

A Review of Robot Learning for Manipulation: Challenges, Representations, and Algorithms

Oliver Kroemer*

*School of Computer Science
Carnegie Mellon University
Pittsburgh, PA 15213, USA*

OKROEMER@ANDREW.CMU.EDU

Scott Niekum*

*Department of Computer Science
The University of Texas at Austin
Austin, TX 78712, USA*

SNIEKUM@CS.UTEXAS.EDU

George Konidaris

*Department of Computer Science
Brown University
Providence, RI 02912, USA*

GDK@CS.BROWN.EDU

Abstract

A key challenge in intelligent robotics is creating robots that are capable of directly interacting with the world around them to achieve their goals. The last decade has seen substantial growth in research on the problem of robot manipulation, which aims to exploit the increasing availability of affordable robot arms and grippers to create robots capable of directly interacting with the world to achieve their goals. Learning will be central to such autonomous systems, as the real world contains too much variation for a robot to expect to have an accurate model of its environment, the objects in it, or the skills required to manipulate them, in advance. We aim to survey a representative subset of that research which uses machine learning for manipulation. We describe a formalization of the robot manipulation learning problem that synthesizes existing research into a single coherent framework and highlight the many remaining research opportunities and challenges.

Keywords: Manipulation, Learning, Review, Robots, MDPs

1. Introduction

Robot manipulation is central to achieving the promise of robotics—the very definition of a robot requires that it has actuators, which it can use to effect change on the world. The potential for autonomous manipulation applications is immense: robots capable of manipulating their environment could be deployed in hospitals, elder- and child-care, factories, outer space, restaurants, service industries, and the home. This wide variety of deployment scenarios, and the pervasive and unsystematic environmental variations in even quite specialized scenarios like food preparation, suggest that an effective manipulation robot must be capable of dealing with environments that neither it nor its designers have foreseen or encountered before.

. * Oliver Kroemer and Scott Niekum provided equal contributions.

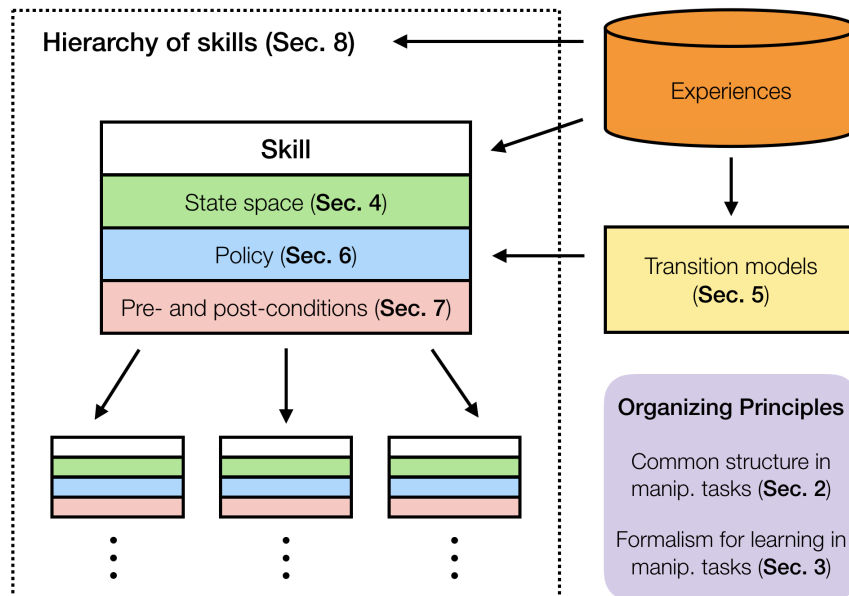


Figure 1: Overview of the structure of the review.

Researchers have therefore focused on the question of *how a robot should learn to manipulate the world around it*. That research has ranged from learning individual manipulation skills from human demonstration, to learning abstract descriptions of a manipulation task suitable for high-level planning, to discovering an object’s functionality by interacting with it, and many objectives in between. Some examples from our own work are shown in Figure 2.

Our goal in this paper is twofold. First, we describe a formalization of the robot manipulation learning problem that synthesizes existing research into a single coherent framework. Second, we aim to describe a representative subset of the research that has so far been carried out on robot learning for manipulation. In so doing, we highlight the diversity of the manipulation learning problems that these methods have been applied to as well as identify the many research opportunities and challenges that remain.

Our review is structured as follows. First, we survey the key concepts that run through manipulation learning, which provide its essential structure (Sec. 2). Section 3 provides a broad formalization of manipulation learning tasks that encompasses most manipulation problems but which contains the structure essential to the problem.

The remainder of the review covers several broad technical challenges. Section 4 considers the question of learning to define the **state space**, where the robot must discover the relevant state features and degrees of freedom attached to each object in its environment. Section 5 describes approaches to learning an environmental transition model that describes **how a robot’s actions affect the task state**. Section 6 focuses on how a robot can learn a motor control policy that directly achieves some goal, typically via **reinforcement learning** (Sutton and Barto, 1998), either as a complete solution to a task or as a component of that solution. Section 7 describes approaches that characterize a motor skill, by learning a

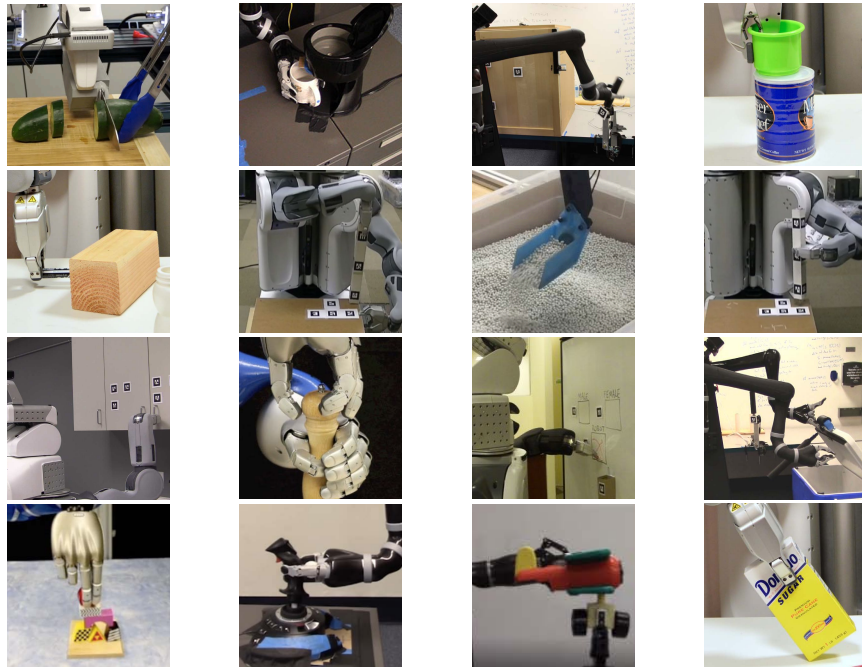


Figure 2: Example manipulation skills including inserting, stacking, opening, pushing, cutting, screwing, pouring, and writing.

description of the circumstances under which it can be successfully executed, and a model of the resulting state change. Finally, Section 8 surveys approaches to learning procedural and state abstractions that enable effective high-level learning, planning, and transfer.

2. Common Concepts in Learning for Manipulation

Manipulation tasks have significant internal structure and exploiting this structure may prove key to efficient and effective manipulation learning. Hence, before formalizing the manipulation learning problem, we will first discuss this internal structure.

2.1 Manipulations as Physical Systems

Every manipulation involves a physical robot interacting with its environment. As a result, all manipulations are subject to the laws of physics and the structure that they impose. This fairly obvious statement has wide-reaching implications for manipulation learning algorithms. Basic physical concepts (e.g., distinct objects cannot occupy the same space, and gravity applies a mass-dependent force to objects) provide strong prior knowledge for manipulation tasks. Concepts from physics, such as irreversible processes and object masses, are so fundamental that we generally take them for granted. However, these concepts provide invaluable prior knowledge and structure that can be exploited by learning algorithms and thus make learning manipulation skills tractable. Most of the concepts discussed in

the remainder of this section are to some extent the result of manipulations being physical processes.

2.2 Underactuation, Nonholonomic Constraints, and Modes in Manipulations

Manipulation tasks are almost always characterized as underactuated systems. Even if the robot is fully actuated, inanimate objects in the environment will contribute a set of independent state variables to the state space, but not increase the robot’s action space. The resulting discrepancy between the number of actuators and the number of DoFs means that the system is underactuated. To change the state of the objects, the robot must first move into a state from which it can alter the object’s state and then apply the desired manipulation, e.g., make contact with an object and then push the object. These requirements can be represented as a set of nonholonomic constraints that define how the robot can move through the full state space based on different interactions with the environment.

Manipulation tasks can be modelled as hybrid systems, wherein the system dynamics are continuous within each of a number of discrete dynamical modes. The dynamics are thus piecewise continuous. In manipulation tasks, the mode switches often correspond to making or breaking of contacts, with different contacts applying corresponding constraints and allowing the robot to interact with various objects. The conditions for transition between modes often correspond to subgoals or obstacles depending on which state variables the robot should change or keep constant. Unfortunately, modes also make manipulation tasks inherently discontinuous. Hence, small changes in the state can have a significant effect on the outcome of a manipulation. It is therefore important that robots monitor their skill executions for unexpected and undesired mode transitions.

2.3 Interactive Perception and Verification

Robots can perceive certain latent object properties by observing the outcomes of different manipulation actions. This process is known as *interactive perception*. Many properties of objects, such as material or kinematic constraints, can only be determined reliably through interactive perception. If the goal of the task is to alter a latent property, then the robot will need to use interactive perception to verify that the manipulation was successful, e.g., pulling on a door to ensure it was locked. Even if a property’s value can be approximated using passive perception, interactive perception often provides a more accurate estimate. In some cases, the estimate from the interactive perception can be used as the ground truth value for learning the passive perception. Interactive perception thus provides the basis for *self-supervised learning*. As the perception depends on the action, interactive perception is often combined with *active learning* to actively select actions that maximize learning performance.

2.4 Hierarchical Task Decompositions and Skill Reusability

Manipulation tasks exhibit a highly hierarchical structure. For example, the task of cleaning a house can be divided into subtasks, such as cleaning the dishes, vaccuuming the floors, and disposing the trash. These subtasks can then be further divided into smaller subtasks, such as grasping a plate or trashbag. Even basic skills, such as grasping, can be further

divided into multiple goal-oriented action phases. This hierarchy divides the primary task into smaller, more tractable problems. The robot can learn skill policies for performing the lowest level tasks and then use these skills as an action basis for performing the next level of tasks. The robot can thus incrementally learn a hierarchical policy of skills, with the resulting policy hierarchy reflecting the task hierarchy. The complexity of the learning challenges at each level of the hierarchy is reduced, enabling faster skill learning.

The hierarchy is also important because it results in a modular structure. Subtasks and skills can often be interchanged to perform tasks in different ways depending on the scenario. Modularity also allows for some components to be predefined and others learned, e.g., an agent may be provided with a basic grasping reflex. More importantly, similar tasks will often appear multiple times within the hierarchy. For example, when cutting vegetables, each slice of the vegetable is a separate and slightly different task. These tasks are however similar enough that the robot should generalize across them rather than treat them as distinct with unique skills. We refer to such sets of similar tasks as *task families*. By exploiting the similarity of these tasks, the robot can efficiently learn skills across entire task families and can thus be reused multiple times. The ability to incorporate this modularity into the robot’s controllers and models is conditioned on having a suitable task decomposition. Discovering this structure autonomously by the robot is thus a major topic for manipulation research.

2.5 Object-Centric Generalization

One common structural assumption for manipulation tasks is that the world is made of up objects and that the robot’s goals will typically be to modify some aspect or attribute of a particular set of objects in the environment. Consequently, *generalization via objects*—both across different objects, and between similar (or identical) objects in different task instances—is a major aspect of learning to manipulate. Object-centric representations of manipulation skills and task models are often sufficient to generalize across task instances, but generalizing across different objects will require both motor skills and object models that adapt to variations in object shape, properties, and appearance. In some cases this can be done implicitly—e.g., with a compliant gripper that automatically adapts its shape to that of an object during grasping. One powerful approach to generalizing across objects is to find an abstract representation under which we can consider a family of objects to be equivalent or identical, even though they vary substantially at the pixel or feature level, and adapt accordingly.

2.6 Discovering Novel Concepts and Structures

Robots working in unstructured environments will often come across new types of objects. Performing new tasks with these objects may require adapting existing skills or learning entirely new skills. Learning in open-world environments is thus not just a matter of the robot filling in gaps in its knowledge base. Instead, the scope of the knowledge bases will continue to expand, sometimes in unforeseen ways. The ability to handle novel concepts is an important aspect of robot autonomy, as it allows robots to handle unforeseen situations. To operate efficiently, robots will need to be capable of generalizing and transferring knowledge from prior experiences to structure the learning processes for these new concepts. This

transfer learning may require more abstract reasoning depending on the similarity of the new concept to previous ones. Fortunately, as explained in this section, manipulation tasks exhibit a significant amount of structure that an autonomous robot can leverage when learning manipulation tasks.

3. Formalizing Manipulation Learning Tasks

Robot learning problems can typically be formulated as individual Markov Decision Processes (or MDPs),¹ described as a tuple:

$$(S, A, R, T, \gamma),$$

where $S \subseteq \mathbb{R}^n$ is a set of states; $A \subseteq \mathbb{R}^m$ is a set of actions; $R(s, a, s')$ is a *reward function*, expressing the immediate reward for executing action a in state s and transitioning to state s' ; $T(s'|s, a)$ is a *transition function*, giving the probability distribution over states s' reached after executing action a in state s ; and $\gamma \in [0, 1]$ is a discount factor expressing the agent’s preference for immediate over future rewards. Here the goal of learning is to find a control policy, π , that maps states to actions so as to maximize the *return*, or discounted sum of future rewards $\sum_{i=0}^{\infty} \gamma^i r_i$, for that specific problem.

This common formulation captures a wide range of tasks, enabling researchers to develop broadly applicable general-purpose learning algorithms. However, as we have discussed in the previous section, the robot manipulation problem has more structure; a major task for robot manipulation researchers is to identify and exploit that structure to obtain faster learning and better generalization. Moreover, generalization is so central to manipulation learning that a multi-task formulation is needed. We therefore model a manipulation learning task as a structured collection of MDPs, which we call a *task family*. Rather than being asked to construct a policy to solve a single task (MDP), we instead aim to learn a policy that generalizes across the entire task family.

A task family is a distribution, $P(M)$, over MDPs, each of which is a *task*. For example, a door-opening task family may model each distinct door as a separate task. Similarly, a vegetable-cutting task family may model each individual slice as a task. The action space is determined by the robot and remains the same across tasks, but each task may have its own state space and transition and reward functions. The reward function is formulated as a robot-dependent background cost function C —shared across the entire family—plus a reward G_i that is specific to that i^{th} task:

$$R_i = G_i - C.$$

The state space of the i^{th} task is written as:

$$S_i = S_r \times S_{e_i},$$

where S_r is the state of the robot and S_{e_i} is the state of the i^{th} environment. S_{e_i} can vary from raw pixels and sensor values, to a highly pre-processed collection of relevant task

1. We should note that the Partially-Observable Markov Decision Process (POMDP) (Kaelbling et al., 1998) is a more accurate characterization of most robot learning problems. While these have been employed in some cases (Hsiao et al., 2007; Vien and Toussaint, 2015a,b, for example), the difficulty of solving POMDPs, especially in the learning setting, means their usage here is so far uncommon.

variables. Many task environments will consist of a collection of objects and the variables describing the aspects of those objects that are relevant to the task. It is therefore common to model the environment as a collection of object states, resulting in a more structured state space where S_{e_i} is partly factorized into a collection of relevant object states:

$$S_{e_i} = S_{w_i} \times \Omega_1^i \times \dots \times \Omega_{k_i}^i,$$

where S_{w_i} is the state of the general environment, Ω_j^i is the state of the j th relevant object in task i , and task i contains k_i objects. The number of relevant objects may vary across, and occasionally within, individual tasks. Modeling tasks in this factorized way facilitates object-centric generalization, because policies and models defined over individual objects (or small collections of objects) can be reused in new environments containing similar objects. This factorization can be clearly seen in symbolic state representations, wherein the modularity of proposition-based (e.g., `CupOnTable=True`) or predicate-based (e.g., `On(Cup,Table)=True`) representations allows the robot to consider only subsets of symbols for any given task. For manipulation tasks, we often employ predicate-based representations for their explicit generalization over objects.

Manipulation tasks also present modularity in their transition functions, i.e., the robot will only be able to affect a subset of objects and state variables from any given state. To capture the underactuated nature of manipulation tasks, we can model the tasks as hybrid systems with piecewise continuous dynamics. Each of the continuous dynamical subsystems is referred to as a *mode*, and the state will often contain discrete variables to capture the current mode. Mode switches occur when the robot enters certain sets of states known as guard regions, e.g., when the robot makes or breaks contact with an object. The robot can thus limit the state variables that it may alter by restricting itself to certain modes.

In some cases there is also structure in the action space, exploited through the use of higher-level actions, often called *skills*. Such skills are typically modeled using the options framework (Sutton et al., 1999), a hierarchical learning framework that models each motor skill as an *option*, $o = (I_o, \beta_o, \pi_o)$, where:

- $I_o : S \rightarrow \{0, 1\}$ is the *initiation set*, an indicator function describing the states from which the option may be executed.
- $\beta_o : S \rightarrow [0, 1]$ is the *termination condition*, describing the probability that an option ceases execution upon reaching state s .
- π_o is the option policy, mapping states in the option’s initiation set to low-level motor actions, and corresponding to the motor skill controller.

The robot may sometimes be pre-equipped with a set of motor skills that it can reuse across the family of tasks; in other settings, the robot discovers reusable skills as part of its learning process.

One of the key challenges of learning a policy, or domain knowledge, across a task family is the need to transfer information from individual tasks to the whole family. A robot can learn the policy to solve a single task as a function of the task state. However, transferring these functions across the family is not trivial as the tasks may not share the same state space. Transfer may be aided by adding extra information to the task—for

example, information about the color and shape of various objects in the task—but since that information does not change over the course of a task execution, it does not properly belong in the state space. We model this extra information as a *context vector* τ that accompanies each task MDP, and which the robot can use to inform its behavior. Like the state space, the context can be monolithic for each task or factored into object contexts. To generalize across a task family, the robot will often have to learn policies and models as functions of the information in the context vector. For example, a cutting skill needs to be adapt to material properties of different vegetable, or a door-opening skill needs to adapt to the masses and sizes of different doors.

In summary, our model of a family of manipulation tasks therefore consists of a *task family* specified by a distribution of manipulation MDPs, $P(M)$. Each manipulation MDP M_i is defined by a tuple $M_i = (S_i, A, R_i, T_i, \gamma, \tau_i)$, where:

- $S_i = S_r \times S_{e_i}$, is the state space, where S_r describes the robot state, and S_{e_i} the environment state. Often the environment state is primarily factored into a collection of object states: $S_{e_i} = S_{w_i} \times \Omega_1^i \times \dots \times \Omega_{k_i}^i$, for a task with k_i objects;
- A is the action space, common across tasks, which may include both low-level primitive actions and a collection of options O ;
- $R_i = G_i - C$ is the reward function, comprising a background cost function C (common to the family) and a task-specific goal function G_i ;
- T_i is the transition function, which may contain exploitable structure across the sequence of tasks, especially object-centric structure;
- γ is a discount factor, and
- τ_i is a vector of real numbers describing task-specific context information, possibly factored into object context: $\tau_i = \tau_1^i \times \dots \times \tau_k^i$, for k objects.

Overview of Learning Problems for Manipulation: The learning problems posed by manipulation tasks can typically be placed into one of five broad categories, which we will discuss in the subsequent sections. An overview of the topics covered in this review are shown in Fig. 3.

When **learning to define the state space** (Sec. 4), the robot must discover the state features and degrees of freedom attached to each object in its environment. This information is assumed to be given in the traditional reinforcement learning and planning settings. That is not the case in robotics, and in particular in learning for manipulation, which involves interacting with objects that the robot’s designers do not have a priori access to. Learned representations of object states can be transferred across the task family as components of each task’s state space.

When **learning a transition model of the environment** (Sec. 5), the robot must learn a model of how its actions affect the task state, and the resulting background cost, for use in planning. This is closely connected to learning to define the state space. If the learned transition models and reward functions are object-centric, then they can be ported across the task family, resulting in a natural means of object-centric generalization across tasks.

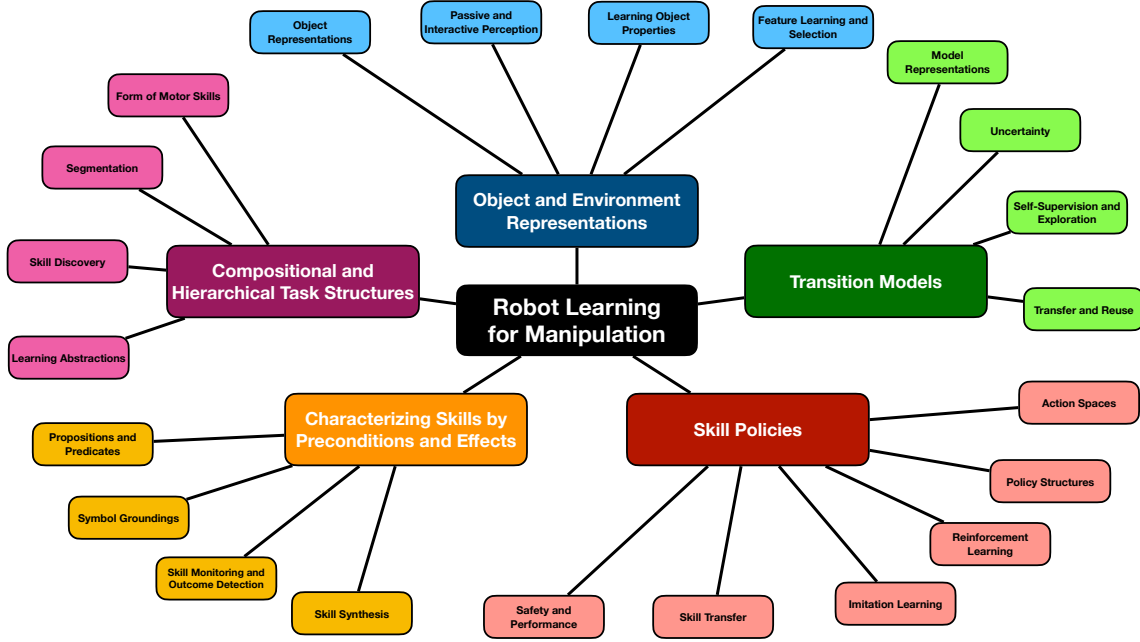


Figure 3: Overview of the different topics covered in this review sections.

When **learning motor skills** (Sec. 6), the robot attempts to learn a motor control policy that directly achieves some goal, typically via reinforcement learning (Sutton and Barto, 1998). Here, the goal ranges from learning task-specific solution policies, to policies that can produce a solution to any task in the task family given the context vector, to useful motor skills that constitute a component of the solution policy but are not themselves a complete solution.

Given a learned motor skill, we may also **learn to characterize that motor skill** (Sec. 7), where the robot learns a description of the circumstances under which it can be successfully executed (often called preconditions, and corresponding to an option’s initiation set I_o), and a model of the resulting state change (often called an effect).

Finally, **learning compositional and hierarchical structure** (Sec. 8) aims to learn hierarchical knowledge that enables the robot to become more effective at solving new tasks in the family. Here, the goal is to learn component motor skills—completely specified options—and models of their operation to construct more abstract representations of the learning task.

4. Learning Object and Environment Representations

Modelling manipulation tasks and generalizing manipulation skills requires representations of the robot’s environment and the objects that it is manipulating. These representations serve as the basis for learning transition models, skill policies, and skill pre- and post-conditions, as discussed in later sections.

This section explains how the object-based state and context spaces of manipulation tasks can be defined and learned. We will also explain how the robot can discover objects

and estimate their properties using passive and interactive perception. Since many of the extracted object properties and features may be irrelevant to learning certain components of manipulation tasks, we conclude the section by discussing how to select and learn relevant features.

4.1 Object Representations

As discussed in Section 2, a robot’s physical environment has considerable structure that it can exploit. In particular, the world can be divided into objects, each of which can be described by a collection of features or properties. Examples include movable objects such as mugs, tables, and doors, and stationary objects such as counters and walls. The robot can create a modular representation by segmenting the environment into objects and then estimating the values of their properties. This representation supports the reuse of skills by allowing the robot to efficiently generalize between similar objects across different tasks.

Object representations capture how objects vary both within tasks and across tasks of the same family. Within-task variations are captured by the *state* space—those features that a manipulation action can change; across-task variations are captured as part of the *context* space—attributes that are fixed in any specific task but aid generalization across pairs of tasks. For example, when stacking assorted blocks, the shapes and sizes of the blocks are fixed for a given task and are thus part of the context. Different stacking tasks may however use different sets of blocks, and thus the context changes across the tasks. Generalizing manipulation skills usually implies adapting, implicitly or explicitly, to variations in both context and state. For example, a versatile pick-and-place skill should generalize over the shapes of different objects (fixed in any specific task) as well as their positions in the environment (modifiable by actions during a task).

4.1.1 TYPES OF OBJECT VARIATIONS

Several types of within- and across-task object variations are common in the literature. **Object pose** (Pastor et al., 2009; Levine and Koltun, 2013; Deisenroth et al., 2015) variations are the most common, and must be included in the state space when they can be manipulated (e.g., by a pick-and-place skill). However, in some cases, these can be fixed within a task but vary across the task family and thus belong in the context (Da Silva et al., 2014; Kober et al., 2011; Jiang et al., 2012; Levine and Koltun, 2013) (e.g., the height of a surface in a wiping task (Do et al., 2014)). **Object shape** may vary within a task, via articulated (Niekum et al., 2015a; Sturm et al., 2010; Katz et al., 2010; Martín-Martín et al., 2016; Sturm et al., 2011), deformable (Schenck et al., 2017; Li et al., 2016; Schulman et al., 2013; Schenck and Fox, 2018a; Li et al., 2018; Seita et al., 2018; Li et al., 2018), or divisible (Lenz et al., 2015b; Wörgötter et al., 2013; Yamaguchi and Atkeson, 2016b) objects. Rigid object shapes may also vary across tasks (Burchfiel and Konidaris, 2018; Brandl et al., 2014), offering both a challenge to and opportunity for generalization (Schenck and Fox, 2018a). Similarly, objects may vary in **material properties**, which can have significant effects on manipulation but typically only vary across-tasks (e.g., cutting objects of different materials (Lenz et al., 2015b)), though there is some work on altering the material properties of manipulated objects (Chitta et al., 2011; Schenck and Stoytchev, 2012; Isola et al., 2015).

Finally, objects may vary in their **interactions or relative properties**, including both robot-object (Bekiroglu et al., 2013; Kopicki et al., 2016) and object-object (Stoytchev, 2005; Sturm et al., 2010; Kroemer et al., 2018; Jund et al., 2018) interactions. Objects may interact with each other resulting on constraints between them (Jain and Kemp, 2013), and manipulation may result in mode switches that add or remove constraints (Niekum et al., 2015a; Baum et al., 2017; Kroemer and Peters, 2014; Baisero et al., 2015). Variance across, rather than within, tasks is also possible—e.g., the properties of the joint connecting a cabinet and its door will remain constant for a given cabinet, but different cabinets can have different constraints (Sturm et al., 2010; Hausman et al., 2015; Niekum et al., 2015a; Dang and Allen, 2010).

