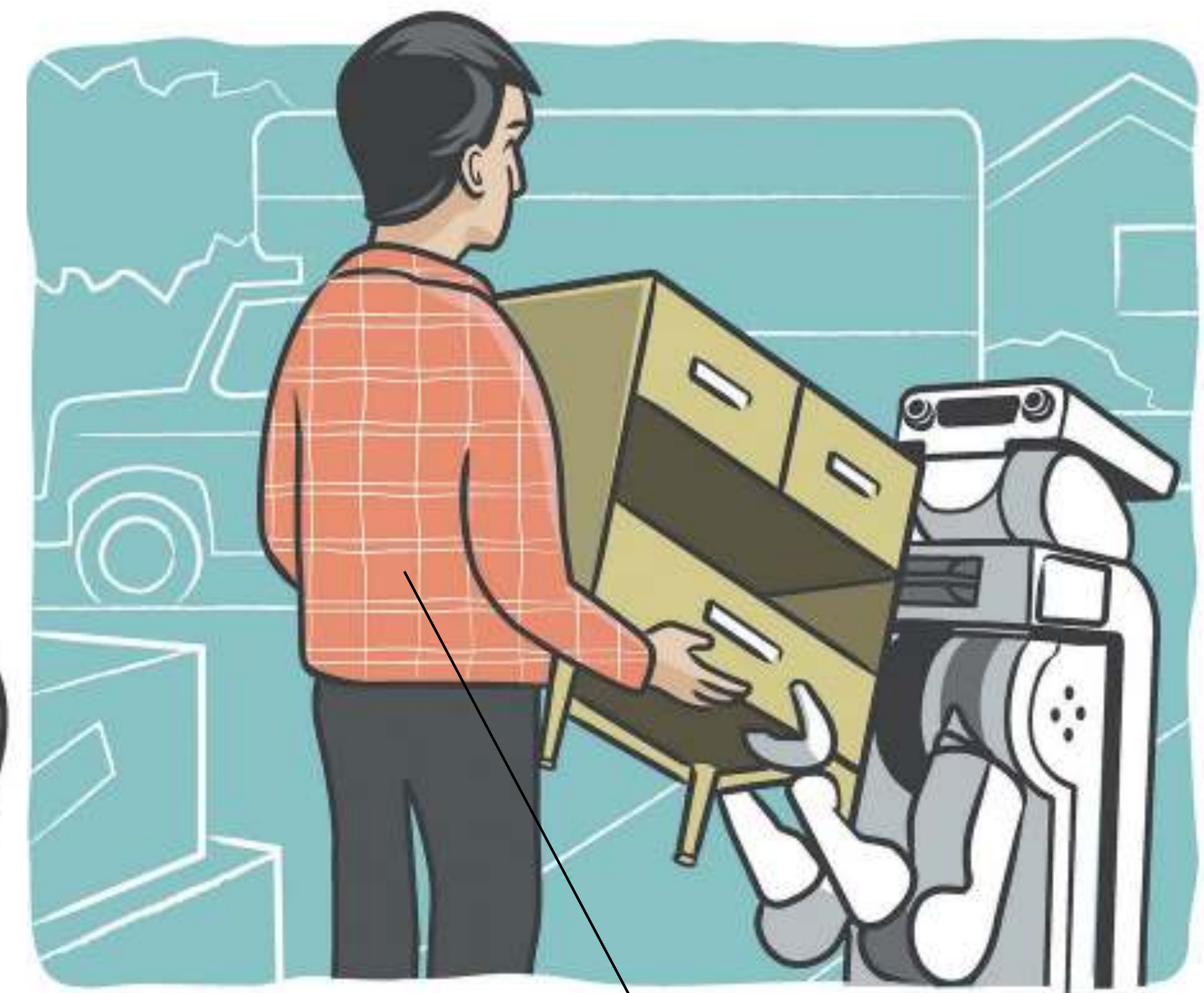
SPECIAL TOPICS: HUMAN-ROBOT INTERACTION

Maya Cakmak

HUMAN-ROBOT INTERACTION

GOAL: More **effective** and **intuitive** interactions

commanding a robot



collaborating with a robot

Illustrations by **Josh Ellingson**

HUMAN-ROBOT INTERACTION

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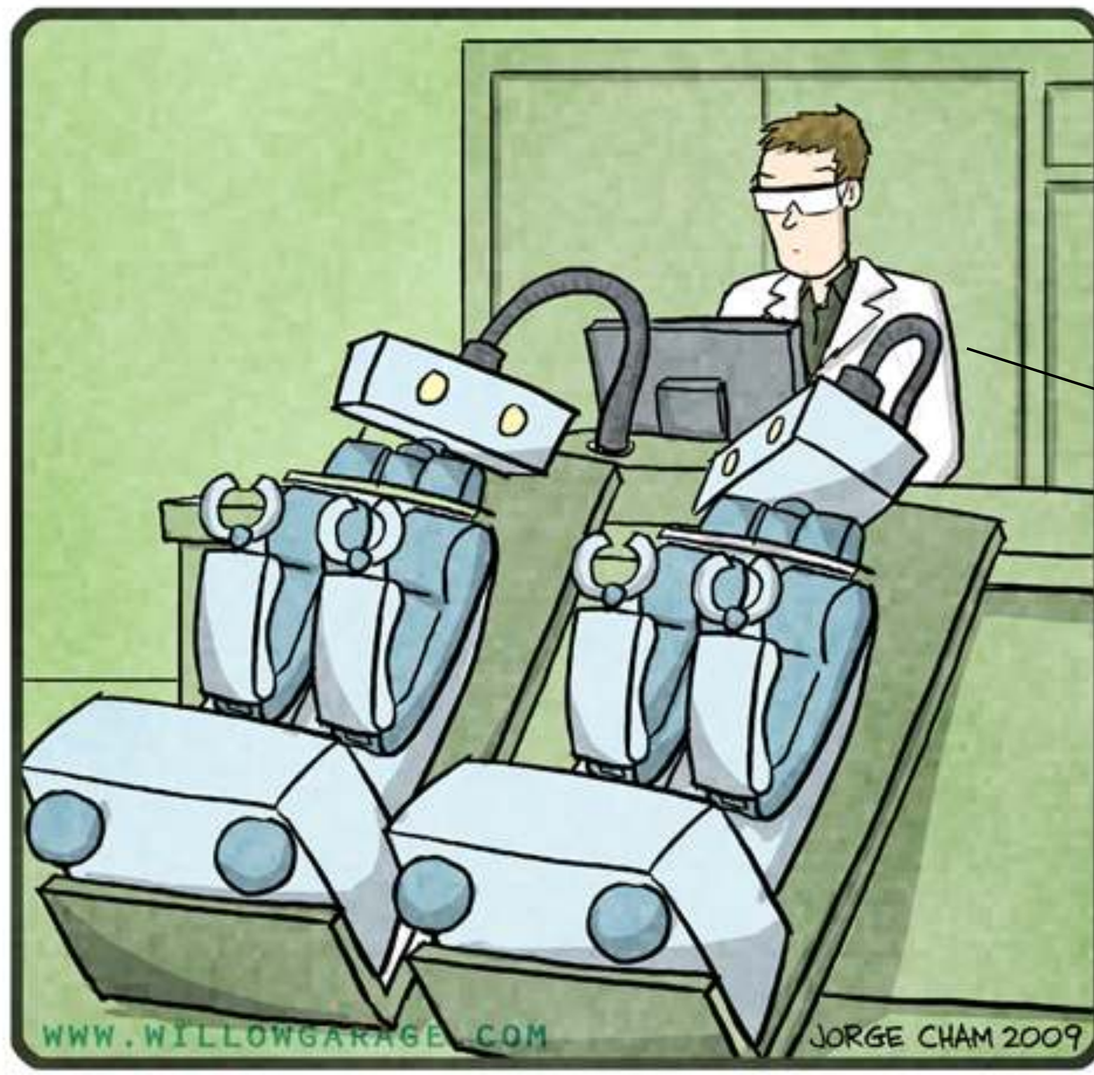
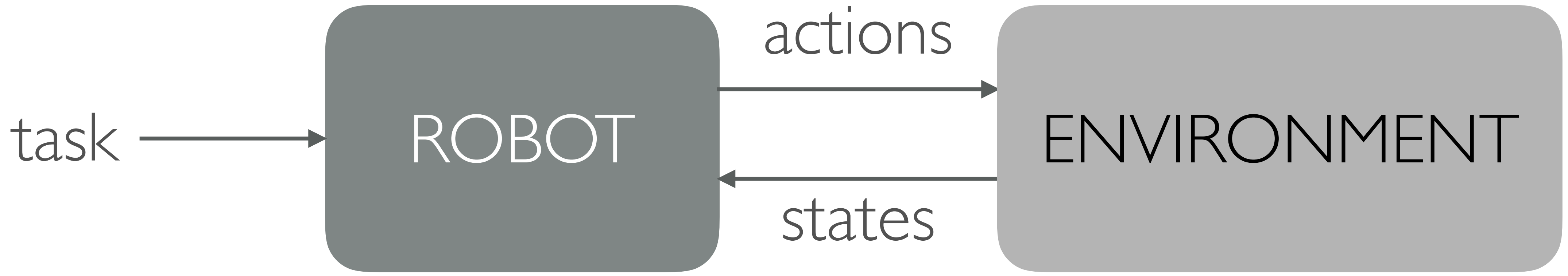
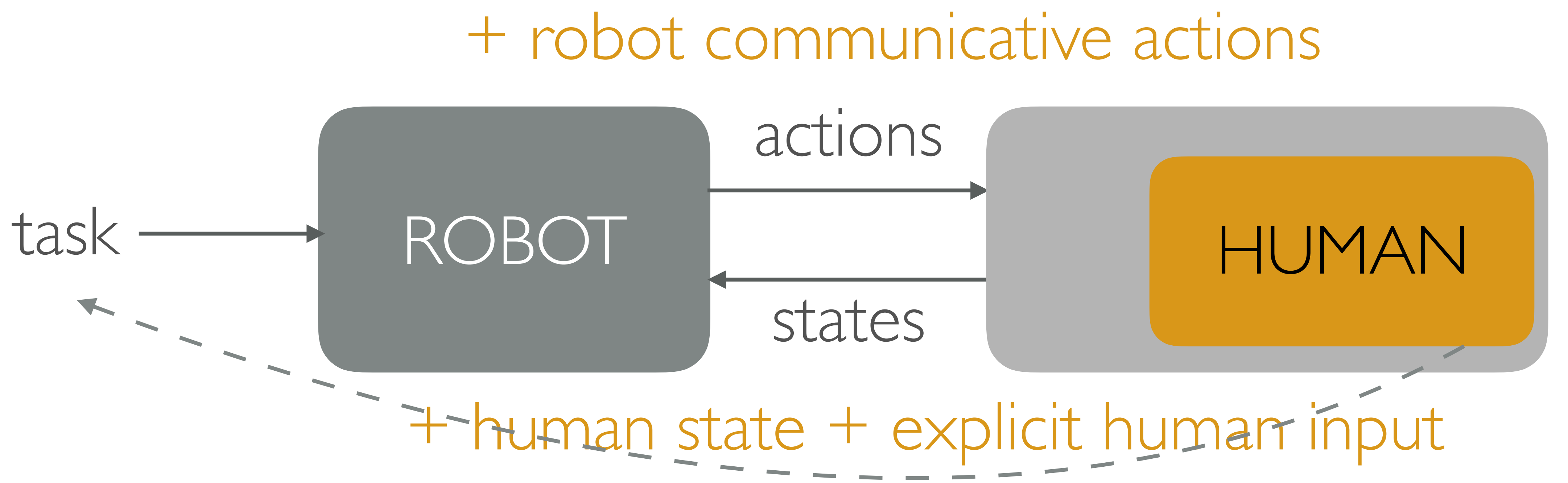


***programming** a robot*

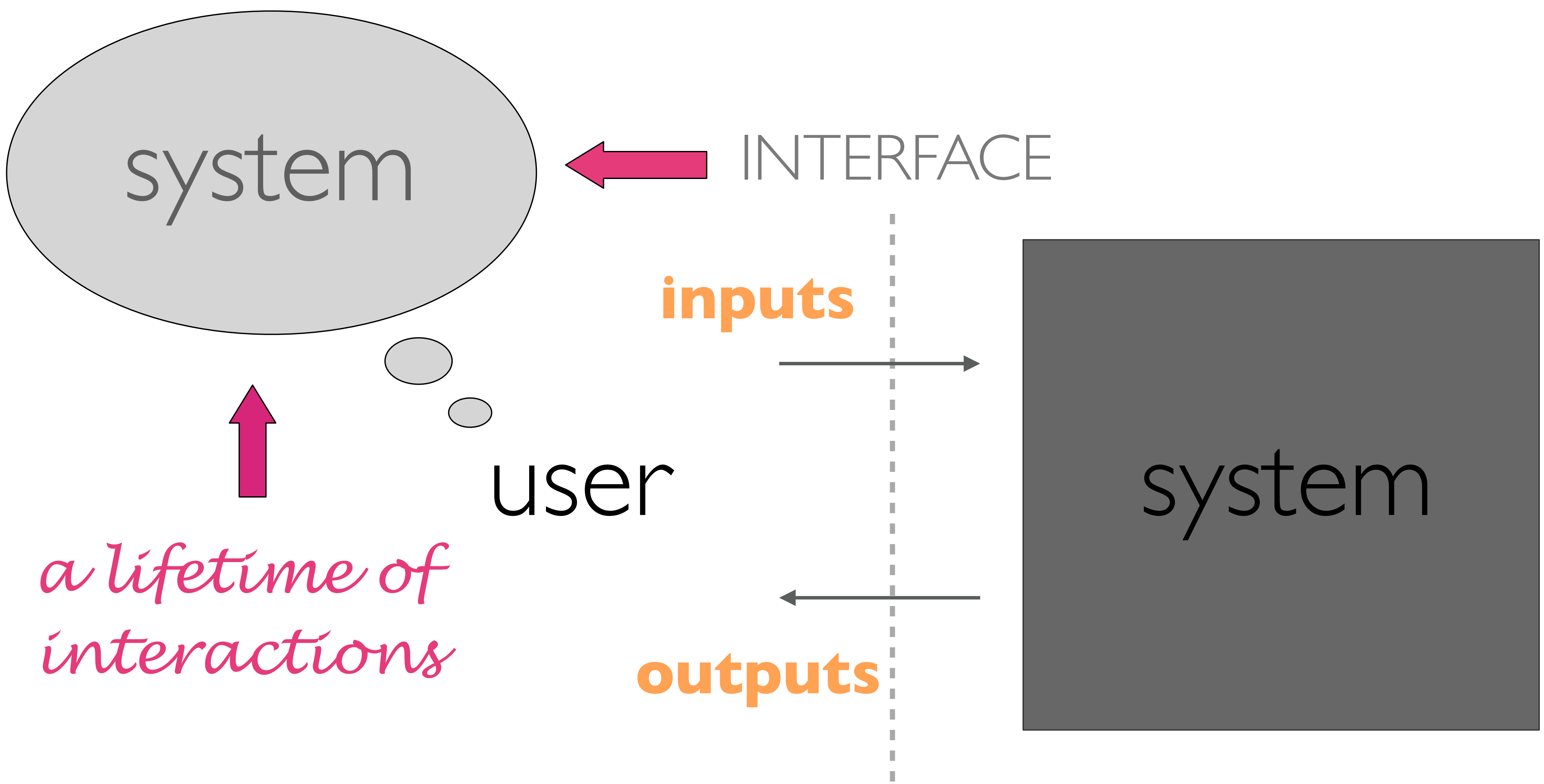
Illustration by **Jorge Cham**

HRI -VS- ROBOTICS





HRI -VS- HCI


system
INTERFACE
inputs
user
system
a lifetime of interactions
outputs

ANTHROPOMORPHISM

- the tendency to attribute human characteristics to inanimate objects, animals and others

HUMAN-ROBOT INTERACTION TAXONOMY

H. Yanko and J. Drury "Classifying Human-Robot Interaction: An updated taxonomy" IEEE International Conference on Systems, Man and Cybernetics, 2004.

- TASK, CRITICALITY
- ROBOT-MORPHOLOGY
- HUMAN-ROBOT-RATIO
- ROBOT-TEAM-COMPOSITION
- SHARED-INTERACTION-LEVEL
- INTERACTION-ROLES
- PHYSICAL-PROXIMITY
- AVAILABLE-SENSORS, PROVIDED-SENSORS, SENSOR-FUSION, PRE-PROCESSING
- TIME, SPACE
- AUTONOMY, INTERVENTION

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- TIME, SPACE
- AUTONOMY, INTERVENTION

- task: urban search&rescue, walking aid for the blind, toy, delivery robot
- criticality: high, medium low

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- AUTONOMY, INTERVENTION

- # of humans/# of robots
- homogeneous, heterogeneous

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- ROBOT-TEAM-COMPOSITION
- **SHARED-INTERACTION-LEVEL**

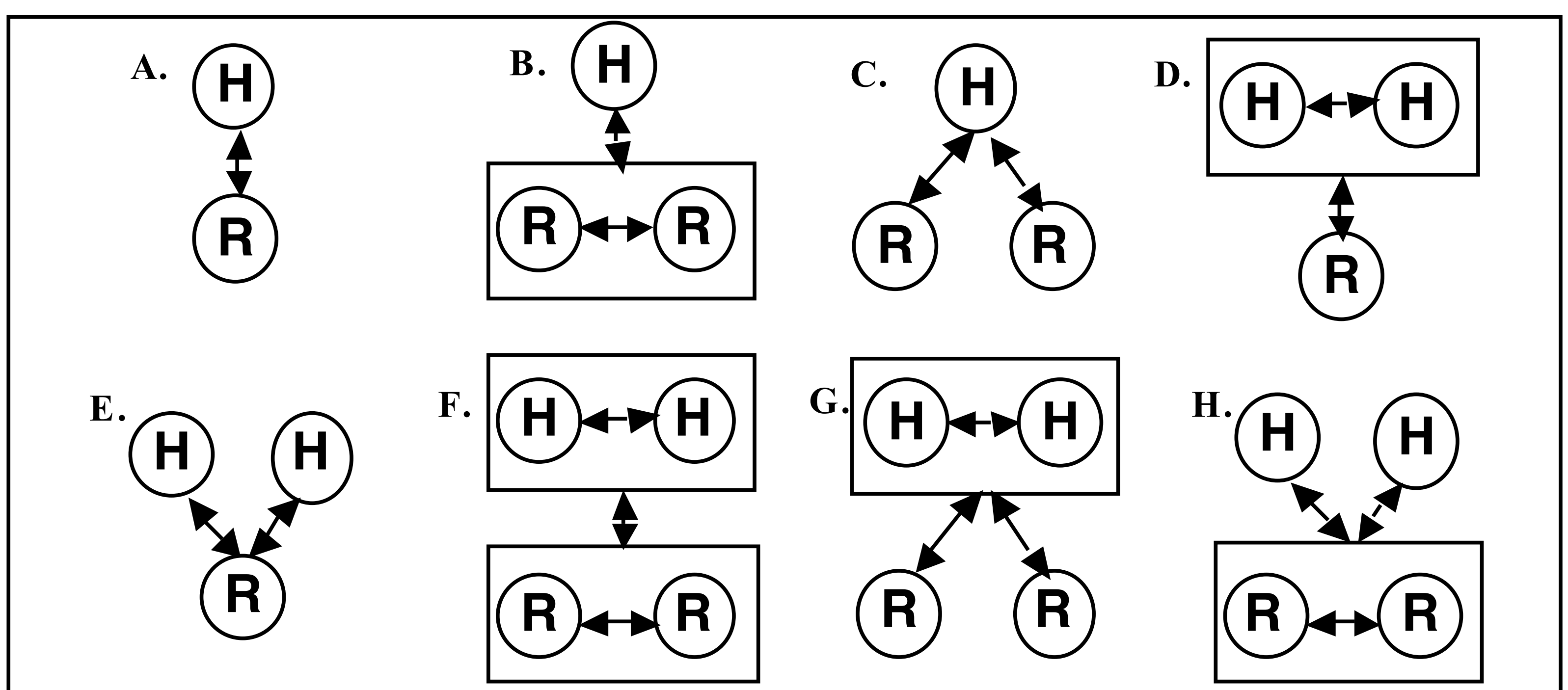

Figure 1. The possible combinations of single or multiple humans and robots, acting as individuals or in teams.

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- HUMAN-ROBOT-RATIO
- ROBOT-TEAM-COMPOSITION
- SHARED-INTERACTION-LEVEL
- **INTERACTION-ROLES**
  - supervisory, operator, teammate, mechanic/programmer, bystander
- PHYSICAL-PROXIMITY
- AVAILABLE-SENSORS, PROVIDED-SENSORS, SENSOR-FUSION, PRE-PROCESSING
- TIME, SPACE
- AUTONOMY, INTERVENTION

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- ROBOT-MORPHOLOGY
- HUMAN-ROBOT-RATIO
- ROBOT-TEAM-COMPOSITION
- SHARED-INTERACTION-LEVEL
- INTERACTION-ROLES
- **PHYSICAL-PROXIMITY**
  - avoiding, passing, following, approaching, touching, none (not co-located)
- AVAILABLE-SENSORS, PROVIDED-SENSORS, SENSOR-FUSION, PRE-PROCESSING
- **TIME, SPACE**
  - synchronous, asynchronous
  - co-located, non-co-located
- AUTONOMY, INTERVENTION

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- SHARED-INTERACTION-LEVEL
- INTERACTION-ROLES
- PHYSICAL-PROXIMITY
- AVAILABLE-SENSORS…
- TIME, SPACE
- **AUTONOMY, INTERVENTION**

- adjustable autonomy
- sliding-scale autonomy
- mixed-initiative
- supervised autonomy
- symbiotic autonomy

TOPIC 1

ROBOTS LEARNING FROM HUMANS

VISION

End-user programmable general-purpose robots

VISION

End-user programmable general-purpose robots

BAXTER, RETHINK

"Baxter ***can be taught*** *via a GUI and through direct manipulation of its robot arms. That means* ***non-technical, hourly workers*** *can train and retrain it right on the line."*

GP8 PALLET, SEEGRID

"it is ***very easy to train the robot*** *by simply first* ***walking it through*** *the route it is to take, load an item it is designed to transport and then push the 'go to work' button"*

WHY IS IT IMPORTANT?

Because **we cannot predict**...

- variability in conditions
- what users want
- how they want it done

WHY IS IT CHALLENGING?

Existing tools assume **good teachers**...

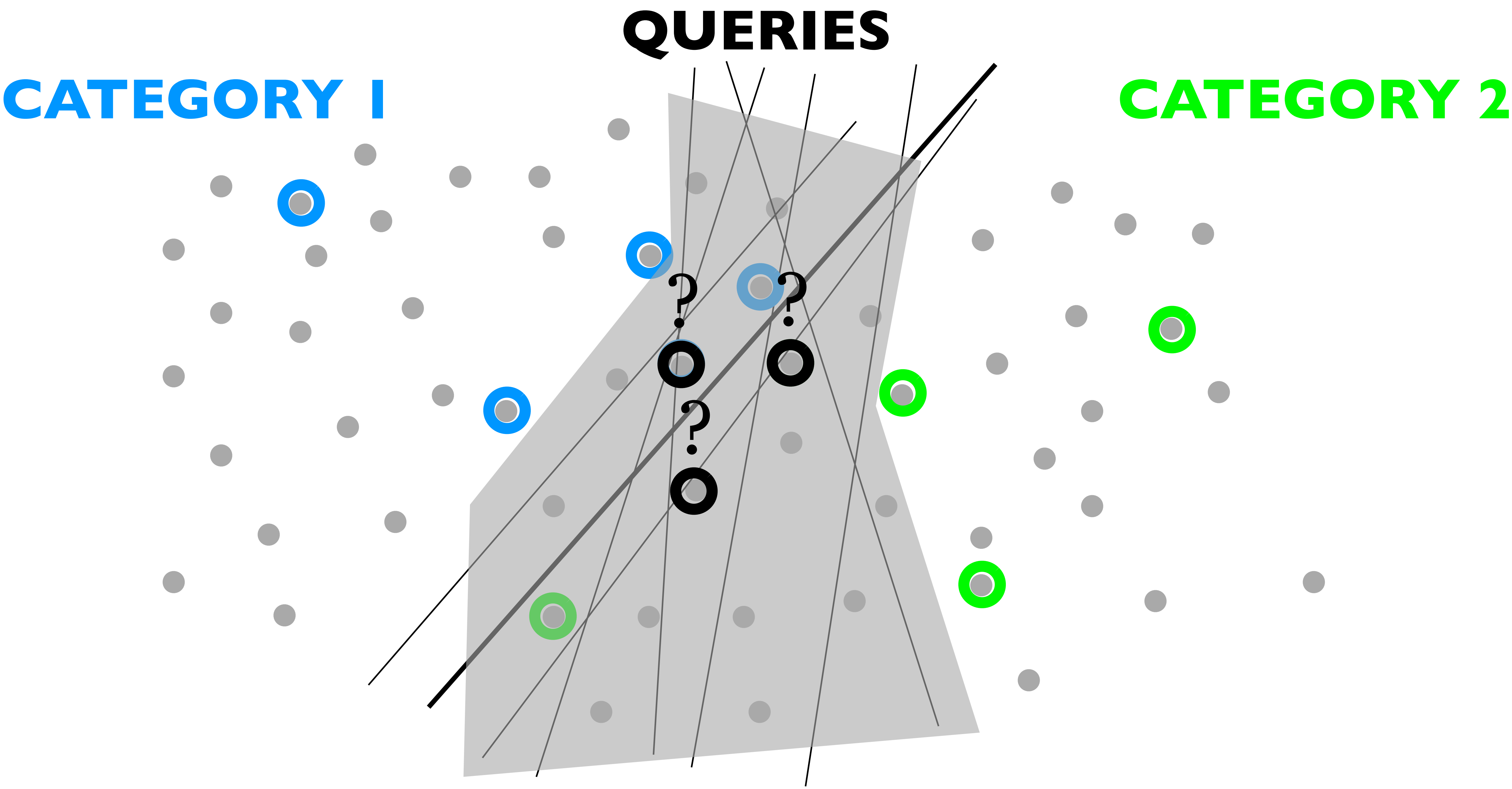
- large number of demos
- variance in demos
- smooth/consistent demos

... **everyday users** are not!

- inaccurate mental model
- limited time, patience, attention, memory

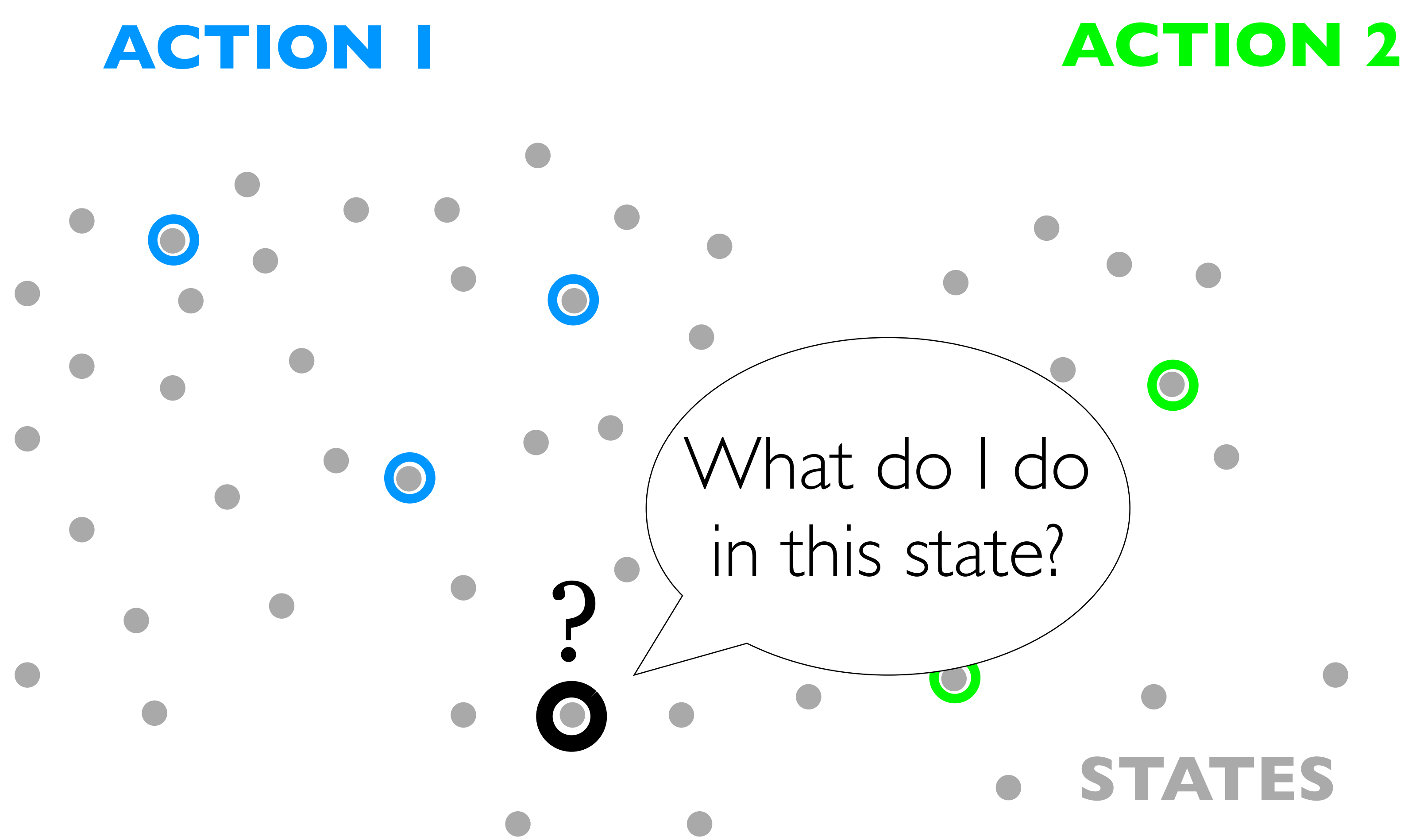
CHALLENGE: **BETTER DEMONSTRATIONS, FASTER!**

ACTIVE LEARNING

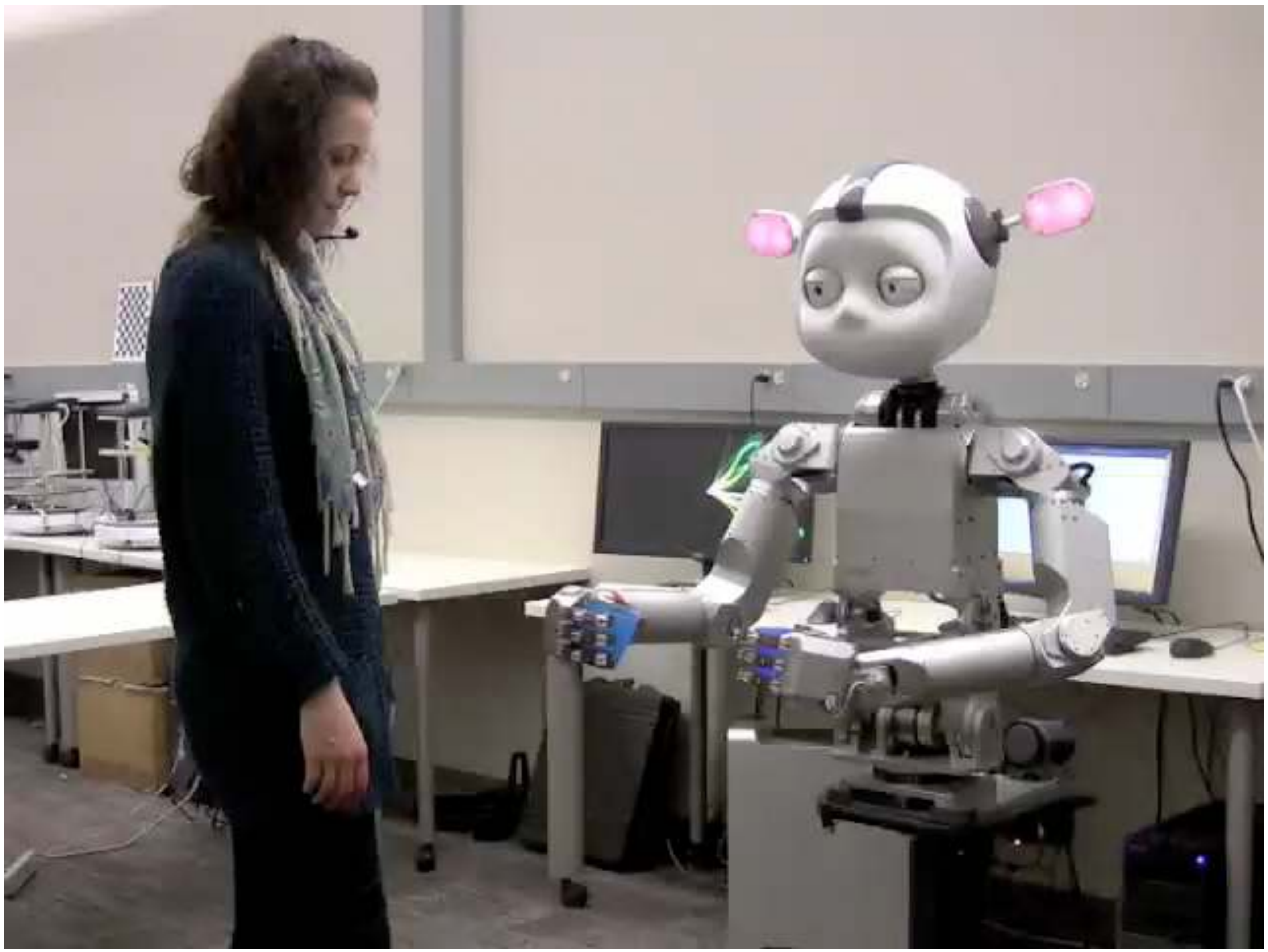


ACTIVE LEARNING IN ROBOTICS

Oudeyer 2007, Grollman 2007, Robbel 2007, Chernova 2009, Rosenthal 2009, Kroemer 2009, Gribovskaya 2010, *among others*.



