Geometric Deep Learning

for Radio Astronomy Project Proposal

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Introduction

Why Geometric Deep Learning?

We want to leverage the power of multibeam setup to accelerate the area of searches.

Deep Learning techniques promises advanced pattern recognition for complex relationships and we suspect potential in assisting detection pipelines

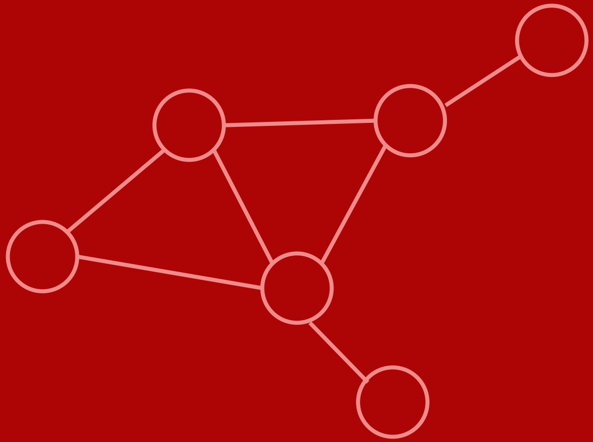
Classical deep learning approaches struggle to leverage arbitrary geometric structures in inference.

Geometric deep learning implements a graph based neural network that we believe could tackle this problem.

As from what we know, this has never been applied to multibeam radio astronomy data.

Building Intuition

Why are Graph Based models powerful?



Graph models can take input data of arbitrary structures by makes ZERO assumptions on spatial configurations yet still leveraging these structures to make inferences.

Unlike convolution ops., here data is only aggregated through rigid grid like pattern of a kernel, graphs allows an arbitrary flow of information to aggregate data.

This means regardless of the spatial pattern of beams formed in the sky, Graph based DL models can take full advantage of the spatial information in a FOV to make inference. Which we know is a highly important metric in rejecting RFI.

Timeline?

Scope of Project

Project involves two main components: **Simulation, Brainstorming approach** and **Model Development**

Simulation: We have limited amount of real observation data. We need to figure out how to realistically augment existing data and characterize our events [2 months?]

Model Development: After assessing different approaches, dedicate time to engineering the model. [2 months]

Brainstorming approach: With the problem at hand, not all Geo. DL methods will work. How do we best leverage existing resources
[1 month]

Infrastructure

Technologies Used

We'd want to move to more "cutting edge" infrastructure and development. Move workload on **GCP** instances ideally training with the new **A100 GPU**'s inside singularity containers.

Software usage - move away from Keras and Tensorflow and move towards **JAX**'s and autodiff libraries for high performance DL. JAXs allows for more custom development and are used by companies like Google and DeepMind. Will require a learning curve but worth the time commitment. If plan fails - move to **PyTorch** as backup.

Results

Deliverables

Two potential result:

1. We'd have a ready to deploy model for **MeerKAT SETI work.** HOWEVER, building a pipeline and integrating with the pipeline would be out of the scope for this timeline.

2. We'd have a pure ML project that can be written into a paper for pure ML journals. Less astronomy focus and more signal processing / ML focus [potentially] We can target **Neurips** or **ICML** conferences