Parallel DYNA

Real-time model learning RL

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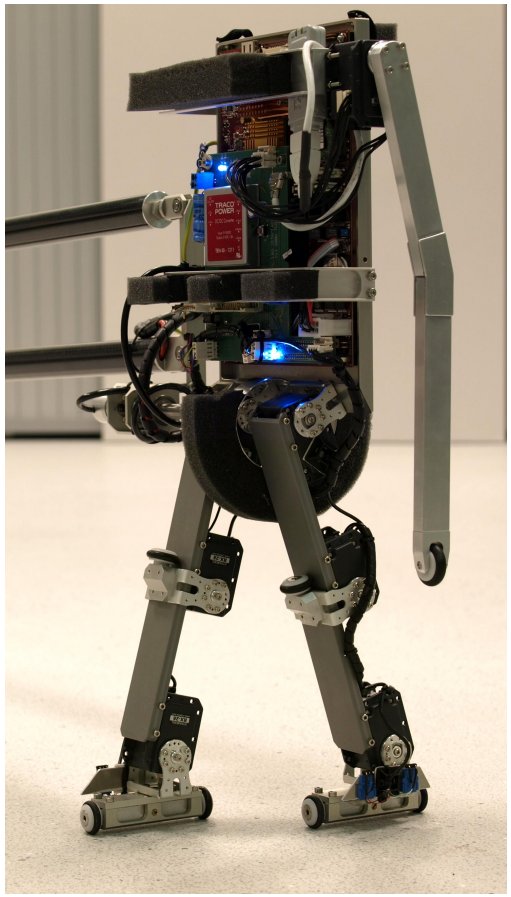
TU Delft

Reinforcement learning for robots

- Sample complexity of traditional RL algorithms is too high
  - Robots break
  - Too slow
- Computational complexity of sample-efficient algorithms is too high
  - System is idle while computing
  - Controlled by outdated control policy

  This may increase total learning time



[Schuitema et al., 2010]

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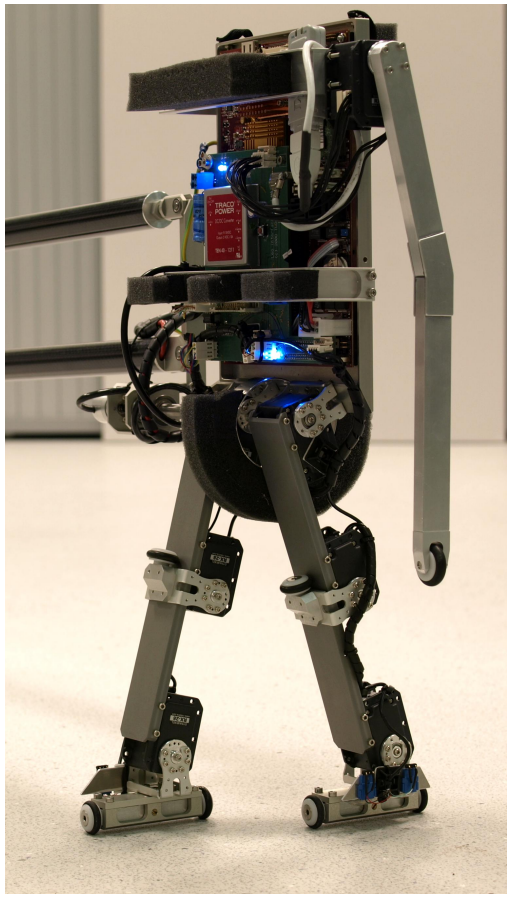

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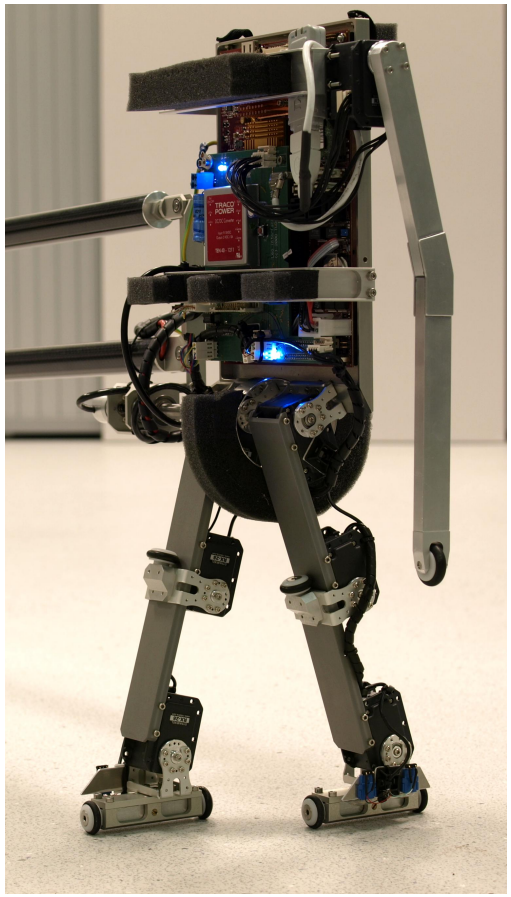

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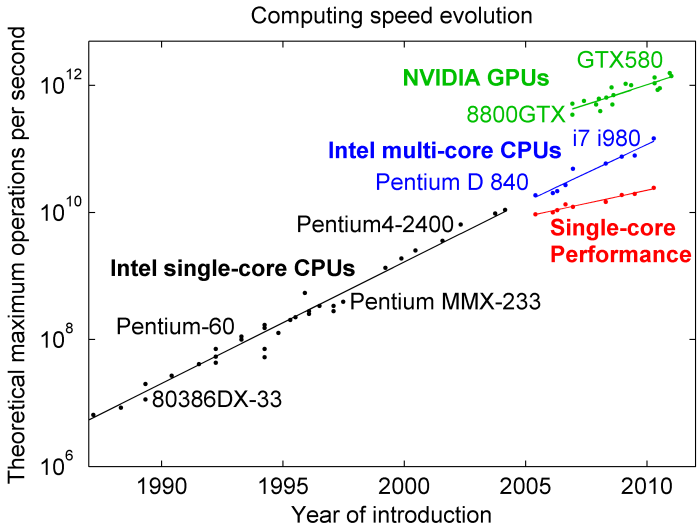
Why parallel reinforcement learning?

