

# Affordances:



The adventures of an  
elephant in the land  
of autonomous  
robots

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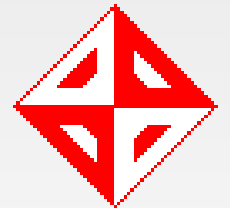
**NiCT**

**ATR**

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Computer Eng., Ankara, Turkey.

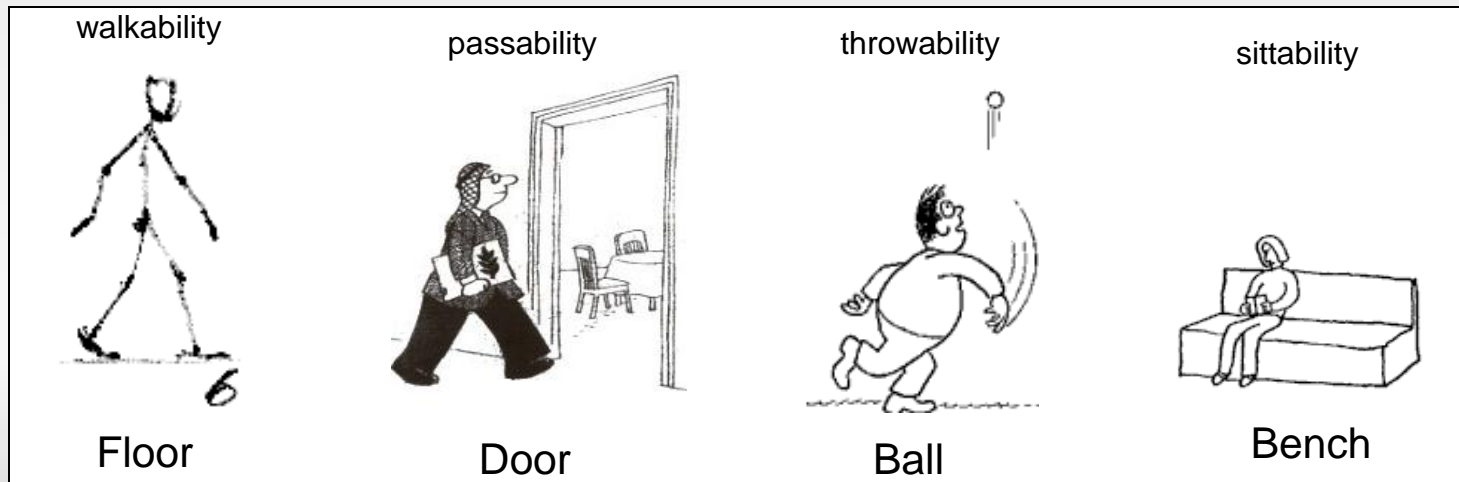


# The notion of affordance



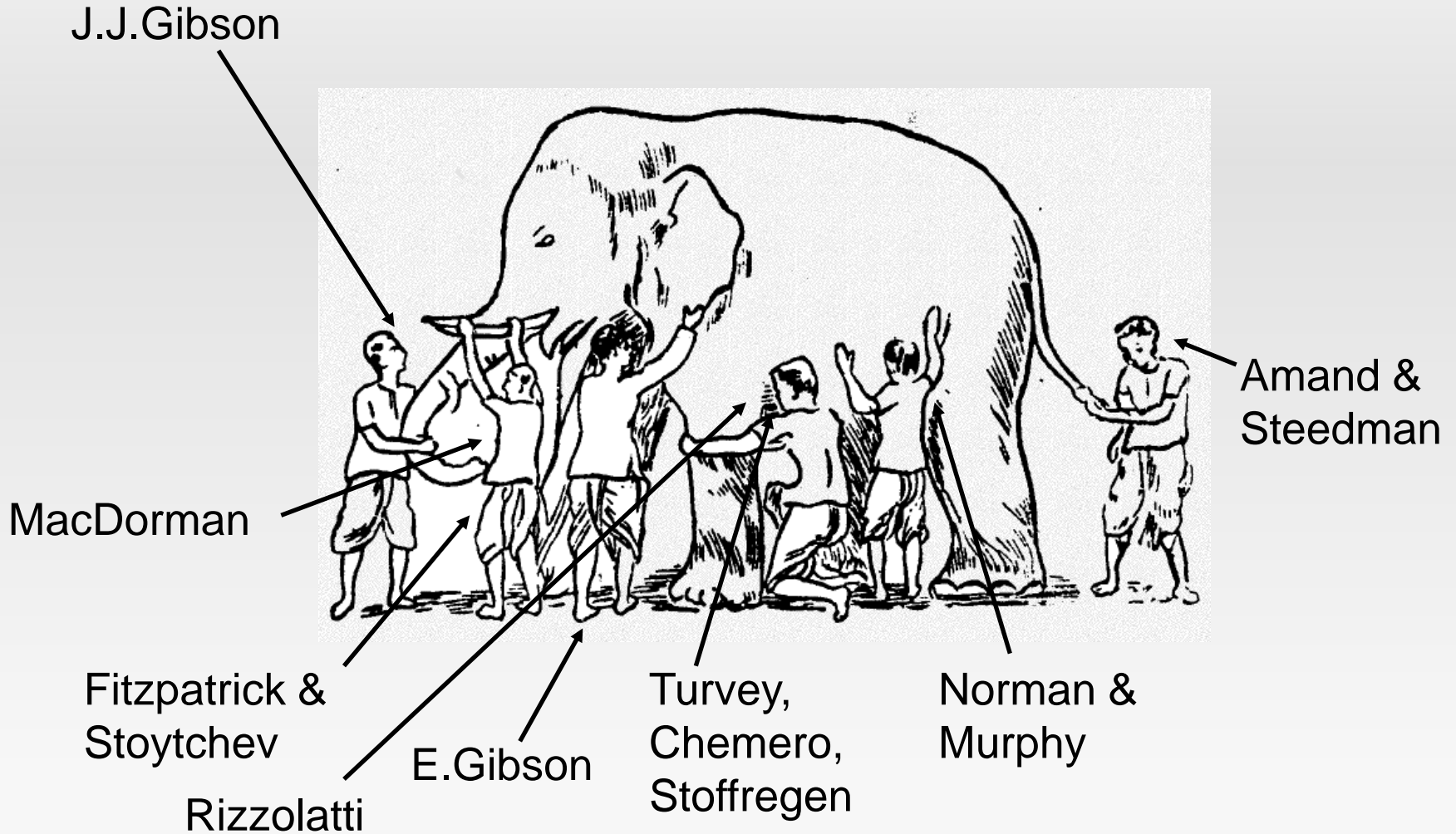
J.J. Gibson (1904–1979)

- Introduced J.J. Gibson to explain
  - how inherent “values” and “meanings” of things in the environment can be directly perceived, and
  - how this information can be linked to the action possibilities offered to the organism by the environment.
- Gibson argued that an organism and its environment complement each other and that studies on the organism should be conducted in its natural environment rather than in isolation





# An Elephant called Affordance

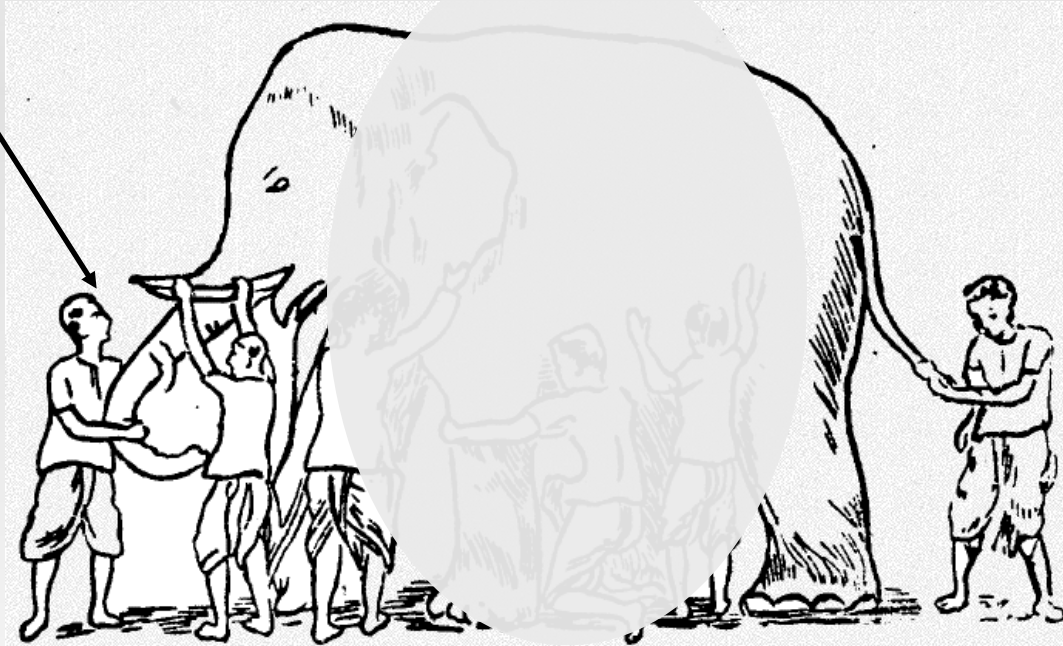


An elusive, yet confusing notion that has influenced a wide range of fields ranging from Human-Computer Interaction and Neuroscience, to Robotics

# Affordances and Elephants



J.J. Gibson



- Gibson's ideas were expressed in verbose descriptions.
- Gibson's own understanding evolved over time and were not finalized during his lifetime.
- Gibson's ideas can be understood only in contrast to the background of contemporary ideas.
- Gibson's ideas were often blended with his work on visual perception.