MANIPULATION SKILLS



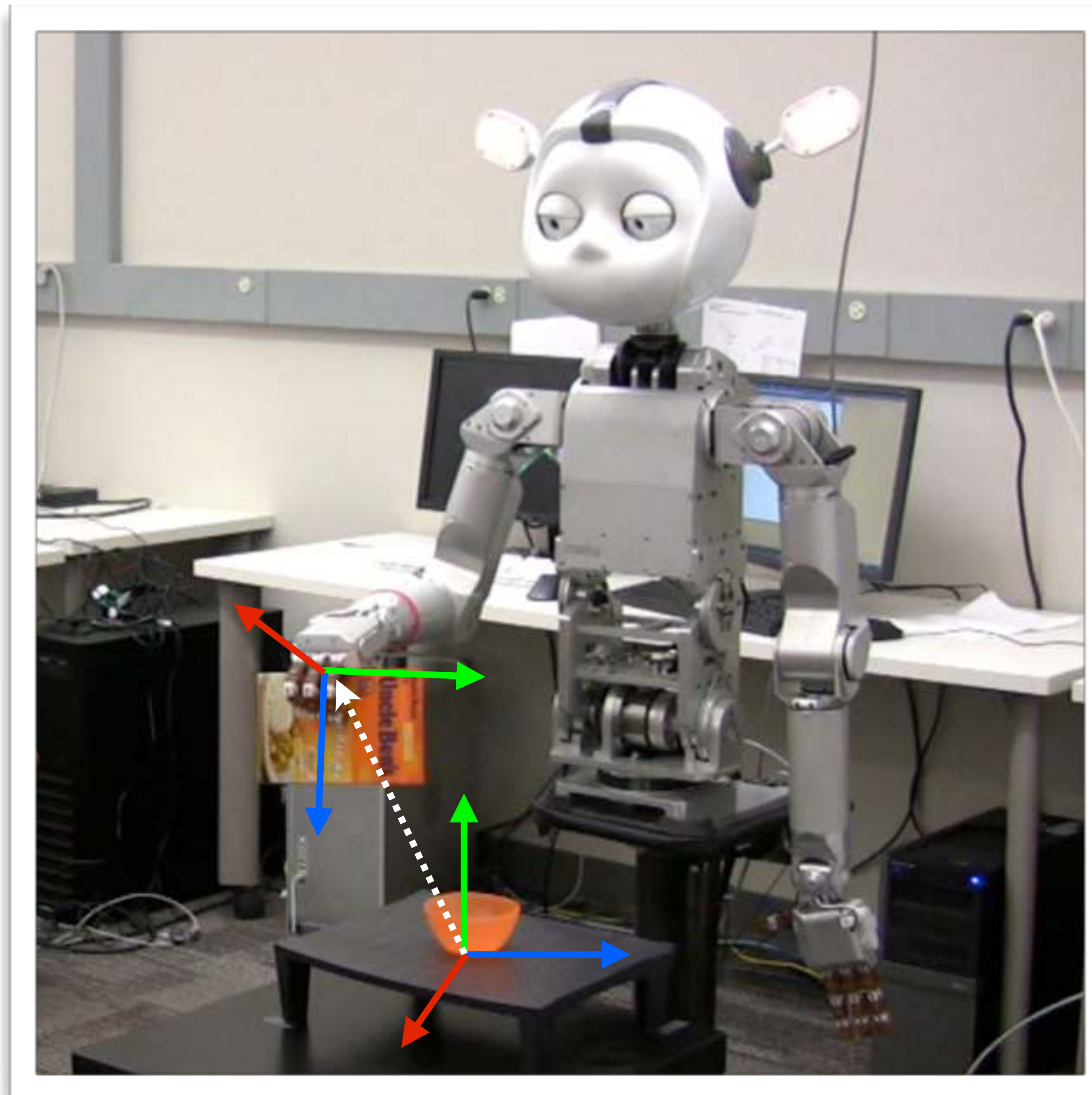
CONTINUOUS ACTION SPACES

SKILL POLICY

$$\pi(s) = a$$

STATE

relative 6D end-effector configuration



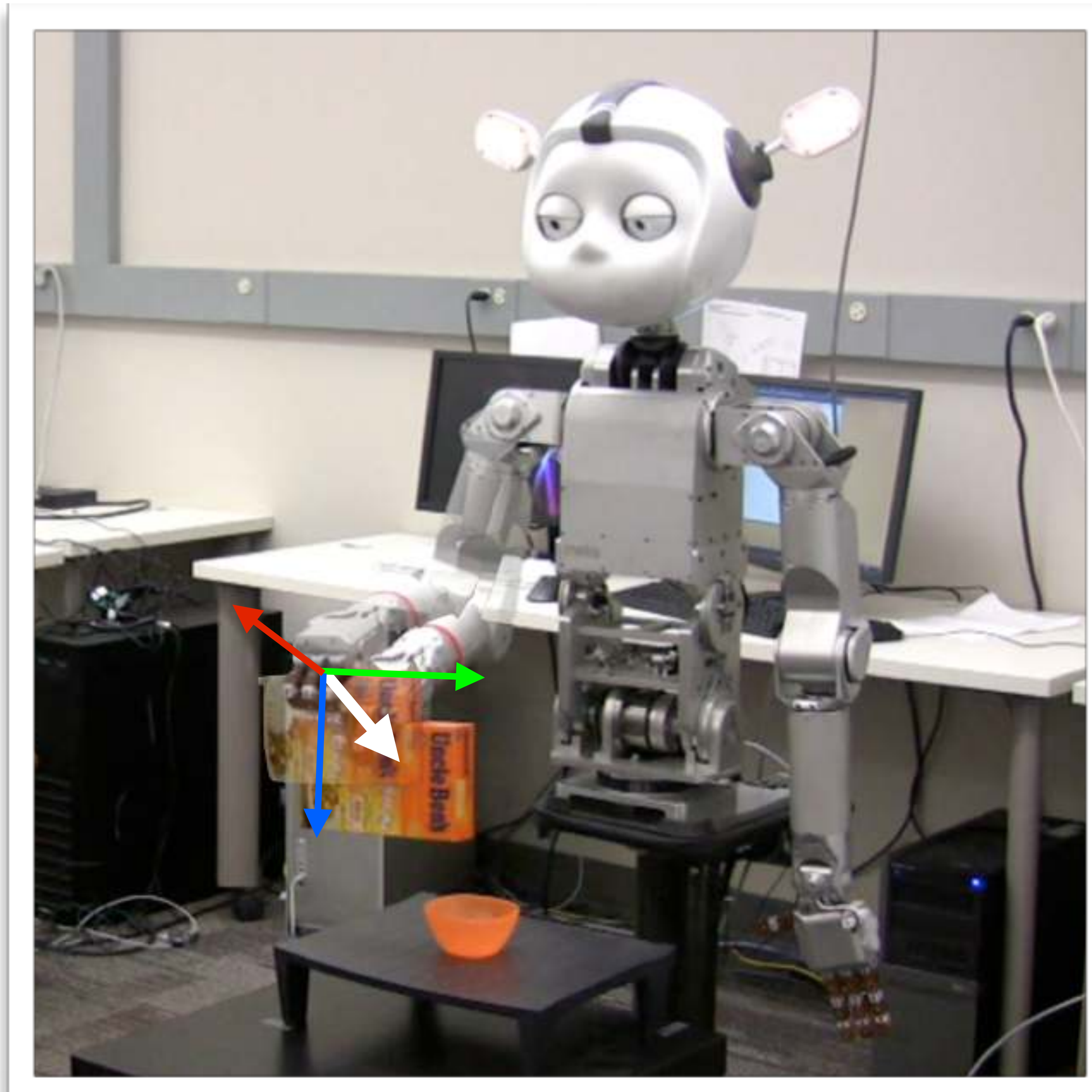
CONTINUOUS ACTION SPACES

SKILL POLICY

$$\pi(s) = a$$

ACTION

change in state

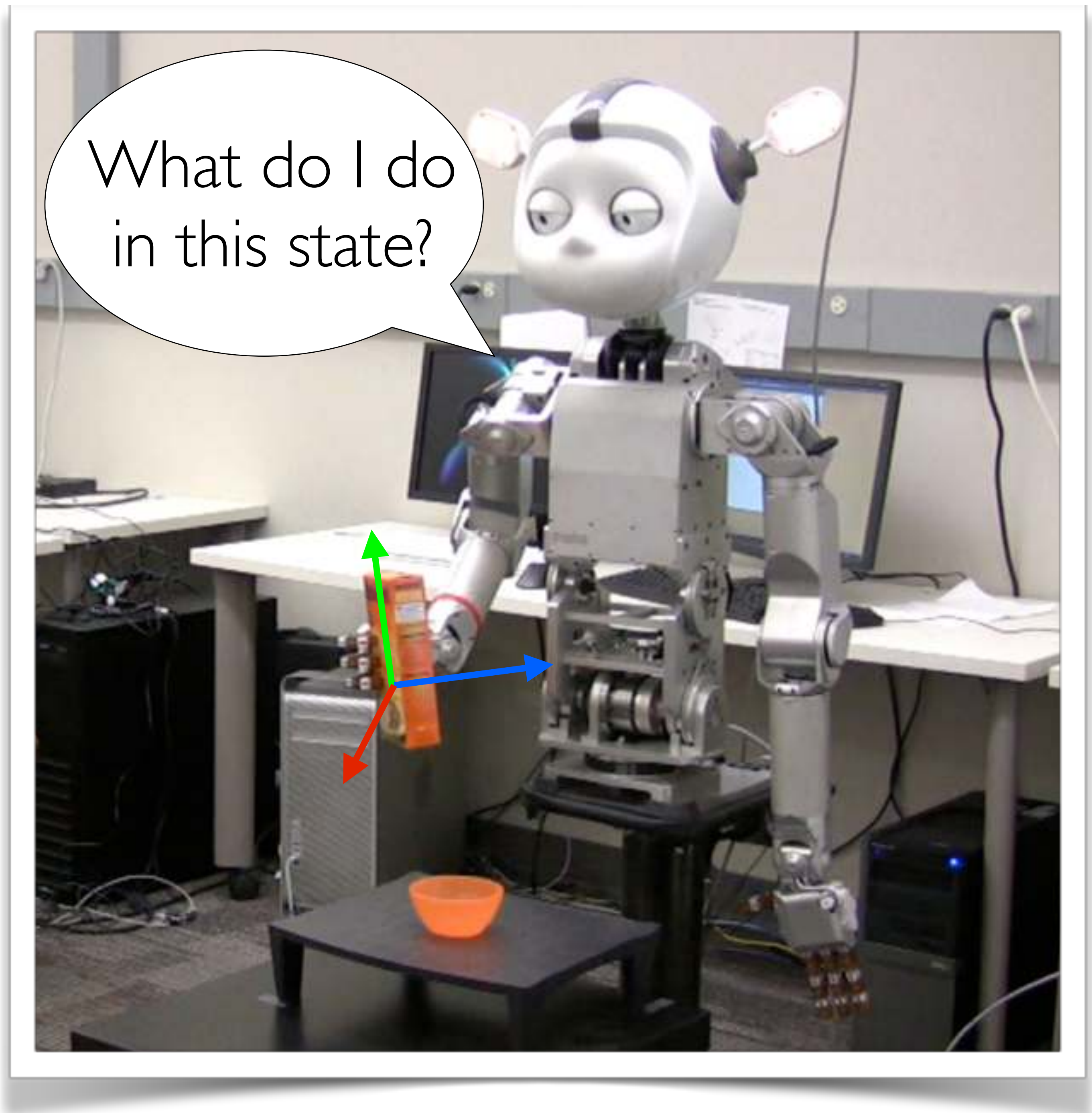


CONTINUOUS ACTION SPACES

$\pi(s) = ?$

QUERY

request change in state



HUMAN QUESTION ASKING

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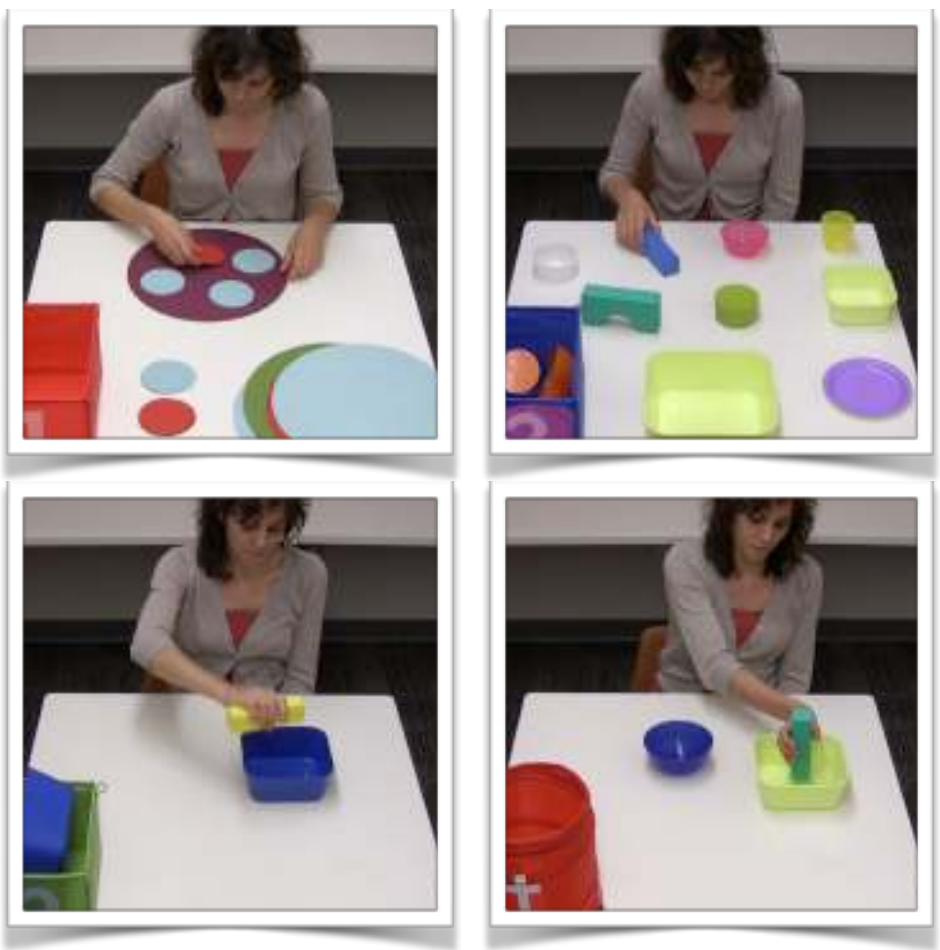
RESEARCH QUESTION	How do humans ask questions?

[Cakmak&Thomaz, HRI 2012]

HUMAN QUESTION ASKING

RESEARCH QUESTION	How do humans ask questions?
DOMAIN	Four abstracted tasks



abstracted scoop&pour

[Cakmak&Thomaz, HRI 2012]

HUMAN QUESTION ASKING

RESEARCH QUESTION	How do humans ask questions?
DOMAIN	Four abstracted tasks
DESIGN	Observational study, task order counterbalanced

DEMONSTRATIONS

x2

QUESTIONS

EXECUTION

x2

[Cakmak&Thomaz, HRI 2012]

HUMAN QUESTION ASKING

RESEARCH QUESTION	How do humans ask questions?
DOMAIN	Four abstracted tasks
DESIGN	Observational study, task order counterbalanced
DATA	N=12, ~25 min, ~40 (SD=13) questions

VIDEO CODING

Question types

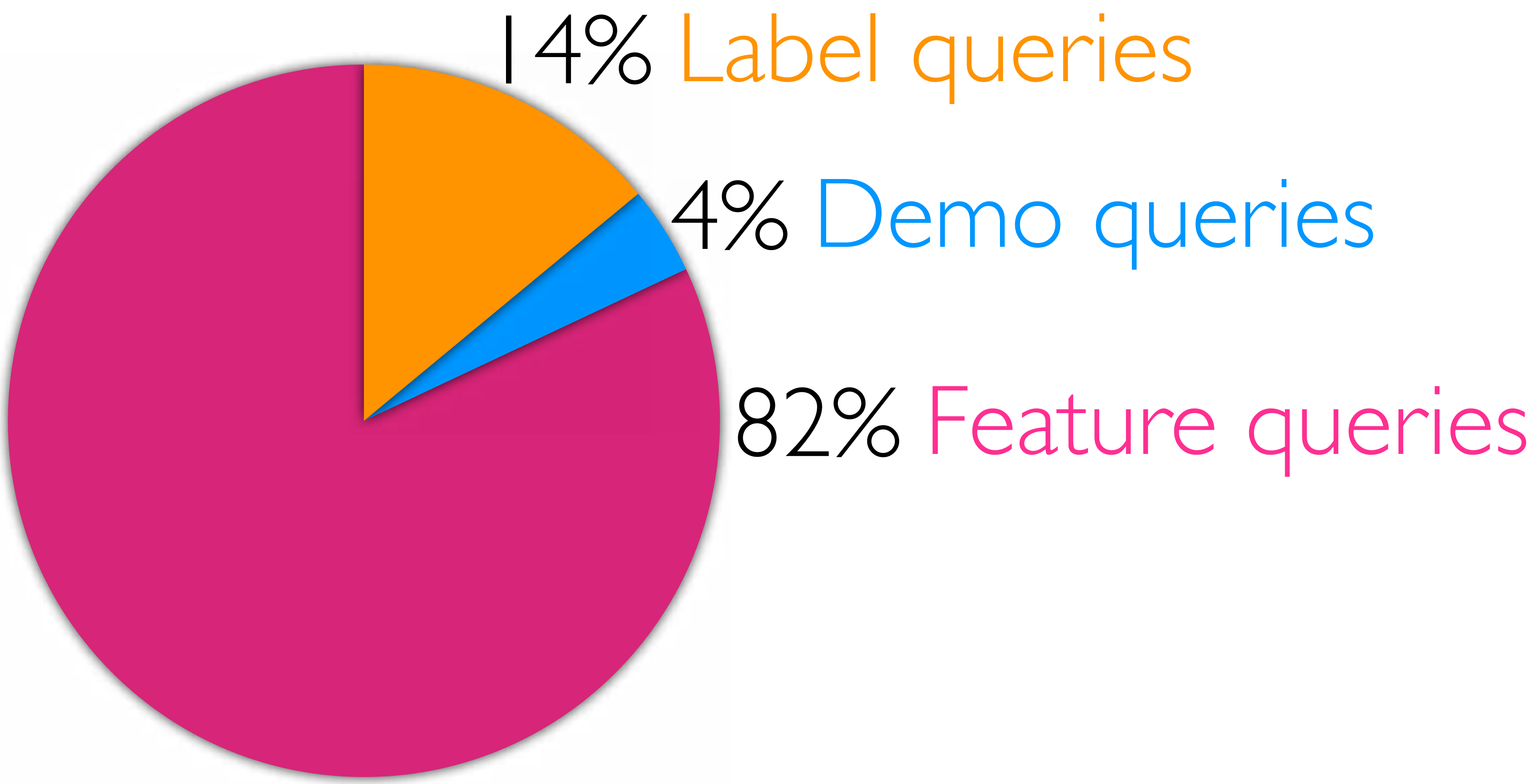
Question forms

Accompanying actions

[Cakmak&Thomaz, HRI 2012]

QUESTION TYPES

[Graesser, 1994]: *Verifications, Example requests, Feature specifications*



[Cakmak&Thomaz, HRI 2012]

QUESTION TYPES

Sub-types of feature queries observed in humans

FEATURE RELEVANCE TEST

28%

FEATURE INVARIANCE TEST

35%

[Cakmak&Thomaz, HRI 2012]

QUESTION TYPES

Sub-type of label queries observed in humans

PARTIAL
LABEL QUERY

60%

[Cakmak&Thomaz, HRI 2012]

QUESTION FORMS

VERBAL QUESTION FORMS [Kearsley, 1976]

INDIRECT (2%)
I guess it doesn't matter which hand I use.

DIRECT (98%)

OPEN (13%)

SIMPLE (9%)
How far do I lower it?

EMBEDDED (3%)
Is there an exact number of small circles?

COMPLEX (1%)
Does it matter what I put into what?

CLOSED (85%)

YES/NO (81%)

SPECIFIED-ALTERNATIVE (4%)
Is color the only criterion or are there other requirements?

SIMPLE (60%)
Can I use other colors?

TAG (2%)
I turn it clockwise, right?

INTONATED (19%)
All shades of blue are fine?

[Cakmak&Thomaz, HRI 2012]

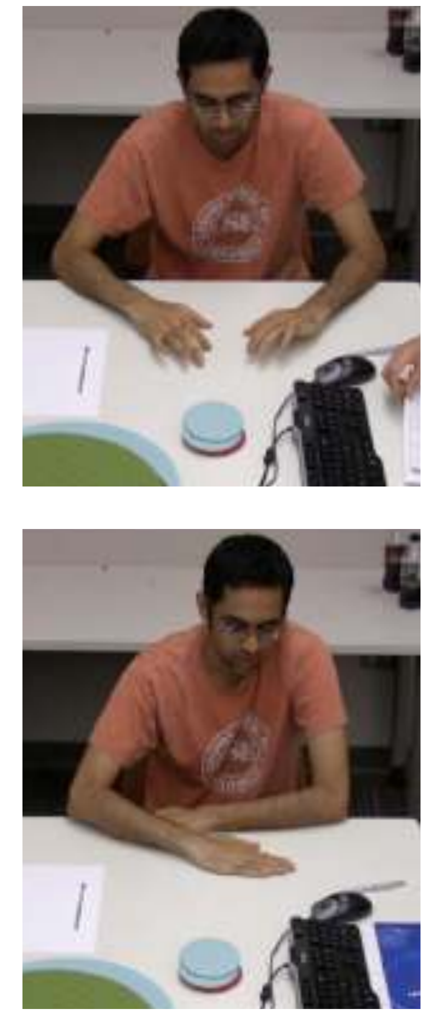
USE OF EMBODIMENT

INSTANTIATIONS

26%

DEICTIC GESTURES

25%



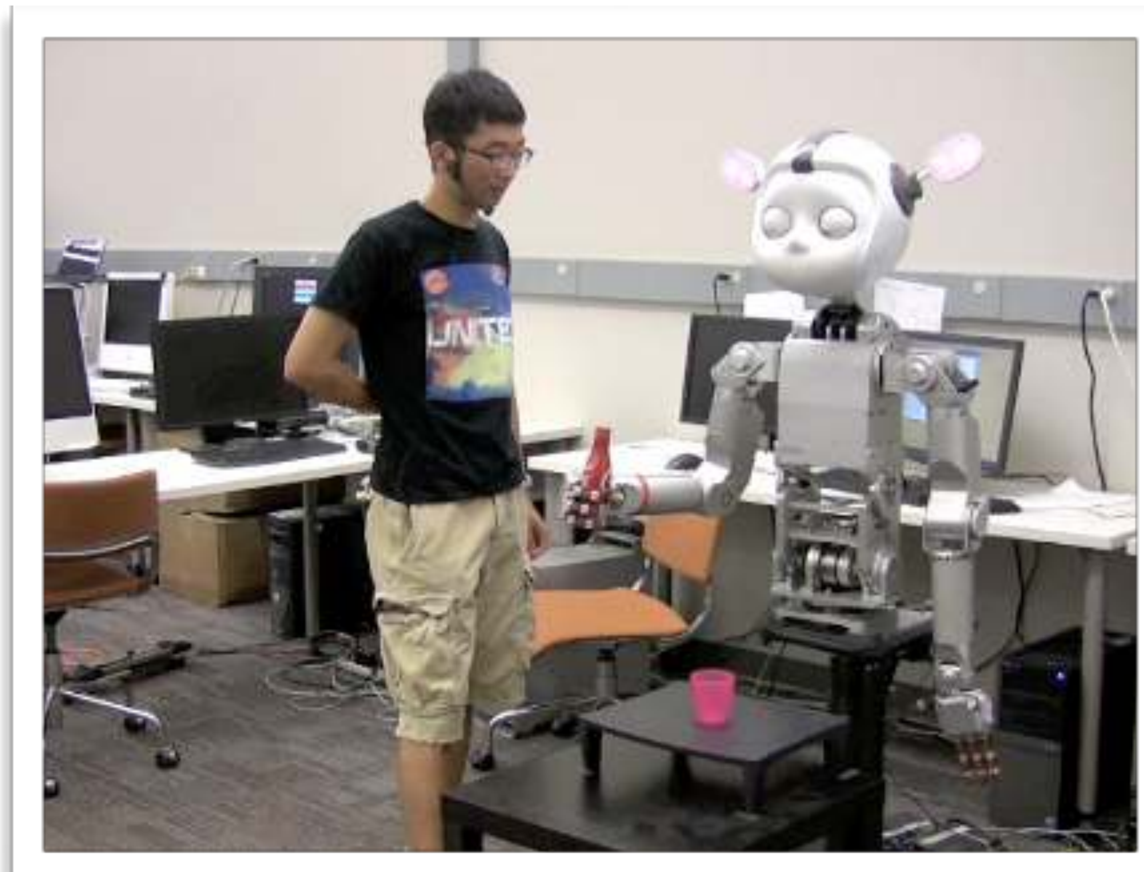
ICONIC GESTURES

8%

[Cakmak&Thomaz, HRI 2012]

USE OF EMBODIMENT

Does
orientation-around-x
matter?



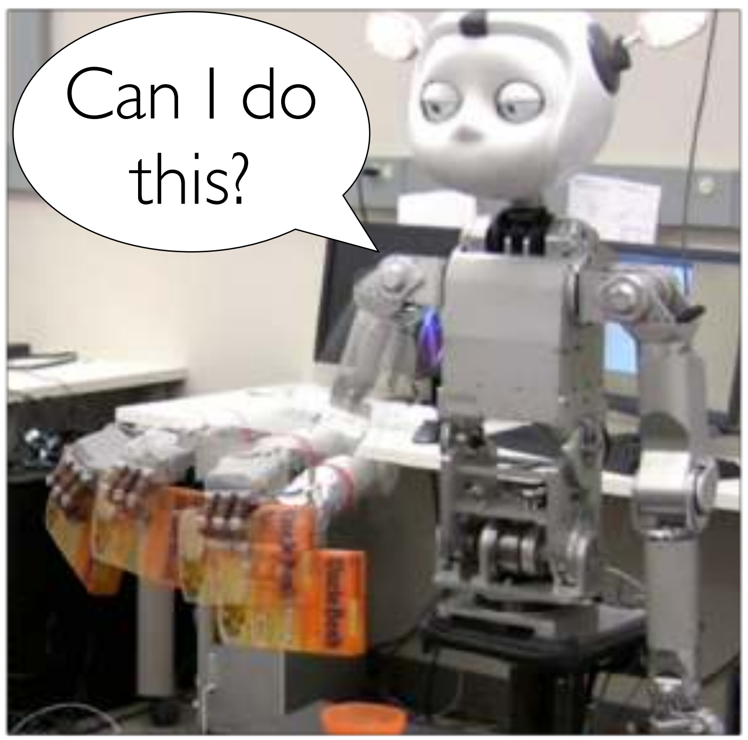
"Does **this orientation** matter?"

