

Conceptualizing verbs, nouns and adjectives

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Who am I?

- Leading KOVAN Research Lab with two other faculty members:

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Vision

- Border Ownership
- Depth Prediction
- Feature Extraction
- Biometric Identification
- Image Retrieval

Cognitive Robotics

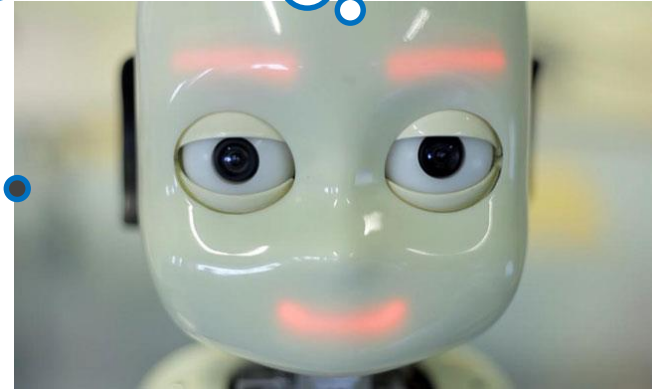
- Conceptualization & Affordances
- Multiple-Levels of Abstraction
- Context

Introduction: Problem



give me the *tall*
cup

What is a *cup*?
What is *tall*?
What does it
mean to *give*?



Verbs Adjectives
Nouns



Introduction: Concepts

- Rule-Based

Apple = {color = “green” AND shape = “round”,...}

- Prototype-Based

OUR CHOICE

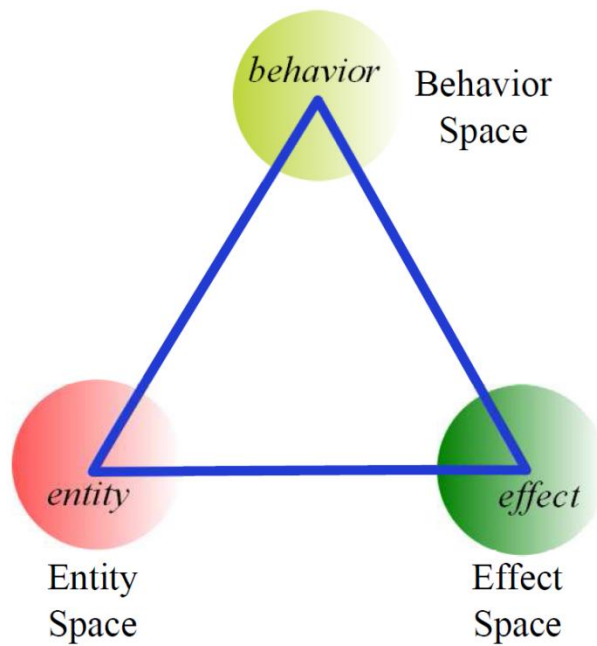
$$\text{APPLE} = \left\{ \begin{array}{ll} \text{colour} & \text{RED, YELLOW or GREEN respectively} \\ & 50\%, 25\% \text{ and } 25\% \text{ of the cases} \\ \text{shape} & \text{🍏} \\ & \dots \end{array} \right.$$

- Exemplar-Based

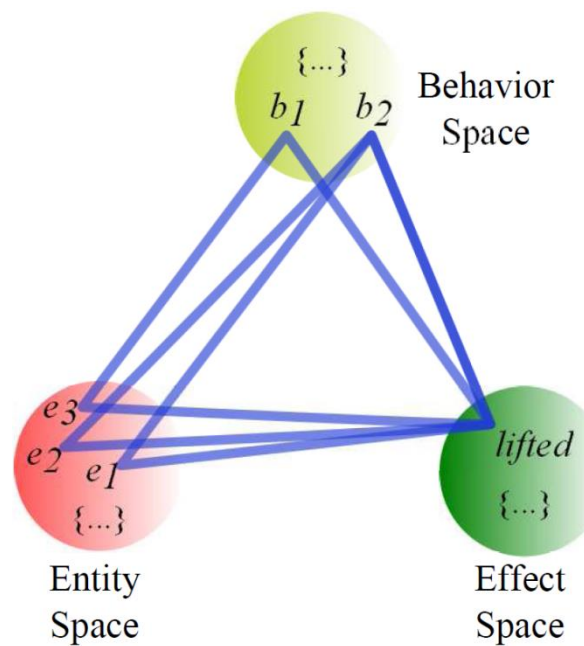
$$\text{APPLE} = \left\{ \text{🍏} \text{🍏} \text{🍏} \text{🍏} \dots \right\}$$

Introduction:

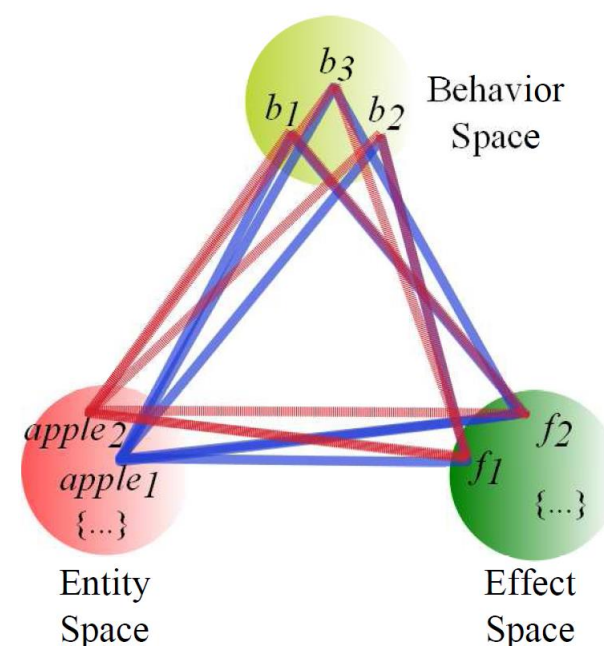
Affordances and Concepts



Affordance Formalization*



Adding Verb Concepts



Adding Noun/Adjective Concepts

Verb, Noun and Adjective Concepts

Verb Concepts

- Verbs tend to correspond to effect categories rather than single behaviors.



Kalkan et al., accepted.
Dag et al., 2010

Noun/Adjective Concepts

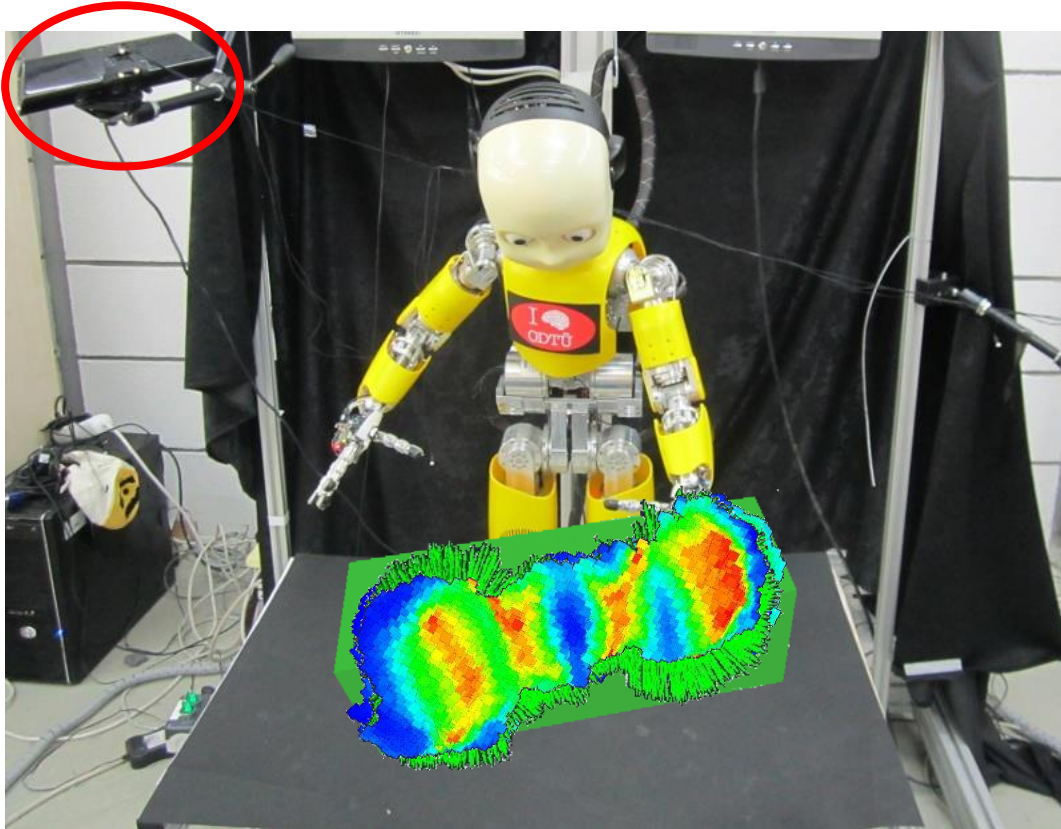
- Based on visual appearance.
- Based on what objects afford.