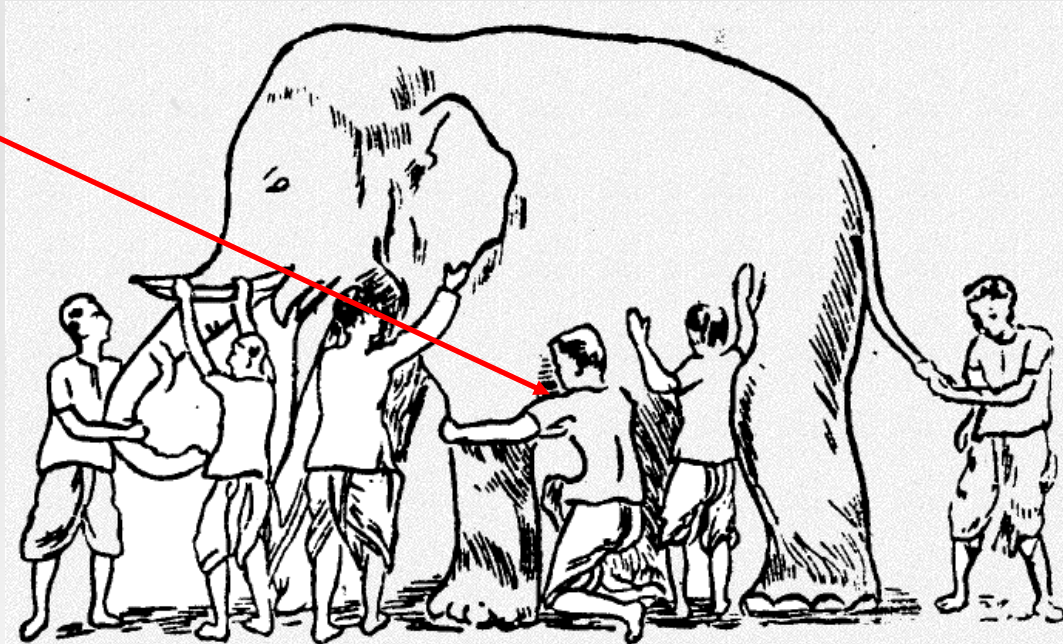


# Affordances and Elephants

## Ecological Psychology



Warren,  
Turvey,  
Chemero,  
Stoffregen



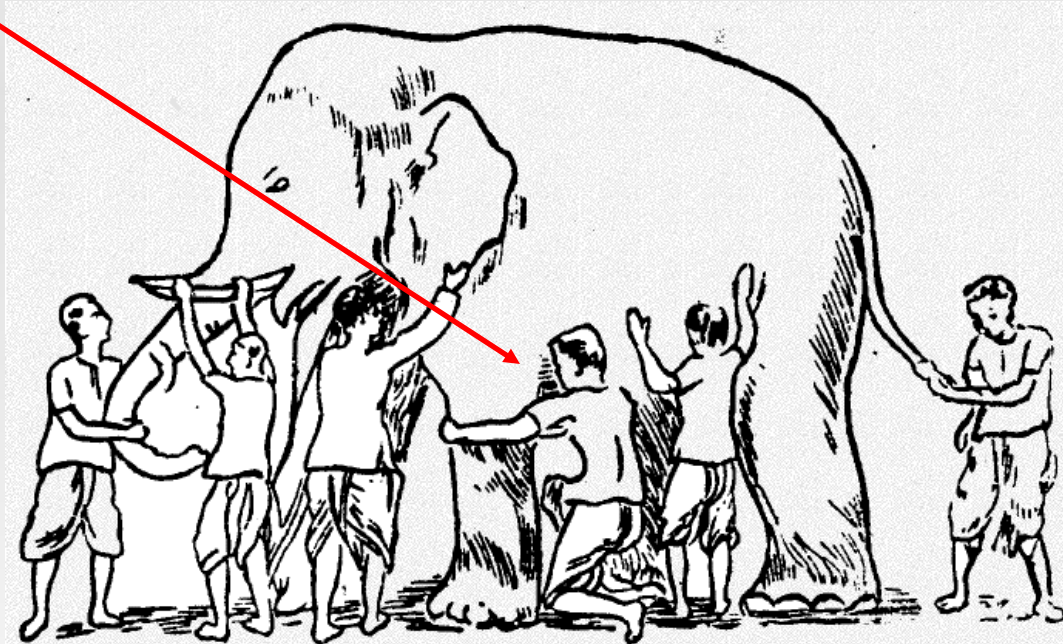
- Affordances are action possibilities that are supported by the environment.
- Organisms tend to perceive the world in terms of body-scaled (intrinsic) metrics not in absolute or global dimensions.
- Affordances exist within the organism-environment system and cannot be attached to the object or to the environment.

# Affordances and Elephants

## Cognitive Science



E.J. Gibson



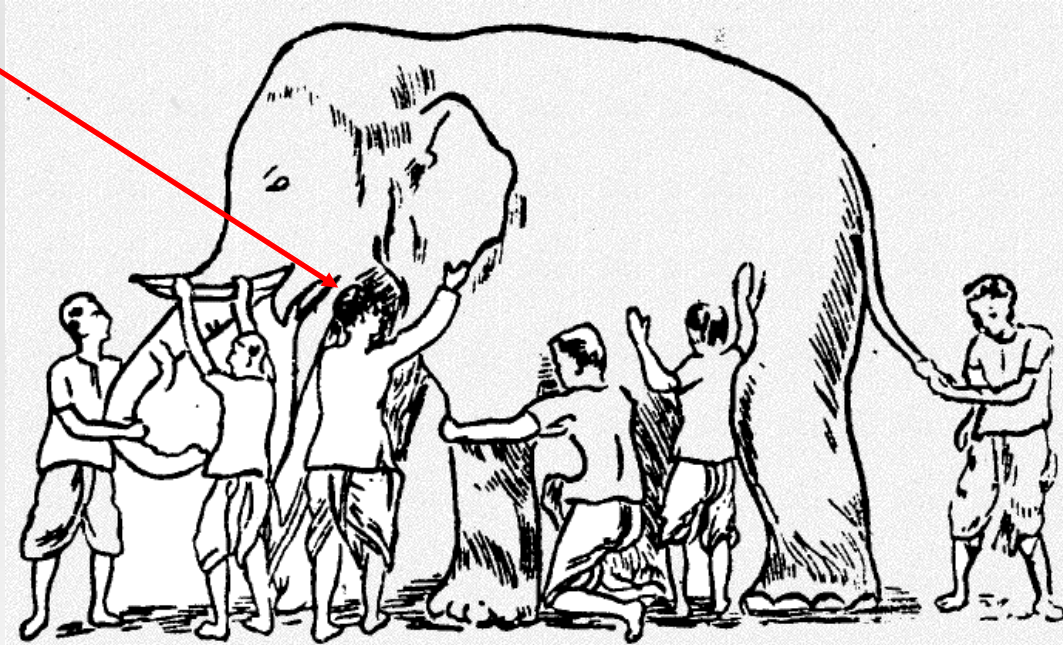
- Learning is “discovering distinctive features and invariant properties of things and events” that specifies an affordance.
- “narrowing down from a vast manifold of (perceptual) information to the minimal, optimal information that specifies the affordance of an event, object, or layout”

# Affordances and Elephants

## Neurophysiology and Neuropsychology



J.Norman,  
Humphreys,  
Rizzolatti et  
al.  
Gallese



- “the pickup of affordances can be seen as the prime activity of the dorsal system.” (J.Norman;2001)
- Mirror and canonical neurons code both motor and perceptual aspects of the organism.
- “Objects are identified and differentiated in relation to the organism acting in the environment.” (Gallese; 2000)

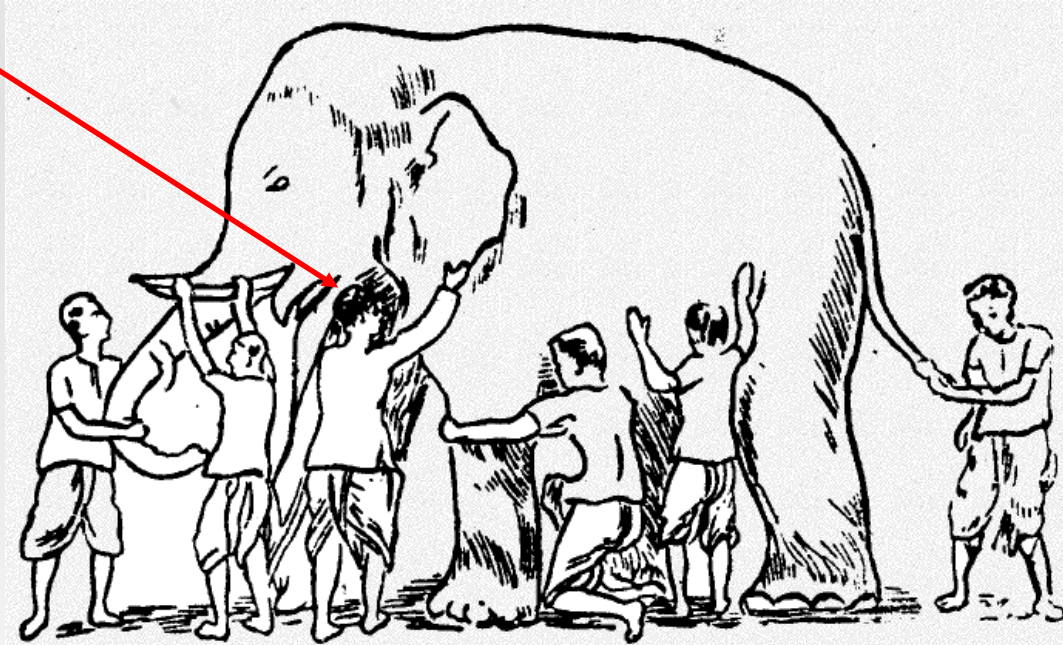


# Affordances and Elephants

## Human Computer Interaction



D.A.Norman,  
McFrenere &  
Ho



- “...affordance refers to the perceived and actual properties of the thing, primarily those fundamental properties that determine just how the thing could possibly be used.”
- “The designer cares more about what actions the user perceives to be possible than what is true.” (D.A.Norman; 1988)



# Affordances and Elephants

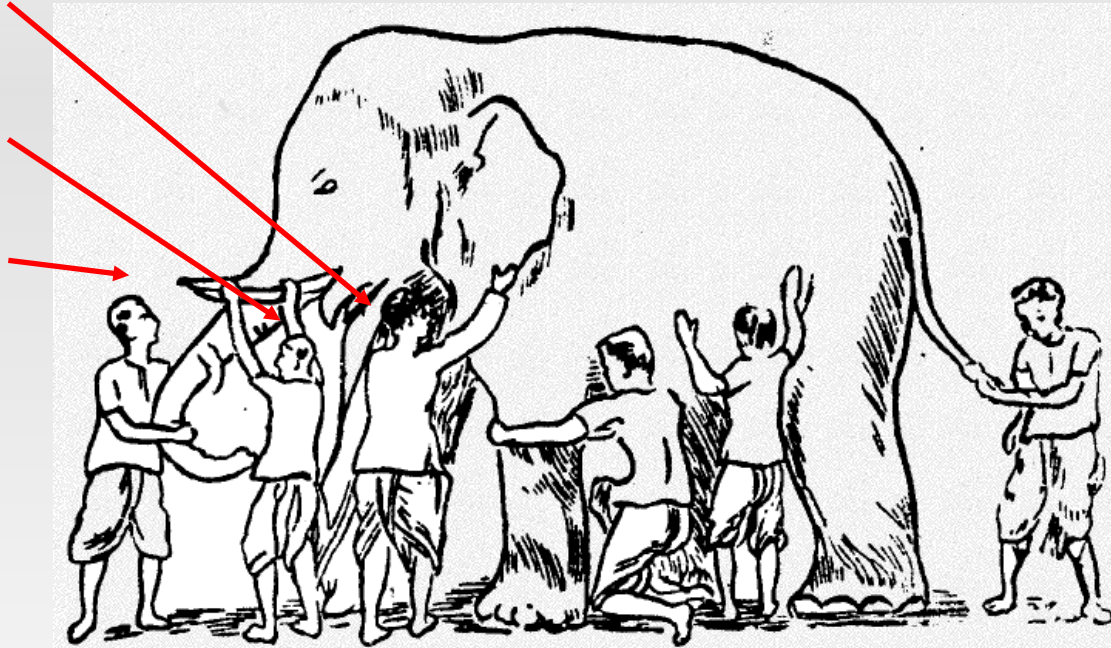
## Robotics



Arkin, Murphy,  
Duchon et al

Fitzpatrick et al,  
Stoytchev et al,

Cos-Aguilera et  
al, MacDorman

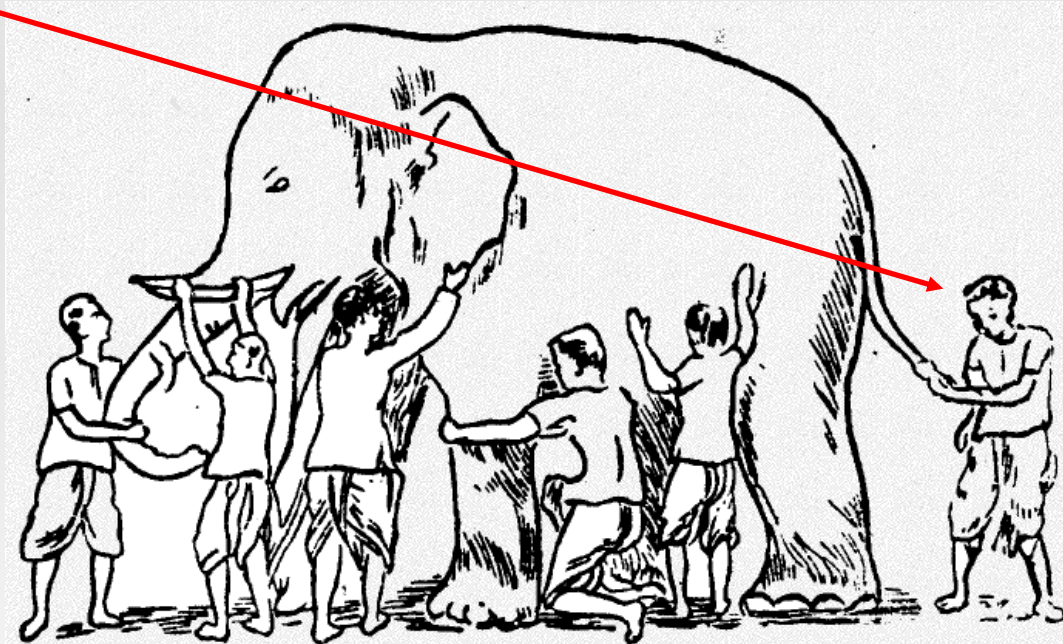


- Can guide the design of behaviors (Arkin, Murphy, Duchon et al.)
- affordance learning is referred to as the learning of the consequences of a certain action in a given situation (Fitzpatrick et al., 2003; Stoytchev, 2005a, 2005b).
- the learning of the invariant properties of environments that afford a certain behavior (Cos-Aguilera et al. 2003, 2004; MacDorman, 2000).

