

**MACHINE LEARNING
FOR ASTROPHYSICS**
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ML Methods For Space Debris Detection in Bistatic Radar Data

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Science & Technology

Outline

1. Scientific Motivation
2. BIRALES: Current Setup & MSDS Detector
3. Dataset: Curation & Preparation
4. Model Selection
5. Preliminary Results
6. Next Steps & Future Work

Scientific Motivation

Scientific Motivation

Tracking Resident Space Objects (RSOs)

- Since the launch of the first satellite in 1957, the near-earth population has been increasingly steadily.
- As the satellite population grew, so did the population of orbital debris.
- **Monitoring RSOs** has become ever more important in order to reduce the risk of a collision.
- Measurements provide us with a deeper understanding of the current environment, including **growth trends and accumulation regions**.
- Ground-based radars play a critical role in space debris monitoring and space situational awareness (SSA) programs.

BIRALES

Current Setup & MSDS Detector

Bistatic Radar for LEO Survey

Current Setup



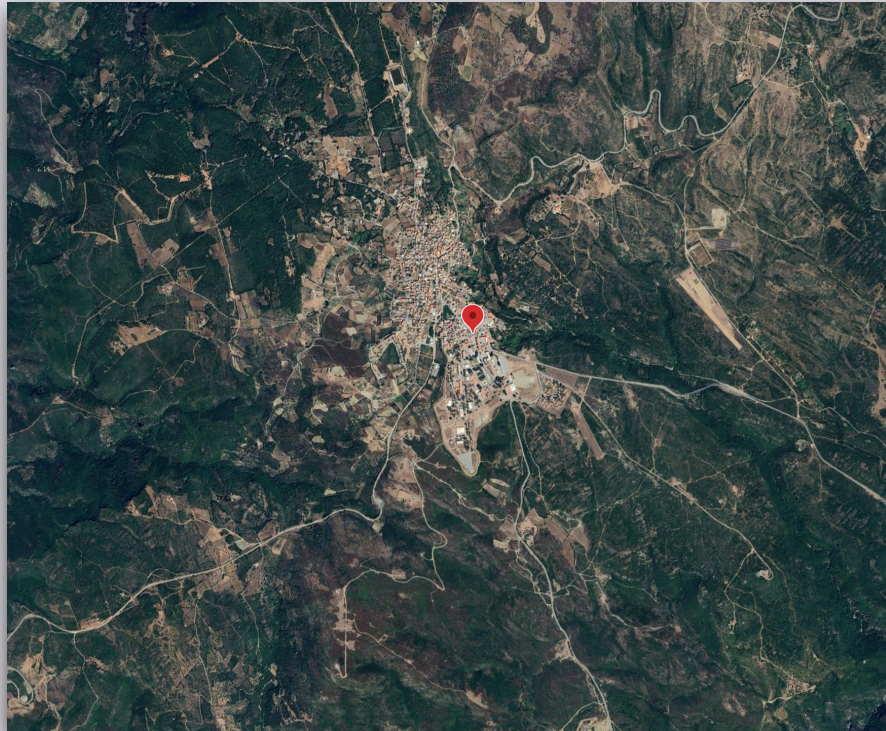
Bistatic Radar for LEO Survey

Current Setup

- 2 Modes: unmodulated Continuous Wave mode & a Compressed Chirp mode
- Sensitivity: small objects with a size of 10 cm at 1,000 km
- Transmitter
 - Diameter 7 m
 - Maximum Power 10 kW
 - Bandwidth 410–415 MHz
 - Beam Size 6 degrees

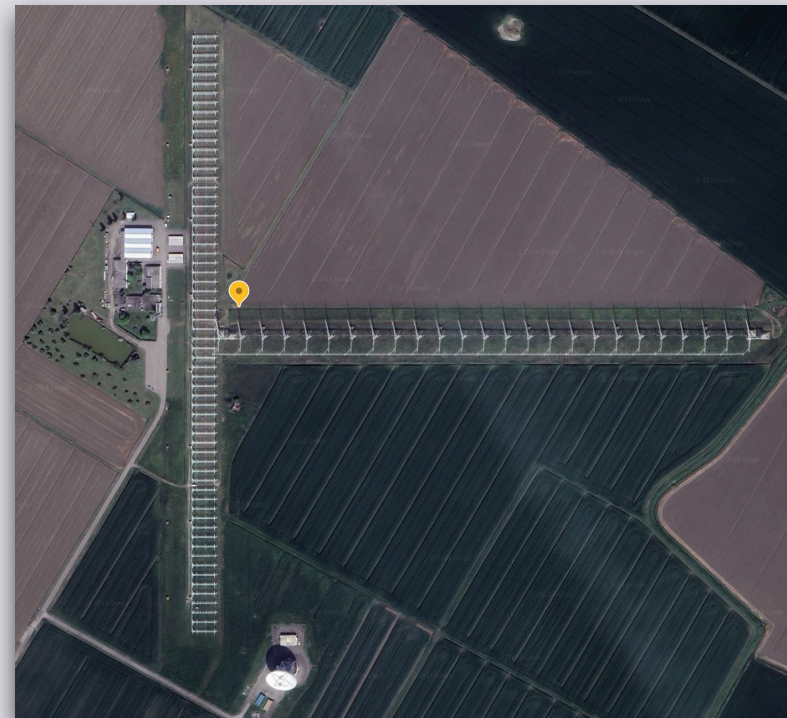
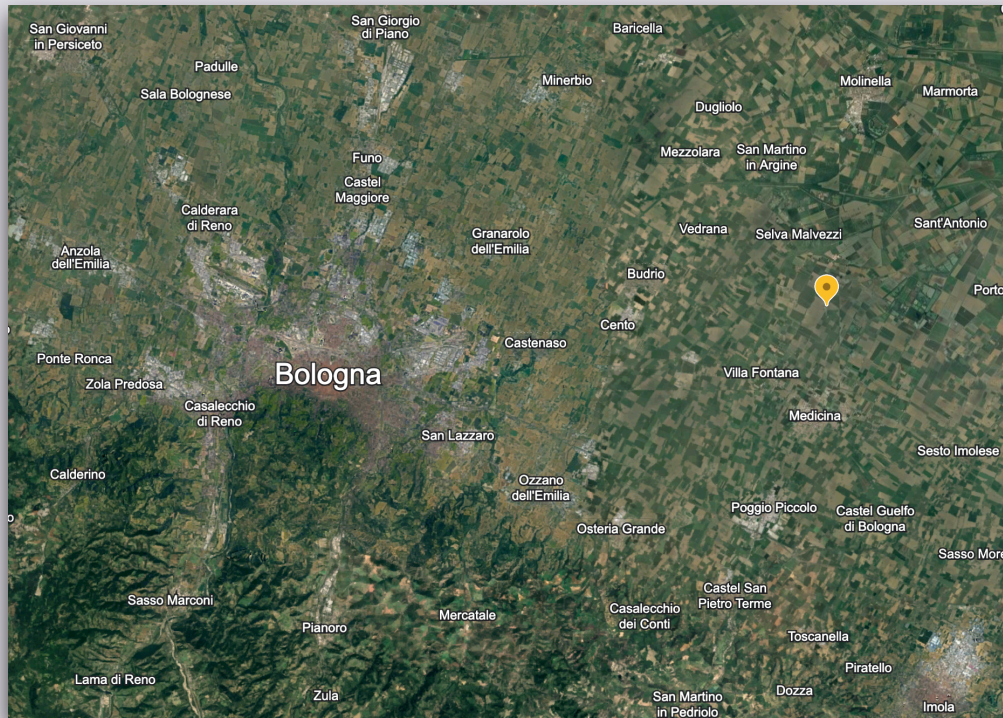
Bistatic Radar for LEO Survey

