

A Survey of Semantic Reasoning Frameworks for Robotic Systems

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Abstract

Robots are increasingly transitioning from specialized, single-task machines to general-purpose systems that operate in diverse and dynamic environments. To address the challenges associated with operation in real-world domains, robots must effectively generalize knowledge, learn, and be transparent in their decision making. This survey examines *Semantic Reasoning* techniques for robotic systems, which enable robots to encode and use semantic knowledge, including concepts, facts, ideas, and beliefs about the world. Continually perceiving, understanding, and generalizing semantic knowledge allows a robot to identify the meaningful patterns shared between problems and environments, and therefore more effectively perform a wide range of real-world tasks. We identify the three common components that make up a computational *Semantic Reasoning Framework*: knowledge sources, computational frameworks, and world representations. We analyze the existing implementations and the key characteristics of these components, highlight the many interactions that occur between them, and examine their integration for solving robotic tasks related to five aspects of the world, including objects, spaces, agents, tasks, and actions. By analyzing the computational formulation and underlying mechanisms of existing methods, we provide a unified view of the wide range of semantic reasoning techniques and identify open areas for future research.

Keywords: Semantic Reasoning, Robotics, Knowledge Bases

1. Introduction

Robots are increasingly transitioning from specialized, single-task machines to general-purpose systems that operate in diverse and dynamic environments. To address the challenges associated with operation in real-world domains, robots must effectively generalize knowledge, learn, and be transparent in their decision making. This survey examines *Semantic Reasoning (SR)* techniques for robotic systems, which enable robots to encode and use semantic knowledge, including concepts, facts, ideas, and beliefs about the world. Just as recognizing linguistic semantics helps a human interpret language, continually perceiving, understanding, and generalizing semantic knowledge allows a robot to identify the meaningful patterns shared between problems and environments, and therefore more effectively perform a wide range of real-world tasks. SR leverages semantic knowledge as an *abstraction* to connect previous experience with new situations, as a *structured prior* to guide robots efficiently explore new environments and problem domains, and as a *common language* to exchange motives and rationales with humans.

In this survey, we identify the three common components (Figure 1) that make up a computational *Semantic Reasoning Framework (SRF)*:

- *knowledge sources* from which raw data is received and semantic knowledge can be extracted,
- *computational frameworks* that define mathematical relationships relating known concepts, and that are used to perform inference (e.g., Bayesian networks), and
- *world representations* that enable the robot to model its environment (objects, spaces, and agents) and behaviors (actions and tasks).

Though semantic reasoning has been applied to a wide range of robotics problems, to our knowledge there exists no established structure for concretely placing work within the broader field. Even approaches solving similar problems often make different assumptions, and their relations to the rest of the field remain largely unaddressed. A categorical structure therefore aids in comparative assessments among applications, as well as in identifying open areas for future research. In contributing our categorization of current approaches, we aim to lay the foundations for such a structure.

The remainder of this section formally discusses the space of SR problems and places this survey in the context of existing research. Section 2 presents the key design decisions for developing a semantic reasoning framework. Sections 3, 4, and 5 each cover one of the three core SRF components listed above. Section 6 follows by analyzing

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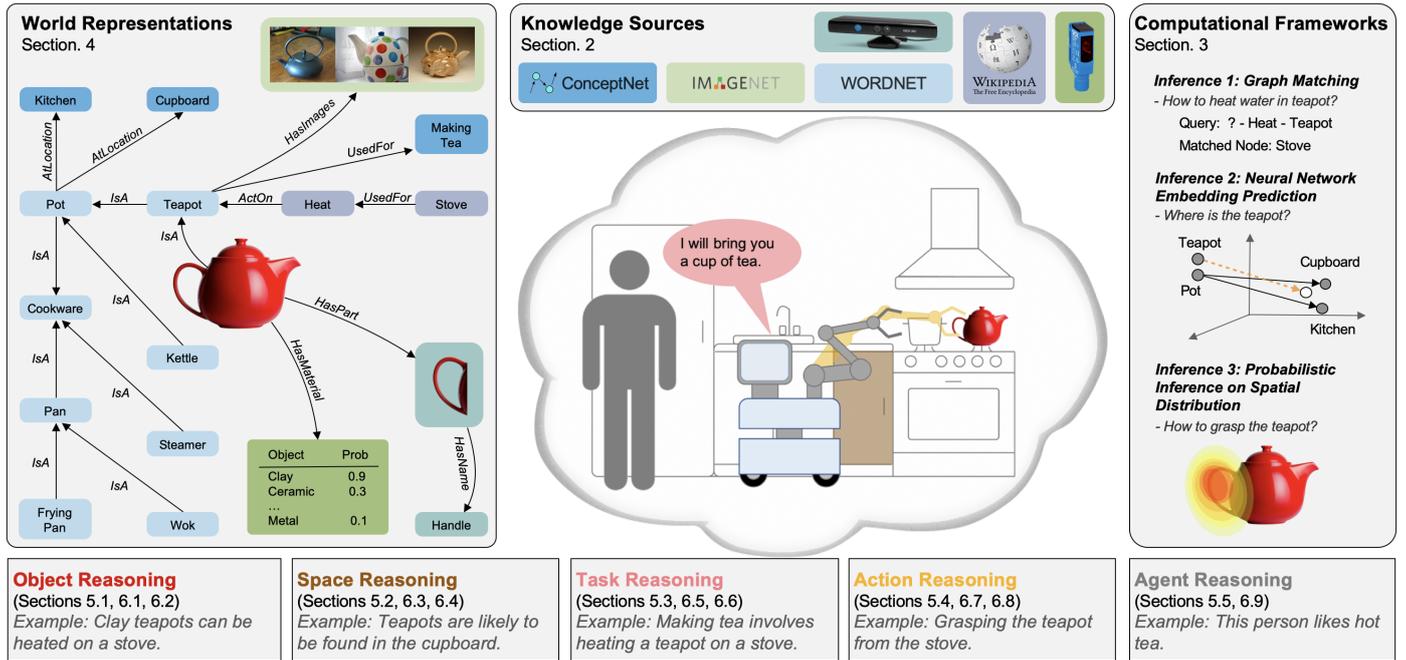


Figure 1: Three core components of semantic reasoning frameworks and five aspects of the world to which semantic reasoning can be applied.

SR applications enabled by the integration of SRF components. To conclude, we discuss open areas of research for future work in Section 7.

1.1. Problem Domain

The space of problems in semantic reasoning for robotics is large and growing. In this survey, we divide the problem domain into categories related to five entity types: *objects*, *spaces*, *agents*, *tasks*, and *actions*. Semantic reasoning about objects, spaces, and agents allows a robot to better understand its environment, while reasoning about tasks and actions aids a robot in achieving more context-aware and robust operation in complex environments. The division of the problem domain into these five categories, along with the three core components our survey is organized around, allows prior systems and problems to be fully categorized and compared.

Additionally, each of the five categories is inherently different in the modalities and underlying structures of its related data. For example, objects can be modeled as independent entities linked by common attributes and affordances. Tasks, on the other hand, require sequential or hierarchical structures to connect causes and effects. However, the distinctions between these problem categories do not prevent them from overlaps and interactions. In fact, one of the strengths of a multi-modal, multi-relational, and multi-domain robot SRF is to enable all concepts to interact and contribute to decision making.

1.2. Survey Scope and Context

This survey introduces the audience to the general subject matter of semantic reasoning within robotics, organizes the technical contributions in space of semantic reasoning for robotics, and gives insight into design decisions

along with the implications that should be taken into account for implementations on robots.

Within the published literature, reasoning about world knowledge has been studied in a variety of distinct areas, including knowledge representation and reasoning, commonsense reasoning, ontology-based reasoning, contextual reasoning, knowledge-enabled robotics, and cognition-enabled robotics. Some of these areas, such as cognition-enabled robotics, draw the analogy with the human mind, while others, such as ontology-based reasoning, focus on implementation specifics. Due to the different emphases of these areas, the approaches proposed within them intersect but do not completely overlap.

We refer to the general category of algorithms that reasons about world knowledge as *semantic reasoning*. Regarding our chosen organization, we note that many legitimate criteria could be used to subdivide SR research. Our review aims to analyze the fundamental mechanisms. We therefore categorize existing approaches according to the techniques required to develop a semantic reasoning framework in robotic applications. By analyzing the computational formulation and underlying mechanisms of existing methods, we aim to provide a united view of the wide range of techniques.

Interested readers may also find useful other surveys related to semantic reasoning for robotics. A broad overview of the cognitive skills required for robot manipulation in the human environment is presented in [1]. The work discusses methods for tackling different subproblems, such as learning affordances and human-robot collaboration. A more focused discussion of knowledge representations for service robotics is presented in [2], covering both comprehensive and specific knowledge representations. Another survey, [3], highlights algorithmic details for using

logic, probabilistic, and planning-based techniques to reason about robot-related concepts, such as time, space, and action plans. Additional reviews related to sub-areas of SRF research are highlighted in respective sections throughout the article. Our work differs from the above publications in that it seeks to present a broad perspective on semantic reasoning for robotics, highlighting the many dependencies, inter-relations, and interactions that occur between the core components of a SRF.

2. Design Choices

A developer faces many design choices when constructing a SRF. Some of these decisions may depend on the problem, while others are up to the preference of the developer. As we discuss in later sections, these design choices strongly influence how the reasoning task is structured and solved. In this section, we highlight several key decisions with a running example in which a robot is tasked to make a cup of tea.

As design choices exist in all three core components of a semantic reasoning framework – knowledge source, computational framework, and world representation – we organize this section accordingly. Despite the order presented here, the designing process is flexible and can vary case-by-case.

Knowledge Source: Developers must consider which types of knowledge are available to the robot, and how they can be represented. Knowledge sources used to seed semantic reasoning frameworks can be categorized as containing *class-level knowledge* that generalizes across an entire class of entities (e.g., “**cups are often found in cupboards**”) or *instance-level knowledge* that pertains to a specific instance of an entity (e.g., “**blueCup2 is on the table**”). Other factors that influence knowledge acquisition include data quality, recoded data modalities, and data representation structure.

Computational Framework: When selecting a computational framework to store semantic knowledge and support inference, a developer must consider five essential characteristics: the need to *model uncertainty*, *expressiveness*, *adaptability*, *explainability*, and *scalability*. The selection of a computational framework further depends on the requirements from other design choices and their associated effects, such as the scale of the problem and the noise level in the selected knowledge sources.

World Representation: A semantic reasoning framework must capture details about the world that are relevant to the reasoning capabilities and objectives of the system. Most existing framework model some subset of *objects*, *spaces*, *tasks*, *actions*, and *agents*. For example, for finding a teacup, we may model space semantics, user preferences, or even object affordances, to help determine likely object locations. Semantic knowledge is most often represented as symbols. Symbols are discrete and abstract,

therefore reduce the dimension of semantic space and facilitate generalization. Within our example, the action of a robot grasping and lifting a teacup can be abstractly encoded as *pickup cup*. Alternately, non-symbolic representations can be used, such as a point cloud representation of the object. When designing a semantic reasoning framework, whether to use symbols depends on many factors such as interpretability, the desired level of abstraction, and the complexity of the data.

Developers must carefully consider each of the core components for semantic reasoning when designing a complete system. Furthermore, interactions between choices made in each component must be compatible. The following sections describe existing implementations of each core component and discuss the synergy of these components to achieve semantic reasoning.

3. Knowledge Sources

Observations of the world through onboard sensors provide the most direct and easily accessible information to a robot. Prior to being incorporated into a semantic reasoning framework, raw sensor readings are typically abstracted into more compact representations [4, 5, 6]. However, learning all knowledge from scratch only through local observations is inefficient, particularly for robots that must perform multiple tasks or operate in multiple environments. Thus, it is useful for robots to have access to other, more general, sources of data that can be mined to supplement knowledge obtained from local observations.

