Human-Robot Co-Creativity: Task Transfer on a Spectrum of Similarity

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Abstract

A *creative* robot autonomously produces a behavior that is novel and useful for the robot. In this paper, we examine creativity in the context of interactive robot learning from human demonstration. In the current state of interactive robot learning, while a robot may learn a task by observing a human teacher, it cannot later transfer the learned task to a new environment. When the source and target environments are sufficiently different, creativity is necessary for successful task transfer. In this paper we examine the goal of building creative robots from three perspectives. (1) Embodied Creativity: How may we ground current theories of computational creativity in perception and action? (2) Robot Creativity: How should a robot be creative within its task domain? (3) Human-Robot Co-Creativity: How might creativity emerge through human-robot collaboration?

Introduction

Robotics provides a challenging domain for computational creativity. This is in part because embodied creativity on a robotic platform introduces a dual-focus on agency and creativity. This is also partly because the robot's situatedness in perception and action in the physical world makes for high-dimensional input and output spaces. This results in several new constraints on theories of computational creativity: *autonomous* reasoning that responds to *high-dimensional*, real-world perceptual data to produce executable *actions* exhibiting a *creative behavior*. Additionally, it requires the robot to exhibit creativity in its *reasoning* as well as *physical* creativity due to its embodiment.

This distinction from other problems of computational creativity is especially evident in a robot that needs to transfer tasks learned in a familiar domain to novel domains. Each *task* consists of a series of *task steps* which are completed in sequence in order to produce the *task goal*. The goal of task transfer is to reuse the learned task steps in a manner that achieves the corresponding task goal in the new environment.

The topic of interactive robot task learning has been studied extensively (Argall et al. 2009; Chernova and Thomaz 2014). A common method for task learning involves the teacher providing the robot with a demonstration of the task, during which the teacher physically guides the robot's arm to complete the task (as shown in Figure 1) (Argall et al. 2009; Akgun et al. 2012). The robot learns from this demonstration by recording the state of each degree-of-freedom in its arm at each time interval, recording the trajectory of its movement in order to train a model which can be used to repeat the task at a later time. Provided that a robot only learns of the task via a demonstration, its representation of that task is initially at the level of perception and action, and does not contain information about the high-level goals or outcomes of that task.

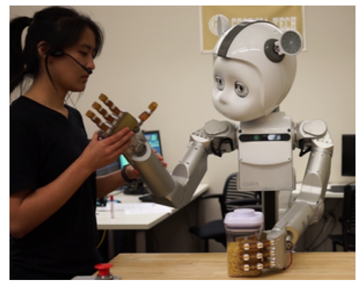


Figure 1: Interactive Task Demonstration

While a robot can learn to complete a task from demonstrations, it cannot immediately transfer the learned task model to perform the task in a new environment. For example, if objects in the new domain (referred to as the *target* domain) are configured differently than those in the original domain (the *source* domain), the robot may be able to apply the learned task model to the target domain *if* it has been parameterized according to the perceived locations of objects. However, if objects have been replaced in the target environment, the model is no longer parameterized based on the correct objects, and the robot cannot transfer the learned model. While a robot can be provided with additional demonstrations so that it generalizes over multiple instances of the task, this is a tedious and time-consuming task for the human teacher.

We address this problem of *task transfer*: transferring a task learned from one demonstration so that it can be reused in a variety of related target environments. As the previous example demonstrates, the difficulty of the task transfer problem increases as the source and target environments become more dissimilar. We propose the use of *human-robot co-creativity* to address difficult task transfer problems that require the robot to perform a novel behavior. Just as creativity is evident in collaboration between humans (e.g. collaborating to assemble a structure out of blocks), human-robot co-creativity involves the coordination of novel, physical actions to achieve a shared goal. We present three perspectives on creative transfer: embodied creativity, robot creativity, and co-creativity. In doing so, we argue that:

- A robot exhibits creativity by (i) reasoning over past task knowledge, and (ii) producing a new sequence of actions that is different from the taught behaviors.
- For sufficiently difficult task transfer problems (in which the robot must produce an action that is different than that originally taught), creativity is necessary for the robot to perform task transfer successfully.
- Co-creativity occurs when the robot collaborates with the human teacher to perform task transfer, and is necessary in order to maintain autonomy while addressing a variety of transfer problems.