Transmitter



Blstatic Radar for LEO Survey

Receiver: The Northern Cross



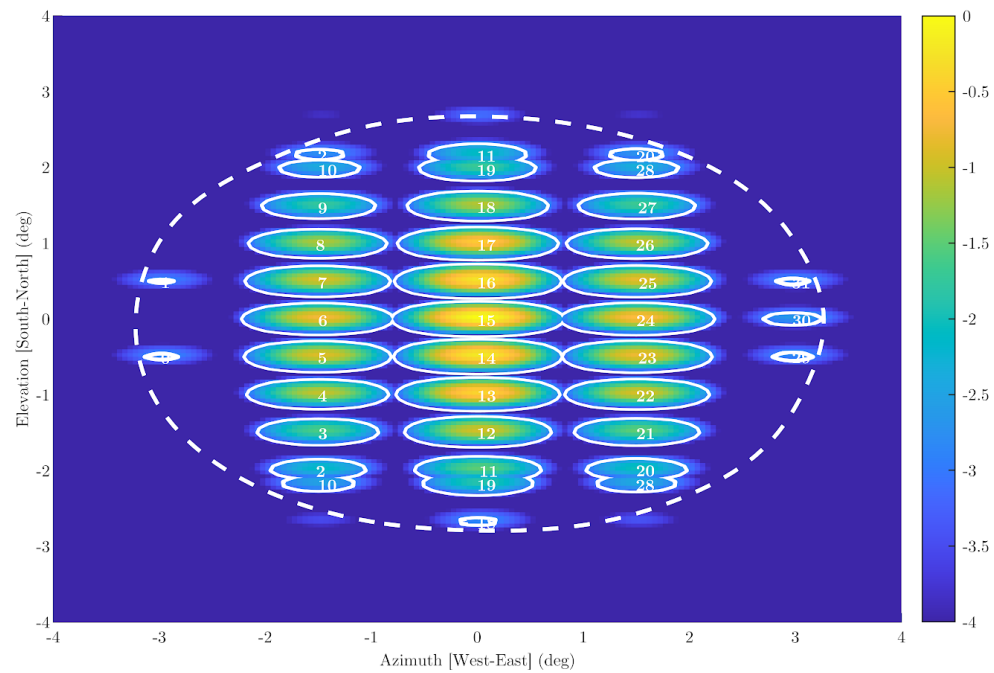
Blstatic Radar for LEO Survey

The Northern Cross

- T-shape array operating at the 408 MHz
- Steerable in declination only.
- The E-W arm is a 564 by 29.4m cylindrical parabolic reflector having a total collecting area of 1,600 m².
- The N-S arm is composed of 64 parallel parabolic-shaped cylindrical antennas (22.6 by 7.5 m) spaced 10 m apart having a total geometrical area of 10,800 m².
- As part of the Square Kilometre Array Design Studies, 32 receivers in 8 cylinders were upgraded to use new analog fibre-optic and coaxial digital links