# Affordances and Elephants Planning



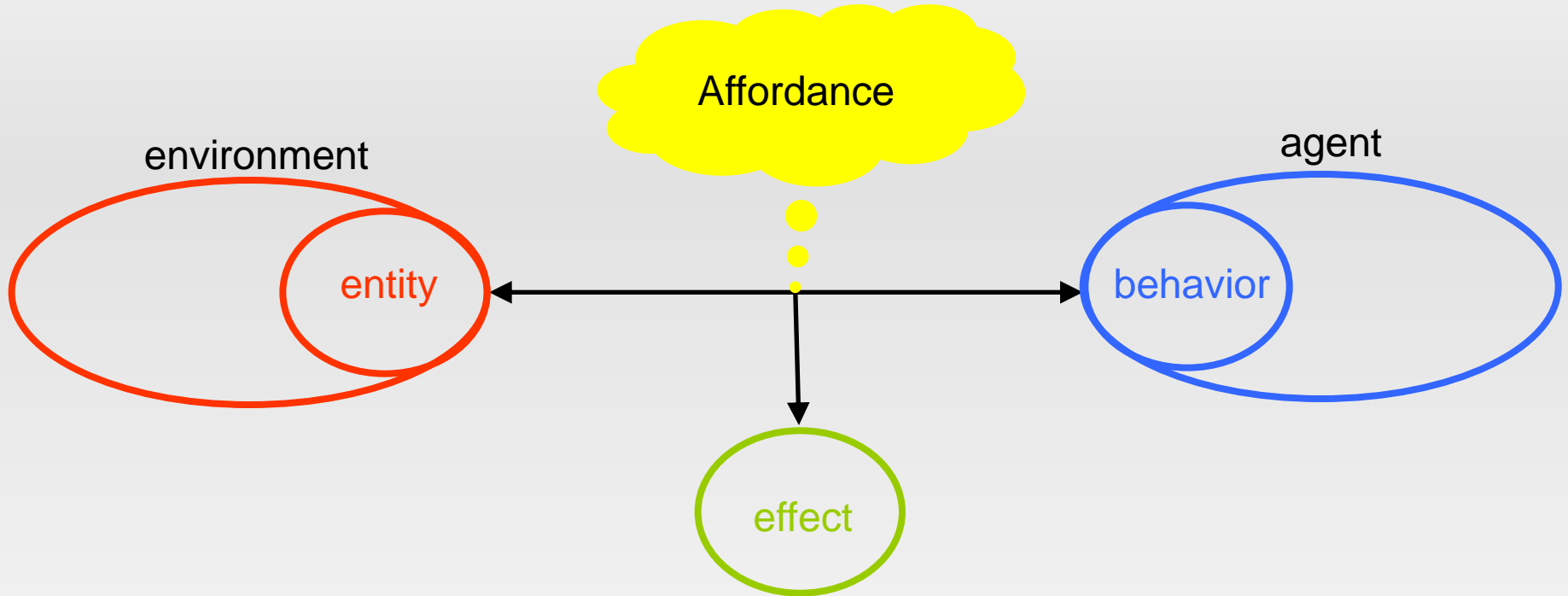
Steedman,  
Amant



- Affordances are related to planning.
- The different actions that are associated with a particular kind of object constitute the affordance-set
- A door is linked with the actions of “pushing” and “going-through,” and the preconditions and consequences of applying these actions to the door.



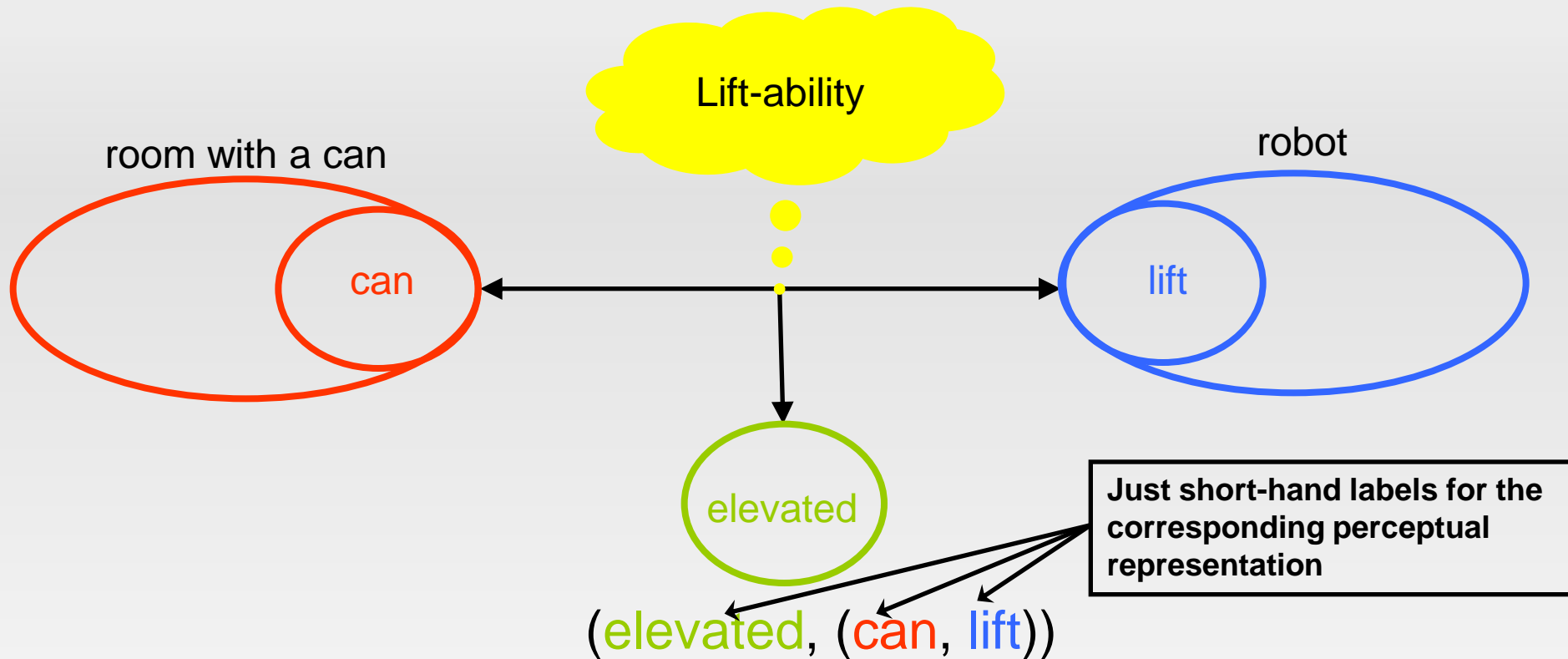
# Formalizing Affordance for Robotics



$(\text{effect}, (\text{entity}, \text{behavior}))$

Definition: An affordance is an acquired relation between a **behavior** of an agent and an **entity** in the environment such that the application of the behavior on the entity generates a certain **effect**.

# Cont'd



The robot applied its **lift** behavior on the **can** and obtained the **elevated** effect.

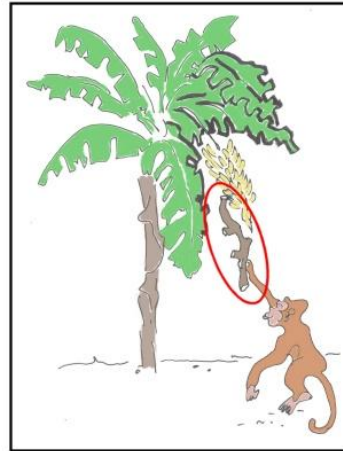
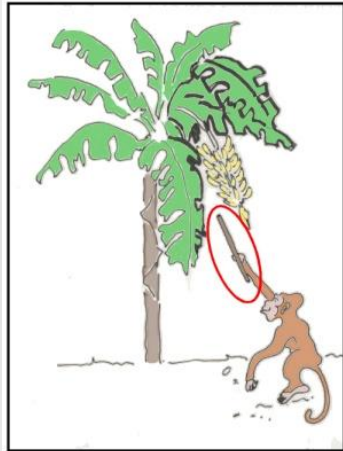
**Can**: The perceptual representation of the can as seen by the robot

**Lift**: The behavior executed by the robot

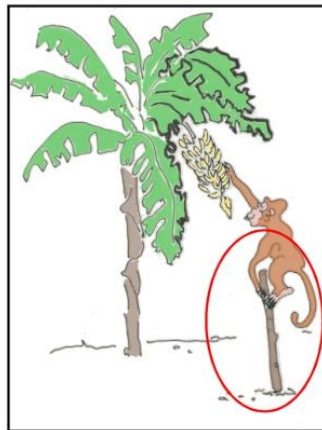
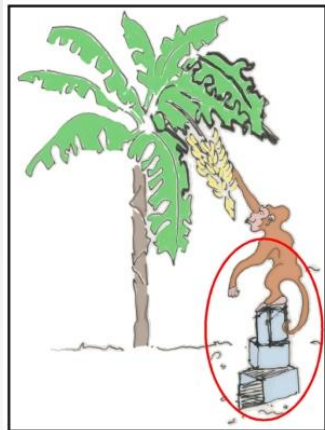
**Elevated**: The effect of the behavior on the environment as perceived by the robot.



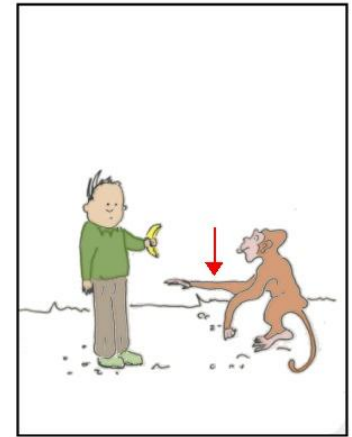
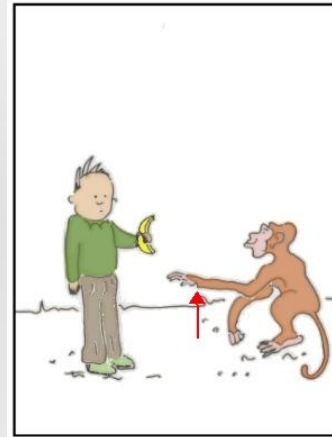
# Equivalence Classes



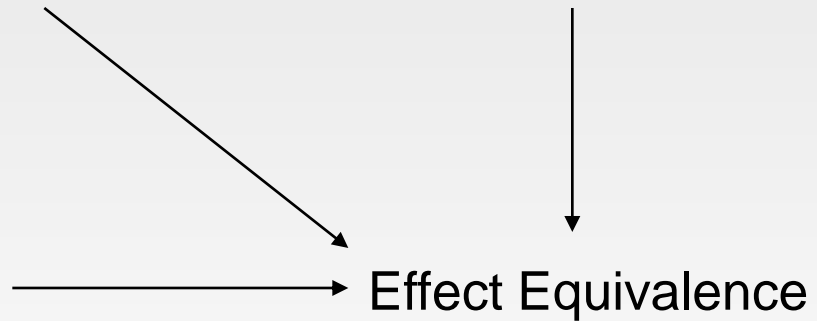
Entity Equivalence  
(effect, (<entity>, behavior))



Affordance Equivalence  
(effect, <(entity, behavior)>)



Behavior Equivalence  
(effect, (entity, <behavior>))



