Assessing the IADC Space Debris Mitigation Guidelines:
A case for ontology-based data management

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ABSTRACT

As the population of man-made debris orbiting the Earth increases, so does the risk of damaging collisions. The Inter-Agency Space Debris Coordination Committee (IADC) has issued space debris mitigation guidelines including a key recommendation that before mission's end, spacecraft should move far enough from GEO so as not to be an operational hazard to other objects in active missions. It can be extremely difficult to determine if a spacecraft or operator is in compliance with this guideline, as it requires prediction of future actions based upon many data types. Furthermore, there has been no comprehensive assessment of the adequacy or validity of the IADC recommendations. The EU strives for a Code of Conduct in space, the United Nations-Committee On Peaceful Uses of Outer Space (UN-COPUOS) strives for guidelines to ensure the Long Term Sustainability of Space Activities (LTSSA), the FAA is concerned with Space Traffic Management (STM), etc. If rules, policies, guidelines, and laws are put in place, how can any entity know who and what is adhering to them, when we don't even know how to quantify and assess behavior of space objects? The University of Arizona aims to address this salient issue.

As part of its new Space Object Behavioral Sciences (SOBS) initiative, the University of Arizona is developing an ontology-based system to support integration, use, and sharing of space domain data. As a first use-case, we will test the system's ability to assess compliance with the IADC recommendation to move beyond GEO at the end of a mission as well as the adequacy and validity of recommendations. We describe the relevant data types gathered for this use-case, present a prototype ontology, and outline methods for combining semantic analysis with astrodynamics modeling. Without loss of generality, we present this method as an approach that will form the foundation of SOBS and be used to address pressing challenges in Space Situational Awareness (SSA), Orbital Safety, LTSSA, and STM.

1. INTRODUCTION

> "It has been a common understanding since the United Nations Committee on the Peaceful Uses of Outer Space (UN-COPUOS) published its Technical Report on Space Debris in 1999 [1], that man-made space debris today poses little risk to ordinary unmanned spacecraft in Earth orbit, but the population of debris is growing, and the probability of collisions that could lead to potential damage will consequently increase. It has, however, now become common practice to consider the collision risk with orbital debris in planning manned missions. So the implementation of some debris mitigation measures today is a prudent and necessary step towards preserving the space environment for future generations." [2]

As the population of debris orbiting the Earth increases, so does the risk of damaging collisions. The risk is particularly high with non-operational spacecraft that cannot be maneuvered to avoid collisions and may degrade over time into multiple objects. The Inter-Agency Space Debris Coordination Committee (IADC) has issued space debris mitigation guidelines [2], but no method currently exists to effectively assess whether or not a spacecraft or operator is in compliance with these guidelines. In this paper, we outline a method for assessing IADC guideline compliance as an initial use case for Space Object Behavioral Sciences (SOBS). The use case is guiding the design and construction of an ontology-based proof of concept decision support system.

2. IADC GUIDELINES

The Inter-Agency Space Debris Coordination Committee (IADC) is an international forum of governmental bodies that coordinates activities related to man-made and natural debris in space. Its primary purposes are to exchange information on research activities, to facilitate opportunities for co-operation in space debris research, to review the progress of ongoing co-operative activities, and to identify debris mitigation options [1]. The IADC defines space debris as "all man-made objects including fragments and elements thereof, in Earth orbit or re-entering the atmosphere, that are non-functional". They have issued guidelines for mitigating the creation of space debris. These guidelines are based on common principles from space debris mitigation standards developed by various national agencies. They cover the overall environmental impact of the missions, especially in protected regions of space such as the Low Earth Orbit Region (LEO) and Geosynchronous Orbit Region (GEO).

IADC guidelines focus on:

1. Limitation of debris released during normal operations
2. Minimization of the potential for on-orbit break-ups
3. Post-mission disposal
4. Prevention of on-orbit collisions.

The guidelines are intended for use during mission planning and spacecraft design and operation, but operators of spacecraft that were launched prior to issuance of the guidelines are encouraged to follow the guidelines to the greatest extent possible.