Yuruten et al., 2012; under revision
Atil et al., 2010

Experimental Setup

Kinect: 3D Range Data

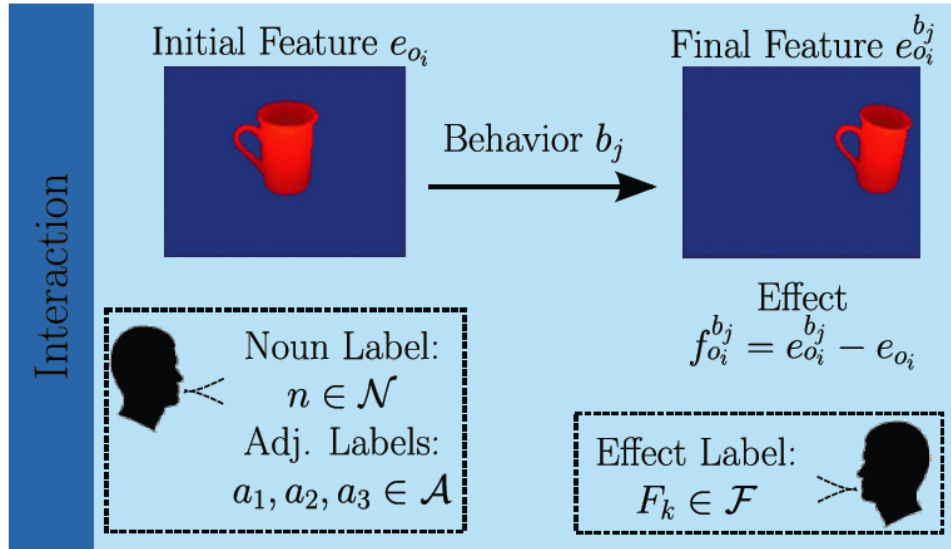


Features:

- 3D size, 3D position, surface normal histogram
curvature histogram, presence

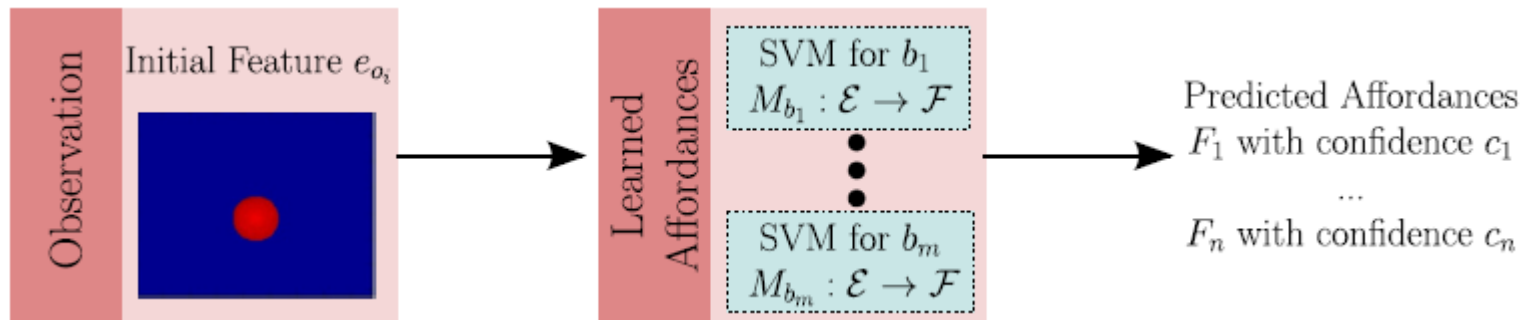
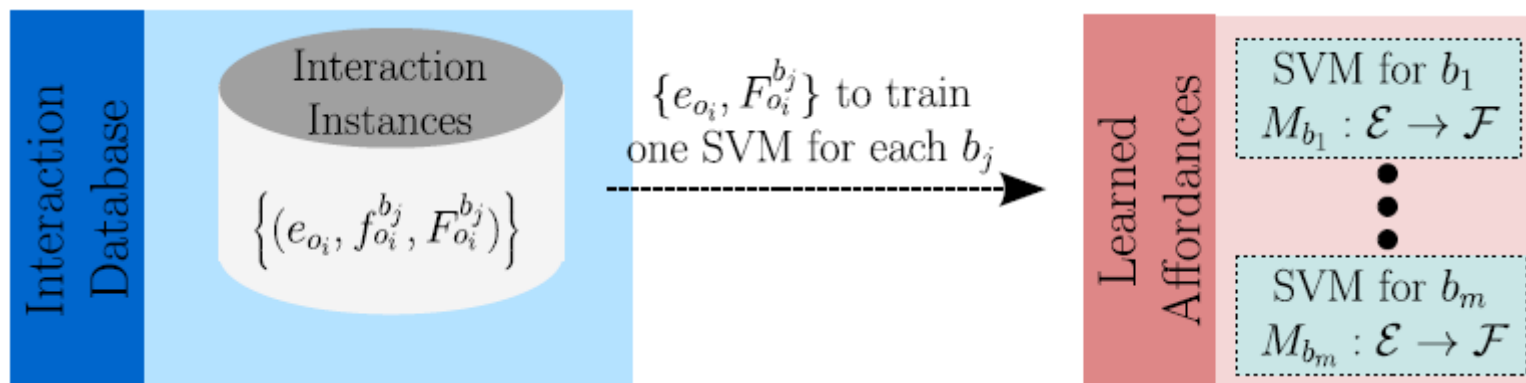
Nouns and adjectives

- Cup
- Box
- Cylinder
- Ball
- Short-tall
- Thin-thick
- Edgy-round



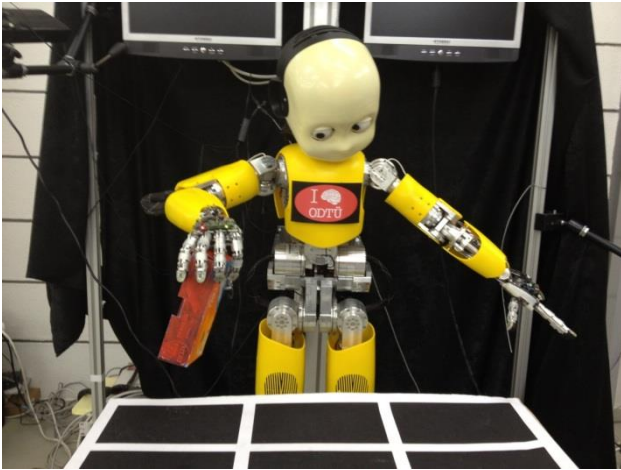
Verbs as effect labels

- moved-left (**ML**)
- moved-right (**MR**)
- moved-forward (**MF**)
- pulled (**P**)
- knocked-down (**K**)
- disappeared (**D**)
- no-change (**NC**)



Experimental Setup:

Behaviors and Effects



Behaviors

- Push-left (**PL**)
- Push-right (**PR**)
- Push-forward (**PF**)
- Pull (**PB**)
- Top-grasp (**TG**)
- Side-grasp (**SG**)

