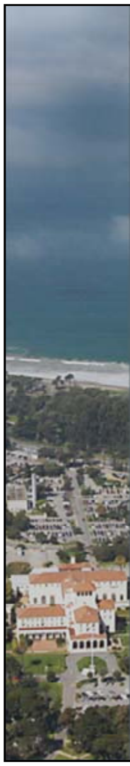


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# Semantic Web and Inferencing Technologies for DoD Systems


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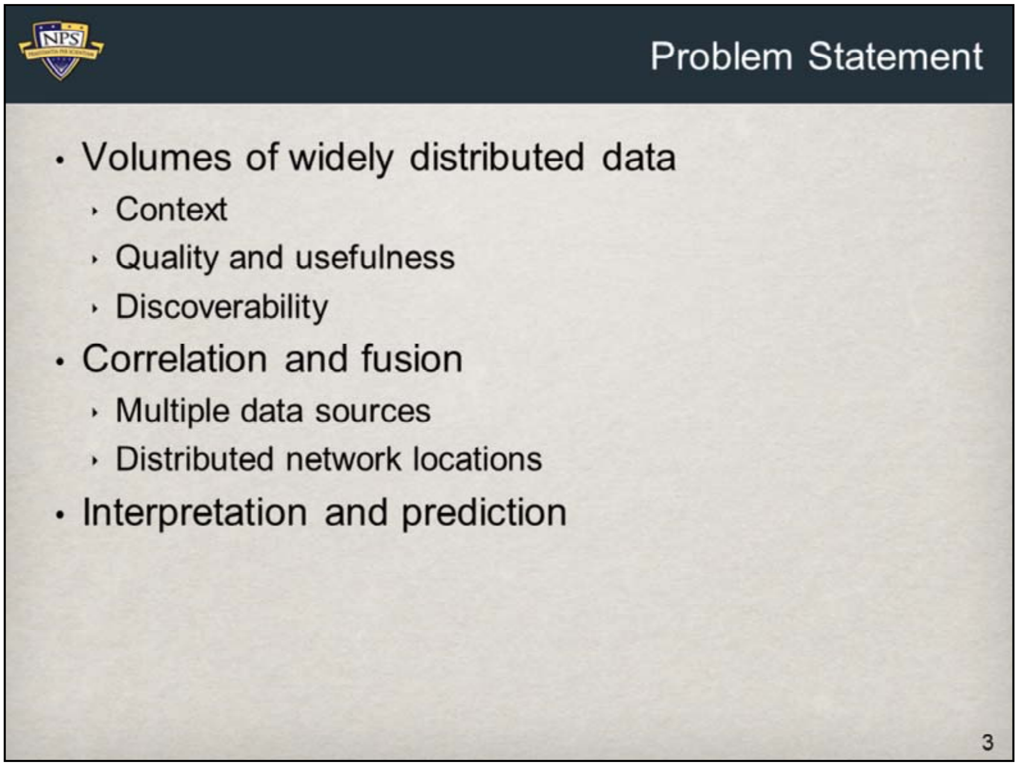
## Overview

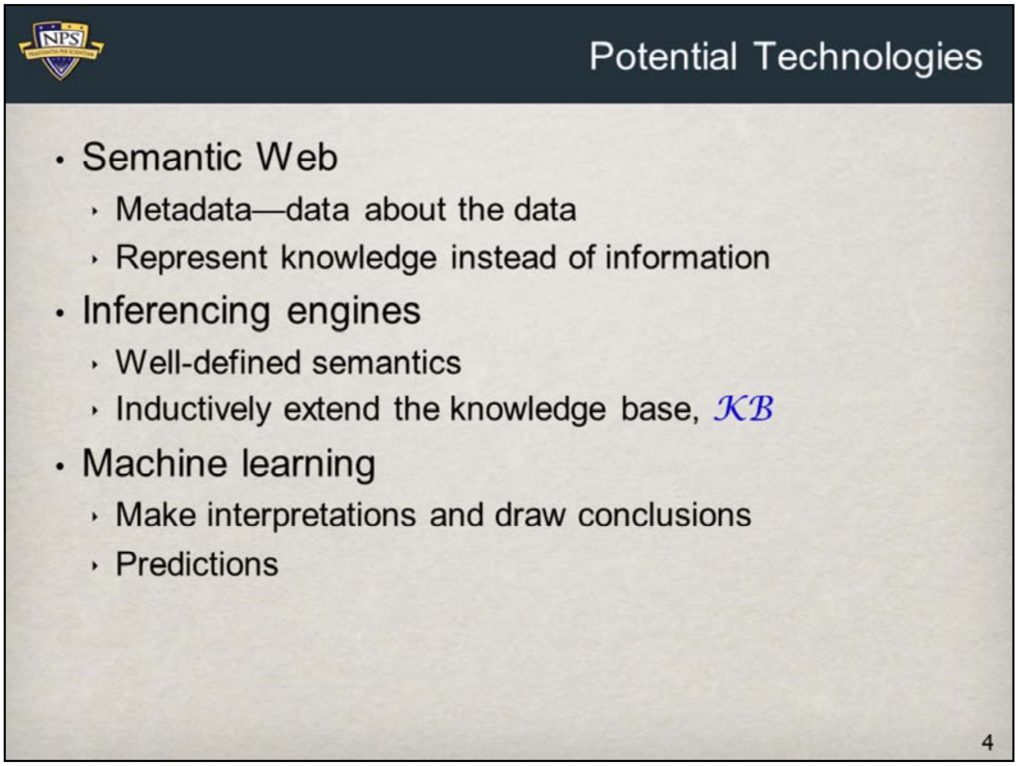
- Introduction
  - Problem statement
  - Available technologies
  - Information versus knowledge
- Description Logics and Knowledge Representation
- Semantic Web
- Description Logic Inferencing
- Machine Learning and the Semantic Web
- Conclusions and Recommendations




Traditional internet technologies, including the World Wide Web, facilitate the access and presentation of networked data. These technologies have obvious applications in both classified and unclassified government systems, and make volumes of potentially useful information available to operational commanders and decision-makers. This information includes raw and annotated data from tactical, strategic, and national sensors; composed and analytic products derived from various data sources; and operational information about friendly assets to name a few.

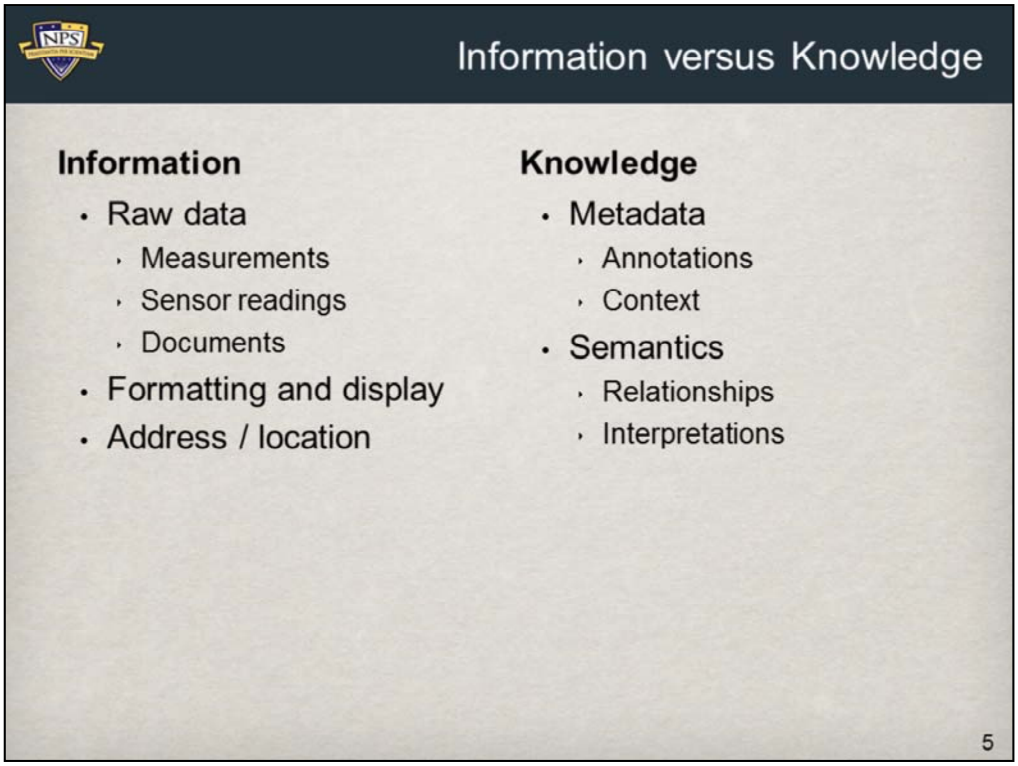
As the amount of available data explodes, however, it becomes more and more difficult to utilize it effectively. Access to hyperlinked documents and web-accessible data repositories does not provide the end user any contextual background or insight into how the information relates to information from other sources. Additionally, it can be difficult to separate useful information from digital clutter. Search engines can locate information based on keywords, but they have no ability to tailor results according to an “understanding” of the encountered data.

In this context, traditional distributed data storage has three significant shortcomings. First, it is difficult to efficiently separate useful data from digital clutter—imagine the difficulty in locating a specific contact of interest in hundreds of hours of unmanned air vehicle imagery over thousands of square miles. A second potential issue is efficient data fusion. Ideally, we would like to process data from multiple sources and locations so that redundant information is eliminated and related data is correlated.  Finally, even after sorting through and fusing the data, we would like to be able to automatically draw conclusions and make predictions based on the available information.

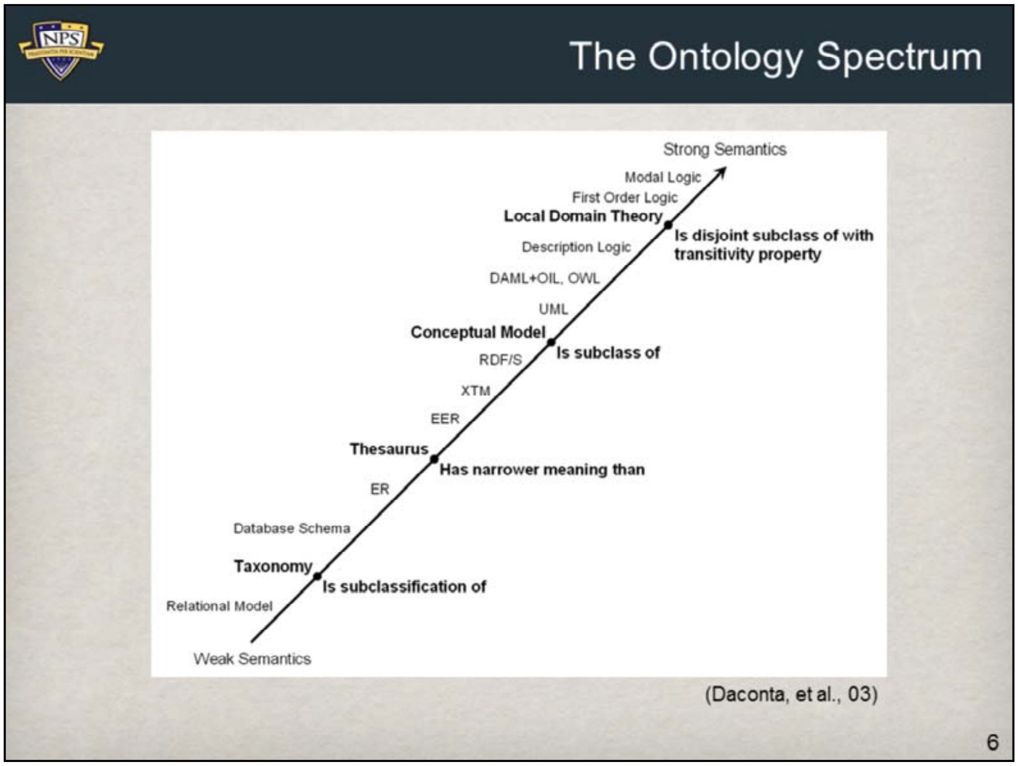



Semantic Web technologies provide not only access to data, but access to contextual information that allows for its interpretation as well. Specifically, the Semantic Web uses ontologies, taxonomies, data models, and other tools to describe content characteristics and relationships. The mathematical rigor of Semantic Web constructs provides for their discovery and utilization by networked applications and also allows for automated inferencing to derive new information and draw conclusions from distributed information.

Realization of the Semantic Web has two crucial requirements. First, is a set of standardized means of representing information. Towards this end, the World Wide Web Consortium (W3C) has approved languages such as the Resource Description Format (RDF), its extension RDF(S), and Web Ontology Language (OWL) that will be discussed in this work. The second essential element involves reasoning about represented data. Formal logic, and specifically Description Logics (DL), has received significant research attention in support of this requirement. (Rudolph, 11)



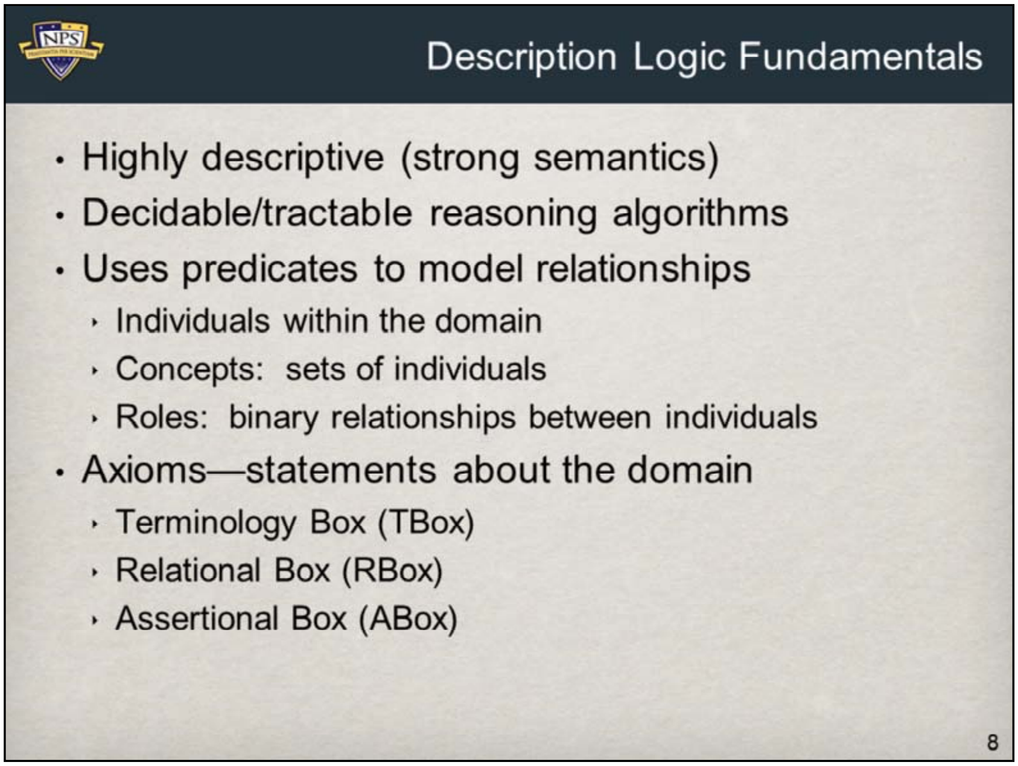

Traditional distributed technologies provide access to information as opposed to knowledge. This means that data is accessible, displayable, and available for manipulation, but there is no basis for more than cursory understanding without human intervention and analysis. Semantic Web technologies, on the other hand, express meaning along with the data by adding formal semantics (Daconta, et al., 03). Formal semantics allow for the development of knowledge bases ($\mathcal{KB}$) that utilize metadata to place information in context, describe relationships, make interpretations and draw conclusions in a mathematically rigorous way (Kashyap, 04). This mathematical rigor, along with recognized standards allows for the expressed knowledge to be machine read and computationally processed in ways that support automation, integration and reuse of data.




Representation of information in a form that effectively conveys knowledge requires more than simple markup of the data comprising the information. It requires a model or language that is capable of representing strong semantics about the data. (Daconta, et al., 03) uses an "Ontology Spectrum" to rank various data expression mechanisms relative to one another. Traditional database techniques including Schemas, Entity-Relationship (ER) Models and Extended Entity-Relationship (EER) Models are on the lower end of this spectrum while logical forms including Description Logic, First Order Logic, and Modal Logic in the figure are on the upper end.

Much of what we might think of as the Semantic Web technology, particularly the aspects that support automated reasoning and inferencing, are based on Description Logics (DL). DLs provide significant expressive power and have been a focus of knowledge engineering research for some time. In addition, there has been significant work in developing reasoning algorithms for working with DLs that can be proven to meet specific mathematical requirements (completeness, soundness, tractability, etc.).

- Introduction
- Description Logics and Knowledge Representation
  - Description Logic Fundamentals and Operations
  - Terminological, Assertional and Role Axioms
  - Basic Reasoning
  - Expressive Description Logics
  - Description Logic Extensions
- Semantic Web
- Description Logic Inferencing
- Machine Learning and the Semantic Web
- Conclusions and Recommendations



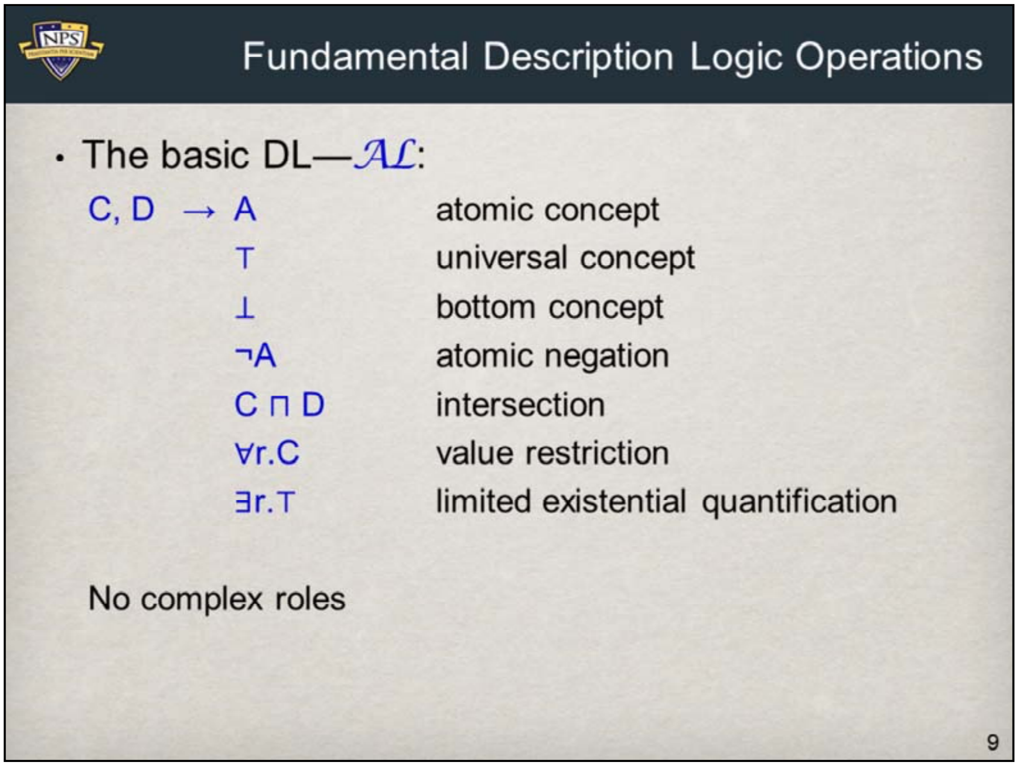

DLs are a family of logic-based knowledge representation systems that fall between Propositional Logic and First Order Logic (FOL) on the Ontology Spectrum of the (Daconta, et al., 03), meaning that they are more semantically expressive than Propositional Logic, but less so than FOL. The advantages that they possess over FOL involve the decidability and tractability of associated reasoning problems. Reasoning with DLs can often be done more efficiently than with FOLs, and reasoning problems are much more likely to be computationally undecidable with FOLs than with DLs (Rudolph, 11).

DLs describe **individuals** within a domain of interest using **concepts** and **roles**, which describe groups of individuals and relationships between individuals respectively. For instance, "Ship" might be a concept that includes individuals (literals) such as "Antietam", "Sullivans", and "Nimitz", and "inBattleGroup" might be a role for declaring that a ship is assigned to a specific battlegroup. DL statements, or **axioms**, take the form of predicates where concepts and roles are the predicate names and individuals are the objects of the predicate (e.g., "Ship(Antietam)" and "inBattleGroup(Antietam, CSG-3)" ). Every name within a DL, then, is either a literal (individual), a unary predicate (named concept), or a binary predicate (named role) from FOL (Rudolph, 11).

DL axioms describing a particular domain are typically separated into three groups: the Terminology Box (TBox) is used to define relationships between concepts, the Relational Box (RBox) is used to define properties of roles, and the Assertional Box

(ABox) makes assertions about individuals. Together, the TBox and RBox define the intensional portion of $\mathcal{KB}$ while the ABox comprises the extensional portion (Haarslev, 06). Only DLs that allow complex roles (i.e., those that include operations for combining and manipulating roles) require an RBox. Not unexpectedly, those languages that do allow complex roles provide additional expressive power at the cost of increased reasoning complexity (Krötzsch, et al., 12).

For this report, discussion will focus primarily on the TBox and ABox. Adding an RBox does not fundamentally change the reasoning algorithms beyond accounting for the role operations available in the particular DL. In practice (and in much of the literature), the TBox and RBox can be implemented and considered as a single entity (Baader, et al., 07).




DLs provide a operators that can be used to build complex concepts. Specific DLs are characterized (and named) according to operations that are permitted. The most commonly utilized DLs are those that fall in the $\mathcal{AL}$ family (AL stands for attributive language). The basic AL allows the definition of atomic concepts and roles and provides the operations described below (C and D represent arbitrary concept descriptions, A and B represent atomic concepts, and r represents an atomic role):

An atomic concept is one utilizing a single unary predicate

The universal concept ($\top$) includes every concept in the domain (i.e., all )

The bottom concept ($\bot$) excludes every concept in the domain

Atomic negation ($\neg A$) describes all individuals for which the concept is false

Intersection ($C \sqcap D$) describes the intersection between two concepts (i.e., all individuals to which both operand concepts apply)

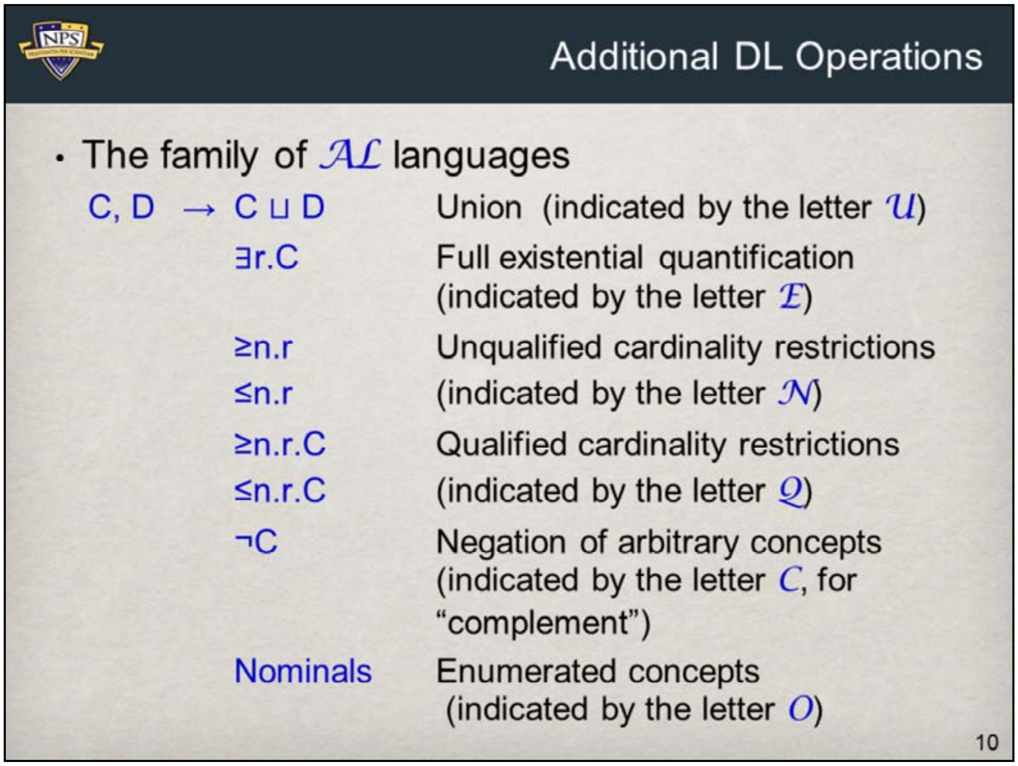
Value restriction ($\forall r.C$) describes all individuals that participate as the first entry of the specified role with *only* individuals from the concept specified by the operand

Limited existential quantification ($\exists r.\top$) describes all individuals that participate as the first individual in the specified role with no restrictions on the other role participant

The following examples demonstrate simple applications of AL operations where “Aircraft”, “Fighter”, “Weapon” are atomic concepts and “payload” is an atomic role:

| | |
|---|---|
| Weapon | denotes all members of the Weapon concept |
| Aircraft $\sqcap$ ¬Fighter | denotes all Aircraft that are not Fighters |
| Aircraft $\sqcap$ ∃payload.$\top$ | denotes all Aircraft with a payload |
| Aircraft $\sqcap$ ∀payload.Weapon | denotes all Aircraft with a Weapon payload |
| Aircraft $\sqcap$ ∀payload.$\bot$ | denotes all Aircraft with a no payload |

In these examples and definitions, it is important to note that negation is only allowed for atomic concepts, and that existential is only universal (i.e., the operator describes all individuals that are participating in the role relationship with no restrictions on the other role participant). Additionally, AL allows only atomic roles, meaning that there are no role-forming constructs that can be used to generate complex roles.




While AL is considered a minimally robust DL, its expressive power is fairly limited. It does, however, form the basis for a family of languages that are used extensively by Semantic Web technologies. Extensions to the AL language are specified by the operations that they add to the basic AL language (a few of the possibilities are described below). The most common operations are union, full existential qualification, unqualified cardinality restrictions, and negation of arbitrary concepts.

Union (C ⊔ D) describes all individuals that are included in either of the operand concepts.

Full existential quantification (∃r.C) extends limited existential qualification of AL to describe individuals participating in the specified role with the second participant restricted to individuals described by a specific concept.

Unqualified cardinality restrictions (≥n.r and ≤n.r) describe all individuals that participate in at least (or at most) role relationships of the specific type (e.g., "≤5.commands" describes individuals participating in five or fewer "commands" relationships) without placing any restrictions on the role's other participating individuals.

Qualified cardinality restrictions (≥n.r.C and ≤n.r.C) are similar to unqualified cardinality restrictions except they only restrict the numbers for role participants of the specified concept (i.e., "≤5.commands.Squadron" describes individuals participating in five or fewer "commands" relationships with individuals to which the "Squadron" concept applies).

Negation of arbitrary concepts (¬C) extends AL's atomic negation beyond atomic concepts by allowing the negation of arbitrary concepts.

Nominals provide a mechanism for defining enumerated concepts in an shorthand fashion (e.g., “AirWing ≡ { SH-60R } ∪ { MH-60F } ∪ { EA=6B } ∪ { E2-C } ∪ { FA-18C } ∪ { FA-18E } ∪ { FA-18F }” defines the “AirWing” concept as consisting of the seven specific individuals listed).

A specific AL-family DL is specified by the letter(s) associated with the extension(s). For example, ALEN is the basic AL language extended to allow full existential quantification and unqualified cardinality restrictions.

By convention, the ALC language also includes union, full existential quantification, and a few other capabilities that will be discussed later in this report (Schmidt-Schaub and Smolka, 91). This language is among the more useful DLs and serves as the basis for what are termed expressive DLs. Because they are among the more useful (and most commonly used) DLs, the DL naming convention uses the shorthand, S, to denote ALC languages (Rudolph, 11).

There are a number of additional extensions are utilized by typical Symantic Web applications that will not be specifically discussed here (Krötzsch, et al., 12). In most cases, they add expressive power to the DL but do not fundamentally change the knowledge representation or inferencing paradigms.

