# Real-World Reinforcement Learning for Autonomous Humanoid Robot Charging in a Home Environment

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# Outline

- Motivation
- Reinforcement learning (RL)
- Neural implementation
- SARSA algorithm
- Experimental results
- Conclusion

# Motivation

- Need for studying humanoid robots within home environments
- Limited energetic capabilities of the Nao robot


http://ksera.ieis.tue.nl/

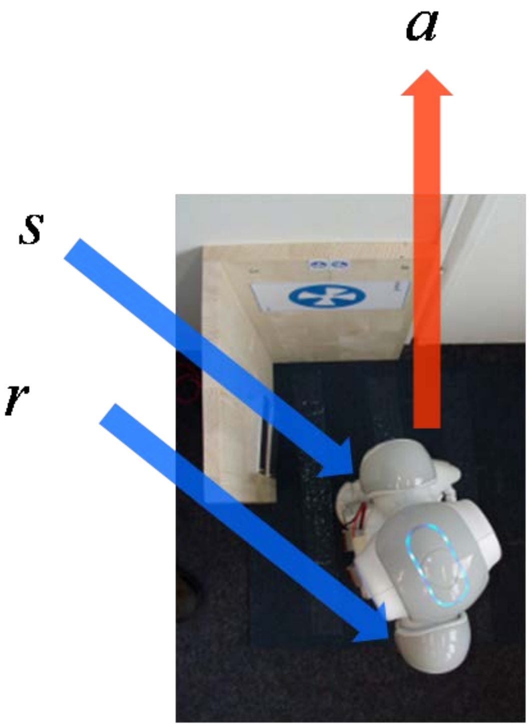
RobotDoC

Robotics for Development of Cognition

http://robotdoc.org/

# Reinforcement learning

- Perceive state ***s***
- Perform action ***a***
- Occasionally, receive reward ***r***
- Perceive state ***s'***
- Perform action ***a'***




Markov Decision Process (MDP)

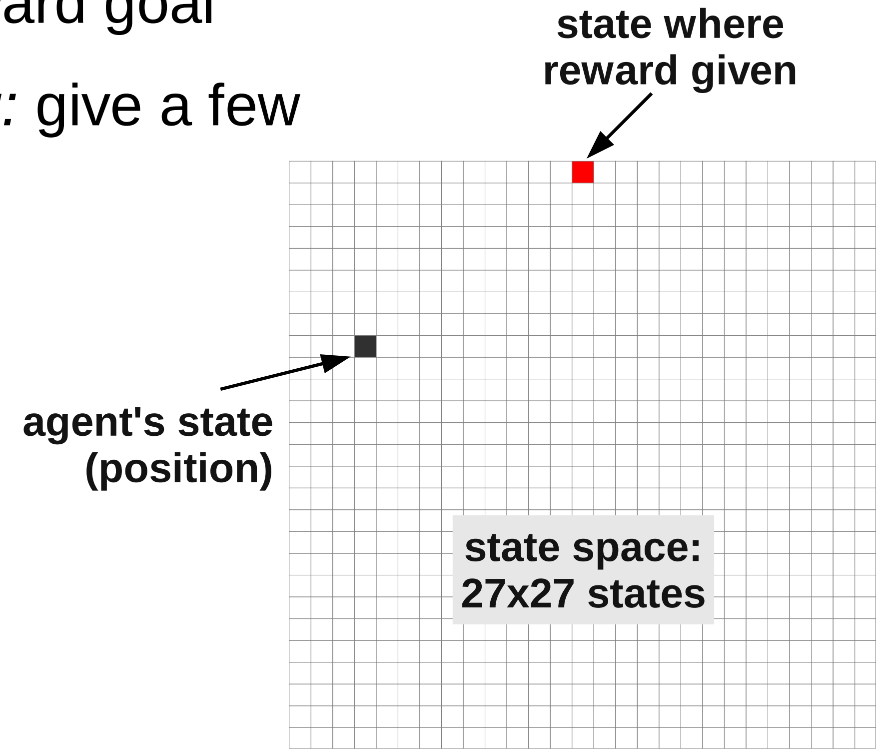
- Fixed transition probabilities
- Next move not depending on history
- Fixed reward probability

