P2-26: Intelligent Systems

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

SHREC Annual Workshop (SAW25-26)

University of Pittsburgh · BYU Brigham Young University · Virginia Tech · UF University of Florida

January 13-14, 2026

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Graduate Students
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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 model scaling for vision transformers
- Improve onboard neural compression pipeline for satellite imagery

T2 — Few-Shot Learning for Space
- Investigate cross-domain, few-shot learning for Earth image classification
- Analyze behavior and limitations of few-shot models under domain shift

T3 — Hybrid Segmentation and Tracking for Space
- Fuse event-based and RGB data for vision foundation models
- Investigate complementary sensing modalities to enhance model performance

T4 — Distributed Training Optimization
- Investigate alternative optimizers on non-traditional distributed compute platforms
- Evaluate accuracy and runtime tradeoffs on different platforms

T1: ML Model Analysis

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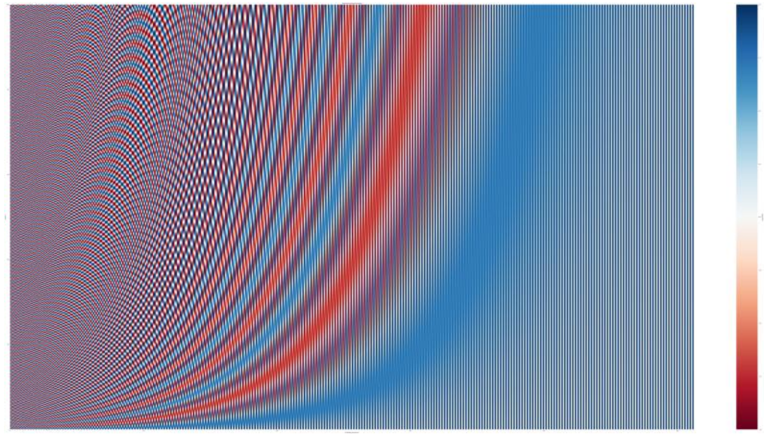
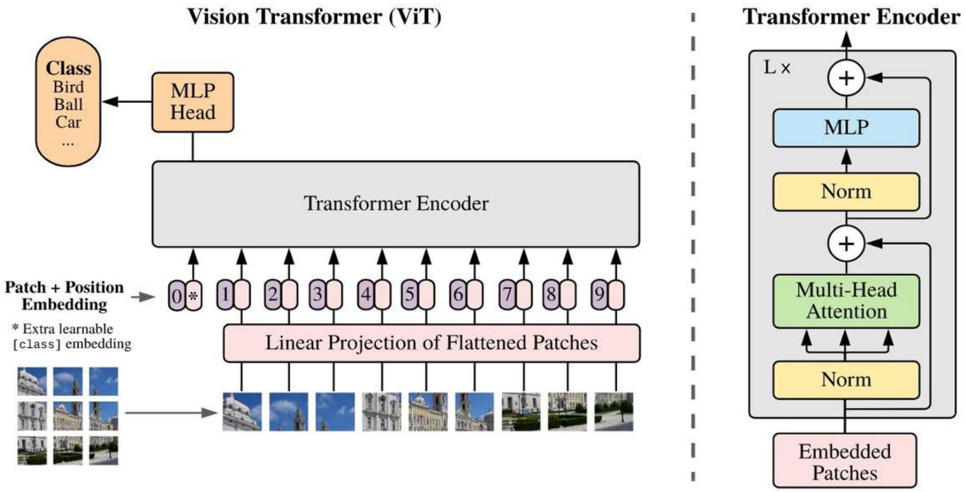
T1: ML Model Analysis – Background

Neural Compression with Transformers
- **Transformers** have become backbone of state-of-the-art AI systems in many domains
- Information theory shows compression abilities directly relate to **model understanding** of distribution





Analysis of ViTs
- **Flexibility** and **scalability** of ViTs have made them architecture of choice for various tasks
- Understanding how **model structure** impacts performance can enable usage of smaller models