4.1.2 OBJECT REPRESENTATION HIERARCHIES

Object models can be represented hierarchically, with layers corresponding to point-, part-, and object-level representations, each decreasing in detail and increasing in abstraction, and affording different types of generalization. This representation hierarchy mirrors the geometric structure of objects and their parts. Geometric properties and features capture *where* the points, parts, and objects are, and non-geometric properties tend to capture the corresponding *what* information defining these elements. Representations at each level of the hierarchy can capture general inherent properties as well as semantic or task-oriented properties (Dang and Allen, 2012; Myers et al., 2015; Jang et al., 2017). In addition to representing individual objects, the robot can also represent interactions between objects at the different layers of the hierarchy.

Point-level Representations: Point-level representations are the lowest level of the hierarchy, and include point cloud, pixel, and voxel representations for capturing the partial or complete shapes of objects in detail (Schenck et al., 2017; Bohg and Kragic, 2010; Klingensmith et al., 2014; Florence et al., 2018; Choi et al., 2018). Point-level representations provide the robot with the most flexible representations for capturing important details of objects and manipulation tasks.

Each element of these representations may be associated with additional features, such as the color or material properties corresponding to this point. Segmentation methods can be used to assign labels to individual points according to which part or object they belong (Schenck and Fox, 2018a; Myers et al., 2015). Interactions may be modeled at this level of the hierarchy as contact points (Kaul et al., 2016; Dang and Allen, 2012; Rosman and Ramamoorthy, 2011; Kopicki et al., 2016; Viña et al., 2013; Su et al., 2015; Veiga et al., 2015; Piacenza et al., 2017).

Generalization across tasks can be accomplished by establishing correspondences between objects and environments at the point level. The robot may identify individual key points of objects (e.g., the tip of a tool (Edsinger and Kemp, 2006)), or use non-rigid registration or geometry warping to determine correspondences of entire sets of points across task instances (Schulman et al., 2013; Hillenbrand and Roa, 2012; Stücker and Behnke, 2014; Rodriguez and Behnke, 2018; Amor et al., 2012). These correspondences can then be used to directly map manipulation skills between tasks or to compute higher-level representations (Stücker and Behnke, 2014).

Part-level Representations: Representations at the part level correspond to sets of multiple contiguous points from the lower level of the hierarchy (Sung et al., 2017a; Detry et al., 2013; Dang and Allen, 2010; Byravan and Fox, 2016), typically focusing on parts associated with certain types of manipulations. For example, a mug can be seen as having an opening for pouring, a bowl for containing, a handle for grasping, and a bottom for placing (Fagg and Arbib, 1998). Each part can then be described by a set of features describing aspects such as shape, pose, color, material, type, and surface properties. Robots can use part-level features to represent interactions or relations between the parts of different objects, or to indicate the types of interactions and constraints imposed between the parts due to the interaction (e.g., a peg must be smaller than the hole for an insertion task).

Defining correspondences at the part level enables generalization across different types of objects (Tenorth et al., 2013; Sung et al., 2015; Detry et al., 2013). Many objects have similar parts that afford similar interactions, although the objects may be very different as a whole. For example, a coin and a screwdriver are distinct types of objects, but they both have short thin metallic edge that can be used to turn a screw. Similarly, many objects have graspable handles; identifying the handle correspondences thus allows for transferring grasping skills (Detry et al., 2013; Kroemer et al., 2012). Part-based representations therefore allow the robot to generalize between different classes of objects without having to reason about individual points of the object (Sung et al., 2015).

Object-level Representations: Object-level representations are important because robots generally select objects, not individual features, to manipulate (Janner et al., 2019; Deisenroth et al., 2015; Gao et al., 2016; Jang et al., 2018). Thus, robots must generalize between the sets of features attached to each object. Useful object-level representations group together object-specific properties such as an object’s pose, mass, overall shape, and material properties (for uniform objects). Semantic object labels can be used to distinguish different types of objects and how they should be manipulated (Jang et al., 2017). Similar to parts, object-level interaction features often define the relative poses, forces, and constraints between objects in manipulation tasks, e.g., relative poses for stacking blocks (Fang et al., 2016; Jain and Kemp, 2013; Ugur and Piater, 2015; Sundaralingam et al., 2019). The robot may also define different types of interactions at this level (e.g., object A is *on* or *inside* object B) or relations between objects (e.g., relative sizes and weights) to capture sets of interactions in a more abstract form (Schenck et al., 2012; Schenck and Fox, 2018a; Kulick et al., 2013; Schenck and Stoytchev, 2012; Fichtl et al., 2014). Generalization across objects typically requires establishing correspondences between distinct objects (Devin et al., 2018) that support similar manipulations.

Robots may also need to represent **groups of objects**—rather than modeling individual objects within the group, it is often more efficient and robust to use features that represent groups of objects as a whole entity. For example, clutter, or the background scene with which the robot should avoid colliding, is often represented in a similar manner to a single deformable or piece-wise rigid object. Identifying and reasoning about individual objects may not be necessary, and may even add additional complexity to learning, causing learning to generalize poorly or be less robust. Manipulating a specific object among a group may require the robot to recognize it, or even actively singulate the object (Gupta et al., 2015; Hermans et al., 2012).

4.2 Passive and Interactive Perception

As embodied agents capable of manipulating their surroundings, robots can use actions to enhance their perception of the environment. Robot perception is therefore broadly divided into passive and interactive perception, with the key difference being whether or not the robot physically interacts with the environment.

The term **passive perception** refers to the process of perceiving the environment without exploiting physical interactions with it, i.e., non-interactive perception (Isola et al., 2015)—for example, recognizing and localizing objects in a scene based on a camera image (Burchfiel and Konidaris, 2018; Tremblay et al., 2018; Wang et al., 2019; Yamaguchi and Atkeson, 2016a). Passive perception allows the robot to quickly acquire a large amount of information from the environment with little effort. Passive perception does not require the environment or the sensor to be stationary; observing a human performing a manipulation task is still passive, as the robot does not itself perform the interaction. Similarly, moving a camera to a better vantage point is still a non-interactive form of perception, as the robot does not apply force to, or otherwise alter, the state of the environment (Saran et al., 2017; Kahn et al., 2015).

In **interactive perception** (Bohg et al., 2017), the robot physically interacts with its surroundings to obtain a better estimate of the environment. For example, a robot may push an object to better estimate its constraints or lift an object to estimate its weight (Barragán et al., 2014; Hausman et al., 2015; Katz and Brock, 2011). Robots can use a wide range of sensor modalities to observe the effects of its interactions, including haptic, tactile, vision, and audio (Lenz et al., 2015a; Chitta et al., 2011; Högman et al., 2016; Griffith et al., 2012; Thomason et al., 2016).

The need to perform actions means that interactive perception requires more time and energy than passive perception. The benefit of interactive perception is its ability to disambiguate between scenarios and observe otherwise latent properties (Tsikos and Bajcsy, 1991; Chitta et al., 2011; Gao et al., 2016), enabling the robot to reduce uncertainty. For example, the robot may not know whether two objects are rigidly connected or simply in contact; interactive perception allows it to test each hypothesis.

Different actions will result in different effects and hence robots can learn about their environment faster by selecting more informative actions (Barragán et al., 2014; Baum et al., 2017; Dragiev et al., 2013; Otte et al., 2014; Kulick et al., 2015; Saran et al., 2017; Kenney et al., 2009). For example, shaking a container will usually provide more information regarding its contents than a pushing action would (Schenck and Stoytchev, 2012; Sinapov et al., 2014; Schenck et al., 2014). Active learning approaches usually estimate the uncertainty of one or more variables in the environment and then select actions based on the resulting entropy, information gain, or mutual information (Otte et al., 2014; Högman et al., 2016; Hausman et al., 2015; van Hoof et al., 2014; Kulick et al., 2015).

The ability to test hypothesis means that interactive perception can also be used as a supervisory signal for learning to estimate properties using passive perception (Griffith et al., 2012; Pinto et al., 2016; van Hoof et al., 2014; Nguyen and Kemp, 2014; Wu et al., 2016; Kraft et al., 2008; Pathak et al., 2018). As an example of interactive learning, a robot may learn to predict the mass of objects from their appearance by first using interactive perception to determine the masses of a set of training objects. This form of self-supervised

learning allows the robot to gather information autonomously and is thus crucial for enabling robots to operate in unfamiliar environments.

4.3 Learning About Objects and Their Properties

Having explained the different types of object variations and types of perception, we now discuss how the robot can learn about the objects around it from data.

4.3.1 DISCOVERING OBJECTS

A common first step in learning is distinguishing the individual objects in the scene, which is a segmentation problem, typically accomplished using passive perception (Kraft et al., 2008; Alexe et al., 2012; Schwarz et al., 2018; Byravan and Fox, 2016; He et al., 2017). However, objects may often be close together in the scene, presenting the robot with ambiguous information about object identity. Here the robot can maintain a probabilistic belief over whether or not different parts belong to the same object (van Hoof et al., 2014; Kenney et al., 2009; Hausman et al., 2012), and use interactive perception or viewpoint selection to disambiguate the scene (Gualtieri and Platt, 2017; Hermans et al., 2012; van Hoof et al., 2014; Hausman et al., 2012).

4.3.2 DISCOVERING DEGREES OF FREEDOM

Once individual objects have been identified, the robot may need to identify their kinematic degrees of freedom (Niekum et al., 2015a; Jain and Niekum, 2020; Hausman et al., 2012; Katz et al., 2010; Baum et al., 2017; Sturm et al., 2010; Katz and Brock, 2011; Abbatematteo et al., 2019). These constraints and articulated connections are fundamental to establishing the objects’ state space for manipulation tasks, as well as for robust pose tracking (Desingh et al., 2018; Schmidt et al., 2015). The different types of joints are usually represented using distinct articulation models, e.g., revolute or prismatic, with their own sets of parameters. For example, a revolute joint model is specified by the position, direction, and limits of its rotation axis (Sturm et al., 2010; Barragán et al., 2014; Niekum et al., 2015a; Sturm et al., 2011). The robot must estimate these context parameters to accurately model the degrees of freedom. Passive perception can be used to estimate the kinematic chains of articulated objects, especially if the object is being moved by a person (Martín-Martín et al., 2016; Niekum et al., 2015a; Pillai et al., 2014; Brookshire and Teller, 2016; Jain and Niekum, 2020). Interactive perception is also well suited for estimating the articulation model parameters and the resulting motion constraints (Sturm et al., 2010; Barragán et al., 2014; Hausman et al., 2015). Given the high-dimensional parameter space of the articulation models, active learning approaches are often used to select informative actions for quickly determining the model parameters (Hausman et al., 2015; Baum et al., 2017), or transfer learning methods may be used (Abbatematteo et al., 2019).

4.3.3 ESTIMATING OBJECT PROPERTIES

Once the robot has identified an object in the environment, the next step is to estimate the object’s properties. Since some properties are only applicable to some classes of objects (Diuk et al., 2008; Bullard et al., 2018; Dragiev et al., 2013; Bhattacharjee et al., 2015;

Schenck and Stoytchev, 2012; Wu et al., 2016; Chitta et al., 2011) the robot must first recognize the object class. For manipulation tasks, object classes are often derived from the actions and interactions that they afford the robot, e.g., container, graspable, and stackable, such that the interaction-relevant properties can be easily associated with the objects.

Here the robot may use passive and interactive perception to estimate object property values (Gao et al., 2016; Isola et al., 2015; Li et al., 2014; Varley et al., 2019). In addition to object recognition, passive perception is often used to estimate the position, shape, and material properties (Li et al., 2018; Bhattacharjee et al., 2015; Wu et al., 2016; Tremblay et al., 2018; Garcia Cifuentes et al., 2017; Schmidt et al., 2015; Burchfiel and Konidaris, 2017; Issac et al., 2016; Burchfiel and Konidaris, 2018; Wüthrich et al., 2015; Yamaguchi and Atkeson, 2016a). However, additional interactive perception can often be used to acquire more accurate estimates of these properties (Chitta et al., 2010; Björkman et al., 2013; Dragiev et al., 2013; Javdani et al., 2013; Petrovskaya and Khatib, 2011; Koval et al., 2017). Material and interaction properties are often difficult to estimate accurately using only passive perception. The estimates can be significantly improved by interacting with the objects and using tactile sensing (Sinapov et al., 2011a,b, 2014; Sung et al., 2017b; Gao et al., 2016; Lenz et al., 2015a; Hsiao et al., 2010; Varley et al., 2019). Exploratory actions can also be used to estimate the dynamic properties of objects, e.g., the center of mass, or the contents of containers (Guler et al., 2014; Schenck et al., 2014; Chitta et al., 2011).

4.4 Feature Learning and Selection

Even though an environment may contain a lot of objects and sensory stimuli, only a few object properties or sensory signals will usually be relevant for a given task. For example, when opening a bottle, the size of the cap is a relevant feature, but the color of the chair is irrelevant. Using a suitable set of relevant features simplifies the skill and model learning problems. It also increases robustness and generalization to new situations. If the set of object properties is sufficiently rich, then the robot may only need to *select* a suitable set of these as features for learning (Devin et al., 2018; Kroemer and Sukhatme, 2017; Montesano et al., 2008; Song et al., 2011; Stramandinoli et al., 2018). In many cases, the robot will however need to *learn* a set of features for the given task.

Unsupervised feature learning methods extract features from unlabeled training data. Dimensionality reduction methods may be used to capture correlations in data and discard noisy components of signals. For manipulation domains, dimensionality reduction approaches can be used to learn compact representations of complex objects or variations within classes of objects (Burchfiel and Konidaris, 2017; Bergström et al., 2012). Dimensionality reduction methods can also be used to reduce the robot’s action space of grasps to better fit common object shapes (Ciocarlie et al., 2007). Clustering methods are used to cluster together similar data samples. For manipulations, clustering method may for example be used to cluster together distinct types of objects or continuous effects of manipulations (Ugur and Piater, 2015).

Supervised approaches learn features as part of the overall model or skill learning process. Decision trees and neural networks are often used to learn features in a supervised setting. Deep learning in particular has become ubiquitous for feature learning in robotics. Different network structures and layers, such as auto-encoders, spatial soft max layers,

convolutions, and segmentation masks, can be used to incorporate architectural priors for learning useful features. For example, segmentation masks can be used to capture the co-movement of nearby points in an image to capture points of objects or parts moving together (Byravan and Fox, 2016; Finn and Levine, 2017). Deep neural network models can be used to represent state spaces for manipulation tasks with high dimensional observation spaces. Representations of manipulation environments can be learned in a task-oriented manner to facilitate subsequent planning and control (Kurutach et al., 2018; Srinivas et al., 2018). Neural networks are also highly effective at combining data from multiple sensor modalities or information sources. For manipulation tasks, robots often use this approach to merge information between passive modalities (e.g., vision) and more interactive modalities (e.g., touch and haptics), or to incorporate additional task information (e.g., instructions) (Gao et al., 2016; Lee et al., 2019; Sung et al., 2017a).

5. Learning Transition Models

The goal of manipulation tasks is to alter the states of objects in the robot’s environment. Learning transition models that capture the changes in state as a result of the robot’s actions is therefore an important component of manipulation learning.

5.1 Representing and Learning Transition Models

Learning a transition model requires a suitable representation. The general form of a transition model for a family of MDPs is either a deterministic function $T : S \times A \rightarrow S$ or a stochastic distribution $T : S \times A \times S \rightarrow \mathcal{R}$ over the next states given the current state and action. The transition models can also depend upon the context vector τ in order to explicitly generalize between contexts. A transition model is often employed iteratively to perform multi-step predictions.

Continuous Models: In manipulation tasks, robots are generally operating in continuous state and action spaces, e.g., the state is given by the continuous poses of objects and the actions are given by desired joint positions or torques. Robots therefore often learn low-level transition models for predicting the next state as a set of continuous values, even when the set of actions is discrete (Scholz and Stilman, 2010). Regression methods, such as neural networks, Gaussian processes, and (weighted) linear regressions, are commonly used for learning transition models (Schenck et al., 2017; Levine and Koltun, 2013; Deisenroth and Rasmussen, 2011; Atkeson et al., 1997a).

The simplest models, such as linear regression models, can be learned from small amounts of data (Stilman et al., 2008), but often underfit the inherent nonlinearities of most manipulation tasks. Hence, the generalization performance of these models is limited. Instead, time-dependent linear models are often used to learn local models for specific regions of the state space (Kumar et al., 2016), e.g., around the trajectory of a skill being learned. These models may be sufficient while maintaining low data requirements, and can be combined with prior models that capture more global information about the task. Gaussian mixture models and neural networks have both been used to learn such informative priors (Fu et al., 2016).

Nonparametric models, including Gaussian processes and locally weighted regression, can flexibly learn detailed transition models (Deisenroth et al., 2015; Kopicki et al., 2017).

The generalization performance of these types of models depends heavily on their hyperparameters and is often fairly limited. However, local models can be learned from relatively small amounts of data. For example, an accurate model for planar pushing of a block may be learned from less than a hundred samples (Bauza and Rodriguez, 2017).

More complex hierarchical models, such as neural networks and decision trees, allow the robot to learn task-specific features that provide better generalization (Lenz et al., 2015a; Schenck et al., 2017; Fu et al., 2016; Janner et al., 2019; Sanchez-Gonzalez et al., 2018; Finn and Levine, 2017; Kurutach et al., 2018; Srinivas et al., 2018; Ye et al., 2018). For example, convolutional encoder-decoder networks can be used to learn models for predicting the transitions of individual points in the scene based on the selected actions (Byravan and Fox, 2016; Finn and Levine, 2017). However, unless the models are pre-trained, learning intermediate features significantly increases the amount of data required for training these models. Broadly speaking, the best representation for learning a continuous transition model often depends on the amount of training data available and the model expressiveness required by the task.

Predictive state representations (PSRs) allow the robot to model the distributions over future observations based on the history of past observations (Littman and Sutton, 2002; Singh et al., 2004; Boots et al., 2013; Stork et al., 2015). These models thus capture latent state information, as part of a POMDP formulation, without explicitly modeling or inferring the latent state. The robot can thus work directly with the observed variables.

More advanced parametric models provide additional structure, up to including entire physics engines (Wu et al., 2015; Scholz et al., 2014; Wu et al., 2016; Li et al., 2015). These engines provide a significant amount of prior structure and information, which improves generalization and data efficiency. However, even given the engine, it is difficult for a robot to map a real world scenario into a simulation environment. The simulation may also still fail to accurately capture certain interactions due to their lack of flexibility. Physics engines are therefore sometimes used to provide a prior or to initialize a more flexible representation by combining analytical models with flexible data-driven models (Ajay et al., 2018).

Discrete Models: Discrete transition models are used to learn transitions for tasks with discrete state and action spaces, typically capturing high-level tasks. For example, a robot may learn a discrete transition model for flipping a pancake, in which the transition probabilities indicate the probability of the pancake being flipped, dropped, or not transitioning. The model can then be used to predict the outcome of attempting multiple flips. Discrete models can also capture low-level transitions where the state space has been discretized. This results in the continuous states corresponding to a single discrete state being considered as identical. It also removes the smoothness assumption between states, such that state transition information is not shared between discrete states. As a result, a very fine-grained discretization will lead to poor generalization and a coarse discretization may not capture enough detailed transition information to perform the task. A suitable discretization should therefore cluster together states that will result in similar transitions given the same actions (Bergström et al., 2012). Adaptive or learned discretizations are a form of feature learning (Guan et al., 2018).

The most basic representations for discrete models are tabular models or finite state machines. Discrete models treat each state as atomic, with a transition distribution independent of all other states. This approach however severely hampers generalization and

transfer. More structured models use collections of symbols to represent discrete state spaces. Proposition-based models define a set of propositions (Konidaris et al., 2018), e.g., `Obj1Grasped` and `Obj2Clear`, which are either true or false and thus define the state. A set of N propositions thus defines a set of 2^N states. The factorization provided by the propositions results in a more compact representation of the state space, and also allows transition information to be shared between these states. In particular, symbolic models are often used to express compact (and sometimes stochastic) action models known as *operators*. Each such operator has a precondition that must be true for the action to be executable, e.g., `WaterReservoirFull=True` and `CoffeeJugFull=False` for a coffee making action. The effects of the action are then given by lists of propositions that become true (e.g., `CoffeeJugFull`) and that become false (e.g., `WaterReservoirFull`), with all other propositions being unchanged by the transition. As the preconditions and effects only refer to a small number of propositions, the operator generalizes across the values of all other propositions that are not mentioned.

These models may be generalized to relational or first-order models (Lang et al., 2012), which support extremely compact action models and enable generalization across objects. This approach allows predicate-based models (e.g., `Full(CoffeeJug)` for a full jug of coffee and `Full(WaterReservoir)` for a full water reservoir) to be used for families of tasks with different numbers of objects and states. This extended generalization can unfortunately also have some unintended effects if distinct situations are treated as the same. For example, a dishwasher loading action would treat a paper plate the same as a ceramic plate unless a suitable predicate, e.g. `IsCeramic(Plate)`, were included to avoid this type of over generalization.

Hybrid Models: Hybrid models combine elements of discrete and continuous models, often resulting from the hierarchical structure of manipulation skills and subtasks. The discrete components of the state are often used to capture high-level task information while the continuous components capture low-level state information.

Robots will often learn continuous models for specific subtasks. For example, a robot may learn separate models for opening a door, moving its body through free space, and stacking newspapers. These models can then be used to predict the effects of actions within each skill. In turn, these models can then become a part of the robot’s overall world model to predict the effects of sequences of skills. This approach allows the robot to exploit the modularity of the distinct subtasks for the discrete high-level transition model. Many works on learning continuous models for individual skills or subtasks can thus be seen as learning part of a larger hybrid model.

One common use of hybrid models is to represent modes in manipulation tasks (Hauser, 2018; Siméon et al., 2004; Kroemer et al., 2015; Lee et al., 2017; Choudhury et al., 2017; Zhou et al., 2018). In these cases, the dynamics are piece-wise continuous with jumps between the modes. These jumps are often defined by guard sets wherein the state transitions to a certain mode if the continuous state enters the guard set. In manipulation tasks, the jumps between modes typically result from contacts being made or broken between objects. The mode switches thus capture the changing dynamics and constraints caused by the changing contacts. Planning approaches for manipulation domains often explicitly take this multi-modal structure into account for planning (Toussaint et al., 2018; Jain and Niekum, 2018). Learning a hybrid model entails learning both the dynamics within each mode and the

conditions for switching between modes. The dynamics within a mode can be learned using standard continuous model approaches. The guard regions can be modeled as explicit sets of states or using classifiers. More flexible models, such as nonparametric and neural network models, may also be able to implicitly capture hybrid dynamics of manipulation tasks (Finn and Levine, 2017). Exploiting the modularity of the hybrid system is however more difficult when using an implicit model of the mode structure.

5.2 Uncertainty in Transition Models

State transitions are often represented using probabilistic models that allow the robot to represent multiple potential outcomes. For example, a robot may choose to move to a trash can and drop an object inside because the resulting state distribution has a lower variance than attempting to throw the object into the trash. When working with probabilistic models, it is important to distinguish between two sources of uncertainty: aleatoric and epistemic uncertainty.

Aleatoric uncertainty: A stochastic process exhibits a randomness in its state transitions. For example, when throwing a block into the air, the side on which the block will land is random. Similarly, due to slight variations in the execution and surface properties, the exact location of an object being placed on a table may follow a Gaussian distribution. Attempting to open a door may only result in the door opening 98% of the time and remaining closed the other 2%.

Stochasticity resulting in aleatoric uncertainty is common in manipulation tasks, for both discrete and continuous state spaces (Kopicki et al., 2017; Lang et al., 2012). Probabilistic models are thus used to capture the process noise and approximate the distributions over next states (Babaeizadeh et al., 2018; Kroemer et al., 2015).

Epistemic uncertainty: In addition to the inherent stochasticity of manipulation, the outcome of an action may be uncertain due to the robot’s limited knowledge of the process. For example, consider the task of placing a closed container into a bowl of water. Whether the container will float or sink is deterministic given its mass and volume. However, the robot’s prediction over the two outcomes may still be uncertain if the robot does not know the mass of the container or because it lacks sufficient training samples to accurately predict the mass threshold at which the container will sink. The probabilistic prediction is thus the result of epistemic uncertainty, or uncertainty over the model parameters, rather than aleatoric uncertainty from inherent stochasticity. Unlike aleatoric uncertainty, epistemic uncertainty can be reduced given additional information, e.g., using interactive perception to better estimate the mass of the container or acquiring additional training samples for estimating the threshold for the model.

Bayesian approaches explicitly capture epistemic uncertainty in their predictions by representing the probability distributions over different potential models (Deisenroth et al., 2015; Scholz et al., 2014). They also incorporate explicit prior beliefs over these model distributions. By contrast, point estimates, such as maximum likelihood or maximum a posteriori MAP estimates, assume a single model given the current data and use this model to predict the next state. Linear Bayesian models are often too simple to capture the complexity of manipulation tasks. Kernel-based Gaussian processes have therefore become one of the most popular Bayesian approaches for learning transition models (Deisenroth

et al., 2015; Högman et al., 2016). Gaussian processes, as well as linear Bayesian regression, both have explicit parameters modeling the stochasticity of the system being represented. The model uncertainty can also be used to guide exploration for learning an accurate model from fewer samples (Wang et al., 2018).

5.3 Self-supervision and Exploration for Learning Transitions

Transition models are usually learned in a self-supervised manner. Given the current state, the robot performs an action and observes the resulting effect on the state. The robot can thus acquire state, action, and next state tuples for training the model. To generalize more broadly, the robot will also need to estimate the context parameters for each task and then incorporate these into the model as well.

The robot can adopt different exploration strategies for acquiring samples. Random sampling is often used to learn general models and acquire a diverse set of samples. A grid approach may be used to ensure that the action samples are sufficiently spread out, but these approaches generally assume that the state can be reset between actions (Yu et al., 2016). Active sampling approaches can be used to select action samples that are the most informative (Wang et al., 2018). If the model is being used to learn and improve a specific skill, the robot may collect samples within the vicinity of the skill using a small amount of random noise (see model-based skill learning in the next section). Another increasingly popular approach to exploring an environment is to use intrinsic motivation (Chentanez et al., 2005; Pathak et al., 2019). In this case, the robot actively attempts to discover novel scenarios where its model currently performs poorly or that result in salient events.

5.4 Transferring and Reusing Transition Models

Transition models are not inherently linked to a specific task, and can therefore often be transferred and reused between different manipulation tasks and even task families. For example, a model learned for pushing an object may be used as the basis for learning push grasps of objects. In order to directly reuse a model, the learned model and the new task must have the same state, action, and context spaces, or a mapping between the spaces may be necessary (Taylor et al., 2007). Given compatible spaces, the ability to transfer or reuse models depends on the overlap between data distributions for training the old and new task models. This issue is known as covariate shift (input varies) and dataset shift (input and output varies). If the previous model was trained on data distinct from the needs of the new task, then the benefit of using the previous model will be limited and may even be detrimental. Assuming a sufficiently rich model, the robot can acquire additional data from the new task and use it to update the model for the new region. In this manner, the robot’s learned model may become more applicable to other tasks in the future. Data can also be shared across models when learning skills in parallel.

6. Learning Skill Policies

All of the robot learning problems discussed thus far are ultimately in service of helping the robot learn a policy that accomplishes some objective. Thus, the final learning goal for the robot is to acquire a behavior, or *skill controller*, that will perform a desired manipulation

task. A common representation for skill controllers is a *stochastic policy* that maps state-action pairs to probabilities (or probability densities in the continuous case). This section discusses the spectrum of different policy parameterizations that can be chosen, algorithms for learning skill policies from experience and demonstrations, methods for transferring knowledge across skills and tasks, and approaches that can provide safety and performance guarantees during learning.