Effects

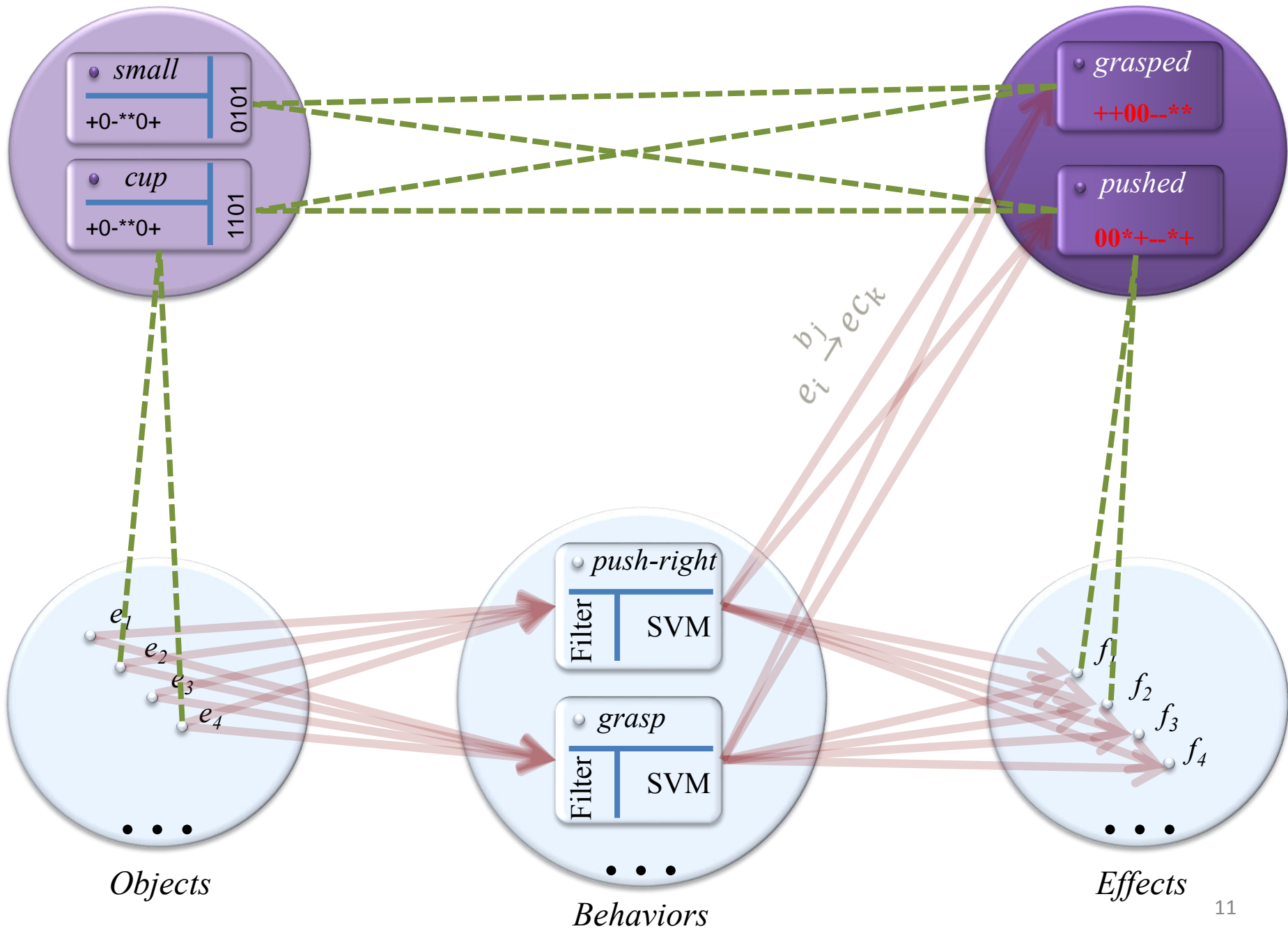
- moved-left (**ML**)
- moved-right (**MR**)
- moved-forward (**MF**)
- pulled (**P**)
- knocked-down (**K**)
- disappeared (**D**)
- no-change (**NC**)



Figure 5. The objects interacted by the robot for learning.

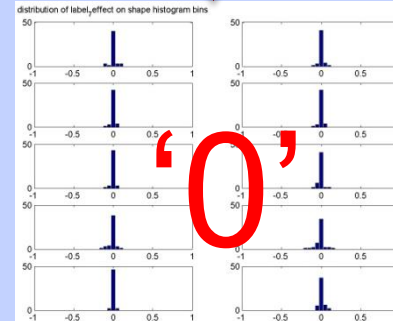
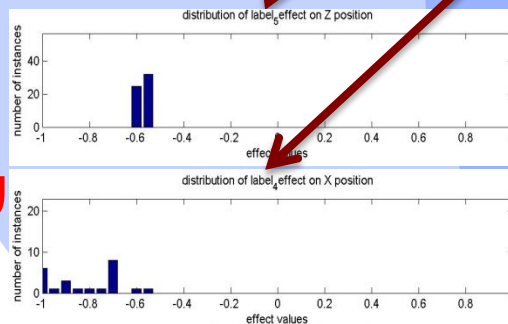
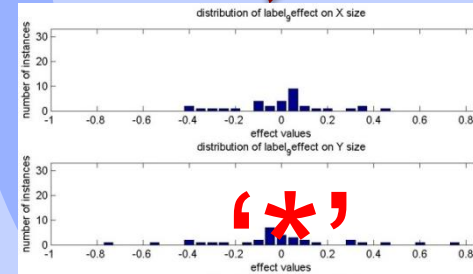
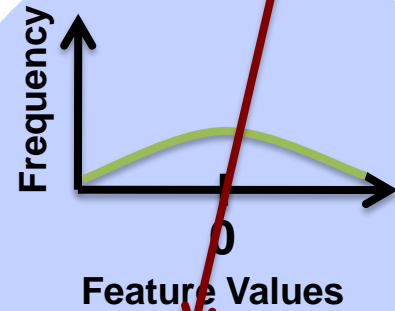
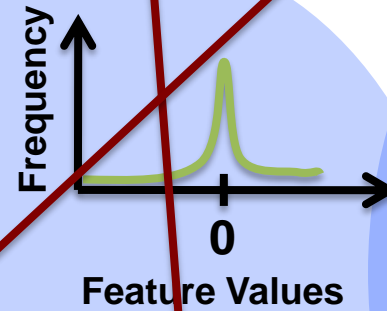
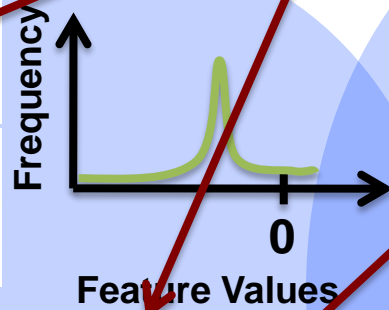
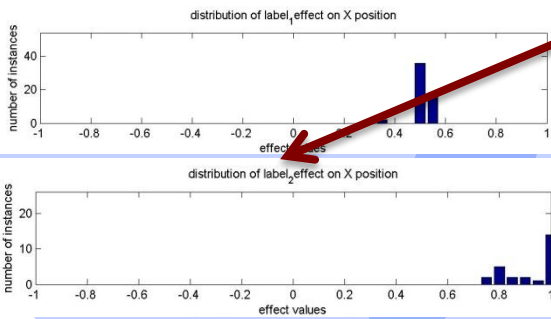
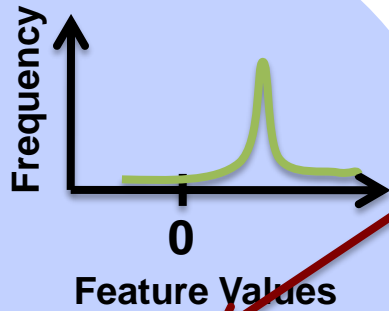
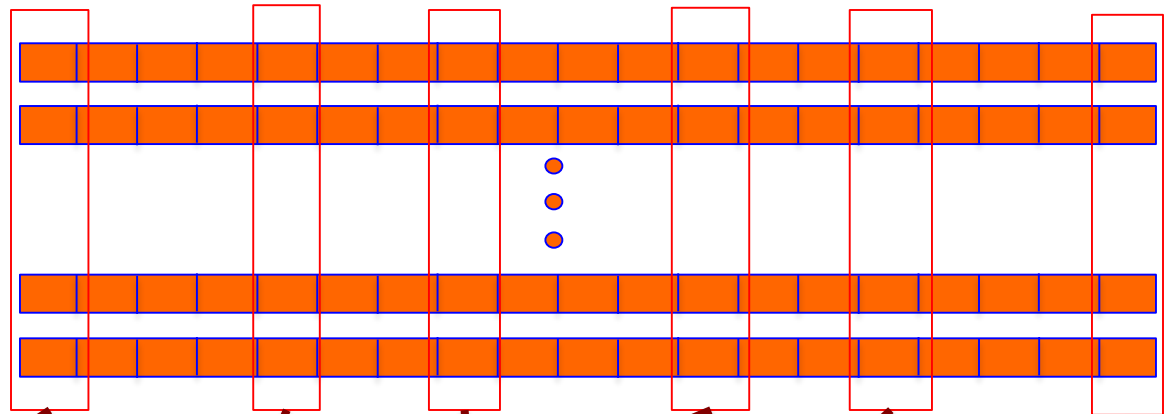
Object Concepts