# Experimental Setup



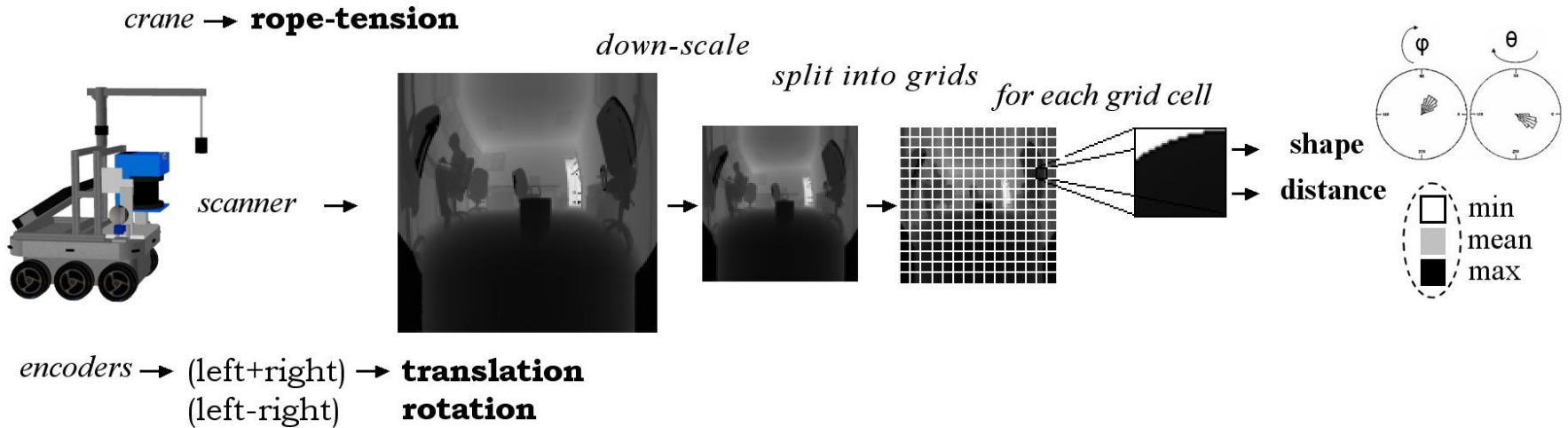
- 6 wheel, differential drive
- 3 DOF crane arm with electromagnetic gripper
- 3-D scanning with SICK laser range finder
  - $\sim 0.25^\circ$  angular resolution
  - 720x720 data points



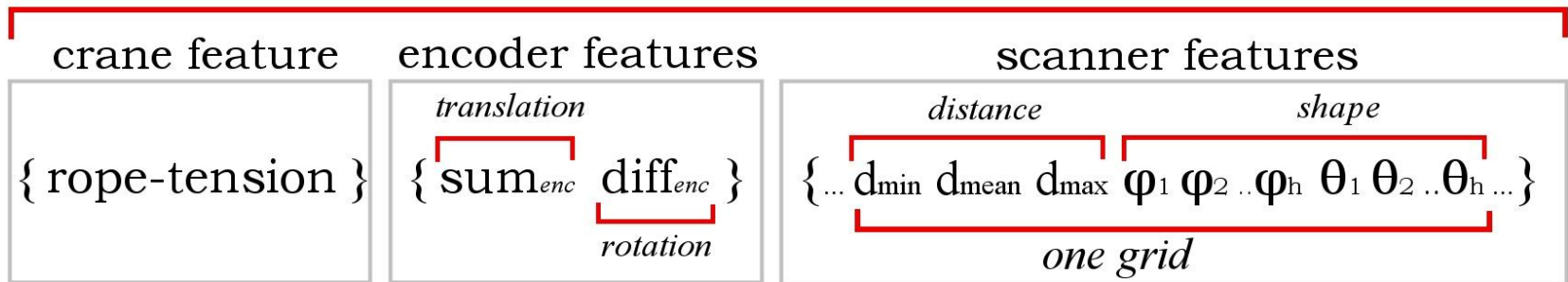
- MACSim : High-fidelity simulation environment
- ODE used as physics engine
- Sensors and actuators are calibrated



# Perceptual Features

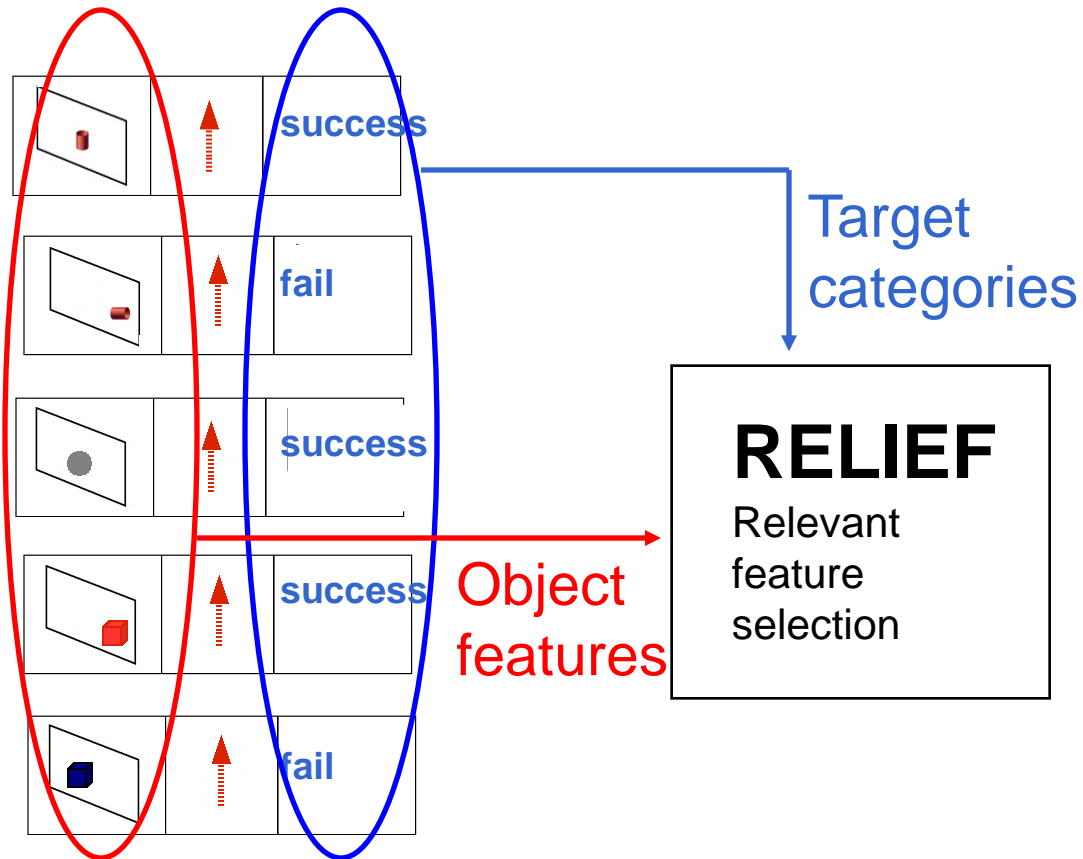


## features



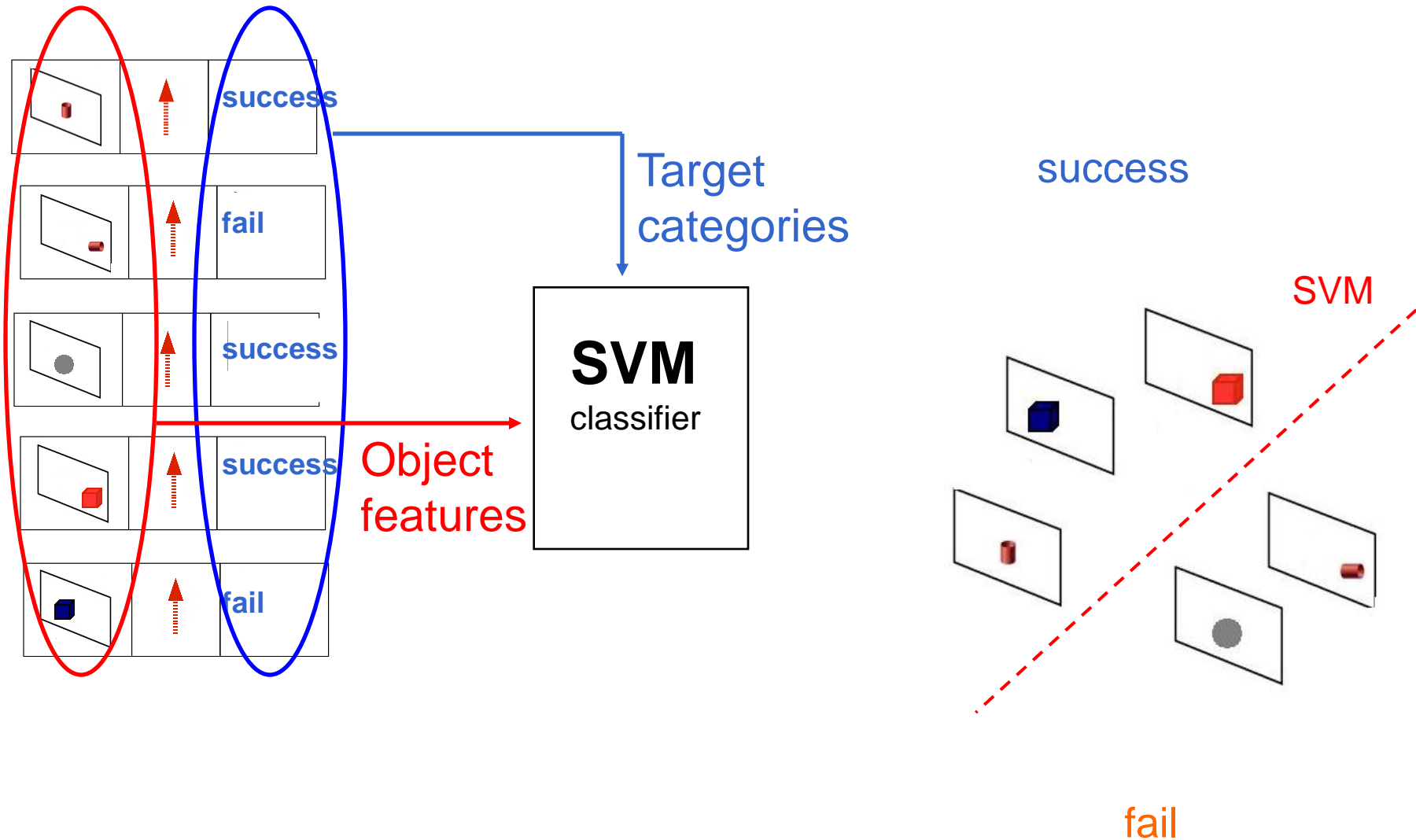
More than 30000 perceptual features!

# Learning invariant features

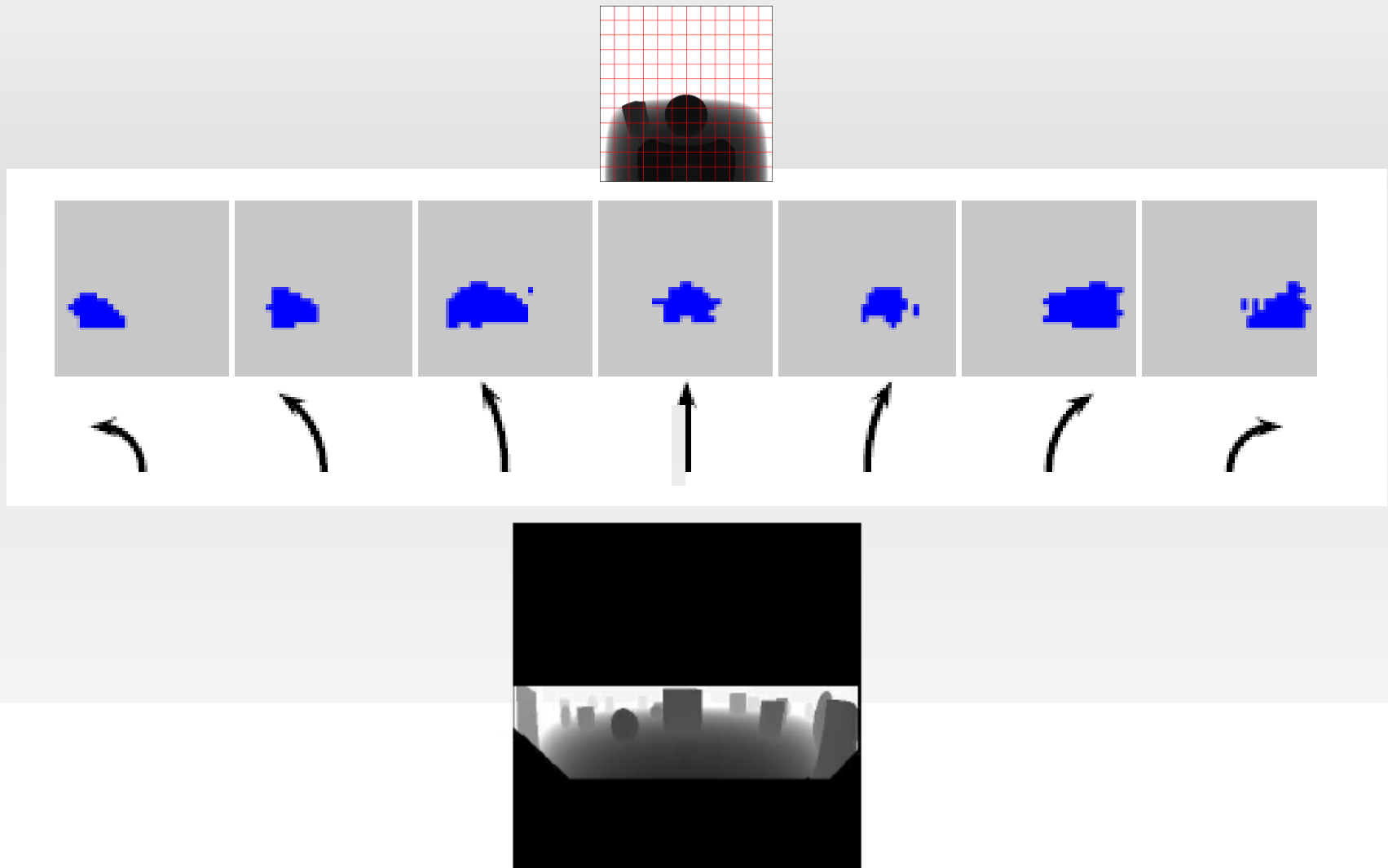




# Learning Entity equivalence classes



# Perceptual Economy



Only 1% of the features are relevant!

