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# From object-action to property-action: Learning causally dominant properties through cumulative explorative interactions

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**Abstract**
Emerging studies from neuroscience in relation to organization of sematic memory in the brain provide converging evidence suggesting that conceptual knowledge is organized in a distributed fashion in ''property specific'' cortical networks that directly support perception and action (and were active during learning). Though learning 'object-action' affordances and using such knowledge for prediction and planning is an active topic in cognitive robotics, this article urges to go beyond and look at ''property-action'' networks instead. To this effect, a brain guided framework for distributed property specific organization of sensorimotor knowledge for humanoid iCub is presented. Two simple learning rules namely 'elimination' and 'growth' are proposed to compare top down anticipation and bottom up real experience to abstract underlying causal relations. An engaging scenario how the robot cumulatively learns and abstracts causally dominant properties that influence motion of various objects when forces are exerted on them is used to validate the neural architecture. The implicit advantage is that such learnt ''property-action'' relations can be effortlessly generalized to a domain of objects for which the robot need not have any past experience/learning but nevertheless share the ''property''. Further, the study has relevance in both better understanding how common causal relations can be cumulatively learnt, represented and exploited, to providing novel embodied frameworks for analogical reasoning.


## Introduction

Affordances are the seeds of action. Being able to identify and exploit them opportunistically in the 'context' of other-

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wise unrealizable goals is a sign of cognition. Despite incessantly encountering novel exemplars of objects we have never interacted with before we can often anticipate about what can be done with them and even exploit them to realize our goals. Based on her past experience of bending flexible pipe cleaners about a year back, Betty the new Caledonian crow quickly fashioned a hook out of a piece of wire to pull her dinner basket trapped in a transparent vertical tube (Weir, Chappell, & Kacelnik, 2002). Studies from animal cognition (Visalberghi & Tomasello, 1997; Whiten, McGuigan, Marshall-Pescini, & Hopper, 2009) indicate that several other primates are able to flexibly reason about physical causality, exploit inherent properties of objects available in the environment: for example choosing a tool of a right length to push out a trapped reward (among others). How by cumulative and explorative interactions with different objects in the world, task relevant physical and causal relations are both abstracted and exploited flexibly in novel contexts is a problem that presents challenges both in terms of representation and learning. In this context, cognitive robots offer a unique opportunity to reenact the gradual process of cumulative learning and investigate the underlying computational basis. The value is both intrinsic i.e. better understanding our own selves and extrinsic i.e. creating a range of artifacts that can flexibly assist us in the environments we inhabit and create.

Learning 'object-action' relations and using such knowledge for prediction and planning is becoming an active topic of study in embodied robotics with approaches ranging from probabilistic Bayesian models, to neural associative networks and symbolic formalisms (Krüger et al., 2011; Montesano, Lopes, Bernardino, & Santos-Victor, 2008; Montesano, Lopes, Bernardino, & Santos-Victorm, 2007). Despite intriguing attempts, both applicability and generalization of the methods to novel contexts and the necessity to facilitate cumulative learning (like natural cognitive agents) have been known bottlenecks. In parallel, emerging results from functional imaging are beginning to provide useful information as to how conceptual knowledge about object concepts and causal relations is organized in the brain (Bressler & Menon, 2010; Buckner, Andrews-Hanna, & Schacter, 2008; Martin, 2007, 2009; Meyer & Damasio, 2009; Patterson, Nestor, & Rogers, 2007). The main findings emerging from these results is that conceptual information is grounded in a ''distributed fashion'' in ''property specific'' cortical networks (Martin, 2009; Patterson et al., 2007) that directly support perception and action (and that were active during learning). Same set of networks are known to be active both during real perception/action, imagination or lexical processing (Martin, 2007; Meyer & Damasio, 2009). Further, there is a fine specialization of areas representing conceptual information related to animate vs. inanimate objects as evident from functional imaging and TMS studies on both normal subjects and semantic dementia patients (Buckner et al., 2008; Patterson et al., 2007). It is also now known that ''retrieval'' or reactivation of the conceptual representation can be triggered based on partial cues coming from ''multiple modalities'': for example sound of a hammer retro activates its shape representation (Meyer & Damasio, 2009), presence of a real object (banana) or a 2D picture of it can still activate the complete network associated with the object (and that was active during learning of it in the first place). These results provide valuable insights to guide development of computational frameworks for organizing information related to perception—action and foster learning of causal relations, importantly in an embodied and cumulative learning setup. The present article is an ambitious adventure in this direction.