In this survey, we define the most important characteristic of a data source as whether it contains class-level or instance-level knowledge. As discussed above, *class-level knowledge* facilitates generalization across domains and provides a prior for new situations, whereas *instance-level knowledge* allows concepts to be physically grounded and applied in robots’ interactions with the world. Ultimately, a robust semantic reasoning framework must have the ability to reason about both types of information, as well as to perform information exchange across these complementary and interdependent data types. In section, we discuss data sources – knowledge bases, datasets, and ontologies – of both types, as well as the interaction between them.

3.1. Class-Level Knowledge

Class-level knowledge is often symbolic and represents information that is asserted across domains, or that generalizes across an entire class of entities. Class-level knowledge is available in various sources, such as encyclopedias, formalized knowledge bases, and specialized semantic networks. Respectively, these sources provide different types of information, such as summaries of concepts from different disciplines, common-sense knowledge, and domain-specific knowledge pertaining to robots. Table 1 shows a representative list of class-level knowledge sources that

<i>AfNet</i> [7]	An ontology of affordances for over 250 commonly found object classes. AfNet describes unique geometric mappings for each affordance (e.g., <i>Contain-ability</i> is defined by high convexity). AfNet also includes definition of object classes in terms of affordances and topological structures of components. <i>Sample use cases:</i> [8, 9]
<i>ConceptNet</i> [10]	A large-scale knowledge graph encoding common-sense knowledge from various sources, including the Open Mind Common Sense (OMCS) project [11], WordNet [12], OpenCyc [13], DBPedia [14], and etc. Data is organized as a weighted graph structure, with edge weights used to convey the estimated reliability of the information. In total, ConceptNet stores over 8M nodes and 21M edges, with 1.5M nodes in English. Example edge relations particularly useful for robotic applications include <i>IsA</i> , <i>AtLocation</i> , <i>HasProperty</i> and <i>UsedFor</i> . Since information comes from various sources and are partially mined in an unsupervised way, inaccurate information is common within the dataset. <i>Sample use cases:</i> [15, 16, 17, 18]
<i>KnowRob Ontology</i> [15, 19, 20, 21]	A robot-centered ontology built on top of OpenCyc. The ontology includes 8K classes covering both a broad range of human knowledge and domain-specific knowledge for robots such as everyday tasks, household objects, and robot parts. The most important branches are the <i>TemporalThings</i> describing temporal concepts such as events and actions, <i>Spatialthings</i> describing spatial concepts such as places, objects, and body parts, and <i>MathematicalObjects</i> describing abstract concepts such as coordinate systems and linear algebra. <i>Sample use cases:</i> [15, 22, 23, 21]
<i>Open Robots Ontology (ORO)</i> [24]	An ontology that focuses on concepts useful for human-robot interaction. Similar to the KnowRob ontology, the Open Robots ontology inherits OpenCyc concepts such as <i>TemporalThings</i> and <i>Spatialthings</i> . The ontology includes additional agent related concepts like <i>desiredBy</i> , <i>focusedOn</i> , and <i>BodyPart</i> . This ontology is also hand coded and has minimum amount of noise. <i>Sample use cases:</i> [24, 25]
<i>OpenCyc</i> [13]	A publicly available subset of the Cyc ontology, which contains formalized common sense knowledge suitable for reasoning and problem-solving in a variety of domains. OpenCyc consists of over 40K terms and over 200K handcrafted commonsense axioms, including taxonomic information and semantic knowledge (i.e., additional facts and rules of thumb). <i>Sample use cases:</i> [26, 15, 24]
<i>WikiHow and EHow</i>	Public websites containing more than 1M step-by-step how-to guides, providing natural language instructions for various tasks, including thousands of household tasks for everyday activities. Because these databases are designed for human users, the instructions often assume prior domain knowledge or require common-sense reasoning to complete. <i>Sample use cases:</i> [27, 28, 29, 18]
<i>Wikipedia</i> [30]	A multilingual, web-based, free-content encyclopedia containing over 40M articles. For robotics applications, it can be used to mine general knowledge about classes of objects. <i>Sample use cases:</i> [26]
<i>WordNet</i> [12]	A large lexical database of English. Nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets are interlinked by means of semantic and lexical relations, such as <i>Hyponymy</i> and <i>Meronymy</i> . <i>Sample use cases:</i> [15, 26, 31, 18]
<i>YAGO</i> [32]	A large knowledge base automatically extracted from Wikipedia categories, Wikipedia infoboxes, WordNet, and GeoNames. YAGO combines the clean taxonomy of WordNet with the richness of the Wikipedia category system, assigning the entities to more than 350K classes. The knowledge base contains over 16M entities anchored in time and space, further connected to each other by 76 hand-defined relations. Due to the selective way information is mined, the data encoded in the dataset is relatively free of noise. <i>Sample use cases:</i> [33]

Table 1: Class-Level Knowledge Sources

		Noise Level	
		Low	High
Data Structure	Hierarchical	KnowRob, ORO, YAGO, OpenCyc, WordNet	
	Graph-Based	AfNet, KnowRob, ORO, YAGO, OpenCyc, WordNet	ConceptNet
	Ordered	WikiHow	
	Unstructured	Wikipedia	

Table 2: Grouping of Class-Level knowledge sources by Data Structure and Noise.

have been utilized in prior work to seed semantic reasoning frameworks with information. We provide a detailed description for each knowledge source, emphasizing its content and intended use. In addition to the types of information, each of the knowledge sources can further be characterized by two factors that affect the design of semantic reasoning frameworks, the *structure* and *noise level* of the data, as shown in Table 2.

3.1.1. Structure of Class-Level Knowledge

The structure of the data encoded in a knowledge base determines what relations can be stored and what inferences can be made from the data. Hierarchical data structures, such as WordNet and OpenCyc, encode super-/sub-class relations (e.g., *isA(apple, fruit)*), thereby facilitating generalization. Graph-based data structures, such as ConceptNet, encode the data in a flat, highly inter-connected representation (e.g., *hasProperty(apple, green)* and *atLocation(apple, table)*), which is more commonly used to represent highly varied or probabilistic data. Ordered data structures organize data according to certain metrics; for example, WikiHow data is ordered chronologically. Finally, unstructured data, such as that found in Wikipedia, contains statements and facts that must first be extracted or parsed before they can be applied to robotic systems. Many knowledge sources that aim to capture a wide variety of information have multiple structures; for example, ConceptNet has both class hierarchies and multi-relational information. The structure of the knowledge source is an important consideration in the design of semantic reasoning frameworks because the structure impacts how knowledge can be applied. For example, the step-by-step instructions in WikiHow naturally map to the sequential arrangement of actions in a task, whereas the hierarchical data encoded within WordNet can be used to better understand the objects the robot is dealing with in the world.

3.1.2. Imperfect Class-Level Knowledge

Class-level knowledge is imperfect as it often has noisy and missing information. The noise of the data determines how much the information can be trusted, and therefore influences the choice of world model and computational framework used within a semantic reasoning framework. Inaccurate information may result from knowledge sources being crowdsourced or automatically mined; many of the existing data sources have avoided this problem through hand-coding by experts (e.g., WordNet) or strong verification policies (e.g., Wikipedia). In general, the amount of noise present in the data affects the choice of computational framework to be used for semantic reasoning, with probabilistic methods being favored when the data is noisier. As another form of imperfect information, missing data is an issue that is harder to avoid and faced by any dataset to some degree. Despite containing millions of facts, large-scale knowledge bases still suffer from this problem [34]. When key concepts are missing from a knowledge source, no evidence is available to support important inferences. For example, when any one of the two concepts: *milk is perishable* and *perishable food is stored in refrigerators* is missing, the robot may be unable to deduce that milk should be stored in a refrigerator. Techniques for combining multiple knowledge sources [35] and explicitly inferring missing information [36] can help mitigate issues regarding incomplete knowledge.

3.2. Instance-Level Knowledge

Instance-level knowledge refers to knowledge that describes specific instances of a class of entities. To connect individual instances to abstract class-level concepts, instance-level knowledge typically includes a text-based label or description in addition to its raw data. Table 3 presents a list of instance-level knowledge sources that have been utilized in prior work. Unlike in the case of class-level knowledge, there is little structure to the data, with most sources consisting of sets of images or lists of entities. Noise remains a contributing factor, with some sources being more reliable than others. However, the most important characteristics of instance-level knowledge sources are the *modality of the data* and its *generalizability* (Table 4), which we discuss next.

3.2.1. Data Modalities of Instance-Level Knowledge

Instance-level knowledge must encode the specific distinguishing characteristics of individual entities, thus relying on richer data modalities, including image, depth, shape, trajectory, and pose information. By contrast, information in class-level knowledge sources is typically encoded in the form of text as commonalities of instances allow for the use of compact and abstract textual representations. For instance-level knowledge, the most commonly used modality is image data, supporting the common idiom “a picture is worth a thousand words”. Frequently, multiple modalities are used to capture the details of a

<i>50 Salad Dataset</i> [37]	A video dataset containing 50 video sequences of 25 people preparing two different salad recipes, which focus on complex interactions between hands, tools, and manipulable objects. Data includes synchronized RGB-D video and accelerometer data of all the kitchen tools. The periods before, during, and after each action being demonstrated are temporally marked and annotated as pre-, core-, post-phases for ground truth phases of each action in the recipe. <i>Sample use cases:</i> [38]
<i>AI2Thor</i> [39]	A virtual simulator that includes 30 highly realistic kitchens, bedrooms, bathrooms, and living rooms (120 rooms total) with actionable objects and physics. Simulated actions include <i>pick up</i> , <i>put down</i> , <i>open</i> , and <i>close</i> (e.g., <i>pick up tomato</i> , <i>open microwave</i>). The simulator provides class names and location information for all objects. <i>Sample use cases:</i> [40]
<i>Amazon, Ebay, etc.</i>	Consumer product websites that offer a wealth of knowledge specific to each type of product. The data is constantly monitored by manufacturers, customers, and sellers so mistakes are relatively infrequent. Previous works have scraped such websites to obtain item size, weight, description, and image information. <i>Sample use cases:</i> [15, 31]
<i>COCO</i> [41]	A large-scale object detection, segmentation, and captioning dataset. The dataset contains over 200K labeled images of approximately 1.5M object instances, labeled within 80 unique object categories (e.g., fork, dog) and 91 stuff categories (e.g., sky, grass). These objects and stuff are in context and include segmentations with roughly 5 captions per image. In addition to object and stuff, COCO also includes 250K instances of people with labeled keypoints that include the body, limbs, and facial features. <i>Sample use cases:</i> [42]
<i>COLD-Stockholm</i> [43]	A dataset consisting of sequences of image, laser range and odometry data for 47 areas belonging to 15 different semantic and functional categories and under several different illumination settings (e.g., cloudy vs sunny weather). <i>Sample use cases:</i> [44, 45]
<i>ImageNet</i> [46]	A large-scale image database that provides an average of over 600 images for the majority of synsets in WordNet (5K synsets and 3.2M images in total). The data is organized hierarchically into 12 subtrees by several types of WordNet relations (e.g., <i>IsA</i>), including topics such as <i>furniture</i> , <i>tool</i> , and <i>fruit</i> . Images of each concept are quality-controlled and human-annotated, resulting in average labeling precision of 99.7%. <i>Sample use cases:</i> [26, 31]
<i>Matterport3D</i> [47]	A dataset containing 10K aligned 3D panoramic views from 194K RGBD images of 90 building-scale scenes of real environments. All data is captured with Matterport’s Pro 3D Camera, and the 3D scenes are hand-labeled with instance-level object segmentation and classifications. <i>Sample use cases:</i> [48]
<i>ShapeNet</i> [49]	A large-scale dataset of 3D CAD models of common objects, organized based on the WordNet taxonomy and including semantic annotations such as real-world dimensions and material composition. The dataset contains 3M 3D shape models, including 220K categorized shape models into 1 of 3135 categories from WordNet synsets. <i>Sample use cases:</i> [50]
<i>Stanford 40 Action Dataset</i> [51]	A medium-scale image dataset labeled with bounding boxes of each person in the image, and the name the action being performed. The dataset contains 9K images, with 180-300 images per action class. <i>Sample use cases:</i> [31]
<i>SUNCG</i> [52]	A virtual simulator with 45K scenes, each scene containing multiple rooms that include bedrooms, kitchens, bathrooms, living rooms, offices, etc. Each room contains objects rendered using meshes which are all semantically labelled, positioned and sized with real world dimensions, and provide full segmentations. <i>Sample use cases:</i> [53]
<i>TACoS Cooking Dataset</i> [54]	A video dataset containing crowdsourced descriptions of cooking activities. Each video is annotated with descriptions at three levels of detail: (1) a detailed description with at most 15 sentences, (2) a short description with 3 to 5 sentences, and (3) a single sentence. The dataset includes 185 videos, and approximately 20 description triplets for each video. <i>Sample use cases:</i> [31]
<i>Visual Genome</i> [55]	A large-scale image dataset consisting of 108K images of 75K unique objects all of which are part of the WordNet taxonomy. Each image is structured as a graph where nodes are concepts (e.g., <i>dog</i> , <i>woman</i> , <i>helping</i>) and edges have predicates specify relations (e.g., <i>in</i> , <i>on</i>). Additionally, the graph also includes object attributes about abstract concepts (e.g., <i>shirt is pink</i> , <i>girl is young</i>) and region descriptions (e.g., <i>the woman teaching the little girl to cook</i>). <i>Sample use cases:</i> [42]
<i>SG14400 Dataset</i> [56]	A grasping dataset consisting of 14K semantic grasps for 44 objects and 7 manipulation tasks. Each grasp is labeled as appropriate or not based on the context of the grasp, which includes the corresponding task, object class, object state, object material, and affordances of object parts. <i>Sample use cases:</i> [56]