Related Work

Creativity in robotics is often discussed in the context of a robot performing behaviors that typically requires human creativity. Gemeinboeck & Saunders (2013) suggested that the embodiment of a robot lends it to be interpreted in the context of and in terms of human behaviors. The robot's enactment in human environments creates meaning to the observer. Gopinath & Weinberg (2016) explore the creative domain of musical robots and propose a generative model for a robot drummer to select natural and expressive drum strokes that are indistinguishable from a human drummer. Schubert & Mombaur (2013) model the motion dynamics that enables a robot to mimic creative paintings.

These are all examples of behaviors that appear novel to human observers and thus manifest social creativity. Bird & Stokes (2006) propose a different set of requirements of a creative robot: autonomy and *self-novelty*. The robot's solutions are novel to itself, regardless of their novelty to a human observer, thus manifesting personal creativity. Saunders, Chee, & Gemeinboeck (2013) address robot control in embodied creative tasks. In such domains, emphasis is placed on the result of the system, particularly how it enables co-creative expression when a human user interacts with it. Kantosalo & Toivonen (2016) propose a method for alternating co-creativity, in which the creative agent interacts with a teacher during a task, iteratively modifying the shared creative concept. Davis et al. (2015) describe *Drawing Apprentice*, which takes turns with a human artist to make drawings.

Colin et al. (2016) describe a creative process for reinforcement learning agents. Rather than focus on producing a creative output, they address the process of creativity by introducing a hierarchy of problem spaces, which roughly represent different abstractions of the original reinforcement learning problem. Vigorito & Barto (2008) also address creativity as a matter of creative process, rather than creative outcome. They address creative reasoning via a process that emphasizes (i) sufficient variation and (ii) sufficient selection of candidate policies. In addressing the first, they propose variation by representing the problem at multiple levels of abstraction. They propose that new behaviors can only be discovered by representing the learning problem (and thus the search space) at a sufficient abstraction such that steps through the space explore a range of variations. By stepping through the search space at one of many levels of abstraction, solutions can be explored which would not be accessible by searching through the space at a lower level of abstraction.

We build off this distinction between creative robots which (i) produce novel output, and/or (ii) reason creatively. Particularly, we argue that a robot which suitably addresses the problem of creative transfer must exhibit creativity in both regards, while also meeting a third criteria of *autonomy*: performing task transfer with as little input from the human teacher as necessary.

Case-based reasoning provides one conceptual framework for exploring task transfer in interactive robotics (Kolodner 1993; Goel and Díaz-Agudo 2017). Analogical reasoning provides another, more general framework (Gentner and Markman 1997; Falkenhainer, Forbus, and Gentner 1989; Gick and Holyoak 1983; Thagard et al. 1990). In analogical reasoning, the difference between source and target problems may lie on a spectrum of similarity (Goel 1997). At one end of this spectrum, the target problem may be identical to the source problem so that memory of the source problem directly supplies the answer to the target. At the other extreme of the similarity spectrum, the target problem is so different from the source problem that transfer between the two is not feasible. In between the two extremes, transfer entails problem abstraction where the level of abstraction may depend on the degree of similarity between the source and target problems (Goel and Bhatta 2004). Olteţeanu & Falomir (2016) describe a method for object replacement, enabling creative improvisation when the original object for a task is unavailable. Fauconnier & Turner (2008) introduced *conceptual blending*: a tool for addressing analogical reasoning and creativity problems, obtaining a creative result by merging two or more concepts to produce a new solution to a problem. Abstraction is enabled by mapping the merged concepts to a *generic space*, which is then grounded in the *blend space* by selecting aspects of either input solution to address each part of the problem. Applied to a robotic agent which uses this creative process to approach a new transfer problem, the robot may combine aspects of several learned tasks to produce a new behavior.

