Machine Learning of Motor Skills for Robotics

From Simple Skills to Robot Table Tennis and Manipulation

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Motivation

How can we create such robots?

Source: Movie iRobot

Motivation

Uncertainty in tasks and environment

Adapt to humans and interact safely

Programming complexity beyond human imagination

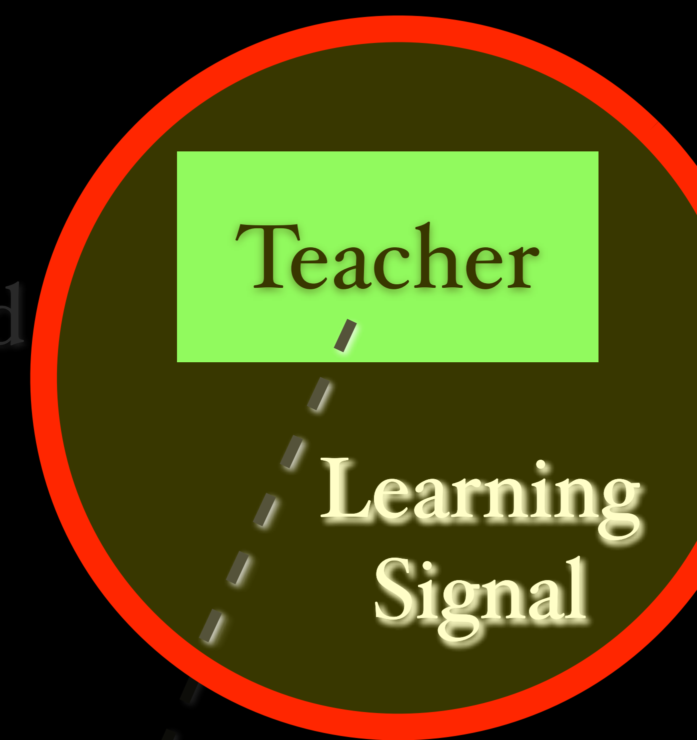
How can we fulfill Hollywood's vision of future robots?

- Smart Humans? Hand-coding of behaviors has allowed us to go *very far*!
- Maybe we should allow the robot to learn new tricks, adapt to situations, refine skills?
- "Off-the-shelf" machine learning approaches? Can they scale?

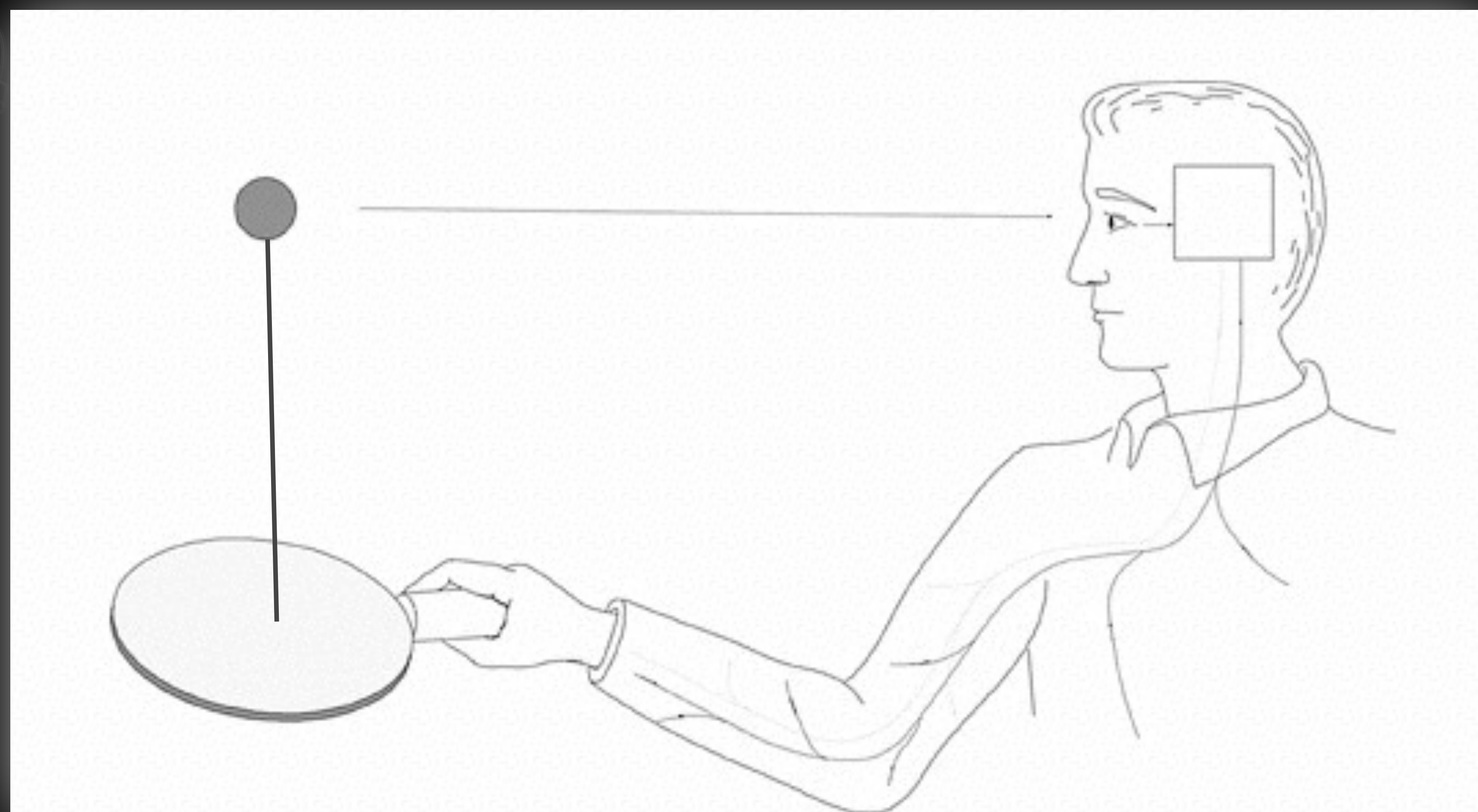
➡ We need to develop **skill learning approaches** for autonomous robot systems!

Outline

1. Introduction
2. How can we develop suitable machine learning methods?
3. How can elementary behavior be learned with such machine learning methods?
4. Can complex skills be learned leveraging on elementary behaviors?
5. How can we adapt to humans and learn interaction?
6. Outlook & Conclusion

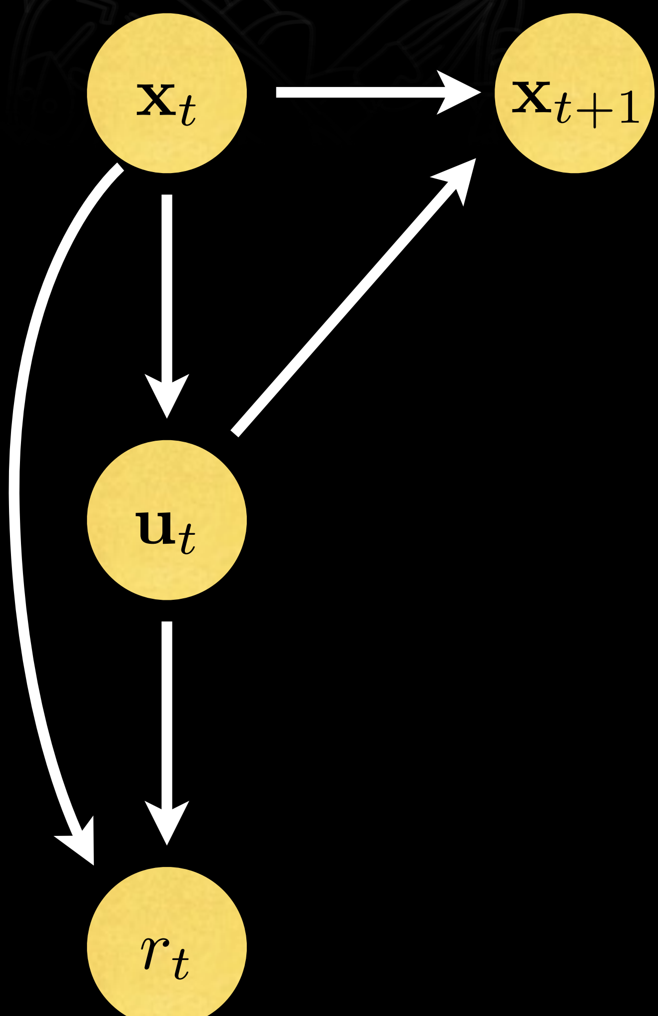


Example:



Internal and external state $\mathbf{x}_t$, action $\mathbf{u}_t$.

Modeling Assumptions



Policy: Generates action $\mathbf{u}_t$ in state $\mathbf{x}_t$.

Should we use a deterministic policy $\mathbf{u}_t = \pi(\mathbf{x}_t)$?

NO! *Stochasticity* is important:

- needed for exploration
- breaks "curse of dimensionality"
- optimal solution can be stochastic

Robot learning implies "policy optimization"!

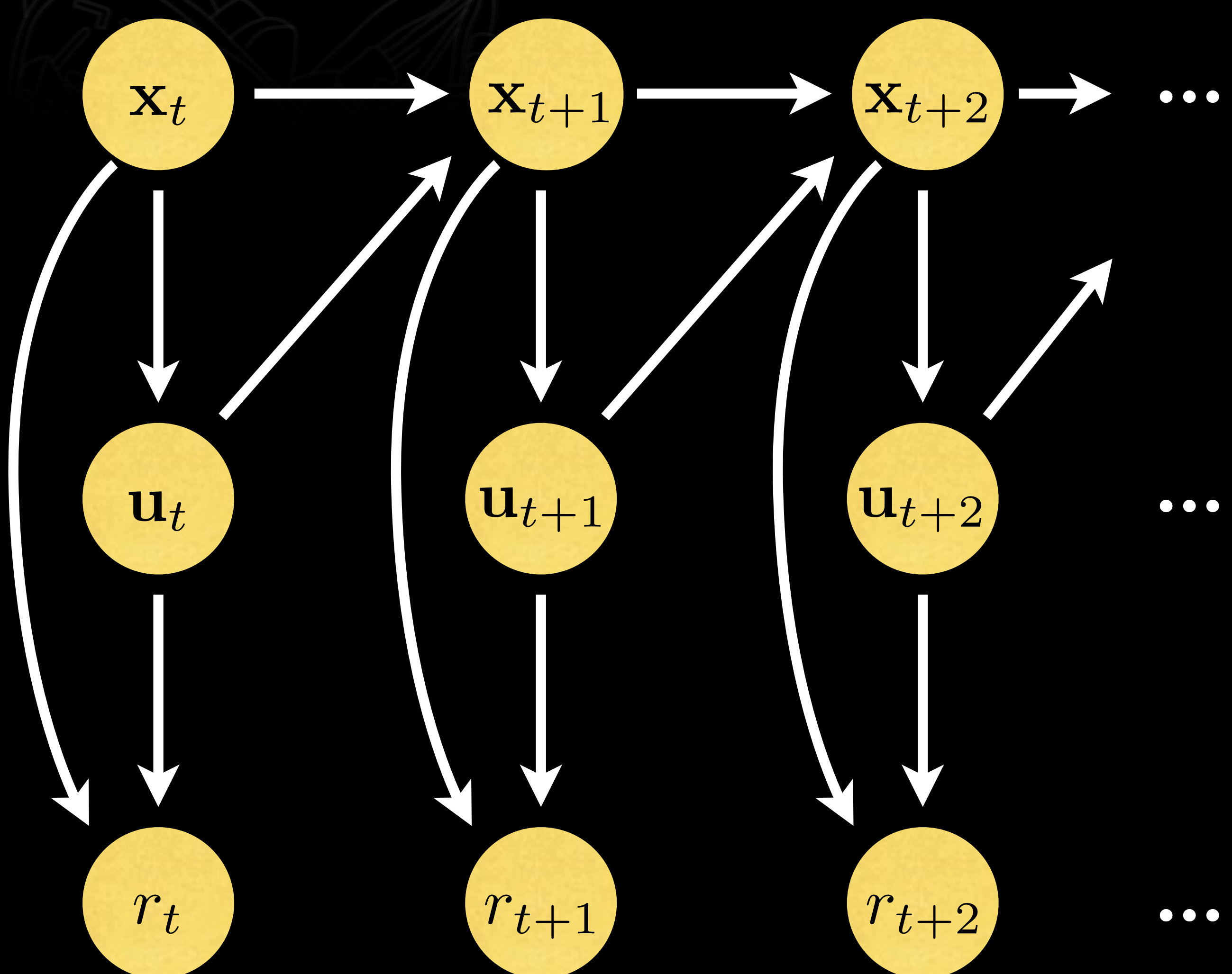
Hence, we use a stochastic policy: $\mathbf{u}_t \sim \pi(\mathbf{u}_t|\mathbf{x}_t)$

Teacher: Evaluates the performance and rates it with r_t.

Environment: An action $\mathbf{u}_t$ causes the system to change state from $\mathbf{x}_t$ to $\mathbf{x}_{t+1}$.

Model in the real world: $\mathbf{x}_{t+1} \sim p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t)$

Let the loop roll out!



Trajectories

$$\boldsymbol{\tau} = [\mathbf{x}_0, \mathbf{u}_0, \mathbf{x}_1, \mathbf{u}_1 \ldots, \mathbf{x}_{T-1}, \mathbf{u}_{T-1}, \mathbf{x}_T]$$

Path distributions

$$p(\tau) = p(\mathbf{x}_0) \prod_{t=0}^{T-1} p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t)\pi(\mathbf{u}_t|\mathbf{x}_t)$$

Path rewards:

$$r(\boldsymbol{\tau}) = \sum_{t=0}^{T} \alpha_t r(\mathbf{x}_t, \mathbf{u}_t)$$

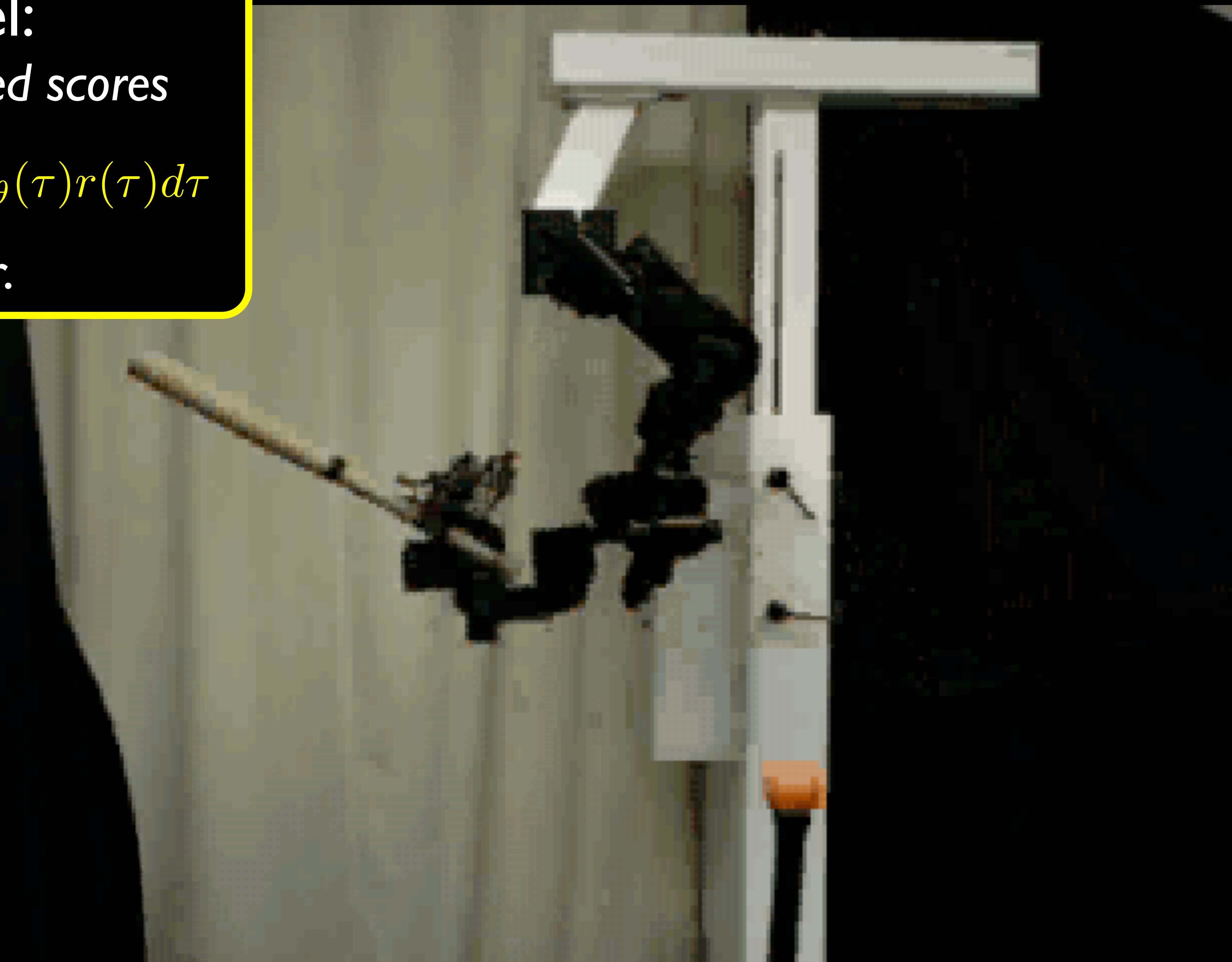
What is learning?

In our model:

Optimize the *expected scores*

$$J(\theta) = E_\tau\{r(\tau)\} = \int_{\mathbb{T}} p_\theta(\tau) r(\tau) d\tau$$

of the teacher.



Peters & Schaal (2003). Reinforcement Learning for Humanoid Robotics, HUMANOIDS

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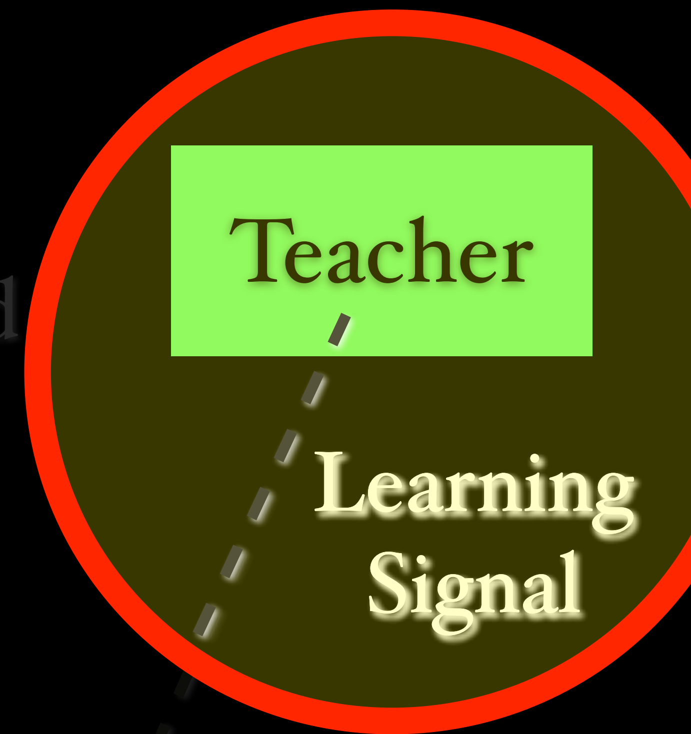


Imitation Learning

Given a path distribution, can we reproduce the policy?

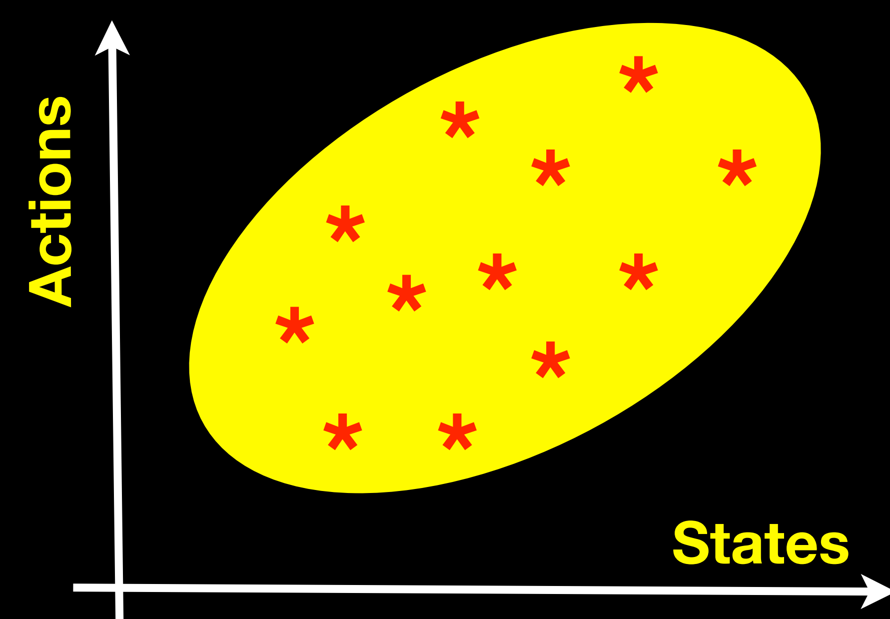
- We need to measure similarity between distributions, e.g., using an *f*-measure as reward

$$r(\tau) = f\left(p_\theta(\tau), p(\tau)\right).$$

- Using $f(p,q) = \log(p/q)$ as f-measure, we obtain

$$J(\pi) = \int_{\mathbb{T}} p_\theta(\tau) \log \frac{p_\theta(\tau)}{p(\tau)} d\tau = -D(p_\theta(\tau)||p(\tau))$$

Imitation



Boularias, A. et al. (2011). Relative Entropy Inverse Reinforcement Learning, AISTATS 2011
Englert, P. et al. (2013). Probabilistic Model-based Imitation Learning, Adaptive Behavior

Imitation Learning

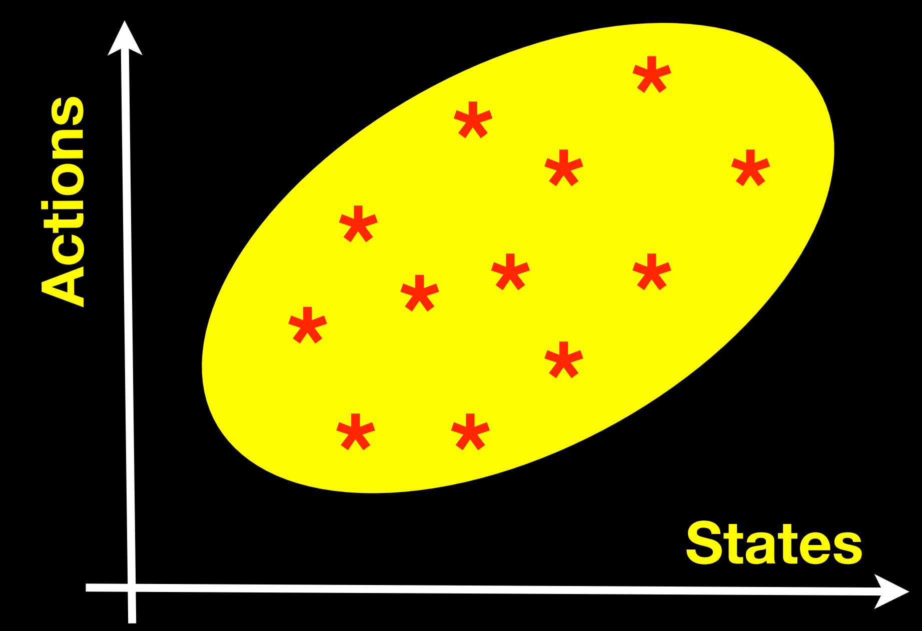
Given a path distribution, can we reproduce the policy?

