DEEP NEURAL NETWORK FOR PROTOPLANETARY DISK IMAGE (PPD) GENERATION

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Abstract

Observations of bright Proto-planetary Disks (PPDs) help in detection of exoplanets which are otherwise quite difficult to observe. The gaps in the PPDs help in inferring various information about the evolving nebulae. But even then, finding such structures across the vast cosmos itself is an arduous task. With the advent in machine learning, we now have the option to generate PPD images and study them. Currently with this ongoing project, we introduce a model to generate PPD images exploiting the power of machine learning. By training a deep neural network on a diverse set of disk-planet hydrodynamic simulations encompassing various planet masses, we've achieved rapid generation of diverse PPD images based on targeted labels, enabling image production within seconds. This innovative approach significantly reduces both time consumption and resource utilization. Additionally, our discussion touches on the network's adaptable nature, soon to incorporate additional input parameters and regression labels. Ultimately, this approach holds promise as an efficient alternative to laborious and resource-intensive hydrodynamic simulations.

1 Introduction

Protoplanetary disks, the birthplaces of planetary systems, are fundamental astrophysical objects that provide crucial insights into the process of planet formation. Understanding their structure and evolution is imperative for advancing our knowledge of planetary system formation and dynamics. The intricate interplay of physical processes within these disks shapes the evolution of planetary systems, making the study of protoplanetary disks a cornerstone of modern astrophysics. Observational techniques like ALMA (Atacama Large Millimetre/submillimetre Array) have significantly enhanced our ability to study these disks, providing high-resolution images. However, observational limitations, such as data incompleteness and noise, pose challenges in obtaining a comprehensive understanding of the underlying disk properties.

Traditionally, understanding the dynamics and properties of these disks has relied on sophisticated numerical simulations and complex analytical models. While these methods have provided invaluable insights, they often present significant computational challenges and can be computationally expensive. Furthermore, the interpretation of observational data from real protoplanetary disks demands advanced data analysis techniques.

In recent years, the field of astrophysics has witnessed a transformative shift, driven by the rapid advancements in deep learning and artificial intelligence. Deep Neural Networks (DNNs), a subset of machine learning, have emerged as powerful tools for addressing complex problems across various domains, including image analysis, natural language processing and even scientific research. In the realm of astrophysics, DNNs have demonstrated their potential to revolutionise our approach to studying protoplanetary disks.

This work explores the innovative application of DNNs to generate high-fidelity images of protoplanetary disks. By harnessing the representation-learning capabilities of neural networks, we aim to bridge the gap between theoretical models and observational data. Our approach makes use of the vast amount of synthetic data, generated from numerical simulations using the FARGO3D hydrodynamics code, empowering us to create realistic visualisations of protoplanetary disks.

The advantages of employing DNNs for this task are multifaceted. These networks have the capacity to learn complex patterns and structures from large datasets, enabling the synthesis of protoplanetary disk images that faithfully capture the diversity of observed disk morphologies.

1.1 Protoplanetary Disks - Cosmic Cradles of Planet Formation

Protoplanetary disks, often referred to as "nurseries of the cosmos," are extraordinary structures encapsulating the early stages of planetary systems' evolution. These disks are predominantly composed of gas and dust, remnants from the formation of the central star. Their formation arises from the conservation of angular momentum during the gravitational collapse of a molecular cloud core. As the collapsing cloud flattens and material moves towards the nascent star, a protoplanetary disk takes shape, exhibiting a characteristic flattened structure due to the conservation of angular momentum. This disk acts as a reservoir for the materials that will eventually coalesce into planets, moons, and other celestial bodies.

The study of protoplanetary disks is fundamentally crucial for various reasons. Firstly, they provide critical insights into the processes of planet formation and the conditions under which this occurs. Understanding the distribution of solids within these disks, their growth into planetesimals, and the subsequent formation of planets is paramount in comprehending the diversity of planetary systems in our galaxy and beyond. Moreover, these disks are rich in organic and inorganic compounds, providing a glimpse into the origins of life. The study of the organic molecules within protoplanetary disks sheds light on the potential for life's emergence in planetary systems.

1.2 Neural Networks - An Intelligent Lens for Probing Protoplanetary Disks

Neural networks, emulating the intricate architecture of the human brain, have emerged as formidable tools in the domain of astrophysics, particularly in the study and interpretation of protoplanetary disks. These computational models are constructed with layers of interconnected nodes, each layer extracting increasingly complex features from the input data. In the context of protoplanetary disks, neural networks play a transformative role in extracting intricate patterns and structures from observational data.