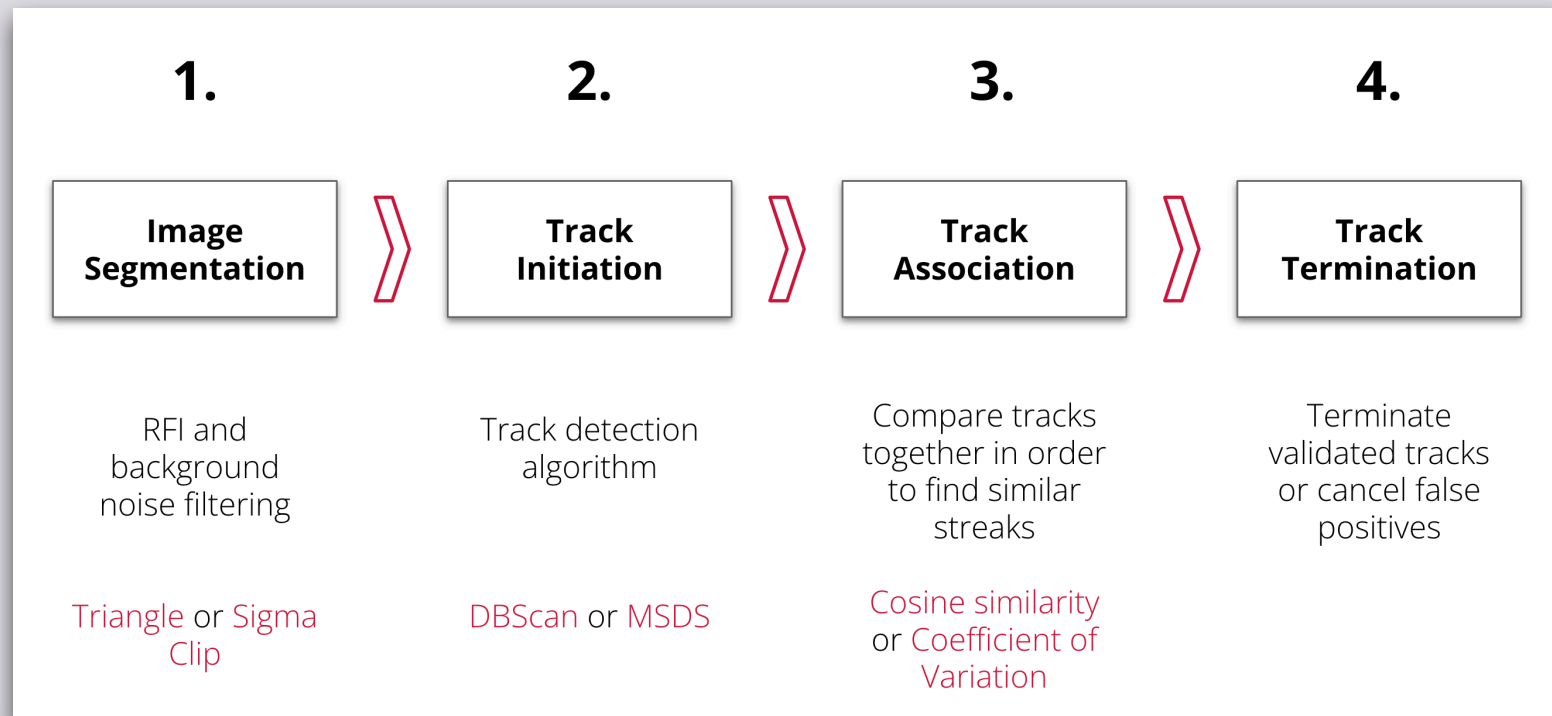
Blstatic Radar for LEO Survey

Multi-Pixel Beam Mapping



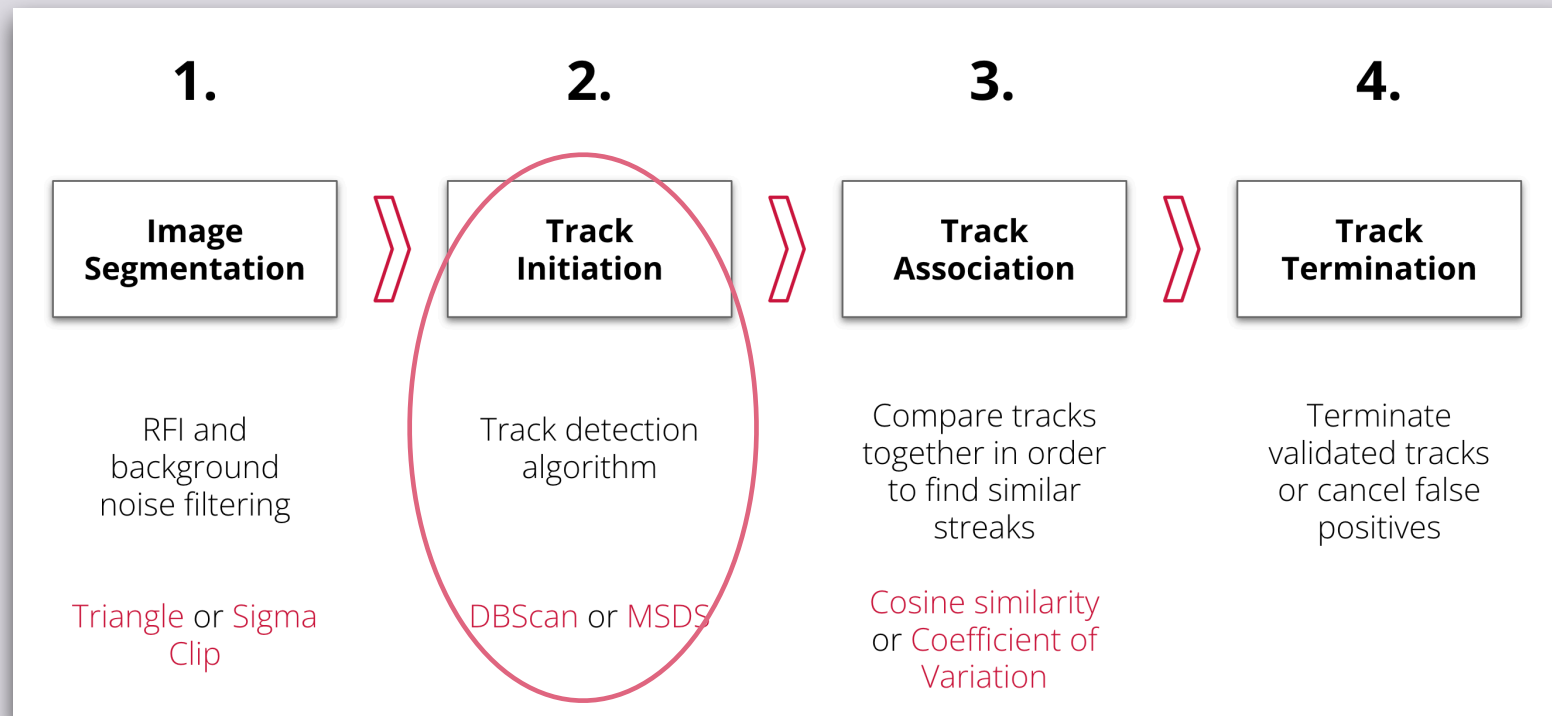
Blstatic Radar for LEO Survey

Detector Pipeline



Blstatic Radar for LEO Survey

Detector Pipeline



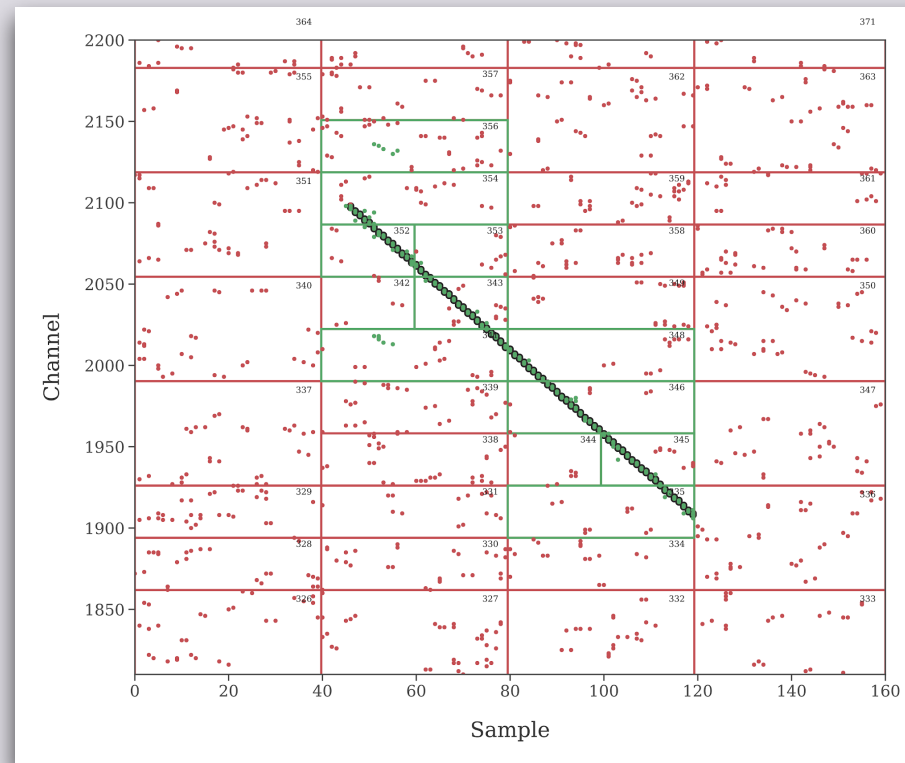
Blstatic Radar for LEO Survey

MSDS Detector

- The current pipeline uses a clustering approach
- Sub-divides the de-noised domain in rectangular boxes using kd binary tree.
 - Each rectangle is further split along an axis (vertical or horizontal) recursively until the number of points within the rectangle reaches a predefined leaf size.
 - Each leaf is checked for a line streak using an Agglomerative hierarchical clustering algorithm.
 - The similarity between clusters is determined, penalising two points whose gradient is not within the expected range.
 - Cluster's shape is checked for linearity using the inertia ratio. In this formulation, an inertia ratio of 1 indicates a circle while a perfect line has an value of 0.
 - The next stage is to correctly merge the individual clusters detected across the leaves into a single larger track.

Blstatic Radar for LEO Survey

MSDS Detector



Cutajar et al (2022)

Blstatic Radar for LEO Survey

Planned Expansion

- An upgrade is scheduled for the BIRALES receiver in Medicina
 - Slated for 2025
- Number of antennas will increase drastically (32 antennas → 684 antennas)
- Sensitivity will increase ~30 times
- Beam will be larger
- Expected Data Rate will mean MSDS will not be able to keep up in real-time.

Dataset

Curation & Preparation

Building a Dataset for the Model

Data Collection & Curation

- Data acquired from the BIRALES archive.