Verb Concepts



Conceptualization:

- Capture how features are distributed



Verb Concepts: A prototype-based representation

Eff. Cat. Name	Δ Azimuth Histograms	Δ Zenith Histograms	Δ Curvature Histograms	Δ Shape Index Histograms	Δ Position (x-y-z)	Δ Orient.	Δ Size (x-y-z)	Δ Object Presence
NC	*000000000 0000000000	0000000000 0000000*00	0000000000 00*0000000	0000000000 000000*000	000	0	000	0
MR	***** *****0*0*	***** *****000	0000000000 00*****	*****0**** **0*0*0***	*+*	*	***	0
ML	*****0000 00***0****	0**0**0000 **0000*000	0000000000 0*****0000	00*0**0*0* **0000*00*	0-0	*	000	0
MF	***** *****	*****000* **000*000	0000000000 00****0***	***0*0**** **00000***	-00	*	000	0
P	***** *****	*****000* **000*000	0000000000 00****0***	***0*0**** **00000***	+00	*	000	0
K	*0***00000 000000**0*	*000000000 0000000000	0000000000 000000000*	0000000000 0000000000	00-	*	00-	0
G	0000000000 0000000000	0000000000 0000000000	0000000000 0000000000	0000000000 0000000000	000	*	000	0
D	0000000000 0000000000	0000000000 0000000000	0000000000 0000000000	0000000000 0000000000	000	0	000	-

NC: No Change
 MR: Moved-right
 ML: Moved-left
 MF: Moved-fwd
 P: Pulled
 K: Knocked
 G: Grasped
 D: disappeared

These prototypes also have mean and standard deviation values of the changes associated with each element.

Comparing conceptualization methods for verbs

1. Prototype-based view 1:

- Effect prototype-based concepts
- ‘+’, ‘-’, ‘0’, ‘*’

2. Prototype-based view 2:

- Using just the mean & variance of change in features

3. Exemplar-based view:

- Using all interaction data for comparison

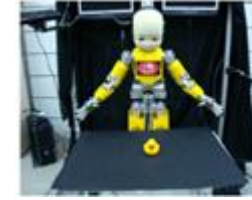
- Comparison using:

- Recognizing an observed interaction
- Planning

“what did I
do?”

Initial

Final



Concepts with prototypes
Concepts with naïve p.
Concepts with exemplars

Concepts with prototypes
Concepts with naïve p.
Concepts with exemplars

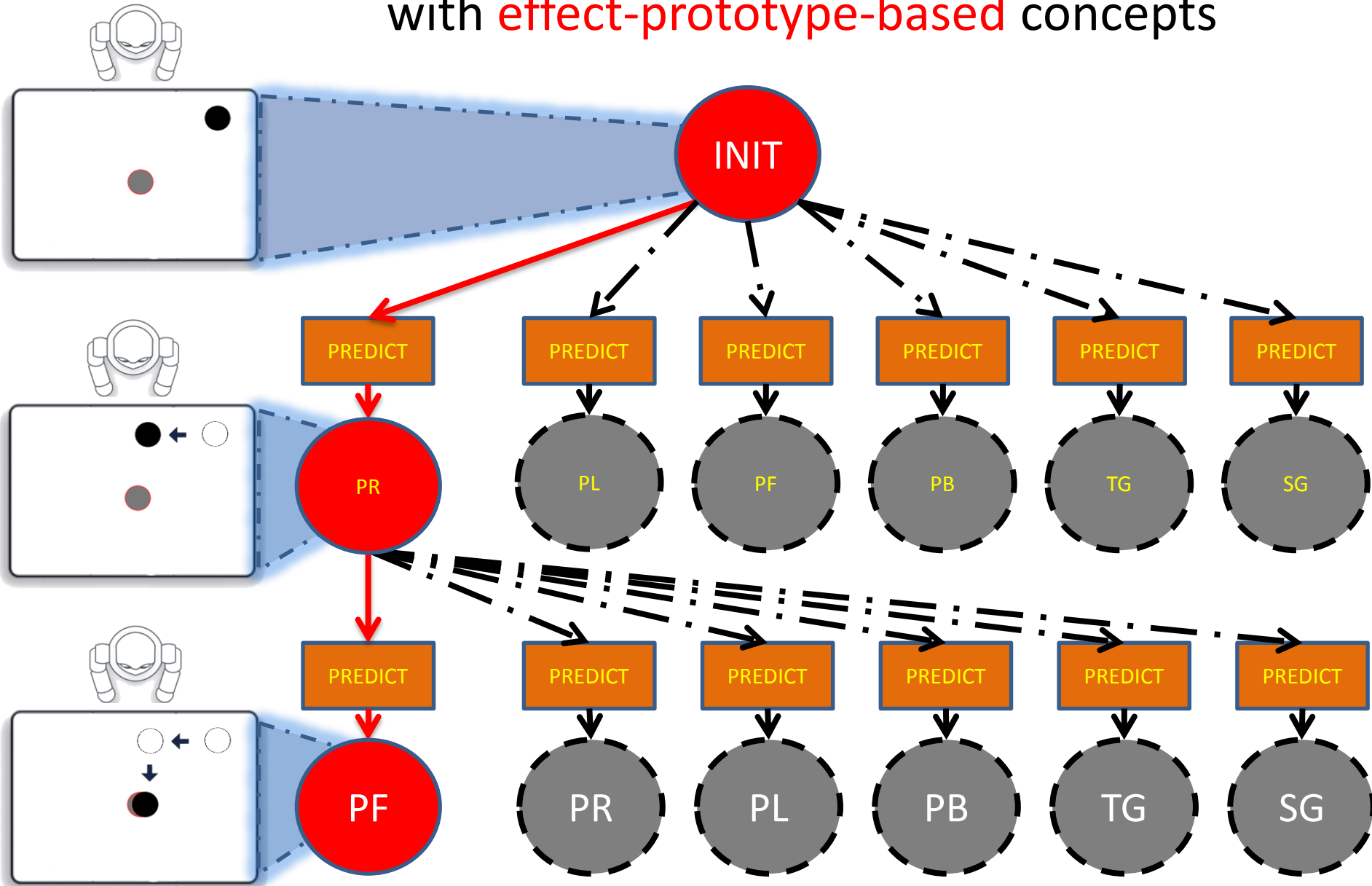
Concepts with prototypes
Concepts with naïve p.
Concepts with exemplars

No Change	Moved Right	Moved Left	Moved Forward	Pulled	Knocked	Grasped	Disappeared
390.81	146.24	372.24	389.21	215.56	215.50	392.11	410.31
392.16	182.13	386.92	416.43	241.06	219.28	395.04	410.31
237.01	236.89	237.42	237.24	237.42	237.42	237.25	236.84
731.36	494.18	416.42	340.71	393.76	358.06	738.04	790.41
732.98	497.02	417.18	426.71	423.17	428.06	741.11	790.41
789.45	789.08	789.83	789.49	789.83	789.83	789.54	788.84
925.41	577.51	267.45	328.75	354.85	354.74	928.16	947.51
929.37	580.26	291.77	369.75	373.37	359.88	929.94	947.51
946.74	946.42	947.03	946.66	947.03	947.03	947.01	946.21

