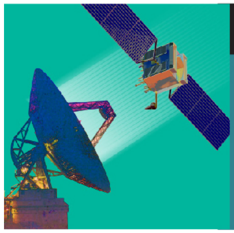
Working Group Outbrief

Ground System Architectures Workshop



Session 11B

Intelligent Systems / Machine Learning for Space Ground Systems

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The Aerospace Corporation

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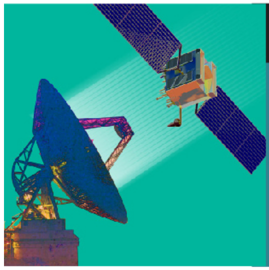


Session 11B

Session Goals

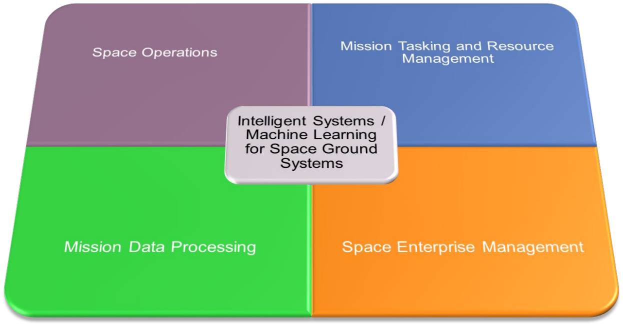
The "Intelligent Systems / Machine Learning for Space Ground Systems" working group seeks to identify and demystify where intelligent systems and machine learning currently exist in space ground systems, discover what emerging capabilities are being developed in the community, and to capture real-world impediments for adoption, and how intelligent systems/machine learning has advanced space systems resilience. It will explore deeper the questions of:

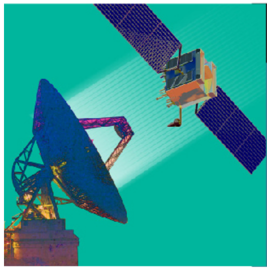
Where do intelligent systems and machine learning currently exist in space ground systems?

- What elements of space ground systems are suited to intelligent systems and machine learning
- What emerging capabilities and technologies are being developed in the community
- What are real-world impediments for adoption
- What capability and technology gaps exist and might seed further research and investment

The Working Group will break into 4 sub-topic areas to explore:

1. Space Operations
2. Mission Tasking and Resource Management
3. Mission Data Processing
4. Space Enterprise Management





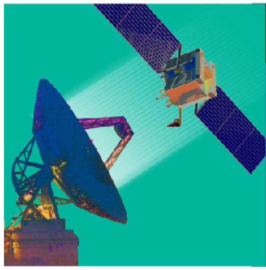
Presenters/Panelists

PRESENTERS

- Thomas Kashangaki:
  - *Working Group Key Themes and Notional Framework*
- Dan Balderston:
  - *GSAW 2018 IS/ML Working Group Recap*
- Dale Schroeder:
  - *Autonomous Driving Using Machine/Deep Learning*
- Ron Birk, Steve Marley:
  - *Framework for Trusted Operations of Autonomous Systems*

BREAKOUT FACILITATORS

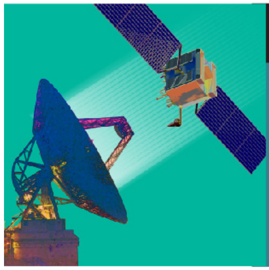
- *James Zalinski, Pablo Settecase (Space Operations)*
- *Vahe Avedissian, Tim O'Brien (Mission Data Processing)*
- *Nehal Desai, Jon Neff (Mission Tasking / Resource Management)*
- *Steve Marley, Andre Chen (Space Enterprise Managment)*



Key Points

- Adaptive, trustworthy, reliable automation and intelligent decision making
- Explainable AI
- Proper balance between human control and autonomy
- Intuitive Human-Machine Interface
- AI for Mission Assurance and Mission Assurance for AI
- V&V to establish Trust
- System/Mission agnostic tools
- Self-learning algorithms
- Agile DevSecOps
- Common Data Pool
- Shadow Ops Center
- Internet of Actions
- EPIC Speed (enterprise, partnerships, innovative, culture)

Culture is the greatest impediment to adoption of AI/ML for Aerospace Ground Systems



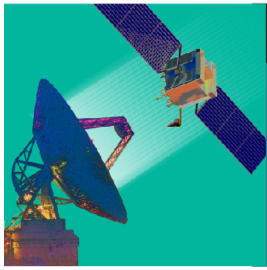
Conclusions – 1. Spacecraft Operations

- Current IS/ML examples
  - *ESA (multiple missions)*
    - Anomaly Detection/Diagnostic support/Planning and Scheduling/Power Budget Model
  - *NASA JPL (MSL and 2 other missions)*
    - Anomaly detection/ Planning and Scheduling
  - *NOAA*
    - NPP/ JPSS-1– Forensic Anomaly Detection using Satellite as a Sensor (SAS) in preparation for real-time deployment on JPSS-2
  - *NASA GSFC – Space Asset Protection Program*
    - End-of-Mission Expirements for Cyber Intrusion
  - *The Aerospace Corporation*
    - ComSats and CubeSats – Forensic Anomaly Analysis

- Areas best suited for IS/ML
  - *Long Term Large Stable Data Sets*
  - *Communication Links*
  - *Automated/out of contact ops*
  - *Large Constellations*
  - *Ground Station Monitoring*