Table 3: Instance-Level Knowledge Sources

Domain Generalization			
	Single	Multiple	
Data Modalities	Text, RGB	Amazon/Ebay, ImageNet, TACoS, Stanford 40 Action	AI2Thor, COCO, SUNCG, Visual Genome
	Text, RGBD, & more	COLD-Stockholm, 50 Salad, ShapeNet, SG14400	Matterport3D

Table 4: Grouping of Instance-Level knowledge sources by Data Modality and Domain Generalization

scene or task. For example, the 50 Salad Dataset records users making salads with synchronized RGBD videos and accelerometer data of multiple kitchen tools. Reasoning about multimodal information is nontrivial because making inference across different modalities is challenging. However, multimodal instance-level knowledge is essential to achieve precise grounding of abstract concepts, as well as for robust task execution.

3.2.2. Generalizability of Instance-Level Knowledge

The second critical factor for instance-level data is its degree of generalizability across domains. In Table 4, we distinguish datasets that are designed for a single application (e.g., classification) or domain (e.g., kitchens), v.s. multiple applications/domains. Examples of data sources designed to address a single application/domain include the TACoS Cooking Dataset, which is only concerned with cooking, and COLD-Stockholm, which applies only to a specific set of indoor office environments. Multipurpose data sources, such as COCO and AI2Thor, contain annotations useful to multiple types of applications (e.g., full object segmentations with labels for object detection and classification) or multiple domains (e.g., images from kitchens, bathrooms, and bedrooms).

3.3. Integrating Class and Instance Knowledge

It is critical to highlight the complementary nature of class and instance knowledge. Class-level knowledge captures high level, generalizable patterns in the data, while instance-level knowledge enables those abstract concepts to be grounded to a specific environment, as well as captures the statistical characteristics of the data. When either type of knowledge is used alone in a semantic reasoning framework, undesirable simplifying assumptions often have to be made. When class-level knowledge is used alone, the process to ground abstract concepts, known as the symbol grounding problem [57, 58], is usually simplified. For example, grounding has been simplified by manually defining mapping functions [59], using visual cues such as fiducial markers [25], or representing objects as blocks

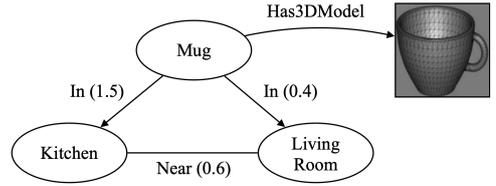


Figure 2: An example semantic graph that includes multimodal data, different types of relations, and local confidence values defined for edges (shown as values in parentheses). The confidence scale is not bounded.

with different colors and shapes [60]. When instance-level knowledge is used alone, general rules in the domain are induced solely from raw data and no prior knowledge is incorporated [61, 62, 56]. Ultimately, a robust semantic reasoning framework must have the ability to reason about both types of information.

At the data level, the synergy between class and instance knowledge can be facilitated through several instance-level knowledge sources, such as ImageNet, ShapeNet, and Visual Genome, which integrate both class and instance knowledge by organizing instances according to the WordNet hierarchy. At the system level, multiple techniques have been developed for integrating instance and class knowledge [63, 64], as will be examined more closely in Section 6.4.

4. Computational Frameworks

Given data acquired from one or more of the data sources described in the previous section, we now discuss computational frameworks – the organizational structures that enable robots to reason about semantics in the data. A wide range of computational methods has been applied across the literature for knowledge representation and reasoning, with no single approach applicable across all scenarios. Each representation offers different mathematical structures, assumptions, and types of inference. In turn, the combination of these factors leads to different performance characteristics with respect to *modeling uncertainty*, *expressiveness*, *adaptability*, *explainability*, and *scalability*. Each of these characteristics varies in its importance for different applications and use cases. For example, the scalability requirements of a computational framework for a single robot reasoning about semantic grasping [65, 56] are different from a framework designed as a shared cloud-based knowledge repository for many robots across different environments [26, 20].

In Sections 4.1-4.7 we present a representative list of computational frameworks that have been used in literature. We describe the different data and mathematical structures upon which these frameworks are built, how their assumptions lead to various tradeoffs and use cases in the context of semantic reasoning. Finally, we compare

these frameworks in terms of the high-level characteristics that are essential for SRFs in Section 4.8.

4.1. Semantic Graphs

A semantic graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is a set of vertices \mathcal{V} connected by directed and/or undirected edges \mathcal{E} , represented by triples $\{(v_i, e_j, v_k) | v_i, v_j \in \mathcal{V} \wedge e_j \in \mathcal{E}\}$. In the context of SRF, vertices \mathcal{V} store one or multiple types of entity information (e.g., text, images, sounds, trajectories, and algorithm parameters) and each edge $e \in \mathcal{E}$ has a predefined edge type that represents the relation between the connected entities. Optional confidence values can also be associated with vertices \mathcal{V} and edges \mathcal{E} in order to represent the certainty of the encoded knowledge. Figure 2 shows an example semantic graph.

Tradeoffs in Context of SRF: A semantic graph is highly adaptable and expandable. New observations can be easily added to a semantic graph in the form of new vertices or edges. Repeated (or lack of) observations of various phenomena can be modeled by increasing (decreasing) confidence values associated with the relevant entities. Vertices can also be merged or split, as in [26], when new knowledge is acquired (e.g., splitting existing entity *Cup* into *Mug* and *Cup*). However, a significant limitation of the graph representation is that it does not support rigorous probabilistic inferences. Furthermore, the belief of an edge or node is not well established, making it difficult to assess the relative certainty of various types of information. An approach uses the Katz centrality to assign an ‘importance’ score to nodes corresponding to particular objects or motions [66], while another incorporates beliefs from disparate knowledge sources or algorithms [26].

Uses and Applications: Reasoning over semantic graphs can be performed at the node, local subgraph, or global graph levels. At the node level, node similarity can be computed by comparing the locations of nodes in the semantic graph. For example, Wu-Palmer similarity [67] is used on WordNet [12] data to generalize manipulation sequences [68] and organizational preferences [69] between similar objects. At the subgraph level, information retrieval on large-scale semantic graphs is performed by matching a query template with the graph [26, 66, 70]. Queries typically take the form (u, e, v) , in which the variables u and v are nodes in the semantic graph and the variable e is a directed edge from u to v . For example, the query $(u, \text{HasAffordance}, \text{scoop})$ can be used to retrieve a list of objects that provide the scooping affordance, and the query $(\text{spoon}, e, \text{kitchen})$ can be used to identify the relationship between a spoon and a kitchen. More complex reasoning can be achieved by chaining multiple queries together, such as the above examples that can be used to identify that going to the kitchen may allow the robot to find an object for scooping [26]. At the global level, graph matching assesses similarity between different models. For example, graph matching over topological models of human spaces and objects provides a solution for place

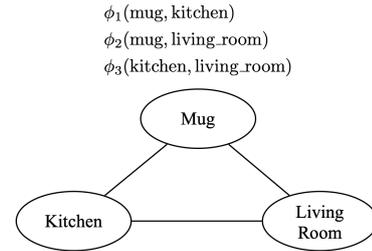


Figure 3: An example Markov network with undirected edges between random variables. The joint distribution can be factorized into clique potentials, denoted by ϕ 's.

recognition and place classification [61], and graph matching over object models of constituent parts enables object recognition [71]. A different approach is used in [72], in which a score over an entire object graph is computed based on object properties and neighboring objects. The importance of different features is learned from demonstrations in order to encode trajectory preference.

4.2. Markov Networks

A Markov network (MN), or Markov Random Field, is a probabilistic graphical model represented by the pair $(\mathcal{H}, \mathcal{P})$. The joint probability distribution \mathcal{P} factorizes over the undirected graph \mathcal{H} , whose nodes represent a set of propositional random variables and edges represent the correlations between random variables, as illustrated in Figure 3. A commonly used type of Markov network is a Conditional Random Field (CRF), in which random variables are divided into a set of target variables Y and a set of observed variables X . Rather than encoding the joint distribution $P(Y, X)$, a CRF represents the conditional distribution $P(Y|X)$.

Tradeoffs in Context of SRF: As a probabilistic model, a MN provides a computational framework for representing a complete probability distribution - the probability of every possible event as defined by the values of all the random variables. Additionally, the independence assertions encoded in the graphical structure allow a distribution to be compactly represented as products of factors, or clique potentials. Since the factorization is over cliques, which are fully connected subsets of the random variables in the graph (e.g., pairs of variables), a Markov network is especially suitable for modeling symmetric or associative relations between variables. When relations between certain variables are hard to elicit due to overlapping information or implicit correlations, a CRF can be used to avoid representing a probabilistic model over these variables. However, the flexibility in defining MNs and CRFs results in a lack of clear semantics, which has several disadvantages. First, each clique contributing to the overall inference result does not help to reveal which random variables affect the result the most. Second, the use of cliques to define a joint distribution makes parameterizing the model by hand more difficult. The second limitation

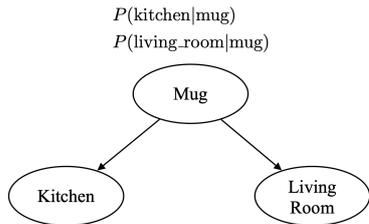


Figure 4: An example Bayesian network with directed edges between random variables. The joint distribution can be factorized into conditional probabilities, denoted by P 's.

leads to the convention of learning clique potentials from training examples, which requires apriori data to converge to reasonable parameters [73, 74, 75].

Uses and Applications: Markov networks have been used to model spatial and contextual relations between objects. Jointly reasoning about these relations helps to improve the robustness of object classification algorithms over those that are based solely on visual features. For example, Relational Markov Networks, an extension of CRFs, have been used to represent the spatial relations between walls and doors in 2D laser scans [74]. Modeling the spatial relations allows this approach to infer labels for line segments that are not confidently classified from the 2D map features alone. Similarly in [75], CRFs are used to exploit contextual and spatial relations between objects in a scene to improve object classification.

4.3. Bayesian Networks

A Bayesian network (BN) is a probabilistic graphical model represented by the pair $(\mathcal{G}, \mathcal{P})$, where the probability distribution \mathcal{P} factorizes over a directed acyclic graph \mathcal{G} . The nodes in \mathcal{G} represent propositional random variables, and edges represent informational or casual dependencies between the variables. Figure 4 shows an example of a BN.