For our proof of concept, we focus on post-mission disposal of resident space objects (RSOs) in GEO, excluding the component of minimizing the potential for post-mission break-ups resulting from stored energy. The IADC Guidelines state the following regarding post-mission disposal:

> Spacecraft that have terminated their mission should be maneuvered far enough away from GEO so as not to cause interference with spacecraft or orbital stage still in geostationary orbit. The maneuver should place the spacecraft in an orbit that remains above the GEO protected region.
>
> The IADC and other studies have found that fulfilling the two following conditions at the end of the disposal phase would give an orbit that remains above the GEO protected region:
>
> 1. A minimum increase in perigee altitude of 235 km + (1000 CR*A/m), where
>
> - C_R is the solar radiation pressure coefficient
> - A/m is the aspect area to dry mass ratio (m^2kg^{-1})
> - 235 km is the sum of the upper altitude of the GEO protected region (200 km) and the maximum descent of a re-orbited spacecraft due to luni-solar & geopotential perturbations (35 km).
>
> 2. An eccentricity less than or equal to 0.003.

3. A SPACE OBJECT BEHAVIOR APPROACH TO ASSESSING IADC COMPLIANCE

Space Object Behavioral Sciences (SOBS) is the study of objects in space to quantify and predict their behavior and support space situational awareness (SSA) and space safety. The mission of University of Arizona (UA)'s SOBS program is "To assemble and lead the world's top multi-disciplinary science and technology research and development talent and focus it to solve problems requiring rigorous and comprehensive capabilities in assessing, quantifying, and predicting the behavior of objects in space, both man-made and natural." The SOBS initiative is developing an ontology-based information fusion system to support integration, use, and sharing of space domain data for applications such as threat assessment and decision support. We describe ongoing development of that system in this paper.

Fig. 1 provides a high level view of the workflow of UA's planned information fusion system. **Source data** from multiple hard (physics-based) and soft (human-based) sources are stored in the CyVerse Data Store [3], where they serve as inputs to **processing (1)** such as Space Object and Event Detection Registration. **Processed data**, annotated with metadata keyed to the Space Object Behavior Ontology (**SOBO**) undergoes **data fusion (2)**, which essentially converts them to instances of SOBO classes in the form of Resource Description Format (RDF) triples [4]. "Triplified" data are stored in the **SOBS-Knowledge Base** (KB), a graph database whose nodes represent instances of entities in SOBO connected by SOBO object, data, and annotation properties. Through various query processes, information is extracted from the KB and used in **knowledge generation (3)** processes such as Bayesian Network analysis, to produce useful information or **figures of merit**, such as whether or not an object is compliant with IADC guidelines and likely to remain so in the future.

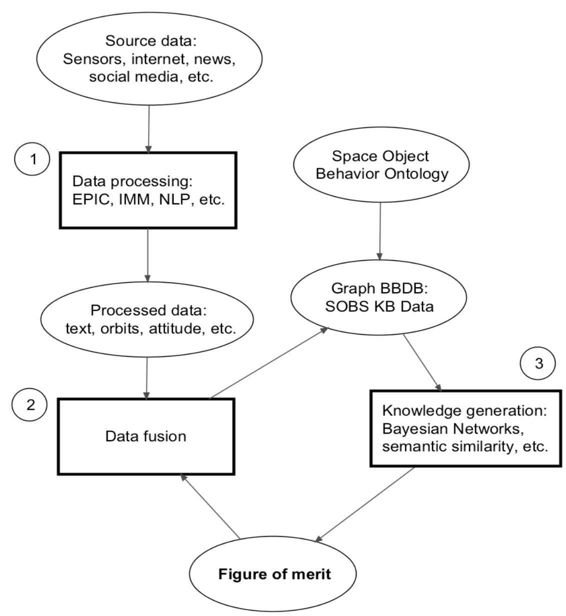

Fig. 1. Overview of the SOBS space data information fusion system.

