# Parallel Real-Time Reinforcement Learning

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# Why real-time reinforcement learning?

## Use real system dynamics

- No model
- Low fidelity simulation

## Characteristics

- Execute learned policy on real system
  - (short) Action selection deadlines
- Update policy while executing
  - Only soft deadlines, but learning is slow if policy changes slowly

Both require fast computation.

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# Outline

1. Computation
   - Complexity
   - Moore's law
   - The many-core era
2. Parallel reinforcement learning
   - Environment
   - Updates
   - Model parallelism
3. Preliminary results
   - Model learning
   - Value function decomposition
4. Summary

# Outline

# Complexity of reinforcement learning

- Sample complexity
  - Time
    - Real time
    - Expensive simulation
  - Damage, hard to set initial condition, etc.
- Computational complexity
  - (batch) Updates
  - Model (construction, readout)

Samples are scarce, but computation is abundant. Data-efficient algorithms trade off sample complexity for computational complexity.

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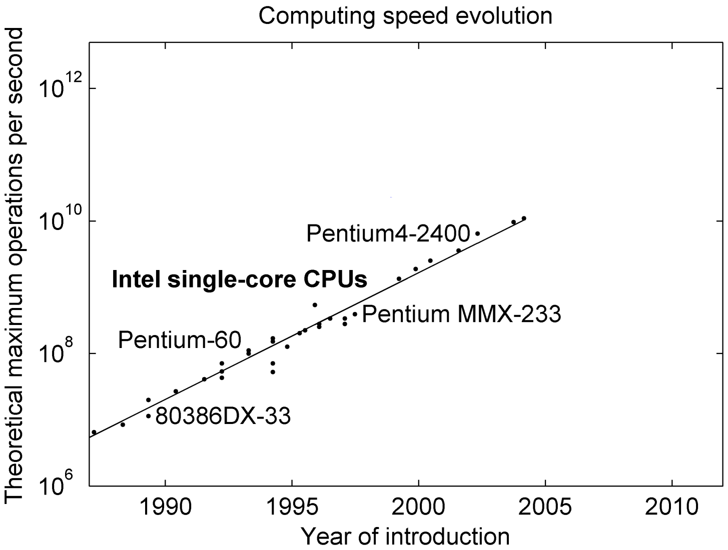
# Moore's law


Computing speed evolution
Theoretical maximum operations per second
$10^{12}$
$10^{10}$
$10^{8}$
$10^{6}$
1990
1995
2000
2005
2010
Year of introduction
Intel single-core CPUs
Pentium4-2400
Pentium MMX-233
Pentium-60
80386DX-33