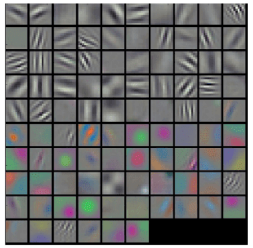
ViT: Vision Transformer

T1: ML Model Analysis – Approach

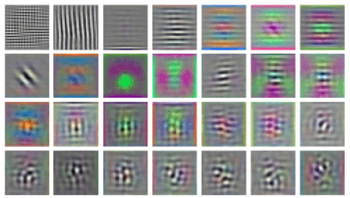
Neural Compression with Transformers – Jeff
- Investigate non-sequential data compression with novel **positional encoding** techniques
- Explore onboard transformer-based neural compression for **satellite imagery**

Analysis of ViTs - Ian
- Characterize relationship between **model structure** and **accuracy/loss**
- Analyze **scaling** of training set size

Alexnet 1st conv filters



ViT 1st linear embedding filters



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T2: Few-Shot Learning for Space

Dikchhya Kharel

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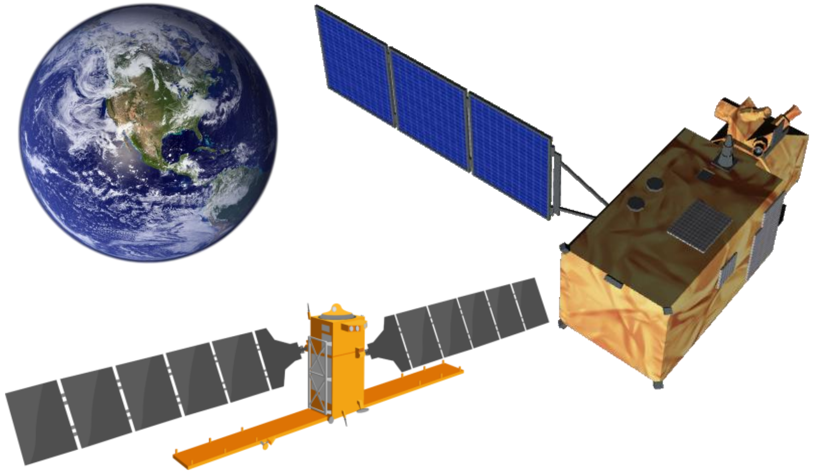
T2: Few-Shot Learning for Space – Background

How Can Few-Shot Learning Help in Space?

- Quickly adapt to classifying **new classes** with few samples
- Handle **domain differences** between ground-trained datasets and orbital imagery
  - Ex: Models trained on everyday ground photos learn close-up textures that don't appear in satellite images, so they may struggle to transfer



Why Is Onboard Earth Classification Challenging?

- Space missions often collect **very limited labeled data**, making it difficult to retrain models in orbit
- Models trained on ground datasets may not generalize well without methods that **quickly adapt to new conditions**

T2: Few-Shot Learning for Space – Approach

What is Next for Few-Shot Learning?
- Benchmark few-shot learning algorithms on **cross-domain datasets**
- Compare effectiveness of different **feature extractors**
- Evaluate how **domain shift** impacts few-shot accuracy across various datasets

Train Domain (Natural)

Test Domain (Aerial)

Understanding Cross-Domain Behavior
- Analyze **feature differences** across domains to understand FSL transfer behavior
- Identify **algorithm weaknesses** when domain shift is large

__FSL__: Few-Shot Learning

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T3: Hybrid Segmentation and Tracking for Space

Joshua Poravanthattil

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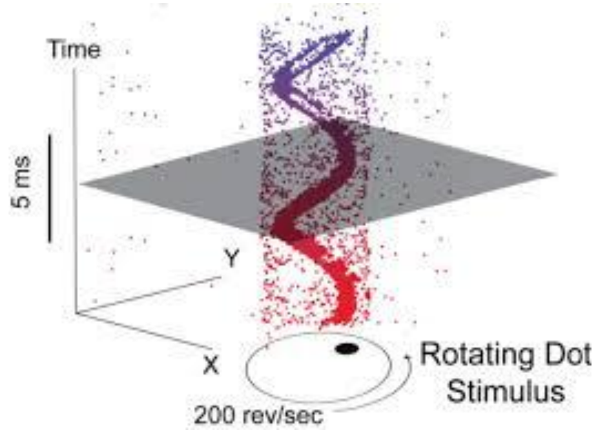
T3: Segmentation and Tracking – Background

