Data Insights, Pedigree, and Automation for Space Domain Awareness

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ABSTRACT

The quantity and quality of data available to space operation centers is critical for operator understanding of the congested and contested space domain. The growing number of commercial Space Situational Awareness (SSA) data providers, advanced sensors, and expansion of common data repositories has increased the number of sources and types of SSA data that legacy systems were not originally designed to process. Decision makers need to quickly gain insights into the pedigree of the Space Domain Awareness (SDA) data feeds used in Space Battle Management (SBM) systems before they can respond to activities in the space domain with confidence. Furthermore, additional sources of information do not always ensure that data is available to users in a timely manner. It is often not feasible for humans to manually understand the pedigree of SDA data because the lack of traceability and the volume of information is too large to interpret.

The research and development efforts conducted to enable space operators to quantify the pedigree and traceability of different SDA data sources are discussed. Automated analytical methods to quickly compare different sources of data and objectively rank data based on metrics such as traceability, latency, and pedigree are identified to help build trust. Additionally, this approach helps users to identify what process improvements would have the greatest impact to their mission. Spacecraft pattern-of-life machine learning algorithms, widely discussed in literature, can be enhanced with different datasets depending on the assessed pedigree. Examples show how these concepts can automate time consuming tasks reducing operator workload. Finally, the value of SDA analytical metrics, augmented with machine learning algorithms, running within space operations centers is highlighted.

1. INTRODUCTION

Trustworthy Space Domain Awareness data is crucial for an effective space battle management capability. Timely access to data pedigree information enables operators and automated systems to make more informed, time-sensitive decisions with less uncertainty. However, these decision makers often find it challenging to quantify confidence in the data available to them. Legacy systems and processes were developed in a different era when space was much less congested and considered a haven for a limited number of critical space assets. Many fielded SSA capabilities were not designed for the challenges facing the space operations community today. Therefore, there is a great need for automated detection, prediction, and confidence assessments of space related events.

Emerging capabilities, both in orbit and on the ground, have significantly changed the current space operating environment. The proliferation of government and commercial constellations has increased the demand on aging space surveillance sensors, making it more challenging to accurately track and obtain a clear picture of activities in space. More recently, multiple nations have demonstrated counterspace capabilities that can hold spacecraft at risk across orbit regimes [1]. Commercial SSA is a growing industry designed to address these needs but faces challenges to integrate with existing systems and processes [2]. While there are numerous commercial SSA capabilities on the market, few are optimized to perform the SBM mission.

There is a need for additional automated capabilities to process large quantities of non-traditional data and produce actionable information that is relevant to SBM use cases [3]. Machine-to-machine interfaces exist; however, satellite state data is often emailed or posted in chat rooms to share across the operations community. In some cases, data processing systems may not be connected through compatible networks, requiring complex numeric data to be manually retyped onto another system. Non-standardized manual processes can induce unintentional errors (e.g., text formatting, wrong data) and recipients are often not provided with enough context to assess data provenance or pedigree for themselves. This can create ambiguity in how space events are interpreted.

Subject matter experts (SMEs) can often draw insightful conclusions from complex datasets, but this is time-consuming, and it can be infeasible to conduct timely SME-level assessments at scale. Automated systems are vital to achieve space security objectives on operational timelines. The capability to ingest traditional and non-traditional data sources and generate pedigree assessments to produce best state data recommendations reduces operator workload, decreases decision timelines, and enables standardized interpretation of events. Over time, additional automation can occur as trust in the system grows.

This paper summarizes the research and development efforts conducted to design an automated SDA insights and pedigree application. Comparisons to consumer safety initiatives are drawn to explore how similar concepts can be modified and tailored to assist the space operations community. Data interface standards and machine learning (ML) algorithms are identified to help provide relevant SBM insights to mission operators. Attention will be brought to a data orchestration architecture and how it enables multiple microservices to process data and generate ML-enabled insights. Operational use cases are highlighted to show how varying levels of automation can be leveraged to achieve different mission outcomes. Finally, the key components of an automated data pedigree assessment web service, which can recommend the best state for a resident space object (RSO) at a given time, is presented. The results highlight the value of an automated SDA insights and pedigree analytics service to improve operator and decision maker confidence in space battle management solutions.

