Building the Next Generation of 3D Dust Maps

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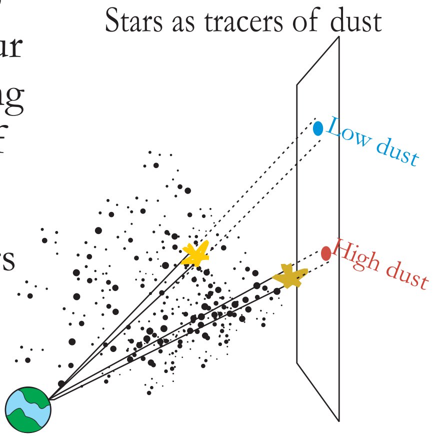
Why Dust?

Generating 3D dust maps can help us get a better understanding of our galactic structure as there is a strong correlation between the location of dust and location of gas.

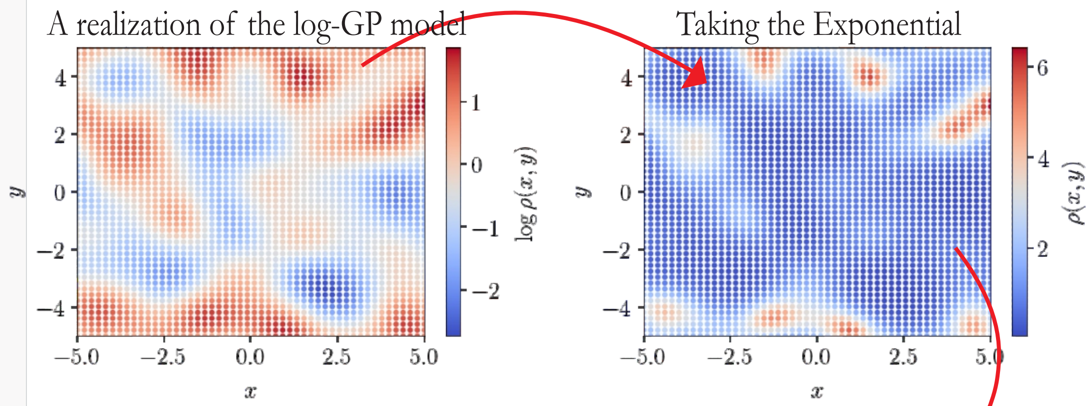
Through using stars as noisy tracers of integrated dust, we attempt at creating smooth dust maps using machine learning methodologies.

(Leike & EnBlin, 2019)

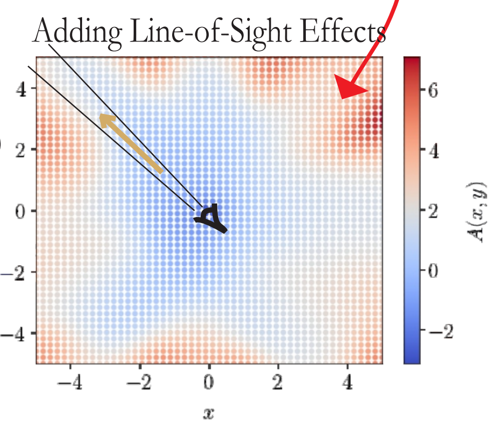


Simulated Data Generation

The baseline model for our data simulation is the logarithm of the dust density log p(X) as a function of position X distributed following a Gaussian Process (GP). Our data simulation is then a random realization of the log-GP model.



We integrate dust along each sightline from a reference point. This is **dust attenuation**, A(x, y) the net dust from the ref point to each position.

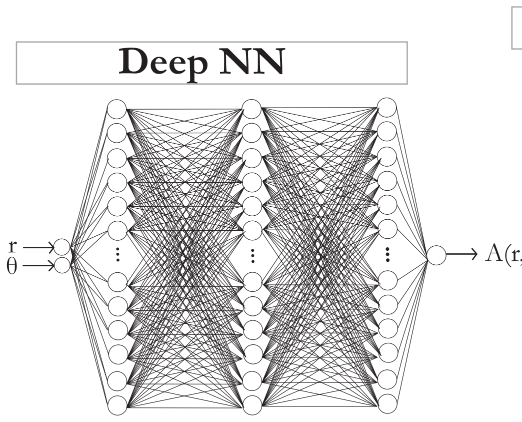


Attenuation is **non-decreasing** along each sightline.