Transfer as a Creativity Problem

In Related Works, we have identified two criteria commonly applied to creative robots: (i) autonomy, and (ii) production of novel output, and/or utilization of a creative reasoning process.

Autonomy Rather than rely on receiving a new demonstration of the entire task, an autonomously creative robot must reason about the task using the representation it has previously learned, while also minimizing its reliance on the human teacher. We claim that this criteria does not preclude the robot from deriving new information from human interaction, provided that (i) the robot does not require a full re-demonstration of the task, and (ii) the robot reasons over what information is needed from the teacher and how to request that information. We refer to a robot that meets these two criteria while collaborating with a human teacher as exhibiting *partial-autonomy*.

Novel output The robot learns to complete a task with respect to the locations of relevant objects (e.g. pouring is an action which is completed with respect to the location of a bowl and a scoop). By parameterizing the skill models (learned from the demonstration) based on object locations, simple adjustments can be made to objects' locations without altering the skill model itself. However, once a transfer problem requires significant changes to the skill model (either in constraints of the model, or a replacement of the model entirely), it no longer produces the same action. The revised model is reflective of a behavior that is both novel to the human teacher (since it is different than what was taught), and novel to the robot (since it is distinct from the output of other skill models the robot may have recorded).

Creative reasoning A robot may need to derive additional information about the task in the target environment. By interacting with a human teacher to request additional task information, the robot would leverage *co-creativity* in which the robot and human teacher collaborate to produce a novel result. As an alternate approach, a robot can address a target environment by combining aspects of its previous experiences. For example, a robot may know how to pour a mug, and separately, how to pick up a bowl. Knowledge of these two tasks may be combined in order to address a new problem, such as the robot needing to pour a bowl. By performing *conceptual blending* in this way, the robot would leverage a creative reasoning process.

Perspectives on Creative Transfer

We now introduce three perspectives on the problem of creative transfer: embodied creativity, robot creativity, and co-creativity. Each of these perspectives highlights a different challenge of the creative transfer problem.

Embodied Creativity

Systems of *embodied creativity*, such as the creative robot we have discussed, introduce challenges as a result of their embodiment. Specifically, the input that is available to the embodied agent and the output that must be produced are at a level of detail that reflects how the agent can perceive or act in the physical world.

Input and Output Requirements An example of this type of input is an agent's perception of its environment using a 3D RGBD camera. This provides the agent with a point-cloud representation of its environment, and can be segmented to identify features of each object (e.g. dimensions, location, color histogram) using methods such as described in (Trevor et al. 2013). Figure 3 depicts an overhead view of a robot's table-top environment, and the corresponding object segments observed by the robot.

In an robot which learns from task demonstrations, the human teacher manually guides the robot's hand (end-effector) to complete a task. During this demonstration, it may record both (i) the position of each joint in its arm, and (ii) the 6D cartesian pose (x, y, z, roll, pitch, yaw) of its end-effector. These recordings are measured at each time interval, resulting in a trajectory of the robot's arm or end-effector positions over time.

