Discovering the structure of our Milky Way Galaxy is essential for understanding its formation and evolution in the context of other galaxies. Our position buried within the disk of the MW, however, makes this extraordinarily difficult. While there is some consensus on the overall structure of the MW, there remains little agreement on the details of what many 3-D structures in the Galaxy actually look like, such as the galaxy's spiral arms. Spiral arms are locations where new stars form from dense clouds of gas, and therefore can be traced by studying the distribution of interstellar gas. Since dust is produced primarily by young stars, it can serve as an effective tracer of interstellar gas. Our project aims to create a smooth 3D distribution of dust using machine learning methods to get a more accurate understanding of our Galactic structure.

Neural networks (NN), as a subset of machine learning, are complex deep learning algorithms that are profound in their ability to recognize patterns such as dust distribution. For our problem, NNs rely on dust data, measured through its effects on the light we see from other stars, to learn and improve their accuracy over time. Once these learning algorithms are fine-tuned for accuracy they become powerful tools, allowing us to predict dust for locations with no observed data. We built and modified several NN architectures to improve performance based on the physics involved in our problem. This included tweaking their design to add a physical constraint that enforces the network to predict non-decreasing accumulated dust further along the line of sight from a reference point. Using simulated data, we demonstrated our NN predictions were on the right track in terms of accuracy but still had room to improve (figure 1).

There are many potential areas where we plan to continue to explore and improve on! We hope to explore new NN architectures to improve performance. In addition, we want to expand our results to better account for noise present in real dust data and we have to be certain that the NN architecture is able to detect and account for this noise. Finally, we hope to apply our methods to real astronomical data in nearby, well-studied molecular clouds to see how our results compare with previous work. Progress on this project can be found here: [github.com/avaove/dust-map](https://github.com/avaove/dust-map)

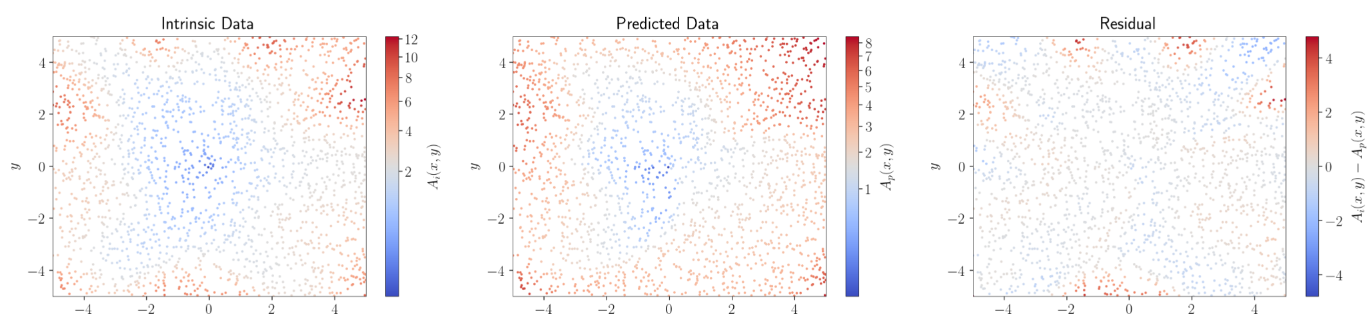


Figure 1: A comparison of how well one of our neural network architectures is able to reproduce simulated observations of accumulated dust, with the intrinsic data shown on the left, the neural network predictions in the middle, and the difference between the two on the right.