NO EMBODIMENT

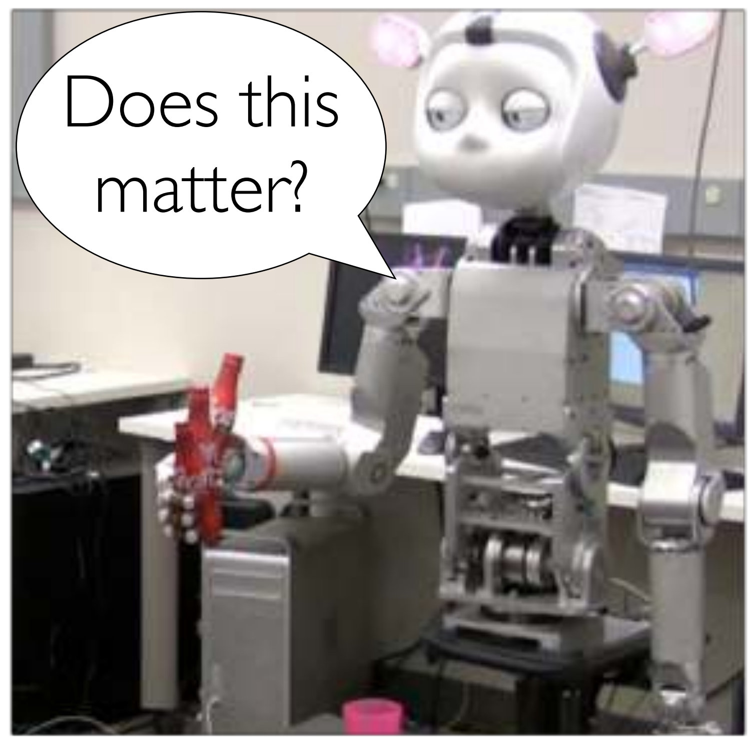
WITH EMBODIMENT

[Cakmak&Thomaz, HRI 2012]

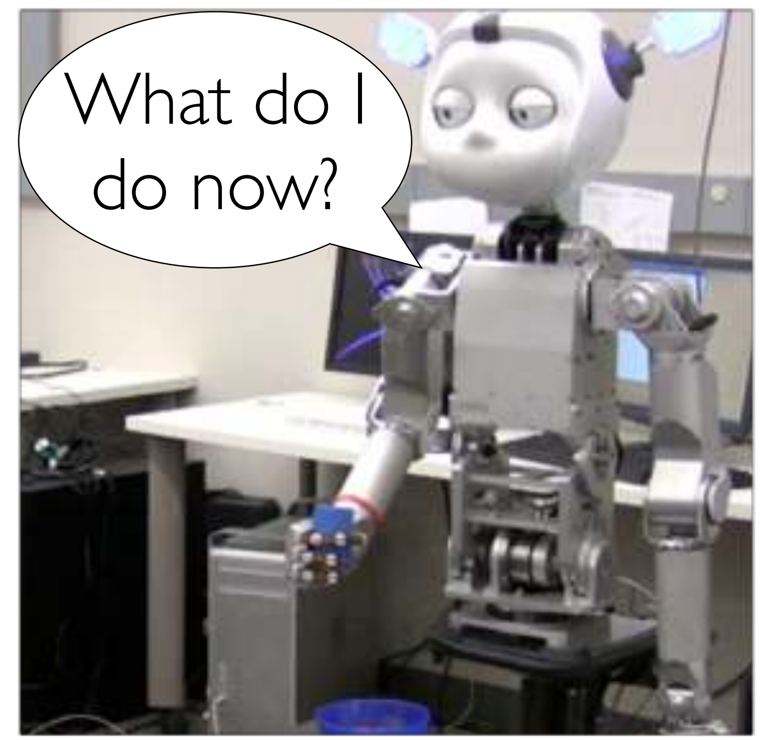
EMBODIED QUERIES



Label Query



Feature Query

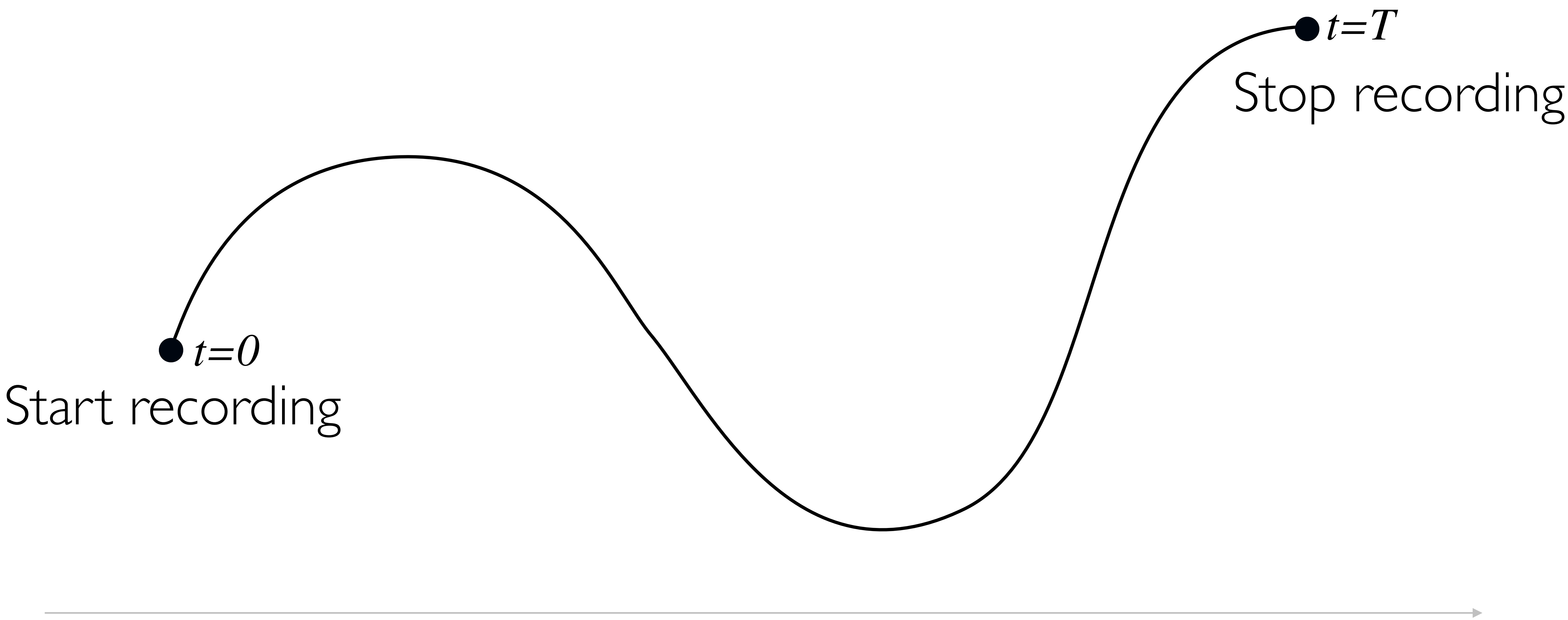


Demo Query

SKILL SEGMENTATION

humans **segment** skills into steps and ask questions about steps

KEYFRAME-BASED SKILL LEARNING



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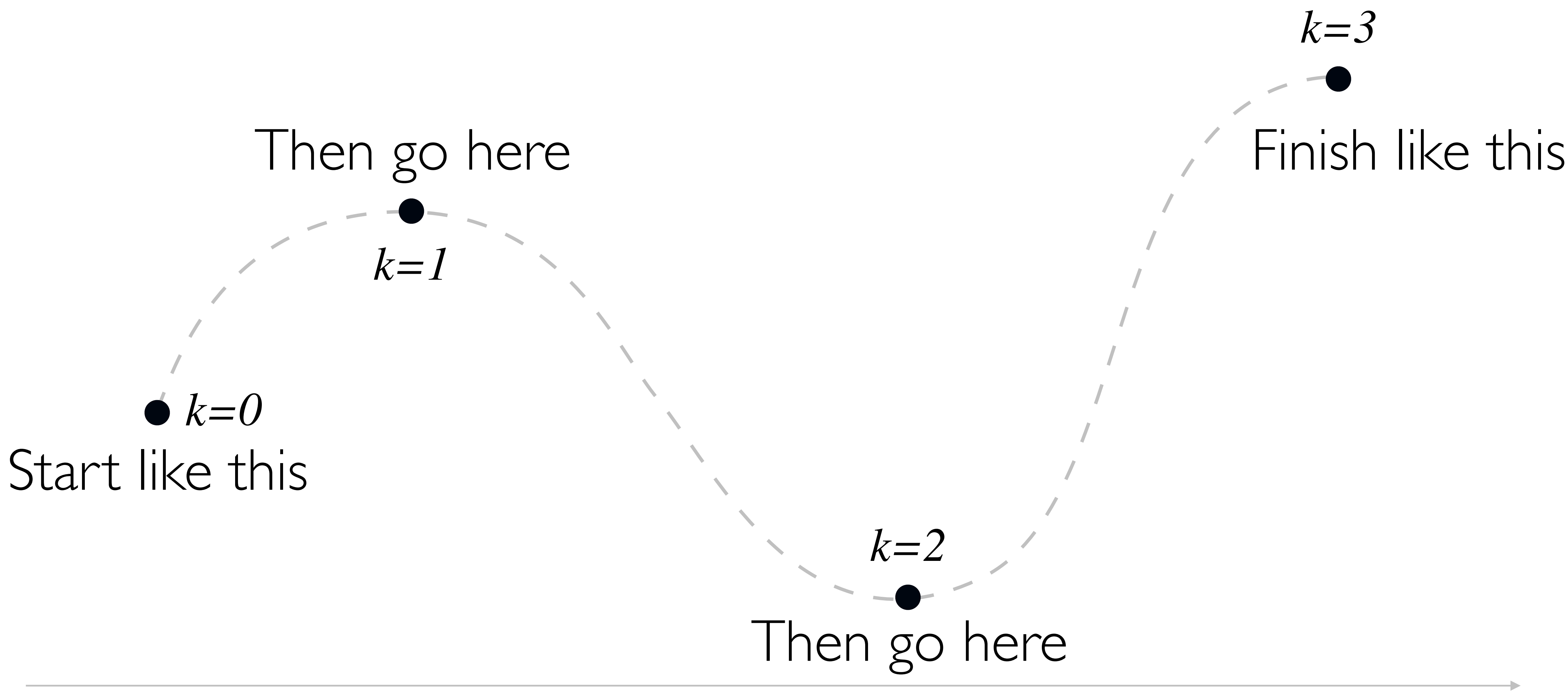

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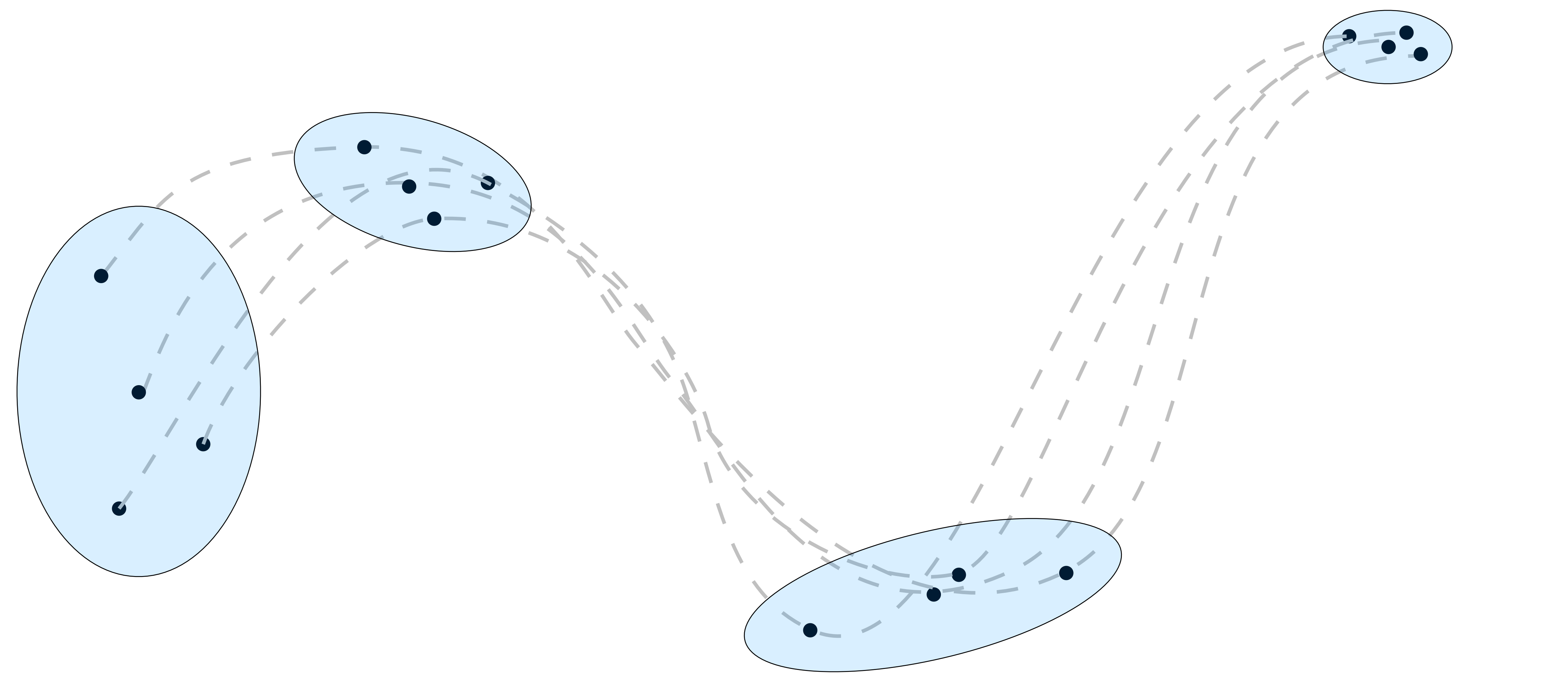

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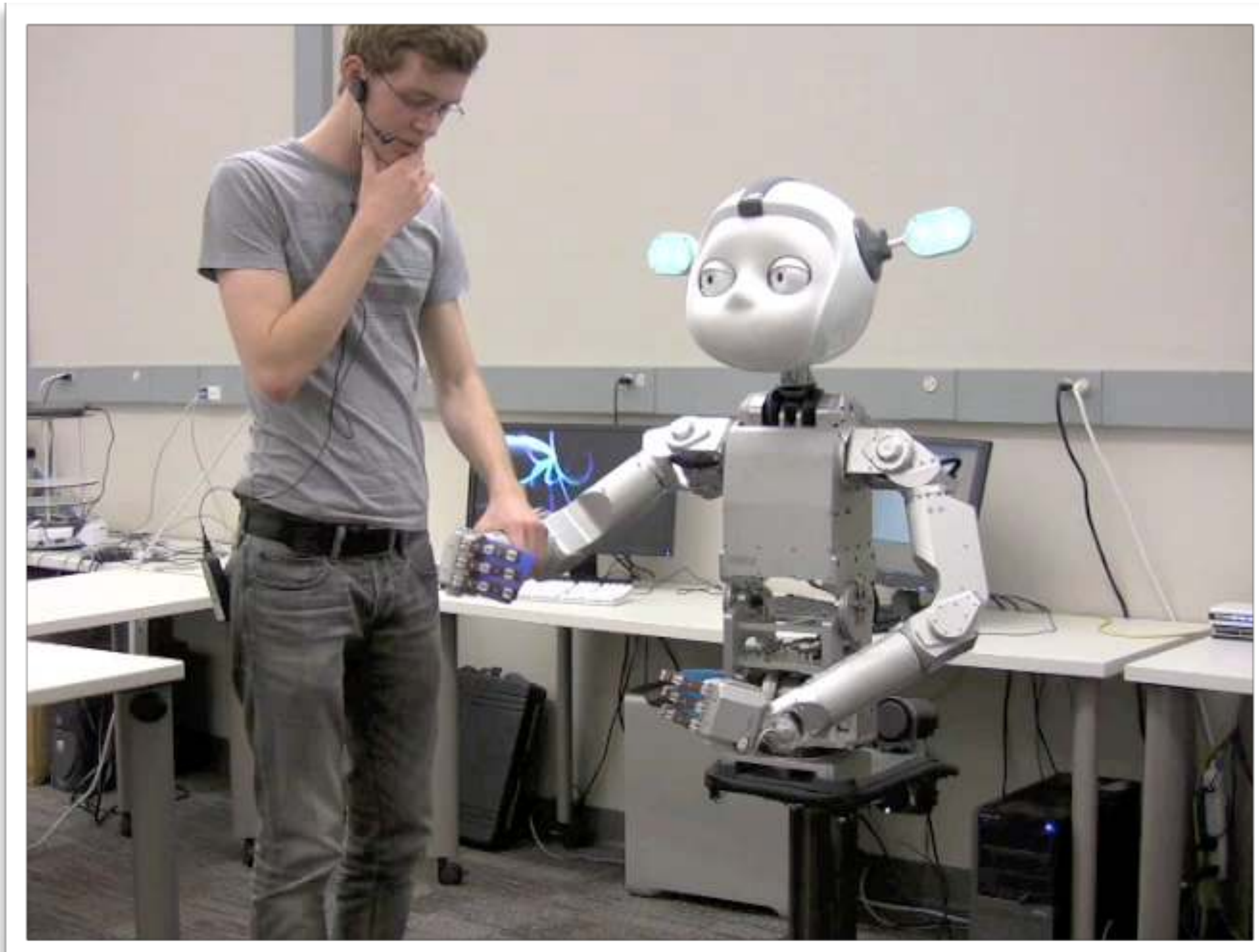
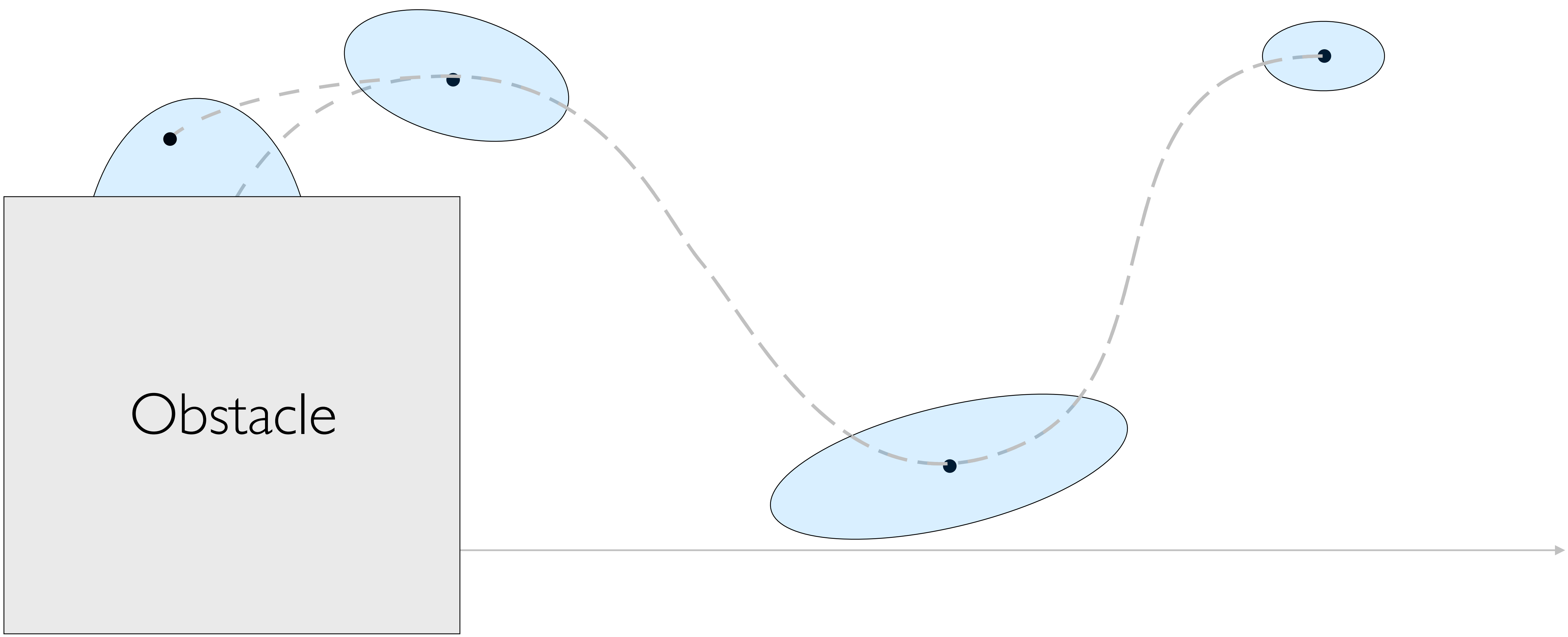


KEYFRAME-BASED SKILL LEARNING

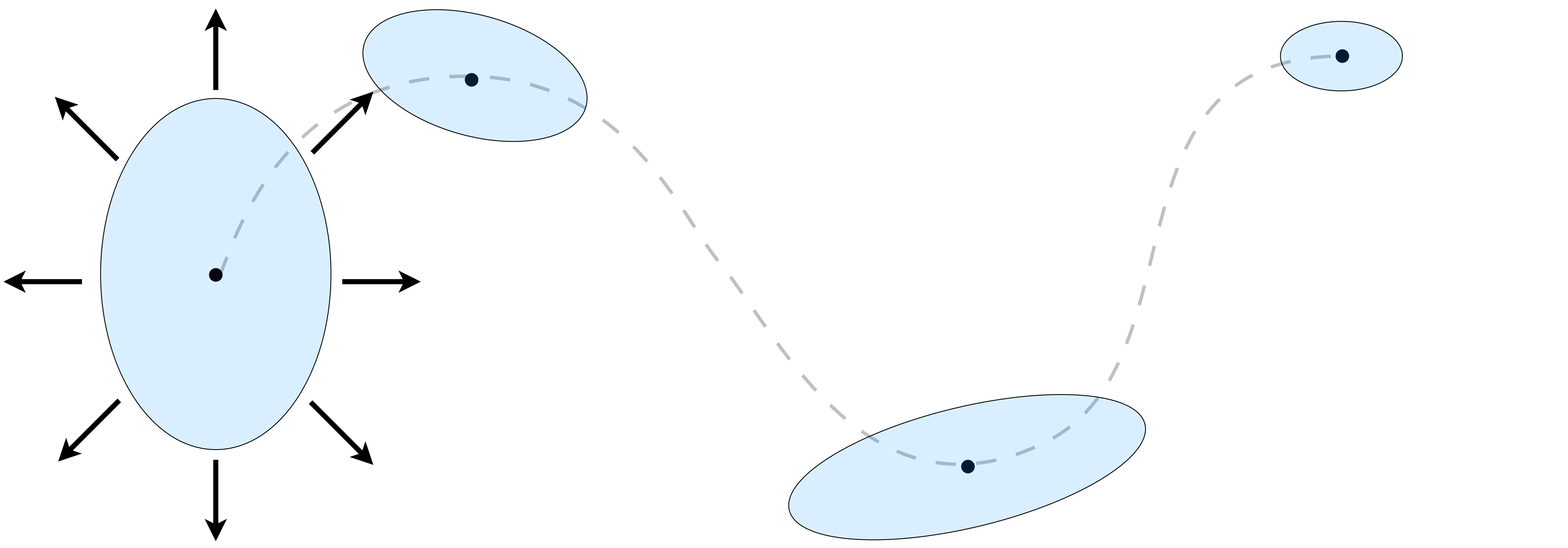
What is the purpose of queries?



KEYFRAME-BASED SKILL LEARNING

What is the purpose of queries?

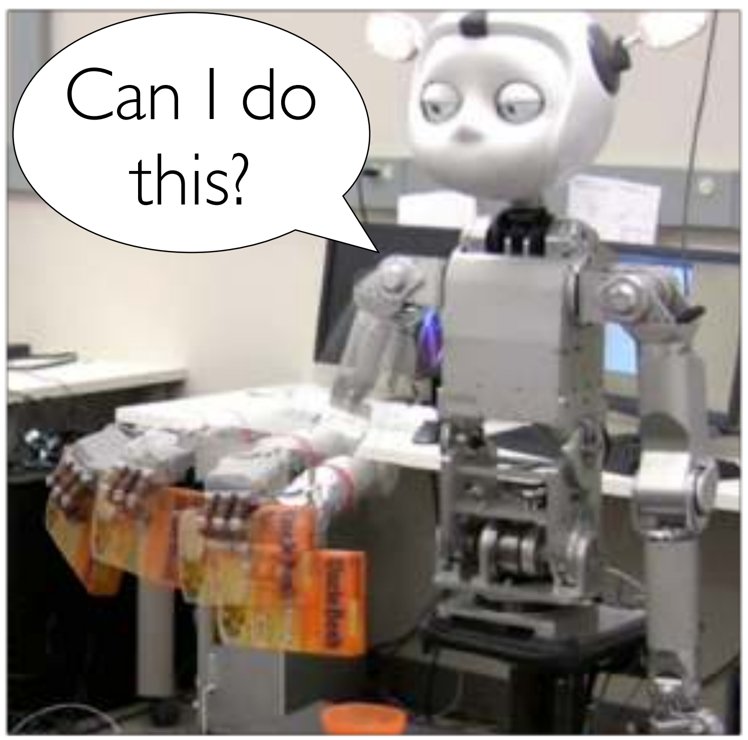
Increase variance!



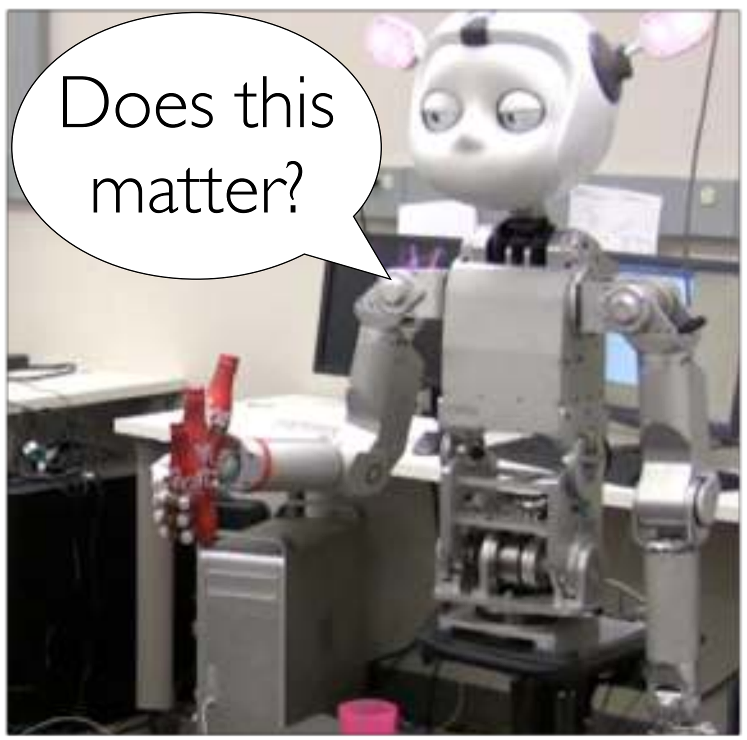
KEYFRAME-BASED SKILL LEARNING

What is the purpose of queries?

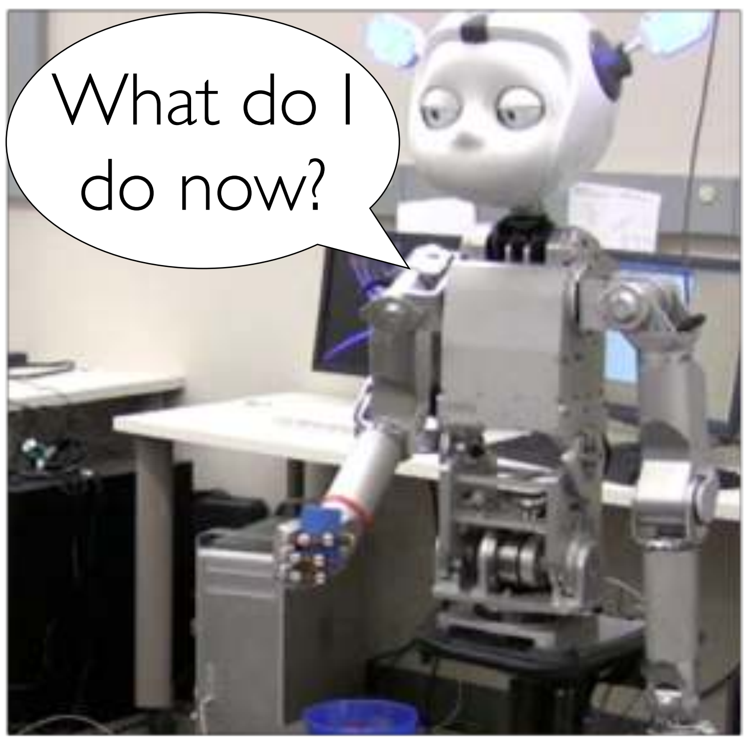
Increase variance! ..with different query types.



Label Query



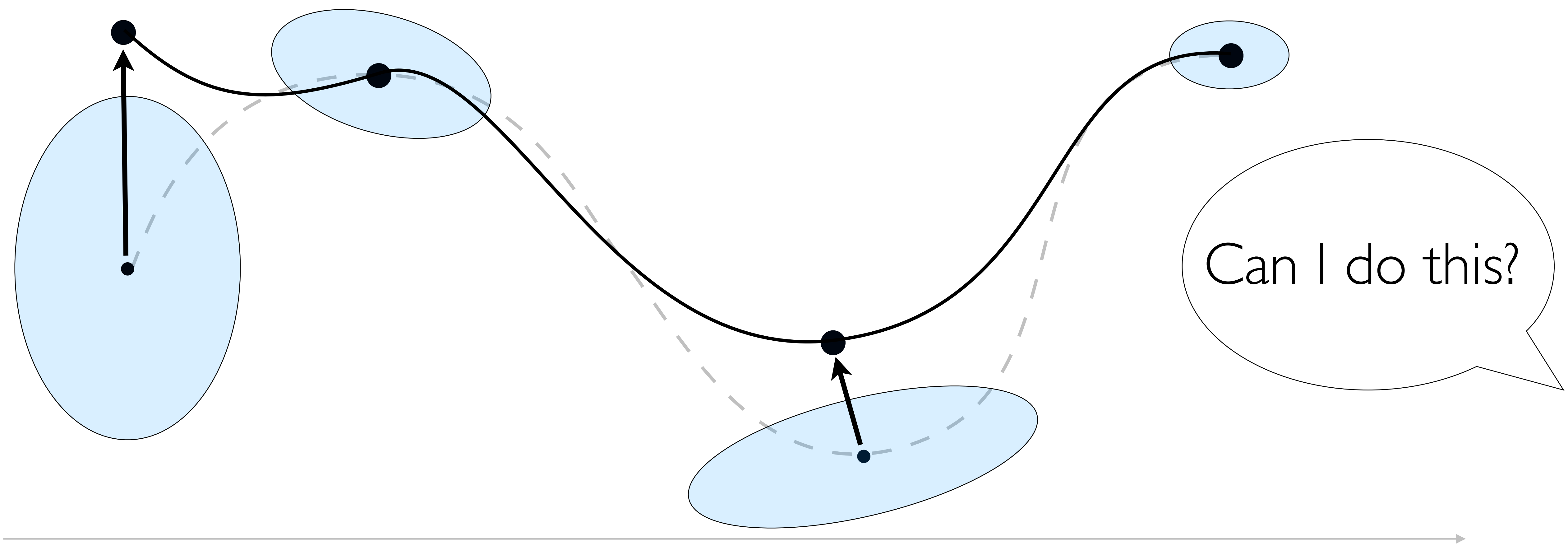
Feature Query



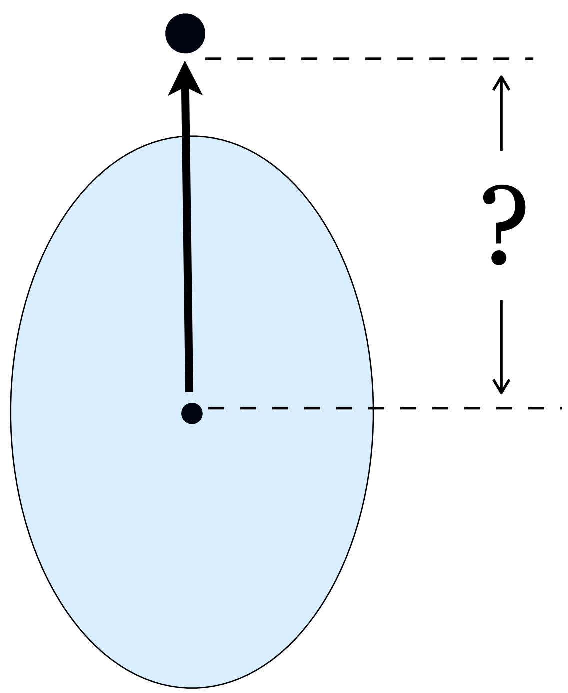
Demo Query

LABEL QUERIES

How much variance? In which direction? Which keyframes?