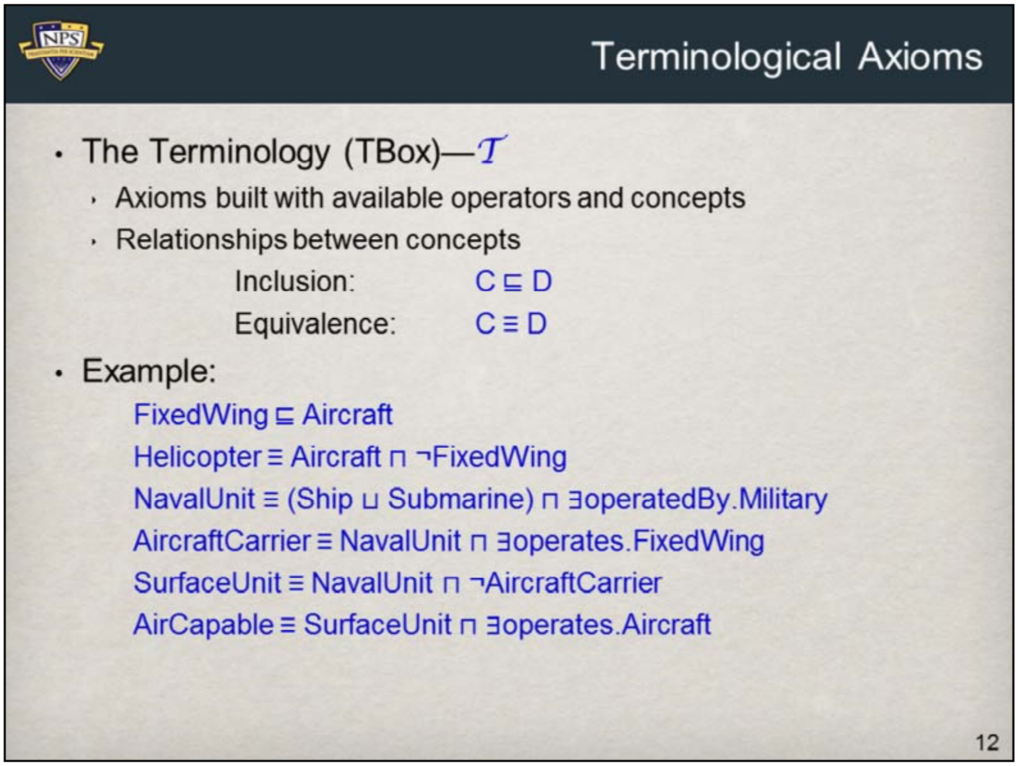
## Interpretations

- Application of semantics to a set of individuals
  - $\Delta^{\mathcal{I}}$ = the domain of the interpretation
  - Interpretation function maps the domain to concepts and roles:
    - For an atomic concept, A: $A^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$
    - For an atomic role r: $r^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$
- DL operators are intuitively (and inductively) applied:
  - $\top^{\mathcal{I}} = \Delta^{\mathcal{I}}$ and $\bot^{\mathcal{I}} = \emptyset$
  - $(\neg A)^{\mathcal{I}} = \Delta^{\mathcal{I}} \setminus A^{\mathcal{I}}$ and $(\neg C)^{\mathcal{I}} = \Delta^{\mathcal{I}} \setminus C^{\mathcal{I}}$
  - $(C \sqcap D)^{\mathcal{I}} = C^{\mathcal{I}} \cap D^{\mathcal{I}}$ and $(C \sqcup D)^{\mathcal{I}} = C^{\mathcal{I}} \cup D^{\mathcal{I}}$
  - $(\forall r.C)^{\mathcal{I}} = \{ a \in \Delta^{\mathcal{I}} \mid \forall b.(a, b) \in r^{\mathcal{I}} \rightarrow b \in C^{\mathcal{I}} \}$
  - $(\exists r.\top)^{\mathcal{I}} = \{ a \in \Delta^{\mathcal{I}} \mid \exists b.(a, b) \in r^{\mathcal{I}} \}$
  - $(\exists r.C)^{\mathcal{I}} = \{ a \in \Delta^{\mathcal{I}} \mid \exists b.(a, b) \in r^{\mathcal{I}} \wedge b \in C^{\mathcal{I}} \}$
  - $(\geq n.r)^{\mathcal{I}} = \{ a \in \Delta^{\mathcal{I}} \mid |\{ b \mid (a, b) \in r^{\mathcal{I}} \}| \geq n \}$
  - $(\leq n.r)^{\mathcal{I}} = \{ a \in \Delta^{\mathcal{I}} \mid |\{ b \mid (a, b) \in r^{\mathcal{I}} \}| \leq n \}$



DLs are utilized through **interpretations** that operate on a domain of interest. The domain of interest is simply the set of all individual entities with which we are concerned. An interpretation function is used to map individuals within the domain of interest to atomic concepts and roles. Each atomic concept will consist of a subset of members the interpretation's domain, while each atomic role will consist of a subset of the cross product of the domain of interest with itself.

Complex concepts (i.e., those that are defined using the DL's available operators) are mathematically computed using the formulas above, which coincide with the descriptions of the previous two slides.

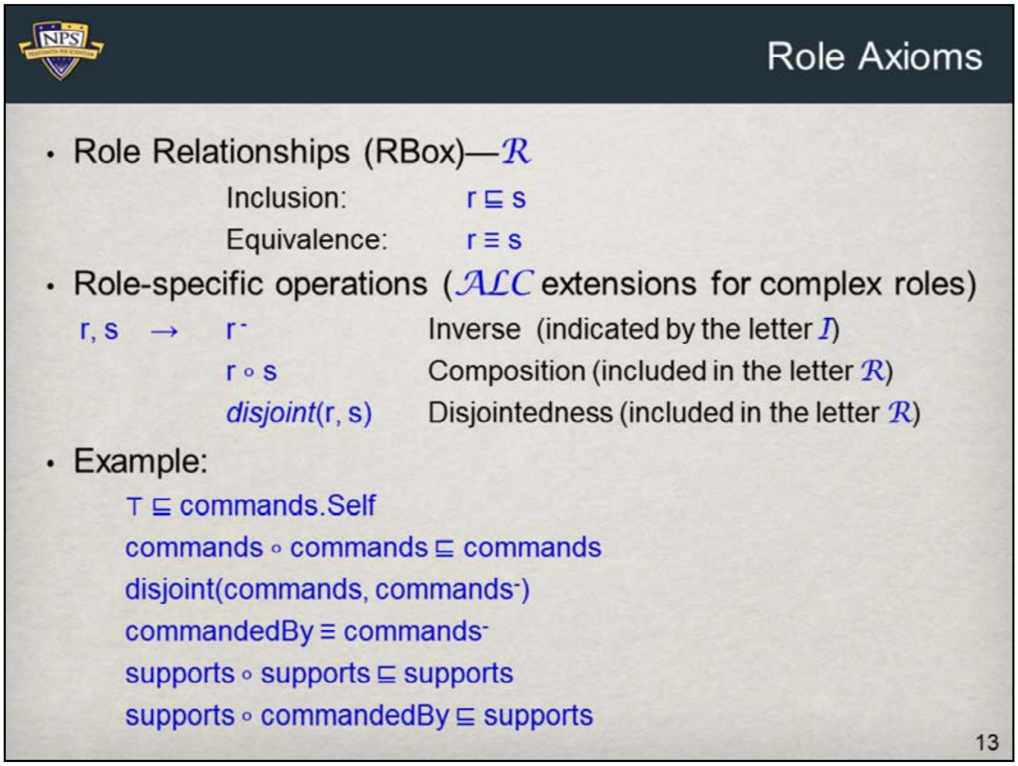



The TBox ($\mathcal{T}$) defines properties and definitions for concepts that will be applied to one or more domains of interest. Essentially, the TBox defines the rules and terminology for the concepts. There are two primary types of TBox relationships: inclusion and equivalence.

Inclusion: $C \sqsubseteq D$ iff $C(a) \rightarrow D(a)$

Equivalence: $C \equiv D$ iff $((C(a) \rightarrow D(a)) \land (D(a) \rightarrow C(a)))$

Axioms defining an equivalence between an atomic concept and another concept are called **definitions**. In the example of the slide, an equivalence relationship between the concept "Helicopter" and the complex concept of an "Aircraft" that is not "FixedWing". "FixedWing", on the other hand, is simply described as being included in the concept "Aircraft". By these definitions, one can infer that any individual that is an "Aircraft" must also be a "Helicopter" or a "FixedWing" (but not both). "NavalUnit", "AircraftCarrier", "SurfaceUnit", and "AirCapable" are similarly defined. If all definitions are **acyclic**, that is, it is not possible for a concept on the left hand side to use itself in its own definition, then definitions can be expanded so that atomic concepts and roles appear only on the right hand side (e.g., "AircraftCarrier ≡ (Ship ⊔ Submarine) ⊓ ∃operatedBy.Military ⊓ ∃operates.FixedWing"). An acyclic TBox is said to be **definitorial**, because if we know what each base symbol is (i.e., those on the right side of the expanded definitions) then the meaning of the name symbols (i.e., those on the left side of the expanded definitions) is completely determined (Baader, et al., 07).




For DLs that allow complex roles, the RBox ($\mathcal{R}$) performs the same function for roles that the TBox does for concepts. That is, it defines the rules and terminology for roles. As with concepts, relationships for roles can be defined in terms of inclusion and equivalence.

Inclusion: $r \sqsubseteq s$ iff $r(a, b) \rightarrow s(a, b)$
Equivalence: $r \equiv s$ iff $((r(a, b) \rightarrow s(a, b)) \wedge (s(a, b) \rightarrow r(a, b)))$

Roles can be defined using many of the same operators that are available for concepts, specifically, the top concept (universal role), bottom concept (empty role), intersection, union, and negation ($\neg r^I \Rightarrow \Delta^I \times \Delta^I \setminus r^I$). In addition, many DLs allow role-specific operators. Among the most important are inversion, composition, disjointedness.

Inverse: $r^- = \{ (a, b) \mid r^{\mathcal{I}}(b, a) \}$ (i.e., the relationship is reversed)
Composition: $r \circ s = \{ (a, c) \mid \exists j.(r^{\mathcal{I}}(a, b) \wedge s^{\mathcal{I}}(b, c)) \}$ (i.e. if an interpretation holds that the role r applies to two individuals, a and b, and the role s applies to individuals b and c, then the role r ∘ s applies to individuals a and “c”)
Disjointedness: disjoint(r, s) = $( r^{\mathcal{I}}(a, b) \rightarrow \neg s^{\mathcal{I}}(a, b) ) \wedge ( s^{\mathcal{I}}(a, b) \rightarrow \neg r^{\mathcal{I}}(a, b) )$ (i.e., if the role r applies to two individuals, a and b, then the role s cannot

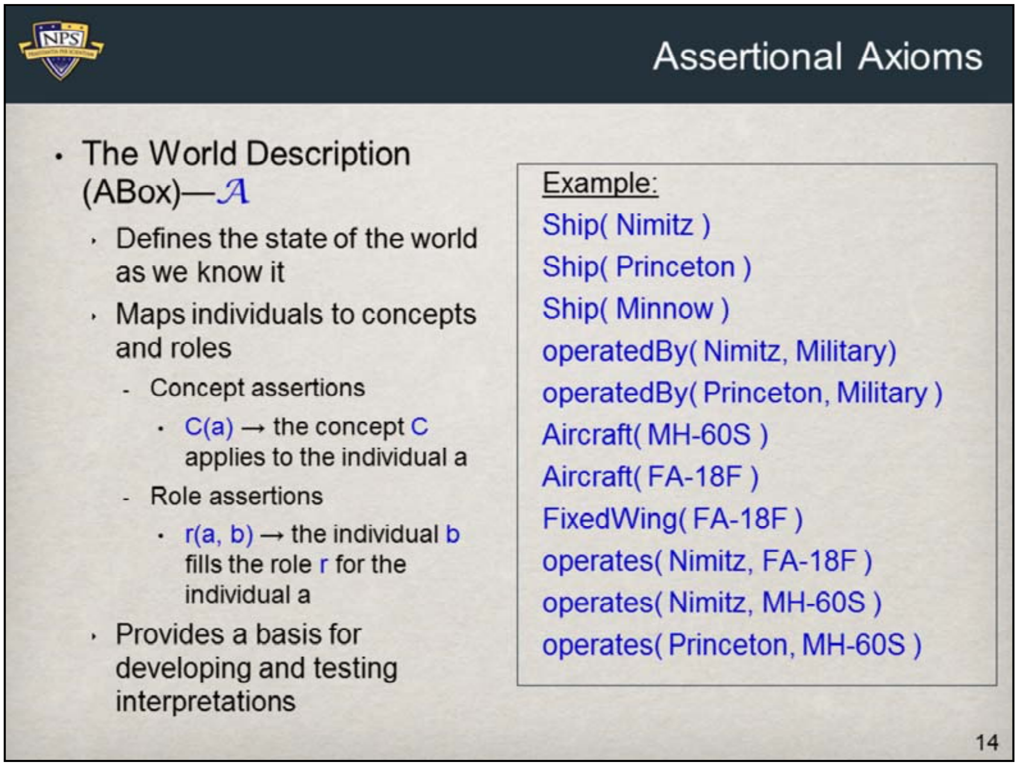
apply, and vice versa).

These particular extensions are particularly important because they allow the definition of a number of important complex roles:

Symmetry: $r \equiv r^{-}$ and asymmetry: disjoint($r$, $r^{-}$)
Transitivity: $r \circ r \sqsubseteq r$
Reflexivity: $\top \sqsubseteq r.\mathrm{Self}$ and areflexivity: $\top \sqsubseteq \neg r.\mathrm{Self}$

The example defines some simple command relationship semantics. The role “commands” is defined to be reflexive (all individuals command themselves), transitive (if an individual, a, commands an individual, b, then individual a also commands any individuals that individual b commands), and asymmetric (two individuals cannot command one another); and the role “commandedBy” is defined as the inverse of commands, which implicitly confers the transitive and disjointedness properties associated with the “commands” role. The role “supports” is defined to be transitive as well, and the composition of the roles “supports” and “commandedBy” is included in the role “supports” (i.e., if an individual, a, supports an individual, b, and individual b is commanded by an individual, c, then individual a also supports individual c).

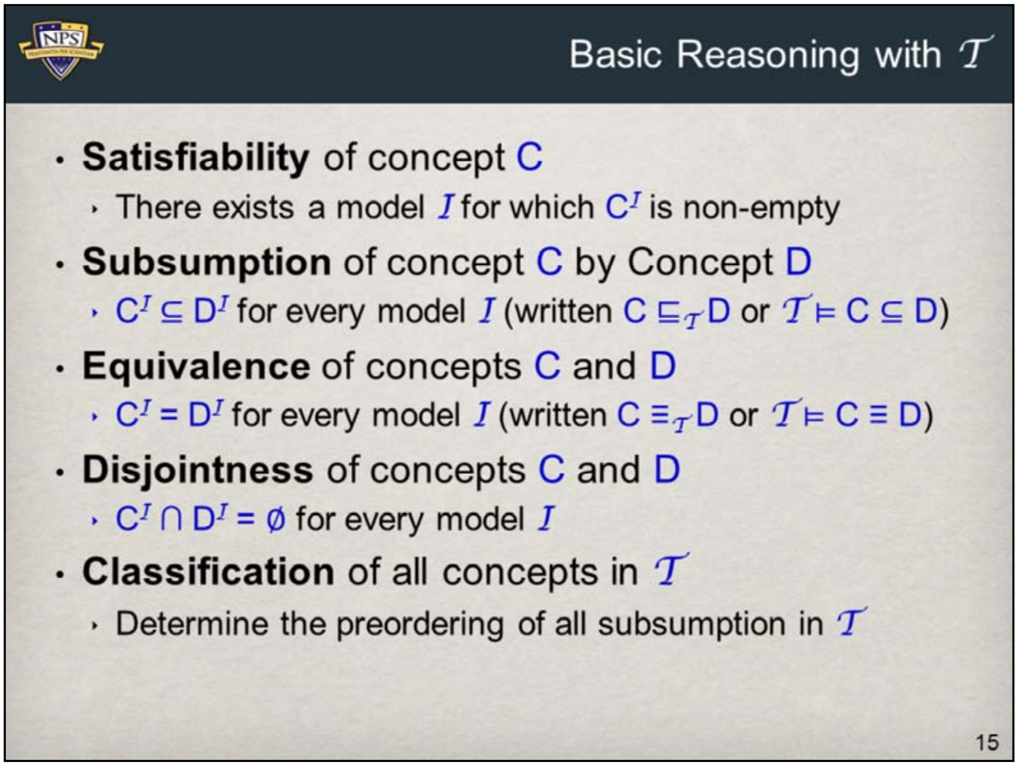
For the remainder of this report, the RBox will be treated as part of the TBox for those DLs allowing complex roles.




The ABox (A) describes what is known about the state of the world by making assertions about individual named entities. Assertions can be either concept assertions or role assertions and can utilize any operators allowed by the specific DL. A concept assertion assigns a named entity to a concept, while a role assertion establishes a role relationship between two named entities. In the example above, assertions are made that the concept “Ship” applies to “Nimitz”, “Princeton”, and “Minnow” and that the pairs “(Nimitz, Military)” and “(Princeton, Military)”.

We can use this information to develop and test interpretations where the domain of interest is made up of named entities from the ABox. An interpretation **satisfies** a concept assertion, C(a), if $a^{\mathcal{I}} \in C^{\mathcal{I}}$. That is if the concept, C, is interpreted to apply to the element in $\Delta^I$ corresponding to individual a (satisfaction of role concepts works similarly). An interpretation satisfies the ABox if it satisfies all of the roles contained in the ABox. If the interpretation also satisfies the TBox then it amounts to a reasonable abstract view of the domain and is said to be a **model** for the ABox and TBox.

It is appropriate at this point to bring up two additional points. First, it is possible for the ABox and TBox to conflict. For instance, an ABox assertion “SurfaceUnit(Nimitz)” would conflict with the TBox definition of the “SurfaceUnit” concept. Second, multiple interpretations might qualify as models for the same ABox/TBox pair, and these interpretations may conflict with one another.  DLs describe only what is known, so anything missing is simply unknown and can be interpreted multiple ways.  In the example, an interpretation that includes “operatedBy(Minnow, Civilian)” satisfies the ABox, but one that includes “operatedBy(Minnow, Military)” does as well.  This is an example of **open-world semantics**. (Baader, et al., 07).   Traditionally databases typically use closed-world semantics, meaning that any missing information is assumed to be false.




Based on the previous slides the notions of TBox **satisfiability**, **subsumption**, **equivalence**, and **disjointness** can be described intuitively. A concept is satisfiable if there exists at least one model interpretation with at least one entity to which the concept applies. By extension, the entire TBox is satisfiable if a modeling interpretation exists in which every concept can be applied to at least one individual. A concept, C, subsumes a concept, D, if the set of individuals to which C applies is a subset of the set of individuals to which D applies for every model interpretation. Concepts C and D are equivalent if the sets of individuals to which they apply are the same for every model interpretation. Finally, concepts C and D are disjoint if for every model interpretation the concepts C and D do not both apply to any individuals. Notice that the requirements for satisfiability are be met by the existence of a single model interpretation, while subsumption, equivalence, and disjointness require that the requirements be met by every model interpretation.

In fact, all four of these reasoning tasks can be reduced to subsumption as described by the following rules (Horrocks and Patel-Schneider, 08):

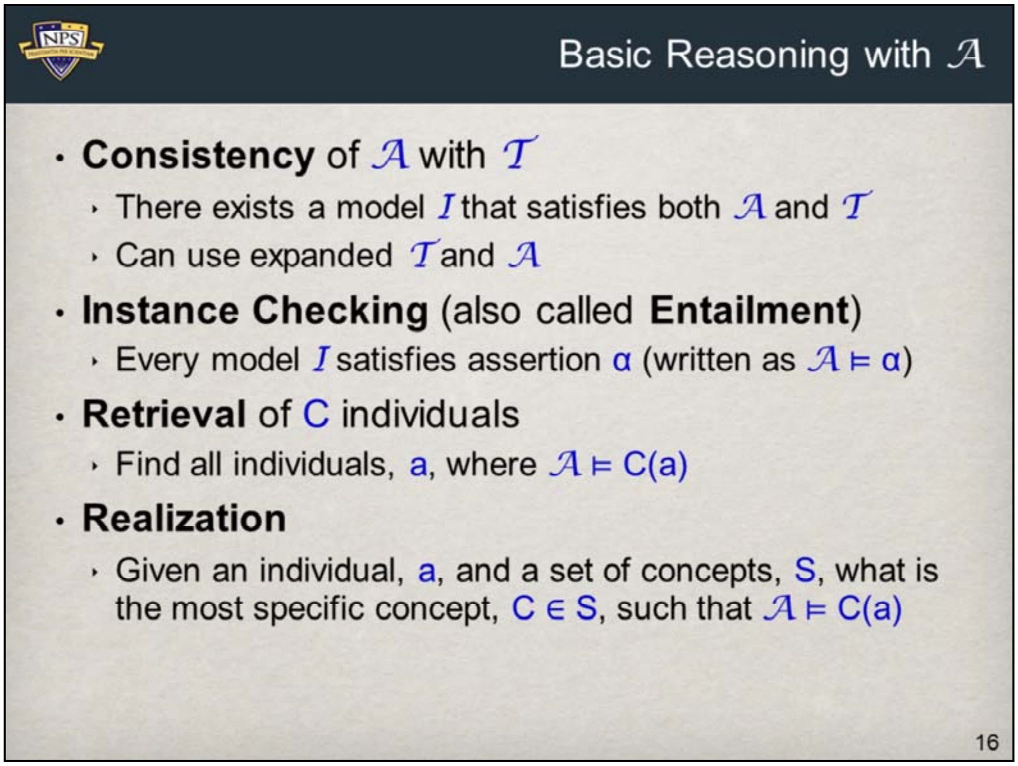
C is satisfiable iff $C \not\sqsubseteq_{\mathcal{T}} \perp$
$C \equiv_{\mathcal{T}} D$ iff $C \sqsubseteq_{\mathcal{T}} D$ and $D \sqsubseteq_{\mathcal{T}} C$
C and D are disjoint iff $(C \cap D) \sqsubseteq_{\mathcal{T}} \perp$

They can also be reduced to unsatisfiability as follows:

$C \sqsubseteq_{\mathcal{T}} D$ iff $(C \sqcap \neg D)$ is unsatisfiable
$C \equiv_{\mathcal{T}} D$ iff $(C \sqcap \neg D)$ and $(D \sqcap \neg C)$ are both unsatisfiable
C and D are disjoint iff $(C \sqcap D)$ is unsatisfiable

The final TBox reasoning task is **classification**, which determines the subsumption hierarchy of all contained concepts. This can be a computationally complex ($n^2$ subsumption checks for a TBox containing n concepts), however, it can be computed off-line with the results stored for later use. TBox classification is particularly useful for ontology design and visualization and is also the basis for many optimizations for other types of reasoning (Rudolph, 11).

The use of satisfiability as the basis for reasoning about the TBox is noteworthy because it is the basis for most implemented reasoning systems.




The most fundamental form of reasoning with an ABox is determining whether or not it is **consistent**. In lay terms, consistency simply means that the ABox is reasonable and does not contain any contradictions either inherently (e.g., asserting both C(a) and ¬C(a) ) or with the definitions of the TBox. Consistency is proven by the existence of an interpretation is a model for both the ABox and TBox. As discussed previously, an acyclic TBox can be expanded so that all definition right hand sides contain only primitives. We can use the definitions from this expanded TBox to generate an expanded ABox that contains only atomic concepts. Taking this approach, consistency checking of the ABox is reduced to checking for inconsistencies in the expanded ABox (Baader, et al., 07). TBoxes with cycles cannot be expanded this way, so this method cannot be used with cyclic TBoxes. Additionally, generating the expanded TBox can be computationally expensive making other approaches attractive even for some acyclic TBoxes.

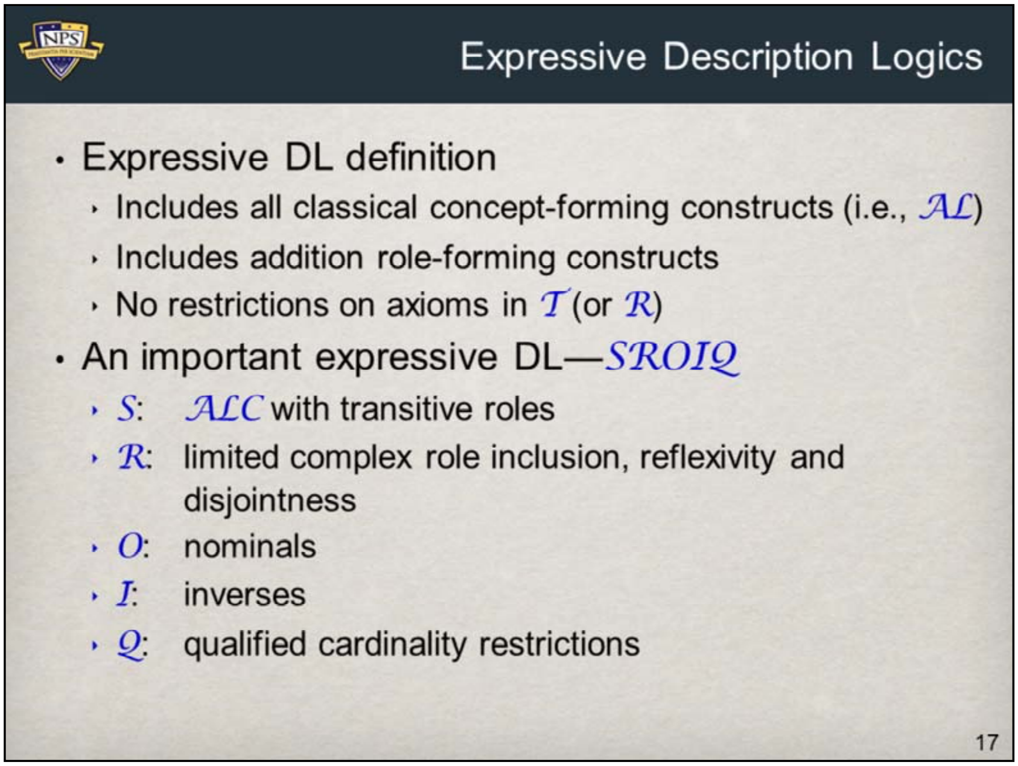
Possibly the most common ABox reasoning task is **instance checking** (or **entailment**), which is used to determine whether or not a specific assertion (concept or role) is satisfied by every model interpretation. Additional reasoning tasks include **retrieval**, which identifies all individuals to which a concept applies; and **realization**, which is used to find the most specific concept of a set of concepts (i.e., most subsumed) that applies to an individual.  All three of these reasoning tasks can be reduced to consistency checking:

Instance checking:    $\mathcal{A} \vDash \alpha$ iff $A \cup \{\neg C(a)\}$ is inconsistent.

Retrieval:  a naïve approach can test every individual in $\mathcal{KB}$ for entailment by the concept (this approach can be optimized).

Realization:   This is essentially a subsumption problem.  If the subsumption hierarchy has been established through TBox classification, realization amounts to finding the most specific concept that entails the individual

The fact that ABox reasoning can so frequently be reduced to consistency checking is important, and it facilitates the development of versatile algorithms that can be applied to numerous problems.  Algorithms often fall into one of three categories.  Simpler DLs can often use structural subsumption algorithms (Küsters and Molitor, 05).  Tableau Algorithms are more broadly applicable and are used in a number of Semantic Web reasoners (Baader and Sattler, 01).  Additional approaches that have proven applicable to working with propositional and first-order logics have proven useful as well when DL inferencing can be reduced to known problems from other areas of artificial intelligence and knowledge management (Rudolph, 11).




DLs that allow complex role definitions are considered **expressive DLs**. These languages can include all of the constructs of the AL-family languages (and must include all of those of AL), but provide additional extensions for defining relationships and rules for roles (Baader, et al., 07). Any language that utililizes an RBox (even if it is implemented as part of the TBox) is considered an expressive DL. Expressive DLs are almost exclusively extensions of ALC (or S, for short) (Ortiz, 10).

Almost all of today's commonly used expressive DLs are sublanguages of the SROIQ language (Rudolph, 11). Importantly, this language is the basis for OWL, which is the W3C-approved standard for developing Semantic Web Ontologies, which will be discussed later in this work.

SROIQ has the following characteristics, most of which have been discussed previously (Rudolph, 11):

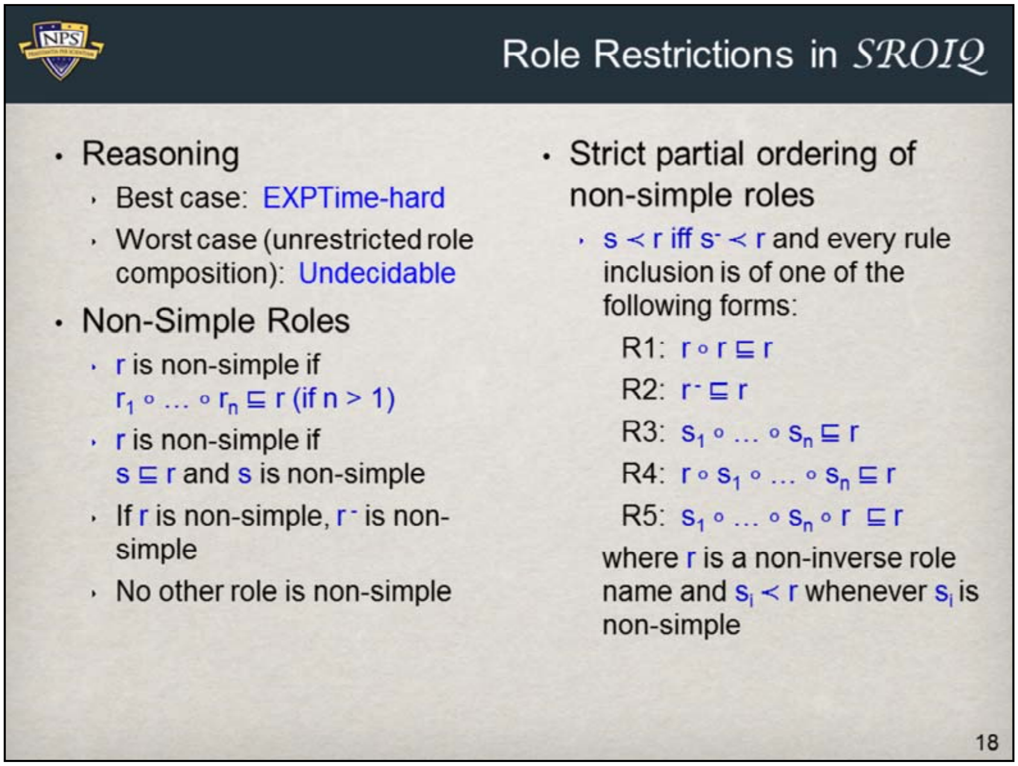
"S" means that SROIQ has all of the characteristics and operations of the ALC language including AL operations, union, universal existential qualification, and transitive roles

"R" provides for limited complex role inclusion and means that roles can be composed for inclusion in other roles. Specific restrictions are required in order to ensure reasoning decidability.  Also included in the ‘R’ designation are the ability to define reflexive and disjoint roles.  The nature of the restrictions will be discussed shortly.

“O” means that nominals are allowed for enumerated definition of concepts.

“I” means that inverses are allowed as in the RBox example.

