# P2-25: Intelligent Systems

Mission-Critical Computing
NSF CENTER FOR SPACE, HIGH-PERFORMANCE, AND RESILIENT COMPUTING (SHREC)

SHREC Annual Workshop (SAW24-25)

University of Pittsburgh
BYU BRIGHAM YOUNG UNIVERSITY
VIRGINIA TECH.
UF UNIVERSITY of FLORIDA

January 14-15, 2025

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University of Pittsburgh

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Researcher
University of Pittsburgh

**Jefferson Boothe**
**Marika Schubert**
**Evan Gretok**
**Ian Peitzsch**
**Mark Ciora**
**Stephen Palli**
**Eileen Wang**
Graduate Students
University of Pittsburgh

Number of requested memberships ≥ 5

# Overview

**Goal:** Investigate **emerging machine-learning** paradigms and devices for space and other diverse applications

**Motivation:** AI promises to expand capabilities for edge-system sensing and processing without compromising performance

**Challenges**: Overcome computational, data, and environmental limitations

# Tasks for 2025

## T1 ML Model Analysis

- Investigate impact of architecture changes on Transformer performance
- Explore performance of non-sequential positional encodings
- Analyze DL inference kernel and subgraph benchmark

## T2 Onboard Earth Observation

- Train tile-classification backbone models on landcover datasets
- Apply few-shot learning to classify novel land features with few samples

## T3 Intelligent Remote Sensing

- Quantize SAR despeckling models for computational performance
- Develop space-based sensor tasking algorithms for missile tracking



**DL**: Deep Learning
**SAR**: Synthetic Aperature Radar

# T1: ML Model Analysis


## Jefferson Boothe
## Ian Peitzsch
## Marika Schubert

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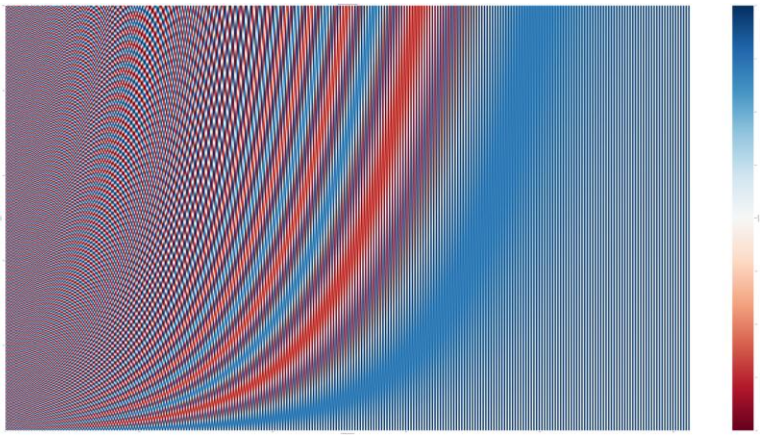
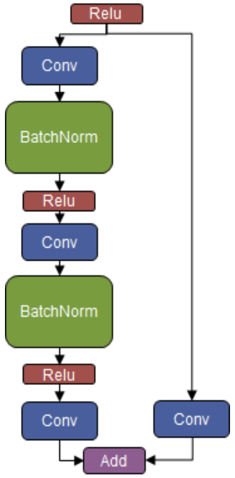
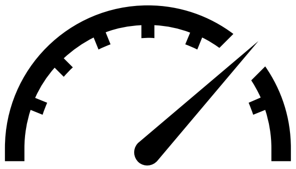
# T1: ML Model Analysis – Background



## Analysis of Transformer Models – Jeff & Ian

- **Transformers** have become the backbone of state-of-the-art AI systems in many domains
- Understanding how **model structure** impacts performance can enable usage of smaller models

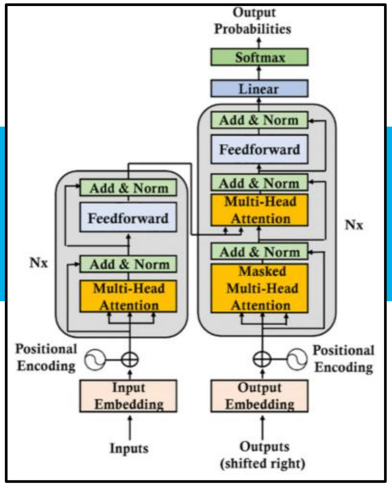


## Analysis through Inference Benchmarks – Marika

- Inference benchmarks **describe performance** of systems in particular use cases
- More **granular benchmarks** are needed to compare hardware and a models

