Machine learning for RSO maneuver classification and orbital pattern prediction

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ABSTRACT

In this paper we present Probabilistic Assessment of Space Threats (PAST) which employs machine learning techniques to assist space domain awareness analysts quickly and accurately. PAST quantitatively categorizes the type of orbital maneuver that a satellite executed and then uses that historical orbit data to determine whether the maneuver is nominal or anomalous. These capabilities provide space domain awareness analysts with quantitative assessments of potentially threatening behaviors in space. PAST addresses three operational challenges that confound rapid and accurate assessment of observed resident space object maneuvers for space situational awareness: (a) producing a quantitative confidence metric for maneuver classifications, (b) performing maneuver classifications with uncertain and/or incomplete data, and (c) assessing whether maneuvers are nominal or anomalous. We tested PAST on the data from the four-week space domain awareness exercise Global Sentinel 2017 (GS17) and proved that PAST provides unique and novel capabilities using Machine Learning and aids in much quicker decision-making after an orbital maneuver is detected.

1. INTRODUCTION

Various Space Situational Awareness (SSA) systems receive radar, optical and passive radio frequency (RF) observations from a sensor network. An example of this would be iSpace [1], a Lockheed Martin developed C2 system. The observations from these sensors are processed and a Resident Space Object (RSO) catalog is updated. Events are then detected (e.g. maneuvers) using the updated information. The ground station of a satellite operating nearby another undergoing a maneuver must have lead-time to react to a potential threat that could play out over hours or even weeks. Analysts must therefore assess potential threats an RSO has on others quickly. The first step is determining the type of maneuver (e.g., station keeping, Hohmann transfer) and whether that maneuver is benign (e.g. routine station keeping) or a potential threat (e.g., a Rendezvous Proximity Operation or RPO). Maneuvers that are classified as transfers are of much higher interest and receive a high level of analyst attention and sensor network monitoring. Even in this first step alone, nuanced analyses are often accomplished manually with uncertain data. This results in lower confidence assessments right out of the box.

The Lockheed Martin Probabilistic Assessment of Space Threats (PAST) microservice automates these analyses with machine learning techniques, while also providing quantitative confidence metrics for those assessments. PAST benefits the human space domain analyst by quickly and accurately predicting the type of maneuver just executed by a satellite. PAST relies on historical orbital behavior patterns to determine if this maneuver is expected or anomalous and considers each RSO's temporal normality pattern. PAST addresses three distinct operational challenges that potentially confound existing methods: (a) producing a quantitative confidence metric for maneuver classifications, (b) performing maneuver classifications with uncertain and/or incomplete data, (c) and assessing whether maneuvers are nominal or anomalous. We cover each of these in the next three sections.

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2. ASSESSING MANEUVER TYPES WITH QUANTITATIVE CONFIDENCE

Maneuvers are classified manually by Subject Matter Experts (SMEs) due to nuances in the data and the need to understand the patterns in maintaining each satellite's orbit. This process begins by reverse engineering a satellite's orbital patterns to see if one can spot pattern of life changes. Difficulties arise in (a) determining which observations occur before and after the maneuver, (b) errors in sensors observations add uncertainty and complexity to the maneuver classification, and (c) having an adequate amount of historical data to assess a reasonable pattern to draw conclusions upon. This is very time consuming and error-prone. Furthermore, in crowded orbital regimes additional challenges arise such as sensor observations being 'cross tagged,' meaning the sensor tagged an observation to the wrong RSO.

PAST helps the analyst resolve these situations where simpler algorithmic approaches to automating maneuver type classification by Lockheed Martin Rotary and Mission Systems (LM RMS) in [1] have proven unsuccessful. Our solution is to use Neural Network Machine Learning techniques that can produce Boltzmann Distribution posteriors [2]. These are probability distributions that PAST uses to express confidence across the various maneuver types. Rapid classification in real-time can give analysts quick assessments of maneuver types once the maneuver is detected. The Boltzmann distribution shows the learner's confidence levels for each maneuver type to the analysts.