LABEL QUERIES



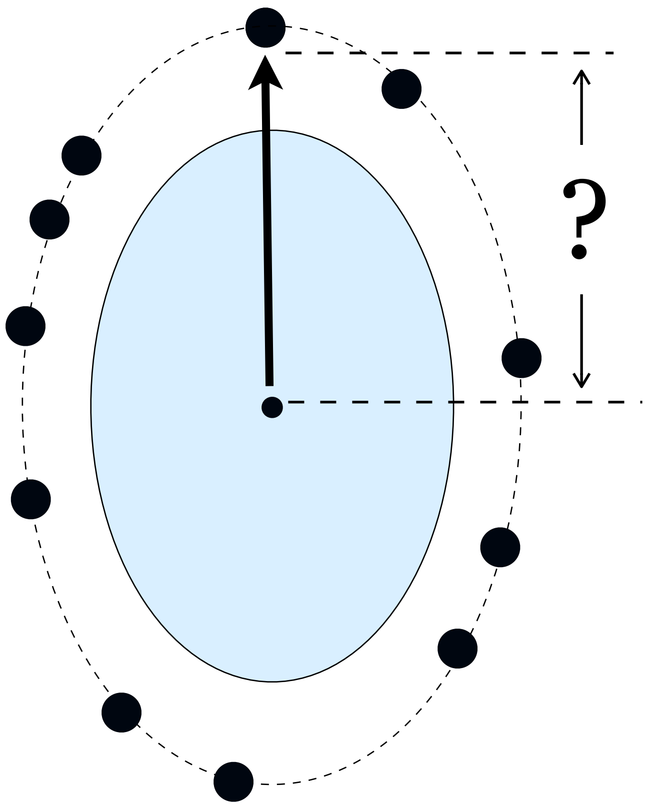
query candidate

MAXIMIZE

$$U_k(s) \propto \underbrace{P(s|\mathcal{D}_k)}_{\text{probability density of the point given data}}\underbrace{(var(\mathcal{D}_k \cup \{s\}) - var(\mathcal{D}_k))}_{\text{increase in the variance if the point is positive}}$$

LABEL QUERIES

query candidate



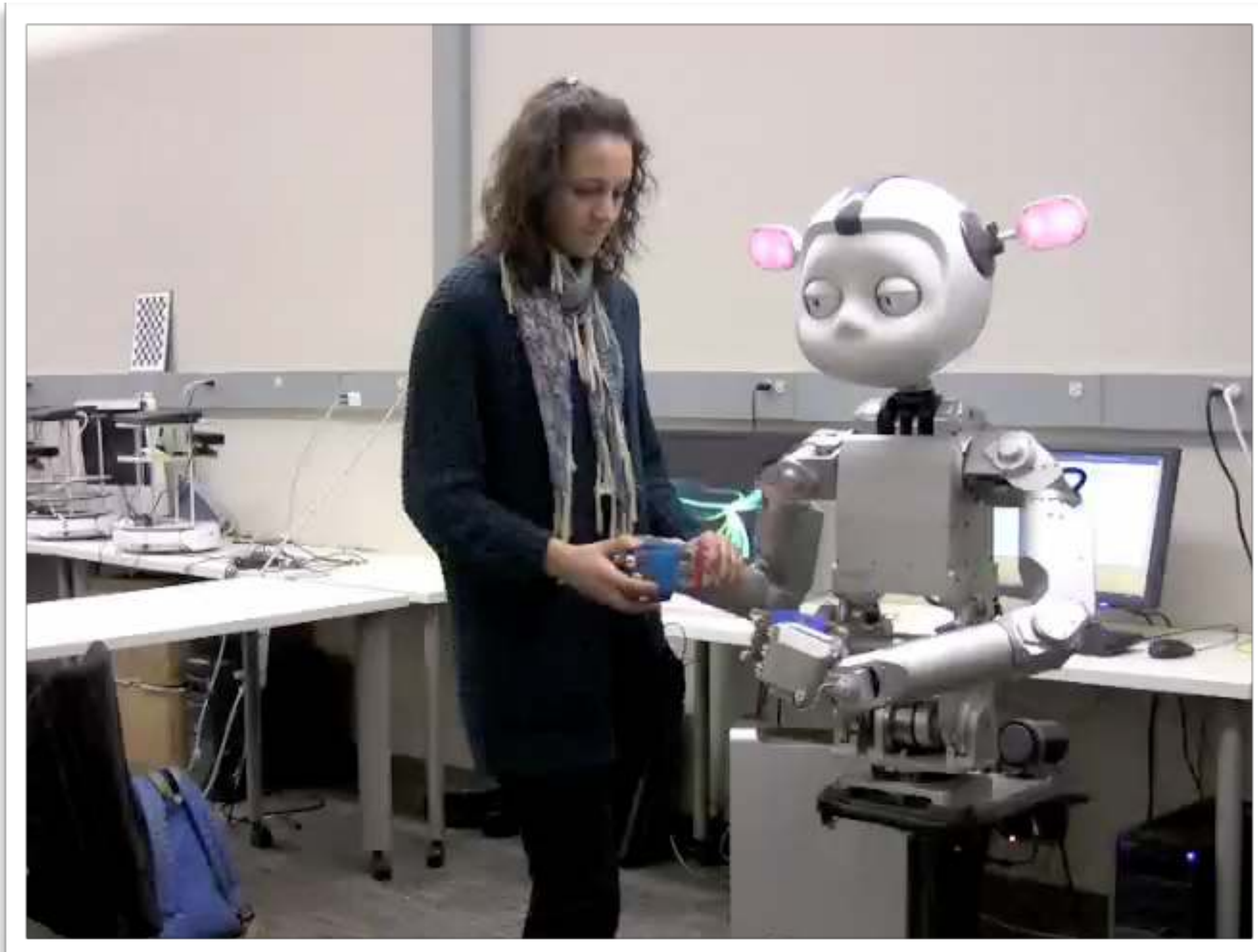
MAXIMIZE

$$U_k(s) \propto P(s|\mathcal{D}_k)(var(\mathcal{D}_k \cup \{s\}) - var(\mathcal{D}_k))$$

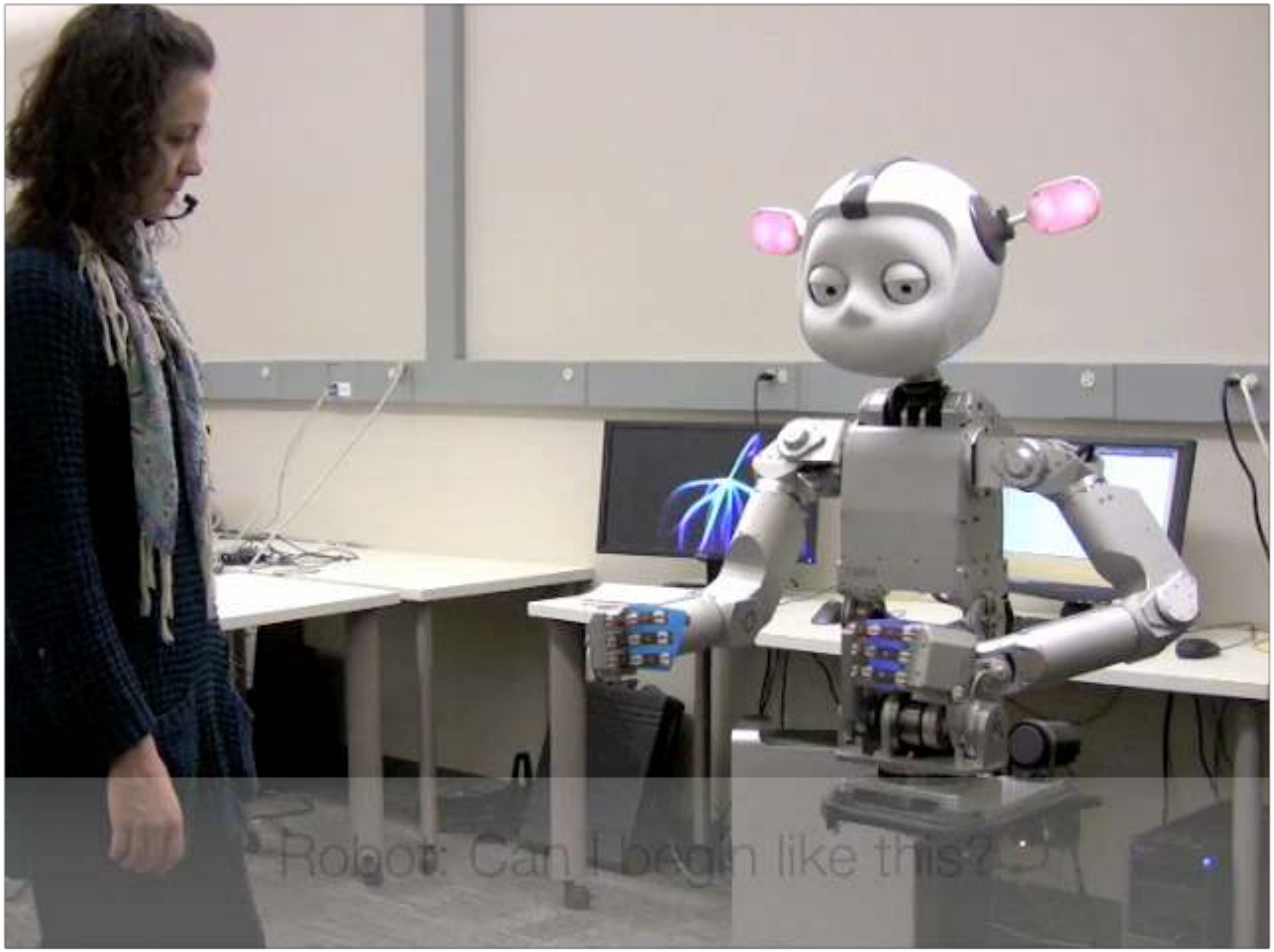
$$\underline{(s-\mu_{\mathcal{D}_k})^T \, \Sigma_{\mathcal{D}_k}^{-1} \, (s-\mu_{\mathcal{D}_k})} = \boxed{3+\frac{1}{n_k}}$$

Mahalanobis distance

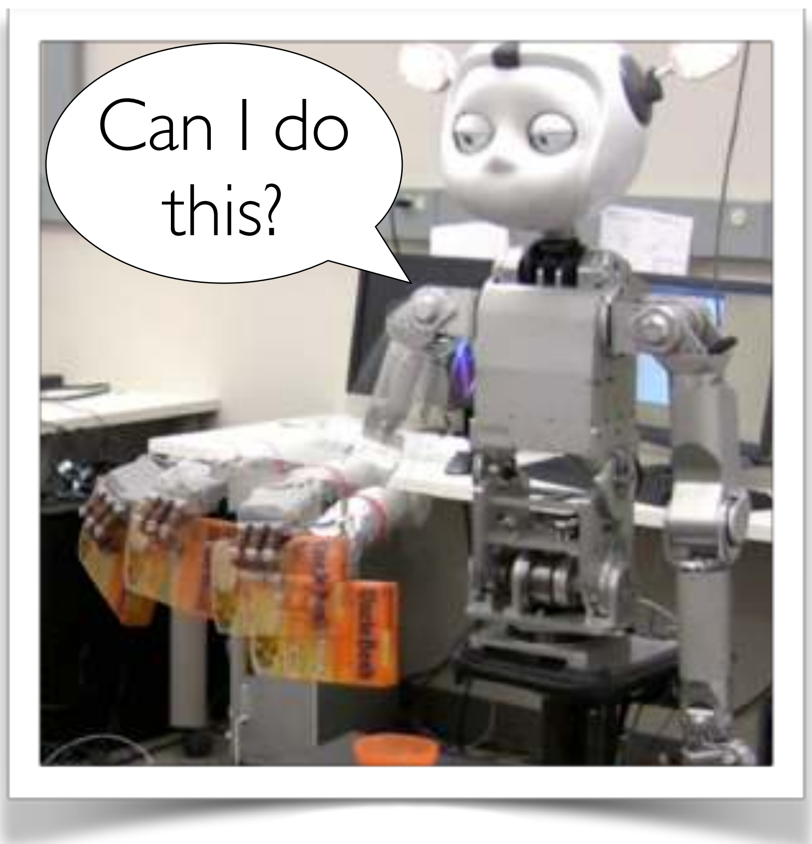
LABEL QUERIES



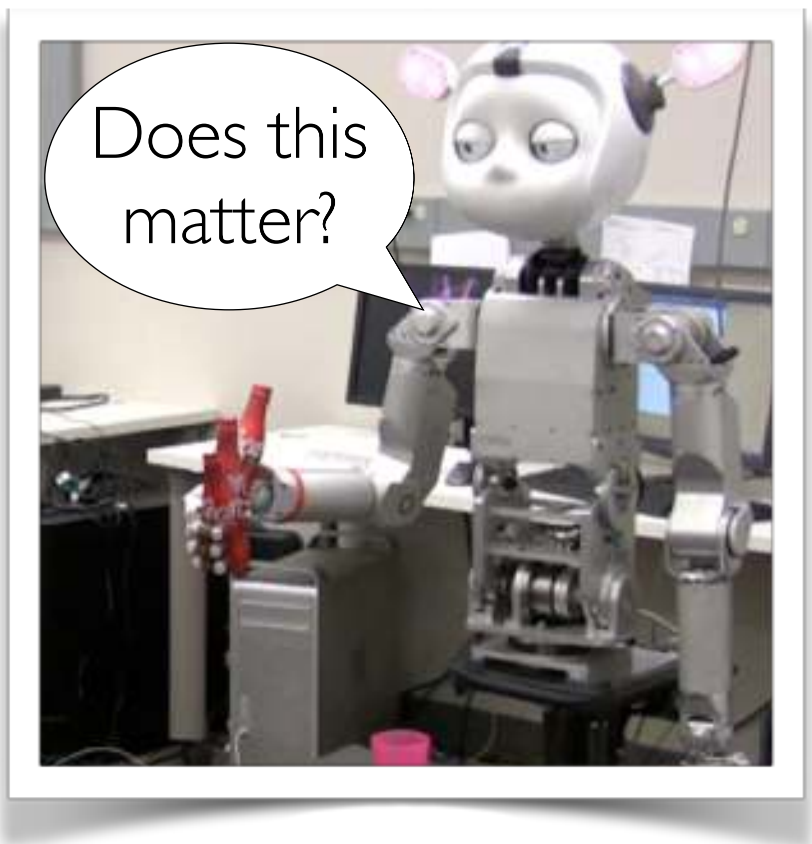
PARTIAL-LABEL QUERIES



EMBODIED QUERY TYPES



Label Query



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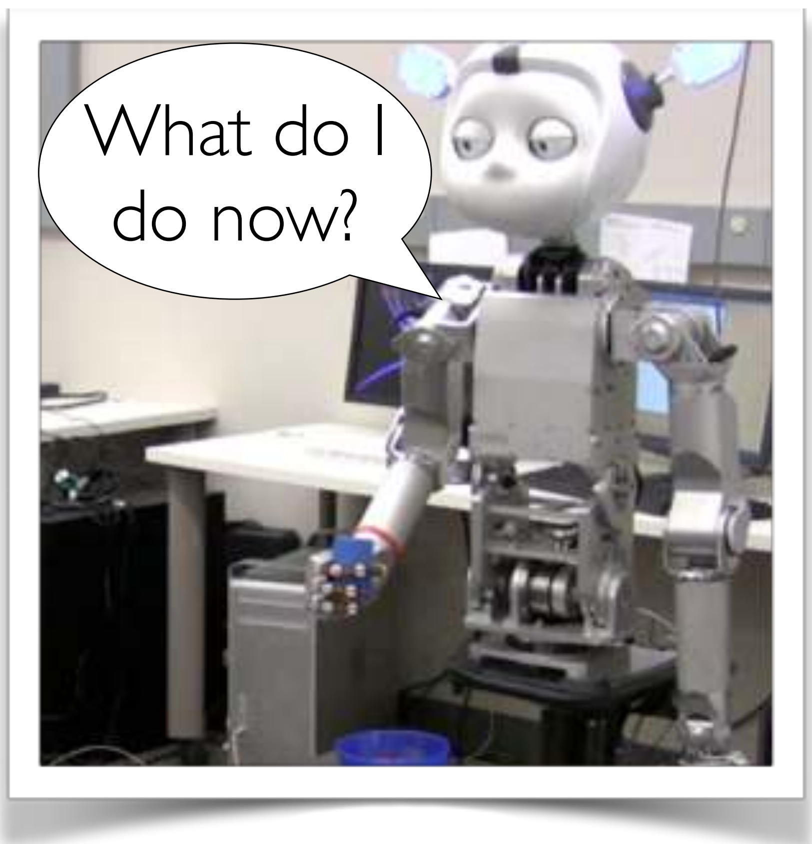
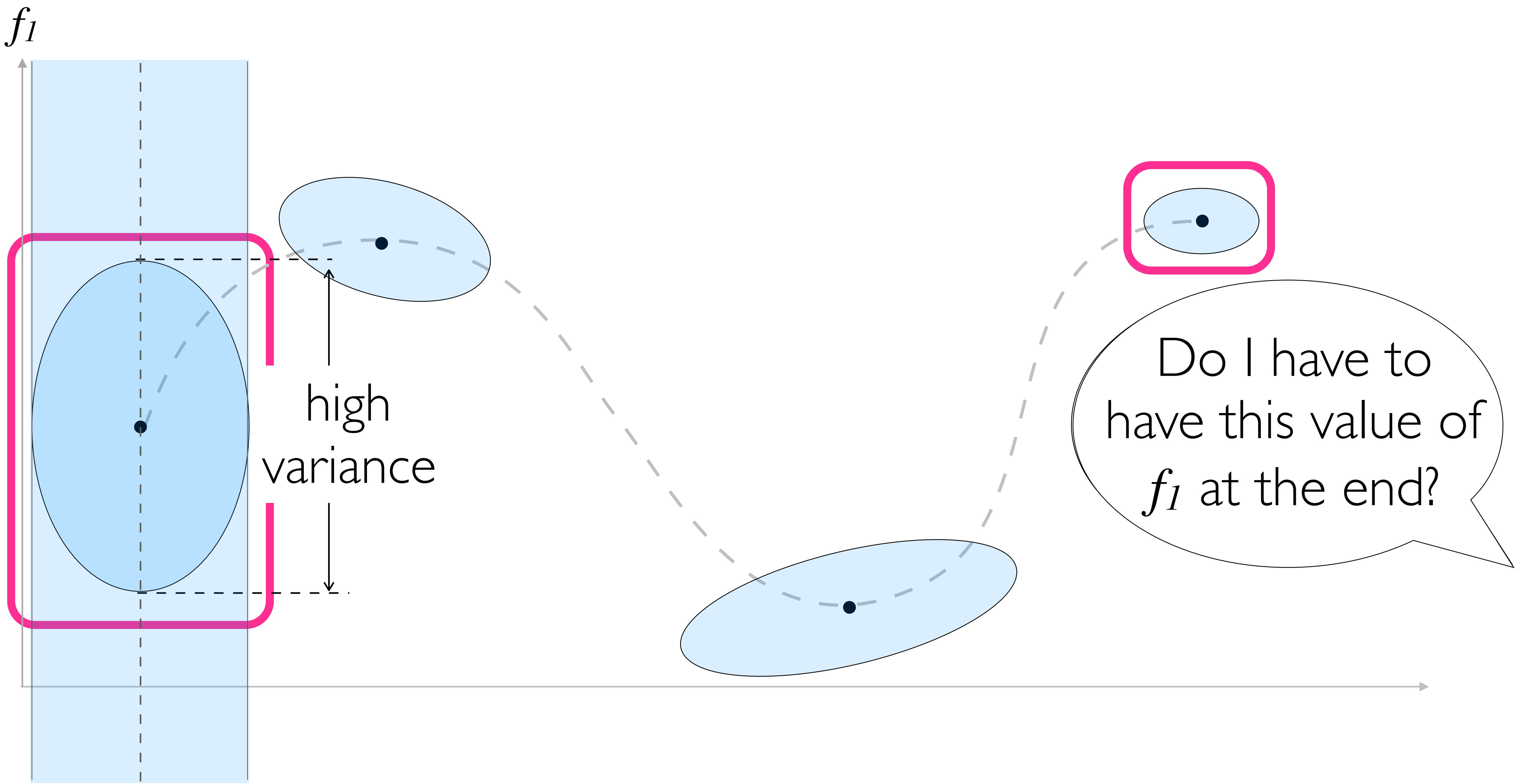


Demo Query

FEATURE QUERIES



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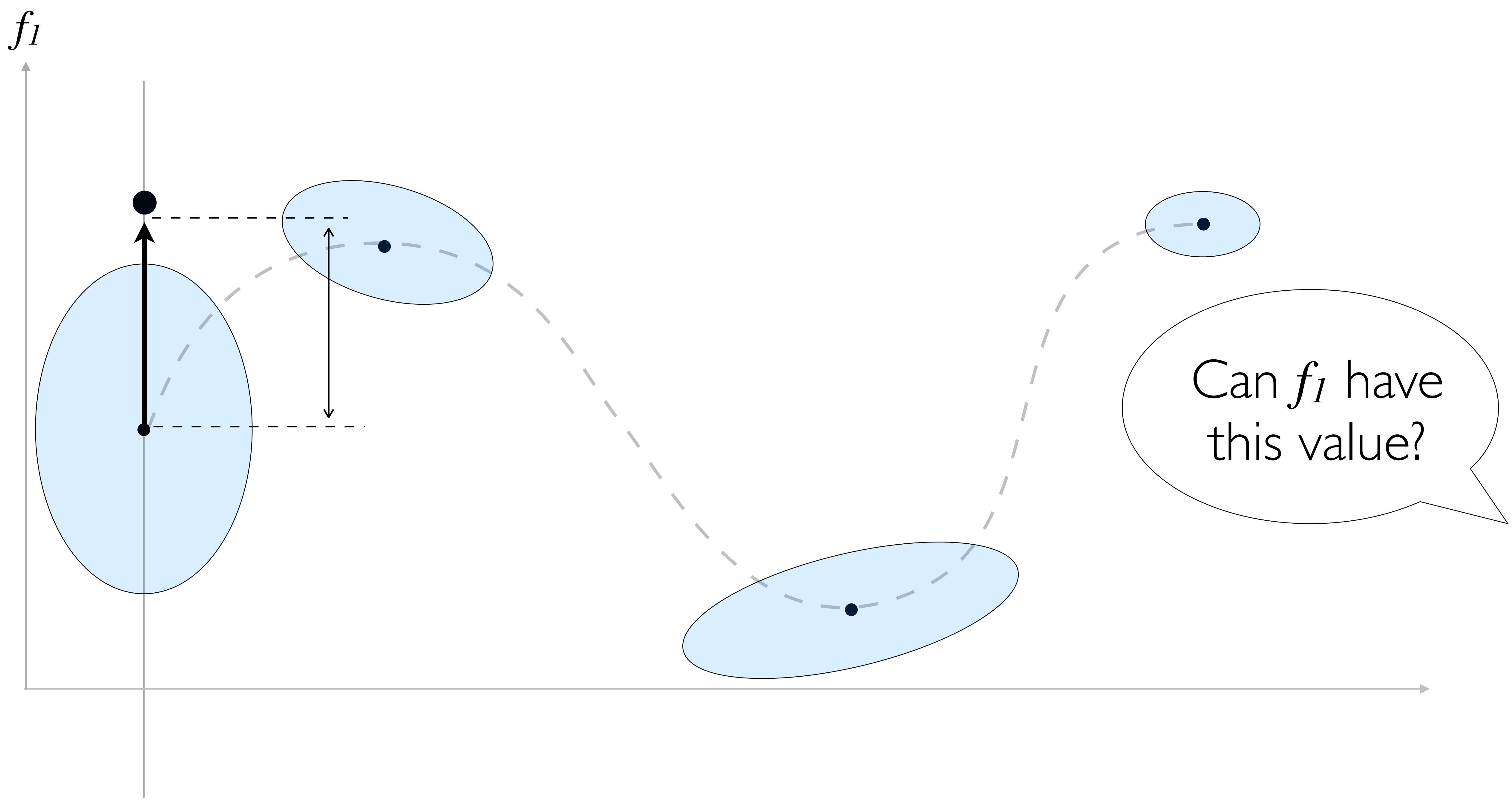

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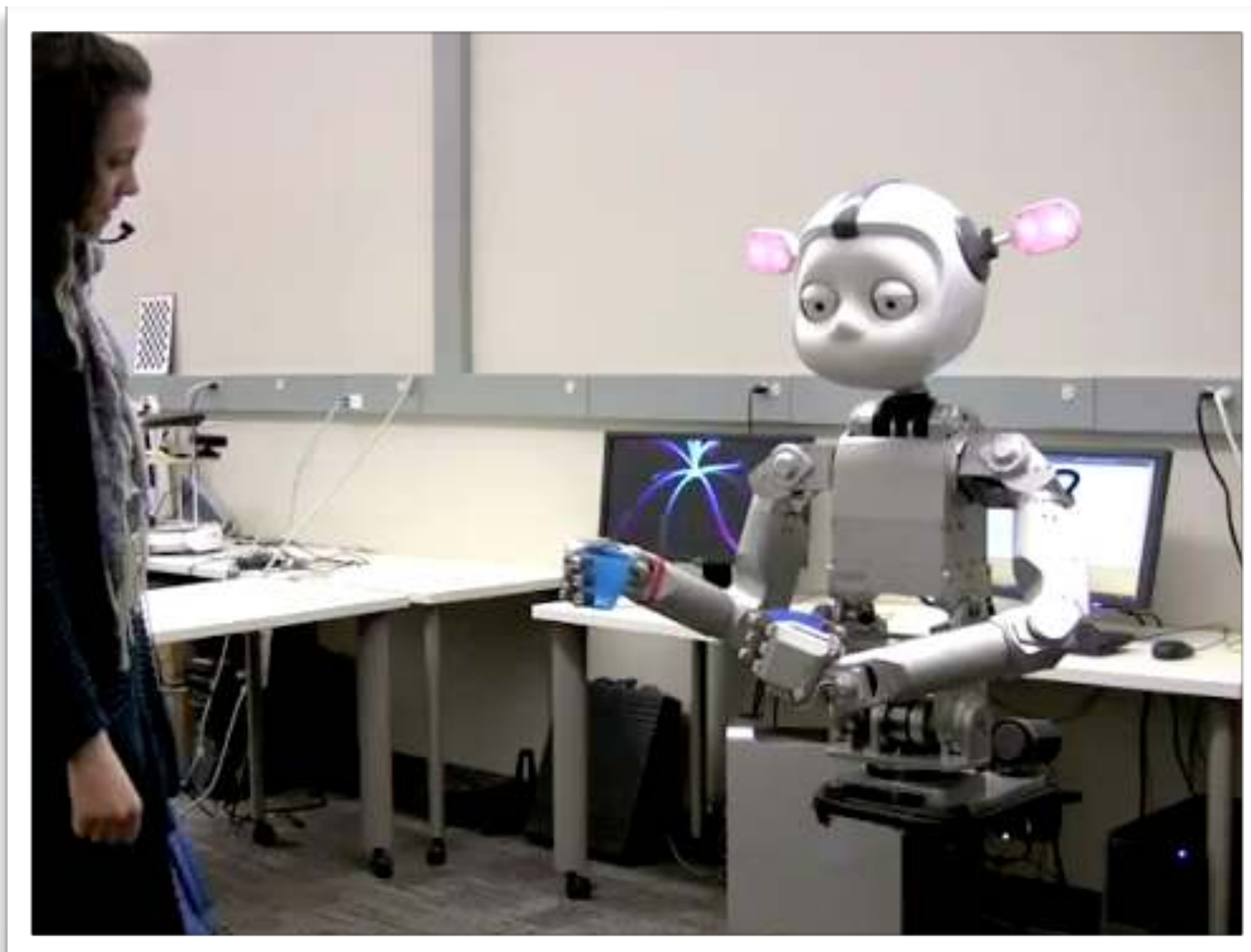


EFFECTIVENESS OF QUERIES

RESEARCH QUESTION	How do different queries help learning?

