. They are empirically shown to capture physical properties of the underlying stars.

3 Similarity & InfoNCE Loss

$$S_C(\mathbf{x}_i, \mathbf{y}_j) = \frac{\mathbf{x}_i \cdot \mathbf{y}_j}{\|\mathbf{x}_i\|_2^2 \|\mathbf{y}_j\|_2^2} = \hat{\mathbf{x}}_i \cdot \hat{\mathbf{y}}_j$$

$$\mathscr{L}(\mathbf{X}, \mathbf{Y}) = -\frac{1}{K} \sum_{i=1}^{K} \log \frac{\exp(S_C(\mathbf{x}_i, \mathbf{y}_j)/\tau)}{\sum_{j \neq i}^{K} \exp(S_C(\mathbf{x}_i, \mathbf{y}_j)/\tau)}$$

K = batch size $\quad$ τ = smoothing parameter

References

1. Fabbro et al. *Roy. Astro. Soc.* 2017.
2. Parker et al. *Roy. Astro. Soc.* 2024.

Acknowledgments

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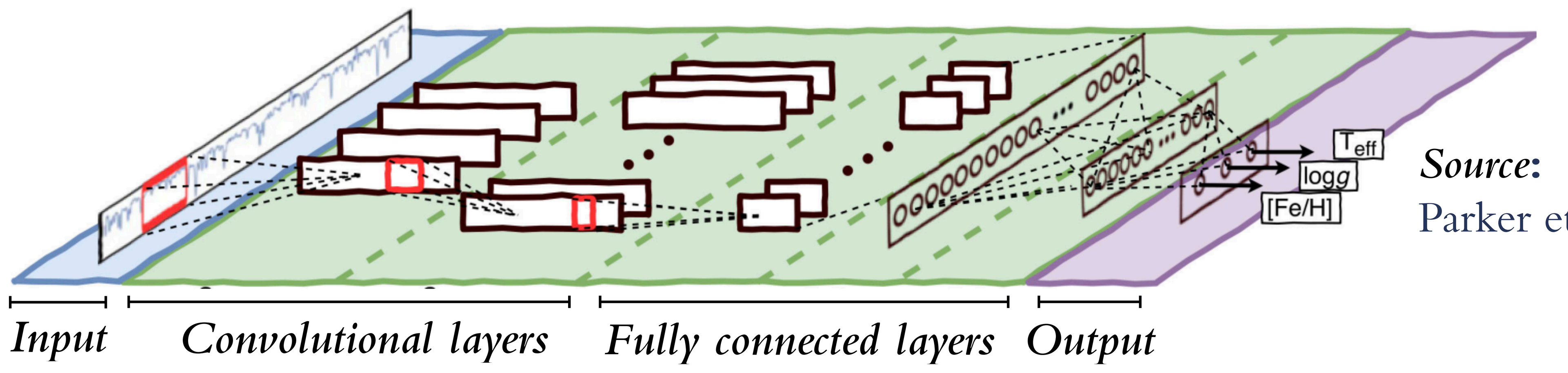
RESULTS