Tradeoffs in Context of SRF: The main advantages of a Bayesian network as a computational framework are its precise probabilistic interpretation and its adaptability. The Markov assumption and directed-acyclic constraints that define the scope of the network, allow for simple interpretation of conditionally independent variables and causal relations between variables. The structure of BNs allows for direct inference over variables and learning of parameters/structures via efficient approximations, such as importance sampling or Gibbs sampling. Factorizing the full joint distribution over \mathcal{G} via conditional probability tables (or distributions) also makes determining the influences of inference results more accessible than MNs. However, managing large-scale conditional probability tables leads to drawbacks in terms of scalability. While the richness of the resulting probabilistic representation is useful to robots reasoning about specific problems, inference and learning in BNs is often intractable for real-world problem sizes involving many random variables and edges in a

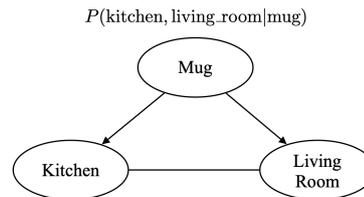


Figure 5: An example partially directed acyclic graph with both directed and undirected edges between random variables. The edge between the two nodes in the same chain component is undirected, while the edges between two nodes in different chain components are directed. The joint distribution can be factorized into conditional probabilities of chain components given their respective parents.

dense network. Thus, due to limited scalability, BNs are rarely used in complex robot environments, but instead are commonly utilized as a foundation for more complex computational frameworks.

Uses and Applications: BNs have been used for semantic grasping by encoding relations between grasps, object features, and task constraints [65]. In this context, Gaussian Mixture Models are used to discretize continuous data for BNs in order to learn the network structures for factors such as object convexity and grasp location. BNs have also been used to generate situated probabilistic models of the environment, enabling the robot to predict likely locations for previously unseen objects [16]. In [76], BNs are extended to incorporate context and temporal relations into action selection using Dynamic Bayesian Networks (DBNs), a representation that presents a compromise between state and space complexity.

4.4. Partially Directed Acyclic Graphs

A partially directed acyclic graph (PDAG), or Chain Graph, is a graphical model represented by the pair $(\mathcal{I}, \mathcal{P})$, where the probability distribution \mathcal{P} factorizes over the hybrid graph \mathcal{I} , which consists of both directed and undirected edges that represent influences between the propositional random variables encoded in the nodes of \mathcal{I} [73]. Figure 5 shows an example PDAG.

Tradeoffs in Context of SRF: PDAGs, which can be thought of as a combination of MNs and BNs, allow for modeling causal as well as associative relationships. However, similar to MNs, the PDAG joint distributions are defined over chain components of cliques in the moralized graph of \mathcal{I} instead of individual conditional probabilities, as in BNs. Factorization over cliques leads to confounding inference results for reasons similar to that of MNs, namely it is difficult to distinguish the variables that contribute to an inference result. Additionally, PDAGs lack clear semantics for model parameters, which makes model parameters difficult to elicit from experts. As a result, the convention, much like for MNs, is to estimate model parameters from training data [44].

Uses and Applications: PDAGs have been used to perform causal and associative reasoning of spatial common-

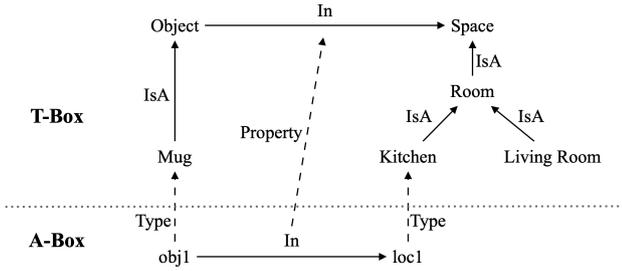


Figure 6: A graphical representation of an example description logic ontology. The T-Box contains axioms defining relations between class-level concepts. The A-Box contains a single fact, which is governed by the constraints defined in T-Box.

sense knowledge in order to build spatial models of indoor environments. In [44], each room instance is connected to one another by undirected edges according to a topological map. The potentials on undirected edges are used to describe typical connectivity between room categories. Within each room, the variable representing the room’s category is linked via directed edges to the room shape, size, appearance, and objects in it, capturing the causal relations between these attributes and the room type. Similarly in [77], undirected edges are used to model connectivity; however in this case, they connect nodes representing waypoints in the map. For each waypoint, causal relations between viewing angles, expected objects in a view, and observations from a robot are modeled by directed edges.

4.5. Description Logics

Description Logics (DLs) are a family of formal knowledge representation languages that are widely used in ontological modeling. DLs represent an application domain using the pair $(\mathcal{T}, \mathcal{A})$, where \mathcal{T} , the T-Box, contains terminological axioms describing relationships between concepts, and \mathcal{A} , the A-Box, contains assertional axioms capturing knowledge about named individuals, i.e., the concepts to which they belong and how they are related to each other [78]. Figure 6 shows an example of a DL ontology.

Tradeoffs in Context of SRF: As a logic language, DLs provide a precise specification of the meaning of ontologies. This precise specification allows DL ontologies to be exchanged without ambiguity of their meaning, and also makes it possible to use logical deduction to infer additional information from the facts stated explicitly in an ontology. As decidable fragments of first-order logic, many DLs also have effective methods to always derive the correct answer. Due to these benefits, DLs are widely used in ontological modeling, and they provide the formalism for the OWL Web Ontology Language, which is standardized by the World Wide Web Consortium (W3C). As a result of the wide use in the Semantic Web community, there are many mature libraries providing tools to manipulate, reason, and query DL ontologies. However, DL cannot be used to reason about uncertainty because DL offers only deterministic reasoning about logic statements.

$$\begin{aligned} \forall x \forall y \text{ IsMug}(x) \wedge \text{IsKitchen}(y) &\Rightarrow \text{AtLocation}(x, y) & 1.5 \\ \forall x \forall y \text{ IsMug}(x) \wedge \text{IsLivingRoom}(y) &\Rightarrow \text{AtLocation}(x, y) & 0.7 \\ \forall x \forall y \text{ IsKitchen}(x) \wedge \text{IsLivingRoom}(y) &\Rightarrow \text{Near}(x, y) & 0.4 \end{aligned}$$

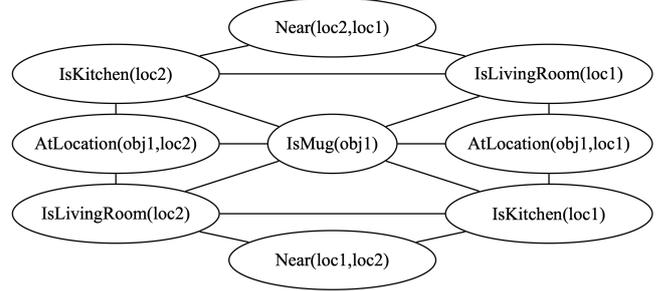


Figure 7: An example Markov logic network and its grounded Markov network. Each formula defining the Markov logic network has an associated weight that reflects how strong a constraint it is. The Markov network has 3 grounded atom: obj1 , loc1 , and loc2 .

The lack of uncertainty modeling makes DL brittle when incorporating new knowledge in situations where logical contradictions arise [24]. However, ignoring uncertainty allows DL-based semantic reasoning frameworks to scale to a greater number of instances, type, and predicates [19]. Therefore, DLs are typically used for providing robots with large-scale knowledge bases containing concepts from various domains.

Uses and Applications: Large-scale DLs have been used to encode contexts, spaces, objects, actions, and features, along with axioms that express inter- and intra-group relations [79, 80, 81]. Custom DLs have also been used to formalize knowledge in specific domains, including industrial robotics [82], swarm robotics [83], and object manipulation [84]. Instead of designing the whole ontology from scratch, the KnowRob ontology is constructed by combining a manually designed ontology with the public OpenCyc ontology, therefore bootstrapping available declarative knowledge with general knowledge that could be leveraged during tasks [59]. The ORO ontology is created in a similar fashion by integrating with the OpenCyc ontology [24]. However, the ORO ontology focuses on human-robot interaction, therefore adding new concepts designed to facilitate interaction.

4.6. First-order Probabilistic Models

First-order Probabilistic Models are formalisms widely used in Statistical Relational Learning (SRL) that combine graphical models with first order relational representations [85], such as Markov Logic Networks (MLNs) [86] and Bayesian Logic Networks (BLNs) [87]. A first-order probabilistic model is typically represented as a collection of first-order logic formulas with confidence scores, as illustrated in Figure 7. More details about SRL can be found in [88] and [89].

Tradeoffs in Context of SRF: The most obvious benefit that results from combining probabilistic reasoning with first-order logic is that relational inferences can be used to

model uncertainty, becoming more flexible to noisy or contradictory evidence. Another advantage of this representation is that its world definitions are more compact because variables act as placeholders for entities, which allows them to make relational rules interchangeable among entities. In contrast, languages based on propositional logic or propositional probabilistic graphical models (e.g., MNs, BNs, and PDAGs) assume each symbol represents a concrete fact or entity. However, while first-order probabilistic models allow the compact writing of rules, their representation rapidly expands when performing probabilistic inference or learning because first-order probabilistic models still need to be grounded to their constituent probabilistic graphical models for computations. For example, a MLN needs to be grounded to a MN, which contains every possible assignment to the variables in the MLN, as illustrated in Figure 7. The scalability of inference and learning can be partially addressed by leveraging structures in the models. For example, domain-lifted inference algorithms exploit symmetries within Markov networks by identifying symmetries directly from first-order structures without grounding MLNs. However, symmetries are difficult to find and can be easily destroyed by evidence. Due to this scalability issue, applications of first-order probabilistic models in large-scale SRFs remain limited.

Uses and Applications: First-order probabilistic models have been used to construct multi-relational probabilistic knowledge bases. In [31], a MLN is used to store knowledge between object properties and affordances by using probabilistic relations such as *isA*, *hasAffordance*, and *hasVisualAttribute*. The MLN allows for a variety of queries, for example, predicting affordance based on properties extracted from object images and inferring typical features of objects with a specific affordance. Similarly in [90], a MLN encoding relations between object properties (e.g., shape, size, and logo) is used to fuse information from different perception routines for collective classification. In [91], a probabilistic programming language, ProbLog, is used to construct a multi-objects affordance model. The probabilistic logical rules can deal with uncertainty in perception and action outcomes. Through the use of placeholder variables in place of individual objects, the relational representation is able to generalize the affordance model learned from 2 objects to any arbitrary numbers of objects. In [92], Distributional Clauses, which is a first-order probabilistic model that supports modeling continuous probability distributions, enables occluded object search by encoding different spatial relations between objects such as co-occurrence and stacking in addition to affordance related relations. A dynamic version of Distributional Clauses is used for object tracking during human activities [93]. The physics laws and common sense knowledge (e.g., if an object is on top of another object, it cannot fall down) that are encoded in probabilistic and continuous first-order rules help robots robustly track objects even with occlusion.

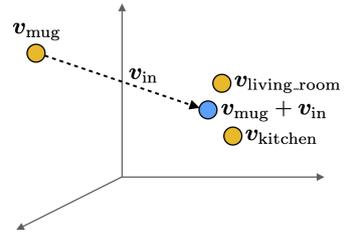


Figure 8: An example neural network embedding. Entities and relations are represented as vectors in a multi-dimensional space. As the embedding aims to store the knowledge that a mug can appear in a kitchen or a living room, the values of both rooms should be close to the value of the *Mug* plus a vector that represents the *In* relation.

