
VADER: A Variational Autoencoder to Infer Planetary Masses and Gas-Dust Disk Properties Around Young Stars

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Abstract

We present **VADER** (Variational Autoencoder for Disks Embedded with Rings), for inferring both planet mass and global disk properties from high-resolution ALMA dust continuum images of protoplanetary disks (PPDs). VADER, a probabilistic deep learning model, enables uncertainty-aware inference of planet masses, α -viscosity, dust-to-gas ratio, Stokes number, flaring index, and the number of planets directly from protoplanetary disk images. VADER is trained on over 100,000 synthetic images of PPDs generated from FARGO3D simulations post-processed with RADMC3D. Our trained model predicts physical planet and disk parameters with $R^2 > 0.9$ from dust continuum images of PPDs. Applied to 23 real disks, VADER’s mass estimates are consistent with literature values and reveal latent correlations that reflect known disk physics. Our results establish VAE-based generative models as robust tools for probabilistic astrophysical inference, with direct applications to interpreting protoplanetary disk substructures in the era of large interferometric surveys.

1. Introduction

Understanding how planets form and evolve requires interpreting the rich substructures seen in high-resolution images of protoplanetary disks. With the advent of ALMA, disks are now routinely resolved into rings, gaps, and spirals—features that potentially trace the dynamical influence of forming planets (Andrews et al., 2018; Isella & Turner, 2018; Huang et al., 2020; Fedele et al., 2018; Bae et al., 2022; Cieza et al., 2021). However, connecting these ob-

served morphologies to physical quantities such as planet mass, disk viscosity, or dust properties remains a formidable inverse problem (Haworth et al., 2016; Rosotti, 2023; Dominik & Dullemond, 2024; Jiang et al., 2024). Traditional approaches rely on running large suites of hydrodynamic simulations and comparing their outputs to observations—a process that is computationally intensive and difficult to scale (Toci et al., 2019; Veronesi et al., 2019; 2021; Teague et al., 2018). Moreover, many disk features are inherently degenerate: multiple combinations of parameters can produce nearly identical images (Kanagawa et al., 2016; Dipierro et al., 2015; Lodato et al., 2019; Zhang et al., 2018; Long et al., 2020).

Machine learning has recently emerged as a promising alternative, offering faster inference by learning mappings from images to physical parameters (Auddy & Lin, 2020; Auddy et al., 2022; Ribas et al., 2020). Most of these methods, however, are based on conventional models like multi-layer perceptrons (Auddy & Lin, 2020) or convolutional neural networks (Auddy et al., 2021; Zhang et al., 2022; Telkamp et al., 2022), which yield deterministic estimates and fail to capture the prediction uncertainties.

In this work, we present **VADER**, a Variational Autoencoder framework that addresses these gaps by modeling the full posterior distribution over planetary and disk parameters from resolved ALMA-like disk images. Trained on synthetic data derived from FARGO3D and RADMC3D, our model encodes disk morphology into a smooth latent space and infers both local and global physical quantities—including masses of up to three embedded planets and disk properties such as α -viscosity and dust-to-gas ratio. Unlike prior models, VADER produces uncertainty-aware predictions and generalizes effectively to real observations. This work lays the foundation for probabilistic inference in planet and disk properties.

2. Methods

2.1. Synthetic Dataset Generation

We train our model on a dataset of over 100,000 synthetic images of protoplanetary disks. These images are generated using the FARGO3D hydrodynamic code and post-processed

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with the RADMC3D radiative transfer package. The dataset emulates ALMA Band 6 dust continuum observations at $1300\ \mu\text{m}$. The simulations include up to three embedded planets and span a wide range of physical parameters: planet masses ($8\ M_{\oplus}$ to $3\ M_J$), α -viscosity (10^{-4} to 5×10^{-2}), dust-to-gas ratio (0.01 to 0.05), Stokes number (10^{-4} to 1.57), and flaring index (0.01 to 0.25), where $M_{\oplus}$ is the mass of Earth and M_J is the mass of Jupiter. Each simulation produces ~ 150 augmented images with randomized inclinations, position angles, and translations, resulting in a diverse training set of axisymmetric disk morphologies.

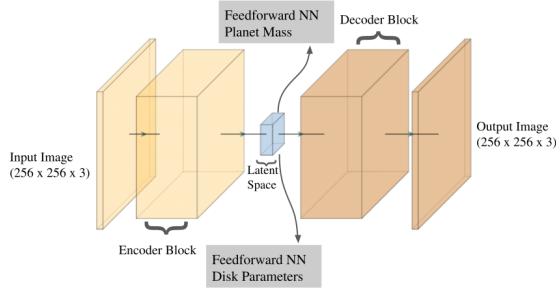


Figure 1. Simplified schematic of the variational autoencoder (VAE) architecture used in this work. The encoder compresses the input dust continuum image of a protoplanetary disk ($256 \times 256 \times 3$) into a 32-dimensional latent space. Two feedforward neural networks independently process the latent vector to infer planetary masses and disk parameters, respectively. The decoder reconstructs the input image from the latent representation.