Convolutional Neural Networks (CNNs), a specialized class of neural networks, have demonstrated remarkable prowess in analyzing images of protoplanetary disks. They can detect intricate features like gaps, spiral arms, and asymmetries within the disks. By discerning these features, CNNs provide critical information about the disk's structure and dynamics, shedding light on the mechanisms that govern its evolution.

Furthermore, Generative Adversarial Networks (GANs) have shown promise in generating realistic protoplanetary disk images based on the learned features from observed data. This generative ability can significantly enhance our understanding of the diverse morphologies that protoplanetary disks can exhibit. By synthesizing new, plausible images, GANs enable researchers to explore a broader spectrum of possible disk configurations, aiding in the interpretation of observational data.

Incorporating these advanced machine learning techniques into protoplanetary disk research revolutionizes our capacity to decipher the underlying physics and morphology of these crucial astrophysical objects. The integration of neural networks equips astrophysicists with powerful tools to navigate and analyze the vast and intricate datasets garnered from various astronomical observations. These tools, in turn, propel our understanding of planetary system formation to new heights, enabling a more comprehensive grasp of our universe's fascinating evolution.

This work provides an in-depth exploration of the methodology behind training and utilising DNNs for protoplanetary disk image generation. We delve into the architectural choices, training strategies, and data augmentation techniques tailored to the unique challenges posed by astrophysical datasets. Additionally, we present the results of our experiments, showcasing the capabilities of our neural network models in reproducing realistic protoplanetary disk images.

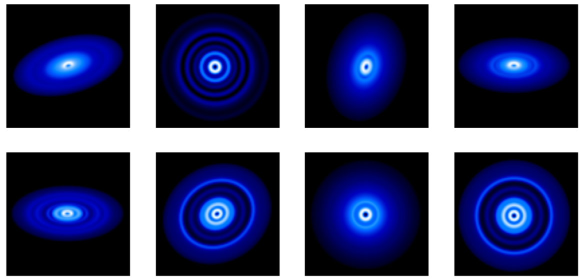

Figure 1: Synthetic Radiative Transfer images from 700 DPNNet2.0 simulations.

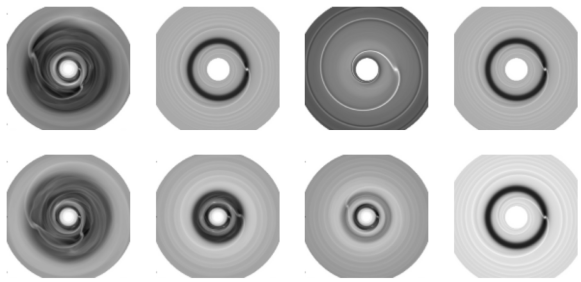

Figure 2: Synthetic Hydrodynamic simulation images.

2 Dataset

Throughout this work, various datasets have been used as per the requirement. All the datasets are obtained from the FARGO3D simulations.

- 105,000 synthetic Radiative Transfer (RT) images from 700 DPNNet2.0 simulations, varying the number of planets, planet mass, epsilon, alpha, aspect ratio, sigmaSlope, flaring index, etc..
- 1000+ synthetic test images with a fixed number of planets, varying planet mass and epsilon.
- 1,000+ synthetic hydrodynamic simulation images with number of planets varying between 1 and 3, varying planet mass, epsilon and alpha.

3 Methodology

We have explored various types of DNNs to read the dataset in different ways to achieve our task. The three main explorations are elaborated in the following sections.

3.1 Variational Auto-encoder

In the pursuit of generating realistic protoplanetary disk images, Variational Autoencoders (VAEs) emerge as a pivotal tool within the domain of deep learning. VAEs, an extension of traditional autoencoders, redefine the approach to studying these celestial objects. By introducing a probabilistic framework to the latent-space, VAEs enable the creation of continuous, structured representations of protoplanetary disk images. The probabilistic nature of VAEs empowers the model to capture intricate patterns and nuances present in the observed data. Unlike deterministic autoencoders, VAEs map input data to probability distributions, allowing for efficient sampling within the latent space. This unique capability facilitates the generation of diverse and novel protoplanetary disk images, enriching our understanding of their varied morphologies and underlying physical processes. In this research, we delve into the transformative impact of VAEs on the generation and analysis of protoplanetary disk images, presenting insights and outcomes that significantly advance the field of astrophysical image synthesis.