6.1 Types of Action Spaces

The choice of action spaces is an important part of designing a manipulation policy. The robot ultimately needs to send a control signal to its actuators to perform actions in the physical world. These signals may, for example, define the desired pressure for a hydraulic or pneumatic actuator (Bischoff et al., 2014; Gupta et al., 2016), the heating for a shape memory alloy actuator (AbuZaiter et al., 2016; Zimmer et al., 2019), the tendon activation for a cable-driven robot (Schlagenhauf et al., 2018; Andrychowicz et al., 2020), or the torque for an electric motor (Nguyen-Tuong and Peters, 2011; Levine et al., 2015). Robots that are difficult to model, such as soft robots and robots with complex dynamics, may often benefit from learning policies that directly output these control signals. However, the outputs of policies often do not work directly at the level of actuator signals.

In practice, an additional controller is often placed between the policy and the actuator (Gullapalli et al., 1994). Using an additional controller allows the robot to leverage a large body of prior work on control for robotics (Spong et al., 2005). Example controllers include simple linear PID controllers as well as more complex model-based admittance and impedance controllers. The policy’s actions then define the desired values for the controller. The action space of the policy often defines the desired positions, velocities, or accelerations for movements or desired forces and torques for interactions.

Both desired position and force information can be defined in the joint space or a Cartesian task space for the end effector. For manipulation tasks, it is often easier to generalize interactions with objects across the robot’s workspace using a Cartesian action space (Mason, 1981; Ballard, 1984). For example, with a Cartesian action space, applying an upward force on a grasped object would be the same action anywhere in the robot’s workspace. The controller is then responsible for mapping these desired signals into the joint space for actuation. For a joint-space action policy, the robot would need to learn different joint torques depending on the arm’s current configuration.

Although the Cartesian actions could be defined in a global or robot-centric coordinate frame, additional generalization can often be achieved by using task frames associated to individual objects or salient features of the environment (Ballard, 1984). These task frames may be predefined, selected, or learned. Using a given object-relative task frame allows the policy learning to focus on how to perform the task rather than where to perform it.

In addition to determining the desired values for inputs to the controller, the policy may also output additional values for adapting the controller. In particular, a policy may define different controller gains as part of its action space (Buchli et al., 2011; Ren et al., 2018). In this manner, the policy can make a robot more compliant or stiffer at different points during the task execution. Otherwise the gains are usually predefined and fixed.

The inclusion of a controller also allows the robot to use a policy that operates at a lower frequency than the controller. While the low-level controllers may operate at 100s or 1000s of Hertz, the policies can operate at lower frequencies. For policies operating at lower frequencies, an additional interpolation step may be used to guide the controller between the desired values.

6.2 The Spectrum of Policy Structure

In robotic manipulation, specific parameterizations are often used that restrict the representational power of the policy; if these restrictions respect the underlying structure of the task, generalization and data efficiency are often improved without significantly impacting asymptotic performance. Thus, the choice of policy representation is a critical design decision for any robot learning algorithm, as it dictates the class of behaviors that can be expressed and encodes strong priors for how generalization ought to occur. This results in a spectrum of policy structures, ranging from highly general (but often sample-inefficient) to highly constrained (but potentially more sample-efficient) representations.

Nonparametric Policies: The most expressive policy representations are nonparametric, growing as needed with task or data complexity. This category includes nearest neighbor-based approaches, Gaussian processes (Rasmussen, 2004), Riemannian Motion Policies (Ratliff et al., 2018), and locally-weighted regression (Atkeson et al., 1997b; Vijayakumar and Schaal, 2000). These representations are the most flexible and data-driven, but they also typically require large amounts of data to produce high-quality generalization. This representational paradigm has been successful in manipulation tasks in which very little task knowledge is given *a priori* to the robot, such as an 88-dimensional octopus arm control problem in which Gaussian Process Temporal Difference learning is used (Engel et al., 2006), and 50-dimensional control of a SARCOS arm via locally weighted projection regression (Vijayakumar and Schaal, 2000).

Generic Fixed-size Parametric Policies: More commonly, fixed-complexity parametric policy representations are used, making stronger assumptions about the complexity and structure of the policy. Common parametric policy representations include look-up tables (Sutton and Barto, 1998), linear combinations of basis functions such as tile coding, the Fourier basis (Konidaris et al., 2011b, 2012), neural networks (Levine et al., 2016), decision tree classifiers (Quinlan, 1986; Huang and Liang, 2002), and support vector machines (Cortes and Vapnik, 1995; Ross et al., 2011). While any given choice of parameters has a fixed representational power, a great deal of engineering flexibility remains in choosing the number and definition of those parameters. Design decisions must also be made about which features will interact and which will contribute independently to the policy (e.g. the fully-coupled vs. independent Fourier basis (Konidaris et al., 2011b)), or more general decisions regarding inductive bias and representational power (e.g. neural network architectures).

The choice of a fixed parameterization makes particular assumptions about how generalization ought to occur across state-action pairs. For example, tabular representations can represent any (discrete) function, but do not intrinsically support generalization to unseen states and actions. By contrast, policies comprised of linear combinations of basis functions (for both discrete and continuous state spaces) more naturally generalize to novel situations

since each parameter (a basis weight) affects the policy globally, assuming basis functions with global support. However, the success of such generalization relies on the correctness of assumptions about the smoothness and “shape” of the policy, as encoded by the choice of basis functions. Some parametric forms make more specific structural assumptions—for example, by construction, convolutional neural networks (Krizhevsky et al., 2012; Levine et al., 2016; Agrawal et al., 2016; Mahler et al., 2017) support a degree of invariance to spatial translation of inputs.

Restricted Parametric Policies: The expressiveness of a policy is only limited by the underlying policy representation; however, sample complexity, overfitting, and generalization often get worse as representational power increases. This has led to the development of specialized policy representations that have limited representational power, but exploit the structure of robotics problems to learn and generalize from less data. However, the quality of the generalization in such methods is highly dependent upon the accuracy of the underlying assumptions that are made. Such methods lie on a spectrum of how restrictive they are; for example, structured neural network architectures (e.g. value iteration networks (Tamar et al., 2016), schema networks (Kansky et al., 2017), etc.) impose somewhat moderate restrictions, whereas other methods impose much stronger restrictions, such as forcing the policy to obey a particular set of parameterized differential equations (Schaal, 2006). However, it is not always clear how to choose the right point along the spectrum from a completely general to highly-specific policy class. The following are some common examples of restricted policy classes.

Linear Quadratic Regulators (LQR) (Zhou et al., 1996) are commonly used to stabilize around (possibly learned) trajectories or points, in which the cost is assumed to be quadratic in state and the dynamics are linear in state. These restrictions are relaxed in Iterative LQR (Fu et al., 2016) and Differential Dynamic Programming (Tassa et al., 2014; Yamaguchi and Atkeson, 2015), in which nonlinear dynamics and nonquadratic costs can be approximated as locally linear and locally quadratic, respectively. LQR-based controllers have also been chained together as LQR-trees, allowing coverage of a larger, more complex space (Tedrake et al., 2010). LQR-like methods also assume that the state is fully observable; Linear Quadratic Gaussian (LQG) control methods further generalize LQR by using a Kalman filter for state estimation, in conjunction with an LQR controller (Levine et al., 2015; Platt et al., 2010). LQR/LQG controllers are optimal when the linear-quadratic assumptions are met, but require full knowledge of the dynamics and cost function, as well as a known trajectory around which to stabilize. Thus, generalization in this case simply translates to being able to stabilize around this known trajectory optimally from anywhere in the state space.

Dynamic Movement Primitives (DMPs) support the learning of simple, generalizable policies from a small number of demonstrations, which can be further improved via reinforcement learning (Schaal, 2006; Pastor et al., 2009). DMPs leverage the fact that many robotic movements can be decomposed into two primary parts—a goal configuration in some reference frame and a “shape” of the motion. For example, screwing in a screw requires a turning motion to get to the desired final configuration with respect to the hole. DMPs use a set of differential equations to implement a spring-mass-damper that provably drives the system to an adjustable goal from any starting location, while also including the influence of a nonlinear function that preserves the desired shape of the movement. DMP

controllers can be learned from very little data, but typically only generalize well in cases in which a good solution policy broadly can be described by a single prototypical motion shape primitive.

Whereas DMPs generate deterministic policies, other approaches treat the problem probabilistically, allowing stochastic policies to be learned. ProMPs are a straightforward probabilistic variant of DMPs that can produce distributions of trajectories (Paraschos et al., 2013). Gaussian Mixture Regression (GMR) (Calinon et al., 2007) models the likelihood of states over time as a mixture of Gaussians, allowing for a multimodal distribution of trajectories that can encode multiple ways of performing a task, as well as the acceptable variance in different parts of the task.

Goal-based Policies: At the far end of the spectrum, the most restrictive policy representations are primarily parameterized by a goal configuration. Given that the goal configuration is the primary parameter, these methods are typically either fixed strategies (such as splining to a goal point (Su et al., 2016), or between keyframes (Akgun et al., 2012)) or have a very small number of adjustable parameters, such as a PID controller or motion planner.

6.3 Reinforcement Learning

For any given policy representation, reinforcement learning (RL) (Sutton and Barto, 1998) can be used to learn policy parameters for skill controllers. In robotics domains, tasks addressed with RL are usually *episodic*, with a fixed number of time steps or a set of terminal states that end the episode (e.g. reaching a particular object configuration), but occasionally may be *continuing* tasks with infinite horizons (e.g. placing a continual stream of objects into bins as fast as possible).

There are many challenges in applying RL to robotics. Due to the time it takes to collect data on physical robots, the tradeoff between exploration and exploitation becomes significantly more important, compared to problems for which fast, accurate simulators exist. Furthermore, few problems in robotics can be strictly characterized as MDPs, but instead exhibit partial observability (Platt et al., 2011) and nonstationarity (Padakandla et al., 2019) (though it often remains practical to cast and solve these problems as MDPs, nonetheless). Since many tasks in robotics are multi-objective (e.g. pick up the mug, use as little energy as possible, and don’t collide with anything), it can be difficult to define appropriate reward functions that elicit the desired behavior (Hadfield-Menell et al., 2016). Due to the episodic nature of most robotics tasks, rewards tend to be sparse and difficult to learn from. Robotics problems also often have high-dimensional continuous state features, as well as multi-dimensional continuous actions, making policy learning challenging.

Here, we categorize RL algorithms using three primary criteria: (1) model-based or model-free, (2) whether or not they compute a value function, and in what manner they use it, and (3) on-policy or off-policy.

Model-Based RL: Accurate models of transition dynamics are rarely available *a priori* and it is often difficult to learn transition models from data. Nonetheless, there have been notable model-based successes in robotic manipulation in which an approximate model is learned from data (Deisenroth and Rasmussen, 2011; Levine et al., 2015; Lenz et al., 2015a; Kumar et al., 2016; Finn and Levine, 2017; Schenck and Fox, 2018b). In these examples, the

model is typically used to guide exploration and policy search, leading to greatly improved data efficiency. More generally, the primary benefits of model-based RL in robotics are that (1) in some domains, an approximate model is simpler to learn than the optimal policy (since supervised learning is generally easier than RL) (2) models allow for re-planning / re-learning on-the-fly if the task changes, and (3) models allow for certain types of data collection that are difficult or impossible in the real world (such as resetting the world to an exact state and trying different actions to observe their outcome). The primary disadvantage of model-based methods, aside from the difficulty of obtaining or learning models, is that incorrect models typically add bias into learning. However, some methods mitigate this by directly reasoning about uncertainty (Deisenroth and Rasmussen, 2011), whereas methods such as doubly robust off-policy evaluation (Jiang and Li, 2016) use a model as a control variate for variance reduction, sidestepping the bias issue. More details on model learning can be found in Section 5.

Model-Free RL: Model-free methods learn policies directly from experiences of the robot, without building or having access to a model. When the dynamics of the environment are complex, as they often are in contact-rich manipulation tasks, it can be significantly easier to learn a good policy than a model with similar performance. Model-free methods can learn how to implicitly take advantage of complex dynamics without actually modeling them—for example, finding a motion that can pour water successfully without understanding fluid dynamics. The downside of the model-free approaches is that they cannot easily adapt to new goals without additional experience in the world, unlike model-based approaches. Furthermore, they typically require a large (sometimes prohibitive) amount of experience to learn. For this reason, some recent approaches have sought to combine the benefits of model-based and model-free methods (Gu et al., 2016; Chebotar et al., 2017; Pong et al., 2018; Feinberg et al., 2018; Englert and Toussaint, 2016).

Value Function Methods: These methods aim to learn the value of states (or more commonly, state-action pairs)—the expected return when following a particular policy, starting from that state(-action pair). Value functions methods are known to be low variance, highly sample efficient, and in discrete domains (or continuous domains with linear function approximation), many such methods can be proven to converge to globally optimal solutions. However, value function methods are typically brittle in the face of noise or poor or underpowered state features, and do not scale well to high-dimensional state spaces, all of which are common in robot manipulation tasks. Furthermore, they are not compatible with continuous actions, severely limiting their application to robotics, except where discretization is acceptable. Actions are often discretized at higher levels of abstraction when they represent the execution of entire skills, rather than primitive actions (Kroemer et al., 2015). Finally, it is difficult to build in useful structure and task knowledge when using value function methods, since the policy is represented implicitly. Nonetheless, value function-based methods such as Deep Q-Networks (Mnih et al., 2015) and extensions thereof have been applied successfully to robotics tasks (Zhang et al., 2015; Kalashnikov et al., 2018).

Policy Search Methods: Policy search methods parameterize a policy directly and search for parameters that perform well, rather than deriving a policy implicitly from a value function. Policy search methods have become popular in robotics, as they are robust to noise and poor features and naturally handle continuous actions, (the direct parameterization of the policy eliminates the need to perform a maximization over values of actions). They also

often scale well to high-dimensional state spaces since the difficulty of policy search is more directly related to the complexity of a good (or optimal) policy, rather than the size of the underlying state space.

Pure policy search approaches eschew learning a value function entirely. These are sometimes referred to as “actor-only” methods, since there is a direct parameterization of the policy, rather than a “critic” value function. Actor-only approaches include the gradient-based method REINFORCE (Williams, 1992), for use when the policy is differentiable with respect to its parameters. However, REINFORCE tends to suffer from high variance due to noisy sample-based estimates of the policy gradient (though a variance-reducing baseline can be used to partially mitigate this) and is only locally optimal. Actor-only policy search also includes gradient-free optimization methods (De Boer et al., 2005; Mannor et al., 2003; Hansen and Ostermeier, 2001; Davis, 1991; Theodorou et al., 2010), which are usable even when the policy is non-differentiable, and in some cases (e.g. genetic algorithms) are globally optimal, given sufficient search time. Unsurprisingly, these advantages often come at the cost of reduced sample efficiency compared to gradient-based methods.

In contrast to actor-only approaches, actor-critic policy search methods (Sutton et al., 2000; Peters and Schaal, 2008; Peters et al., 2010; Lillicrap et al., 2015; Mnih et al., 2016; Schulman et al., 2015, 2017; Wang et al., 2017; Wu et al., 2017; Haarnoja et al., 2018) use both a value function (the critic) and a directly parameterized policy (the actor), which often share parameters. These methods typically have most of the advantages of actor-only methods (the ability to handle continuous actions, robustness to noise, scaling, etc), but use a bootstrapped value function to reduce the variance of gradient estimates, thereby gaining some of the sample efficiency and low-variance of critic-only methods. The unique advantages of actor-critic methods have made them state of the art in many robotic manipulation tasks, as well as in the larger field of deep reinforcement learning.

On-Policy vs Off-Policy Learning: When using RL to improve a policy, on-policy algorithms are restricted to using data collected from executions of that specific policy (e.g. SARSA (Sutton and Barto, 1998)), whereas off-policy algorithms are able to use data gathered by any arbitrary policy in the same environment (e.g. Q-learning (Watkins and Dayan, 1992)). This distinction has several consequences which are notable in robotic domains for which data collection has significant costs. On-policy algorithms are not able to re-use historical data during the learning process—every time the behavior policy is updated, all previously collected data becomes off-policy. It is also often desirable to use collected data to simultaneously learn policies for multiple skills, rather than only a single policy; such learning is impossible in an on-policy setting. However, despite these advantages, off-policy learning has the significant downside of being known to diverge under some conditions when used with function approximation, even when it is linear (Sutton and Barto, 1998). By contrast, on-policy methods are known to converge under mild assumptions with linear function approximation (Sutton and Barto, 1998).

Exploration Strategies: A significant, but often overlooked, part of policy learning is the exploration strategy employed by the agent. This design decision can have enormous impact on the speed of learning, based on the order in which various policies are explored. In physical robotic manipulation tasks, this is a particularly important choice, as data is much more difficult to collect than in simulated domains. Furthermore, in the robotics

setting, there are concerns related to safety and possible damage to the environment during exploration, as will be further discussed in Section 6.6.

The most common exploration strategies involve adding some form of noise to action selection, whether it be in the form of direct perturbation of policy parameters (Theodorou et al., 2010), Gaussian noise added to continuous actions (Lillicrap et al., 2015), or epsilon-greedy or softmax action selection in discrete action spaces (Mnih et al., 2015). Unsurprisingly, random exploration often fails to efficiently explore policy space, since it is typically confined to a local region near the current policy and may evaluate many similar, redundant policies.

To address these shortcomings, exploration strategies based on the psychological concept of *intrinsic motivation* (Chentanez et al., 2005; Oudeyer and Kaplan, 2009) have used metrics such as novelty (Huang and Weng, 2002; Bellemare et al., 2016; Hart, 2009; Ecoffet et al., 2019; Burda et al., 2018), behavioral diversity (Lynch et al., 2019), uncertainty (Martinez-Cantin et al., 2007), and empowerment (Mohamed and Rezende, 2015) to diversify exploration in a more effective way. However, these methods are heuristic-based and may still lead to poor performance. In fact, many essentially aim to use intrinsic motivation to uniformly explore the state space, ignoring structure that may provide clues about the relevance of different parts of the state space to the problem at hand. By contrast, other approaches have taken advantage of structure specific to robotic manipulation by directing exploration to discover reusable object affordances (Montesano et al., 2008), or learning exploration strategies that exploit the distribution of problems the agent might face via metalearning (Xu et al., 2018b). Finally, as discussed in the next subsection, the difficulty of exploration in RL is sometimes overcome by leveraging demonstrations of good behavior, rather than learning from scratch.

6.4 Imitation Learning

In contrast to reinforcement learning, which learns from a robot’s experiences in the world (or a model of it), imitation learning (Schaal, 1999; Argall et al., 2009) aims to learn about tasks from demonstration trajectories. This can be thought of as a form of programming, but one in which the user simply shows the robot what to do instead of writing code to describe the desired behavior. Learning from demonstration data has been extensively studied in several different settings, because it can enable the robot to leverage the existing task expertise of (potentially non-expert) humans to (1) bypass time-consuming exploration that would be required in a reinforcement learning setting, (2) communicate user preferences for how a task ought to be done, and (3) describe concepts, such as a good tennis swing, that may be difficult to specify formally or programmatically. It is worth noting that imitation learning and reinforcement learning are not mutually exclusive; in fact, it is common for imitation learning to be followed by reinforcement learning for policy improvement (Kober and Peters, 2009; Taylor et al., 2011).

Demonstrations in imitation learning are typically represented as trajectories of states or state-action pairs. There are several mechanisms by which a robot may acquire such demonstration trajectories, including teleoperation, shadowing, kinesthetic teaching, motion capture, which are discussed in greater detail in the survey by Argall et al. (Argall et al., 2009). More recently, keyframe demonstrations (Akgun et al., 2012), virtual reality

demonstrations (Zhang et al., 2018; Yan et al., 2018), and video demonstrations in the so-called learning from observation setting (Liu et al., 2018) have also become more commonly used.

Behavioral Cloning: The simplest way to use demonstration data to learn a motor skill is to use it as supervised training data to learn the robot’s policy. This is commonly called *behavioral cloning*. Recall that a deterministic policy π is a mapping from states to actions: $\pi : S \rightarrow A$, whereas a stochastic policy maps state-action pairs to probabilities (which sum to 1 at each state when marginalizing over actions): $\pi : S \times A \rightarrow \mathcal{R}$. The demonstration provides a set of state-action pairs (s_i, a_i) , that can be used as training data for a supervised learning algorithm to learn policy parameters that should, ideally, be able to reproduce the demonstrated behavior in novel scenarios.

Behavioral cloning is often used as a stand-alone learning method (Ross et al., 2011; Bagnell et al., 2007; Torabi et al., 2018; Pastor et al., 2009; Cederborg et al., 2010; Akgun et al., 2012; Duan et al., 2017; Hayes and Demiris, 1994; Schaal et al., 2005), as well as a way to provide a better starting point for reinforcement learning (Pastor et al., 2011a), though this additionally requires the specification of a reward function for RL to optimize. Other recent work has focused on expanding the purview of behavioral cloning by unifying imitation learning and planning via probabilistic inference (Rana et al., 2017), utilizing additional modalities such as haptic input (Kormushev et al., 2011), learning to recognize and recover from errors when imitating (Pastor et al., 2011b,a), and scaling behavioral cloning to complex, multi-step tasks such as IKEA furniture assembly (Niekum et al., 2015b).

Reward Inference: Rather than learning a policy directly from demonstration data, an alternative approach is to attempt to infer the underlying reward function that the demonstrator was trying to optimize. This approach aims to extract the intent of the motion, rather than the low-level details of the motion itself. This approach is typically called inverse reinforcement learning (IRL) (Ng et al., 2000), apprenticeship learning (Abbeel and Ng, 2004; Boularias et al., 2012), or inverse optimal control (Moylan and Anderson, 1973; Englert et al., 2017; Englert and Toussaint, 2018a). The inferred reward function can then be optimized via reinforcement learning to learn a policy for the task.

The IRL paradigm has several advantages. First, if the reward function is a function of the objects or features in the world and not the agent’s kinematics, then it can be naturally ported from human to robot (or between different robots) without encountering the correspondence problem. In addition, reward functions are often sparse, thereby providing a natural means of generalizing from a small amount of training data, even in very large state spaces. In addition, the human’s behavior may encode a great deal of background information about the task—for example, that an open can of soda should be kept upright when it is moved—that are easy to encode in the reward function but more complex to encode in a policy, and which can be reused in later contexts. Unfortunately, IRL also presents several difficulties. Most notably, the IRL problem is fundamentally ill-posed—infinitely many reward functions exist that result in the same optimal policy (Ng et al., 2000). Thus, the differentiation between many IRL algorithms lies in the metrics that they use to disambiguate or show preference for certain reward functions (Abbeel and Ng, 2004; Abbeel et al., 2010; Boularias et al., 2012; Aghasadeghi and Bretl, 2011; Englert et al., 2017; Englert and Toussaint, 2018a).

Maximum Entropy IRL (Ziebart, 2010) addresses the problems of demonstrator suboptimality and ill-posedness by leveraging a probabilistic framework and the principle of maximum entropy to disambiguate possible reward functions. Specifically, they develop an algorithm that assigns equal probability to all trajectories that would receive equal return under a given reward function and then use this distribution to take gradient steps toward reward functions that better match the feature counts of the demonstrations (Ziebart et al., 2008), while avoiding having any additional preferences other than those indicated by the data. Rather than generating a point estimate of a reward function, which forces an algorithm to face the ill-posedness of IRL head on, Bayesian IRL (Ramachandran and Amir, 2007) instead uses Markov Chain Monte Carlo to sample from the distribution of all possible reward functions, given the demonstrations. Finally, in the more restricted case of linearly-solvable MDPs, the IRL problem is well-posed, avoiding these problems (Dvijotham and Todorov, 2010).

All of the IRL algorithms mentioned so far rely on reward functions specified as a linear combination of features. While this does not restrict the expressivity of reward functions in practice (more complex features can always be provided), it burdens the designer of the system to ensure that features can be learned from in a linear manner. By contrast, Gaussian Process and nonparametric IRL (Levine et al., 2011; Englert et al., 2017) and various neural network-based methods (Ho and Ermon, 2016; Finn et al., 2016; Wulfmeier et al., 2015; Fu et al., 2017) aim to partly relieve this burden by searching for reward functions that are a nonlinear function of state features. However, such flexibility in representation requires careful regularization to avoid overfitting (Finn et al., 2016).

Many of the aforementioned methods have an MDP solver in the inner loop of the algorithm. Computational costs aside, this is especially problematic for robotics settings in which a model is not available and experience is expensive to collect. Some recent IRL methods that have been shown to work in real robotic domains sidestep this obstacle by alternating reward optimization and policy optimization steps (Finn et al., 2016) or framing IRL as a more direct policy search problem that performs feature matching (Doerr et al., 2015; Ho and Ermon, 2016). If available, ranked demonstrations can be used to get rid of the need for inference-time policy optimization or MDP solving entirely, by converting the IRL problem to a purely supervised problem; furthermore, this approach allows the robot to potentially outperform the demonstrator (Brown et al., 2019a,b). Alternately, active learning techniques have been used to reduce the computational complexity of IRL (Brown et al., 2018; Cui and Niekum, 2018; Lopes et al., 2009), as well as strategies that make non-I.I.D. assumptions about the informativeness of the demonstrator (Brown and Niekum, 2019; Kamalaruban et al., 2019). Finally, outside of an imitation learning framework, goals for the robot are sometimes specified via natural language commands that must be interpreted in the context of the scene (Tellex et al., 2011).

Learning from Observation: A relatively new area of inquiry aims to learn from demonstrations, even when no action labels are available and the state is not exactly known. For example, a robot may visually observe a human performing a task, but only have access to raw pixel data and not the true underlying state of the world, nor the actions that the human took. This problem is referred to Learning from Observation (LfO), and several recent approaches have addressed problems including unsupervised human-robot correspondence learning (Sermanet et al., 2018), context translation (Liu et al., 2018),

adversarial behavioral cloning (Torabi et al., 2018), and IRL from unsegmented multi-step video demonstrations (Goo and Niekum, 2019a; Yang et al., 2015). In an extreme version of the LfO setting, the agents is expected to infer an objective from single-frame goal-state images, rather than a full trajectory of observations (Zeng et al., 2018; Xie et al., 2018).

Corrective Interactions: Rather than learning from full demonstrations in batch, it is often advantageous to solicit (potentially partial) corrective demonstrations or other forms of feedback over time. For example, a human could intervene in a pouring task and adapt the angle of the cup and the robot’s hand mid-pour. This provides a natural mechanism to collect data in situations where it is most needed—for example, situations in which mistakes are being made, or where the robot is highly unsure of what to do. Some approaches actively ask users for additional (partial) demonstrations in areas of the state space in which confidence is low (Chernova and Veloso, 2009) or risk is high (Brown et al., 2018), while others rely on a human user to identify when a mistake has been made (Niekum et al., 2015b). Higher level information can also be used to make more robust corrections, such as grounded predicate-based annotations of corrections (Mueller et al., 2018) and action suggestions in a high-level finite state machine (Holtz et al., 2018). The robot can also actively solicit assistance when needed, for example, via natural language (Knepper et al., 2015). Finally, rather than using corrective demonstrations, the TAMER framework uses real-time numeric human feedback about the robot’s performance to correct and shape behavior (Knox et al., 2013).

6.5 Skill Transfer

Given the high sample complexity of learning in complex robotics tasks, skills learned in one task are often transferred to other tasks via a variety of mechanisms, thereby increasing the efficiency of learning.