# T1: ML Model Analysis – Approach




**Analysis of Transformer Models – Jeff & Ian**

- Characterize relationship between **model structure** and **accuracy/loss**
- Investigate non-sequential data compression with novel **positional encoding** techniques

**Subgraph Benchmark – Marika**

- Propose ONNX specification of subgraphs to benchmark **DL vision systems**
- Compare performance across devices with **ModelGauge** tool

ONNX

# T2: Onboard Earth Classification

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# T2: Onboard Earth Classification – Background

### How Can Few-Shot Learning Help in Space?
- Quickly adapt to classifying **new classes** with few samples
- Maintain high accuracies on data with **different GRDs** than it was originally trained on
  - Ex: Images with a higher GRD contains smaller objects in **higher detail** than lower GRD images

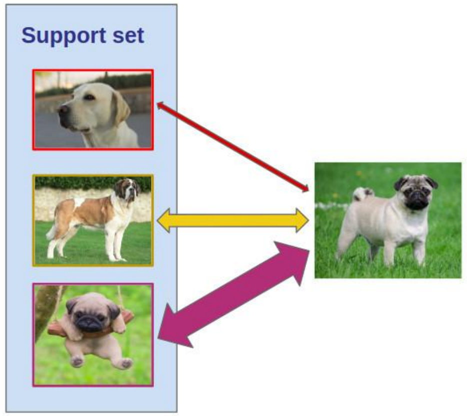
3.0 m/px GRD

30 m/px GRD

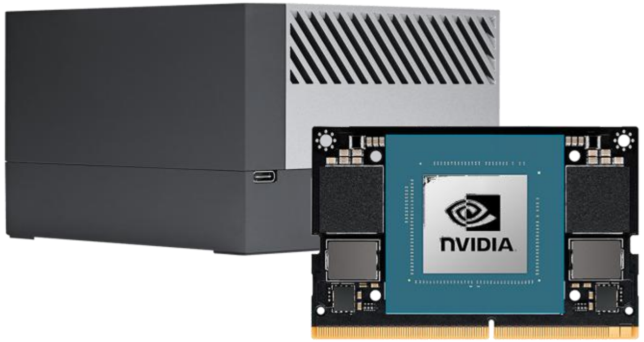
### How Can Previous Tile-Classification Research Help?
- Now have transfer-learning datasets for multiple **GRDs**
- Can train **backbones** on one or more desired scales
- Tailored scale backbones should improve **accuracy**

**GRD**: Ground-Resolved Distance

# T2: Onboard Earth Classification – Approach

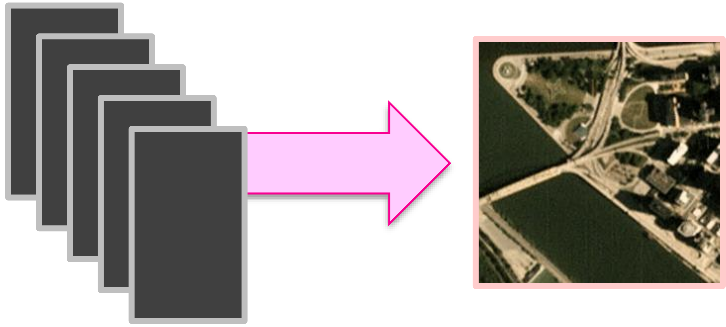



**What is Next for Few-Shot Learning? - Eileen**
- Benchmark popular **few-shot** learning algorithms on various Earth-observation **datasets**
- Compare effectiveness of different **feature extractors**




**What is Next for Tile Classification? - Evan**
- Now that datasets are complete, train and test additional **models**
- Collect inference **performance** data on space CPUs and eGPUs

**What About All That CASPR Data? - Evan**
- Combine frames into color images, tile, and sort into **dataset**
- Compare CASPR imagery to Planet, prepare models for **H12**