“Q” means that qualified cardinality restrictions are supported.

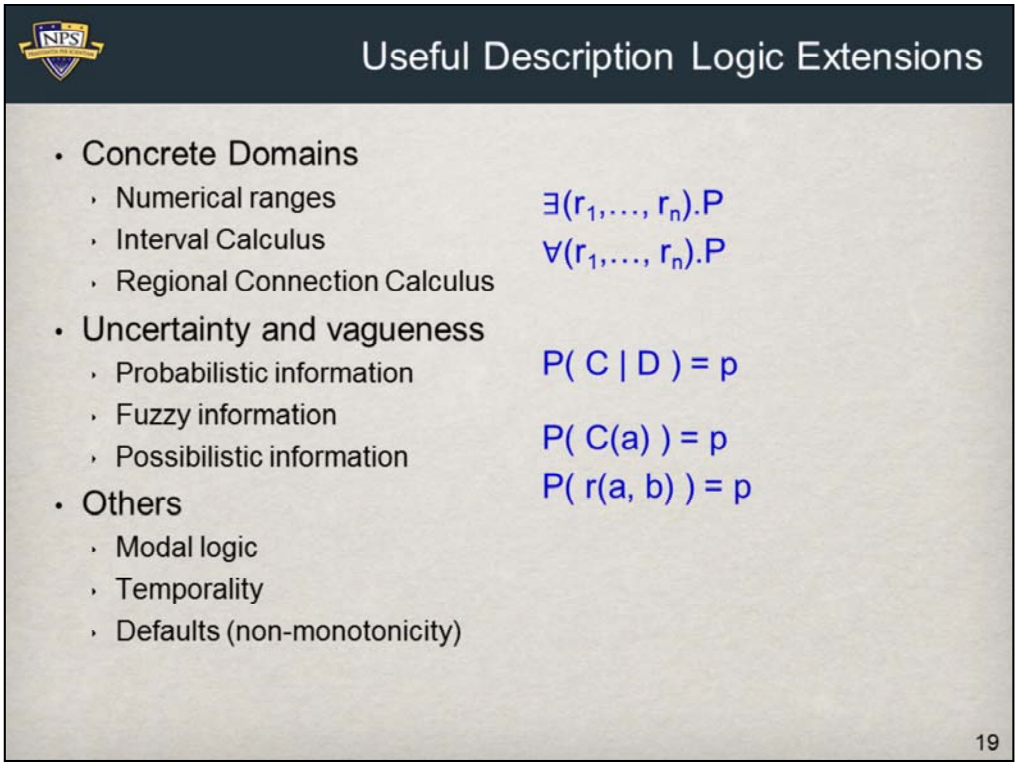



SROIQ is a powerful DL, but the expressive power greatly complicates reasoning. Reasoning even with simple DLs, such as AL, is proven to be EXPTime-hard (Baader, et al., 07), but unrestricted role composition leads to undecidability (Rudolph, 11). Strict partial ordering of non-simple roles ensures decidability of reasoning problems with the SROIQ DL and ensures that the reasoning process will terminate.

A non-simple role, as depicted above, is one that includes a rule composition, another non-simple role, or is the inverse of a non-simple role.

To determine whether or not a $\mathcal{KB}$ complies with strict partial ordering, all simple roles must be ordered so that if an atomic role is ordered below another atomic role, then so is its inverse. Each role inclusion axiom for non-simple roles must then comply with one of a number of forms (Horrocks, et al., 06):

R1: The role inclusion axiom (RIA) conveys transitivity of role r.
R2: The role includes its inverse.
R3: The RIA consists only roles of lower order.
R4: The RIA consists of r composed with roles of lower order (r must come first).
R5: The RIA consists of roles of lower order with r (r must come last).




The DLs discussed thusfar are highly expressive, but their ability to capture certain types of knowledge is limited. Specifically, the knowledge capable of being expressed is limited to time-independent, objective, and certain knowledge (Baader, et al., 07). It is possible, however, to implement extensions that can convey this sort of information without compromising decidability.

Concrete domains provide a means of bounding data. The most obvious concrete domains are numerical, but they can also be used to capture any bounded data for which relationships can be defined. Allen's temporal calculus for defining expressing temporal relationships (Allen, 83) and regional connection calculus for expressing spatial relationships (Randell, et al., 92 and Bennett, 97) are two notable examples. Concrete domains can be expressed extending the DL to include the following existential predicate restriction:

$$\exists(r_1, \ldots, r_n).P$$

where P is a range-restricting predicate and $r_1$ through $r_n$ is a chain of functional roles to which the restricting predicate is applied in order. For instance, the declaration

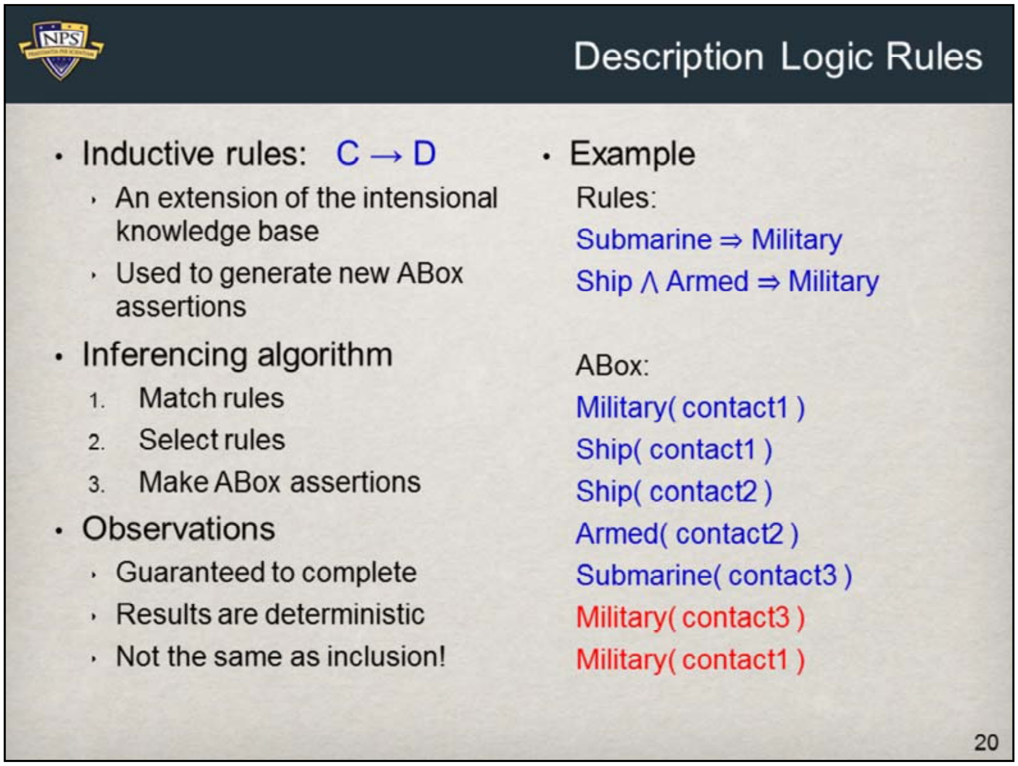
$$\text{AirContact} \sqcap \exists(\text{inArea.Restricted, isActive.Radar}).\text{overlapsWith}$$

uses a predicate taken from Allen's Interval Calculus to describe "AirContacts" that were found in a restricted area while emitting radar.

Typical DLs are also not capable of representing uncertainty. Extensions have been proposed for expressive DLs that provide for the expression of probabilistic, fuzzy, and probabilistic knowledge.

Probabilistic information is expressed through the addition of TBox rules for conditional probabilities of the form P(C|D)=p and ABox assertions of the form P(C(a))=p and P(r(a,b))=p. Reasoning with probabilistic knowledge bases involves finding upper and lower probability bounds for each concept, which amounts to an optimization problem that can be solved with linear regression (Baader, et al., 07) or other techniques. Fuzzy information describes the degree to which concepts and roles hold. This requires extending the typical Boolean operators from the set { 0, 1 } to the range [ 0, 1 ] and redefining the DL operators (e.g., conjunction is minimum, disjunction is maximum, etc.) (Straccia, 01). Possibilistic DLs can be considered as between probabilistic and fuzzy approaches in that they are used to model uncertainty but use fuzzy set semantics (Baader, et al., 07). A number of inductive reasoning techniques that will be discussed later can also be used to effectively model uncertainty within a KB.

A few additional extensions are worth mentioning briefly as well. Modal logic provides for the specification of dynamic information such as belief, obligation, and other types of information that can change over time. Temporal extensions are a special type of modal logic for capturing timing. Finally, default values provide for the specification of non-monotonic knowledge, that is concepts and implications that are usually true, but can be false in some cases. (Baader, et al., 07) Many of these extensions can also be captured by inductive reasoning algorithms to be discussed.




A number of DL systems provide for the definition of inductive rules that can be used to extend $\mathcal{KB}$. These rules take the form of **trigger rules** expressed as FOL implications of the form C → D. Trigger rules are typically restricted to Horn clauses, which restrict the form of the consequent of the implication (D) to an atomic role or concept. The antecedent of a trigger rule (C), on the other hand, can be comprised of an arbitrary number of disjunctive (possibly complex) concepts and roles. A trigger rule expresses the notion that a specific conclusion can be asserted if certain facts are known. Thus, the statement C → D is saying that if the ABox contains assertions to support the concept "C" for an individual, then the concept "D" also applies to that individual. This provides a powerful mechanism for inductively extending a knowledge base.

Rules can be used to extend a knowledge base using the following inferencing algorithm:

Match rules—find all rules with left hand sides satisfied by contents of the ABox for which no assertion for the right hand side exists

Select rules—determine which rules to fire in a particular iteration of the algorithm.

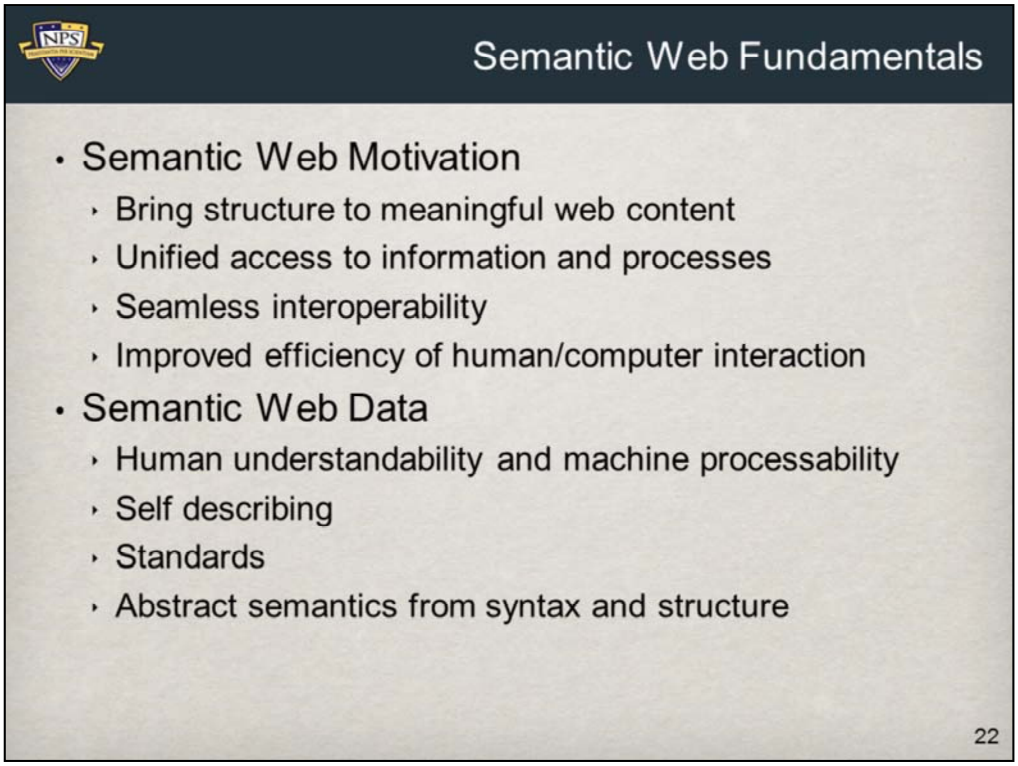
Make assertions—for the selected rules, add an appropriate assertion matching the rule's right hand side.

This algorithm can be repeated until the first step returns no results. The algorithm is guaranteed to complete because both the ABox and rule set are finite. Also, the results are deterministic regardless of the order of rule application. Upon completion of the algorithm, the resultant knowledge base is referred to as the **procedural extension** of the original knowledge base. (Baader, et al., 07)

In the example, the original ABox initially contains the first five depicted assertions. Using a simple first-rule-that-matches selection heuristic, the first application of the algorithm will add "Military(contact3)" to the ABox. The second application will add "Military(contact1)" after which no more additions will be possible.

Because of the open-world semantics of DLs, there is a subtle, but important issue regarding the implementation of DL trigger rules. In FOL, an implication is equivalent to its contrapositive (i.e., $A \rightarrow B \equiv \neg B \rightarrow \neg A$). With open-world semantics, however, we cannot assume $\neg B$ to be true based on the absence of a positive assertion of B, and we therefore cannot conclude $\neg A$ without an explicit assertion of $\neg B$. For this reason, trigger rules cannot be implemented as inclusions in the TBox (e.g., Submarine $\sqsubseteq$ Military). From a mathematical standpoint, trigger rules can be implemented by extending the DL with an epistemic concept operator as described in (Baader, et al., 07). In practice, rule bases are typically implemented as an adjunct to the DL, so the intensional portion of $\mathcal{KB}$ is not impacted (Sing and Karwayun, 10).

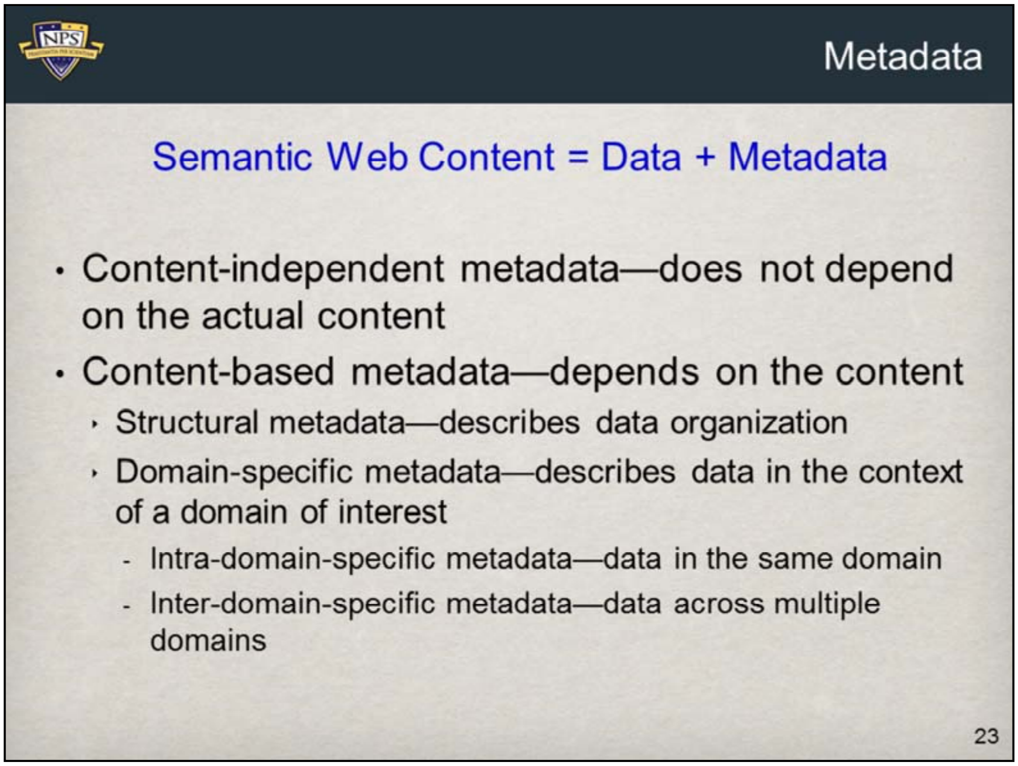
- Problem Statement
- Description Logics and Knowledge Representation
- Semantic Web
  - Metadata
  - Ontologies
  - OWL
  - Ontology Matching and Data Integration
  - Ontologies and Rule Languages
- Description Logic Inferencing
- Machine Learning and the Semantic Web
- Conclusions and Recommendations




The explosion of web-accessible data has already been noted as a primary motivator for the development of Semantic Web technologies. To paraphrase an early description of Semantic Web potential, goals of these technologies include bringing mathematically rigorous structure to previously disorganized data; providing unified access to distributed, heterogeneous data stores and services; facilitating seamless runtime interoperability between applications; and ultimately, improving the efficiency and productivity of human-computer interaction (Berners-Lee, et al., 01).

Mathematically rigorous web data organization fosters information discovery and use, effectively making it possible for web-based agents to eliminate meaningless and irrelevant data in favor of more meaningful and important data. Unified access requires that information be accessible to disparate applications that are not aware of its existence, much less its structure and format and semantics until runtime. Essentially, a *lingua franca* of sorts for web applications will be necessary for applications to process and interpret data so that services and applications can operate together effectively. In the end, Semantic Web technologies will allow applications to process more information without a human in the loop so that the human-computer interactive experience is more efficient and productive.

These overarching goals have a number of implications for Semantic Web content. First, Semantic Web content should be able to be understood by humans and automatically processed by machines. Both of these goals are directly supported by data that is self describing—that is, data combined with meta-data describing what the data is, what units and formats are used, and the relationships between various data items. All of these goals rely on standards that provide a well-defined vocabulary for creating metadata descriptions. In practice, metadata frameworks for Semantic Web technologies allow for abstraction of content semantics from syntax and structure. This allows applications to meaningfully process information without regard for storage, implementation, or display details. (Kashyap, et al., 08)




Metadata is the fundamental underpinning of Semantic Web technologies—so much so that Semantic Web content can accurately be described as the data itself combined with the associated metadata. Metadata can be divided into a number of intuitive categories and subcategories.

**Content-independent metadata** is information about data that does not describe the data itself. Examples might include a contact report number, a data store location (URI), or an intelligence summary author identifier. This sort of metadata does not say anything about the actual data but can be useful in organizing, locating, and classifying data.

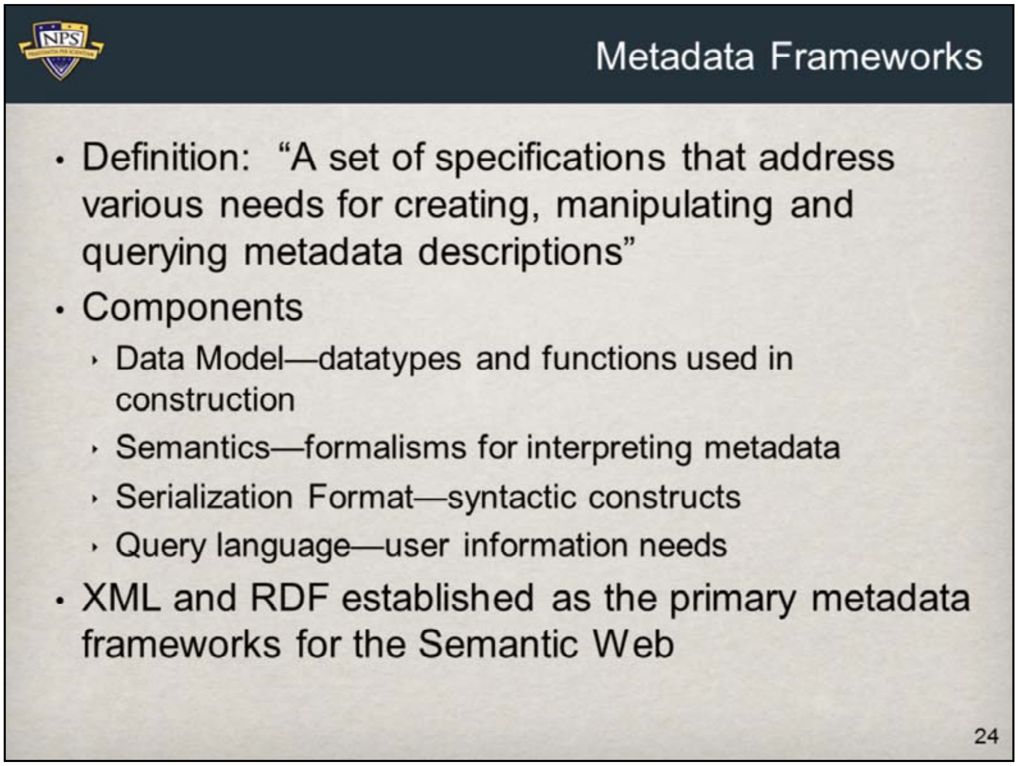
**Content-based metadata**, on the other hand, describes some aspect of the actual data. Content-based metadata can be subcategorized into structural metadata and domain-specific metadata.

**Structural metadata** describes how the data is stored and organized. Metadata of this type can be as simple as the size of a data record or file, but a more useful example might be metadata that describes the sections of an operation order to which portions of a data record apply. Data of this sort is largely independent of the domain of the data itself. Rather, it describes how the data record is arranged so that the various pieces can be parsed and applied to specific domains of interest.

**Domain-specific metadata** describes data in the context of a particular domain of interest.  Terminology and vocabulary are key aspects of this type of metadata, as it is this metadata that enables applications to actually locate and interpret relevant data.  Domain-specific metadata can be further subcategorized into two further sub-categories:

**Intra-domain-specific metadata** captures relationships  and associations between data in a single domain.  As an example, consider an air contact report for a specific type of aircraft.  Intra-domain-specific metadata in the threat data domain might be used to categorize the contact according to the types of ordnance that it carries, missions that it executes, and the countries from which it operates.

**Inter-domain-specific metadata**, on the other hand, captures relationships between data across two or more domains.  Continuing with the air contact report example, inter-domain-specific metadata might be useful in correlating this particular contact with intelligence assessments (i.e., inter-domain-specific metadata describing associations between the threat data domain and the intelligence domain to provide additional context between the contact report and the current operation).




A metadata framework is the formal mechanism for creating metadata; associating it with actual data; and manipulating, processing, and querying it (Kashyap, et al., 08). In order to be useful, a metadata framework has a number of fairly well-vetted components.

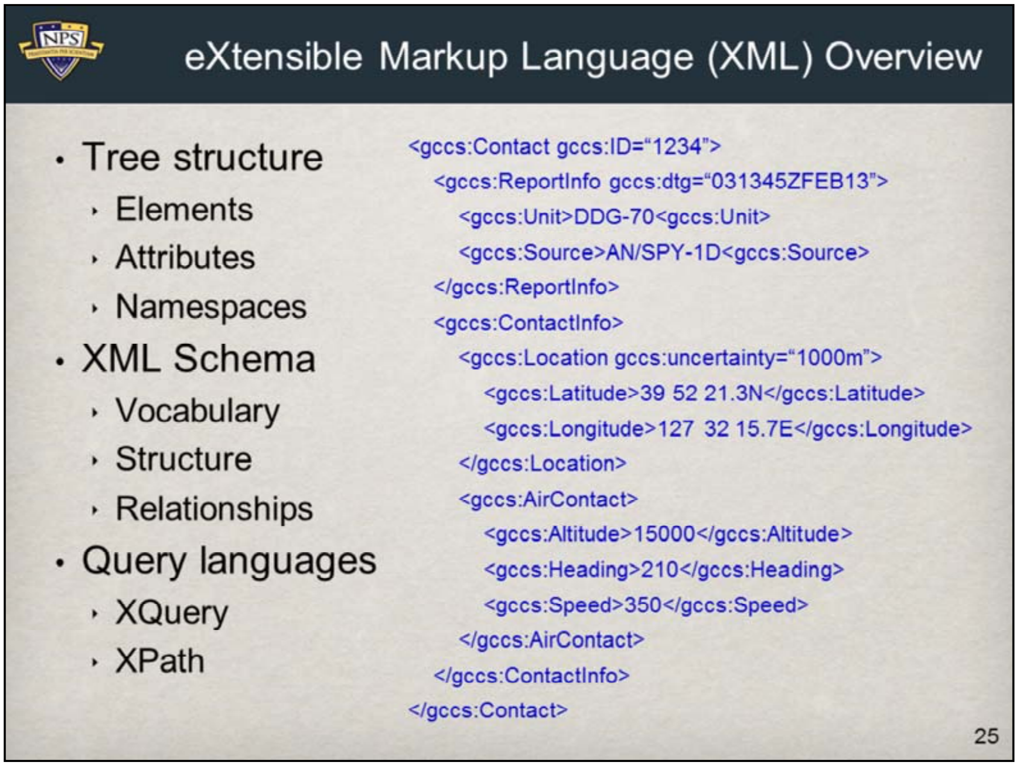
First, the framework provides a well-defined **data model**. The data model defines a collection of datatypes suitable for defining abstract views of web content. Available datatypes might include strings, integers, single- and double-precision floating point numbers, URLs, and hyperlinks. In addition to the atomic datatypes, a data model will typically provide rules and mechanisms for defining complex data types or restrictions on existing data types. For instance, the atomic integer type might be restricted to non-negative values to represent a count, or multiple atomic types might be combined to represent a geographic location (this would require range restrictions on the atomic data types as well).

**Semantics** provide the mathematical foundation for interpreting metadata. Semantics for a metadata framework are typically described in terms of model-theoretic semantics (Marker, 07).

**Serialization format** provides a formal specification for how the metadata is encoded. The most common serialization format for metadata frameworks is the eXtensible Markup Language (XML), but this is by convention, not necessity (XML is designed to be human understandable and machine processable, so it aligns well with Semantic Web goals).

Finally, one or more **query languages** are usually available so that users (including applications) can process metadata.  The query language is the mechanism by which specific data is located within a document or data source.

XML and the Resource Description Framework (RDF) have become well-established as the preeminent metadata frameworks for the Semantic Web (Berners-Lee, et al., 01).



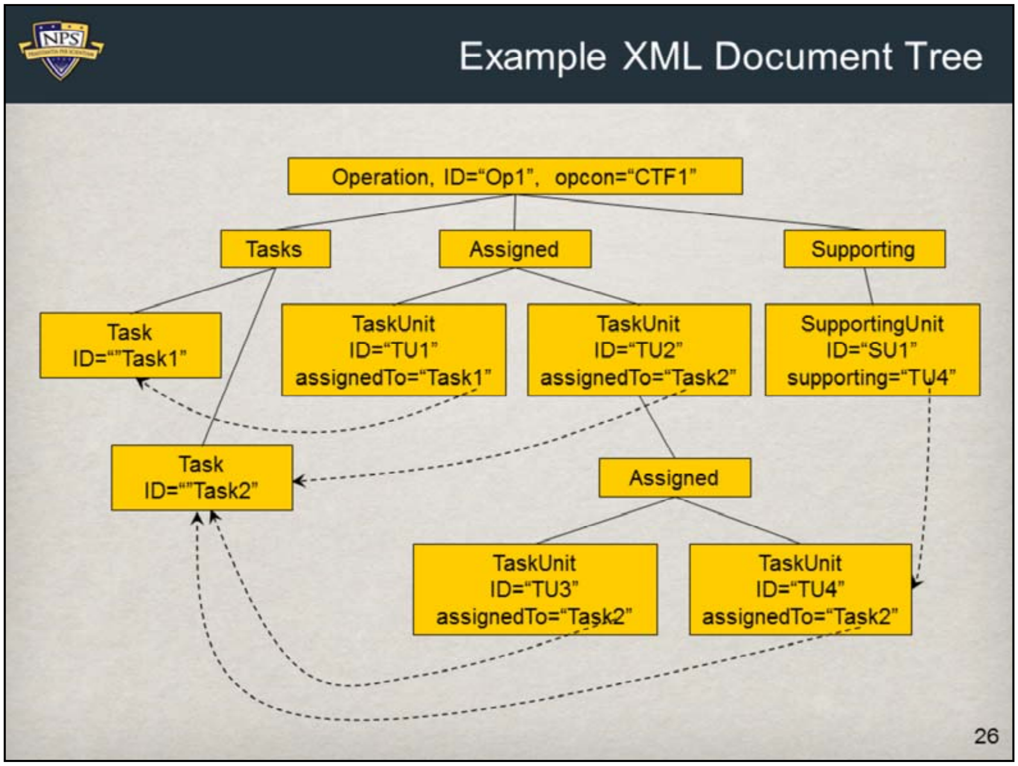

XML (Bray, et al., 08) stores both data and content-based metadata in a tree structure. Each node in the tree is a named **element** that can have named **attributes** and child elements. In addition, namespaces are frequently used to identify the vocabulary from which element and attribute names are drawn.

The inclusion of metadata in the form of named elements, named attributes, and namespaces make XML documents self describing to a point. The structural requirements of the document and the actual nature of the relationships implied by the tree structure are not explicitly contained in the document, however.

**XML Schema** (XML(S)) (Gao, et al., 12 and Peterson, et al., 12) provides a limited mechanism for conveying semantics of compliant XML documents. The schema for an XML document defines its vocabulary and structure, and to a degree the relationships between elements. The types of relationships and properties that can be implicitly conveyed by an XML schema are primarily limited to the "part of" relationship implied by the tree structure, the "refers to" relationship of the ID/IDREF construct, the "has characteristic of" property conveyed by attributes, and the semantics inherent in the vocabulary defined by a particular schema.

Query capability is provided by **XQuery** (Boag, et al., 10) and **XPath** (Clark and DeRose, 99) as described in (Deutsch, et al., 99).

The (partial) document of the example provides a simplified description of a contact report.  All element and attribute names are in the “gccs” namespace, which in combination with the governing schema (not indicated in the excerpt) define the domain and vocabulary.  This particular report includes information about the report in the “gccs:reportInfo” element.  The element’s structure makes it clear that the report information includes the unit making the report, the sensor source for the report, and the date and time of the report (using the “gccs:dtg” attribute).  The portion of the document relating to the contact itself is similarly encoded in the “gccs:contactInfo” element.