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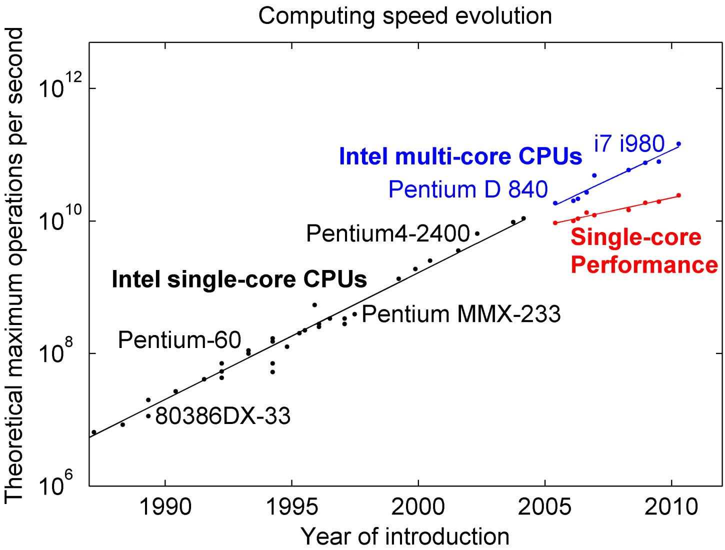
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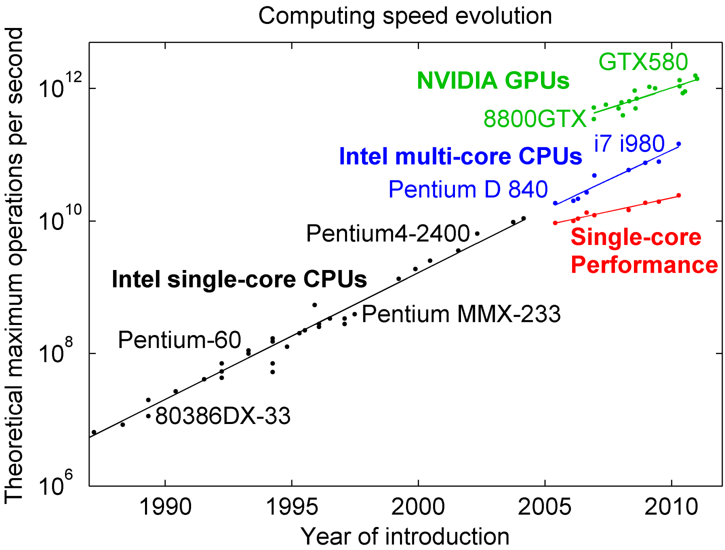
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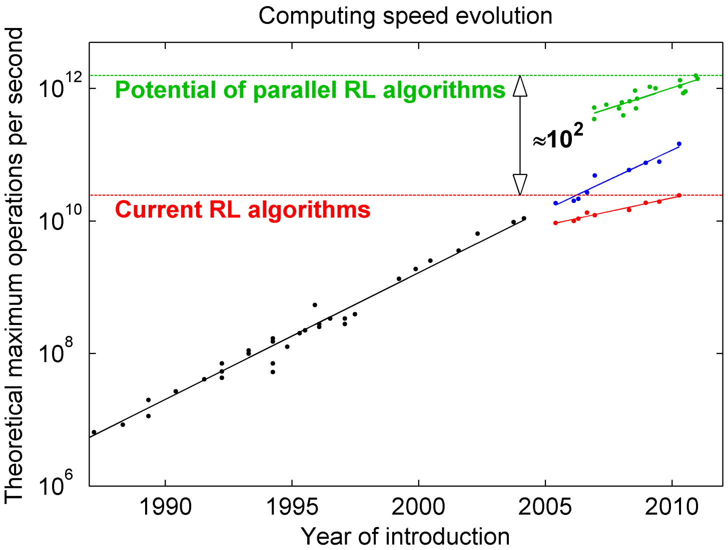
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Potential of parallel RL algorithms
≈$10^2$
Current RL algorithms
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# Abundance of computation

Moore's law no longer speeds up sequential processes. In order to take advantage of the abundance of computation, algorithms must be parallel. Massively parallel.

# Many-core architectures

- Computation
  - Hundreds to thousands of processors
  - Individually less capable
  - Partial SIMD
- Data access
  - Not significantly more memory than single processors
  - Distributed
  - Non-local access has high latency
- Sequential operation count is a poor predictor for performance
  - $O(n^2)$ may be faster at $n = 1000$ than $O(n)$

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# Parallelism in the environment

- Multiple systems
  - Evolutionary robotics
  - Single value function
  - Multiple value functions with exchange
- Concurrent simulation
  - Integrate heterogeneous updates
- Parallel simulation
  - GPU physics acceleration


Figure: Kohl and Stone, 2004.

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# Parallel updates

- Single value function
  - Domain decomposition
  - Needs multiple update sources
    - Experience replay
    - Multiple systems
    - Model
- Multiple value functions
  - Learn different things
- Batch
  - Parallel backpropagation
  - Parallel LSPI

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# Parallel model readout

Depending on the model, construction or readout can be parallel.

Locally linear regression

- Find k nearest neighbors
- Fit linear least-squares model

Both can be efficiently parallelized on GPUs.

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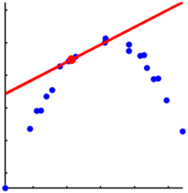

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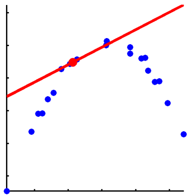

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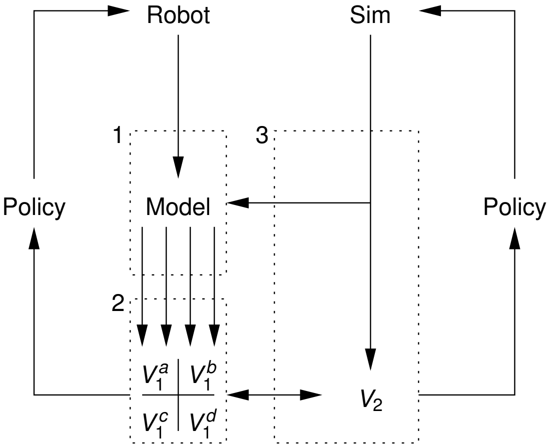
# Global scheme