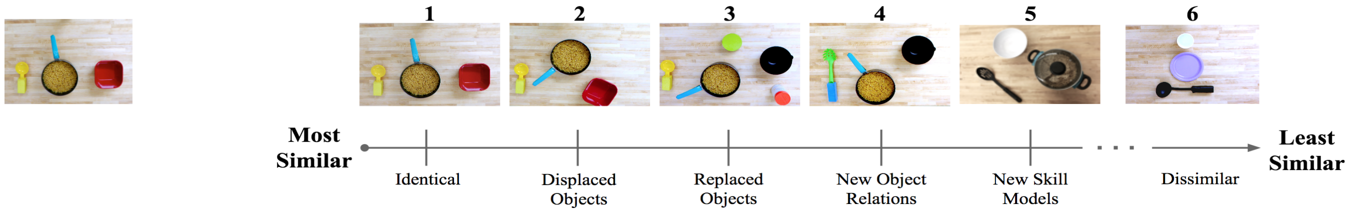
A *skill model* can then be trained on this trajectory, such that a similar motion can be repeated at a later time. Many skill models have been proposed which encode the task demonstration and are used to plan a motion trajectory reproducing the task at a later time (Chernova and Thomaz 2014; Argall et al. 2009; Akgun et al. 2012; Pastor et al. 2009; Niekum et al. 2012; Bruno, Calinon, and Caldwell 2014). Should the robot receive multiple demonstrations of the task, the skill model provides a generalization over the full set of demonstrations. Object locations are used to parameterize the skill model, so that differences in object locations in the target environment can be accounted for by using segmented object features as parameters.

The agent's embodiment also enforces a specific output type: a motion trajectory which reproduces the task in the target environment. This trajectory must indicate the position of each joint at each time interval, over the entire course of the task.

Role of Embodiment in Creativity We propose that the role of embodiment in creativity can be expressed on a spectrum. At one end of the spectrum, embodiment plays no role in the creative process until the creative result is to be executed on the robot. Systems which perform in a creative domain (e.g. Schubert and Mombaur 2013) typically operate at this level, where the emphasis is on engaging in creative domains that exist in the physical world (and thus must be executed by an embodied agent). At the other end of the spectrum, the embodiment is an integral element of the creative model. Creative reasoning is performed with respect to the constraints of embodiment. Intermediate methods have been proposed, where the embodiment is modeled alongside, but separately from, the creative task (e.g. Gopinath and Weinberg 2016).

In previous work (Fitzgerald, Goel, and Thomaz 2015), we have defined the Tiered Task Abstraction (TTA) representation for tasks learned from demonstrations. This representation is intended to perform creative transfer by integrating the agent's embodiment into the task representation itself. The TTA representation contains the following elements:

- Skill Models: The task demonstration is segmented into *task steps*, each of which is represented by a separate *skill model*. These models are parameterized in terms of a start and end location, while maintaining the trajectory "shape" of the demonstrated action.
- Parameterization Functions: These reflect constraints which guide the start and end position of each task step as an offset from an object location. For example, scooping ends with the robot's end-effector 5 cm above the pasta



(a) Source (b) Potential Target Environments

Figure 2: Spectrum of Similarity Between Source and Target Environments

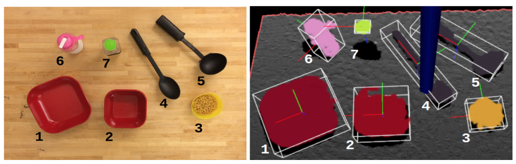


Figure 3: An overhead view of a table-top environment (left) and the segmented point cloud representation (right)

bowl, before continuing with the next task step. The corresponding parameterization function is: $<o_x, o_y, o_z + 5>$, where o is a reference to the relevant object (in this case, the location of the pasta bowl).

- Object Labels: These are the labels which are uniquely associated with each object instance identified in the environment. Each labeled object represents a single object which is consistent over a range of feature values.
- Object Features: These are the feature values associated with each object label. While the label represents a static object, the specific feature values may differ depending on the environment, e.g. object locations, color (based on lighting conditions), spatial configurations, and properties.

Note that each element is parameterized by the next; by omitting one or more elements from the task representation, the resulting representation is one that is *abstracted*. In doing so, a task can be represented at a level of abstraction which is common to both the source and target environments. However, once a representation is abstracted, it must be *grounded* in the target environment in order to produce an output which is executable by the robot. In an embodied system, grounding refers to parameterizing a representation based on perception in the physical world. A representation is *grounded* in a target environment when each of its elements (skill models, parameterization functions, object labels, and object features) are present and defined based on information derived in the target environment (either by perception or interaction in the target environment). This challenge of abstraction and grounding is at the core of embodied creativity.