The simple example of the slide captures information for a single “Operation” represented by the root element of the tree. The name and commander of the operation are represented using the “ID” and “opcon” elements respectively. The elements of the operation are implicitly represented using the “Tasks” element and their “Task” children. The subordinate units that will be assigned specific tasks are depicted under the “Assigned” element as “TaskUnit” elements, while the units that will be supporting the operation are included in the “Supporting” element.

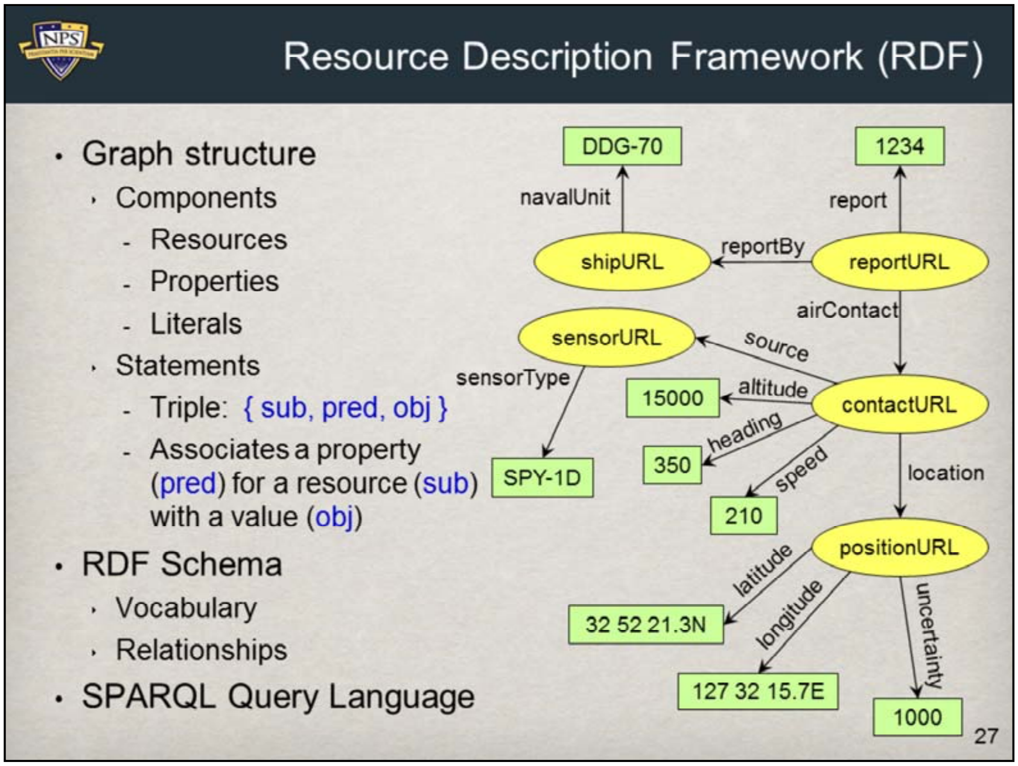
The tree data structure has a significant limitation that becomes evident even in this simple example. Specifically, the “assignedTo” and “supporting” attributes of the “TaskUnit” and “SupportingUnit” elements indicate the relevant task and unit in a human-understandable way, but given no other information there is no way to definitively associate the relevant element in a machine-processable way. XML provides the ID and IDREF datatypes to effectively extend the tree structure by which the data is encoded to a logical graph. In the example, each “Task”, “TaskUnit”, and “SupportingUnit” element is assigned a unique ID. The “assignedTo” and “supporting” attributes use the IDREF datatype to reference the relevant element. In this way, complex relationships between the various elements can be captured in an unambiguous way. The actual XML document associated with the graph of the example might be encoded as follows:

```
<opord:Operation opcon=“CTF1”>Op1</opord:Operation>
   <opord:Tasks>
```

```
      <opord:Task>Task1<opord:Task/>
      <opord:Task>Task2<opord:Task/>
   </opord:Tasks>
   <opord:Assigned>
      <opord:TaskUnit opord:assignedTo="Task1">TU1</opord:TaskUnit>
      <opord:TaskUnit opord:assignedTo="Task2">TU2</opord:TaskUnit>
         <opord:Assigned>
            <opord:TaskUnit opord:assignedTo="Task2">TU3</opord:TaskUnit>
            <opord:TaskUnit opord:assignedTo="Task2">TU3</opord:TaskUnit>
         </opord:Assigned>
      </opord:TaskUnit>
   </opord:Assigned>
   <opord:Supporting>
      <opord:SupportingUnit opord:supporting="TU4">SU1</opord:SupportingUnit>
   </opord:Supporting>
</opord:Operation>
```

Although XML has the capability of expressing significant semantics, particularly when the vocabulary and structure is governed by an XML schema, it is not without shortcomings. Specifically, while it is possible to overcome the limitations of the tree structure of XML documents through the use of the ID and IDREF datatypes, this can quickly become cumbersome in practice. Also, it is difficult or impossible to enforce relationships that might be obvious to humans. For instance, in the example "TU4" is a subordinate of "TU2", so "TU4" should be assigned only to tasks that have been assigned to "TU2". Unfortunately, there is no structural constraint that would prevent TU4's assignment to a task associated with "TU1" or some other entity.

Because of the issues noted (and others not discussed here), XML on its own is not capable of expressing semantics with the mathematical rigor required of Semantic Web applications (Kashyap, et al., 08). It does however provide an underlying encoding that can be used as the basis for more expressive frameworks (Berners-Lee, et al., 01).




Whereas XML encodes data in a tree structure, RDF utilizes a more generic graph structure.

Basic RDF components include **resources**, **properties**, and **literals**. Resources are the things being described and are referred to in RDF using a URL. A resource might be an individual data record or item, a subsection of a data record, or a collection of records (additional possibilities also exist). Properties are specific aspects, characteristics, attributes or relationships that are used to describe resources. Literals are simply names that are used in RDF statements.

An RDF **statement** can be thought of as a triple of the form **{ subject, predicate, object }** where “subject” is a resource, “predicate” is a property that is being ascribed to that resource, and “object” is the value that is being ascribed. The object of a statement can be either a literal or another resource. Underlying encoding of RDF data can take a number of forms (the W3C recommendation calls for an XML encoding), but a triples-based approach will be used here.

As an example consider the previous contact report XML example. This example might be encoded with RDF using the following statements (note: shorthand is used for the URLs for clarity):

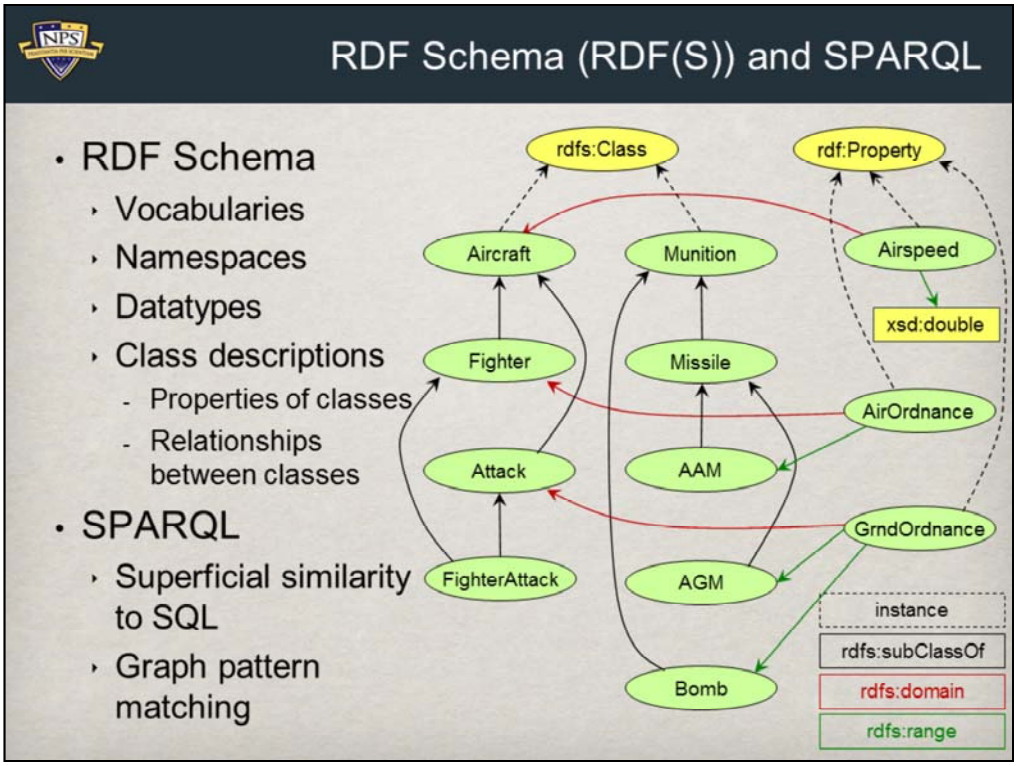
{ shipURL, navalUnit, DDG-70 }

{ sensorURL, sensorType, SPY-1D }
{ reportURL, report, 1234 }
{ reportURL, reportBy, shipURL }
{ reportURL, source, SPY-1D }
{ reportURL, airContact, contactURL }
{ contactURL, location, positionURL }
{ positionURL, latitude, “32 52 21.3N” }
{ positionURL, longitude, “127 32 15.7E” }
{ positionURL, uncertainty, 1000 }
{ contactURL, altitude, 15000 }
{ contactURL, heading, 210 }
{ contactURL, speed, 350 }

This RDF description has resources for the ship, the sensor, the report, the contact info, and the position; properties for associating characteristics to these objects; and literals for the concrete names and values. The statements above define the relationships as depicted in the slide.

The **RDF Schema** (RDF(S)) (Brickley and Guha, 04) provides facilities in the “rdf” and “rdfs” namespaces to define vocabularies, classes, and relationships between classes. Graphs defined in a document governed by an RDF schema are required to comply with the rules and structure defined in the schema in the same way that an XML document governed by an XML schema must comply with its constraints.

The **SPARQL** Query Language for RDF (Klyne and Carroll, 08) provides a language for accessing specific information from RDF descriptions.




Both XML(S) and RDF(S) are used to constrain the content of governed documents. As discussed previously, XML(S), is used to define the vocabulary, structure, and datatypes of governed documents, but is limited in its ability to convey the relationships and semantics. RDF(S), on the other hand, provides a vocabulary that is more suited to describing relationships. In particular, RDF(S) enables the specification of subclass and subproperty relationships, property domains and ranges (subject class and object class respectively), and other useful characteristics.

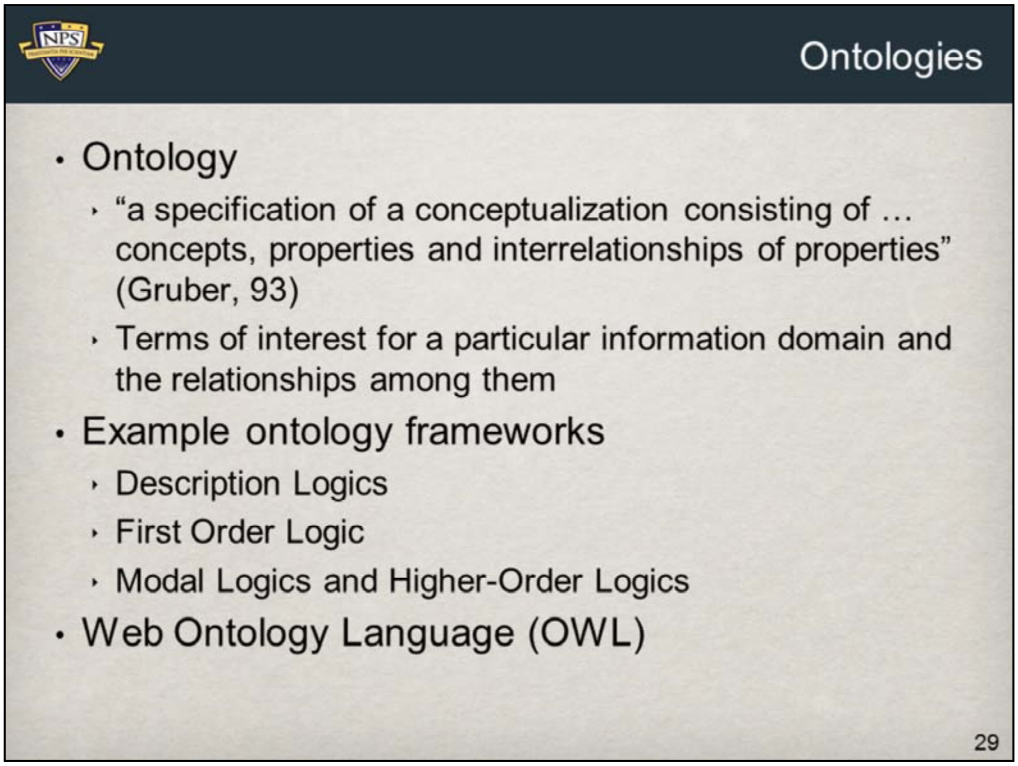
In diagram of the slide represents a simple RDF(S) description. In this diagram, “Aircraft” and “Munition” are instances of the RDF(S) “rdfs:Class”. “Fighter” and “Attack” are subclasses of “Aircraft”, and “FighterAttack” is a subclass of both “Fighter” and “Attack”. Similar subclasses are depicted for the “Munition” class. Properties, “Airspeed”, “AirOrdnance”, and “GrndOrdnance”, are defined as instances of the RDF(S) type “rdf:Property”. The domain (“rfds:domain”) classes for each property are depicted with red arrows, and range classes (“rdfs:range”) are depicted with green arrows. In the example, the range for the “Airspeed” property is specified as a double precision floating point number from the XML(S) namespace (“xsd”).

The SPARQL query language bears a superficial resemblance to Structured Query Language (SQL). SPARQL is capable of significantly more robust queries than SQL, however. SPARQL uses a pattern matching paradigm that takes into account the relationships defined in the RDF document and governing RDF(S) schema (Kashyap, et al., 08). For example, the following query will return all of the air ordnance carried by F-16 aircraft (the example assumes that a “Type” property has been defined).

```
SELECT $ordnance
WHERE {
   $acft Type “F-16”
   $acft AirOrdnance $ordnace
         }
```

Mechanisms are provided to allow for significantly more complex queries that return multiple values, place restrictions or conditions on the query, perform set operations, etc. The subclass and subproperty relationship descriptions available with RDF(S) have also facilitated the extension of SPARQL to perform many reasoning tasks appropriate for DLs (e.g., entailment) (Patel-Schneider and Simeon, 02 and Hayes, 04).

It is evident that RDF and RDF(S) provide a significantly richer mechanism for semantic expression than XML, however, they are still limited in their ability to express semantics. They are not capable, for instance, of constraining or expressing cardinality or defining conjunctive classes (Horrocks, 08). More generally, RDF, RDF(S), and SPARQL do not possess the semantic expressiveness of the basic expressive DL, ALC, or even the “minimally interesting” DL, AL. They do, however, provide a framework that can be used as the basis for implementing the required expressiveness.

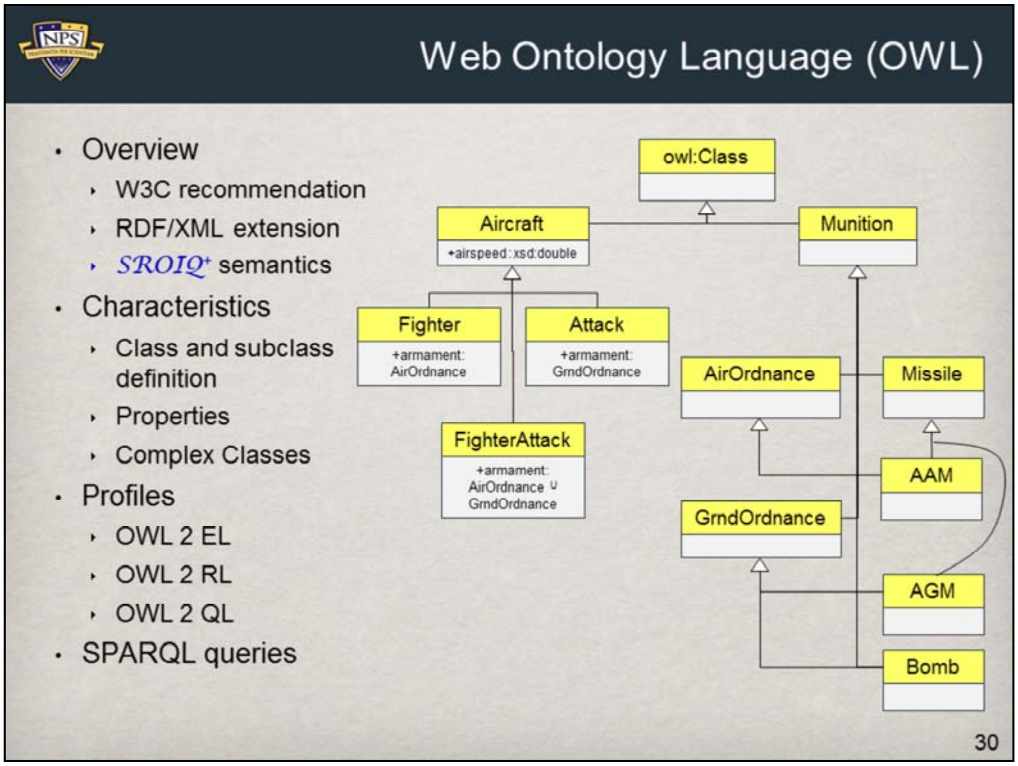



The metadata descriptions with the semantic expressiveness required for the Semantic Web are in the form of ontologies. In the context of knowledge representation, an ontology is "a specification of a conceptualization consisting of a collection of concepts, properties and interrelationships of properties" (Gruber, 93). Ontologies for the Semantic Web define the terms of interest for a particular information domain and describe the relationships among them. Semantic Web data described in terms of a specific ontology can therefore be processed alongside, compared to, and combined with other data described with the same ontology regardless of location, source, format, or composition (Horrocks, 08).

An argument can be made that many model forms might reasonably be considered ontologies. Database schemas, ER/EER Models, Unified Modeling Language (UML) Models, XML schemas, and RDF schemas all define terminologies and describe relationships to one degree or another. As discussed previously, however, even the most semantically rich of these modeling approaches are insufficient for realizing the goals of the Semantic Web. These models can represent information and can be queried, but they do not support automated interpretation and reasoning required by Semantic Web applications.

Description logics, first-order logics, modal logics provide robust description capabilities and mathematically rigorous mechanisms for reasoning. Of these, description logics have proven most applicable to Semantic Web applications. FOLs and higher logics highly expressive semantically, but reasoning problems are often undecidable (Baader, et al., 07). Description logics, on the other hand, provide both significant semantic expressiveness and decidable reasoning (Ortiz, 10).

The Web Ontology Language (OWL) has emerged as the ontology definition mechanism of choice for Semantic Web content (Horrocks, 08).




OWL is a World Wide Web Consortium (W3C) recommendation for the specification of Semantic Web ontologies. OWL allows for the definition of classes and subclasses, the association of specific properties to classes, and the definition of conjunctive classes by means of DL-based axioms. OWL is an extension of RDF meaning that OWL ontologies can be used to extend existing RDF data stores.

The OWL 1 recommendation was released in 2004 and was based on the SHOIN DL (Horrocks, 08) which included the operations of the basic expressive DL, ALC, plus role hierarchy, role transitivity, role inverses, unqualified cardinality restrictions, and nominals (Baader, et al., 08). OWL 1 included three profiles, OWL Lite, OWL DL, and OWL Full, of which OWL DL provided the most broadly applicable blend of expressiveness and decidability (Kashyap, et al., 08).

The OWL 2 recommendation was released in 2008 as an extension of OWL 1 (i.e., all OWL 1 ontologies are also valid OWL 2 ontologies). OWL 2 implements SROIQ semantics described previously along with additional features for data typing (Horrocks, et al., 06 and W3C, 12).

The RDF(S) description presented earlier might be described by an OWL ontology as depicted in the slide. OWL, however, is capable of expressing significantly more complex semantics than this simple example. Even here, one advantage of OWL might be evident. Properties in this example are associated with classes rather than having classes (resources) tied to properties using the “rdfs:domain” and “rdfs:range”. Association of properties with classes (and instances of classes) is a more semantically accurate representation than associating classes with properties which probably do not have instances outside of the context of specific class instances.

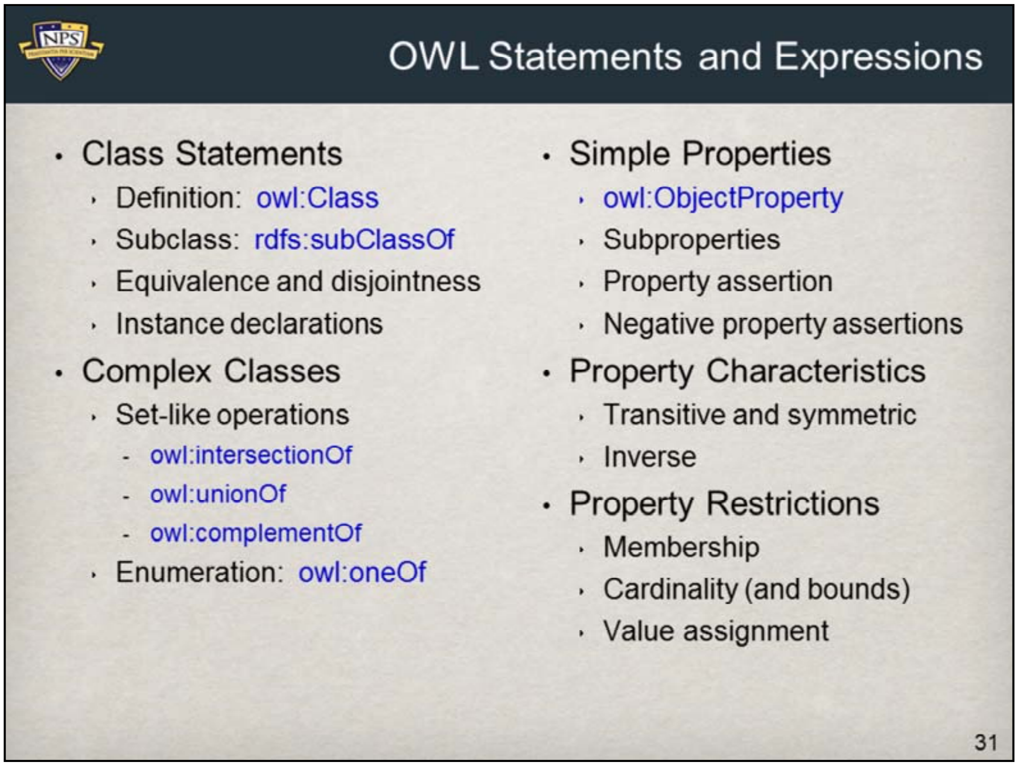
In addition to OWL 2 Full, the OWL 2 specification provides three profiles—OWL 2 EL, OWL 2 RL, and OWL 2 QL—that restrict modeling features to improve reasoning performance. Algorithms designed specifically for reasoning with each of these profiles have been developed that execute in polynomial time (Krötszch, 12).

OWL 2 EL derives its name from the EL family of DLs which provide only existential quantification. This profile is particularly useful for large ontologies (i.e., those containing a large number of named classes and properties). (Motuk, et al., 12)

OWL 2 RL has different rules for the left and right sides of inclusion axioms. For instance, value restriction is not permitted on the right side of an axiom, while union is not allowed on the left side. This profile is the most expressive of the three. The RL acronym reflects that reasoning can be implemented using a standard rule language. (Motuk, et al., 12)

OWL 2 QL is the least expressive of the three profiles, but is useful for applications that work with large sets of instance data. The OWL 2 QL profile includes most of the key features of UML and ER models that are often used with databases. The QL name reflects that queries can be implemented using a standard query language. (Motuk, et al., 12)

Because OWL is an extension of RDF, SPARQL queries can be utilized to query OWL ontologies.




OWL ontologies are commonly encoded with either an RDF/XML syntax or functional syntax. Examples in this section will follow this RDF/XML convention, but they are not presented as complete or consistent documents (e.g., references may not refer to actual resources, examples may conflict with one another, etc.), and they should be interpreted here individually as excerpts from larger ontologies.

**Class Statements**
**Definition**: <owl:Class rdf:ID="Aircraft"/>
<owl:Class rdf:ID="Munition"/>
<owl:Class rdf:ID="Contact"/>
**Subclass**: <owl:Class rdf:ID="Missile"><rdfs:subClassOf rdf:resource="#Munition"/></owl:Class>
<owl:Class rdf:ID="AirContact"><rdfs:subClassOf rdf:resource="#Contact"/></owl:Class>
**Equivalence**: <owl:Class rdf:ID="AttackMunition">
<owl:equivalentClass rdf:resource="#GroundMunition"/>
</owl:Class>
**Disjointness**: <owl:AllDisjointClasses>
<owl:members rdf:parseType="Collection">
<owl:Class rdf:resource="#FriendlyContact"/>
<owl:Class rdf:resource="#HostileContact"/>
<owl:Class rdf:resource="#UnknownContact"/>
</owl:members/>

</owl:AllDisjointClasses>

**Instances**: <AirContact rdf:ID="air1234">

**Set operations**

**Intersection**: <owl:Class rdf:ID="FriendlyContact">
<owl:intersectionOf rdf:parseType="Collection">
<owl:Class rdf:resource="#Contact"/>
<owl:Class rdf:resource="#Friendly"/>
</owl:intersectionOf>
</owl:Class>

**Union and complement**: <owl:Class rdf:ID="unknownContact">
<owl:complementOf rdf:parseType="Collection">
<owl:Class>
<owl:unionOf rdf:parseType="Collection">
<owl:Class rdf:resource="FriendlyContact"/>
<owl:Class rdf:resource="HostileContact"/>
</owl:unionOf>
</owl:Class>
</owl:complementOf>
</owl:Class>

**Enumeration**: <owl:Class rdf:ID="NavalUnitType">
<owl:oneOf rdf:parseType="Collection"/>
<owl:Thing rdf:about="#CVN"/>
<owl:Thing rdf:about="#CG"/>
<owl:Thing rdf:about="#DDG"/>
<owl:Thing rdf:about="#FFG"/>
</owl:oneOf>
</owl:Class>

**Simple Properties**

**Definition**: <owl:ObjectProperty rdf:ID="reportedBy">
<rdfs:domain rdf:resource="#ContactReport"/>
<rdfs:range rdf:resource="#ReportingUnit"/>
</owl:ObjectProperty>

**Subproperties**: <owl:ObjectProperty rdf:ID="#canDeliverGround">
<rdfs:subPropertyOf rdf:resource="#canDeliver"/>
<rdfs:range rdf:resource="#GroundOrdnance"/>
</owl:ObjectProperty>

**Assertion**: <owl:PropertyAssertion>
<owl:sourceIndividual rdf:resource="#air1234"/>
<owl:assertionProperty rdf:resource="#airspeed"/>
<owl:targetValue
rdf:datatype="$xsd;unsignedinteger">350</owl:targetValue>
</owl:PropertyAssertion>

**Negative assertion**: <owl:NegativePropertyAssertion>
<owl:sourceIndividual rdf:resource="#HOPPER"/>
<owl:assertionProperty rdf:resource="#reporting"/>
<owl:targetValue rdf:resource="#air1234"/>
</owl:NegativePropertyAssertion>

**Property Characteristics**
<owl:ObjectProperty rdf:ID="isLinkedWith">
**Transitive**: <rdf:type rdf:resource="&owl;TransitiveProperty"/>
**Symmetric**: <rdf:type rdf:resource="&owl;SymmetricProperty"/>
<rdf:domain rdf:resource "#LinkUnit"/>
<rdf:range rdf:resource "#LinkUnit"/>
</owl:ObjectProperty>

**Inverse**: <owl:ObjectProperty rdf:ID="reporting">
<owl:inverseOf rdf:resource="reportedBy"/>
</owl:ObjectProperty>

**Property restrictions**:
<owl:Class rdf:resource="#AttackAcft">
<owl:Restriction>
<owl:onProperty rdf:resource="#canDeliver"/>
…. (statements below go here)
</owl:Restriction>
</owl:Class>

**Membership**: <owl:allValuesFrom rdf:resource="#GroundOrdnance"/> or
<owl:someValuesFrom rdf:resource="#GroundOrdnance"/>

**Cardinality**: <owl:cardinality
rdf:datatype="$xsd;nonNegativeInteger"/>3</owl:cardinality>

**Assignment**: <owl:hasValue rdf:resource="#air1234"/>

It is worth noting that class and property definitions are not required to be contiguous, so class properties do not have to be contained within the "owl:Class" declaration and can use the "rdf:resource" attribute to extend existing classes and properties. Also, the inclusion of both "owl" and "rdf" namespace items in the examples clearly demonstrate the relationship between OWL and RDF (i.e., that OWL is an extension of RDF).

These examples demonstrate only a small subset of the available OWL structures. A complete description of OWL components, semantics, and encodings is available in (W3C, 12).