Direct Skill Re-use: One of the simplest ways to transfer a skill policy is to directly re-use it in a new task related to the one it was learned on. Typically, some amount of adaptation is required to achieve good performance in the new task. One simple way to perform such refinement is to initialize a new skill with an existing skill’s policy parameters and adapt them for the new task via reinforcement learning (Pastor et al., 2009). However, a naive realization of this approach only works when the original task and the new task have identical state representations. When this is not the case, transfer can still occur via a subset of shared state features that retain semantics across tasks. This is sometimes called an *agent space* (Konidaris and Barto, 2007), since these are typically agent-centric, generic features (e.g. laser scanner readings), rather than problem-specific features, or a *deictic representation* (Platt et al., 2019). Since an agent space only covers some subset of the features in a problem, transfer occurs via initialization of a value function, rather than policy parameters.

More generally, it is often useful to find a state *abstraction*—a minimal subset of state features required to perform some skill. Abstractions facilitate transfer by explicitly ignoring parts of the state that are irrelevant for a particular skill, which could otherwise serve as distractors (e.g. irrelevant objects), as well as allowing transfer to state spaces of different sizes (as also seen in agent spaces, which are a type of abstraction). In some state spaces, such as the visual domain, the state space is not factored in a manner that makes abstraction

easy (e.g. the texture of an object is not a separate state feature, but distributed across many pixels). One popular way of forcing a deep neural network to abstract away complex variables such as texture and color is *domain randomization* (Tobin et al., 2017; Bousmalis et al., 2018), which is discussed in greater detail later in this section.

Parameterized Skills: In certain task families, only some aspects of the task context change, while all other task semantics remain the same or are irrelevant. For example, it may be desirable to transfer a policy that can hit one goal location on a dartboard, in order to hit a different goal location; similarly, transfer learning could acquire a policy for completing a pendulum swing-up task with different pendulum lengths and masses. In these restricted cases, specialized *parameterized skills* can be learned that facilitate transfer via mechanisms that modulate the policy based on the aspect of the task context parameter that is changing (Calinon, 2018; Englert and Toussaint, 2018b).

Dynamic Movement Primitives (Schaal, 2006; Pastor et al., 2009) use a simple spring-mass-damper system to smoothly adjust to new initial and goal locations. Another approach uses manifold learning to smoothly modulate policy parameters based on a variable task parameter (Da Silva et al., 2014). Contextual policy search uses a hierarchical, two-level policy for low-level control and generalization across contexts, respectively (Kupcsik et al., 2013). Universal value function approximators (Schaul et al., 2015; Andrychowicz et al., 2017) track a value function for all $\langle \text{state}, \text{action}, \text{goal} \rangle$ triplets, rather than only $\langle \text{state}, \text{action} \rangle$ pairs, allowing policy similarities across nearby goals to be leveraged explicitly.

Metalearning: Rather than re-using a skill directly for initialization, metalearning approaches aim to “learn to learn”—in other words, learn something about a distribution of tasks that allows for more efficient learning on any particular task from that distribution in the future. Thus, metalearning facilitates transfer within a task family by performing learning across samples from a task distribution at training time, rather than performing transfer sequentially and on-line as problems are encountered, as in the direct re-use case.

Model Agnostic Metalearning (MAML) (Finn et al., 2017) searches for a set of policy parameters that can be adapted quickly for particular tasks drawn from some distribution. Reptile (Nichol et al., 2018) simplifies MAML by replacing a complex optimization with an approximate approach that only requires standard stochastic gradient descent to be performed on each sampled task individually. Another related metalearning approach learns an attention-based strategy that allows the robot to imitate novel manipulation tasks, such as block-stacking, from a single demonstration (Duan et al., 2017).

Other forms of metalearning have focused on reward functions rather than policies. While many problems in robotic manipulation have simple sparse reward formulations (e.g. +1 when peg is in hole, -1 otherwise), *potential-based* shaping rewards (Ng et al., 1999) can be added to any reward function to encourage faster learning (across some distribution of problems) without changing the optimal policy of the MDPs. More generally, modified reward functions can help to overcome multiple forms of *agent boundedness* (Sorg et al., 2010b) and can be found via gradient descent (Sorg et al., 2010a), genetic programming (Niekum et al., 2010), or other evolutionary methods (Houthoofd et al., 2018).

Some metalearning approaches have been developed to directly modify the representation of the policy itself, or other parts of the learning algorithm, rather than only the settings of policy or reward parameters. This includes methods that evolve the structures of neural networks (Stanley et al., 2009), or that learn skill embeddings (Hausman et al.,

2018), structured exploration strategies (Gupta et al., 2018), transfer feature relevances between families (Kroemer and Sukhatme, 2017), reusable network modules (Alet et al., 2018), or that co-learn a differentiable model and trajectory optimizer (Srinivas et al., 2018).

Domain Adaptation: In contrast to parameterized skills, some task families retain all of their high-level semantics across instances, differing only in lower-level details. In these cases, *domain adaptation* techniques are commonly used to bridge the so-called domain gap between two (or more) domains. For example, in the “sim2real” problem, when switching from a simulated task to a physical robot, the low-level statistics of the visual scene and physics may change, while the high-level steps and goals of the task stay fixed. Grounded action transformations address the physics domain gap by iteratively modifying agent-simulator interactions to better match real-world data, even when the simulator is a fixed black box (Hanna and Stone, 2017). Domain randomization is a data synthesis technique used to address visual domain gaps by randomizing environmental attributes such as texture, color, and dynamics in simulation, as to force the system to be invariant to statistical changes in the properties (Tobin et al., 2017; Bousmalis et al., 2018; Peng et al., 2018). A different type of visual shift can result from changes in viewpoint, often encountered in the setting of learning from unstructured videos. Approaches to this problem have included unsupervised learning of correspondences between first-person and third-person task demonstrations (Stadie et al., 2017), as well as imitation-from-observation approaches that work from multi-viewpoint data (Liu et al., 2018). Other approaches attempt to learn disentangled representations that lead naturally to robust policies that are tolerant of domain shift (Higgins et al., 2017).

In some tasks, the state and action space may change in a manner that requires an analogy to be made between the domains, as in the case of transferring a manipulation policy between two robot arms with different kinematic structures by finding a shared latent space between the two policy representations (Gupta et al., 2017). Time Contrastive Networks take a self-supervised metric-learning approach to a similar problem, learning representations of behaviors that are invariant to various visual factors, enabling robot imitation of human behaviors without an explicit correspondence (Sermanet et al., 2018). Other methods perform a more direct mapping between states and actions (Taylor et al., 2007), but assume that there exists a complete mapping, while the aforementioned latent space approach is able to discover partial mappings.

Sequential Transfer and Curriculum Learning: While the aforementioned transfer paradigms primarily consider instances of transfer individually, it is sometimes advantageous to view multiple instances transfer as a sequential learning problem. For example, Progressive Neural Networks (Rusu et al., 2016) use a neural network to learn an initial task, transferring this knowledge to subsequent tasks by freezing the learned weights, adding a new column of layers for the new task, and making lateral layer-wise connections to the previous task’s neurons. Sequential transfer learning is also a useful paradigm for mastering tasks that are too difficult to learn from scratch. Rather than attack the final task directly, *curriculum learning* presents a sequence of tasks of increasing difficulty to the agent, which provides a smoother gradient for learning and can make positive rewards significantly less sparse in an RL setting. Such methods often use curricula provided by human designers (Bengio et al., 2009; Sanger, 1994; Pinto and Gupta, 2016), though several recent methods

seek to automatically generate a curriculum (Narvekar et al., 2016; Svetlik et al., 2017; Florensa et al., 2017).

Scheduled Auxiliary Control (Riedmiller et al., 2018) learns to sequentially choose from a set of pre-defined auxiliary tasks in a manner that encourages efficient exploration and learning of the target task. Guided Policy Search (Levine et al., 2015) first learns simple time-dependent controllers for individual task instances, which are then used to generate data to train a more complex neural network. Universal Value Function Approximators (UVFAs) (Schaal et al., 2015) can learn and transfer knowledge more efficiently in curriculum-like settings by estimating the value of a state and action *conditioned upon the current goal*, rather than for a single fixed goal. Hindsight Experience Replay (HER) provides additional goal settings for UVFAs by simply executing actions, and in hindsight imagining that every state that the agent ends up in was actually a goal (Andrychowicz et al., 2017).

Reverse curriculum learning (Florensa et al., 2017) begins at the goal and works backwards, trying to learn to get to the goal successfully from more and more distant states. This stands in contrast to standard curriculum learning that typically starts in some distant state, slowly moving the goal of the subtasks closer and closer to the true goal. This idea is also related to that of skill chaining (Konidaris and Barto, 2009b; Konidaris et al., 2012), which will be discussed in further detail in Section 8.1.

6.6 Safety and Performance Guarantees

Whether a policy is learned directly for a specific task or transferred from a previous task, an important but understudied question is “How well will the policy perform across the distribution of situations that it will face?”. This is an especially important question in robotic manipulation, in which many future applications will require behaviors that are safe and correct with high confidence: robots that operate alongside humans in homes and workplaces must not cause injuries, destroy property, or damage themselves; safety-critical tasks such as surgery (Van Den Berg et al., 2010) and nuclear waste disposal (Kim et al., 2002) must be completed with a high degree of reliability; robots that work with populations that rely on them, such as the disabled or elderly (Goil et al., 2013), must be dependable. While the term “safety” has taken on many different meanings in the literature, in this section, we take a broad view of safe learning to include all methods that aim to bound a performance metric with high confidence.

Performance Metrics: Most performance metrics for robotic manipulation tasks can be represented as cumulative reward under some reward function—for example, the preferences of completing a task accurately, finishing within a certain amount of time, or never (or with low probability) visiting certain states can all be described with particular reward functions and acceptable thresholds on cumulative reward, or *return*. Thus, for simplicity, we will discuss the problem of bounding performance as being equivalent to that of lower-bounding some function of return. However, it is worth noting that certain preferences, such as some temporal logic statements, cannot be expressed as a reward function without augmenting the state space; some cannot be expressed by any reward function at all (Littman et al., 2017).

The principle axis of variation regarding performance metrics is whether the *expected* return of a policy is being bounded, or whether a risk-aware function of return is used—

for example, a robust worst-case analysis (Ghavamzadeh et al., 2016), a PAC-style bound (Strehl et al., 2006), or bounded value-at-risk (Chow et al., 2015; Brown et al., 2020). Risk-aware metrics are generally more appropriate for safety-critical tasks in which the robot could cause damage or injury in a single trial that goes poorly, whereas expected performance is often used in scenarios in which long-term performance (e.g. percentage of correctly manufactured items) matters more than the outcome of any single trial.

Finally, one important distinction to make is *when* a policy must obey performance bounds. Some robotics tasks, such as learning to manipulate a fragile object, demand performance guarantees during the exploration and learning phase, rather than only after deployment of the final policy. For example, in one recent work, demonstrations were used to constrain exploration in safety-critical manipulation tasks (Thananjeyan et al., 2019). By contrast, other tasks may lend themselves to safe practice, such that only the final policy needs to be accompanied by guarantees. For example, a legged robot may learn a walking gait while attached to a support rig so that it cannot catastrophically fall while learning.

Classes of Guarantees and Bounding Methods: Given that standard policy learning in robotics is a challenging open problem, in part due to limited real-world data collection abilities, it is not surprising that safe learning is even more difficult. Safe learning methods are typically significantly more data-hungry and/or require more accurate models than standard learning methods, as they need to provide guarantees about the quality of the policy. For this reason, very few safe learning methods (e.g. from the reinforcement learning community) have been used in robotics applications. This is a significant gap in the current literature and an opportunity for future work that can provide strong performance guarantees in low-data and poor-model robotics settings.

Safe learning methods fall roughly into two categories: Exact methods and probabilistic high-confidence bounds. Formal verification-based approaches are exact methods that use a known model, along with a safety specification (e.g. a finite-state automata) to guarantee (or bound the probability, in the stochastic case) that following a policy will not lead to an unsafe outcome (Fu and Topcu, 2014; Fainekos et al., 2009; Chinchali et al., 2012; Chen et al., 2013; Alshiekh et al., 2018). However, some research has focused on control synthesis that obeys linear temporal logic constraints without access to a model (Sadigh et al., 2014). By contrast, probabilistically safe approaches aim to provide lower-bounds on expected return, rather than utilizing logical specifications of safety (Thomas et al., 2015b,a; Jiang and Li, 2016; Hanna et al., 2017; Thomas and Brunskill, 2016). While probabilistic methods appear to be promising for robotics applications (since they do not require a model), to the best of our knowledge, they have not been used in real robotics problems, potentially due to their high sample complexity.

Thus far, we have only considered performance guarantees in a standard MDP setting, in which either (1) the reward function is known, or (2) samples from the reward function are available. However, this description of the problem does not cover a common scenario that occurs when learning from demonstrations—having access to states and actions, but not rewards. In the inverse reinforcement learning setting, several approaches have examined how to bound the policy loss between the the robot’s policy (commonly a policy learning via RL under the inferred reward function) and the optimal policy under the ground-truth reward function of the demonstrator, even though it is unknown (Abbeel and Ng, 2004; Brown and Niekum, 2018; Brown et al., 2020).

7. Characterizing Skills by Preconditions and Effects

Executing a manipulation skill alters the state of the robot’s environment; if the robot is to use its skills to achieve a specific goal, it requires a model of those outcomes. This model is termed a *postcondition*, and describes the regions in the state space that the robot will find itself in after skill execution. The robot must also model the circumstances under which the skill can be executed—termed its *preconditions*. Knowledge of these two models for each skill can be used to determine whether, for example, a sequence of skills can be executed from a particular state (Konidaris et al., 2018). Pre- and postconditions are used to sequence skills (or actions) for task planning. The planner searches through sequences of actions with the constraint that the postconditions of each skill must fulfill the preconditions of the next skill.

7.1 Pre- and Postconditions as Propositions and Predicates

The pre- and postconditions of manipulation skills are typically represented abstractly as either *propositions* or *predicates* (Krüger et al., 2011; Kulick et al., 2013; Konidaris et al., 2018; Beetz et al., 2010; Shapiro and Ismail, 2003; Ugur and Piater, 2015) that are either true or false in any specific state. For example, the robot may represent the outcome of a particular navigation skill using the boolean proposition `AtTableB`. It could also use a predicate representation, `At(TableB)`, which supports more compact and efficient representations, and allows for easier generalization across objects. We therefore use predicate-based symbols for the remainder of this section although most of the explanation also applies to proposition symbols.

The *grounding* or anchoring of a predicate refers to the mapping between the (often continuous) low-level state and context and the predicate’s truth value; it defines the meaning of the symbol (Konidaris et al., 2018; Coradeschi et al., 2013). To avoid confusion, we will not use the term grounding for assigning objects to predicates as is done in the planning literature (Russell and Norvig, 2003).

Classifier Representation: The grounding of a predicate can be modelled as a binary classifier (Konidaris et al., 2018; Kroemer and Sukhatme, 2016; Konidaris et al., 2015). The classifier represents the mapping from the state and context to either true or false. If a predicate is defined for a subset of objects, then the state and context features of those objects are used as the input to the predicate classifier (Kroemer and Sukhatme, 2016). For example, the predicate `Grasped(KnifeA, RHand)` would consider the state and context of the knife and hand to determine if the knife was being grasped by the the hand. The robot may learn a probabilistic classifier to determine the likelihood that the predicate is true given the current state and context. In this manner, the robot may handle situations where the predicate is only sometimes valid, or when the classifier has been learned and the robot is uncertain of its true value in states it has not encountered before (Konidaris et al., 2018).

Distribution Representation: Alternatively, predicates can be modelled as probability distributions over the state space (Konidaris et al., 2018; Detry et al., 2011). The distributions are defined in the state and context space. For a non-probabilistic approach, the distribution defines the set of states and contexts where the distribution is true, and the predicate is false otherwise. For a probabilistic approach, the distribution defines a proba-

bility density over the states and contexts given that the predicate is true (Konidaris et al., 2018; Detry et al., 2011). The distribution may be defined only for the objects assigned to the predicate. This distribution is useful for sampling states and contexts in which the predicate is true.

Modularity and Transfer: One precondition proposition and one postcondition proposition for each skill are sufficient for skill sequencing. These predicates can be monolithic representations that define the sets of states and contexts for that specific skill. However, by decomposing the conditions into modular predicates, the robot can share knowledge between different skills and tasks. These predicates can often be defined for subsets of objects, e.g., `Full(mug, water)` and `Grasped(mug, hand)`. The predicates often define labels for individual objects, e.g., `Container(obj1)`, and the relationships between the objects, e.g., `Above(obj1, obj2)`. Modular predicates will often capture the contact-based manipulation modes between pairs of objects, e.g., `Grasped(Obj1, Hand)` or `On(Obj2, Obj3)`. Previous works have explored methods for learning specific predicates or discovering suitable sets of predicates (Kulick et al., 2013; Montesano et al., 2008; Konidaris et al., 2018; Hjelm et al., 2014).

Learning the preconditions and postconditions is generally easier when reusing predicates from previous tasks rather than learning from scratch. However, some discrepancies may exist between tasks and thus require additional learning (Ugur and Piater, 2015). For example, a robot may require a specific type of grasp for performing a task. The predicate `Grasped(obj3, hand)` is thus not sufficient. The robot should instead learn a general predicate for transferring knowledge between tasks, and a task-specific predicate for incorporating additional constraints (Detry et al., 2017; ten Pas et al., 2017; Gualtieri and Platt, 2018; Lu and Hermans, 2019; Bohg et al., 2012; Hjelm et al., 2014). The latter predicate is generally easier to learn given the former predicate. For example, a robot may learn to identify stable grasps for a wide range of objects, and subsequently learn to identify a subset of grasps for specific objects or to grasp handles of cooking utensils without relearning to grasp from scratch (Detry et al., 2017; Gualtieri and Platt, 2018; ten Pas et al., 2017).

7.2 Learning Pre- and Postcondition Groundings

The robot can train the pre- and postcondition predicate classifiers using samples of states and contexts where the conditions were known to be true or false. The ground truth labels could be provided by a human supervisor, although this approach would limit the autonomy of the robot and may require substantial expertise from the user. In some cases a human can provide data for *desired* post- and preconditions—what the skill should achieve, from which conditions—but the actual conditions will ultimately depend on the robot’s capabilities.

Instead of relying on manual labeling, the robot can learn the condition labels from experience. The labels for the preconditions can be learned given a fixed postcondition — all states from which a skill execution leads to a state satisfying the postcondition are positive examples, and all other states are negative examples. The robot should use a probabilistic classifier to capture the stochasticity of the transitions. The robot can thus obtain the precondition labels by executing the skill from different states and observing the resulting outcomes.

The postconditions are less trivial to define. A human may predefine a desired postcondition, but to achieve autonomy the robot must *discover* different postconditions on its own. Distinct postconditions can be learned by clustering the outcomes of the skill from different initial states and contexts (Dogar et al., 2007; Ugur et al., 2009; Ugur and Piatier, 2015). Manipulation skills often have distinct effects, e.g., a box remained upright or toppled over, which can be extracted through clustering or by detecting salient events. Each distinct postcondition cluster will then be associated with its own preconditions. This approach is often employed in developmental learning to discover specific useful skills from more general skill policies, e.g., grasping and pushing from reaching (Oztop et al., 2004; Juett and Kuipers, 2018).

A more goal-oriented approach to specifying postconditions is to construct skills where the postcondition is either the goal of the task or another skill’s precondition (Konidaris and Barto, 2009b; Konidaris et al., 2011a). This approach directly learns pre- and postconditions for constructing skills that can be sequentially executed, and may avoid learning conditions that are irrelevant to the robot’s task set, but it introduces dependencies between the robot’s skills.

Finally, pre- and postcondition predicates can be grounded in sensory data with the assistance of natural language, for example, as part of an interactive dialogue between a human and a robot (Thomason et al., 2016). Conversely, knowledge of pre- and postconditions of skills can help to ground natural language commands to those skills, especially when the language description is incomplete (Misra et al., 2014). For example, the command “Stir the soup” may imply picking up a spoon first, which could be determined via the precondition to a stirring skill.

7.3 Skill Monitoring and Outcome Detection

Most skills will have distinct pre- and postconditions with some of the predicates changing as a result of the skill execution, e.g., executing a grasping skill on a book should result in `Grasped(Book, RHand)=True` once the book has been grasped (Dang and Allen, 2012; Garrett et al., 2018). The predicates may also change due to errors in the skill execution. For example, when executing a placing skill, the predicate values `On(Book, Table)=False` or `InCollision(Book, Obstacle)=True` would correspond to errors. To perform manipulation tasks robustly, the robot must monitor its skill executions and determine if and when it has achieved the intended outcome or whether an error has occurred.

Learning Goal and Error Classifiers: Goals and errors in skill executions can be modeled as distinct predicates with values that are switched for the postconditions. Detecting goals and errors can thus be modelled as a classification problem (Bekiroglu et al., 2013; Rodriguez et al., 2010). Rather than using only the current state, the robot can incorporate action and sensor information from the entire skill execution (Bekiroglu et al., 2013; Madry et al., 2014; Rodriguez et al., 2010), although it is often better to stop a skill early when an error occurs (Pastor et al., 2012; Su et al., 2016; Sukhoy et al., 2012). Transient events, such as vibrations from mode transitions or incipient slip can then be used to better detect the predicate switches (Park et al., 2016; Veiga et al., 2015; Su et al., 2016). The robot can use a variety of sensor modalities, including vision and audio, to detect the predicate switches, e.g., a robot can use tactile sensing to determine if a grasp attempt

succeeded `Grasped(obj)=True` (Calandra et al., 2018; Dang and Allen, 2012; Madry et al., 2014; Dang and Allen, 2013). A robot can also learn optimal locations for placing a camera, or other sensor, to reliably verify if a desired postcondition has been fulfilled (Saran et al., 2017).

Detecting Deviations from Nominal Sensory Values: Stereotypical executions of a manipulation skill will usually result in similar sensations during the execution. Larger deviations from these nominal values often correspond to errors (Yamaguchi and Atkeson, 2016b). Hidden Markov models can be used to track the successful progress of a skill’s execution based on sensory signals (Park et al., 2016; Lello et al., 2013; Hovland and McCarragher, 1998; Bekiroglu et al., 2010). The robot may also learn the nominal sensory signals as a regression problem (Pastor et al., 2011a; Kappler et al., 2015; Sukhoy et al., 2012). Significant deviations from the expected sensory values would then trigger the stopping of the current skill. An error may also trigger a corresponding recovery action (Dang and Allen, 2013; Veiga et al., 2018; Yamaguchi and Atkeson, 2017). Unlike the outcome classifiers from the previous section, these models are trained using only data from successful trials.

Verifying Predicates: The pre- and postconditions of skills often change the values of predicates corresponding to modes and constraints between objects. For example, a placing skill can make `On(DishC,DishB)=True` and an unlocking skill can make `Locked(DoorA)=False`. The robot can verify these switches in the predicate values using *interactive perception*. In some cases the predicate can be verified by directly performing the next skill in the sequence, e.g., attempting to lift an object after it has been grasped (Pinto and Gupta, 2016; Kalashnikov et al., 2018). For contact constraints, the robot can often perform small perturbations to verify the predicate’s final value (Debus et al., 2004; Wang and Kroemer, 2019). In both examples, the robot can obtain a better estimate of the predicate by performing the additional skill and observing the effect. However, the additional skills can sometimes also change the predicates, and hence some care needs to be taken when verifying predicates.

7.4 Predicates and Skill Synthesis

Skills will often have additional high-level arguments that define how to execute the skill (Ugur et al., 2011). For example, a grasping skill may take in a grasping pose, or a scrubbing skill may take in a desired force (Bohg et al., 2014). In this manner, a higher-level policy may adapt the skill to its specific needs.

Representing and Synthesizing Skill Parameters: Similar to the predicate representations, these policy parameter arguments can be modeled as additional input features for the precondition classifier or as distributions over valid and invalid argument values (Detry et al., 2011; Jiang et al., 2012). Many of these arguments can even be thought of as virtual or desired object states (Jiang et al., 2012). For example, one could sample potential hand positions for grasping objects and model each one as a symbol for specifying the grasping action (Garrett et al., 2018; Bohg et al., 2014). To obtain valid grasp frames, the robot can learn a classifier to determine if sampled grasp frames will lead to successful grasps (Saxena et al., 2008; Nguyen and Kemp, 2014; Herzog et al., 2014; Pinto and Gupta, 2016), or sample from a learned probability density over successful grasps or cached grasps

from similar objects (Detry et al., 2011; Brook et al., 2011; Goldfeder et al., 2009; Choi et al., 2018). The process of learning the pre- and post- conditions with additional policy arguments is thus similar to learning the preconditions without the arguments.

Once the robot has learned the pre- and postconditions over the arguments, it can use these to select skill parameters for new situations. This process usually involves sampling different parameter values and evaluating them in terms of the pre- and postconditions. The robot could use sampling and optimization methods to select argument values with high likelihoods of successful skill executions. As these parameters are often lower dimensional than full skills, active learning and multi-armed bandit methods can be used to select suitable argument values (Montesano and Lopes, 2012; Mahler et al., 2016; Kroemer et al., 2010). When the positive distribution is learned directly, the robot can sample from the distribution and then evaluate if it is consistent with other predicates, e.g., not in collision (Ciocarlie et al., 2014). The arguments are usually selected in order to achieve certain predicates in the postconditions. One can therefore think of the argument selection process as *predicate synthesis* (Ames et al., 2018).

Preconditions and Affordances: Affordances are an important concept in manipulation and a considerable amount of research has explored learning affordances for robots (Sahin et al., 2007; Min et al., 2016; Jamone et al., 2018). The affordances of an object are the actions or manipulations that the object affords an agent (Gibson, 2014). An object that can be used to perform an action is thus said to *afford* that action to the agent. For example, a ball affords bouncing, grasping, and rolling. Affordances are thus closely related to the preconditions of skills. As affordances connect objects to skills (Montesano et al., 2008), affordance representations often include skill arguments that define how the skill would be executed (Ugur et al., 2011; Kroemer et al., 2012).

The exact usage of the term *affordances* tends to vary across research papers (Jamone et al., 2018). In most cases, affordances can be seen as a form of partial preconditions. The affordances often correspond to specific predicates that the robot learns in the same manner as the preconditions. The other components of the precondition are usually constant or at least all valid, such that the success or failure of the skill only depends on the component being learned. As partial preconditions, some affordances are more specific than others, e.g., balls can be rolled versus balls on a plane within reach of the robot can be rolled. Ultimately, the full preconditions need to be fulfilled to perform the skill. However, the partial preconditions of affordances provide modularity and can help the robot to search for suitable objects for performing tasks.

8. Learning Compositional and Hierarchical Task Structures

In the previous sections, we have focused on learning models of individual objects, or on learning to perform or characterize individual motor skills. However, manipulation tasks often have a substantial *modular* structure that can be exploited to improve performance across a family of tasks. Therefore, some research has attempted to decompose the solution to a manipulation task into *component skills*. Decomposing tasks this way has several advantages. Individual component skills can be learned more efficiently because each skill is shorter-horizon, resulting in a substantially easier learning problem and aiding exploration. Each skill can use its own internal skill-specific abstraction (Diuk et al., 2009; Konidaris and

Barto, 2009a; van Seijen et al., 2013; Cobo et al., 2014; Jiang et al., 2015) that allows it to focus on only relevant objects and state features, decomposing a problem that may be high-dimensional if treated monolithically into one that is a sequence of low-dimensional subtasks. A skill’s recurrence in different settings results in more opportunities to obtain relevant data, often offering the opportunity to generalize; conversely, reusing skills in multiple problem settings can avoid the need to relearn elements of the problem from scratch each time, resulting in faster per-task learning. Finally, these component skills create a *hierarchical structure* that offers the opportunity to solve manipulation tasks using higher-level states and actions—resulting in an easier learning problem—than those in which the task was originally defined.

8.1 The Form of a Motor Skill

The core of hierarchical structure in manipulation learning tasks is identifying the component skills from which a solution can likely be assembled.