- PREVIOUS STATE
- CURRENT STATE
- TARGET STATE

Multi-step planning

with **effect-prototype-based** concepts



Multi-step planning

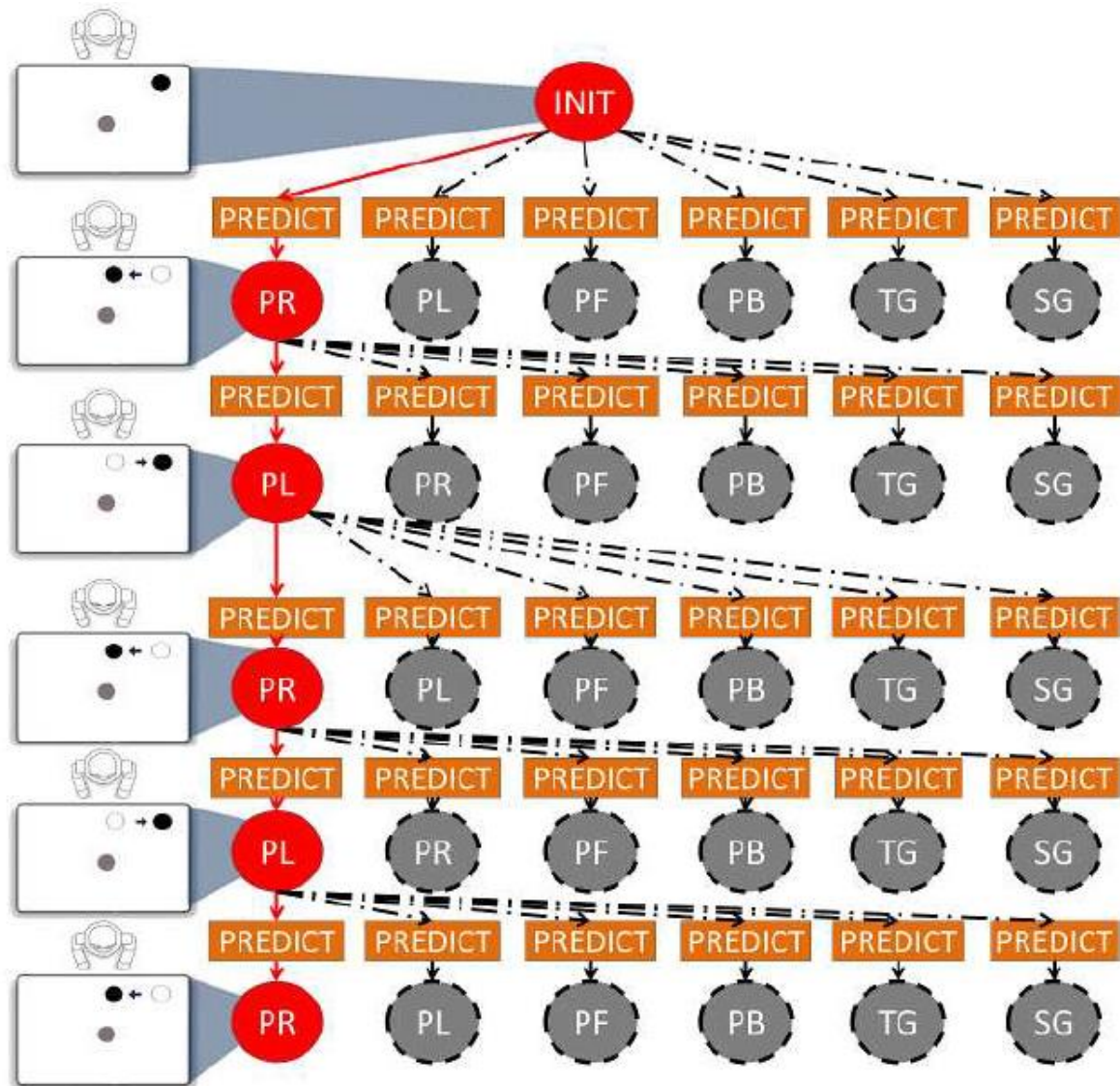
with **effect-prototype-based** concepts