# Concepts of SARSA and supervised RL

*Objective*: get to the reward quickly

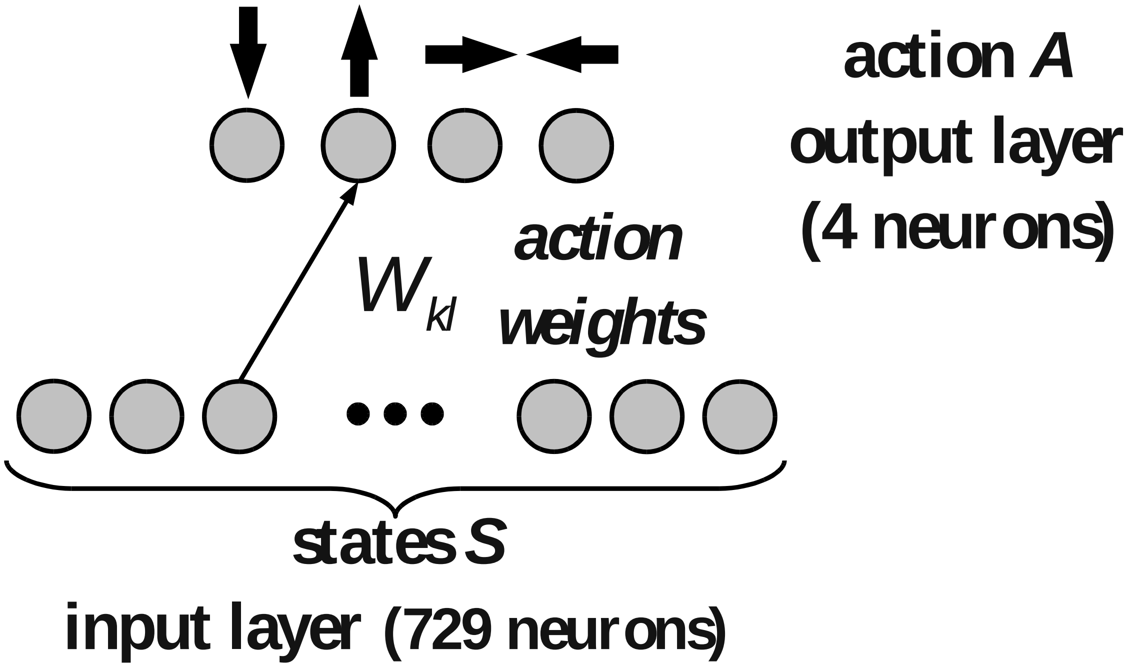
*Principle*: sample ***s***, ***a*** and ***r***, ***s***, ***a*** (SARSA) in MDP trials, and learn principle: state-action values Q(*s*, *a*), which increase toward goal

*Supervised reinforcement learning:* give a few correct training examples initially



# Neural implementation

1-layer feed forward network maps state to action



# SARSA algorithm

| | | |
|---|---|---|
| (i0) | Place the robot in a random position for a new trial | |
| (i1) | Compute states | $s$ |
| (i2) | Compute action strength | $h_i = \sum_l W_{il} s_l$ |
| (i3) | Select action | $P_{(a_i=1)} = \frac{e^{\beta h_i}}{\sum_k e^{\beta h_k}}$ |
| (i4) | Current estimate | $Q_{(s,a)} = \sum_{k,l} W_{kl} a_k s_l$ |

| | | |
|---|---|---|
| Repeat until trial ends successfully ($r$=1) | | |
| (0) | Execute action | $a$ |
| (1) | Compute new states and check for reward | $s'$ |
| (2) | Compute action strength | $h_i = \sum_l W_{il} s'_l$ |
| (3) | Select action | $P_{(a'_i=1)} = \frac{e^{\beta h_i}}{\sum_k e^{\beta h_k}}$ |
| (4) | Current estimate | $Q_{(s',a')} = \sum_{k,l} W_{k,l} a'_k s'_l$ |
| (5) | Compute Prediction error | $\delta = (1-r)\gamma Q_{(s',a')} + r - Q_{(s,a)}$ |
| (6) | Weight update | $\Delta W_{ij} = \epsilon \delta a_i s_j$ |
| (7) | New turns old | $s, a \leftarrow s', a'$ |

# SARSA algorithm

Gaussian state activation to "blur" the activation around the "currently active state unit".