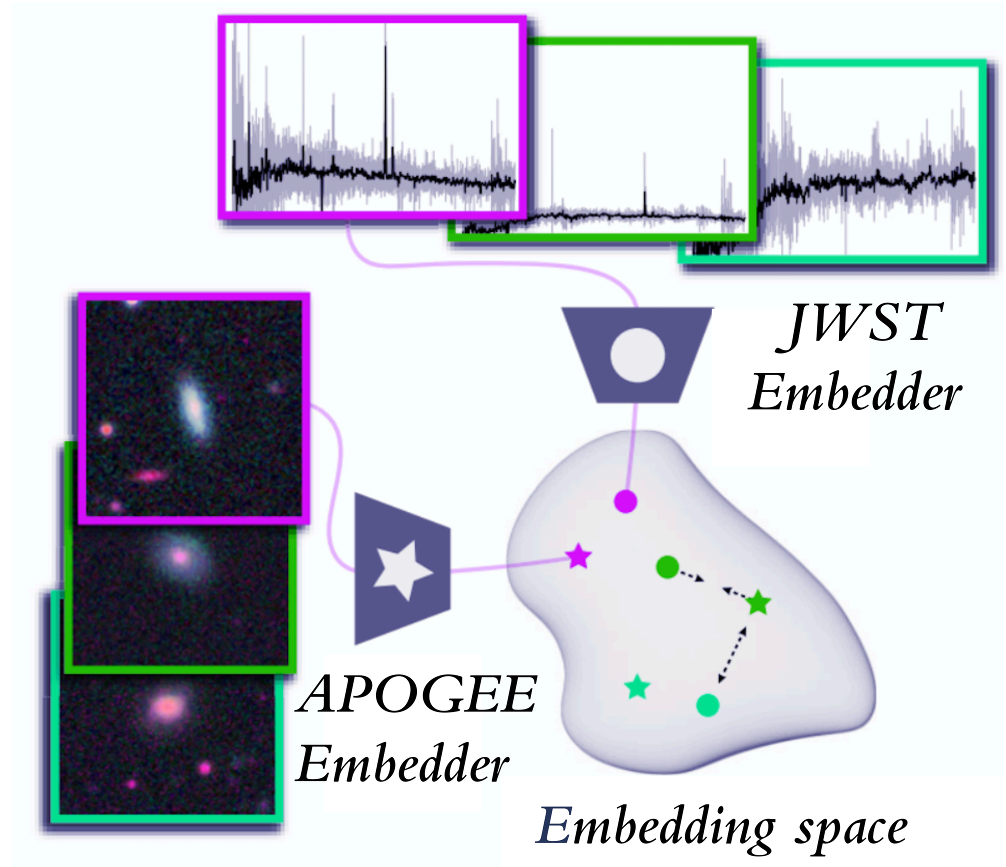
1 Supervised CNN for Predicting JWST Stellar Labels



Source: Parker et al.

Fig. 1. CNN architecture, which learns mapping from JWST spectra to labels: T_{eff} (MSE = 53.3), $\log(g)$ (0.001) and 18 metallicities $[X/H]$ (0.000).

2 CLIP Model for Embedding and Aligning JWST-APOGEE pairs



Source: Fabbro et al.

Fig. 2. JWST-APOGEE pairs are embedded using CNN in **1.** Embedded representations are aligned using cross-modal InfoNCE loss.

4 Stellar Retrieval using Cosine Similarity Search in Embedding Space

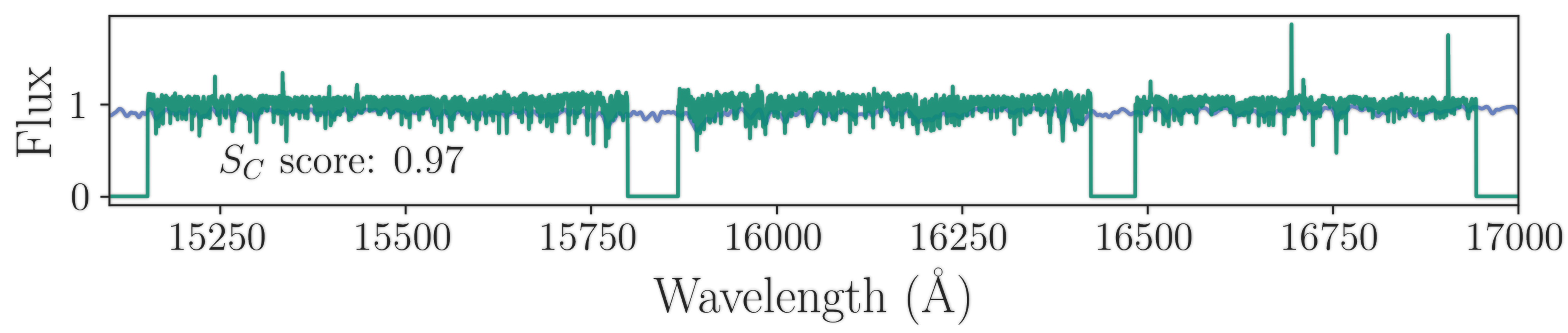


Fig. 3. Example of retrieved APOGEE embedding (*green*) given a queried JWST embedding (*blue*), sharing the greatest cross-modal cosine similarity: 0.97.