Recall that skills are often modeled as options, each of which is described by a tuple $o = (I_o, \beta_o, \pi_o)$, where:

- $I_o : S \rightarrow \{0, 1\}$ is the initiation set, which corresponds to a precondition as discussed in Section 7.
- $\beta_o : S \rightarrow [0, 1]$, the termination condition, describes the probability that option o ceases execution upon reaching state s . This corresponds to a goal as discussed in Section 7, but is distinct from an effect; the goal is the set of states in which the skill *could* (or perhaps *should*) terminate, whereas the effect describes where it *actually* terminates (typically either a subset of the goal or a distribution over states in the goal).
- π_o is the option policy.

In many cases, option policies are defined indirectly using a reward function R_o , often consisting of a completion reward for reaching β_o plus a background cost function. π_o can then be obtained using any reinforcement learning algorithm, by treating β_o as an absorbing goal set. The core question for finding component skills when solving a manipulation problem is therefore to define the relevant termination goal β_o —i.e., identify the target goal—from which R_o can be constructed.

The robot may construct a *skill library*, consisting of a collection of multiple skills that can be frequently reused across tasks. This requires extracting a collection of skills, either from demonstrations, or from behaviors generated autonomously by the robot itself. The key question here is how to identify the skills, which is a difficult, and somewhat under-specified, challenge. There are two dominant approaches in the literature: segmenting task solution trajectories into individual component skills, or directly including skill specification as part of the overall problem when learning to solve tasks.

8.2 Segmenting Trajectories into Component Skills

One approach to identifying a skill library is to obtain solution trajectories for a collection of tasks, and segment those trajectories into a collection of skills that retroactively decompose

the input trajectories. This is commonly done using demonstration trajectories, though it could also be performed on trajectories generated autonomously by the robot, typically after learning (Hart, 2008; Konidaris et al., 2011a; Riano and McGinnity, 2012). However they are generated, the resulting trajectories must be segmented into component skills. The literature contains a large array of methods for performing the segmentation, which we group into two broad categories.

Segmentation Based on Skill Similarity: The most direct approach is to segment demonstration trajectories into repeated subtasks, each of which may occur in many different contexts (Dang and Allen, 2010; Meier et al., 2011). Identifying such repeated tasks both reduces the size of the skill library (which in turn reduces the complexity of planning or learning which skill to use when) and maximizes the data available to learn each skill (Lioutikov et al., 2015). This requires a measure of *skill similarity* that expresses a distance metric between two candidate skill segments, or more directly models the probability with which they were generated by the same skill. Therefore, several approaches have used a measure of skill similarity to segment demonstration trajectories, often based on a variant of a Hidden Markov model, where the demonstrated behavior is modeled as the result of the execution of a sequence of latent skills; segmentation in this case amounts to inferring the most likely sequence of skills.

The most direct approach (Jenkins and Matarić, 2004; Chiappa and Peters, 2010; Grollman and Jenkins, 2010; Niekum et al., 2015b; Meier et al., 2011; Daniel et al., 2016b) is *policy similarity*, which measures skill similarity by fitting the data to a parameterized policy class and measuring distance in parameter space. Alternative approaches to policy similarity fit models to the underlying value function (Konidaris et al., 2012) or the unobserved reward function that the skill behavior is implicitly maximizing (Ranchod et al., 2015; Krishnan et al., 2019; Michini and How, 2012; Choi and Kim, 2012; Babes et al., 2011). Some approaches segment demonstration trajectories and then merge similar skills in a separate post-processing step (Konidaris et al., 2012), while the most principled probabilistic approaches infer shared skills across a collection of trajectories as part of the segmentation process (Niekum et al., 2015b; Ranchod et al., 2015). Rather than using a parametric model, a latent space can be discovered that efficiently encodes skills, which are either learned from experience in a reinforcement learning context, or via a latent-space segmentation of trajectories in an imitation learning setting (Hausman et al., 2017, 2018). Other recent approaches have relied on observations only, learning to segment videos of multi-step tasks into composable primitives (Goo and Niekum, 2019b; Yu et al., 2018; Huang et al., 2019; Xu et al., 2018a).

A less direct approach is to measure skill-similarity based on *pre- and post-condition similarity*, where the skill policy or trajectory itself is not used for segmentation. Instead, trajectory segments that achieve the same goal can be clustered together, while those that do so from very different initial conditions could be split (Kroemer et al., 2014). Thus, reaching and pushing motions are different skills due to their distinct pre- and post- conditions, i.e., moving or not moving an object, even if the skill policies are similar or the same. This approach is often used in developmental learning approaches to discover skills (Weng et al., 2001); the robot executes a skill policy in a variety of scenarios and then clusters together the post- and pre- conditions to create distinct skills (Xie et al., 2018; Niekum and Barto, 2011; Ugur et al., 2011; Ugur and Piater, 2015; Ugur and Piater, 2015).

Segmentation Based on Specific Events: Several approaches use pre-designated events to indicate skill boundaries. These can range from hand-specified task-specific events to more generally applicable principles.

One common approach is to segment by *salient sensory events* defined by haptic, tactile, audio, or visual cues (Juett and Kuipers, 2018; Su et al., 2016; Fitzpatrick et al., 2006; Aksoy et al., 2011). For example, insertion skills are easier to monitor if they result in a distinct *click* upon successful completion. Similarly, we can determine if a light switch was properly pushed if the light goes on or the button cannot be pushed any further. Human-made objects are often designed to provide salient event feedback to reduce errors while using the objects. Such skills have the advantage that their termination conditions are easy to detect and monitor.

Another important class of pre-defined segmentation events is *transitioning between modes* (Baisero et al., 2015; Kroemer et al., 2015). Switching between modes allows the robot to switch between the ability to interact with different objects. Hence, the robot must first transition to a suitable mode to manipulate an object. Skills for transitioning to specific modes allow the robot to decouple accessing a mode and using the mode to perform a manipulation task. Grasping, lifting, placing, and releasing are all examples of skills used to switch between modes in pick-and-place tasks. Mode transitions can also be verified by applying additional actions to determine if the skill execution was successful. However, multiple skills within a mode, e.g., squeezing, shaking, and tilting a held object, cannot be detected using only this type of decomposition.

8.3 Discovering Skills While Solving Tasks

An alternative approach is to discover component motor skills *during* the process of learning to solve one or more manipulation tasks. This has two crucial advantages over solution trajectory segmentation. First, learned skills could aid in solving the tasks to begin with; many complex manipulation tasks cannot be solved directly without decomposing them into simpler tasks, so it will be infeasible to require that a complete solution precede skill discovery. Second, imposing hierarchical structure *during* learning can inject bias that results in much more compact skill libraries. For example, there may be multiple ways to turn a switch; there is no reason to expect that a robot that independently learns to solve several tasks involving switches will find a similar policy each time. However, if the learned policy for turning a switch is identified and retained in the first task, then it will likely be reused in the second task.

Broadly speaking, there are substantially fewer successful approaches that learn skills while solving tasks than there are approaches that retroactively segment, in part because the problem is fundamentally harder than segmentation. For example, skill similarity approaches are difficult to apply here. However, some researchers have applied methods based on specific salient events (Hart, 2008) to trigger skill creation. These methods could be combined with skill chaining (Konidaris and Barto, 2009b; Konidaris et al., 2011a)—an approach where skills are constructed to either reach a salient event or to reach another skill’s preconditions—to learn the motor skills online. An alternative is to structure the policy class with which the robot learns to include hierarchical components which can be extracted after learning and reused. This approach naturally fits recent research using deep neural

networks for policy learning (Nachum et al., 2018; Vezhnevets et al., 2017; Levy et al., 2019), which are sometimes structured to be successively executable in a manner similar to skill chaining (Kumar et al., 2018), but have been used in other more compact representations (Daniel et al., 2013, 2016a). Another approach aims to incrementally discover hierarchical skills that progressively learn to control factorized aspects of the environment, such as objects (Chuck et al., 2020). These new results are exciting but have only just begun to scratch the surface of how component motor skills can be learned during the robot’s task learning process.

8.4 Learning Decision-Making Abstractions

A collection of abstract motor skills provides *procedural* abstraction to the robot; it can abstract over the low-level details of what it must *do* to solve the task. However, these motor skills also provide an opportunity for abstracting over the input the robot uses to decide which skill to execute. Learning such abstract structures have two potential advantages: First, the new abstract input may make learning for new tasks easier (or even unnecessary by enabling generalized abstract policies that work across tasks) and support abstract, task-level planning. Second, the resulting abstract representations may be much easier for a non-expert to edit, update, and interpret.

Broadly speaking, the literature contains two types of learned abstractions for decision-making. The first type learns an abstract policy directly, while the second learns an abstract state space that serves as the basis for either planning or much faster learning in new tasks.

Learning Abstract Policy Representations: Here the goal is to learn a generalized abstract policy that solves a class of problems. Often this policy encodes a mapping from abstract quantities to learned motor skills. For example, the policy for opening a door might include first checking to see if it is locked and if so, executing the unlock skill; then grasping the handle, turning it, and opening the door. Here the motor skills subsume the low-level variations in task execution (e.g., turning differently shaped doorknobs) while the abstract quantities subsume differences in task logic (e.g., checking to see if the door is locked). Approaches here differ primarily by the representation of the policy itself, ranging from finite-state machines (Niekum et al., 2015b) to associative skill memories (Pastor et al., 2012) to hierarchical task networks (Hayes and Scassellati, 2016) to context-free grammars (Lioutikov et al., 2018). In some cases these result in a natural and intuitive form of incremental policy repair and generalization (Niekum et al., 2015b; Hayes and Scassellati, 2016).

Learning Abstract State Spaces: Alternatively, the robot could learn abstract representations of *state*, which when combined with abstract actions result in a new, but hopefully much simpler, and typically discrete, MDP. The robot can then use that simpler MDP to either learn faster, or to learn a task model and then plan. Several approaches have been applied here, for example using the status of the skills available to the robot as a state space (Brock et al., 2005; Hart, 2008), finding representations that minimize planning loss (Kulick et al., 2013; Jetchev et al., 2013; Ugur and Piater, 2015; Ugur and Piater, 2015), using qualitative state abstractions (Mugan and Kuipers, 2012) and constructing compact MDPs that are provably sound and complete for task-level planning (Konidaris, 2016; Konidaris et al., 2018; Ames et al., 2018). These approaches offer a natural means

of abstracting away the low-level detail common to learning for manipulation tasks, and exploiting the structure common to task families to find minimal compact descriptions that support maximally efficient learning.

Taken together, hierarchical and compositional approaches have great promise for exploiting the structure in manipulation learning tasks, to reduce sample complexity and achieve generality, and have only begun to be carefully explored. This is a challenging area full of important questions, and where several breakthroughs still remain to be made.

9. Conclusion

This paper has presented an overview of key manipulation challenges and the types of robot learning algorithms that have been developed to address these challenges. We explained how robots can represent objects and learn features hierarchically, and how these features and object properties can be estimated using passive and interactive perception. We have discussed how the effects of manipulations can themselves be captured by learning continuous, discrete, and hybrid transition models. Different data collection strategies and model types determine how quickly the robot can learn the transition models and how well the models generalize to new scenarios.

Skill policies can often be learned quickly from human demonstrations using behavioural cloning or apprenticeship learning, while mastery of manipulation skills often requires additional experience and can be achieved using model-based or model-free reinforcement learning. Given a skill, the robot can learn its preconditions and effects to capture its utility in different scenarios. Learning to monitor manipulation skills by detecting errors and goals imbues them with an additional level of robustness for working in unstructured environments.

Finally, we have seen how a robot can exploit the modular nature of manipulation tasks, such that each learned skill can be incorporated into a larger hierarchy to perform more advanced tasks, promoting reusability and robustness of skills across different tasks.

Given the multi-faceted nature of manipulation, researchers have found great utility in being able to draw from methods that span the breadth of machine learning. However, despite access to these excellent generic machine learning methods, the challenges of learning robust and versatile manipulation skills are still far from being resolved. Some—but by no means all—of these pressing challenges are:

- Integrating learning into complete control systems
- Using learned components as they are being learned (*in situ* learning)
- Safe learning, and learning with guarantees
- Exploiting and integrating multiple sensory modalities, including human cues
- Better exploration strategies, possibly based on explicit hypotheses or causal reasoning
- Exploiting common-sense physical knowledge
- Better algorithms for transfer across substantially different families of tasks

- Drastically improving the sample complexity of policy learning algorithms, while avoiding having to empirically tune hyper-parameters

As the community tackles these and other challenges, we expect that the core themes that have emerged repeatedly in manipulation learning research—modularity and hierarchy, generalization across objects, and the need for autonomous discovery—will continue playing a key role in designing effective solutions.

Acknowledgments

The authors would like to thank Animesh Garg for all of his help and insightful discussions, and Ben Abbatematteo, Daniel Brown, Caleb Chuck, Matt Corsaro, Yuchen Cui, Eren Derman, Wonjoon Goo, Prasoon Goyal, Reymundo Gutierrez, Ajinkya Jain, Timothy Lee, Qiao (Jacky) Liang, Rulldolf Liutikov, Matt Mason, Akanksha Saran, Mohit Sharma, and Garrett Warnell for their feedback and comments on the draft.

This work was supported in part by the National Science Foundation (IIS-1724157, IIS-1638107, IIS-1617639, IIS-1749204, IIS-1717569), the Office of Naval Research (N00014-18-2243, N00014-18-1-2775) and the Sony Corporation.

References

- B. Abbatematteo, S. Tellex, and G. Konidaris. Learning to generalize kinematic models to novel objects. In *Proceedings of The 3rd Conference on Robot Learning*, Proceedings of Machine Learning Research, pages 1289–1299, 2019.
- P. Abbeel and A. Y. Ng. Apprenticeship learning via inverse reinforcement learning. In *Proceedings of the 21st International Conference on Machine learning*, pages 1–8, 2004.
- P. Abbeel, A. Coates, and A. Y. Ng. Autonomous helicopter aerobatics through apprenticeship learning. *International Journal of Robotics Research*, 29(13):1608–1639, 2010.
- A. AbuZaiter, M. Nafea, and M. S. Mohamed Ali. Development of a shape-memory-alloy micromanipulator based on integrated bimorph microactuators. *Mechatronics*, 38:16 – 28, 2016. ISSN 0957-4158.
- N. Aghasadeghi and T. Bretl. Maximum entropy inverse reinforcement learning in continuous state spaces with path integrals. In *Proceedings of the 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 1561–1566, 2011.
- P. Agrawal, A. V. Nair, P. Abbeel, J. Malik, and S. Levine. Learning to poke by poking: Experiential learning of intuitive physics. In *Advances in Neural Information Processing Systems 29*, pages 5074–5082, 2016.
- A. Ajay, J. Wu, N. Fazeli, M. Bauza, L. P. Kaelbling, J. B. Tenenbaum, and A. Rodriguez. Augmenting physical simulators with stochastic neural networks: Case study of planar pushing and bouncing. In *Proceedings of the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3066–3073, 2018.

- B. Akgun, M. Cakmak, K. Jiang, and A. L. Thomaz. Keyframe-based learning from demonstration: Method and evaluation. *International Journal of Social Robotics*, 4(4):343–355, 2012.
- E. E. Aksoy, A. Abramov, J. Dörr, K. Ning, B. Dellen, and F. Wörgötter. Learning the semantics of object-action relations by observation. *International Journal of Robotics Research*, 30(10):1229–1249, 2011.
- F. Alet, T. Lozano-Perez, and L. P. Kaelbling. Modular meta-learning. In *Proceedings of The 2nd Conference on Robot Learning*, volume 87 of *Proceedings of Machine Learning Research*, pages 856–868, 2018.
- B. Alexe, T. Deselaers, and V. Ferrari. Measuring the objectness of image windows. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(11):2189–2202, 2012.
- M. Alshiekh, R. Bloem, R. Ehlers, B. Könighofer, S. Niekum, and U. Topcu. Safe reinforcement learning via shielding. In *Proceedings of the 32nd AAAI Conference on Artificial Intelligence*, 2018.
- B. Ames, A. Thackston, and G. Konidaris. Learning symbolic representations for planning with parameterized skills. In *Proceedings of the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 526–533, 2018.
- H. B. Amor, O. Kroemer, U. Hillenbrand, G. Neumann, and J. Peters. Generalization of human grasping for multi-fingered robot hands. In *Proceedings of the 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 2043–2050, 2012.
- M. Andrychowicz, F. Wolski, A. Ray, J. Schneider, R. Fong, P. Welinder, B. McGrew, J. Tobin, O. P. Abbeel, and W. Zaremba. Hindsight experience replay. In *Advances in Neural Information Processing Systems 30*, pages 5048–5058, 2017.
- M. Andrychowicz, B. Baker, M. Chociej, R. Józefowicz, B. McGrew, J. Pachocki, A. Petron, M. Plappert, G. Powell, A. Ray, J. Schneider, S. Sidor, J. Tobin, P. Welinder, L. Weng, and W. Zaremba. Learning dexterous in-hand manipulation. *International Journal of Robotics Research*, 39(1):3–20, 2020.
- B. D. Argall, S. Chernova, M. Veloso, and B. Browning. A survey of robot learning from demonstration. *Robotics and Autonomous Systems*, 57(5):469–483, 2009.
- C. G. Atkeson, A. W. Moore, and S. Schaal. Locally weighted learning. *Artificial Intelligence Review*, 11(1-5):11–73, 1997a.
- C. G. Atkeson, A. W. Moore, and S. Schaal. Locally weighted learning for control. *Artificial Intelligence Review*, 11(1-5):75–113, 1997b.
- M. Babaeizadeh, C. Finn, D. Erhan, R. H. Campbell, and S. Levine. Stochastic variational video prediction. In *Proceedings of the 2018 International Conference on Learning Representations*, 2018.

- M. Babes, V. Marivate, K. Subramanian, and M. L. Littman. Apprenticeship learning about multiple intentions. In *Proceedings of the 28th International Conference on Machine Learning*, pages 897–904, 2011.
- J. Bagnell, J. Chestnutt, D. M. Bradley, and N. D. Ratliff. Boosting structured prediction for imitation learning. In *Advances in Neural Information Processing Systems 19*, pages 1153–1160, 2007.
- A. Baisero, Y. Mollard, M. Lopes, M. Toussaint, and I. Lutkebohle. Temporal segmentation of pair-wise interaction phases in sequential manipulation demonstrations. In *Proceedings of the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 478–484, 2015.
- D. Ballard. Task frames in robot manipulation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 1984.
- P. Barragán, L. P. Kaelbling, and T. Lozano-Perez. Interactive Bayesian identification of kinematic mechanisms. In *Proceedings of the 2014 IEEE International Conference on Robotics and Automation*, pages 2013–2020, 2014.
- M. Baum, M. Bernstein, R. Martín-Martín, S. Höfer, J. Kulick, M. Toussaint, A. Kacelnik, and O. Brock. Opening a lockbox through physical exploration. In *Proceedings of the 2017 IEEE-RAS International Conference on Humanoid Robots*, pages 461–467, 2017.
- M. Bauza and A. Rodriguez. A probabilistic data-driven model for planar pushing. In *Proceedings of the 2017 IEEE International Conference on Robotics and Automation*, pages 3008–3015, 2017.
- M. Beetz, L. Mösenlechner, and M. Tenorth. CRAM: A cognitive robot abstract machine for everyday manipulation in human environments. In *Proceedings of the 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 1012–1017, 2010.
- Y. Bekiroglu, D. Kragic, and V. Kyrki. Learning grasp stability based on tactile data and hmms. In *Proceedings of the 19th International Symposium in Robot and Human Interactive Communication*, pages 132–137, 2010.
- Y. Bekiroglu, D. Song, L. Wang, and D. Kragic. A probabilistic framework for task-oriented grasp stability assessment. In *Proceedings of the 2013 IEEE International Conference on Robotics and Automation*, pages 3040–3047, 2013.
- M. Bellemare, S. Srinivasan, G. Ostrovski, T. Schaul, D. Saxton, and R. Munos. Unifying count-based exploration and intrinsic motivation. In *Advances in Neural Information Processing Systems 29*, pages 1471–1479, 2016.
- Y. Bengio, J. Louradour, R. Collobert, and J. Weston. Curriculum learning. In *Proceedings of the 26th International Conference on Machine Learning*, pages 41–48, 2009.
- N. Bergström, C. H. Ek, D. Kragic, Y. Yamakawa, T. Senoo, and M. Ishikawa. On-line learning of temporal state models for flexible objects. In *Proceedings of the 2012 IEEE-RAS International Conference on Humanoid Robots*, pages 712–718, 2012.

- T. Bhattacharjee, J. Wade, and C. Kemp. Material recognition from heat transfer given varying initial conditions and short-duration contact. In *Robotics: Science and Systems XI*, 2015.
- B. Bischoff, D. Nguyen-Tuong, H. Van Hoof, A. Mchutchon, C. E. Rasmussen, A. Knoll, J. Peters, and M. P. Deisenroth. Policy search for learning robot control using sparse data. In *Proceedings of the 2014 IEEE International Conference on Robotics and Automation*, pages 3882–3887, 2014.
- M. Björkman, Y. Bekiroglu, V. Högman, and D. Kragic. Enhancing visual perception of shape through tactile glances. In *Proceedings of the 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3180–3186, 2013.
- J. Bohg and D. Kragic. Learning grasping points with shape context. *Robotics and Autonomous Systems*, 58(4):362–377, 2010.
- J. Bohg, K. Welke, B. León, M. Do, D. Song, W. Wohlking, M. Madry, A. Aldóma, M. Przybylski, T. Asfour, H. Martí, D. Kragic, A. Morales, and M. Vincze. Task-based grasp adaptation on a humanoid robot. In *Proceedings of the 10th IFAC Symposium on Robot Control*, pages 779–786, 2012.
- J. Bohg, A. Morales, T. Asfour, and D. Kragic. Data-driven grasp synthesis—a survey. *IEEE Transactions on Robotics*, 30(2):289–309, 2014.
- J. Bohg, K. Hausman, B. Sankaran, O. Brock, D. Kragic, S. Schaal, and G. S. Sukhatme. Interactive perception: Leveraging action in perception and perception in action. *IEEE Transactions on Robotics*, 33(6):1273–1291, 2017.
- B. Boots, A. Gretton, and G. J. Gordon. Hilbert space embeddings of predictive state representations. In *Proceedings of the 29th International Conference on Uncertainty in Artificial Intelligence*, pages 92–101, 2013.
- A. Boularias, O. Kroemer, and J. Peters. Structured apprenticeship learning. In P. A. Flach, T. De Bie, and N. Cristianini, editors, *Machine Learning and Knowledge Discovery in Databases*, pages 227–242. Springer Berlin Heidelberg, 2012.
- K. Bousmalis, A. Irpan, P. Wohlhart, Y. Bai, M. Kelcey, M. Kalakrishnan, L. Downs, J. Ibarz, P. Pastor, K. Konolige, et al. Using simulation and domain adaptation to improve efficiency of deep robotic grasping. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, 2018.
- S. Brandl, O. Kroemer, and J. Peters. Generalizing pouring actions between objects using warped parameters. In *Proceedings of the 2014 IEEE-RAS International Conference on Humanoid Robots*, pages 616–621, 2014.
- O. Brock, A. Fagg, R. Grupen, R. Platt, M. Rosenstein, and J. Sweeney. A framework for learning and control in intelligent humanoid robots. *International Journal of Humanoid Robotics*, 2(3):301–336, 2005.

- P. Brook, M. Ciocarlie, and K. Hsiao. Collaborative grasp planning with multiple object representations. In *Proceedings of the 2011 IEEE International Conference on Robotics and Automation*, pages 2851–2858, 2011.
- J. Brookshire and S. Teller. Articulated pose estimation using tangent space approximations. *International Journal of Robotics Research*, 35(1-3):5–29, 2016.
- D. Brown, W. Goo, P. Nagarajan, and S. Niekum. Extrapolating beyond suboptimal demonstrations via inverse reinforcement learning from observations. In *Proceedings of the 36th International Conference on Machine Learning*, pages 783–792, 2019a.
- D. S. Brown and S. Niekum. Efficient probabilistic performance bounds for inverse reinforcement learning. In *Proceedings of the 32nd AAAI Conference on Artificial Intelligence*, 2018.
- D. S. Brown and S. Niekum. Machine teaching for inverse reinforcement learning: Algorithms and applications. In *Proceedings of the 33rd AAAI Conference on Artificial Intelligence*, 2019.
- D. S. Brown, Y. Cui, and S. Niekum. Risk-aware active inverse reinforcement learning. In *Proceedings of the 2nd Conference on Robot Learning*, pages 362–372, 2018.
- D. S. Brown, W. Goo, and S. Niekum. Better-than-demonstrator imitation learning via automatically-ranked demonstrations. In *Proceedings of The 3rd Conference on Robot Learning*, Proceedings of Machine Learning Research, pages 330–359, 2019b.
- D. S. Brown, R. Coleman, R. Srinivasan, and S. Niekum. Safe imitation learning via fast bayesian reward inference from preferences. In *Proceedings of the 37th International Conference on Machine Learning*, 2020.
- J. Buchli, F. Stulp, E. Theodorou, and S. Schaal. Learning variable impedance control. *International Journal of Robotics Research*, 30(7):820–833, 2011.
- K. Bullard, S. Chernova, and A. L. Thomaz. Human-driven feature selection for a robotic agent learning classification tasks from demonstration. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, pages 6923–6930, 2018.
- B. Burchfiel and G. Konidaris. Bayesian eigenobjects: A unified framework for 3D robot perception. In *Robotics: Science and Systems XIII*, 2017.
- B. Burchfiel and G. Konidaris. Hybrid Bayesian eigenobjects: Combining linear subspace and deep network methods for 3D robot vision. In *Proceedings of the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 6843–6850, 2018.
- Y. Burda, H. Edwards, A. Storkey, and O. Klimov. Exploration by random network distillation. In *Proceedings of the 2018 International Conference on Learning Representations*, 2018.
- A. Byravan and D. Fox. SE3-nets: Learning rigid body motion using deep neural networks. In *Proceedings of the 2016 IEEE International Conference on Robotics and Automation*, pages 173–180, 2016.

- R. Calandra, A. Owens, D. Jayaraman, J. Lin, W. Yuan, J. Malik, E. H. Adelson, and S. Levine. More than a feeling: Learning to grasp and regrasp using vision and touch. *IEEE Robotics and Automation Letters*, 3(4):3300–3307, 2018.
- S. Calinon. Robot learning with task-parameterized generative models. In A. Bicchi and W. Burgard, editors, *Proceedings of the 2018 International Symposium on Robotics Research*, pages 111–126, 2018.
- S. Calinon, F. Guenter, and A. Billard. On learning, representing, and generalizing a task in a humanoid robot. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 37(2):286–298, 2007.
- T. Cederborg, M. Li, A. Baranes, and P.-Y. Oudeyer. Incremental local online Gaussian mixture regression for imitation learning of multiple tasks. In *Proceedings of the 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 267–274, 2010.
- Y. Chebotar, K. Hausman, M. Zhang, G. Sukhatme, S. Schaal, and S. Levine. Combining model-based and model-free updates for trajectory-centric reinforcement learning. In *Proceedings of the 34th International Conference on Machine Learning*, pages 703–711, 2017.
- T. Chen, M. Kwiatkowska, A. Simaitis, and C. Wiltsche. Synthesis for multi-objective stochastic games: An application to autonomous urban driving. In *Proceedings of the 2013 International Conference on Quantitative Evaluation of Systems*, pages 322–337, 2013.
- N. Chentanez, A. G. Barto, and S. P. Singh. Intrinsically motivated reinforcement learning. In *Advances in Neural Information Processing Systems 17*, pages 1281–1288, 2005.
- S. Chernova and M. Veloso. Interactive policy learning through confidence-based autonomy. *Journal of Artificial Intelligence Research*, 34:1–25, 2009.
- S. Chiappa and J. Peters. Movement extraction by detecting dynamics switches and repetitions. In *Advances in Neural Information Processing Systems 23*, pages 388–396, 2010.
- S. Chinchali, S. C. Livingston, U. Topcu, J. W. Burdick, and R. M. Murray. Towards formal synthesis of reactive controllers for dexterous robotic manipulation. In *Proceedings of the 2012 IEEE International Conference on Robotics and Automation*, pages 5183–5189, 2012.
- S. Chitta, M. Piccoli, and J. Sturm. Tactile object class and internal state recognition for mobile manipulation. In *Proceedings of the 2010 IEEE International Conference on Robotics and Automation*, pages 2342–2348, 2010.
- S. Chitta, J. Sturm, M. Piccoli, and W. Burgard. Tactile sensing for mobile manipulation. *IEEE Transactions on Robotics*, 27(3):558–568, 2011.
- C. Choi, W. Schwarting, J. DelPreto, and D. Rus. Learning object grasping for soft robot hands. *IEEE Robotics and Automation Letters*, 3(3):2370–2377, 2018.