4.7. Neural Networks

A Neural Network (NN) is a parameterized function approximator \mathcal{F} that defines a mapping from input data \mathcal{X} to output results \mathcal{Y} (i.e. $\mathcal{Y} = \mathcal{F}(\mathcal{X}, \Theta)$, where Θ represents parameters of \mathcal{F}) [94]. The NNs used in semantic reasoning frameworks usually have two distinctive features. First, these NNs often make use of data containing semantic features, such as natural language descriptions of manipulation actions [62], or subgraphs from a knowledge graph [95]. Second, the objective of these NNs is to learn not only the mapping from input to output, but also the structure and semantic relations that underlie the data [56]. Embedding methods [96], in particular, represent a family of NNs that focus on encoding the structure of data by projecting input data into vector spaces in which spatial relations reflect the semantic relations of the input data.

Tradeoffs in Context of SRF: NNs are a flexible computational framework capable of learning highly complex relations from data that are often difficult to encode manually. NNs can also take data of almost any form (e.g., task label, natural language instruction, image, point cloud, grasp pose, and trajectory), thereby allowing multimodal data to be combined and reasoned about collectively in a principled way. However, the adaptability of NNs comes at a cost to semantic reasoning for robotic applications. First, training NNs requires large amounts of data, which is often challenging to obtain, particularly in physical environments. Second, NNs are not as transparent as logic or probabilistic models, therefore reducing the explainability of the decision-making process. Additionally because the learned semantics within the NNs are challenging to extract, a NN trained in one domain may not transfer well to another (e.g., simulation vs real-world). While progress continues to be made on this front in the deep learning community, it is still a serious concern for practical applications involving physical robots operating autonomously in real-world environments.

Uses and Applications: Neural networks have been used in a number of semantic reasoning frameworks to learn mappings from semantic features to desired robot behaviors. In [56], contextual information, such as object

affordances, materials, and intended manipulation tasks, represented in the form of text labels, are used as inputs to a NN to predict the compatibility of grasps with given tasks. In [62], neural networks are applied to multimodal data, including trajectories, point clouds, and language inputs, to transfer manipulation trajectories to previously unseen objects. Graph Neural Networks, which model dependencies between nodes in a graph and thus can be used to leverage knowledge graphs, have been applied to the problems of recognition of novel objects [42] and visual semantic navigation in novel environments [64]. As noted above, embedding methods also have been widely used in semantic reasoning frameworks to capture relations within the data. In [97], knowledge graph embeddings are used to capture relations between household objects and their attributes, enabling the robot to predict locations of objects, likely materials for objects, and affordances of objects. Word embeddings capturing similar word meanings are used in [98] and [99] to perform multi-modal language grounding and learn common sense navigational knowledge, respectively. The work of [100] explores a multi-modal embedding that mapped trajectory, language instruction, and object point cloud data to the same embedding space.

4.8. Summary of Computational Frameworks

Robots operating in complex human environments, such as homes, offices, and hospitals, require the ability to model uncertainty in the environment, reason about the world at varying levels of abstraction, adapt to changes in schedule, task requirements or object placement, be transparent in their reasoning and choices, and scale to multiple domains. Each of these challenges can be aided by semantic reasoning. Therefore in the context of SRF, we associate these challenges to five crucial characteristics of computational frameworks:

1. *Modeling uncertainty* - ability to model the inherent uncertainty and variability of the real world;
2. *Expressiveness* - ability to represent reasoning patterns at different levels of complexity, such as propositional, first-order, second-order, and etc;
3. *Adaptability* - ability to efficiently adapt the knowledge representation in response to new observations;
4. *Explainability* - ability to communicate information in a clear way and the transparency of the decision making process;
5. *Scalability* - ability to effectively model complex, real-world environments consisting of hundreds of objects.

Existing computational frameworks have succeeded in meeting one or more of these challenges, though no framework to date has excelled in all five areas.

Modeling uncertainty: Probabilistic models, including MNs, BNs, PDAGs, and first-order probabilistic models, are inherently effective at modeling uncertainty. When

using other frameworks in situations with nondeterministic information, probabilistic variants of these frameworks, such as Bayesian Neural Networks [101] and Probabilistic Description Logics [102], can be selected.

Expressiveness: First-order frameworks such as DLs and first-order probabilistic models are more expressive than probabilistic graphical models (e.g., MNs, BNs, and PDAGs), which use propositional random variables. Recent work on NNs has also shown to be able to approximate first-order logic, therefore producing more expressive reasoning patterns [103, 104, 105].

Adaptability: Incorporating new information into probabilistic models is hard as it often entails learning new parameters or structures. In contrast, new knowledge can be more easily added as new assertions in DLs and as new nodes or edges in semantic graphs. Since NNs are typically capable of generalizing learned models to new data, new information can also be reasoned without retraining.

Explainability: Symbolic frameworks, including all frameworks previously introduced except NNs, are typically easier to interpret than non-symbolic approaches. Within symbolic approaches, reasoning in a DL or a semantic graph often is involved with a subset of contained information while reasoning in a probabilistic model depends on all random variables in the model. The modular and local reasoning mechanism, as a result, provides more interpretability.

Scalability: NNs, semantic graphs, and DLs have all been used with large-scale data [97, 26, 106]. In contrast, probabilistic models are less efficient at handling a large amount of information. As for first-order probabilistic models specifically, scalable inference and learning are still open research problems.

When using existing computational frameworks for semantic reasoning, trade-offs between the five characteristics mentioned will need to be considered according to the reasoning problem domain, available knowledge, and formal verification requirements. However, a direction for future work is to continue to push toward a framework that excels in all five areas.

5. Building World Representations from Data

In this section, we turn our attention to constructing world representations that encode various types of semantic knowledge. Specifically, we consider world representations that model five semantically meaningful entity types: *objects*, *spaces*, *agents*, *tasks*, and *actions*. These five categories cover different aspects of the world a robot interacts with, and each is also inherently different in the modality and underlying structure of its data. By analyzing these five categories of representations, we aim to provide developers the useful languages to build up multi-modal, multi-relational, and multi-domain semantic reasoning frameworks that can accurately model and reason about the world.

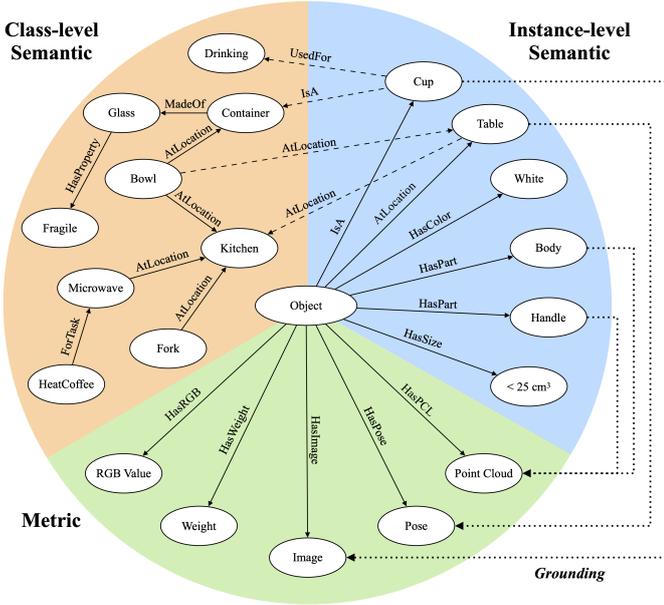


Figure 9: Structure of object representations

5.1. Representing Objects

In this survey, objects refer to the physical entities that robots can perceive and interact with. Representations of objects model object properties and the relations between these properties. Leveraging object representations helps create robot behaviors that are intelligent (e.g., manipulation based on object functionality [107, 56]) and robust (e.g., recovery of task failure with object substitution [108]). In addition to storing information associated with objects, object representations also serve as a foundation for representations of other entity types. For example, modeling the function of a space depends on modeling its contained objects, and modeling the belief state of an agent often requires modeling the agent’s perception and understanding of objects.

In discussing the structure of object representations, we refer to three types of encoded information: metric, instance-level semantic, and class-level semantic, as illustrated in Figure 9:

- *Metric*: Metric representations of objects contain information unique to each object instance (e.g., image, point cloud, and pose). As these representations store high-fidelity information, they are often numerical and continuous. Aggregating these low-level data for each instance or across instances allows robots to build features that are used to recognize objects and properties, enabling grounding [58]. Meaningful semantics and suitable abstraction can also be automatically discovered from the metric data [100]. Maintaining the raw data, in addition, helps avoid the combinatorial explosion that would arise from storing all possible qualitative semantic representations (e.g., pair-wise relations between objects) [106].

- *Instance-level Semantic*: Instance-level semantic representations include abstract concepts about each object instance, which are grounded in a robot’s observations. For example, in Figure 9, the object is classified as a cup from its image. Since these representations are abstract, they tend to be qualitative and discrete. The compact form of instance-level semantic representations facilitates efficient semantic reasoning but they also maintain enough information that can distinguish between object instances and guide precise robot behaviors [56, 65].
- *Class-level Semantic*: Class-level semantic representations encode abstract knowledge that generalizes across an entire class of objects. For example, a cup is a container and can be used for drinking. Similar to instance-level semantic representations, the class-level representations often are symbolic. Though class knowledge cannot be readily perceived, it encodes many useful priors that can be extracted from semantic knowledge sources or manually created by experts [59, 25, 109].

Together these three types of object representations allow a robot to ground perceivable symbols, learn class attributes from instances, and relate objects to other abstract semantic concepts. These three types of information are observed in many complete semantic reasoning frameworks such as KnowRob [59], RoboBrain [26], ORO [25], and OUR-K [81]. To provide concrete examples, we now discuss how a variety of object properties and relations have been modeled in representations of each type.

Metric representations have been used to store complete and accurate information about object appearance, shape, location, and use. Specifically, 2D images [26] and 3D CAD models, meshes, and point clouds [59, 110, 26, 62, 100] encode raw visual and geometric information. Intermediate representations such as image features [79, 26], primitive shape models [59, 79], and object dimensions [92] store processed 2D and 3D information. Objects are also represented by parts extracted from methods like curvature-based segmentation [59, 107, 111] and Reeb-graph segmentation [71]. Apart from visual and geometric information, object poses are also maintained in the numeric form, which enables both metric reasoning [75, 93, 112, 61] and extractions of qualitative spatial relations [106, 59]. Object functions are often described in the language of affordance, which is introduced by Gibson as the properties of an object that determine possible actions to perform on it [113]. At the metric level, the spatio-temporal representation of affordance defines both the 3D location of interaction on an object, and the motion trajectory for manipulating it [112, 114]. Articulation models are also included in prior work to specify manipulation trajectories for objects such as doors and drawers [110, 111].

Instance-level semantic representations have been used to encode a variety of abstract information about individual objects. Class labels represent object categories,

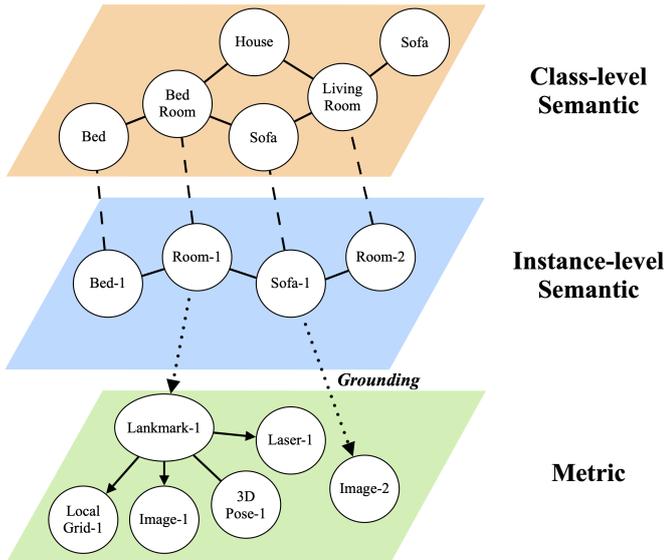


Figure 10: Structure of space representations

which can be predicted from end-to-end image classifiers or grounded in low-level and semantic features [79, 75, 71, 115, 116]. Shape labels extracted from metric data are used to infer affordance [91, 92, 7] and guide grasping [65]. Affordance labels are also directly extracted from visual data [56, 7]. Another widely used representation is object part labels, the definitions of which are based on common object parts (e.g., door knob) [106, 107, 111, 79], affordances (e.g., pourable and containable) [56, 7, 114], and other heuristics (e.g., top and bottom) [115]. Object states [115, 56], materials [56, 7], and other more open-ended language descriptions [22, 98] have also been used to characterize object instances.