- Sequential CPU speed is not increasing to compensate for increased computational complexity
  - Moore's Law is about # of transistors, not clock frequency
  - More transistors can only do so much for single-threaded applications
  - Multi-core is the primary vectory of speed increase



Parallelism is the way to reduce computation time

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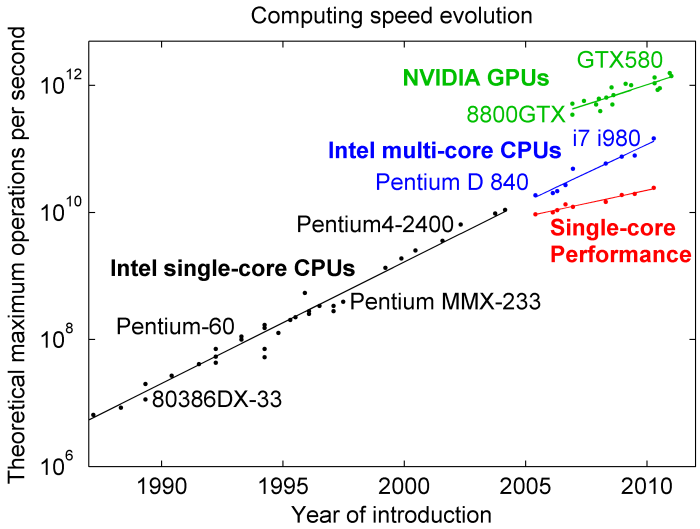

Parallelism is the way to reduce computation time

Outline

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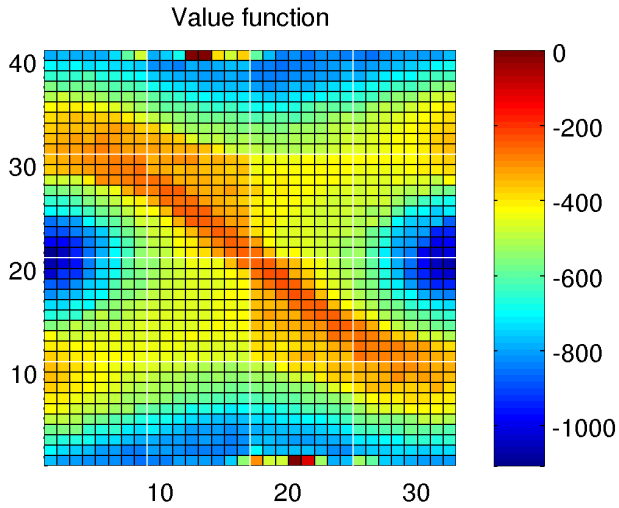
Traditional parallel RL

- State-space decomposition
  - Split up state space
  - Each processor learns in one subdomain
  - Value exchange across borders
- Multiple learners
  - Many agents learning the same task
  - Shared or replicated value function
  - Periodic or prioritized value exchange



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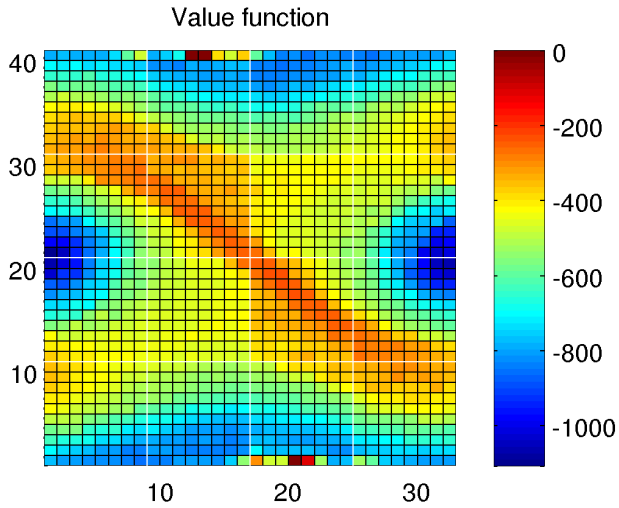
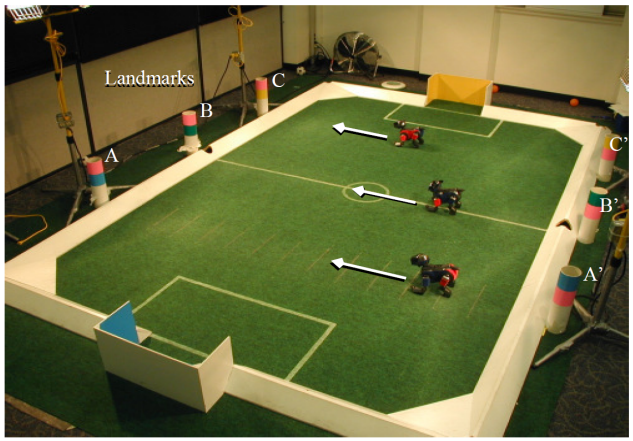


Problems

- Requires multiple systems
  - Robots
    May differ between each other
  - Simulations/models
    Differ from real system
- Limited by control frequency
  - Typically 20-100 Hz on real systems
  - Not a problem with simulations



[Kohl & Stone, 2004]

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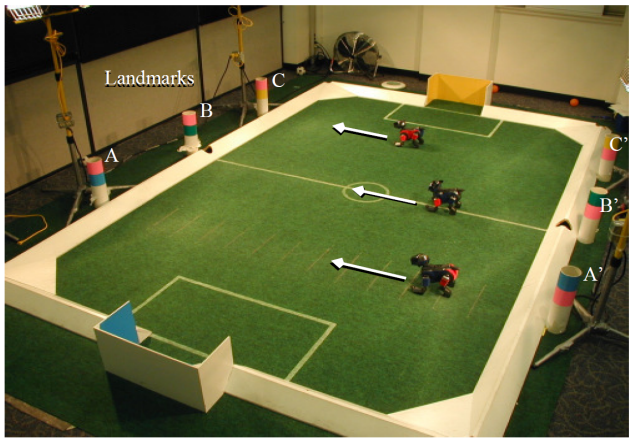

[Kohl & Stone, 2004]

Other approaches

- Model learning
  - Multiple agents reading out single model
  - Model readout is faster than control frequency
- Experience replay
- Parallelization of function approximator
  - ANN
  - LSTD-Q
- Learning multiple tasks
  - Horde architecture

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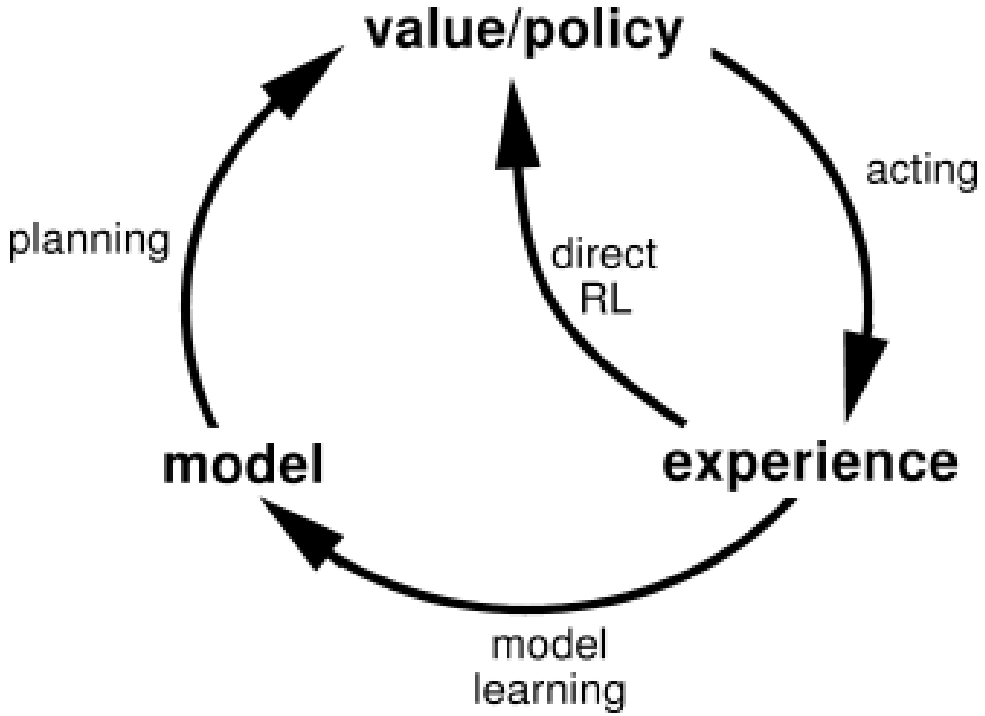
DYNA architecture