Robot Creativity

Related to an embodied, creative agent, a *creative robot* must also account for issues of embodiment (e.g. input from real-world perception and output as an executable trajectory). We now address additional challenges which result from robot domains, particularly the types of *tasks* which a robot may be expected to perform. Given enough demonstrations of a task, a robot can learn a model which generalizes across them, enabling it to address target environments which are similar to the source environments it has observed. However, this introduces several constraints:

1. The human teacher must be able to provide several demonstrations of the task, which can be time-consuming and tedious.
2. The teacher must know what target environments the robot is likely to address, so that similar source environments can be selected for demonstrations.
3. The robot is still limited to addressing target environments which are closely similar to the observed source environments.

While providing more demonstrations does increase the model's generalizability, these constraints still apply. This precludes many opportunities for addressing realistic transfer problems, in which the robot needs to make broader generalizations. Examples of such tasks include stacking plates after learning to stack wood blocks, or pouring a coffee pot after learning to pour a cup. Without a representation of the relation between objects in the source and target environments, the robot is unable to parameterize its task model based on the correct objects in the target environment. Furthermore, more difficult transfer problems are also plausible, such as tasks in which new constraints are added in the target environment which could not be learned in the source environment.

Task Similarity Spectrum In previous work (Fitzgerald, Goel, and Thomaz 2015), we have discussed task transfer as a problem which ranges in the similarity between the source and target environments. The outcome of this is that task transfer problems may vary in difficulty. While we will argue that some categories of task transfer do require a co-creative approach, task transfer does not inherently necessitate creativity. For example, a task demonstrated in a source environment (e.g. Fig. 2a) can be directly reused in a target environment which either (i) does not require modification of the learned task (image 1 in Fig. 2b), or (ii) requires parameterization based on object location (image 2 in Fig. 2b), provided that it has been parameterized according to the locations of objects. Since the learned skill models are reused to address these transfer problems (albeit, modified to account for new object locations), the outcome is

	Identical Problem	Displaced Objects	Replaced Objects	New Object Relations	New Skill Models
Retained Knowledge	Goal Skill models Param functions Object labels Object features	Goal Skill models Param functions Object labels	Goal Skill models Param functions	Goal Skill models	Goal
Grounded Knowledge	None	Object features	Object labels Object features	Param functions Object labels Object features	Skill models Param functions Object labels Object features

Figure 4: Summary of retained and grounded elements at each level of abstraction

novel to neither the robot nor the human teacher, and thus is not an example of creativity. Similarly, in transferring a task to a target environment which requires an object mapping (image 3 in Fig. 2b), the original skill model can still be reused; prior to parameterizing it according to object locations, the robot must first obtain a *mapping* between objects in the source and target environments. With this mapping, the skill model can be re-parameterized according to the correct objects. Again, the learned skill models are reused (this time after applying an object mapping and re-parameterizing the skill models), and so the resulting action is not novel to the robot or human teacher.

In contrast to these three examples, consider target environments 4 and 5 in Figure 2b. Figure 4 differs from the source in Figure 2a in that objects are: (i) displaced, (ii) replaced, and now (iii) *constrained* because of the new scoop size. The robot's actions must now be constrained such that its end-effector remains higher above the table in order to complete the task successfully. The skill model parameters, which reflect constraints of the task by indicating the relation between the robot's end-effector and object locations, cannot be directly reused in this target environment. In order to address this problem, new *parameterization functions* must be identified in the target environment, applying constraints to the learned skill models that are distinct from those of the original demonstration. Provided that a robot can identify the new parameterization functions with some degree of autonomy (e.g. does not simply receive a new demonstration of the task in the target environment), this category of transfer problems meets the criteria for creative transfer: partial-autonomy and novel output.