- match given path distribution $p(\tau)$ with a new one $p_\theta(\tau)$, i.e.,

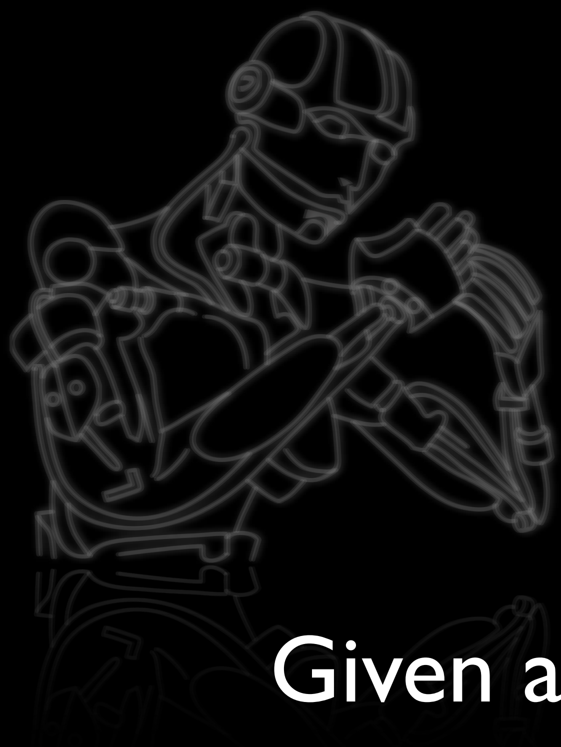
$$D(p_{\boldsymbol{\theta}}(\boldsymbol{\tau})||p(\boldsymbol{\tau})) \rightarrow \min$$

- adapt the policy parameters θ
- possible model-free, purely sample-based (Boularias et al., 2011) and model-based (Englert et al.,2013)
- results in one-shot and expectation maximization algorithms

Imitation



Boularias, A. et al. (2011). Relative Entropy Inverse Reinforcement Learning, AISTATS 2011
Englert, P. et al. (2013). Probabilistic Model-based Imitation Learning, Adaptive Behavior



Reinforcement Learning

Given a path distribution, can we find the optimal policy?

- *Goal*: maximize the return of the paths $r(\tau)$ generated by path distribution $p_\theta(\tau)$
- Optimization function is an ***arbitrary*** expected reward

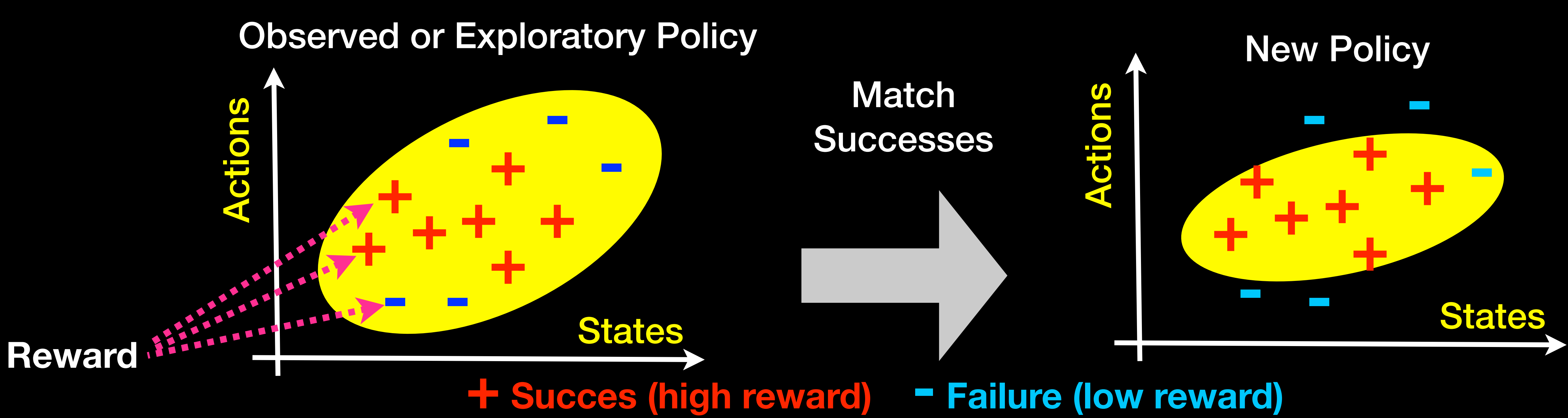
$$J(\boldsymbol{\theta}) = \int_{\mathbb{T}} p_{\boldsymbol{\theta}}(\boldsymbol{\tau}) r(\boldsymbol{\tau}) d\boldsymbol{\tau}$$

- This part usually results into a greedy, softmax updates or a `vanilla' policy gradient algorithm...
- *Problem*: Small steps, optimization bias, results ‘fragile’.

Success Matching

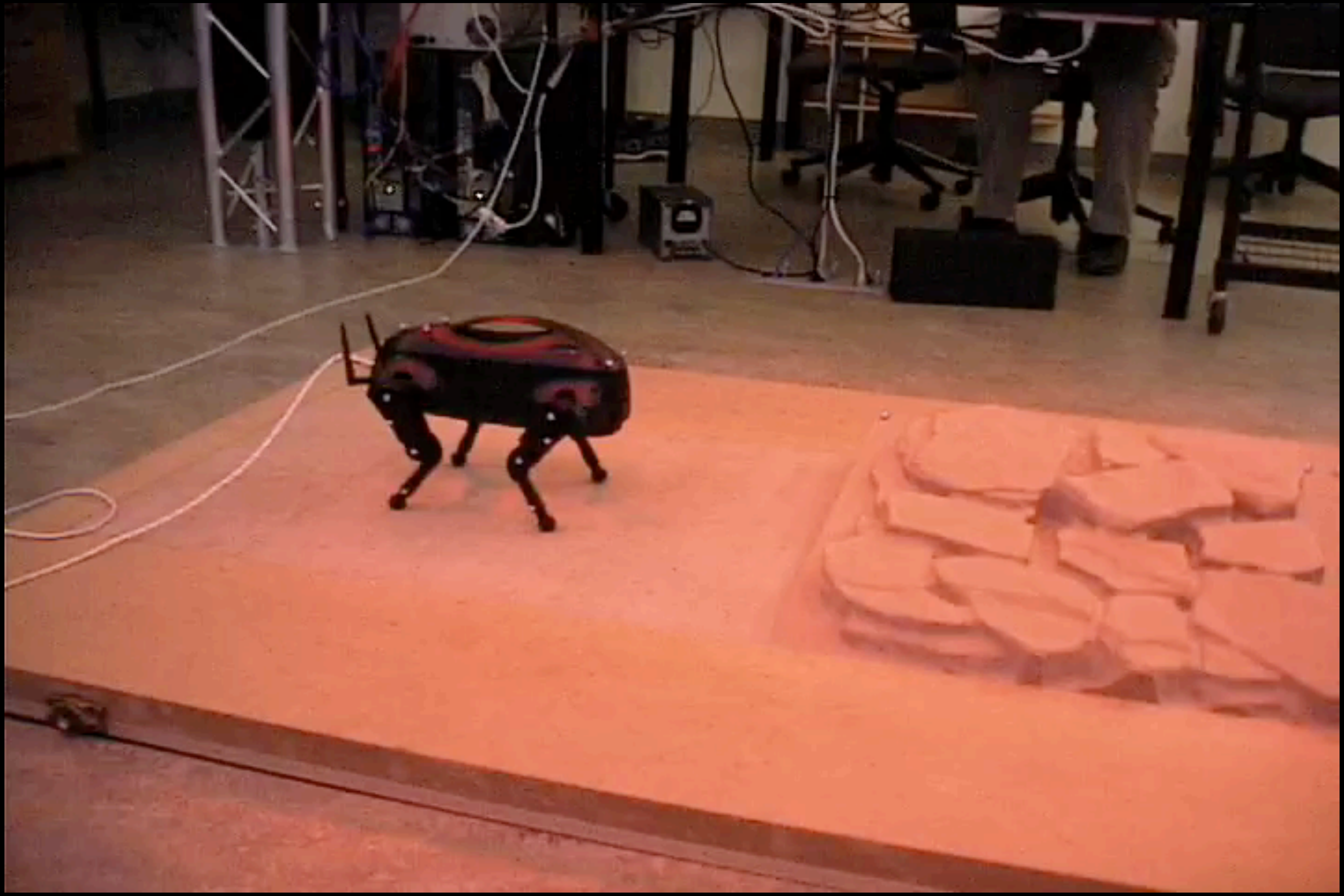
"When learning from a set of their own trials in iterated decision problems, humans attempt to match not the best taken action but the reward-weighted frequency of their actions and outcomes" (Arrow, 1958).

Can we create better policies by matching the reward-weighted previous policy ?



Many related frameworks, e.g., (Dayan&Hinton 1992;Andrews,'03;Attias,'04;Bagnell,'03;Toussaint,'06;...).

Illustrative Example
Foothold Selection



Match successful footholds!

Reinforcement Learning by Return-Weighted Imitation

Matching successful actions corresponds to minimizing the Kullback-Leibler ‘distance’

$$D(p_{\boldsymbol{\theta}}(\boldsymbol{\tau})||r(\boldsymbol{\tau})p(\boldsymbol{\tau})) \rightarrow \min$$

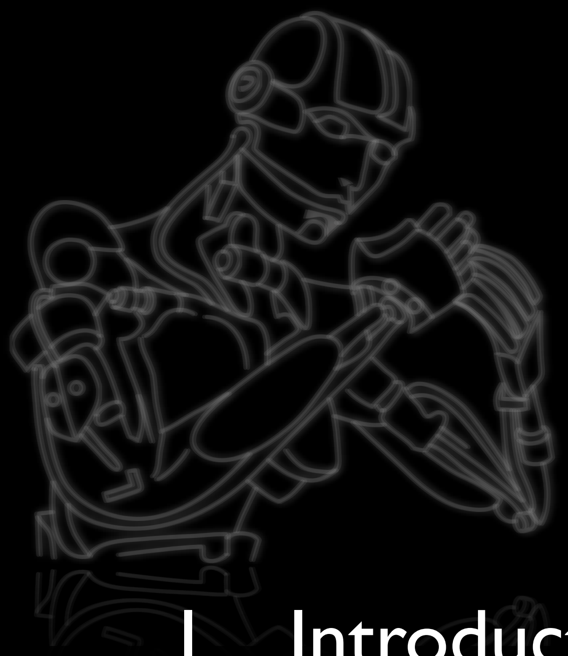
For a Gaussian policy $\pi(\mathbf{u}|\mathbf{x}) = \mathcal{N}(\mathbf{u}|\phi(\mathbf{x})^T\boldsymbol{\theta}, \sigma^2\mathbf{I})$, we get the update rule

$$\boxed{\theta_{k+1} = (\mathbf{\Phi}^T\mathbf{R}\mathbf{\Phi})^{-1}\mathbf{\Phi}^T\mathbf{R}\mathbf{U}}$$

New Policy Parameters　Features　Returns　Actions

➡Reduces Reinforcement Learning onto Return-Weighted Regression!

Peters & Schaal (2007). Policy Learning for Motor Skills, International Conference on Machine Learning (ICML)
Kober & Peters (2009). Policy Search for Motor Primitives in Robotics, Advances in Neural Information Processing Systems (NIPS)



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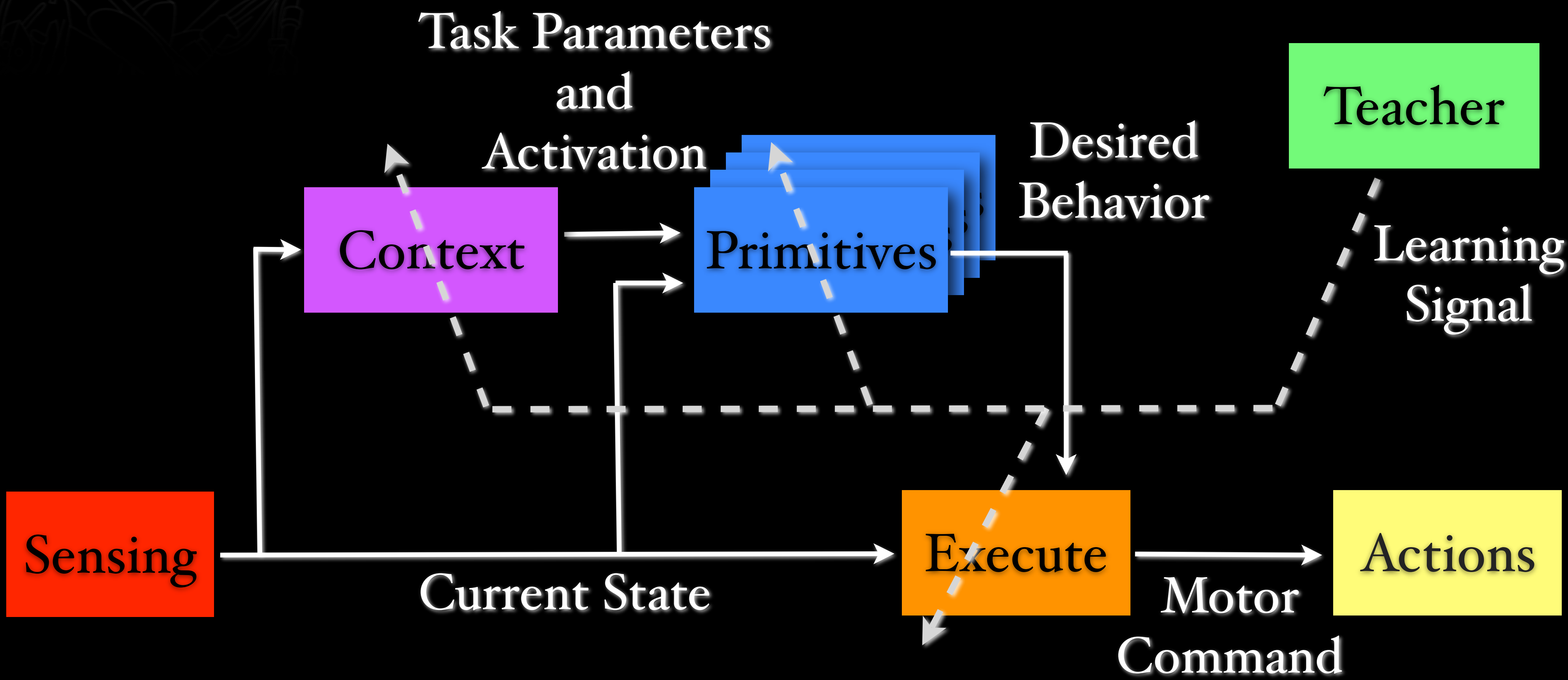
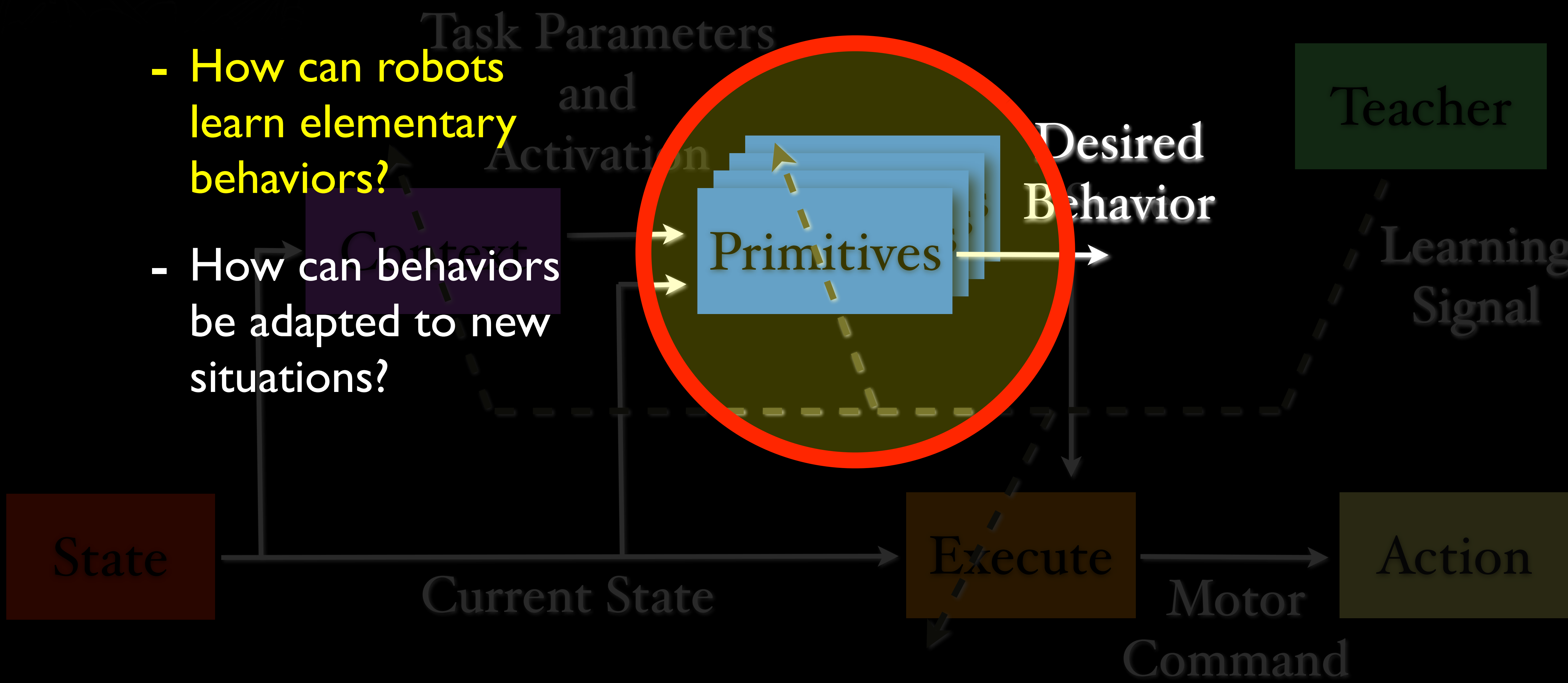
A Blue Print for Skill Learning?

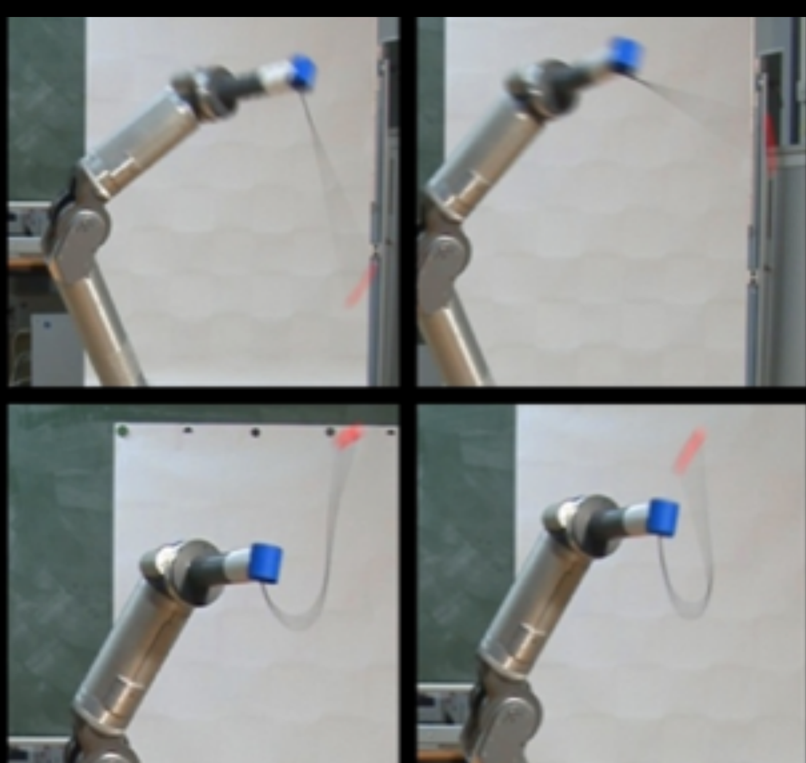


Outline

- How can robots learn elementary behaviors?
- How can behaviors be adapted to new situations?



Motor Primitives



How can we represent, acquire and refine elementary movements?