2. APPROACH

Concepts Drawn from Consumer Food Safety Initiatives

There are not enough SMEs to determine the best course of action (COA) for all space related events. Manual SME intervention is not sufficient nor scalable to address these challenges in the space domain on operational timelines. Space operators should be provided standardized metadata and metrics for the data they rely on, so they do not need to be experts in every nuance of astrodynamics and space operations. After conducting research on analogous challenges faced in other industries, the food safety industry was found to have effective approaches that could be adapted to mitigate challenges faced when assessing SDA data insights and pedigree at scale.

The public depends on government regulatory bodies such as the U.S. Department of Agriculture (USDA) and U.S. Food and Drug and Administration (FDA) for food safety. These agencies ensure food quality, inspect processing facilities, establish best practices for manufacturers and producers, and publicize food recalls [4] [5]. Without mandatory reporting requirements, there is little incentive for manufacturers to highlight negative product characteristics, which can obfuscate crucial data from consumers. If a food product is found to be misbranded or contaminated, a recall is disseminated publicly. This allows distributors and consumers to take appropriate action to reduce the potential for negative health impacts. While recalls are generally volunteered by manufacturers, this process is essential to protect consumer health and maintain public trust of producers. Food safety regulatory bodies provide a platform to share recall information with consumers in a consistent and timely manner.

Space operators are consumers of SDA data much like the public are consumers of food products at grocery stores. Space surveillance data is a critical product consumed by operators, decision makers, and SBM systems. Data providers are incentivized to support critical missions which drives funding and additional support. Like the food industry, there is little natural incentive to provide users metadata about products that may divulge limitations of their systems. Today, if an erroneous state is published, there is no standardized process to recall the data. The dataset may be removed from a database and replaced with better data, but if a system already queried the data, the end user may have no idea that the information should not be used. In many cases, data is not removed from the repository, which puts the onus on an orbit analyst to filter out anomalous time history data. Data providers may argue that publishing metadata could reveal propriety information or create an operational security concern. Therefore, SDA data recalls should not necessarily be made public in all cases but should be available to those with appropriate Need-to-Know.

The FDA and USDA empower consumers to make informed decisions about their food choices by mandating the inclusion of specific nutrients on products in a standardized format called the Nutrition Facts Label. This standardized approach allows consumers to compare a core group of nutrients across different products, regardless of where they shop. While regulatory agencies are important entities to help maintain national food safety, consumers have the responsibility to make decisions appropriate for their individual health. Standardized labels enable consumers to take ownership of their health and nutrition. A consumer is more likely to buy a gallon of milk that lists nutrients, name of the dairy farm, and an expiration date than a carton without any labels or markings.

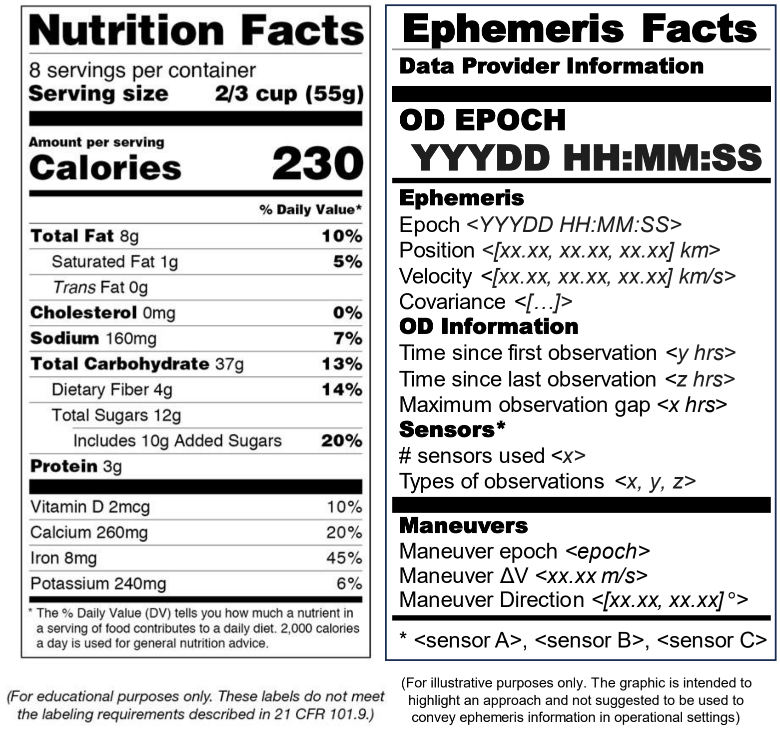

Fig. 1 Operators and decision makers should have access to the equivalent of *Nutrition Facts* [6] or *Ephemeris Facts* for the SDA data they consume.