## Relationship of OWL to DLs

| | Owl Functional Syntax | DL Syntax |
|---|---|---|
| Axioms | SubClassOf( C D ) | $C \sqsubseteq D$ |
| | ClassAssertion( C a ) | C( a ) |
| | ObjectPropertyAssertion( p a b ) | p( a, b ) |
| Class Expressions | ObjectIntersectionOf( C D ) | $C \sqcap D$ |
| | ObjectUnionOf( C D ) | $C \sqcup D$ |
| | ObjectComplementOf( C ) | $\neg C$ |
| | owl:Thing | $\top$ |
| | owl:Nothing | $\bot$ |
| | ObjectSomeValuesFrom( p C ) | $\exists p.C$ |
| | ObjectAllValuesFrom( p C ) | $\forall p.C$ |
| | ObjectInverseOf( p ) | $p^-$ |

(W3C, 12)

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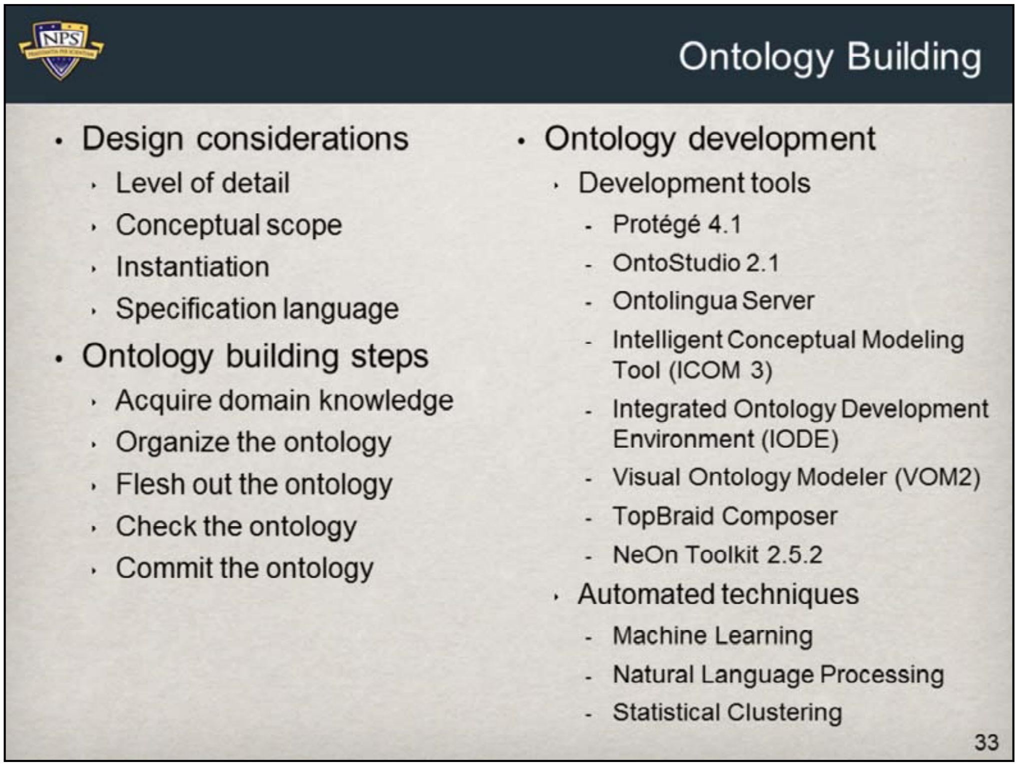
The table above provides a few examples of the relationship between statements in an OWL ontology and DLs. The examples of this slide utilize the OWL 2 functional syntax, which aligns more closely with the DL syntax of previous sections.




The discussion thus far might lead to one of two equally erroneous conclusions: that ontology definition is trivially easy, or that it is extremely difficult. Ontology development is, in fact, difficult and requires significant collaboration between domain subject matter experts and ontology implementers.

Prior to developing an ontology, a number of considerations must be taken into account (Vidya and Punitha, 12):

**Level of detail**: To what level of detail must the concepts and relationships be defined? What level of semantic description is required?
**Conceptual scope**: How broad or narrow is the domain to be described (e.g., joint operational planning versus strike planning). Is the ontology a detailed component of an upper level ontology? Are the way in which the concepts and relationships are described constrained in any way?
**Instantiation**: Will the the ontology itself include instantiated individuals? Historically, all ontologies include a terminological component and applications build (or add to) the assertional knowledge base. It might be beneficial, however, to build assertional components directly into the ontology as well.
**Specification language**: Numerous mechanisms for defining ontologies are available (particularly if the term is loosely applied to include taxonomies, thesauri, database schemas, etc.). This work assumes that OWL ontologies will be utilized.

Once high-level decisions requirements are determined and decisions made, ontologies are commonly developed in a stepped process along the lines of the following (Daconta, et al., 03):

**Acquire domain knowledge**: assemble information resources and expertise to formally describe the domain of interest.
**Organize the ontology**: identify the domain's principle concrete concepts and properties, identify relationships, create abstract organizational concepts and features.
Flesh out the ontology: add concepts, relations, and individuals to obtain the required level of detail.
**Check the ontology**: locate and correct syntactic errors, and logical and semantic inconsistencies. This can be partially completed using reasoning techniques that check for consistency of an ontology. This is also an appropriate time for domain subject matter experts to verify the ontology.
**Commit the ontology**: completed ontologies must be published and made available to the applications that will rely on them.

In practice, this process will not progress as linearly as described, and might involve piecemeal development, correction, additional information gathering and consultation, etc. Further, ontology definition can still be daunting even when following a systematic development process. In fact, useful ontologies are often large enough that full human conceptualization, much less manual implementation, is impractical or impossible. The SNOMED Clinical Terms ontology contains over 400,000 named classes (Horrocks, et al., 08). Fortunately, authoring tools are available that make ontology development and maintenance tractable.

The following provides a short comparison of a number of commonly utilized tools for ontology development and maintenance. This summary focuses on tools that support OWL ontology development and maintenance. For a more complete comparison of the most ubiquitous tools, see (Kashyap, et al., 08), (Kapoor and Sharma, 10), and (Vidya and Punitha, 12)

**Protégé 4.1** (4.2 in beta) (CBIR, 13): Protégé is a free, open source software project implemented in Java and managed by the Stanford University Center for Biomedical Informatics Research. Protégé is a standalone system that uses a plug-in architecture to support extension. Protégé uses frames, first-order logic, and metaclasses (as opposed to a purely DL-based approach) for knowledge representation A Protégé-OWL extension is available for support of OWL ontologies. It provides a built-in inference engine, consistency checking, and also supports selected external inference engines. It does not include support for distributed ontology development.

**OntoStudio** (Semafora, 08): OntoStudio is a powerful ontology modeling environment commercially developed by the German Company Semafora Systems.

It utilizes frames and first-order logic for knowledge representation, and plugins are available for inferencing, consistency checking, rule-based inference, and collaborative ontology development.  OntoStudio does not support external inference engines but its built-in inference engine provides consistency checking and other inferencing services.

**Ontolingua Server** (KSL, 13):  Ontolingua Server is a set of tools and services developed and maintained by the Stanford University Knowledge Systems, AI Laboratory (KSL) for building of shared ontologies between distributed groups.  Ontolingua utilizes the same knowledge representation mechanism as Protégé but utilizes a client-server model.  Ontolingua does not include a built-in inference engine, but consistency checking and limited support for external inference engines is provided.

**ICOM** (Franconi, 10):  The Intelligent Conceptual Modeling Tool (ICOM) is an open source tool for conceptual design of information systems maintained by the Free University of Bozen-Bolzano, Italy.  ICOM is based on an entity-relationship model, but utilizes DL-based knowledge representation.  Consistency checking is provided, but built-in inferencing relies on connectivity with the ICOM server.  ICOM does, however, support external inferencing engines.

**IODE** (Highfleet, 13):  The Integrated Ontology Development Environment (IODE) is a commercially produced modeling tool by Highfleet Semantic Technologies (previously Ontology Works) that was designed to support ontology development for database applications.  IODE is a standalone system that represents knowledge using common logic (based on first-order logic) with extensions for temporal reasoning and quantification.  It includes a built-in inference engine and consistency checking, but does not support external inference engines.

**Visual Ontology Modeler** (Sandpiper, 13):  Visual Ontology Modeler™ 2.0 (VOM2) is a commercial product of Sandpiper Software for visual development of component-based ontologies.  VOM2 uses DLs for knowledge representation and includes fairly robust facilities for merging, version control, and life-cycle maintenance.  VOM2 does not include a built-in inference engine, but supports multiple DL reasoners and rules engines.

**TopBraid Composer** (TopQuadrant, 11):  The TopBraid™ Composer is a product of TopQuadrant, Inc. that is implemented as a standalone Eclipse plugin (Eclipse is an open-source software integrated development environment).  TopBraid is designed as an enterprise-class modeling environment for developing Semantic Web ontologies and applications and represents OWL and RDF knowledge directly.  It provides built-in constraint and consistency checking but does not include a built-in inference engine.  It does, however, support multiple external inference engines.

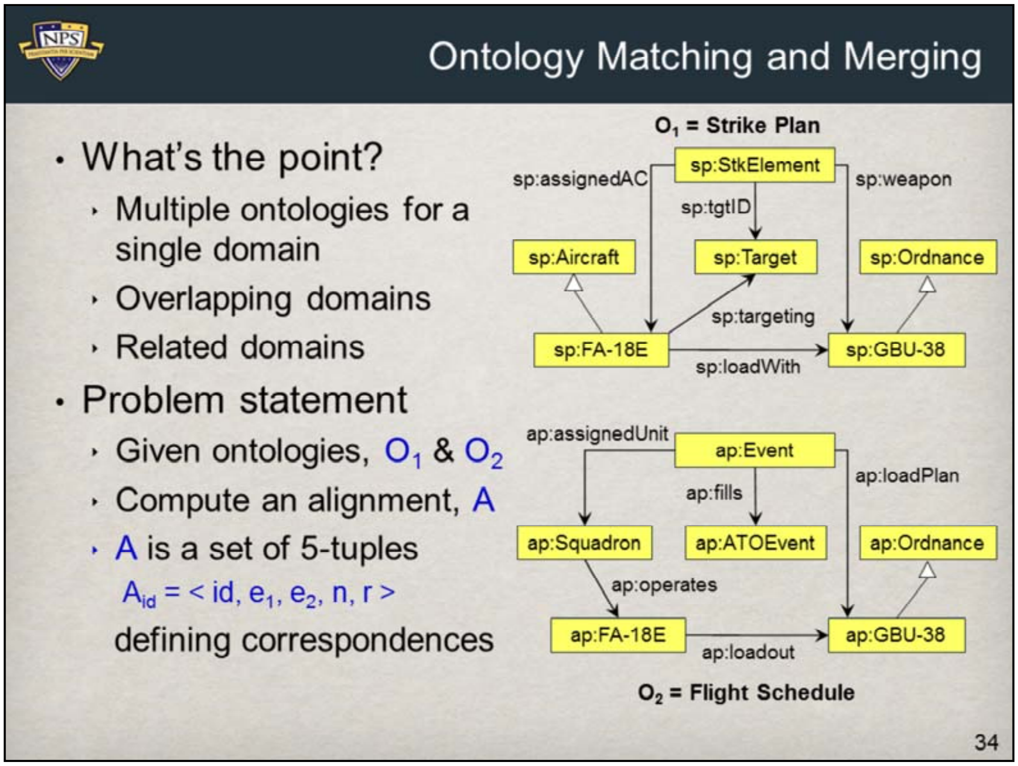
**NeOn Toolkit** (Suárez-Figueroa, 12): The NeOn Toolkit is an open source ontology engineering environment implemented as a standalone Eclipse plugin. Knowledge representation relies on Frame Logic (an alternative to DLs for ontology definition), OWL, and RDF. NeOn provides built-in constraint and consistency checking and includes a built-in inference engine. It also supports external inference engines.

Given the inherent difficulties of the ontology development process, it is not surprising that automatic ontology development is an area of ongoing research. Three general approaches have been proposed.

Supervised Machine learning employs (often manually generated) positive and negative examples to “train” the tool (i.e., tune the algorithmic parameters and thresholds). The utility of machine learning approaches to automated ontology development is limited by the requirement for large numbers of training examples. Nevertheless, examples of automated and semi-automated machine-learning-based approaches to ontology development are available (Maedche, et al., 03 and Kashyap, et al., 08).

Natural language processing (NLP) has also been used as the basis for automated ontology development as well. This is not surprising in light of the direct application of DLs to the field of NLP. In particular, the Suggested Upper Merged Ontology (SUMO) has produced a mapping between WordNet parts of speech and SUMO classes (Pease, 04) that can be used to extract meaning and relationships from free-form text documents (Lin and Sandkuhl, 08).

Statistical clustering and data mining have also been utilized to cull patterns and groupings from large volumes of data. Although effective at identifying related entities and visualizing data, these approaches do not lend themselves to identifying the nature of relationships or generating labels for statistically grouped entities (Kashyap, et al., 08).




Experiences in the development of Semantic Web technologies have clearly demonstrated a need for ontology matching and merging. Development of ontologies in isolation has inevitably led to multiple ontologies being applied to a single domain, overlapping of domains, and definition of ontologies for different but related domains. In all three cases, differences in terminology, level of detail, definition of concepts and relationships and other factors will occur. In order to fully leverage ontologies' knowledge representation, it must be possible to align differing ontologies to enable Semantic Web applications to utilize all available data.

In the depicted example, $O_1$ is an excerpt from a notional strike planning ontology and $O_2$ is an excerpt from a notional flight scheduling ontology. It might be obvious to a human observer that the elements "sp:FA-18E" and "sp:GBU-38" in $O_1$ are equivalent to "ap:FA-18E" and "ap:GBU-38" respectively in $O_2$. It is also the case in this example that all members of the "sp:ATOEvent" class are also members of the "sp:StkElement" class (the reverse is not, however, true). Finally, it might also be inferred that $O_1$'s "sp:assignedAC" property is related to $O_2$'s "ap:assignedUnit" and "ap:operates" properties.

Taking advantage of these relationships effectively increases the size of an ontology and potentially improves the fidelity as well. In the case of multiple ontologies in a single domain, additional classes, relationships and individuals are effectively added to both ontologies. This is also the case with merging overlapping ontologies for the region of overlap, but the merge yields the additional benefit of making the relationships between the two domains exploitable by applications as well. Similarly, formally defining the relationships between two disparate but related domains enables Semantic Web applications to exploit those relationships and use knowledge from both domains.

The problem of ontology matching can be formally defined as follows: given two ontologies $O_1$ and $O_2$, determine an alignment, A, defining correspondences between $O_1$ and $O_2$ where A is a set of correspondences defined as 5-tuples of the form $\mathbf{A_{id}}$ = **< id, $\mathbf{e_1}$, $\mathbf{e_2}$, n, r >** (Shvaiko and Euzenat, 08). The tuple components are defined as follows:

**id** is a unique identifier for the correspondence.
$\mathbf{e_1}$ and $\mathbf{e_2}$ are entities (classes, relationships, individuals, data values, etc.) from $O_1$ and $O_2$ respectively.
**n** is a confidence value (typically in the [0, 1] range) for the alignment between $e_1$ and $e_2$. In the matching process, the confidence level will be used by the matching algorithm to determine whether or not to actually apply the presumed relation based on the application's requirements. If the relation confidence reduces to a binary value (0 or 1), then the correspondences can be specified as 4-tuples of the form $\mathbf{A_{id}}$ = **< id, $\mathbf{e_1}$, $\mathbf{e_2}$, r >** (Shvaiko and Euzenat, 13).
**r** is a relation holding between $e_1$ and $e_2$. The relationship does not have to be equivalence (although it can be), but can be any relation definable within the ontologies (e.g., more general ($\sqsupseteq$), less general ($\sqsubseteq$), disjoint ($\perp$), overlapping ($\sqcap$), etc.).

## Ontology Matching and Merging Techniques

- Terminological techniques
  - String based
  - Linguistic
- Structural techniques
  - Graph or taxonomic similarity
  - Taxonomic similarity
- Semantic techniques
  - Description Logic reasoning
  - Rule-based inferencing
- Extensional techniques
  - Object comparison

| System | Terminological | Structural | Semantic | Extensional |
|---|---|---|---|---|
| Falcon | I-SUB, virtual documents | Structural proximity, clustering | - | Object similarity |
| DSSim | Tokenization, WordNet | Leaf-based graph similarity | Rule-based fuzzy inference | - |
| RiMOM | Edit distance, vector distance, WordNet | Similarity propagation | - | Vector distance |
| ASMOV | Tokenization, string equality, WordNet | Iterative fix-point computation, hierarchical | Rule-based inference | Object similarity |
| Anchor-Flood | Tokenization, string equality, WordNet | Internal, external similarity, anchors | - | - |
| AgreementMaker | Edit distance, substrings, WordNet | Descendant, sibling similarity | - | - |

Ontology matching is an area of significant ongoing research. Matching techniques are typically placed into one of four categories: terminological, structural, semantic, or extensional (Shvaiko and Euzenat, 13).

**Terminological matching** can be either string-based or linguistic. **String-based** matching directly compares strings and substrings from the two ontologies. Basic string comparison techniques include prefix/suffix checking (i.e., does one string start or end with the other), edit distance (number of changes required to “transform” one string into the other), n-gram testing (common sequences of n characters in both strings), tokenization, and other manipulations that provide metrics that can be compared from string to string. **Linguistic matching** utilizes the linguistic characteristics of the entities being compared. These approaches leverage general or domain-specific knowledge contained in external thesauri, dictionaries or taxonomies (WordNet is the most frequently utilized common knowledge source) to facilitate interpretation of individual names. Linguistic matching techniques exploit known relationships and definitions associated with ontological terms to infer relationships between the entities with which they are associated.

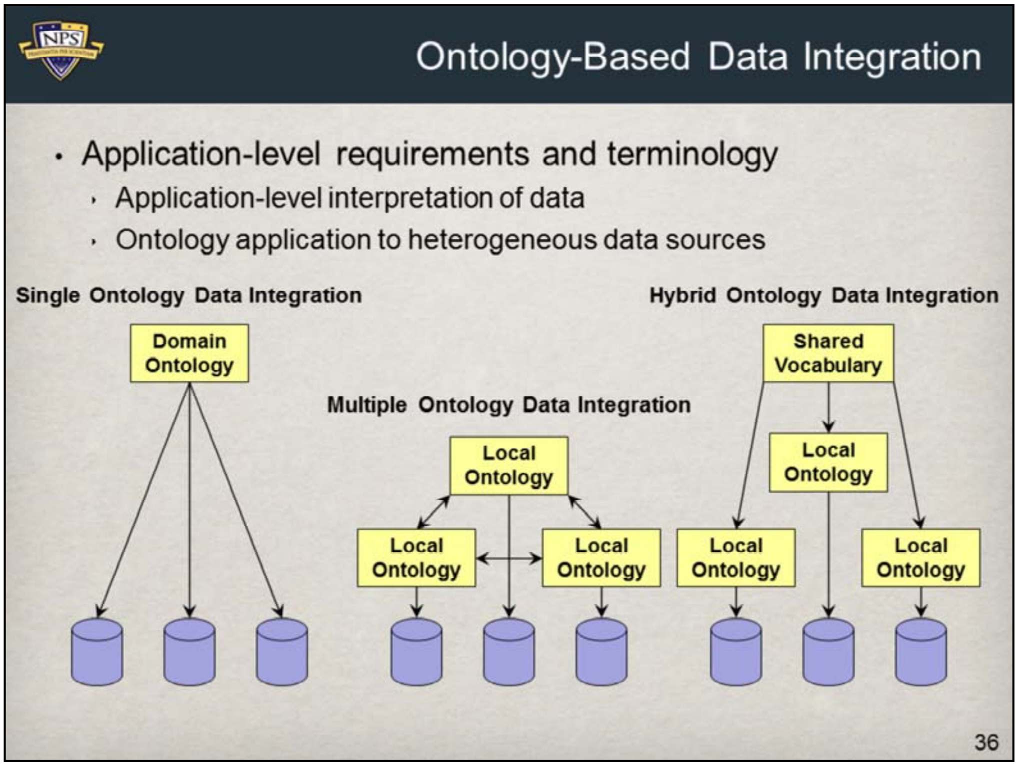
**Structural matching** analyzes the graph structures of portions of the ontologies to find similarly structured sections. Structural similarity between inner ontology nodes can be based on the similarity of their children, their leaves, their relations or some combination of the three. Graph matching is typically encoded as an optimization problem where a match minimizes some dissimilarity measurement (Kashyap, et al., 08). Alternatively, approaches that compare graphs based on similar hierarchical (is-a, has-a) characteristics or predetermined anchors (i.e., matches that are known *a priori*) have been shown to be effective (Schvaiko and Euzenat, 13).

**Semantic matching** utilizes model-theoretic analysis to make comparisons. These methods rely on DL- or rule-based reasoning, or other logical reasoning to deduce correspondences. Although the mathematical foundations of these approaches are well vetted, they have only recently received significant attention in research and production systems for ontology matching.

**Extensional matching** attempts to find relationships between instantiated instances of ontology classes. These approaches can use many of the previous techniques to identify matching or related individuals in the two ontologies.

A comparison of a few state-of-the-art ontology matching/merging systems is provided above. A reasonable conclusion to be drawn from the comparison is that no single technique is likely to prove sufficient. Rather, each of the depicted systems uses a number of techniques to achieve reasonable results. Even so, ontology matching is not an error-free process: benchmark testing documented in (Schvaiko and Euzenat, 13) yielded precision, recall, and F-measure results in the 0.8 to 0.95 range, however testing on difficult real-world problems yielded results in the 0.4 to 0.65 range. For this reason, ontology matching is not yet a fully-automated process. All of the systems summarized above generate recommended correspondences that can be either accepted or rejected by a human operator.

A more thorough comparison of each system, including benchmark metrics is provided in (Schvaiko and Euzenat, 13).

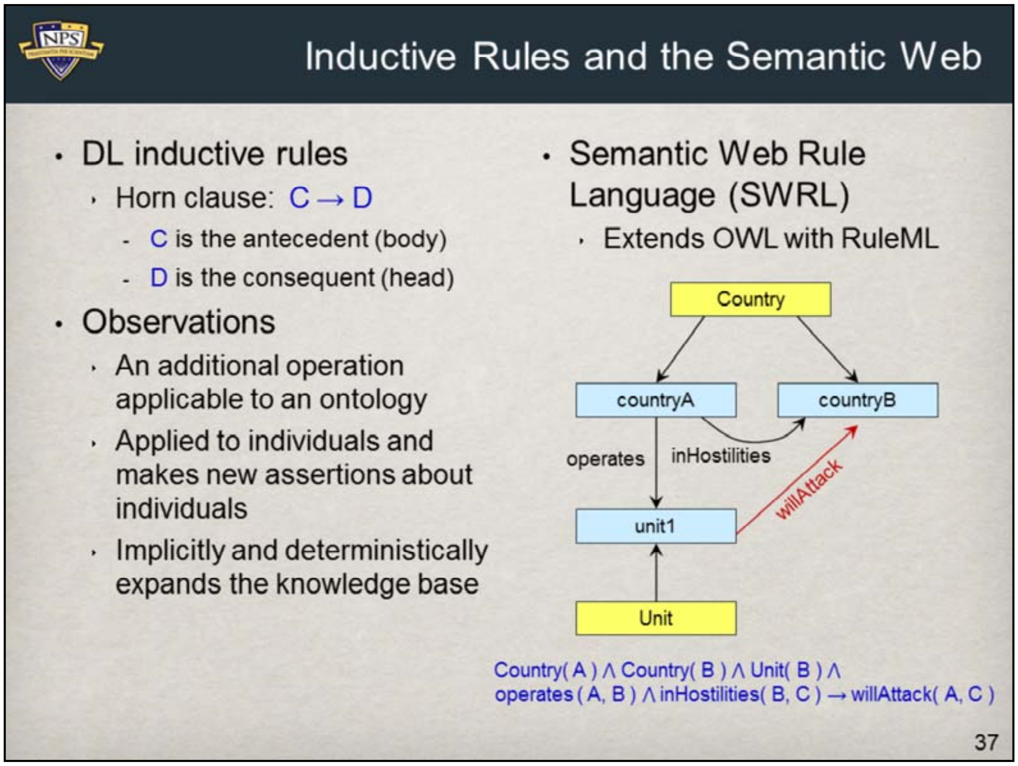



Closely related to the issue of ontology matching and merging is **data integration**, which deals with actual utilization of web-accessible data by Semantic Web applications. Data must frequently be drawn from databases and other types of archives that are not governed by any sort of ontology. In order for these data sources to be used by Semantic Web applications, the data must be integrated into an ontology. Three general approaches have been utilized for this purpose: a **single ontology approach**, a **multiple ontology approach**, and a **hybrid approach** (Kashyap, et al., 08).

With the single ontology approach, a single domain ontology is used by the application to access multiple data stores. This method has proven useful in cases where all of the data sources view the domain similarly. Even so, differences in level of granularity can make the definition of a single ontology into which all of the data can be integrated difficult. As the heterogeneity of the various data stores increases (i.e., the less they overlap) or the similarity of their views of the data decreases the definition of a single ontology for working with all of them becomes more difficult. The tendency towards a prohibitively monolithic ontology can be partially overcome through modularity, however the difficulties cannot be completely eliminated in this manner.

With a multiple ontology approach, a separate ontology is defined for each data source. The advantage of this approach is that each ontology can be designed around the specific data sources to which it will apply. In practice, however, differences in terminology and organization require significant ontology match/merge efforts to enable an application to utilize all of the data stores together.

The hybrid ontology approach attempts to combine the advantages of the single and multiple ontology approaches. With this approach, a single shared vocabulary (which might, itself, be defined as an ontology) is utilized for the application domain, and local ontologies based on the shared vocabulary are developed for specific data sources. Because the shared vocabulary does not have to include all of the relationships and semantics of the individual data stores, it can be more easily defined than can a single ontology. On the other hand, because the terminology is available, matching between local ontologies is not required (the shared vocabulary makes merging implicit).




Recall from the material on DLs that inductive **trigger rules** can be implemented as a DL extension. These take the form of implications where the truth of a consequent clause is implied by the truth of an antecedent clause: C → D. In order to be useful, rules are typically constructed as Horn clauses, meaning that the consequent (D) consists of an atomic concept or role and the antecedent is a disjunctive series (0 or more) of complex and/or atomic concepts and roles.

Rules can be added to an ontology as an additional layer that effectively extends the semantic expressiveness of the ontology. For instance, the following trigger rule expresses the notion that if an individual, A, is operated by an individual, B, and individual B is in hostilities with a third individual, C, then individual A will attack individual C:

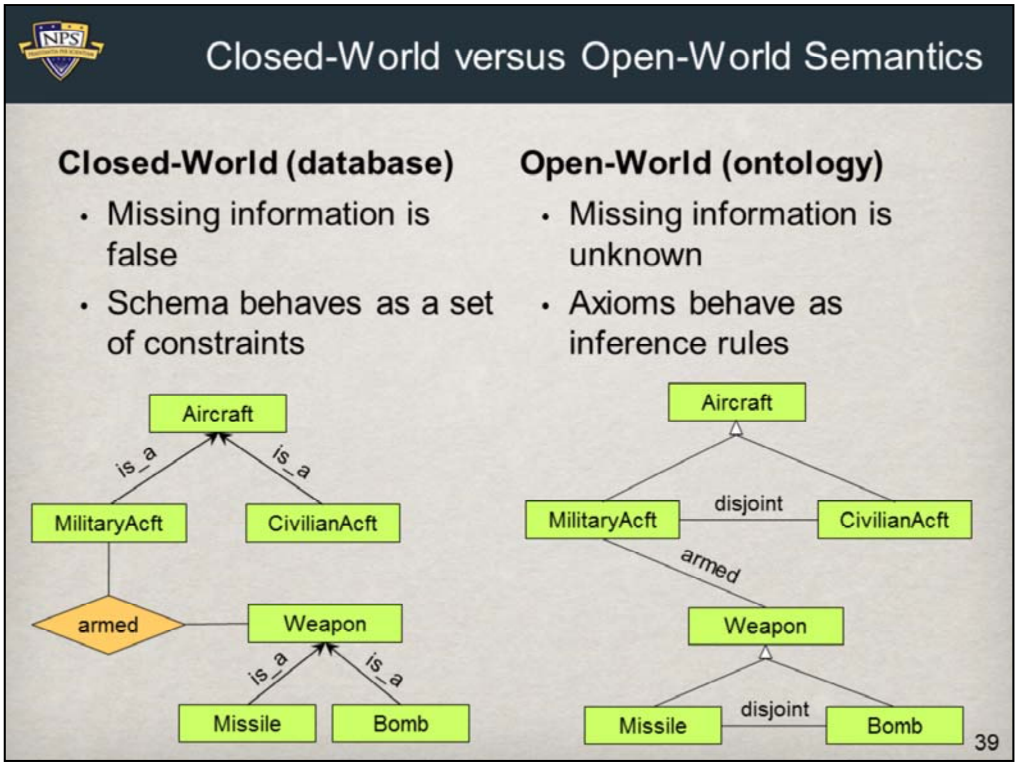
Country( A ) ∧ Unit( B ) ∧ Country( C ) ∧ operates ( A, B ) ∧ inHostilities( B, C ) → willAttack( A, C )

The notion of this example is difficult or impossible to express with most DLs and is not possible with OWL.

A number of relevant observations can be made regarding the utilization of Horn-clause-based rules with ontologies. First, rules can be thought of as an extension of an ontology framework that provides an additional expressive operation (Baader, et al., 07). Also, rules are applied to individuals to make new assertions about those individuals: the rule itself is universally quantified (i.e., it applies to every set of applicable individuals), but it is only executed (i.e., assertions are only made) in cases where the antecedent conditions hold for specific individuals. Further, since the knowledge base is finite, there is are finite possible rule applications. Thus, once every possible rule execution has been triggered, the knowledge base will have been deterministically expanded.

The Semantic Web Rule Language (**SWRL**) (Horrocks, et al., 04) is a W3C member submission that extends OWL by adding Horn-like rules from the Rule Markup Language (RuleML).

- Problem Statement
- Description Logics and Knowledge Representation
- Semantic Web
- Description Logic Inferencing
  - Reasoning with Ontologies
  - Inference Engines and Inductive Rules
- Machine Learning and the Semantic Web
- Conclusions and Recommendations




The notion of open-world semantics was discussed previously in the context of DLs, but bears further discussion here. The distinction between open-world and closed-world semantics is particularly important in the context of reasoning with ontologies. With the closed-world semantics of traditional databases (typically characterized by ER, EER, or UML models), missing information is treated as false. The database schema, therefore, can be viewed as a set of constraints on the contained data. With the open-world semantics of ontologies, missing information is considered unknown. The axioms of the ontology, therefore, can be viewed as inference rules for expanding $\mathcal{KB}$ (Horrocks, 08).