As an initial use-case, we aim to demonstrate the feasibility of a system for gathering hard data inputs (e.g., orbit parameters) for both active and retired objects in or just beyond GEO, associating them with the semantic content of an ontology, and determining if the objects are in compliance with the IADC recommendation to move beyond GEO at mission's end. An auxiliary but important goal of this use-case is to promote open-source development of resources for safe space operations.

4. DATA COLLECTION

Ultimately we plan to collect softs data related to purposive human behavior, including news stories, space agency reports, and social media (Tweets), along with hard data. In this paper, we focus on hard data collection and analysis.

4.1 <u>Astrometric and photometric data</u>

We are observing three classes of objects: (1) active GEO satellites, (2) inactive satellites that have been successfully placed in the GEO graveyard orbit and (3) inactive satellites known not to have been disposed of into the graveyard orbit (Table 1). We will also attempt to observe satellites that are reported to be near the end of their life or are being transitioned to the GEO graveyard orbit. Astrometric data (i.e. time-tagged line-of-sight detections) for our targets are collected from (a) (Dorne) Tucson, Arizona, and (b) (Westeros) Fresno, California using Raven-class telescopes (Table 2). Nightly observations are made remotely in an automated scripted mode from astronomical twilight to dawn. Charged Couple Device (CCD) camera exposure times of 3-5 seconds are used to prevent significant trailing of field stars in the rate-tracked images for atrometric measurements. The observing cadence for objects in GEO for orbit determination requires three observations every 18 minutes, with at least three tracking revisits in the course of a single night [5]. Complementary to astrometric observations, we are collecting photometric (observed spatio-temporal space object flux intensity) data to infer the rotation state of RSOs. The observational cadence for this task depends upon the rotation period of the object.

Table 1. Example list of satellites for observation

Active in GEO	**Inactive, in GEO Graveyard**	**Inactive, not in GEO Graveyard**
33278 INMARSAT-4 F3	38868 BREEZE-M R/B	3691 TACSAT 1
28868 ANIK F1R	26761 XM-1 (ROLL)	25924 ABS 6 (LMI 1)
28884 GALAXY 15	23816 INTELSAT 707	14134 PALAPA B1

Table 2. Telescope and detector parameters used for initial data collection

Site	Telescope	Detector	Field of View	Pixel Scale
Dorne	0.5-m F/2.9 Newtonian	KAF6303	38.3'x38.3'	0.56"/pixel (unbinned)
Westeros	0.37-m F/9 RC	KAF16803	60'x41.2'	1.21"/pixel (unbinned)

Automated hard data collection is accomplished using a set of Python scripts that control various hardware components including initialization, sorting two-line elements (TLEs) to calculate the position of the target, sensor pointing, and CCD camera control and focus. Collection requires minimal human intervention during the course of the observing process. The data are transferred to our CyVerse cloud data store in near real time (NRT) for processing.

4.2 Processing of astrometric and photometric data products

Our initial assessment of a given RSO's compliance with IADC guidelines is based on foundational knowledge of that RSO's orbit, orientation, and inferred maneuver behavior, and history (where relevant). The activities, methods, and tools being used to compute these data include the following tools:

- Air Force Research Laboratory (AFRL)'s **Ananke** software provides methods to model and evaluate candidate sensors and algorithmic approaches to generating Space Domain Awareness (SDA) knowledge. Ananke is a single integrated simulation and analysis tool that possesses dynamical systems and Bi-directional Reflectance Distribution Function (BRDF) modeling, verified sensor models, as well as advanced initial orbit determination and characterization filters. Ananke will be used to generate simulated measurements to test the Multiple Model Adaptive Estimation (MMAE) and Interactive Multiple-Model (IMM) algorithms.
- Applied Defense Solution (ADS)'s **Efficient Photometry In-Frame Calibration (EPIC)** software [6] is used to automatically produce photometric and astrometric data from raw telescope image frames. EPIC implements an automated background normalization technique that eliminates the requirement to capture dark and flat calibration images. The technique simultaneously corrects for dark noise, shot noise, and CCD quantum efficiency/optical path vignetting effects. With EPIC, a constant detection threshold is applied for constant false alarm rate (CFAR) object detection without the need for aperture photometry corrections. The detected pixels are summed (without further correction) for an accurate instrumental magnitude estimate.
- AFRL's **Constrained Admissible Region-Multiple Hypothesis Filter (CAR-MHF)** [7] performs orbit determination and data association (i.e. assigning detections to unique RSOs) for multiple objects using astrometric data derived from EPIC's output. CAR-MHF combines the statistical track initialization capability of the CAR with an MHF that implements an unscented Kalman filter (UKF) to associate future measurements to the newly initialized track and recursively refine the trajectory and uncertainties.
- Space object attitude (inertial-to-body orientation) profiles are determined using an **MMAE** [8]. The MMAE uses a parallel bank of filters, each operating under a different hypothesis to determine an estimate of the physical system under consideration. Each filter employs the UKF estimation approach, processing astrometric and photometric data to refine the RSO's orbit while inferring the RSO's attitude and body rates.
- The **IMM** is used to detect orbital maneuvers [9]. The IMM estimator has the ability to "switch" from one model to another in a probabilistic manner, modeled by a Markov sequence. Like the MMAE approach, the IMM estimator also consists of a bank of model based filters running in parallel at each cycle. As opposed to the MMAE which converges to a "winner take all" method, the initial IMM estimate at the beginning of each cycle for each filter is a mixture of all the most recent estimates from the single-model-based filters. This feature enables the IMM estimator to effectively take into account the history of the RSO behavior modes without the exponential growth in the computation and storage requirements needed by the optimally derived estimator.

5. A PROTOTYPE SPACE OBJECT BEHAVIOR ONTOLOGY

Ontologies are a way to represent knowledge within a given domain, by describing the types of entities (classes) in the domain and the logical relations among them, using machine-readable language. By providing standardized, computable definitions for the terms used by scientists, ontologies make information explicit to both humans and computers and contribute to reproducible science. Ontologies support computer applications that need to find, retrieve, integrate, and analyze large quantities of data from multiple and disparate sources. We are developing the Space Object Behavior Ontology (SOBO) as part of an information fusion and decision support system that can ingest data from multiple sources in an automated fashion and aid data and knowledge discovery.

The SOBO is an application ontology—that is, an ontology built for a specific set of purposes and needs. This is in contrast to a domain ontology, which strives to thoroughly model a particular domain such as RSOs or planetary features, and must serve a broad variety of use cases. Fig. 1 shows a set of domains that will ultimately be needed to support SOBO. The existence of domain ontologies such as [10-12] can support SOBO, and we support the principle of reusing existing ontologies. However, we recognize that reuse may conflict with our goal of open source development, so we remain open to various reuse approaches.

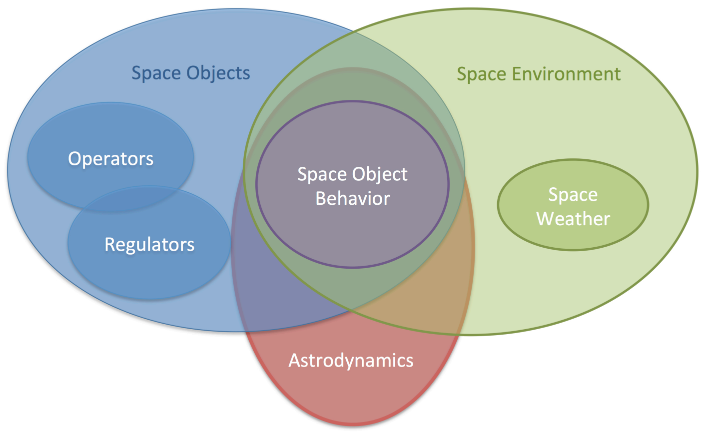

Fig. 1. Domains needed to describe Space Object Behavior

5.1 <u>Design elements of SOBO</u>

Design and development of SOBO follows widely-accepted best practices including modularity, compatibility with other ontologies and semantic web applications, consistent internal application of ontology design patterns (ODPs), and reuse of existing ODPs [13]. Based upon the successful application and utility of many biological ontologies (e.g., [14-16]), along with our desire to build an open resource, we adhere to OBO Foundry principles [17] such as openness, versioning, text definitions, and maintenance. We use the Basic Formal Ontology [18] as an upper ontology, because it provides a solid logical framework that already has been put to the test in many scientific ontologies. SOBO is open source and freely available through our GitHub organization [19]. SOBS community members can provide suggestions or feedback using the GitHub issue tracker.