- PREVIOUS STATE
- CURRENT STATE
- TARGET STATE

Multi-step planning

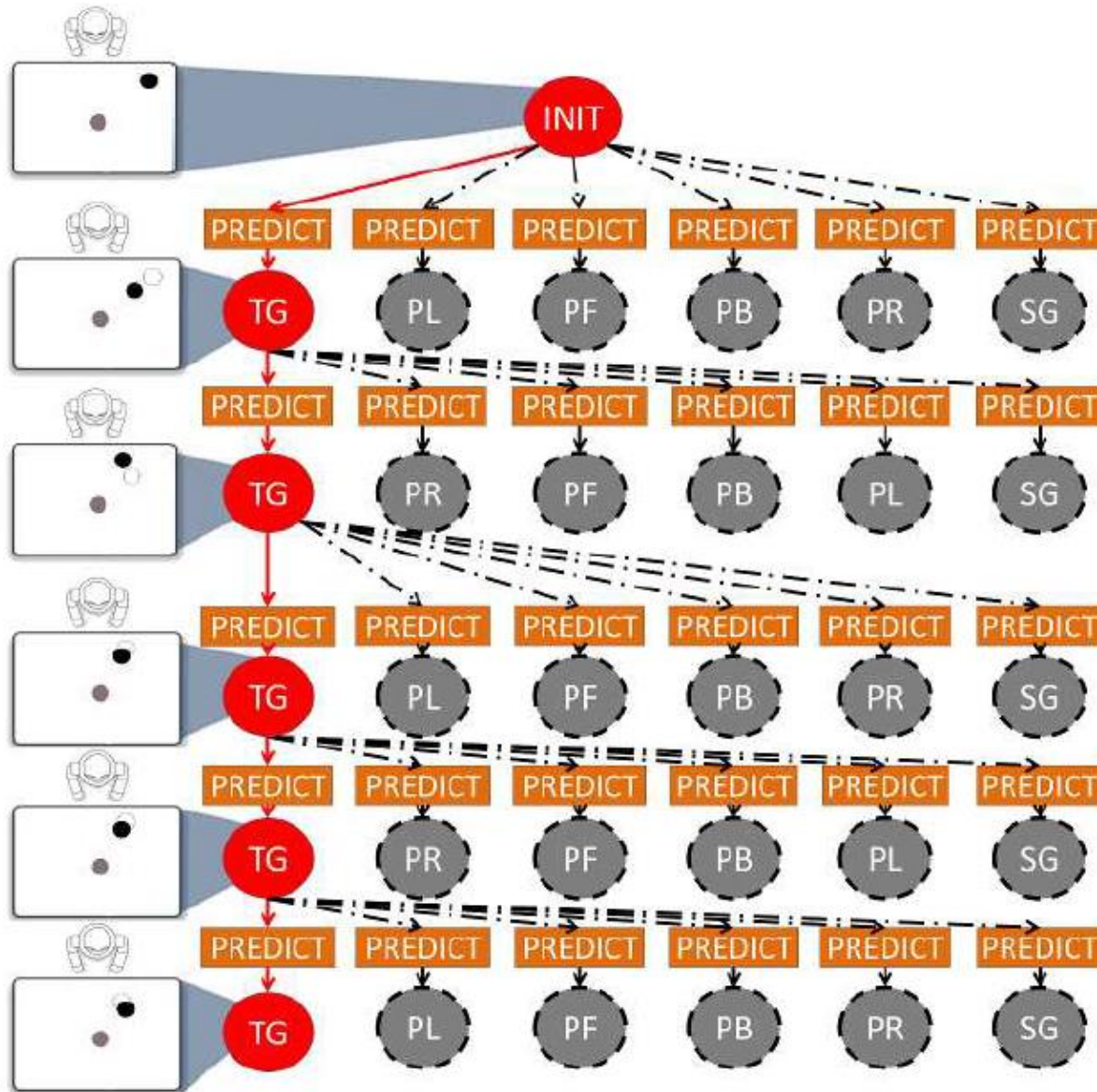
with naïve-prototype-based concepts



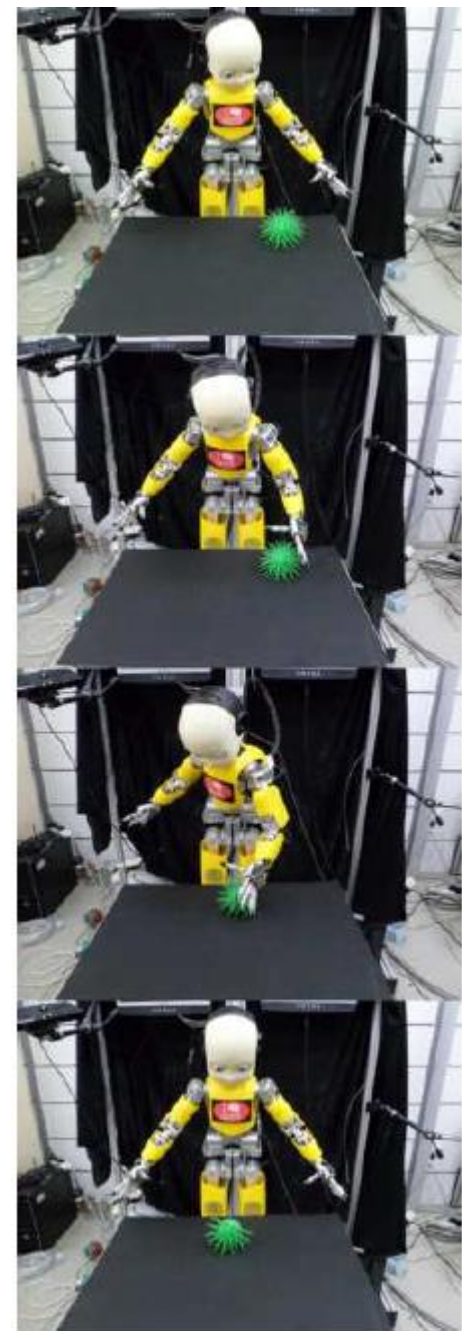
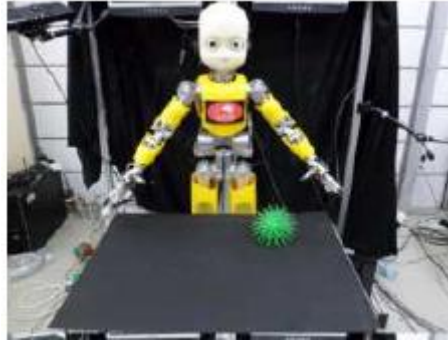
- PREVIOUS STATE
- CURRENT STATE
- TARGET STATE

Multi-step planning

with **exemplar-based** concepts



Verb Concepts: Goal Specification



“iCub, do:

*****-*****0”

Position along y

Presence

Find most similar verb concept:

$$f_{pro}^* = \arg \min_{f_{pro}} d_{EP}(f_{goal}, f_{pro}),$$

Find the behavior producing the verb concept best:

$$b^* = \arg \max_b d_{EP}(\text{SVM}(e_{o_k}, b), f_{pro}^*),$$

d_{EP} : Mahalanobis distance²⁰

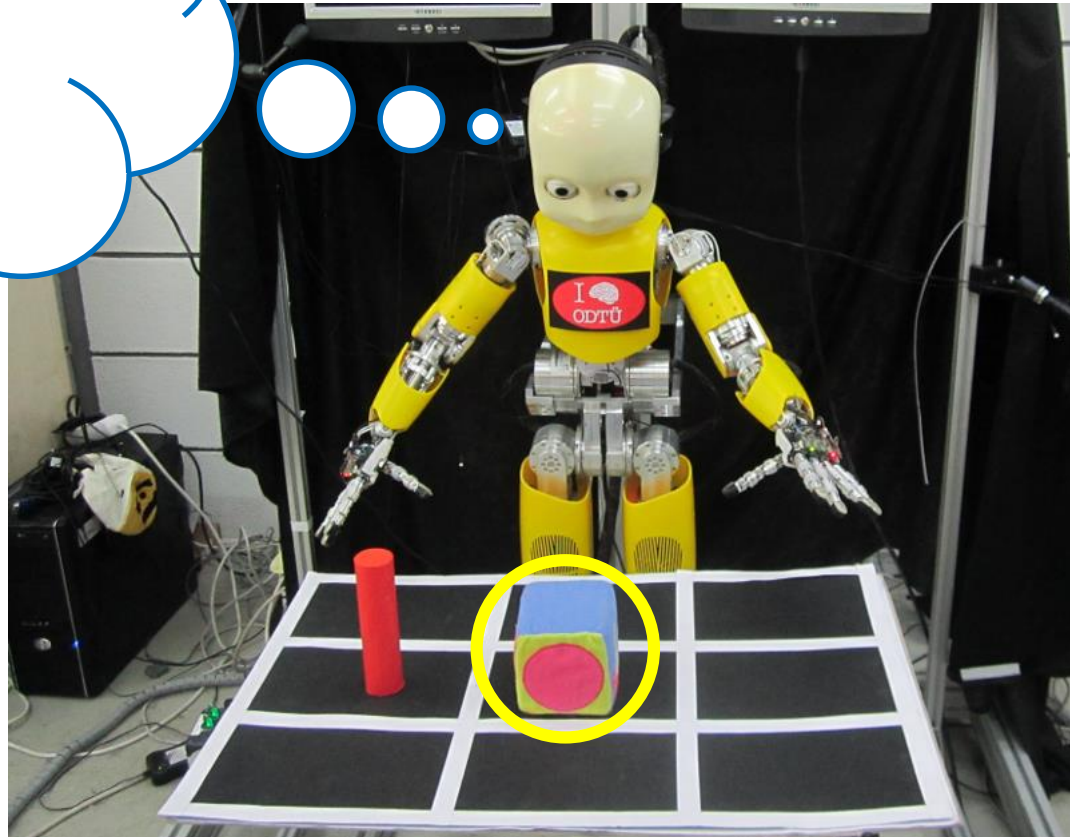
Mid-summary

- There are alternative ways for abstraction over behaviors/actions
- Prototype-based conceptualization based on effects is a good alternative
 - efficient planning
 - condensation
 - easy goal specification
 - Disadvantage: no information about the “how” part (not yet 😊).

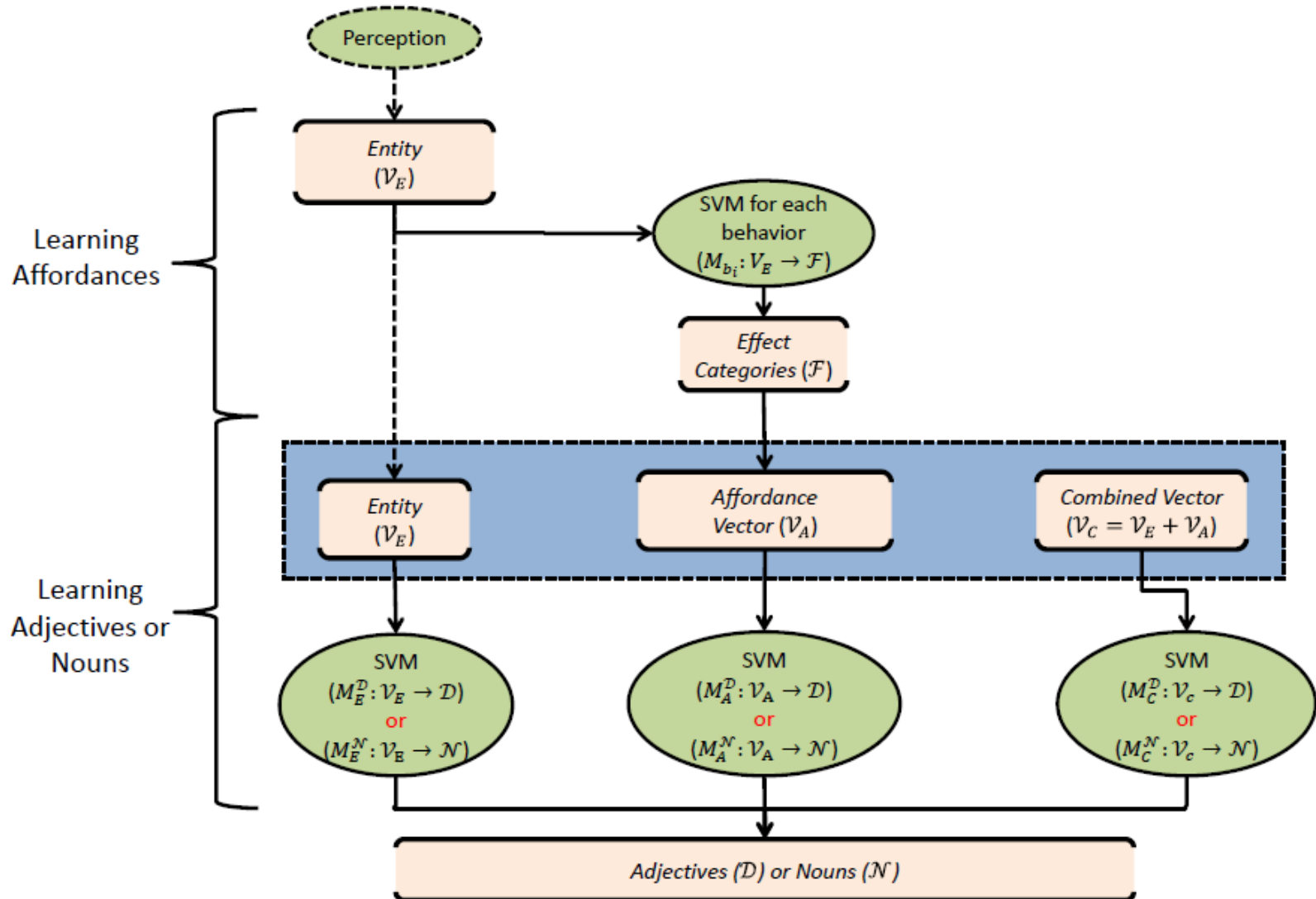
Adjectives & Nouns based on Affordances & Visual Appearance