Satellite tracking is commonly affected by first making observations/measurements of the position and (components of) the velocity of a given satellite, and then attempting to estimate its state, typically expressed in terms of its Keplerian orbital elements (OEs). An RSO's orbit varies over time due to exogenous factors such as but not limited to: gravitational variation, atmospheric drag, and solar wind. Hence, the RSO's corresponding OEs do as well. These variations are small and manifest gradually and when subject only to these influences, satellite movement through "OE space" can be modeled as a smooth curve.

Active satellites are in orbit to perform tasks, and often being able to do so requires that they maintain orbits that exhibit particular characteristics (e.g., geostationary). Consequently, after a satellite has deviated significantly from its desired state (where significance is obviously a strong function of its task/purpose), it is necessary to make corrections to the orbit. Most active satellites possess some means of directed propulsion, i.e., the ability to "nudge themselves" out of one orbit and into another (nearby) one. Due to the nature of orbital mechanics, these maneuvers are usually constrained: there are certain types or classes that occur more frequently and these can often be recognized by their effects on the OEs, or more directly on quantities derived therefrom, e.g., orbital period, etc. For the purpose of this document, the analysis of satellite maneuvers has been divided into two types: classification and pattern-of-life analysis. The former is focused on estimation of a posterior probability distribution over a space of maneuver types, while the latter deals with computing similarity metrics that quantify a distance between a given maneuver and a satellite's maneuver history. These analyses will be described in the sections that follow.

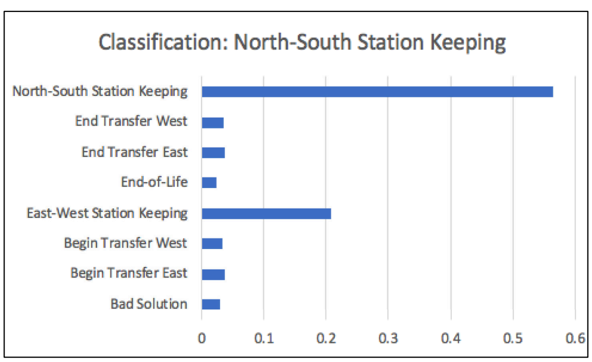


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Fig. 1: PAST classifier produces a Boltzmann Distribution over possible maneuver types

A common method for maneuver detection entails the use of observations of kinematic property deltas. As we noted earlier, these types of changes can be grouped in classes; to each class, an analyst can attach a descriptive label (e.g., "East-West Station Keeping," "Begin/End Transfer," "End-of-Life"). It is important to note that for now, an analyst decides on a labeling based solely on kinematic measurements and does not consider any other factors, e.g., previous maneuver history. Our classification tool exploits an ML-based algorithm to learn how to compute a posterior distri-

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bution over the class types (i.e., a finite categorical space) given measurements of changes in orbital characteristics. Hence, the output of classification is not a declaration of the form "Maneuver is of Class A," but rather is a set of probabilities over all classes.

An example of this is depicted in Figure 1. Note that the histogram provides the probability that a maneuver belongs to a particular class given the kinematic deltas (inputs) that appear on the right. In the case shown, there is about a 56% chance that the maneuver is of type "North-South Station Keeping". A user choosing an appropriate value for the detection threshold determines whether this amount of certainty represents an acceptable level of risk, i.e., if she is willing to live with the implied tradeoff of detection probability (Pd) vs. the probability of false alarm (PFA). How this tradeoff varies as the detection threshold is varied can be illustrated in a Receiver Operating Characteristic (ROC) curve; an example of one is shown in Figure 2.