$$s_j = \frac{1}{2\pi\sigma^2} \cdot e^{-\frac{(x_j-\mu_x)^2+(y_j-\mu_y)^2}{2\sigma^2}}$$

| | | |
|---|---|---|
| (i0) | Place the robot in a random position for a new trial | |
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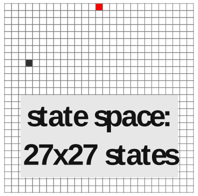


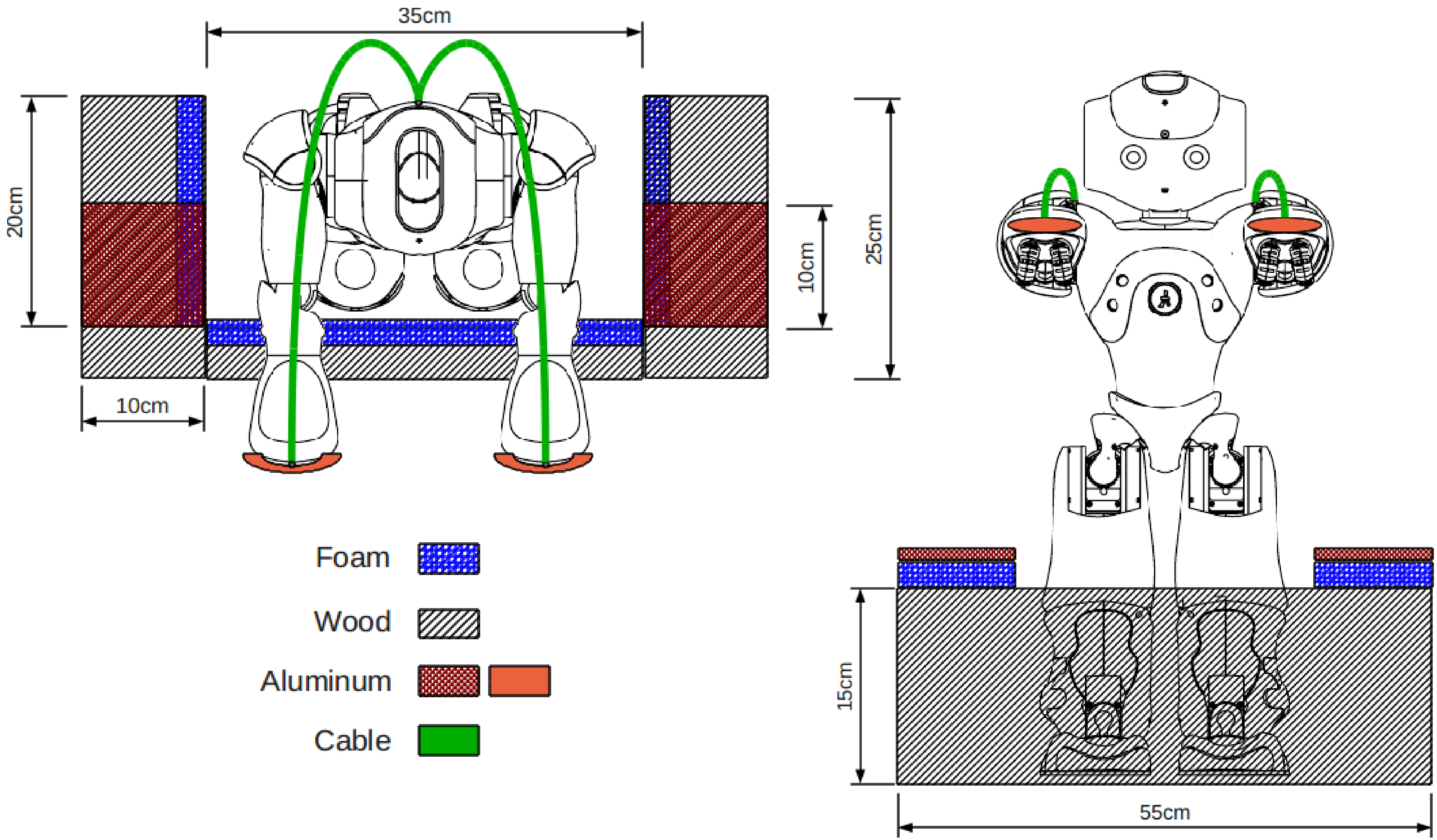

# Analysis of Supervised Reinforcement Learning

Table summarizes avg. # of steps to solve a trial after training (taken over 10 trials)