A biologically inspired framework for distributed property specific organization of sensorimotor knowledge for humanoid iCub is presented with an emphasis on learning ''property-action'' relations. The implicit advantage is that such learnt ''property-action'' relations can be effortlessly generalized to a do-main of objects for which the robot need not have any past experience/learning but nevertheless share the ''property''. An engaging scenario how the robot cumulatively learns and abstracts causally dominant properties that influence motion of various objects when forces are exerted on them is used to validate the neural architecture. It is known from studies on animal behavior that different species have different levels of understanding of the causality related to this task (Visalberghi & Tomasello, 1997; Whiten et al., 2009). In addition to the multiple utilities of the ''push/pull'' action itself in the context of day to day interactions with objects, what makes it interesting is the sheer range of physical concepts that have to be ''learnt'' and ''abstracted''. For example, it has to be learnt that contact is necessary to push, object properties influence pushability (balls roll faster than cubes and it does not matter what is the color of the ball or the cube), pushing objects gives rise to path of motion in specific directions (the inverse applies for goal directed pushing), pushing can be used to support grasping, bring objects to proximity. The requirement to capture/learn such a wide range of physical concepts through cumulative ''playful interactions'' of the robot with different objects makes this task both interesting and challenging.

The rest of the article is organized as follows: Section 'Distributed ''property specific'' organization of sensorimotor information and the basic Pushing forward/inverse model' describes the organization of sensorimotor information in iCub taking guidance from emerging results from neurosciences. How the basic Pushing forward/Inverse model i.e. anticipating how objects move and inversely generating goal directed pushing actions is learnt is illustrated. Section 'Cumulatively abstracting ''causal dominant properties'' related to pushing' introduces two learning rules namely elimination and growth' that augment the distributed property specific organization of sensorimotor information to facilitate the robot to abstract properties that are causally dominant through cumulative explorative interactions. A discussion concludes.

## Distributed ''property specific'' organization of sensorimotor information and the basic pushing forward/inverse model

Emerging trends from the fields of connectomics, functional imaging studies in relation to organization of semantic and episodic memory in the brain (Bressler & Menon, 2010; Buckner et al., 2008; Martin, 2009; Patterson et al., 2007) now provide numerous insights to guide development of brain guided computational framework for organization

