

# Integrating Machine Learning into Space Operations

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## ABSTRACT

There are significant challenges with managing activities in space, which for the scope of this paper are primarily the identification of objects in orbit, maintaining accurate estimates of the orbits of those objects, detecting changes to those orbits, warning of possible collisions between objects and detection of anomalous behavior. The challenges come from the large amounts of data to be processed, which is often incomplete and noisy, limitations on the ability to influence objects in space and the overall strategic importance of space to national interests.

The focus of this paper is on defining an approach to leverage the improved capabilities that are possible using state of the art machine learning in a way that empowers operations personnel without sacrificing the security and mission assurance associated with manual operations performed by trained personnel. There has been significant research in the development of algorithms and techniques for applying machine learning in this domain, but deploying new techniques into such a mission critical domain is difficult and time consuming. Establishing a common framework could improve the efficiency with which new techniques are integrated into operations and the overall effectiveness at providing improvements.

## 1. INTRODUCTION

Machine Learning describes a set of algorithms and techniques for deriving information from data using algorithms that evaluate statistical features in the data to better model the underlying processes and to predict future outcomes. The use of machine learning algorithms has expanded in recent years in a number of areas, especially marketing, Internet search, voice and image recognition.

Commercial use of machine learning is expanding in multiple areas. Three of the largest companies using machine learning to enhance capabilities are Amazon, Facebook and Google, and those companies have also provided results of their research and development in this area, published detailed technical papers and allowed open access to the source code of their machine learning frameworks, which has led to adoption of these frameworks by developers outside those companies [1] [2] [3].

In addition, improvements in processor technology and reduction in the cost of computing hardware have made computationally intensive algorithms achievable at reasonable cost. Graphical processor units (GPU) are particularly well suited for the matrix operations that form the basis of many of the machine learning techniques. In addition, some cloud service providers make GPU-assisted environments available among their processing options, enabling the use of the commercial cloud for improved scalability, resiliency and security.

But implementation of the algorithms is only part of the story. The management of data, security and utilization of information derived from the machine learning techniques in mission critical applications requires appropriate architectures, organization and policies. At the risk of stating the obvious, the use of machine learning techniques in mission critical applications, as opposed to typical commercial uses, requires a much higher level of performance verification and security. These requirements form the core of the implementation discussion below. The use of machine learning in mission critical applications is on par with its use in self-driving cars [4] where failures can result in injury and loss of life.

### 1.1 Machine Learning Overview

The term “machine learning” has become popular in the past few years, referring to a broad range of statistical techniques for data analysis; deriving information from data that can be used to detect and estimate the state of

internal processes and for predicting future states by defining a function to fit a set of data. The process of using machine learning generally involves defining a set of representative data and using the statistical properties of this data set to define the response of the machine learning system in a process called “training”. Then, when presented with new data the response will be one that corresponds most closely to the response defined for similar training data.

There is a range of machine learning techniques from simple linear methods to non-linear, neural network algorithms and multilayer Deep Learning Networks. It can be helpful to see these as a family of techniques that are appropriate for a similarly varied range of problems.

- Linear algorithms, such as
  - Simple filters that adjust weights based on input, like Automatic Gain Control (AGC)
  - Optimal filters, such as the Kalman Filter that uses knowledge about the quality of measurements and some understanding of the observation processes and the underlying non-linear system to compute optimal estimates of system state, in part by creating estimates of the state of un-observable factors
  - Classification algorithms, like Support Vector Machines, that categorize data based on its location in state space and Clustering algorithms that determine groupings of data points based on statistical properties
- Neural networks, such as
  - Convolutional neural networks where the front end of the machine learning system is a filter that is scanned over the incoming data (a convolution of the subspace filter over the image)
  - Recurrent neural networks where later stages in the machine learning network provide feedback to earlier stages improving the performance with time domain data
  - Deep Learning Networks which consist of a neural network made up of multiple layers, often with convolutional neural networks in the earlier stages and recurrent neural networks in the higher stages, to model complex systems and patterns of activity

Complex systems can require combinations of different machine learning techniques in multiple stages, with initial stages that generate an estimate of system state from noisy data, or perform some initial classification of the system, followed by later stages that could include deep learning networks that combine the output of the initial stages with other information that provides context and produces an output that provides the user with useful information. For this reason, frameworks commonly used for machine learning, such as Apache Spark [5], are in essence data processing workflow managers where the algorithms for machine learning or any other processing are treated as modules that process a data feed, either in a single or multi-stage manner.