Class-level semantic representations have been used to store general knowledge about object classes. External knowledge graphs and ontologies, such as WordNet, ConceptNet, and Cyc, are connected to objects through class labels [109, 97, 16, 99, 64, 98]. To deal with partial and inaccurate information from these knowledge sources, some methods have used these priors as high-level constraints or probabilistic statements instead of ground-truths [106, 59, 31, 42]. General spatial knowledge is also expressed in terms of object classes (e.g., a kitchen typically has a sink and a microwave), which we will discuss in more detail in Section 5.2. Prior work has also modeled the relations between different types of class-level knowledge and used them to infer missing or unknown information such as affordances and possible object locations [97, 16, 117, 99]. A unique representation at the class level is word senses, which eliminate the ambiguities between objects with the same name but different meanings (e.g., a bowl as a container or as a stadium) [118, 16, 18].

5.2. Representing Spaces

Spaces in this survey refer to continuous expanses with specific volumes defined by their boundaries. We distin-

guish the concepts of *map* and *semantic spatial model* in the context of semantic reasoning. The primary purpose of a map, as used in the literature [119, 120, 121], is for use in navigation and localization. We introduce the concept of *semantic spatial models*, which are also designed to represent spaces, but with the purpose of facilitating task execution. For example, semantic spatial models often encode semantic object types and attributes in addition to space occupancy or room topology, which enables task planning [109, 45]. By using semantic spatial models, queries can be made to reason about not only spaces but also other objects, agents, actions, or tasks associated with them.

In discussing the structure of semantic spatial models, we define three main layers: metric, instance-level semantic, and class-level semantic (Figure 10). Note that the structures of semantic spatial models and object representations are closely related as they share similar levels of abstraction.

- *Metric*: The metric layer of a semantic spatial model describes spaces and contained entities quantitatively through various numeric measurements (e.g., laser scan, 3D pose of landmark, occupancy grid, and topological map). Metric representations allow robots to interpret the geometry of environments but lack the abstraction and semantic meaning required to perform efficient reasoning.
- *Instance-level Semantic*: The instance-level semantic layer of a semantic spatial model enriches the metric layer by assigning semantic meaning to measurements [60]. This layer has nodes that represent observed concepts (e.g., recognized objects and rooms) and edges that represent observed relations (e.g., spatial relations and part-whole relations), from which belief states can be extracted to be used by task planners.
- *Class-level Semantic*: The class-level semantic layer of a semantic spatial model allows for further generalization by including general knowledge of class types. This layer can store abstract properties about the class types (e.g., bedrooms and living rooms are rooms in house environments) and encode common rules (e.g., sofa and TV are typically observed in living rooms) [109, 44].

Prior work has explored techniques for combining information across various subsets of these layers, as discussed below.

In many semantic spatial models, all three layers are in use. This is particularly true for models of large spaces composed of many rooms or locations, such as an entire kitchen [19] or a whole office floor [44]. In these spaces, all three layers are crucial as robots need to navigate with the metric information, efficiently reason about individual entities with the instance-level semantic knowledge, and generalize with the class-level semantic knowledge. The

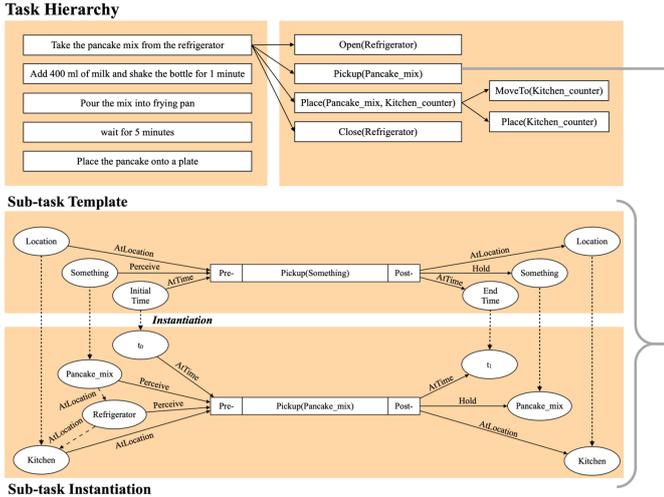


Figure 11: Structure of task representations

exact details of how information is encoded at each layer differ across frameworks. In [80, 81, 60, 109], class-level knowledge about typical room types (e.g., a bedroom has a bed) are encoded in expert-created ontologies. In order to overcome the rigidity of rule-based systems, co-occurrence statistics of objects and room types are stored as conditional probabilities [122, 61]. In [44, 45, 77], room-object relations, room-appearance relations, and room-room connections are simultaneously represented in PDAGs. In [19], class-level knowledge about objects and spaces are obtained by establishing connections to external common-sense ontologies.

All three spatial layers are not always needed, and sub-set pairs have been used in some applications. For example, metric and instance-level semantic layers are commonly used to reason about spatial relations between objects in a single space (e.g., a cabinet or a tabletop). The metric information provides precise specifications for the qualitative spatial relations in instance-level semantic representations, allowing for contextual reasoning [75, 92], perspective-taking [25], and temporal reasoning [59]. With only abstract knowledge, the instance- and class-level semantic layers are used to qualitatively reason about missing objects in different scenes [106, 63, 117]. Some approaches model spaces only at the class-level. The abstract knowledge about types of spaces provides high-level guidance for object search [97] and semantic navigation [64].

5.3. Representing Tasks

Tasks in this survey are defined as structures that encapsulate and organize grounded actions. Task planning of robots in the physical domain poses challenges such as intractable domains, partial observations, stochastic effects, and disconnected goals. Semantic reasoning is used to alleviate these problems by adding organized information. We show three essential structures of semantic task models in Figure 11. The two upper panels of Figure 11 show

how tasks can be organized as sub-tasks in a class-level task hierarchy. This structure is used to represent tasks at an abstract level. The two lower panels of Figure 11 show how each sub-task could be represented and linked to information in representations of other entity types in class-level sub-task template and class-level sub-task instantiation. The example structures illustrated in Figure 11 and defined below illustrate one approach by which semantic knowledge can be incorporated into tasks.

- *Class-level Task Hierarchy*: recursively decomposes a task into sub-tasks until a known set of class-level sub-task templates are reached. A task hierarchy uses different levels of abstraction to enable re-use of task plans and effectively represents the sequential nature of tasks with multiple steps [123].
- *Class-level Sub-task Template*: defines a sub-task by placeholder actions and placeholder conditions. This structure serves as the blueprint of the class-level sub-task instantiations and allows for better generalization by grouping instantiations from the same template [45].
- *Class-level Sub-task Instantiation*: inherits all the restrictions from the class-level sub-task template by instantiating pre- and post-conditions in terms of class-level concepts in other world representations. Connection to other representations help infer missing information in tasks and infer the correct ordering of sub-tasks. (For the example in the figure, because the refrigerator is connected to pancake mix in object representation and kitchen in space representation, perceiving refrigerator is added as a pre-condition to help the robot find pancake mix in execution).

It is worth noting that the instance level of task specification is not shown here because its conditions are specified as concepts in other representations. For example, the realization of a sub-task is an action. The grounding of class-level concepts of tasks are discussed separately in Sections 5.1, 5.2, 5.4, and 5.5.

Prior work has explored techniques for utilizing different subsets of structures to organize tasks. Incorporating hierarchical structure into task representations, which can be learned from a repository of tasks [124, 108, 125], or encoded by an expert [126, 81, 123], promotes robustness and efficiency of task execution and planning. Decomposing tasks in hierarchies helps promote robustness to stochastic task outcomes [123, 127] and representational efficiency through the re-use of tasks [124, 20]. Additionally, a hierarchical task decomposition enables more efficient planning by planning at different abstraction levels (e.g., planning at class-level) [127], or executing partial plans (e.g., only planning to decision points which require execution) [123].

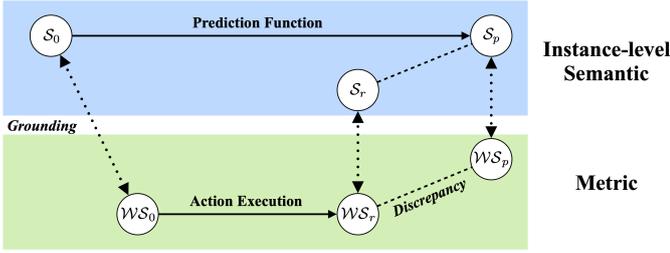


Figure 12: Structure of action representations

In addition, class-level task hierarchies have been widely used in prior work to express the ordering of task steps both explicitly in symbols [18, 128, 45, 129, 66], or implicitly in neural architectures [130, 131, 124]. The ordering constraints within the class-level task hierarchy structure enables robots to infer a sequence of actions to reach a goal state [132, 60], select the next action given the current state [40, 130], and repair failed task plans [45, 77]. In addition to modeling robot tasks, class-level task hierarchies have been used to model instructions provided by humans during interactions [18, 25].

Besides encoding sequential and hierarchical structures of tasks in task representations, prior work has also adopted class-level sub-task template and instantiations by ensuring correspondences between generic and task-specific information [133, 59, 127]. Several methods leverage class-level sub-task instantiations to establish the connection to other world representations. In [81], pre- and post-conditions are defined in terms of concepts in object and space representations. Similarly in [60], conditions link to semantic maps and topological maps. In [59], conditions additionally incorporate temporal information for inferring and explaining temporal order of tasks.

5.4. Representing Actions

Actions in this survey refer to physically grounded robot behaviors. Inherently, actions are continuous, stochastic, and require feedback. In the context of SRF, each action also has related semantic representations, which create a high-level abstraction for the low-level sensor-motor experience and associate the action with contextual information. The semantic representations of actions are compact and can be easily connected with high-level objectives and task plans. By leveraging the encoded information in these representations, robots can generalize behaviors to novel situations [134, 62] and take actions appropriate for the context [72].

In discussing the structure of action representations used in prior work, we build on the framework of object-action complex (OAC) [126], which aims to bridge the gap between high-level abstract reasoning and low-level control knowledge for actions. We adapt the OAC representation in the context of SRF so it is consistent with the language of this survey. Specifically, action representations have two

layers: metric and instance-level semantic, as illustrated in Figure 12.

- *Metric*: The metric representations contain low-level information related to actions. The representations can be divided into representations of the world states (e.g., an image of the scene, a pose of the manipulated object) and representations of actions themselves (e.g., a trajectory, a feedback controller). Executing an action causes changes in the physical world that transform the initial world state \mathcal{WS}_0 to the resulting world state \mathcal{WS}_r .
- *Instance-level Semantic*: The instance-level semantic representations create high-level abstractions for actions. The word instance-level emphasizes that these representations are grounded in the metric level data. Similar to the metric layer, the semantic layer consists of semantic representations of world states and semantic representations of actions. The semantic representation of an action can be a prediction function that models how the semantic world state will transform from the initial semantic state \mathcal{S}_0 to the predicted semantic state \mathcal{S}_p if the action is executed [126]. However, the semantic representation of an action can also be as simple as a language description of the action [62].

Another essential feature of action representations is the tight connections between these two layers. As robot actions are noisy, keeping the mappings from metric to semantic representations of world states allow robots to discover the discrepancies between the physical actions and imagined actions. For example, the difference between \mathcal{S}_r and \mathcal{S}_p , or the difference between \mathcal{WS}_r and \mathcal{WS}_p , as illustrated in Figure 12.