[Sutton & Barto, 1998]

Options

- Model approximator
  - Grid of state transition probabilities
  - Grid of feature transition probabilities
  - ANN, LWR, GP, etc.
- Value approximator
  - Tile coding
  - Basis functions
  - ANN, LWR, etc.
- Choice of model updates
  - Random
  - Trajectories (from current state)
  - Prioritized sweeping
- Updates per control step (K)

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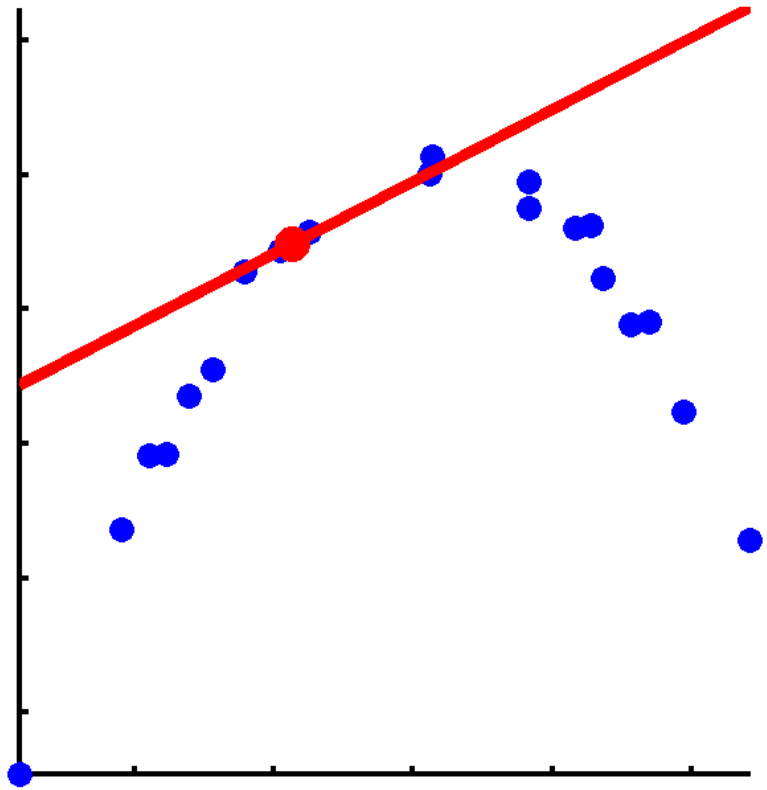
Locally weighted regression

- Find k nearest neighbors
  - Approximate nearest neighbor search
- Weigh according to distance

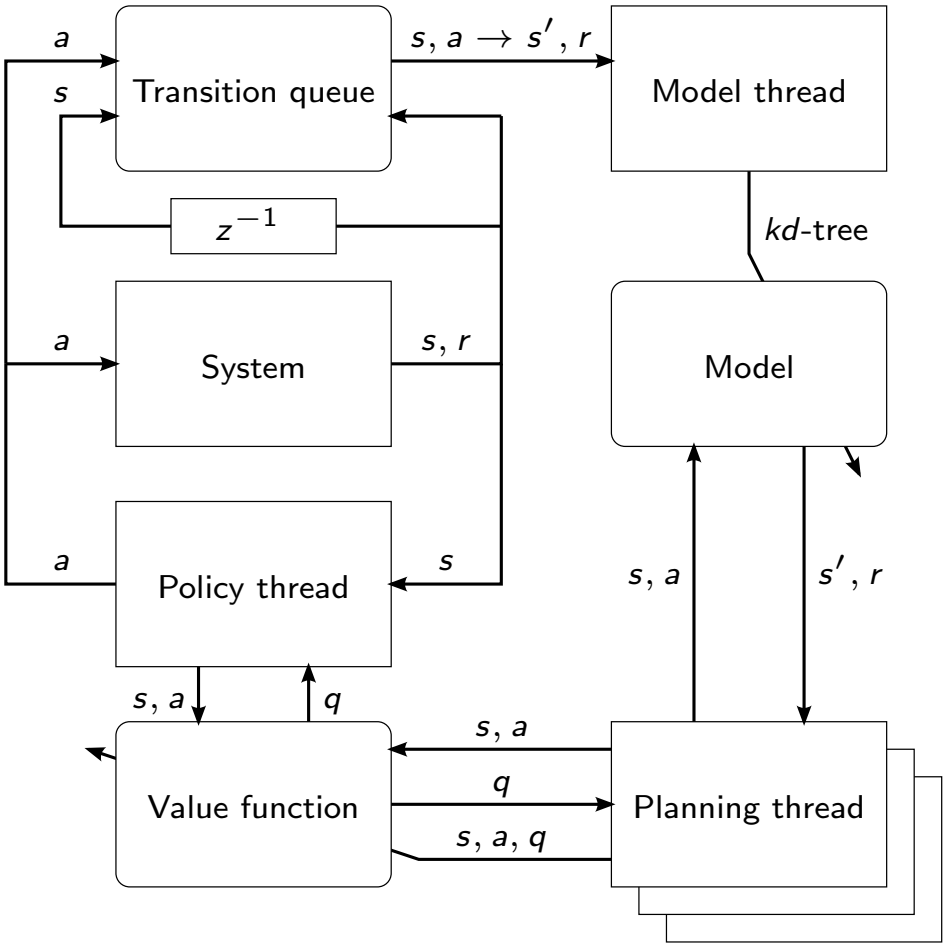
$$w(p) = e^{-\left(\frac{|p-q|_2}{h}\right)^2}$$

where h is the distance to the kth nearest neighbor

- Fit linear model using least-squares regression



Parallel DYNA



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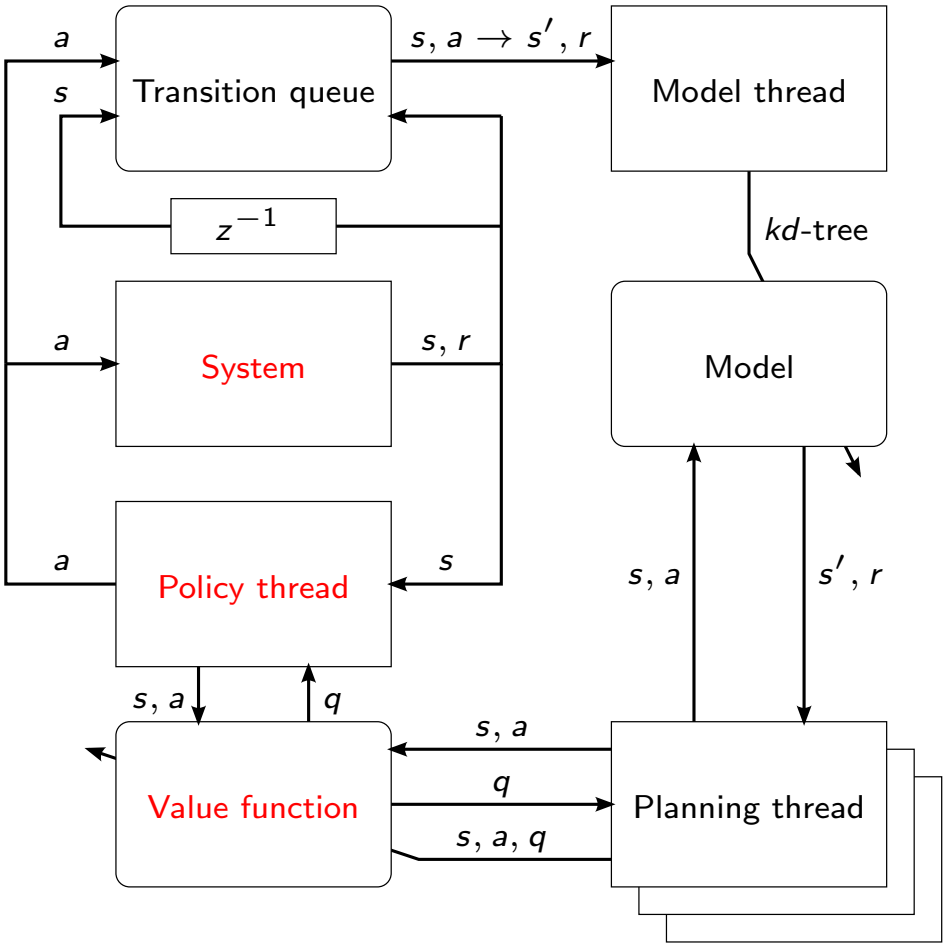

