An Introduction to Hard and Soft Data Fusion via Conceptual Spaces Modeling for Space Event Characterization

Chapman Jeremy
University at Buffalo, The State University of New York

David Kasmier
University at Buffalo, The State University of New York

John Crassidis
University at Buffalo, The State University of New York

Barry Smith
University at Buffalo, The State University of New York

An Introduction to Hard and Soft Data Fusion via Conceptual Spaces Modeling for Space Event Characterization

Jeremy R. Chapman,[*] David Kasmier,[†] John L. Crassidis,[‡] James Llinas,[§] Barry Smith[¶]

University at Buffalo, The State University of New York, Amherst, NY, 14260

Alexander P. Cox[‖]

CUBRC Inc., Buffalo, NY 14225

Abstract

This paper describes an AFOSR-supported basic research program that focuses on developing a new framework for combining hard with soft data in order to improve space situational awareness. The goal is to provide, in an automatic and near real-time fashion, a ranking of possible threats to blue assets (assets trying to be protected) from red assets (assets with hostile intentions). The approach is based on Conceptual Spaces models, which combine features from traditional associative and symbolic cognitive models. While Conceptual Spaces are revolutionary, they lack an underlying mathematical framework. Several such frameworks have attempted to represent Conceptual Spaces, but by far the most robust is the model developed by Holender. His model utilizes integer linear programming in order to obtain an overall similarity value between observations and concepts that support the formation of hypotheses. This paper will describe a method for building Conceptual Spaces models for threats that utilizes ontologies as a means to provide a clear semantic foundation for this inferencing process; in particular *threat ontologies* and *space domain ontologies* are developed and employed in this approach. A space situational awareness use-case is presented involving a kinetic kill scenario and results are shown to assess the performance of this fusion-based inferencing framework.

Keywords— Data Fusion, Conceptual Spaces, Kinetic Kill, Space Domain Ontology, Ontology, Threat, Space Situational Awareness

[*] Graduate Student, Department of Mechanical & Aerospace Engineering. Email: jeremych@buffalo.edu.

[†] Postdoctoral Researcher, Department of Philosophy. Email: djkasmie@buffalo.edu.

[‡] SUNY Distinguished Professor and Samuel P. Capen Chair Professor, Department of Mechanical & Aerospace Engineering. Email: johnc@buffalo.edu.

[§] Emeritus Research Professor, Department of Industrial & Systems Engineering. Email: llinas@buffalo.edu.

[¶] SUNY Distinguished Professor and Julian Park Chair of Philosophy, Department of Philosophy. Email: phismith@buffalo.edu.

[‖] Senior Ontologist, Data Science and Information Fusion Group. Email: alexander.cox@cubrc.org.

1 Introduction

The idea of Conceptual Spaces was originally developed by Peter Gärdenfors [1]. It is utilized here as a new foundation for the application of data and information fusion. Cognitive models have two overarching goals as stated by Gärdenfors [2]; The first goal is *explanatory*: by studying the cognitive activities of humans and other animals one can formulate *theories* about different aspects of cognition. The second goal is *constructive*: by building *artifacts* one attempts to construct systems that can accomplish various cognitive tasks. Before Gärdenfors, cognitive models were traditionally broken down into two classes: symbolic or associative. Gärdenfors' Conceptual Spaces model sought to bridge the gap between these two alternatives by using an approach that employs geometrical principles.

Space event characterization is the focal problem domain throughout this paper, with the overall goal of increasing space situational awareness (SSA) for a better understanding of components, events and behaviors. The definition of SSA varies, but it is accepted that one component of SSA involves maintaining knowledge of the space domain for aiding in risk assessment. Kinetic kill events are the primary space event that will be modeled in this paper. A spacecraft kinetic kill occurs when the operator of a malicious satellite, called a *red* satellite, performs an intentional act of bringing about a physical collision between itself and an assumed target, known as a *blue* satellite, with the intention of damaging or destroying some or all of the blue satellite's capabilities. Other prominent malicious space events include, but are not limited to, laser dazzling and spacecraft shadowing (performed, for example, by the Russian satellite Cosmos 2542, shadowing an American KH-11 satellite identified as USA245 in January 2020).

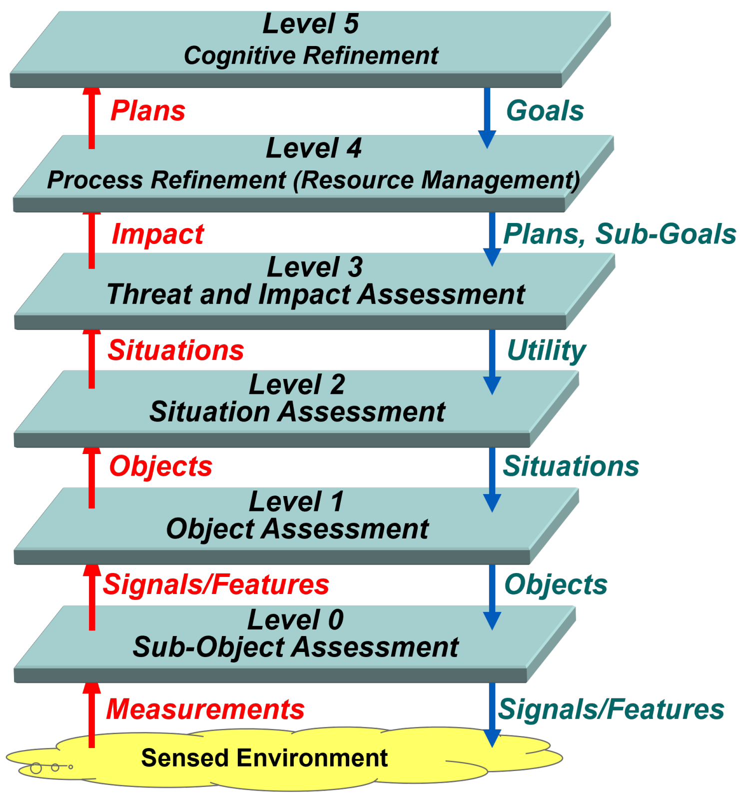


Figure 1: Joint Director of the Labs (JDL)/Data Fusion Information Group Model

In order to increase SSA it is important to fuse data and information from multiple sources. In the mid 1980s the Joint Directors of Laboratories (JDL) formed the Data Fusion Subpanel, later became the Data Fusion Information Group (DFIG), which developed a model of data fusion seen in Figure 1. This model is a visual representation for how data fusion occurs, starting at the bottom with a sensed environment of real world processes and working through the various levels of data fusion up to level 5 (cognitive refinement).

Cognitive refinement was added to the original JDL model to involve aspects related to the human role in the fusion process such as visualization, decision aids, and human factor-based tools. As data is fused together, the complexity of the situation (labelled in blue) evolves from simple signals/features all the way up to goals.

Methods based on Conceptual Spaces are considered an appealing paradigm for fusing data to support inferencing at the Level 2/3 fusion node, defined as Situation Assessment and Impact Assessment (or Threat Refinement). This level of data fusion was originally thought to require human driven fusion, as it was believed that machines were capable only of data fusion at Level 1 (Object Assessment). Conceptual Spaces can be used for object assessment but also have the capability of higher level data fusion for situation and impact assessment.

Data utilized in Conceptual Spaces can come in many forms. For example, one form is measurable information, such as observation data that is derived from instruments such as radar and telescopes used to determine a satellite's position and to provide photometry information. This measurable information is known as *hard data* and it is generally easily quantifiable. Other sources of information can be textual in nature and are not derived directly from instrument measurements but rather from human perception, judgment and analysis. This form of information is generally referred to as *soft data*.