EFFECTIVENESS OF QUERIES

RESEARCH QUESTION	How do different queries help learning?
DESIGN	Four conditions: **unguided** versus **with queries**

Unguided
naive teacher

-VS-

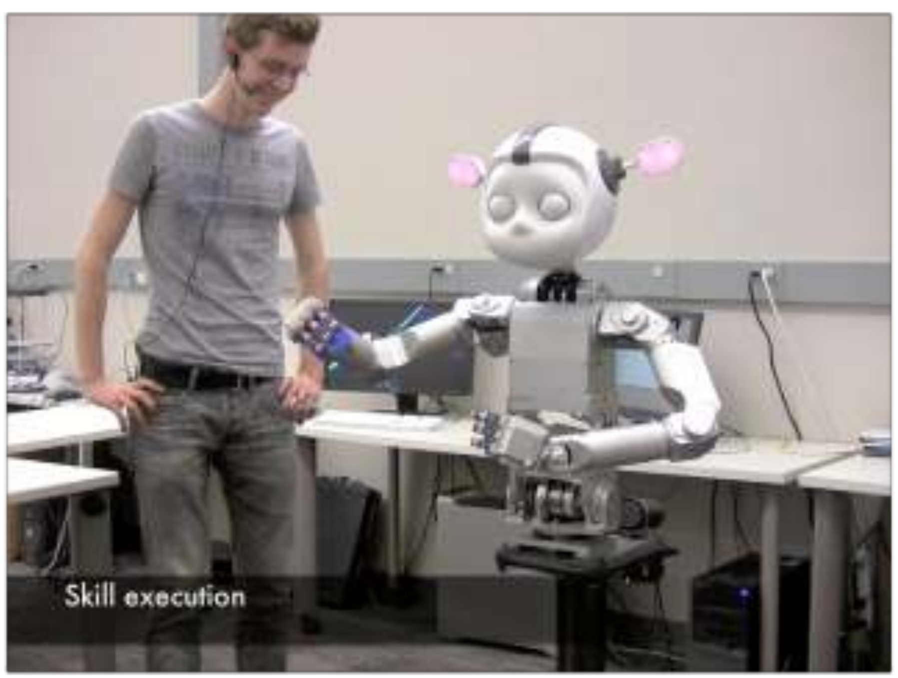
Label

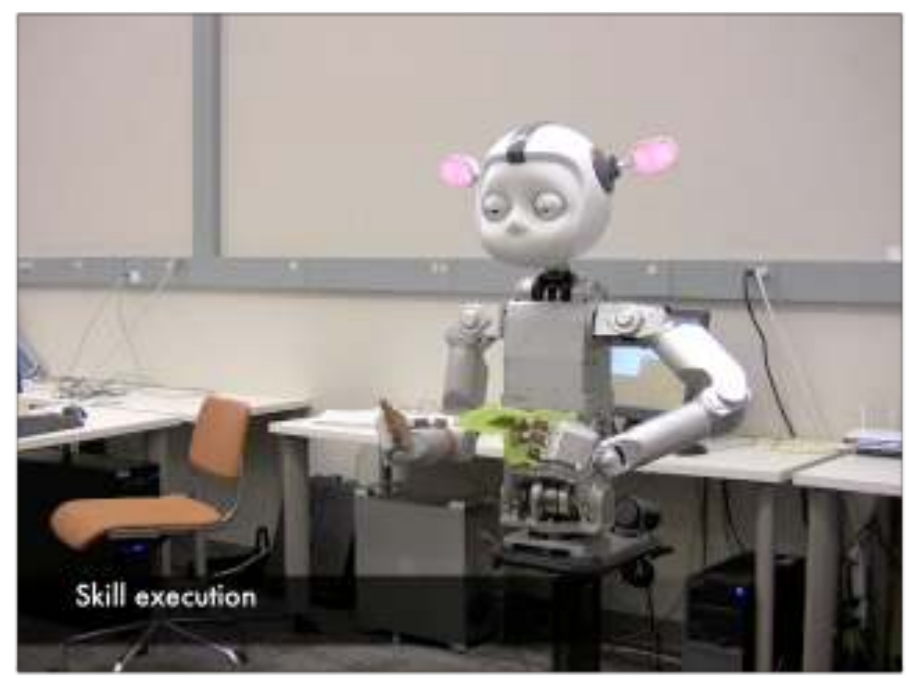
Feature

Demo

EFFECTIVENESS OF QUERIES

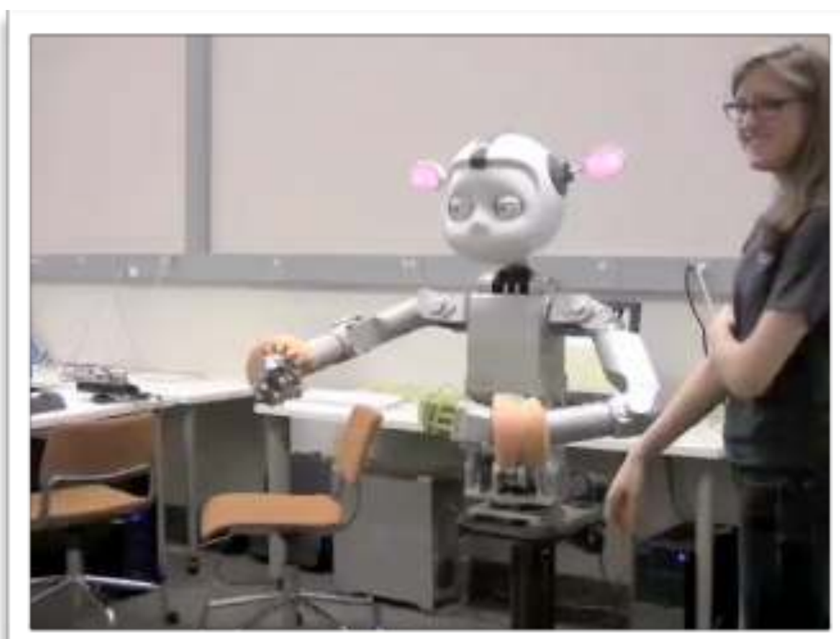
RESEARCH QUESTION	How do different queries help learning?
DESIGN	Four conditions: **unguided** versus **with queries**
DOMAIN	Bi-manual manipulation skills

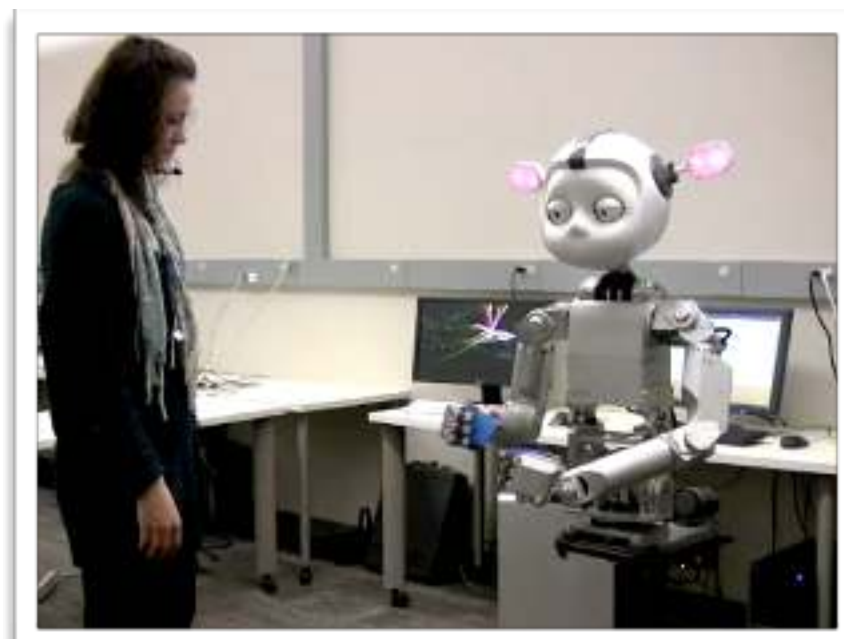




EFFECTIVENESS OF QUERIES

RESEARCH QUESTION	How do different queries help learning?
DESIGN	Four conditions: **unguided** versus **with queries**
DOMAIN	Bi-manual manipulation skills
METRICS	Applicability (in 50 tests) and Success (in 5 tests)



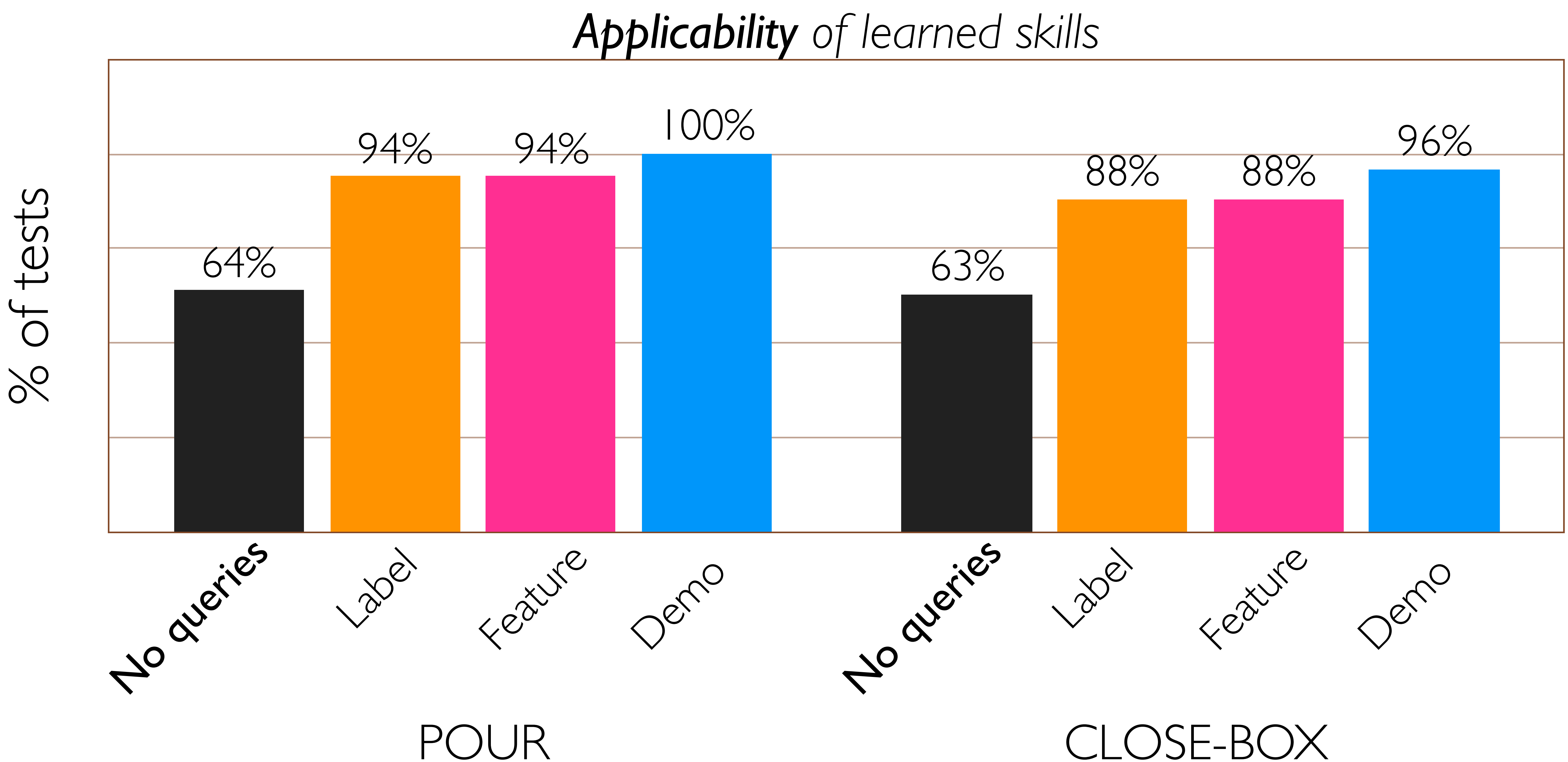


EFFECTIVENESS OF QUERIES

RESEARCH QUESTION	How do different queries help learning?
DESIGN	Four conditions: **unguided** versus **with queries**
DOMAIN	Bi-manual manipulation skills
METRICS	Applicability (in 50 tests) and Success (in 5 tests)
DATA	N=12, demonstrations for 5 mins

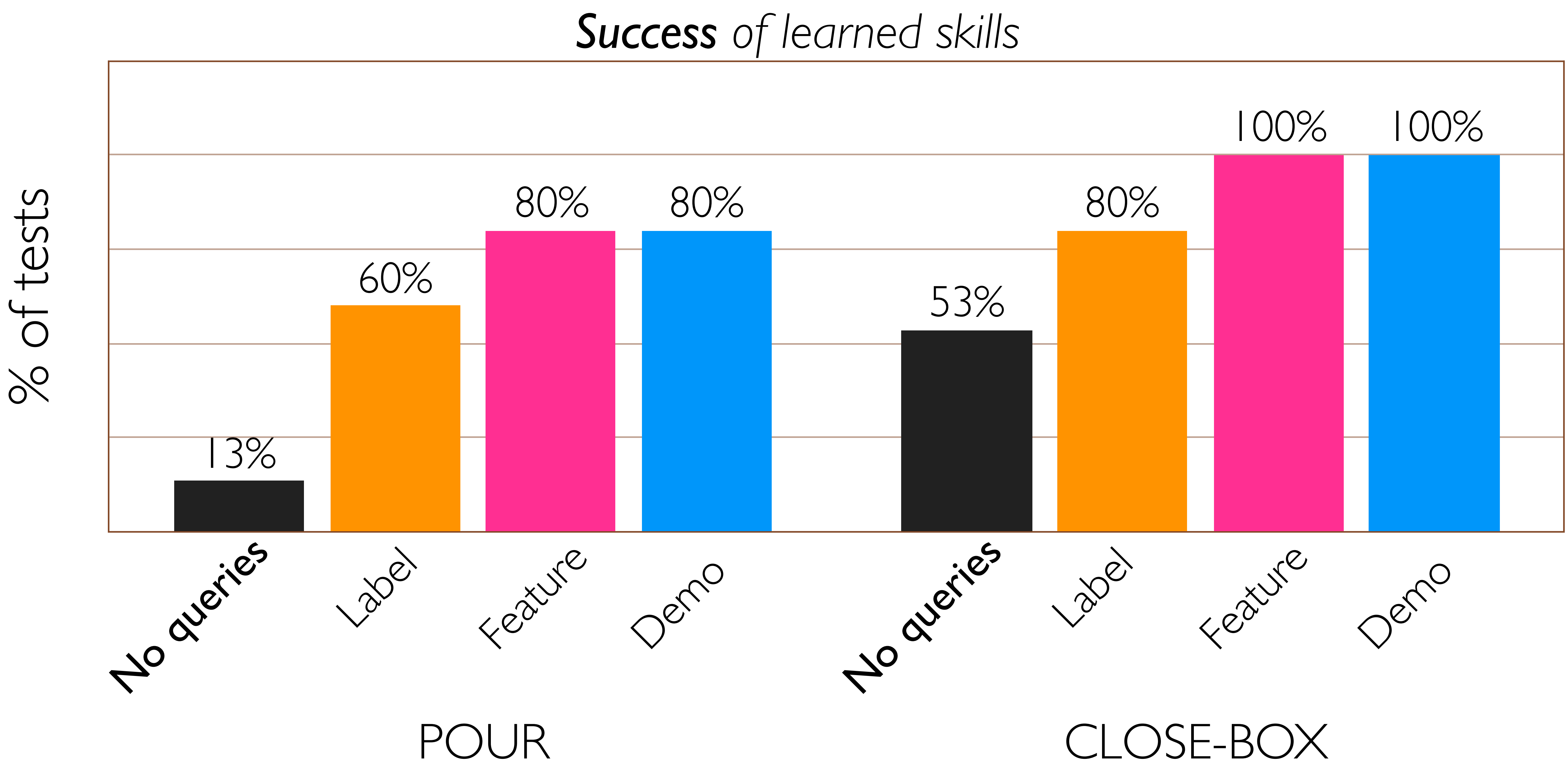
EFFECTIVENESS OF QUERIES

All queries lead to more applicable skills



EFFECTIVENESS OF QUERIES

All queries lead to more successful skills



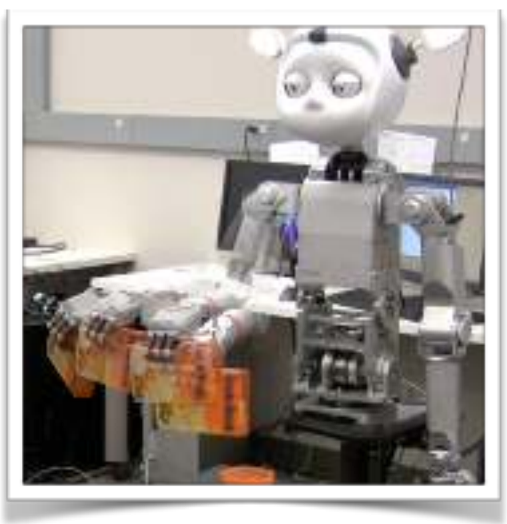
INTUITIVENESS OF QUERIES

RESEARCH QUESTION	Can people easily answer different queries? Which do they prefer?

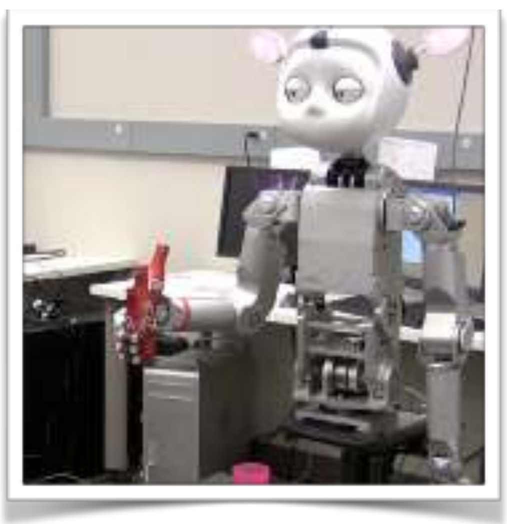
[Cakmak&Thomaz, HRI 2012]

INTUITIVENESS OF QUERIES

RESEARCH QUESTION	Can people easily answer different queries? Which do they prefer?
DESIGN	Within-subject study, 3 different **query types**
DOMAIN	Goal-directed skills (pouring salt, cereal, coke)



Label



Feature

Demo

[Cakmak&Thomaz, HRI 2012]

INTUITIVENESS OF QUERIES

RESEARCH QUESTION	Can people easily answer different queries? Which do they prefer?
DESIGN	Within-subject study, 3 different **query types**
DOMAIN	Goal-directed skills (pouring salt, cereal, coke)
METRICS	Subjective (perceived *smartness*, *ease*, *informativeness*) and objective (time to answer)
DATA	N=18, 2 demonstrations, 2 queries in each condition

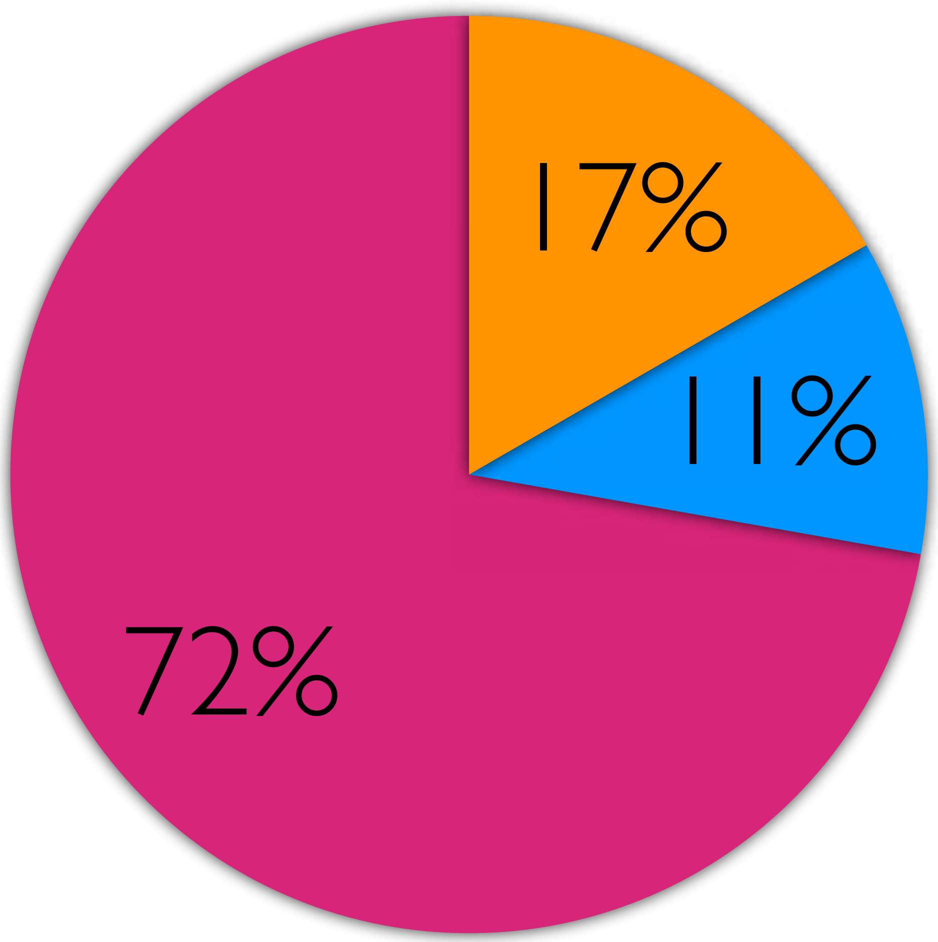
[Cakmak&Thomaz, HRI 2012]

INTUITIVENESS OF QUERIES

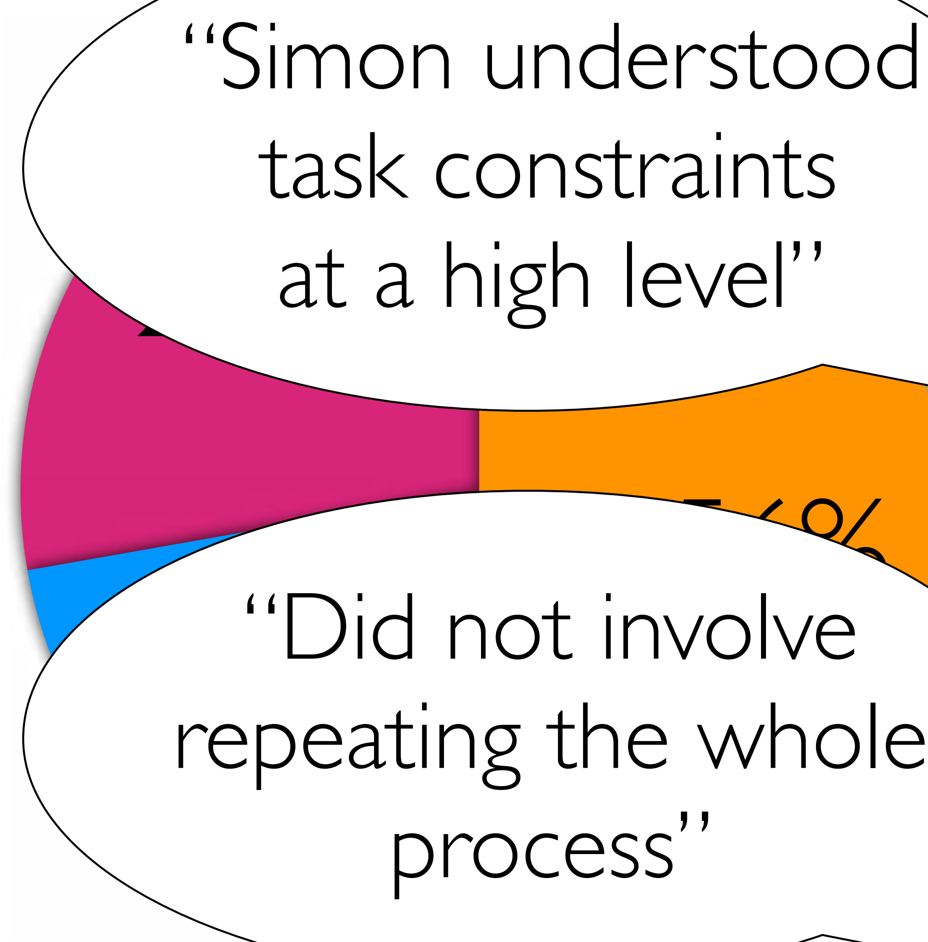
Subjective evaluation of different query types

Smartest

Feature queries



Easiest to answer



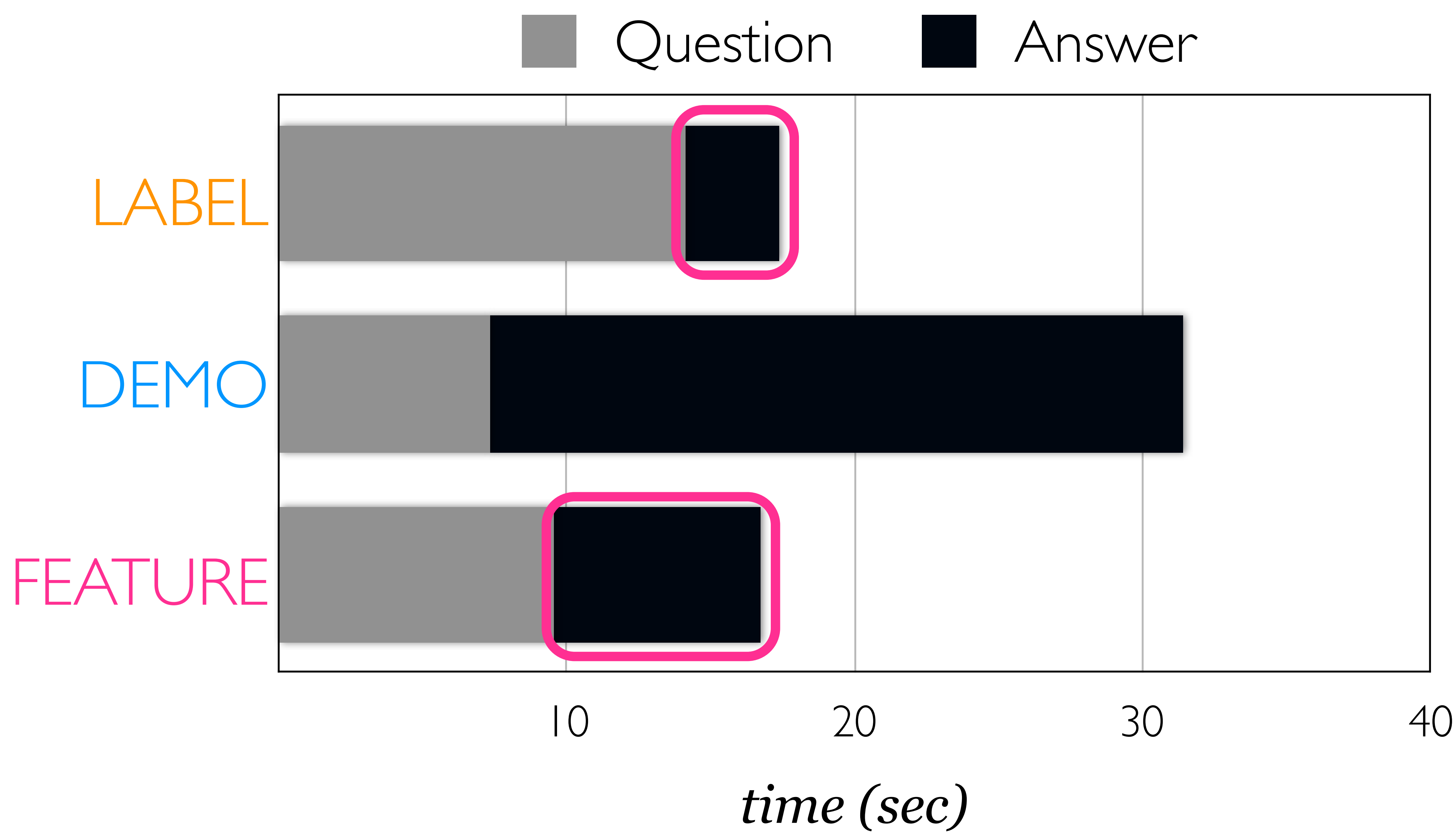
"Simon understood task constraints at a high level"

"Did not involve repeating the whole process"

[Cakmak&Thomaz, HRI 2012]

INTUITIVENESS OF QUERIES

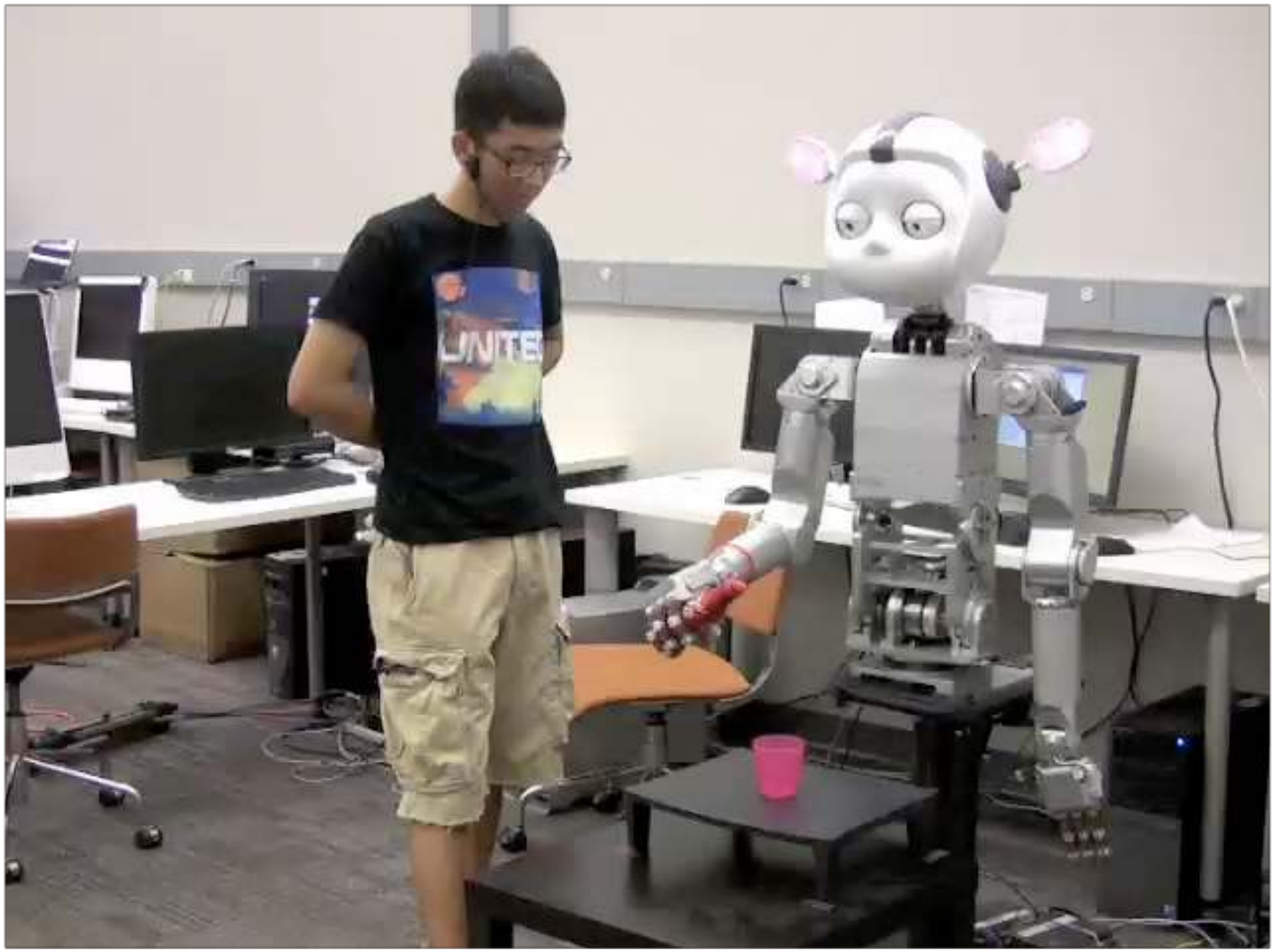
Objective evaluation of different query types



[Cakmak&Thomaz, HRI 2012]

INTUITIVENESS OF QUERIES

Feature queries harder to interpret



[Cakmak&Thomaz, HRI 2012]

SUMMARY

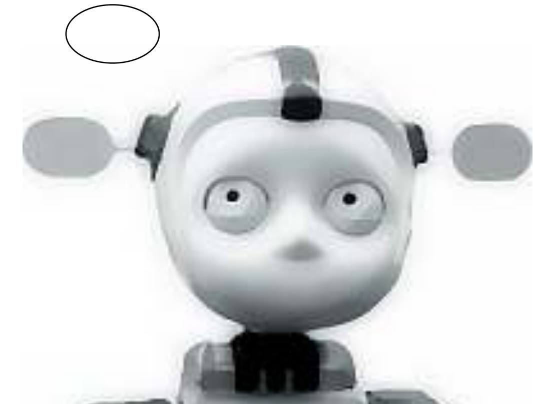
- Challenges with everyday users and the need for active learning
- Human question asking
- Human-like robot question asking

[HRI 2012a] M. Cakmak and A.L. Thomaz. **Designing Robot Learners that Ask Good Questions.** International Conference on Human-Robot Interaction (HRI), 2012.

[HRI 2012b] B. Akgun, M. Cakmak, J.W. Yoo and A.L. Thomaz. **Trajectories and Keyframes for Kinesthetic Teaching: A Human-Robot Interaction Perspective.** HRI, 2012.

[TAMD 2010] M. Cakmak, C. Chao and A.L. Thomaz. **Designing Interactions for Robot Active Learners.** IEEE Transactions on Autonomous Mental Development, March, 2010.

Any queries?



Supported by **NSF, ONR** & **Honda**

TOPIC 2

HUMAN-ROBOT HAND-OVERS

WHY IS IT HARD?