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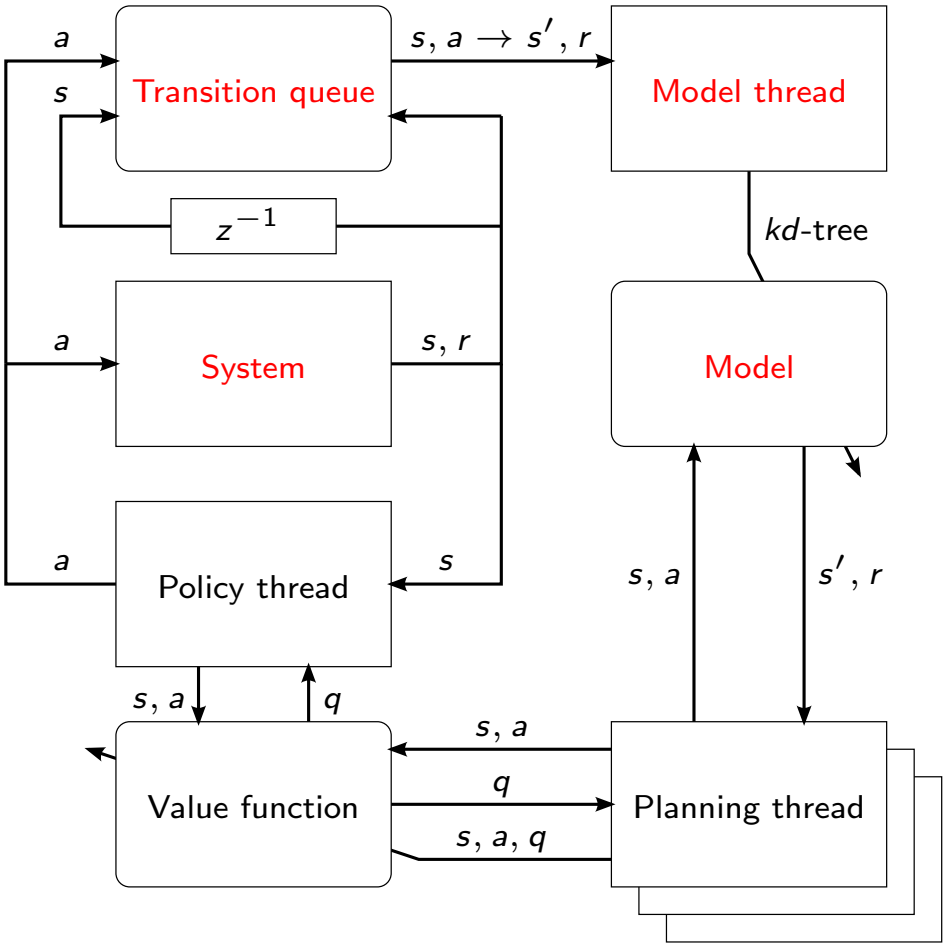