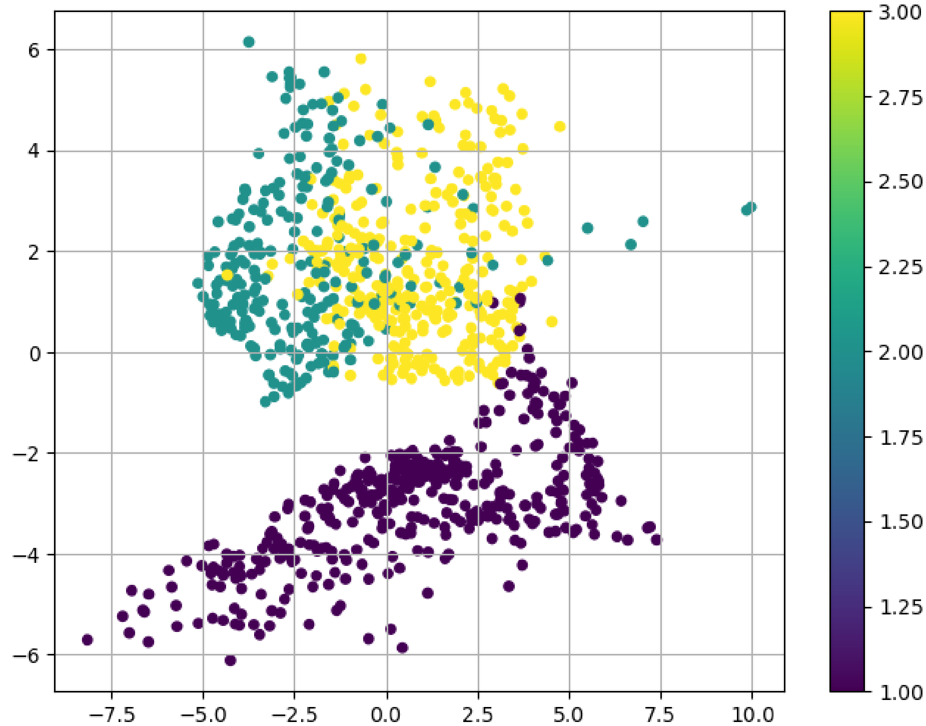

Figure 3: Plotting latent space according to number of planets, 1-planet(violet), 2-planets(greenish blue) and 3-planets(yellow).

3.1.1 Training

The goal with the CVAE was to observe the latent space and check if the network is able to clearly differentiate between different types of images, given our training data is limited.

1. We first load 1228 synthetic hydrodynamic simulation PPD images, with varying planet mass and epsilon.
2. The labels are set for conditioning, 1-2-3 corresponding to the number of planets.
3. The image dataset along with the labels is then shuffled and split into training and testing sets.
4. The neural network is then created, with the definition of loss function and the encoder and the decoder having the necessary dense layers and convolutional layers.
5. The network is trained for 1000 epochs, making sure that there is no overfitting.
6. The latent dimension plot is obtained.

3.1.2 CVAE Results

We hence can observe that given the provided labels, the CVAE network is successful in its attempt to classify images with varying physical parameters. The latent space was observed to distinctly form three separate clusters corresponding to three separate types of images. The clusters had a distribution spread, which is expected because the images had other varying parameters as well, like planet mass and alpha. The points on the latent space signified the various dataset images, and their positions correspond to the closeness of latent variables.

The next task is to be able to generate new images of PPDs. For this, we employ a different architecture.

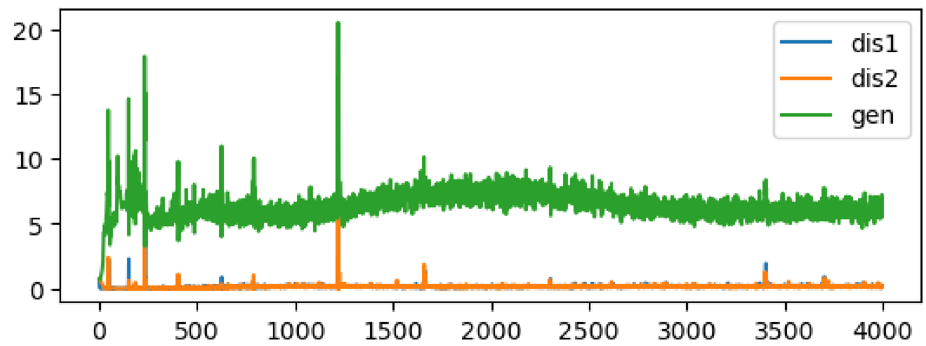

Figure 4: Discriminator and Generator losses, over 500 epochs with 8 batch-iterations in each epoch.