- Humans appear to rely on context-driven motor primitives (Flash & Hochner, TICS 2005)
- Many favorable properties:
  - Invariance under task parameters
  - Robust, superimposable, ...

➡ *Resulting approach:*
  - Use the dynamic system-based motor primitives (Ijspeert et al. NIPS2003; Schaal, Peters, Nakanishi, Ijspeert, ISRR2003).
  - Initialize by Imitation Learning.
  - Improve by trial and error on the real system with Reinforcement Learning.

Motor Primtives

Task/Hyperparameter

Trajectory Plan Dynamics

$$\begin{cases} \dot{z} = \alpha_z\left(\beta_z\left(g - y\right) - z\right) \\ \dot{y} = \alpha_y\left(f\left(x, v\right) + z\right) \end{cases}$$

where

Canonical Dynamics

$$\begin{cases} \dot{v} = \alpha_v\left(\beta_v\left(g - x\right) - v\right) \\ \dot{x} = \alpha_x v \end{cases}$$

Linear in learnable Policy Parameters

Local Linear Model Approx.

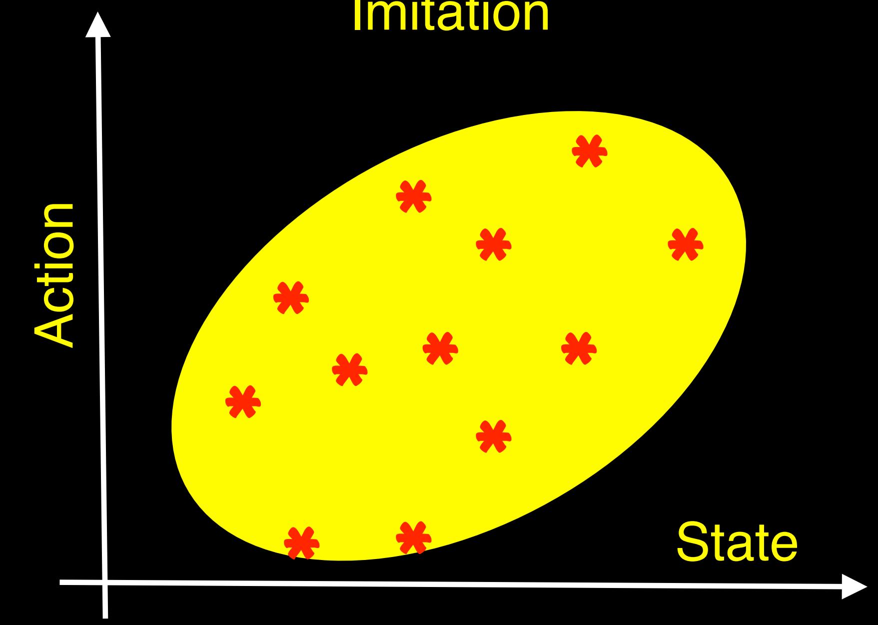
$$\begin{cases} f\left(x, v\right) = \dfrac{\sum_{i=1}^{k} w_i b_i v}{\sum_{i=1}^{k} w_i} \\ w_i = \exp\left(-\dfrac{1}{2} d_i \left(\bar{x} - c_i\right)^2\right) \text{ and } \bar{x} = \dfrac{x - x_0}{g - x_0} \end{cases}$$

(Ijspeert et al., NIPS 2003; Schaal, Peters, Nakanishi, Ijspeert, ISRR 2003)

Acquisition by Imitation

Teacher shows the task and the student reproduces it.

- maximize similarity



Kober & Peters (2009). Learning Motor Primitives, ICRA

Self-Improvement by Reinforcement Learning

Student improves by reproducing his successful trials.

- maximize reward-weighted similarity

Kober & Peters (2009). Policy Search for Motor Primitives in Robotics, NIPS

Outline

- How can robots learn elementary behaviors?
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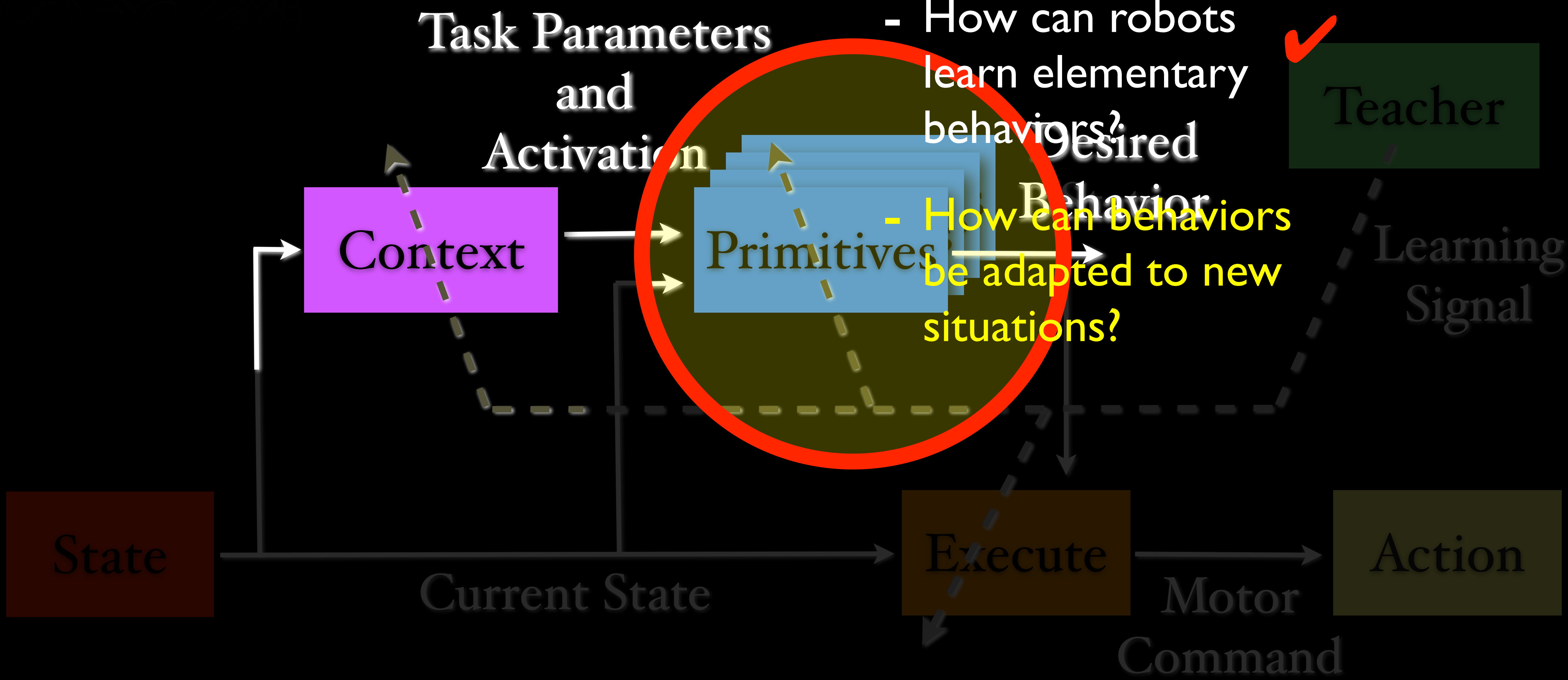

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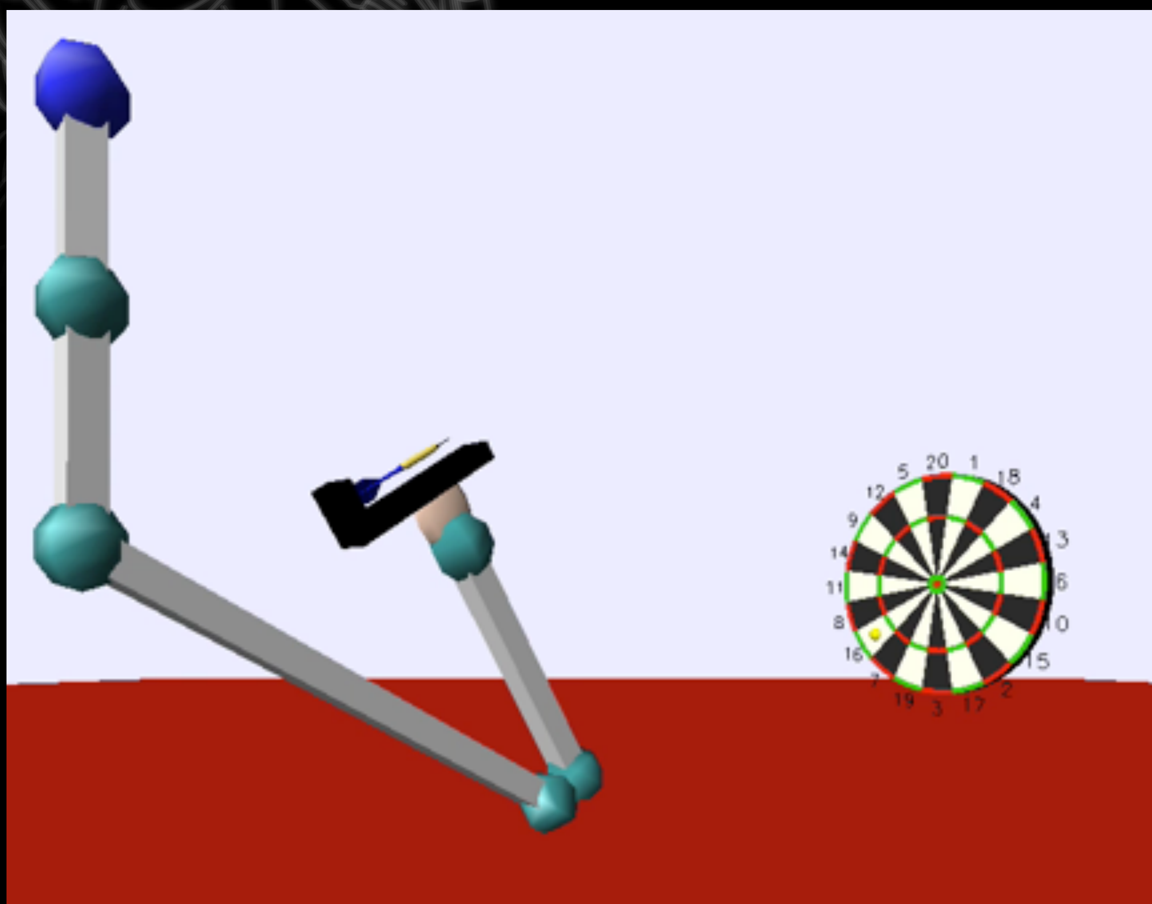
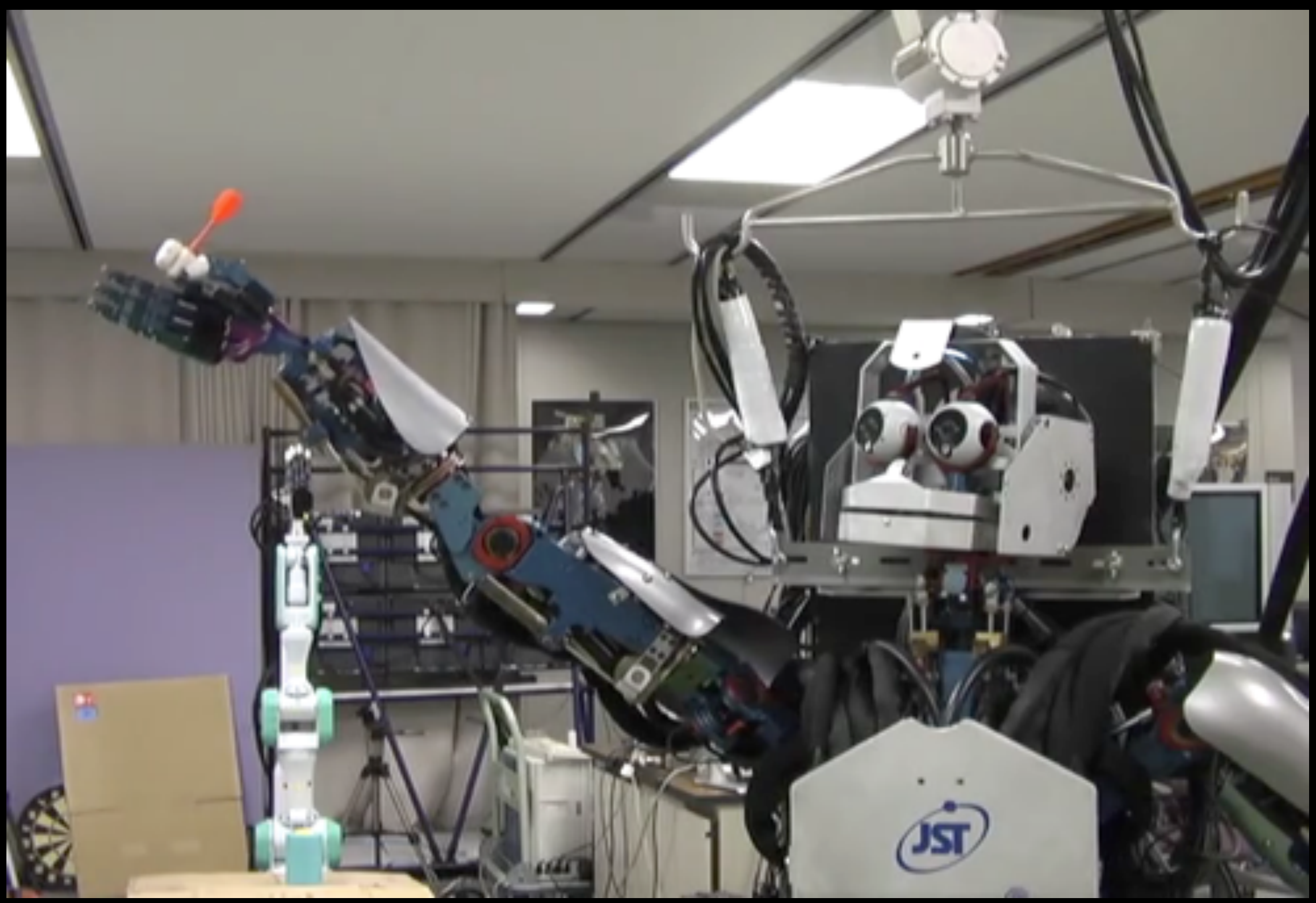
(Ijspeert et al., NIPS 2003; Schaal, Peters, Nakanishi, Ijspeert, ISRR 2003)

Task Context: Goal Learning



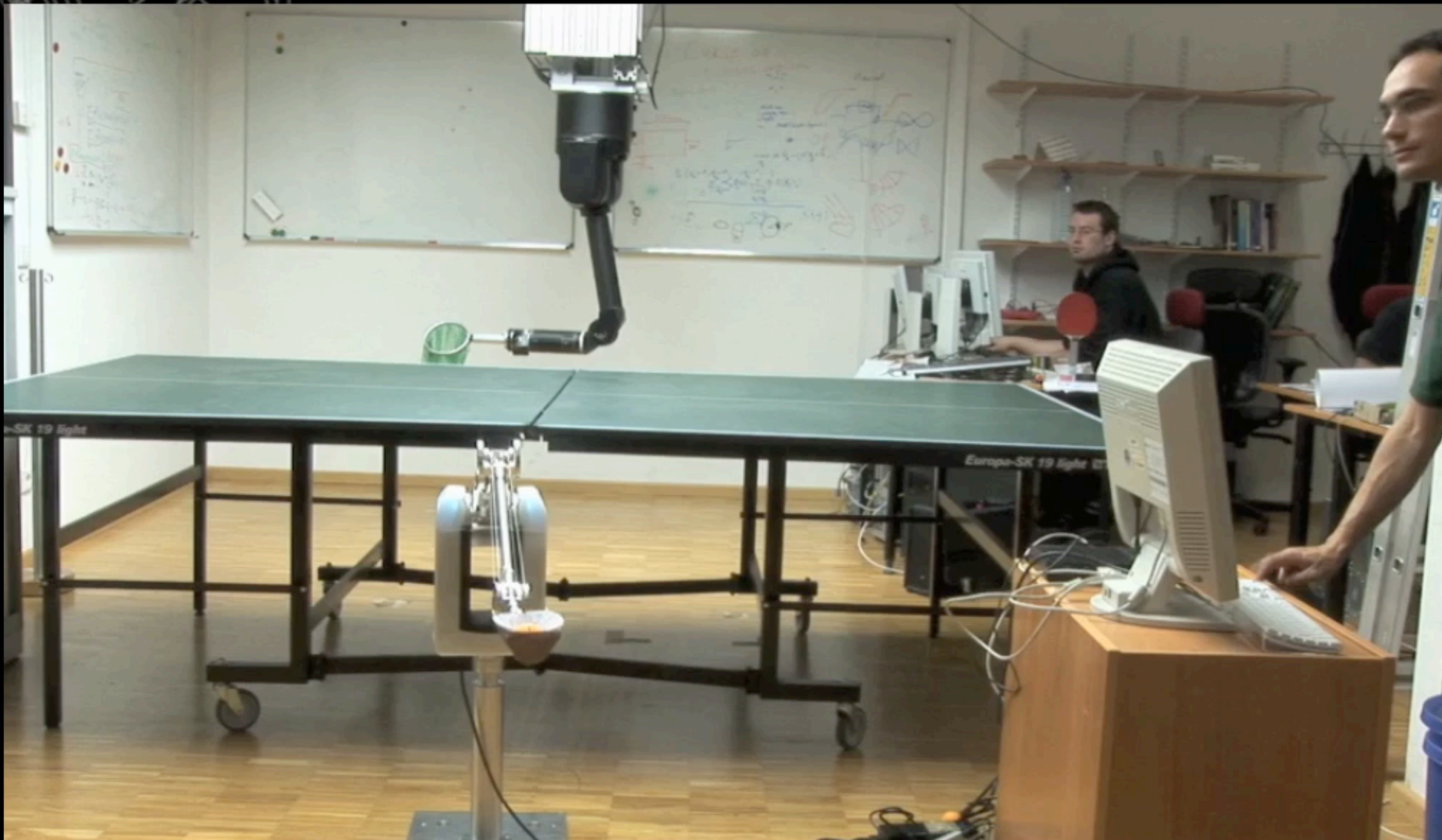


Adjusting Motor Primitives through their Hyperparameters:

1. learn a single motor primitive using imitation and reinforcement learning
2. learn policies for the goal parameter and timing parameters by reinforcement learning

Kober, Oztop & Peters (2012). Goal Learning for Motor Primitives, Autonomous Robots

Throwing and Catching...



Kober, J; Muelling, K.; Peters, J. (2012). Learning Throwing and Catching Skills, IROS

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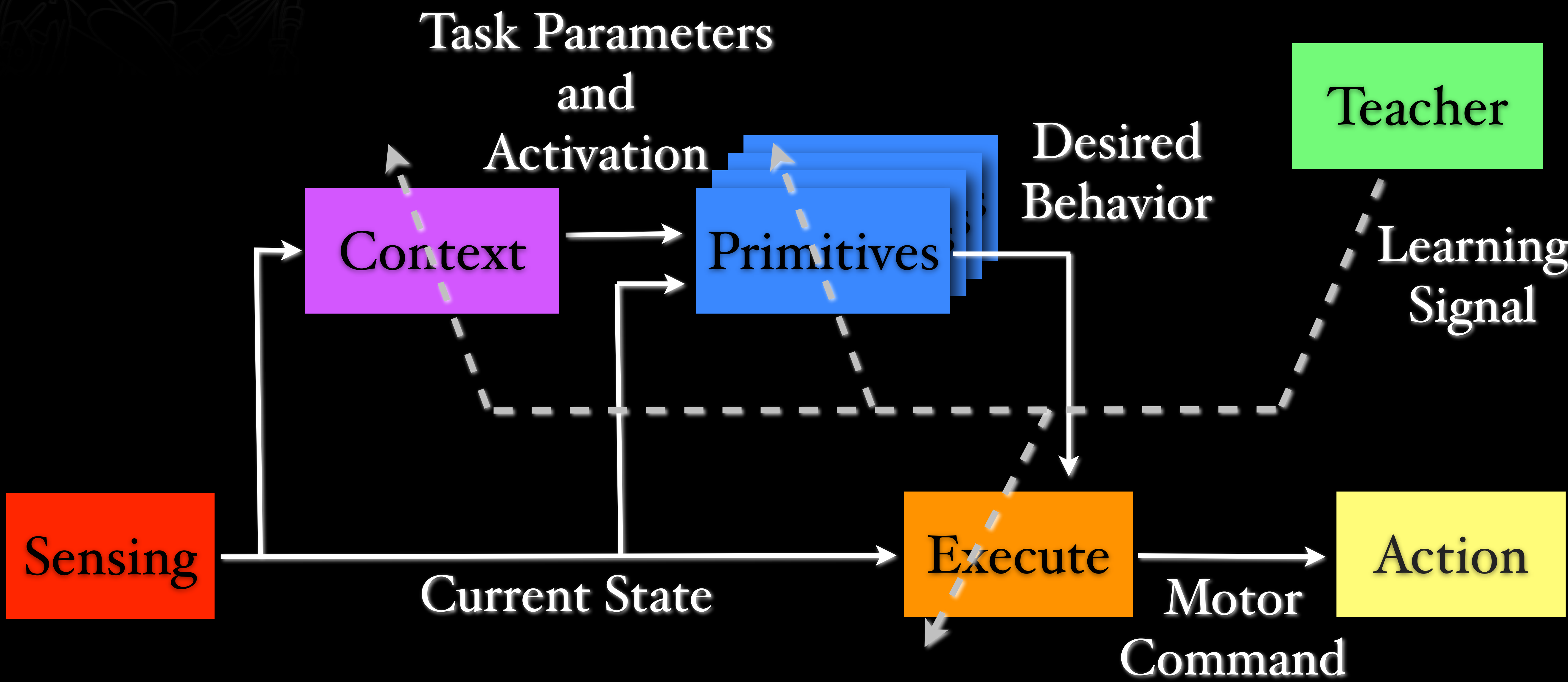
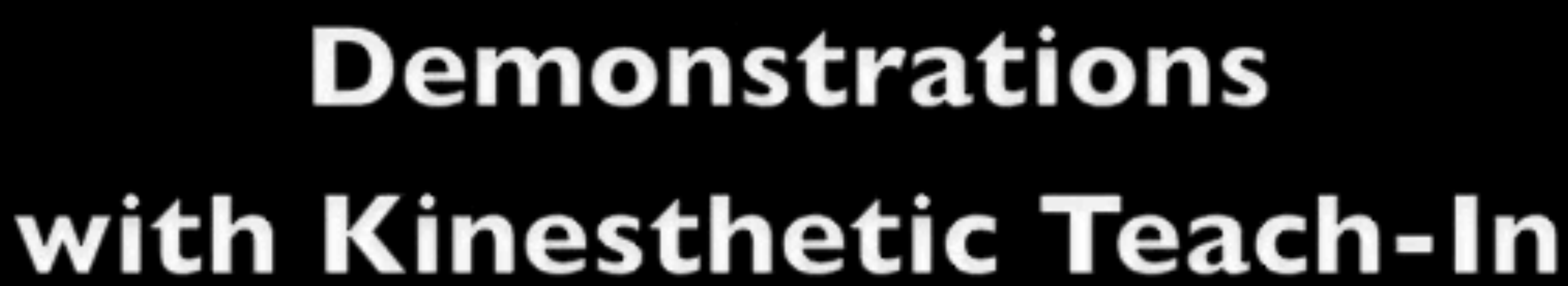
Composition by
Selection, Superposition & Sequencing



Let us put all these elements together!