Space operators should have access to the equivalent of nutrition facts for the SDA data they consume. Fig. 1 shows how a standardized set of orbit determination (OD) information for an ephemeris state is analogous to a Nutrition Facts Label. Consistent access to this data would allow users to prioritize data providers and sensors that provide quality and reliable data on an RSO-by-RSO basis. This creates quantifiable metrics that decision makers can use to build additional trust in the data used to make SBM decisions.

A carton of milk that does not have an expiration date may be perfectly suitable to consume with no ill effects, but a consumer incurs a risk that their ability to smell spoiled milk is insufficient. A Two-Line Element set (TLE), representing an estimate of the position and velocity of an RSO, provides about the same amount of information that a milk label without an expiration date offers. Instead, the TLE epoch is more comparable to the date that a food product arrived at a grocery store. The vast majority of TLEs published are useful and valid to use, however, it is often difficult to have confidence in quality of the data. Most users of TLE data do not have insights into the sensor and observation data that was used to create the state estimate.

In 2006, trans fat was added to the required list of nutrients on the Nutrition Facts Label. A study conducted by the USDA showed that the *"… trans-fat content of food declined, and the number of products marketed as containing no trans-fat increased"* between 2005 and 2010. These trends suggest that *"mandatory disclosure of ingredients […] can lead food manufacturers to reformulate their products to make them healthier"* [4]. More informed consumers are more likely to make better choices about the products they purchase and consume, rewarding producers of higher-quality products and compelling those with lower-quality products to adapt to changing market demands.

The authors hypothesize a similar trend would be observed in the space operations community if standardized metrics were routinely published. A time history analysis of this metadata would inevitability highlight high-performing and underperforming SDA data providers. SDA data users could use this data to provide quantifiable evidence to inform requirements for future system development and identify specific process improvements that would yield better mission outcomes.

Space Domain Awareness Insights and Pedigree

Space operators often receive SDA data without associated pedigree information, or descriptions of the data quality and the processing steps performed to derive the data [7]. The growing number of commercial SSA data providers and advanced sensors has increased global capability, but more needs to be done to build operator trust. One way to increase user trust in SDA data is to leverage community standards to improve interoperability between users [8]. Leveraging standardized file and data formats also reduce non-recurring engineering costs for new programs to integrate into larger SBM systems. Operators should receive a standardized set of metadata that describes the pedigree for state estimates and observations like a Nutrition Facts Label.

The Consultative Committee for Space Data Systems (CCSDS) is an international group with the purpose to support the "*development of communications & data systems standards for spaceflight*" [9]. CCSDS Recommended Standards, or Blue Books, describe interfaces and message formats that can be applied to space missions enabling consistent interfaces between systems. The Orbit Comprehensive Message (OCM) is an example message format that can be used to provide additional insights to operators [10]. The OCM orbit determination section includes several fields that are valuable to operators to understand data pedigree. Table 1 shows some of the OCM fields that are core parameters or "nutrients" that allow users, who are not orbit determination SMEs, to make informed data comparisons and decisions.

Table 1. The OCM file format orbit determination section includes several fields that are valuable to describe ephemeris data pedigree.