- J. Choi and K.-E. Kim. Nonparametric Bayesian inverse reinforcement learning for multiple reward functions. In *Advances in Neural Information Processing Systems 25*, pages 305–313, 2012.
- S. Choudhury, Y. Hou, G. Lee, and S. S. Srinivasa. Hybrid DDP in clutter (CHDDP): trajectory optimization for hybrid dynamical system in cluttered environments. *CoRR*, abs/1710.05231, 2017. URL <http://arxiv.org/abs/1710.05231>.
- Y. Chow, A. Tamar, S. Mannor, and M. Pavone. Risk-sensitive and robust decision-making: a cvar optimization approach. In *Advances in Neural Information Processing Systems 28*, pages 1522–1530, 2015.
- C. Chuck, S. Chockchowwat, and S. Niekum. Hypothesis-driven skill discovery for hierarchical deep reinforcement learning. In *Proceedings of the 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2020.
- M. Ciocarlie, C. Goldfeder, and P. Allen. Dimensionality reduction for hand-independent dexterous robotic grasping. In *Proceedings of the 2007 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3270–3275, 2007.
- M. Ciocarlie, K. Hsiao, E. G. Jones, S. Chitta, R. B. Rusu, and I. A. Şucan. Towards reliable grasping and manipulation in household environments. In O. Khatib, V. Kumar, and G. Sukhatme, editors, *Proceedings of the 2014 International Symposium on Experimental Robotics*, pages 241–252, 2014.
- L. Cobo, K. Subramanian, C. Isbell, A. Lanterman, and A. Thomaz. Abstraction from demonstration for efficient reinforcement learning in high-dimensional domains. *Artificial Intelligence*, 216:103–128, 2014.
- S. Coradeschi, A. Loutfi, and B. Wrede. A short review of symbol grounding in robotic and intelligent systems. *Künstliche Intelligenz*, 27(2):129–136, 2013.
- C. Cortes and V. Vapnik. Support-vector networks. *Machine Learning*, 20(3):273–297, 1995.
- Y. Cui and S. Niekum. Active reward learning from critiques. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, pages 6907–6914, 2018.
- B. C. Da Silva, G. Baldassarre, G. D. Konidaris, and A. G. Barto. Learning parameterized motor skills on a humanoid robot. In *Proceedings of the 2014 IEEE International Conference on Robotics and Automation*, pages 5239–5244, 2014.
- H. Dang and P. K. Allen. Robot learning of everyday object manipulations via human demonstration. In *Proceedings of the 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 1284–1289, 2010.
- H. Dang and P. K. Allen. Learning grasp stability. In *Proceedings of the 2012 IEEE International Conference on Robotics and Automation*, pages 2392–2397, 2012.
- H. Dang and P. K. Allen. Semantic grasping: Planning robotic grasps functionally suitable for an object manipulation task. In *Proceedings of the 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2012.

- H. Dang and P. K. Allen. Grasp adjustment on novel objects using tactile experience from similar local geometry. In *Proceedings of the 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 4007–4012, 2013.
- C. Daniel, G. Neumann, O. Kroemer, and J. Peters. Learning sequential motor tasks. In *Proceedings of the 2013 IEEE International Conference on Robotics and Automation*, pages 2626–2632, 2013.
- C. Daniel, G. Neumann, O. Kroemer, and J. Peters. Hierarchical relative entropy policy search. *Journal of Machine Learning Research*, 17(1):3190–3239, 2016a.
- C. Daniel, H. Van Hoof, J. Peters, and G. Neumann. Probabilistic inference for determining options in reinforcement learning. *Machine Learning*, 104(2-3):337–357, 2016b.
- L. Davis. *Handbook of Genetic Algorithms*. Chapman & Hall, 1991.
- P.-T. De Boer, D. P. Kroese, S. Mannor, and R. Y. Rubinstein. A tutorial on the cross-entropy method. *Annals of Operations Research*, 134(1):19–67, 2005.
- T. J. Debus, P. E. Dupont, and R. D. Howe. Contact state estimation using multiple model estimation and hidden Markov models. *International Journal of Robotics Research*, 23(4-5):399–413, 2004.
- M. Deisenroth and C. E. Rasmussen. PILCO: A model-based and data-efficient approach to policy search. In *Proceedings of the 28th International Conference on Machine Learning*, pages 465–472, 2011.
- M. P. Deisenroth, D. Fox, and C. E. Rasmussen. Gaussian processes for data-efficient learning in robotics and control. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 37(2):408–423, 2015.
- K. Desingh, S. Lu, A. Opipari, and O. C. Jenkins. Factored pose estimation of articulated objects using efficient nonparametric belief propagation. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, 2018.
- R. Detry, D. Kraft, O. Kroemer, L. Bodenhagen, J. Peters, N. Krüger, and J. Piater. Learning grasp affordance densities. *Paladyn*, 2(1), 2011.
- R. Detry, C. H. Ek, M. Madry, and D. Kragic. Learning a dictionary of prototypical grasp-predicting parts from grasping experience. In *Proceedings of the 2013 IEEE International Conference on Robotics and Automation*, pages 601–608, 2013.
- R. Detry, J. Papon, and L. Matthies. Task-oriented grasping with semantic and geometric scene understanding. In *Proceedings of the 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3266–3273, 2017.
- C. Devin, P. Abbeel, T. Darrell, and S. Levine. Deep object-centric representations for generalizable robot learning. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, pages 7111–7118, 2018.

- C. Diuk, A. Cohen, and M. L. Littman. An object-oriented representation for efficient reinforcement learning. In *Proceedings of the 25th International Conference on Machine Learning*, pages 240–247, 2008.
- C. Diuk, L. Li, and B. Leffler. The adaptive k -meteorologists problems and its application to structure learning and feature selection in reinforcement learning. In *Proceedings of the 26th International Conference on Machine Learning*, pages 249–256, 2009.
- M. Do, J. Schill, J. Ernesti, and T. Asfour. Learn to wipe: A case study of structural bootstrapping from sensorimotor experience. In *Proceedings of the 2014 IEEE International Conference on Robotics and Automation*, pages 1858–1864, 2014.
- A. Doerr, N. D. Ratliff, J. Bohg, M. Toussaint, and S. Schaal. Direct loss minimization inverse optimal control. In *Robotics: Science and Systems XI*, 2015.
- M. R. Dogar, M. Cakmak, E. Ugur, and E. Sahin. From primitive behaviors to goal-directed behavior using affordances. In *Proceedings of the 2007 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 729–734, 2007.
- S. Dragiev, M. Toussaint, and M. Gienger. Uncertainty aware grasping and tactile exploration. In *Proceedings of the 2013 IEEE International Conference on Robotics and Automation*, pages 113–119, 2013.
- Y. Duan, M. Andrychowicz, B. Stadie, O. J. Ho, J. Schneider, I. Sutskever, P. Abbeel, and W. Zaremba. One-shot imitation learning. In *Advances in Neural Information Processing Systems 30*, pages 1087–1098, 2017.
- K. Dvijotham and E. Todorov. Inverse optimal control with linearly-solvable MDPs. In *Proceedings of the 27th International Conference on Machine Learning*, pages 335–342, 2010.
- A. Ecoffet, J. Huizinga, J. Lehman, K. O. Stanley, and J. Clune. Go-explore: a new approach for hard-exploration problems. *arXiv preprint arXiv:1901.10995*, 2019.
- A. Edsinger and C. C. Kemp. Autonomous detection and control of task relevant features. In *Proceedings of the 2006 IEEE International Conference on Development and Learning*, 2006.
- Y. Engel, P. Szabo, and D. Volkinshtein. Learning to control an octopus arm with Gaussian process temporal difference methods. In *Advances in Neural Information Processing Systems 19*, pages 347–354, 2006.
- P. Englert and M. Toussaint. Combined optimization and reinforcement learning for manipulation skills. In *Robotics: Science and Systems XII*, 2016.
- P. Englert and M. Toussaint. Learning manipulation skills from a single demonstration. *International Journal of Robotics Research*, 37(1):137–154, 2018a.
- P. Englert and M. Toussaint. Kinematic morphing networks for manipulation skill transfer. In *Proceedings of the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 2517–2523, 2018b.

- P. Englert, N. Vien, and M. Toussaint. Inverse KKT: Learning cost functions of manipulation tasks from demonstrations. *International Journal of Robotics Research*, 36(13-14):1474–1488, 2017.
- A. H. Fagg and M. A. Arbib. Modeling parietal-premotor interactions in primate control of grasping. *Neural Networks*, 11(7):1277 – 1303, 1998.
- G. E. Fainekos, A. Girard, H. Kress-Gazit, and G. J. Pappas. Temporal logic motion planning for dynamic robots. *Automatica*, 45(2):343–352, 2009.
- Z. Fang, G. Bartels, and M. Beetz. Learning models for constraint-based motion parameterization from interactive physics-based simulation. In *Proceedings of the 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 4005–4012, 2016.
- V. Feinberg, A. Wan, I. Stoica, M. I. Jordan, J. E. Gonzalez, and S. Levine. Model-based value expansion for efficient model-free reinforcement learning. *arXiv preprint arXiv:1803.00101*, 2018.
- S. Fichtl, A. McManus, W. Mustafa, D. Kraft, N. Krüger, and F. Guerin. Learning spatial relationships from 3D vision using histograms. In *Proceedings of the 2014 IEEE International Conference on Robotics and Automation*, pages 501–508, 2014.
- C. Finn and S. Levine. Deep visual foresight for planning robot motion. In *Proceedings of the 2017 IEEE International Conference on Robotics and Automation*, pages 2786–2793, 2017.
- C. Finn, S. Levine, and P. Abbeel. Guided cost learning: Deep inverse optimal control via policy optimization. In *Proceedings of the 33rd International Conference on Machine Learning*, pages 49–58, 2016.
- C. Finn, P. Abbeel, and S. Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In *Proceedings of the 34th International Conference on Machine Learning*, pages 1126–1135, 2017.
- P. Fitzpatrick, A. Arsenio, and E. R. Torres-Jara. Reinforcing robot perception of multi-modal events through repetition and redundancy and repetition and redundancy. *Interaction Studies*, 7(2):171–196, 2006.
- P. R. Florence, L. Manuelli, and R. Tedrake. Dense object nets: Learning dense visual object descriptors by and for robotic manipulation. In *Proceedings of the 2nd Conference on Robot Learning*, pages 373–385, 2018.
- C. Florensa, D. Held, M. Wulfmeier, M. Zhang, and P. Abbeel. Reverse curriculum generation for reinforcement learning. In *Proceedings of The 1st Conference on Robot Learning*, volume 78 of *Proceedings of Machine Learning Research*, pages 482–495. PMLR, 2017.
- J. Fu and U. Topcu. Probably approximately correct MDP learning and control with temporal logic constraints. *arXiv preprint arXiv:1404.7073*, 2014.

- J. Fu, S. Levine, and P. Abbeel. One-shot learning of manipulation skills with online dynamics adaptation and neural network priors. In *Proceedings of the 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 4019–4026, 2016.
- J. Fu, K. Luo, and S. Levine. Learning robust rewards with adversarial inverse reinforcement learning. In *Proceedings of the 2017 International Conference on Learning Representations*, 2017.
- Y. Gao, L. A. Hendricks, K. J. Kuchenbecker, and T. Darrell. Deep learning for tactile understanding from visual and haptic data. In *Proceedings of the 2016 IEEE International Conference on Robotics and Automation*, pages 536–543, 2016.
- C. Garcia Cifuentes, J. Issac, M. Wüthrich, S. Schaal, and J. Bohg. Probabilistic articulated real-time tracking for robot manipulation. *IEEE Robotics and Automation Letters*, 2(2): 577–584, 2017.
- C. R. Garrett, T. Lozano-Perez, and L. P. Kaelbling. FFRob: Leveraging symbolic planning for efficient task and motion planning. *International Journal of Robotics Research*, 37(1): 104–136, 2018.
- M. Ghavamzadeh, M. Petrik, and Y. Chow. Safe policy improvement by minimizing robust baseline regret. In *Advances in Neural Information Processing Systems 29*, pages 2298–2306, 2016.
- J. J. Gibson. *The ecological approach to visual perception*. Psychology Press, 2014.
- A. Goil, M. Derry, and B. D. Argall. Using machine learning to blend human and robot controls for assisted wheelchair navigation. In *Proceedings of the 2013 IEEE International Conference on Rehabilitation Robotics*, pages 1–6, 2013.
- C. Goldfeder, M. Ciocarlie, J. Peretzman, H. Dang, and P. K. Allen. Data-driven grasping with partial sensor data. In *Proceedings of the 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 1278–1283, 2009.
- W. Goo and S. Niekum. Learning multi-step robotic tasks from observation. In *Proceedings of the 2019 IEEE International Conference on Robotics and Automation*, 2019a.
- W. Goo and S. Niekum. One-shot learning of multi-step tasks from observation via activity localization in auxiliary video. In *Proceedings of the 2019 IEEE International Conference on Robotics and Automation*, 2019b.
- S. Griffith, V. Sukhoy, T. Wegter, and A. Stoytchev. Object categorization in the sink: Learning behavior-grounded object categories with water. In *ICRA 2012 Workshop on Semantic Perception, Mapping, and Exploration*, 2012.
- D. Grollman and O. Jenkins. Incremental learning of subtasks from unsegmented demonstration. In *Proceedings of the 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 261–266, 2010.

- S. Gu, T. Lillicrap, I. Sutskever, and S. Levine. Continuous deep Q-learning with model-based acceleration. In *Proceedings of the 33rd International Conference on Machine Learning*, pages 2829–2838, 2016.
- M. Gualtieri and R. Platt. Viewpoint selection for grasp detection. In *Proceedings of the 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 258–264, 2017.
- M. Gualtieri and R. Platt. Learning 6-DoF grasping and pick-place using attention focus. In *Proceedings of the 2nd Conference on Robot Learning*, pages 477–486, 2018.
- C. Guan, W. Vega-Brown, and N. Roy. Efficient planning for near-optimal compliant manipulation leveraging environmental contact. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, pages 215–222, 2018.
- P. Guler, Y. Bekiroglu, X. Gratal, K. Pauwels, and D. Kragic. What’s in the container? classifying object contents from vision and touch. In *Proceedings of the 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3961–3968, 2014.
- V. Gullapalli, J. A. Franklin, and H. Benbrahim. Acquiring robot skills via reinforcement learning. *IEEE Control Systems Magazine*, 14(1):13–24, 1994.
- A. Gupta, C. Eppner, S. Levine, and P. Abbeel. Learning dexterous manipulation for a soft robotic hand from human demonstration. In *Proceedings of the 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3786–3793, 2016.
- A. Gupta, C. Devin, Y. Liu, P. Abbeel, and S. Levine. Learning invariant feature spaces to transfer skills with reinforcement learning. In *Proceedings of the 2017 International Conference on Learning Representations*, 2017.
- A. Gupta, R. Mendonca, Y. Liu, P. Abbeel, and S. Levine. Meta-reinforcement learning of structured exploration strategies. In *Advances in Neural Information Processing Systems 31*, pages 5302–5311, 2018.
- M. Gupta, J. Müller, and G. S. Sukhatme. Using manipulation primitives for object sorting in cluttered environments. *IEEE Transactions on Automation Science and Engineering*, 12(2):608–614, 2015.
- T. Haarnoja, A. Zhou, P. Abbeel, and S. Levine. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. In *Proceedings of the 35th International Conference on Machine Learning*, pages 1861–1870, 2018.
- D. Hadfield-Menell, S. J. Russell, P. Abbeel, and A. Dragan. Cooperative inverse reinforcement learning. In *Advances in Neural Information Processing Systems 29*, pages 3909–3917, 2016.
- J. P. Hanna and P. Stone. Grounded action transformation for robot learning in simulation. In *Proceedings of the 21st AAAI Conference on Artificial Intelligence*, pages 3834–3840, 2017.

- J. P. Hanna, P. Stone, and S. Niekum. Bootstrapping with models: Confidence intervals for off-policy evaluation. In *Proceedings of the 16th International Conference on Autonomous Agents and Multiagent Systems*, pages 538–546, 2017.
- N. Hansen and A. Ostermeier. Completely derandomized self-adaptation in evolution strategies. *Evolutionary Computation*, 9(2):159–195, 2001.
- S. Hart. Intrinsically motivated hierarchical manipulation. In *Proceedings of the 2008 IEEE International Conference on Robotics and Automation*, pages 3814–3819, 2008.
- S. Hart. An intrinsic reward for affordance exploration. In *Proceedings of the 2009 IEEE International Conference on Development and Learning*, pages 1–6, 2009.
- K. Hauser. *Motion Planning for Legged and Humanoid Robots*. PhD thesis, Stanford University, 2018.
- K. Hausman, C. Bersch, D. Pangercic, S. Osentoski, Z.-C. Marton, and M. Beetz. Segmentation of cluttered scenes through interactive perception. In *ICRA 2012 Workshop on Semantic Perception and Mapping for Knowledge-enabled Service Robotics*, 2012.
- K. Hausman, S. Niekum, S. Osentoski, and G. S. Sukhatme. Active articulation model estimation through interactive perception. In *Proceedings of the 2015 IEEE International Conference on Robotics and Automation*, pages 3305–3312, 2015.
- K. Hausman, Y. Chebotar, S. Schaal, G. Sukhatme, and J. J. Lim. Multi-modal imitation learning from unstructured demonstrations using generative adversarial nets. In *Advances in Neural Information Processing Systems 30*, pages 1235–1245, 2017.
- K. Hausman, J. T. Springenberg, Z. Wang, N. Heess, and M. Riedmiller. Learning an embedding space for transferable robot skills. In *Proceedings of the 2018 International Conference on Learning Representations*, 2018.
- B. Hayes and B. Scassellati. Autonomously constructing hierarchical task networks for planning and human-robot collaboration. In *Proceedings of the 2016 IEEE International Conference on Robotics and Automation*, pages 5469–5476, 2016.
- G. M. Hayes and J. Demiris. *A robot controller using learning by imitation*. University of Edinburgh, Department of Artificial Intelligence, 1994.
- K. He, G. Gkioxari, P. Dollár, and R. Girshick. Mask R-CNN. In *Proceedings of the 2017 IEEE International Conference on Computer Vision*, pages 2961–2969, 2017.
- T. Hermans, J. M. Rehg, and A. Bobick. Guided pushing for object singulation. In *Proceedings of the 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 4783–4790, 2012.
- A. Herzog, P. Pastor, M. Kalakrishnan, L. Righetti, J. Bohg, T. Asfour, and S. Schaal. Learning of grasp selection based on shape-templates. *Autonomous Robots*, 36(1-2):51–65, 2014.

- I. Higgins, A. Pal, A. A. Rusu, L. Matthey, C. P. Burgess, A. Pritzel, M. Botvinick, C. Blundell, and A. Lerchner. DARLA: Improving zero-shot transfer in reinforcement learning. In *Proceedings of the 34th International Conference on Machine Learning*, pages 1480–1490, 2017.
- U. Hillenbrand and M. A. Roa. Transferring functional grasps through contact warping and local replanning. In *Proceedings of the 2012IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 2963–2970, 2012.
- M. Hjelm, R. Detry, C. H. Ek, and D. Kragic. Representations for cross-task, cross-object grasp transfer. In *Proceedings of the 2014 IEEE International Conference on Robotics and Automation*, pages 5699–5704, 2014.
- J. Ho and S. Ermon. Generative adversarial imitation learning. In *Advances in Neural Information Processing Systems 29*, pages 4565–4573, 2016.
- V. Högman, M. Björkman, A. Maki, and D. Kragic. A sensorimotor learning framework for object categorization. *IEEE Transactions on Cognitive and Developmental Systems*, 8(1):15–25, 2016.
- J. Holtz, A. Guha, and J. Biswas. Interactive robot transition repair with SMT. In *Proceedings of the 28th International Joint Conference on Artificial Intelligence*, pages 4905–4911, 2018.
- R. Houthooft, Y. Chen, P. Isola, B. Stadie, F. Wolski, O. J. Ho, and P. Abbeel. Evolved policy gradients. In *Advances in Neural Information Processing Systems 31*, pages 5400–5409, 2018.
- G. E. Hovland and B. J. McCarragher. Hidden Markov models as a process monitor in robotic assembly. *International Journal of Robotics Research*, 17(2):153–168, 1998.
- K. Hsiao, L. Kaelbling, and T. Lozano-Perez. Grasping POMDPs. In *Proceedings of the 2007 IEEE International Conference on Robotics and Automation*, pages 4685–4692, 2007.
- K. Hsiao, L. P. Kaelbling, and T. Lozano-Perez. Task-driven tactile exploration. In *Robotics: Science and Systems VI*, 2010.
- D.-A. Huang, S. Nair, D. Xu, Y. Zhu, A. Garg, L. Fei-Fei, S. Savarese, and J. C. Niebles. Neural task graphs: Generalizing to unseen tasks from a single video demonstration. In *Proceedings of the 2019 IEEE Conference on Computer Vision and Pattern Recognition*, 2019.
- H.-P. Huang and C.-C. Liang. Strategy-based decision making of a soccer robot system using a real-time self-organizing fuzzy decision tree. *Fuzzy Sets and Systems*, 127(1): 49–64, 2002.
- X. Huang and J. Weng. Novelty and reinforcement learning in the value system of developmental robots. In *Proceedings of the 2nd International Workshop on Epigenetic Robotics*, pages 47–55, 2002.

- P. Isola, J. J. Lim, and E. H. Adelson. Discovering states and transformations in image collections. In *Proceedings of the 2015 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1383–1391, 2015.
- J. Issac, M. Wüthrich, C. Garcia Cifuentes, J. Bohg, S. Trimpe, and S. Schaal. Depth-based object tracking using a robust gaussian filter. In *Proceedings of the 2016 IEEE International Conference on Robotics and Automation*, pages 608–615, 2016.
- A. Jain and C. C. Kemp. Improving robot manipulation with data-driven object-centric models of everyday forces. *Autonomous Robots*, 35(2-3):143–159, 2013.
- A. Jain and S. Niekum. Efficient hierarchical robot motion planning under uncertainty and hybrid dynamics. In *Proceedings of the 2nd Conference on Robot Learning*, pages 757–766, 2018.
- A. Jain and S. Niekum. Learning hybrid object kinematics for efficient hierarchical planning under uncertainty. In *Proceedings of the 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2020.
- L. Jamone, E. Ugur, A. Cangelosi, L. Fadiga, A. Bernardino, J. Piater, and J. Santos-Victor. Affordances in psychology, neuroscience, and robotics: A survey. *IEEE Transactions on Cognitive and Developmental Systems*, 10(1):4–25, 2018.
- E. Jang, S. Vijayanarasimhan, P. Pastor, J. Ibarz, and S. Levine. End-to-end learning of semantic grasping. In *Proceedings of The 1st Conference on Robot Learning*, Proceedings of Machine Learning Research, pages 119–132, 2017.
- E. Jang, C. Devin, V. Vanhoucke, and S. Levine. Grasp2vec: Learning object representations from self-supervised grasping. In *Proceedings of the 2nd Conference on Robot Learning*, volume 87 of *Proceedings of Machine Learning Research*, pages 99–112, 2018.
- M. Janner, S. Levine, W. T. Freeman, J. B. Tenenbaum, C. Finn, and J. Wu. Reasoning about physical interactions with object-oriented prediction and planning. In *Proceedings of the 2019 International Conference on Learning Representations*, 2019.
- S. Javdani, M. Klingensmith, J. A. D. Bagnell, N. Pollard, and S. Srinivasa. Efficient touch based localization through submodularity. In *Proceedings of the 2013 IEEE International Conference on Robotics and Automation*, pages 1828–1835, 2013.
- O. Jenkins and M. Matarić. Performance-derived behavior vocabularies: data-driven acquisition of skills from motion. *International Journal of Humanoid Robotics*, 1(2):237–288, 2004.
- N. Jetchev, T. Lang, and M. Toussaint. Learning grounded relational symbols from continuous data for abstract reasoning. In *ICRA 2013 Workshop on Autonomous Learning*, 2013.
- N. Jiang and L. Li. Doubly robust off-policy value evaluation for reinforcement learning. In *Proceedings of the 33rd International Conference on Machine Learning*, pages 652–661, 2016.

- N. Jiang, A. Kulesza, and S. Singh. Abstraction selection in model-based reinforcement learning. In *Proceedings of the 32nd International Conference on Machine Learning*, pages 179–188, 2015.
- Y. Jiang, M. Lim, C. Zheng, and A. Saxena. Learning to place new objects in a scene. *International Journal of Robotics Research*, 31(9):1021–1043, 2012.
- J. Juett and B. Kuipers. Learning to grasp by extending the peri-personal space graph. In *Proceedings of the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 8695–8700, 2018.
- P. Jund, A. Eitel, N. Abdo, and W. Burgard. Optimization beyond the convolution: Generalizing spatial relations with end-to-end metric learning. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, pages 1–7, 2018.
- L. P. Kaelbling, M. L. Littman, and A. R. Cassandra. Planning and acting in partially observable stochastic domains. *Artificial intelligence*, 101(1-2):99–134, 1998.
- G. Kahn, P. Sujan, S. Patil, S. Bopardikar, J. Ryde, K. Goldberg, and P. Abbeel. Active exploration using trajectory optimization for robotic grasping in the presence of occlusions. In *Proceedings of the 2015 IEEE International Conference on Robotics and Automation*, pages 4783–4790, 2015.
- D. Kalashnikov, A. Irpan, P. Pastor, J. Ibarz, A. Herzog, E. Jang, D. Quillen, E. Holly, M. Kalakrishnan, V. Vanhoucke, and S. Levine. Scalable deep reinforcement learning for vision-based robotic manipulation. In *Proceedings of The 2nd Conference on Robot Learning*, volume 87 of *Proceedings of Machine Learning Research*, pages 651–673, 2018.
- P. Kamalaruban, R. Devidze, V. Cevher, and A. Singla. Interactive teaching algorithms for inverse reinforcement learning. *arXiv preprint arXiv:1905.11867*, 2019.
- K. Kanksy, T. Silver, D. A. Mély, M. Eldawy, M. Lázaro-Gredilla, X. Lou, N. Dorfman, S. Sidor, S. Phoenix, and D. George. Schema networks: Zero-shot transfer with a generative causal model of intuitive physics. In *Proceedings of the 34th International Conference on Machine Learning*, pages 1809–1818, 2017.
- D. Kappler, P. Pastor, M. Kalakrishnan, M. Wüthrich, and S. Schaal. Data-driven online decision making for autonomous manipulation. In *Robotics: Science and Systems XI*, 2015.
- D. Katz and O. Brock. A factorization approach to manipulation in unstructured environments. In C. Pradalier, R. Siegwart, and G. Hirzinger, editors, *Proceedings of the 2011 International Symposium on Robotics Research*, pages 285–300, 2011.
- D. Katz, A. Orthey, and O. Brock. Interactive perception of articulated objects. In *Proceedings of the 2010 International Symposium on Experimental Robotics*, pages 1–15, 2010.
- L. Kaul, S. Ottenhaus, P. Weiner, and T. Asfour. The sense of surface orientation - a new sensor modality for humanoid robots. In *Proceedings of the 2016 IEEE-RAS International Conference on Humanoid Robots*, pages 820–825, 2016.