- ~100 Observations, (~7% Tracking Observations, ~93% Survey Observations) from April to November 2023
- Every observation was labelled using the offline detection pipeline already installed in Medicina.
- The MSDS algorithm was used to label the data by providing the channel/sample values of all detected streaks for each beam. It serves as the current benchmark with which the new algorithms will be compared against.

Building a Dataset for the Model

Data Preparation

- From the collated detections for every observation, the data was prepared as follows:
 - As a general format, all beams were tiled as 1024×1024 images, normalised as grayscale images.
 - Will need further tiling prior to being fed to specific models to avoid resizing.
 - Data Augmentation to further increase the number of annotated images was done by taking randomly shifted tiles across the face of the beam.
 - If any annotations are present within a tile, values are converted
 - time sample and receiver frequency → pixel coordinates
 - COCO format was used for all image, annotations, and category mapping

Building a Dataset for the Model

Data Preparation

- To avoid introducing systematics and ensure that the training, validation and test sets are balanced, stratified shuffle splitting was done based on:
 - Beam
 - ratio of single/multiple annotations
 - Maximum Raw Power prior to normalisation, stratified by interquartile range bins.
 - Maximum Width of annotations in image, stratified by interquartile range bins.

Building a Dataset for the Model

Data Preparation

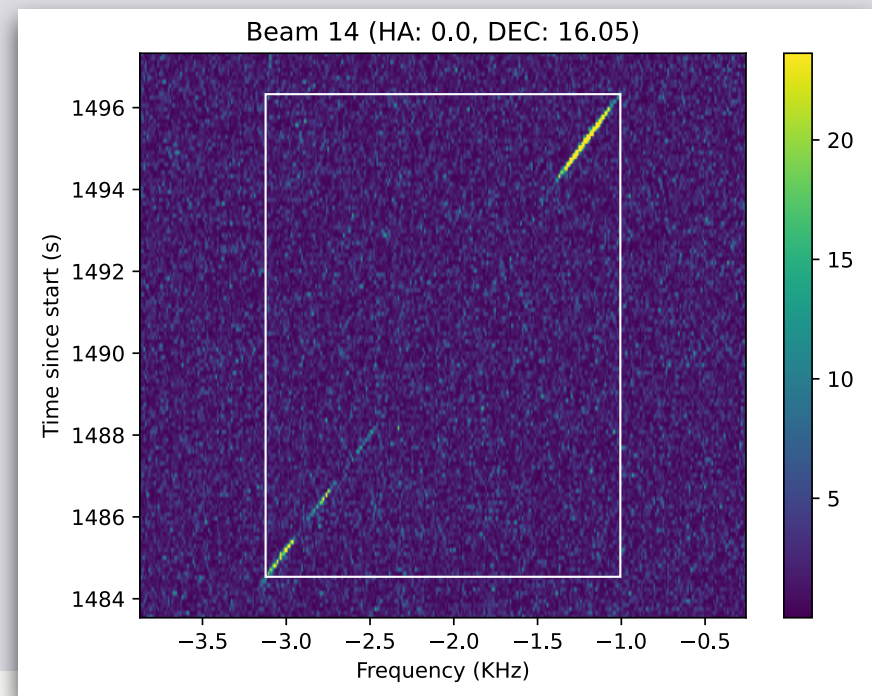
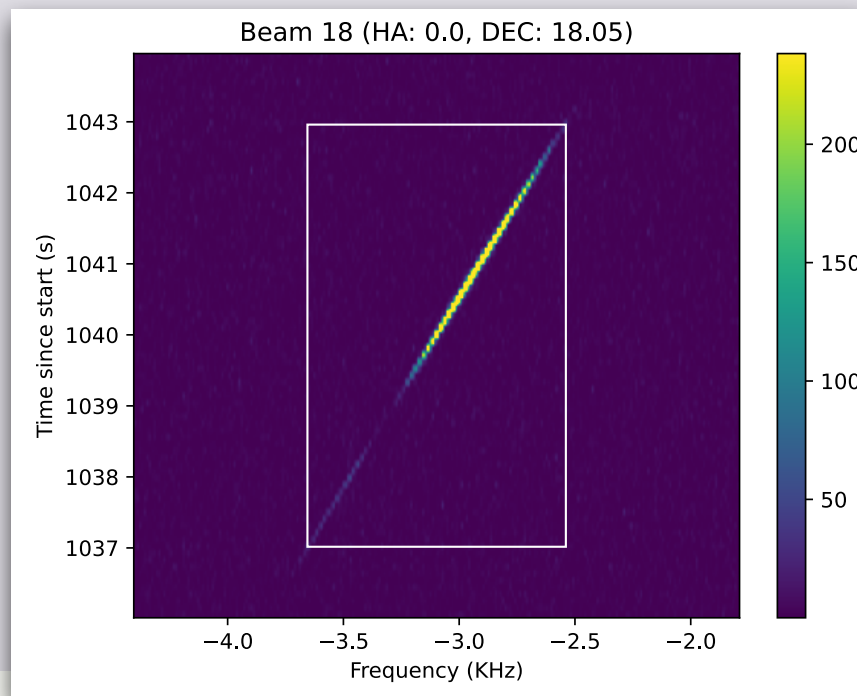
- Full dataset size with annotations: 50,749 samples