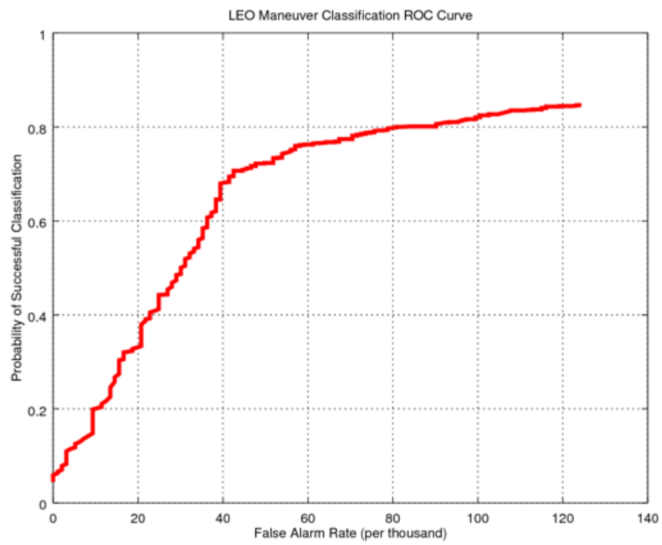

Fig. 2: Typical ROC Curve Characterizing Classifier Performance

In Figure 2, the horizontal axis presents false alarm statistics in terms of False Alarm Rate (FAR) rather than P_{FA} as is standard. Consequently, by judicious choose of detection threshold a user can accommodate a range of requirements. They do so by balancing the costs of non-declaration due to insufficient confidence (a missed detection) with that of possible misclassification (a false alarm).

2.1 Maneuver Classification Data

Training data for PAST was created using maneuver data from Global Sentinel exercises 2016 and 2017 (GS16, GS17). Two-Line Element Sets (TLE) [3] from space-track.org were analyzed by SMEs for the presence of a maneuver. The presence of an East-West Station Keeping or a Transfer maneuver is indicated by a distinct change in the orbital period of the satellite that is not due natural perturbative forces. Similarly, the presence of a North-South Station Keeping maneuver is indicated by a distinct change in the inclination. The SME selected pre and post maneuver element sets were then used to produce an estimation of the maneuver parameters. LM iSpace [1] uses a schema to describe these TLE parameters which was also used in PAST. See Table 1. More details on our SMEs and their backgrounds can be found in section 8.

2.2 Machine Learning Models

We follow machine learning practices by splitting the training such that 70% of the data is used to train the models and 30% for testing the models. PAST makes several passes over the training set to generate multiple machine learning models to provide varying levels of fidelity. PAST then uses the highest fidelity model available during classification.

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Symbol	TLE Parameter	Units
Dist	Distance	km
dE	Delta Eccentricity	N/A
dIncl	Delta Inclination	Degrees
dPeriod	Delta Period	Minutes
dRa	Delta Apogee Height	km
dRp	Delta Perigee Height	km
dU, dV, dW	Delta Position UVW	km
dVel	Delta Velocity	km/sec
dvHom	Delta Velocity Hohmann	km/sec
dvPln	Delta Velocity Plane	km/sec

Table 1: iSpace Maneuver Alerts provide PAST with the parameters for model training and maneuver classification

Relative Fidelity	Model Class	Description
High	Mission	Models maneuvers of satellites from a common mission (e.g., GPS, Comms)
Medium	Regime	Models maneuvers by their orbit regime (e.g., LEO, MEO, GEO)
Low	Generic	Default model regardless of satellite specifics

Table 2: PAST supports models of varying fidelity

Example model types are listed in Table 2. If the higher fidelity model is not available for the satellite in question, PAST will try to use the next lower-fidelity model. Models are generated offline and stored in a model repository where the operational PAST service can access them, as shown in Figure 3.

PAST follows a microservice model to ensure minimal downtime. Because of this, the models can be updated without restarting PAST allowing subject matter experts to create new training data examples throughout the life of the system. Each class of model will be created if there exists sufficient training data for that level of fidelity, where sufficiency is determined when the accuracy of the model against the test set exceeds 0.8. As the model fidelity decreases, so does the resulting confidence of classifications produces from them. Therefore, when PAST provides output distributions to iSpace, it also provides the model class that was used to generate it, allowing analysts to better understand how the results were derived.

The PAST maneuver classification models were trained with historical and simulated maneuvers using subject matter expert labels for each maneuver. With existing models, PAST is capable of classifying the maneuver types listed in Table 3. PAST's models, however, can be extended to support other maneuver types as necessary.