NOT CONSCIOUS IN HUMANS

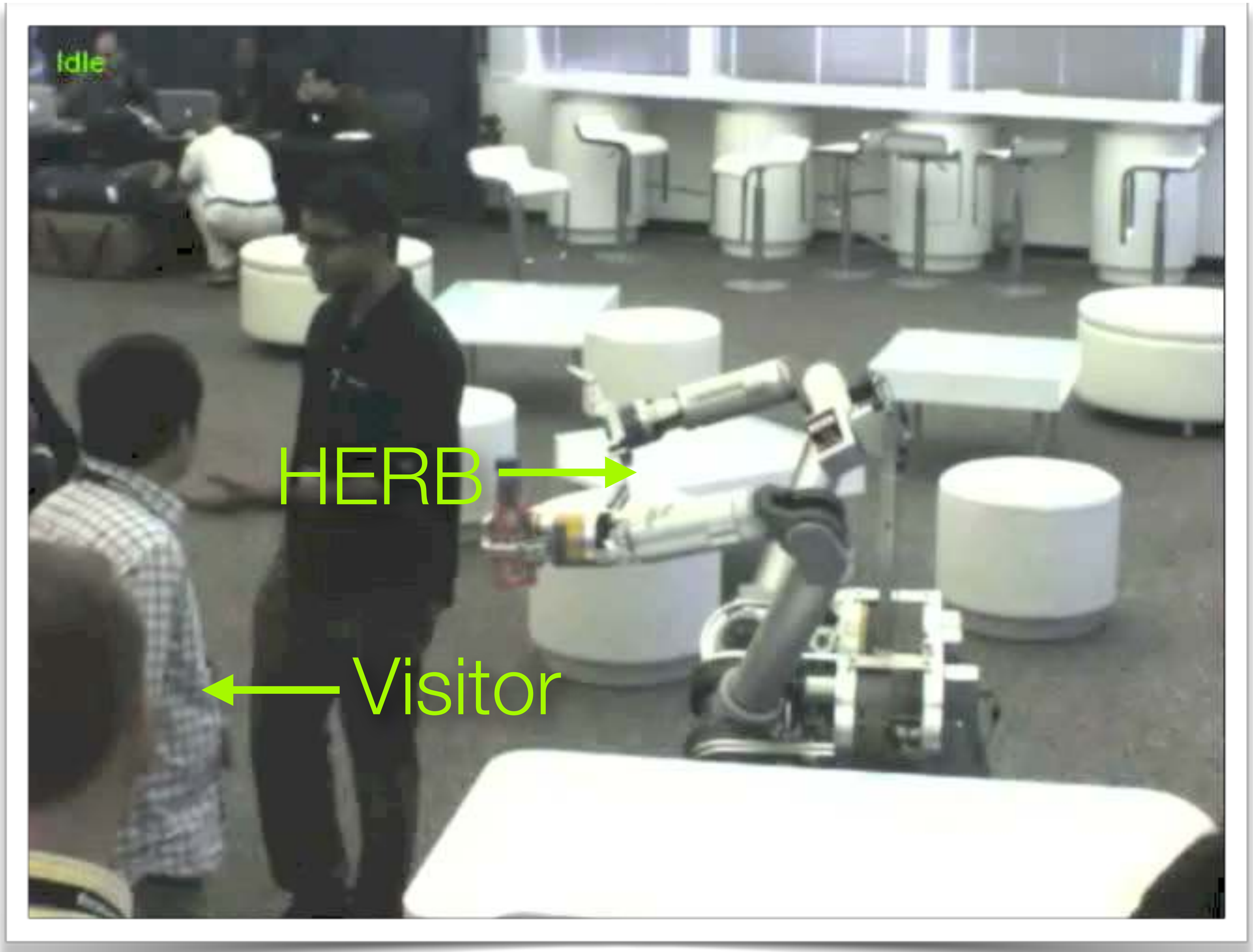
HARD TO ARTICULATE "GOOD"

HUMAN-HUMAN HAND-OVERS

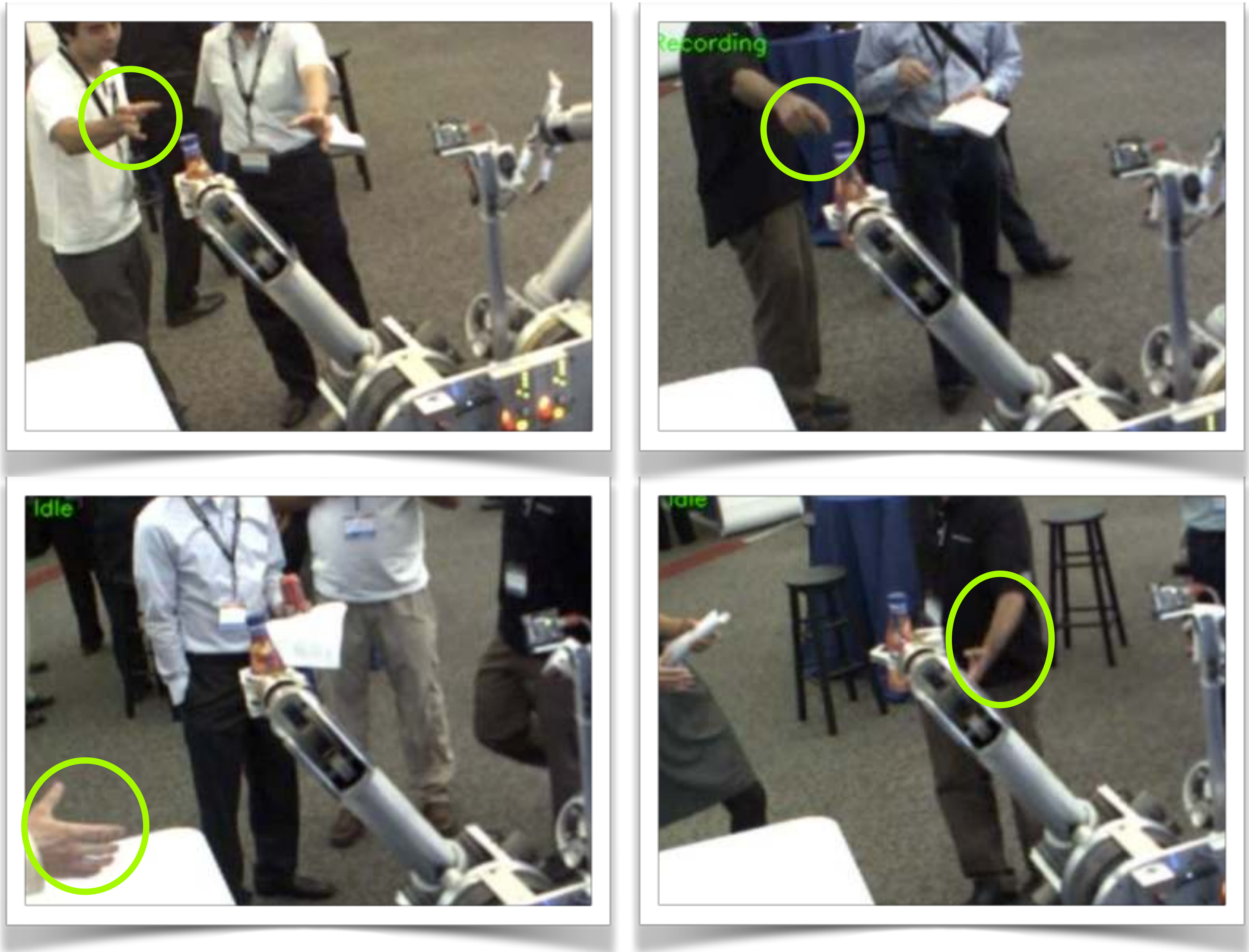
COMMON PROBLEMS

- Hand hanging in the air
- Multiple attempts
- Holding object together
- Robot waiting for a long time
- Need prompt and help from staff
- Pulling in different directions
- Need to change grasp
- Need to re-grasp after hand-off

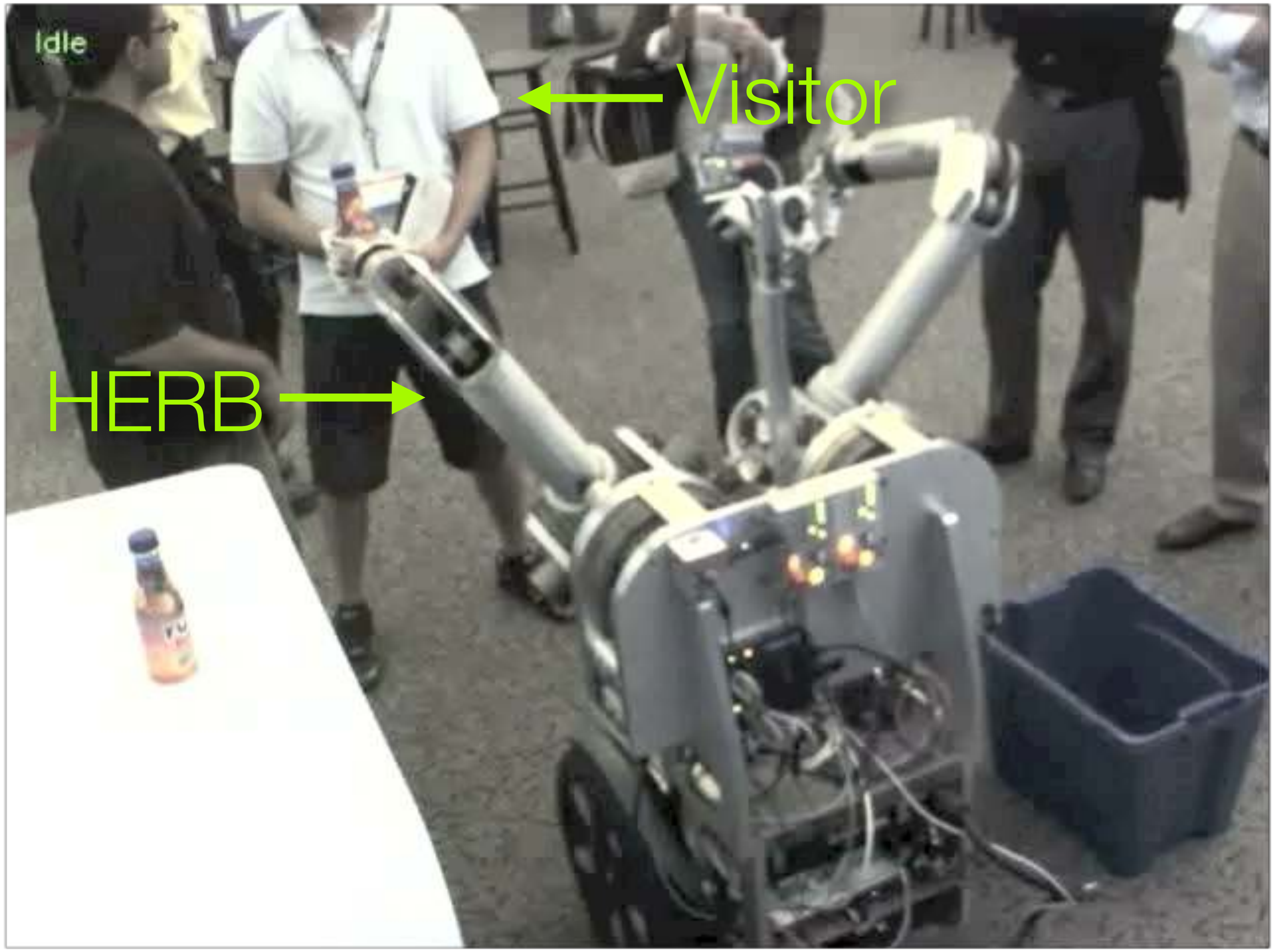
> Recorded hand-over attempts: 147
> Successful hand-overs to novices: 7



PROBLEM 1 - COMMUNICATION OF INTENT

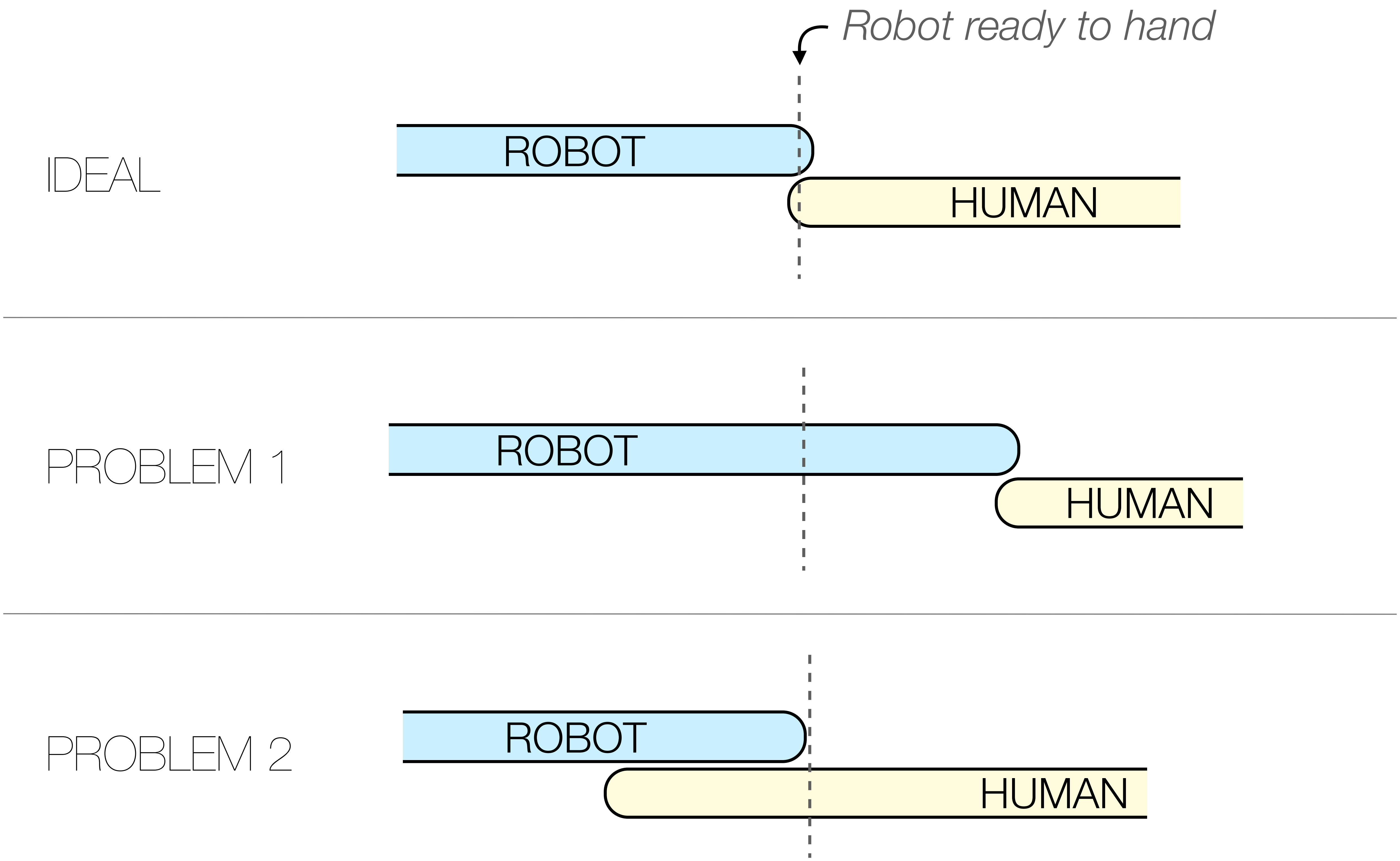


PROBLEM 1 - COMMUNICATION OF INTENT



PROBLEM 2 - COMMUNICATION OF TIMING

NOT JUST HERB…



PROBLEMS IN FLUENCY

VERSUS

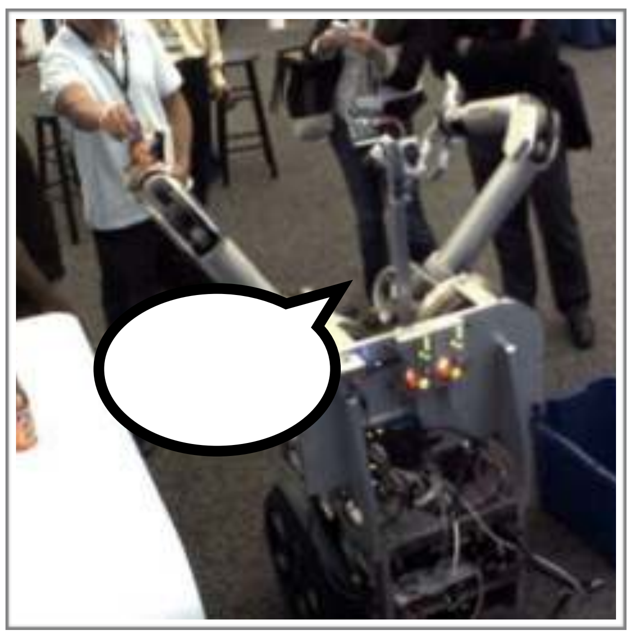
COMMUNICATION OF INTENT

COMMUNICATION OF TIMING

PROBLEM 1

Spatial Contrast

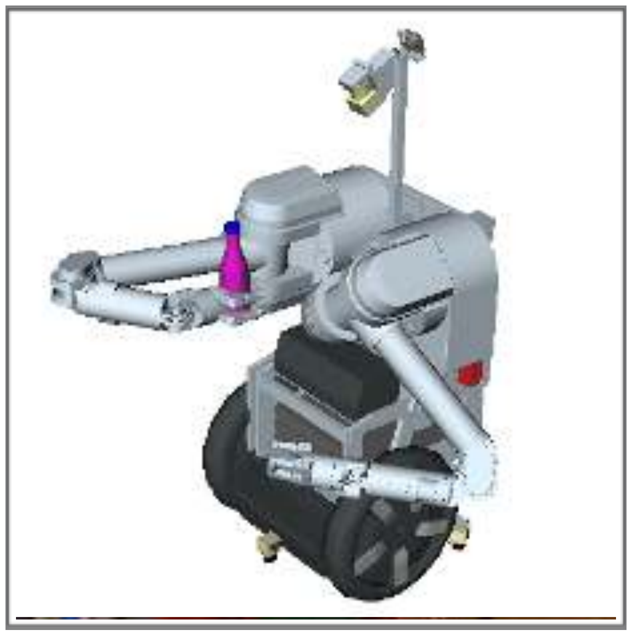
PROBLEM 2

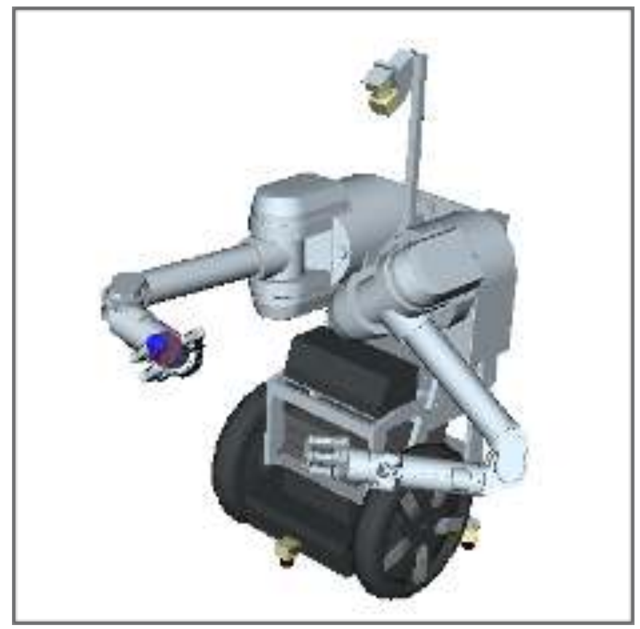


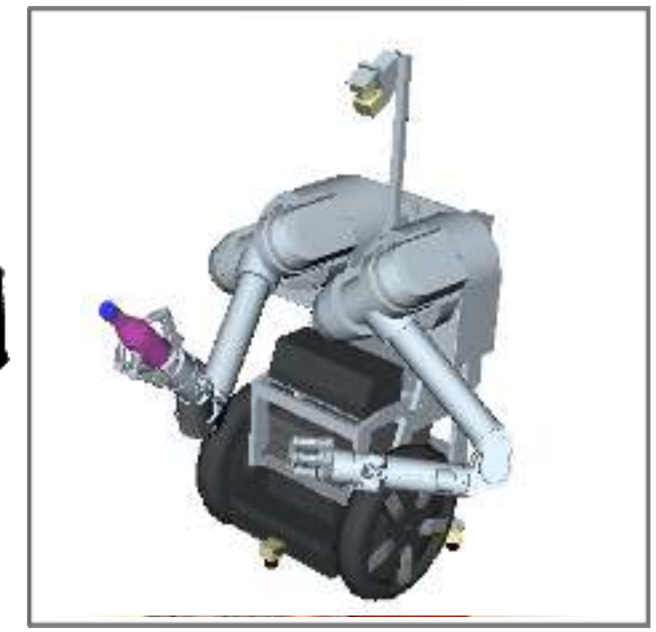
Temporal Contrast

PROPOSED SOLUTIONS

HANDING OVER?

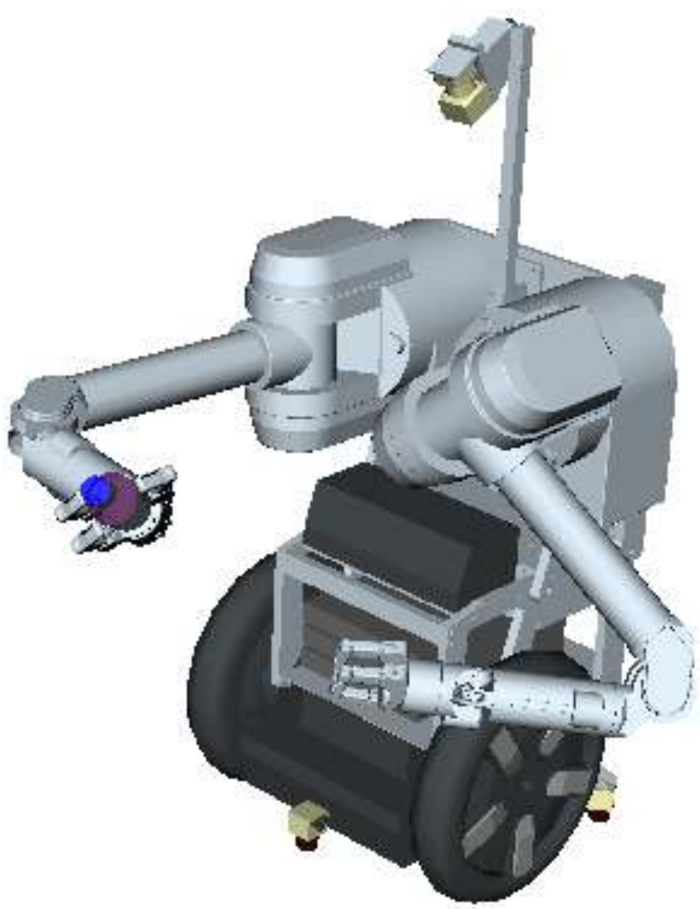






HAND-OVER POSES FOR HERB

Survey: What is the robot doing?

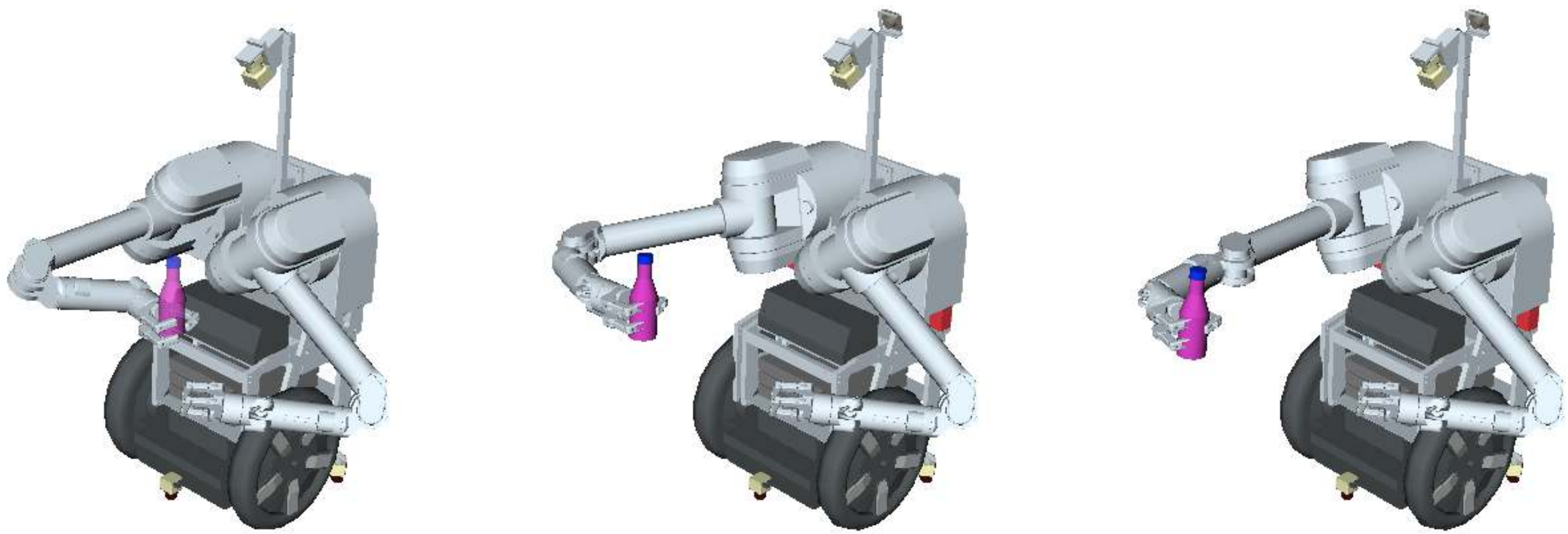


- ☐ Holding the bottle
- ☐ Looking at the bottle
- ☐ Handing the bottle
- ☐ Showing the bottle
- ☐ Other

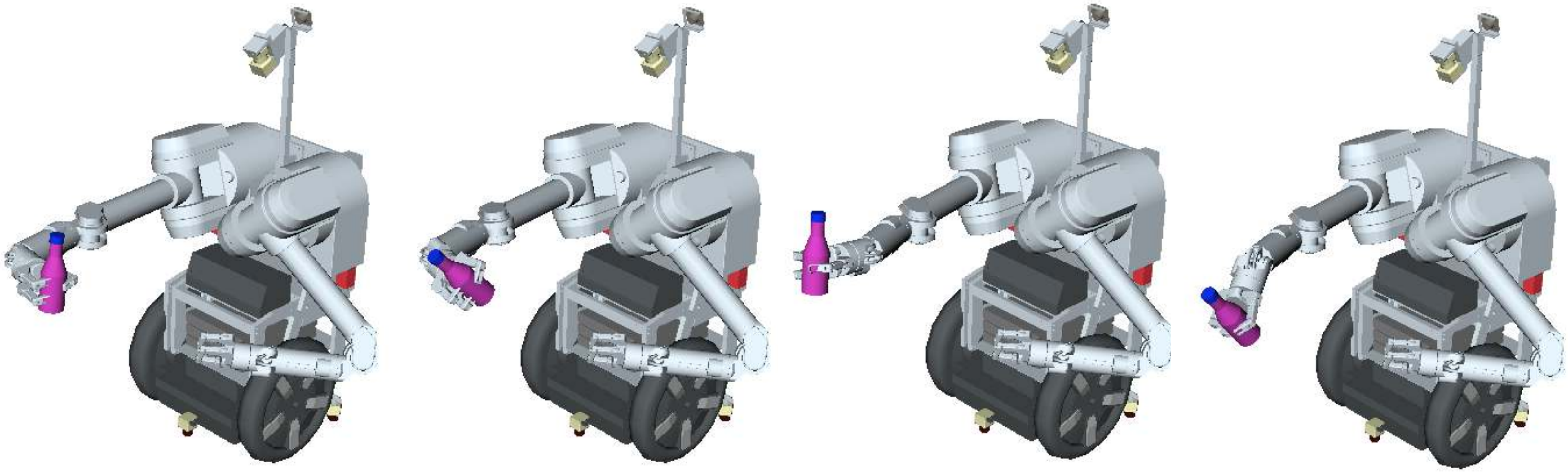
POSE PARAMETERS

Object tilt

Arm extension



Spatial contrast: Arm extended, object exposed

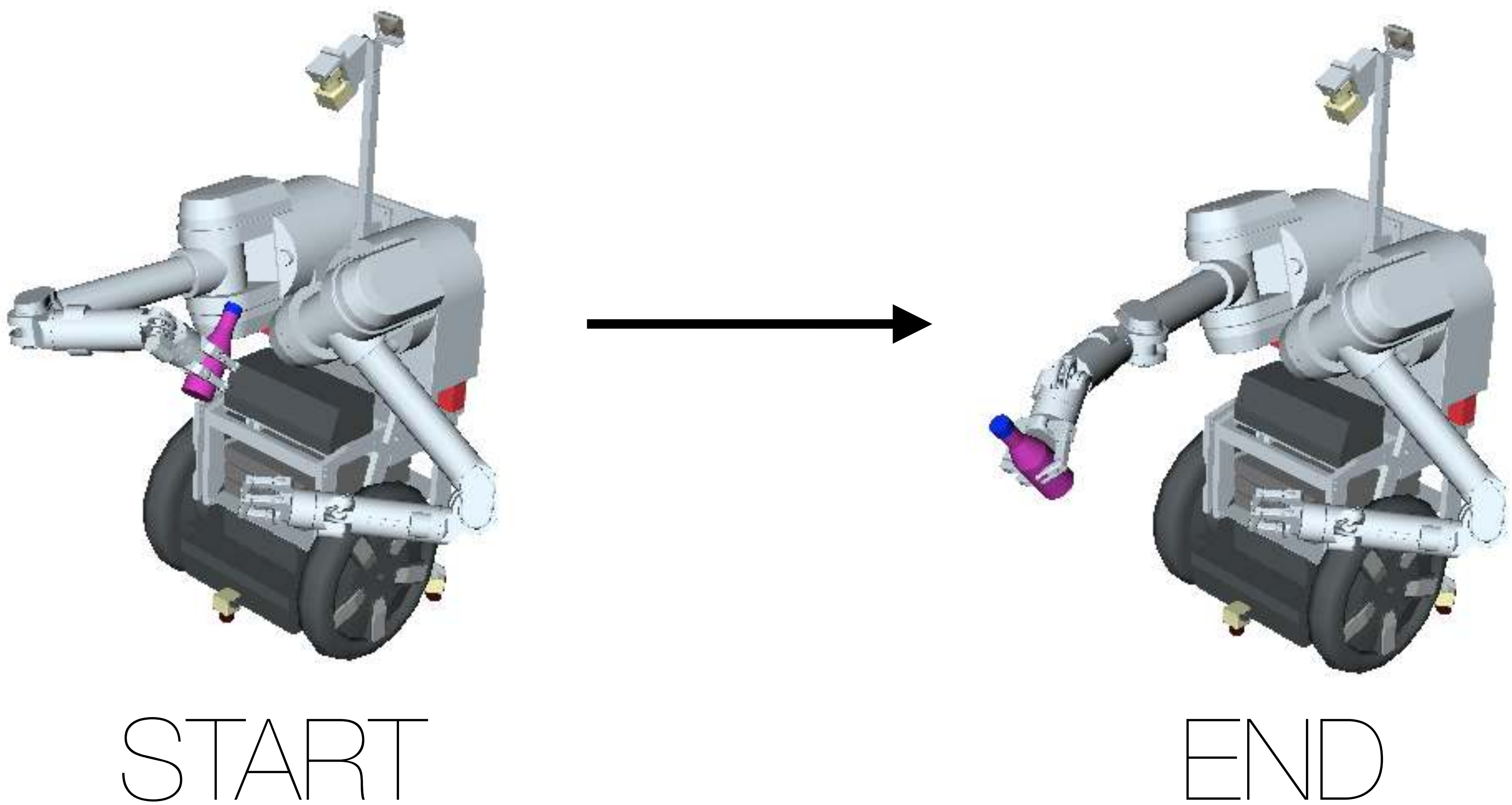


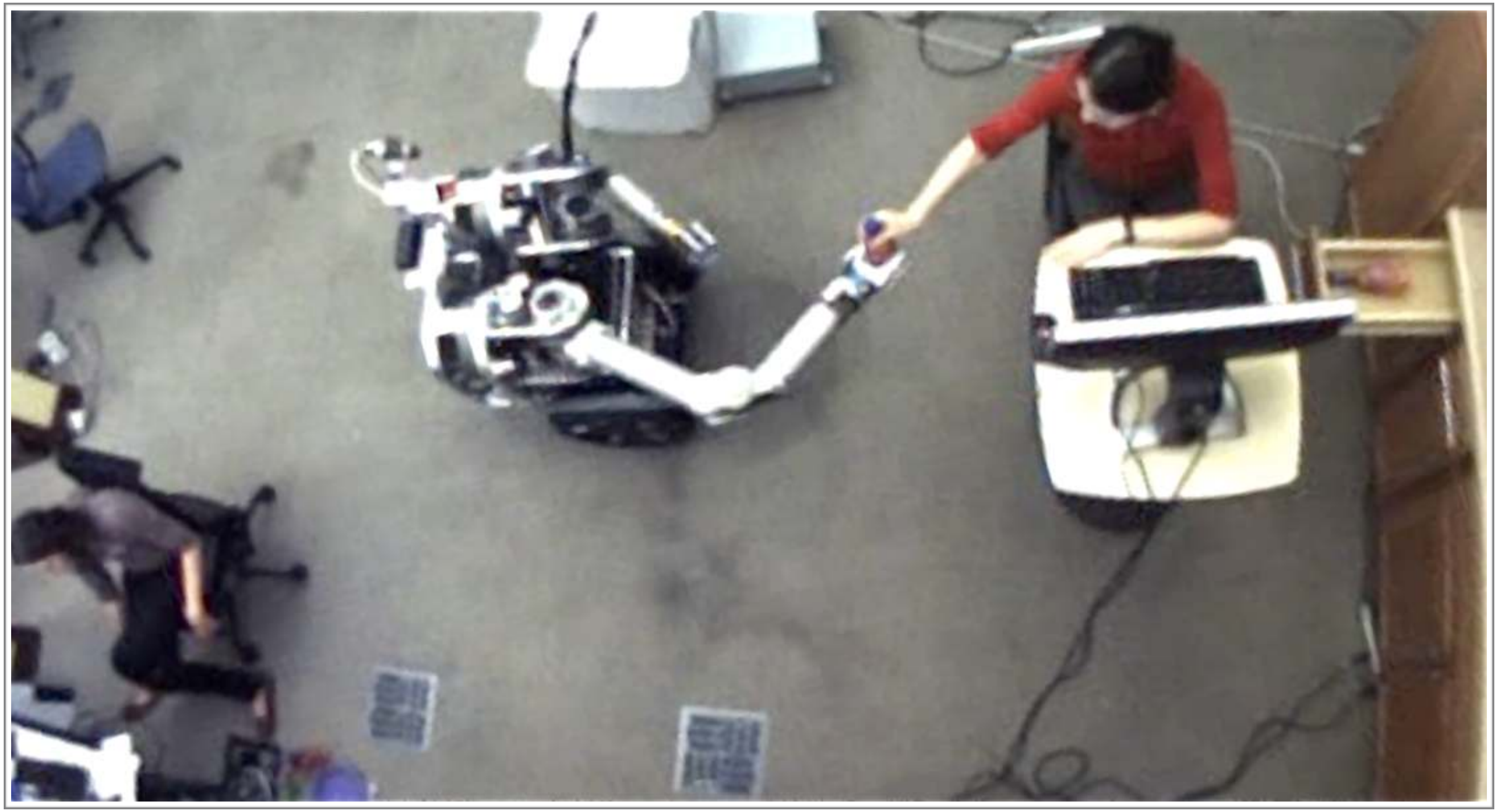
37% 40% 81% 92%

Poses that are picked as handing more (N=50)