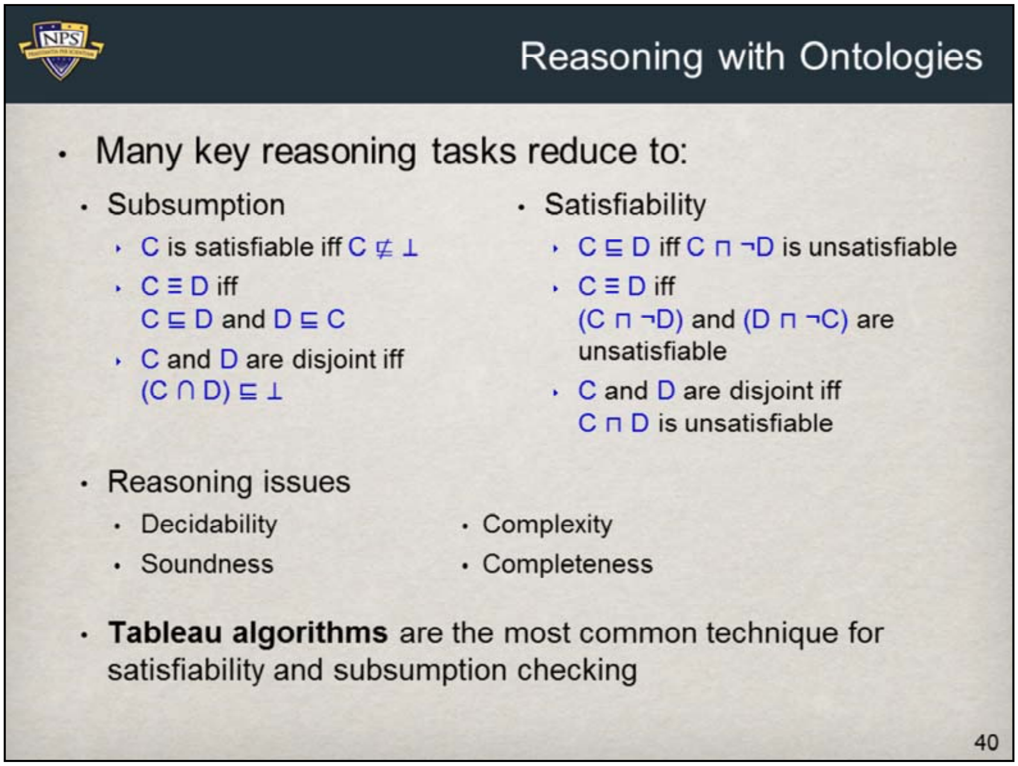
Consider the examples of the slide.

The simplified EER diagram on the left specifies that “MilitaryAcft” and “CivilianAcft” are both subtypes of the “Aircraft” supertype and that “Missile” and “Bomb” are subtypes of “Weapon”. In order to add a record specifying that an individual aircraft, “FA-18_172396”, is armed with an “AIM-120X”, it must already be known (i.e., present in the appropriate database tables) that “FA-18_172396” is an “Aircraft”, that it is a “MilitaryAcft”, and that “AIM-120X” is a “Weapon”.

Similar relationships are specified in the ontology diagram depicted on the right. Specifically, that “MilitaryAcft” and “CivilianAcft” are (disjoint) subclasses of “Aircraft”, that “Missile” and “Bomb” are (disjoint) subclasses of “Weapon”, and that an entity of the class “MilitaryAcft” can have an “armed” property associating it with entities of the “Weapon” class. With open-world semantics, however, the $\mathcal{KB}$ does not need to include any information about “FA-18E_172396” prior to adding the assertion “armed( FA-18E_172396, AIM-120X )”. Further once this assertion has been included in the $\mathcal{KB}$, we can add the following assertions by inference:

MilitaryAcft( FA-18E_172396 )
Aircraft( FA-18E_172396 )
¬CivilianAcft( FA-18E_172396 )
Weapon( AIM-120X )

In this case, we have implicitly increased the $\mathcal{KB}$ by five assertions with a single explicit assertion. Note, however, that this assertion does not provide a basis for concluding that “AIM-120X” is a member of either the “Missile” or “Bomb” class. In fact, either of these interpretations would satisfy (model) the ontology (an interpretation wherein “AIM-120X” was a member of both subclasses would not satisfy the ontology because the “Missile” and “Bomb” classes are disjoint).




Subsumption and satisfiability are among the most basic reasoning problems for ontologies. Extrapolating the definition from DLs to ontologies, subsumption can be defined as a relationship between two classes, A and B, where every individual of class A is also a member of class B (in this instance, B subsumes A). Using the OWL term for this relationship, A is a subclass of B. The DL definition of satisfiability can be applied to ontologies in similar fashion—a class is satisfiable if it is possible for an individual of the class to exist without violating the rules of the ontology.

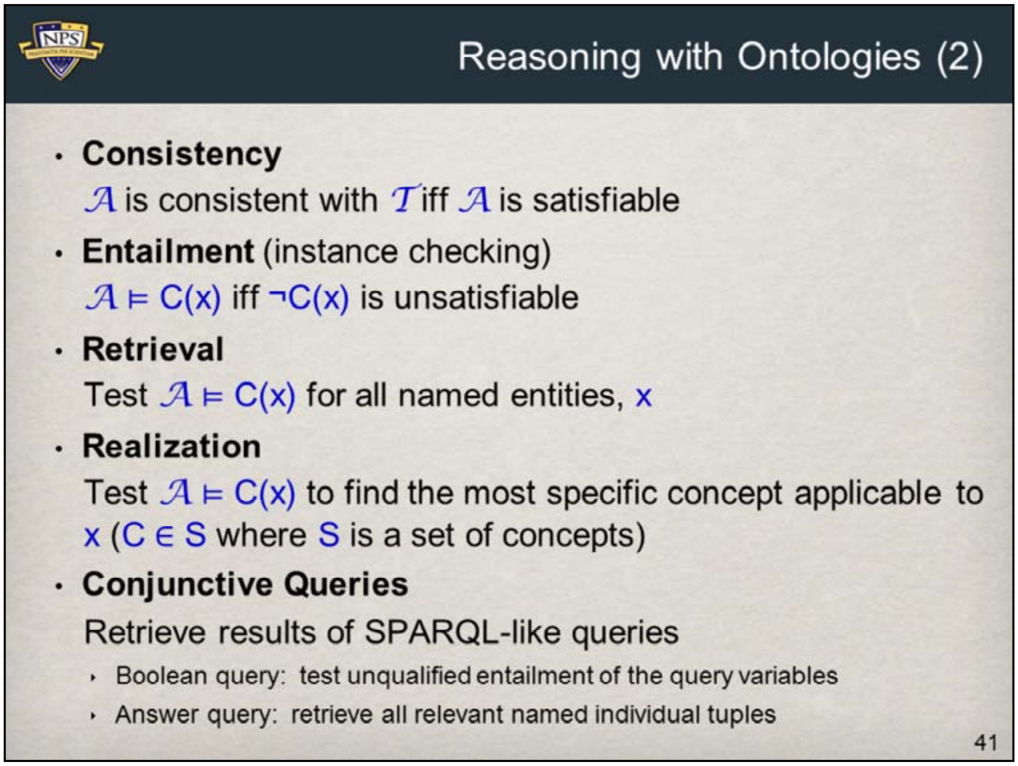
A number of key reasoning tasks can be reduced to either subsumption and satisfiability as depicted in the slide (Baader, et al., 08), meaning that if either satisfiability or subsumption can be computationally solved, then all of the problems reduceable to that task are also solvable. Stated differently, reasoning about equivalence, subsumption, satisfiability, and disjointness can all be accomplished by reasoning about either subsumption or satisfiability. In addition, TBox classification is evidently determined through subsumption or satisfiability reasoning as well.

A few issues must be considered when assessing the suitability of a reasoning algorithm for a particular problem. First, the problem must be **decidable** (i.e., does an algorithm exist that will solve the problem). Although seemingly a trivial concern, subsumption and satisfiability are potentially undecidable with many expressive DLs. In fact, decidability is an open question for many reasoning tasks with OWL 2 (W3C, 12).

The second issue is **complexity**, that is, how many computational steps are required by the algorithm. Early DL reasoning algorithms operated in polynomial time, however, these algorithms proved unsuitable for expressive DLs (Baader, et al., 07). The ability to reason in polynomial time was the primary motivation behind the OWL 2 EL, RL, and QL profiles (Krötzch, 12). Reasoning with OWL 2 Full ontologies typically requires algorithms with exponential complexity (W3C, 12).

**Soundness** and **completeness** have to do with the reasoning algorithm itself. An algorithm is sound if and only if every solution that it finds is correct, and an algorithm is complete if it is guaranteed to find a solution if one exists (Baader, et al., 07).

Given the requirements above, **tableau algorithms** have been the most frequently utilized tools for ontology reasoning for production and research systems (Baader and Sattler, 01 and Rudolph, 11).




As the previous slide shows, satisfiability and subsumption are fundamental ontology-reasoning tasks that form the basis for more complex reasoning tasks such as equivalence, disjointness checking, and classification that are typically associated with DL TBoxes. In practice, they also provide for reasoning with ABox axioms.

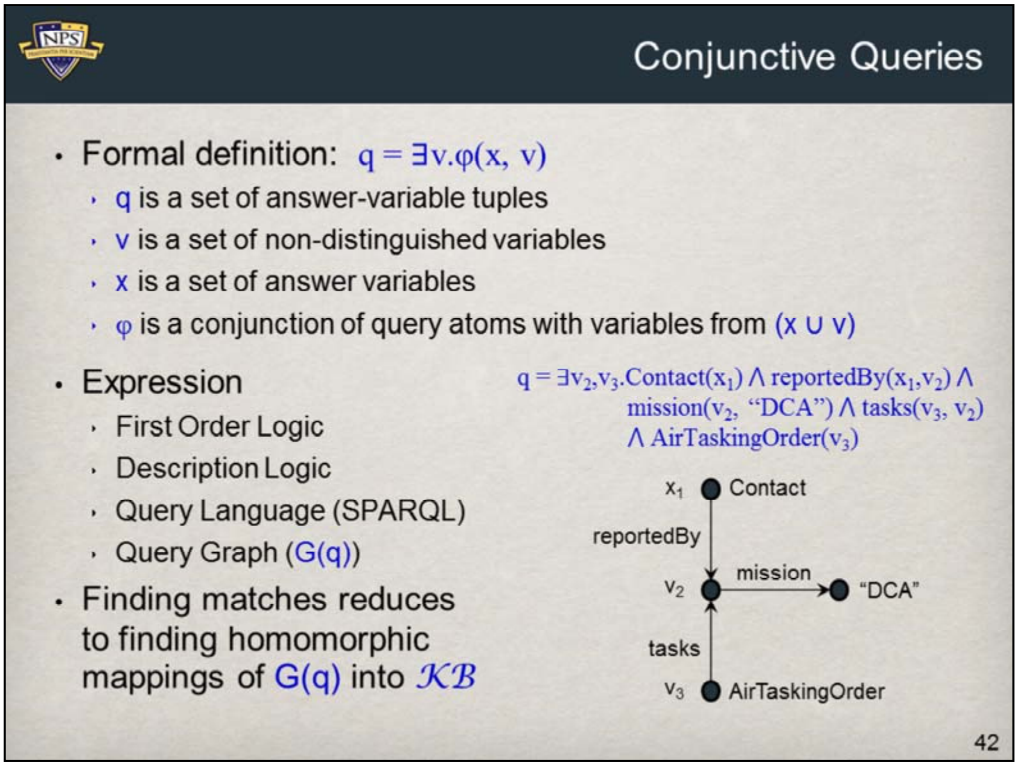
**Consistency** checking (i.e., testing the ABox and TBox together for contradictions) can be accomplished by testing the ABox as a whole for satisfiability—the ABox is consistent with the TBox if none of the ABox axioms introduce a contradiction. Notice that consistency does not require that all TBox concepts be satisfiable, so it is possible for a consistent knowledge base to contain TBox concepts that are unsatisfiable (a TBox of this sort would be considered incoherent but satisfiable).

**Entailment**, or **instance checking**, checks whether or not a particular assertion is true in every model interpretation (regardless of whether or not it is explicitly asserted with an ABox axiom). Entailment of concept for a particular individual (i.e., A ⊨ $C(x)$) is easily checked by testing the satisfiability of ¬C(x). If ¬C(x) is unsatisfiable, then the ABox entails C(X).

**Retrieval** of all named individuals entailed by a concept can be accomplished by testing for entailment of each named individual in $\mathcal{KB}$. For even moderately complex knowledge bases, computational complexity makes this approach impractical (Rudolph, 11). Optimization can often be achieved, however, based on the structure of the ontology (e.g., subsumption preordering; disjoint, transitive, and reflexive relationships, etc.) (Ortiz, 10). In addition, in many cases, the underlying data storage can facilitate the process by retrieving or eliminating multiple named entities at once (e.g., relational databases or XML documents to which XPath can be applied).

The worst-case scenario for reasoning about **realization** for an individual requires entailment testing of the individual for each concept in S followed by subsumption testing for each of the concepts entailing the individual. If a TBox classification is available, however, realization testing only requires entailment tests of increasingly specialized concepts of S according to the preorder of the TBox.

**Conjunctive queries** (CQ) and Unions of Conjunctive Queries (UCQ) require retrieval-like reasoning for complex combinations of concepts and roles. They can be comprised of multiple concepts and roles that contain multiple variables. CQs and UCQs are commonly expressed as first-order logic or DL expressions or SPARQL queries.




CQ answering (and retrieval and UCQ answering) is an important reasoning task that bears further discussion. A conjunctive query can be formally defined with the equation $q = \exists v.\varphi(x, v)$ where v is a set of **non-distinguished variables** for which only existence is being queried, x is a set of **answer variables** for which the actual values are queried, and φ is a set of $\mathcal{KB}$ concepts and roles utilizing only elements of x and v. The answer to the query, q, is the set of tuples corresponding to answer variable matches. As an example, consider the following query expressed as a FOL expression:

$$q = \exists v_2,v_3.\mathrm{Contact}(x_1) \wedge \mathrm{reportedBy}(v_1,v_2) \wedge \mathrm{mission}(v_2, \text{“DCA”}) \wedge \mathrm{tasks}(v_3, v_2) \wedge \mathrm{AirTaskingOrder}(v_3)$$

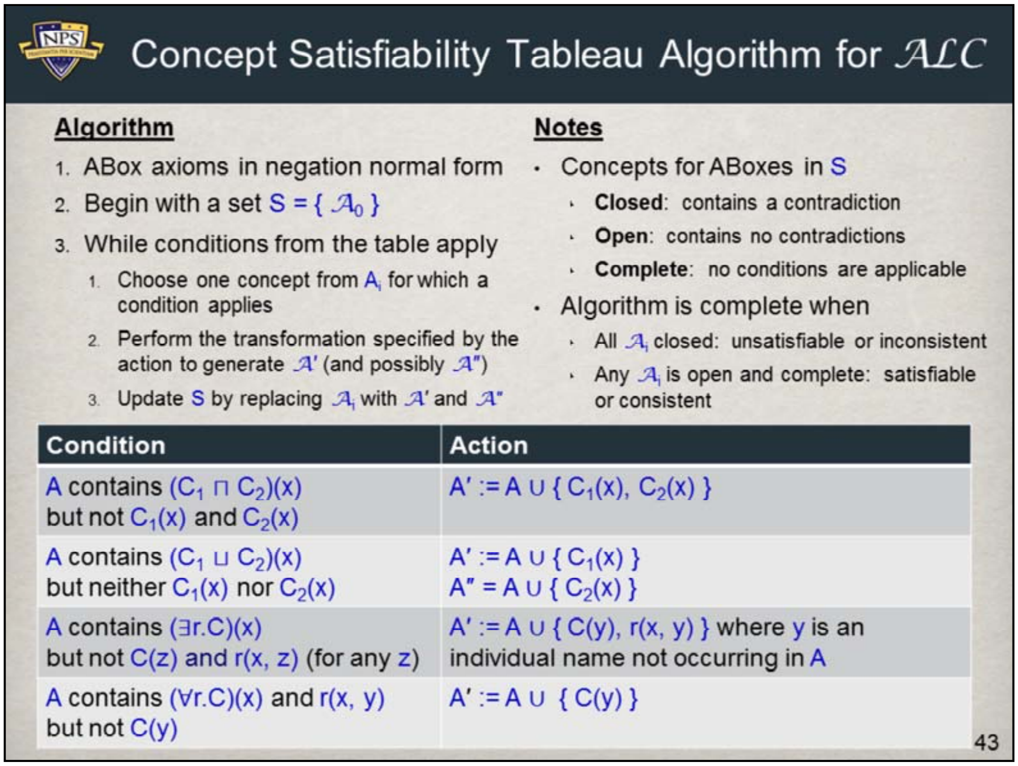
This first-order logic expression is requesting all of those cases where for specific individuals, $x_1$, $v_2$, and $v_3$, where Contact($x_1$), reportedBy($v_1$, $v_2$), mission($v_2$, “DCA”), tasks($v_3$, $v_2$) and AirTaskingOrder($v_3$) are all entailed. In this example, $x_1$ is the only answer variable, so the result of the query will be the set of all contacts that were reported by a unit that was tasked by an air tasking order to conduct a “DCA” mission.

Although typically specified using FOL, a DL, or a query language (e.g., SPARQL), it is possible to represent a CQ as a directed graph with nodes representing the query's concepts and arcs representing the query's roles. Viewed in this manner, answering a query amounts to finding a homomorphic mapping from the query graph to subgraphs of $\mathcal{KB}$ *(Ortiz and* Šimkus*, 12)*.

Queries that contain no answer variables determine whether the query is entailed by KB for any specific (i.e., bound) non-distinguished variables. Queries that contain one or more answer variables return all specific bindings for the answer variables and are referred to as answer queries.

In the most straightforward implementation, CQ and UCQ reasoning can be implemented by repeated testing of bindings of variables to ABox individuals and testing for entailment. This evidently requires $n^m$ entailment tests (n is the number of ABox individuals and m is the number of query variables), however, optimizations taking advantage of TBox-defined relationships and query structure can significantly reduce the number of required checks (Ortiz, 10).

The complexity and potential optimizations for CQ and UCQ reasoning are evidently comparable to those of concept retrieval. Both problems have 2EXPComplete complexity for many expressive DLs (Ortiz, 10). However, computational requirements for concept retrieval grow linearly with the number of named individuals in the ABox while requirements for CQ and UCQ answering grows exponentially based on the number of named individuals in the ABox and the number of variables in the query. Optimizations can eliminate large sections of the potential search space to make queries tractable, but CQ and UCQ remains an area of significant research interest.




The first example of a tableau algorithm was described in (Schmidt-Schaub and Smolka, 91) and has provided the basis for all subsequent tableau algorithms for expressive DLs. The algorithm is useful for reasoning about satisfiability and consistency with ontologies of the ALC family of DLs. The algorithm can be used to test the satisfiability of one or more concepts (or the consistency of the entire ABox) and works by attempting to construct an interpretation that satisfies all of the ABox concepts. The basic tableau algorithm for ALC works as follows (the example determines satisfiability or unsatisfiability for a single concept; consistency can be determined by beginning the algorithm with $A_0$ equal to the entire ABox being tested):

1. Develop $A_0$ in negation normal form (all named concepts are atomic and negations are applied only to atomic concepts). This can be accomplished in linear time by re-expressing named complex concepts with their TBox definitions and applying de Morgan's rules to negated complex concepts.

2. Begin with a set of ABoxes being tested that contains $A_0$ as the sole element.

3. Perform the following three steps repeatedly until the algorithm is complete.

   1. Choose one element of S, $A_i$, for which a condition from the table applies
   2. Perform the action associated with the condition on $A_i$ to generate A' (and A" for the third condition of the table)

3. Remove $A_i$ from S. Replace it with A' (and A" as applicable) iff no contradictions are contained.

An ABox that contains a contradiction (i.e., { P(x), ¬P(x) } ⊆ Ai for some concept P and individual x) is said to be **closed**, while an ABox that contains no contradictions is said to be **open**. An ABox for which no condition from the table applies is said to be **complete**.

The algorithm is complete when ALL elements of S are closed. If A' (or A") is found to be closed when the action from the table is applied, it does not need to be added to S. Thus, an empty S indicates that contradictions have been identified in all candidate ABoxes. In this case, the concept(s) being tested are unsatisfiable (or the ABox is inconsistent if $A_0$ contained the entire knowledge base).

Alternatively, the algorithm is also complete when ANY element of S is both open and complete. Since the candidate ABox has been fully expanded without generating a contradiction, the original concept has been shown to be satisfiable (or the ABox has been shown to be consistent if $A_0$ contained the entire knowledge base).

This basic algorithm highlights two important points concerning tableau algorithms in general. First, the action associated with existential quantification generates two ABoxes. The algorithm then, can be viewed as generating trees with each action being applied to a leaf node to generate one or two child nodes. The depth of the tree is bounded by the size of $A_0$ and the branching factor is bounded by the number of existential quantifications. At any point in the algorithm's execution, the tree's leaves are represented by the ABoxes contained in S. The second observation is that the action associated with value restriction condition instantiates a new hypothetical individual, which is allowed under the open-world semantics.

While the ALC DL with which this particular algorithm works is far less expressive than OWL, it can be extended in a relatively straightforward way to work with other expressive DLs, including OWL's SROIQ.

## Extending the Basic Tableau Algorithm

| Condition | Action |
|---|---|
| A contains $(\geq nr)(x)$ but no names $z_1, \ldots, z_n$ where $r(x, z_i)$ $(1 \leq l \leq n)$ and $z_i \neq z_j$ $(1 \leq i < j \leq n)$ | $A' := A \cup \{ r(x, y_i) \mid 1 \leq l \leq n \} \cup \{ y_i \neq y_j \mid 1 \leq i < j \leq n \}$ |
| A contains $(\leq nr)(x)$ and $r(x, y_i)$ for all $i = 1$ to $n+1$ but not $y_i \neq y_j$ for some $i$ and $j$ $(1 \leq i < j \leq n+1)$ | For $y_i$ and $y_j$ $(1 \leq i < j \leq n)$ where $y_i \neq y_j$ is not in A, generate $A_{i,j}$ by replacing each occurrence of $y_i$ in A with $y_j$ |
| A contains $(\leq nr.C)(x)$ and $r(x, y)$ but neither $C(y)$ nor $\neg C(y)$ | $A' := A \cup \{ C(y) \}$<br>$A'' := A \cup \{ \neg C(y) \}$ |
| A contains $(\exists r.C)(x)$ but not $C(z)$ and $s(x, z)$ (for any $z$, $s$ is a sub-role of $r$) | $A' := A \cup \{ C(y), r(x, y) \}$ where $y$ is an individual name not occurring in A |
| A contains $(\forall r.C)(x)$ and $s(x, y)$ (where $s$ is a sub-role of $r$) but not $C(y)$ | $A' := A \cup \{ C(y) \}$ |
| A contains $(\forall s.C)(x)$ and $r(x, y)$ and $r$ is a transitive sub-role of $s$ | $A' := A \cup \{ (\forall r.C)(y) \}$ |
| A contains $s^{-}(x, y)$ and $(\forall r.C)(y)$ | $A' := A \cup \{ C(x) \}$ |

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The rules depicted in the slide extend the tableau algorithm of the previous slide to reason with more expressive DLs.

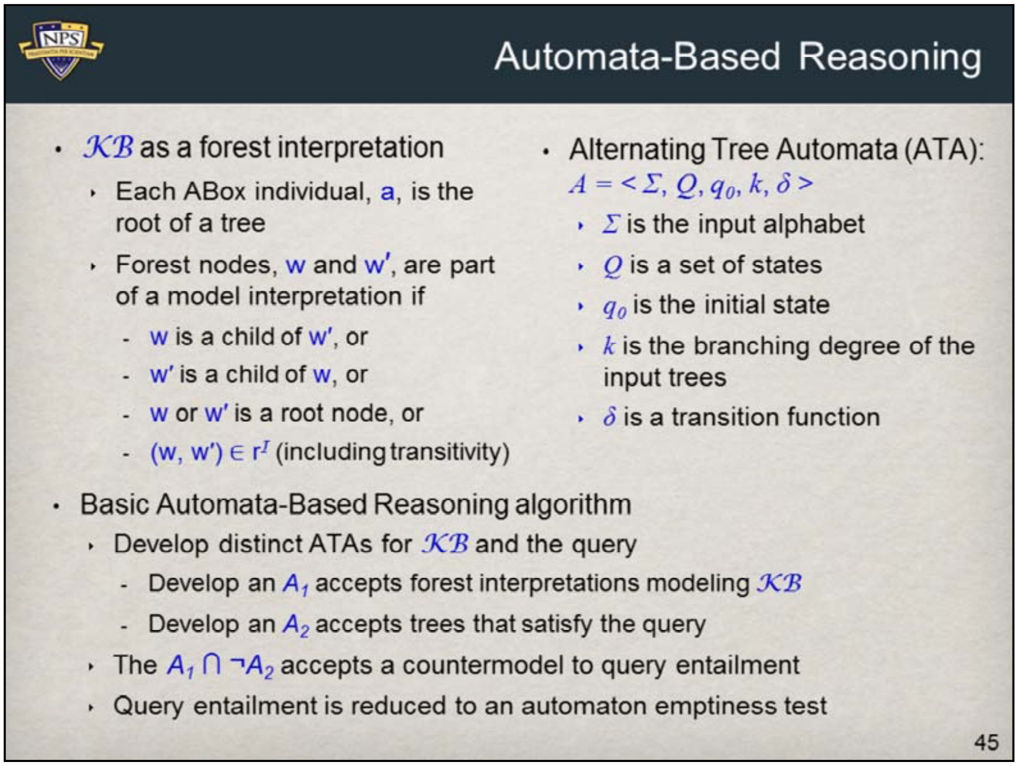
The first two rules provide for unqualified cardinality restrictions (the $\mathcal{ALCN}$ DL). The first rule accounts for greater-than rules by adding enough unique role instances to A meet the required minimum. The second accounts for the less than relationship by combining role instances that have not been explicitly declared unequal (i.e., replace "r(x, $y_1$)" and "r(x, $y_2$)" with a single occurrence of "r(x, $y_1$)" unless an assertion of "$y_1 \neq y_2$" is contained in A). The method of checking A for closure must be augmented to account for these new rules as well.

The third rule provides for qualified cardinality restrictions (the $\mathcal{ALCQ}$ DL) by adding "C(y)" to A' and "¬C(y)" to A" for all y in the qualified role with x that are not already identified in A as either C or ¬C.

The fourth and fifth roles provide for role hierarchies (role/sub-role relationships) by modifying the existential quantification and value restriction rules of the original algorithm.

The sixth and seventh rules provide for transitivity and inverse roles.

In combination, these rules provide a basis for algorithmically reasoning with $\mathcal{SHIQ}$ ontologies and can be extended further to reason with $\mathcal{SHOIQ}$ ontologies expressible with OWL.




Automata-based reasoning for DLs has been a topic of significant recent research. Automata-based approaches have limited implementation examples to date because of the requirement to generate an exponentially large automaton (Calvanese, et al., 11). Nevertheless, they have characteristics that may provide for improved performance for reasoning tasks for which tableau algorithms are demonstrably inefficient such as retrieval and conjunctive query answering (Ortiz, 10).

Automata-based techniques are similar to tableau algorithms in that they conduct queries by verifying (or refuting) the existence of modeling interpretations that satisfy the reasoning task requirements (Rudolph, 11).

Automata-based algorithms rely on KB forest interpretations, that are constructed in accordance with the rules depicted in the slide. This type of interpretation serves two purposes: 1) it limits counter-example search area (which is the mechanism used by both tableau and automata-based algorithms), and 2) automata techniques have been utilized successfully with infinite tree structures on problems closely related to DL reasoning (Ortiz, 10).

The second component of automata-based reasoning systems is an **alternating tree automata** (ATA) that accepts or rejects KB trees (or more recently, a whole forest) (Ortiz and Šimkus, 12). ATAs are nondeterministic finite automata that accept trees as input described as depicted in the slide. Nondeterminism comes into play when the ATA attempts to resolve unions, intersections, cardinality restrictions, or other operations with potentially disjoint or parallel realizations. In these instances, the algorithm branches to test all possible or necessary realizations (Glimm, et al., 08).

All automata-based algorithms follow the same general algorithm. First an ATA, $A_1$, is developed that will accept forest interpretations that model KB. Second, a query-specific automaton, $A_2$, is developed that will accept trees containing query matches. The intersection of $A_1$ and the complement of $A_2$ provides an automaton that accepts counter-models to query entailment (i.e., it accepts trees that model KB for which the query is false). Because query entailment requires that the query be true for every model of KB, the set of trees accepted by $A_1 \cap \neg A_2$ will be empty if the query is entailed (Calvanese, et al., 09 and Calvanese, et al., 11).

Automata-based algorithms have been utilized for many expressive DLs approaching the expressiveness of OWL 2. (Calvanese, et al., 09) and (Calvanese, et al., 11) propose automata-based algorithms for reasoning with the SRIQ, SROQ and SROI DLs. Algorithms for CQ reasoning with DLs more expressive than these are not available at present, and the question of whether or not CQ reasoning with full SHOIQ DL of OWL 1 or SROIQ of OWL 2 is decidable is currently an open question (Rudolph, 11).