- Final Dataset sizes:
 - Training Set: 30,447 samples
 - Validation Set: 10,152 samples
 - Test Set: 10,150 samples

Building a Dataset for the Model

Things to Keep in Mind About the Data

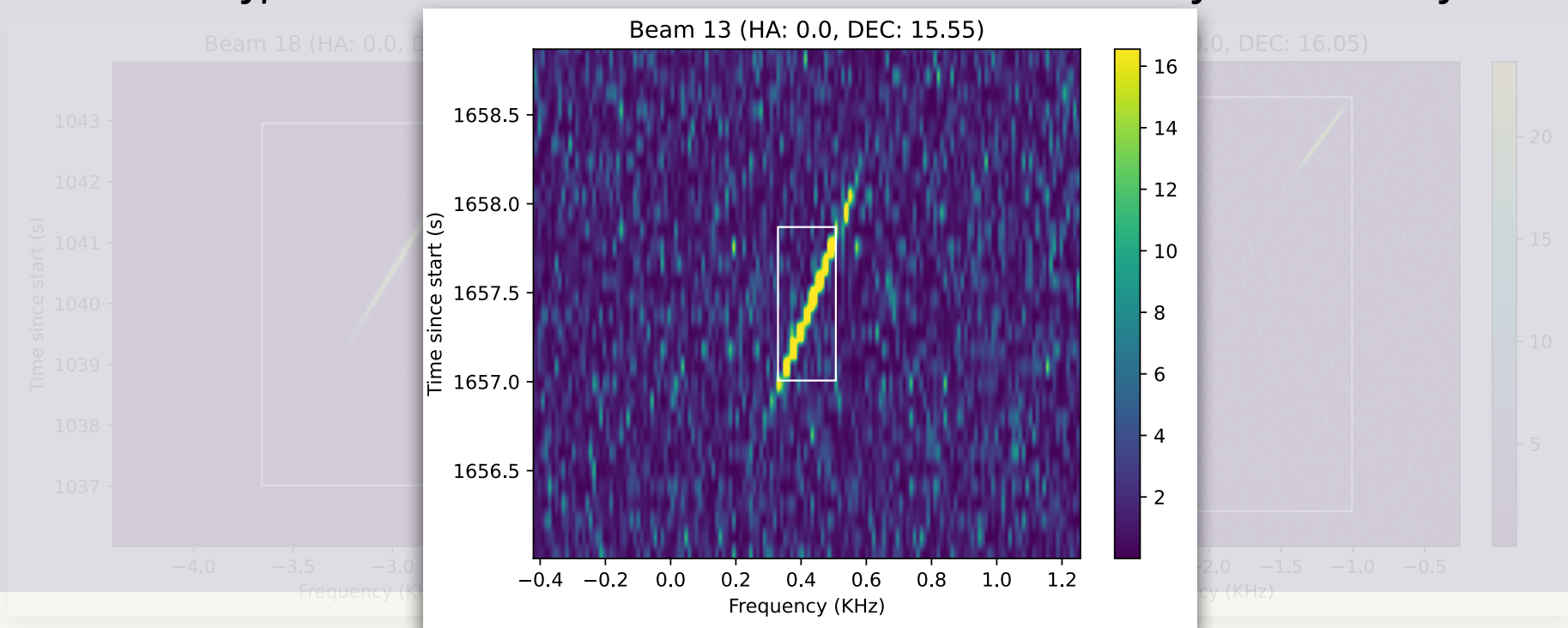
- The visibility, duration and nature of the debris echoes will vary substantially.



Building a Dataset for the Model

Things to Keep in Mind About the Data

- The visibility, duration and nature of the debris echoes will vary substantially.



Building a Dataset for the Model

Things to Keep in Mind About the Data

- The visibility, duration and nature of the debris echoes will vary substantially.
- A large amount are a pixel wide, some only having a width and height of ~20 pixels.
 - Image Rescaling prior to being fed into any model needs to be avoided.
- Any model used will need significant adjustment for this use case. So a large dataset and substantial training time/resources will be required.
- Since the data is labelled by the MSDS detector, it will be limited to a degree by the detector's recall and precision.
 - Important that any final model is significantly regularised.

Model Selection

Choosing the Right ML Model

Object Detection

- Care needs to be taken about selecting the right model for the job.
- Important that training and running inference from the model used is not computationally expensive and number of trainable parameters is manageable with our resources.
- Transfer learning from a pre-existing model that is versatile and reliable for different use cases would be ideal.