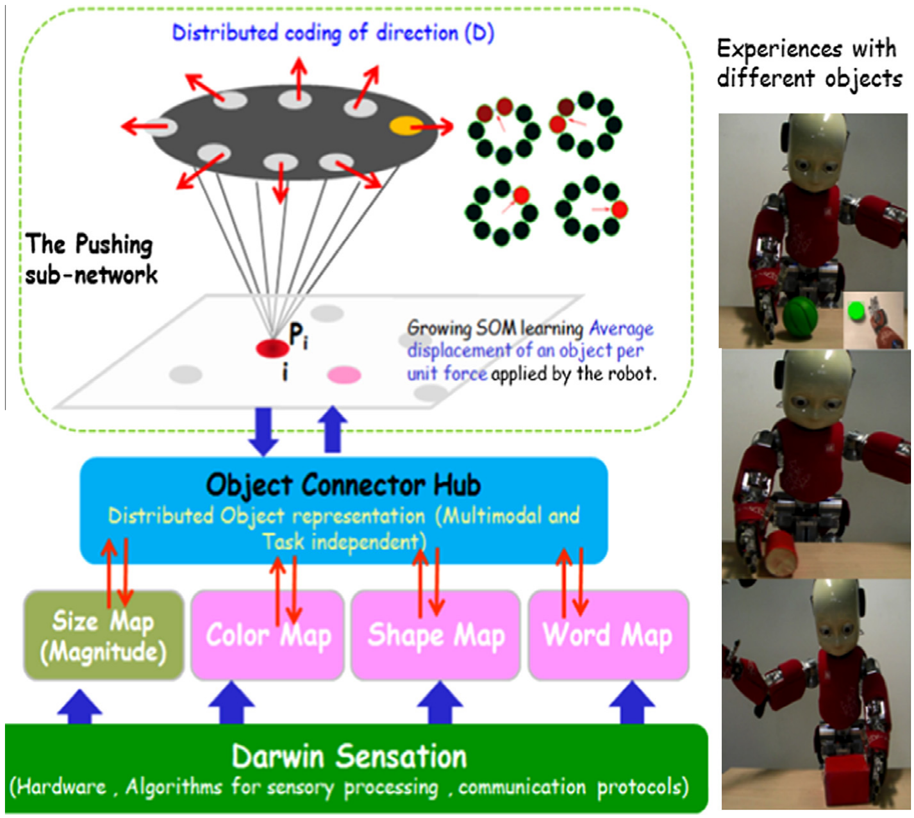


**Fig. 1** Left panel shows a block diagram of how sensorimotor information is organized. Results of perceptual analysis activate the layer 1 neural maps organized in a property specific fashion ultimately leading to a distributed representation of the perceived object in the connector hub (layer 2). An interesting aspect of such kind of organization is that as we move upwards in the hierarchy information becomes more and more integrated and multimodal and as we move downwards information is more and more differentiated to the level of perceived properties. The connectivity between hubs and property specific maps is essentially bidirectional hence allowing information to move ''top down, bottom up or in cross modal'' fashion. The pushing sub-network, connected to the object hub consists of two networks: one a growing SOM encoding average displacement of an object per unit force exerted (averaged over several trials of interactions) and another representing distributed coding of direction. These networks together enable learning and representing the forward/inverse model for pushing while the property specific organization facilitates learning which properties are causally dominant. Right panel shows the robot interacting with different objects during the episodes of cumulative learning.

and use of memory in cumulatively learning embodied robots. Fig. 1 shows a block diagram of how sensorimotor information is organized in the proposed computational framework with the focus of the ''Pushing'' sub-network. At the bottom is the Darwin[*] sensory layer that includes the sensors, associated communication protocols and algorithms to analyze properties of the objects mainly color, shape and size (Cai, Werner, & Matasm, 2013). Word information is an additional input coming from the teacher either to issue user goals or interact with the robot. Results of perceptual analysis activate various neural maps organized in a property specific fashion ultimately leading to a distributed representation of the perceived object in the connector hub (layer 2). In this sense, a red cylinder and red cube will have identical activity in the color map, but different activity in the shape map, ultimately leading to a distributed representation in the connector hub. How these self-organizing maps are learnt is out of scope for this article, but uses standard techniques (Fritzke, 1995; Kohonen, 1995). Interested reader is referred to a recent article (Mohan, Morasso, Sandini, & Kasderidis, 2013) that goes into formal details of the algorithms with experimental results.

An interesting aspect of such kind of organization is that as we move upwards in the hierarchy information becomes more and more integrated and multimodal and as we move downwards information is more and more differentiated to the level of perceived properties. The connectivity between hubs and property specific maps is essentially bidirectional hence allowing information to move ''top down, bottom up or in cross modal'' fashion. For example, as illustrated in Mohan et al. (2013), when issued a user goal to Grasp a ''Red Container'' (a new combination of known words describing an object the robot has not encountered before), bottom up activity in the word map can spread through the provincial hub leading to anticipatory top down activations in the neural maps processing color and shape information (corresponding to what the robot anticipates the object

[*] The acronym Darwin stands for the ongoing EU funded project **D**exterous **A**ssembler **R**obot **W**orking with embodied **In**telligence (www.darwin-project.eu).

i.e. the red container to be). If top down activation of the property specific maps resonates with their bottom up activation (through perceptual stream) this is sufficient to lead to the inference that the novel object being perceived is most probably the one the user requested to grab (Mohan et al., 2013). What is relevant as far as the present article is concerned are mainly two things: (1) The bottom up processing leads to a distributed representation of the perceived objects (in relation to its perceptual properties color, shape, size) in the object connector hub that identifies the object (i.e. in other words coding for 'what is it'). (2) Due to reciprocal connectivity between the hubs and property specific maps, it becomes possible to go beyond ''object-action'' and learn things at the level of ''property-action'' instead.