2.2. Model Architecture

Our framework consists of a Variational Autoencoder (VAE) paired with two feedforward neural networks (FNNs) for parameter inference. The VAE compresses a 256×256 RGB disk image into a 32-dimensional latent vector via a 3-layer convolutional encoder. The decoder reconstructs the original image using transposed convolutions. From the latent vectors, one FNN predicts the masses of up to three planets (regression), while the second predicts disk properties such as α -viscosity, dust-to-gas ratio, Stokes number, flaring index, and number of planets (mapped to ordinal labels, treated as regression targets). Both FNNs consist of 7 hidden layers with batch normalization and ReLU activations.

2.3. Training Objective

The VAE model is trained by minimizing the reconstruction and regularization loss terms

$$\mathcal{L}_{\text{VAE}} = \mathbb{E}_{q_{\phi}(z|x)} [\log p_{\theta}(x|z)] - D_{\text{KL}}(q_{\phi}(z|x) || p(z)), \quad (1)$$

where $q_{\phi}(z|x)$ is the encoder, $p_{\theta}(x|z)$ is the decoder, and $p(z) = \mathcal{N}(0, I)$ is the prior over the latent space. The encoder maps the high-dimensional input image x into a latent space z . The goal of the decoder is to reconstruct the original input x from z . We use mean squared error (MSE) for the reconstruction loss and KL divergence for regularization. After training the VAE, the two FNNs are trained independently. Each FNN receives the 32-dimensional latent vectors from the trained VAE as input and predicts planet mass or disk properties by minimizing the MSE loss.

2.4. Optimization Details

All networks are trained using the Adam optimizer with a learning rate of 10^{-3} and batch size of 32. We train for 150 epochs and select the best checkpoint based on validation set performance. During evaluation, we sample multiple latent vectors per image to obtain predictive uncertainties for each parameter.

3. Results

We evaluate VADER on both synthetic test data and real ALMA observations, assessing reconstruction quality, parameter inference accuracy, and uncertainty quantification.

3.1. Synthetic Performance

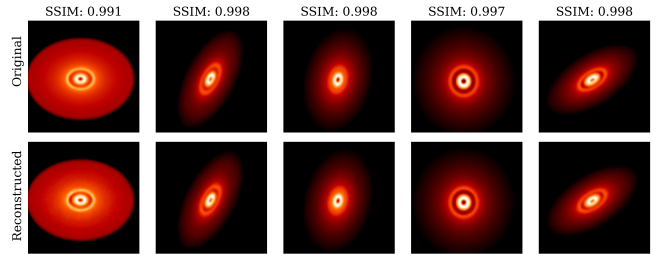


Figure 2. Comparison of original (top row) and reconstructed (bottom row) sample images from the test set using our VAE model. Each image was randomly selected, and the SSIM between the original and reconstructed images exceeds 0.99.

Figure 2 shows examples of input and reconstructed disk images. VADER achieves a mean Structural Similarity Index (SSIM) exceeding 0.99 across the test set, indicating near-perfect morphological recovery of complex structures including concentric rings, asymmetries, and gaps.

To assess parameter inference, we compare predicted and ground-truth values for planetary masses and disk parameters. For planet masses, VADER achieves $R^2 > 0.9$ (Figure 3), with uncertainties growing proportionally as the predicted masses diverge from the true values. For uncertainty quantification, we sample 500 latent points from the

distribution formed by the 32 dimensional latent space and pass each through the FNNs which after 500 iterations give us the posterior distribution for a given parameter.

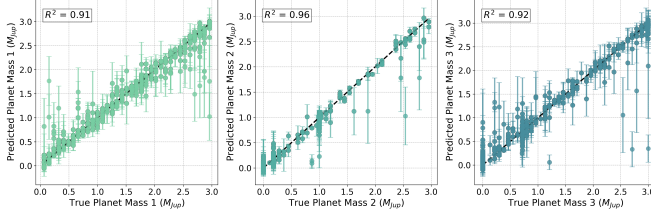


Figure 3. Actual vs. predicted values for the mass of each of the three possible embedded planets, with error bars indicating uncertainty in the predictions. For all cases, the coefficient of determination (R^2) exceeds 0.9, demonstrating strong predictive performance.