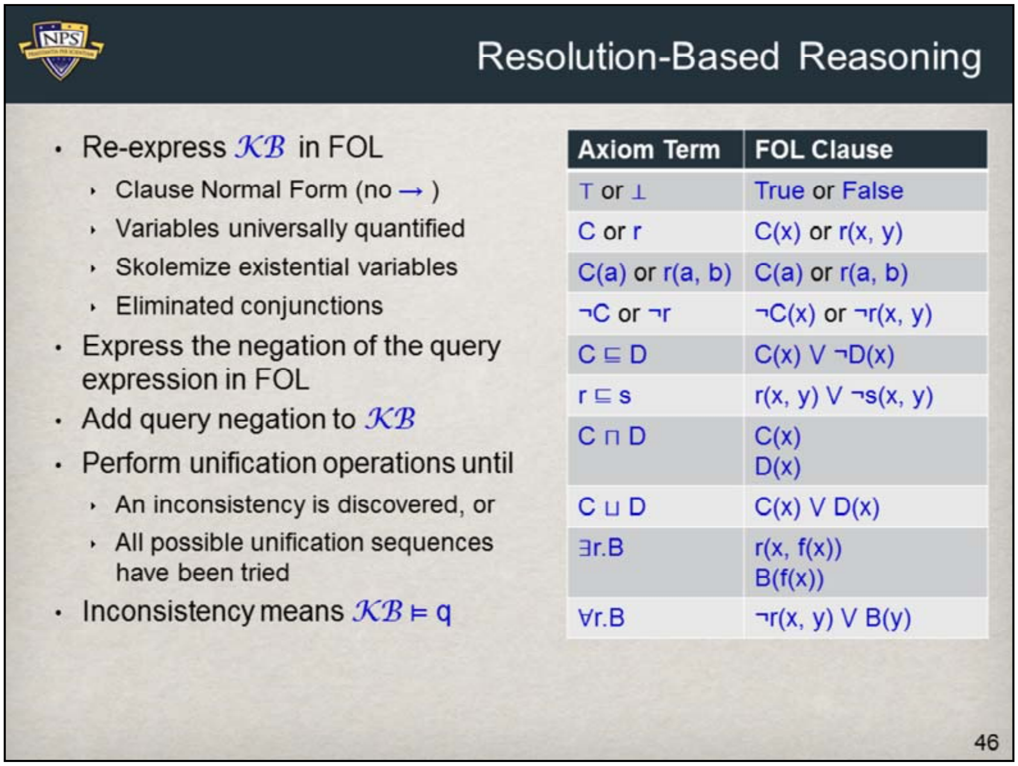



Tableau algorithms and automata algorithms both reason about satisfiability by attempting to develop a model for the expression being tested (i.e., if a model exists, then the expression must be satisfiable). Methods of this sort utilize model-theoretic reasoning (Rudolph, 11).

Resolution, on the other hand, uses a proof-theoretic approach where the axioms of KB are converted to Clause Normalized Form (CNF) FOL clauses to which resolution calculus rules are applied.

A CNF FOL description equivalent to KB can be defined as follows:
Replace axiom elements with the substitutions of the table (and others not depicted)
Move all negations to the atom level through application of FOL rules
Skolemize all of the existentially quantified variables
e.g., ∃armed.Sidewinder ⇒ armed(x, f(x)) ∧ Sidewinder(f(x))
All other variables are implicitly universally quantified
Manipulate clauses to eliminate embedded conjunctions
Break conjunctive clauses into separate clauses

Once the KB has been converted to CNF FOL clauses, the query is negated, converted to CNF clauses, and notionally added to KB. Unification rules are then iteratively applied until an inconsistency is discovered or all possible unifications have been tried. Unifications are conducted by finding two clauses with complimentary atoms, at least one of which contains an unbound variable. For example, the following two clauses

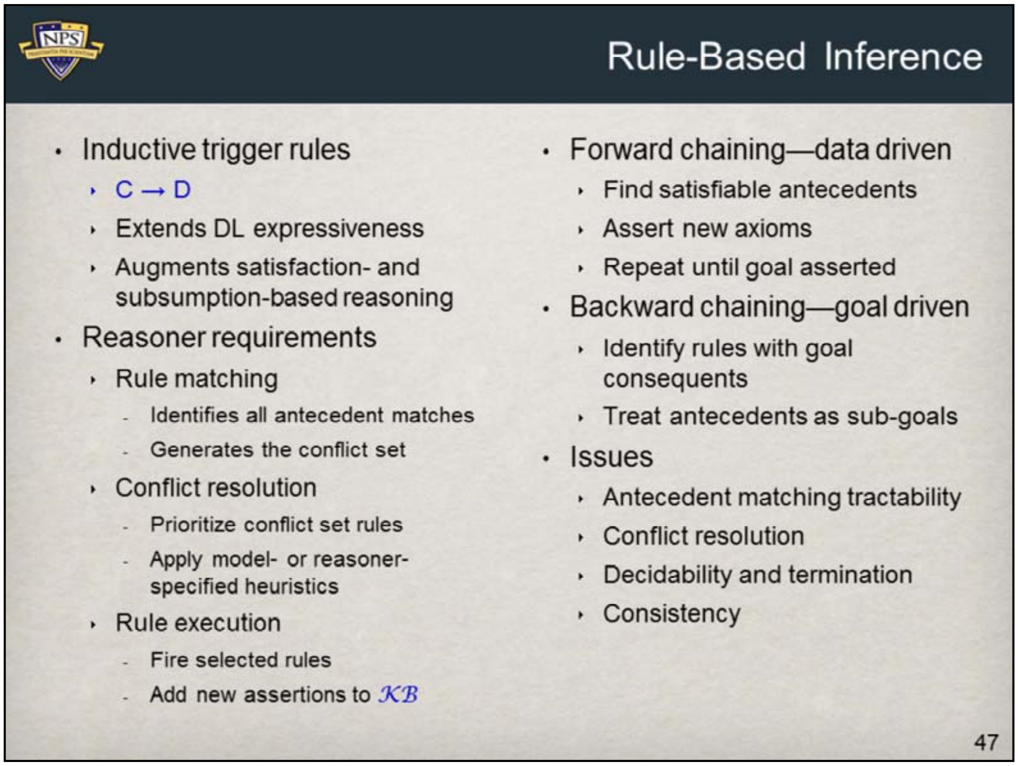
$\neg A(x) \lor B(z) \lor s(x, z)$
$C(a) \lor r(b, c) \lor \neg s(b, 5)$

can be unified because the first contains "s(x, z)" and the second contains "¬s(b, 5)". The unification rule relies on a unification pairs of { b/x, z/5 } as follows:

$(\neg A(b) \lor B(5) \lor s(b, 5)) \land (C(a) \lor r(b, c) \lor \neg s(b, 5)) \Rightarrow \neg A(b) \lor B(5) \lor C(a) \lor r(b, c)$

If an inconsistency is uncovered (i.e., KB includes clauses for both A(x) and ¬A(x)), then the original query is satisfiable (by showing that KB ∪ { ¬q } is unsatisfiable).

Resolution-based algorithms have been described for DLs up to SHOIQ with specific restrictions applied to ensure termination and decidability (Motik and Sattler, 06 and Kazakov and Motik, 08).




Inductive rules that extend a DL can allow for the expression of relationships that cannot be defined solely with DLs. Trigger rules consisting of an antecedent and a consequent can be used to add new facts to the database—if the antecedent of the rule is satisfied, then the consequent of the rule can be added to KB.

Alternatively, rules can be viewed as augmenting satisfaction- and subsumption-based reasoning. If the KB's TBox includes a set of trigger rules, then all ABox axioms that are entailed by the ontology are implied by the rules (as with other relationships that are not explicitly asserted). Reasoning about specific goals, then, is a different form of entailment testing.

Reasoning with trigger rules is typically conducted in three steps, the execution of which can be modeled as a finite state machine (Singh and Karwayun, 10)

A rule matcher identifies all rules, referred to as the **conflict set**, whose antecedents are satisfied and whose consequents are not present in KB. If the antecedent portion of a rule is entailed by KB, then that rule can potentially be used to add axioms. Once the conflict set has been generated, a conflict resolver is used to determine which rules to actually "fire". Finally, a rule executor fires selected conflict set rules and adds their consequents to KB.

Two general methods are used for rule-based inferencing. **Forward chaining** is a data driven approach. Forward chaining algorithms begin by identifying all rule antecedents that are matched by existing KB axioms. Selected rules from the conflict set are fired to assert new axioms, and the process repeats until a specified goal is achieved, the rule matcher returns an empty conflict set, or a predetermined number of algorithm iterations have been executed. Forward chaining is most applicable when the intent is to build the knowledge base out as much as possible rather than to determine whether or not a specific goal is entailed by KB.

**Backward chaining** is a goal-driven approach to reasoning. These algorithms begin with a specific goal and attempt to find an inference chain that will support the addition of the goal to KB. The initial conflict set for a backward chaining algorithm, then, contains all rules for which the goal is the consequent. A goal from the conflict set is selected and used as a sub-goal for a recursive call to the algorithm. The recursive base case is reached when the goal is contained in KB (success) or is not the consequent of any rules (failure). Backward chaining can be naïvely implemented with a simple depth-first or breadth-first strategy, but can be more efficiently implemented with directed search strategies such as A* search, means-ends analysis, or GraphPlan (Russell and Norvig, 10). Not surprisingly, backward chaining algorithms are useful when the intent is to determine whether or not a specific goal is entailed by KB. From this standpoint, backward chaining is analogous to entailment checks discussed previously.

A number of issues might be apparent:

First is the question of antecedent matching tractability. Taken to the extreme, matching rule antecedents potentially requires conjunctive query answering for every rule KB. In practice, this is unrealistic, so rule matches are usually based on axioms that are explicitly included in KB. Additionally, the composition of rule antecedents can be restricted to improve matching performance and maintain decidability (Horrocks, et al., 04).

The second issue regards conflict resolution, of particular importance with forward chaining algorithms (but also relevant with backward chaining). If KB is large, the conflict set is likely to be large as well, making the algorithm's performance highly dependent upon the order in which new axioms are added to KB. The selection strategy can be hard-coded into the reasoner, or it can be included as part of the model.

Decidability is a function of the DL itself and also of language used to specify trigger rules. Trigger rules are generally restricted Horn clauses with additional restrictions to the antecedent to make the rule matching process tractable. Termination of both forward and backward chaining algorithms is guaranteed by the finite size of KB (Baader, et al., 07).

Finally, consistency of KB is potentially more problematic if trigger rules are included.

The consistency check algorithms that have been discussed do not account for trigger rules. Therefore, the possibility that a trigger rule will make an assertion that compromises the ontology's consistency cannot be discounted.

## Commercial and Research Reasoners

### Comparison of Selected Reasoners

| Reasoner | DL | Algorithm | Entailment | Consistency | Rules | CQs |
|---|---|---|---|---|---|---|
| *Pellet | $\mathcal{SROIQ}$ | Tableau | Yes | Yes | Yes | Yes |
| ***RacerPro | $\mathcal{SHIQ}$ | Tableau | Yes | Yes | Yes | Yes |
| *FaCT++ | $\mathcal{SROIQ}$ | Tableau | Yes | Yes | No | Partial |
| ***SHER | $\mathcal{SHIN}$ | Rules | Yes | Yes | Yes | Yes |
| *Jena | None | Rules | Partial | Partial | Yes | No |
| **KAON2 | $\mathcal{SHIQ}$ | Resolution | Yes | No | Yes | Yes |

* Open source product
** Free, closed source product
*** Commercial product

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Both commercial and open source reasoners are available for use with OWL ontologies. A few of the more popular and more capable ones are included in this comparison.

**Pellet** (Sirin, et al., 07), a Java-based, open source reasoner for OWL ontologies, was the first reasoner to fully implement the full OWL 1 DL capability (the SHOIN DL) and has been extended to support OWL 2 features (SROIQ DL). It uses an optimized tableau algorithm for most reasoning tasks and an optimized “rolling up” technique (which, like tableau and automata algorithms, takes advantage of an OWL ontology’s tree model property) for conjunctive queries with non-distinguished variables. In addition, Pellet includes support for multi-ontology reasoning and non-monotonic reasoning.

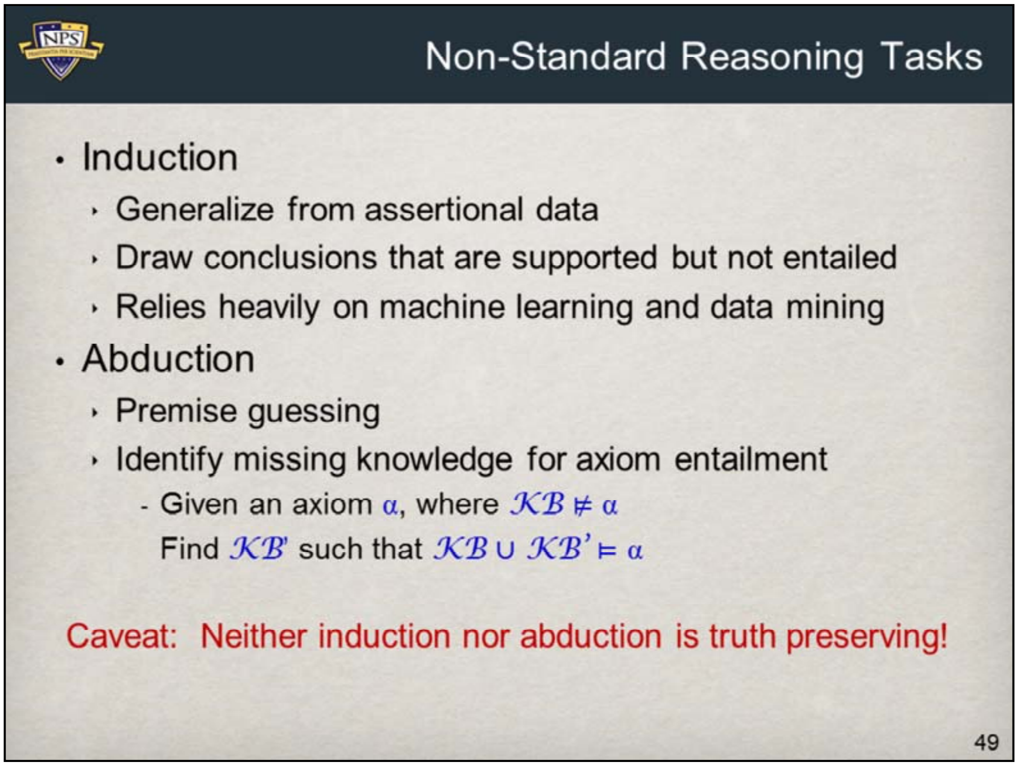
**RacerPro** (Haarslev, et al., 12) is a commercial product of Racer Systems GmbH & Co. KG for reasoning with the SHIQ subset of OWL 2. It uses an optimized tableau algorithm for reasoning. A robust proprietary language (nRQL) is used for specifying conjunctive queries and inductive rules (including facilities for defining when rules fire and under what circumstances they are active), and RacerPro also supports SPARQL queries and SWRL rules. In addition, RacerPro provides a number of interesting additions such as TBox and ABox retractions (i.e., non-monotonicity).

**FaCT++** (Tsarkov and Horrocks, 06) is an open source reasoner providing full support for OWL 1 DL and partial support for OWL 2 (keys and typing are not fully supported). FaCT++ uses an optimized tableau algorithm for reasoning, but does not support rules and only supports a restricted set of conjunctive queries.

The Scaleable Highly Expressive Reasoner (**SHER**) (Dolby, et al., 09) is a commercial product of IBM developerWorks® that is built upon the functionality of the open source Pellet reasoner. SHER is specifically designed to work with very large knowledge bases. Efficiency is gained by reasoning with an in-memory summary of the complete ABox, through the use of polynomial-time algorithms for subsets of the full SHIN DL (e.g., EL+), and applying fast and sound (but not necessarily complete) reasoners to find obvious solutions quickly.

**Jena** (Apache, 13) is an open source Semantic Web framework with a Java Application Programming Interface (API) for working with RDF graphs. Although intended for RDF, Jena does provide support for OWL. It does not fully support any specific DLs, however, and as a result, provides only limited reasoning capabilities. It does provide rule support, but utilizes its own format and does not allow rules to be specified with SWRL.

The **KAON2** reasoner (Motik, 08) and its commercial counterpart, Semafora Systems' OntoBroker, are unique among the reasoners discussed here in that it utilizes a resolution-based algorithm for reasoning. KION2 uses a client-server system for maintaining ontologies and supports conjunctive queries specified in SPARQL and inductive rules specified in SWRL. One interesting addition provided by KAON2 is the Java Application Programming Interface that makes it possible to programmatically manage, manipulate, and reason with ontologies.



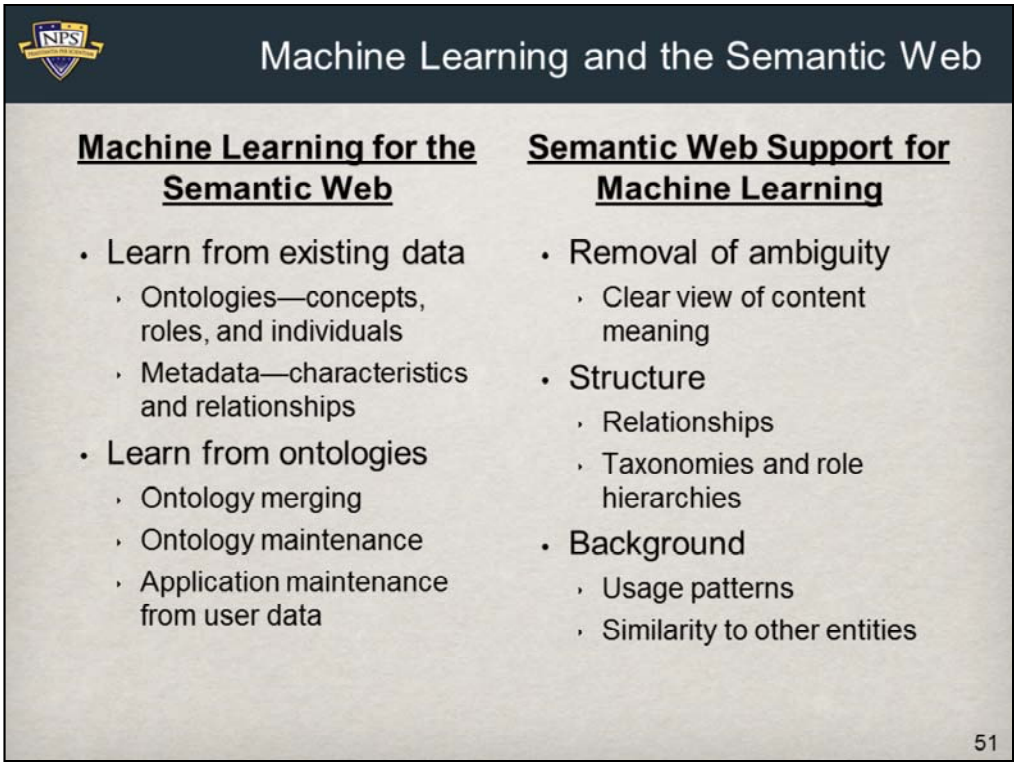

With the exception of inductive rules, all of the reasoning tasks discussed thus far can be reduced to satisfaction checking. These *standard reasoning tasks* are deductive in nature and draw logical conclusions from the KB itself. Although inductive in nature, rule systems also provide a mechanism for drawing logical conclusions from the knowledge base. In all of these cases, the reasoning conclusions are guaranteed to be entailed by KB. On the other hand, it is sometimes desirable to make inferences from a knowledge base that are not fully entailed by the axioms contained in the KB.

Induction is a process of drawing generalized conclusions from a KB's assertional data or drawing conclusions about individuals or groups represented in KB that are not fully entailed. Induction relies heavily on concepts of machine learning and data mining that will be discussed shortly. Induction is useful when decisions or conclusions need to be based on a preponderance of the evidence rather than on conclusive evidence. Inductive Logic Programming (ILP) (Muggleton and Raedt, 94) has proven particularly applicable in the area of induction reasoning with ontologies (Rudolph, 11).

Abduction, on the other hand, attempts to identify missing premises that if present would result in the entailment of desirable (or presumed) axioms. Stated differently, if an axiom, α is not entailed by KB, what additional axioms, KB', would result in α's entailment were they added to KB. Abductive reasoning services are useful when a desirable or suspected outcome is not entailed, and one wants to identify the missing information. Abduction is also an intuitive application of ILP (Muggleton and Raedt, 94).

It is important to note that, unlike standard reasoning tasks, induction and abduction algorithms are not truth preserving. That is, assertions may be added to KB that turn out to be false as more information is gathered.

- Problem Statement
- Description Logics and Knowledge Representation
- Semantic Web
- Description Logic Inferencing
- Machine Learning and the Semantic Web
  - Inductive Logic Programming
  - Feature-Based Statistical Learning
  - Relational Matrices and Tensors
  - Other applicable techniques
- Conclusions and Recommendations




The most prominent areas of machine learning research relating to the Semantic Web concern the use of machine learning techniques to develop and maintain ontologies. Machine learning was identified early on as a means of facilitating the growth and development of the Semantic Web, with an early W3C white paper proposing five specific applications (Maedche, 01). These can be roughly divided into the use of machine learning to build Semantic Web content from existing web data and the use of machine learning to improve and maintain Semantic Web content. Ontology extraction and Metadata extraction fall into the first category, while ontology merging, ontology maintenance, and application management fall into the second.

Ontology extraction from existing web data requires the analysis of existing structured and unstructured data to identify relationships and concepts. Data can range from completely unstructured material such as written documents, images, and steaming data to highly structured data stores such as relational databases, taxonomies, and dictionaries.

Extraction of relational metadata from existing web data involves the identification of characteristics of individuals and relationships between individuals. Metadata extraction might be viewed as a preliminary step in automated ontology development in that characteristics and relationships identified in this stage can be leveraged later.

Merging and mapping ontologies involves identifying common concepts, roles, and individuals. Although ontology matching might be viewed as simpler than developing an ontology from scratch, it is complicated by the fact that similar terms may be defined differently and common concepts and relationships can have overlapping but not identical meanings. As pointed out previously, current automated ontology merging approaches provide recommendations, but do not typically merge concepts, roles, or individuals without the concurrence of a human supervisor.

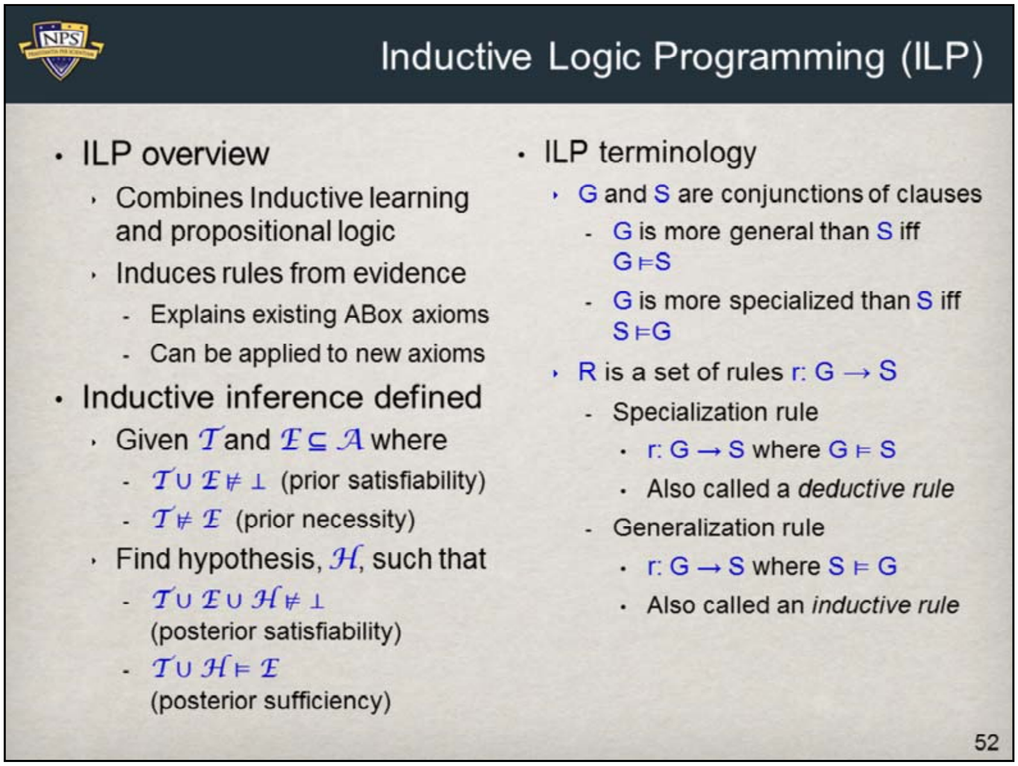
Maintaining ontologies by analyzing instance data involves the development of new TBox axioms from instance data contained in the ABox. Commonly referred to as ABox mining, this operation typically involves analyzing RDF statements to derive taxonomical classes and their relationships. Metadata extraction and ABox mining together can be used as sequential steps in the larger ontology extraction process.

Finally, the use of machine learning for application maintenance has been proposed as a means of improving Semantic Web services through analysis of user activity.

Despite its importance to the evolution of the Semantic Web, automated generation of Semantic Web content through machine learning is not as important to data fusion and correlation. These tasks might, however, benefit from the application of machine learning techniques. In particular, the inductive reasoning task is the assertion of new ABox axioms to capture presumed or predicted information. The process amounts to drawing the most likely conclusions based on the available data, and is clearly analogous to traditional machine learning.

When compared to the use of machine learning to build the Semantic Web, the use of existing Semantic Web data to support machine learning is less ubiquitous. This is in part due to the fact that most of the web is still not yet semantically described. Nevertheless, Semantic Web content has characteristics that are well-suited to its use in machine learning, and mining Semantic Web content is an active area of research (Tresp, et al., 08). Specifically, semantic description of web data removes ambiguity, imposes structure, and captures background information. All of these can be used by machine learning techniques that rely on interpretations of web content and organization of individual entities.

Semantic Web content can be effectively applied to most machine learning techniques, however, there are a few techniques that have proven particularly relevant.




Inductive Logic Programming (ILP) combines aspects of propositional logic, inductive learning, and logic programming to derive inference rules (Tresp, et al., 08). The idea is to apply propositional calculus to KB in such a way as to derive new inductive rules from existing rules (the TBox) and evidence (the ABox) that fully explains the evidence.

The general premise of all inductive inference can be stated as follows: given background knowledge, B, and evidence, E, where E does not contradict B (prior satisfiability) but B does not fully explain E (prior necessity), inductive inference attempts to find a hypothesis, H, such that adding the hypothesis to the background knowledge fully explains the evidence (posterior sufficiency) and maintains satisfiability of the knowledge base (posterior satisfiability) (Muggleton and Raedt, 94) . This can be expressed in terms of KB with the following expressions:

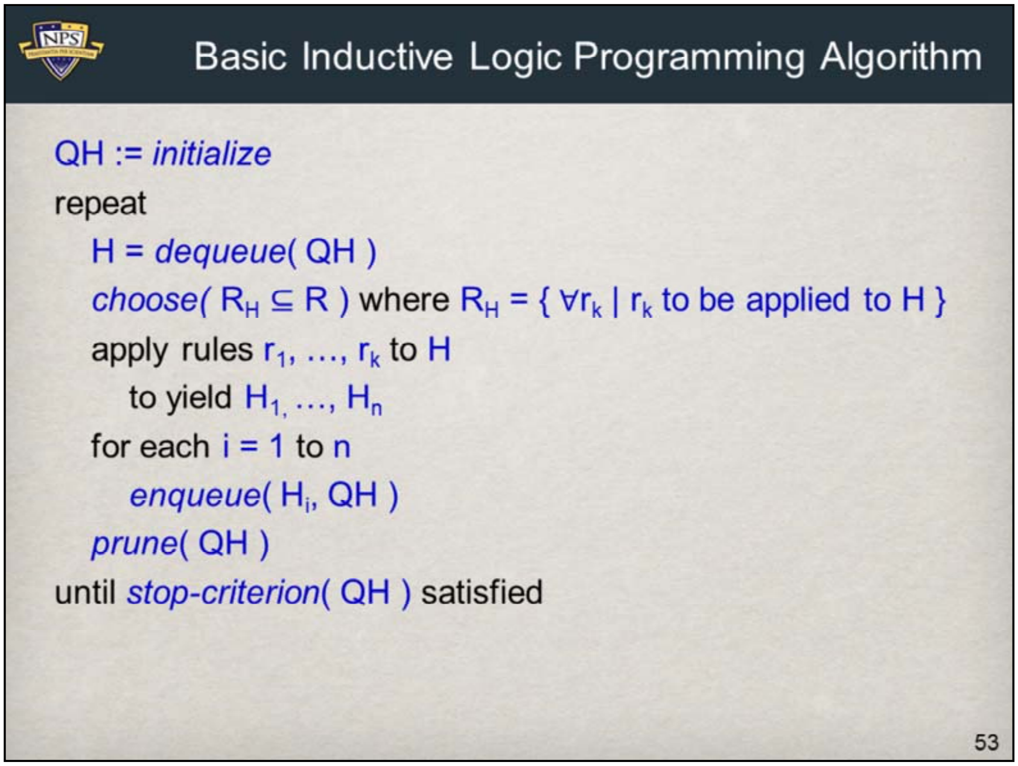
Given KB = < T, A > and $E \in A$
$\mathcal{T} \cup \mathcal{E} \nvDash \bot$ (prior satisfiability)
$T \nvDash E$ (prior necessity)
$\mathcal{T} \cup \mathcal{E} \cup \mathcal{H} \nvDash \bot$ (posterior satisfiability)
$\mathcal{T} \cup \mathcal{H} \vDash E$

The ILP algorithm works by iteratively applying transformation rules to conjunctions of clauses to make them more generalized or specialized. A conjunction of clauses, G, is said to be more general than a conjunction of clauses, S, if and only if G entails S. Conversely, G is said to be more specialized than S if and only if S entails G. Rules are considered either deductive or inductive based on whether they perform a specialization or generalization role respectively (Muggleton and Raedt, 94). As an example, consider the following rule for absorption (A and B are unbound variables for clauses, and p and q are unbound variables for atoms).

$$\text{Absorption:}\quad \frac{p \leftarrow A \wedge B \qquad q \leftarrow A}{p \leftarrow q \wedge B \qquad q \leftarrow A}$$

This is an inductive rule that can be applied to any pair of clauses of the form $p \leftarrow q \wedge B$ and $q \leftarrow A$ to yield two new clauses with forms $p \leftarrow A \wedge B$ and $q \leftarrow A$. The reverse of the rule can applied inductively, to clauses of the form $p \leftarrow A \wedge B$ and $q \leftarrow A$ to generate new clauses of the form $p \leftarrow q \wedge B$ and $q \leftarrow A$ (this is essentially resolution).