Different objects move in different ways when force is exerted on them, some do not move too. By interacting with various objects, the goal of the robot is to learn a general forward/inverse model for 'pushing action': i.e. being able to predict how an object will move when pushed (forward model) and being able to generate goal directed pushing actions in order to displace an object to a desired location. When presented with any 'object', different property specific neural maps are activated bottom up leading to a distributed representation of the concerned object in the object connector hub. Since object properties influence pushing, activity in the object connector hub influences the pushing forward/inverse model and hence is bidirectionally connected to it (connectivity learnt by experience). The push sub network is represented using two neural maps:

1. A growing SOM learning ''average displacement of an object per unit force'' and
2. That represents a distributed coding of direction in which the object is moving.

The former neural map is empty to start with and is gradually grown as the robot interacts with different objects. Note that ''average displacement per unit force'' basically measures in abstract terms the ''mobility'' of the object when a certain amount of force is exerted on it. Inversely, this information allows the robot to predict how an object will move when force is exerted on it (useful while generating goal directed pushing). For every object presented, the robot is allowed to explore displacing it to a distance of 15 cm (in eight different directions. Averaging the result of this experience, the parameter $P_i$ (average displacement/unit force) for the neuron ''$i$'' coding for a particular object is estimated. Growth in this neural SOM only takes place if there is a contradiction between ''the robots anticipation of how a novel object might move'' and ''how it actually moves in reality''. Cubes, cylinders and balls of different colors and sizes (some heavy ones), few MECCANO blocks (from the MECCANO 2+ kit for 2 year olds) were presented gradually.

The inverse operation i.e. pushing an object to a desired location can be achieved through the following 4 steps (that depict how the learnt forward model (how something moves) can be used to perform inverse operation (how the object can be moved as desired):

1. Detect and localize the current position '$X(x,y,z)$' of the object and the target '$X_T(x_T,y_T,z_T)$' (where the object has to be displaced).
2. Compute the desired direction ''$\theta$'' to push using information on $X$ and $X_T$; This activates the neurons in the motor map responsible for directional coding. Based on the instantaneously computed direction, we also see distributed activity the 8 neurons coding for different directions.
3. Anticipate the average displacement of the object in the desired direction for an incremental iteration where unit force is applied on it ($P_i$).
4. Iterate steps 1—3, to get a virtual trajectory in space. The synthesized virtual trajectory can then be fed as a moving point attractor to the iCub action generation system (Mohan & Morasso, 2011) to compute the motor commands for the body chain executing the goal directed pushing. The process (1—4) is like smooth sliding of an object along a predicted trajectory created due to past experience. Fig. 2 shows the virtual trajectories (moving attractors) and real trajectories during goal directed pushing of a red cuboid and a ball. Activity in the neurons responsible for distributed coding of direction during the synthesis of the motor actions is shown at the top. Note that while pushing a ball the end effector needs to be displaced just by a small amount along an estimated virtual trajectory (green trajectory) like kicking a football to the goal. Cubes move more uniformly with the displacement of the end effector and have to be pushed gradually to the destination. Note that, time is also implicitly represented. This is because every ''dot'' in the virtual trajectory represents iteration in time: the virtual trajectory is very short while pushing the ball, almost uniform while pushing the small cube and longer when pushing the heavy/large objects.

## Cumulatively abstracting ''causal dominant properties'' related to pushing

The previous section described how the robot by interacting with different objects can learn the Pushing forward inverse model i.e. predicting how an object will move when force is exerted on it or inversely generating goal directed pushing actions to displace an object to a goal location. In this section, we will present results on how the proposed bio inspired framework for sensorimotor organization further allows the robot to additionally learn and abstract ''which properties are causally dominant'' for the task. To this effect we introduce two simple learning rules that facilitate abstraction of causally dominant properties by comparing the present experience with a recalled past experience. Let us consider that $\Delta$ property is the difference in activity in a property specific map (Fig. 1) when activated bottom up through sensory layer during present experience and when activated top down from the pushing SOM while recalling a past experience. Let $\Delta$ Contradiction be the difference between the robots anticipation of how an object might behave and the real observed behavior. Then the two learning rules are as follows