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# Model learning

- Learn a model from interactions with the real world
- Use computational abundance to perform many model updates
  - Random
  - Prioritized sweeping
  - Sequential (imitate real trials)
- Direct updates become insignificant

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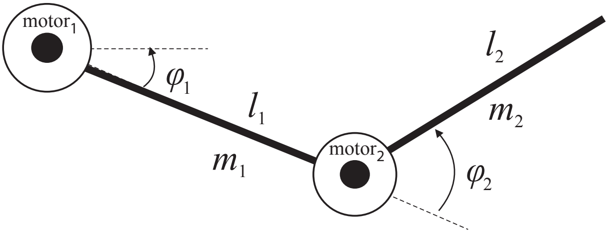
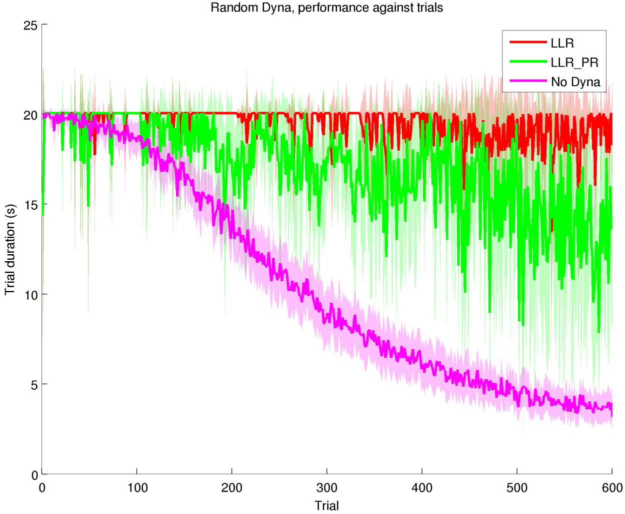
# Two-link manipulator

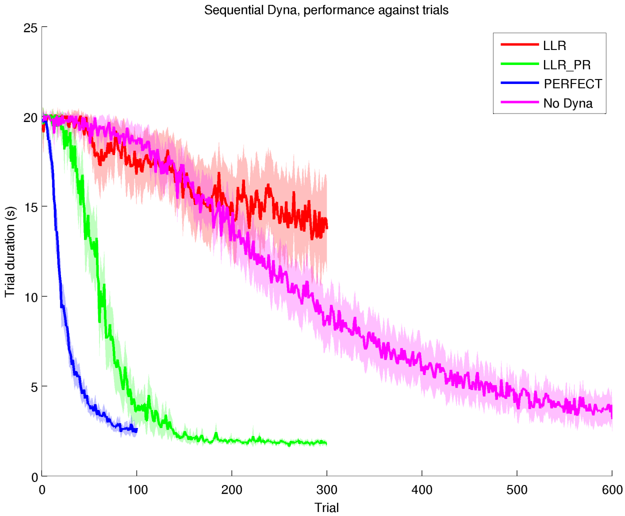



- Reward & termination when $\phi_1 = \phi_2 = \dot{\phi}_1 = \dot{\phi}_2 = 0$
- Constant time penalty
- 4 state dimensions, 2 action dimensions, tile coding
- 5 discretized actions per dimension
- SARSA