It must be noted that inductive rules are not logically sound meaning that they are a mechanism through which the truthfulness of KB can be compromised. Consider the preceding example. If KB contains a clause of the form $q \leftarrow C$ in addition to $q \leftarrow A$ (for the same q), the antecedent of the new clause, $p \leftarrow q \wedge B$, can be satisfied in cases where the antecedent of original clause, $p \leftarrow A \wedge B$, is not (e.g., $\neg A \wedge C$ is entailed).




The basic ILP algorithm as depicted in the slide (Muggleton and Raedt, 94) works by maintaining a queue of candidate hypotheses, QH. At each iteration of the algorithm, a single hypothesis is removed from QH and a set of applicable rules are chosen from R. The rules are applied (either exhaustively or by some other criterion) to H to produce a new set of hypotheses, $H_1$ through $H_n$. Promising are then added to QH and the process is repeated until a specified completion criterion is reached. The ILP algorithm equates, therefore, to an extension of standard DL reasoning algorithms that leverage the tree-model property of ontologies to derive models for KB.

The algorithm contains a number of generic procedures (denoted with italics) that must be defined for the particular application.

The initial QH may contain a single hypothesis containing the ground truth TBox and ABox (or subsets), or it may contain one or more hypotheses that include desirable or suspected axioms (i.e., abductive reasoning as previously defined).

The set of inference rules, R, consists of an arbitrary set of inductive and deductive rules as described. R can contain both domain-independent rules such as the absorption example and domain-specific rules containing information directly applicable to KB.

Rules are chosen based on applicability to the hypothesis being expanded and according to application-specific criteria. It is not the case that all applicable rules will be selected. As an example, it is permissible to apply rules either deductively or inductively, but in most cases inductive application is preferred (deduction can be accomplished through standard DL reasoning techniques). Additionally, exhaustive rule application will evidently lead to exponential growth of QH, so the rule-selection heuristics must prioritize rules based on whether or not they make progress towards the desired end state and select rules for inclusion in $R_H$ accordingly.

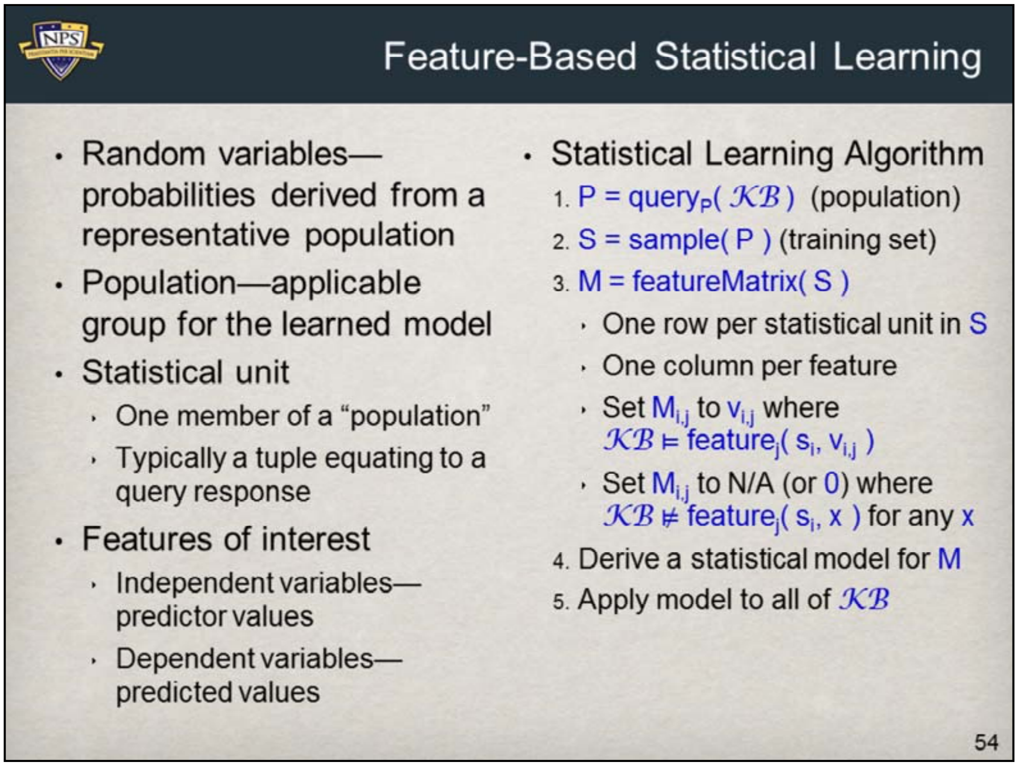
The makeup of QH requires consideration of similar issues. The depicted algorithm uses the standard "enqueue" and "dequeue" terminology from the computer science field to represent the operations for adding and removing hypotheses from QH. In practice one or both of these operations must account for the likelihood that particular hypotheses will lead to the best solution. Even with highly selective rule selection heuristics, traditional queue operations will result in an inefficient breadth-first search of hypotheses. Efficiency can be improved by implementing QH as a priority queue ordered according to an evaluation metric. The evaluation metric provides an assessment of each hypothesis based on its proximity to a solution and effectively implements the algorithm as a best-first search.

The "prune" operation of the algorithm allows the removal of impossible hypotheses without further evaluation. This step is required because rules from R are applied irrespective of the evidence—there is no requirement that the consequent of a rule maintain consistency. Because any final solution must be satisfiable, hypotheses that are inconsistent with KB can be eliminated without further evaluation.

In addition to eliminating inconsistent hypotheses, the pruning function can be used to eliminate highly unlikely hypotheses. As discussed earlier, the application of inductive rules introduces uncertainty—the likelihood of a new hypothesis is a function of the likelihood of its parent hypothesis and the uncertainty introduced by the inductive rule. Each hypothesis, therefore, can be assessed according to its likelihood, and the unlikely ones can be eliminated without further evaluation (Muggleton and Raedt, 94). Bayesian approaches that probabilistically evaluate hypothesis likelihood based on the empirical probabilities contained in KB and inductively deduced additions can be intuitively applied for this purpose. It might also be the case that an oracle (i.e., a user or other arbitor) can be invoked to eliminate unsuitable hypotheses.

Evidently, the stop-criterion function can be satisfied in one of two cases. Either a hypothesis has been derived that meets both the posterior satisfiability and posterior sufficiency requirements, or QH contains no more hypotheses for evaluation. In the first case, the inductively derived rules of the satisfying hypothesis can be added to KB to "explain" the tested subset of the ABox (or they formulate the missing information in the case of abductive reasoning). An empty QH, on the other hand, indicates that KB does not contain enough information to explain the initial hypotheses. It is important to recognize that this does not equate to a refutation of the initial hypotheses. Additionally, computational exigencies might necessitate the imposition of other stop criteria. In most cases this will amount to restricting the algorithm to a predetermined number of iterations.

ILP is a well-researched learning mechanism that is well suited to reasoning with DLs. The most significant limiting factor is computational complexity that does not scale well and will limit its usefulness with large ontologies (Rettinger, et al., 12).




Feature-based statistical learning treats relationships in KB as random variables where RDF triples are associated with probabilities that equate to confidence levels (Trest, et al., 13). Probabilities are computed based on statistical measurements on a representative population. The population that is the subject of the algorithm is typically comprised of a set of tuples equating to a query response. For instance, a particular learning algorithm population from a command and control system might contain tuples of the form "< contactID, contactType, contactSource >". Individual members of the population set are called statistical units.

Features of interest for each for the population include both independent (or explanatory) variables and dependent (or predicted) variables. Independent variables are those that the learning algorithm will use to derive predictions. Independent variables can include feature values that are used to define the population and any additional features. Dependent variables are those whose values the algorithm will attempt to predict. (Trest, et al., 08)

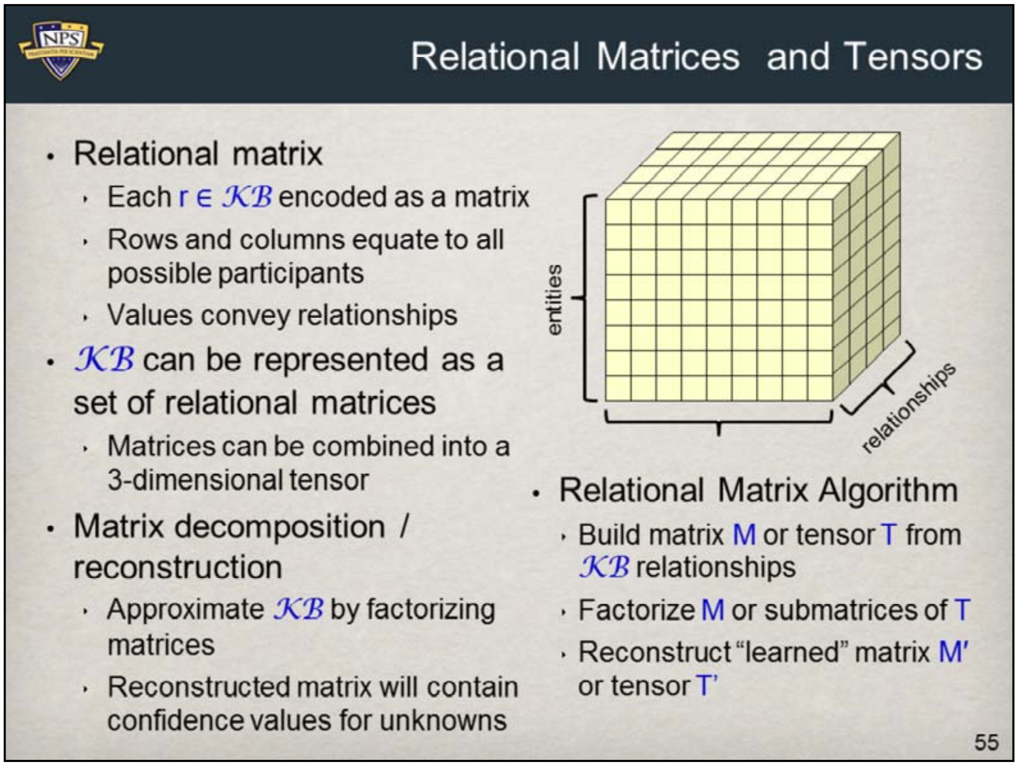
The basic statistical learning algorithm is depicted in the slide.

In the first two steps, KB is queried to retrieve tuples of the target population, P, and the set of all population members is sampled to yield a training set, S. The query-sample sequence of steps one and two presume a distributed ontology of linked data where query retrieval takes the form of a web search. With distributed source retrieval, identification of all population instances is unrealistic, but a representative sample can be obtained. It is important, however, to minimize the effects of search engine bias.

In step three, a feature matrix, M, is constructed where each row corresponds to a statistical unit of the sample set and each column corresponds to a feature. Matrix entries, therefore, correspond to feature values for specific statistical units. It is often the case that statistical units do not have values for every feature. In these cases a value of “N/A” or “0” can be entered into the matrix to signify a non-value.

Following generation of matrix, M, analysis is conducted to derive a statistical model. Strictly speaking, there are numerous machine learning paradigms that can be applied to this purpose including case-based reasoning, neural networks, genetic algorithms, and many others. It is usually the case, however, that the learning algorithm is used to generate a probabilistic Bayesian model for M. Commonly utilized models include naïve Bayes models, hierarchical Bayesian models, and Bayesian networks (Trest, 08).

When developing the statistical model of M, it is important to properly account for missing data. Feature-based statistical learning sometimes imposes closed-world semantics on M in which missing values are assumed to be false. However, M is frequently a sparse matrix, and treating missing values as false can unacceptably skew the results. For this reason, missing values are often ignored during statistical analysis or assigned values that minimize their impact on the model.




Relational matrices and tensors can be viewed as an extension of the feature-based statistical learning paradigm in that they represent characteristics of individuals as a matrix of truth values. The use of relational matrices as a machine learning mechanism is well-documented, and they have proven applicable to a large class of relational learning problems (Singh, 09). Their applicability to learning with semantic graphs and ontologies is fairly obvious.

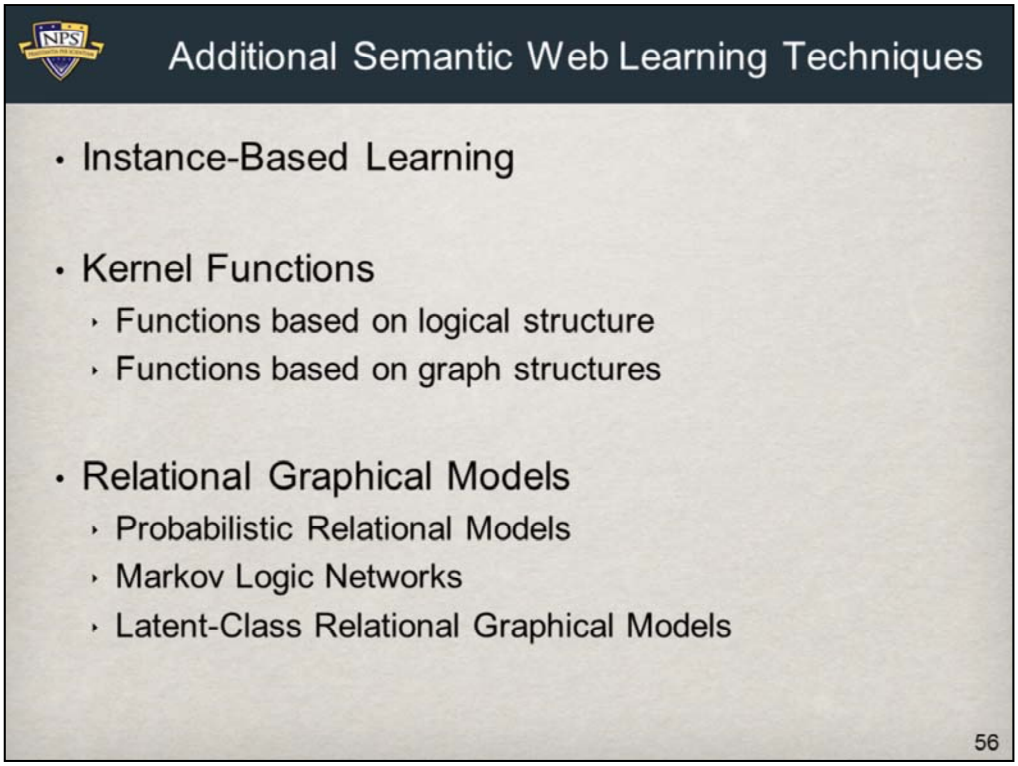
The general idea is that a matrix is used to represent a single ontological relationship and all potential participants. The rows and columns of the matrix represent individual entities that may participate in the relationship. Matrix cells are assigned a value of “1” if the relationship exists (in row-column order) between the entities in the row and column and “0” otherwise.

Each entity in a matrix is described by a small set of parameters that play the role of independent variables. As a rule, if an entity is present in more than one matrix, the same parameters will be used for every matrix. The matrices themselves contain the dependent variables.

Learning is conducted by decomposing the matrix using factorization functions to generate an approximation of the original matrix. After matrix reconstruction, the contained values can be interpreted as confidence values that the relationship holds between the represented values (Rettinger, et al., 12). (Singh, 09) provides an overview of factorization techniques that can be utilized with relational matrices with emphasis on scalability.

Until recently, most applications of relational matrices to learning Semantic Web relationships focused on individual matrices (Trest, et al., 08). More recently, work has expanded to the use of 3-dimensional tensors that are comprised of layered relationship matrices (Huang, et al., 13 and Rettinger, et al., 12). These approaches have a number of potential advantages. First, the tensor can be sliced in various ways to process the contents from different perspectives. For instance, a frontal slice contains a matrix for a single relationship as previously described, while a horizontal slice describes all relationships as they relate to a single subject individual and lateral slices describe the relationships as they relate to a single predicate individual. These multiple perspectives enable the consideration of all relationships simultaneously so that their interelationships can be captured (Huang, et al., 13).

Relational matrices are among the most promising learning mechanisms for Semantic Web applications because of their scalability, which is a byproduct of the sparse nature of most tensors (Rettinger, 12).




ILP and feature-based learning (which includes relational matrices and tensors) are among the most important approaches to machine learning with Semantic Web content. There are other approaches, however, that have shown promise and bear mentioning.

**Instance-based learning** utilizes a feature vector to identify concepts applying to individuals. The algorithm works by comparing the feature vector of an individual being tested to feature vectors associated with a particular class or concept (determined through a training process). If the comparison meets specified criteria, then the test individual is presumed to be a member of that class. The most common comparison mechanisms use distance functions that take in numerical feature vectors for two individuals and a weight vector and compute a disimilarity measure between 0 and 1 (d'Amato, et al., 08). The individuals characterized by the input feature vectors are determined to be members of the same class if the disimilarity measure is below a predetermined threshold.

Instance-based learning is well-suited to testing whether or not a concept can be applied to an individual. Not surprisingly, it is most widely used for instance checking and retrieval. Although the application scope is limited, instance-based learning is more efficient than standard reasoning algorithms, so it remains popular for these tasks (Rettinger, et al., 12).

**Kernel functions** are functional mappings from an input domain (individuals) to a feature space. The function effectively partitions the feature space into regions such that application to an individual will map it to the region most appropriate for its classification. Support Vector Machines are the most well-known kernel functions, however kernel functions can be developed to support many well-known learning algorithms (Rettinger, et al., 12).

The first kernel functions applied to Semantic Web content assessed the logical structure of the individual being tested and the semantics of the primitive concepts (Fanizzi and d'Amato, 07) and these methods remain popular. Logical structure kernel functions are often resemble the similarity functions used with instance-based reasoning. Kernels that work with a portion of the semantic network graph associated with the individual being tested are also popular. These methods have the advantages of not requiring manual feature definition and not being based on *a priori* assumptions on the data structure (Rettinger, et al., 12).

**Relational Graphical Models** (RGM) represent ontological statements with random variables and can be thought of as extensions of earlier models including Bayesian networks, Markov networks, dependency networks (Trest, et al., 08). RGMs represent all possible links in an RDF graph as nodes (vertices), where the actual existence of the link is probabilistically expressed as a binary random variable. Connections (edges) in the graph are represent interdependencies between the nodes.

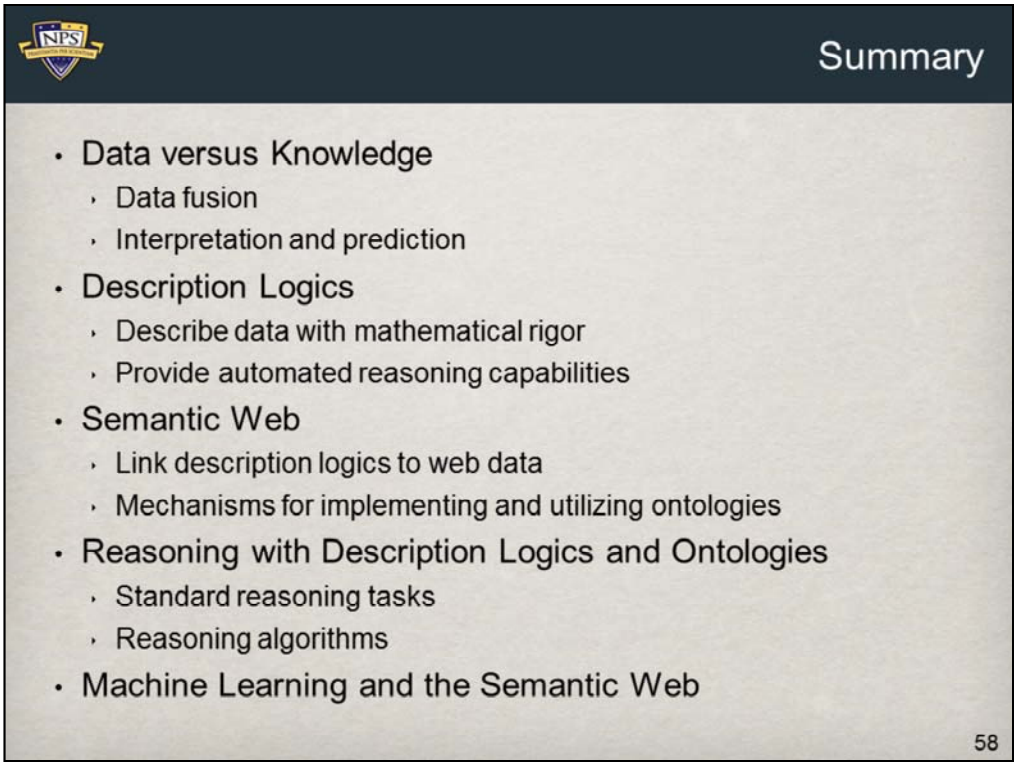
Probabilistic Relational Models (PRM) are a form of RGM where nodes capture the probability distribution of object attributes and links represent relationships between objects. Early PRMs required that the relationships between objects be known, but extensions have made it possible to utilize PRMs to consider cases where relationships are unknown (Getoor, et al., 07).

Markov Logic Networks (MLNs) follow the pattern described above for defining nodes and links. Probabilities are formulaically assigned based on the number of grounded inputs to the nodes (i.e., the confidence in the values upon which the relationships rely) and weights assigned to each formula (Trest, et al., 08). MLN learning involves estimating the appropriate weights for each formula.

Latent-Class RGMs attempt to incorporate hidden variables that may be present in an ontology. These hidden variables are incorporated into a Bayesian network comprised of relationships specified by KB. Presumed latent variables are introduced for each entity as a parent of all nodes with which the entity is involved. Because the links in the underlying Bayesian network are completely specified by the KB, training with Latent-Class RGMs amounts to determining weights for nodes corresponding to latent variables (Trest, et al., 08).

The most significant drawback to RGMs is that they are not factorable into individual data points, meaning that the whole data set essentially comprises a single data point and complicating inferencing and learning (Rettinger, et al., 12).

- Problem Statement
- Description Logics and Knowledge Representation
- Semantic Web
- Description Logic Inferencing
- Machine Learning and the Semantic Web
- Conclusions and Recommendations




The difference between information and knowledge is an important factor when considering solutions to the data fusion problem. The amount of data available to operators and decision-makers has exploded in recent years, but increased data availability has not necessarily translated into more efficient operations or better decision-making. The term "information overload" has become a cliché, but it accurately reflects the current state of affairs.

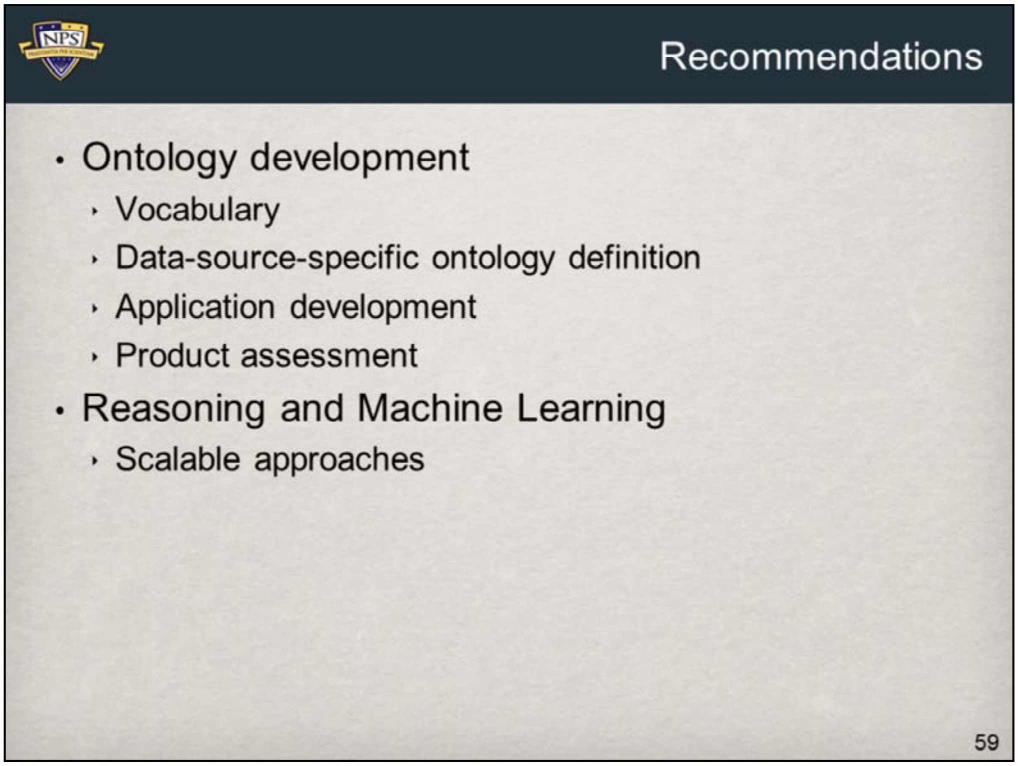
What is required are means of automatically converting the abundance of information into an abundance of knowledge. This includes mechanisms for computationally interpreting, categorizing, and correlating information to develop a knowledge base and using that knowledge base to draw conclusions, make predictions, and aid the decision-making process. This is an area to which the Semantic Web technologies described in this report can be directly applicable.

Description Logics (DL) provide the mathematical foundation for the Semantic Web. A subset of First-Order Logic, DLs use concepts and roles to describe individuals and their relationships. DLs provide operators for defining complex concept and role definitions that provide powerful expressive capabilities. Additionally, because of their foundation in First-Order Logic, DLs provide a basis for making logical inferences on the knowledge bases that they define.

Semantic Web technologies apply the mathematical rigor of DLs to the web. The Semantic Web provides a framework that brings structure to web content, provides for unified access to data, and ultimately improves the efficiency of human/computer interactions. It does this through a set of standards (or proposed standards) for defining and using ontologies. The most significant of these are the Resource Description Framework (RDF) and the Web Ontology Language (OWL). Taken together, RDF and OWL fully capture the semantics of the expressive DL, SROIQ, and can be used to describe web content in a semantically rich way.

Among the most significant advantages of the Semantic Web is the ability to computationally reason about ontologies. The most common ontological reasoning tasks are satisfiability, subsumption, equivalence, disjointness, classification, consistency, instance checking, retrieval, and conjunctive query answering. All of these can ultimately be reduced to a single task—satisfaction. Tableau algorithms are among the most common algorithms for reasoning and are utilized by most of the well-developed production and research systems. Automata-based algorithms, and resolution-based algorithms are also utilized, and other methods based in First-Order Logic have also been used in applications that are isomorphic to decidable First-Order Logic problems.

Standard reasoning with ontologies (i.e., those tasks that can be reduced to satisfaction) are useful for identifying knowledge that is implicitly contained in the knowledge base. They are not, applicable to the tasks of induction and abduction, however, because these reasoning tasks infer things that might be true from the ground truth of the knowledge base. Machine learning is appropriate for this type of reasoning, and it is not surprising that a number of techniques from this field have been applied to the Semantic Web. Among the most important of these are Inductive Logic Programming and relational matrices (with relational tensors providing a promising area for future research). Instance-Based Learning, kernel functions, and relational graphs have also shown promise in Semantic Web applications.




Effective utilization of Semantic Web technologies to support situational awareness and decision-making will be facilitated by efforts in a few specific areas. Vocabulary definition is among the most important. The practical difficulty of ontology definition has been mentioned, but the process can be aided by agreement concerning terminology and definitions. Implementation of Semantic Web technologies in the civilian sector has been hampered by a lack of coordination, parallel development, competing interests, and many more factors. Semantic Web implementation for government use, on the other hand, is still in its infancy. A number of efforts are already underway to define domain-specific vocabularies that can be leveraged for Semantic Web applications, and aligning these efforts will facilitate the development of a common vocabulary.

Ontology-development is the next logical step following vocabulary definition. As discussed previously, it is unlikely that a single ontology can be developed that will meet all requirements. Rather, a more reasonable approach is to define ontologies that capture the semantics of specific data sources. This will enable the development of reasonable ontologies that can be incorporated into distributed applications later. The availability of a well-defined common vocabulary will facilitate future incorporation of disparate data sources into applications using the hybrid approach described earlier.

Once Semantic Web content is made available through the development of compatible ontologies for various data sources, application development will be a straightforward proposition.  Each application can access and utilize appropriate data sources and maintain their own interpretations of the distributed knowledge base.

Finally, formal product evaluation should be conducted.  Ontology development products are available that will meet envisioned ontology development and maintenance requirements.  Further, these products include well-vetted, state-of-the-art reasoning algorithms that are regularly updated as technology evolves.  Thus, funded research in the area of tool development or improvement of standard ontology reasoning technologies is unlikely to yield tangible results.

On the other hand, there is significant potential in exploiting machine learning efforts focused on the Semantic Web.  Technologies that leverage Semantic Web content in abductive and inductive reasoning are not available in commercial systems, but will be critical components of future Semantic Web support for decision-aid systems. Although many machine learning techniques can be applied to Semantic Web content, primary consideration must be given to scalability.  Of the techniques that have been the subject of significant research, relational matrices and tensors are the most likely to yield results in the near term.  Additionally, Instance-Based Reasoning should be explored for the applications to which it is well-suited.  Other approaches from (Rettinger, et al., 12) might prove useful at some point, but are less likely to provide significant benefit in the near term.

Questions?

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