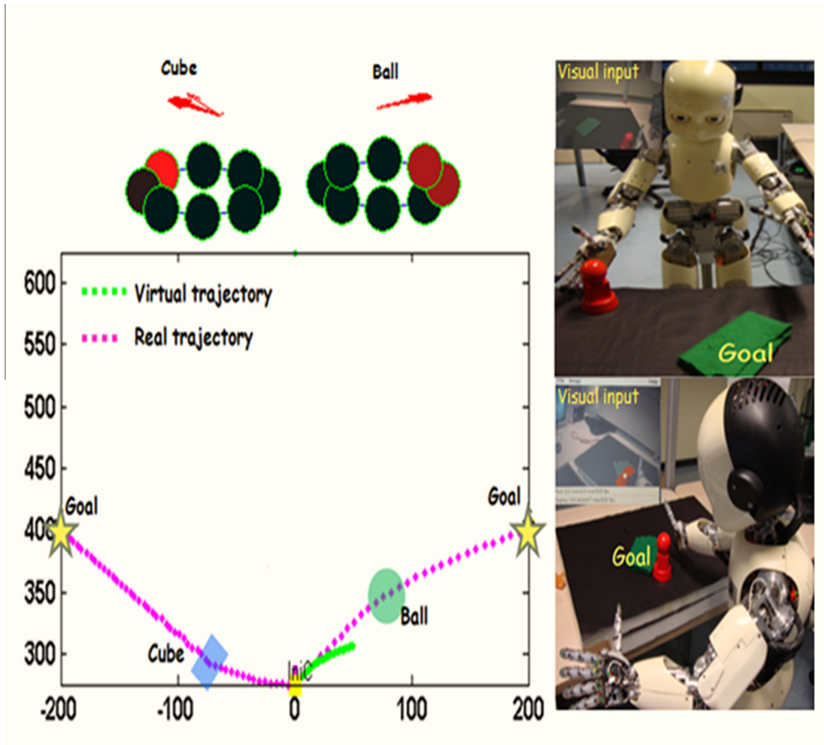


**Fig. 2** Left panel shows the virtual trajectories (attractors) and real trajectories during goal directed pushing of a cube and ball from the initial condition to the target. Activity in the neurons responsible for distributed coding of direction during the synthesis of the motor actions is shown at the top. Note that while pushing a ball the end effector needs to be displaced just by a small amount along an estimated virtual trajectory (green trajectory) like kicking a football to the goal. Cubes move more uniformly with the displacement of the end effector and have to be pushed gradually to the destination. Right panel shows a snapshot of the iCub engaging in goal directed pushing.

**Elimination rule:** If change in ''property'' does not cause ''contradiction'' between anticipation and real experience, then that property is not causally dominant. The result is a drastic reduction in the connection strength between associated maps (hence reducing the capability of activating each other).

**Growth rule:** If change in ''property'' causes ''contradiction'' between anticipation and observed behavior, then that property is causally dominant. *Contradiction implies that there is something new that has not been learnt in the past episodes of experiences*.

Two different scenarios are presented in the subsections that exploit the elimination and growth rule to enable the robot to abstract causally dominant properties by cumulative interactions with objects.

## Small cubes: learning that ''color'' of objects does not affect the way they move

Fig. 3 shows the activations in the various neural maps when the robot explores pushing cubes. The first 3 columns show the activity in the color-word-shape maps. The fourth column shows the distributed activity in the object hub representing in a distributed manner ''what the object is''. In episode 1, there is no anticipated activity in the pushing SOM (since there are no connections between the Pushing SOM and the connector hub because no experience has been gained before and nothing is known about the behavior of the cube). After experience of pushing red cube in different directions, there is one neuron (winner) in the pushing SOM that is coding the average displacement of the red cube when pushed by the robot. For cubes this ratio is approximately 0.8, averaged over 10 trials of pushing. The connections between the active neurons in the ''object hub'' (column 4) and the winner in the pushing SOM are also built. This is standard Hebbian learning with the effect that in future if a ''small red cube'' is presented, the robot can both anticipate how it will move and also generate goal directed actions to push it to the desired location (based on the steps outlined in the previous section). In the next episode the robot is presented with a ''small blue cube''. Bottom up activity form the sensory layer activates different neural SOM's (episode 2, column 1—3) which activate the object hub (column 4). Because of episode 1, there exists now some connectivity between the object hub and the Pushing SOM, enabling the object hub to activate the ''only'' existing winner in the pushing SOM (the robot does not know anything about small blue cubes, but it knows something about small red cubes). So it anticipates that blue cubes should also behave the same way and this indeed turns out to be the case from real experience. The