# Generalization



(a)



(b)



(c)



(d)

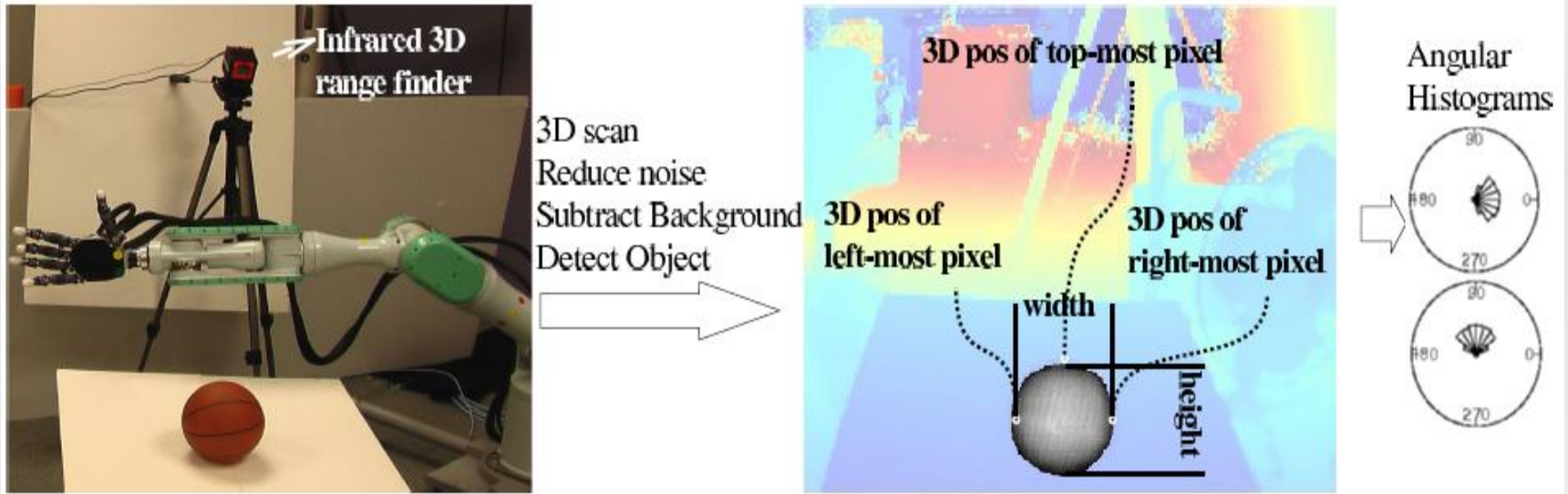


(e)



(f)

# Perception



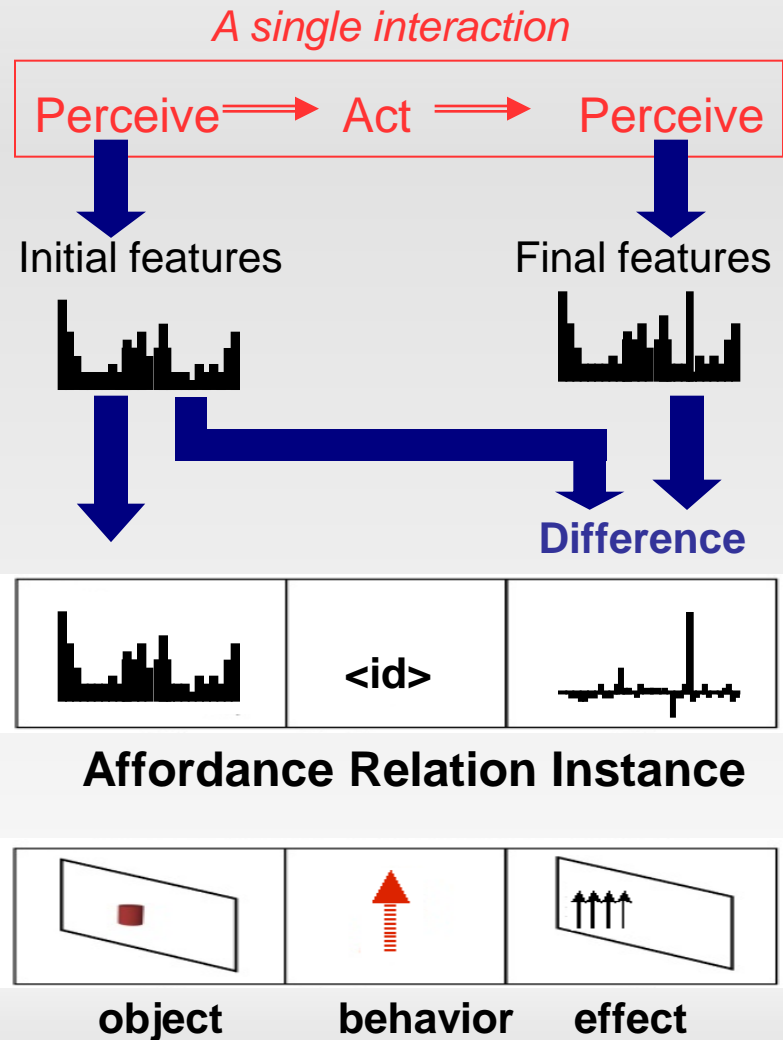
Feature vector for an object includes:

- **1 object visibility** feature
- **36 shape** related features (frequency values of angular histograms of normal vectors)
- **1 distance** related: avg. distance
- **4x3 position** related: boundary coordinates of region
- **3 size** related: width, height, and depth

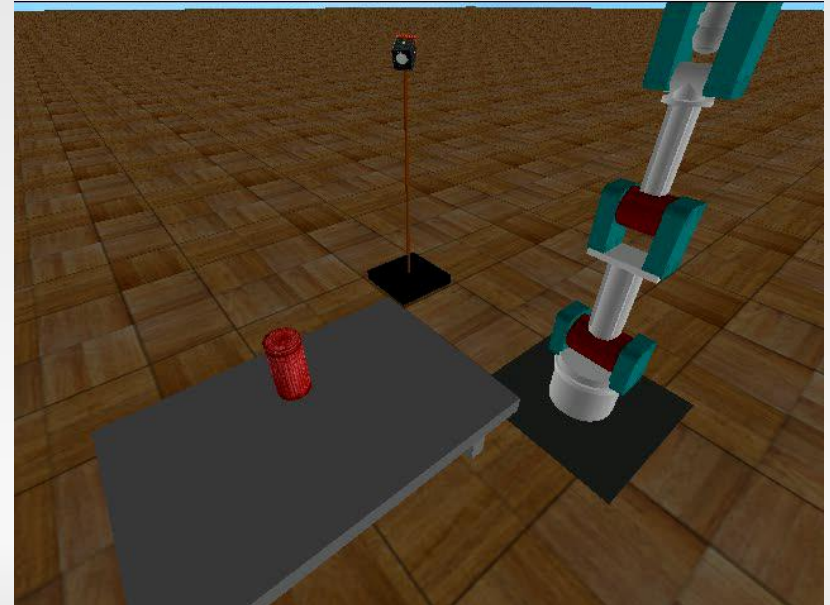




# Exploration Phase

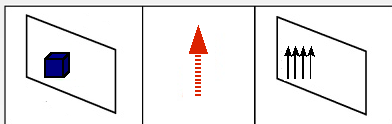
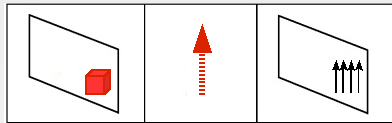
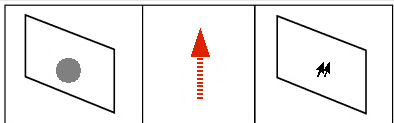
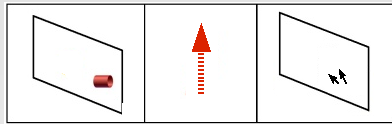
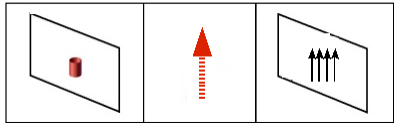


- Random orientation
- Random position
- 
- 1000 different interactions for each push and lift behavior





# Find Effect Categories

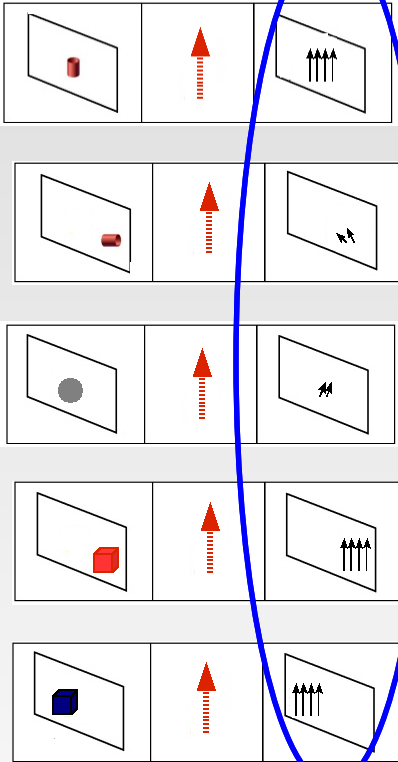


- Each behavior creates a number of qualitatively distinct effects
- Corresponds to different affordances
  - Grasp-ability, lift-ability
  - Push-ability, roll-ability, fall-ability
  - Reach-ability
- Effect categories: clustering in effect space

# Find Effect Categories



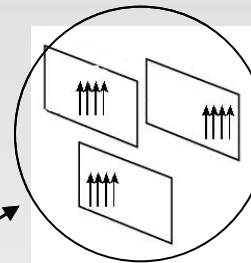
LIFT BEHAVIOR



⋮

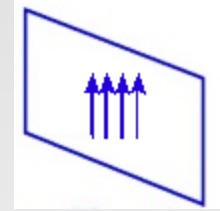
Clustering  
( $k=2$ )