By themselves Conceptual Spaces models lack the sort of underlying mathematical framework that is needed for computational implementations. There have been several attempts to develop such frameworks. This paper uses the framework developed by Holender [3, 4] called 'Complex Conceptual Spaces – Single Observation.' Any model for event characterization, including space event characterization, requires a systematic breakdown of how threats and other aspects of the event are related. Throughout the work that is reported in this paper, ontologies are utilized to develop these needed relationships and to provide semantic specificity to the terms employed.

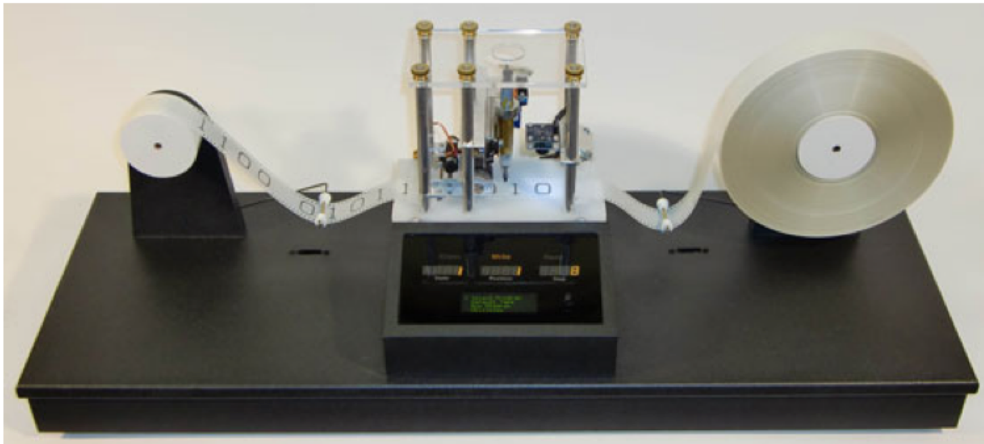
Once a Conceptual Spaces model is developed, it can be utilized to assess the overall similarity between an observation and the associated feature of reality, where the latter is identified in the model as a concept. The higher the similarity value between observation and concept, the more likely it is that the modeled concept is in fact happening in reality. If the concept is the threat level of a particular space event such as a kinetic kill, then the association similarity will represent the threat level from a malicious satellite that is about to perform a kinetic kill. An overall ranking of satellites that are vulnerable to a kinetic kill can help predict the possibility of such an event occurring before it occurs, thereby providing a tool which operators controlling blue assets can use for assessing which assets are most vulnerable to aid with anticipatory decision making.

2 Cognitive Models

Conceptual Spaces were developed by Gärdenfors as a cognitive model to represent human perceptions of concepts. The model is intended to bridge the gap between traditional symbolic and associative models. To begin understanding how Conceptual Spaces work, one must first have an understanding of symbolic and associative models. A review of these models is given in this section.

2.1 Symbolic Models

Symbolic cognitive models were originally based on the work of Newell and Simon's Physical Symbol System Hypothesis (PSSH), to the effect that: "A physical symbol system has the necessary and sufficient means for general intelligent action [5]." Symbolic models can be thought to take the form of Turing machines [6], seen in Figure 2 below, which are derived from a mathematical model of computations as processes that manipulates symbols on a strip of tape (a "program") according to a table of rules. The rules involve looking at the symbol on the tape and either manipulating the symbol or leaving it unchanged, then moving either one box to the left or one box to the right, and then following another rule. A Turing machine was originally designed with the motivation to build a theoretical "human computer" that can solve problems in an algorithmic way. It did so by follow a set of rules until the machine reaches a halting state. Once the halting state is reached, then what is left on the tape should in theory be the answer to the problem that was originally asked. Essentially, symbolic cognitive models represent human thinking as a kind of symbolic manipulation. For a Turing machine there is an input that is known and then an output that can be seen; what happens inside the machine does not matter, so the machine operates essentially as a black box.



	Current State A			Current State B			Current State C		
	Write Symbol	Move Tape	Next State	Write Symbol	Move Tape	Next State	Write Symbol	Move Tape	Next State
Tape Symbol is 0	1	Right	B	1	Left	A	1	Left	B
Tape Symbol is 1	1	Left	C	1	Right	B	1	None	Halt

Figure 2: Turing Machine

2.2 Associative Models

The second kind of model for cognitive thinking is the associative model, where associations between different types of information elements are the means of representation [2]. This form of cognitive model works on the principle of association. For example, if the words 'bacon,' 'eggs' and 'juice' are mentioned, then the human mind starts to think about the concept of breakfast [7]. Associative models of data can be developed for certain entities that store information about associated data. For example, for a vehicle it might store the vehicle's registration number, make, model, color, owner information and other identifying features [8]. If, now, certain features of the vehicle have been identified, then an association to other features of the vehicle can be made.

2.3 Conceptual Spaces

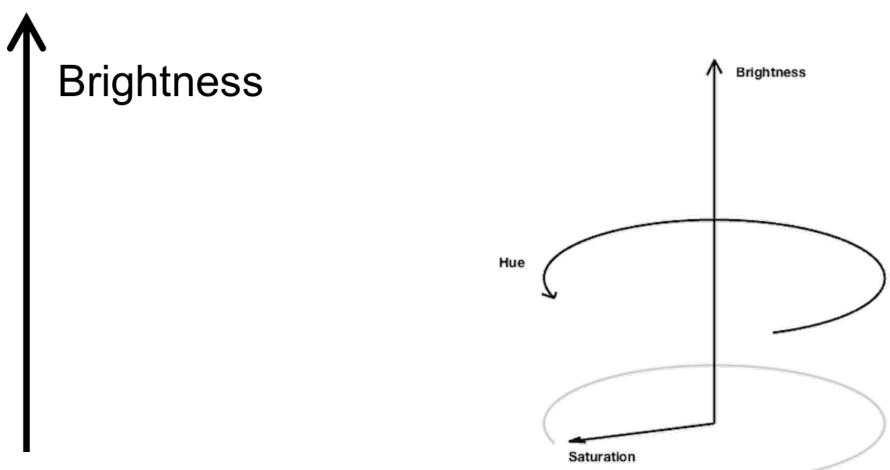
Against this background it can now be shown how Gärdenfors' model provides a desirable approach to bridging the gap between these two models. Gärdenfors looked for a way to represent associations between observations and concepts that could be represented in a systematic way and used in a symbolic model in order to come up with a measure of similarity between observations and concepts.

To start developing a Conceptual Spaces model one needs to have an understanding of the underlying *world* that is being worked in. Utilizing an appropriate set of ontologies, as well as domain knowledge experts, helps guarantee that the appropriate world is being utilized. Take for example the world of birds versus the world of emus. In the latter there could be a sub species of emu that is considered small; in the world of birds, however, even a small emu would still be considered large. Since the focus of this paper is primarily space events (events involving satellites) it should be understood that the world that is being dealt with involves space. Domain ontologies can then be utilized to help assist in defining various aspects of space events.

To obtain a better understanding of how Conceptual Spaces work, some key terms need to be defined. The fundamental building blocks are *quality dimensions* and *domains*. These are what are utilized to *build the world* that is required to represent the concepts at issue.

Quality dimensions are the most basic building blocks of Conceptual Spaces. A dimension is any quantifiable quality whose magnitude can be represented as a distance in a geometric space. Take for example the dimension of brightness within the color domain; Figure 3a shows an example of what this dimension would look like. Two or more dimensions are called integral (meaning 'integrated') when a value can be assigned to any one dimension only by simultaneously assigning values to the other dimensions [2, 9, 10]. Consider the color domain. Information about the brightness, hue and saturation would all be required to define a color. Dimensions that are not integral are called separable. For colors, an example of this is hue and pitch, since pitch relates not to colors but to sounds.