All the described components of action representations are observed in prior work. In OAC [126], the discrepancies between the effects of actions in the semantic and metric layers have been used as feedback to both improve the prediction function for push actions and facilitate the learning of task-agnostic and specific grasps. In [91], a prediction function for primitive actions is implemented in a SRL formalism. Having the conceptual model of actions allows a robot to pick actions most likely to produce desired effects on objects.

Besides learning conceptual models of actions, semantic representations of actions are also commonly used for creating generalizable actions. In [135, 134], the controllers of the robot manipulators are parameterized by task functions grounded in geometric features of objects (e.g., keep the main axis of the spatula pointed at the center of the oven). Actions are generalized to new objects by imposing these task functions as semantic constraints on functionally meaningful geometric features (e.g., handles). Another approach combines low-level trajectories and point clouds of object parts with high-level language instructions

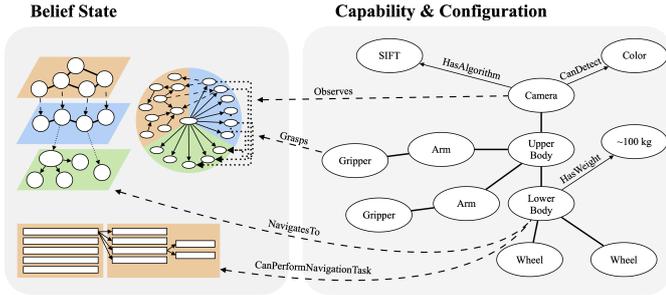


Figure 13: Structure of agent representations

in NNs to create generalizable representations of actions [62, 100].

Semantic representations of actions also allow high-level constraints to be easily incorporated. In [72], user preferences of trajectories are modeled as a scoring function that is computed from both metric information (e.g., robot arm configurations and distances to surrounding surfaces) and semantic representations (e.g., properties of objects that are near to the trajectory). Many existing approaches to semantic grasping have also leveraged semantic representations to compactly encode contextual information [56, 65, 115].

5.5. Representing Agents

Agents in this survey are defined as a robot itself, other robots, and humans in the environment. Inferring human belief states is often vital for Human-Robot Interaction (HRI), while understanding the capabilities of the robot’s self and others is often necessary for task-collaboration and knowledge sharing. The representation of each agent (i.e., the self, other robots, and humans) includes that agent’s capabilities, configurations, and belief states, as illustrated in Figure 13. While an agent has direct access to its own belief states and capabilities, the belief states and capabilities of other agents can be received through message exchange between agents [20] or inferred from perceptions [136].

- *Capabilities & Configuration:* The capabilities of an agent can be inferred from its physical configuration. In addition to spatial poses and dynamics of body parts, physical configurations can include semantic descriptions linking properties, algorithms, and other semantics to reason about overall agent capability with respect to actions or tasks [21].
- *Belief States:* The belief states of agents can consist of the previously mentioned representations (i.e., object, space, task, action) or attributes specific to agents (e.g., intent) [25]. Within the agent’s belief state, the different representations will interact as the world state changes and the representations are updated.

Human agents have been modeled in semantic reasoning frameworks to enable naive user interaction with complex semantic reasoning frameworks [24, 25, 18] and to adapt semantic reasoning from data provided by naive users [15, 69, 114, 31, 15, 137]. Semantic reasoning frameworks that leverage ontologies [24, 25, 19] have modeled human agents by including relevant classes (e.g., agent, embodied agent, human, robot, body part), properties (e.g., *is desired*, *sees*, *has in hand*), and alternative cognitive models that may be globally inconsistent following theory of mind principles. The addition of these classes and properties has enabled complex interaction [25, 24] and learning of human preferences such as where to perform actions [19, 111]. In addition to deterministic representations, MLNs have been leveraged to reason probabilistically about human actions in relation to objects in use [31] and human commands in relation to the robot’s perceived environment [18]. Other methods have modeled human agents through the use of an a conditional random field to predict future human activities [26, 138] and have learned manipulation tasks from human demonstrations through text [118] or videos [2, 125].

When multiple robot agents need to collaborate, it is crucial to distinguish between robots and their capabilities. In [82] and [83], each robot has its own ontology and all robots are defined in a global ontology. Because different robots perceive and interact with the world differently due to different capabilities or perspectives, each robot should have its own world representation. The work of [116] differentiates object representations of different agents by defining object affordances with respect to not only object properties but also locations, properties, and capabilities of agents (e.g., push affordance of refrigerator door requires the agent to have push ability and be in kitchen). A coordinator, which has access to each agent’s ontology and the common goal, can then reason about task assignments based on each agent’s affordances in the environment. Similarly in [139], an ontology is combined with a PDDL planner to coordinate multiple heterogeneous robots by using robot specific skills.

The semantic robot description language (SRDL) [21] has been used in [20] to model agent capabilities. SRDL allows for the unambiguous definition of a robot’s hardware, configuration, and software, which in turn helps specify its capabilities. Specifically, hardware and configuration refer to the physical parts of a robot (e.g., parallel jaw gripper, 2D hokuyo laser range sensor, servo motor) and the arrangement of these parts (e.g., link and joint locations, ranges of an N-DoF arm), respectively. Software encompasses both algorithms the robot use (e.g., 3D-ObjectRecognitionAlgorithm) and world representations it has access to (e.g. 3d-ObjectModel for Cup). Using SRDL, a robot can reason about the likelihood of successfully performing specific tasks based on both its capabilities and experience from previous attempts. SRDL also aids a robot in selecting models and algorithms available online based on its capabilities.

World Representation					Reasoning Objectives	Referenced Works
O	S	T	Ac	Ag		
✓						[26]
✓	✓				Inferring Object Affordance	[91, 97, 16, 117]
✓			✓			[112, 114]
✓				✓		[31]
✓						
✓					Object Perception	[79, 80, 81, 7, 42]
✓	✓					[75, 93, 74, 117, 140]
✓			✓			[22]
✓	✓				Inferring Missing Object	[117]
✓				✓		[141]
✓	✓				Space Classification	[80, 81, 44, 45, 60, 61, 142]
✓	✓				Semantic Navigation	[81, 60, 64]
✓	✓				Inferring Object Location	[59, 19, 122, 80, 44, 60, 109, 92, 63, 97, 16, 143, 99]
✓	✓			✓		[69]
	✓	✓			Inferring Suitable Location for Task	[20, 110]
✓	✓				Reasoning about Spatial Relations	[59, 117, 75, 92]
✓	✓			✓		[25]
✓		✓			Inferring Task Hierarchy and Ordering	[15, 20, 91, 124, 133, 18, 45, 128, 133, 68, 108]
✓		✓			Inferring Manipulation Task from Objects	[70, 125, 18]
✓	✓	✓			Invoking Task for Decision Confidence	[60, 45, 127, 130, 77]
✓	✓	✓			Enlarging Task State Space	[133]
		✓			Task Instance Domain Reduction	[133]
✓	✓	✓			Task Monitoring & Perception	[22, 81, 141, 128]
✓			✓		Semantic Specification of Manipulation	[23, 134]
✓			✓		Semantic Grasping	[107, 71, 65, 115, 56]
✓			✓		Generalizing Manipulation Trajectory	[62, 100]
✓			✓		Learning Preference over Trajectory	[72]
✓		✓	✓		Learning Task Level Behavior from Action	[126, 91]
✓	✓	✓		✓	Natural Language Interaction	[18, 25]
✓			✓	✓	Human Pose Prediction	[31]
✓	✓	✓		✓	Heterogeneous Robot Team Planning	[116, 139]
		✓		✓	Task Capability Matching	[20, 21, 139]

Table 5: Referenced object (O), space (S), task (T), action (Ac), and agent (Ag) semantic reasoning works with related world representations. Check marked world representations on the left side of the table are used to accomplish corresponding reasoning objectives listed on the right. Gray shading is used to highlight groupings of techniques that address object-, space-, task-, action-, and agent-focused problems.

6. Combining SRF Components for Intelligent Robot Behavior

Many intelligent robot behaviors can be achieved through semantic reasoning – the inference and computation processes that require all three core component of semantic reasoning frameworks. Examples of such processes include discovering the semantic similarity between environments, inferring missing information from underspecified instructions or partially observable world state, or parameterizing robot tasks to be appropriate for the context. In this section, we study the reasoning capabilities that are enabled by combining multiple of the previously discussed SRF

core components.

In Table 5, we characterize various semantic reasoning tasks by the world representations and reasoning objectives. For example in [44], a robot joins the object model (O), which encodes attributes that potentially influence objects’ locations, with the spatial model (S), which stores typical spatial appearance of objects, to accomplish the “Inferring Object Location” reasoning objective. While the table provides a full summary of techniques, in Sections 6.1-6.9 below, we more closely examine the integration of SRF components in several reasoning tasks.

6.1. Top-down and Bottom-up Object Perception

Object classification techniques typically fall into one of two approaches: bottom-up and top-down. Bottom-up machine learning algorithms, such as [5] and [144], train models to recognize objects based entirely on low-level object appearance features. Top-down techniques, such as those in [22, 79, 80, 7], classify objects based on abstract characteristics of objects (e.g., a refrigerator is a white hexahedron with a door). Both approaches have limitations – bottom-up techniques are prone to provide ambiguous results [75] and have lower performance when objects are partially occluded [93], while top-down techniques are too rigid to capture the diversity of instances in many object classes.

Several semantic reasoning frameworks have developed techniques for combining bottom-up and top-down reasoning to leverage their relative strengths. In [140], maximum a posteriori estimation integrates bottom-up object classification scores with top-down inference over occurrence probabilities of spatially related objects. Similarly in [74, 75], MNs model object features and spatial relations to combine reasoning from both directions. In addition to object recognition, in [93], physical laws and commonsense knowledge (e.g., a small object can fall inside a large box) defined in a SRL model help track objects even when they go out of sight. High-level knowledge can also result in more efficient learning of bottom-up methods. In [42, 95], few-shot and zero-shot object recognitions are achieved by generalizing visual classifiers in Graph Neural Networks that capture high-level semantic similarities between objects.

6.2. Inferring Object Affordances

The ability to reason about affordances enables robots to choose actions that are suitable for a given object and produce the desired effects. Most prior work has modeled affordances as intrinsic properties of an object that determine possible actions to perform on it (e.g., a cup is pourable, and a fork is stab-able and lift-able). To obtain this data, affordance labels are retrieved from a semantic graph based on objects’ class labels [26]. Furthermore, by modeling the correlations between affordance labels and other object properties (e.g., materials, locations, and shapes), an object’s affordance can be predicted from its properties using an MLN [31], BLN [16], or NN Embedding [97].

However, reasoning about affordance labels alone ignores the essential interaction between objects and the environment. In [91], a BLN models this interaction by representing objects, actions, and effects as separate random variables. Reasoning about affordances is modeled as various sub-tasks, such as estimating the effect of an action performed on an object, or predicting the action given the desired effect on an object. Although this decoupled affordance model reflects the connection between objects and the environment, discrete labels of actions and effects still cannot be directly used by robots to produce continuous

behaviors. As a result, a spatio-temporal representation of affordance is used in [112] that reasons about continuous manipulation actions through joint probabilistic inference over spatial and temporal distributions.

6.3. Reasoning about the Semantics of Space

Reasoning about semantic spatial models gives rise to new capabilities, such as visual navigation, and provides further robustness to localization and mapping. Using the knowledge of common objects in different room types, a robot can recognize its location (i.e., which room it is in) [80, 81, 44, 45, 61, 142] and detect high-level localization errors when odometry fails [60]. Querying an ontology containing typical spatial relations between objects (e.g., a tv is near a sofa) allows a robot to find a target object that is not directly in its view by continuously navigating to spatially related objects [80, 60]. The same reasoning pattern is behind many recent methods for visual semantic navigation [40, 64, 145]. In these methods, inference on neural networks, instead of logic rules, is used to determine navigation actions given observations of the scene. Besides representing object knowledge in semantic spatial models, task information can also be incorporated. In [110], reasoning about the relation between execution success rates and robot locations in a Gaussian Mixture Model facilitates task reproduction.