ML Methodologies: Designing Neural Networks (NN)

We randomly select 6k positions from the simulated map as our **training set**, a set of all data available to fit our ML models. We compare two neural network models.

Deep NN

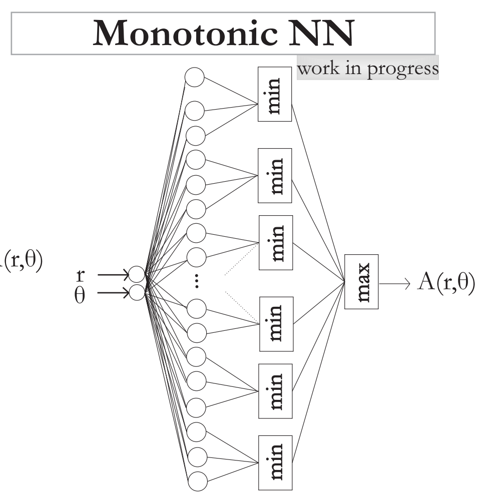


☹ Decreasing dust along sightline allowed

- 3 hidden layers, deep model

Monotonic NN

work in progress



☺ Predicted dust along sightline is nondecreasing

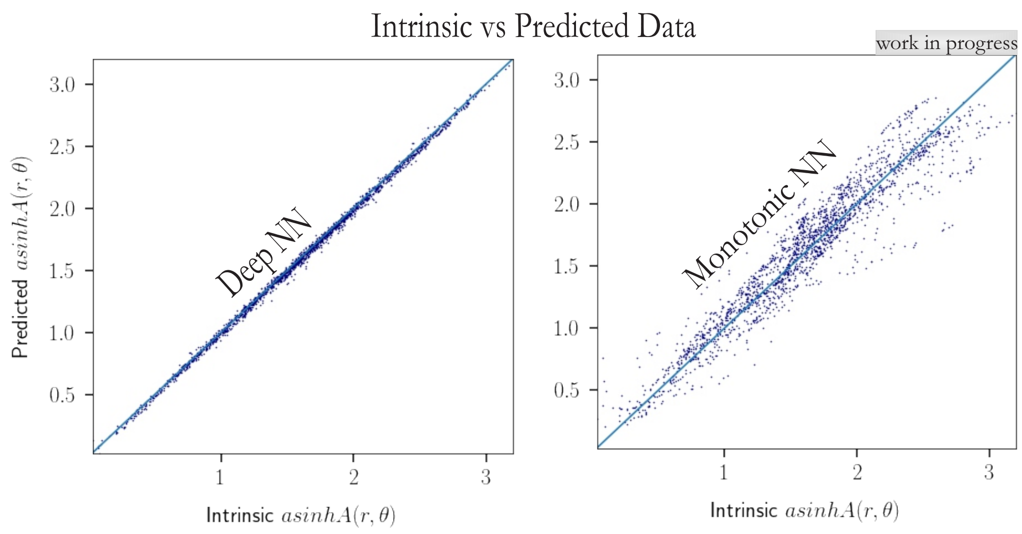
- 1 hidden layer, wide model
- Has a min and a max layer

(Daniels & Velikova, 2010)