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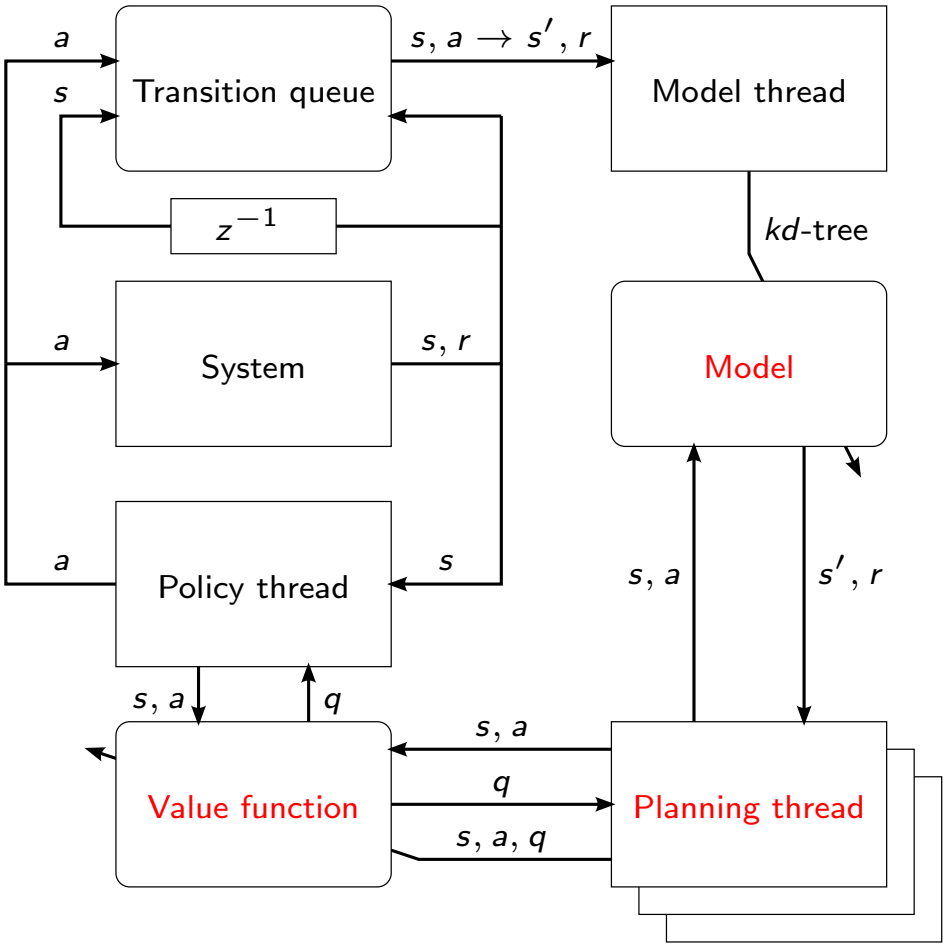
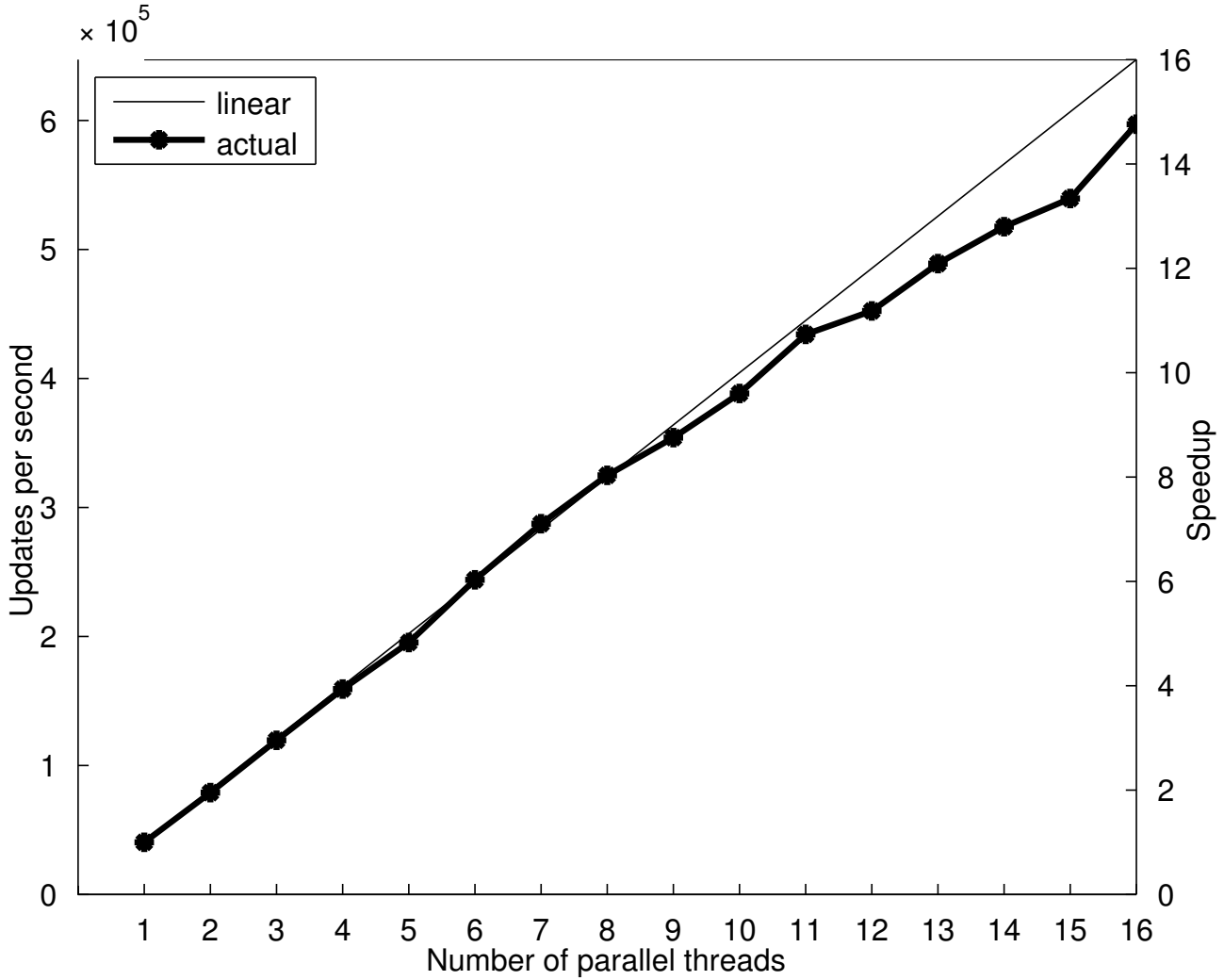
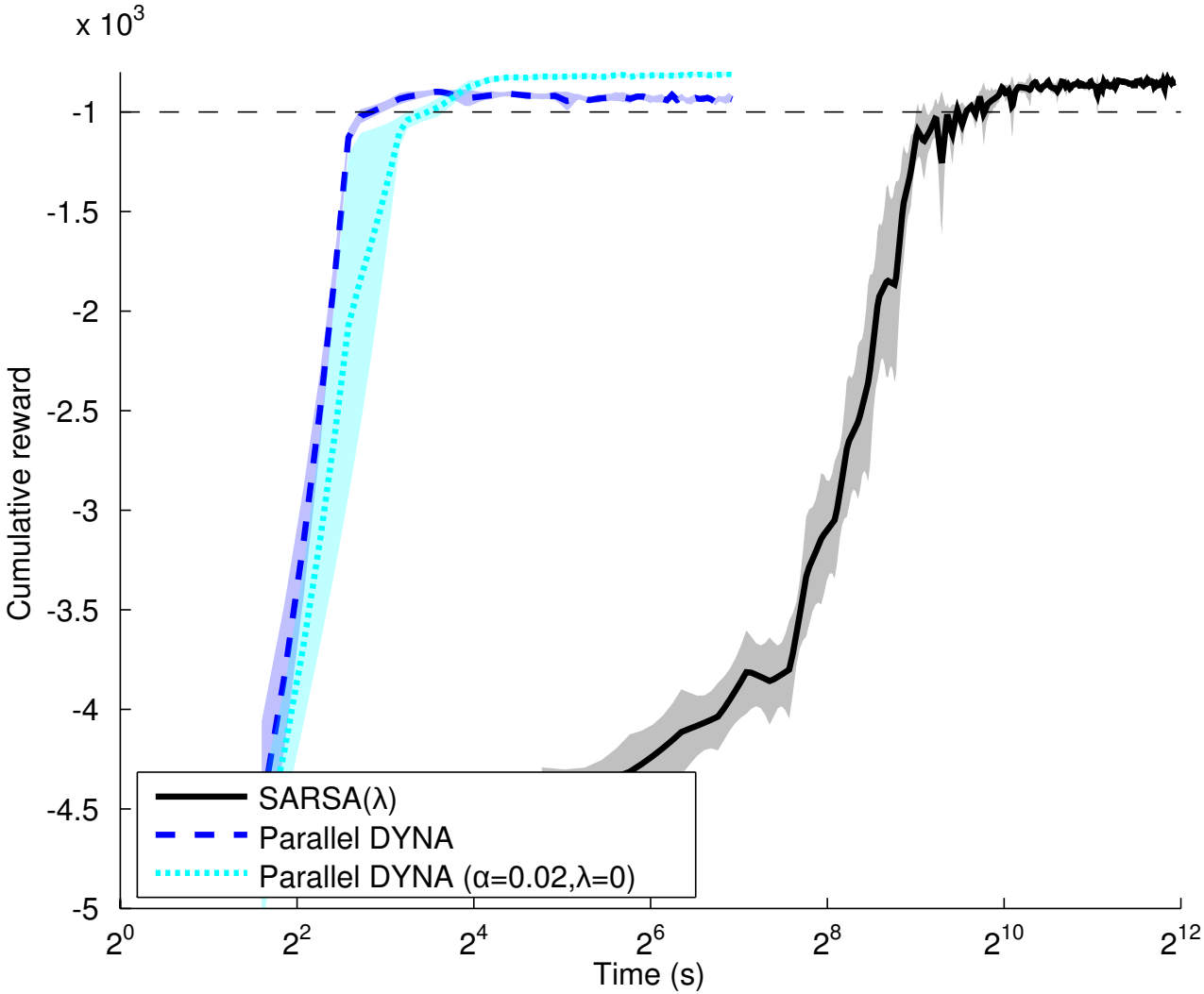