SOTA Segmentation & Tracking Models

- Current VFMs excel at **generalization**, **robust**, and **long-term** segmentation and tracking
- **Strong performance** incentivizes onboard implementations for EO tasks
- Current VFMs incur excess **computational and energy costs**



Event-Based Sensing Modality

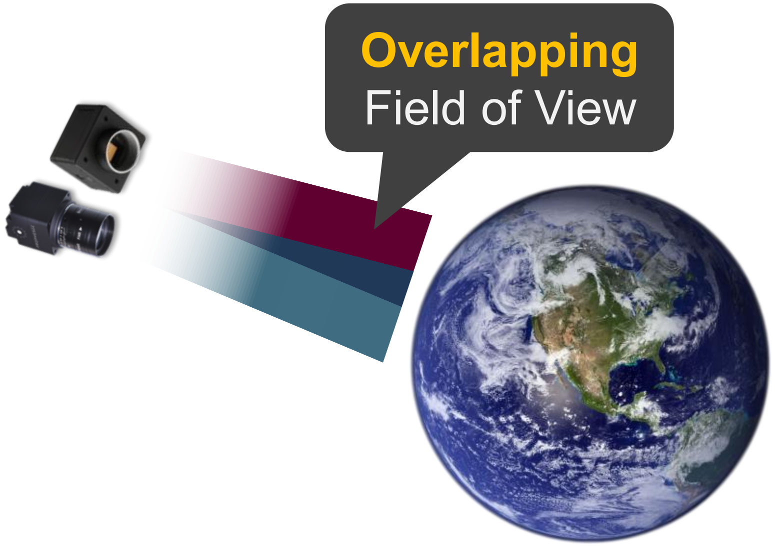
- Event-based sensors offer **asynchronous motion features**
- Low power and high dynamic range allow for **robust data capture**
- Combine with RGB features to enable **enhanced tracking capabilities**

SOTA: State-of-the-Art
VFM: Vision Foundation Model

T3: Segmentation and Tracking – Approach

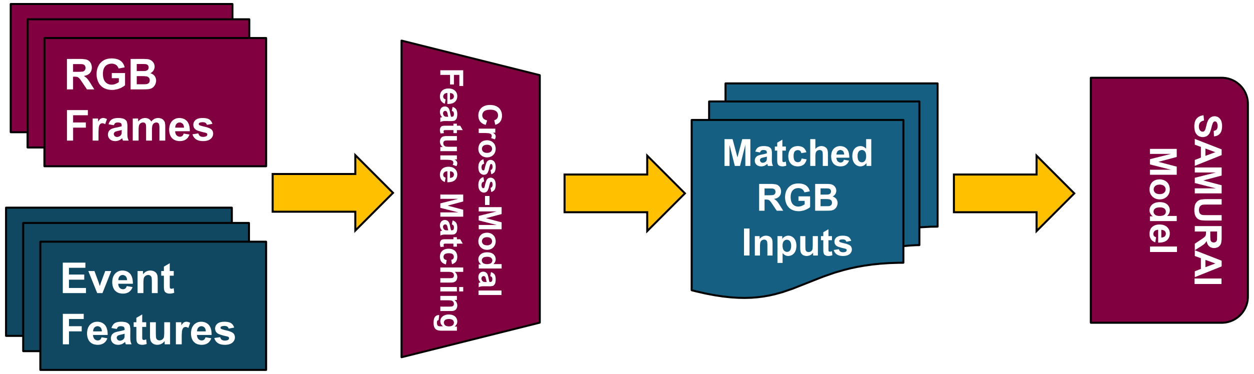
Event-Based Feature Detection and Matching

- Identify **relevant motion features** from event-based modality
- Cross-modal **feature matching** to map event clusters to RGB pixel space
- **Filter event noise** for accurately matched RGB and event features



SAMURAI Initialization and Tracking

- SAMURAI offers competitive segmentation and tracking **robust to occlusions**
- Enable object selection and VFM initialization via **matched RGB inputs**
- Assess **tracking performance** of target
- Benchmark performance to reveal **bottlenecks**



VFM: Vision Foundation Model
SAMURAI: SAM-based Unified and Robust zero-shot visual tracker with Motion-Aware Instance-Level Memory