5 k-NN Zero-Shot Inference

6 t-SNE & UMAP

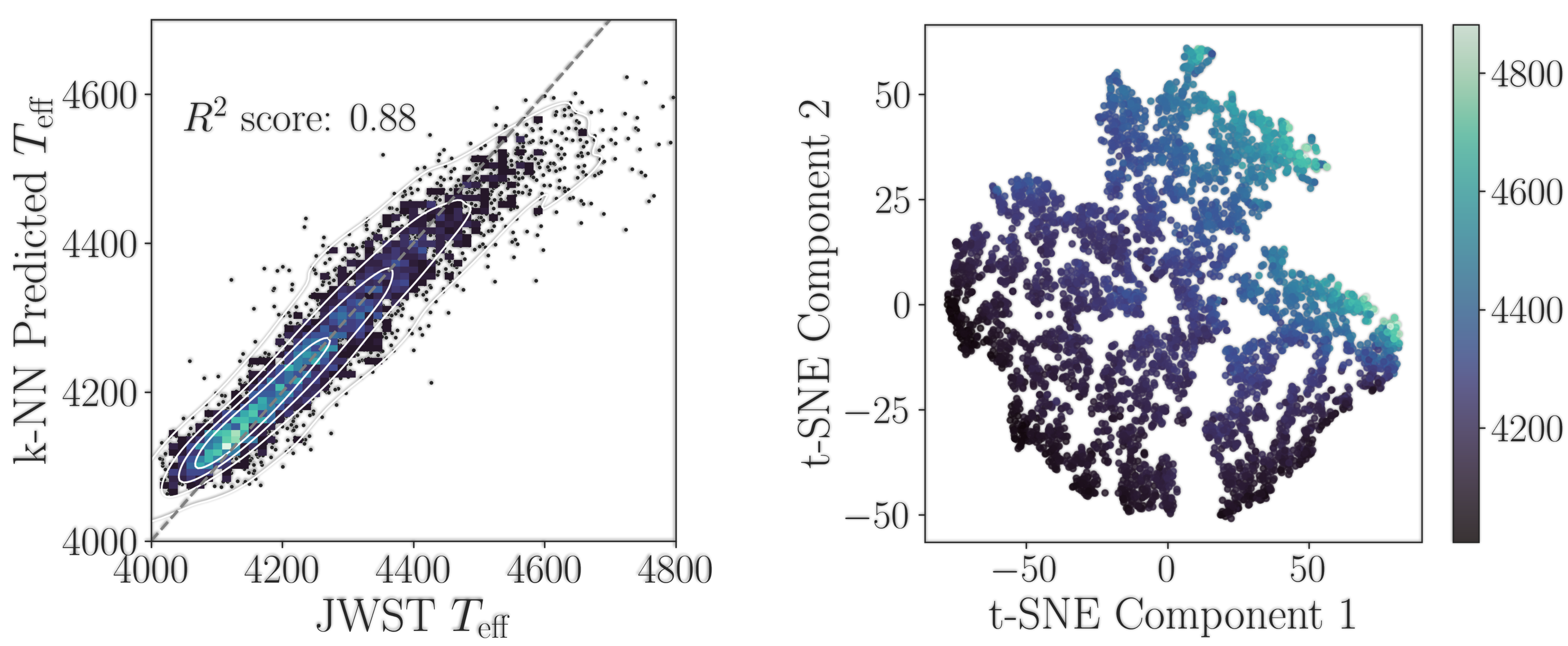


Fig. 4. *Left*: k-NN algorithm applied on JWST embeddings to predict T_{eff}. *Right*: t-SNE projection of 20-dim. latent space to 2-dim., showing T_{eff}-gradient.