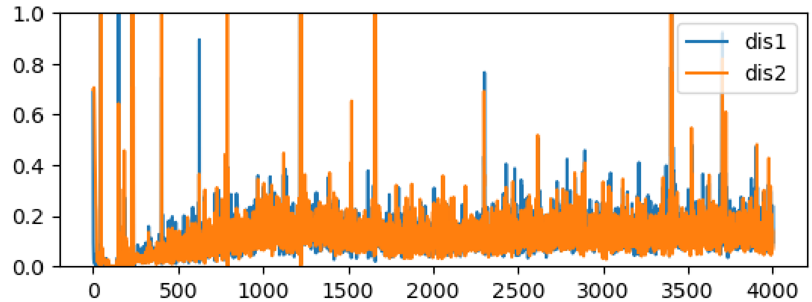

Figure 5: Discriminator loss for real (blue) and fake (orange) images, over 500 epochs with 8 batch-iterations in each epoch.

3.2 Generative Adversarial Network

Generative Adversarial Networks (GANs) represent a revolutionary framework in machine learning, devised by Ian Goodfellow in 2014. GANs consist of two neural networks, the generator and the discriminator, engaged in a competitive game. The generator creates synthetic data, aiming to produce samples that resemble real data, while the discriminator evaluates whether the generated data is authentic or fake. Through this adversarial process, GANs learn to generate highly realistic data that mirrors the original dataset's distribution.

On the other hand, Conditional Generative Adversarial Networks (CGANs) extend the GAN framework by incorporating additional information, such as class labels or specific features, into both the generator and discriminator. This additional conditioning enables CGANs to generate data samples conditioned on specific attributes or classes, adding a new dimension of control and specificity to the generated outputs.

3.2.1 Training

The goal with the CGAN is to generate new PPD images which we may use to further study the disks. The initial data-loading process remains quite similar to that in CVAE.

1. We first load 1228 synthetic hydrodynamic simulation PPD images, with varying planet mass and epsilon.
2. The labels are set for conditioning, 1-2-3 corresponding to the number of planets.
3. The image dataset along with the labels is then shuffled. We have no need of splitting the dataset into training and testing this time, we want to maximize our training dataset.
4. The discriminator and the generator blocks were defined to fit the purpose of our task, and provisions were kept to supply the labels.

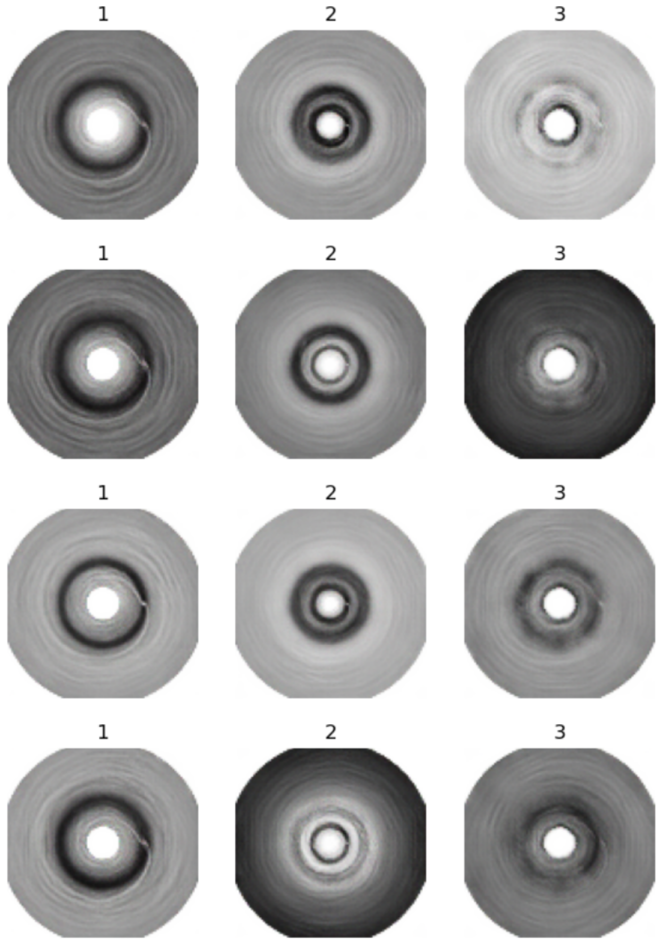

Figure 6: CGAN trained with number of planets as labels, 1-planet(left), 2-planets(centre) and 3-planets(right).