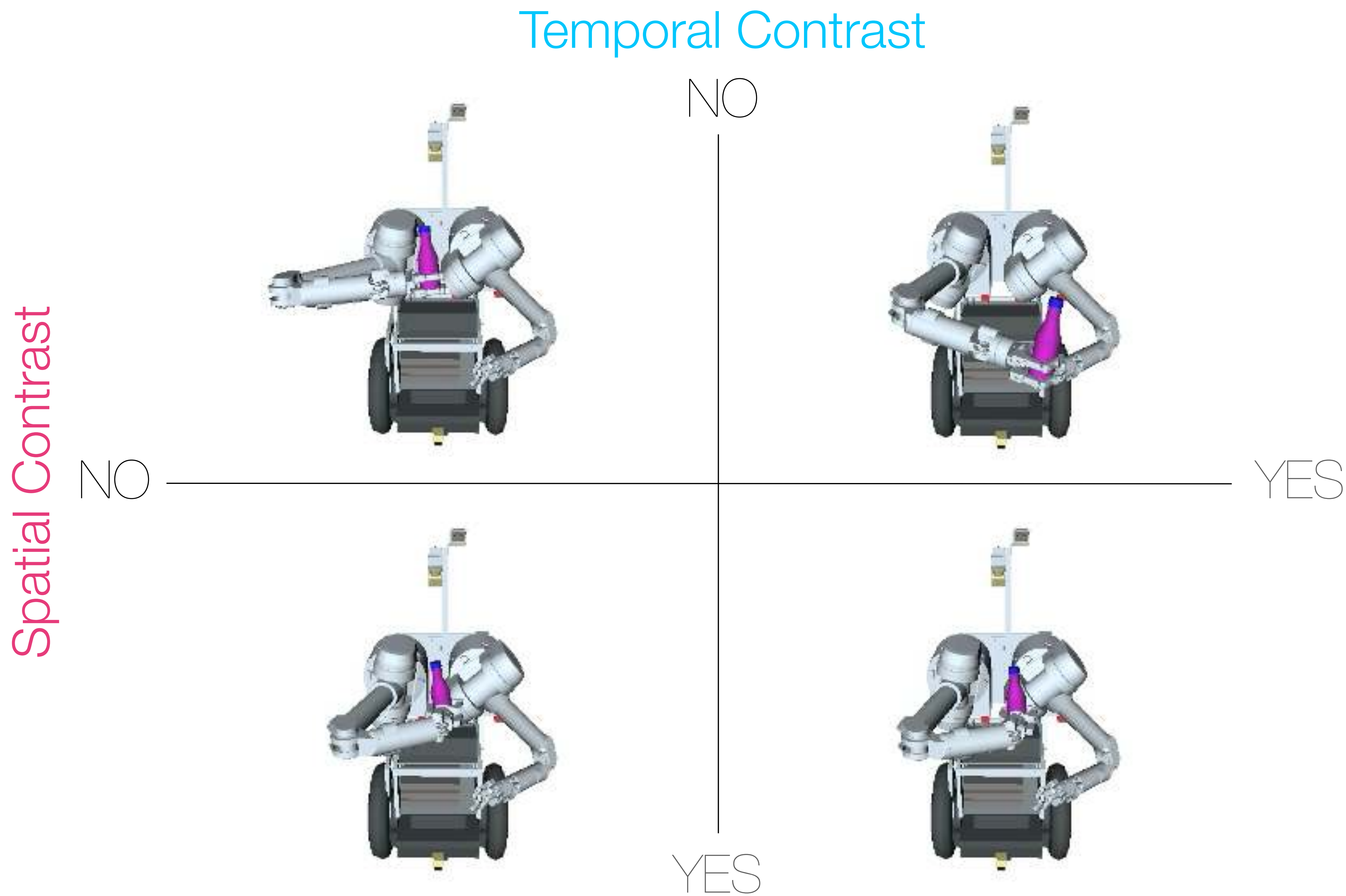
HAND-OVER POSES FOR HERB

Temporal contrast: Non-handing to handing





N=24 (9 female & 15 male, Ages: 20-45)

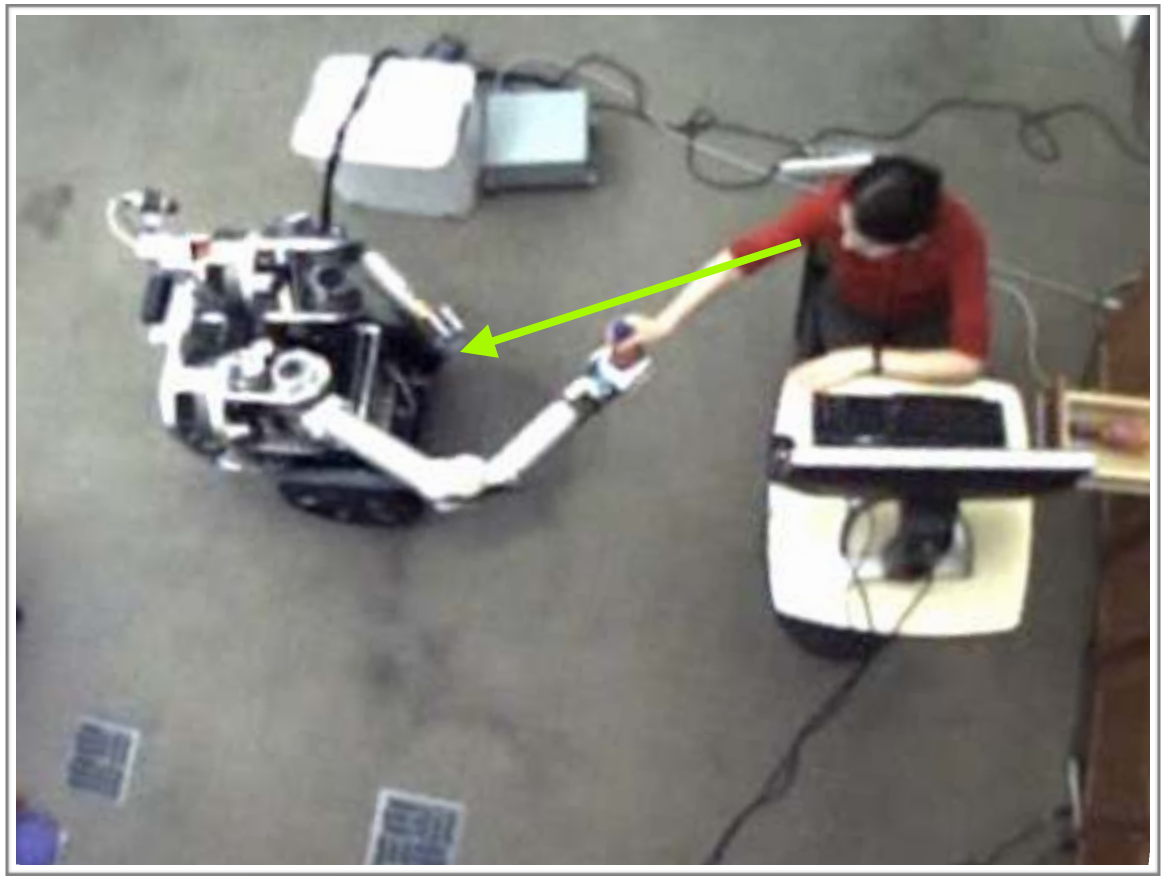


Within-groups, order counter-balanced

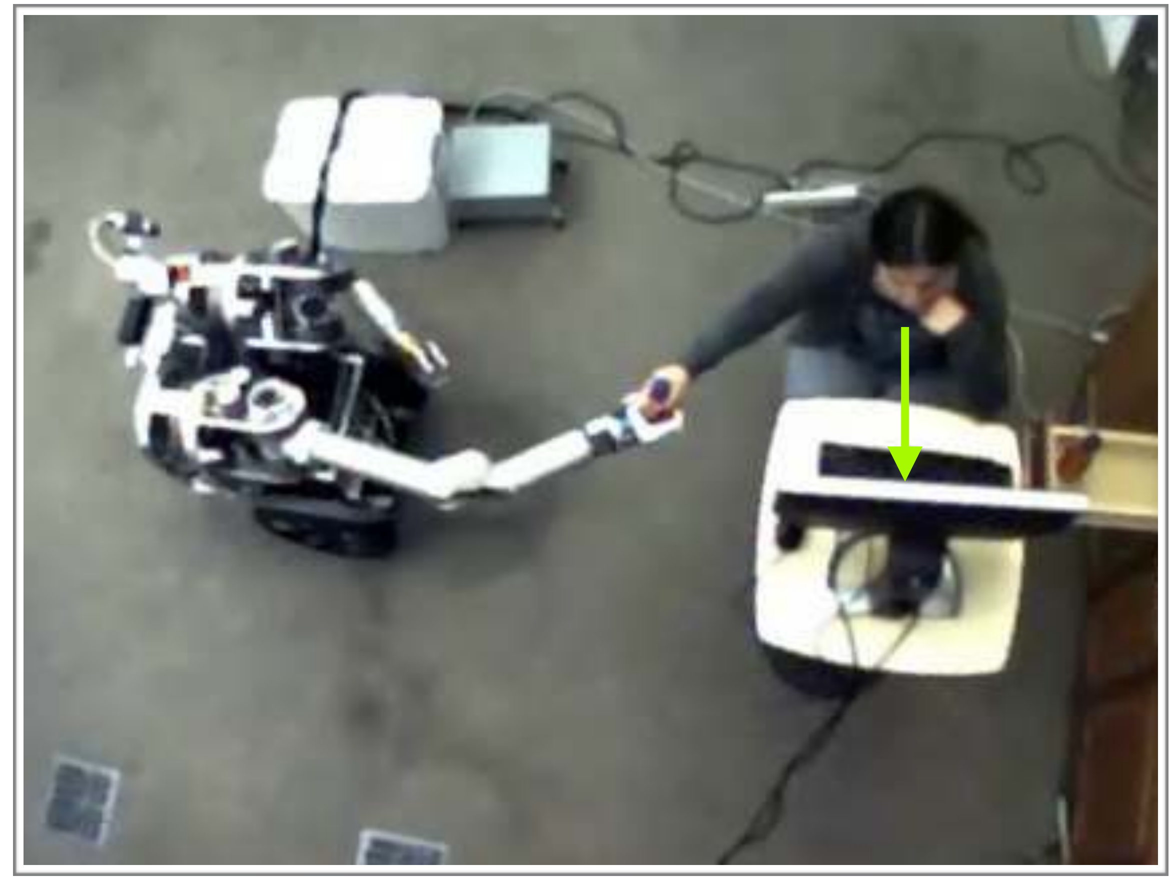
INDEPENDENT VARIABLES

AVAILABLE

BUSY



Watching the robot



Doing attention test

Between-groups

EXTRANEOUS VARIABLE

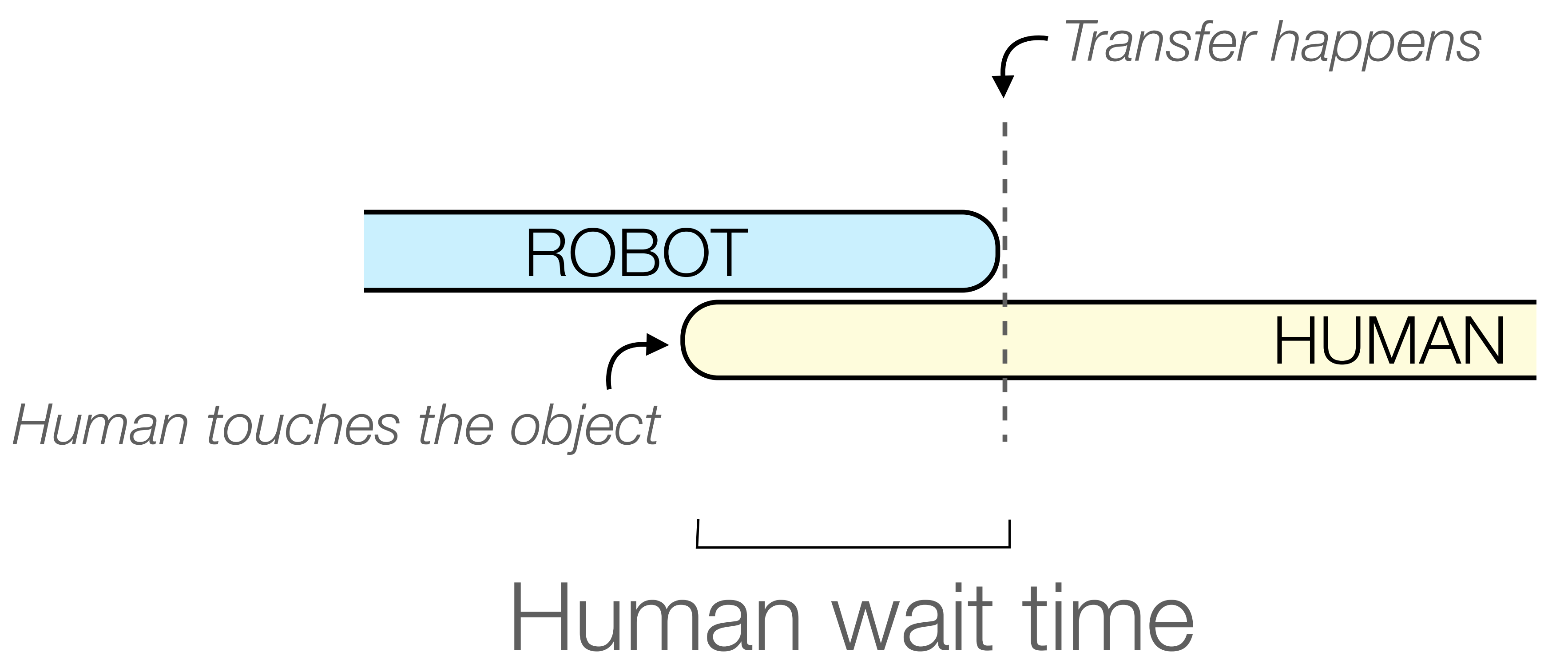
- Object transfer location

- Trajectory splining method
- Arm movement speed

FIXED VARIABLES

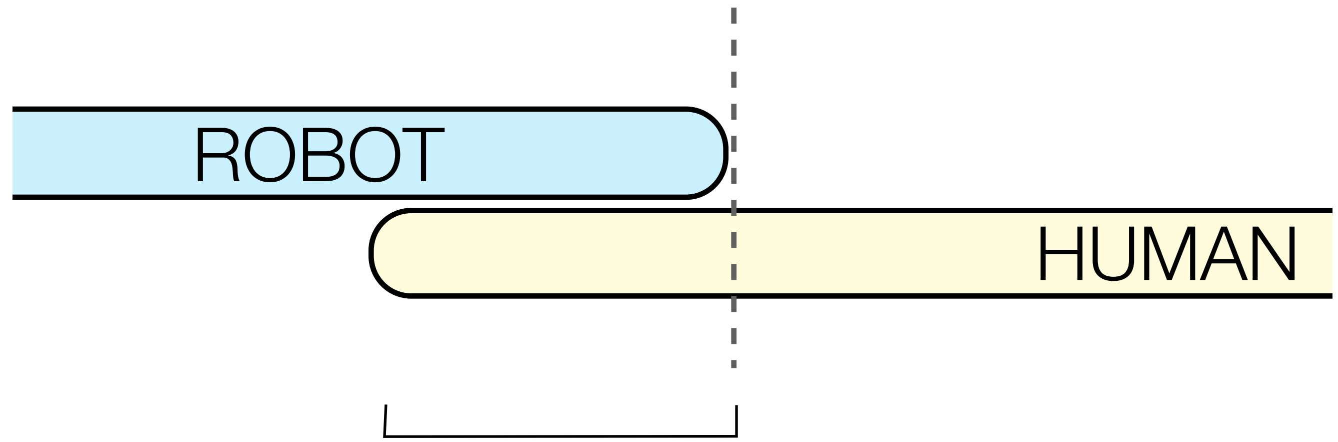
- ☐ Temporal contrast improves fluency
- ☐ Spatial contrast has no effect

RESULTS



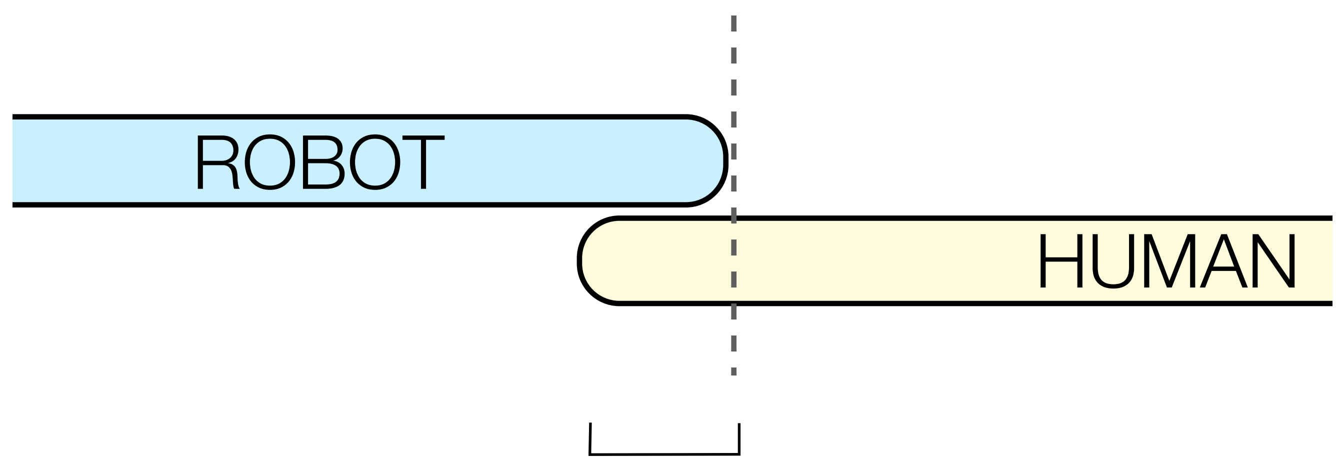
EFFECT OF TEMPORAL CONTRAST

No Temporal Contrast



2.5 sec (SD=1.8)

Temporal contrast



1.4 sec (SD=0.9)

EFFECT OF TEMPORAL CONTRAST

EXAMPLES | NO TEMPORAL CONTRAST

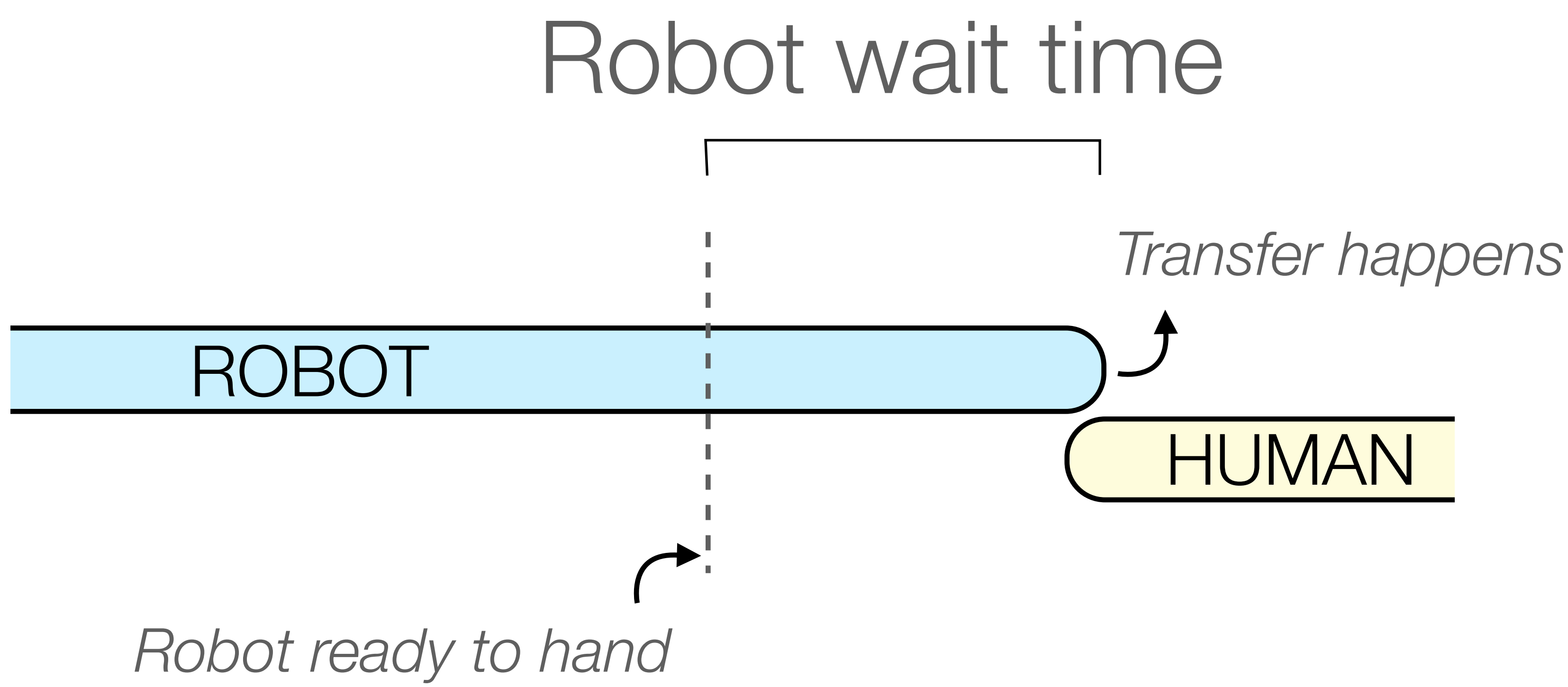
Early hand-over attempts

No Temporal Contrast	9 attempted
Temporal Contrast	0 attempted

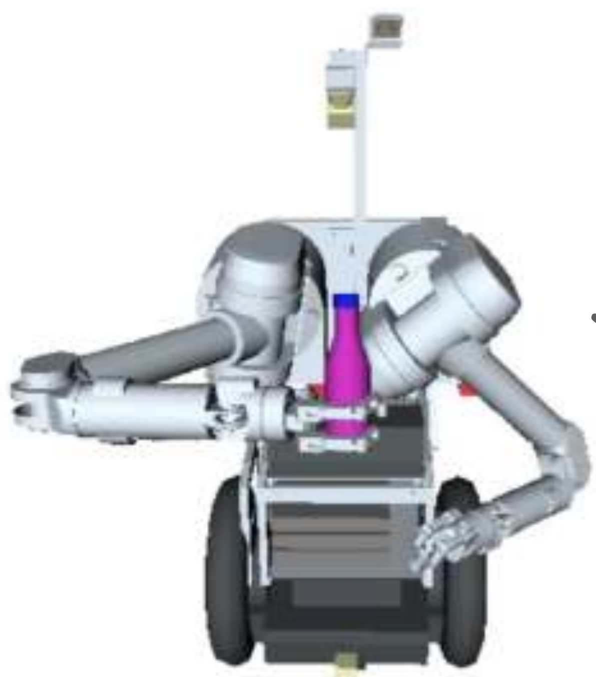
Missed responses in attention test

No Temporal Contrast	~3
Temporal Contrast	~2

EXAMPLES | WITH TEMPORAL CONTRAST



EFFECTS OF SPATIAL CONTRAST



VERSUS

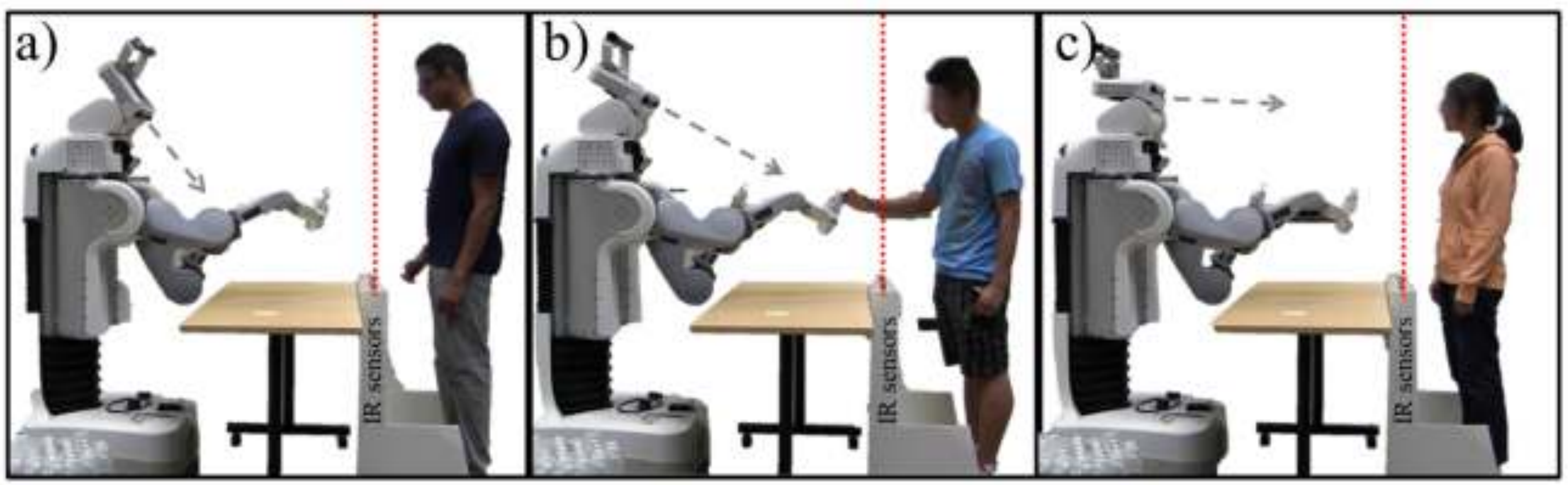
NO EFFECT. WHY?

- Conveying intent was not an issue
- Intent was also conveyed by arm movement

EFFECTS OF SPATIAL CONTRAST

- ☐ Spatial contrast to communicate hand-over intent
- ☐ Temporal contrast to communicate hand-over timing

HIDE & REVEAL

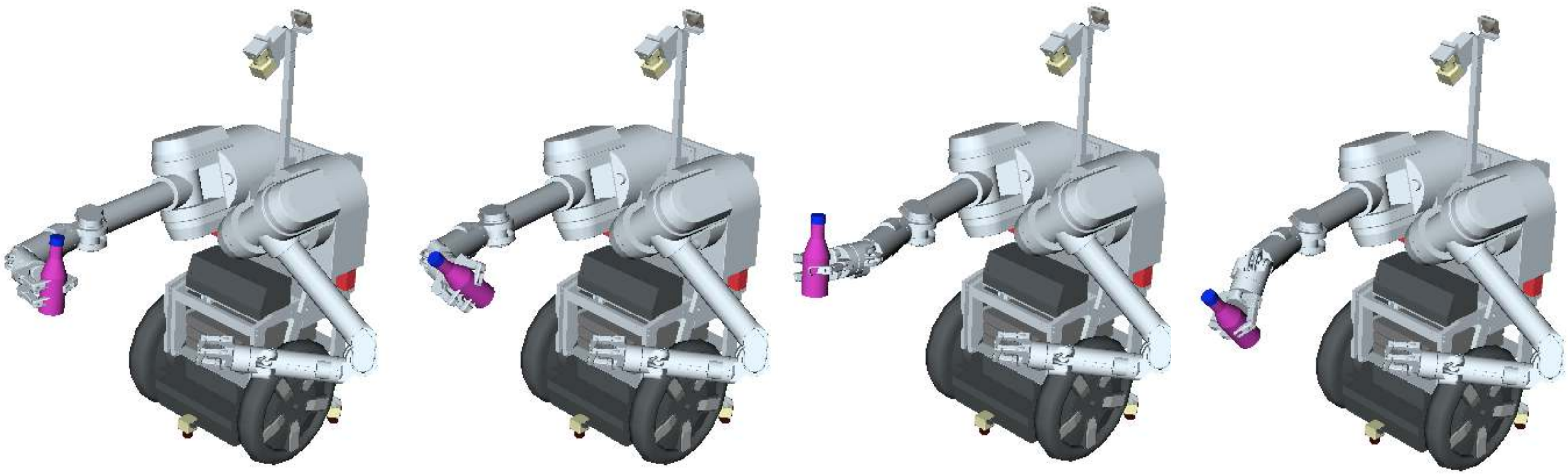


MOON ET AL. HRI 2014

SUMMARY

HOW TO PRESENT THE OBJECT?