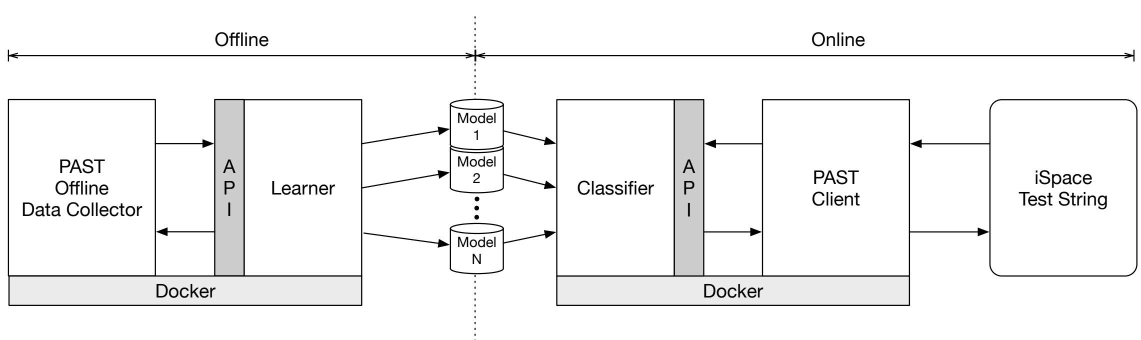

Fig. 3: PAST Learning and Classification supports multiple models

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GEO Orbits	LEO Orbits
Begin Hohmann Transfer East	Drag Makeup
Begin Hohmann Transfer West	Altitude Change
East-West Station Keeping	Plane Change
North-South Station Keeping	Deorbit
End-of-Life	
End Hohmann Transfer East	
GEO End Hohmann Transfer West	

Table 3: Existing PAST models for maneuver classification

3. UNCERTAIN AND/OR INCOMPLETE MANEUVER DATA

Real-world orbit data may be based on low-fidelity observations and may come from commercial sensors whose configurations are not easily adjusted. This may result in missing or low-certainty maneuver data and false maneuver alerts. Most state-of-the-practice machine learners will fail with missing or highly inaccurate feature data. PAST's neural network can marginalize the missing or uncertain features to produce posterior distributions with the available feature data, producing lower-confidence yet viable classifications. Lower-confidence distributions can be generated with early TLE data post-maneuver and refined later with more accurate TLEs. The machine learner can detect when the input features do not adequately match any trained data, resulting in a "bad solution" classification. This, in addition to very low confidence classifications, can help analysts quickly identify potential false alarm maneuver alerts. By using distribution estimation rather than classification declaration, PAST can accommodate cases of partial information.

For example, suppose that only a subset of measurements were available to an analyst and she wanted to produce a posterior distribution based only on the information available to her (i.e., the reduced measurement set). During training, the algorithm is designed so that it learns not only how to calculate estimates to the posterior distributions (as was illustrated previously), but also builds and stores an approximation to the entire prior distribution for the input space. As a consequence, by application of Bayes Theorem the classification tool is able to produce a posterior given any subset of possible input values. Standard ML techniques cannot do this; they would need to be trained on each such subset separately. Looking at the example shown in Figure 1 with 12 input values, one would need to perform $2^{12} - 1 = 4095$ (ignoring the empty set) different training runs, and produce 4095 different models in anticipation of any potential subset of input data. With PAST's approach, this is not necessary.

4. ASSESSING NOMINAL VS ANOMALOUS MANEUVERS

Real-world satellites often maneuver due to natural effects (e.g., atmospheric drag, gravitational perturbations) as well as mission-specific behaviors (e.g., intentional new orbit). Analysts need to quickly assess a maneuver in light of historical behavior patterns. PAST models each satellite class as its own periodic stochastic process to learn normalcy models for its behaviors/maneuvers. PAST can determine if a maneuver is benign or typical based on historical data. Atypical maneuvers can indicate threatening behavior by a satellite. The pattern of life (PoL) model can also assist analysts by predicting the next expected maneuver for each satellite.