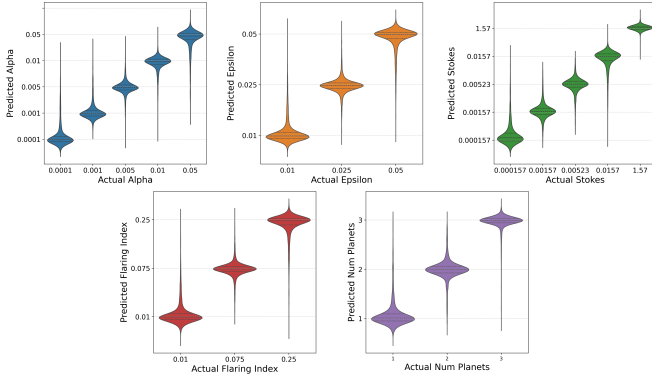


Figure 4. Violin plots comparing predicted and actual parameter values for protoplanetary disks across five disk parameters in the test data: α -viscosity (top left), dust-to-gas ratio ϵ (top center), Stokes number (top right), flaring index (bottom left), and number of embedded planets (bottom right). For each parameter, the violin shows the distribution of corresponding predictions made by our model. The interior dashed lines within each violin denote the 25th, 50th (median), and 75th percentiles of the predictive distribution, illustrating both the central tendency and spread.

Disk parameters are drawn from a discrete set but treated via ordinal regression. Violin plots (Figure 4) show the distributions of predicted values for each true category (e.g., α -viscosity, dust-to-gas ratio, Stokes number). Predictions are tightly concentrated around correct classes with minimal category overlap, capturing both ordinal structure and physical scaling. This suggests that VADER can reliably recover global disk properties despite inherent morphological degeneracies.

3.2. Application to Observational Data

We apply VADER to 23 protoplanetary disks observed with ALMA and benchmark against literature values. Figure 5 compares our predicted planet masses (black squares) with prior estimates from DBNets (Ruzza et al., 2024) and hydrodynamic modeling studies (Zhang et al., 2018; Dong & Fung, 2017). Our predictions agree within 1σ of published values for the majority of systems. This supports the generalization capability of the model beyond synthetic training distributions. We perform disk parameter predictions on two of the most studied protoplanetary disks: HL Tau and HD 163296

For HL Tau, VADER predicts three embedded planets with masses $1.81 \pm 0.23 M_{\text{Jup}}$, $0.18 \pm 0.11 M_{\text{Jup}}$, and $1.72 \pm 0.35 M_{\text{Jup}}$, all consistent with ALMA gap locations and prior inferences (Jin et al., 2016). Disk parameters such as $\alpha \sim 10^{-3} - 5 \times 10^{-3}$, $\epsilon \sim 0.025$ and Stokes Number $\sim 10^{-3} - 10^{-2}$ align with expectations from disk evolution models (Pinte et al., 2015; Wu et al., 2018) and aligns well with planet formation scenarios.

In HD 163296, VADER identifies three planets of masses $0.571 \pm 0.3 M_{\text{Jup}}$, $0.95 \pm 0.44 M_{\text{Jup}}$, and $1.25 \pm 0.33 M_{\text{Jup}}$, in agreement with predictions from (Zhang et al., 2018). It infers $\alpha \sim 10^{-3}$ and Stokes numbers $\sim 10^{-3} - 5 \times 10^{-3}$, matching ranges suggested by CO kinematic analysis and dust trapping studies (Teague et al., 2018; Rodenkirch et al., 2021). Dust-to-gas ratios inferred by our model fall between 1% and 2.5%, consistent with multi-wavelength modeling (Isella et al., 2016).

3.3. Scientific Implications

VADER uncovers a population of sub-Jovian to Jovian planets at wide separations (10–100 AU), consistent with expectations from disk–planet interaction theory. The ability to yield probabilistic parameters from images, positions VADER as a useful tool to study and categorize newly forming disk–planet systems in the era of high-resolution ALMA imaging.

Impact Statement

This paper presents work whose goal is to advance the field of machine learning and its application to astrophysical inference. We introduce VADER, the first variational autoencoder framework capable of full uncertainty-aware parameter inference on protoplanetary disk observations. Our model can infer disk and planetary parameters in seconds, significantly accelerating analysis compared to traditional simulation-based pipelines. By enabling fast, probabilistic interpretation of high-resolution observations, VADER opens new avenues for population-level studies of planet formation.