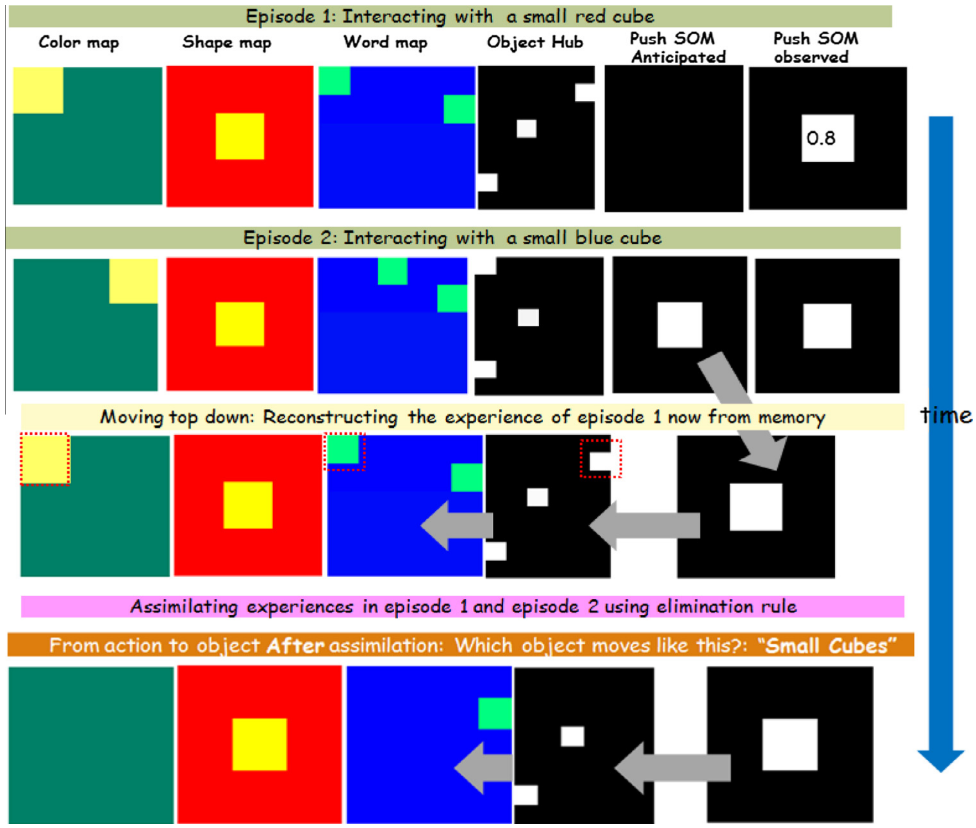


**Fig. 3** Every row is an episode of interaction with some object and activity in various maps are plotted. As we move down, we also move ahead in time (when either a new object is presented to play with) or assimilation of learnt knowledge takes place (using the learning rules). In episode 1 (pushing a small red cube), there is no anticipatory activity in the Pushing SOM (as there is no knowledge in the system). But after learning bottom up, a new neuron is grown in the Pushing SOM that codes for the behavior of red cubes. Now in episode 2 when presented with a blue cube, we see anticipatory activity in the pushing SOM (it anticipates blue cubes will also move like the red cubes, there is some similarity as seen in the activity of the property specific maps). The anticipation of the robot correlates with what is experienced by direct interaction with the new object. Due to reciprocal connectivity between the pushing SOM and the property specific maps, it becomes possible to move top down form the pushing SOM and reconstruct from memory the activity in the property specific maps that were active when this experience was originally encoded. As seen in row 3, the past experience of pushing the red cube is reconstructed successfully. Comparing row 2 (bottom up: present experience with the blue cube) and the past experience with the red cube (reconstructed top down), it is easy to observe that elimination rule applies (change in property not causing a contradiction in anticipation). What the robot abstracts is that color of objects do not affect their mobility when forces are exerted on them (row 4). The Net effect of assimilation is that the connectivity of the Push SOM with the color SOM is now reduced drastically and they no longer retroactivate each other. Row 4, shows the activity in different maps when we move top down from the pushing SOM after elimination rule is applied. Note that the color map is no longer activated as the robot has now learnt that color is a irrelevant property as far as how objects move when pushed. This is in fact equivalent to querying the robot ''which object moves like this'' note that the word map generates linguistic outputs. Before assimilation the answer would have been ''small red cubes'', after assimilation the answer is just ''small cubes''!

anticipation of the robot correlates with what is experienced by direct interaction with the new object. Due to reciprocal connectivity between the pushing SOM and the property specific maps, it becomes possible to move top down form the pushing SOM and reconstruct from memory the activity in the property specific maps that were active when this experience was originally encoded. As seen in row 3, the past experience of pushing the red cube is reconstructed successfully. Comparing row 2 (bottom up: present experience with the blue cube) and the past experience with the red cube (reconstructed top down), it is easy to observe that elimination rule applies (change in property not causing a contradiction in anticipation).