Built upon dimensions are domains, which are any set of integral dimensions taken together. Not all domains have well understood underlying dimensions; this is the case, for example, for the shape domain or for the more abstract domains such as friendship discussed in [11]. The color domain can be represented as seen in Figure 3b. One interesting feature of domains is that sometimes there are options when choosing which dimensions are necessary to represent the features that one is trying to highlight. For example, with the color domain, one can use as set of dimensions either {*hue*, *brightness*, *and saturation*} or {*red*, *green*, *and blue*}.



(a) Brightness Dimension, one of the Three Underlying Dimensions in the Color Domain

(b) Color Domain Represented by Hue, Brightness and Saturation

Figure 3: The Fundamental Building Blocks for Conceptual Spaces: Dimensions and Domains

Once the dimensions and domains are defined, *properties* within the domains can be identified. Properties are a convex region within a single domain that represent a certain feature, as seen in Figure 4. An important aspect of properties is that they can occupy only a single domain and thus cannot span across multiple domains. Spanning across multiple domains would be considered a *concept*, which will be defined later. But what *is* a property? It has to be something that different objects can have in common. To say that two objects have the same property is to say that they are in some respect similar to each other. The properties will change depending upon the world of concepts that are being examined. When, for example, when looking at emus, the word "small" could represent a certain breed of emu. However, when referring to the species of birds in general, a small emu would not a small bird. Therefore, if a world is being built to identify types of emus the property of being small will take on different parameters than if the world to be built identifies rather types of birds. In the latter case all emus might be identified as large. Essentially the world that is being worked on has an effect on the properties that will be distinguished. For the focus of this paper the world that is being examined is the world that is relevant to the space domain.

Now that there is an understanding of properties, a *concept* can be defined. A concept is an abstract

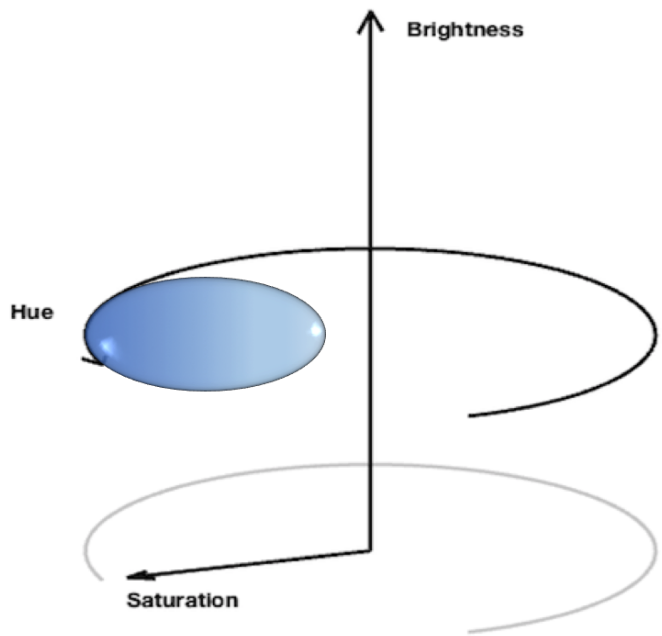


Figure 4: Property in the Color Domain Representing the Region of Blue

region of a Conceptual Spaces model that spans across several domains, as seen in Figure 5. The distinction between a property and a concept is that a property is based on a single domain whereas a concept can be based on multiple domains. A property is thus by definition a type of concept. One way to think about the distinction is to compare it with the semantic difference between adjectives and nouns. Adjectives would describe *properties*, such as "red," "short" and "loud," which all fall under a single domain. Nouns such as "car," "banana" and "city." in contrast, contain information from multiple domains, and thus pick out concepts [1]. Concepts in Conceptual Spaces are not only a limited to nouns (i.e. person, place or thing), [12] shows that events, too, can be represented as concepts.

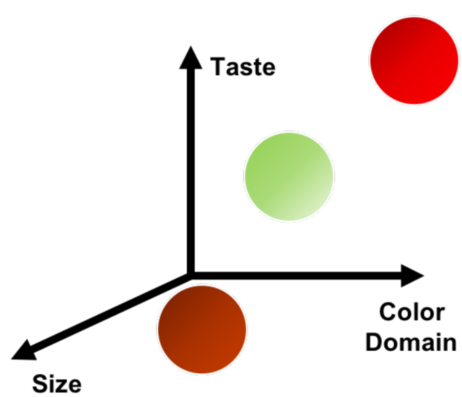


Figure 5: Concept that Represents Several Regions Across Multiple Domains of the CS Model

The final term in Conceptual Spaces that needs to be defined is *object*. An object is essentially just a point within the Conceptual Spaces model, as seen in Figure 6. Objects represent an actual observation of a physical item or event with measurable features.

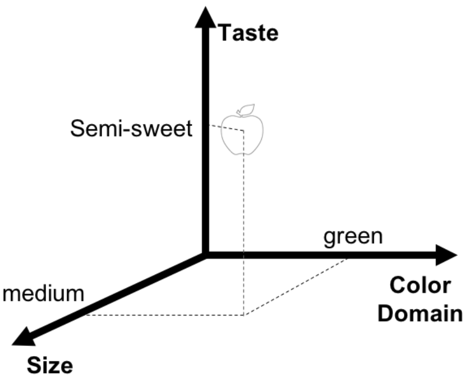


Figure 6: An Object Represents a Single Point in the Conceptual Spaces Model as Represented by an Apple

3 Mathematical Framework

It is important to note that Gärdenfors was a cognitive scientist and did not develop an underlying mathematical model to represent Conceptual Spaces. After the advent of Conceptual Spaces several models have been developed with the goal of providing a mathematical framework for representing Conceptual Spaces, as seen in [13, 14, 15, 3, 4, 16]. Having a functional mathematical model is important for the development of an automated inferencing process. The model that will be discussed in this paper is the Complex Conceptual Spaces − Single Observation model, developed by Holender in [3, 4]. This appears to be the most versatile model and also the model most widely implemented in practice.

The formulation for Holender's approach will now be discussed. Holender's approach works off the mathematical principles of integer linear programming. Linear programming was originally invented in 1939 by Leonid Kantorovich [17], as a technique for optimizing linear objective functions subject to linear equality and inequality constraints. Integer linear programming is a specific form of linear programming that involves only using integer (i.e. whole or counting numbers that don't have fractions). Linear programs are problems that can be expressed in conical form as

$$\begin{array}{lr} \text{Find a Vector} & \mathbf{x} \\ \text{That Maximizes} & \mathbf{c}^T\mathbf{x} \\ \text{Subject to} & \mathbf{A}\mathbf{x} \leq \mathbf{b} \\ \text{and} & \mathbf{x} > \mathbf{0} \end{array}$$

For Holender's approach to modeling Conceptual Spaces the starting point should be to define the world, W, that is being considered. Within that world there will be a library of m defined concepts, C. These concepts will be defined on the basis of a set of properties, P, from different domains, D. The world can then be defined on the basis of the following:

$$\begin{aligned}
W &= \text{World of interest composed of } m \text{ concepts} \\
C &= \text{Set of concepts } \{k_1, k_2, ..., k_m\} \\
D &= \text{Set of domains} \\
k &= \text{The concept that is being examined within the set of concepts} \\
D^k &= \text{Subset of domains, } D^k \subset D, \text{ in concept } k \text{ for } k \in C \\
O &= \text{Set of observations} \\
P^i &= \text{Set of properties of domain } i \text{ for } i \in D \\
F^k &= \text{Set of } (i,j) \text{ mutually exclusive, where } j \in P^i and i, i^{'} \in D^k, k \in C \\
m &= \text{Maximum number of distinct concepts that could be observed} \\
n &= \text{Number of domains in the concept representation} \\
n_i &= \text{Number of properties in domain } i \text{ for } i \in D \\
F &= \text{Set of property combinations } (i,j) \text{ and } (i^{'}, j^{'}) \text{ that are mutually exclusive} \\
&\quad \text{ that can be observed for a concept} \\
x_{ij} &= \begin{cases} 1, & \text{if property } j \text{ from domain } i \text{ is considered} \\ 0, & \text{otherwise} \end{cases} \\
s_{ij} &= \text{Similarity values between observation and concept for} \\
&\quad \text{property } j \text{ from domain } i \\
I &= \text{Set of } (i,j) \text{ and } (i', j') \text{ that are mutually exclusive}
\end{aligned}$$

The overall goal is to optimize the objective function given by

$$\max \sum_i \sum_j s_{ij} x_{ij} \tag{1}$$

where s_{ij} is the similarity value between observation and concept for property j from domain i. In integer programming the user is trying to find the vector, $\mathbf{x}$, that optimizes a given objective function. This vector, $\mathbf{x}$, contains elements formally known as the decision variables. For Holender's model these decision variables are restricted to only two possibilities either: $x_{ij} = 1$ indicates that the property j from domain i is being taken into account, or $x_{ij} = 0$ indicates that property j from domain i is not being taken into account. The objective function represents the similarities between the observed object and the property in question. It is optimized in such a way that the results model Conceptual Spaces appropriately.