**eGPU**: Embedded Graphics Processing Unit

# T3: Intelligent Remote Sensing

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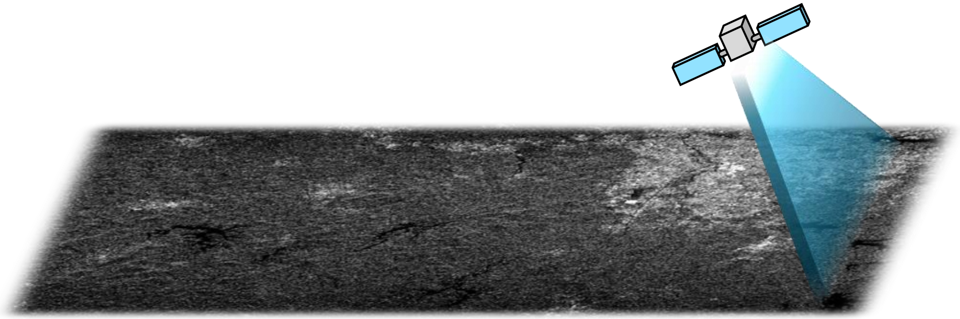
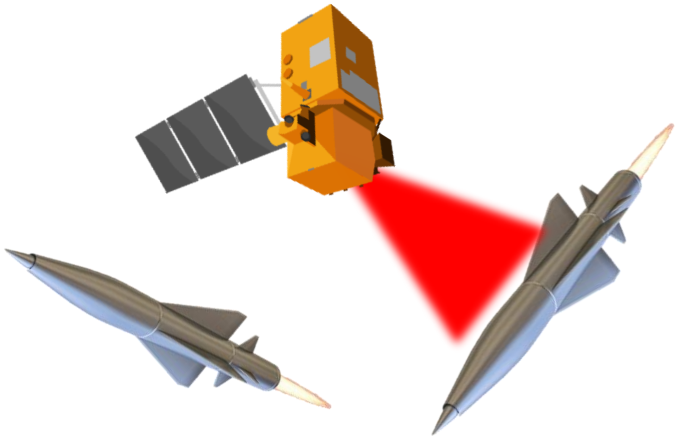
# T3: Intelligent Remote Sensing – Background

**Synthetic Aperture Radar (SAR) - Steve**

- Remote sensing method that collects information about a **target area** using radar
- Constructed 2D images contain noise called **"speckle"** that needs to be removed
- ML approaches despeckle with **higher accuracy** than spatial methods





**Sensor Tasking for Missile Tracking - Mark**

- Sensors must be **assigned to targets** in real time for **missile tracking**
- Resource allocation problem
- Long-term and short-term optimization
- Standard methods **myopic or slow to compute**