## Small cylinders: learning that ''Shape'' is a dominant property

In Section 'Small cubes: learning that ''color'' of objects does not affect the way they move' the robot learnt colors of objects do not causally affect their mobility when forces are exerted on them. Now the robot is presented with a small green cylinder. The loop form bottom up and top

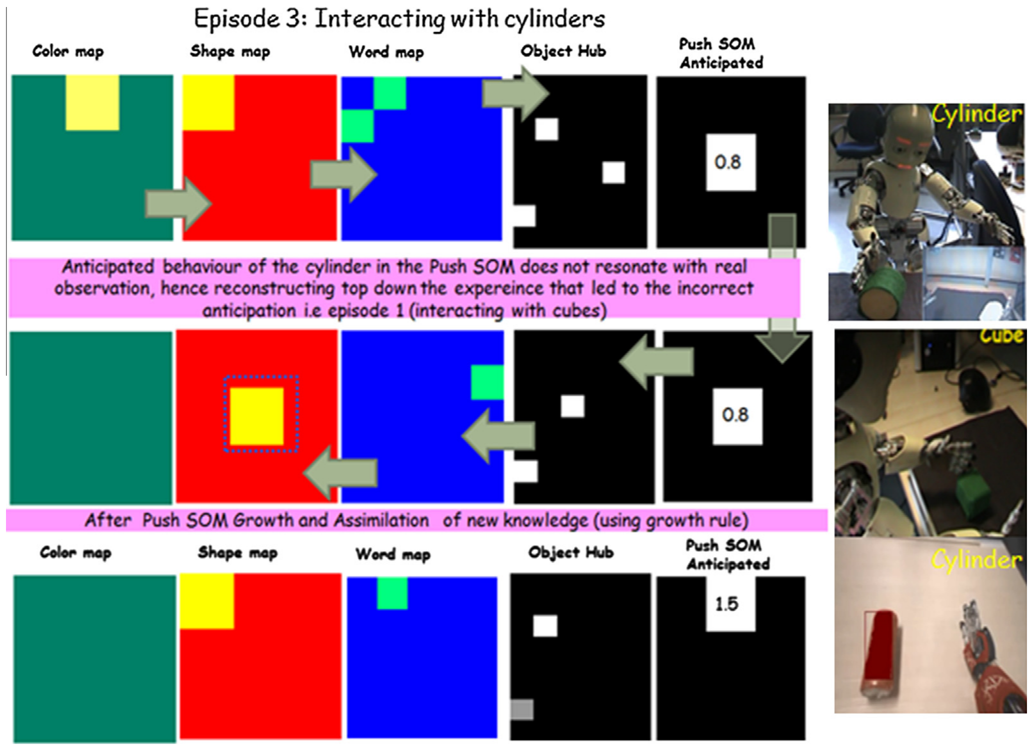


**Fig. 4** The bottom up and top down information flow while interacting with a green cylinder is shown in rows 1 and 2. Contradiction between the robots anticipations and the real experience is also correlated with a difference in the shape map. This leads to application of the growth rule, encoding the behavior of the cylinders in the pushing SOM. In few episodes of cumulative interaction, the robot is able to learn and represent that color of objects do not matter, but shape does and cylinders roll much faster than cubes when forces are exerted on them. An interesting aspect of the proposed framework is that it computationally explains why top down and bottom up information flow must share computational/neural substrates. Such a shared neural basis provides a computationally efficient means to directly compare and put into context the present experience with what has been learnt in the past, and thereby triggering mechanisms related to consolidation.