In integer programming it can be seen that the optimization problem is subject to constraints, defined by $\mathbf{Ax} \leq \mathbf{b}$, these constraints are governed by the concept that is being constructed. Since the decision variables represent properties from a given domain the constraints will represent restrictions on which properties are and are not allowed within the concept. Equality constraints show what properties are allowed within a given domain. These are given by

$$\sum_{j=1}^{n_i} x_{ij} \;=\; \begin{cases} 1 \;\forall P^i \neq \emptyset \text{ (Domain } i \text{ exists within the concept} \\ 0 \;\forall P^i = \emptyset \text{ (Domain } i \text{ doesn't exist within the concept)} \end{cases}$$

Inequality constraints show what cross domain properties must exist for a given concept. Theses are given by

$$x_{ij} + x_{i'j'} \leq \; 1 \;\forall\; \{(i,j), (i', j')\} \;\in\; F$$

Once all of the constraints are built they will represent a given topic. An example of this will be shown later for the concept of an apple.

It is important to note most objects can have multiple properties that are feasible within a single domain. Considering an example of an apple and the color domain, an apple can be either brown, green or red. The particular color that an apple possesses does not matter as long as that color exists in the concept for an apple. This optimization process is essentially looking for the property that is the most apparent in the observation.

The constraint set consists of equality and inequality constraints that outline the feasible region (which is a set of all possible points that satisfied the optimization problem) of the concept. The equality constraints only allow for one property from each domain to be represented per observation. The reason for only allowing one property from each domain to be represented is so that the optimization problem only looks for the property that is most apparent in the observation. The inequality constraint sets, on the other hand, represents the associations between cross-domain properties. Examples of cross-domain property constraints would be that a red apple tastes generally sweet while a brown apple tastes generally bitter. The solution to the optimization problem will be an optimal value which can be normalized by the number of domains in the concept representation, n, to obtain a value depicting the similarity between the concept and the observed object [3].

Consider the simple example problem for an apple. While doing this the subscripts for each domain will be defined as x_{ij}, where i represents the domain and j represents the property. These domains and properties can be seen by

$$\begin{aligned}
&\text{Color} = \text{Blue } x_{11}, \quad \text{Green } x_{12}, \quad \text{Red } x_{13}, \quad \text{Brown } x_{14}, \quad \text{Purple } x_{15}, \quad \text{Yellow } x_{16} \\
&\text{Taste} = \text{Bitter } x_{21}, \quad \text{Sour } x_{22}, \quad \text{Sweet } x_{23}, \quad \text{Spicy } x_{24} \\
&\text{Texture} = \text{Smooth } x_{31}, \quad \text{Rough } x_{32}, \quad \text{Liquid } x_{33}
\end{aligned}$$

Since all three domains will be considered in the concept the generalized constraints can be generated through

$$\begin{aligned}
&x_{11} + x_{12} + x_{13} + x_{14} + x_{15} + x_{16} = 1 \\
&x_{21} + x_{22} + x_{23} + x_{24} = 1 \\
&x_{31} + x_{32} + x_{33} = 1
\end{aligned}$$

Next the following constraints can be made for the concept of an apple:

$$\begin{array}{rccc}
 & x_{12} + x_{21} \le 1 & x_{14} + x_{23} \le 1 & x_{14} + x_{33} \le 1 \\
 & x_{12} + x_{23} \le 1 & x_{14} + x_{24} \le 1 & x_{21} + x_{31} \le 1 \\
x_{12} + x_{13} + x_{14} = 1 & x_{12} + x_{24} \le 1 & x_{12} + x_{32} \le 1 & x_{21} + x_{33} \le 1 \\
x_{21} + x_{22} + x_{23} = 1 & x_{13} + x_{21} \le 1 & x_{12} + x_{33} \le 1 & x_{22} + x_{32} \le 1 \\
x_{31} + x_{32} = 1 & x_{13} + x_{22} \le 1 & x_{13} + x_{32} \le 1 & x_{22} + x_{33} \le 1 \\
 & x_{13} + x_{24} \le 1 & x_{13} + x_{33} \le 1 & x_{23} + x_{32} \le 1 \\
 & x_{14} + x_{22} \le 1 & x_{14} + x_{31} \le 1 & x_{23} + x_{33} \le 1
\end{array}$$

According to the chosen constraints, the set of property combinations that are mutually exclusive for an apple, F_{apple}, are $F_{apple} = \{$(*red*, *sweet*, *and smooth*), (*green*, *sour*, *and smooth*) or (*brown*, *bitter*, *and rough*)$\}$, as seen in Figure 7. The first three generalized constraints indicate that at least one property from each domain must be represented. The three equality constraints for the concept express that the apple can only be either $\{$*red*, *green*, *or brown*$\}$ followed by only $\{$*sweet*, *sour*, *or bitter*$\}$ followed by only $\{$*smooth or rough*$\}$. Note that from Holender's derivation every pair of properties that cannot exist needs to be stated as a constraint.

Thus, if it is known that an apple is red and sweet, constraints need to be made to indicate that the apple is not red and bitter, red and sour, or red and spicy, leaving only the option for the apple to be red and sweet. Next, if observations were made of a green apple the following properties would be identified $s_{12} = 1$, $s_{22} = 1$ and $s_{31} = 1$. Of course in reality there might not be 100% confidence about the properties which will result in lower similarity to the concept and uncertainties in the similarity. After running the above observation through an integer linear optimization and normalizing the results, the answer retrieve is one. This indicates that there is a 100% chance of this observation being the concept in question (i.e. an apple).

Next, how the Conceptual Spaces model can be built for more complicated examples such as a space event will be discussed.

Figure 7: Three Different Types of Apples that Represents the Concept of Apples

4 Building a Conceptual Spaces Model Utilizing Ontologies

To begin the discussion of how to build a Conceptual Spaces framework there needs to be an understanding of the underlying World, W, that is being worked in. With the example of birds and emus, different worlds will result in different definitions of properties. In order to better understand the world of the space domain, the Space Domain Ontologies will be utilized. Ontologies are controlled vocabularies consisting of general terms and relational expressions representing the types or classes of entities in some subject area and the relations between them. The controlled vocabulary of terms is organized hierarchically on the basis of the relation of greater and lesser generality, and curated by experts. Ontologies have the ability to make information more accessible and discoverable. How the Space Domain Ontologies fit into the structure of ontologies can be seen in Figure 8.