5. The blocks are then connected and their abilities to get updated and trained were further modified, thereby completing the entire CGAN network.

6. The network is then trained for 500 epochs, making sure that there the network stays stable overtime.

7. Having been trained, the model is then saved.

8. The generator block is then invoked to sample some random latent points and generate new PPD images.

3.2.2 CGAN Results

After a painstaking process of trial and error, we were finally able to have a CGAN network which was stable, and was able to give us the desired result. The learning rates and batch size were changed to observe their effects on the network, since proper implementation of CGANs requires careful selection of hyper-parameters and proper parameter initialization, failure results in non-convergence or mode-collapse.

The final result obtained clearly depicts the planet numbers in the images, with a single ring corresponding to 1-planet PPD image and 2 rings corresponding to 2-planet PPD image. The images for 3 planets are a bit unclear, which of course would correspond to the fact that we had limited data to work with on such a complicated stellar phenomenon.

4 Discussion

The key to a good model is a comprehensive dataset that reflects the underlying connection between the input labels and the output images. This necessitates the inclusion of data that incorporate not only a broad parameter space but also capture the diverse disk morphologies due to disk–planet interaction. However, as the initial step in project, we have only explored a limited range, due to finite resources. This restricts the scope of our network and its applications, as discussed below.

4.1 Practical Applications

The CVAE network is able to read a large dataset and tell us about how closely the various images are, by training itself to detect the latent variables. And the network wonderfully captures the latent space! But beyond that, the network is not doing much. It is a simple network to test the validity of a dataset and check if the hidden features, which are indistinguishable to the naked eye, are even significant enough or not.

4.2 Network Limitations

The CGAN a network which is quite good at providing us with various images corresponding to different labels (planet mass). But the network suffers from lack of dataset, therefore encountering unstable training process. Mode collapse has been a strong adversary to this adversarial network, and we had to put in a lot of effort in finding the right combination by varying the hyper-parameters to get the network working. Even then, the network might again face the same challenge when working with a smaller dataset or a completely different dataset altogether.

The conventional datasets available to check such complex networks are very large, consisting of thousands of images. To get the network working on such a small dataset and produce these wonderful images reflecting the latent variables was a wonderful achievement for us!

5 Conclusion

To encapsulate the project's vision, the objective extends beyond merely producing new PPD images. Instead, our ambition is to forge an adept model that, when presented with requisite inputs—such as planetary data, epsilon, alpha-index, and more—can swiftly generate a solitary image reflecting the specified conditions. Although current methods utilize cluster computing for highly accurate simulations based on diverse physical parameters, these processes are laborious and demand substantial resources. Simulating such images often spans hours, if not days. Our ultimate aim is to harness the potency of machine learning to craft a model capable of performing this task within mere seconds.

Adapting existing CGANs, primarily designed for categorical conditions like class labels, requires a recalibration. We are tailoring these frameworks to be conditioned on regression (continuous) labels, which poses distinct mathematical challenges. This adaptation is crucial as planetary masses span a continuum, necessitating a latent space that aligns seamlessly with regression-based labels for accurate outcomes. However, this adjustment presents its own complexities, notably the scarcity (or even absence) of real images for certain regression labels. This poses challenges in minimizing empirical versions of CGAN losses. Additionally, the nature of scalar and infinite regression labels renders conventional label input methodologies inapplicable, demanding a novel approach.

Our ongoing efforts revolve around reformulating loss functions to address continuous labels and integrate regression labels into both the generator and discriminator. Also, adapting both the entities to process multiple label inputs corresponding to varied input parameters is a current focus.

The optimism within our endeavor stems from the pursuit of an efficient, time-saving model characterized by a multi-dimensional latent space, which can generate unique and accurate images from points within this space, based on a spectrum of input parameters. Improved and new physics can be accommodated by adding more variables to the training set, as far as the neural network is concerned. Soon, with the aforementioned modifications, we will potentially make the model versatile enough to entirely replace hydrodynamical simulations for observers and modelers.