Demonstrations



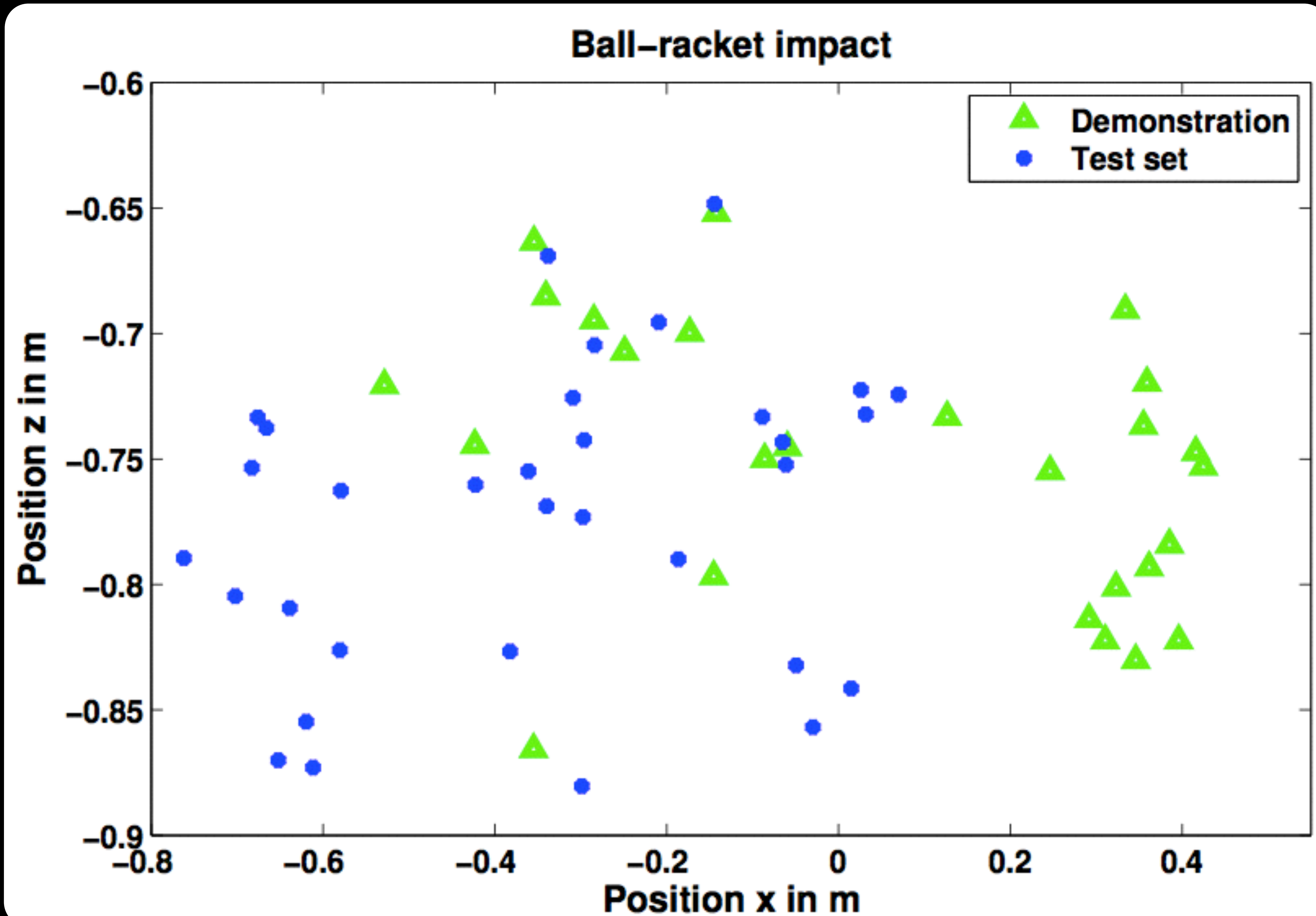
Mülling, K.; Kober, J.; Kroemer, O.; Peters, J. (2013). Learning to Select and Generalize Striking Movements in Robot Table Tennis, International Journal on Robotics Research.

Select & Generalize

From Imitation Learning we obtain 25 Movement Primitives

Mülling, K.; Kober, J.; Kroemer, O.; Peters, J. (2013). Learning to Select and Generalize Striking Movements in Robot Table Tennis, International Journal on Robotics Research.

Covered Situations



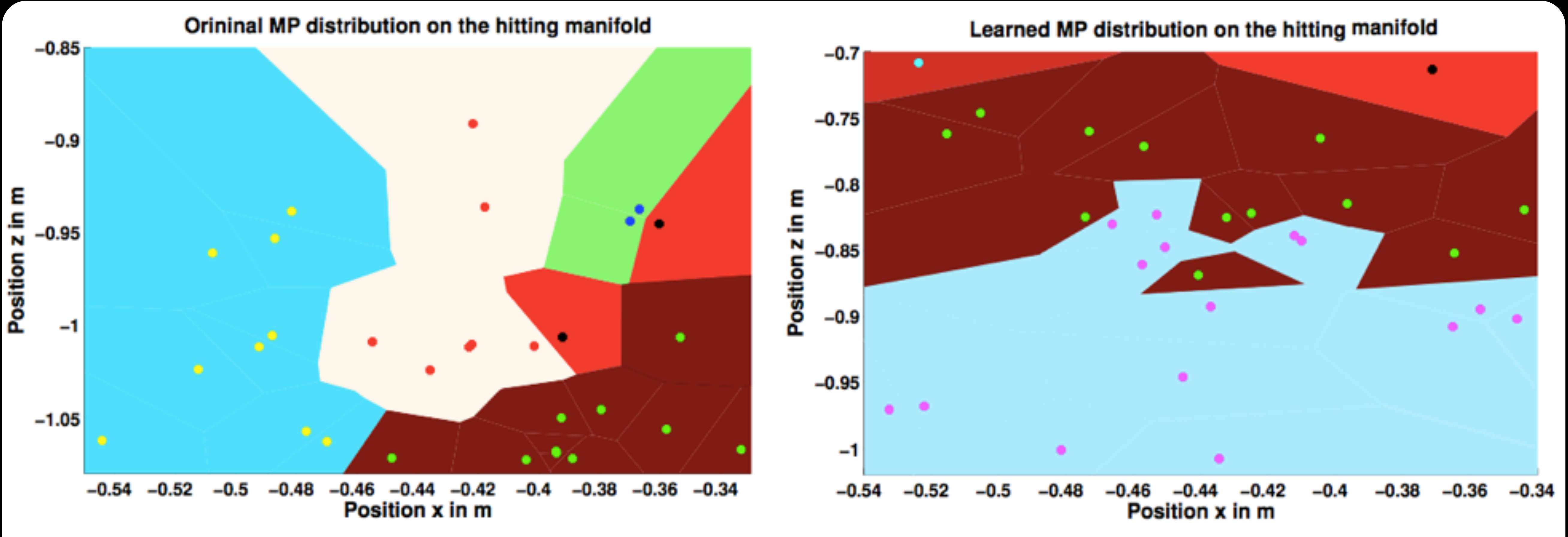
Mülling, K.; Kober, J.; Kroemer, O.; Peters, J. (2013). Learning to Select and Generalize Striking Movements in Robot Table Tennis, International Journal on Robotics Research.

Self-Improvement

Training a Hitting Region with an Initial Success Rate of 0%

Mülling, K.; Kober, J.; Kroemer, O.; Peters, J. (2013). Learning to Select and Generalize Striking Movements in Robot Table Tennis, International Journal on Robotics Research.

Changed Primitive Activation

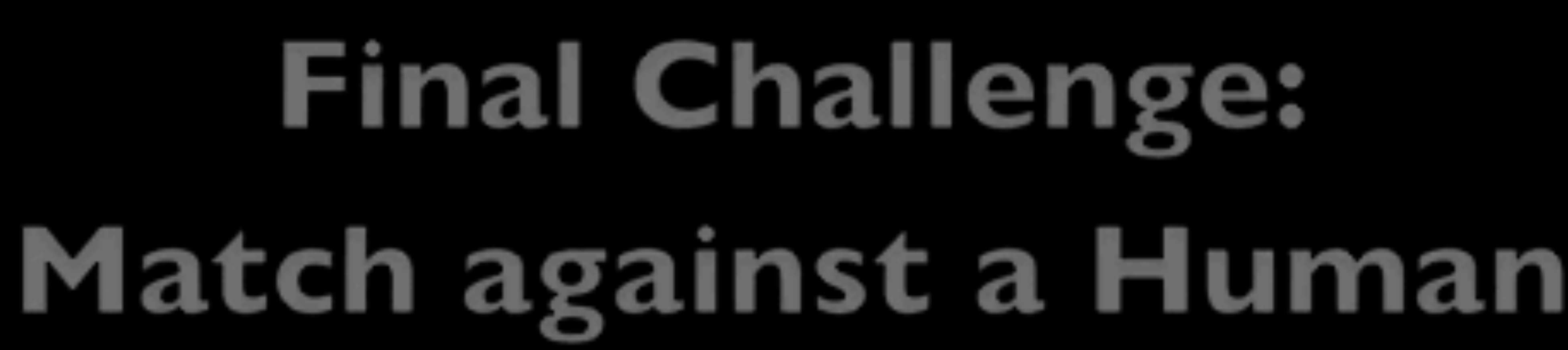


(a) Before training.

(b) After training.

Mülling, K.; Kober, J.; Kroemer, O.; Peters, J. (2013). Learning to Select and Generalize Striking Movements in Robot Table Tennis, International Journal on Robotics Research.

Current Gameplay

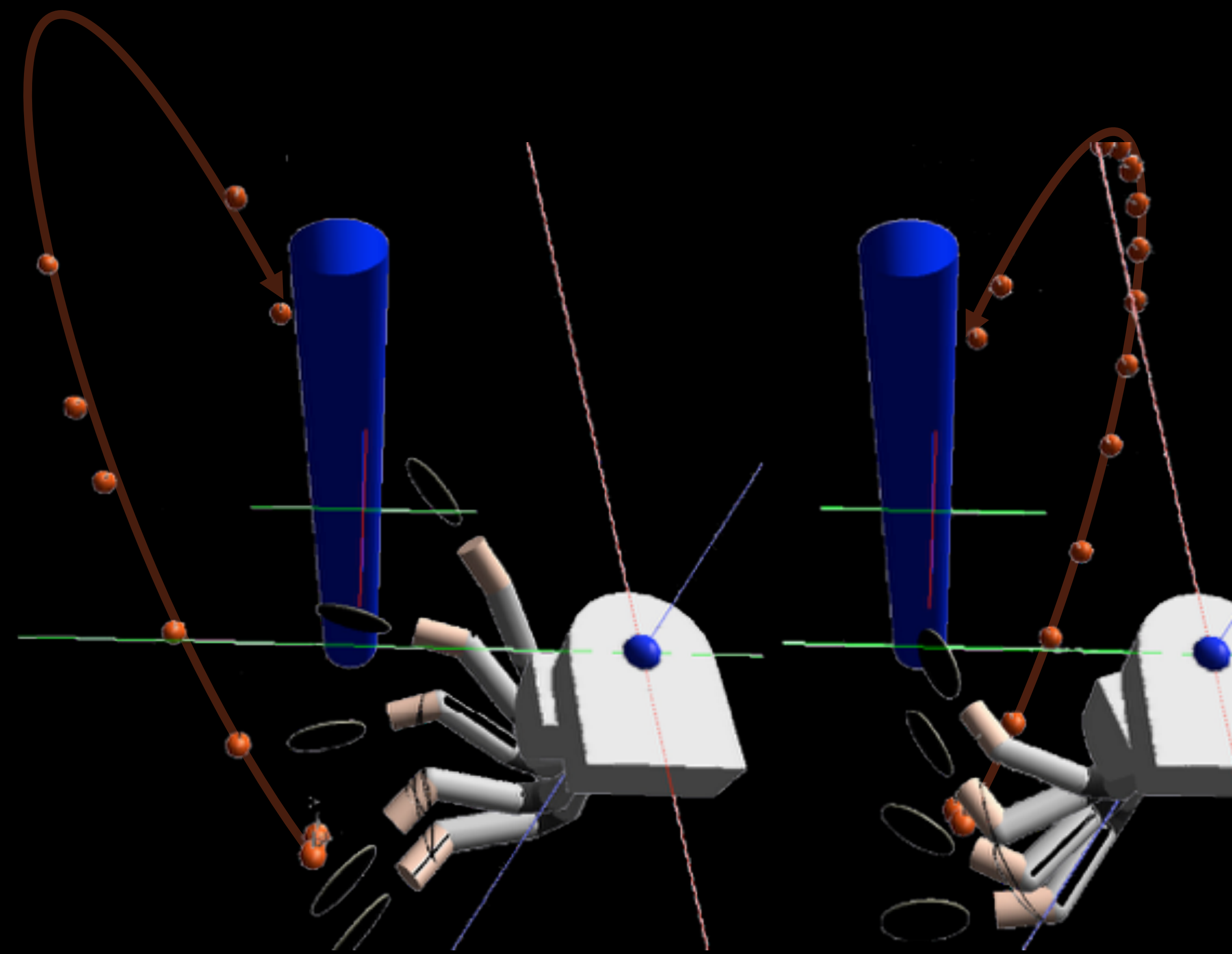


Müllling, K.; Kober, J.; Kroemer, O.; Peters, J. (2013). Learning to Select and Generalize Striking Movements in Robot Table Tennis, International Journal on Robotics Research.

Selection and Superposition of Motor Primitives

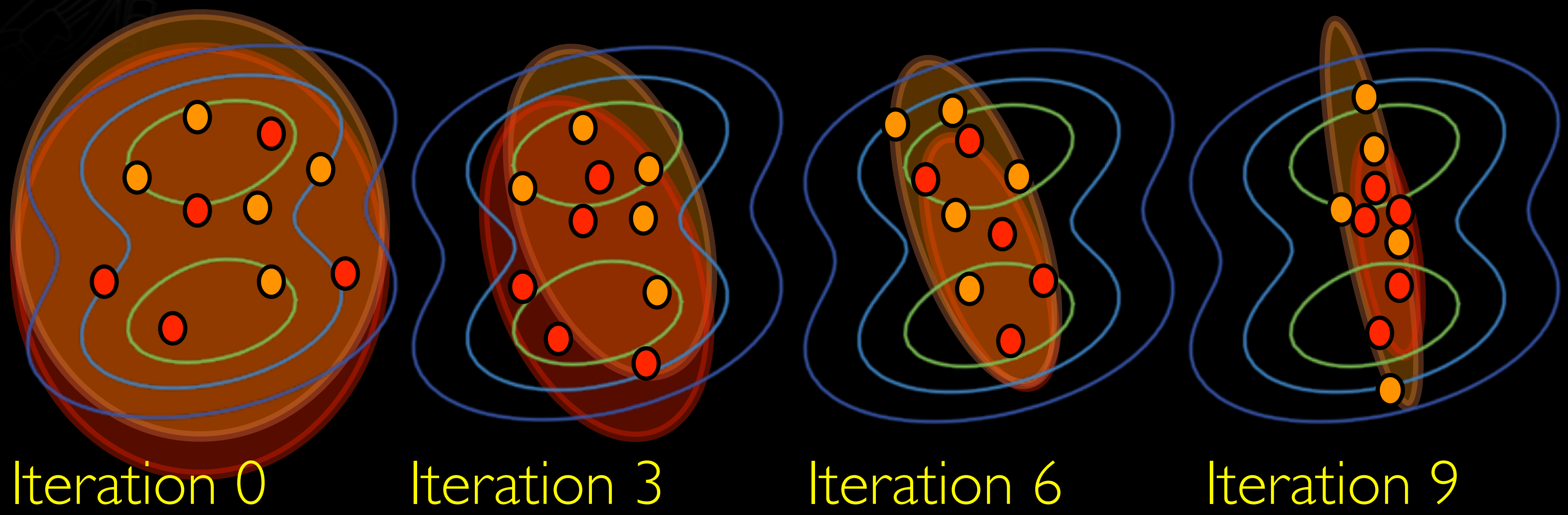
Problems with the "Naïve" Approach?

1. Weighted superposition works well in Robot Table Tennis:
   - convex combinations possible
   - few primitives are equally responsible for an incoming ball
2. It fails if **selection** is needed!



Daniel, Neumann & Peters (in press). Hierarchical Relative Entropy Policy Search, JMLR

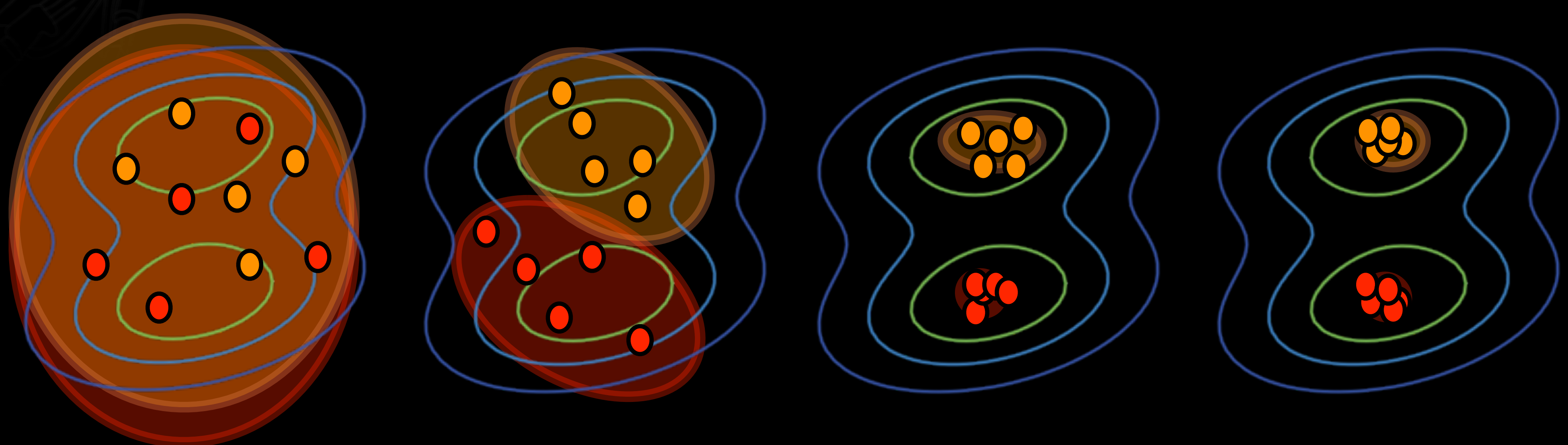
Problems with the Naïve Approach



If all primitives are equally responsible, we can represent versatile behavior but it will never be parsimonious.

Daniel, Neumann & Peters (in press). Hierarchical Relative Entropy Policy Search, JMLR

Localized behavior can be learned efficiently!



Iteration 0 Iteration 3 Iteration 6 Iteration 9

We can reduce to the number of needed primitives!