The upper-level ontology used is the Basic Formal Ontology (BFO) ISO/IEC 21838 [18], which is a small, very general ontology that is designed for use in supporting information retrieval, analysis and integration in scientific as well as other domains. BFO was created to promote interoperability among its domain ontologies built through a process of downward population from BFO terms via the creation of increasingly specific term definitions. BFO is currently used by more than 350 ontology-driven endeavors. Extending from BFO is the mid-level Common Core Ontologies (CCO) which is a candidate INCITS 573-2 standard mid-level ontology and consists of a suite of 12 ontologies outlined in blue in Figure 8 [19, 20]. Underneath the Common Core Ontologies, domain ontologies come into play by extending terms in the CCO hierarchy. The Space Domain Ontologies is a suite of 5 ontologies that represent entities relevant to the space domain, such as space objects and events [21, 22]. As can be seen, some domain ontologies in Figure 8 are tangential to the space domain ontology.

4.1 An Ontological Analysis of Threat and Vulnerability

The starting point of this paper is, first that space events involving different satellites are being observed. Secondly, the threat levels for certain types of future space events involving one or more of these satellites are attempted to be quantify. Thus, in addition to utilizing the Space Domain Ontologies, an ontology dealing with entities in the realm of threats is needed. An ontological analysis of threat and vulnerability was developed by Little and Rogova in [23].

The first requirement for an ontological analysis of threat is a formal definition of the term ‘threat,’ which was defined by the Joint Directors of Laboratories (JDL) − Data Fusion Subpanel in [24] as

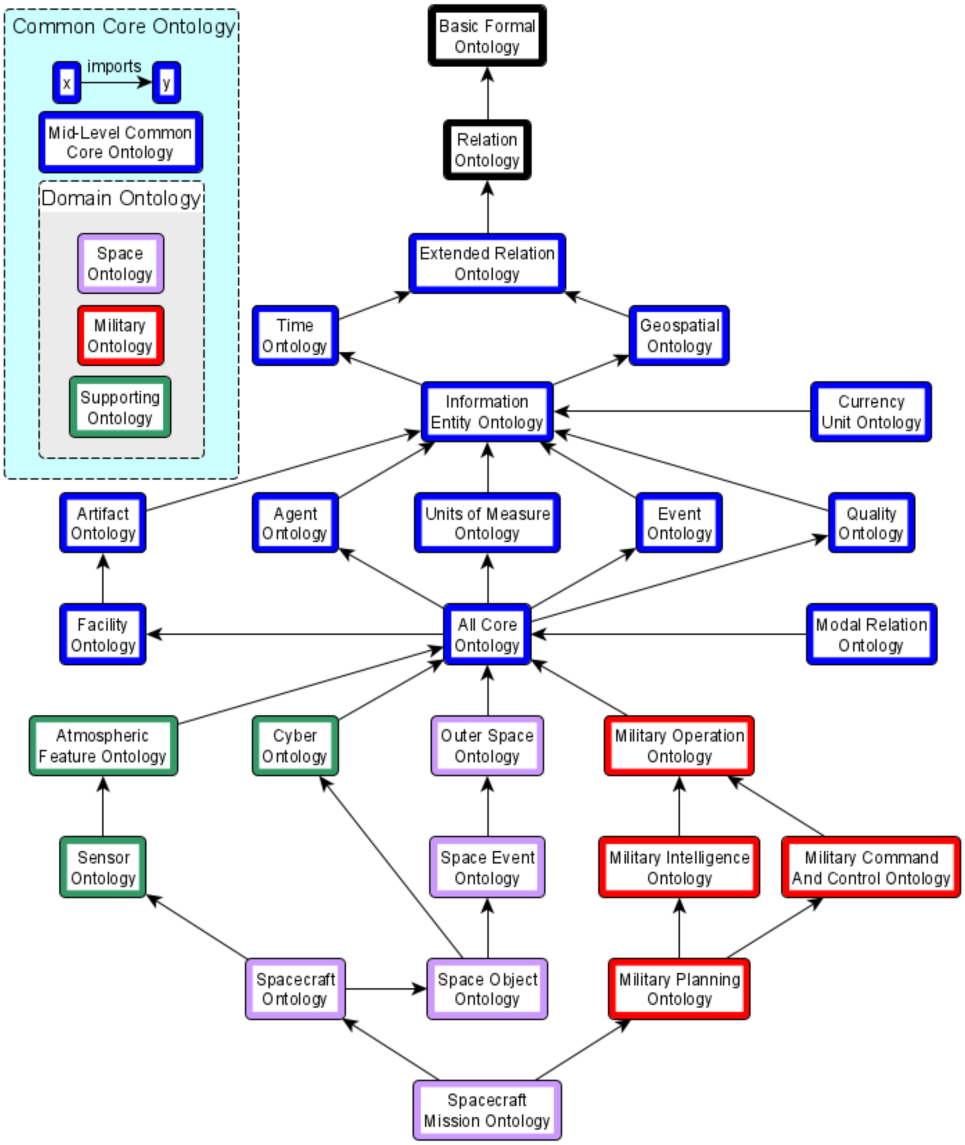


Figure 8: Hub and Spokes Diagram for the Space Domain Ontologies

> *The process of estimation and prediction of effects on situations of planned or estimated/predicted actions by the participants; to include interactions between action plans of multiple players (e.g. assessing susceptibilities and vulnerabilities to estimated/ predicted threat actions given one's own planned actions).*

Essentially, threat can be broken down into three interrelated parts, namely:

1. *Intentions*: The plan or goal of the adversary. This aspect of threat represents the psychological component of threats and can be deeply influenced by the adversary's capabilities and opportunities.
2. *Capabilities*: The adversary's physical assets, such as expendable satellites (red satellites) and their attributes (such as: being equipped with munitions) and behaviors (such as orbital repositioning) that can inflict a level of harm to debilitate part or all of the capability of the adversary's target (i.e. a blue satellite).
3. *Opportunities*: The spatio-temporal relationship of the red country's asset with respect to a blue

country's asset. For space events this spatio-temporal relationship can be determined by solving Lambert's Problem to determined when the window of opportunity for an attack is feasible.

In addition to threat there is a state of vulnerability that is inherent in the blue asset which will make a particular blue asset a more feasible candidate for an attack from a red asset. This state of vulnerabilities is an inherent part of the blue asset, including it's capabilities and intentions. A visual representation of how threat is broken down in the space domain can be seen in Figure 9.