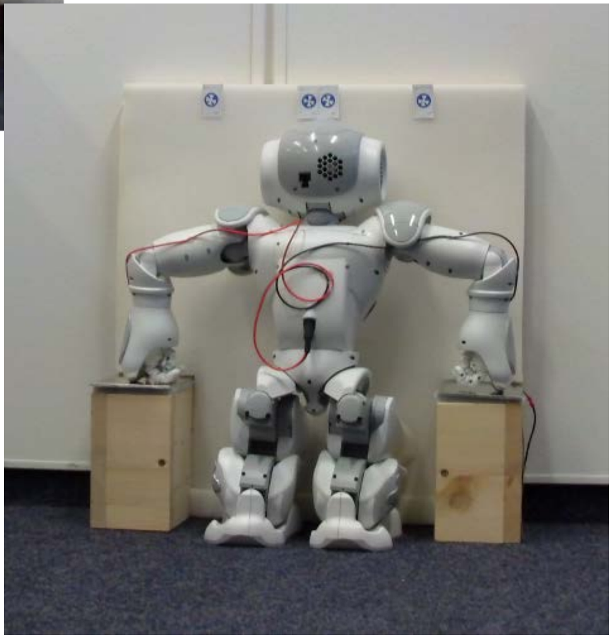
| Tele-operated by User | | | | |
|---|---|---|---|---|
| state activation | Single | | **Gaussian*** | |
| off-line training trials | 180 | 300 | 180 | 300 |
| avg. # of steps | 111.90 | 86.10 | 56.10 | **39.60** |

- 10 training examples generated by user with avg. # of steps = 39.6
- Avg # of steps = 451.26 during random exploration