%15 Disappearable,
%85 Pushable,
%10 Knockable,
%25 Graspable

Therefore,
Short, **thick**, **edgy**



Overview



Methodology: the Affordance Vector (V_A)

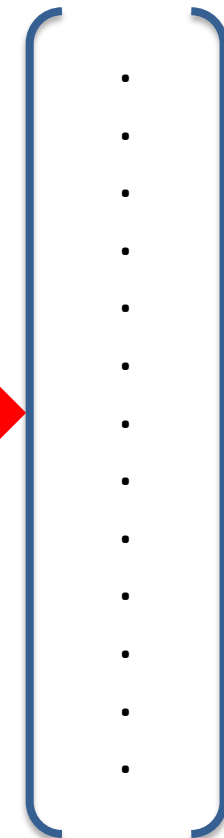
Probability of obtaining an effect from a behavior

Behaviors vs Effects	PR	PL	PF	PB	TG	SG
Mov. Right	0.93	0.0	0.0	0.01	0.01	0.02
Mov. Left	0.0	0.96	0.0	0.02	0.03	0.15
Mov. Fwd.	0.0	0.0	0.89	0.01	0.01	0.04
Pulled	0.0	0.0	0.0	0.87	0.01	0.02
Disappeared	0.0	0.0	0.0	0.09	0.0	0.03
Grasped	0.0	0.0	0.0	0.0	0.23	0.17
Knocked	0.03	0.02	0.08	0.0	0.07	0.10
No-change	0.04	0.02	0.03	0.0	0.64	0.47

All
Values



Affordance
Vector



PR: Push Right, **PL**: Push Left, **PF**: Push Forward
PB: Pull, **TG**: Top Grasp, **SG**: Side Grasp

48 x 1₂₄

Objects & labels



(a) cups



(b) boxes



(c) balls



(d) cylinders



(a) round



(b) edgy



(c) short



(d) tall








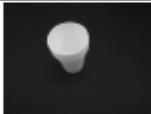


(e) thin



(f) thick

Predicted adjectives and nouns of novel objects.







Object		Adjectives			Nouns		
		M_A^D	M_E^D	M_C^D	M_A^N	M_E^N	M_C^N
O_1		edgy (54%) short (97%) thin (59%)	edgy (89%) short (55%) thin (52%)	edgy (60%) short (80%) thin (52%)	box (74%)	box (97%)	box (56%)
O_2		round (77%) short (77%) thin (89%)	edgy (79%) short (58%) thin 67%	round (65%) short (68%) thin (62%)	ball (83%)	ball (97%)	ball (80%)
O_3		edgy (63%) short (94%) thin (96%)	edgy (64%) tall (67%) thin (84%)	edgy (60%) tall (68%) thin(80%)	cyl. (87%)	cyl. (95%)	cyl. (60%)
O_4		round (84%) short (98%) thick (91%)	round (77%) short (68%) thin (62%)	round (75%) short (71%) thick (51%)	box (94%)	cyl. (86%)	cyl. (52%)
O_5		round (84%) short (97%) thick (95%)	round (89%) short (67%) thick (58%)	round (80%) short (66%) thick (54%)	box (89%)	box (94%)	box (62%)
O_6		edgy (84%) short (98%) thin (92%)	edgy (79%) tall (55%) thick (62%)	edgy (75%) short (65%) thick (52%)	cup (89%)	box (46%)	box (45%)
O_7		edgy (62%) short (98%) thick (78%)	round (84%) short (54%) thick (68%)	edgy (60%) short (56%) thick (66%)	box (89%)	box (93%)	box (64%)
O_8		round (72%) short (98%) thick (79%)	edgy (89%) short (67%) thick (52%)	round (62%) short (69%) thick (53%)	cup (89%)	cup (98%)	cup (61%)

\mathcal{M}_A : Learner from affordance vector

\mathcal{M}_E : Learner from appearance

\mathcal{M}_C : Learner from Appearance+Affordance

Predicted adjectives and nouns of novel objects from the KIT Dataset
(Kasper et al., 2012).

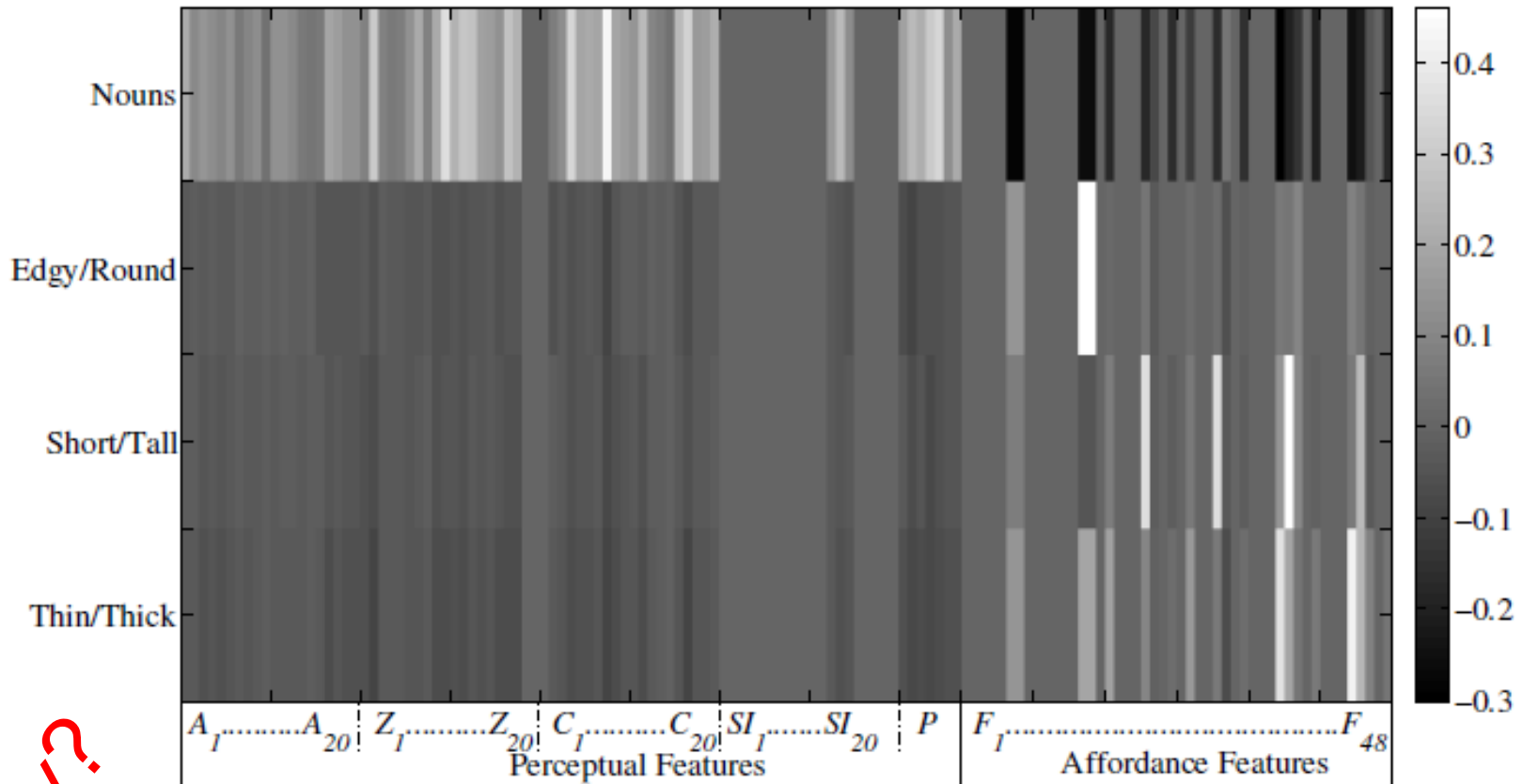
Object		Adjectives		
		M_A^D	M_E^D	M_C^D
K_1		round (60%) tall (97%) thick (76%)	edgy (92%) tall (100%) thick (96%)	round (60%) tall (80%) thin (52%)
K_2		round (55%) tall (96%) thick (72%)	edgy (90%) tall (98%) thick (91%)	round (62%) tall (82%) thick (54%)
K_3		edgy (55%) tall (97%) thin (72%)	edgy (92%) tall (95%) thin (93%)	edgy (92%) tall (79%) thin (81%)
K_4		round (58%) tall (98%) thick (87%)	edgy (76%) tall (100%) thick (86%)	edgy (82%) tall (83%) thick (70%)
K_5		round (55%) tall (95%) thick (71%)	edgy (76%) tall (98%) thick (94%)	edgy (80%) tall (80%) thick (52%)
K_6		edgy (59%) tall (92%) thick (92%)	edgy (83%) tall (96%) thick (90%)	edgy (62%) tall (78%) thick (52%)