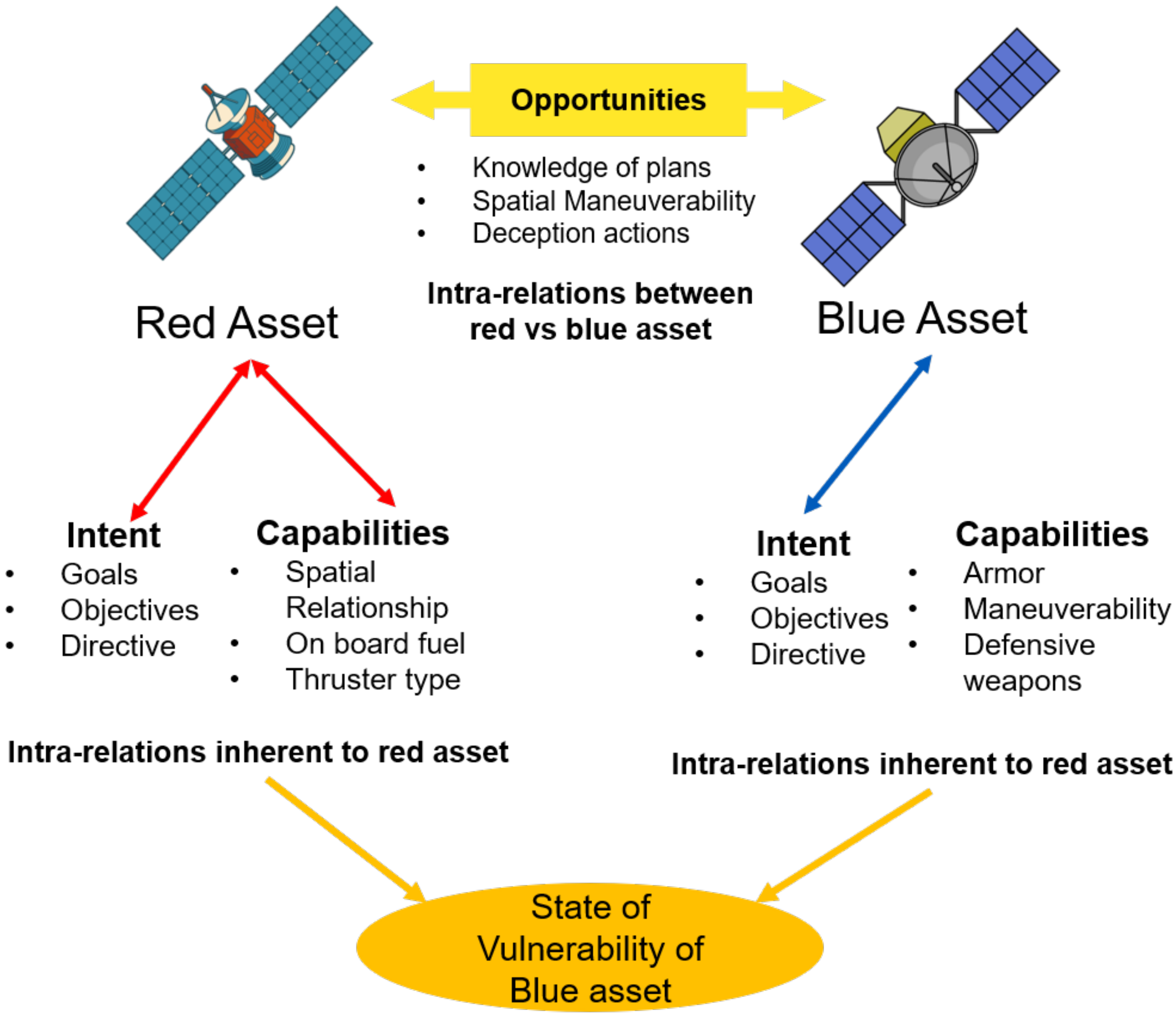


Figure 9: Ontological Analysis of Threat Breakdown for Space Events

5 Conceptual Spaces Modeling for Space Event Characterization

As seen throughout this paper Conceptual Spaces can be a powerful tool for hard and soft data fusion regardless of the world that is being focused on. Continuing on the work done in [25, 26], the work of this paper primarily focuses on SSA with a more concentrated focus on identifying the level of a given threat that a kinetic kill event will occur. As defined previously, a kinetic kill event occurs when a red satellite makes a maneuver with the intentions of physically hitting a blue satellite in such a way as to disable some or all of the blue satellite's capabilities. The goal is to formulate a Conceptual Spaces model that can accurate illustrate this event.

To begin making a Conceptual Spaces model for defining space events, there needs to be an overall understanding that the world in play is the Space Domain world. The Space Domain ontologies should be referenced to get definitions for anything that is ambiguous to the user to ensure that definitions utilized are represented in the space domain.

Once the world is understood, domains for the concept can start to be built. Since the concept of interest for this paper is the threat level present from a space event the ontological analysis of threat and vulnerability analysis from [23] can be used to help define domains. For utilizing Conceptual Spaces for space events, the Conceptual Spaces model is broken down into three domains that were outlined by the ontological analysis of threat: intentions, capabilities and opportunities. These domains are abstract in nature such as the shape domain or friendship domain and thus the underlying dimensions are not well understood or known. Work done by Lucas Bechberger in [11] illustrates how the underlying dimensions of a domain are not necessary for the identification of similarities between observations and properties.

5.1 Intention

Within the domain of intention there are a few contributing factors that must be considered when accessing the intentions of the political entities controlling the red satellite. These factors include the strength of the tension between adversaries, the ease of being triggered on the part of the controlling agency, and the clarity or specifics of any associated plan. Breaking this down even further, there are a number of geopolitical indices that can be utilized as a guide to help measure the tension between countries. If the tension between adversaries is high, this is a clear indication that the threat level of an attack will be greater. These indices include the Geopolitical Risk Index, the World Economic Forum Annual Global Risk Report, the Heidelberg Institute for International Conflict Research Conflict Barometer, and the EU Global Conflict Risk Index [27, 28, 29, 30].

Another factor that will determine the intentions of a country is the ease with which that country can be triggered to perform a certain act. This is both indicated by geopolitical policies as well as by leadership. On the geopolitical policy side, it is known that some government structures need to get approval from other branches of government before they can decree that an attack will occur, and this will result in a check and balance effect making it harder for an attack to occur and thus requiring that there are strong grounds for such an attack. However, other government structures such as a monarchy or dictatorship might have fewer geopolitical restrictions when it comes to executing an attack. In addition to this, the geopolitical leader(s) of the country might be physiologically evaluated to get an indication of their ease of being triggered. Some leaders have a higher deposition to attack while others will be more reserved and less likely to make an aggressive move. Physiological experts will need to develop a metric or construct a ranking of geopolitical leaders for there to be a better understanding of which leaders will have a higher ease of being triggered.

Another indicator of intention would be the clarity or specifications of the plans. This would come from intelligence data or news reports about the actions that the red country intends to do. If there appears to be a clearly stated plan for a non-provoked offensive mission with malicious intentions this indicates high intention. If intelligence data shows that there is a well organized and thought through plan of a new mission this is also a good indication of high intentions to bring about its execution.

Once all of these (and potentially other) factors of intention are considered and metrics are taken into account, the domain will need to be divided down into properties that represent different aspects of threat. Most likely, this will occur by clustering together satellites associated with relatively similar intentions on the part of those who control them. Let's assume this domain can be broken into three distinct properties indicating high, medium, and low intentions, with high intentions being the primary indicator of a high threat level for a kinetic kill attack to occur.

5.2 Capabilities

The next domain that will be discussed will be *capabilities*. These include the red country's physical assets. When evaluating this domain one would have to look at these assets and determine their attributes and behaviors. For a kinetic kill event the assets of importance are satellites that are in the observed red country's possession and/or control. Certain countries may own satellites that are in part or completely controlled by another country or by a corporation or business. A satellite owned and controlled by an industry may not be obligated or willing to conduct a government operation, such as a kinetic kill event. Of course, this depends on the country's political policies when it comes to how assets can be used. In addition, it should be noted that if a country physically does not have access to given assets capable of an attack, then they should not be considered a threat at all and will need to be pre-filtered out of the analysis.

Another aspect that needs to be evaluated is the capability inherent in the assets that the red country controls. From a physics standpoint, given the position of a red asset and a blue asset, the impact velocity that would occur from a collision at any given time can be determined by solving Lambert's Problem for the two body problem of one satellite trying to reach another. Essentially, a satellite is trying to leave an orbit which can be idealized as a circular orbit with radius of r_1. It does so by using all of its thrust capability denoted by using its maximum thrust impulse Δv_1. With the goal of obtaining another circular orbit of radius r_2. Upon arrival to this orbit a higher speed is required from an impulse of Δv_2 to maintain orbit, as seen in Figure 10. In addition this intelligence, other information about the red country's assets needs to be taken into account such as: each satellite's available fuel, thruster capabilities, mass, and shape. By combining all of this information an overall score for a red adversary's capability can be determined. Once this overall capabilities score is calculated, properties in this domain can be assigned to regions of high, medium and low.