Effect category  
id-1

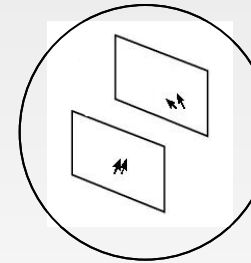


mean

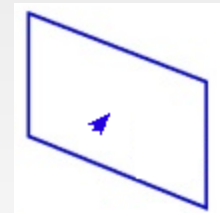
Effect  
prototype-1



Effect category  
id-2



mean

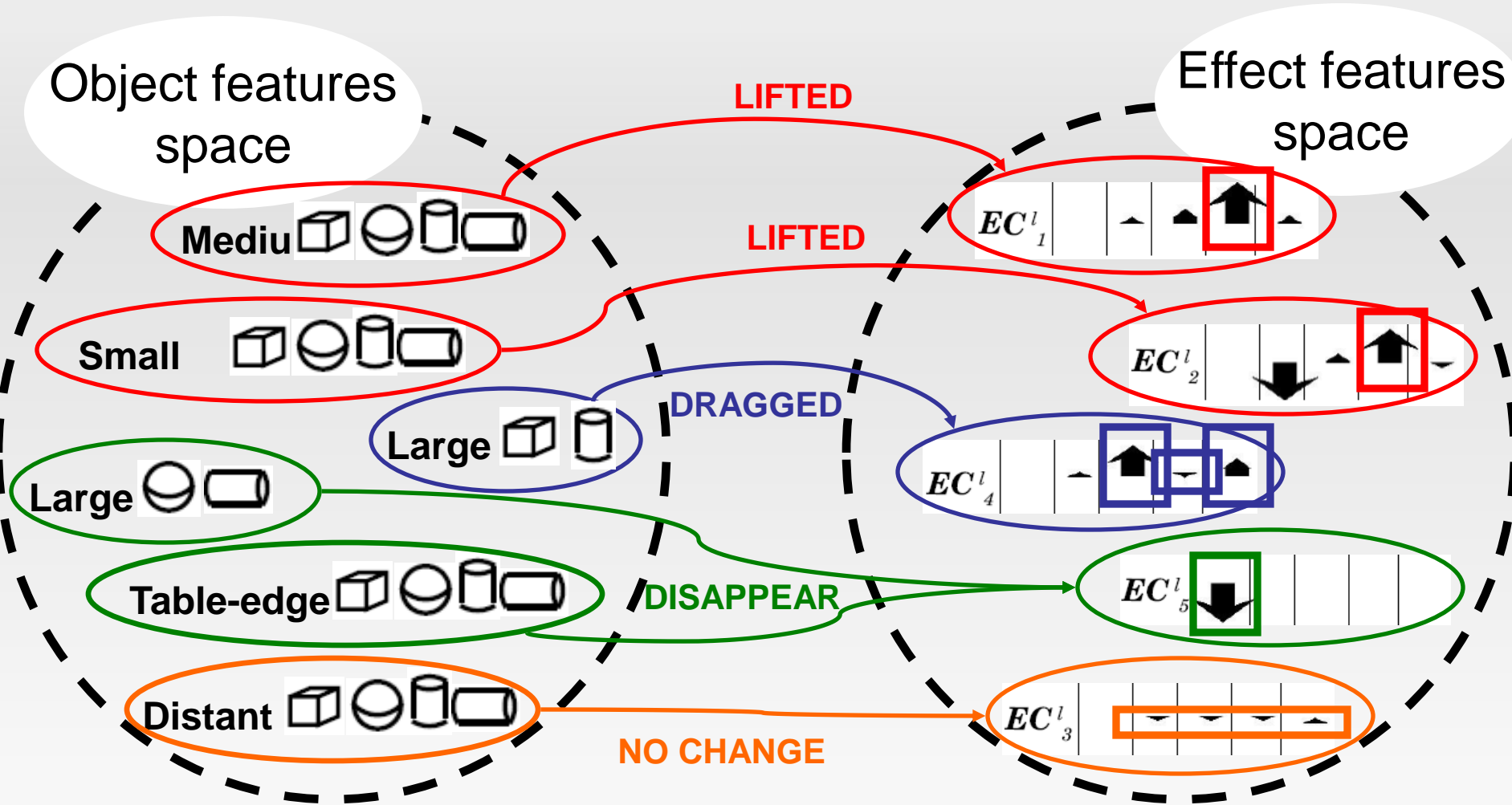


Effect  
prototype-2

No fail/success criteria!



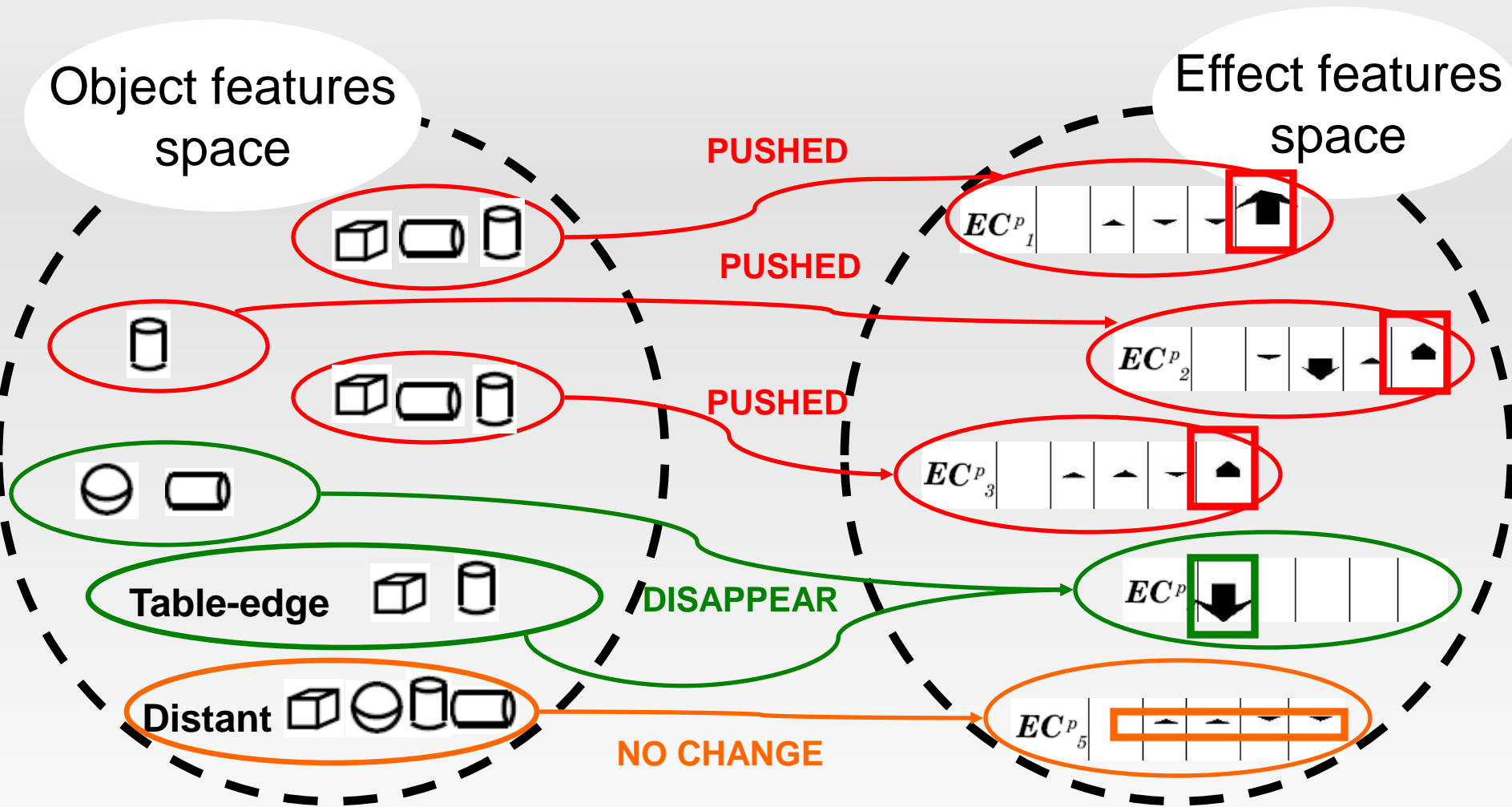
# Effect Categories for Lift



5 different effect categories are found by X-means



# Effect Categories for Push



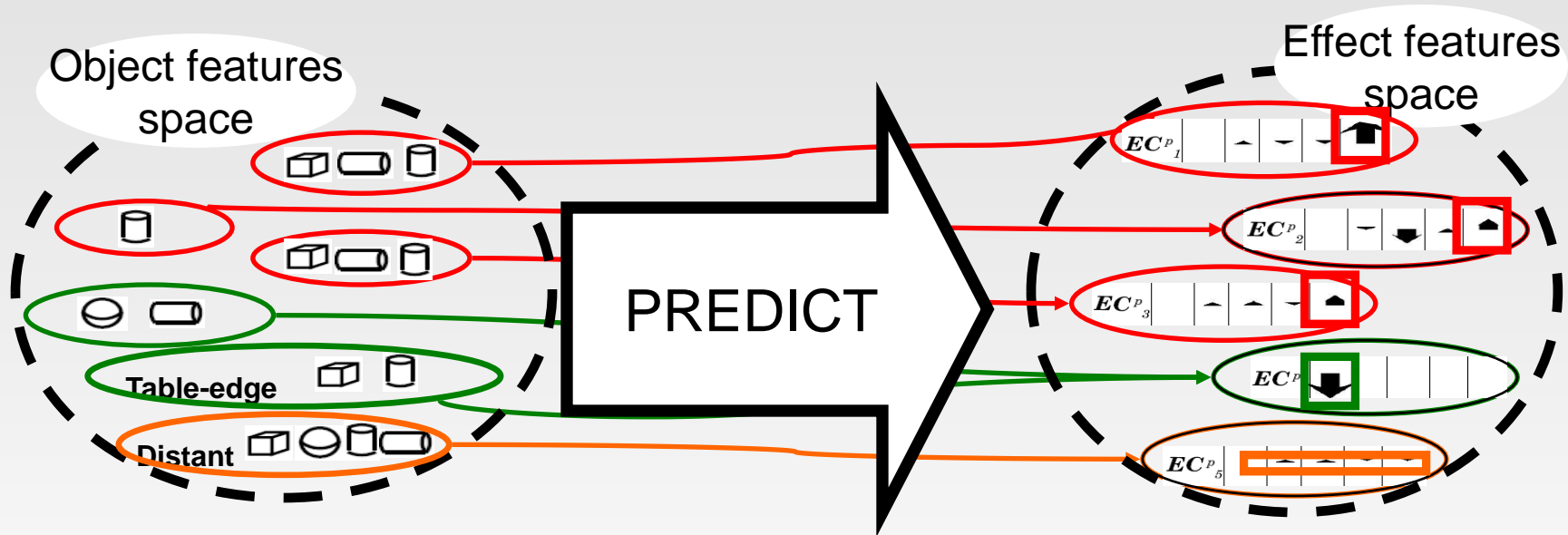
5 different effect categories are found by X-means





