Representation Learning for Gaia XP DR3

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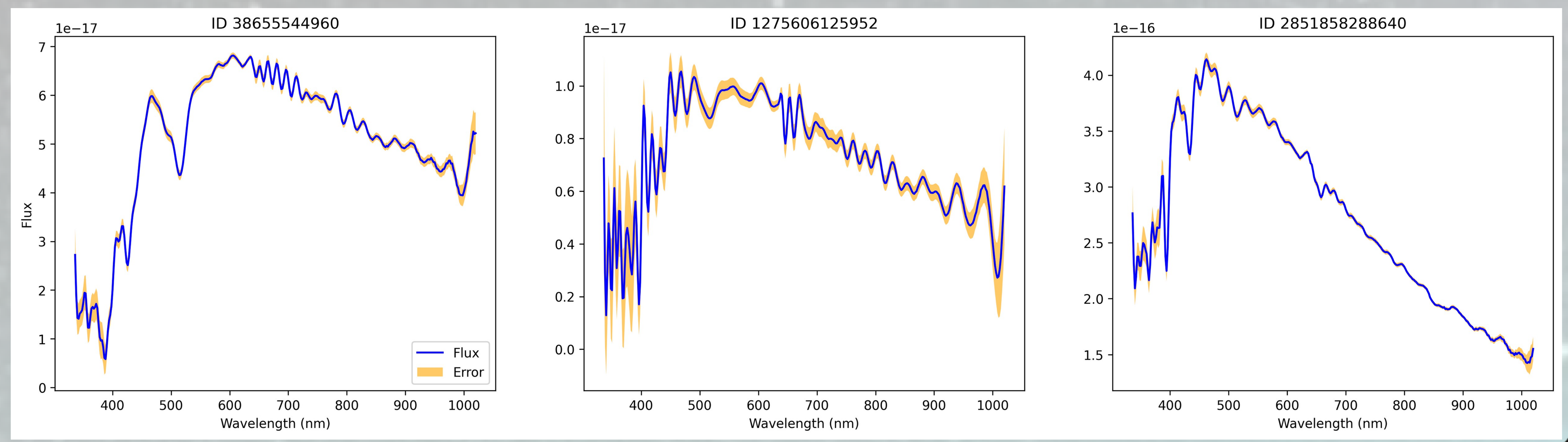
We present a novel representation learning framework for the **Gaia XP DR3 stellar** dataset that leverages two advanced tools: **Spherinator and HiPSter**. Spherinator provides a method for learning compact representations of high-dimensional data, including images, point clouds, data cubes, time series, and spectra. Our training process uses variational autoencoders with **hyperspherical latent spaces** to efficiently and robustly extract physically meaningful parameterizations of data properties. Our approach explicitly incorporates **uncertainties from experiments** into representation learning, which produces more robust and physically consistent latent representations. HiPSter generates and serves HiPS-based (hierarchical progressive surveys) representations of learned features, enabling the scalable visualization and exploration of the latent space using **Aladin-Lite**.

We demonstrate the scientific potential of our method using observational data from Gaia XP DR3 and showcase the effectiveness of **cross-disciplinary** tools developed under the **EU SPACE** initiative to enhance data-driven astronomy.

Data: Gaia XP DR3 Spectroscopic Survey

The Gaia Data Release 3 (DR3) represents the largest spectroscopic survey ever conducted, encompassing approximately **220 million low-resolution spectra**. The survey captures data across two photometric channels: the blue photometer (BP, 330-680 nm) and red photometer (RP, 630-1050 nm), collectively known as XP spectra. Each spectrum in DR3 represents a time-averaged mean spectrum, parameterized using **Hermite polynomial basis functions** with 55 coefficient amplitudes per channel, enabling efficient storage and transmission of spectral information.