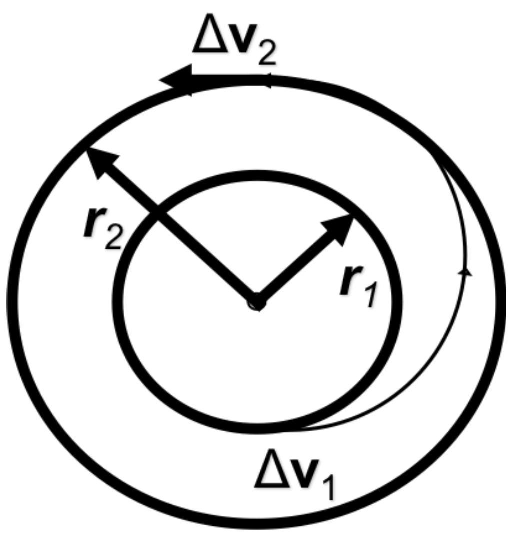


Figure 10: Two-Body Problem for Repositioning a Satellite from Orbit 1 to Orbit 2

5.3 Opportunity

The last domain that will be discussed is that of *opportunity.* This should be used as a pre-filter to eliminate options that will make the overall threat zero. This pre-filtering occurs by looking at the spatio-temporal relationship between a red asset and a blue asset and then again utilizing Lambert's Problem to determine the window of opportunity. When Lambert's Problem is solved, it will show the thrust required for one satellite to reach another. The satellite's thrust capabilities should then be examined to see if it has the required thrust for a kinetic kill to occur. If the thrust capabilities are not there, then a kinetic kill cannot occur at this time. Additionally, the opportunity will be higher when there is an excess of thrust available as compared to what is required for a kinetic kill attack, since this will result in a higher impulse force. In addition, the fact that the operators of the red asset will likely perform a cost/benefit analysis before making an attack to determine if there is an opportunity for success needs to be taken into account. This domain, like the other domains, can be broken down into three possible options of high, medium, and low.

6 Formalizing Problem

Now that the domains are defined and the properties are known for each domain, it can be seen that there are three domains and three properties in each. Next, for a high threat to occur, each of these domains would have the property of high. The domains and properties are given by

Intention Domain: High (x_{11}), Medium (x_{12}), Low (x_{13})
Capability Domain: High (x_{21}), Medium (x_{22}), Low (x_{23})
Opportunity Domain: High (x_{31}), Medium (x_{32}), Low (x_{33})

Now since all three domains are being considered in the concept, the following generalized constraints can be generated:

$$x_{11} + x_{12} + x_{13} = 1$$
$$x_{21} + x_{22} + x_{23} = 1$$
$$x_{31} + x_{32} + x_{33} = 1$$

The next step is to define the equality constraints developed by Eq. (3). Since it is known that the concept that is being looked for is the concept of high threat, these constraints become the following:

$$x_{11} = 1$$
$$x_{21} = 1$$
$$x_{31} = 1$$

The final steps will be to develop the inequality constraints in a way that represents a high indication of threat. This is done by inferring from the assumption that the highest threat will come from having a high threat level from each of the three domains the following inequality constraints:

$$\begin{array}{lll} x_{11} + x_{22} \leq 1 & x_{21} + x_{12} \leq 1 & x_{31} + x_{12} \leq 1 \\ x_{11} + x_{23} \leq 1 & x_{21} + x_{13} \leq 1 & x_{31} + x_{13} \leq 1 \\ x_{11} + x_{32} \leq 1 & x_{21} + x_{32} \leq 1 & x_{31} + x_{22} \leq 1 \\ x_{11} + x_{33} \leq 1 & x_{21} + x_{33} \leq 1 & x_{31} + x_{23} \leq 1 \end{array}$$

For this example, one blue asset will be considered and seven different red assets will be considered. Each pair of red-blue assets will result in a single observation. A random sample for 5 observations is generated with the following random similarity values to each domain, along with one perfect observation having s_{11}, s_{21} and s_{31} equivalent to 1, and one case where s_{11}, s_{21} and s_{31} all have similarity values equivalent to zero.

Similarity values of s_{11}, s_{21} and s_{31} equivalent to 1 will indicated perfect correlation between property 1 from domains 1, 2, and 3 which represents high threat in each other three domains. While, s_{11}, s_{21} and s_{31} equivalent to 0 indicates no similarity of the observation between property 1 (i.e. high) from domains 1, 2, and 3. Keep in mind, if certain aspects of the observation do not exist, then they should be ignored as they cannot produce a threat value. The following seven similarity values for the observations then result:

Observation 1: $s_{11} = 0.3946,\ s_{12} = 0.0723,\ s_{13} = 0.0156,\ s_{21} = 0.5891,\ s_{22} = 0.6365,$
$s_{23} = 0.4148,\ s_{31} = 0.5490,\ s_{32} = 0.0050,\ s_{33} = 0.3402$

Observation 2: $s_{11} = 0.4691,\ s_{12} = 0.0926,\ s_{13} = 0.1921,\ s_{21} = 0.1854,\ s_{22} = 0.9796,$
$s_{23} = 0.6590,\ s_{31} = 0.7446,\ s_{32} = 0.7152,\ s_{33} = 0.5702$

Observation 3: $s_{11} = 0.1230,\ s_{12} = 0.7176,\ s_{13} = 0.6508,\ s_{21} = 0.4402,\ s_{22} = 0.6850,$
$s_{23} = 0.9362,\ s_{31} = 0.0416,\ s_{32} = 0.5077,\ s_{33} = 0.6152$

Observation 4: $s_{11} = 0.3569,\ s_{12} = 0.0478,\ s_{13} = 0.7658,\ s_{21} = 0.2388,\ s_{22} = 0.5831,$
$s_{23} = 0.3797,\ s_{31} = 0.5742,\ s_{32} = 0.8616,\ s_{33} = 0.8731$

Observation 5: $s_{11} = 0.6039,\ s_{12} = 0.7280,\ s_{13} = 0.0181,\ s_{21} = 0.3977,\ s_{22} = 0.0521,$
$s_{23} = 0.2547,\ s_{31} = 0.3904,\ s_{32} = 0.1741,\ s_{33} = 0.7688$

Observation 6: $s_{11} = 1,\ s_{12} = 0,\ s_{13} = 0,\ s_{21} = 1,\ s_{22} = 0,$
$s_{23} = 0,\ s_{31} = 1,\ s_{32} = 0,\ s_{33} = 0$

Observation 7: $s_{11} = 0,\ s_{12} = 0.8708,\ s_{13} = 0.4777,\ s_{21} = 0,\ s_{22} = 0.4332,$
$s_{23} = 0.6055,\ s_{31} = 0,\ s_{32} = 0.3355,\ s_{33} = 0.0769$

After integer linear optimization is performed with the above constraints, the following similarity results are obtained:

$$\begin{aligned}
\text{Similarity to Concept for Observation 1} &= 51.09\% \\
\text{Similarity to Concept for Observation 2} &= 46.64\% \\
\text{Similarity to Concept for Observation 3} &= 20.16\% \\
\text{Similarity to Concept for Observation 4} &= 39.00\% \\
\text{Similarity to Concept for Observation 5} &= 46.40\% \\
\text{Similarity to Concept for Observation 6} &= 100\% \\
\text{Similarity to Concept for Observation 7} &= 0\%
\end{aligned}$$

It is important to note here that the observation that would have been a theoretically most threatening scenario, i.e. Observation 6, did prove to have a 100% similarity to the concept. While the observation that would have been the theoretically least threatening scenario, i.e. Observation 7, came out as having 0% similarity to the concept. This corresponds with what the expected results should be. However, it should be noted that these theoretical scenarios are extremely unlikely to happen in reality.

7 Conclusion

Conceptual Spaces have proven to be a powerful tool in data fusion and are capable of handling data sources from multiple different facets. This data can come from hard sources such as sensor information or soft sources such as judgements from knowledge domain experts. This paper described a mathematical formalization that integrates multiple necessary operations for constructing a computational framework that exploits the foundational ideas of the Conceptual Spaces approach. This involves the partitioning of a space into domains that contain properties, as well as explaining how constraints need to be formulated to represent the concept.