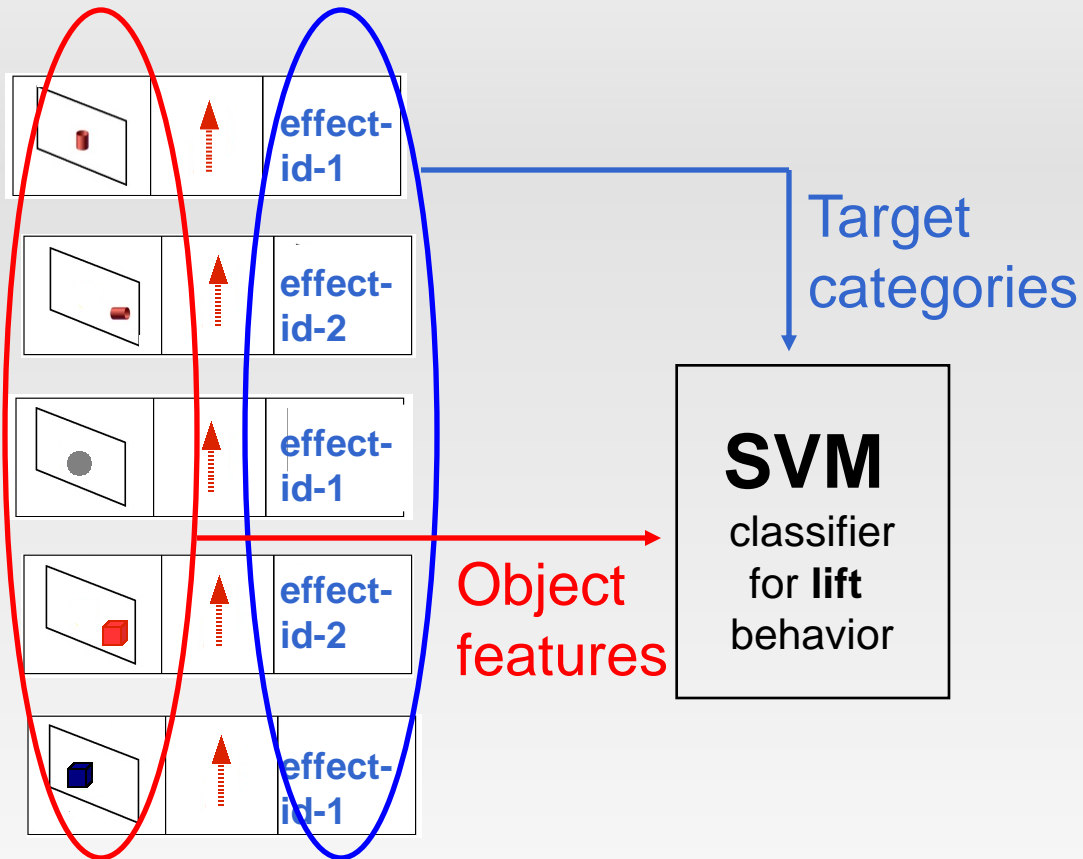
# Prediction is required for planning

- Given object features & behavior  
→ Predict effect category

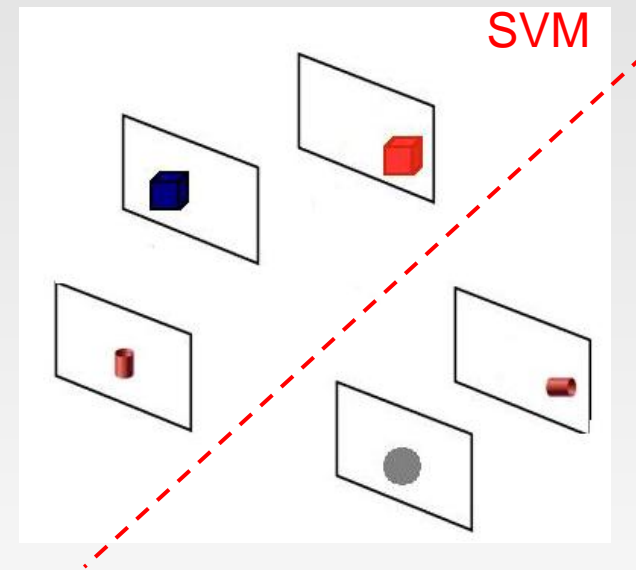
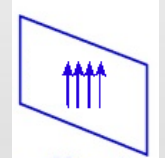


- Train a classifier for each behavior

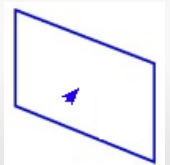
# Prediction of effect categories



Effect prototype  
for effect-id-1:

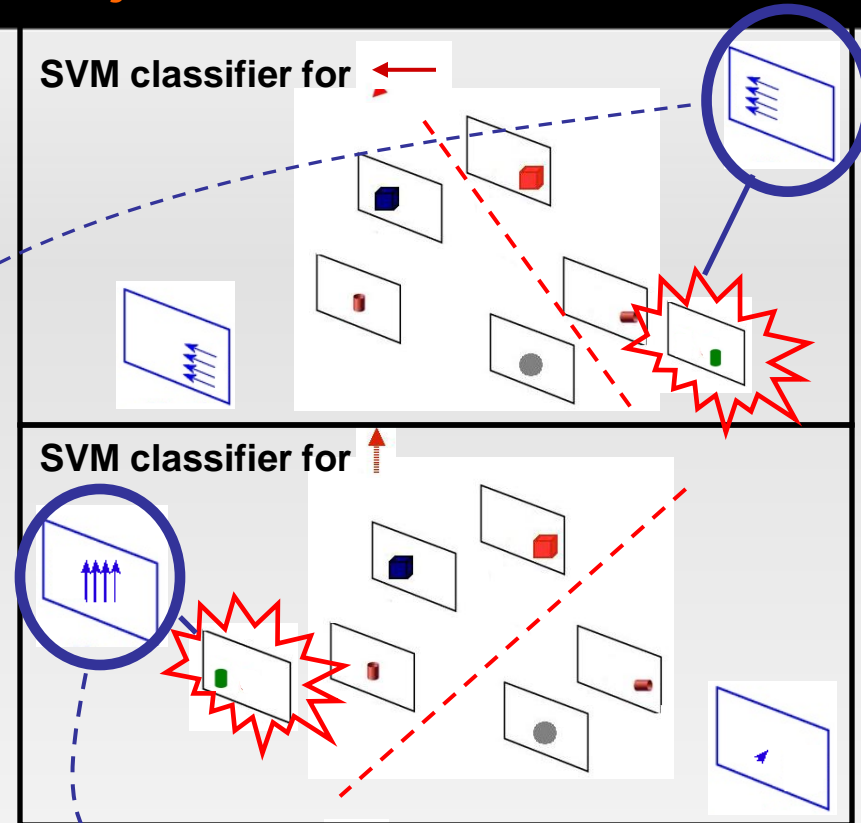
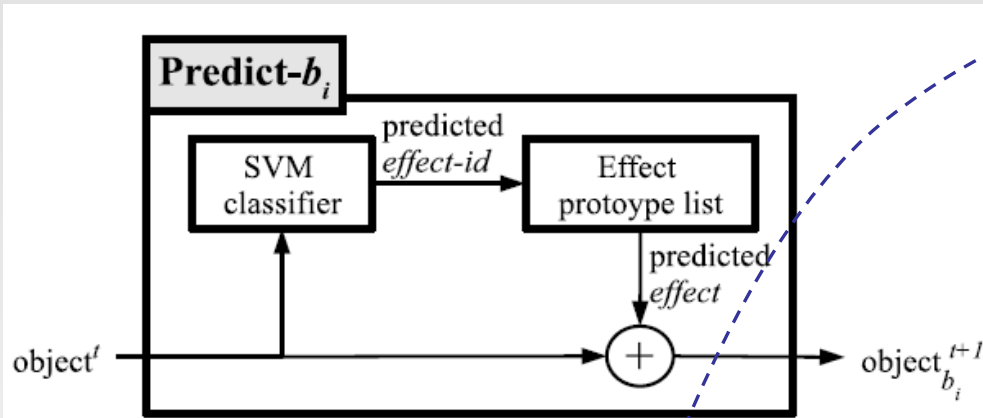


Effect prototype  
for effect-id-2:





# Prediction of Future Object Features



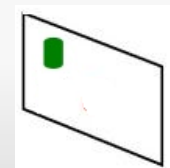
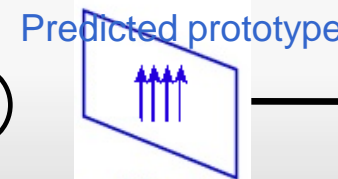
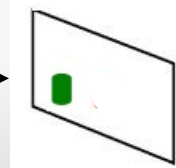
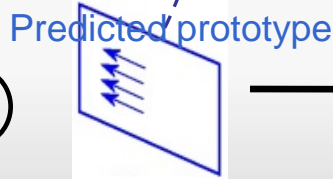
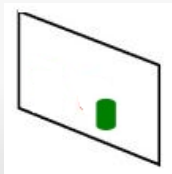
Initial object features

Push-left ←

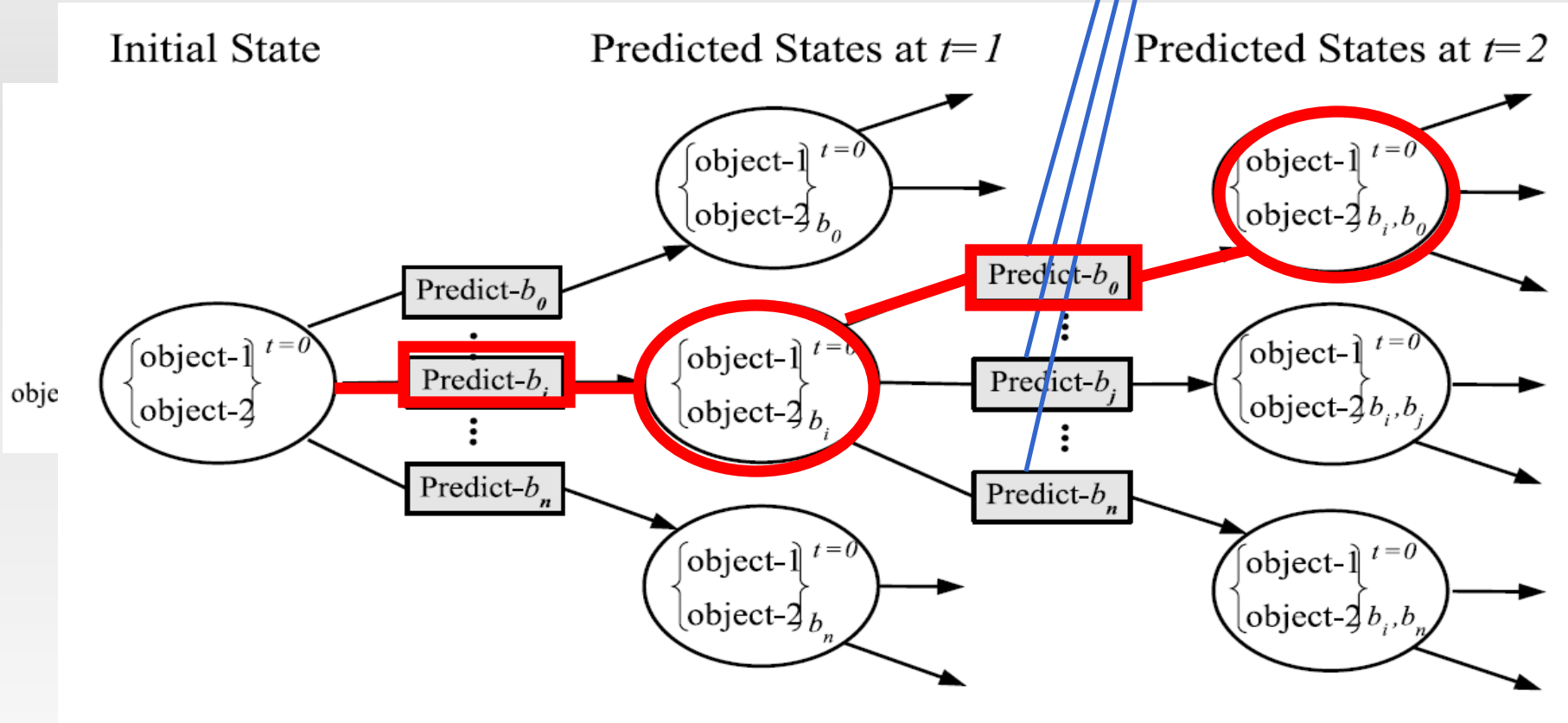
Predicted object features

Lift ↑

Predicted object features



# Forward chaining with



$$S_{\{b^1 \dots b^{t-1}\}}^t = [\mathbf{p}_{o_1, \{b^1 \dots b^{t-1}\}}^t \cdot \dots \cdot \mathbf{p}_{o_m, \{b^1 \dots b^{t-1}\}}^t]$$

# 1<sup>st</sup> Task: Keep table clean

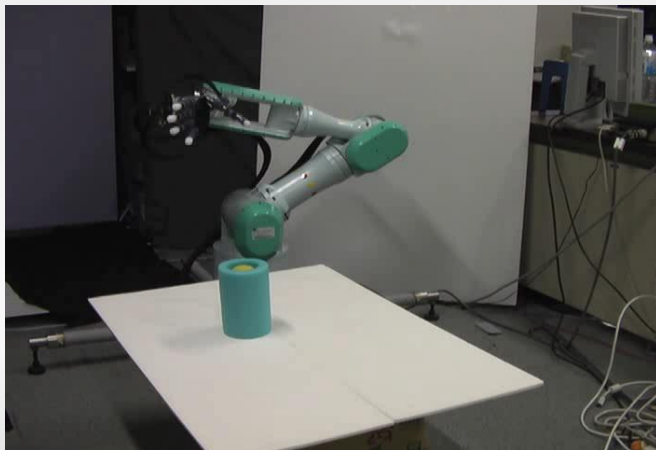
- Goal: A future object feature vector where *object-visible* feature is predicted to be 0 (false).