You Only Look At One Sequence (YOLOS)

YOLO Vision Transformer (ViT)

- YOLOS leverages the ViT architecture, enabling it to effectively capture spatial relationships in images.
 - Particularly beneficial for detecting irregularly shaped and positioned objects
- Originally trained using DETR loss on ImageNet-1k (200 epochs) and COCO2017 (150 epochs).
- The base-size model achieves an AP of 42 on COCO2017 validation.
- We select the small variant (*hustvl/yolos-small*) for a good balance between performance and manageability.
 - Number of trainable parameters: 30.7M

You Only Look At One Sequence (YOLOS)

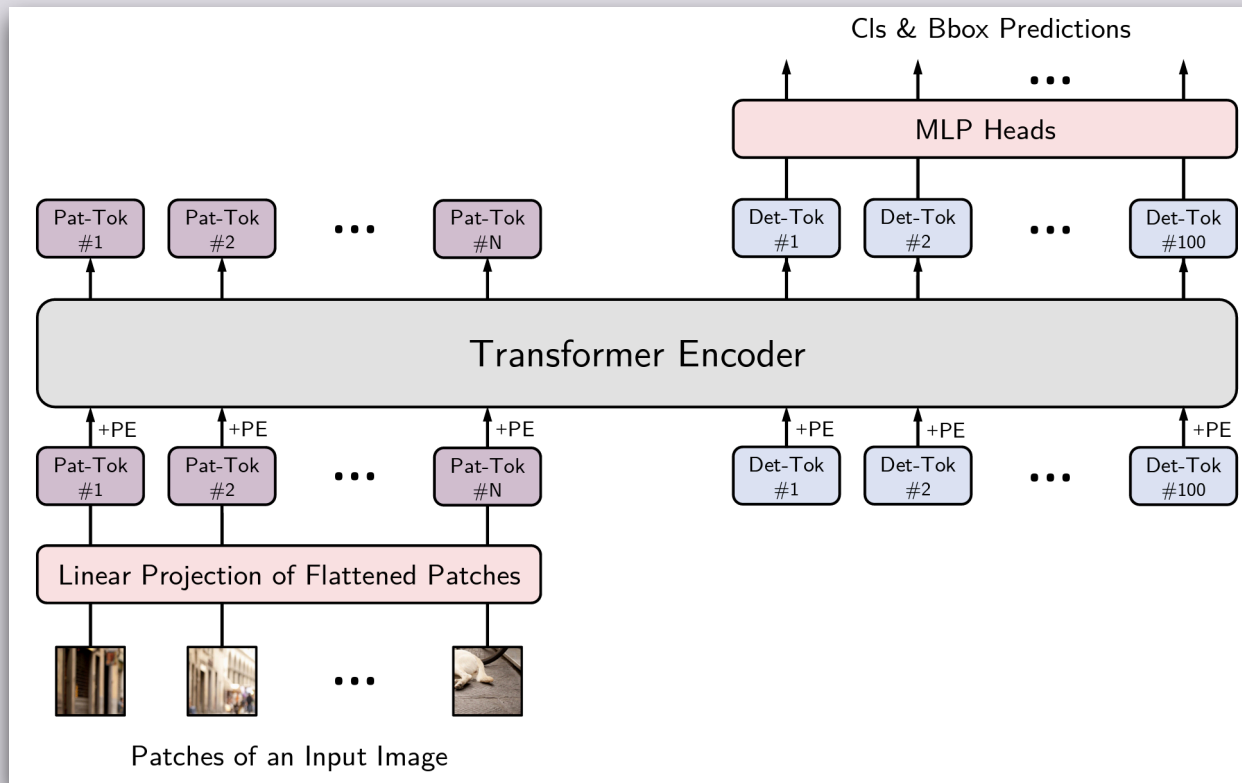
YOLO Vision Transformer (ViT)

- Trained using a bipartite matching loss
 - Hungarian matching algorithm achieves a 1-1 mapping from the 100 object queries given by the model to a padded list of annotations in the image.
 - To optimise model parameters, a combined loss of the cross-entropy (label classifier) and the L1 & Generalised IoU loss (bbox predictor) is used.

$$\text{Loss} = \lambda_{class} \text{ClfLoss} + \lambda_{box} L_1 \text{Loss} + \lambda_{gIoU} \text{gIoULoss}$$

You Only Look At One Sequence (YOLOS)

YOLO Vision Transformer (ViT)



Fang et al (2021)

You Only Look At One Sequence (YOLOS)

YOLO Vision Transformer (ViT)

- Some further preprocessing on our data is required to ensure it is suitable as an input for YOLOS.
 - Images are 'converted' from grayscale to RGB shape.
 - To ensure z-score normalisation is consistent across the dataset, a sample of 2000 images are taken to calculate the average image mean and std.
 - Images are further tiled to match the 512×864 shape input. This ensures that all resizing is avoided.
 - Only tiles with annotations are kept.