Target 5 in Figure 2b differs from the source in similar respects, with one additional difference: an extra step is needed in order to lift the lid off the pasta pot prior to scooping the pasta. As a result, the original skill models learned in the source cannot be directly transferred. In addition to deriving new parameterization functions in the target environment, this problem also requires that the robot derive or learn a new skill model to account for the missing step. In a later section, we discuss potential methods for deriving this information via further interaction with the human teacher; however, regardless of what method is used, the robot (i) autonomously transfers the task representation (since it does not rely on receiving a full re-demonstration of the task), (ii) produces action that is novel to both the robot and the human teacher, and (iii) utilizes a creative reasoning method (by blending previously and newly learned skill models). Therefore, a robot that successfully completes transfer problems of this kind meets the criteria for creativity.

These task differences illustrate a *spectrum* of similarity between the source and target; at one end of the spectrum, the source and target differ in small aspects such as object configurations. At the other end of the spectrum, they contain more differences, until finally (as in target 6), the target environment cannot be addressed via transfer. While we have highlighted discrete levels of similarity in this spectrum, we do not claim this to be an exhaustive categorization of transfer problems. Figure 2 illustrates that without addressing problems of creative transfer, task transfer methods are limited to addressing a narrower set of transfer problems: those in which the target environment does not require novel behavior or reasoning to address. By examining problems of creative transfer, we broaden the range of problems that a robot can address from transferring a single task demonstration.

Transfer Via Task Abstraction In previous work, we have found that as the source and target environments become more dissimilar (according to the similarity spectrum in Fig. 2), the task must be represented at increasing levels of abstraction for transfer to be successful (Fitzgerald, Goel, and Thomaz 2015). We have summarized these task differences in Figure 4. For problems of non-creative transfer, we have also demonstrated that the abstracted representation can be grounded through perception (e.g. by completing the *object features* element based on perception of the target environment) and/or interaction with the human teacher (e.g. by using interaction with the teacher in the target environment to infer the *object labels* element).

To address problems in which objects are displaced in the target environment, the *object features* element must be grounded in the target environment, while other elements of the original representation can be retained. This grounding occurs by observing the new object locations in the target (Pastor et al. 2009; Fitzgerald, Goel, and Thomaz 2015).

To address problems in which objects are replaced in the target environment, both the object features and *object labels* must be grounded in the target environment. We have demonstrated a method for grounding this information by inferring an *object mapping* from guided interaction with the human teacher (Fitzgerald et al. 2016). An object mapping indicates which objects in the source environment correspond to each object in the target environment, and is used to ground object labels in the target environment. By asking the teacher to assist in the object mapping by indicating the first object the robot should use in the target environment, the robot can attempt to infer the remainder of the object mapping.

To similarly abstract and ground the task representation in order to address problems of creative transfer (including problems in the New Object Relations and New Skill Models categories), two elements of the TTA representation must be grounded in the target environment: the parameterization functions (for both categories of creative transfer problems) and skill models (for creative transfer problems involving new skill models). This is a challenge because these two elements cannot be directly observed via perception (as was possible when grounding object features) and cannot be inferred (as was possible when inferring an object mapping). Rather, they are dependent on knowledge of the goal of the task, which the robot does not have. We next discuss interactive solutions to challenge by taking a co-creative perspective on creative transfer.

Co-Creativity

In the context of an embodied robot which is situated in a task domain, a robot may continue to interact with a human teacher during task transfer. Thus, the robot may leverage the human teacher's knowledge of the task domain in order to engage in a co-creative transfer process.

As discussed in the previous section, the robot required little assistance in order to address problems of non-creative transfer. The first two categories of transfer problems (e.g. identical and displaced-objects environments) could be addressed by the robot with full autonomy. The third category of transfer problems (e.g. replaced-objects environments) required some assistance from the human teacher in order to indicate which objects the robot should use in the first few steps of the task.