## **2. REQUIREMENTS OF MISSION CRITICAL SYSTEMS**

Mission critical systems require a high level of security, resiliency and correctness because the consequences of acting on false inputs, not acting because of system failure or doing the wrong thing can result in material loss or worse. These attributes are discussed below and later, in Section 4, are architectural elements that can support them.

- Security: For mission critical systems the three pillars of information security - confidentiality, integrity and authentication – are necessary at all times. While all communications are not necessarily confidential, some data may be modified or corrupted and some identities are anonymous or untrustworthy, and it is important to recognize the difference. Architectural support to enhance the security of machine learning systems should include, in addition to the common software security support typically supplied by Public Key Infrastructure (PKI), the information about the provenance and reliability of the data - the “chain of trust” such that information derived from that data can inherit the appropriate level of trust. There is currently a lot of development on approaches for providing secure trust include block chain-based approaches [6] [7] [8].
- Resiliency: Mission critical systems need to be able to respond to disruptions and failures by reconstituting capability to minimize the loss. Approaches to enhancing resiliency include distributing execution across a robust infrastructure, self-monitoring system performance for faults and anomalies, and restarting or replacing malfunctioning subsystem when faults or anomalies are detected [9]. Support to machine learning systems

should include the ability to restart subsystems with different training data or learned coefficients when these appear to be causing problems, such as when mislabeled training data causes erroneous outputs when the system is presented with similar data.

- **Correctness:** To say that the mission critical systems must act correctly is obvious but defining an architecture that supports ensuring high likelihood of correctness is not trivial. One approach is to focus on evaluating a wide range of test cases in realistic simulation. A complementary approach is to provide the identical inputs to multiple similar systems and ensure that the outputs are similar with an approach that uses voting to determine the most likely correct result. Support for both of these approaches can be accomplished by integrating features into the architecture that support injection of simulated data and verification of results. Having this support integrated into the architecture facilitates verification and test over the life cycle of the application, from development through operations and maintenance, for verification, performance evaluation and training.

### **3. INTEGRATING MACHINE LEARNING WITH EXISTING OPERATIONAL SOFTWARE**

Integrating machine learning technologies with the existing operational software can be simplified by implementing a parallel path, where inputs to the operational system are replicated as inputs to the machine learning system, along with the outputs from the operational software and user responses.

This approach accomplishes a few key objectives:

- Eliminate any possibility of the machine learning system from providing inputs directly to operational systems. If the machine learning system were tightly coupled to the operational system this would be difficult to ensure. Using this decoupled approach, operator intervention is necessary to implement an actions proposed by the machine learning subsystem.
- Avoid requiring any changes to the operational system. In general, the operational systems are under strict configuration control and require extensive testing before significant changes can be approved. Segregating the machine learning system such that it appears to the operational system as a passive data tap simplifies the configuration control.

Also, while autonomous, machine-to-machine application of machine learning technology may have some future use in space operations, in general, mission critical decisions will have some level of man-in-the-loop for review and approval of resulting tasking. In this paper the approach is primarily on using machine learning techniques to improve the capabilities of operations personnel by prioritizing available information and providing recommendations for tasking and courses of action.

Functionally, this makes the proposed machine learning system appear as what is commonly referred to as a recommendation system; suggesting actions for the user's review using approaches similar to the recommendation systems that augment applications for shopping, travel, news, etc. Recommendation systems do not make decisions for the user, instead they aggregate incoming data and using statistically derived information from past data and the user's responses generate and prioritize alerts and recommendations for possible actions.

For the remainder of this paper the machine learning system will be referred to as the Recommendation Application. As shown in the figure below, the Recommendation Application takes in the same data as the operational command and control application, as well as its outputs, and presents information to the users.

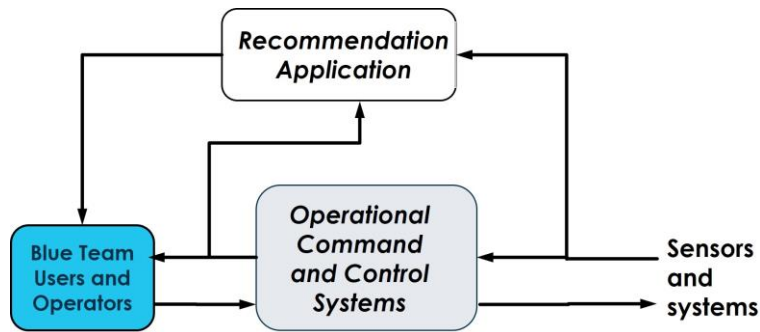


Figure 1 Recommendation Application and System Architecture

#### 4. ARCHITECTURAL CONSIDERATIONS FOR FACILITATING INTEGRATION AND IMPROVING PERFORMANCE

Improvements in the key performance measures described above can be facilitated by using a software framework where security and reliability are designed into the framework, along with the components needed for testing and performance evaluation. Having a structure that defines a set of agents with specific roles should be useful for domain-specific development, test and operations.