In the analysis of a satellite's PoL, we attempt to characterize and encode its maneuver history. As a preliminary approach, we could simply classify each maneuver that has occurred over some period of time in the past (or perhaps record the distributions that were estimated, using the tool described in Section II.A) However, given a historical record that comprises an asynchronous sequence of time-tagged satellite Two Line Elements (TLEs), we can effect a more complete, and potentially more informative, analysis.

Being presented with a satellite's TLE is tantamount to being given its orbital elements (OEs). An OE is a six dimensional specification of an orbit; where the first five of these are geometric in nature: semi-major axis, eccentricity, inclination, argument of perigee and right ascension of the ascending node. These geometric specifications fix the orbit's size, shape and orientation about the Earth. The sixth, time of perigee, specifies where on the orbit the satellite lies at any given instant. Hence, we may consider orbits to be points in a five dimensional space; specifically, a five

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dimensional real manifold. One way of characterizing the likelihood that a "new" orbit fits into a pattern determined by past orbits is to estimate a probability distribution on the orbital manifold; areas of high probability are associated to those regions in which the satellite appeared before. Using the estimate of the distribution we can associate to the orbit into which the satellite has transitioned a numerical likelihood. This provides a quantitative metric that will allow an analyst to ascertain how similar this latest orbit is to those that came before.

In addition, we can examine the history of the times at which previous maneuvers occurred. More precisely, we focus not on the absolute times, but rather the amount of time that elapsed between maneuvers. It turns out that a potential model the (stochastic) process that drives the production of these "waiting times" is not simply Poisson, but rather can be captured in a suitably modified difference of Poisson processes. The modification essentially accounts for the fact that a simple difference of Poisson processes would assign non-zero probability to negative time increments, which is of course nonsensical. Consequently, we use a distribution function that is conditioned on the occurrence of only non-negative values.

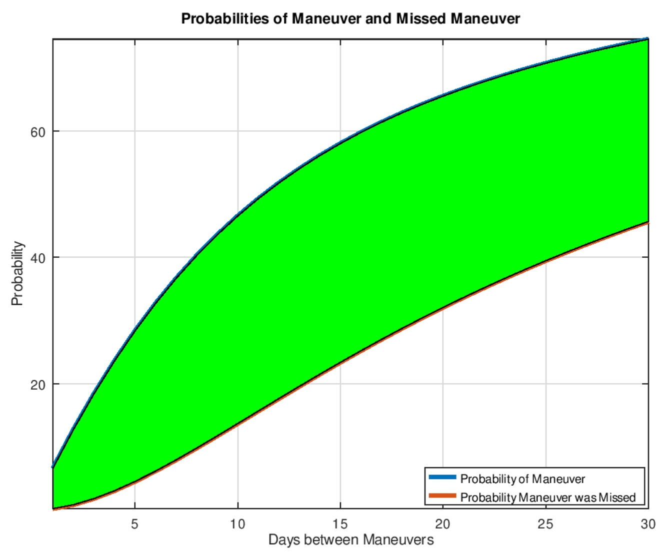

Fig. 4: Likelihoods of maneuver time

Using this distribution, we can calculate the likelihood that the time at which a newly observed maneuver is in keeping with the pattern of times between previous maneuvers. In Figure 4, we depict two probabilities: first, that a maneuver occurs after a given number of days (upper, blue curve) and second, that a maneuver should have occurred before this number of days has elapsed (bottom, red). The green shaded area represents the range of probabilities that correspond to exactly one maneuver. It becomes clear, as time passes, it not only becomes more likely that a maneuver will occur, but also that more than one maneuver will occur. In a manner similar to that employed when looking at ROC curves, a user can balance the credibility associated to historical data. For example, again referring to Figure 4, if a maneuver is observed 16 days since the previous maneuver, there is about a 60% chance that it is a maneuver following an observed maneuver pattern, and only about a 22% chance that it is not. Note that these are not mutually exclusive events, as there is also a probability (about 18%) that no maneuver would have taken place in that 16 day span. Consequently, we see that we can distill both geometric and temporal information from historical PoL data and use this to attach likelihoods to future observations. As intimated earlier, it is also possible to incorporate these distributions into a Bayesian framework that could be used to estimate probabilities of observing maneuvers a priori, rather than a posteriori.