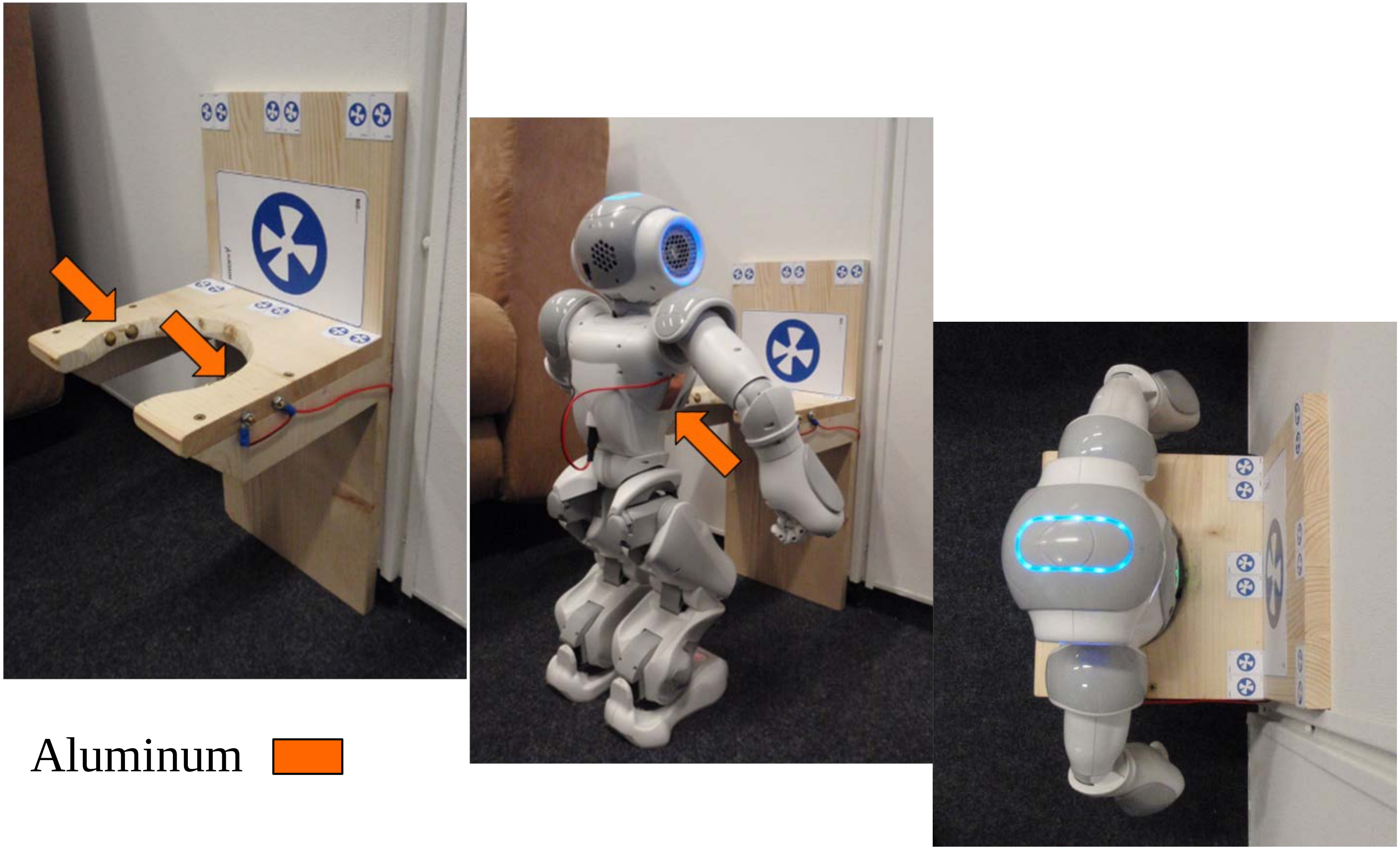
# Towards a solution: First prototype



# Towards a solution : First prototype

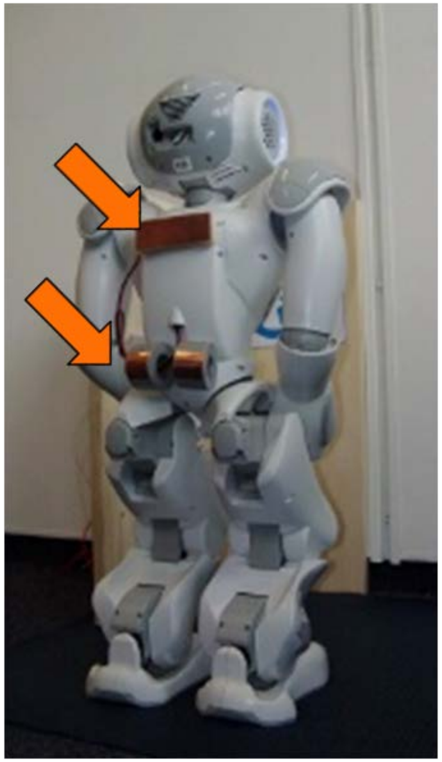


# Towards a solution : Second prototype



Aluminum

# Towards a solution : Third prototype



Aluminum
Landmark

# Towards a solution: Robot behaviour

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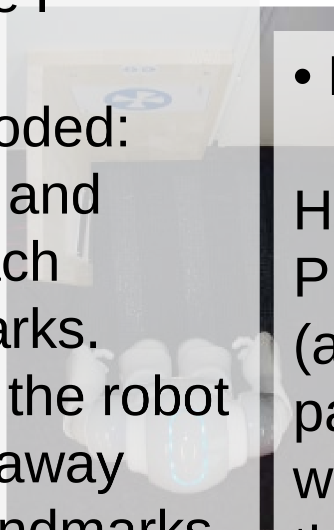
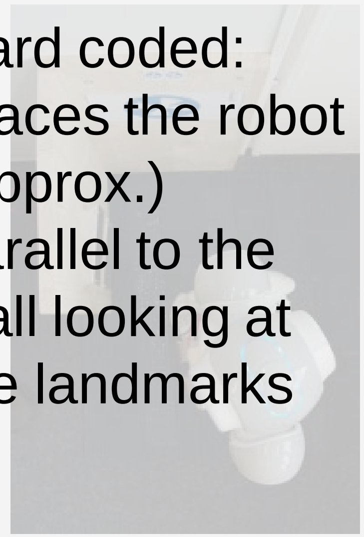
- Phase I