Gaia Intro

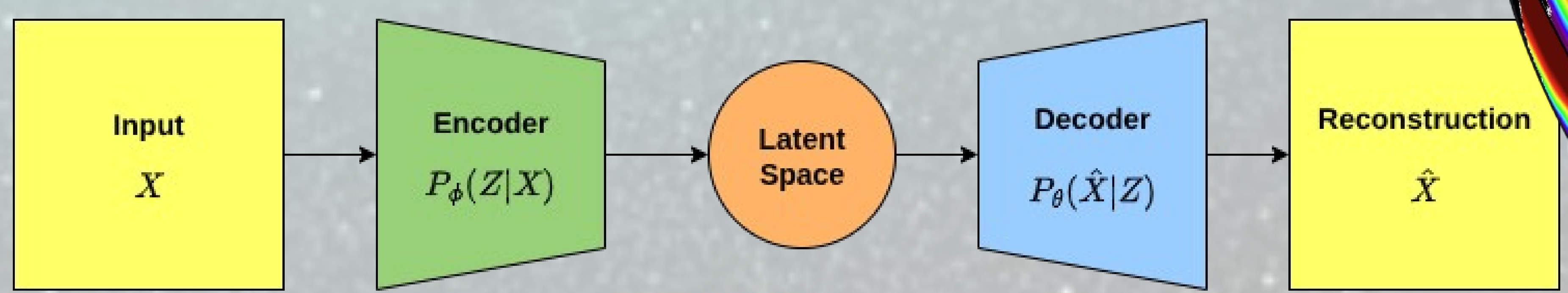


PEST: Data Preparation Pipeline

The **Preprocessing Engine for Spherinator Training (PEST)** serves as a comprehensive data preparation tool designed to handle diverse input formats. PEST integrates all preprocessing steps into a unified workflow, producing standardized data containers using the **Apache Parquet** format for optimal performance and portability.

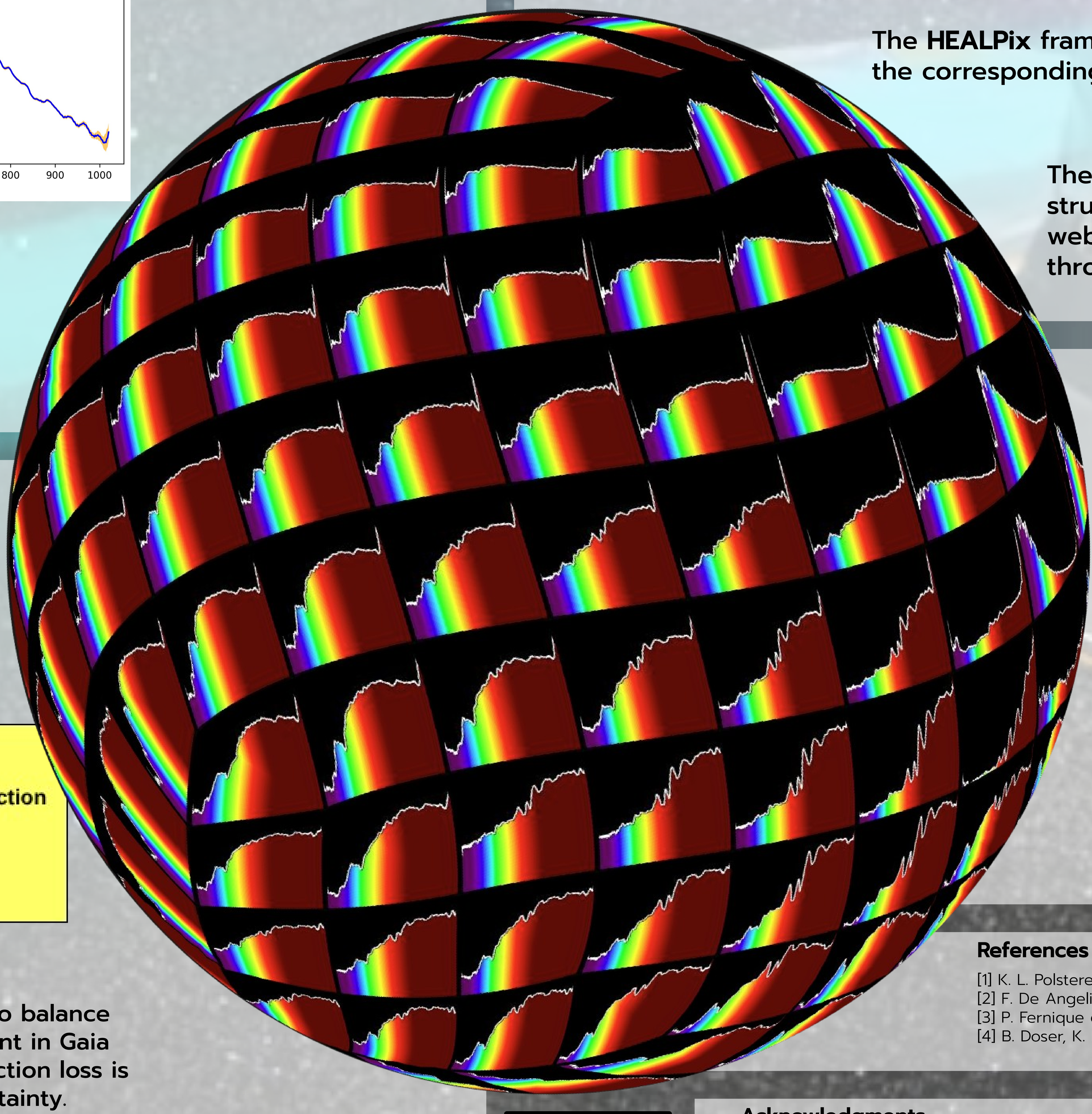
Spherinator: Variational Autoencoder Architecture