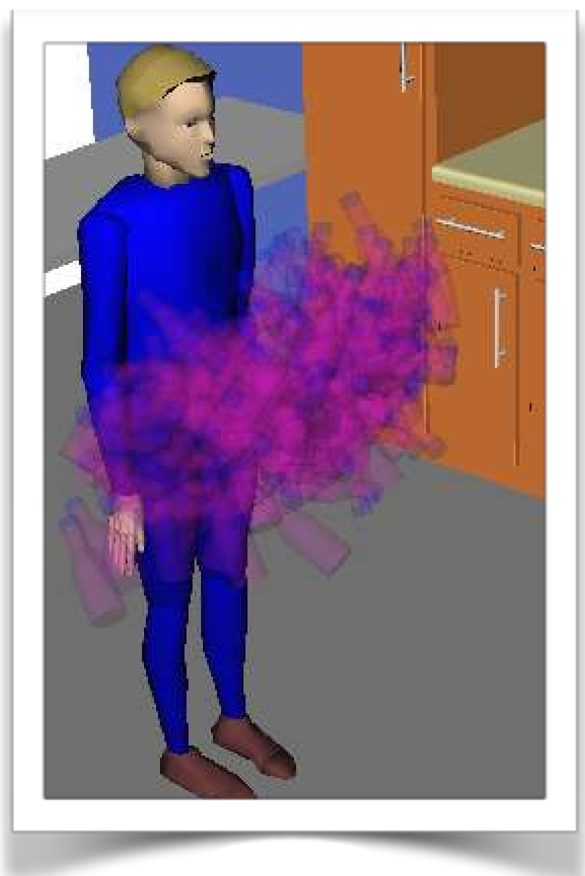
to convey intent

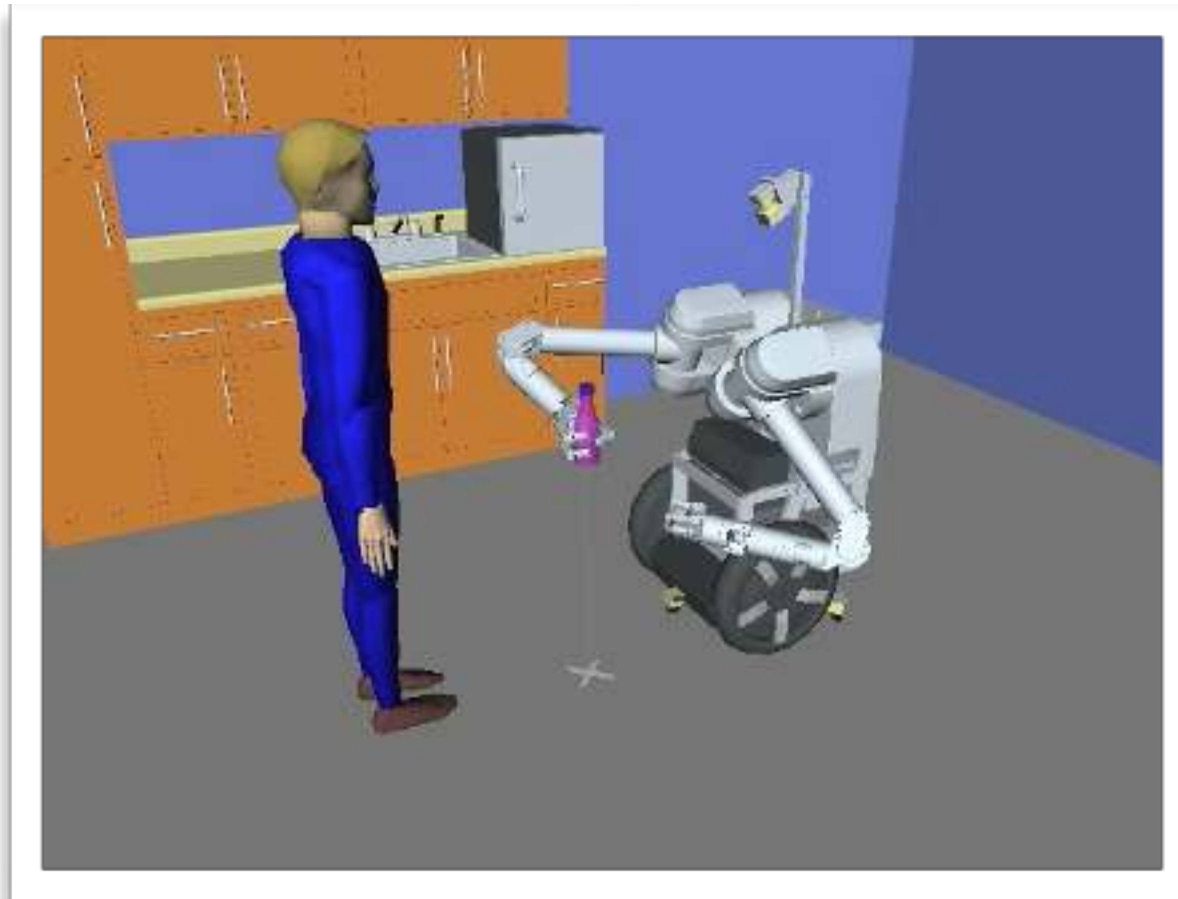


HOW TO PRESENT THE OBJECT?

to convey intent

to make it easy/intuitive to take for human





PLANNING/
OPTIMIZATION

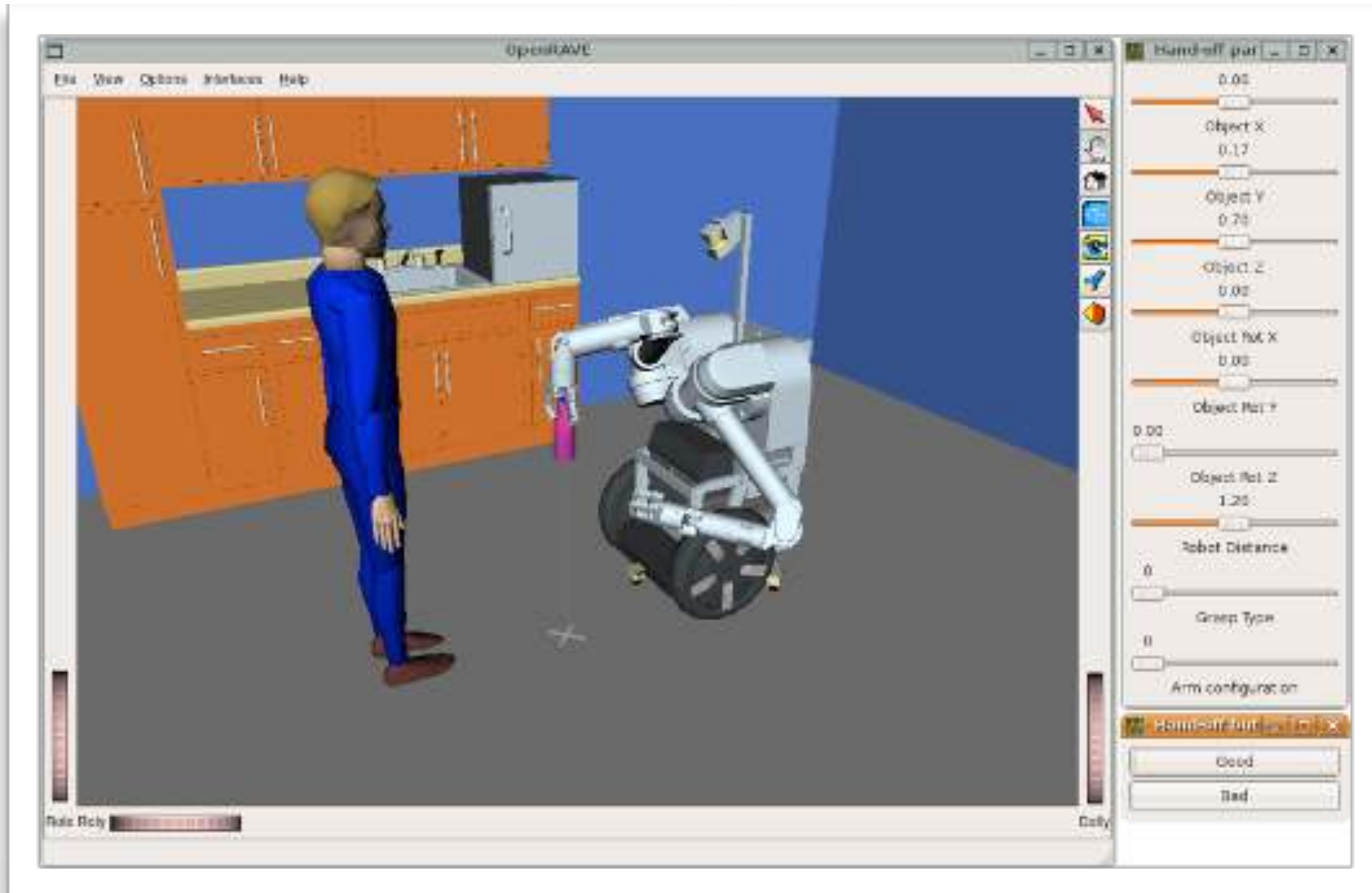
LEARNING
FROM EXAMPLES

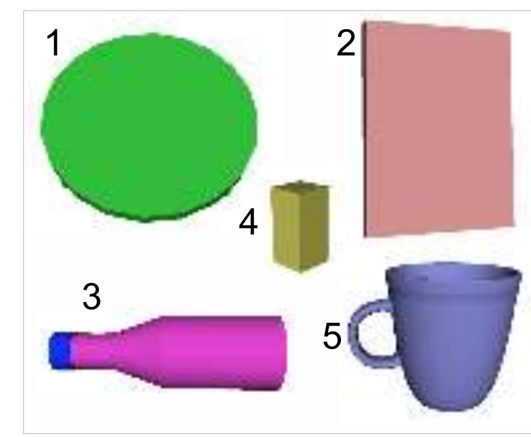
HAND-OVER PARAMETERS

N=10 (8 male, 2 female)

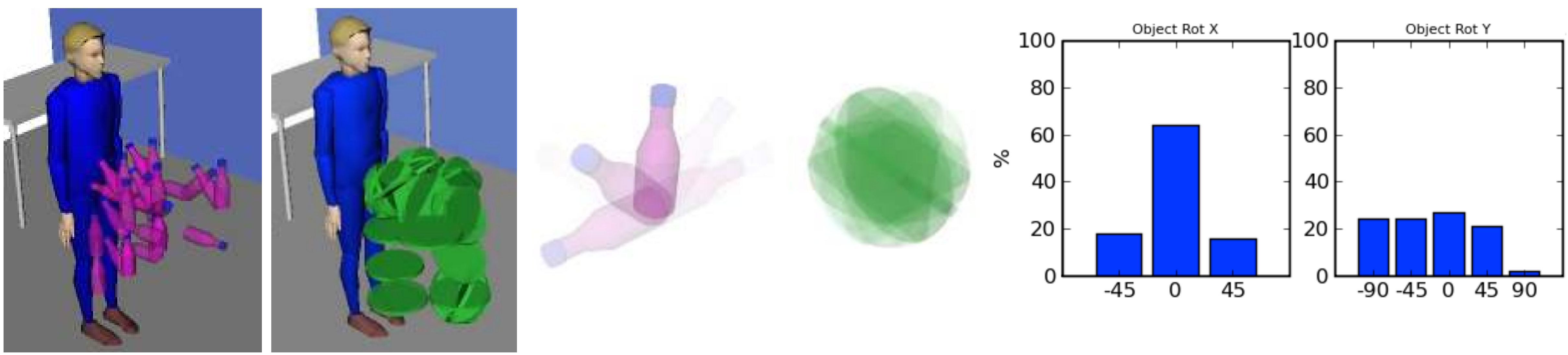
3 good 3 bad examples

5 objects





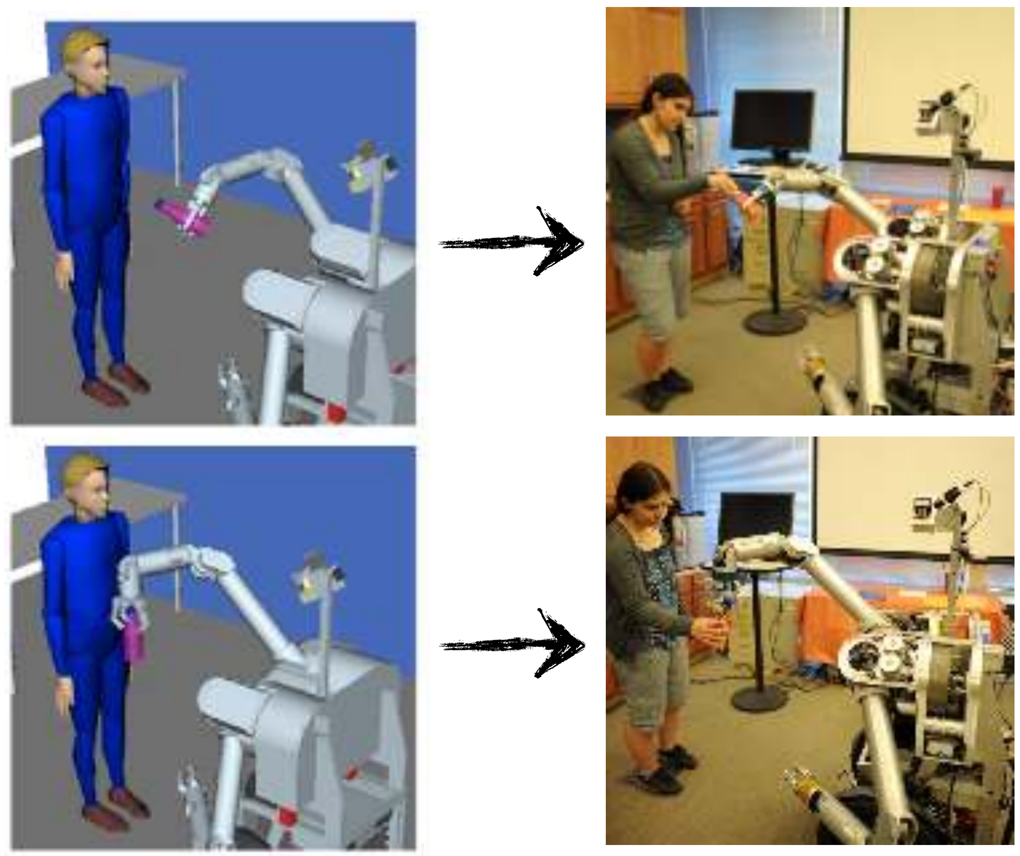
LEARNING HAND-OVER CONFIGURATIONS



COLLECTED DATA

PLANNING

LEARNING



Which one did you prefer?

Which one looked more natural?

Which one was easier to take?

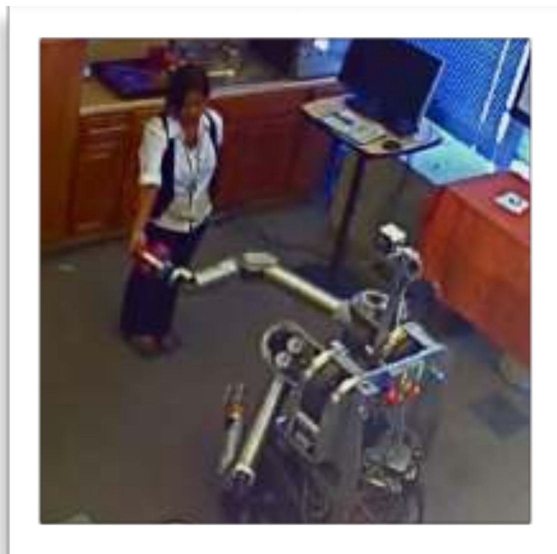
Which one was more appropriate?

EVALUATION

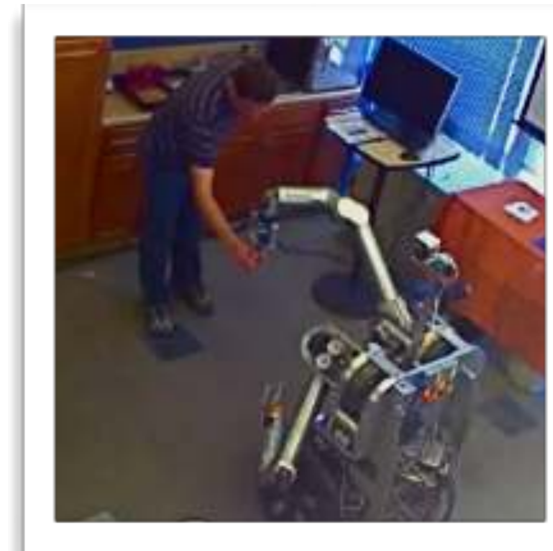
N=10 (6 male, 5 female), 5 objects

	PLANNING	LEARNING		
Preference	38%	62%	$\chi2(1,N=50)=2.88$, $p=.09$	
Naturalness	36%	64%	$\chi2(1,N=50)=3.92$, $p=.05$	*
Practicality	46%	54%	$\chi2(1,N=50)=0.32$, $p=.57$	
Appropriateness	38%	62%	$\chi2(1,N=50)=2.88$, $p=.09$	

Subjective user evaluation



	PLANNING	LEARNING
Bottle	2	16
Mug	5	1
Notebook	2	7
Plate	6	3
Shaker	13	19

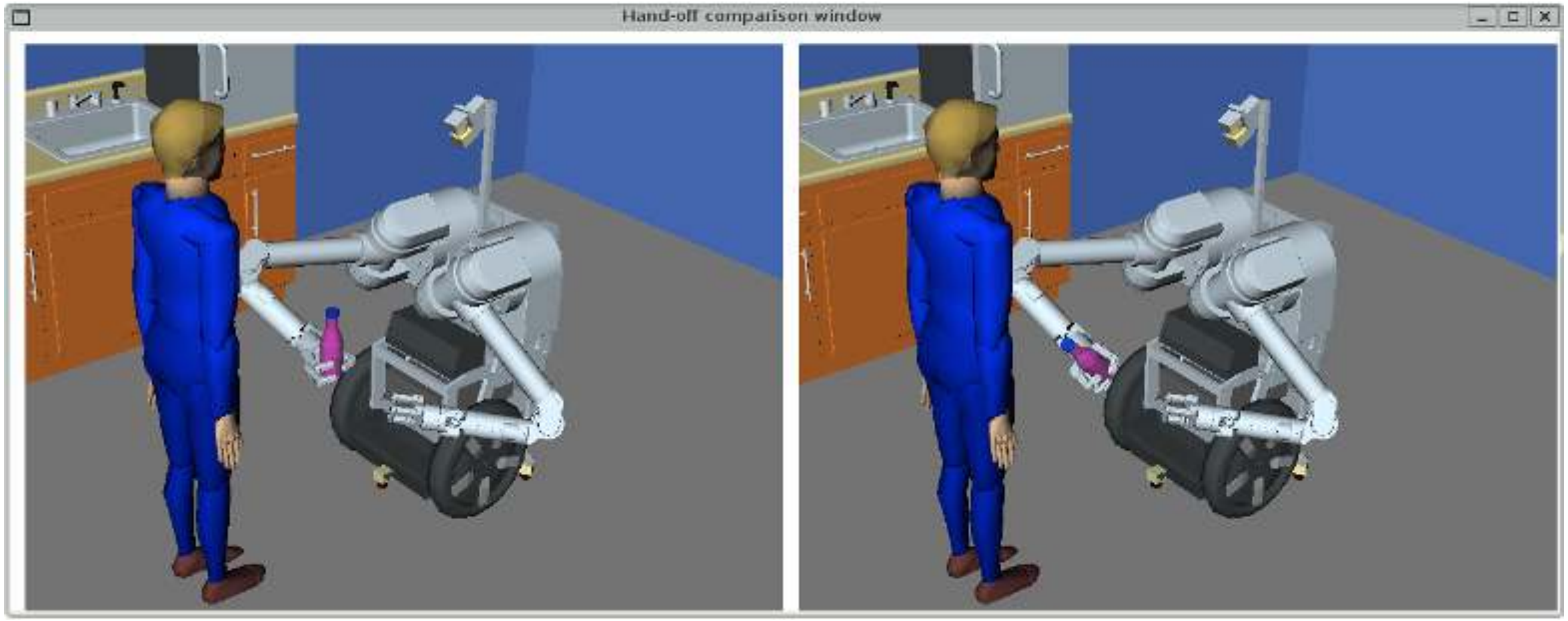


Number of events: bending, stepping forward, full arm extension

FINDINGS

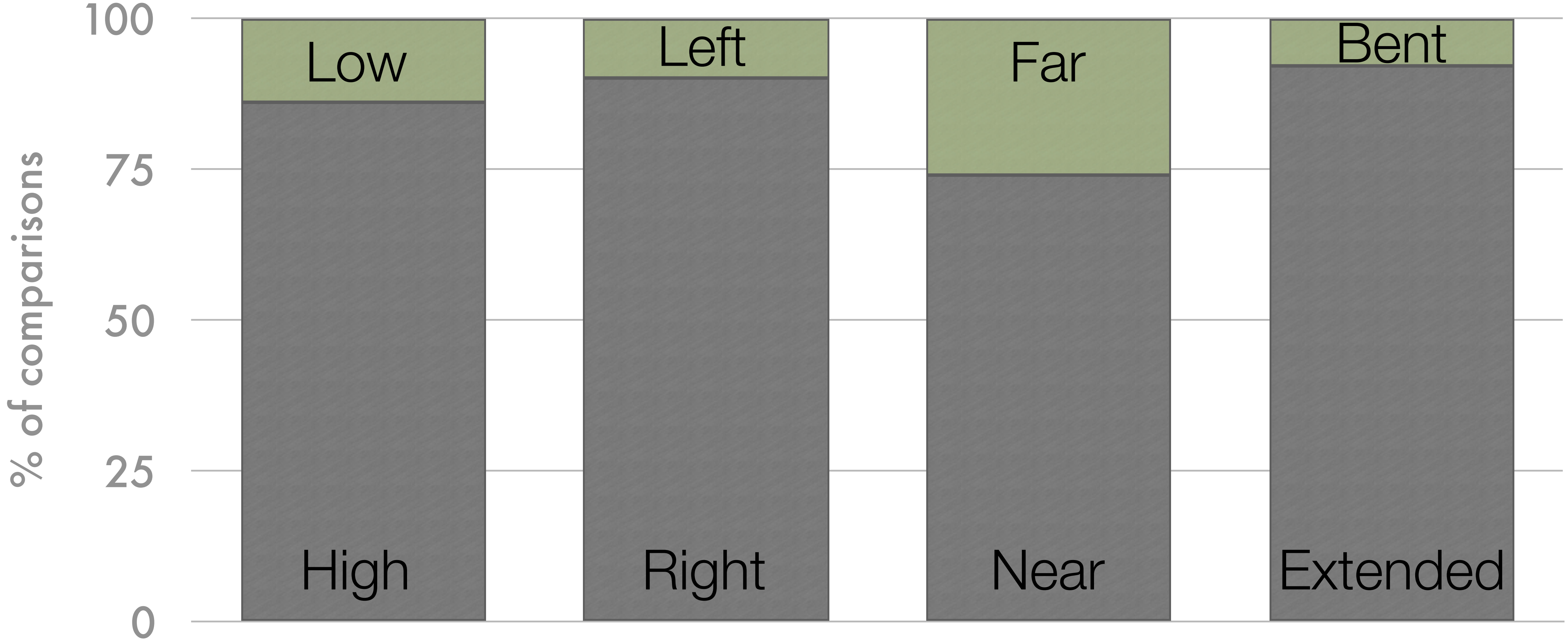
TEXT

WHICH ONE IS BETTER?

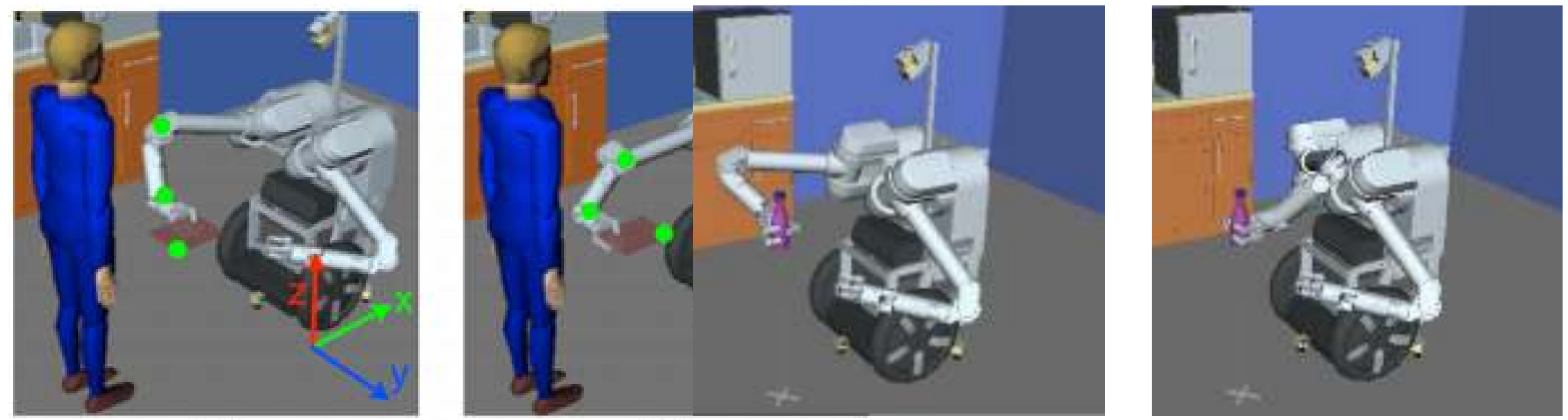


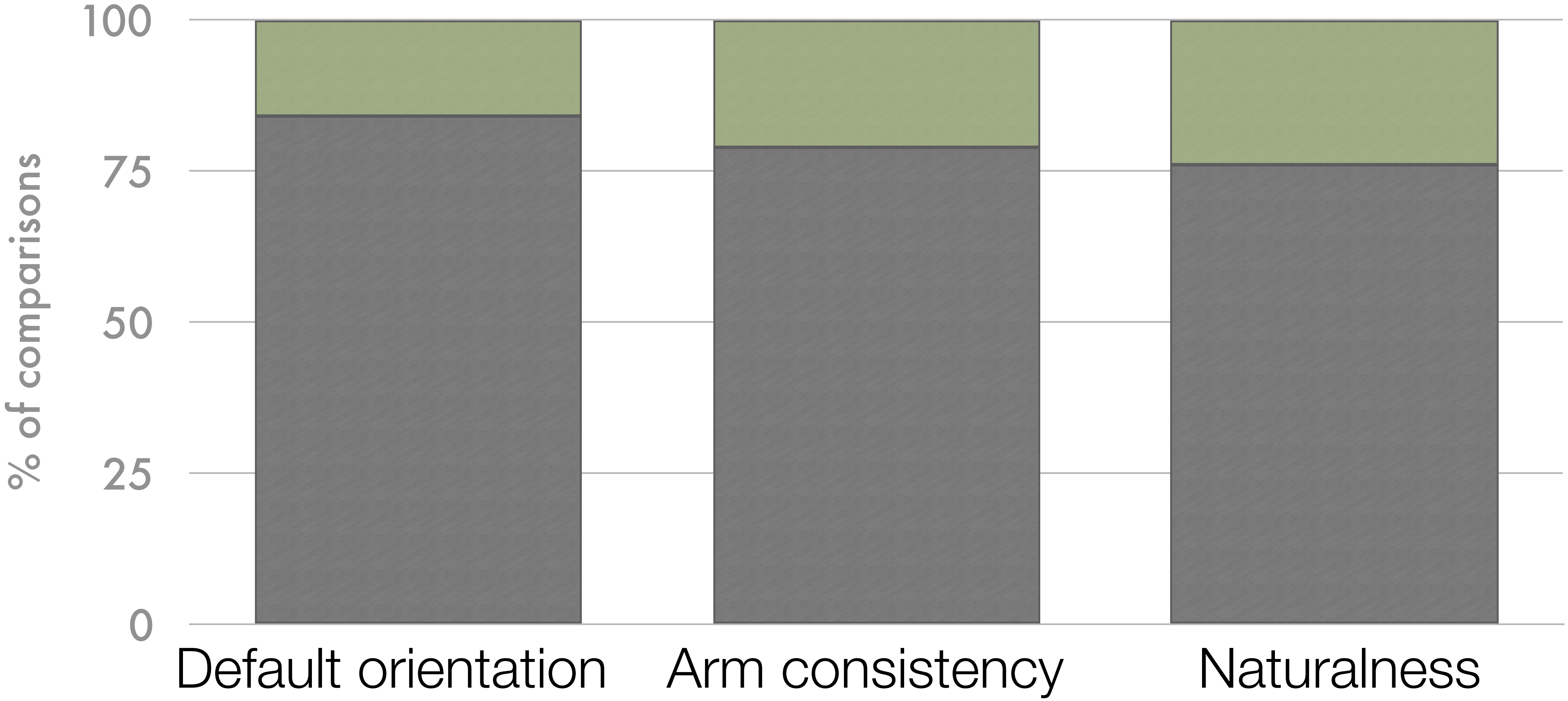
N=10 (8 male, 2 female)

61 pairwise comparisons



PREDICTIVE VARIABLES





PREDICTIVE (LATENT) VARIABLES

HEURISTICS

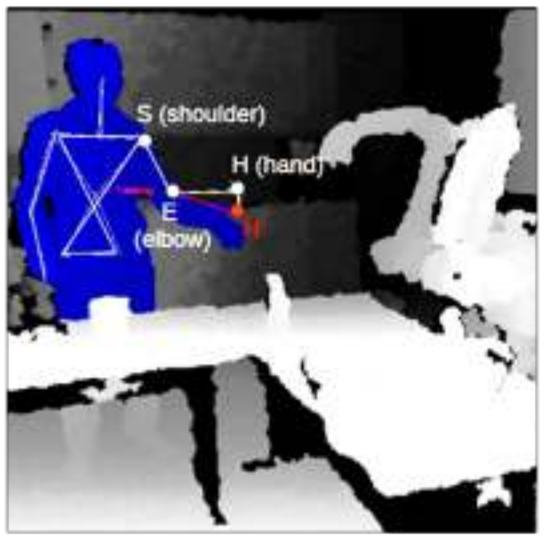
PLANNING/ OPTIMIZATION

LEARNING FROM EXAMPLES

Scalable/generalizable

Preferred

WHAT? WHO? WHEN? WHERE? HOW?



Perception

Object affordances

Human-to-robot

MORE PROBLEMS

K. Strabala, M.K. Lee, A. Dragan, J. Forlizzi, S.S. Srinivasa, M. Cakmak and V. Micelli. Towards Seamless Human-Robot Handovers. International Journal of Human-Robot Interaction. Vol. 1, No. 1, March, 2013.

S. Srinivasa, S. Berenson, M. Cakmak, A. Collet, M. Dogar, A. Dragan, R. Knepper, T. Niemueller, K. Strabala, M. Vande Weghe, and J. Ziegler. HERB 2.0: Lessons Learned from Developing a Mobile Manipulator for the Home. Proceedings of the IEEE, January, 2012.

M. Cakmak, S.S. Srinivasa, M.K. Lee, J. Forlizzi and S. Kiesler. Human Preferences for Robot-Human Hand-over Configurations. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2011.

M. Cakmak, S.S. Srinivasa, M.K. Lee, S. Kiesler and J. Forlizzi. Using Spatial and Temporal Contrast for Fluent Robot-Human Hand-overs. International Conference on Human-Robot Interaction (HRI), 2011.

M.K. Lee, J. Forlizzi, S. Kiesler, M. Cakmak, S.S. Srinivasa. Predictability or Adaptivity? Designing Robot Handoffs Modeled from Trained Dogs and People. Late-breaking Report, International Conference on Human-Robot Interaction, 2011.

THAT'S IT!