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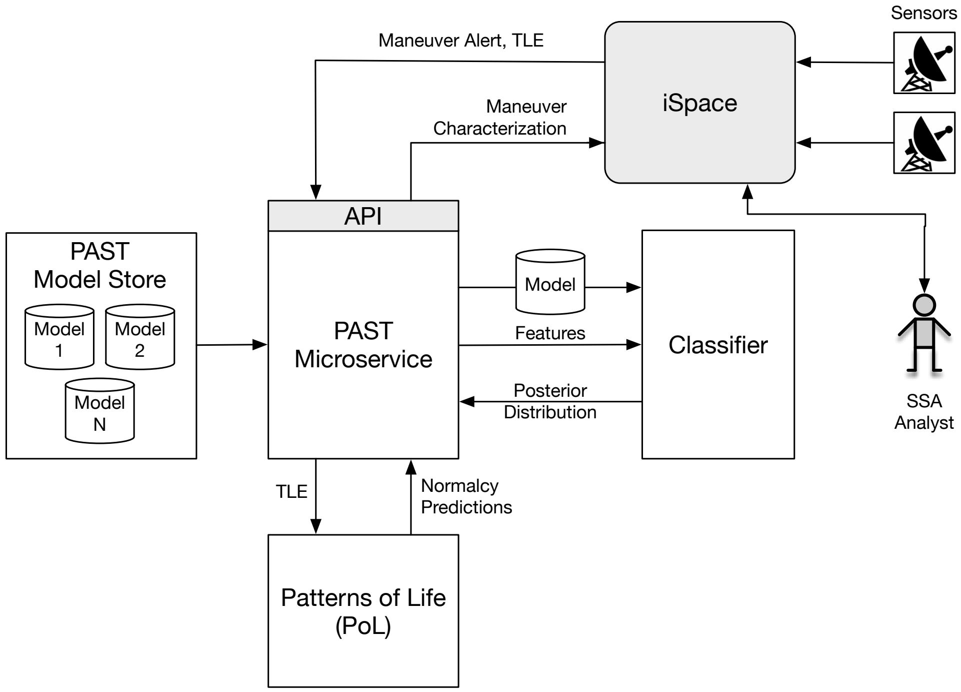

Fig. 5: The PAST Microservice provides maneuver classification and patterns of life analysis to iSpace

5. ISPACE INTEGRATION

PAST is designed and implemented as a REST-based [4] microservice [5] deployed within a Docker container [6]. This microservice was integrated with and hosted by the LM RMS iSpace SSA framework. As shown in Figure 5, iSpace provides the interface to the SSA Analyst (users) and ingests and manages sensor data from one or more sources. iSpace also maintains a REST-based API that facilitates clients and microservices (such as PAST) to subscribe for information feeds about RSOs. To support maneuver classification and patterns-of-life (POL) analysis, PAST subscribes to two information streams (described in Table 4): Maneuver Alerts and TLE Updates. Whenever iSpace receives new sensor information about an RSO, it may refine its orbital parameters in and stream the updated orbit model in the form of a Two-Line Element (TLE). PAST uses the TLE information as an input into its POL analysis. Additionally, iSpace analyzes RSOs and if a maneuver is detected, it issues a Maneuver Alert to PAST, which initiates the maneuver analysis capabilities in PAST. Once the maneuver has been classified and the POL assessment conducted, PAST sends a Maneuver Characterization message back to iSpace (see Table 4) which allows the SSA Analyst to see the quantitative maneuver classification and POL results along with the Maneuver Alert. Because PAST is an independent microservice with its own API, it can also easily integrate with other data sources and SSA frameworks that can provide TLE updates and maneuver alerts.