##### 4.1 Model-View-Controller

The proposed architecture for the Recommendation Application is the Model-View-Controller (MVC) architecture. The MVC architecture is commonly used for interactive applications. It segregates functionality into the three major components

- **Model:** contains the data and algorithms for data processing. For the Recommendation Application it manages the collection of new data, database management, data analysis and machine learning.
- **View:** presents the outputs of the Model to the user. These presentations organize and prioritize the information based on the identity and role of the user.
- **Controller:** receives commands from the user and provides them, as appropriate, to the Model and the View

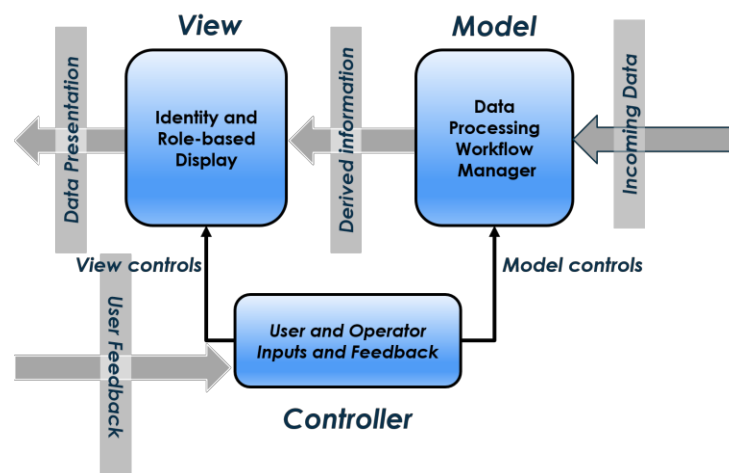


Figure 2 Model-view-controller architecture

## 4.2 Organizing Agents with Roles and Responsibilities of Mission-focused Organizations

Borrowing a concept commonly used for operational testing of and training for mission critical systems the framework is structured with three primary agents:

- Blue Team: Users of the application, presented with a View and providing input to the Controller. Blue Team agent behavior can be performed by human users or automated with software.
- Red Team: Controls the injection of data and events to the application, including both “real world” and simulated data.
- White Team: Manages execution, monitors performance and reports status. The White Team elements are used for verification of results for testing and for monitoring performance in real-time.

By architecting the framework with these three classes of actors both simulated and normal operations are always monitored by the same white team evaluation subsystem.

This approach is commonly used for a range of test activities, from testing software, firmware and hardware, up to complete systems.