push-right



push-left

push-right



1. Push-left ?
2. Push-left ?
3. Push-left ?

1. Lift
2. Push-forward

**Release behavior emerges !**

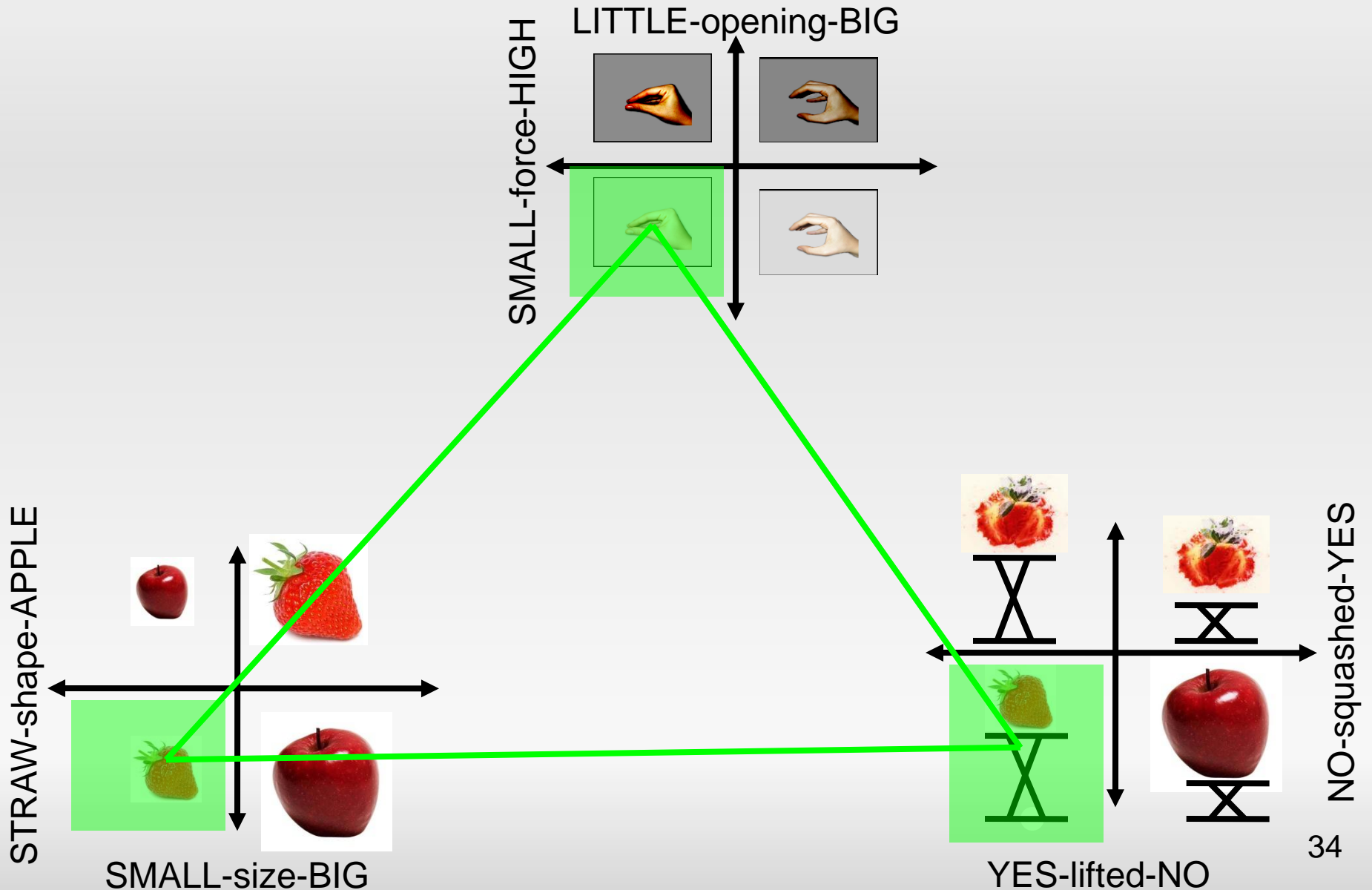


## 2<sup>nd</sup> Task: Bring the object to a target position

- Goal: A future object feature vector where *object-pos* feature is predicted to be in a certain range.

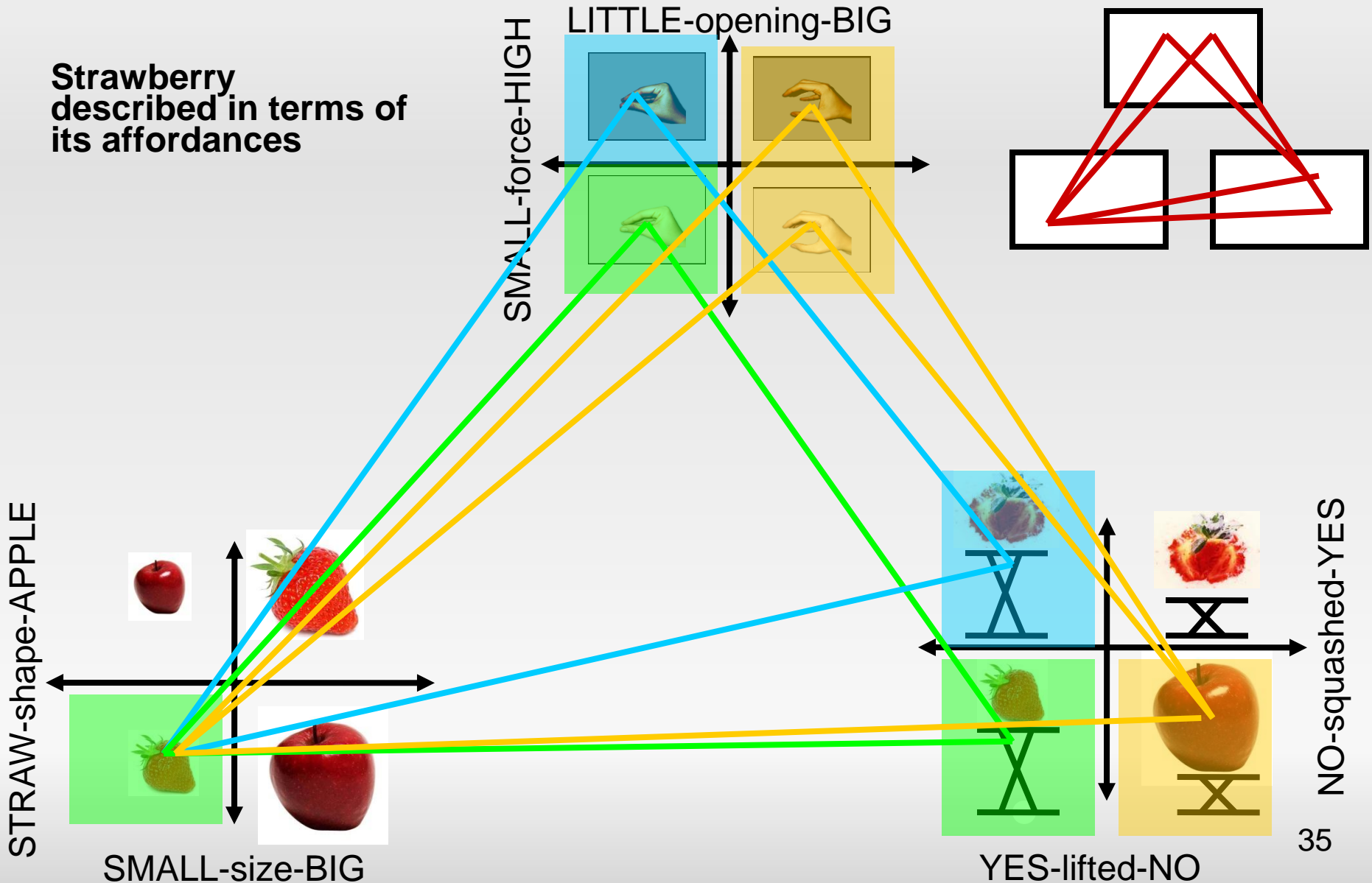


# Affordances as relations



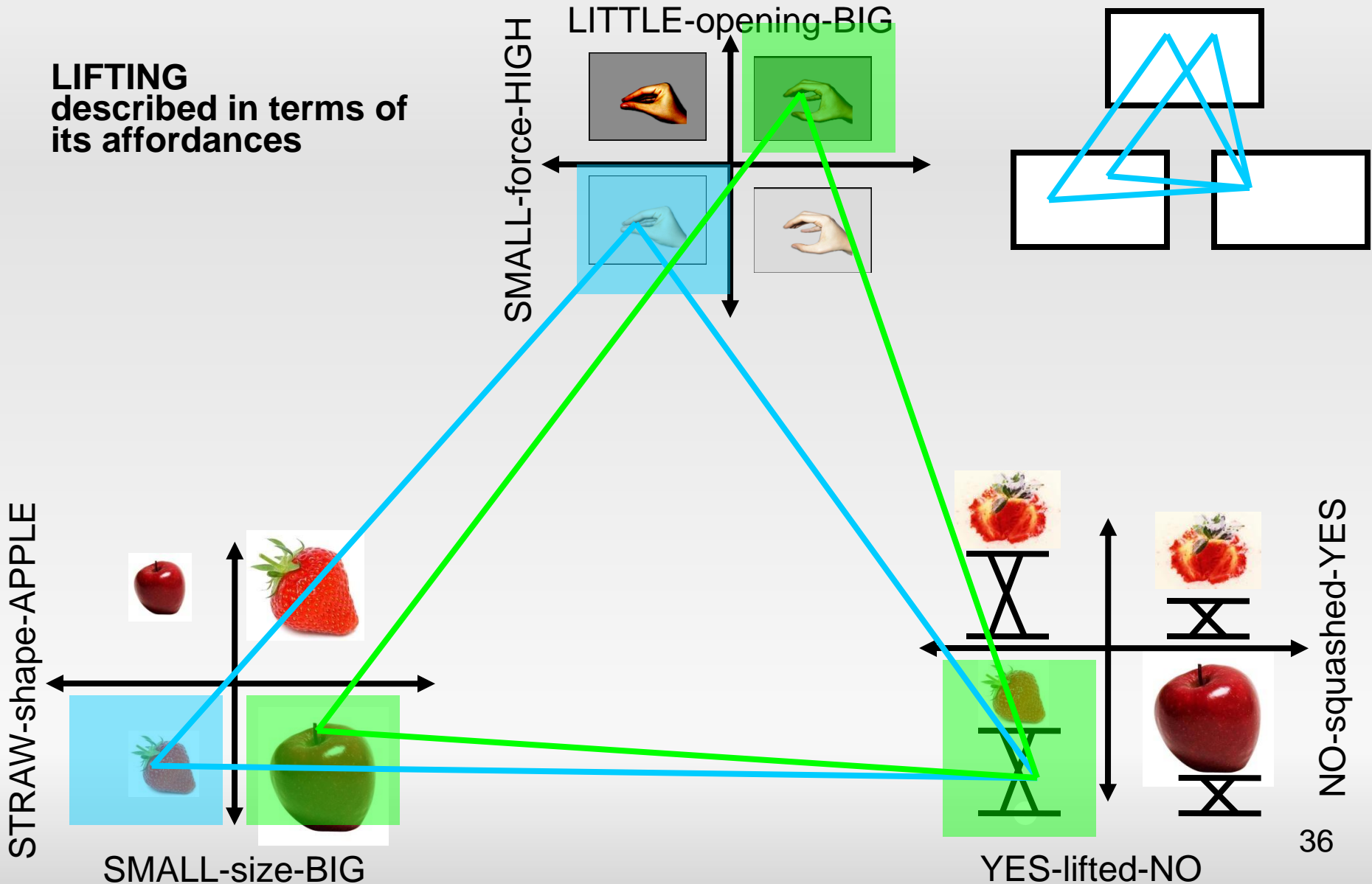
# The concept of a strawberry

Strawberry described in terms of its affordances



# The concept of lifting

**LIFTING**  
described in terms of  
its affordances





# Acknowledgements



Emergence of communication in RObots through  
Sensorimotor and Social Interaction



This project is also partially funded by TUBITAK through Project 109E033.



We also acknowledge Maya Cakmak and Mehmet R. Dogar for conducting prior studies that this study is based on.