Message	Source	Trigger	Contents
Orbit Update	iSpace	iSpace receives new sensor data about a satellite's orbit	Refined Two-Line Element (TLE) for each updated RSO
Maneuver Alert	iSpace	RSO Maneuver detected	Difference between pre- and post-maneuver TLEs
Maneuver Characterization	PAST	Maneuver Alert received and analyzed	Maneuver Type classification Boltzmann distribution, Model used for classification, POL "Expected Maneuver" score

Table 4: PAST-iSpace Interfaces

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6. EXPERIMENT AND RESULTS

In November 2018, Lockheed Martin conducted an experiment that assessed PAST's maneuver classifications in an operationally realistic test environment, where the primary goal was to determine the accuracy and efficiency for maneuver classification. This was accomplished by integrating PAST with iSpace as shown in Figure 5, and processing a long-duration high-fidelity data set replay that contains a large number of RSO maneuvers.

To understand how we validate PAST, we used training and validation data that had been classified by our Subject Matter Experts (SMEs) as presented in section 8. We also had Day-in-the-Life data from GS17 that had not been classified by a SME. The SME went back and looked at the GS17 maneuvers and manually classified them, and then compared them to how PAST classified them.

During the Global Sentinel 2017 experiment (from which data was captured one year earlier, 2016), PAST received over 300 maneuvers of geostationary (GEO) satellites to classify from the LM iSpace system in real-time. For 90.0% of this data, PAST was able to classify the maneuver and our SMEs determined these classifications as being correct. Some maneuvers are easier to verify. Figure 6 shows an easy case, where the change in the orbital period of the orbit of Satellite 25639 on 5/5/2016 is readily discernible. Other maneuvers are more difficult for a SME to identify, such as what is shown for Satellite 28134 in Figure 6.

Of the remaining 10.0% of the data not verified, the SMEs could not score the classifier results due to the complexity of the maneuver. In these case, PAST produced an answer that could not be easily validated which underlines the difficulty of doing this work manually as described in section 2. It is possible in these situations, although not verified, that PAST's neural network could produce better answers where analysts could not figure out the maneuver type, or at a minimum provide relative confidences via Bolztmann posteriors.

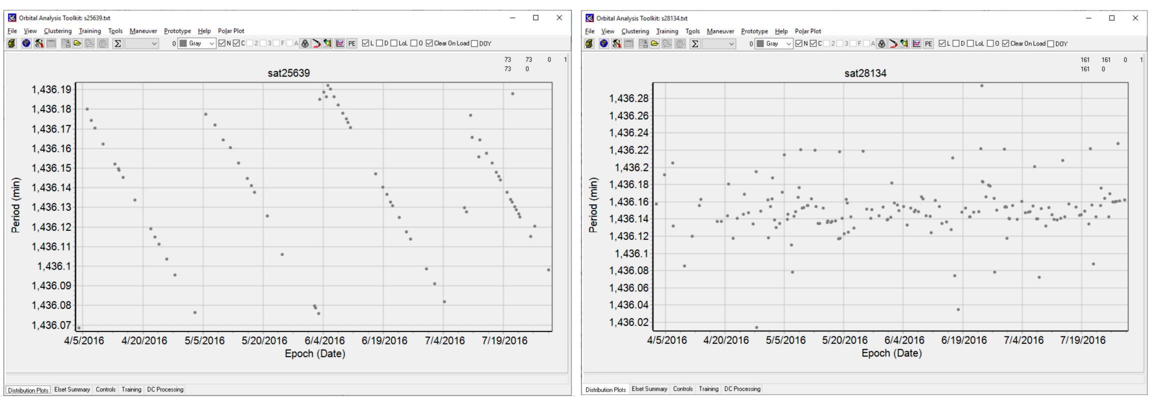

Fig. 6: Easily Discernible Maneuver (Sat 25639) and a Difficult-to-discern Maneuver (Sat 28134)

There are many factors that can contribute to the inability of a SME to definitively classify a maneuver, and chief among them is the quantity and quality of the sensor observation data that contributed to the maneuver detection. These overly complex maneuvers indicate the need to gather more data and to collaborate with the satellite Owner/Operator, if possible. Satellite 28134, has been historically difficult for human analysis due to its very frequent and very small maneuvers. In this case, PAST correctly classified its 4/27/2016 maneuver as an East-West Station Keeping maneuver in milliseconds (execution time).