Field	Description	Value to Mission Operators
OD_EPOCH	Time of the OD solved-for state	The time difference between the state epoch and OD epoch can provide insight into how much a state (e.g., new maneuver) could have changed since the last time the RSO was observed.
DAYS_SINCE_FIRST_OBS	Time since first observation used to estimate state and OD_EPOCH	Used with DAYS_SINCE_LAST_OBS to determine timespan over which observations were collected.
DAYS_SINCE_LAST_OBS	Time since last observation used to estimate state and OD_EPOCH	The time difference between the OD epoch and last observation can provide insight into how much a state (e.g., new maneuver) could have changed since the last time the RSO was observed.
OBS_USED	The number of observations used within OD span	Provides qualitative insights into how well the orbit was observed when used with maximum observation gap and data timespan.
MAXIMUM_OBS_GAP	The maximum time between observations within the OD span	Provides qualitative insights into how well the orbit was observed when used with number of observations used and data timespan.
SENSORS_N	Number of contributing sensors	In general, more sensors will have more diverse sensing geometry and provide better state estimates.
SENSORS	Names of contributing sensors	Operators learn to trust some sensors over others based on experience. Automated processing can trend sensor biases over time and improve operator trust.
DATA_TYPES	Description of types of observations used to estimate state	More diverse data types can result in better state estimates through data fusion. State estimates are also less susceptible to potential denial and deception activities.

The table includes a small subset of the fields contained within the OCM orbit determination section. Other OCM sections such as covariance and maneuver information should also be included, but are omitted here because they are more commonly available to operations centers. These OD fields were identified to provide the most value when assessing pedigree of data processing. From these fields, derived pedigree metrics can be calculated.

Data timeliness and reduced latency are crucial to the success of any space operation. Analysts can use statistical methods to assess COA probability of success when the mean time to task, collect, detect, track, and identify RSOs are numerically quantified [11]. Different systems are often used to conduct each part of the SDA processing chain. This means that the time between event occurrence and data availability to operators and processing systems is not always consistent. TLEs include an epoch of the state but are often disseminated without a timestamp stating when it was generated. The TLE age, or the time between state epoch and system ingest time, can be used to estimate the data latency. This is represented as one of the blue dashed lines shown in Fig. 2. The time latency between an ephemeris state epoch and system ingest time can be misleading because TLE epochs do not necessarily indicate the last time the RSO was observed [12]. The "OD epoch" and "time since last observation" fields in the OCM provide better latency metrics because they are relative to the time a specific action occurred.

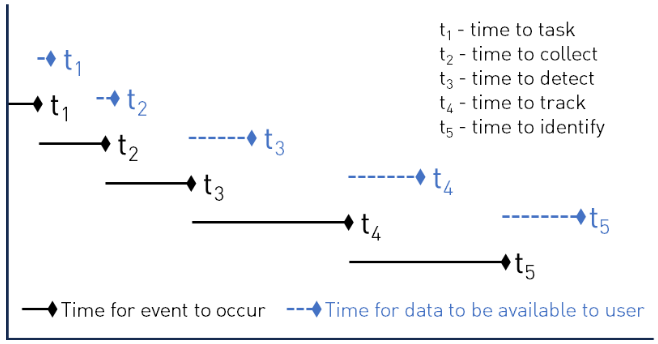

Fig. 2. SDA mission success is dependent upon information becoming available to users on operationally relevant timelines

Understanding data latency does not improve data in real time, but latency trends help operators determine if the data is timely enough for future decision making timelines. Data providers may provide lower latency data on some RSOs due to sensor capabilities. Decision makers may choose to prioritize tasking specific sensors for selective RSOs depending on latency trends. An automated capability to trend SDA data latency should be made available to users to provide quantitative evidence of process inefficiencies. The process to generate this evidence is often cumbersome and challenging if the SDA metadata is not available.

Data providers and regulatory bodies should be responsible to ensure quality and accurate SDA data is disseminated to users. Operators and decision makers should not need to worry about every nuance of orbit determination and ephemeris state processing. However, operators have a responsibility to use the best data available to achieve mission objectives. High-level metadata, which describes the orbit determination process that was used to create a state estimate, enables operators and processing systems to make that determination. This should include the number of observations, types of sensors, and ideally the specific sensors that were used to generate the state. For example, a more diverse set of sensors (e.g., optical, radar, passive RF) is likely to produce higher quality states due to improved observability and different geometries. An operator does not need to be an OD expert to make better decisions when this information is available to them.

Modifying processing systems to include additional SDA metadata may not be realistic in the near term due to budgets and competing priorities. Many systems are reliant on state data like TLEs which do not include this information and will not be widely available. Providers that can produce state data with additional metadata should have requirements to share orbit determination data on repositories like the Unified Data Library (UDL). In the interim, additional pedigree insights can be extracted from existing datasets that have minimal associated metadata.