In order to address problems of creative transfer, the robot must ground the (i) parameterization functions and (ii) skill models in the target environment. These are the two elements of the TTA representation which contain the most high-level information about the task: the constraints between the robot's hand and objects in the environment, and the skill model which preserves the trajectory shape of the demonstrated action, respectively. Because these represent high-level information and are informed by the goal of the task, they cannot be grounded by the robot with complete autonomy. Presuming that the human teacher is aware of the goal of the task, and how that goal should be met in the target environment, we posit that the teacher is available to assist the robot in reaching that goal. It is advantageous for the robot to continue to interact with the human teacher in order to ground these representation elements, since the teacher does know how the task should be performed to achieve the task goal. The aim of this *co-creative* approach is to produce a solution that (i) is partially autonomous (the robot interacts with a human teacher and may receive additional instruction, but does not require a full re-demonstration of the task), (ii) enables collaboration with the human teacher so that the robot may infer information about the task in the target environment, (iii) results in parameterization functions and/or skill models that can ground an abstracted task representation, and (iv) grounds the TTA representation such that a trajectory can be executed in the target environment.

Figure 4 summarizes the representation elements which must be retained or grounded for each category of transfer problems. This relation between (i) task similarity and (ii) assistance from the human teacher introduces a second dimension to the aforementioned similarity spectrum; as the source and target environments become more dissimilar, the robot's level of transfer autonomy decreases and its dependence on interaction with the human teacher increases. We now discuss two forms of interaction for human-robot co-creativity.

Grounding Parameterization Functions In order to address problems in the New Object Relations category, three representation elements must be grounded: object features, object labels, and parameterization functions. In previous work (Fitzgerald et al. 2016), we demonstrated a simulated robot asking for assistance to identify the object mapping between objects in the source and target environments. In implementing this system on a physical robot, a robot could request assistance after each step of the task by asking "What do I use next?", to which the teacher would respond by handing the robot the next object involved in the task. Each assistance would provide a single correspondence (e.g. the red bowl is mapped to the blue bowl). Additional assistance would be derived by asking the teacher where to place the object, to which the teacher would respond by pointing at the next goal location. After each hint, the remainder of the object mapping (e.g. the mapping of objects for which the robot has not yet received assistance) would be predicted by calculating mapping confidence after each assistance.

Similarly, when grounding parameterization functions, the robot should interact with the teacher so that it infers the necessary information to ground missing elements of the task representation, without requiring too much information and time from the human teacher (so as to maximize the robot's autonomy). We propose a method for grounding parameterization functions in a manner similar to object mapping. Rather than evaluate only the object mapping confidence at each step of the task, the robot should also verify its confidence in using the next step's parameterization function. One method of measuring confidence may be to compare the objects used in the next step to those which the robot would have used in the source environment. Assuming that similarly-shaped objects can be manipulated in similar ways, dissimilar objects may need to be manipulated differently despite serving the same purpose. Olteţeanu & Falomir (2016) proposed a method for identifying the suitability of object replacements in simulation, based on features such as shape and affordances. We expect that similar features will play a role in evaluating the robot's confidence in using a novel object, and must be extracted from a physical robot's perception (similar to how object features were obtained in Fitzgerald et al. 2016). If the robot is not confi-

Algorithm 1 Grounding Parameterization Functions

```
function GROUNDPARAMFUNCTIONS(S)
    map ← empty mapping
    while target task is incomplete do
        if map is incomplete then
            h ← next mapping hint from teacher
            map ← map+PredictMapping(h)
        end if
        s ← GetNextStep(source demo C_s)
        o_n ← GetNextObject(s, map, target objects O_t)
        if ObjectSim(o_n, source objects O_s) < β then
            ask teacher to reposition end-effector
            r ← record end-effector displacement from nearest object
            SetParamFunction(s, r)
        end if
        ExecuteNextStep(s)
    end while
end function
```