Due to the limited amount of Low Earth Orbit (LEO) satellite training data, this experiment only classified GEO maneuvers. This experiment provided LM ATL with historical data to construct PoL models for satellite orbits. Therefore, this capability was not scored during the experiment.

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7. CONCLUSIONS

PAST provides Space Situational Awareness analysts with a rapid assessment of satellite maneuvers. Maneuver type classifications offer Bolztmann probability distributions of each maneuver type so that the analysts can understand and gain confidence in the underlying models of the system, providing visualizations of the primary and alternative classifications for each maneuver. The patterns of life analysis gives analysts rapid assessment of whether the maneuver in question is nominal (i.e., expected) or anomalous based on that satellite's historical behavior, providing an early indication of whether that maneuver is a potential threat to other satellites. These two capabilities work together to overcome traditionally time-consuming and error-prone calculations that give decision makers probabilistically-grounded confidences in millisecond response times. The microservice architecture employed by PAST offers a simple, loosely-coupled integration into iSpace or another SSA framework. PAST provides a discriminating capability that offers SSA analysts a quantitative assessment of satellite maneuver type classification and threat based on historical patterns.

Ongoing research for PAST will extend its pattern of life analysis to also learn patterns among satellites encompassing a constellation. By analyzing the orbital history of a related group of satellites, inter-satellite patterns can also be assessed to determine not only whether a single satellite is maneuvering abnormally, but also whether elements of the constellation are executing behaviors that do not match the historical patterns. For example, it may fall within the bounds of normalcy if one satellite executes a maneuver a little earlier than usual. But if multiple satellites within a constellation also make slightly altered changes to their orbits, this may constitute a coordinated behavior by the group, and could indicate an emerging tactic or action by the constellation. This research, coupled with its extant capabilities, will facilitate SSA for an evolving space domain.

We are seeking additional SMEs beyond those used by the iSpace team to better qualify our results. In a follow on experimentation we would like to use the expertise of actual analysts who do this activity every day. For this, we plan on being more rigorous than our initial experiment as described in this paper. First, we would like to use real maneuver data from the Joint Space Operations Center (JSpOC) with necessary sponsorship. We'd also like to tap into the Unified Data Library [7] to access additional data to build longer (historical) patterns of satellite behaviors using commercial sources.

8. ACKNOWLEDGING OUR SUBJECT MATTER EXPERTS

The authors would like to acknowledge the advice and analysis from our Subject Matter Experts (SMEs) and express our gratitude. The SMEs consulted in our experiment were:

Mr. Dave Cappellucci: Dave is a subject matter expert in space systems, orbital analysis, modeling and simulation, software and systems engineering and application development. Space subject matter expert for the Space Surveillance Network (SSN), satellite tracking, orbital debris issues, unknown object processing, lost satellite issues, sensor response models and general orbital motion analysis. Dave has an impressive career with Lockheed Martin as lead Astrodynamics on the JMS/HAC proposal effort, lead analyst for the SPADOC Operations Working Group, and as an astrodynamics expert for the Space Fence program. For PAST, Dave was instrumental in building our training data sets and evaluating the outcomes of our initial prototypes.

Mr. James (Jim) Foster: Over his accomplished career at Lockheed Martin, Jim worked with operational users as a liaison to the system developers. He supported currently operational systems used for satellite catalog maintenance, event processing (e.g., maneuvers, conjunctions, decays, proximity operations, launch, directed energy), and space surveillance sensor management. He also supported prototype systems that are in the process of replacing existing systems, providing feedback to the developers and assisting the operators in transitioning the systems to operational use. For PAST, Jim was instrumental in assessing the experimentation results with the Global Sentinel 2017 data set.

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