- J. Kenney, T. Buckley, and O. Brock. Interactive segmentation for manipulation in unstructured environments. In *Proceedings of the 2009 IEEE International Conference on Robotics and Automation*, pages 1343–1348, 2009.
- K. Kim, H. Lee, J. Park, and M. Yang. Robotic contamination cleaning system. In *Proceedings of the 2002 IEEE/RSJ International Conference on Intelligent Robots and Systems*, volume 2, pages 1874–1879, 2002.
- M. Klingensmith, M. Hermann, and S. Srinivasa. Object modeling and recognition from sparse, noisy data via voxel depth carving. In *Proceedings of the 2014 International Symposium on Experimental Robotics*, June 2014.
- R. A. Knepper, S. Tellex, A. Li, N. Roy, and D. Rus. Recovering from failure by asking for help. *Autonomous Robots*, 39(3):347–362, 2015.
- W. B. Knox, P. Stone, and C. Breazeal. Training a robot via human feedback: A case study. In *Proceedings of the 2013 International Conference on Social Robotics*, pages 460–470, 2013.
- J. Kober and J. R. Peters. Policy search for motor primitives in robotics. In *Advances in Neural Information Processing Systems 22*, pages 849–856, 2009.
- J. Kober, E. Oztop, and J. Peters. Reinforcement learning to adjust robot movements to new situations. In *Proceedings of the 22nd International Joint Conference on Artificial Intelligence*, pages 2650–2655, 2011.
- G. Konidaris. Constructing abstraction hierarchies using a skill-symbol loop. In *Proceedings of the 25th International Joint Conference on Artificial Intelligence*, pages 1648–1654, 2016.
- G. Konidaris and A. Barto. Efficient skill learning using abstraction selection. In *Proceedings of the 21st International Joint Conference on Artificial Intelligence*, pages 1107–1112, July 2009a.
- G. Konidaris and A. G. Barto. Building portable options: Skill transfer in reinforcement learning. In *Proceedings of the 20th International Joint Conference on Artificial Intelligence*, pages 895–900, 2007.
- G. Konidaris and A. G. Barto. Skill discovery in continuous reinforcement learning domains using skill chaining. In *Advances in Neural Information Processing Systems 22*, pages 1015–1023, 2009b.
- G. Konidaris, S. Kuindersma, R. Grupen, and A. Barto. Autonomous skill acquisition on a mobile manipulator. In *Proceedings of the Twenty-Fifth Conference on Artificial Intelligence*, pages 1468–1473, 2011a.
- G. Konidaris, S. Osentoski, and P. S. Thomas. Value function approximation in reinforcement learning using the Fourier basis. In *Proceedings of the 25th AAAI Conference on Artificial Intelligence*, pages 380–385, 2011b.

- G. Konidaris, S. Kuindersma, R. Grupen, and A. Barto. Robot learning from demonstration by constructing skill trees. *International Journal of Robotics Research*, 31(3):360–375, 2012.
- G. Konidaris, L. Kaelbling, and T. Lozano-Perez. Symbol acquisition for probabilistic high-level planning. In *Proceedings of the 24th International Joint Conference on Artificial Intelligence*, pages 3619–3627, 2015.
- G. Konidaris, L. P. Kaelbling, and T. Lozano-Perez. From skills to symbols: Learning symbolic representations for abstract high-level planning. *Journal of Artificial Intelligence Research*, 61:215–289, 2018.
- M. Kopicki, R. Detry, M. Adjigble, R. Stolkin, A. Leonardis, and J. L. Wyatt. One-shot learning and generation of dexterous grasps for novel objects. *International Journal of Robotics Research*, 35(8):959–976, 2016.
- M. Kopicki, S. Zurek, R. Stolkin, T. Moerwald, and J. L. Wyatt. Learning modular and transferable forward models of the motions of push manipulated objects. *Autonomous Robots*, 41(5):1061–1082, 2017.
- P. Kormushev, S. Calinon, and D. G. Caldwell. Imitation learning of positional and force skills demonstrated via kinesthetic teaching and haptic input. *Advanced Robotics*, 25(5):581–603, 2011.
- M. C. Koval, M. Klingensmith, S. S. Srinivasa, N. Pollard, and M. Kaess. The manifold particle filter for state estimation on high-dimensional implicit manifolds. In *Proceedings of the 2017 IEEE International Conference on Robotics and Automation*, pages 4673–4680, 2017.
- D. Kraft, N. Pugeault, E. Baseski, M. Popovic, D. Kragic, S. Kalkan, F. Wörgötter, and N. Krüger. Birth of the object: Detection of objectness and extraction of object shape through object-action complexes. *International Journal of Humanoid Robotics*, 5(2):247–265, 2008.
- S. Krishnan, A. Garg, R. Liaw, B. Thananjeyan, L. Miller, F. T. Pokorny, and K. Goldberg. SWIRL: A sequential windowed inverse reinforcement learning algorithm for robot tasks with delayed rewards. *International Journal of Robotics Research*, 38(2-3):126–145, 2019.
- A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems 25*, pages 1097–1105, 2012.
- O. Kroemer and J. Peters. Predicting object interactions from contact distributions. In *Proceedings of the 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3361–3367, 2014.
- O. Kroemer and G. Sukhatme. Meta-level priors for learning manipulation skills with sparse features. In D. Kulić, Y. Nakamura, O. Khatib, and G. Venture, editors, *Proceedings of the 2017 International Symposium on Experimental Robotics*, pages 211–222, 2017.

- O. Kroemer and G. S. Sukhatme. Learning spatial preconditions of manipulation skills using random forests. In *Proceedings of the 2016 IEEE-RAS International Conference on Humanoid Robots*, pages 676–683, 2016.
- O. Kroemer, E. Ugur, E. Oztop, and J. Peters. A kernel-based approach to direct action perception. In *Proceedings of the 2012 IEEE International Conference on Robotics and Automation*, pages 2605–2610, 2012.
- O. Kroemer, H. van Hoof, G. Neumann, and J. Peters. Learning to predict phases of manipulation tasks as hidden states. In *Proceedings of the 2014 IEEE International Conference on Robotics and Automation*, pages 4009–4014, 2014.
- O. Kroemer, C. Daniel, G. Neumann, H. van Hoof, and J. Peters. Towards learning hierarchical skills for multi-phase manipulation tasks. In *Proceedings of the 2015 IEEE International Conference on Robotics and Automation*, pages 1503–1510, 2015.
- O. Kroemer, S. Leischnig, S. Luetzgen, and J. Peters. A kernel-based approach to learning contact distributions for robot manipulation tasks. *Autonomous Robots*, 42(3):581–600, 2018.
- O. B. Kroemer, R. Detry, J. Piater, and J. Peters. Combining active learning and reactive control for robot grasping. *Robotics and Autonomous Systems*, 59(9):1105–1116, 2010. doi: 10.1016/j.robot.2010.06.001.
- N. Krüger, C. Geib, J. Piater, R. Petrick, M. Steedman, F. Wörgötter, A. Ude, T. Asfour, D. Kraft, D. Omrčen, A. Agostini, and R. Dillmann. Object-action complexes: Grounded abstractions of sensory-motor processes. *Robotics and Autonomous Systems*, 59(10):740 – 757, 2011. ISSN 0921-8890.
- J. Kulick, M. Toussaint, T. Lang, and M. Lopes. Active learning for teaching a robot grounded relational symbols. In *Proceedings of the 23rd International Joint Conference on Artificial Intelligence*, pages 1451–1457, 2013.
- J. Kulick, S. Otte, and M. Toussaint. Active exploration of joint dependency structures. In *Proceedings of the 2015 IEEE International Conference on Robotics and Automation*, pages 2598–2604, 2015.
- V. Kumar, E. Todorov, and S. Levine. Optimal control with learned local models: Application to dexterous manipulation. In *Proceedings of the 2016 IEEE International Conference on Robotics and Automation*, pages 378–383, 2016.
- V. Kumar, S. Ha, and C. Liu. Expanding motor skills using relay networks. In *Proceedings of the 2nd Conference on Robot Learning*, pages 744–756, 2018.
- A. G. Kupcsik, M. P. Deisenroth, J. Peters, G. Neumann, et al. Data-efficient generalization of robot skills with contextual policy search. In *Proceedings of the 27th AAAI Conference on Artificial Intelligence*, pages 1401–1407, 2013.

- T. Kurutach, A. Tamar, G. Yang, S. J. Russell, and P. Abbeel. Learning plannable representations with causal InfoGAN. In *Advances in Neural Information Processing Systems 31*, pages 8733–8744, 2018.
- T. Lang, M. Toussaint, and K. Kersting. Exploration in relational domains for model-based reinforcement learning. *Journal of Machine Learning Research*, 13(1):3725–3768, 2012.
- G. Lee, Z. Marinho, A. M. Johnson, G. J. Gordon, S. S. Srinivasa, and M. T. Mason. Unsupervised learning for nonlinear piecewise smooth hybrid systems. *arXiv preprint arXiv:1710.00440*, 2017.
- M. A. Lee, Y. Zhu, K. Srinivasan, P. Shah, S. Savarese, L. Fei-Fei, A. Garg, and J. Bohg. Making sense of vision and touch: Self-supervised learning of multimodal representations for contact-rich tasks. In *Proceedings of the 2019 IEEE International Conference on Robotics and Automation*, 2019.
- E. D. Lello, M. Klotzbücher, T. D. Laet, and H. Bruyninckx. Bayesian time-series models for continuous fault detection and recognition in industrial robotic tasks. In *Proceedings of the 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 5827–5833, 2013.
- I. Lenz, R. A. Knepper, and A. Saxena. Deepmpc: Learning deep latent features for model predictive control. In *Robotics: Science and Systems XI*, 2015a.
- I. Lenz, H. Lee, and A. Saxena. Deep learning for detecting robotic grasps. *International Journal of Robotics Research*, 34(4-5):705–724, 2015b.
- S. Levine and V. Koltun. Guided policy search. In *Proceedings of the 30th International Conference on Machine Learning*, pages 1–9, 2013.
- S. Levine, Z. Popovic, and V. Koltun. Nonlinear inverse reinforcement learning with gaussian processes. In *Advances in Neural Information Processing Systems 24*, pages 19–27, 2011.
- S. Levine, N. Wagener, and P. Abbeel. Learning contact-rich manipulation skills with guided policy search. In *Proceedings of the 2015 IEEE International Conference on Robotics and Automation*, pages 156–163, 2015.
- S. Levine, C. Finn, T. Darrell, and P. Abbeel. End-to-end training of deep visuomotor policies. *Journal of Machine Learning Research*, 17(1):1334–1373, 2016.
- A. Levy, G. Konidaris, R. Platt, and K. Saenko. Learning multi-level hierarchies with hindsight. In *Proceedings of the 2019 International Conference on Learning Representations*, 2019.
- Y. Li, C. Chen, and P. K. Allen. Recognition of deformable object category and pose. In *Proceedings of the 2014 IEEE International Conference on Robotics and Automation*, pages 5558–5564, 2014.

- Y. Li, Y. Yue, D. Xu, E. Grinspun, and P. K. Allen. Folding deformable objects using predictive simulation and trajectory optimization. In *Proceedings of the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 6000–6006, 2015.
- Y. Li, X. Hu, D. Xu, Y. Yue, E. Grinspun, and P. K. Allen. Multi-sensor surface analysis for robotic ironing. In *Proceedings of the 2016 IEEE International Conference on Robotics and Automation*, pages 5670–5676, 2016.
- Y. Li, Y. Wang, Y. Yue, D. Xu, M. Case, S. Chang, E. Grinspun, and P. K. Allen. Model-driven feedforward prediction for manipulation of deformable objects. *IEEE Transactions on Automation Science and Engineering*, 15(4):1621–1638, 2018.
- Y. Li, J. Wu, R. Tedrake, J. B. Tenenbaum, and A. Torralba. Learning particle dynamics for manipulating rigid bodies, deformable objects, and fluids. In *Proceedings of the 2018 International Conference on Learning Representations*, 2018.
- T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wierstra. Continuous control with deep reinforcement learning. *arXiv preprint arXiv:1509.02971*, 2015.
- R. Lioutikov, G. Neumann, G. Maeda, and J. Peters. Probabilistic segmentation applied to an assembly task. In *Proceedings of the 2015 IEEE-RAS International Conference on Humanoid Robots*, pages 533–540, 2015.
- R. Lioutikov, G. Maeda, F. Veiga, K. Kersting, and J. Peters. Inducing probabilistic context-free grammars for the sequencing of movement primitives. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, pages 1–8, 2018.
- M. L. Littman and R. S. Sutton. Predictive representations of state. In *Advances in Neural Information Processing Systems 14*, pages 1555–1561, 2002.
- M. L. Littman, U. Topcu, J. Fu, C. Isbell, M. Wen, and J. MacGlashan. Environment-independent task specifications via GLTL. *arXiv preprint arXiv:1704.04341*, 2017.
- Y. Liu, A. Gupta, P. Abbeel, and S. Levine. Imitation from observation: Learning to imitate behaviors from raw video via context translation. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, pages 1118–1125. IEEE, 2018.
- M. Lopes, F. Melo, and L. Montesano. Active learning for reward estimation in inverse reinforcement learning. In *Proceedings of the 2009 Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 31–46, 2009.
- Q. Lu and T. Hermans. Modeling grasp type improves learning-based grasp planning. *IEEE Robotics and Automation Letters*, 4(2):784–791, 2019.
- C. Lynch, M. Khansari, T. Xiao, V. Kumar, J. Thompson, S. Levine, and P. Sermanet. Learning latent plans from play. In *Proceedings of the 3rd Conference on Robot Learning*, pages 1113–1132, 2019.

- M. Madry, L. Bo, D. Kragic, and D. Fox. ST-HMP: Unsupervised spatio-temporal feature learning for tactile data. In *Proceedings of the 2014 IEEE International Conference on Robotics and Automation*, pages 2262–2269, 2014.
- J. Mahler, F. T. Pokorny, B. Hou, M. Roderick, M. Laskey, M. Aubry, K. Kohlhoff, T. Kröger, J. Kuffner, and K. Goldberg. Dex-Net 1.0: A cloud-based network of 3D objects for robust grasp planning using a multi-armed bandit model with correlated rewards. In *Proceedings of the 2016 IEEE International Conference on Robotics and Automation*, pages 1957–1964, 2016.
- J. Mahler, J. Liang, S. Niyaz, M. Laskey, R. Doan, X. Liu, J. A. Ojea, and K. Goldberg. Dex-net 2.0: Deep learning to plan robust grasps with synthetic point clouds and analytic grasp metrics. In *Robotics: Science and Systems XIII*, 2017.
- S. Mannor, R. Y. Rubinstein, and Y. Gat. The cross entropy method for fast policy search. In *Proceedings of the 20th International Conference on Machine Learning*, pages 512–519, 2003.
- R. Martín-Martín, S. Höfer, and O. Brock. An integrated approach to visual perception of articulated objects. In *Proceedings of the 2016 IEEE International Conference on Robotics and Automation*, pages 5091 – 5097, 2016.
- R. Martinez-Cantin, N. de Freitas, A. Doucet, and J. A. Castellanos. Active policy learning for robot planning and exploration under uncertainty. In *Robotics: Science and Systems III*, pages 321–328, 2007.
- M. T. Mason. Compliance and force control for computer controlled manipulators. *IEEE Transactions on Systems, Man, and Cybernetics*, 11(6):418–432, 1981.
- F. Meier, E. Theodorou, F. Stulp, and S. Schaal. Movement segmentation using a primitive library. In *Proceedings of the 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3407–3412, 2011.
- B. Michini and J. How. Bayesian nonparametric inverse reinforcement learning. In *Machine Learning and Knowledge Discovery in Databases*, pages 148–163, 2012.
- H. Min, C. Yi, R. Luo, J. Zhu, and S. Bi. Affordance research in developmental robotics: A survey. *IEEE Transactions on Cognitive and Developmental Systems*, 8(4):237–255, 2016.
- D. K. Misra, J. Sung, K. Lee, and A. Saxena. Tell me Dave: Context sensitive grounding of natural language to mobile manipulation instructions. In *Robotics: Science and Systems X*, 2014.
- V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, et al. Human-level control through deep reinforcement learning. *Nature*, 518(7540):529–533, 2015.

- V. Mnih, A. P. Badia, M. Mirza, A. Graves, T. Lillicrap, T. Harley, D. Silver, and K. Kavukcuoglu. Asynchronous methods for deep reinforcement learning. In *Proceedings of the 33rd International Conference on Machine Learning*, pages 1928–1937, 2016.
- S. Mohamed and D. J. Rezende. Variational information maximisation for intrinsically motivated reinforcement learning. In *Advances in Neural Information Processing Systems 28*, pages 2125–2133, 2015.
- L. Montesano and M. Lopes. Active learning of visual descriptors for grasping using non-parametric smoothed beta distributions. *Robotics and Autonomous Systems*, 60(3):452–462, 2012.
- L. Montesano, M. Lopes, A. Bernardino, and J. Santos-Victor. Learning object affordances: from sensory–motor coordination to imitation. *IEEE Transactions on Robotics*, 24(1):15–26, 2008.
- P. Moylan and B. Anderson. Nonlinear regulator theory and an inverse optimal control problem. *IEEE Transactions on Automatic Control*, 18(5):460–465, 1973.
- C. Mueller, J. Venicx, and B. Hayes. Robust robot learning from demonstration and skill repair using conceptual constraints. In *Proceedings of the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 6029–6036, 2018.
- J. Mugan and B. Kuipers. Autonomous learning of high-level states and actions in continuous environments. *IEEE Transactions on Autonomous Mental Development*, 4(1):70–86, 2012.
- A. Myers, C. L. Teo, C. Fermüller, and Y. Aloimonos. Affordance detection of tool parts from geometric features. In *Proceedings of the 2015 IEEE International Conference on Robotics and Automation*, pages 1374–1381, 2015.
- O. Nachum, S. Gu, H. Lee, and S. Levine. Data-efficient hierarchical reinforcement learning. In *Advances in Neural Information Processing Systems 31*, pages 3303–3313, 2018.
- S. Narvekar, J. Sinapov, M. Leonetti, and P. Stone. Source task creation for curriculum learning. In *Proceedings of the 15th International Conference on Autonomous Agents and Multiagent Systems*, pages 566–574, 2016.
- A. Y. Ng, D. Harada, and S. Russell. Policy invariance under reward transformations: Theory and application to reward shaping. In *Proceedings of the 16th International Conference on Machine Learning*, pages 278–287, 1999.
- A. Y. Ng, S. J. Russell, et al. Algorithms for inverse reinforcement learning. In *Proceedings of the 17th International Conference on Machine Learning*, pages 663–670, 2000.
- H. Nguyen and C. C. Kemp. Autonomously learning to visually detect where manipulation will succeed. *Autonomous Robots*, 36(1-2):137–152, 2014.
- D. Nguyen-Tuong and J. Peters. Incremental online sparsification for model learning in real-time robot control. *Neurocomputing*, 74(11):1859 – 1867, 2011. ISSN 0925-2312.

- A. Nichol, J. Achiam, and J. Schulman. On first-order meta-learning algorithms. *arXiv preprint arXiv:1803.02999*, 2018.
- S. Niekum and A. G. Barto. Clustering via Dirichlet process mixture models for portable skill discovery. In *Advances in Neural Information Processing Systems 24*, pages 1818–1826, 2011.
- S. Niekum, A. G. Barto, and L. Spector. Genetic programming for reward function search. *IEEE Transactions on Autonomous Mental Development*, 2(2):83–90, 2010.
- S. Niekum, S. Osentoski, C. G. Atkeson, and A. G. Barto. Online Bayesian changepoint detection for articulated motion models. In *Proceedings of the 2015 IEEE International Conference on Robotics and Automation*, pages 1468–1475, 2015a.
- S. Niekum, S. Osentoski, G. Konidaris, S. Chitta, B. Marthi, and A. G. Barto. Learning grounded finite-state representations from unstructured demonstrations. *International Journal of Robotics Research*, 34(2):131–157, 2015b.
- S. Otte, J. Kulick, M. Toussaint, and O. Brock. Entropy-based strategies for physical exploration of the environment’s degrees of freedom. In *Proceedings of the 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 615–622, 2014.
- P.-Y. Oudeyer and F. Kaplan. What is intrinsic motivation? a typology of computational approaches. *Frontiers in neurorobotics*, 1(6):1 – 14, 2009.
- E. Oztop, N. S. Bradley, and M. A. Arbib. Infant grasp learning: a computational model. *Experimental Brain Research*, 158(4):480–503, Oct 2004.
- S. Padakandla, S. Bhatnagar, et al. Reinforcement learning in non-stationary environments. *arXiv preprint arXiv:1905.03970*, 2019.
- A. Paraschos, C. Daniel, J. R. Peters, and G. Neumann. Probabilistic movement primitives. In *Advances in Neural Information Processing Systems 26*, pages 2616–2624, 2013.
- D. Park, Z. Erickson, T. Bhattacharjee, and C. C. Kemp. Multimodal execution monitoring for anomaly detection during robot manipulation. In *Proceedings of the 2016 IEEE International Conference on Robotics and Automation*, pages 407–414, 2016.
- P. Pastor, H. Hoffmann, T. Asfour, and S. Schaal. Learning and generalization of motor skills by learning from demonstration. In *Proceedings of the 2009 IEEE International Conference on Robotics and Automation*, pages 763–768, 2009.
- P. Pastor, M. Kalakrishnan, S. Chitta, E. Theodorou, and S. Schaal. Skill learning and task outcome prediction for manipulation. In *Proceedings of the 2011 IEEE International Conference on Robotics and Automation*, pages 3828–3834, 2011a.
- P. Pastor, L. Righetti, M. Kalakrishnan, and S. Schaal. Online movement adaptation based on previous sensor experiences. In *Proceedings of the 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 365–371, 2011b.

- P. Pastor, M. Kalakrishnan, L. Righetti, and S. Schaal. Towards associative skill memories. In *Proceedings of the 2012 IEEE-RAS International Conference on Humanoid Robots*, pages 309–315, 2012.
- D. Pathak, Y. Shentu, D. Chen, P. Agrawal, T. Darrell, S. Levine, and J. Malik. Learning instance segmentation by interaction. In *CVPR 2018 Workshop on Benchmarks for Deep Learning in Robotic Vision*, 2018.
- D. Pathak, D. Gandhi, and A. Gupta. Self-supervised exploration via disagreement. In *Proceedings of the 36th International Conference on Machine Learning*, 2019.
- X. B. Peng, M. Andrychowicz, W. Zaremba, and P. Abbeel. Sim-to-real transfer of robotic control with dynamics randomization. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, 2018.
- J. Peters and S. Schaal. Natural actor-critic. *Neurocomputing*, 71(7-9):1180–1190, 2008.
- J. Peters, K. Mülling, and Y. Altun. Relative entropy policy search. In *Proceedings of the 24th AAAI Conference on Artificial Intelligence*, pages 1607–1612, 2010.
- A. Petrovskaya and O. Khatib. Global localization of objects via touch. *IEEE Transactions on Robotics*, 27(3):569–585, 2011.
- P. Piacenza, W. Dang, E. Hannigan, J. Espinal, I. Hussain, I. Kyriassis, and M. T. Ciocarlie. Accurate contact localization and indentation depth prediction with an optics-based tactile sensor. In *Proceedings of the 2017 IEEE International Conference on Robotics and Automation*, pages 959–965, 2017.
- S. Pillai, M. R. Walter, and S. Teller. Learning articulated motions from visual demonstrations. In *Robotics: Science and Systems X*, Berkeley, CA, 2014.
- L. Pinto and A. Gupta. Supersizing self-supervision: Learning to grasp from 50k tries and 700 robot hours. In *Proceedings of the 2016 IEEE International Conference on Robotics and Automation*, pages 3406–3413, 2016.
- L. Pinto, D. Gandhi, Y. Han, Y.-L. Park, and A. Gupta. The curious robot: Learning visual representations via physical interactions. In *Proceedings of the 2016 European Conference on Computer Vision*, pages 3–18. Springer, 2016.
- R. Platt, R. Tedrake, L. Kaelbling, and T. Lozano-Perez. Belief space planning assuming maximum likelihood observations. In *Robotics: Science and Systems VI*, 2010.
- R. Platt, L. Kaelbling, T. Lozano-Perez, and R. Tedrake. Efficient planning in non-Gaussian belief spaces and its application to robot grasping. In *Proceedings of the 2011 International Symposium on Robotics Research*, pages 253–269, 2011.
- R. Platt, C. Kohler, and M. Gualtieri. Deictic image mapping: An abstraction for learning pose invariant manipulation policies. In *Proceedings of the 33rd AAAI Conference on Artificial Intelligence*, 2019.

- V. Pong, S. Gu, M. Dalal, and S. Levine. Temporal difference models: Model-free deep RL for model-based control. In *Proceedings of the 2018 International Conference on Learning Representations*, 2018.
- J. R. Quinlan. Induction of decision trees. *Machine Learning*, 1(1):81–106, 1986.
- D. Ramachandran and E. Amir. Bayesian inverse reinforcement learning. *Urbana*, 51(61801):1–4, 2007.
- M. A. Rana, M. Mukadam, S. R. Ahmadzadeh, S. Chernova, and B. Boots. Skill generalization via inference-based planning. In *RSS 2017 Workshop on Mathematical Models, Algorithms, and Human-Robot Interaction*, 2017.
- P. Ranchod, B. Rosman, and G. Konidaris. Nonparametric bayesian reward segmentation for skill discovery using inverse reinforcement learning. In *Proceedings of the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 471–477, 2015.
- C. E. Rasmussen. Gaussian processes in machine learning. In *Advanced Lectures on Machine Learning*, pages 63–71. Springer, 2004.
- N. D. Ratliff, J. Issac, D. Kappler, S. Birchfield, and D. Fox. Riemannian motion policies. *CoRR*, abs/1801.02854, 2018.
- T. Ren, Y. Dong, D. Wu, and K. Chen. Learning-Based Variable Compliance Control for Robotic Assembly. *Journal of Mechanisms and Robotics*, 10(6), 09 2018.
- L. Riano and T. McGinnity. Automatically composing and parameterizing skills by evolving finite state automata. *Robotics and Autonomous Systems*, 60(4):639–650, 2012.
- M. Riedmiller, R. Hafner, T. Lampe, M. Neunert, J. Degraeve, T. Van de Wiele, V. Mnih, N. Heess, and J. T. Springenberg. Learning by playing-solving sparse reward tasks from scratch. In *Proceedings of the 35th International Conference on Machine Learning*, pages 4344–4353, 2018.
- A. Rodriguez, D. Bourne, M. Mason, G. F. Rossano, and J. Wang. Failure detection in assembly: Force signature analysis. In *Proceedings of the 2010 IEEE International Conference on Automation Science and Engineering*, pages 210–215, 2010.
- D. Rodriguez and S. Behnke. Transferring category-based functional grasping skills by latent space non-rigid registration. *IEEE Robotics and Automation Letters*, 3(3):2662–2669, 2018.
- B. Rosman and S. Ramamoorthy. Learning spatial relationships between objects. *International Journal of Robotics Research*, 30(11):1328–1342, 2011.
- S. Ross, G. Gordon, and D. Bagnell. A reduction of imitation learning and structured prediction to no-regret online learning. In *Proceedings of the 14th International Conference on Artificial Intelligence and Statistics*, pages 627–635, 2011.