Algorithm 2 Grounding Skill Models

```
function GROUNDSKILLMODELS(S)
    map ← empty mapping
    while target task is incomplete do
        if map is incomplete then
            h ← next mapping hint from teacher
            map ← map+PredictMapping(h)
        end if
        s ← GetNextStep(source demo C_s)
        o_n ← GetNextObject(s, map, target objects O_t)
        if ObjectSim(o_n, source objects O_s) < β then
            find a demo with step s_new containing o_n
            if ActionSimilarity(s_new, s) < α then
                ask teacher to demonstrate next step
                a ← record demonstrated task step
                r ← record end-effector displacement from nearest object
                SetSkillModel(s,TrainSkillModel(a))
                SetParamFunction(s, r)
            else
                s ← s_new
            end if
        end if
        ExecuteNextStep(s)
    end while
end function
```

dent in this similarity (meaning its confidence value is below some threshold β), it can request the human teacher to align its end-effector in preparation to complete the next step of the task. The robot would then record the parameterization function as an offset from the closest object. Algorithm 1 outlines this process.

Grounding Skill Models To address tasks requiring new skill models (such as the final target environment image in Figure 4), the robot will need to ground the same elements as before (object features, object labels, and parameterization functions) in addition to the new skill models. To do this, we hypothesize that the robot can again evaluate its confidence for completing each step of the task. We introduce an additional threshold to this evaluation process: if object similarity is below a second threshold α (such that $\alpha < \beta$), then the robot searches for other previously-learned task demonstrations which contain the unfamiliar object. If there exists another demonstration using the same object, the robot should then evaluate the similarity between (i) the task step involving the object in the original source environment and (ii) the task step in the newly-retrieved demonstration that involves the new object. If the two task steps appear similar, then the newly-retrieved task step may be an alternate version of the step adapted for that object, and can be applied toward reproducing the task in the target environment. If they are not similar, then the robot may ask the teacher to re-demonstrate that particular step of the task. Algorithm 2 outlines this process.

Directions for Continued Work

We have introduced three perspectives on the problem of creative transfer. *Embodiment* introduces challenges of perception and action which must be integrated into the creative process. The domains that a *creative robot* encounters adds additional constraints; we have argued that for some categories of task transfer problems, creativity is necessary for the robot to transfer past task knowledge and produce a new action which is different from the originally taught behaviors. By interacting with the human teacher to produce a result which is both (i) distinct from that of the original task demonstration and (ii) achieved through a combination of the robot's reasoning and the teacher's assistance, the robot and human teacher use a *co-creative* process to address the task transfer problem. This enables the robot to leverage the teacher's knowledge of the task goals and how they are achieved in the target environment, while also minimizing the time required of the human teacher to provide assistance.

We propose several directions for continued work on co-creative transfer. First, we hypothesize that there are several alternative approaches to interactive task grounding. For example, the robot may use speech as the assistance modality by asking about objects prior to attempting to perform the task. Alternatively, the robot could instead rely on the teacher to correct its actions (rather than proactively ask for assistance) after each task step. Transfer problems of increased difficulty may be also addressed via exploration, in which the robot collaborates with the human teacher to creatively explore new actions, to which the human teacher can respond by guiding the robot's exploration. Second, we have proposed two algorithms for co-creative transfer, and suggest that future work should implement these on a physical robot. This will also engender questions of interaction; how should the robot request specific types of assistance from the teacher? We expect that the implementation of this will result in additional questions of how the robot should behave in order to best leverage the teacher's knowledge. Finally, we have identified two categories of creative transfer problems, and associated each with a task abstraction which can be used to address problems in these categories. However, we do not claim this to be an exhaustive list of creative transfer problem categories. We propose an area of continued work to identify other applications of creative task transfer, which may occur in problems which require more creativity to address. We suggest that further work on creative transfer explore the dimensions along which a creative transfer problem becomes more (or less) difficult.

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