The Spherinator implements a novel variational autoencoder (VAE) that maps input data to a **(hyper-)spherical latent space**, built using the **PyTorch Lightning** framework. This architecture offers exceptional flexibility, supporting **multiple data modalities** including images, spectra, data cubes, graphs, and point clouds through modular encoder-decoder designs. For spectroscopic data processing, the model employs a **one-dimensional convolutional neural network (1D-CNN)** architecture optimized for sequential spectral features.



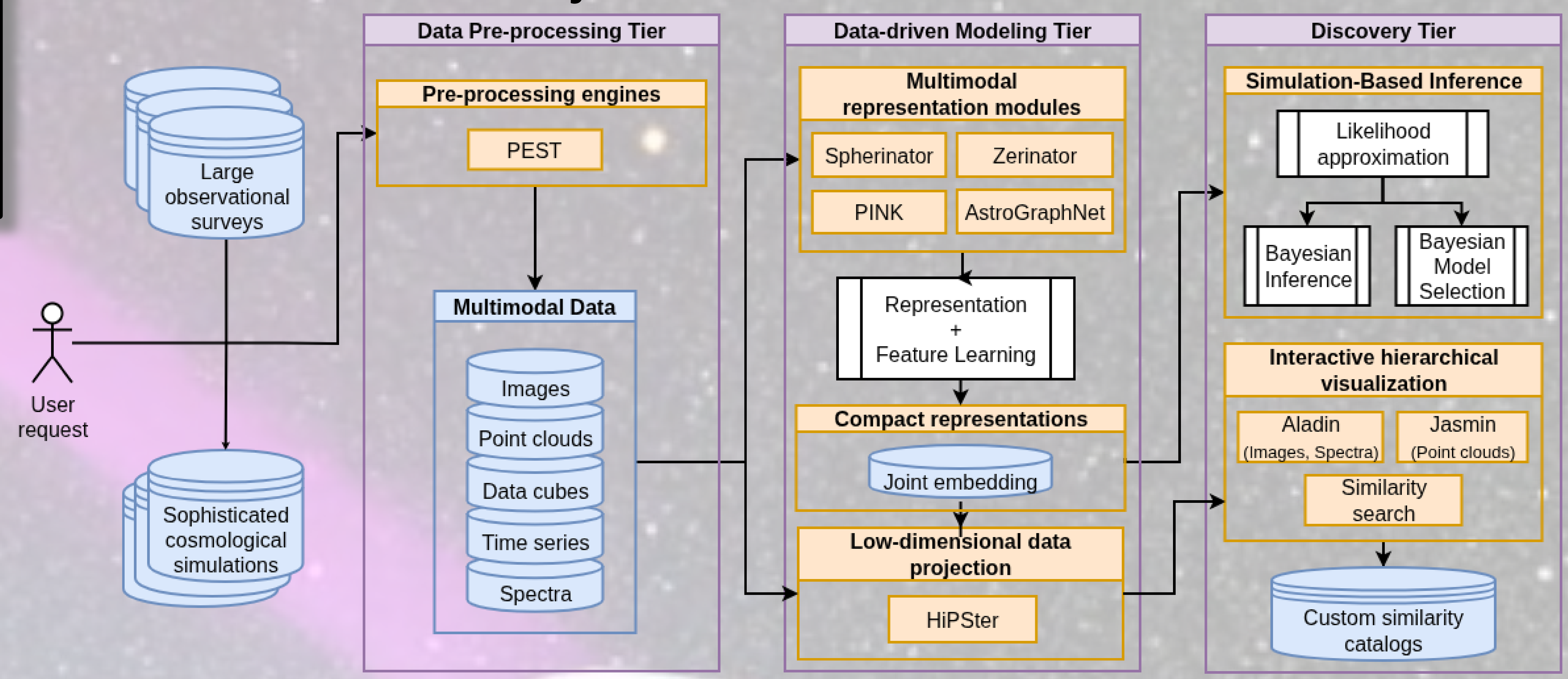
Uncertainty-Aware Loss Function

The VAE loss function combines **Kullback-Leibler (KL) divergence** with a reconstruction term to balance latent space regularization and data fidelity. To incorporate observational uncertainties inherent in Gaia flux measurements, we employ a **negative log-likelihood (NLL)** approach where the reconstruction loss is computed against a normal distribution parameterized by the observed flux and its 1-σ uncertainty.