Outline

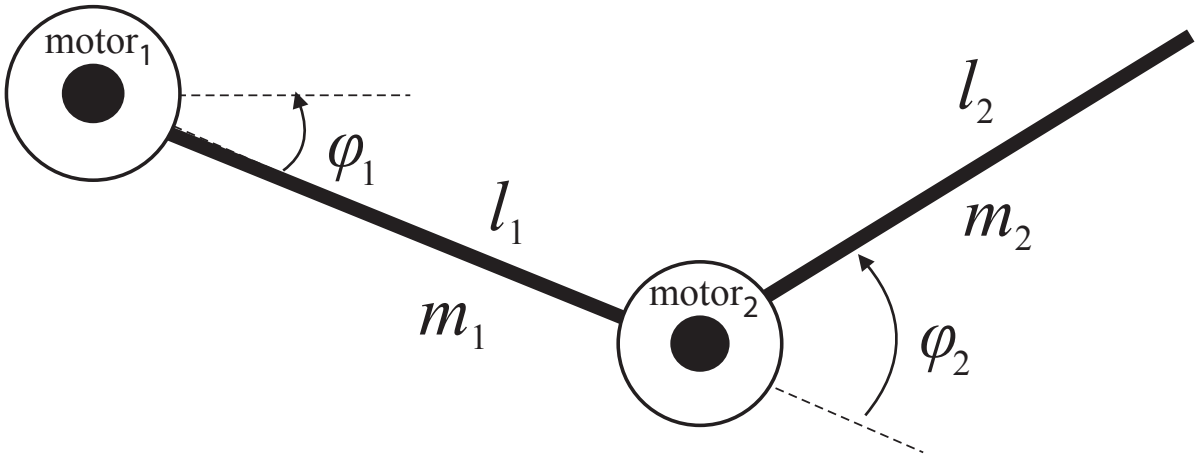
Computational efficiency



Inverted pendulum



Two-link manipulator



- Reward $-5\phi_1^2 - 0.05\dot{\phi}_1^2 - 5\phi_2^2 - 0.05\dot{\phi}_2^2$
- 4 state dimensions, 2 action dimensions, tile coding
- 3 discretized actions per dimension