T4: Distributed Training Optimization

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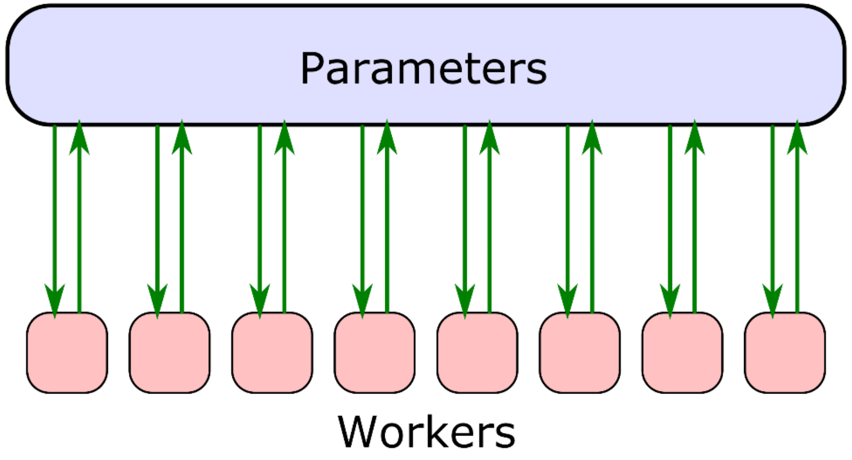
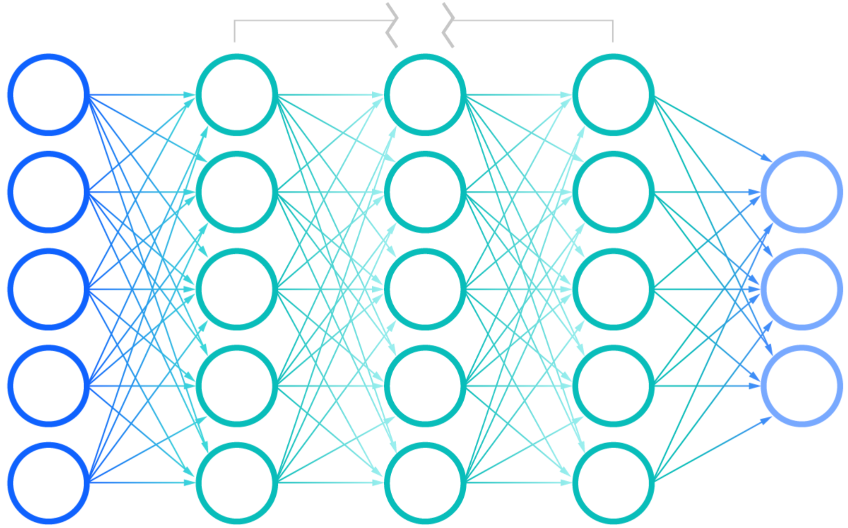
T4: Training Optimization – Background

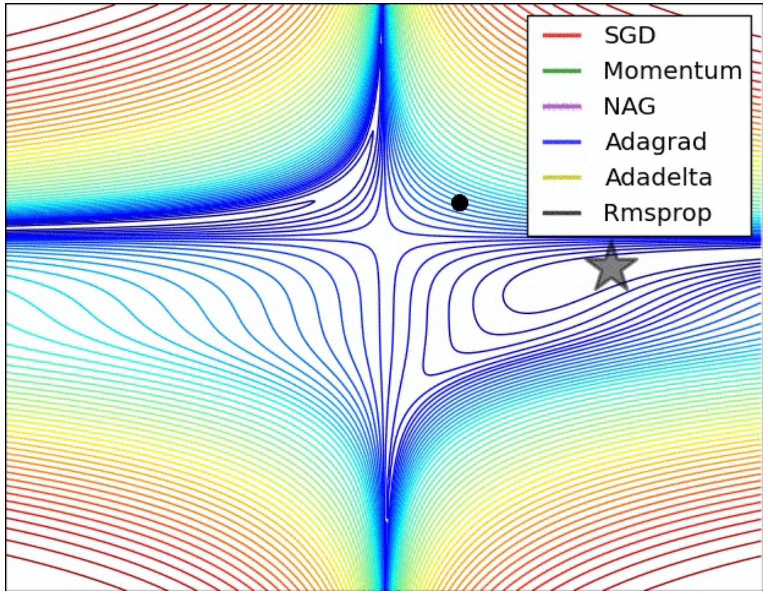
Distributed Training
- Data centers remain primary environment to train **large models** but are not always **accessible**
- Training efficiently on other **hardware** and **environments** is desirable for many applications