Primary considerations for the design of SOBO are the dynamic nature of RSOs, uncertainty associated with estimates of their states, and the role of data provenance in assigning confidences or probabilities to final estimates of RSO states. In addition to classes for man-made space objects and the processes they are involved in (e.g., orbits, maneuvers, communication), SOBO covers the qualities or states of RSOs (orbit and attitude state, and are they active or inactive, compliance with IADC guidelines, etc.). Because SOBO is being built to fuse data from multiple sources, classes for observation and data are key elements.

Time is an essential aspect of SOBO, because RSOs can change their state through time: Maneuvers or passive processes can change the orbit and attitude of an RSO from one observation to the next, and an active satellite one day can change to debris the next. Time is incorporated into SOBO in several ways. First, RSOs are classified by the processes in which they participate such as orbits, maneuvers, and communication. Processes incorporate time intrinsically, because they unfold over time [20]. All instance level data annotated to SOBO will include properties such as the time of observation or maneuver. Second, because object properties linking instances are generally defined as being valid at some time, we will capture the time during which a property holds between two instances in our datasets. If needed, we will model changes in RSO states as related to states at past or future time periods. The W3C (World Wide Web Consortium) Time Ontology [21] already provides a set of classes needed to describe time.

Provenance is the other key aspect of SOBO, supporting use cases that involve assessing trust in data. Provenance will be captured in our data ingestion workflow (section 6), by specifying the inputs and outputs of different analyses (Fig. 2). This information is automatically captured for analyses performed in the CyVerse Discovery Environment and will be standardized for other data sources. Ontological reasoning can be used to report the chain of inputs used to generate data, along with metadata about parameters, methods, and who gathered or analyzed data.

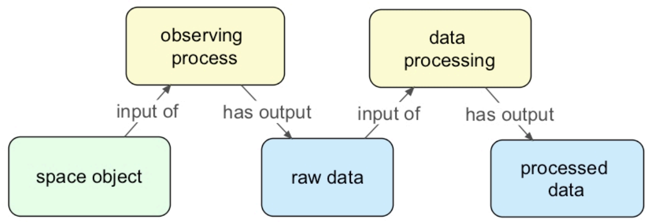

Fig. 2. A simple example showing how SOBO can link processed data such as orbit parameters to a space object via the inputs and outputs of processes. Each element in the graph can have metadata associated with it. Green boxes = material entities, yellow boxes = processes, blue boxes = information content entities.

5.2 Example hierarchy

The left side of Fig. 3 shows a hierarchy for processes under development in the SOBO. Processes include activities such as attitude control, orbital maneuvers, and stationkeeping, as well as orbits, communications, and operator history. We also include a class for "IADC compliance determination process", which is not a process in which an RSO participates, but rather a process carried out as part of our use-case. This class is needed for generation of Bayesian Networks (BN) from the SOBO, discussed briefly in section 6.3. The right side of Fig. 3 shows an example of a logical definition specified in the Web Ontology Language (OWL). The class 'activity determination process' is defined as a process that has as output some data item about an activity state. Logical definitions such as this help us to automatically classify data and track provenance.