- S. J. Russell and P. Norvig. *Artificial Intelligence: A Modern Approach*. Pearson Education, 2 edition, 2003.
- A. A. Rusu, N. C. Rabinowitz, G. Desjardins, H. Soyer, J. Kirkpatrick, K. Kavukcuoglu, R. Pascanu, and R. Hadsell. Progressive neural networks. *arXiv preprint arXiv:1606.04671*, 2016.
- D. Sadigh, E. S. Kim, S. Coogan, S. S. Sastry, and S. A. Seshia. A learning based approach to control synthesis of Markov decision processes for linear temporal logic specifications. In *Proceedings of the 53rd Annual Conference on Decision and Control*, pages 1091–1096, 2014.
- E. Sahin, M. Cakmak, M. R. Dogar, E. Ugur, and G. Ucoluk. To afford or not to afford: A new formalization of affordances toward affordance-based robot control. *Adaptive Behavior*, 15(4):447–472, 2007.
- A. Sanchez-Gonzalez, N. Heess, J. T. Springenberg, J. Merel, M. Riedmiller, R. Hadsell, and P. Battaglia. Graph networks as learnable physics engines for inference and control. In *Proceedings of the 35th International Conference on Machine Learning*, pages 4470–4479, 2018.
- T. D. Sanger. Neural network learning control of robot manipulators using gradually increasing task difficulty. *IEEE Transactions on Robotics and Automation*, 10(3):323–333, 1994.
- A. Saran, B. Lakic, S. Majumdar, J. Hess, and S. Niekum. Viewpoint selection for visual failure detection. In *Proceedings of the 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 5437–5444, 2017.
- A. Saxena, J. Driemeyer, J. Kearns, C. Osondu, and A. Y. Ng. Learning to grasp novel objects using vision. In O. Khatib, V. Kumar, and D. Rus, editors, *Proceedings of the 2008 International Symposium on Experimental Robotics*, pages 33–42, 2008.
- S. Schaal. Is imitation learning the route to humanoid robots? *Trends in Cognitive Sciences*, 3(6):233–242, 1999.
- S. Schaal. Dynamic movement primitives—a framework for motor control in humans and humanoid robotics. In *Adaptive Motion of Animals and Machines*, pages 261–280. Springer, 2006.
- S. Schaal, J. Peters, J. Nakanishi, and A. Ijspeert. Learning movement primitives. In *Proceedings of the 2005 International Symposium on Robotics Research*, pages 561–572. Springer, 2005.
- T. Schaul, D. Horgan, K. Gregor, and D. Silver. Universal value function approximators. In *Proceedings of the 32nd International Conference on Machine Learning*, pages 1312–1320, 2015.
- C. Schenck and D. Fox. Perceiving and reasoning about liquids using fully convolutional networks. *International Journal of Robotics Research*, 37(4-5):452–471, 2018a.

- C. Schenck and D. Fox. SPNets: Differentiable fluid dynamics for deep neural networks. In *Proceedings of the 2nd Conference on Robot Learning*, volume 87 of *Proceedings of Machine Learning Research*, pages 317–335, 2018b.
- C. Schenck and A. Stoytchev. The object pairing and matching task: Toward Montessori tests for robots. In *Humanoids 2012 Workshop on Developmental Robotics*, 2012.
- C. Schenck, J. Sinapov, and A. Stoytchev. Which object comes next? grounded order completion by a humanoid robot. *Cybernetics and Information Technologies*, 12(3):5–16, 2012.
- C. Schenck, J. Sinapov, D. Johnston, and A. Stoytchev. Which object fits best? Solving matrix completion tasks with a humanoid robot. *IEEE Transactions on Autonomous Mental Development*, 6(3):226–240, 2014.
- C. Schenck, J. Tompson, S. Levine, and D. Fox. Learning robotic manipulation of granular media. In *Proceedings of the 1st Conference on Robot Learning*, pages 239–248, 2017.
- C. Schlagenhauf, D. Bauer, K. Chang, J. P. King, D. Moro, S. Coros, and N. Pollard. Control of tendon-driven soft foam robot hands. In *Proceedings of the 2018 IEEE-RAS International Conference on Humanoid Robots*, pages 1–7, 2018.
- T. Schmidt, R. A. Newcombe, and D. Fox. DART: dense articulated real-time tracking with consumer depth cameras. *Autonomous Robots*, 39(3):239–258, 2015.
- J. Scholz and M. Stilman. Combining motion planning and optimization for flexible robot manipulation. In *Proceedings of the 2010 IEEE-RAS International Conference on Humanoid Robots*, pages 80–85, 2010.
- J. Scholz, M. Levihn, C. Isbell, and D. Wingate. A physics-based model prior for object-oriented MDPs. In *Proceedings of the 31st International Conference on Machine Learning*, pages 1089–1097, 2014.
- J. Schulman, J. Ho, C. Lee, and P. Abbeel. Learning from demonstrations through the use of non-rigid registration. In *Proceedings of the 2013 International Symposium on Robotics Research*, pages 339–354. Springer, 2013.
- J. Schulman, S. Levine, P. Abbeel, M. Jordan, and P. Moritz. Trust region policy optimization. In *Proceedings of the 32nd International Conference on Machine Learning*, pages 1889–1897, 2015.
- J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.
- M. Schwarz, A. Milan, A. S. Periyasamy, and S. Behnke. RGB-D object detection and semantic segmentation for autonomous manipulation in clutter. *International Journal of Robotics Research*, 37(4-5):437–451, 2018.
- D. Seita, N. Jamali, M. Laskey, R. Berenstein, A. K. Tanwani, P. Baskaran, S. Iba, J. Canny, and K. Goldberg. Robot bed-making: Deep transfer learning using depth sensing of deformable fabric. *arXiv preprint arXiv:1809.09810*, 2018.

- P. Sermanet, C. Lynch, Y. Chebotar, J. Hsu, E. Jang, S. Schaal, S. Levine, and G. Brain. Time-contrastive networks: Self-supervised learning from video. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, pages 1134–1141, 2018.
- S. C. Shapiro and H. O. Ismail. Anchoring in a grounded layered architecture with integrated reasoning. *Robotics and Autonomous Systems*, 43(2):97 – 108, 2003.
- T. Siméon, J.-P. Laumond, J. Cortés, and A. Sahbani. Manipulation planning with probabilistic roadmaps. *International Journal of Robotics Research*, 23(7-8):729–746, 2004.
- J. Sinapov, T. Bergquist, C. Schenck, U. Ohiri, S. Griffith, and A. Stoytchev. Interactive object recognition using proprioceptive and auditory feedback. *International Journal of Robotics Research*, 30(10):1250–1262, 2011a.
- J. Sinapov, V. Sukhoy, R. Sahai, and A. Stoytchev. Vibrotactile recognition and categorization of surfaces by a humanoid robot. *IEEE Transactions on Robotics*, 27(3):488–497, 2011b.
- J. Sinapov, C. Schenck, K. Staley, V. Sukhoy, and A. Stoytchev. Grounding semantic categories in behavioral interactions: Experiments with 100 objects. *Robotics and Autonomous Systems*, 62(5):632–645, 2014.
- S. Singh, M. R. James, and M. R. Rudary. Predictive state representations: A new theory for modeling dynamical systems. In *Proceedings of the 20th International Conference on Uncertainty in Artificial Intelligence*, pages 512–519, 2004.
- D. Song, C. H. Ek, K. Huebner, and D. Kragic. Multivariate discretization for Bayesian network structure learning in robot grasping. In *Proceedings of the 2011 IEEE International Conference on Robotics and Automation*, pages 1944–1950, 2011.
- J. Sorg, R. L. Lewis, and S. P. Singh. Reward design via online gradient ascent. In *Advances in Neural Information Processing Systems 23*, pages 2190–2198, 2010a.
- J. Sorg, S. P. Singh, and R. L. Lewis. Internal rewards mitigate agent boundedness. In *Proceedings of the 27th International Conference on Machine Learning*, pages 1007–1014, 2010b.
- M. Spong, S. Hutchinson, and M. Vidyasagar. *Robot modeling and control*. Wiley, 2005.
- A. Srinivas, A. Jabri, P. Abbeel, S. Levine, and C. Finn. Universal planning networks: Learning generalizable representations for visuomotor control. In *Proceedings of the 35th International Conference on Machine Learning*, pages 4732–4741, 2018.
- B. C. Stadie, P. Abbeel, and I. Sutskever. Third-person imitation learning. In *Proceedings of the 2017 International Conference on Learning Representations*, 2017.
- K. O. Stanley, D. B. D’Ambrosio, and J. Gauci. A hypercube-based encoding for evolving large-scale neural networks. *Artificial Life*, 15(2):185–212, 2009.

- M. Stilman, K. Nishiwaki, and S. Kagami. Learning object models for whole body manipulation. In *Proceedings of the 2008 IEEE-RAS International Conference on Humanoid Robots*, pages 174–179, 2008.
- J. A. Stork, C. H. Ek, Y. Bekiroglu, and D. Kragic. Learning predictive state representation for in-hand manipulation. In *Proceedings of the 2015 IEEE International Conference on Robotics and Automation*, pages 3207–3214, 2015.
- A. Stoytchev. Behavior-grounded representation of tool affordances. In *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*, pages 3060–3065, 2005.
- F. Stramandinoli, V. Tikhonoff, U. Pattacini, and F. Nori. Heteroscedastic regression and active learning for modeling affordances in humanoids. *IEEE Transactions on Cognitive and Developmental Systems*, 10(2):455–468, 2018.
- A. L. Strehl, L. Li, E. Wiewiora, J. Langford, and M. L. Littman. PAC model-free reinforcement learning. In *Proceedings of the 23rd International Conference on Machine Learning*, pages 881–888, 2006.
- J. Stückler and S. Behnke. Adaptive tool-use strategies for anthropomorphic service robots. In *Proceedings of the 2014 IEEE-RAS International Conference on Humanoid Robots*, pages 755–760, 2014.
- J. Sturm, A. Jain, C. Stachniss, C. C. Kemp, and W. Burgard. Operating articulated objects based on experience. In *Proceedings of the 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 2739–2744, 2010.
- J. Sturm, C. Stachniss, and W. Burgard. A probabilistic framework for learning kinematic models of articulated objects. *Journal of Artificial Intelligence Research*, 41(2):477–526, 2011.
- Z. Su, K. Hausman, Y. Chebotar, A. Molchanov, G. E. Loeb, G. S. Sukhatme, and S. Schaal. Force estimation and slip detection/classification for grip control using a biomimetic tactile sensor. In *Proceedings of the 2015 IEEE-RAS International Conference on Humanoid Robots*, pages 297–303, 2015.
- Z. Su, O. Kroemer, G. E. Loeb, G. S. Sukhatme, and S. Schaal. Learning to switch between sensorimotor primitives using multimodal haptic signals. In *From Animals to Animats*, pages 170–182, 2016.
- V. Sukhoy, V. Georgiev, T. Wegter, R. Sweidan, and A. Stoytchev. Learning to slide a magnetic card through a card reader. In *Proceedings of the 2012 IEEE International Conference on Robotics and Automation*, pages 2398–2404, 2012.
- B. Sundaralingam, A. Lambert, A. Handa, B. Boots, T. Hermans, S. Birchfield, N. Ratliff, and D. Fox. Robust learning of tactile force estimation through robot interaction. In *Proceedings of the 2019 IEEE International Conference on Robotics and Automation*, 2019.

- J. Sung, S. H. Jin, and A. Saxena. Robobarista: Object part-based transfer of manipulation trajectories from crowd-sourcing in 3D pointclouds. In *Proceedings of the 2015 International Symposium on Robotics Research*, 2015.
- J. Sung, I. Lenz, and A. Saxena. Deep multimodal embedding: Manipulating novel objects with point-clouds, language and trajectories. In *Proceedings of the 2017 IEEE International Conference on Robotics and Automation*, pages 2794–2801, 2017a.
- J. Sung, J. K. Salisbury, and A. Saxena. Learning to represent haptic feedback for partially-observable tasks. In *Proceedings of the 2017 IEEE International Conference on Robotics and Automation*, pages 2802–2809, 2017b.
- R. Sutton, D. Precup, and S. Singh. Between MDPs and semi-MDPs: A framework for temporal abstraction in reinforcement learning. *Artificial Intelligence*, 112(1-2):181–211, 1999.
- R. S. Sutton and A. G. Barto. *Reinforcement Learning: An Introduction*. MIT press, 1998.
- R. S. Sutton, D. A. McAllester, S. P. Singh, and Y. Mansour. Policy gradient methods for reinforcement learning with function approximation. In *Advances in Neural Information Processing Systems 13*, pages 1057–1063, 2000.
- M. Svetlik, M. Leonetti, J. Sinapov, R. Shah, N. Walker, and P. Stone. Automatic curriculum graph generation for reinforcement learning agents. In *Proceedings of the 31st AAAI Conference on Artificial Intelligence*, pages 2590–2596, 2017.
- A. Tamar, Y. Wu, G. Thomas, S. Levine, and P. Abbeel. Value iteration networks. In *Advances in Neural Information Processing Systems 29*, pages 2154–2162, 2016.
- Y. Tassa, N. Mansard, and E. Todorov. Control-limited differential dynamic programming. In *Proceedings of the 2014 IEEE International Conference on Robotics and Automation*, pages 1168–1175, 2014.
- M. Taylor, P. Stone, and Y. Liu. Transfer learning via inter-task mappings for temporal difference learning. *Journal of Machine Learning Research*, 8(1):2125–2167, 2007.
- M. E. Taylor, H. B. Suay, and S. Chernova. Integrating reinforcement learning with human demonstrations of varying ability. In *Proceedings of the 10th International Conference on Autonomous Agents and Multiagent Systems*, pages 617–624, 2011.
- R. Tedrake, I. R. Manchester, M. Tobenkin, and J. W. Roberts. LQR-trees: Feedback motion planning via sums-of-squares verification. *The International Journal of Robotics Research*, 29(8):1038–1052, 2010.
- S. Tellex, T. Kollar, S. Dickerson, M. R. Walter, A. G. Banerjee, S. Teller, and N. Roy. Understanding natural language commands for robotic navigation and mobile manipulation. In *Proceedings of the 25th AAAI Conference on Artificial Intelligence*, pages 1507–1514, 2011.

- A. ten Pas, M. Gualtieri, K. Saenko, and R. Platt. Grasp pose detection in point clouds. *International Journal of Robotics Research*, 36(13-14):1455–1473, 2017.
- M. Tenorth, S. Profanter, F. Balint-Benczedi, and M. Beetz. Decomposing CAD models of objects of daily use and reasoning about their functional parts. In *Proceedings of the 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 5943–5949, 2013.
- B. Thananjeyan, A. Balakrishna, U. Rosolia, F. Li, R. McAllister, J. E. Gonzalez, S. Levine, F. Borrelli, and K. Goldberg. Extending deep model predictive control with safety augmented value estimation from demonstrations. *arXiv preprint arXiv:1905.13402*, 2019.
- E. Theodorou, J. Buchli, and S. Schaal. A generalized path integral control approach to reinforcement learning. *Journal of Machine Learning Research*, 11(1):3137–3181, 2010.
- P. Thomas and E. Brunskill. Data-efficient off-policy policy evaluation for reinforcement learning. In *Proceedings of the 33rd International Conference on Machine Learning*, pages 2139–2148, 2016.
- P. Thomas, G. Theodorou, and M. Ghavamzadeh. High confidence policy improvement. In *Proceedings of the 32nd International Conference on Machine Learning*, pages 2380–2388, 2015a.
- P. S. Thomas, G. Theodorou, and M. Ghavamzadeh. High-confidence off-policy evaluation. In *Proceedings of the 29th AAAI Conference on Artificial Intelligence*, pages 3000–3006, 2015b.
- J. Thomason, J. Sinapov, M. Svetlik, P. Stone, and R. J. Mooney. Learning multi-modal grounded linguistic semantics by playing “I Spy”. In *Proceedings of the 25th International Joint Conference on Artificial Intelligence*, pages 3477–3483, 2016.
- J. Tobin, R. Fong, A. Ray, J. Schneider, W. Zaremba, and P. Abbeel. Domain randomization for transferring deep neural networks from simulation to the real world. In *Proceedings of the 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 23–30, 2017.
- F. Torabi, G. Warnell, and P. Stone. Behavioral cloning from observation. In *Proceedings of the 28th International Joint Conference on Artificial Intelligence*, pages 4950–4957, 2018.
- M. Toussaint, K. Allen, K. A. Smith, and J. B. Tenenbaum. Differentiable physics and stable modes for tool-use and manipulation planning. In *Robotics: Science and Systems XIV*, 2018.
- J. Tremblay, T. To, B. Sundaralingam, Y. Xiang, D. Fox, and S. T. Birchfield. Deep object pose estimation for semantic robotic grasping of household objects. In *Proceedings of the 2nd Conference on Robot Learning*, pages 306–316, 2018.
- C. J. Tsikos and R. Bajcsy. Segmentation via manipulation. *IEEE Transactions on Robotics and Automation*, 7(3):306–319, 1991.

- E. Ugur and J. Piater. Bottom-up learning of object categories, action effects and logical rules: From continuous manipulative exploration to symbolic planning. In *Proceedings of the 2015 IEEE International Conference on Robotics and Automation*, pages 2627–2633, 2015.
- E. Ugur and J. Piater. Refining discovered symbols with multi-step interaction experience. In *Proceedings of the 2015 IEEE-RAS International Conference on Humanoid Robots*, pages 1007–1012, 2015.
- E. Ugur, E. Sahin, and E. Öztop. Predicting future object states using learned affordances. In *Proceedings of the 24th International Symposium on Computer and Information Sciences*, pages 415–419, 2009.
- E. Ugur, E. Öztop, and E. Sahin. Going beyond the perception of affordances: Learning how to actualize them through behavioral parameters. In *Proceedings of the 2011 IEEE International Conference on Robotics and Automation*, pages 4768–4773, 2011.
- J. Van Den Berg, S. Miller, D. Duckworth, H. Hu, A. Wan, X.-Y. Fu, K. Goldberg, and P. Abbeel. Superhuman performance of surgical tasks by robots using iterative learning from human-guided demonstrations. In *Proceedings of the 2010 IEEE International Conference on Robotics and Automation*, pages 2074–2081, 2010.
- H. van Hoof, O. Kroemer, and J. Peters. Probabilistic segmentation and targeted exploration of objects in cluttered environments. *IEEE Transactions on Robotics*, 30(5):1198–1209, 2014.
- H. van Seijen, S. Whiteson, and L. Kester. Efficient abstraction selection in reinforcement learning. *Computational Intelligence*, 30(4):657–699, 2013.
- J. Varley, D. Watkins-Valls, and P. K. Allen. Multi-modal geometric learning for grasping and manipulation. In *Proceedings of the 2019 IEEE International Conference on Robotics and Automation*, 2019.
- F. Veiga, H. van Hoof, J. Peters, and T. Hermans. Stabilizing novel objects by learning to predict tactile slip. In *Proceedings of the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 5065–5072, 2015.
- F. Veiga, J. Peters, and T. Hermans. Grip stabilization of novel objects using slip prediction. *IEEE Transactions on Haptics*, 11(4):531–542, 2018.
- A. Vezhnevets, S. Osindero, T. Schaul, N. Heess, M. Jaderberg, D. Silver, , and K. Kavukcuoglu. FeUdal networks for hierarchical reinforcement learning. In *Proceedings of the 34th International Conference on Machine Learning*, pages 3540–3549, 2017.
- N. Vien and M. Toussaint. Touch-based POMDP manipulation via sequential submodular optimization. In *Proceedings of the 2015 IEEE-RAS International Conference on Humanoid Robots*, pages 407–413, 2015a.

- N. Vien and M. Toussaint. POMDP manipulation via trajectory optimization. In *Proceedings of the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 242–249, 2015b.
- S. Vijayakumar and S. Schaal. Locally weighted projection regression: An $O(n)$ algorithm for incremental real time learning in high dimensional space. In *Proceedings of the 17th International Conference on Machine Learning*, pages 288–293, 2000.
- F. E. Viña, Y. Bekiroglu, C. Smith, Y. Karayiannidis, and D. Kragic. Predicting slippage and learning manipulation affordances through Gaussian process regression. In *Proceedings of the 2013 IEEE-RAS International Conference on Humanoid Robots*, pages 462–468, 2013.
- A. S. Wang and O. Kroemer. Learning robust manipulation strategies with multimodal state transition models and recovery heuristics. In *Proceedings of the 2019 IEEE International Conference on Robotics and Automation*, 2019.
- H. Wang, S. Sridhar, J. Huang, J. Valentin, S. Song, and L. J. Guibas. Normalized object coordinate space for category-level 6d object pose and size estimation. In *Proceedings of the 2019 Conference on Computer Vision and Pattern Recognition*, 2019.
- Z. Wang, V. Bapst, N. Heess, V. Mnih, R. Munos, K. Kavukcuoglu, and N. de Freitas. Sample efficient actor-critic with experience replay. In *Proceedings of the 2017 International Conference on Learning Representations*, 2017.
- Z. Wang, C. R. Garrett, L. P. Kaelbling, and T. Lozano-Perez. Active model learning and diverse action sampling for task and motion planning. In *Proceedings of the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 4107–4114, 2018.
- C. J. Watkins and P. Dayan. Q-learning. *Machine Learning*, 8(3-4):279–292, 1992.
- J. Weng, J. McClelland, A. Pentland, O. Sporns, I. Stockman, M. Sur, and E. Thelen. Autonomous mental development by robots and animals. *Science*, 291(5504):599–600, 2001.
- R. J. Williams. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Machine Learning*, 8(3-4):229–256, 1992.
- F. Wörgötter, E. E. Aksoy, N. Krüger, J. Piater, A. Ude, and M. Tamosiunaite. A simple ontology of manipulation actions based on hand-object relations. *IEEE Transactions on Autonomous Mental Development*, 5(2):117–134, 2013. ISSN 1943-0604.
- J. Wu, I. Yildirim, J. J. Lim, B. Freeman, and J. Tenenbaum. Galileo: Perceiving physical object properties by integrating a physics engine with deep learning. In *Advances in Neural Information Processing Systems 28*, pages 127–135, 2015.
- J. Wu, J. J. Lim, H. Zhang, J. B. Tenenbaum, and W. T. Freeman. Physics 101: Learning physical object properties from unlabeled videos. In *Proceedings of the 2016 British Machine Vision Conference*, 2016.

- Y. Wu, E. Mansimov, R. B. Grosse, S. Liao, and J. Ba. Scalable trust-region method for deep reinforcement learning using Kronecker-factored approximation. In *Advances in Neural Information Processing Systems 30*, pages 5279–5288, 2017.
- M. Wulfmeier, P. Ondruska, and I. Posner. Maximum entropy deep inverse reinforcement learning. *arXiv preprint arXiv:1507.04888*, 2015.
- M. Wüthrich, J. Bohg, D. Kappler, C. Pfreundt, and S. Schaal. The coordinate particle filter - a novel particle filter for high dimensional systems. In *Proceedings of the 2015 IEEE International Conference on Robotics and Automation*, pages 2454–2461, 2015.
- A. Xie, A. Singh, S. Levine, and C. Finn. Few-shot goal inference for visuomotor learning and planning. In *Proceedings of the 2nd Conference on Robot Learning*, volume 87 of *Proceedings of Machine Learning Research*, pages 40–52, 2018.
- D. Xu, S. Nair, Y. Zhu, J. Gao, A. Garg, L. Fei-Fei, and S. Savarese. Neural task programming: Learning to generalize across hierarchical tasks. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, pages 1–8, 2018a.
- T. Xu, Q. Liu, L. Zhao, W. Xu, and J. Peng. Learning to explore via meta-policy gradient. In *Proceedings of the 35th International Conference on Machine Learning*, pages 5463–5472, 2018b.
- A. Yamaguchi and C. G. Atkeson. Differential dynamic programming with temporally decomposed dynamics. In *Proceedings of the 2015 IEEE-RAS International Conference on Humanoid Robots*, pages 696–703, 2015.
- A. Yamaguchi and C. G. Atkeson. Stereo vision of liquid and particle flow for robot pouring. In *Proceedings of the 2016 IEEE-RAS International Conference on Humanoid Robots*, pages 1173–1180, 2016a.
- A. Yamaguchi and C. G. Atkeson. Combining finger vision and optical tactile sensing: Reducing and handling errors while cutting vegetables. In *Proceedings of the 2016 IEEE-RAS International Conference on Humanoid Robots*, pages 1045–1051, 2016b.
- A. Yamaguchi and C. G. Atkeson. Implementing tactile behaviors using fingervision. In *Proceedings of the 2017 IEEE-RAS International Conference on Humanoid Robots*, pages 241–248, 2017.
- X. Yan, J. Hsu, M. Khansari, Y. Bai, A. Pathak, A. Gupta, J. Davidson, and H. Lee. Learning 6-dof grasping interaction via deep geometry-aware 3d representations. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, pages 1–9, 2018.
- Y. Yang, Y. Li, C. Fermuller, and Y. Aloimonos. Robot learning manipulation action plans by “watching” unconstrained videos from the world wide web. In *Proceedings of the 29th AAAI Conference on Artificial Intelligence*, pages 3686–3692, 2015.
- T. Ye, X. Wang, J. Davidson, and A. Gupta. Interpretable intuitive physics model. In *Proceedings of the 2018 European Conference on Computer Vision*, pages 89–105, 2018.

- K. Yu, M. Bauzá, N. Fazeli, and A. Rodriguez. More than a million ways to be pushed. A high-fidelity experimental dataset of planar pushing. In *Proceedings of the 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 30–37, 2016.
- T. Yu, P. Abbeel, S. Levine, and C. Finn. One-shot hierarchical imitation learning of compound visuomotor tasks. *arXiv preprint arXiv:1810.11043*, 2018.
- Z. Zeng, Z. Zhou, Z. Sui, and O. C. Jenkins. Semantic robot programming for goal-directed manipulation in cluttered scenes. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, pages 7462–7469, 2018.
- F. Zhang, J. Leitner, M. Milford, B. Upcroft, and P. Corke. Towards vision-based deep reinforcement learning for robotic motion control. *arXiv preprint arXiv:1511.03791*, 2015.
- T. Zhang, Z. McCarthy, O. Jowl, D. Lee, X. Chen, K. Goldberg, and P. Abbeel. Deep imitation learning for complex manipulation tasks from virtual reality teleoperation. In *Proceedings of the 2018 IEEE International Conference on Robotics and Automation*, pages 1–8, 2018.
- K. Zhou, J. C. Doyle, and K. Glover. *Robust and Optimal Control*. Prentice Hall, 1996.
- Y. Zhou, B. Burchfiel, and G. Konidaris. Representing, learning, and controlling complex object interactions. *Autonomous Robots*, 42(7):1355–1367, 2018.
- B. D. Ziebart. *Modeling Purposeful Adaptive Behavior with the Principle of Maximum Causal Entropy*. PhD thesis, Carnegie Mellon University, 2010.
- B. D. Ziebart, A. L. Maas, J. A. Bagnell, and A. K. Dey. Maximum entropy inverse reinforcement learning. In *Proceedings of the 22nd AAAI Conference on Artificial Intelligence*, pages 1433–1438, 2008.
- J. Zimmer, T. Hellebrekers, T. Asfour, C. Majidi, and O. Kroemer. Predicting grasp success with a soft sensing skin and shape-memory actuated gripper. In *Proceedings of the 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 7120 – 7127, November 2019.