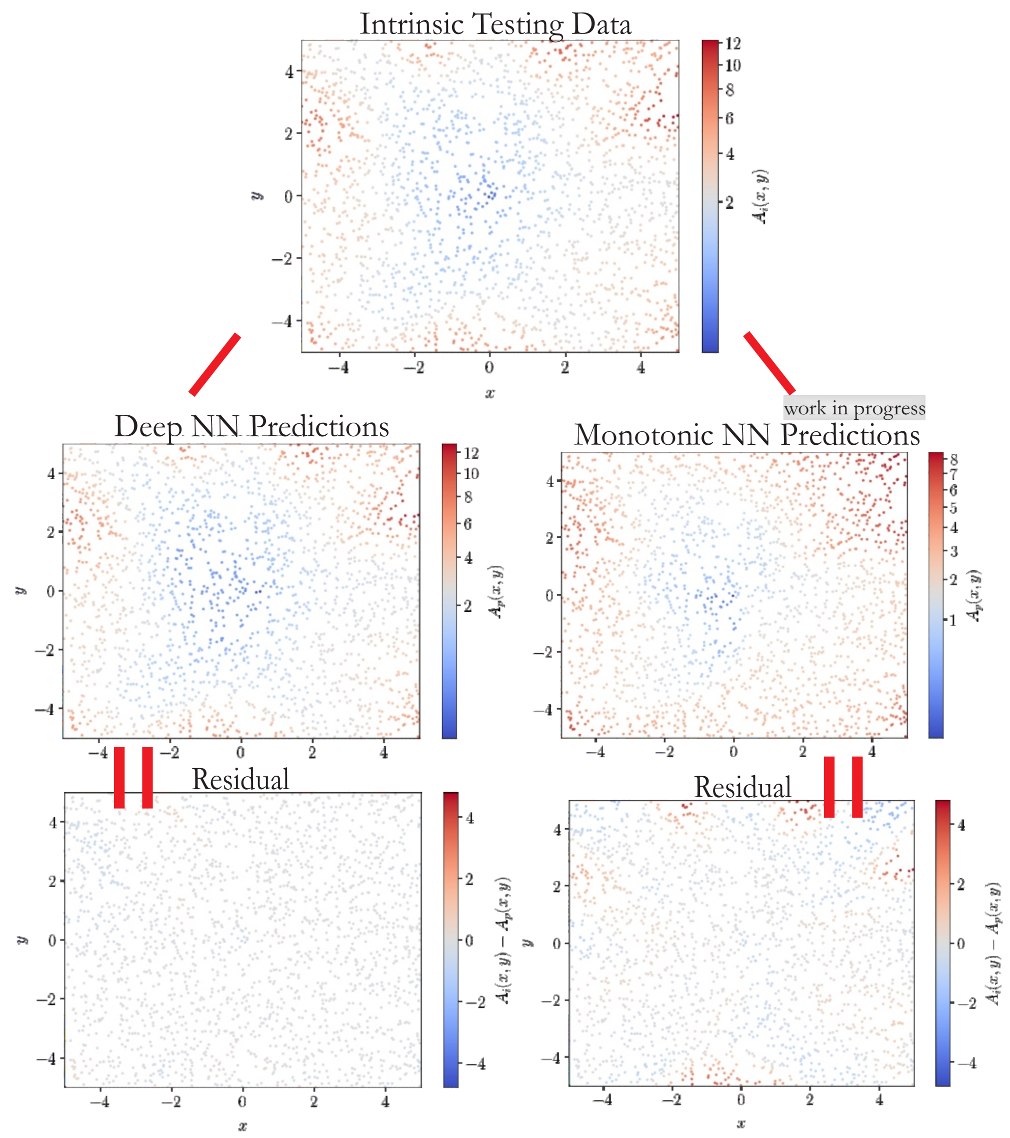
Testing Model Predictions

We randomly select 6k X positions independent of the training set from the simulated map as our testing set. Using both trained models we get predictions of dust attenuation A(r, θ) for each datapoint.

We show the accuracy of the final predictions compared with the intrinsic attenuation of the testing data.



We also compare the intrinsic attenuation data with the predictions by subtracting them and getting the residual.



Learn more?

Notebook and code:
github.com/avaove/dust-map

Next Steps?

Applying models on real astronomical data

Upgrading models and maps to incorporate 3D positions

Improving monotonic NN performance

Incorporating errors in distance r and A(r,θ)

Comparing results with previous ML methods to create dust maps

References
Daniels, H., & Velikova, M. (2010). Monotone and Partially Monotone Neural Networks. IEEE Transactions on Neural Networks, 21(6), 906–917. https://doi.org/10.1109/tnn.2010.2044803
Leike, R. H., & Enßlin, T. A. (2019). Charting nearby dust clouds using Gaia data only. Astronomy & Astrophysics, 631, A32. https://doi.org/10.1051/0004-6361/201935093