down is shown in row 1—2 of Fig. 4. The flow of information is indicated by arrows. Row 1 Bottom UP: To start with we move from property specific maps to the object hub and then to the Pushing SOM. As seen in column 5, the robot anticipates that small cylinders may also move like small cubes that are all it knows so far. But real experience with cylinders reveals a different behavior, they roll much faster, dis-placement/unit force is much higher as compared to cubes. But we need to know ''what caused this contradiction''. The trick is to go top down to reconstruct from memory the past experience that resulted in the wrong anticipation and compare it with the new experience (row 2). Note that color map is no longer activated top down, due to assimilation in the past episode. Further directly comparing top down with bottom up it is possible to infer which property is causing the contradiction (shape map shows change). Growth rule applies here because a change in property causes contradiction be-tween anticipation and observed behavior. As a result of application of growth rule, there is now a new neuron in the Pushing SOM that is coding for how cylinders move when force is exerted on them. Appropriate connections between the new winner in the push SOM and the object hub are developed.

In sum, cumulatively interacting with different objects and exploiting the dissonance or resonance between real experience and anticipations, it becomes possible to learn which properties are causally dominant for a particular task. Applying the elimination and growth rule, the robot in few episodes of interaction learnt that color of objects do not matter, but shape does and cylinders roll much faster than cubes when forces are exerted on them. Further, the forward model anticipating how objects move naturally solves the inverse problem of generating goal directed pushing of any object to a target location as seen in Section 'Distributed ''property specific'' organization of sensorimotor information and the basic pushing forward/inverse model'. The same mechanism can be used to eliminate any irrelevant property like the end effector used (stick, left hand, right hand etc.), the starting and initial positions from where the object is in fact pushed and so on. All of these are not ''casually dominant'' as far as the task is concerned, the learner can abstract all of this by the process of assimilating what is experienced in the present with what was experienced in the past.

## Discussion

To wipe off a spider web on the top most corner of a room, it does not matter if a red colored broom or yellow colored broom or even a long stick is deployed. Any object that has the specific property ''length'' in this case will suffice. Similarly, colors of objects do not affect the way they move when pushed but shape and size do. At the same time, color does play a causally dominant role in numerous other tasks (for example, traffic rules). The article explores the issue of how causally dominant properties relevant to different tasks can be learnt through cumulative episodes of interactions. Part of the problem is solved by taking guidance from emerging results from brain science providing converging evidence that conceptual information is organized in a ''distributed fashion'' in ''property specific'' cortical networks that directly support perception and action and that were active during learning. To supplement such property specific organization, two learning rules namely elimination and growth where proposed, that modulate the connectivity between associated neural maps based on contradictions between the robots top down anticipations and the bottom up experience. A well investigated scenario from animal cognition (Visalberghi & Tomasello, 1997) i.e. pushing was used to illustrate the basic framework. Both how the robot acquires the forward model i.e. anticipating how objects move when forces are exerted and the inverse model i.e. generating goal directed pushing actions with different objects was described. Going beyond the acquisition of the basic forward/inverse model, how causally dominant properties can be abstracted within the proposed framework was illustrated. An interesting aspect of the proposed framework is that it computationally explains why top down and bottom up information flow must share computational/neural substrates. Several studies from functional imaging related to organization of conceptual information in the brain support that the same set of cortical networks are known to be active both during real perception/action, imagination and lexical processing. Our framework points out such a shared basis provides a computationally efficient means to directly compare and put into context the present experience with what has been learnt in the past, and thereby triggering mechanisms related to consolidation. Further, several nonhuman primates are also known to exploit implicit properties in novel objects to realize otherwise unrealizable goals. A classic example is of the new Caledonian crow Betty that based on her past experience of bending flexible pipe cleaners a year back, fashioned a hook out of a piece of wire to pull her dinner basket trapped in a transparent vertical tube (Weir et al., 2002). In this context, the implicit advantage of the proposed architecture is that learnt ''property-action'' relations can be effortlessly generalized to a domain of objects for which the robot need not have any past experience/learning but nevertheless share the ''property''. This might explain the reasoning of Betty (Meyer & Damasio, 2009) when she used the flexible piece of wire to fashion a hook, recalling the context relevant past experience she had a year ago. In general, further work in this direction has the potential to provide a bio inspired and embodied framework for reasoning by analogy (attributing causality to a novel class of objects based on what has been learnt and experienced in the past). At the same time, learning and anticipation goes hand in hand (and continuously in life time of the learner): more experience driving better anticipation and inconsistencies in reasoning driving new learning.

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