- Impediments, real-world barriers
  - *Data Access/Processing*
  - *Access to Ops Environment*
  - *Complexity of Space systems and Ground systems*
  - *Culture / stove-pipes / limits to innovation (Trust)*
  - *Security/ Classification Levels*
  - *Lack of trust of the AI algorithms (black box)*
  - *Algorithm Transparency*
  - *Cost and Schedule*

- Emerging capabilities, technologies, approaches
  - *Re-defining Space/Ground boundaries - Concurrent Design*
  - *Edge AI capabilities*
  - *Improving / Optimizing data capture (data types/cadence/bandwidth*
  - *HW design for improved observability (sensors)*
  - *Unsupervised learning*
  - *Dedicated AI/ML SV processing capacity*
  - *Explainable AI*



Conclusions – 2. Tasking, Resource Management

Current IS/ML examples

- Hubble SSPS (1994)
- EO-1 and DS-1 onboard planning (1995-2000)
- AEGIS onboard planning on Mars Curiosity Rover
- Digital Globe (?)

- There is a lot of optimization, not a lot of AI – not widespread

Areas best suited for IS/ML

- Ground station contact scheduling (AFSCN)
- Ground and space system resource management
- Dynamic re-planning
- Determining intent of mission tasking – translate to executable plan
- Forecasting demand
- Tasking commercial spacecraft- priorities, economics, high profile customers

Impediments, real-world barriers

- Ops culture is risk averse
- We don't know what we want
- Lack of technical expertise in workforce
- Balancing governance and autonomy
- Lack of visibility into algorithms- not explainable
- "Bolting on" AI to existing systems that were not designed this way- cost to change architecture
- Centralized vs. distributed tasking, planning
- Hard to capture expert knowledge

Emerging capabilities, technologies, approaches

- Kubernetes-like tasking- specify end state
- Synthetic data generation: simulation, augmentation, transfer learning, GANs
- Automate bringing in contextual data
- Rapidly improving ML/AI technologies: CNN, RNN, GAN, GFT, Bayesian approaches
- Combined hybrid techniques
- Better hardware (in space and on ground): GPUs, neuromorphic chips, etc.

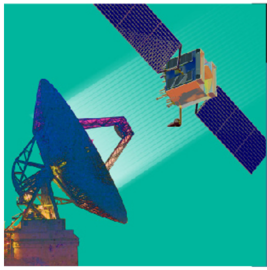
Conclusions – 3. Mission Data Processing

- Current IS/ML examples
  - *Provide warning of failing sensors*
  - *Predict degradation of HW*
  - *Tracking space objects*
  - *Find leading indicators*
  - *Anomaly detection from telemetry & mission data*
  - *Image processing*
  - *Volcanic lava tracking*
  - *ML on satellite to reduce data volume*

- Areas best suited for IS/ML
  - *Image detection, classifications, tracking*
  - *Fire prediction*
  - *Fusion of satellite sensors and ground sensors*
  - *Predictive maintenance and sustainment*

- Impediments, real-world barriers
  - *Cost of SW*
  - *Access to large volumes of high quality labeled data*
  - *Configuration of dependencies (ie. Libraries)*
  - *Training – lots of time*
  - *Confidence in decisions made by tools*
  - *Quantify confidence level of results*
  - *IT Security is a huge barrier!*
  - *People don't want to share data*

- Emerging capabilities, technologies, approaches
  - *Unet (type of neural network)*
  - *Cubesats, large constellations*
  - *Proprietary GPUs (faster, less power)*
  - *Neuromorphic processing*
  - *On board processing (AI in space)*
  - *Auto ML*
  - *GAN's, (generative adversarial networks), re-enforcement learning*



Conclusions – 4. Space Enterprise Management

- Current IS/ML examples
  - *Classic anomaly*
    - Fraud, Telemetry
  - *Image/Pattern/Voice Recognition*
    - Often in an augmentation mode
    - Medical imaging analysis
  - *ML/AI to extract environmental parameters from observations (e.g. sea ice, Sea Surface Temperature)*
  - *Research on autonomous space systems (NASA)*
  - *Big Data Analytics*
    - Cyber security; Launch Readines; Documentation

- Areas best suited for IS/ML
  - *Can't completely automate the value chain*
  - *Exploitation of data for decision support cannot be fully automated*
  - *The question is less about where AI can be applied, but more about where does HI need (for culture, trust concerns) needs to be applied*
  - *Augmented Operations may be more viable from a trust perspective as well as overall operational adaptability*

- Impediments, real-world barriers
  - *Lack of explainability for AI Decisions*
  - *Accountability for the impact of decisions*
  - *Cultural, political limitations in the adoption of AI*
  - *"Acceptable" performance for AI in this program space is tighter than for commercial applications*
  - *How do you hold commodity initiatives to appropriate standards (performance & ethical) that protect high-value assets*
  - *"rust belting" the current generation of operators*

- Emerging capabilities, technologies, approaches
  - *Need explainable AI to establish trust in the decisions*
  - *Need to have the ability the check the AI results*
  - *Need to develop community/social engineering techniques to promote adoption*
  - *Community/national standards for AI (ethics?)*
  - *Deriving enterprise performance risk from AI*
  - *Use AI to extract the true signal from the noise*