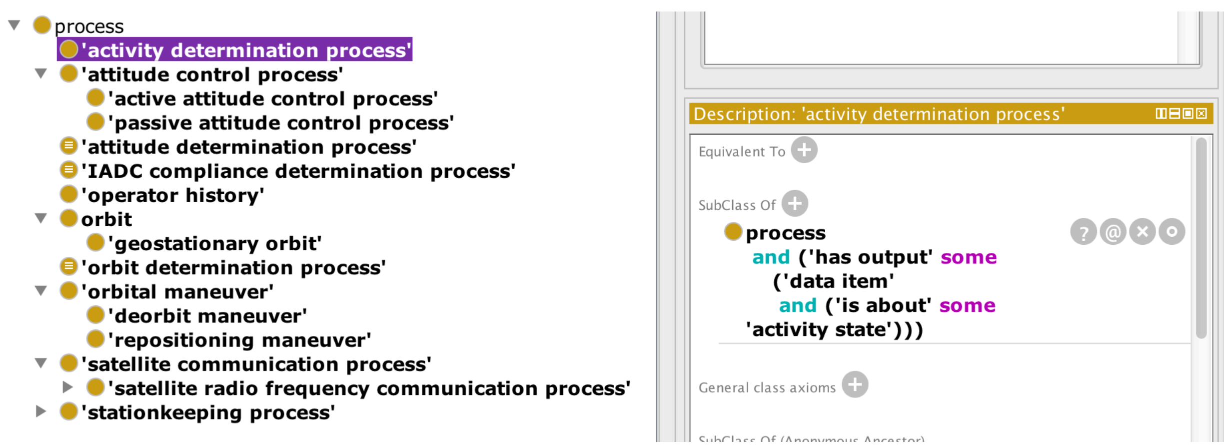

Fig. 3. Screen shot of the process hierarchy under development in the Space Object Behavior Ontology, from the Protégé Ontology editor.

6. BUILDING THE SOBS-KB

6.1 Workflow

The instantiation of our initial workflow for space domain information fusion is shown in Fig. 4. From left to right: Observations of RSOs generate hard and soft data that are stored and processed within the CyVerse analysis platform. Soft data is analyzed using methods such as natural language processing (NLP). Sensor data from telescopes is fed into EPIC software to produce astrometric and photometric data on RSOs. The astrometric data are provided to (a) CAR-MHF to determine the orbits of RSOs, (b) an IMM Estimator to detect and characterize RSO orbital maneuvers, and (c) an MMAE to determine RSO attitude profiles. The orbit, attitude, and maneuver data and associated uncertainties are annotated and ingested into the SOBS KB, stored as a graph database.

6.2 Graphs Database

We will build a graph database (DB) to house the SOBS-KB, which will include all data and metadata needed to address our use case. Like a relational database, a graph DB is used to store data that can be retrieved with a query language, but it is optimized to store data in the form of interconnected "triples" consisting of subject, predicate and object. The graph format supports queries and inference based on the ontology structure. Customs scripts for data ingestion, based on work such as SciGraph [22], are under development. These scripts take tabular data generated as part of the data processing workflow (purple box, Fig. 4) and convert them to triples associated with SOBO terms. The graph DB, SOBO, and query interface form the backbone of the SOBS-KB (pink box).