Preliminary Results

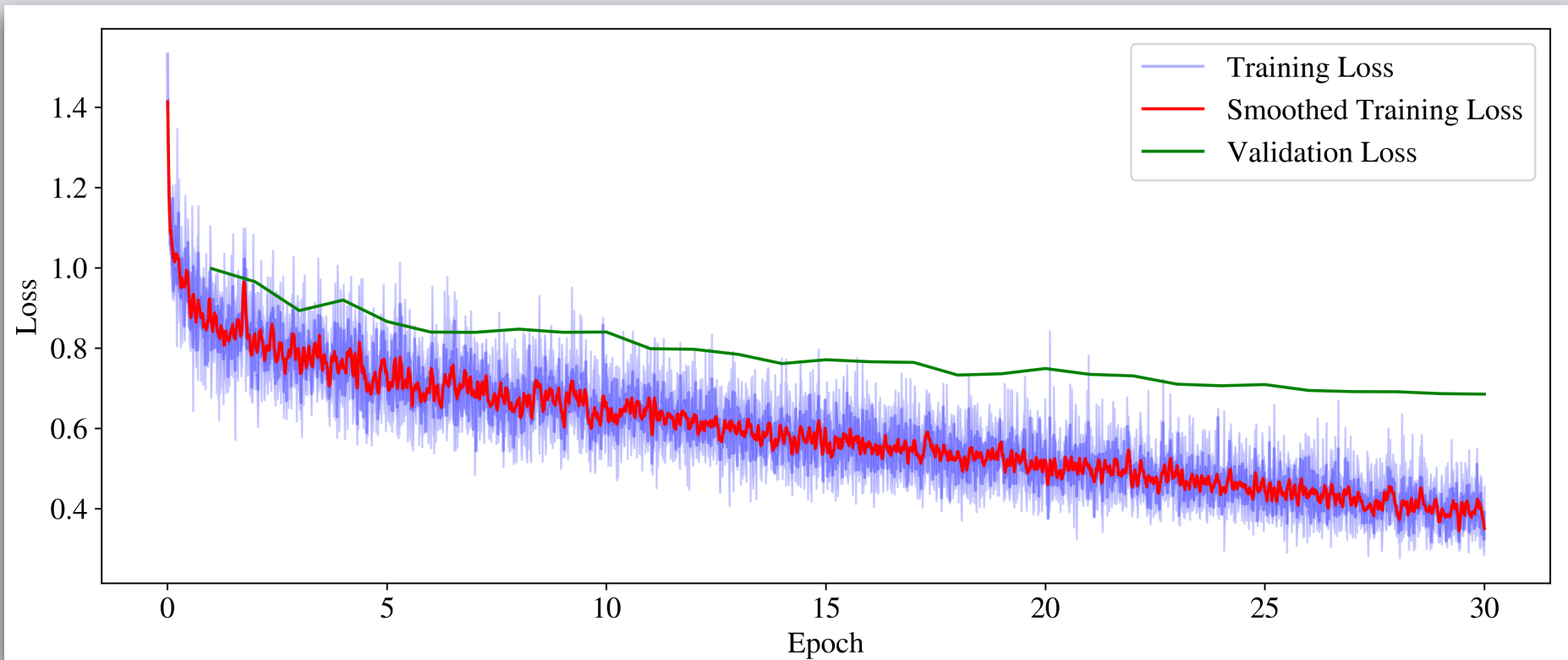
(Very) Preliminary Results

Training Curves

- We are still in the stage of trying to minimise the training loss
- The results presented here have been trained on 20,643 tiles (10k images) and validated on 15,682 tiles (10k images).
- Training was done on a single Tesla P100-SXM2-16GB GPU
 - Batch size = 8
 - Linear scheduling with a starting learning rate of the order of 10^{-5} .
 - ~34 hours for 30 epochs

(Very) Preliminary Results

Training Curves



(Very) Preliminary Results

Training Curves

- Further Hyperparameter tuning is needed to first continue to minimise the training loss as much as possible
 - Both in terms of the model configuration and optimisation during training
- The loss has not plateaued just yet, so with more epochs and more data, further minimisation is likely.
- Regularising the model to further minimise overfitting will be the next important step.

(Very) Preliminary Results

Promising Inference

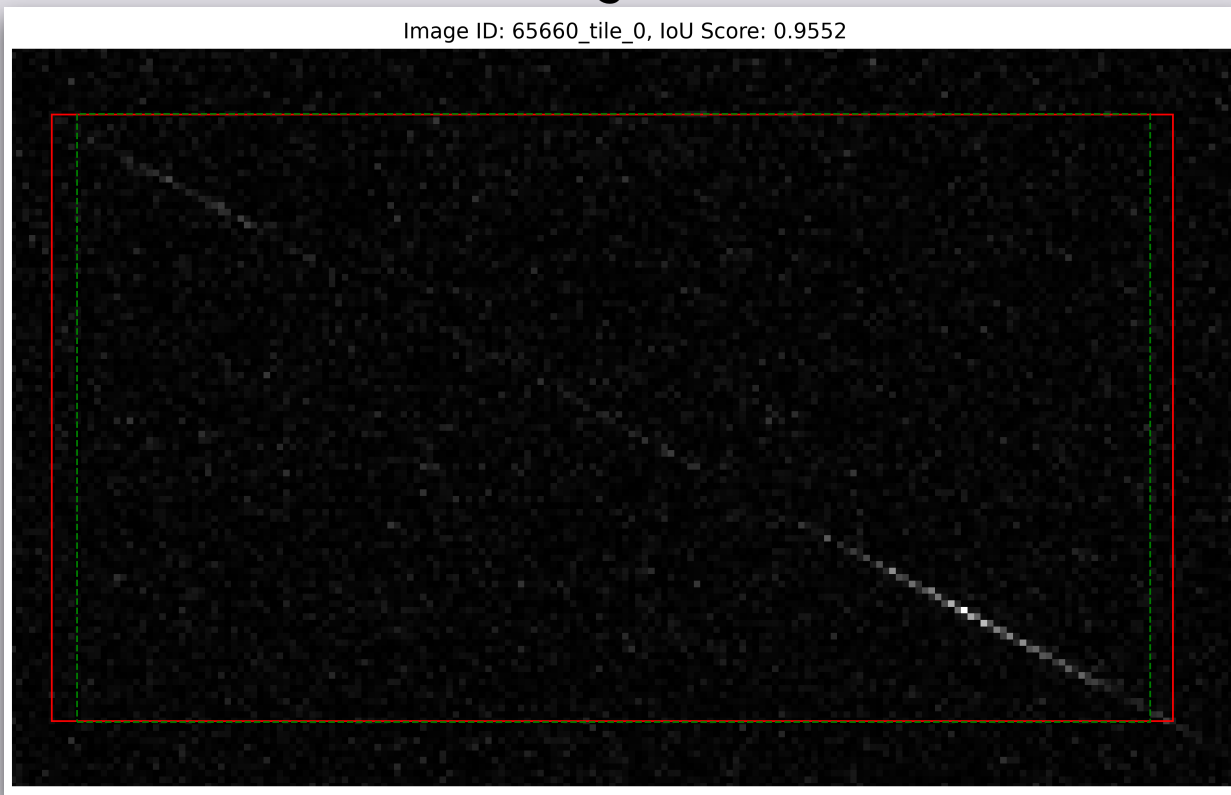
- After 30 epochs, the number of FPs, even on the training set, is still very high, highlighting the need to minimise the loss further.
- However, there are consistently a number of inferences with promising Intersection over Union (IoU) scores that show that the model is starting to learn.
- Tends to perform best with longer, wider echoes
 - Expected since the pre-trained model was trained on datasets in which the targets are either on the foreground or take up a significant portion of the image.