TLEs are one of the most widely used formats to distribute RSO state estimates and is the primary ephemeris message format for many space operations centers. Since TLEs are distributed with minimal metadata, it is challenging to determine if a RSO maneuvered between state updates. While maneuver detection is better suited to occur during metric observation processing, many operations centers do not receive observation data. Even if observations are available, operations centers are not necessarily equipped to process observations. Unless a maneuver message is received, operators need a way to detect possible maneuvers and filter out bad data that may erroneously look like a maneuver occurred. Ideally, data providers would include maneuver alerts with state updates, but this is unlikely to become a standard procedure due to legacy interfaces and processes.

Machine Learning

A TLE-based maneuver detection algorithm was created to generate a history of RSO maneuvers. Similar approaches are widely discussed in literature, thus not the primary objective for this research [13] [14] [15]. Maneuver detection is conducted using relative state differences with the ability to apply different thresholds on a specific orbit or satellite basis. Maneuvers are estimated in the radial, in-track, and cross-track (RIC) orbital frame to support maneuver characterization analysis. A single TLE update is not sufficient to distinguish between a real maneuver and an anomalous update. As new data is ingested into the system, historical pattern-of-life data can be leveraged to help confirm if a previously identified maneuver is a false alarm. This is an ideal use case for a ML algorithm to improve state anomaly detection as additional data is processed.

A feedforward neural network (FNN) machine learning algorithm was trained on multiple GEO satellite maneuver datasets generated with the maneuver detection algorithm described above. Different FNN models were trained depending on the orbit and specific RSO activity that was to be characterized. For example, a GEO RSO station keeping model was trained using six years of publicly available Milstar TLE data because station keeping is conducted on a routine frequency for this constellation. The model performance was then tested against SJ-17 TLEs from June 2019 – January 2024 containing over 150 maneuvers which were manually classified by an orbit analyst. Table 2 shows some of the key features used to characterize east-west station keeping, north-south station keeping, and non-station keeping maneuvers conducted by GEO RSOs.

Table 2. Important features extracted from TLEs used in FNN machine learning algorithm to characterize satellite maneuver patterns-of-life in GEO.

Maneuver epoch	Time between maneuvers
ΔSMA caused by maneuver	Maneuver longitude and latitude
SMA before maneuver	Longitudinal drift rate change caused by maneuver
Maneuver magnitude and direction	

The FNN station-keeping model correctly identified station-keeping vs non-station-keeping maneuvers with 94% accuracy compared to the manual orbit analyst maneuver classification approach. The output from the station-keeping classification model is shown in Fig. 3. While this is a relatively small dataset for training a ML model, it shows the methodology works. The model was trained on one type of constellation and then successfully demonstrated on an RSO with a different owner and operator. The value of this model is that it can characterize maneuvers without future data. This allows the model to be used in a near-real-time maneuver characterization mode and provide potential maneuver indications to operators as soon as data becomes available. If an anomalous TLE change is detected around the time that a station-keeping maneuver was expected to occur, it can quickly build confidence that the data is correct.