Concepts in Conceptual Spaces can be either objects or events and a Conceptual Spaces model can be built for any group of one or more concepts. Once the concept is constructed, observations in the real world can be made and similarities to properties can be recorded. After this is done, the mathematical model provided can be utilized to find overall similarity values between an observation and a concept in order to support inferencing. The concept of threat was broken down into intention, capabilities and opportunities, for space events (e.g. kinetic kill events), the ontological breakdown of into three domains made for a well-suited characterization of the threat concept.

Acknowledgments

Our research team would like to thank Dr. Erik Blasch, Air Force Office of Scientific Research, for continuous support and funding of this project. Our group would also like to show our gratitude to Ms. Carolyn Sheaff, of the Air Force Research Laboratory Information Directorate, and her colleagues for their continuous technical support on this project.

References

[1] Gärdenfors, P., *Conceptual Spaces: The Geometry of Thought*, MIT Press, Cambridge, MA, 2000, doi:10.7551/mitpress/2076.001.0001.

[2] Gärdenfors, P., "Conceptual Spaces as a Framework for Knowledge Representation," *Mind and Matter*, Vol. 2, 01 2004, pp. 9–27, doi:10.1016/j.isci.2020.101429.

[3] Holender, M., Sudit, M., Nagi, R., and Rickard, J., "Information Fusion Using Conceptual Spaces: Mathematical Programming Models and Methods," *10th International Conference on Information Fusion (FUSION)*, IEEE, Quebec City, Quebec, Aug. 2007, pp. 1 – 8, doi:10.1109/ICIF.2007.4408111.

[4] Holender, M. N., *Conceptual Spaces as a Modeling System for Information Fusion*, Ph.D. thesis, University at Buffalo, State University of New York, 2008.

[5] Newell, A. and Simon, H. A., "Computer Science as Empirical Inquiry: Symbols and Search," *Communications of the ACM*, Vol. 19, No. 3, March 1976, pp. 113–126, doi:10.1145/1283920.1283930.

[6] Lewis, R., "Cognitive Modeling, Symbolic," *The MIT Encyclopedia of the Cognitive Sciences*, edited by R. Wilson and F. Keil, Vol. cxxxii, MIT Press, Cambridge, MA, 1999, pp. 140–142, doi: 10.7551/mitpress/1888.001.0001.

[7] Carlston, D. E., *Associative Network*, SAGE Publications, Inc., Thousand Oaks, California, 2007, doi:10.4135/9781412956253.

[8] Williams, S., "Associative Model of Data," *Journal of Database Marketing & Customer Strategy Management*, 07 2001, pp. 336–359, doi:10.1057/palgrave.jdm.3240049.

[9] Garner, W. R., *The Processing of Information and Structure*, Erlbaum, Potomac, MD, 1st ed., 1974, doi:10.4324/9781315802862.

[10] Melara, R. D., "6The Concept of Perceptual Similarity: From Psychophysics to Cognitive Psychology," *Psychophysical Approaches to Cognition*, edited by D. Algom, Vol. 92 of *Advances in Psychology*, North-Holland, 1992, pp. 303–388, doi:10.1016/S0166-4115(08)61782-3.

[11] Bechberger, L. and Kühnberger, K., "Towards Grounding Conceptual Spaces in Neural Representations," *CoRR*, Vol. abs/1706.04825, 2017.

[12] Warglien, M., Gärdenfors, P., and Westera, M., "Event Structure, Conceptual Spaces and the Semantics of Verbs," *Theoretical Linguistics*, Vol. 38, 2012, pp. 159–193, doi:10.1515/tl-2012-0010.

[13] Aisbett, J. and Gibbon, G., "A General Formulation of Conceptual Spaces as a Meso Level Representation," *Artificial Intelligence*, Vol. 133, No. 1-2, 2001, doi:10.1016/s0004-3702(01)00144-8.

[14] Martin, R., "Formalizing Conceptual Spaces," *Third International Conference on Formal Ontology in Information Systems*, 01 2004, pp. 153–164, doi:10.1007/978-3-319-67190-1-5.

[15] Rickard, J., "A Concept Geometry for Conceptual Spaces with Applications to Levels 2 & 3 Fusion," *Fuzzy Optimization and Decision Making*, Vol. 5, 10 2006, pp. 311–329, doi:10.1007/s10700-006-0020-1.

[16] McConky, K. T., *Applications of Location Similarity Measures and Conceptual Spaces to Event coreference and Classification*, Ph.D. thesis, University at Buffalo, State University of New York, 2013.

[17] Kantorovich, L. V., "Mathematical Methods of Organizing and Planning Production," *Manage. Sci.*, Vol. 6, No. 4, July 1960, pp. 366–422, doi:10.1287/mnsc.6.4.366.

[18] International Standards Organization, "Information Technology − Top-Level Ontologies (TLO) − Part 2: Basic Formal Ontology (BFO)," Standard, International Organization for Standardization, Geneva, CH, Oct. 2019.

[19] CUBRC, "Common Core Ontologies," `https://github.com/CommonCoreOntology/CommonCoreOntologies`, 2017-2020.

[20] CUBRC, "An Overview of the Common Core Ontologies 1.1," `https://github.com/CommonCoreOntology/CommonCoreOntologies/blob/master/documentation` AnOverviewoftheCommonCoreOntologies1.1.docx, 2019.

[21] Cox, A. P., Nebelecky, C. K., Rudnicki, R., Tagliaferri, W. A., Crassidis, J. L., and Smith, B., "The Space Object Ontology," *19th International Conference on Information Fusion (FUSION)*, IEEE, 2016, pp. 146–153.

[22] Cox, A. P., Nebelecky, C. K., Rudnicki, R., Tagliaferri, W. A., Crassidis, J. L., and Smith, B., "The Space Domain Ontologies," *National Symposium on Sensor & Data Fusion Committee (NSSDF)*, Military Sensing Symposia (MSS), 2021.

[23] Little, E. G. and Rogova, G. L., "An Ontological Analysis of Threat and Vulnerability," *9th International Conference on Information Fusion (FUSION)*, IEEE, 2006, pp. 1–8, doi: 10.1109/ICIF.2006.301716.

[24] Llinas, J., Bowman, C., Rogova, G., Steinberg, A., Waltz, E., and White, F., "Revisions and Extensions to the JDL Data Fusion Model II," *7th International Conference on Information Fusion (FUSION)*, 01 2004, pp. 1218–1230.

[25] Chapman, J., Kasmier, D., Limbaugh, D., Gagnon, S., Crassidis, J., Llinas, J., Smith, B., and Cox, A., "Conceptual Space Modeling for Space Event Characterization," *23rd International Conference on Information Fusion (FUSION)*, IEEE, Rustenburg, South Africa, July 2020, pp. 1–8, doi:10.23919/FUSION45008.2020.9190163.

[26] Chapman, J. R., Crassidis, J. L., Kasmier, D., Limbaugh, D., Gagnon, S., Llinas, J., Smith, B., and Cox, A. P., *Conceptual Spaces for Space Event Characterization via Hard and Soft Data Fusion*, AIAA, 2021, doi:10.2514/6.2021-1163.

[27] Caldara, D. and Iacoviello, M., "Measuring Geopolitical Risk," International Finance Discussion Papers 1222, Board of Governors of the Federal Reserve System (U.S.), Feb. 2018, doi:10.17016/IFDP.2018.1222.

[28] Franco, E. G., *The Global Risk Report 2020*, World Economic Forum, 15th ed., 2020, doi: 9782940631247.

[29] Geugjes, M., Linke, F., and Stüber, V., *Conflict Barometer 2018*, Heidelberg Institute for International Conflict Research (HIIK), March 2019.

[30] Stamatia, H., Ferri, S., Ines, J., Saporiti, F., and Kauffmann, M., *The Global Conflict Risk Index (GCRI) Regression Model: Data Ingestion, Processing, and Output Methods*, Publication Office of the European Union, 2017, doi:10.2760/303651.