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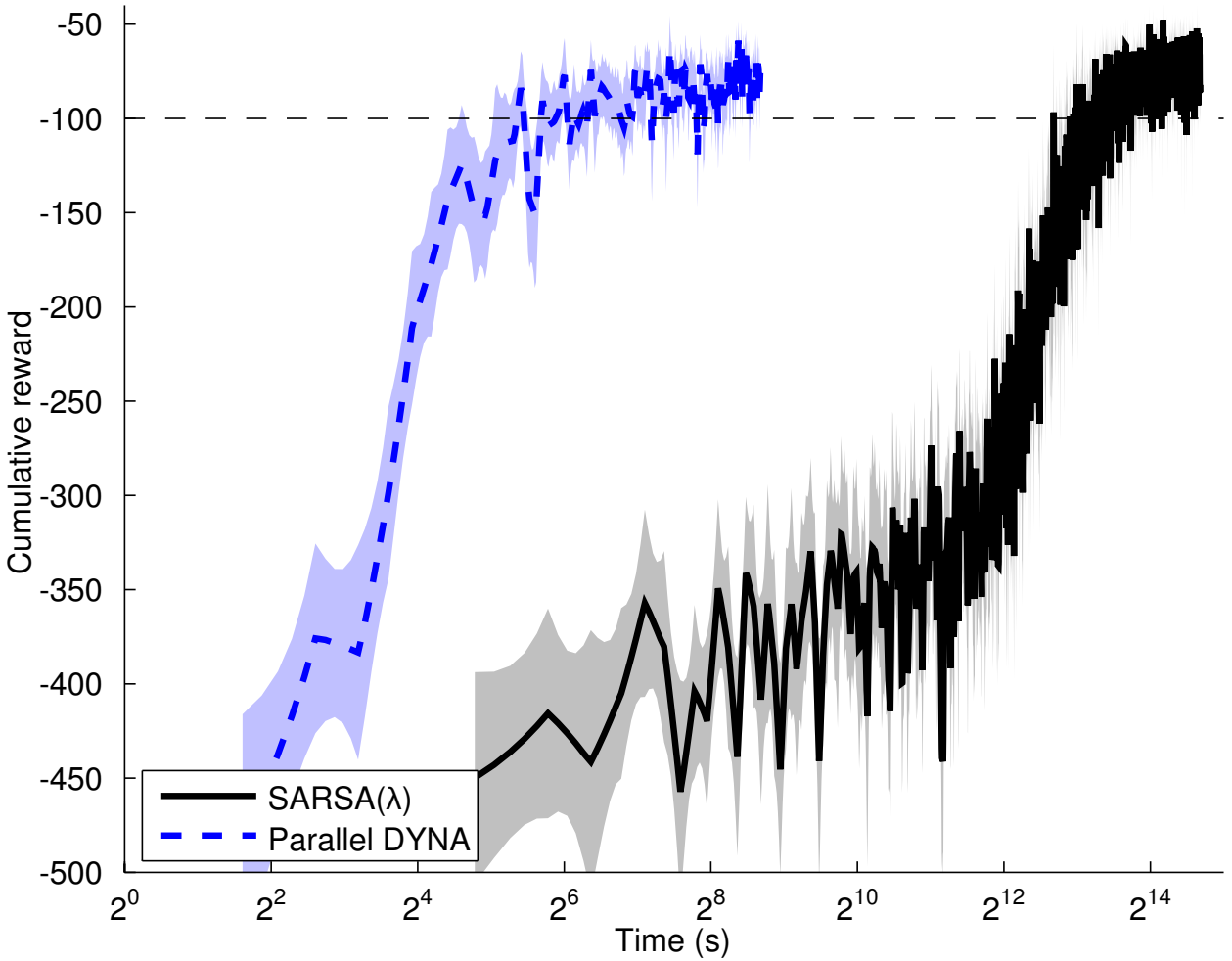
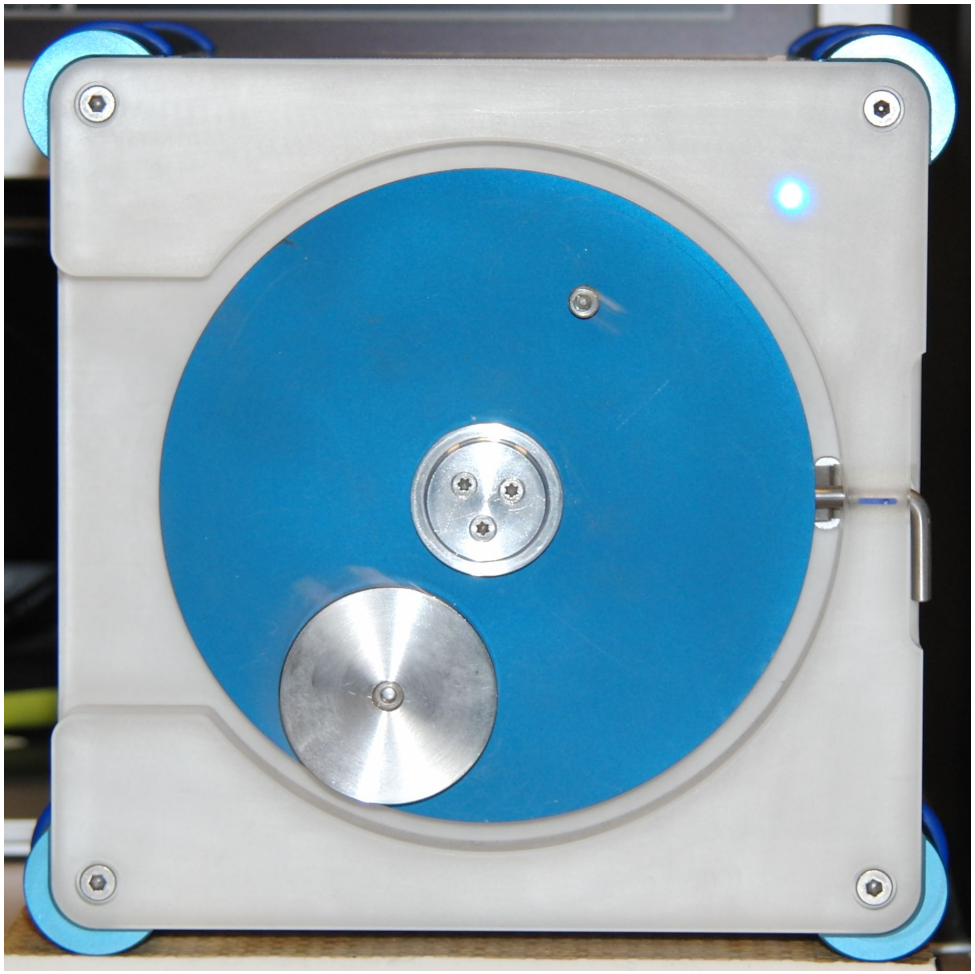
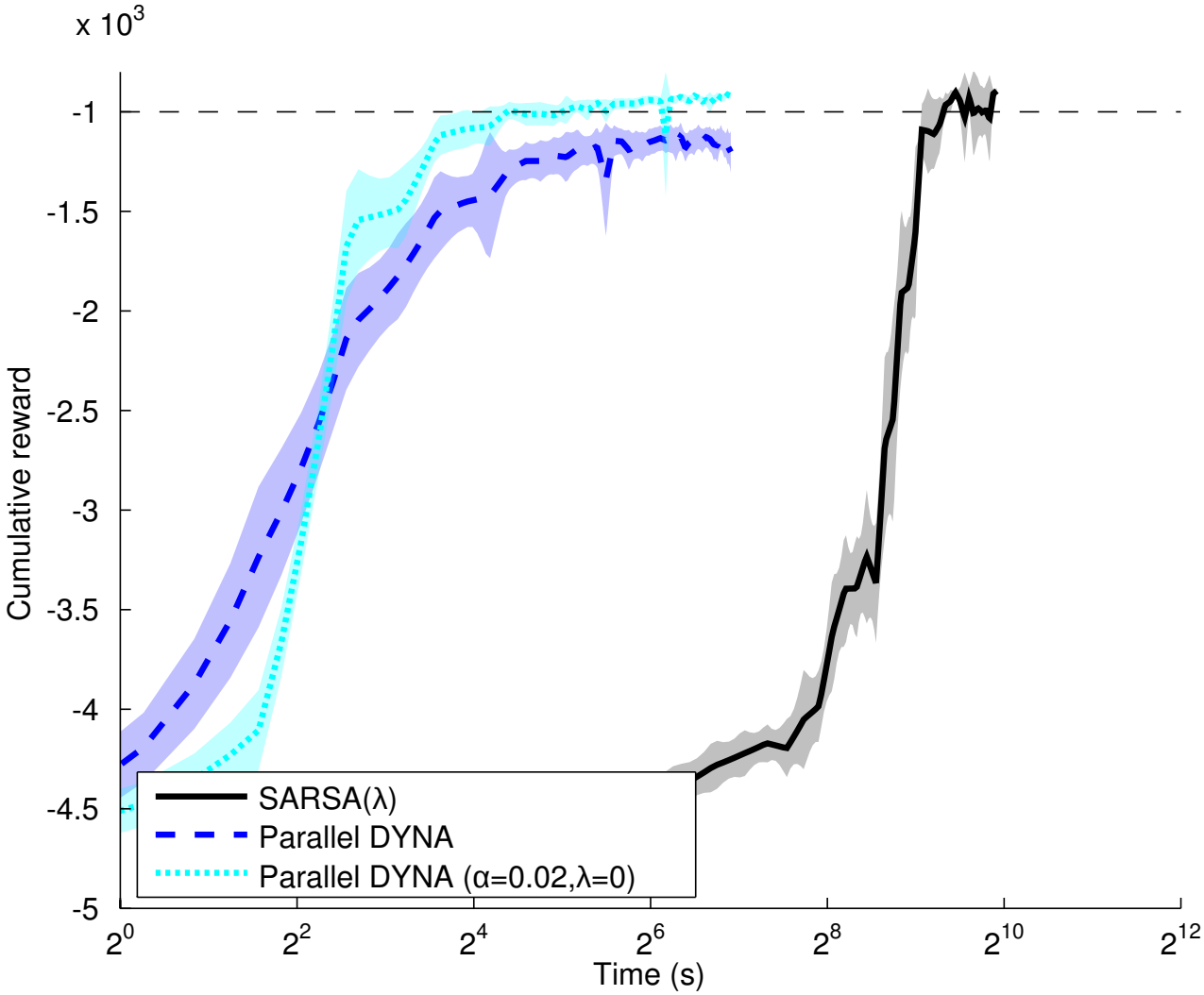