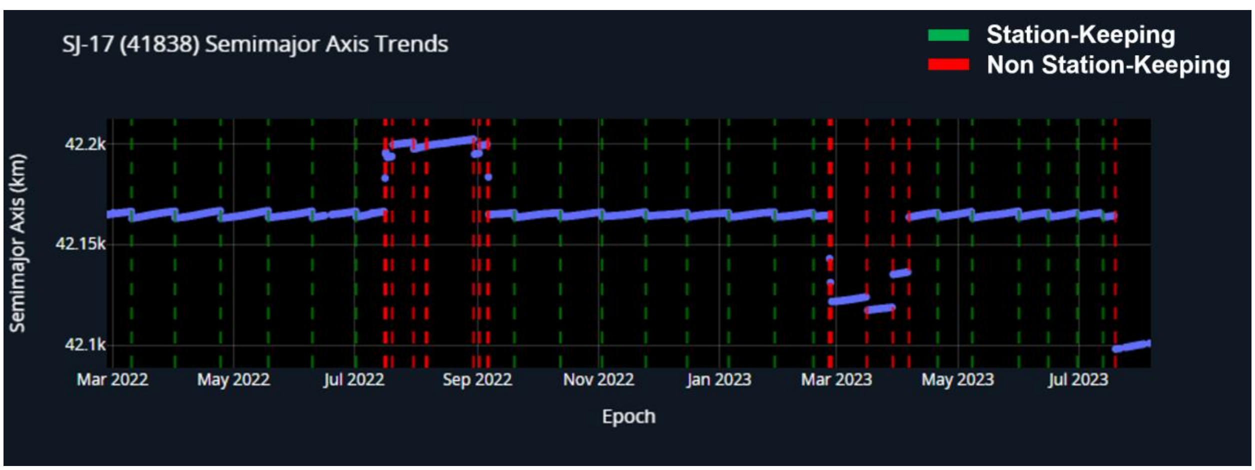

Fig. 3. SJ-17 semi-major axis derived from publicly available TLEs shown in blue. Maneuvers are shown with vertical dashed lines, and colors represent FNN assigned classification with 94% accuracy.

As a pattern-of-life history is created, anomalous state updates can be automatically classified. Without observation data to corroborate TLE estimates, subsequent state updates that change one or more orbital elements from one value to another and then back to the original value is considered anomalous and a bad state update. It is time consuming to conduct this type of analysis manually and at scale, and it reduces an operator's ability to confidently make critical decisions without waiting for subsequent TLEs. Anomalous state identification can be used to generate state update anomaly rates on a data provider and RSO basis. Some providers may have a harder time tracking a given RSO. If that is the case, the overall confidence level for that provider data associated with the RSO could be reduced.

Automation

As of August 2024, there are over 45,000 objects regularly tracked by the 18th Space Defense Squadron (SDS) [16]. Automated capabilities are essential because there are simply too many objects on orbit to generate pedigree metrics manually. Beyond reducing operator workload, automation creates standardized methodologies to consistently interpret complex datasets. This minimizes the variability in results when users with varying levels of training and expertise take different approaches on what input data to use.

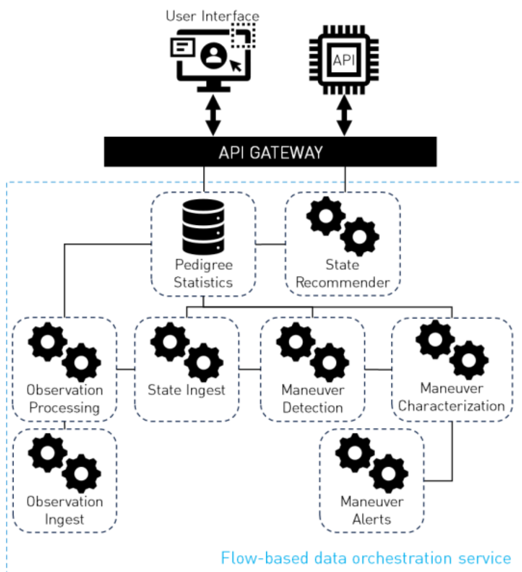

Fig. 4. A flow-based data orchestration service enables microservices based on different technologies to be easily configured.

The data pedigree capabilities described in the previous section were developed as separate microservices shown in Fig. 4. This allows more flexibility when developing new capabilities and minimizes the overhead of multiple teams contributing to the larger effort. Apache NiFi, a flow-based programming software package, was chosen as the data orchestration software to connect microservices together [17]. NiFi allows new data sources to be integrated with minimal effort and modifications to processing steps without changing the overall architecture. A new process can be added independently of other algorithms to perform custom data conversion and cleansing using the NiFi user interface shown in Fig. 5. NiFi can run on cluster nodes to easily scale and manage compute resources as processing demands increase.