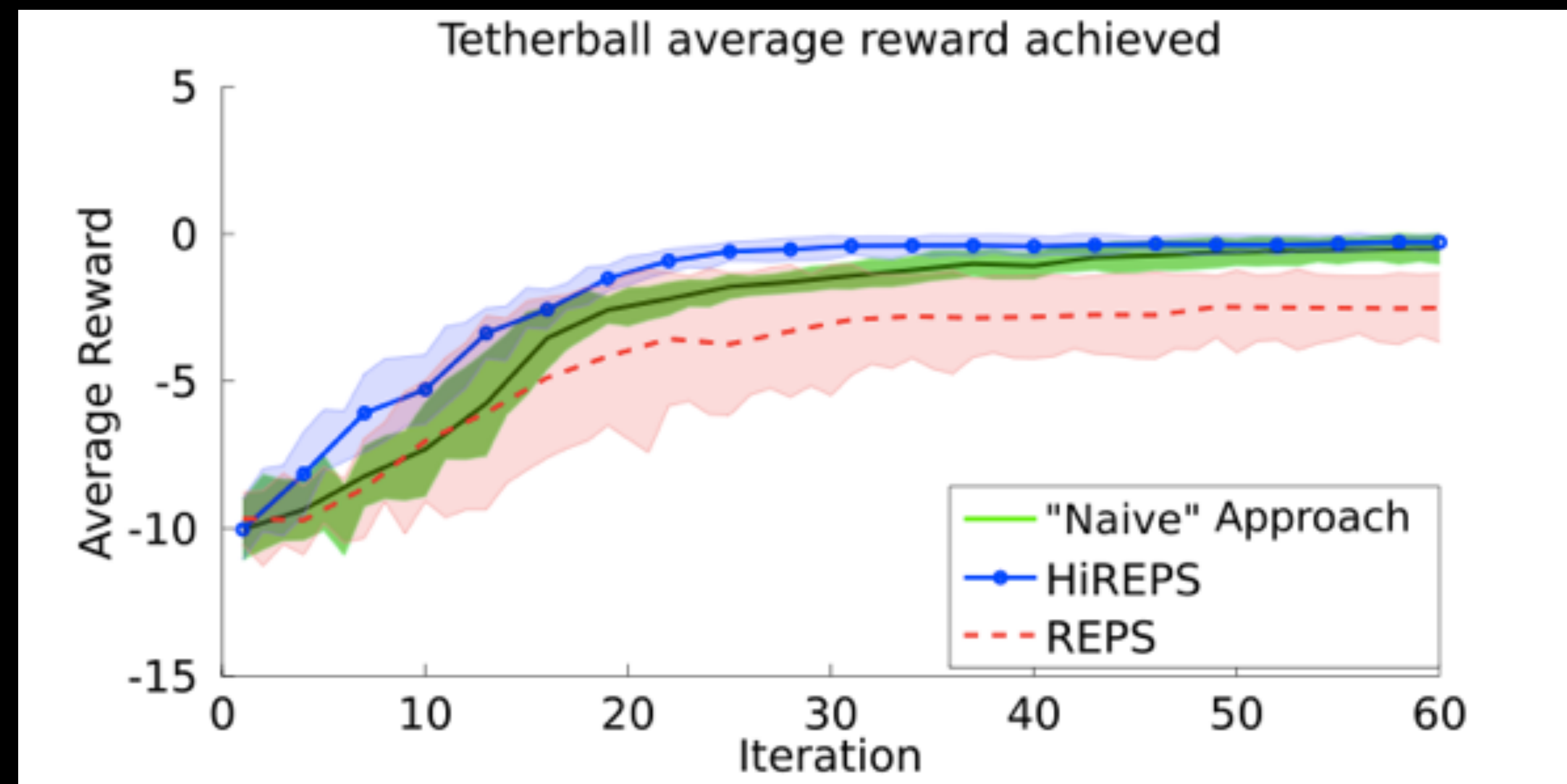
$$\kappa \geq \mathbb{E}_{\boldsymbol{s},\boldsymbol{a}}\left[\sum_{o} -p(o|\boldsymbol{s},\boldsymbol{a}) \log p(o|\boldsymbol{s},\boldsymbol{a})\right]$$

Force the primitives to limited responsibility

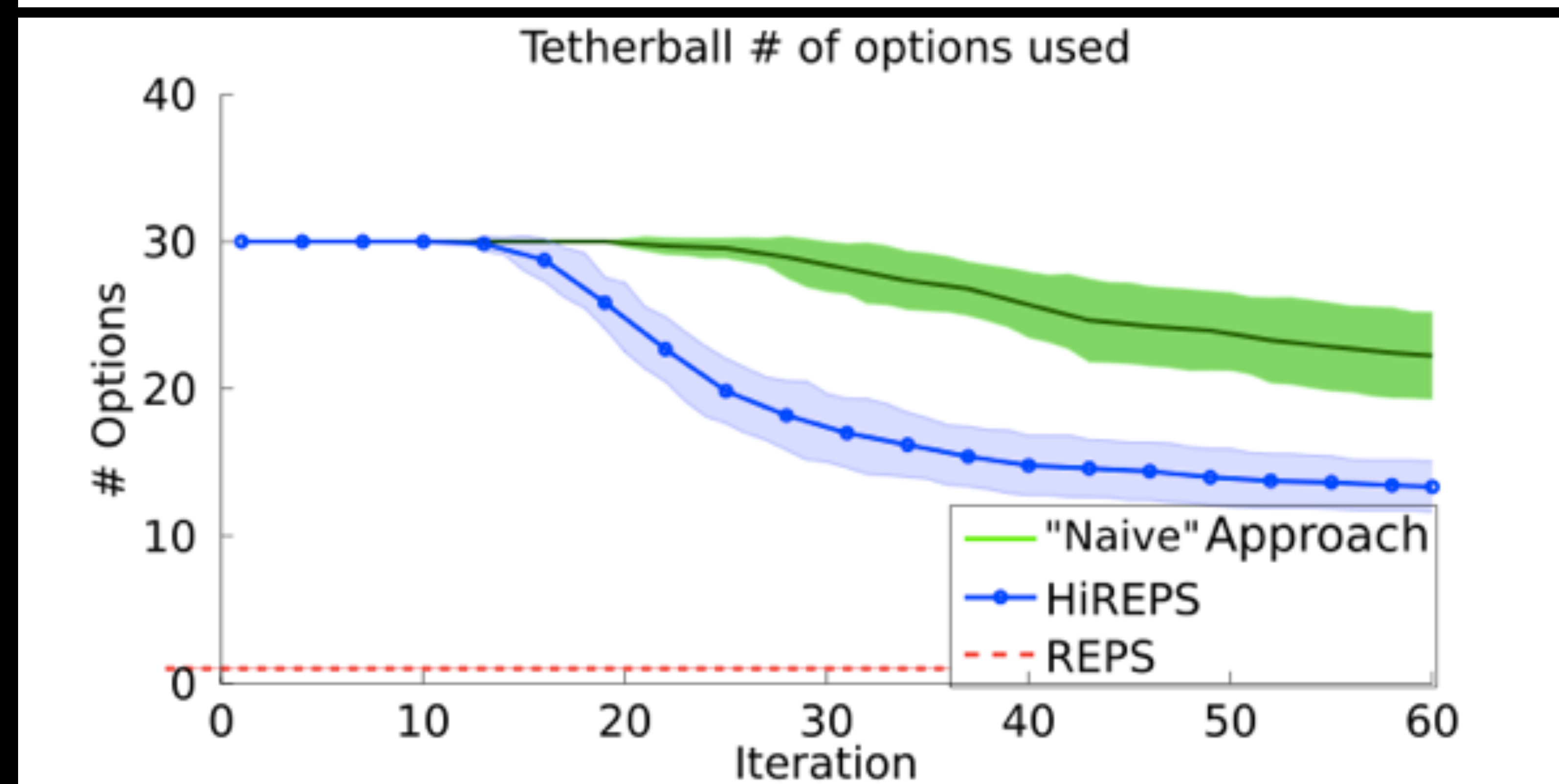
Daniel, Neumann & Peters (in press). Hierarchical Relative Entropy Policy Search, JMLR

Localized behavior can be learned efficiently!

Good performance

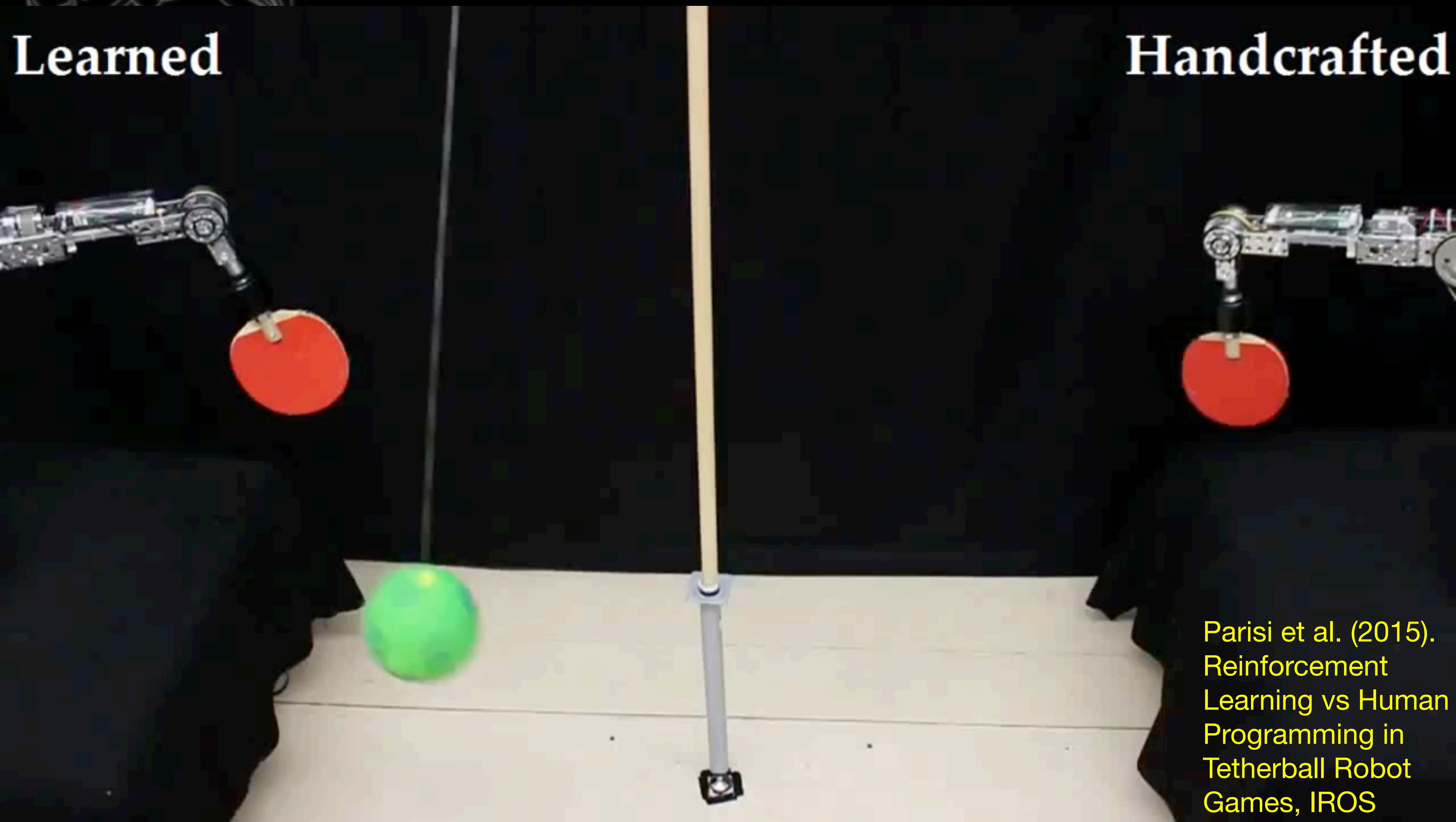


Fast reduction in the number of primitives



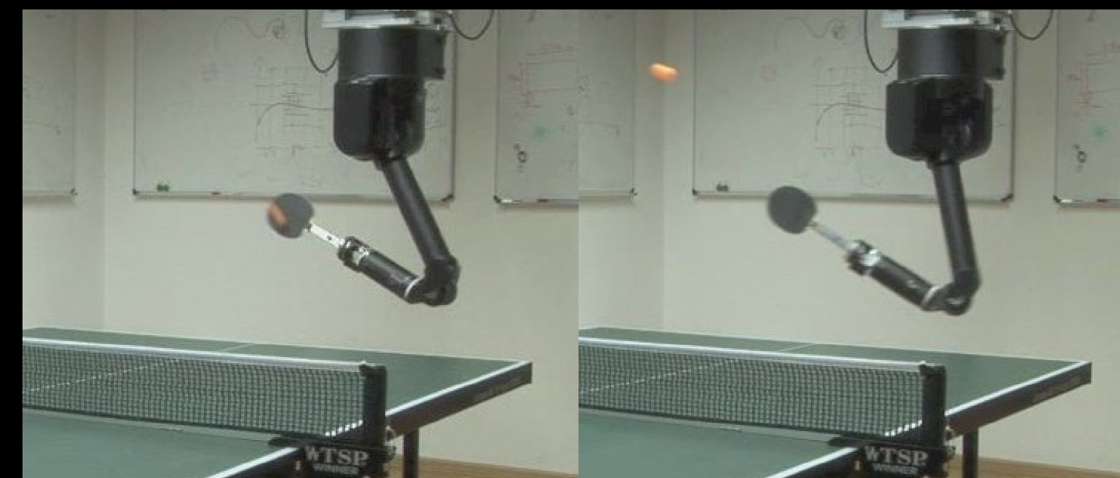
Daniel, Neumann & Peters (in press). Hierarchical Relative Entropy Policy Search, JMLR

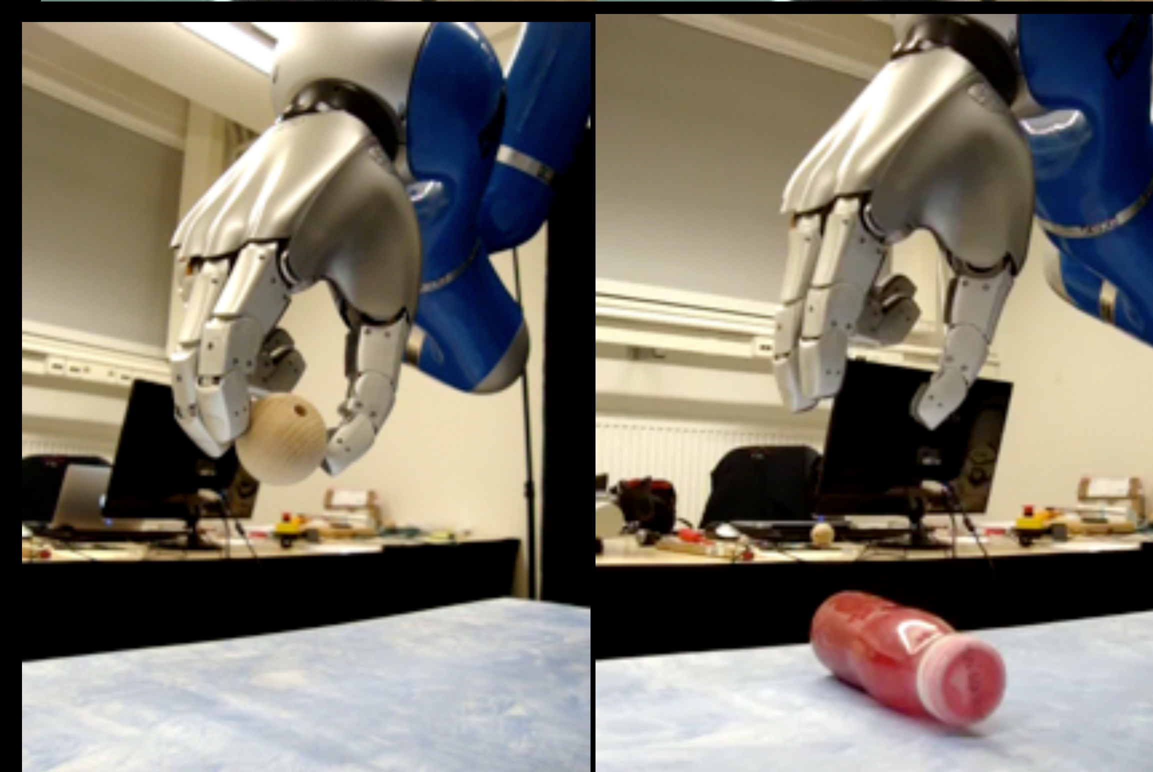
What's next? The Reinforcement Learning Games!



Parisi et al. (2015). Reinforcement Learning vs Human Programming in Tetherball Robot Games, IROS

Transfer from Robot Table Tennis



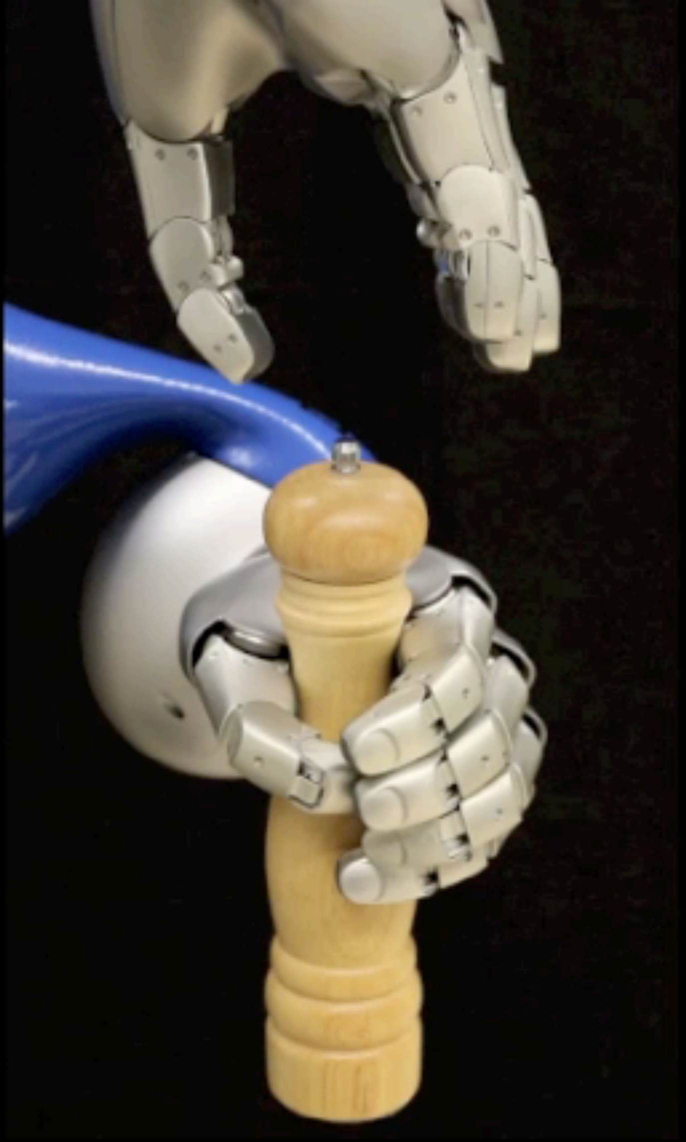


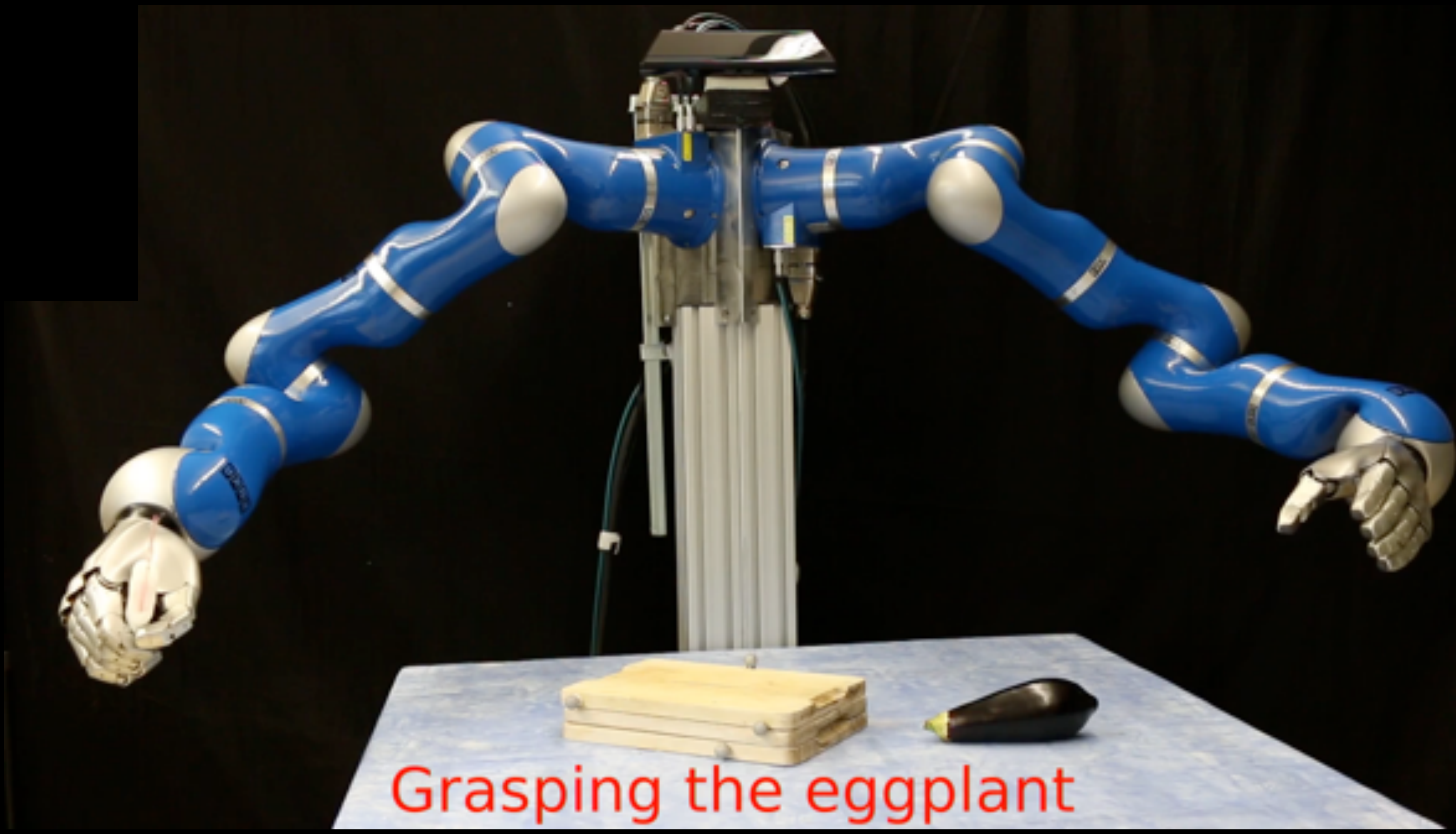
Grasping with Dynamic Motor Primitives

- Hitting a ball: Velocity at hitting point
- Reaching and grasping
  - Avoiding obstacles
  - Approach direction
  - Adjusting fingers to object

Kroemer, O.; Detry, R.; Piater, J.; Peters, J. (2010). Grasping with Vision Descriptors and Motor Primitives, *(ICINCO)*.

Transfer from Robot Table Tennis: First Examples





Kroemer, O.; van Hoof, H.; Neumann, G.; Peters, J. (2014). Learning to Predict Phases of Manipulation Tasks as Hidden States, Proceedings of 2014 IEEE International Conference on Robotics and Automation (ICRA).