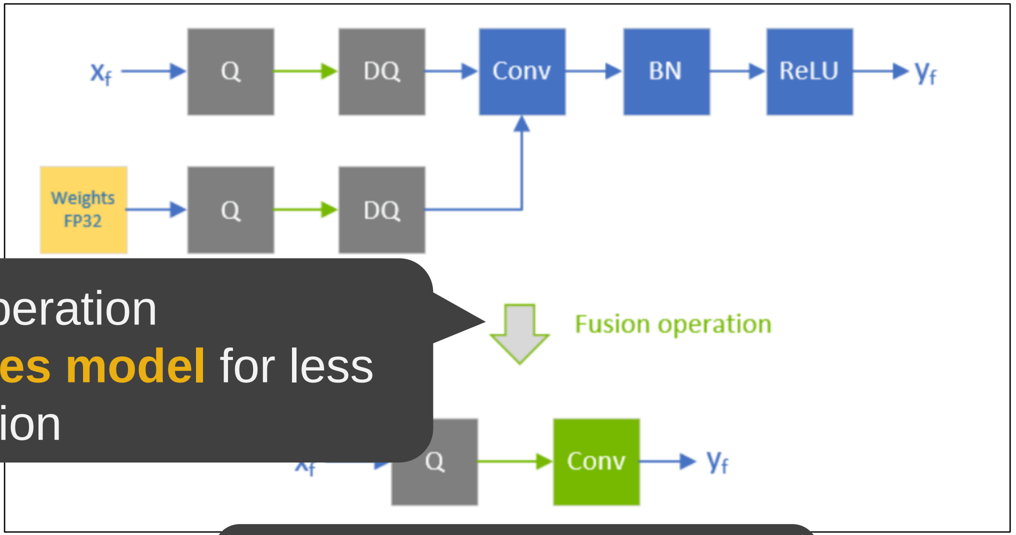


**SAR**: Synthetic Aperture Radar

# T3: Intelligent Remote Sensing – Approach

**SAR Despeckling Quantization - Steve**

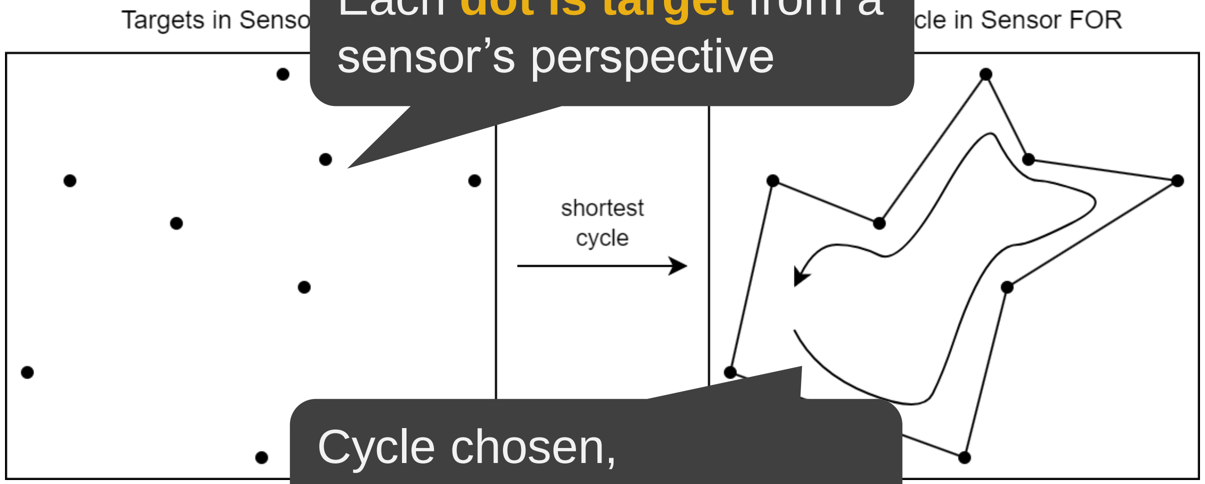
- **Quantize** commonly used SAR despeckling models with QAT
- Evaluate PTQ, QAT, and full-precision SAR despeckling models with **synthetic data**
- Compare model performance on **real SAR data**




Fusion operation **condenses model** for less computation

**Missile Tracking Cyclic Sensor Tasking - Mark**

- Sensor tasking algorithm designed to **plan into future**
- Slewing cycle is chosen and followed with **optimal** period and observation times
- Strategies for handling **moving targets** and **multiple sensors** are necessary




Each **dot is target** from a sensor's perspective

Cycle chosen, **sensor slews along path**

**SAR**: Synthetic Aperture Radar
**PTQ**: Post-Training Quantization
**QAT**: Quantize-Aware Training

# Milestones, Deliverables, Budget

## Milestones

SMW25 (June 2025): Showcase **preliminary results** on all project tasks

SAW25-26 (January 2026): **Completion** of all project tasks

## Deliverables

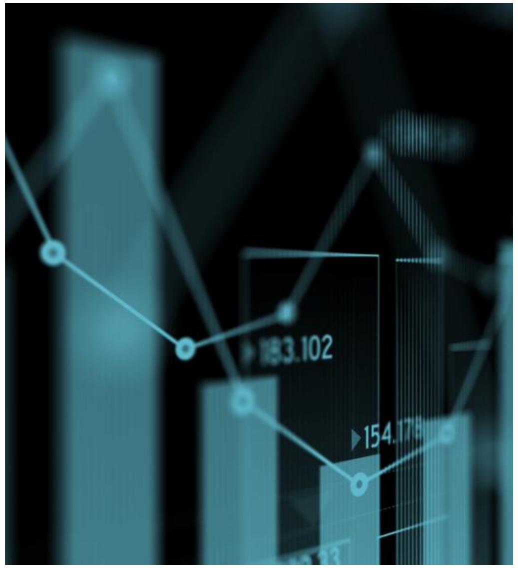
Monthly **progress reports** from all projects

Midyear and end-of-year **full reports** from all projects

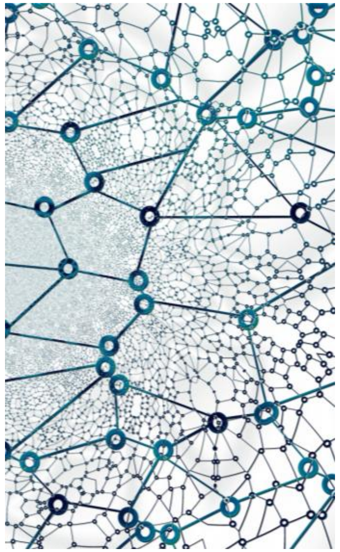
1-2 conference or journal **publications** per task

## Budget

Minimum recommended:
**Five (5) memberships**
(250 Votes)



# Conclusions and Member Benefits



## Conclusions

- **ML Model Analysis** can increase understanding of model behavior and lead to performance improvements
- **Few-shot learning** enables accurate onboard classification with less labelled data and can even generalize its training to never-before-seen samples
- **Intelligent Remote Sensing** is necessary in efficient processing of data and modern missile-tracking applications

## Member Benefits

- Direct influence over **architectures and paradigms** studied
- Direct influence over **apps and datasets** studied
- Direct benefit from new **methods, data, code, models, and insights from metrics, benchmarks, and emulations**