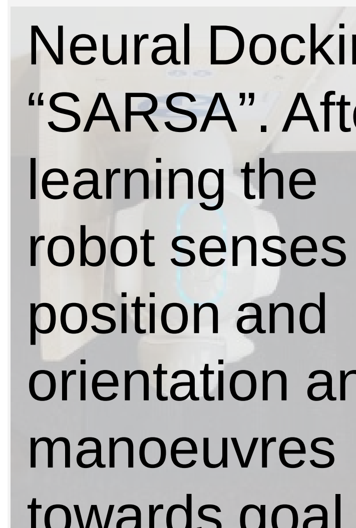
Hard coded: search and approach landmarks. Places the robot 40 cm away from landmarks

- Phase II



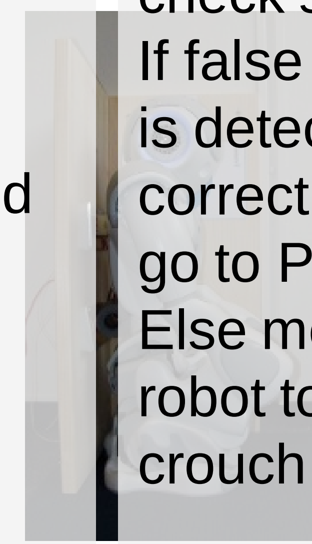
Hard coded: Places the robot (approx.) parallel to the wall looking at the landmarks

- Phase III



Neural Docking: “SARSA”. After learning the robot senses position and orientation and manoeuvres towards goal

- Phase IV



Hard coded: check sensors. If false positive is detected, correct pose or go to Phase III. Else move the robot to a crouch pose

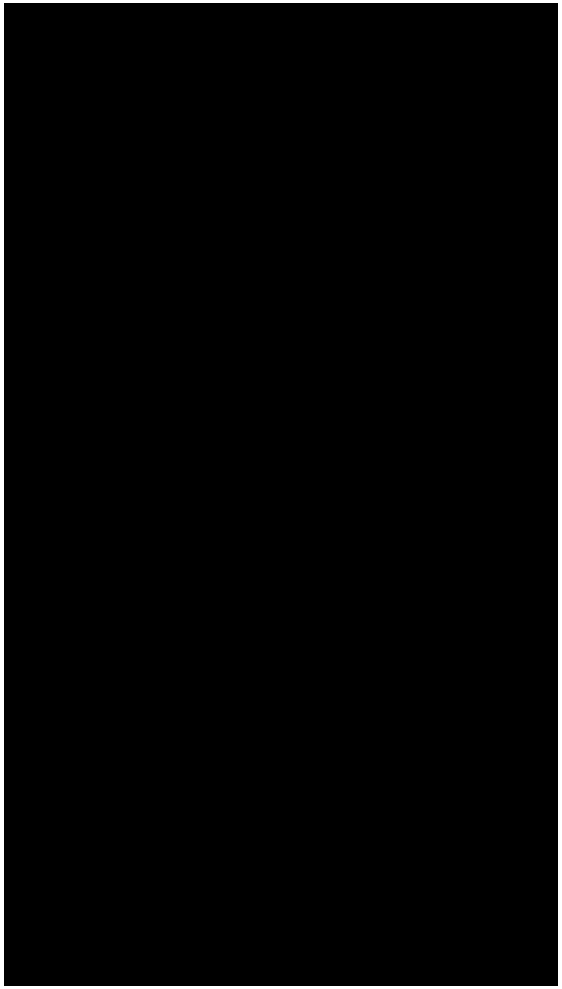
# Experimental results

Table summarizes no steps needed to solve 10 trials after training

| State activation | Action-state pairs learned (%) | # of success | # false positive | # aborted | Avg. # steps on success | Std. Deviation |
|---|---|---|---|---|---|---|
| Single | 4 | **6** | **1** | **3** | 23,80 | 8,23 |
| Gaussian* | 34 | **5** | **3** | **2** | 23,60 | 14,30 |

- Grid world of 11x11x15 = 1,815 states
- 6 actions: forward, backward, m_right, m_left, turn_right, turn_left
- 50 training examples generated by user
- Off-line training: 300 trials

# Demonstration



# Conclusion

- Use of appropriate training examples (“supervised”) proved to be a key factor for real-world learning scenarios.
- Gaussian distributed states activation has a helpful state space reduction effect.

**Thank you for your attention!**

**Any questions?**

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