Lioutikov, R.; Kroemer, O.; Peters, J.; Maeda, G. (2014). Learning Manipulation by Sequencing Motor Primitives with a Two-Armed Robot, Proceedings of the 13th International Conference on Intelligent Autonomous Systems (IAS).

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Problems in Robot Table Tennis

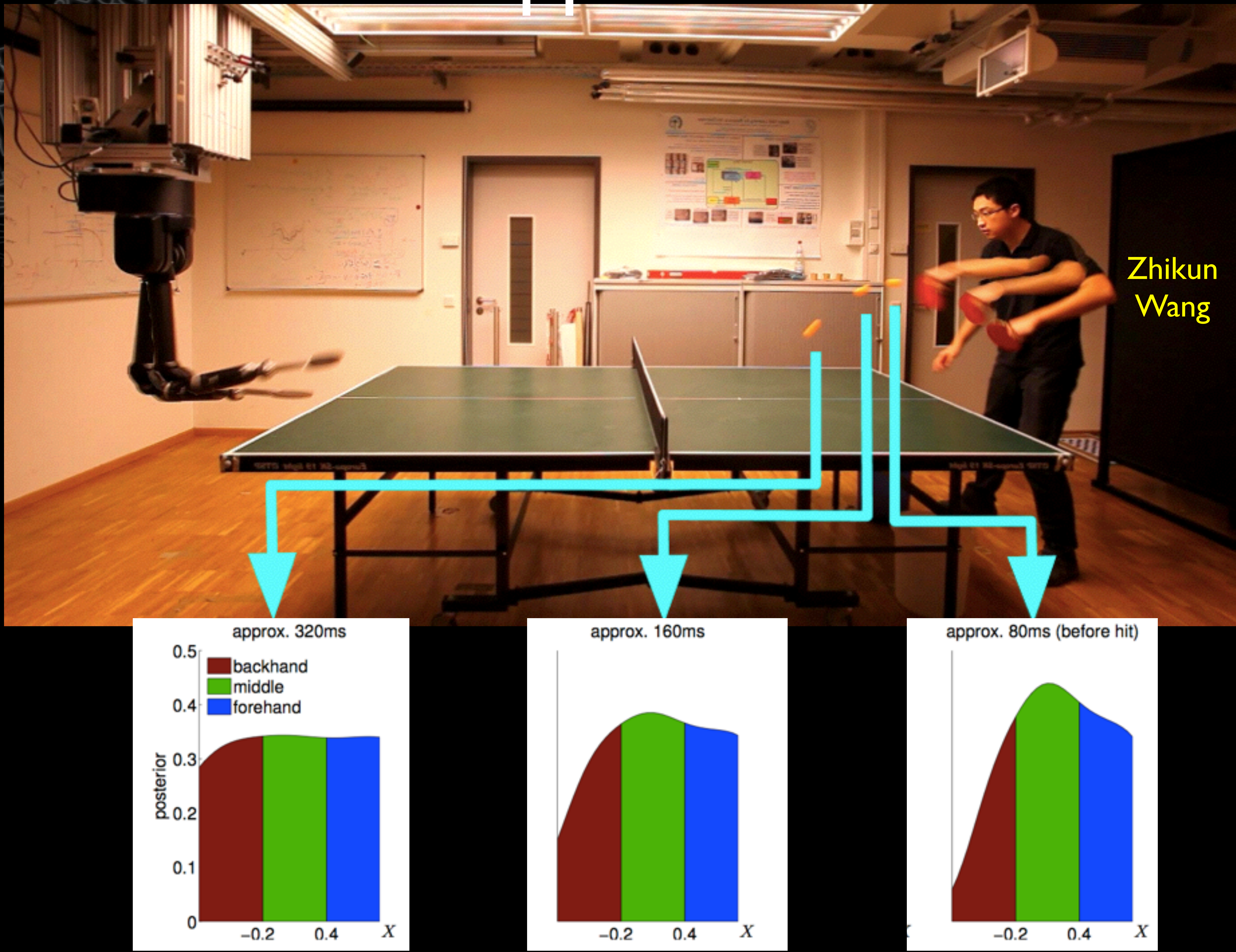
Problem I: Workspace is too limited.

Problem II: Arm accelerations are too low.

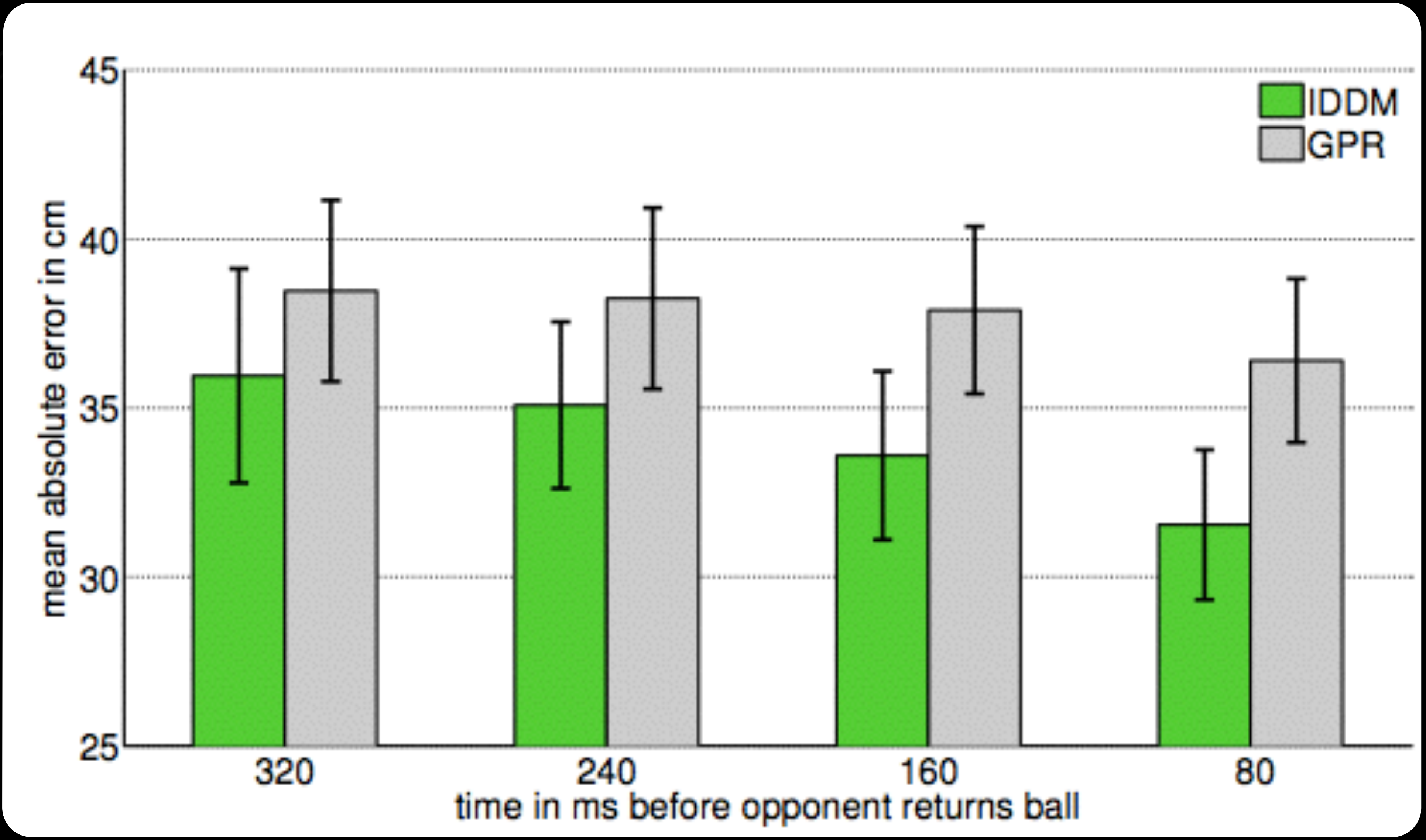
Problem III: Limited reaction time.

Problem III: Reaction Time

Reactive Opponent Prediction



Reactive Opponent Prediction



Wang, Z. et al. (2012). Probabilistic Modeling of Human Movements for Intention Inference, Robotics: Science and Systems (R:SS), in press at the International Journal on Robotics Research (IJRR)

Opponent Predictiom

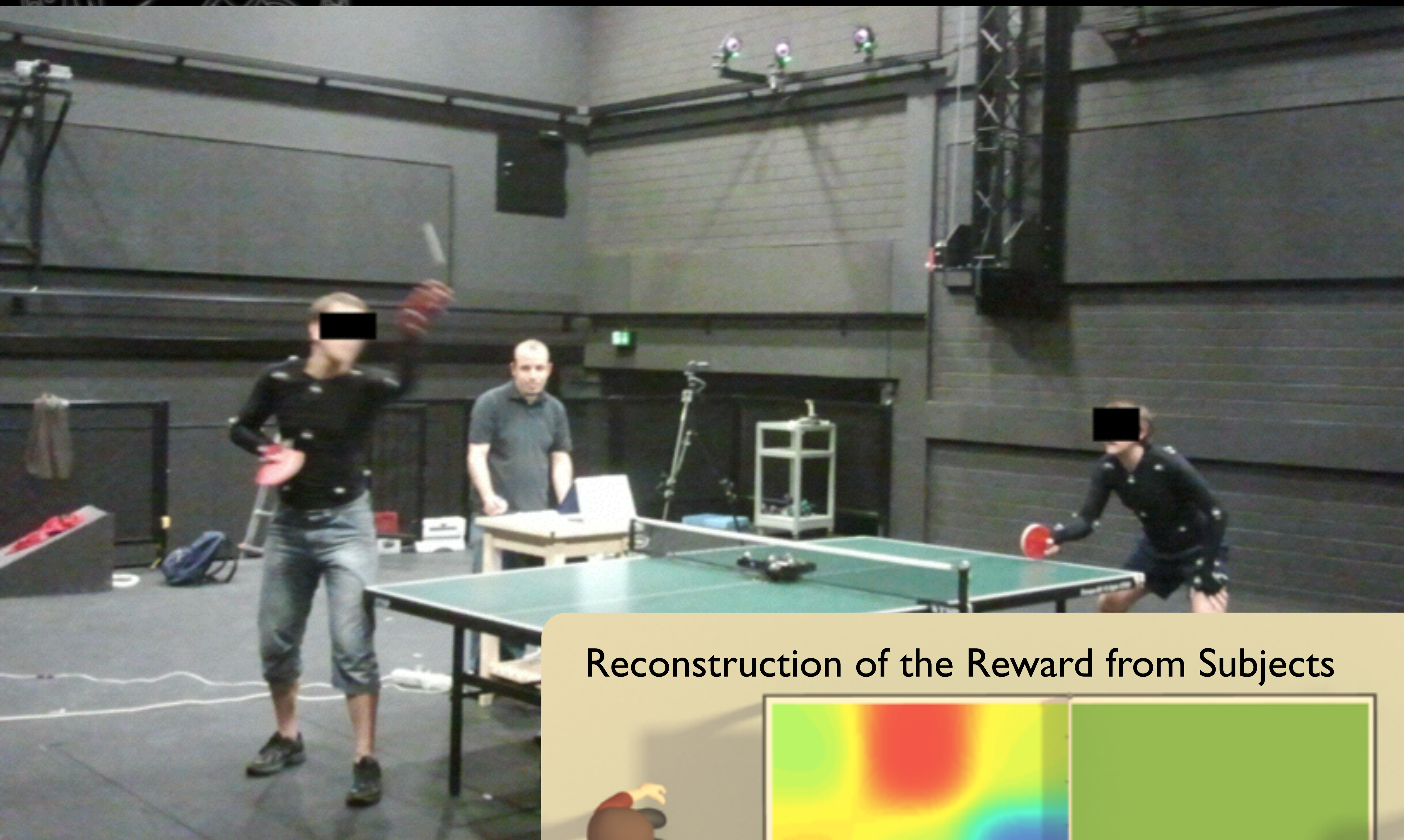
Probabilistic Modeling of Human Movements for Intention Prediction

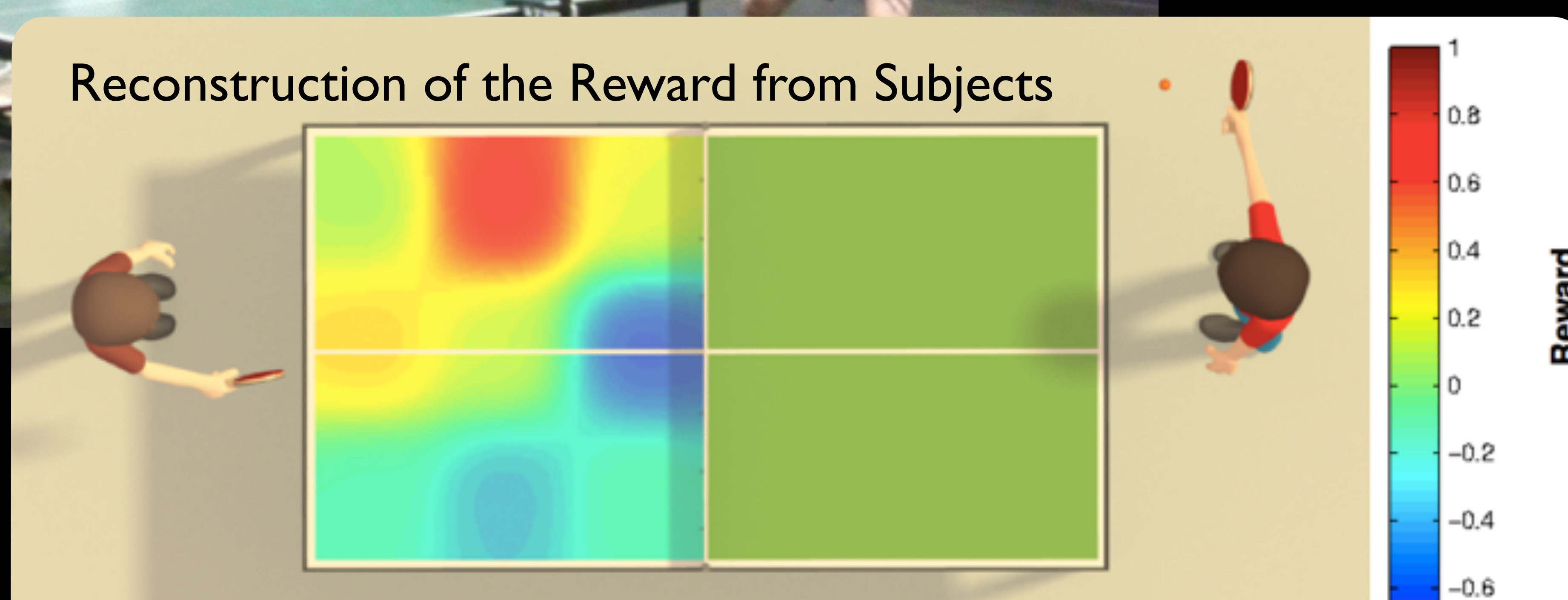
prototype system

Z. Wang, K. Muelling, M. Deisenroth, B. Schoelkopf, and J. Peters

Wang, Z. et al. Probabilistic Modeling of Human Movements for Intention Inference, R:SS 2012, IJRR 2013

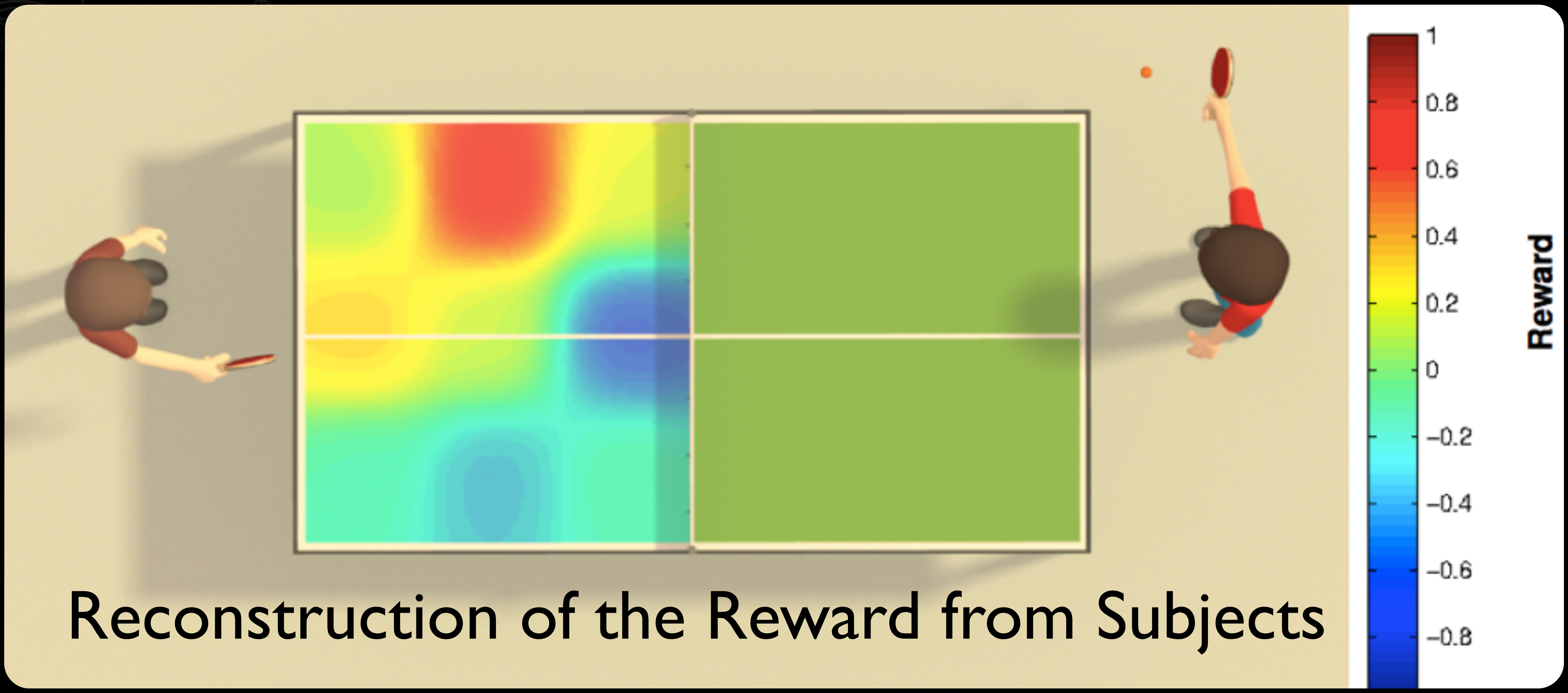
Extracting Strategies from Game Play





Mülling, K. et al. (2014). Biological Cybernetics.

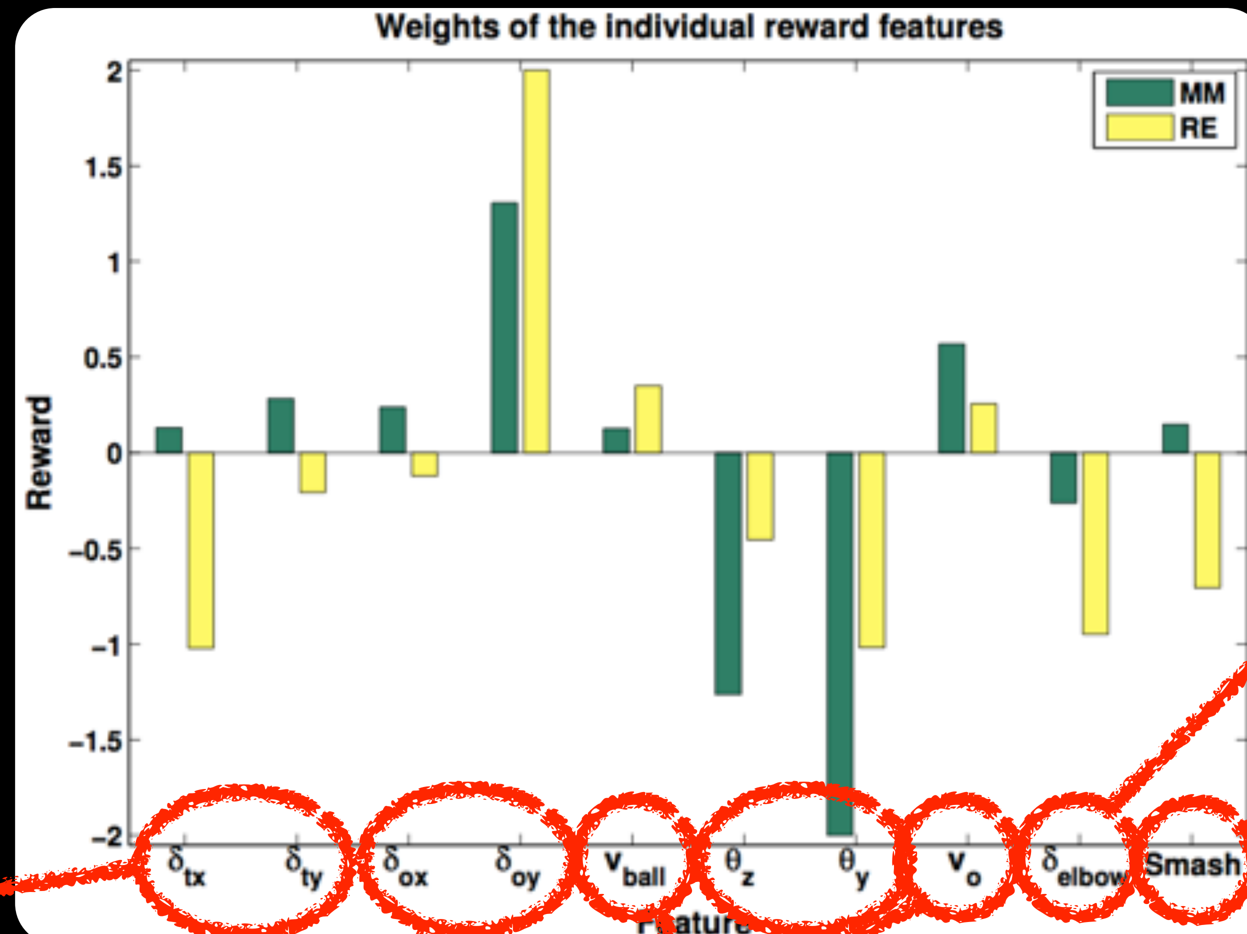
Extracting Strategies from Game Play



Reconstruction of the Reward from Subjects

Extracting Strategies from Game Play

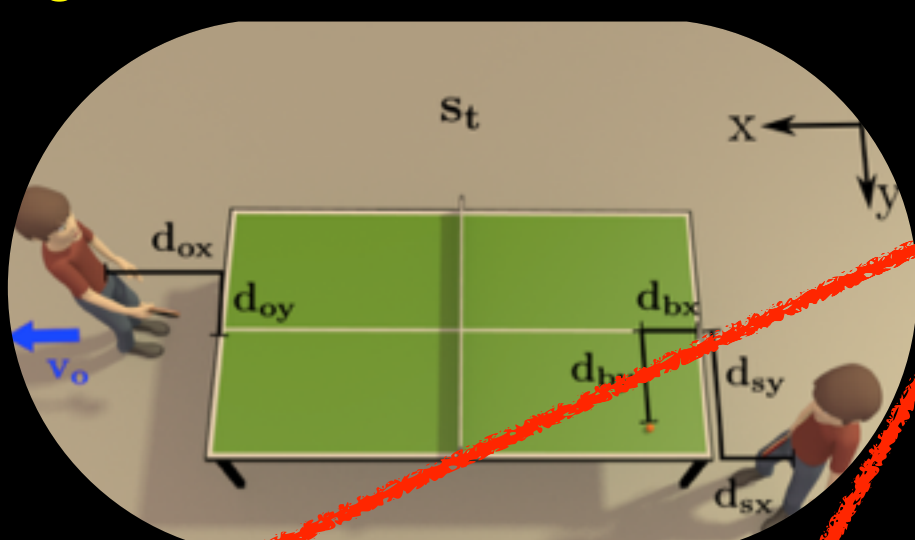
Weights of the most relevant features!