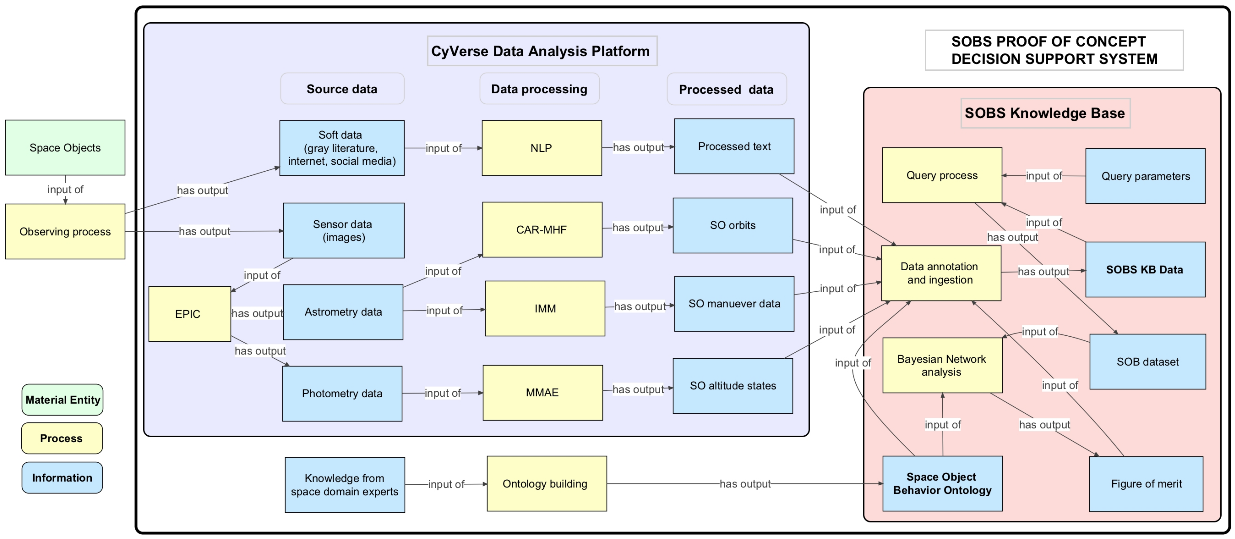

Fig. 4. Instantiation of a proof of concept workflow for fusing hard and soft data to generate figures of merit about RSO compliance with IADC guidelines. Square-cornered boxes represent instances of SOBO classes.

6.3 Incorporating uncertainty with Bayesian Networks

Ontologies are by nature poor at representing uncertainty – something either is or is not an instance of a class in most OWL reasoners. However, estimates of RSO parameters and states are by nature uncertain, as they are based on probabilistic models. To capture the uncertainty associated with RSO state estimates, we combine ontologies with BN analysis [23-27]. BNs will be generated automatically from the SOBS-KB using a set of pre-defined classes and properties, as in [27]. The BNs are then used to generate distributions of the probability that an RSO is in compliance with IADC guidelines. The use of BNs and inference methods is discussed more in [28].

7. DISCUSSION

The biggest challenge for most integrative research today is not collecting the data, but making data from a diversity of sources work together. Ontologies such as SOBO provide the logical structure for data fusion, but the practical tasks of associating data to ontology terms and transforming them into compatible formats without loss of information remain prohibitively labor intensive. We are using next generation information management methods to demonstrate a semi-automated method of data fusion, which, through future efforts, could be more fully automated. Our goal is to build a pipeline that not only processes data in an efficient manor, but also collects and preserves the scientific and provenance metadata necessary for data reuse and downstream decision making. We are able to build this pipeline rapidly by reusing existing technologies developed and tested in the life sciences community, such as CyVerse cyberinfrastructure, the IRODS data and metadata system, workflow managers, and graph databases. Each of these technologies has been proven independently, but we are combining them in a novel way to produce a system with benefits that have not been previously demonstrated. The combination of probabilistic methods with ontologies provides additional benefits in the form of figures of merit that include probability distributions based on mechanistic explanations, rather than simple yes/no answers. Our initial implementation focuses on a single use case, in order to minimize risk, but the system has broad applicability not only for SSA, but any discipline that requires data fusion, semantics, and probabilistic reasoning.

Community members who would like to follow or contribute to SOBO development should use the SOBO GitHub repository: https://github.com/SpaceObjectBehavioralScience/sobo. Readers who are interested in following progress of the SOBS-KB development may access the SOBS wiki space (https://wiki.cyverse.org/wiki/display/SOBS/SOBS+Community+Home+Page) on the CyVerse wiki with a CyVerse user account. Sign up for a CyVerse account at https://user.cyverse.org/ and learn how to use the wiki at https://wiki.cyverse.org/wiki/display/start/Using+the+CyVerse+Wiki.

8. NEXT STEPS

Out next steps are to publish a stable version of SOBO, finalize the data analysis and ingestion workflows, and carry out BN analyses. With these, we will be able to produce data on IADC compliance for an initial set of RSOs, which we can compare to known states to assess the accuracy of our workflow. Future work will include fusing hard data with soft data inputs such as gray literature, news reports, and social media to assess other aspects of the IADC guidelines such as minimizing debris generation and breakups or the role of operator history in calculating the likelihood of compliance.

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