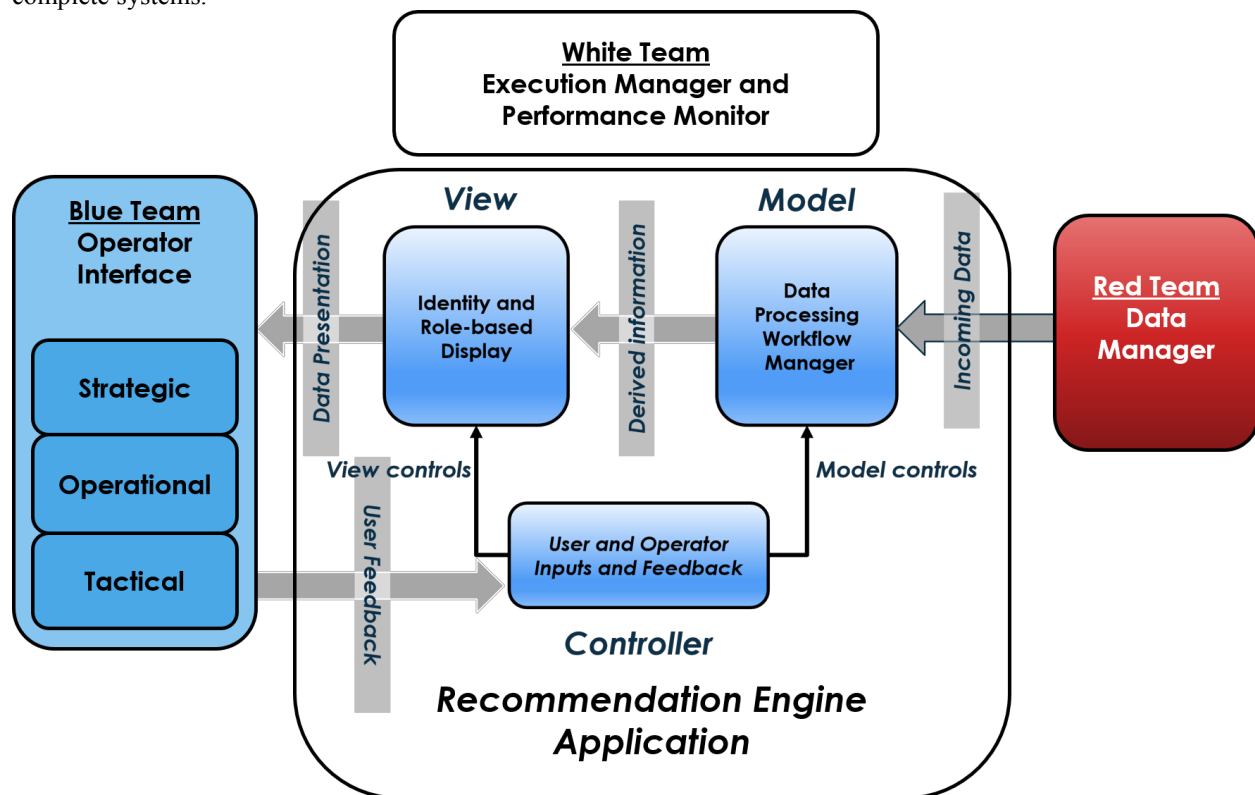


Figure 3 Recommendation System Architecture

## 4.3 Aligning the Operator Interface with the Command and Control Hierarchy

Many organizations are hierarchically organized with three major layers, the strategic, operational and tactical that segregate roles and responsibilities. By creating templates for classes of users within the Blue Team that align with these layers the framework facilitates the implementation of views and appropriate restrictions on controls resulting in better integration between the Recommendation Application and the using organization.

Typical roles and responsibilities for the strategic, operational and tactical blue team agents include:

- Strategic-level users have the ability to set and modify goals and priorities

- Operational-level users convert strategic goals into prioritized taskings, align those taskings with resources and monitor the performance of the tactical team against goals
- Tactical-level users monitor the environment, execute taskings and respond to developing situations

## 5. APPLICATION OF MACHINE LEARNING TO SPACE OPERATIONS

There are a number of areas where the data analysis capabilities that are possible using Machine Learning technology can support space control operations.

- **Orbital analysis and maneuver detection:** Potential improvements in orbit determination over standard methods, like Kalman filters, may be possible with machine learning algorithms that attempt to fit unmodelled nonlinear effects. Analysis of metric data collected on objects in orbit is used to detect changes in their orbits and to improve models of natural phenomena (primarily atmospheric drag, gravitational anomalies and solar weather) that impact that object's orbit. In one example, orbital determination for small satellites based on the Doppler shift of their telemetry has been demonstrated using machine learning techniques [10].
- **Object identification:** utilization of signature data from objects in orbit, such as the object's reflected sunlight, RF emissions and radar returns. It has been shown that it is often possible to determine significant information about an object's structure from the signature data received from optical and radar systems. Research and development has been done on techniques using machine learning to derive that structural information [11] [12] as well as information about the composition of the satellite [13].
- **Anomaly detection and pattern recognition:** By combining data over time and from multiple sources, such as object's orbit or signature to detect subtle changes or unusual activity [14]. For space surveillance, collective anomaly detection, searching for patterns of across a number of objects such as a constellation of satellites, could be especially important in the future as large constellations of small satellites become more common.

Transitioning capability from the a demonstration in the lab to support on the ops floor is always difficult, but it can be facilitated when there is an architectural framework in place where new technologies can be integrated in a manner that is efficient, secure and verifiable. Like standard pylon attachments on aircraft or standard satellite buses, a standard set of interfaces facilitate the introduction of new technology. The United States Air Force Research Laboratory recognizes the importance of standards in the introduction of machine learning into operational systems and data analysis and is supporting the development of standards in the Streamlined Machine Learning effort [15].

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