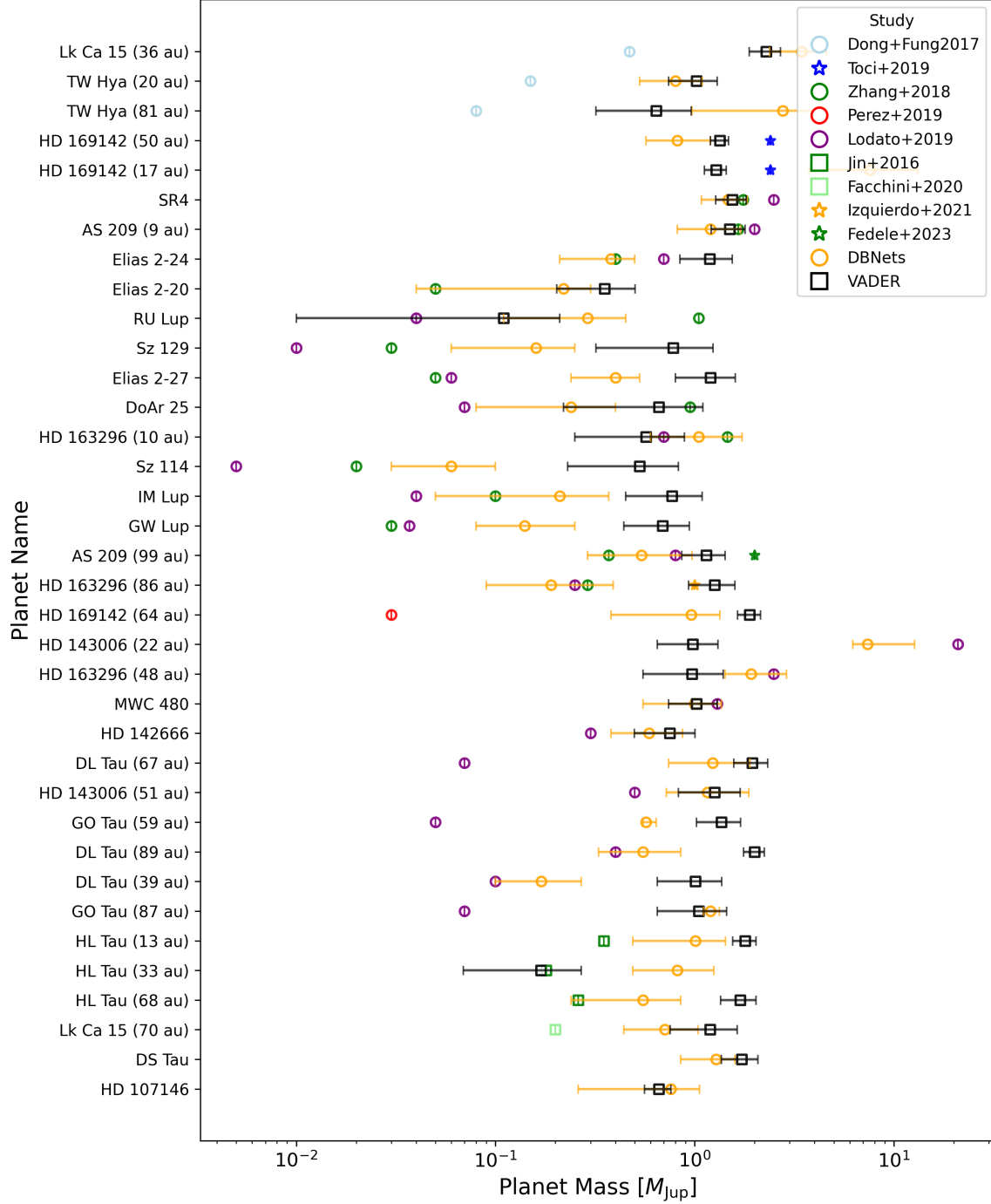


Figure 5. Comparison of predicted planet masses from our model with estimates from previous studies across different protoplanetary systems (Dong & Fung, 2017; Toci et al., 2019; Zhang et al., 2018; Pérez et al., 2019; Lodato et al., 2019; Jin et al., 2016; Facchini et al., 2020; Izquierdo et al., 2022; Fedele et al., 2018; Ruzza et al., 2024). The error bars indicate the uncertainty in mass predictions, with our VAE-based predictions shown in black squares. A key validation of our model is that many of its predicted masses are within 1σ of the values reported in prior studies, demonstrating strong agreement with independent analyses. Additionally, the predictions from DBNets (orange circles) are shown for reference, further supporting the consistency of our results.

In future applications, this framework can be extended to support multimodal astronomy by integrating heterogeneous observational inputs—including dust continuum maps, infrared emission, and CO gas velocity fields—into a unified latent space. Such a capability would enhance the fidelity of astrophysical inference by combining complementary constraints from diverse data sources.

Our method is designed for scientific use and does not involve human-related data or downstream decision-making systems. We do not foresee ethical risks or negative societal impacts arising from this work. Nonetheless, we encourage responsible deployment and transparent communication when using machine learning models for scientific discovery.

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