6.4. Inferring Object Locations Based on Class- & Instance-level Knowledge

Class-level knowledge provides a general prior of typical object locations, while instance-level knowledge models the appearances of objects in each specific environment. Both types of knowledge have been used in prior work.

Class-level knowledge treats spaces and containing objects as general concepts (e.g., a bowl can be often found in cabinets, sinks, and dishwashers). Inferring object locations is achieved by retrieving typical locations of objects from ontologies [80, 81, 59] or logic rules [60, 109]. Leveraging the intuition that related objects appear in similar places, a work predicts object locations by finding semantically similar objects using the Wu-Palmer similarity measure [67] computed on an object hierarchy [59]. A method based on neural network embedding takes a step further by modeling different types of semantic relations between object properties and locations to infer locations of objects [97].

A different approach is to utilize instance-level knowledge, which pertains to the locations of objects in a specific environment. Existing methods often learn the co-occurrence statistics of objects in different locations. In [122], these statistics are modeled by conditional probabilities. In [69], the Collaborative Filtering technique from the data mining community for addressing personalized user recommendations stores user-specific statistics. The work in [92] applies a SRL model to reason about different types of co-occurrences distinguished by spatial relations.

Ultimately, class- and instance-level knowledge should be reasoned collectively. In [63], a factor graph joints commonsense knowledge at the class-level as well as long term and short term memory at the instance-level. Similarly in [64], a Graph Neural Network combines continuous local observations with general prior knowledge from Concept-Net to help a robot navigate to target objects.

6.5. Task Planning and Learning

Reasoning about task semantics (see Section 5) has enabled improvements over the execution of task reasoning objectives in Table 5. Two fundamental challenges when reasoning about tasks involve either planning sequences of primitive actions that lead to the completion of goals [18, 25, 45, 133, 128, 146, 132, 139] or learning from sequences of primitive actions that demonstrate the completion of goals [40, 66, 124, 131, 118, 108]. Reasoning about semantic properties of tasks can help to improve task planning efficiency and accuracy while promoting generalization within task learning.

Many semantic properties of tasks have been leveraged to improve task planning and learning. Planning at different levels of abstraction leads to planning computational efficiencies by reducing the planning state space to classes of objects (i.e., t-box in description logics) while executing over instances of objects [133, 127, 147, 148]. The integration of uncertainties with distinct semantics through graphical or relational models helps infer the most likely task plan given unobserved world states or under-specified instructions [18, 45]. Additionally, due to semantically ambiguous world states, planners with multiple world states can generate plans that reduce such uncertainties [60, 77, 81, 130]. The hierarchical structure of tasks helps task learning generalize because of modularization enabled through the reuse of subtasks [20, 146, 124]. The prediction of future world states as tasks are executed, planned, or learned allows agents to detect, interpret, or explain plan failures [45, 81, 131]. The propagation of pre- and post- conditions in under-specified tasks allow missing task specifications to be inferred [15, 18, 132].

6.6. Enriching Task Planners

Although tasks themselves contain rich semantics (e.g., pre-conditions, hierarchies), many works have exposed task planners to even more semantic knowledge. Enriching task planners with semantic knowledge further promotes reasoning objectives, such as task generation for decision confidence, task monitoring, and other reasoning objectives specific to tasks in Table 5. Generally, the semantic knowledge being exposed includes precepts about the situated environment or default knowledge (e.g., fridge likely contains food). These newly exposed semantics further enable task planners to make more robust primitive action plans.

Streaming the perceived world state to task planners increases situational awareness, making task plans more

fit to the current world state. In [128, 149], the world state is exposed in semantically meaningful ways to task planners to enable data-efficient state updates while promoting generalization. Sensor streams are processed into semantically meaningful axioms and predicates in [22, 141] to update planners with environment variables that might become useful in later parts of tasks, such as the location of an item required in a later step of a task. In [22, 141], planners can call perception routines to allow for active acquisition of environment states and semantic information when planning.

In addition to the perceived world state, exposing semantics about default knowledge regarding specific tasks, domains, and general concepts enables more robust task planning. Observations from multiple environments or execution histories are used to learn generalized rules or correlations between semantic concepts, such as rooms and objects, enabling task planners to prioritize task plans that are more likely to satisfy task goals based on observed correlations from prior environments [45, 133, 127]. Ontologies about common domains, such as households, provide task planners information useful during task execution such as object locations, uses, and suitable locations for certain actions and tasks [15, 19, 81, 133]. General knowledge such as type hierarchies, semantic similarity, generic relationships, and other forms of general knowledge can be used to bootstrap task planners with a knowledge base when operating in new environments or repairing existing task plans to add robustness [16, 18, 108]. Encoded task-specific semantic knowledge can improve planning efficiency when the set of tasks are predefined by enabling planners to prune branches of plans that cannot satisfy task goals (e.g., searching a bathroom for an oven.) [60, 77]. Additionally, semantics about human agents have been exposed to task planners to improve human-aware task planning capabilities, such as including human preferences in tasks and modeling human belief states during task execution [25, 69].

6.7. Semantic Grasping

Instance-level semantic knowledge provides precise and generalizable information for semantic grasping, which is the problem of selecting stable grasps that are functionally suitable for specific object manipulation tasks (e.g., when passing a knife to a person, a robot should grasp the blade instead of the handle) [150]. Some existing approaches to semantic grasping use metric data because reasoning about the specific locations and orientations of grasps requires detailed information about an object [150, 151]. However, discovering structures in high-dimensional and irregular low-level features is hard and has prevented these methods from generalizing to a wider range of objects and tasks. Compared to metric data, instance-level semantic knowledge provides the necessary abstraction while also maintaining enough distinctive information to guide accurate selections of semantic grasps. A commonly used instance-level semantic feature is object part information. Suitable

grasp regions based on segmented object parts have been manually defined in logic assertions [107] and a SRL formalism [115]. In data-driven approaches, semantic grasps learned from task demonstration are reproduced on new objects by matching Reeb graphs that represent object decompositions [71]. Learning the relations between object parts and other contextual information, such as materials, states, and tasks, in a NN enables generalizable yet accurate reasoning of semantic grasps [56].

6.8. Reasoning about Continuous Actions

Semantic reasoning about actions requires the ability to perform inference on continuous data. Determining the appropriate level of abstraction for actions is challenging, as illustrated in the study of the egg cracking problem [152]. A large number of complex logic assertions are required to axiomatize the reasoning of the egg cracking action because associated continuous behaviors and events have to be discretized differently for different aspects of the problem. Instead of developing a complete symbolic representation of actions, many works explore certain aspects of action semantics. For example, semantic representation of grasps are derived from affordances and materials of object parts [56], user preferences for trajectories are based on nearby objects [72], constraint-based motion control are grounded to abstract descriptions of object parts [134], and tool-use trajectories are characterized by physical properties such as displacement and velocity [114]. Other works leverage computational frameworks that can directly perform inference on continuous data. Learning in these computational frameworks also allows structure and appropriate level of abstraction to be discovered directly from data. In [65], a Gaussian Mixture Model is used within a BN to reason about continuous variables such as grasp position and orientation. In [112], Gaussian Processes with graphical models together aid representation and reasoning of manipulation trajectories of objects. In [62, 100], neural networks are used to encode manipulation trajectories in the shared semantic space with their matching language descriptions and point cloud of the target objects. Executing actions in simulation is another direction for reasoning about continuous actions. Though predicting action effects and retrieving motion parameters are demonstrated in [110], the speed and fidelity of simulation-based reasoning are still open challenges.

6.9. Enabling Interaction through Agent Semantics

Reasoning about agent semantics is crucial for robots to collaborate with other agents successfully. Robots operating in human environments often need to fill in knowledge gaps required to interpret and execute tasks. In addition, modeling and reasoning about other agents is especially useful to enable interaction.

Interacting with other agents is a difficult task because differences in mental models result in knowledge gaps across agents, which is especially true of human-robot interaction. Several works have leveraged the diverse

semantic knowledge of humans by directly incorporating human declarations into ontologies and knowledge bases [18, 24, 25]. In addition to incorporating declarations, works have used human-robot dialogues to capture and update human beliefs, following theory-of-mind [24, 25]. Other works have filled human-robot knowledge gaps when interpreting semantic commands by gathering and interpreting demonstrations of tasks from resources like online recipes, web videos and images, or user preferences to enable capabilities like inferring tools involved during tasks or preferred organizations of items [19, 31, 68, 69, 125, 138, 118, 153]. Recognizing the value of such resources, many works have moved further to organize various agent representations into large knowledge bases for reuse across tasks or agents [20, 23, 26, 31, 68].

Aside from human agents, reasoning about robot agents, including a robot itself and other robots, allows for interaction between robot systems and the sharing of learned abilities. Prior work has looked at reasoning about the semantics of agent configuration and available hardware to define heuristics in a centralized task allocation model among multiple agents [116]. Other works have constructed shared knowledge bases that contained annotations encoding the semantics of action capabilities accounting for hardware and software, objects models, and maps [20, 21]. These annotations allow a robot to reason about which actions it could perform, search for any missing object models or maps needed in order to perform the actions, and calculate the likelihood an action would succeed based on the robot’s previous attempts. Recent work has further enabled collaboration between robotic agents by leveraging hardware capabilities across agents to enable collaborative task planning [139].

7. Open Challenges in SR for Robotics

Semantic reasoning for robotics represents a very broad and rapidly expanding area of interest. As highlighted by the discussion in the previous sections, current approaches to semantic reasoning address a wide variety of problems, under many different conditions and assumptions. Below, we highlight a number of open problems and challenges the research field faces, as well as promising directions for future work.

Benchmark, Datasets, Comparisons: Existing works within this research area lack datasets and benchmarks required to make comparisons between various approaches. The lack of comparisons among approaches makes it difficult for researchers to build upon the best approaches, therefore slowing progress to goals the community wishes to achieve. Due to the broad range of problems and approaches within semantic reasoning, it is unlikely any single dataset would sufficiently cover all problems. Additionally, such datasets would need to include multiple modalities for each reasoning objective to enable testing of a broad range of approaches that integrate different knowledge sources, world representations, and computational

frameworks. The development of these datasets and benchmarks for various system aspects would be a strong catalyst for promoting the maturation of this research area, as has been seen in the computer vision and natural language processing communities. Furthermore, updating these datasets and benchmarks towards larger, more complex problems that more closely model real-world applications must remain an ongoing concern as different implementations of systems sufficiently solve each dataset or benchmark.

Computational Frameworks: As benchmarks mature to become more challenging, computational frameworks, which support the main infrastructure to relate semantic knowledge, will need to improve. There is yet to exist a computational framework that can balance scalability, model uncertainty, allow for complex conditioning of queries, and be highly adaptable. While there will likely continue to be trade-offs with regard to these aspects, improvements of existing approaches and development of new representations must continue to support systems tackling more challenging problems and domains. Exhaustive quantitative comparisons of the various computational frameworks in combinations with different semantic reasoning applications should be further explored to better understand which frameworks best suit particular sets of applications.

Using Context: Targeting more challenging benchmarks will require more massive, complex computational frameworks and knowledge sources. As problems scale to real-world robotics applications, context is an increasingly important and under-explored feature that encompasses many aspects of the semantic reasoning for robots problem. For example, [16, 18] use environment context to filter Bayesian and Markov-Logic Networks down to manageable sizes that can be used to infer task plans. In addition to filtering of concepts, context can help select the appropriate abstraction levels to reason about specific tasks leading to better inferences [152]. Context will likely be used as a key feature in new ways as the complexity of problems increases.

Merging Knowledge Sources: Another challenge of semantic reasoning for robots that remains unexplored is updating and combining semantic knowledge sources. This is difficult because some sources might only express binary beliefs (e.g., there exists a relation between x and y) while others might include confidence levels for beliefs and still others might have distributions over possible beliefs. Combining such sources into a unified representation to perform inference is challenging. Additionally, the symbols and data types across knowledge sources could be distinct creating knowledge gaps or duplicated requiring disambiguation.

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