(Very) Preliminary Results

Promising Inference

Image ID: 65660_tile_0, IoU Score: 0.9552

- Ground Truth
- - Inference



(Very) Preliminary Results

Promising Inference

Image ID: 667172_tile_3, IoU Score: 0.984

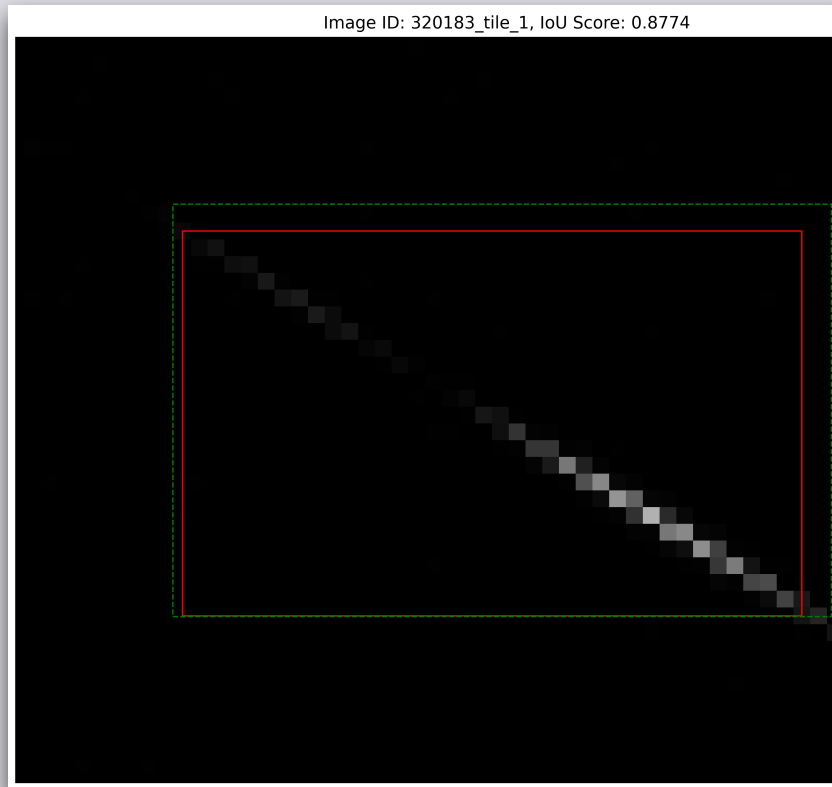
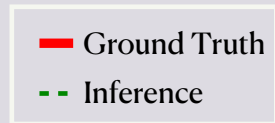
— Ground Truth
- - Inference



(Very) Preliminary Results

Promising Inference

Image ID: 320183_tile_1, IoU Score: 0.8774

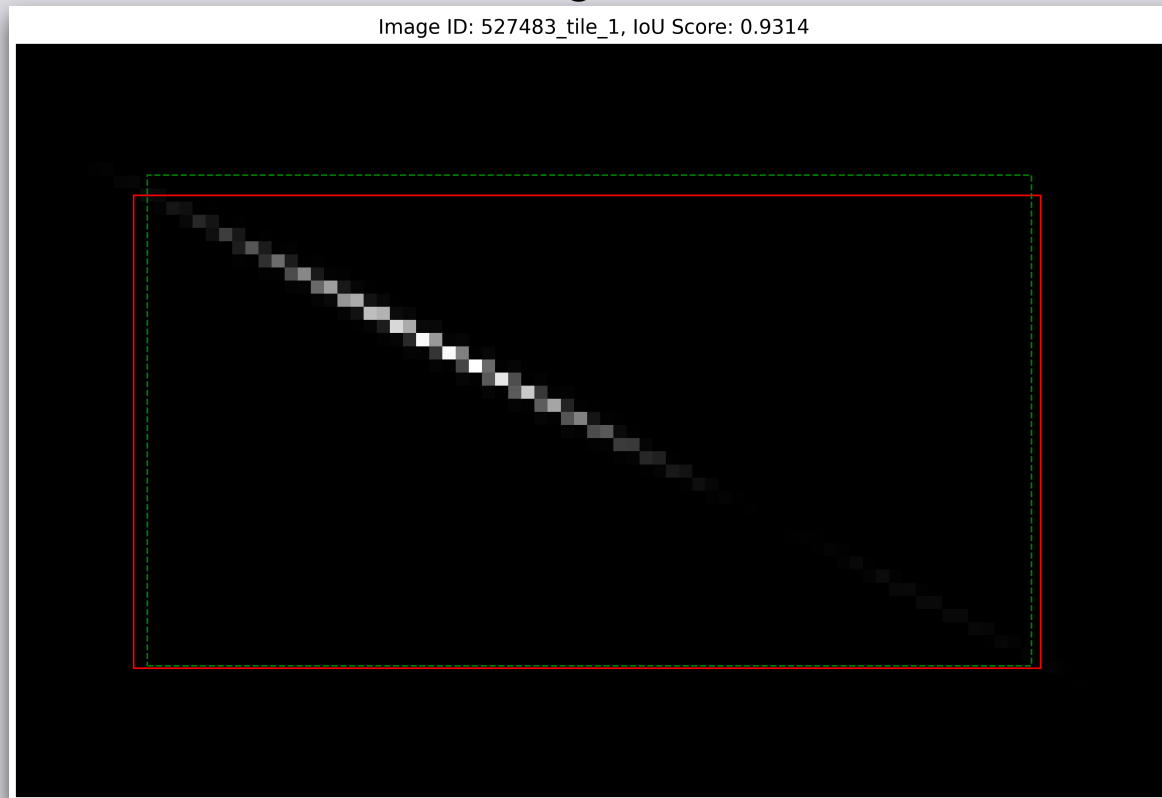


(Very) Preliminary Results

Promising Inference

Image ID: 527483_tile_1, IoU Score: 0.9314

- Ground Truth
- - Inference



Next Steps & Future Work

Next Steps & Future Work

Short-Term

- Hyperparameter Tuning, both in terms of model and training configuration
 - Get the Training Loss down
 - Regularise the model for stable generalisation
- Explore model performance across observation SNR, duration & beams.
- Test a number of other YOLO (CNN-based & transformer-based) pre-trained models, as well as other popular model architectures.

Next Steps & Future Work

Longer-Term

- Develop a simulator to mitigate the reliance on observational data.
 - A mix of observational and synthesised instances will be ideal.
- Explore whether models trained entirely on our dataset leads to stronger & more stable performances.
- Investigate whether segmentation models perform better or worse than object detection models.
- Integrate the most successful models into the BIRALES detection pipeline and ensure real-time performance is maintained.

Thank You For
YourAttention!

Feel free to ask any questions