Opponent Elbow

Smash or not

Distance to the Edge of the Table



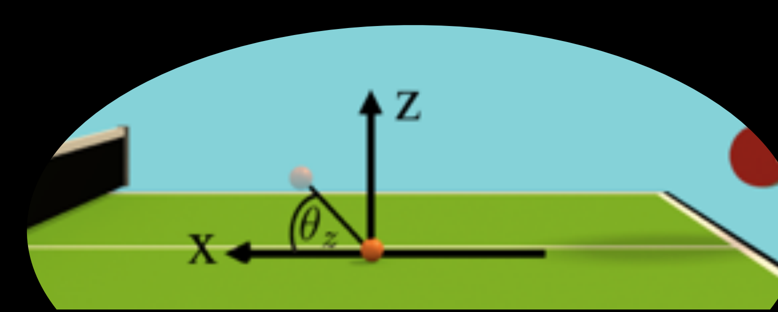
Angle of Incoming Bouncing Ball

Velocity of the Ball

Movement Direction of the Opponent

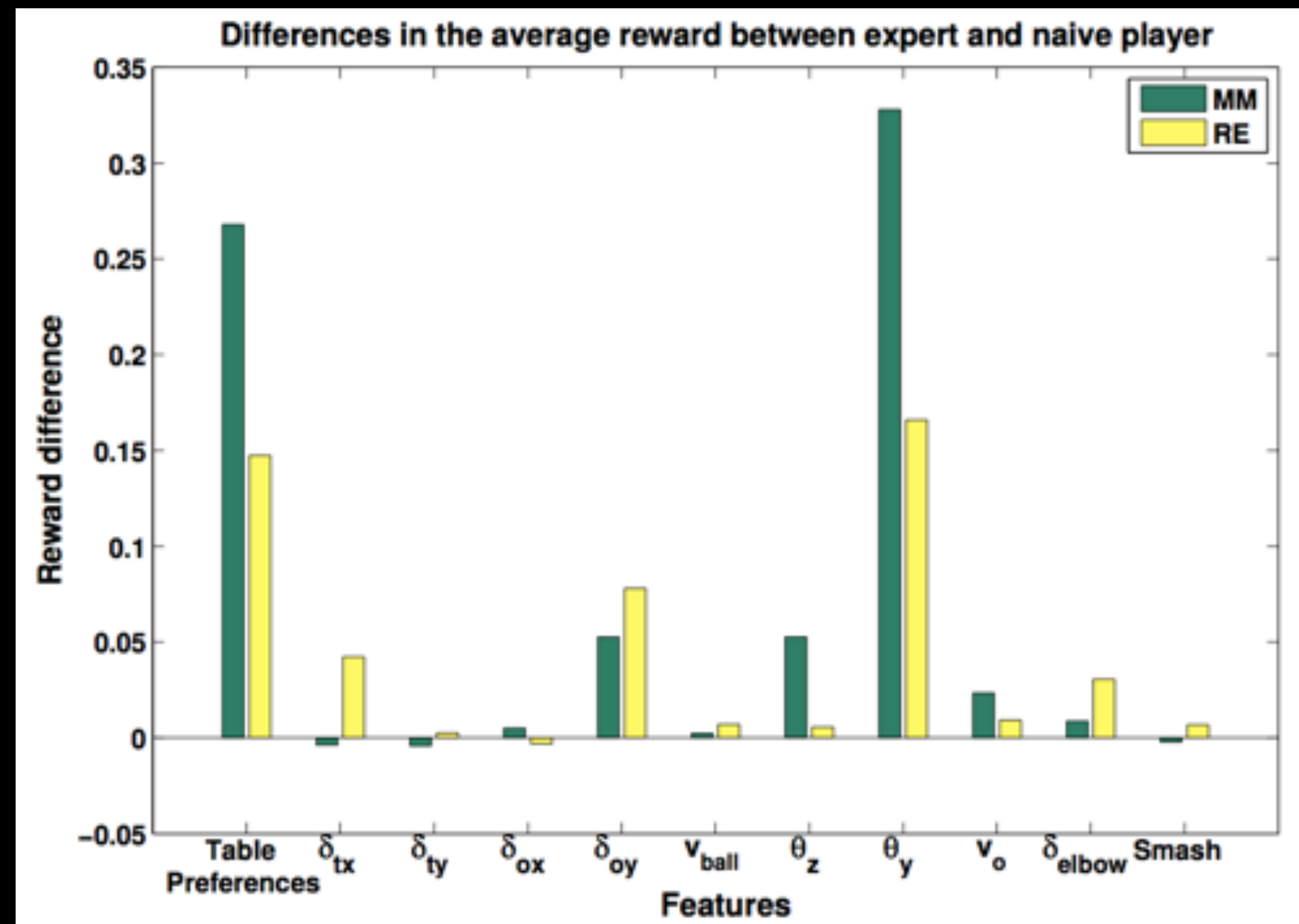
Distance to the Opponent

Mülling, K. et al. (2014) Biological Cybernetics.



Extracting Strategies from Game Play

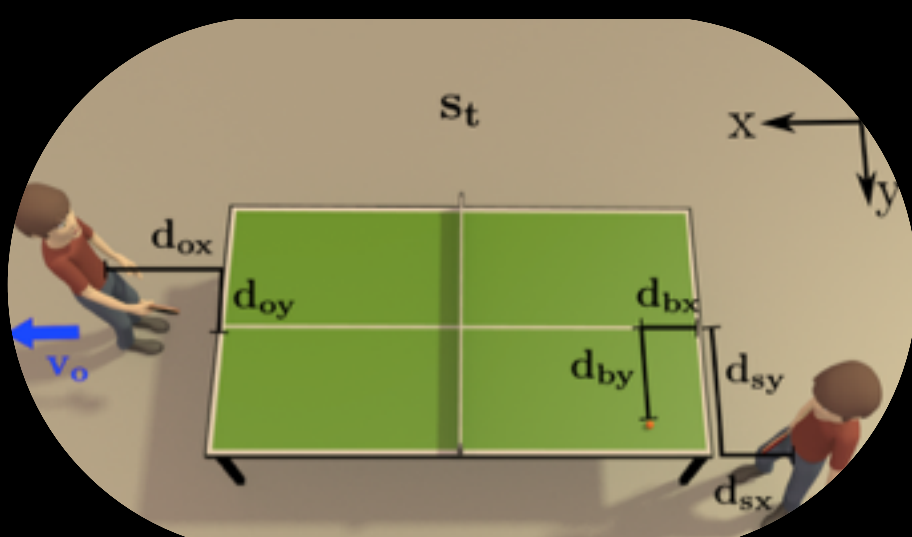
Differences between Experts and Naive Player only in few features!



Opponent Elbow

Smash or not

Distance to the Edge of the Table



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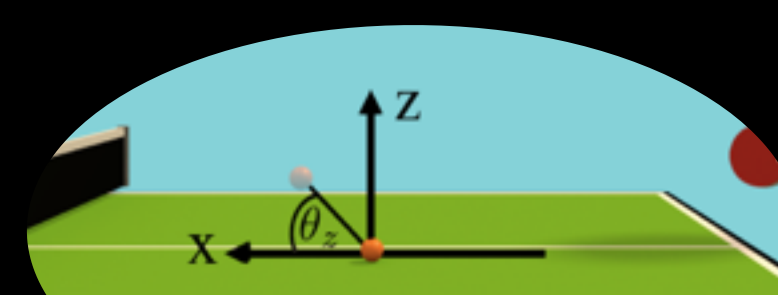
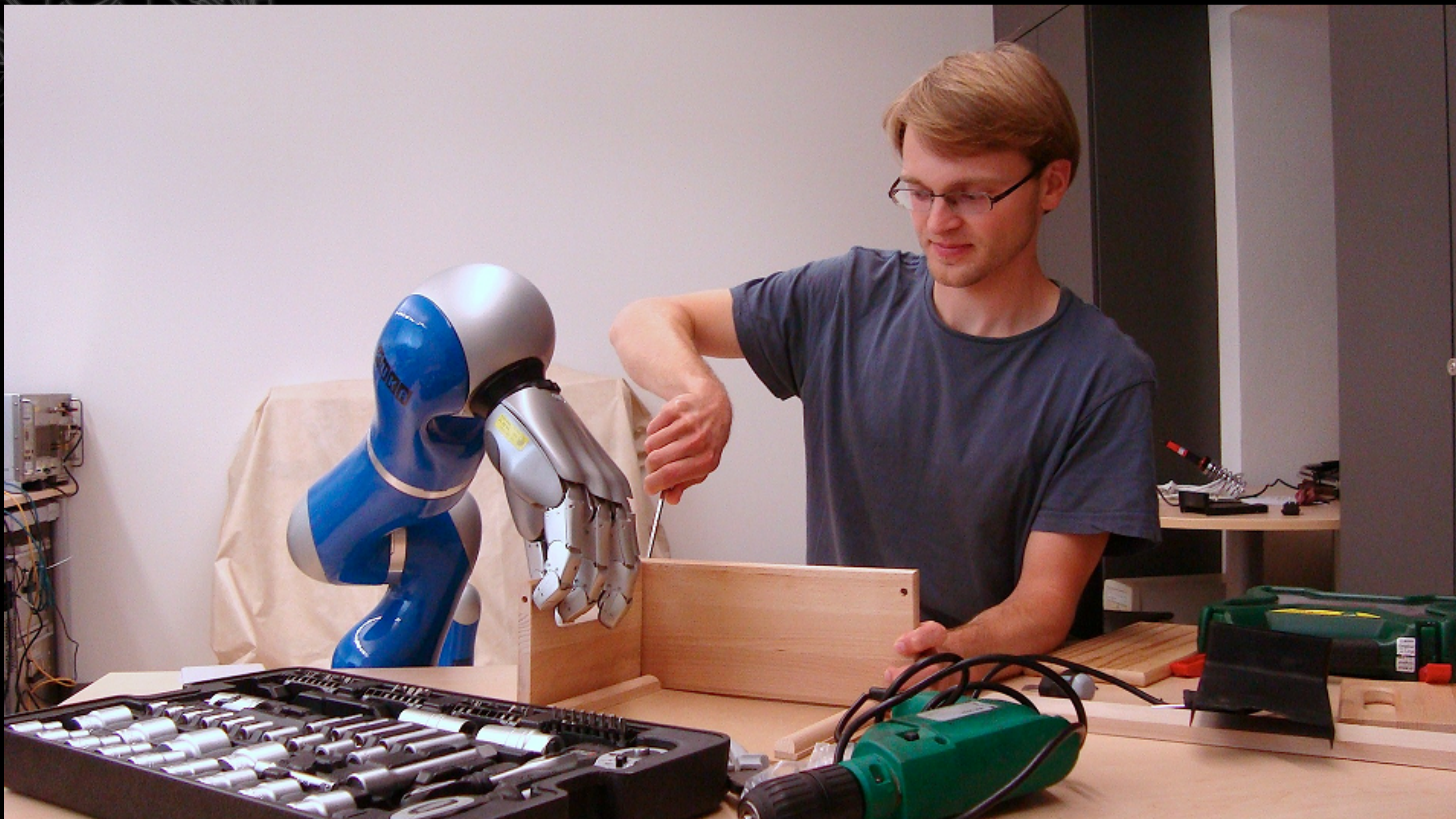


Interaction Primitives for a Semi-Autonomous 3rd Hand?



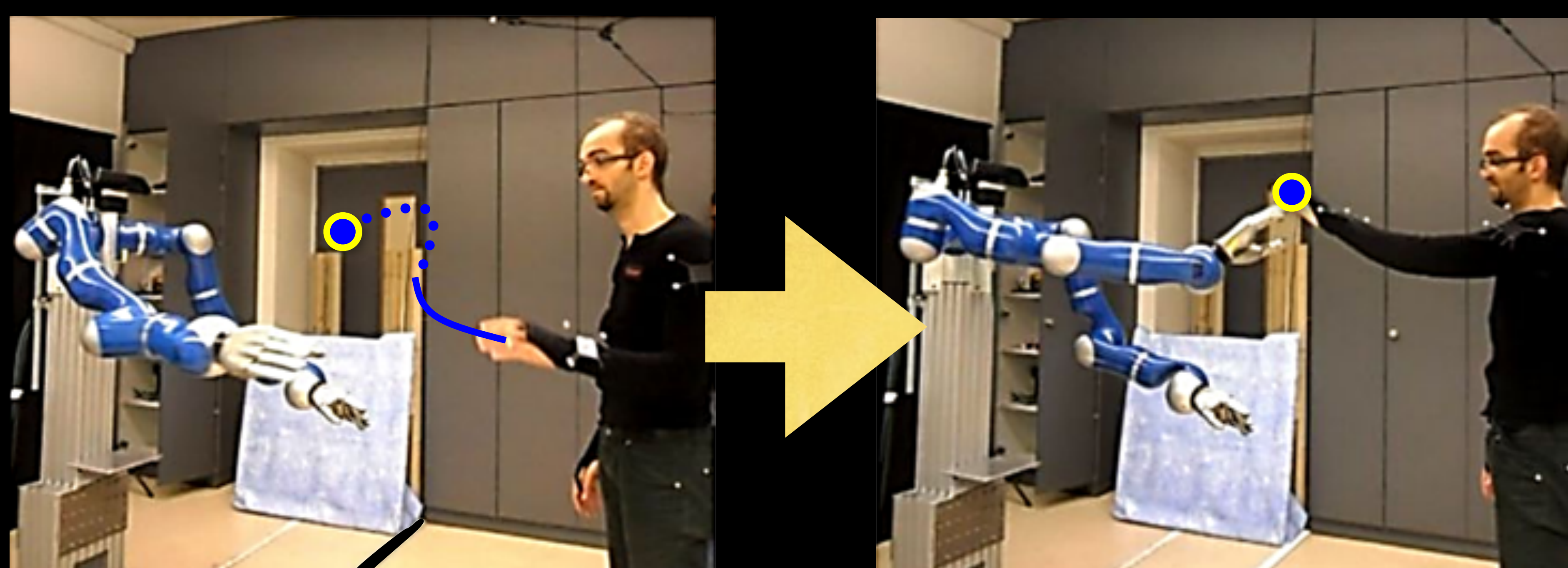
Ben Amor, H.; Neumann, G.; Kamthe, S.; Kroemer, O.; Peters, J. (2014). Interaction Primitives for Human-Robot Cooperation Tasks , Proceedings of 2014 IEEE International Conference on Robotics and Automation (ICRA).

Interaction Primitives

The High-Five Task

- **Infer the task (aka primitive)**
- **Infer the human trajectory**

Generate the appropriate robot trajectory



Observed trajectory   Predicted trajectory   Predicted goal

Interaction Primitives

known agent **unknown agent**

Agent 1 (M joints)

Agent 2 (N joints)

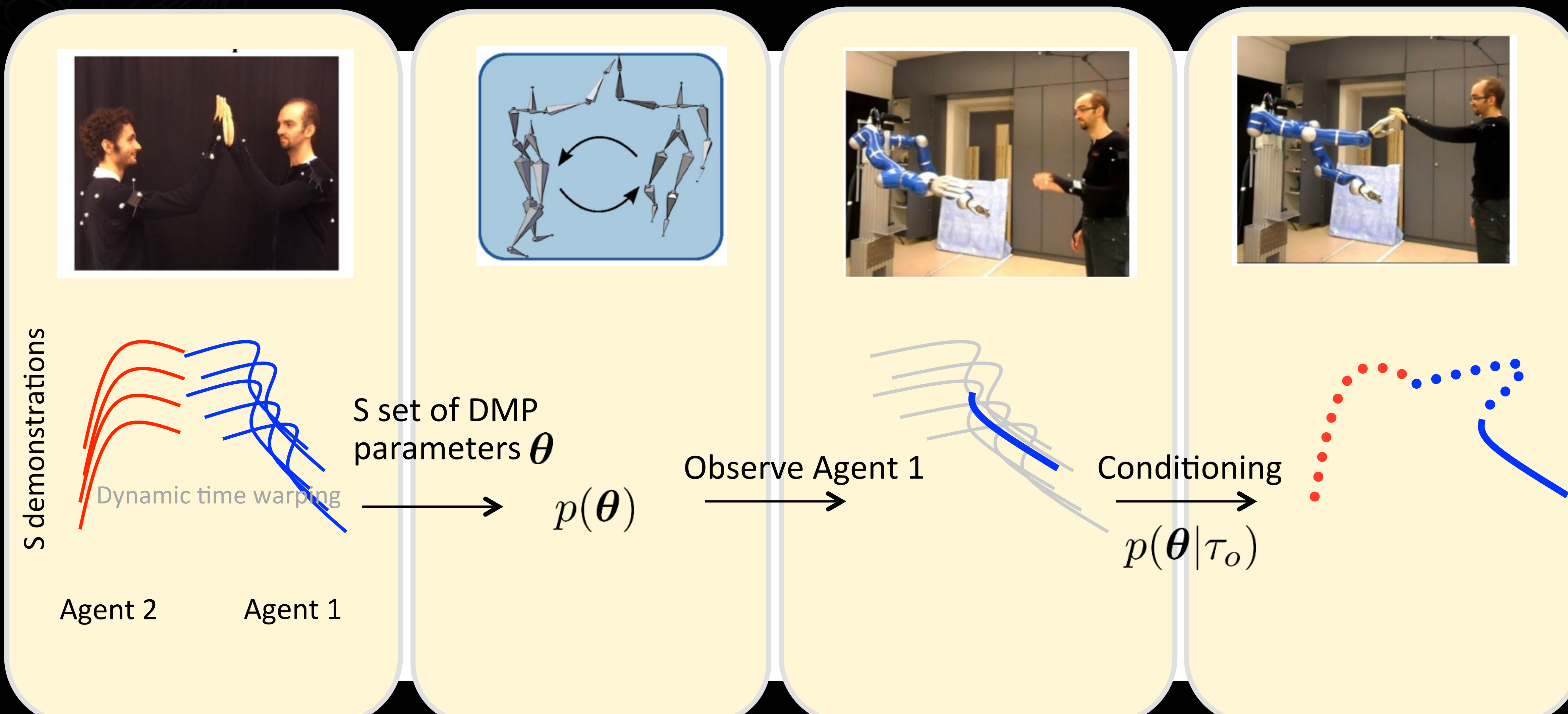
$$\boldsymbol{\theta}^{[1]} = [\ \boldsymbol{w}_1^T\ g_1\ \ldots\ \boldsymbol{w}_M^T\ g_M\ \ \boldsymbol{w}_1^T\ g_1\ \ldots\ \boldsymbol{w}_N^T\ g_N\ ]$$

Goal

$$\mathbf{w}_1 = [w_{1,1}\ \ldots\ w_{B,1}]^T$$

An Interaction primitive can simply be a motor primitive that includes both the known agent and the unknown agent.

