**Motivation**

Generative models have had great success in commercially with generative models such as DALL-E and midjourney, and have been successful in fields such as image, video, text, and sound generation. Furthermore, machine learning methods have been applied in various fields, topics, and applications in different sciences. However, the most common purpose of machine learning model utilization in sciences has been classification and prediction tasks. In “hard sciences”, such as physics, cosmology, chemistry, biology and others, generative models have not had the same progress and achievements. The data in these fields have different and more complex structures and patterns, which indicates that it is a challenging task to apply generative models to these fields. However, in many of these science fields, generative model can have a great impact on efficiency and progression. Robles et al. (2019, 2022) [2, 3] applied generative models to the cosmological problem of simulating and creating halo merger trees. With the rapidly advancing field of generative models in machine learning, the potential of utilizing such ideas in hard sciences should be explored and improved. My intention is to develop the achievements of Robles et al. (2019, 2022) [2, 3] and improve their results in halo merger tree generation by utilizing a different generative approach.

In modern galaxy formation theory, halo merger trees have a central role, especially as a main component of SAMs. SAMs role is in galaxy formation theory is significant because its predictions is necessary to understand the fundamentals of central processes which could possibly imprint observational features on galaxies. New approaching methods in observational practices require consistent and robust predictions from SAMs. Furthermore, reliable and stable evolution of the galaxies in SAMs require information of regarding the mass assembly history of the dark matter haloes that host the galaxies. SAMs depend on halo merger trees, because they provide exactly that. Well-constructed, realistic and consistent merger trees and precise halo identification are both necessities for SAMs. [2] [3]

Being able to simulate, generate, and construct well-constructed halo merger trees are an important contribution to the field of galaxy formation and evolution in astrophysical and cosmology because SAMs rely on robust halo merger trees, and SAMs are the best option for comparing theoretical predictions with galaxy investigations. [2] SAMs are the most reliable option due to their flexibility to investigate physical phenomena computationally inexpensively in various dissimilar methods. [139], [138], [137], [136], [135], [134], [133], [132], [131], [130], [124] [2]. Additionally, SAMs have the ability to simulate large cosmological volumes while they manage to describe the galaxy formation and evolution processes more straightforward. [2] [3]

[2] and [3] managed to produce a new tool for halo merger tree construction using machine learning, more specifically image generation, using a GAN model and with it opened up for the possibility of employing machine learning methods in the specific field. Developing their framework further, utilizing more complex, efficient, or different models or architectures have the possibility to provide improved and more consistent and well-constructed halo merger trees that can be utilized by SAMs and therefore understand push the understanding of galaxy formation and the nature of processes evolving galaxy formations.

Two important questions to ask regarding the development of the methods proposed by [2] and [3] is if GANs are the best option for this specific task, and if not, what is the best option or a natural next step?

To answer the first question, regular GANs [7] was for long the state-of-the art in image generation (synthesis) [31, 36, 33]. However, in recent years the image synthesis field have developed rapidly with new models and architectures. Simple GANs have been outdated by more complex models like diffusion models, transformer based generative models, and combination of GANs and other models [35, 24, 34]. Additionally, the drawbacks of GANs makes them notoriously hard to train to convergence without mode collapse [30, 31]. As a results, a lot of effort has been completed to accomplish SOTA GAN-like generative sample quality with likelihood-based models [35,13, 34, 32].

Reasonably enough, [2] used a GAN model since it was the SOTA generative model back then [31, 36, 33]. Models like Diffusion models didn’t take off until later (2020) after Song et al. (2019) [100], Ho et al. (2020) [13], Song et al (2021) [14], Nichol & Dharwial (2021) [10, 24] and other papers was published which gave the model traction. A lot have happened in the field of generative models in recent years with the introduction and integration of AI, specifically generative pretrained transformers (GPTs) and their image generation model DALL-E and other image generation models like Midjourney, which uses stable diffusion.

A natural next step from the models proposed by [2] are diffusion-based models, because they don’t have an issue with convergence in training, and they have been reported to perform better than GANs on image synthesis tasks in terms of quality and diversity in the generated samples [10, 24, 34]. Advantages of diffusion models compared to GANs are many [10, 24, 34, 35]. However, one downside of diffusion models is the sampling speed, which is very slow [4, 10, 14]. On the other side, sampling speed might be a decent tradeoff if the model manages to compute well-constructed, realistic and robust halo merger trees which can be utilized by SAMs.

Other aspects from [2] and [3] which might be interesting to develop their halo merger tree criteria to compare and test the quality of constructed merger trees. In other words, extend and improve the criteria proposed by [2] and [3] to create a robust set of evaluation criteria for evaluating the quality and consistency of constructed halo merger trees.