Read The Docs

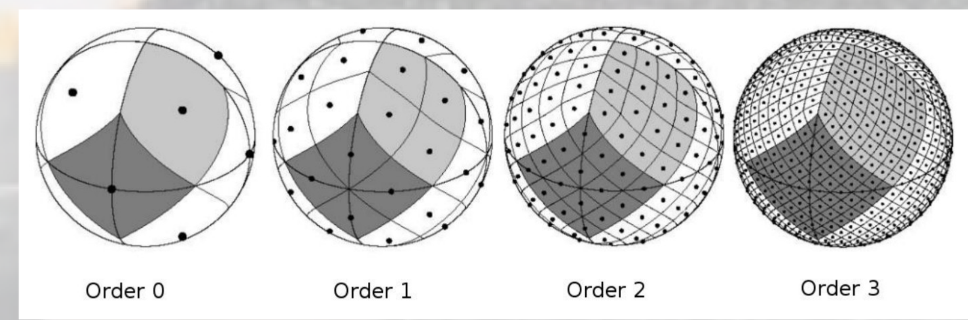
Project X: The Workflow



HIPSter: Inference and Visualization

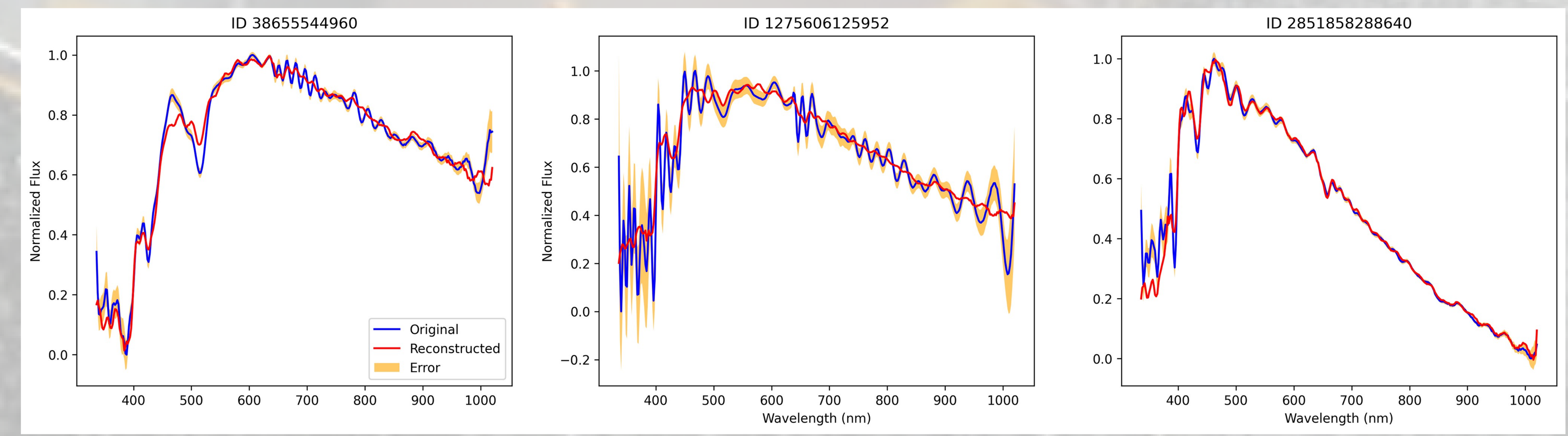
The **HEALPix** framework is used to generate a **Hierarchical Progressive Survey (HiPS)** [3] to map the corresponding spherical latent space positions.

The resulting HiPS data structure is optimized for web-based visualization through **Aladin-Lite**.



Reconstruction Performance

The Spherinator model demonstrates excellent reconstruction capabilities on Gaia XP spectra, successfully capturing the relevant broad spectral features. The uncertainty-aware training approach results in reconstructions that appropriately reflect the confidence levels in different spectral regions, with higher fidelity in well-constrained wavelength ranges and appropriate uncertainty propagation in noisier regions.



References

[1] K. L. Polsterer, B. Doser, A. Fehlner, and S. Trujillo-Gomez, ADASS XXXIII (2024).
[2] F. De Angeli et al., Astronomy & Astrophysics, 674, A2 (2023).
[3] P. Fernique et al., Astronomy & Astrophysics 578, A114 (2015).
[4] B. Doser, K. L. Polsterer, A. Fehlner, and S. Trujillo-Gomez, ADASS XXXIV (2025).

TRY IT OUT

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