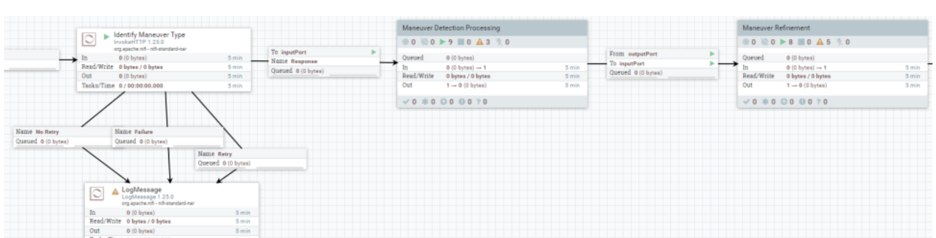

Fig. 5. A screenshot of the Maneuver Detection Process Group highlights the flexibility of the NiFi user interface to add new processing blocks.

There are multiple operational mission use cases for a data insights system. The use cases can be broadly broken down into three categories: human-in-the-loop (HITL), human-on-the-loop (HOTL), and human-out-of-the-loop (HOOTL).

Human-in-the-Loop
Test and training activities are critical to maintain a ready and effective SBM capability. This capability, when used in a HITL mode, is useful for training and exercise events, allowing operators to replay real data or simulate different space events. Regardless of automation, operators should have the ability to process high priority events in-the-loop when SMEs want complete control of a specific outcome. This drives the need for a user interface, shown in Fig. 4. The user interface also allows operators to analyze historical data and collect quantitative evidence on past system performance to help improve future system processes. Finally, in this mode, SMEs tune the system to improve results during HOTL or HOOTL operations and help build trust in the system.

Human-on-the-Loop
HOTL operations can also be used for test and training activities to help increase operator expertise in SDA processing. This mode is necessary when operators want to have complete control of decisions but there are too many concurrent high priority events that a human cannot make every decision. Operators can monitor lower priority decisions to ensure that the system is operating as expected with the ability to make ad hoc decision overrides. This is the next level of building trust in automated systems without giving up full control.

Human-out-of-the-Loop
Complete autonomy (HOOTL) is needed when many concurrent events or time sensitive events are occurring. There is a long processing and decision chain supporting space battle management and small delays early in processing can be detrimental to mission success. HOOTL operations are critical when conducting operations with proliferated constellations. SMEs may not be accessible 24/7, but autonomous systems can consistently make data-driven decisions, ensuring reliable outcomes even outside of typical business hours. Ultimately a tuned system will reduce operator burden and enable reprioritization of resources; for example, SMEs can be allocated to solving longer-term technical challenges.

Working towards a fully automated capability that, to date, is mostly driven by subjective SME experience should be a measured approach. SMEs should begin with HITL operations for day-to-day operations. Once SMEs are more confident with the general approach, day-to-day low priority RSOs should be processed using HOTL for training operators and then transitioned to HOOTL operations once procedures have been codified. Automation, when approached methodically, can significantly improve space battle management solutions and reduce manual workload in space operations centers.

3. RESULTS

Satellite State Recommender
When operators have access to multiple sources of ephemeris data spanning commercial companies and government organizations, it can be challenging to determine which data should be used. The automated pedigree metrics described above allow for a “latest or greatest” state recommender service to be created. This service makes recommendations to a user or system on which state should be used for a given RSO. The service recommends states based on available data such as pedigree, state age, and data uncertainty as shown in Table 3.

Table 3. Quantitative and qualitative comparisons along with data provider history is used to generate an ephemeris state recommendation.

Quantitative State Comparison	Qualitative State Comparison	Data Provider History
Multi-source ephemeris comparison	Transparency of data provenance	Maneuver false alarm statistics on RSO-specific basis
Probability maneuver occurred between last observation and OD	OD information included (# sensors, # observations, etc.)	Historical anomalous state statistics on RSO-specific basis
State covariance comparisons as available	Geographic and sensor modality diversity	Manual user input preferences derived from operations experience

Consumers use recommendation systems to help find a new restaurant to try or the best product to buy given some criteria. Consumers are not required to use the top recommendation, but the system provides information that they may not have found on their own. Similarly, users of the state recommender service do not need to use the highest-ranking state, but rather receive a ranked listing of recent states with associated ranking justification. Users have the choice to use the highest-ranking state by default or can pick a lower ranked state based on their own reasoning.