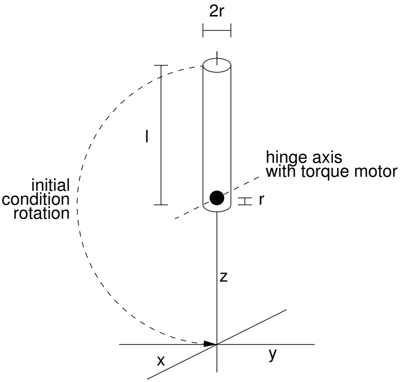
# Random dyna, n=10000

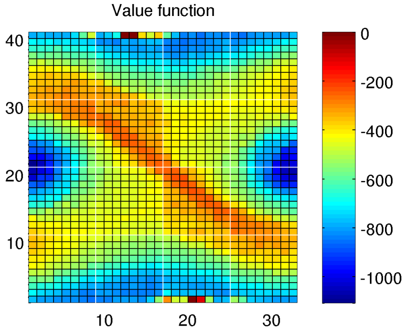


# Sequential dyna, n=10000

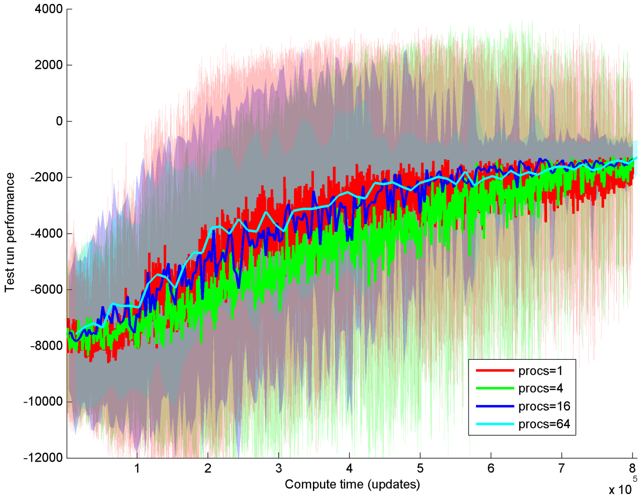


# Pendulum swing-up

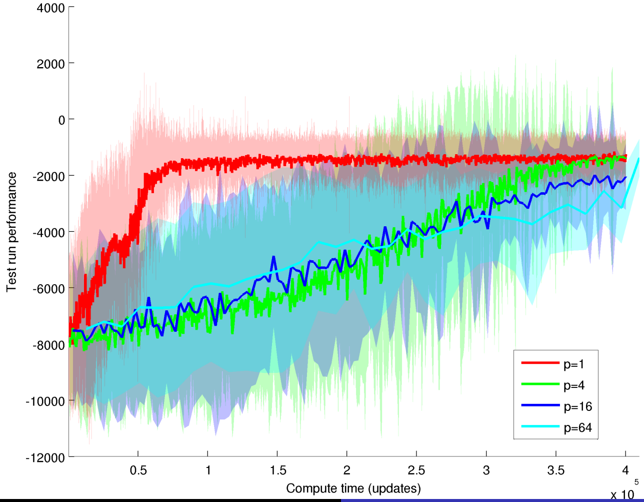


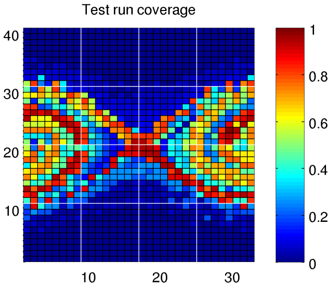
# Performance

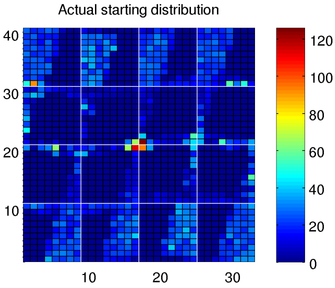


# Real-world performance

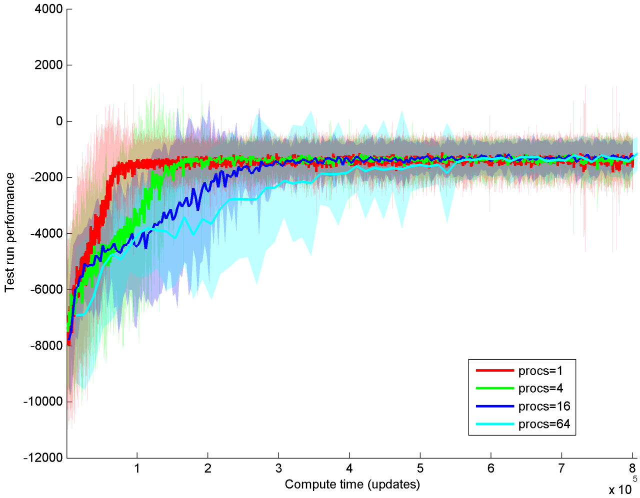


# Starting state distribution



# Testrun-guided starting states



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# Summary

- Moore's Law won't speed up our algorithms anymore unless they are parallel. Parallelism can be employed at many levels, but must do effective work. Conventional computational complexity is losing validity.
- Outlook
  - Find parallelism in current algorithms.
  - Design new algorithms with parallelism in mind.