Nouns		
M_A^N	M_E^N	M_C^N
cyl. (61%)	cyl. (98%)	cyl. (56%)
cyl. (56%)	cyl. (98%)	cyl. (58%)
box (58%)	box (97%)	box (59%)
cup (61%)	cup (96%)	cup (68%)
cup (56%)	cup (98%)	cup (56%)
box (56%)	box (99%)	box (62%)

\mathcal{M}_A : Learner from affordance vector
 \mathcal{M}_E : Learner from appearance
 \mathcal{M}_C : Learner from Appearance+Affordance

Nouns vs. Adjectives

- Relevance of features to the category labels (acquired using ReliefF – Kononenko (1994))



Why?

Nouns prefer perceptual features whereas adjectives prefer affordance features.

Nouns vs. adjectives

- Psychology (Fernald, Thorpe, Marchman, 2009; Sandhofer, Smith, 2007):
 - Young children have more difficulty learning/interpreting noun modifying adjectives.
- Language (Sasson, 2011):
 - Adjectives are related to changes only in one/two dimensions whereas nouns depend on many dimensions in the feature space.

Conceptualization of Adjectives

Adjective prototypes obtained via learner with full affordance vector (V_{48})

(-): Highly confident that effect may not occur

(+): Highly confident that effect may occur

(*): Not confident about effect's occurrence

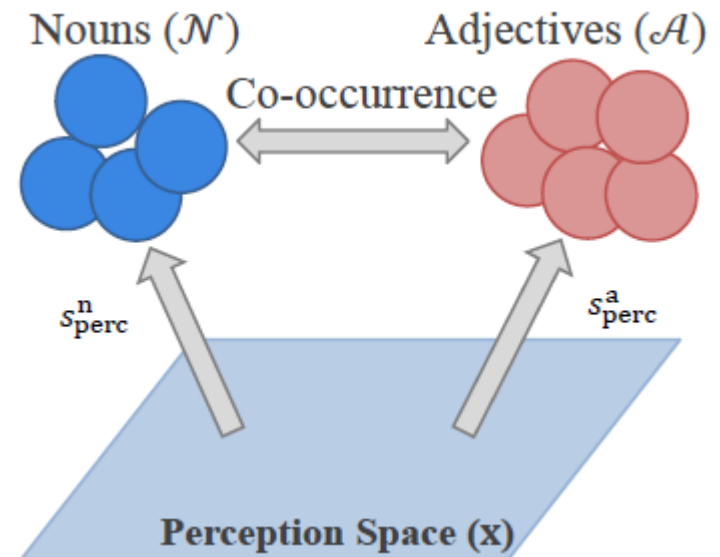
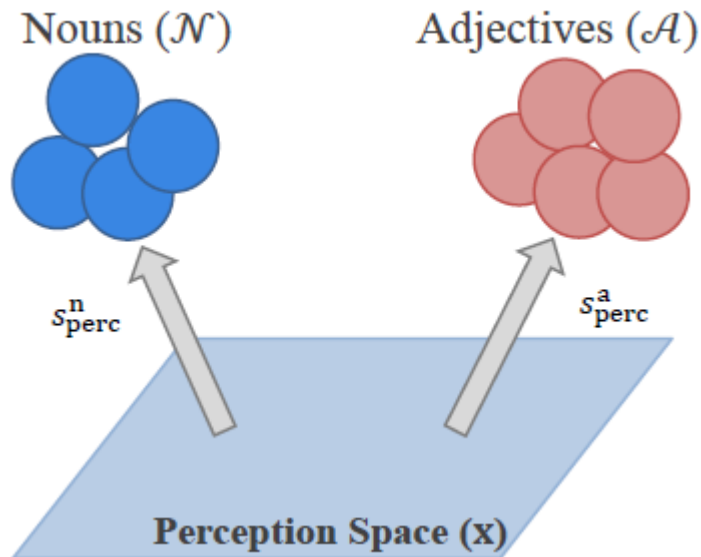
Adjective	TG <i>abcdefgh</i>	SG <i>abcdefgh</i>	PR <i>abcdefgh</i>	PL <i>abcdefgh</i>	PF <i>abcdefgh</i>	PB <i>abcdefgh</i>
Edgy	-----⊕--	-----**-	*---**--+	-*---**--+	---***--+	---*++-+
Round	-----**-	-----+-	*---+*-⊕	-*---+*-+	---**+-*	---**+-*
Short	-----**-	-----⊕--	+---**--+	-+---**--+	---+**--+	---+*+++
Tall	-----**-	-----**-	*---⊕*--+	-*---+*-+	---*++-*	---*++-*
Thin	-----⊗*-	-----**-	*---+*-+	-*---+*-+	---*+*-+	----++-+
Thick	-----⊕--	-----**-	*---**-*	-*---**-*	---**+-*	---+*+-*

PR: Push Right, **PL:** Push Left, **PF:** Push Forward

PB: Pull, **TG:** Top Grasp, **SG:** Side Grasp

a: moved right b: moved left
c: moved forward d: pulled
e: knocked f: no change
g: Grasped h: Disappeared

Co-learning nouns and adjectives



Mid-summary

- Nouns & Adjectives:
 - There is a functional/underlying difference between them
- This can shed some light to developmental psychologists & linguists
- Yuruten et al., "Learning Adjectives and Nouns from Affordances on the iCub Humanoid Robot ", SAB, 2012.
- Yuruten et al., "Learning of Adjectives and Nouns from Affordance and Appearance Features", Adaptive Behavior, under revision.
- Dag et al., "*Learning Affordances for Categorizing Objects and Their Properties*", ICPR, 2010.

Conclusion

- Theories on concepts from Psychology
- Hopefully, I have given some ideas:
 - for new experiments
 - explanations for existing ones
- There is still a lot to do regarding:
 - Verb Concepts
 - Adjectives
 - Nouns

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**Emergence of communication in RObots through
Sensorimotor and Social Interaction**



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111E287.**



RobotCub.org

More info available @ <http://kovan.ceng.metu.edu.tr/>