A decision maker can have increased confidence in their understanding of the space domain when there is a general agreement among all ephemeris state predictions. This indicates a higher level of accuracy and reliability in the data used for space situational awareness and decision-making. When states diverge from each other, some may be trusted more than others, or in other cases there is not enough information to determine which state is best to use. When there is no clear “best state”, this should prompt operators to request sensor tasking to collect additional information and minimize uncertainty.

Quantitative State Comparison Score × Weight + Qualitative State Comparison Score × Weight + Data Provider History Score × Weight = State Pedigree Score

Fig. 6. The state pedigree score can be tuned by users by modifying the weights of quantitative and qualitative scoring.

Fig. 6 shows how the scoring process for ranking different states can be tuned by modifying the weights of each component. A balance is required to allow users to change parameters to suit their needs while not perturbing the scoring process so much such that it provides little value. In general, quantitative state comparisons should be weighted the most. Restricted bounds on custom weighting ensures that consistent results are still produced while preventing large changes without proper justification. State recommendations may be different on an RSO-by-RSO basis which allows operators to leverage better data across a wide range of space operations.

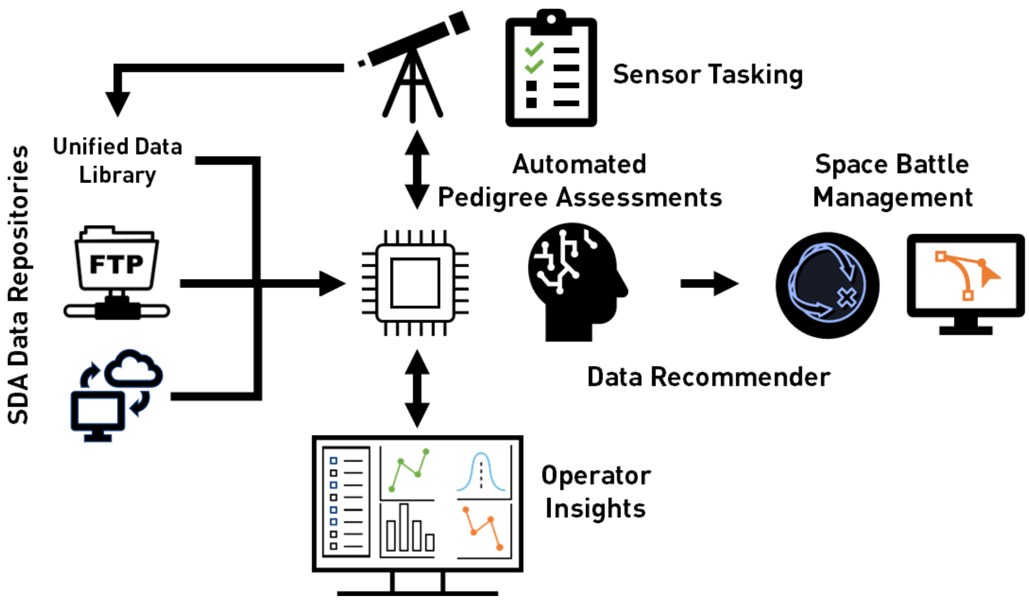

Fig. 7. A Space Domain Awareness Data Insights system supports varying levels of automation to improve mission outcomes.

The state recommender service, shown as part of the larger Space Domain Awareness data insights and pedigree application in Fig. 7, should improve operator and decision maker confidence in space battle management solutions. Operators do not need to worry about every state database update because automated capabilities can ingest much more data. Decision makers can rely on a consistent methodology to select states which is less dependent on specific user knowledge and skillsets.

4. CONCLUSION

In conclusion, the increasing complexity and congestion of the space operating environment necessitate the development of automated capabilities for Space Domain Awareness data insights and pedigree assessments. Research and development was conducted to design an automated SDA insights and pedigree application, drawing concepts from consumer food safety initiatives to empower space operators to make informed decisions about the data they consume. By establishing standardized data interface standards and leveraging machine learning algorithms, the system can provide relevant SBM insights to mission operators and recommend the best state for a RSO at a given time. An automated data pedigree assessment web service was created leveraging a data orchestration architecture that enables multiple microservices to process data in a flexible manner. This service highlights the value of an automated SDA insights and pedigree analytics capability and improve operator and decision-maker confidence in space battle management solutions.

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