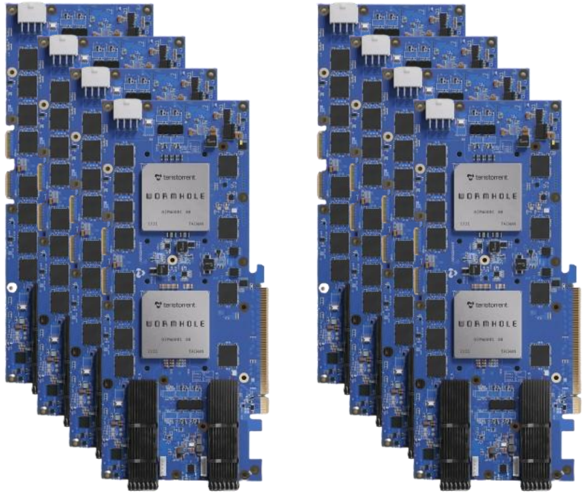
Optimizers
- **Integral component** of machine-learning training
- Many underresearched methods exist, but **Adam** and **AdamW** remain dominant in field

T4: Training Optimization – Approach



Why Use Other Optimizers?

- Popular optimizers work well on **NVIDIA server-grade** hardware
- Recent research suggests alternatives could **outperform AdamW** on other devices



tenstorrent

Understanding Optimizer Tradeoffs

- **Evaluate training time** and **accuracy** of different optimizers on various platforms
- Target environments include clusters of **Tenstorrent devices** and edge CPUs

Milestones, Deliverables, Budget

Milestones

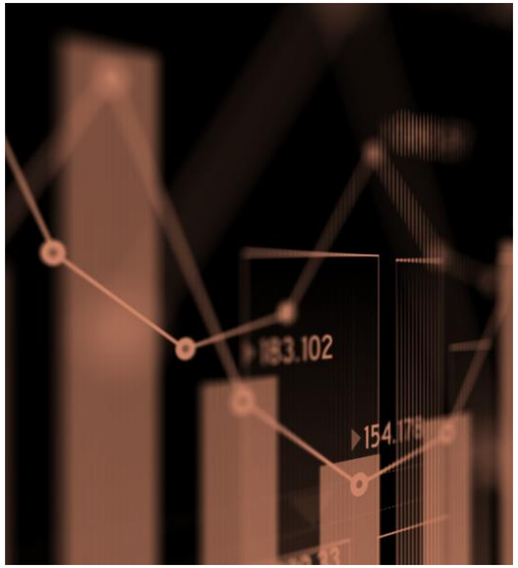
- SMW26 (Summer 2026): Showcase **preliminary results** on all project tasks
- SAW26-27 (January 2027): **Completion** of all project tasks

Deliverables

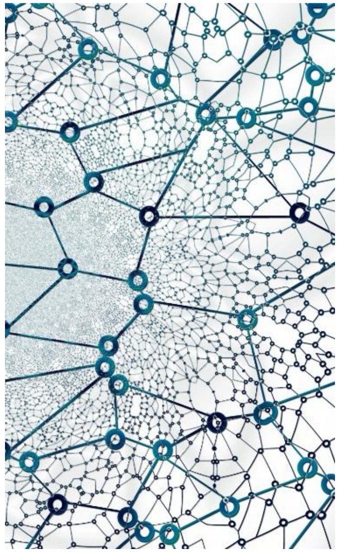
- Monthly **progress reports** from all projects
- Midyear and end-of-year **full reports** from all projects
- 1-2 conference or journal **publications** per task

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
- **Hybrid Segmentation and Tracking** aims to exploit complementary data modalities for robust and efficient tracking
- **Distributed Training Optimization** explores performance tradeoffs of alternative optimizers on hardware beyond traditional data centers

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**