Interaction Primitives for a Semi-Autonomous 3rd Hand



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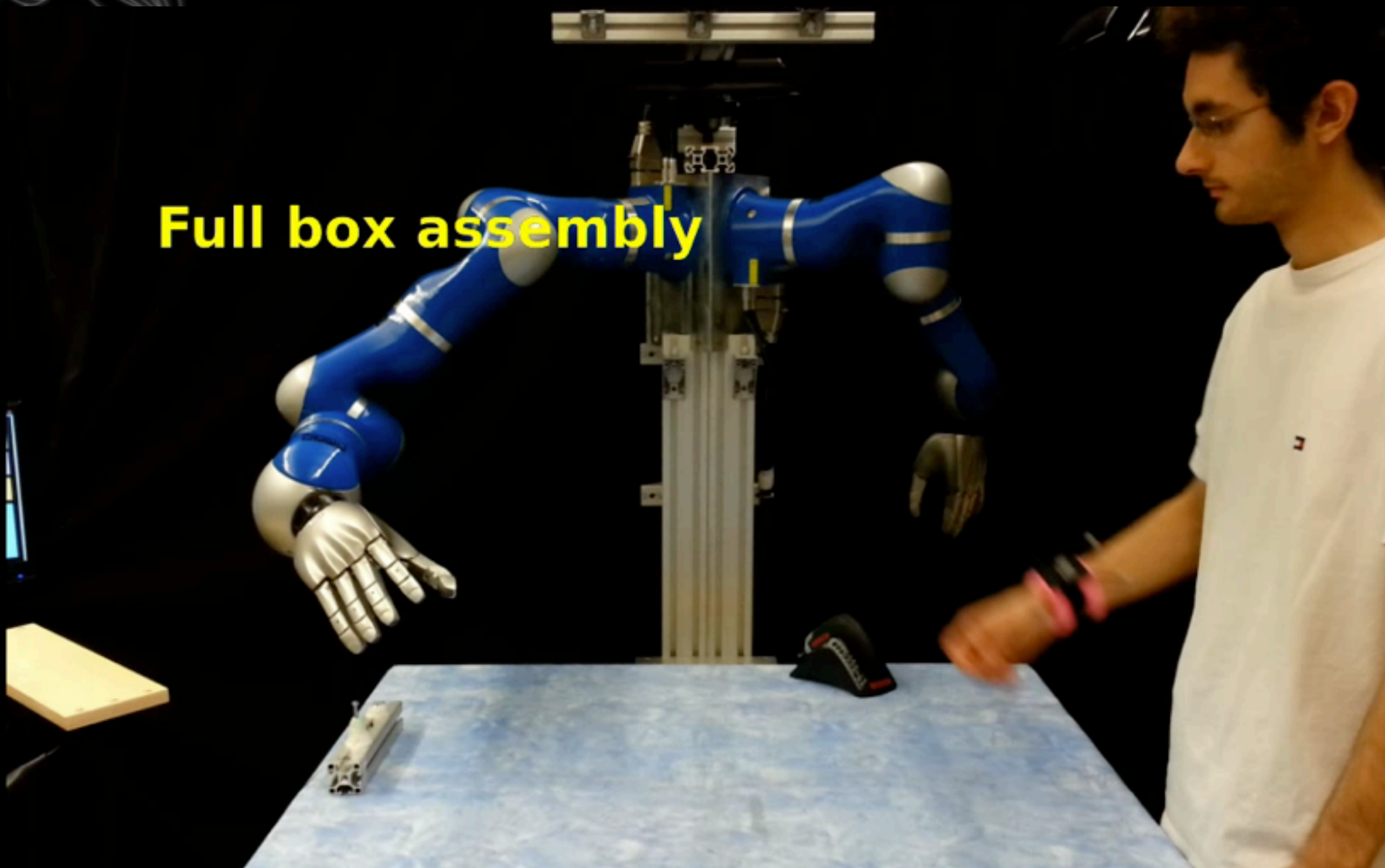
Interaction Primitives for a Semi-Autonomous 3rd Hand



Ewerton, M.; Neumann, G.; Lioutikov, R.; Ben Amor, H.; Peters, J.; Maeda, G. (2015). Learning Multiple Collaborative Tasks with a Mixture of Interaction Primitives, International Conference on Robotics and Automation (ICRA).

Outline

1. Introduction
2. How can we develop suitable machine learning methods?
3. How can elementary behavior be learned with such machine learning methods?
4. Can complex skills be learned leveraging on elementary behaviors?
5. How can we adapt to humans and learn interaction?
6. Outlook & Conclusion

It’s not all Table Tennis...

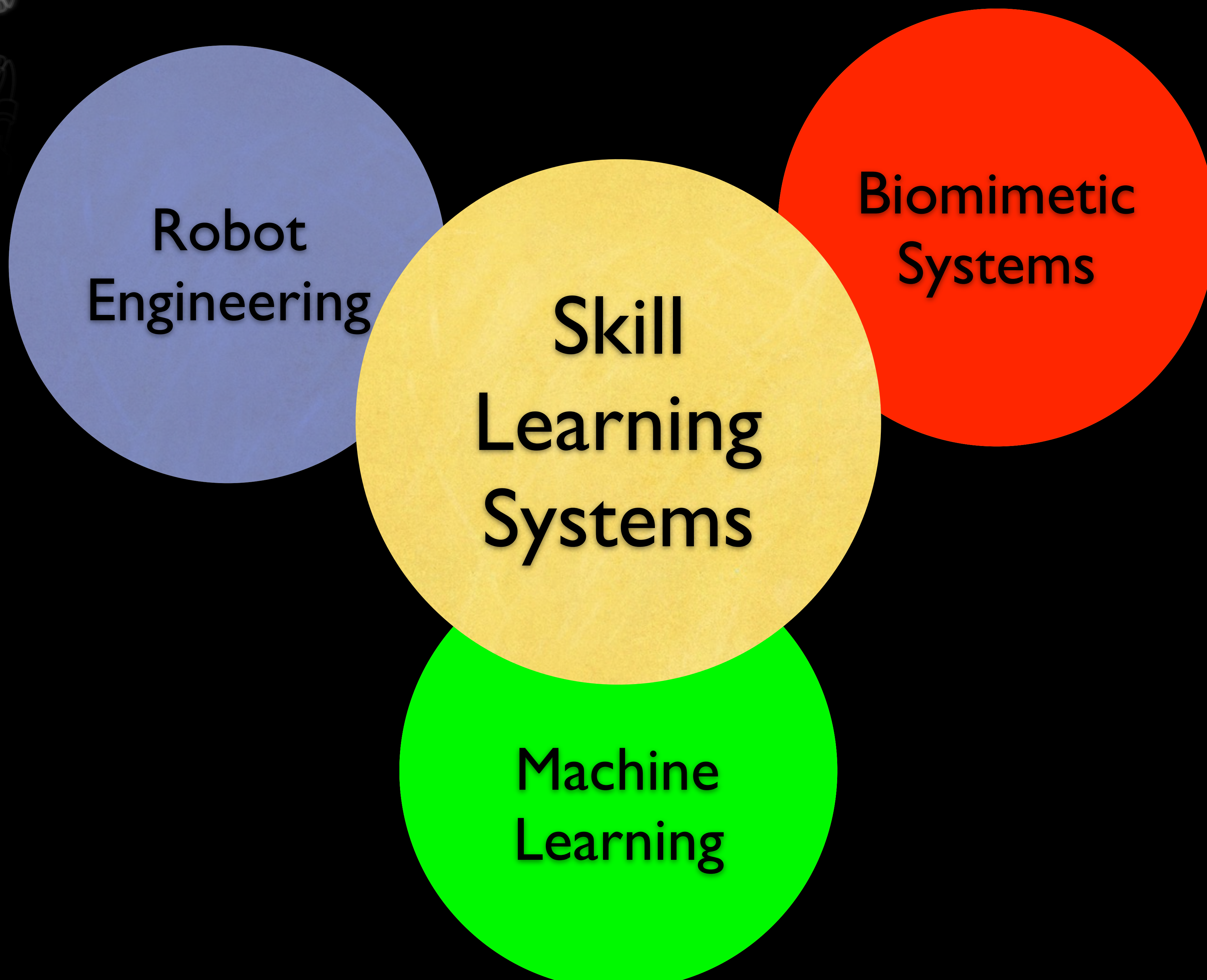
Industrial Application: Key bottleneck in manufacturing is the high cost of robot programming and slow implementation.

> **Bosch**: *If a product costs less than 50€ or is produced less than 10.000 times, it is not competitive with manual labor.*

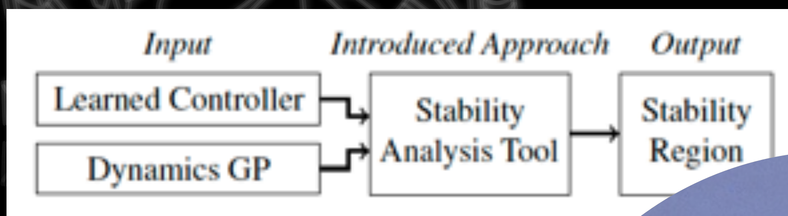
Assistive Robots & Companion Technologies: In hospital and rehablitation institutions, nurses need to “program” the robot – not computer scientists.

Robots@Home: Robots need to adapt to the human and “blend into the kitchen”.

Outlook


Robot Engineering
Skill Learning Systems
Biomimetic Systems
Machine Learning

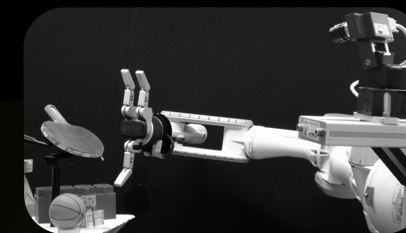
Robot Systems

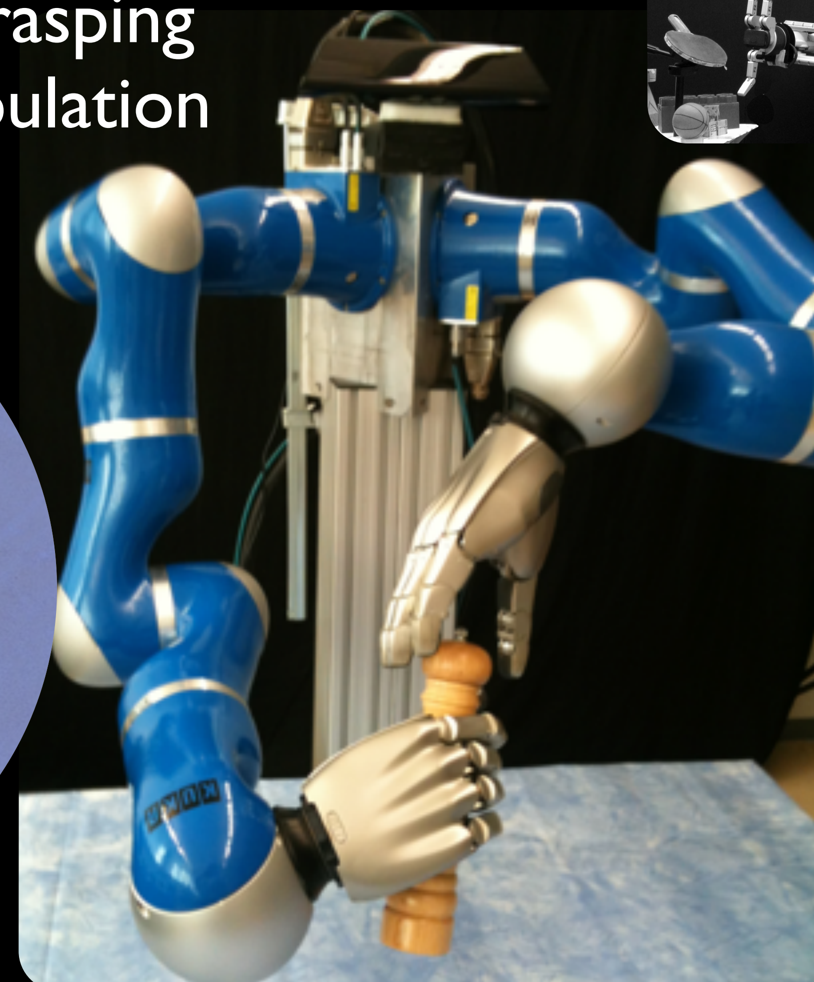


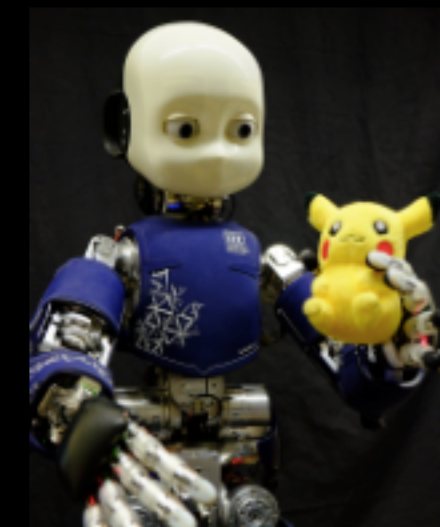
Automated Stability Proofs

Robot Engineering

Robot Grasping and Manipulation

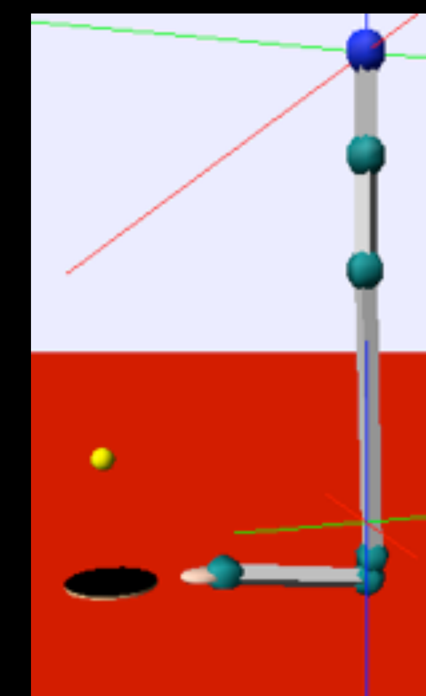




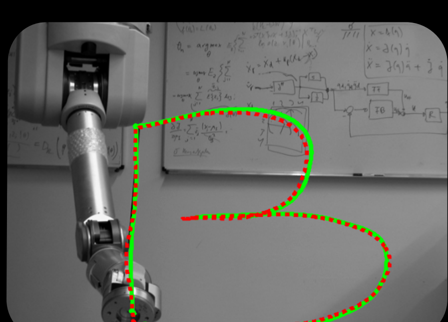


Humanoid Robotics

Real-Time Software & Simulations for Robots



High-Speed Real-Time Vision



Nonlinear Robot Control

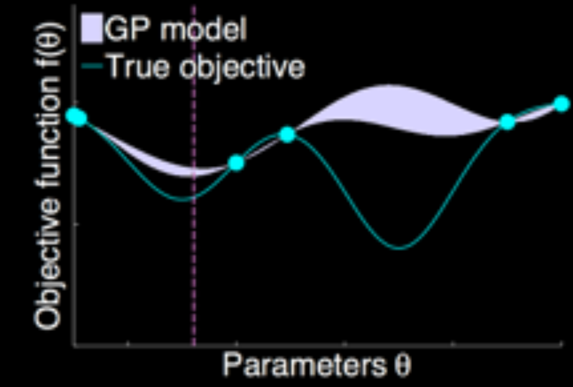
Tactile Perception & Sensory Integration

Industrial Partnership with Honda, ABB and Bosch.

Machine Learning

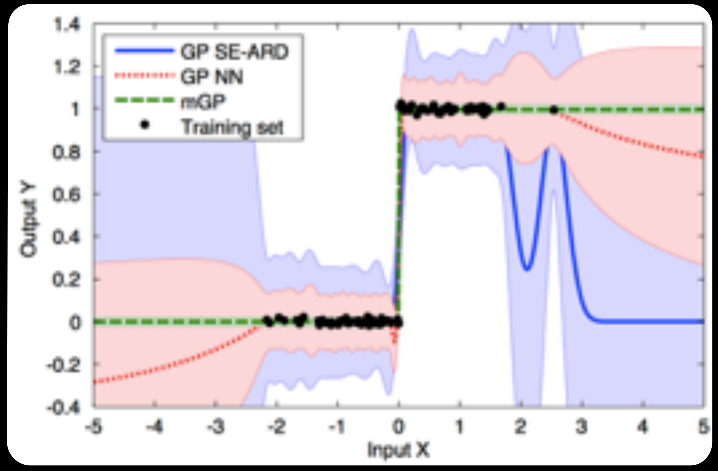
Real-Time Regression
(Nguyen-Tuong & Peters, Neurocomputing 2011)

Bayesian Optimization
(Calandra et al, 2014)



Much more Reinforcement Learning...

Model Learning
(Nguyen-Tuong & Peters, Advanced Robotics 2010)



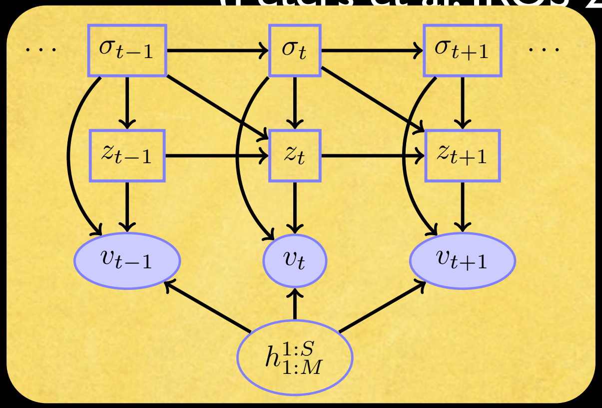
Maximum Entropy
(Peters et al., AAAI 2010; Daniel, Neumann & Peters, AIStats 2012)

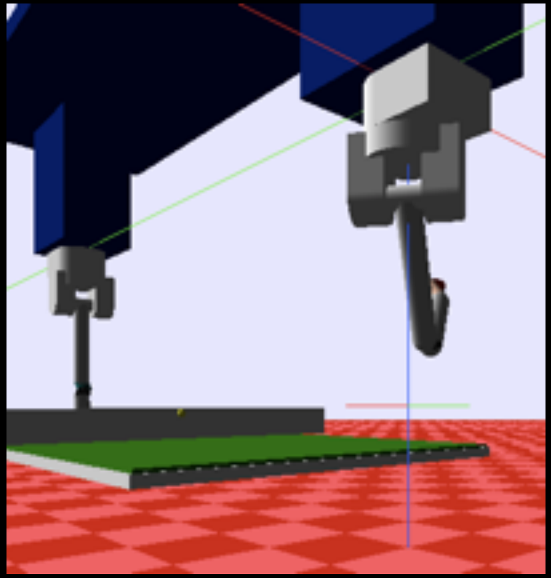
Probabilistic Movement Representation
(Paraschos et al. NIPS 2013)

Partnership with the Max Planck Institute for Intelligent Systems.

Manifold Gaussian Processes
(Calandra et al, 2014)

Policy Gradient Methods
(Peters et al. IROS 2006)





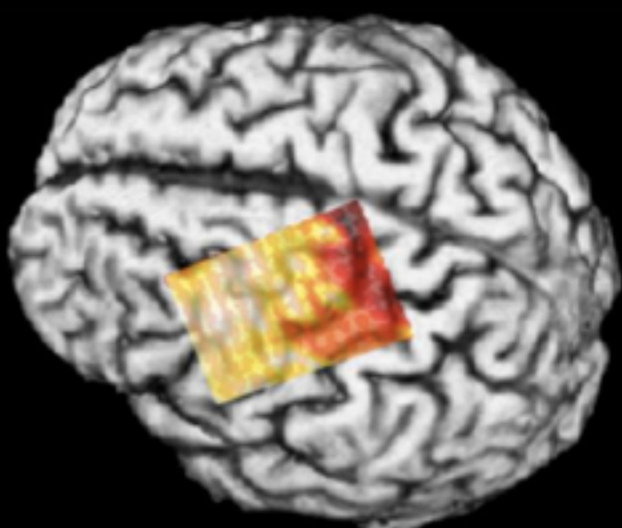
Machine Learning for Motor Games
(Wang, Boularias & Peters, AAAI 2011)

Machine Learning

Pattern Recognition in Time Series
(Alvarez, Peters et al., NIPS 2010a; Chiappa & Peters, NIPS 2010b)

Biological Inspiration and Application

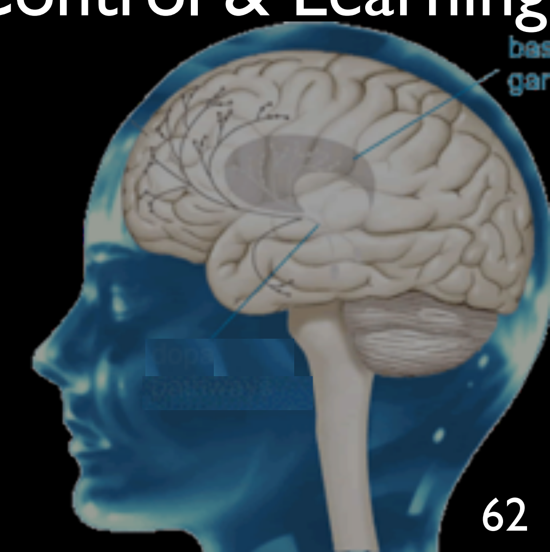
Brain-Computer Interfaces with ECoG for Stroke Patient Therapy
(Gomez, Peters & Grosse-Wentrup, Journal of Neuroengineering 2011)



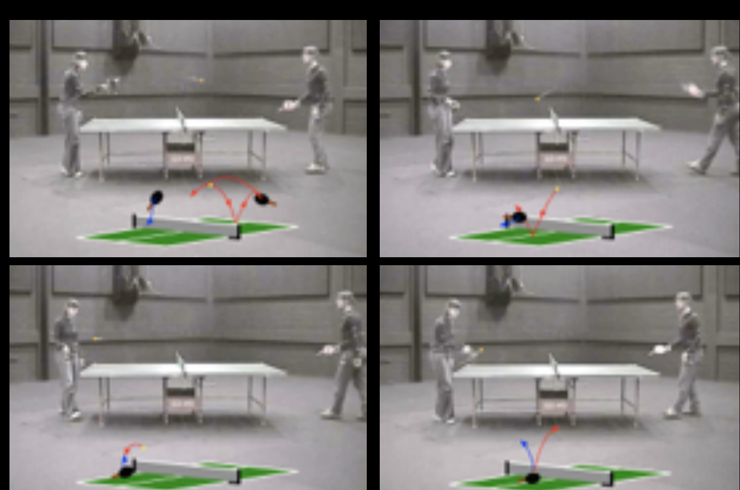
Brain Robot Interfaces
(Peters et al., Int. Conf. on Rehabilitation Robotics, 2011)

Biomimetic Systems

Computational Models of Motor Control & Learning



Collaboration with the Max Planck Institute for Intelligent Systems and the Tübingen University Hospital.



Understanding Human Movements
(Mülling, Kober & Peters, Adaptive Behavior 2011)

Conclusion

- Motor skill learning is a promising way to avoid programming all possible scenarios and continuously adapt to the environment.
- We have efficient Imitation and Reinforcement Learning Methods which scale to anthropomorphic robots.
- Basic skill learning capabilities of humans can be produced in artificial skill learning systems.
- We are working towards learning of complex tasks such as table tennis and a semi-autonomous 3rd hand.


Thanks for your Attention!
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