Real-world pendulum

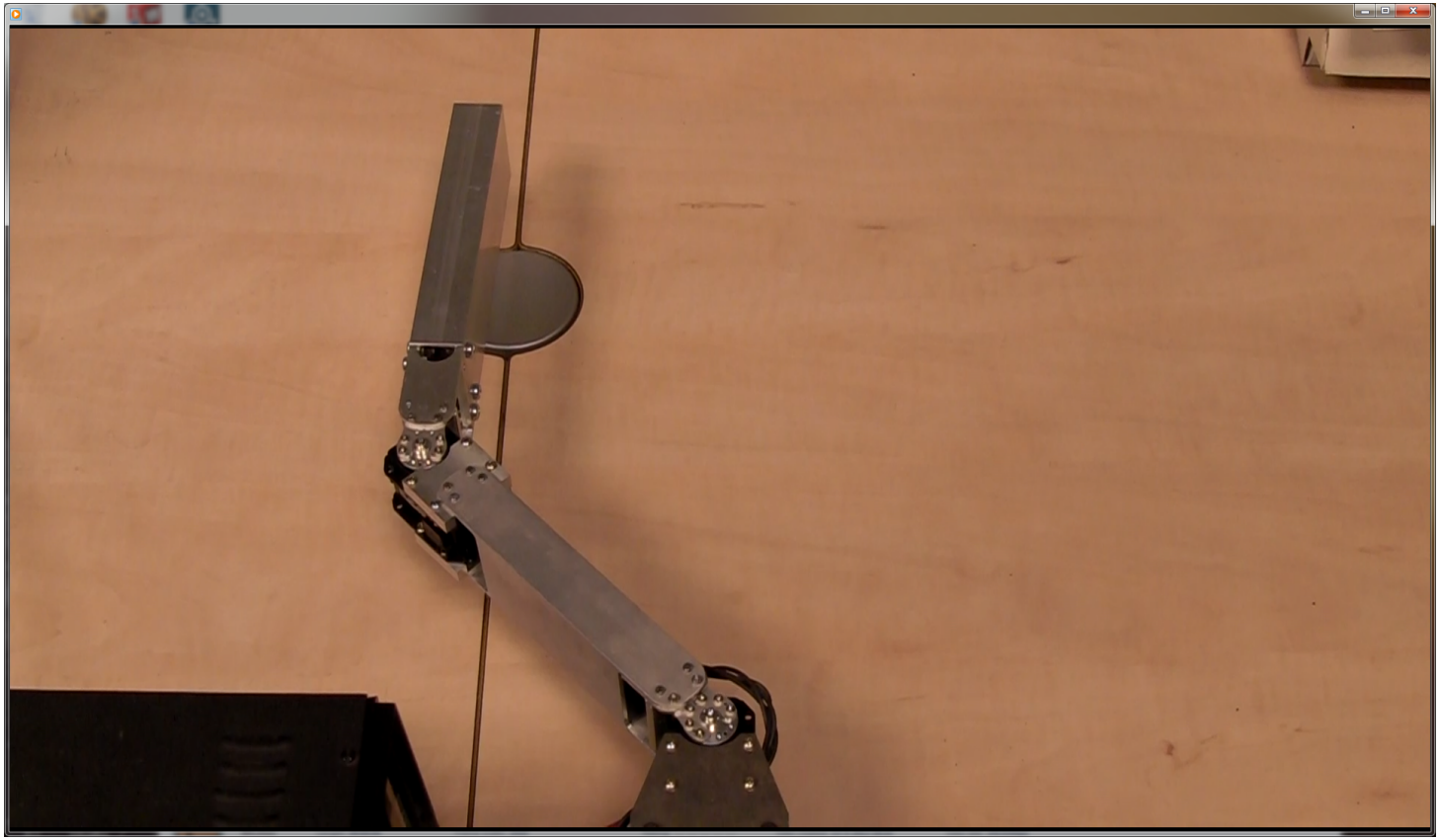


DCSC DC Motor Setup

Real-world pendulum

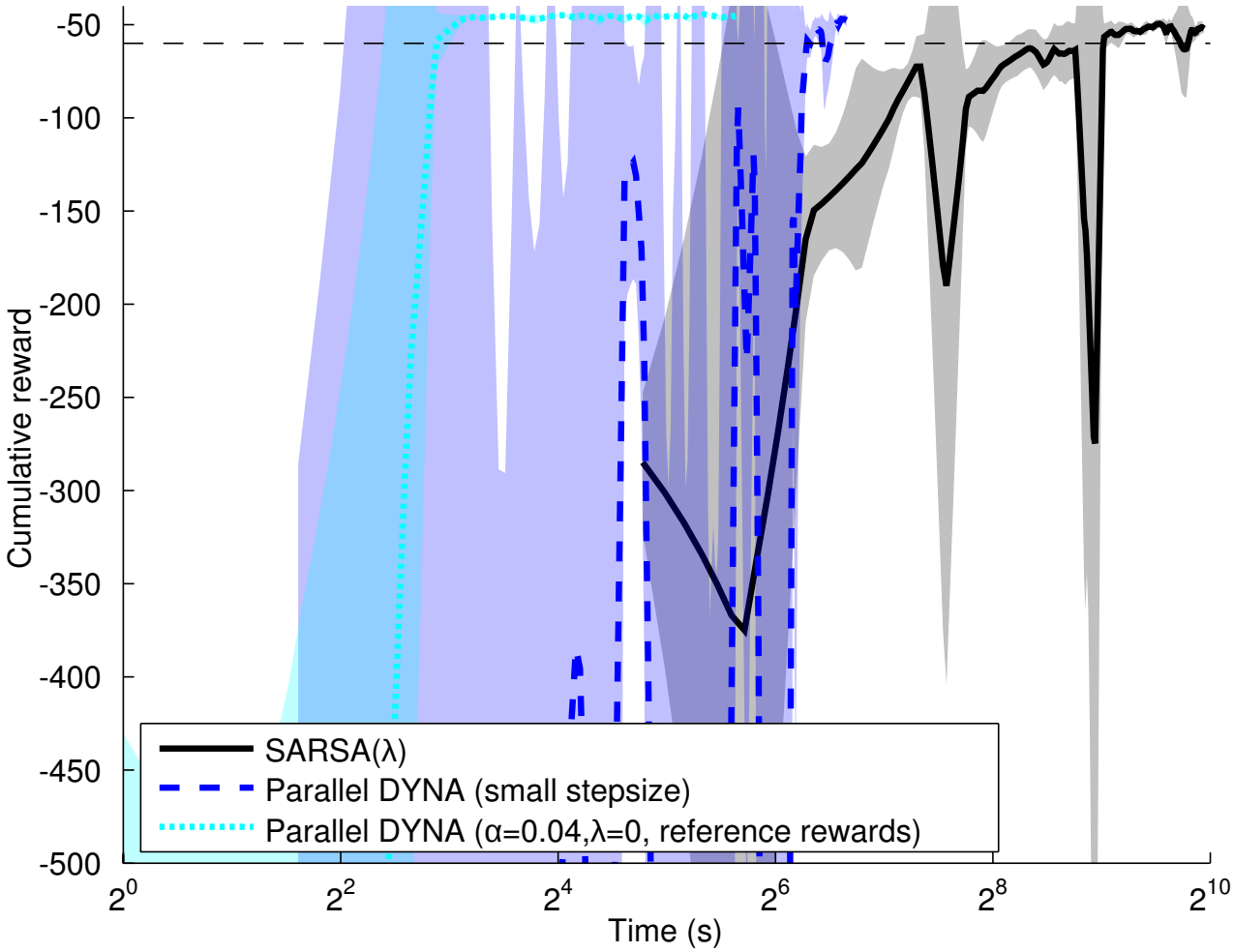


Real-world pick and place



- 2 Dynamixel RX-28 servos
- Move from pick to place

Real-world pick and place



Movie

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Summary

- RL on robots requires reduced sample complexity without increasing computation time.
- Moore's Law won't speed up our algorithms anymore unless they are parallel.
- Traditional parallel reinforcement learning won't work on robots, because we have only one system and it is limited by the control frequency.
- Model learning (parallel DYNA) solves this problem, leading to significant speedups.

The bottleneck is now model learning speed.

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Experimental data

Task	Setting	Rise time (s)	Perf	Speedup
Pendulum (sim)	SARSA(λ)	650	-848	
	PDYNA	9.1	-935	72x
	PDYNA[1]	12.6	-812	52x
Pendulum (real)	SARSA(λ)	561	-1027	
	PDYNA		-1153	
	PDYNA[1]	28.1	-932	20x
Manipulator (sim)	SARSA(λ)	4521	-76	
	PDYNA	41.8	-81	108x
Manipulator (real)	SARSA(λ)	417	-55	
	PDYNA[1]	73.9	-57	6x
	PDYNA[12]	6.9	-45	60x

[1]Decreased learning rate, no eligibility traces [2]Using reference model for rewards